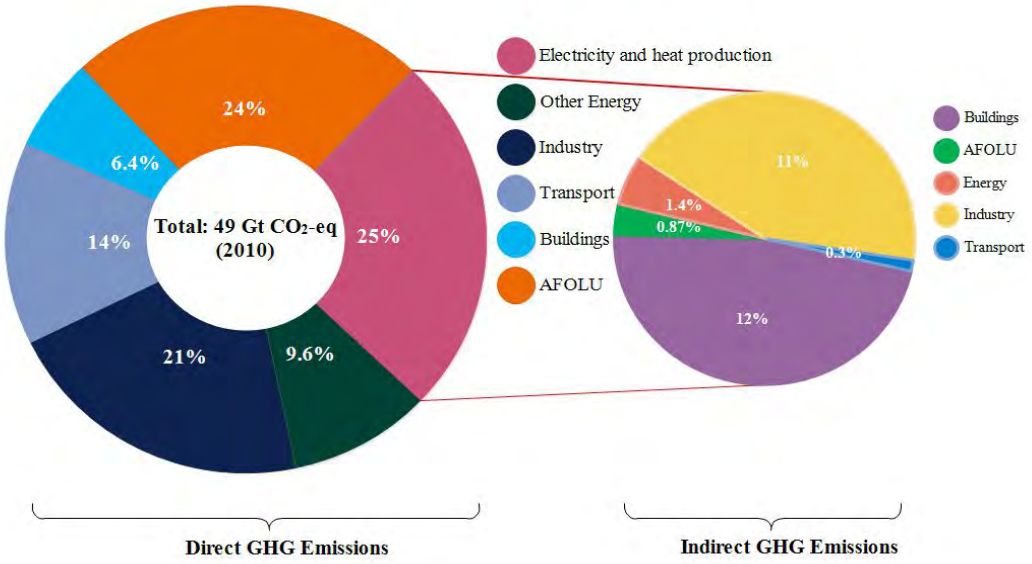
Assessing the Drivers, Policies and Measures that Affect Greenhouse Gas Emissions: An Econometric Analysis



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MACQUARIE University

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Cover photo:

Breakdown of Greenhouse gas emissions by Trade and Industrial Sectors, Adapted from IPCC 5th Assessment Report

This doctoral thesis is dedicated to my wife, Phebe Asantewaa Owusu and my son, Supernatural Emmanuel Asumadu-Sarkodie.

Acknowledgement

I will bless the Lord at all times; his praise shall continually be in my mouth. My soul makes its boast in the Lord; let the afflicted hear and be glad. O magnify the Lord with me, and let us exalt his name together! I sought the Lord, and he answered me, and delivered me from all my fears (Psalm 34:1-4 RSV).

This journey would not have been easy without the collective effort of the following individuals who played a major role in this success story.

Appreciation goes to Macquarie University, Australia for funding my Ph.D. through the International Macquarie University Research Training Program (iMQRTP) Scholarship.

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I cannot forget my colleagues namely Israel Doyi, Eva Tabuaa Gyamfi, Michael Ackah, Ernest Frimpong Asamoah, Haftom Weldekidan, and among others at the Environmental Science department, who contributed immensely to my emotional stability — As written in the Holy Bible: A cheerful heart is good medicine, but a broken spirit saps a person's strength (Proverbs 17:22 NLT).

Finally, gratitude goes to my wife, Phebe Asantewaa Owusu, my son, Supernatural Emmanuel Asumadu-Sarkodie, and the Asumadu-Sarkodie family, who have been a backbone throughout my academic life.

To everything there is a season, and a time for every matter or purpose under heaven (Ecclesiastes 3:1 AMP).

Declaration

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Samuel Asumadu-Sarkodie

March 2019

Abstract

As a contribution to the global debate on mitigating climate change and its impacts, this thesis examined the drivers of greenhouse gas emissions using an econometric approach. The investigation of the nexus between environmental pollution economic growth in Africa confirms the validity of the EKC hypothesis in Africa at a turning point of US$ 5,702 GDP per capita. However, the nexus between environmental degradation and economic growth reveals a U shape at a lower bound GDP of US$ 101/capita and upper bound GDP of US$ 8,050/capita, at a turning point of US$ 7,958 GDP per capita, confirming the scale effect hypothesis. The empirical findings revealed that energy consumption, food production, economic growth, permanent crop, agricultural land, environmental pollution, birth rate, and fertility rate play a major role in environmental degradation and pollution in Africa, thus, supporting the global indicators for achieving the Sustainable Development Goals by 2030.

In accordance with the Sustainable Development Goal 17 of improving global partnership for sustainable development, we examined the effect of foreign direct investment inflows, economic development, and energy consumption on greenhouse gas emissions from 1982-2016 for the top five emitters of greenhouse gas emissions from fuel combustion in the developing countries, namely; China, India, Iran, Indonesia and South Africa. The study employed a panel data regression with Driscoll-Kraay standard errors, Utest estimation approach and panel quantile regression with non-additive fixed-effects. The study found a strong positive effect of energy consumption on greenhouse gas emissions and confirmed the validity of the pollution haven hypothesis. The environmental Kuznets curve hypothesis is valid for China and Indonesia at a turning point of US$ 6,014 and

US$ 2,999; second, a U-shape relationship is valid for India and South Africa at a turning point of US$ 1,476 and US$ 7,573. Foreign direct investment inflows with clean technological transfer and improvement in labor and environmental management practices will help developing countries to achieve the sustainable development goals. Mitigation of greenhouse gas emissions depends on enhanced energy efficiency, adoption of clean and modern energy technologies, such as renewable energy, nuclear, and the utilization of carbon capture and storage for fossil fuel and biomass energy generation processes.

To examine the factors contributing to adverse greenhouse gas emission and economic impacts relative to their development, we examined the EKC and Environmental Sustainability curve hypotheses for Australia, China, Ghana and the USA from 1971-2013. The study revealed that a decline of carbon dioxide emissions in developed countries can be attributed to a paradigm shift and structural change from high-energy intensive and carbon-intensive industries to services and information-intensive industries. The increasing levels of carbon dioxide emissions in developing and least developing countries can be attributed to the economy driven agriculture, transport, and services. Environmental policies and regulations in developing and least developing countries are weaker compared to developed countries, as such, they become a haven for high-energy and carbon-intensive industries. The high awareness of environmental sustainability, technological advancement, stringent environmental regulations and policies in developed countries result in a decline in energy intensity and a decline in carbon dioxide emissions. The Environmental Sustainability Curve hypothesis shows that the affecting factors include economic growth, energy consumption patterns and carbon dioxide

emissions. The study reveals electric power consumption as the main contributor of energy intensity in the selected countries. Decoupling economic growth from electric power consumption and improving energy efficiency in China, Ghana, Australia, and the USA will enhance energy security and decline the economic related dynamics and activities on the environment.

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Author Contribution

Chapter One: A Review on Environmental Kuznets Curve Hypothesis Using Bibliometric and Meta-Analysis.

Sarkodie, S.A., Strezov, V., 2019. A review on Environmental Kuznets Curve hypothesis using bibliometric and meta-analysis. *Science of The Total Environment* 649, 128-145

Sarkodie, S.A. contributed 80%, while Strezov, V. contributed 20% of the publication. Sarkodie, S.A. developed the conceptual framework, the econometric model and writing the article. Strezov, V. supported the development of the conceptual framework, editing and reviewing of the manuscript.

Chapter Two: The Invisible Hand and EKC Hypothesis: What Are the Drivers of Environmental Degradation and Pollution In Africa?

Sarkodie, S.A., 2018. The Invisible Hand and EKC Hypothesis: What Are the Drivers of Environmental Degradation and Pollution In Africa? *Environmental Science and Pollution Research* 25, 21993–22022.

Sarkodie, S.A. contributed 100% of the publication, by developing the conceptual framework, the econometric model and writing the entire article.

Chapter Three: Effect of foreign direct investments, economic development, and energy consumption on greenhouse gas emissions in developing countries.

Sarkodie, S.A., Strezov, V., 2019. Effect of foreign direct investments, economic development, and energy consumption on greenhouse gas emissions in developing countries. *Science of The Total Environment* 646, 862-871.

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Chapter Four: Empirical study of the Environmental Kuznets curve and Environmental Sustainability curve hypothesis for Australia, China, Ghana, and USA.

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Chapter Five: Assessment of contribution of Australia's energy production to CO_2 emissions and environmental degradation using statistical dynamic approach.

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the article. Strezov, V. supported the development of the conceptual framework, editing and reviewing of the manuscript.

Chapter Six: Renewable energy, nuclear energy, and environmental pollution: Accounting for political institutional quality in South Africa.

Sarkodie, S.A., Adams, S., 2018. Renewable energy, nuclear energy, and environmental pollution: Accounting for political institutional quality in South Africa. Sci. Total Environ. 643, 1590-1601.

Sarkodie, S.A. contributed 70%, while Adams, S. contributed 30% of the publication. Sarkodie, S.A. developed the conceptual framework, the econometric model and writing the article. Adams, S. wrote the introduction and literature review.

Chapter Seven: Economic, social and governance adaptation readiness for mitigation of climate change vulnerability: evidence from 192 countries.

Sarkodie, S.A., Strezov, V., 2019. Economic, social and governance adaptation readiness for mitigation of climate change vulnerability: Evidence from 192 countries. *Science of The Total Environment* 656, 150-164.

Sarkodie, S.A. contributed 80%, while Strezov, V. contributed 20% of the publication. Sarkodie, S.A. developed the conceptual framework, the econometric model and writing the article. Strezov, V. supported the development of the conceptual framework, editing and reviewing of the manuscript.

Introduction

Overview

Climate change poses a great danger to humanity and the natural system due to manmade activities and interferences in recent decades. Recent climate-related events include floods, droughts, cyclones, heat waves, wildfires, and among others, show how human and natural systems are exposed and vulnerable to variability in climate change (Ipcc, 2014b). Impacts of the aforementioned climate-related events alter ecosystems, disrupts water supply and food production, cause destruction to settlements and infrastructures, climate-related mental health, morbidity, and mortality. Thus, the impact of climate change on countries will depend on the level of development and the preparedness for variability in climate change events.

Problem Statement

Anthropogenic greenhouse gas (GHG) emissions, namely carbon dioxide emissions, nitrous dioxide, methane, perfluorocarbons, hydrofluorocarbons, and sulfur hexafluoride have a direct influence on global climate change. An increase in the concentrations of atmospheric GHG contributes to global warming, a situation that affects sustainable development (DiSano, 2002).

Figure 1 shows the interconnectedness of GHG emission drivers. According to the Intergovernmental Panel on Climate Change (IPCC) 5th Assessment Report, the

immediate drivers that partake in the decomposition of GHG emissions include population growth, per capita economic growth, energy intensity and GHG intensity (Ipcc, 2014a). The underlying factors that influence the immediate drivers of GHG emissions include behavior, level of development, trade, infrastructural choices and capacity, industrialization, urbanization, technological innovation and diffusion, governance and institutional quality and natural resource availability (Blanco et al., 2014). Policies and measures that help in the mitigation or exacerbation of climate change include awareness creation, economic incentives, non-climate policies, planning, direct regulations, provision of information, and research and development.

Against the backdrop, this thesis examined the drivers, policies, and measures that affect greenhouse gas emissions using econometric analysis.

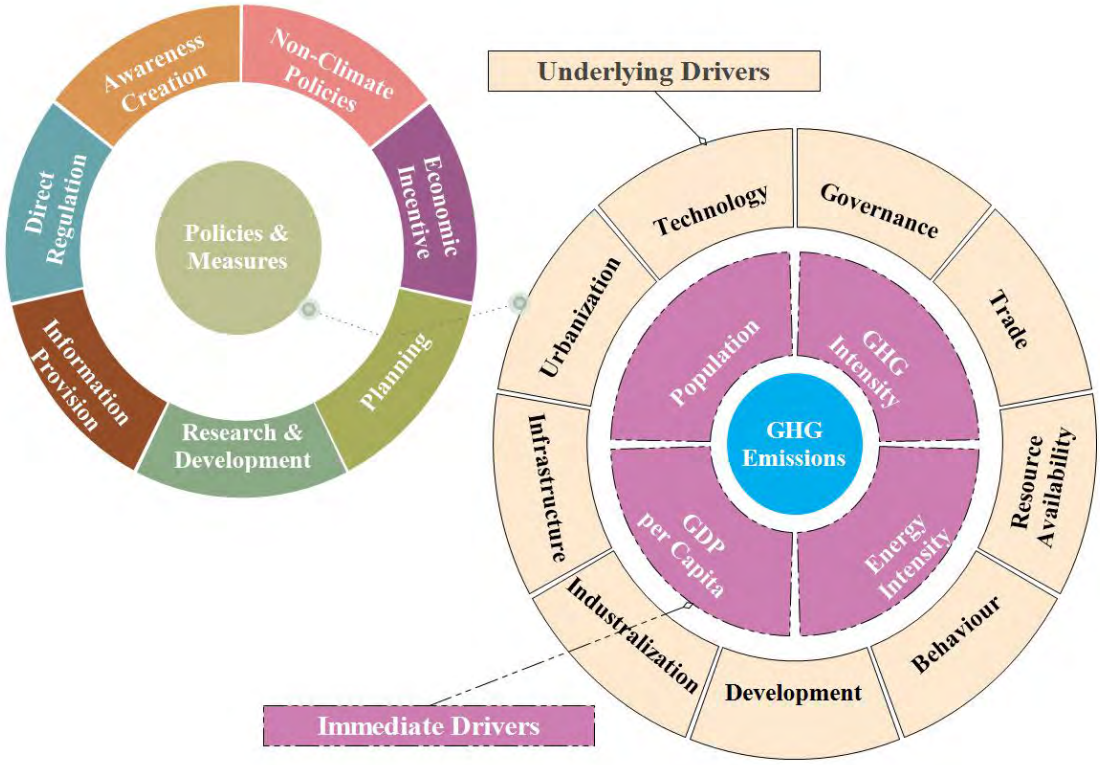

Figure 1. The interconnectedness of GHG emission drivers

Justification

The complexities of climate change and its impacts have triggered much investment, research and development and attention from development cooperation. The recent Paris Agreement instructs member countries to evaluate their contribution to the global anthropogenic GHG emissions in order to limit the increasing global average temperature to less than 2℃ warming by 2100 (UNFCC, 2015). However, a recent study by Raftery et al. (2017) reveals that the global average temperature expectation is unlikely. They predict a rise in global temperature between 2-4.9℃ unless there is a decline in carbon intensity. Motivated by the global fight against climate change and its topicality, this thesis incorporated the concept of sustainable development in the research hypothesis and adopted approaches and econometric methodologies that provide innovative ideas to hasten the transformation towards achieving the sustainable development goals by 2030.

Research Objectives

To achieve the aim of this thesis, the following research objectives were adopted:

1. Examined previous literature on the environmental Kuznets curve (EKC) hypothesis and their corresponding environmental indicators used for the study (Sarkodie and Strezov, 2019c).
2. Examined the current state of environmental degradation and pollution in 17 countries in Africa by testing the validity of the EKC hypothesis (Sarkodie, 2018).
3. Investigated both pollution haven and EKC hypotheses — determined the effect of foreign direct investments, economic development, and energy consumption on greenhouse gas emissions in developing countries (Sarkodie and Strezov, 2019b).

4. Examined the factors underpinning the EKC and the Environmental Sustainability curve hypotheses relative to energy intensity and greenhouse gas emissions for a selected range of countries such as Australia, China, Ghana and the USA (Sarkodie and Strezov, 2018b).
5. Used locally compiled data inventory on energy and its related services to ascertain the real evidence of the role of disaggregate energy production, energy imports, energy exports and economic development in environmental pollution and degradation in Australia (Sarkodie and Strezov, 2018a).
6. Examined how institutional environment moderates energy-environment degradation link (Sarkodie and Adams, 2018).
7. Examined the role of economic, social and governance adaptation readiness in the mitigation of climate change vulnerability (Sarkodie and Strezov, 2019a).

Contribution of the Study

1. Previous attempts employed the traditional method (qualitative) of literature review, however, we utilized meta-analytic and bibliometric methods in addition to qualitative assessment for literature review (Sarkodie and Strezov, 2019c).
2. The study accounted for cross-sectional dependence in the Westerlund Error-Correction Model-based panel cointegration tests using the bootstrapping approach for 1,000 samples. The Utest method was used to validate the EKC hypothesis, alongside fixed- and random effect estimators, and panel causality test (Sarkodie, 2018).

3. The study employed Driscoll-Kraay covariance estimator that does not restrict the limiting behavior of the panels and further produces robust standard errors. We further accounted for distributional heterogeneity using panel quantile regression. Robust estimations were derived using an adaptive Markov Chain Monte Carlo optimization based on 1,000 draws (Sarkodie and Strezov, 2019b).
4. The study for the first time examined the empirical relationship between environmental sustainability and economic growth nexus; environmental sustainability and energy consumption nexus; and environmental sustainability and CO_2 emissions nexus (Sarkodie and Strezov, 2018b).
5. The study employed the statistically inspired modification of partial least squares capable of eliminating multicollinearity problems reported in previous literature. The study undertook sustainability sensitivity analysis capable of estimating how environmental pollution and degradation can be minimized while increasing economic development and energy security (Sarkodie and Strezov, 2018a).
6. We did a comparative analysis of the effect of nuclear energy, renewable and non-renewable energy on carbon emissions. Second, we examined the independent and moderating role of urbanization on energy-environmental pollution nexus. Third, the political economy of the energy-environmental pollution link was investigated. Finally, we employed a more robust technique; ARDL bounds testing procedure with critical values and approximate p-values based on response surface regression and CUSUM test for detecting structural breaks (Sarkodie and Adams, 2018).

7. The study for the first time examined the impact of aggregate and disaggregate adaptation readiness on climate change vulnerability using spatial analysis and panel quantile regression model accounting for heterogeneity and unconditional distribution across quantiles (Sarkodie and Strezov, 2019a).

Study Area

Figure 2 shows the geographical representation of the study areas. For a comprehensive study on climate change mitigation and its impacts, the entire thesis was based on 192 United Nations countries namely Afghanistan, Albania, Algeria, Andorra, Angola, Antigua and Barbuda, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bhutan, Bolivia Plurinational State of, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Cape Verde, Central African Republic, Chad, Chile, China, Colombia, Comoros, Congo, Congo the Democratic Republic of, Costa Rica, Cote d'Ivoire, Croatia, Cuba, Cyprus, Czech Republic, Denmark, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Estonia, Ethiopia, Fiji, Finland, France, Gabon, Gambia, Georgia, Germany, Ghana, Greece, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran, Islamic Republic of, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kiribati, Korea, Democratic People's Republic, Korea, Republic of, Kuwait, Kyrgyzstan, Lao People's Democratic Republic, Latvia, Lebanon, Lesotho, Liberia, Libyan Arab Jamahiriya, Liechtenstein, Lithuania, Luxembourg, Macedonia, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshall Islands, Mauritania, Mauritius, Mexico,

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Organization of the Thesis

This thesis is organized as follows:

Chapter One — A Review on Environmental Kuznets Curve Hypothesis Using Bibliometric and Meta-Analysis.

Chapter Two — The Invisible Hand and EKC Hypothesis: What Are the Drivers of Environmental Degradation and Pollution In Africa?

Chapter Three — Effect of foreign direct investments, economic development, and energy consumption on greenhouse gas emissions in developing countries.

Chapter Four — Empirical study of the Environmental Kuznets curve and Environmental Sustainability curve hypothesis for Australia, China, Ghana, and USA.

Chapter Five — Assessment of contribution of Australia's energy production to CO_2 emissions and environmental degradation using statistical dynamic approach.

Chapter Six — Renewable energy, nuclear energy, and environmental pollution: Accounting for political institutional quality in South Africa.

Chapter Seven — Economic, social and governance adaptation readiness for mitigation of climate change vulnerability: evidence from 192 countries.

Appendix 1 — Publication Eight: Determinants of energy consumption in Kenya: A NIPALS approach

Appendix 2 — Publication Nine: Investigation of environmental Kuznets curve for ecological footprint: The role of energy and financial development

Appendix 3 — Publication Ten: Does energy consumption follow asymmetric behavior? An assessment of Ghana's energy sector dynamics

Appendix 4 — Publication Eleven: Another look at the relationship between energy consumption, carbon dioxide emissions, and economic growth in South Africa

Appendix 5 — Publication Twelve: Toward a sustainable environment: Nexus between CO_2 emissions, resource rent, renewable and nonrenewable energy in 16-EU countries

Appendix 6 — Publication Thirteen: Environmental sustainability assessment using dynamic Autoregressive-Distributed Lag simulations—Nexus between greenhouse gas emissions, biomass energy, food and economic growth

Appendix 7 — Supplementary Material for Chapter Two

Appendix 8 — Supplementary Material for Chapter Three

Appendix 9 — Supplementary Material for Chapter Four

Appendix 10 — Supplementary Material for Chapter Five

Appendix 11 — Supplementary Material for Chapter Seven

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Sarkodie, S.A., Strezov, V., 2019a. Economic, social and governance adaptation readiness for mitigation of climate change vulnerability: Evidence from 192 countries. Sci. Total Environ. 656, 150-164. doi:https://doi.org/10.1016/j.scitotenv.2018.11.349

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Chapter One: A Review on Environmental Kuznets Curve Hypothesis Using Bibliometric and Meta-Analysis.

Chapter One presents the following review article:

- **Sarkodie, S.A.**, Strezov, V., 2019. A review on Environmental Kuznets Curve hypothesis using bibliometric and meta-analysis. *Science of The Total Environment* 649, 128-145.

Contrary to the traditional method of review on the environmental Kuznets curve (EKC) hypothesis, this review employs bibliometric and meta-analytic methods to qualitatively and quantitatively examine existing literature on the scope of the study. In this way, historical trends and empirical results on the EKC hypothesis can be deduced.

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Review

A review on Environmental Kuznets Curve hypothesis using bibliometric and meta-analysis

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HIGHLIGHTS

- The review examined existing literature on the EKC hypothesis.
- We employed meta-analysis to examine the turning points of income level.
- The bibliometric analysis reveals "China" as the most popular term.
- Meta-analysis reveals a turning point of an annual income level of US$8910.
- Majority of the studies on EKC hypothesis are based on atmospheric indicators.

GRAPHICAL ABSTRACT

11

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ABSTRACT

The Environmental Kuznets Curve (EKC) hypothesis dates back in decades and is still topical presently due to its importance in environmental policy formulation. There are several systematic reviews of the EKC hypothesis using traditional review method. However, this review employs bibliometric and meta-analysis to track historical trends on the theme using the VOSviewer software and meta-analytic methods. The review translates the network analysis into visualized forms based on authors' contribution, the impact of the research by countries, citations count, and text corpus modeling using a network data extracted from Web of Science. The meta-analysis reveals that the collection of studies that validate the inversed-U shaped relationship has an average of US$8910 as the turning point of annual income level. Low income and middle-income countries are found below the thresholds of annual income level while high-income countries are above. Heterogeneity is confirmed among turning point in studies on EKC hypothesis due to differences in the period of study and econometric methods used in model estimation. The empirical findings reveal that most of the studies on EKC hypothesis are based on atmospheric indicators, while literature is sporadic and limited on EKC hypothesis which employs land indicators, oceans, seas, coasts and biodiversity indicators, and freshwater indicators.

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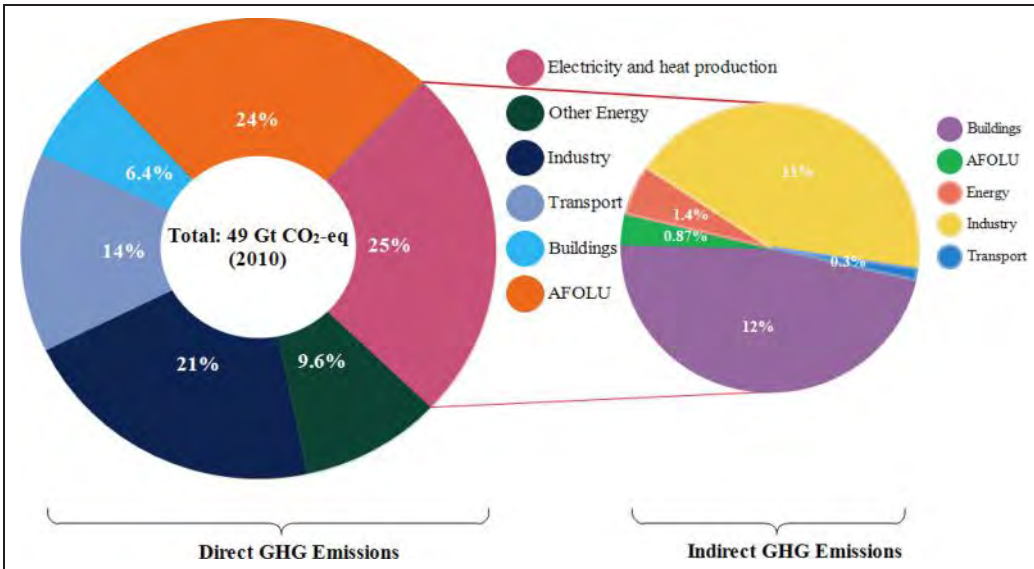
1. Introduction

Environmental degradation and the decline of environmental quality has become a global concern and has attracted significant attention from development cooperation. Anthropogenic greenhouse gas emissions have risen from 27 $GtCO_2eq$/year to 49 $GtCO_2eq$/year between 1970 and 2010 (see Box 1). According to the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment report, greenhouse gas emissions in 2010 grew by 330% in Asia, 70% in the Middle East and Africa, 57% in Latin America, 22% in Economic Co-operation and Development (OECD) countries, and 4% in Economies in Transition (IPCC, 2014). Several factors affect greenhouse gas emissions ranging from per capita production and consumption growth, population growth, technology, and innovation obsolesce, behavior and infrastructural

Box 1
Breakdown of Greenhouse gas emissions by Trade and Industrial Sectors, Adapted from IPCC 5th Assessment Report.



In accordance with the IPCC 5th Assessment Report, in terms of the contribution by trade and industrial sectors to greenhouse gas emissions, Electricity and heat production is the highest contributor (25%) followed closely by Agriculture, forestry and land use (AFOLU) 24%, industry (21%), transport (14%), other energy forms (9.6%), and buildings (6.4%), respectively.

choices. Carbon dioxide emissions from fossil fuel energy combustion, utilization, and industrial processes contributed almost 78% of the total greenhouse emissions from 2000 to 2010 (Blanco et al., 2014). Fossil-fuel related carbon dioxide emissions for heat and electricity generation have increased consistently in the last four decades. The quest to ensure the availability and accessibility of affordable energy supply to meet the growing energy demand and a sustained economic development has led to the overdependence on fossil fuel energy sources (Sarkodie and Owusu, 2016). Even though the relationship between economic growth and energy consumption is complex over time, however, the provision of energy and its related services are critical to economic development (United Nations, 2015). The identification of the causal factors of economic development and the nature of the nexus between economic development and the environment is complex and uncertain. The sources of economic growth are critical because the level at which technological change drives economic growth as opposed to the increased use of resources and the accrual of capital will strongly affect climate change and its impacts (Sarkodie, 2018). Thus, economic growth in developing countries will be more carbon-intensive than the economic growth in developed countries due to technological advancement and innovation. The systematic relationship between economic development and environment provides the premise for the Environmental Kuznets Curve hypothesis. The Environmental Kuznets Curve hypothesis posits that early stages of economic development are characterized by a high use of resources which inevitably reduce the biocapacity[1] and increase ecological footprint, thus, leading to rapid growth in pollution levels (Panayotou, 1993; Sarkodie and Strezov, 2018a). Multidimensional poverty is often high within the initial stages of economic development, as such, environmental conservation and management policies are often ignored, with the main agenda of polluting to make wealth and clean later. However, in the later stages of economic development, there is a substantial rise in income levels coupled with effective institutional quality, awareness of environmental sustainability and high diffusion of technology and innovation, which causes a decline in environmental deterioration. Due to the assertiveness of the policies that emanate from the Environmental Kuznets Curve hypothesis, there is enormous literature in the scope of the study due to its topicality. Nevertheless, there is no consensus between studies using the same or varying econometric methods, or based on the same location. Based on the opposing arguments in the existing literature, it is important to examine the empirical studies conducted on the Environmental Kuznets Curve hypothesis. Previous attempts employ the traditional method of literature review, however, to the best of our knowledge, there is no available study that employs meta-analytic and bibliometric methods for literature review. As a contribution, this study employs a bibliometric and meta-analysis to examine existing literature on the Environmental Kuznets Curve hypothesis.

2. Conceptual framework of EKC hypothesis

The Kuznets curve hypothesis stems from the initial work of Kuznets (1955) who revealed an inversed-U shaped relationship between income per capita and income inequality. As income per capita increases at the initial stages, income inequality follows the same path but begins to decline after reaching a turning point. In this regard, the initial stage of income growth is characterized by an unequal income distribution, however, as economic productivity increases, income distribution moves towards equality (Kuznets, 1955). The Environmental Kuznets Curve hypothesis attracted significant much attention in the nineties after the seminal work of Grossman and Krueger (1991) revealed that environmental deterioration and income per capita follow an inversed-U shaped relationship hypothesized by Kuznets (1955). Studying the nexus between air quality and economic development, Grossman and Krueger (1991) found an inversed-U shaped relationship between air pollutants (sulfur dioxide and smoke) and income per capita, thus, confirming the validity of the Environmental Kuznets Curve hypothesis coined by Panayotou (1993). Their study revealed an increase in the concentrations of air pollutants with income level, but the concentrations of air pollutants declined at higher income levels. Panayotou (1993) further expounded the inversed-U shaped analogy by examining the nexus between environmental degradation and income per capita depicted in Fig. 1. Confirming the validity of the Environmental Kuznets Curve (EKC) hypothesis, Panayotou (1993) revealed that policy distortions such as subsidies on carbon and energy-intensive economic structures, industrial protectionism, market failures and natural resource underpricing tend to influence the steepness of the inversed-U shaped curve.

Factors affecting the inversed-U shaped relationship between environmental deterioration and income levels include income elasticity, scale, composition and technique effects, and international trade (i.e. foreign direct investments, diffusion of modern technologies, pollution haven hypothesis, and among others) [see Box 2].

2.1. Income elasticity of environmental quality

Income elasticity of environmental quality demand is the proportional change in environmental quality demand per the proportional change in income level. People opt for a higher standard of living and willingness to pay for a cleaner environment as income level grows. At a higher income level, people intuitively crave for quality rather than quantity and care more about the environment (Baldwin, 1995). As such, they demand better environmental services which induce the structural change in the economy, thus, resulting in a decline of environmental deterioration. In relationship to the EKC, a higher income level gradually tends to change behavioral patterns and lifestyles towards energy-intensive and carbon-intensive products. Consumer behavior of rich people tilts towards energy efficient products and services (Edenhofer et al., 2011; Girod et al., 2014; Selden and Song, 1994). Other behaviors such as donations to environmentally friendly organizations and defensive expenditure become a characteristic of the rich (Dinda, 2004). Studies on the EKC hypothesis have emphasized the role of income elasticity in the decline of environmental degradation (Acaravci and Ozturk, 2010; Dinda, 2004; Sarkodie and Strezov, 2018a). Sarkodie and Strezov (2018a) revealed that a structural change in Australia's economy based on renewable energy

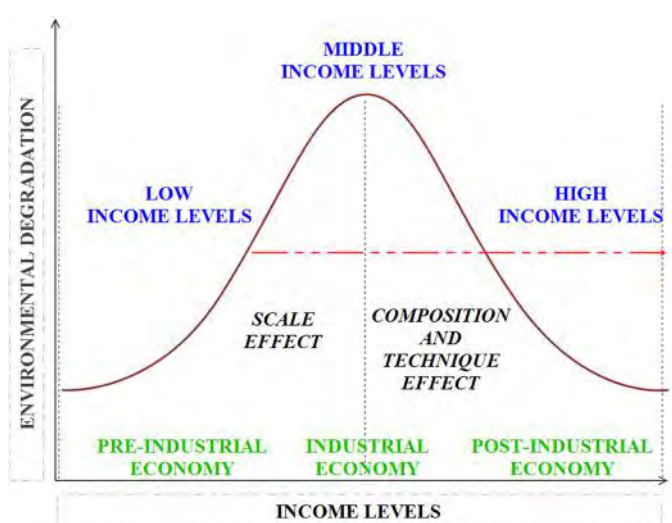


Fig. 1. The relationship between environmental degradation and income levels.

[1] "Biocapacity is defined by Global Footprint Network as the capacity of ecosystems to regenerate what people demand from those surfaces. Life, including human life, competes for space. It is therefore the ecosystems' capacity to produce biological materials used by people and to absorb waste material generated by humans, under current management schemes and extraction technologies Global Footprint Network (2017a). About the Data: Key Terms. Retrieved from http://data.footprintnetwork.org/aboutTheData.html."

Box 2
Factors that influence the shape of the EKC hypothesis.

The shape of the EKC hypothesis is influenced by many factors including, but not limited to:

- Income Elasticity of Environmental Quality
- Scale, Composition and Technique Effects
- International Trade

technologies reduces both natural resource depletion and environmental pollution. On the contrary, poor society cares little about environmental sustainability and demands for quantity rather than quality. The demand for quantity translates into the exploitation of natural resources and the manipulation of environmental regulations and industry standards in order to lure polluting industries from developed countries (Sarkodie and Strezov, 2019).

2.2. Scale, composition and technique effects

The nexus between environmental deterioration and economic development occurs in three stages namely: scale, composition and technique effects (Grossman and Krueger, 1991). As presented in Fig. 1, the scale effect implies that economic development has a negative impact on the environment. Higher production output requires more exploited natural resource base to meet the demand, as such increases environmental degradation. In the same way, economic development is characterized by high energy consumption from fossil-fuel energy sources which remain cheaper and the obvious choice compared to renewable energy. The dependence on fossil-fuel energy consumption for industrial processes may reduce production cost and aid in the expansion of goods and services to meet the growing demand, yet, propels industry related emissions (Edenhofer et al., 2011; Owusu and Asumadu, 2016). The composition effect implies that economic development has a negative and/or positive impact on the environment, depending on the structural change in the economy. Environmental degradation tends to increase with increasing economic growth as agrarian economy shifts to energy-intensive and carbon-intensive industries. As pollution-intensive industries contract and shift to service-oriented industries, environmental degradation begins to decline (Sarkodie and Strezov, 2018a). The technique effect implies that economic development has a positive impact on the environment. As higher-income countries tend to spend more on Research and Development, the replacement of polluting and vintage technologies with cleaner and sophisticated technologies coupled with stringent environmental regulations and industry standards will improve environmental quality. Thus, the EKC hypothesis suggests that the negative impact of income levels on the environment due to the scale effect only occurs at the initial stages of economic development but the positive impact of a combination of composition and technique effects will compensate the previous environmental damage, hence, decline emission levels (Dinda, 2004; Sarkodie and Strezov, 2018b).

2.3. International trade

Trade policy is one of the important factors that explain the EKC hypothesis. Trade liberalization causes countries to specialize in sectors where they have a competitive advantage. If the sector with a competitive advantage stems from lax environmental regulations, then the effect of the trade liberalization will damage the environment, because each country will specialize in sectors with weak environmental regulations and shift from industrial production with high pollution abatement cost (Grossman and Krueger, 1991). The net effect of pollution levels will depend on the state of pollution-intensive industries and the environmental regulations in place. Trade liberalization, through the composition effect, can be attributed to the pollution haven hypothesis even though free trade can be beneficial by creating jobs, improving skills and raising income levels, which will, in turn, contribute to a cleaner environment. However, if environmental regulations in developing countries are weak, they attract a shift of pollution-intensive and energy-intensive industries from developed countries. Thus, the pollution haven hypothesis posits that high-income countries with stringent environmental standards will transfer their pollution-intensive industries to poor countries with laxed environmental pollution policies (Sarkodie and Strezov, 2019; Solarin et al., 2017). Weak environmental policies and regulations in poor countries become a source of comparative advantage, and hence, a shift in trade pattern, thus, promote environmental degradation in poor countries (Sarkodie and Strezov, 2019; Sun et al., 2017). In the same way, if innovation, research and development, and clean and modern technologies are transferred through foreign direct investment from developed countries to developing countries, vintage technologies can be replaced to reduce the level of pollution.

3. Empirical estimation of EKC

Regardless of the different methods employed in existing studies on EKC hypothesis, almost all follow a similar model specification. Using a panel data series, the nexus between environmental pressure or pollution level and income level is expressed in a reduced form as:

$$y_{i,t} = \alpha_{i,t} + \beta_1 x_{i,t} + \beta_2 x^2{}_{i,t} + \beta_3 x^3{}_{i,t} + \beta_4 z_{i,t} + \varepsilon_{i,t} \quad (1)$$

where α is the constant, y represents the environmental pressure indicators, x, x^2, and x^3 denote the income level, squared of income level and cubic of income level, z represents other variables that affect environmental deterioration, $\beta's$ are the coefficient estimates of the regressors, ε denotes the white noise across the cross-sectional units i in time t. Based on the empirical specifications in Eq. (1), the relationship between pollution level and income level can produce several interpretations such as (see Box 3):

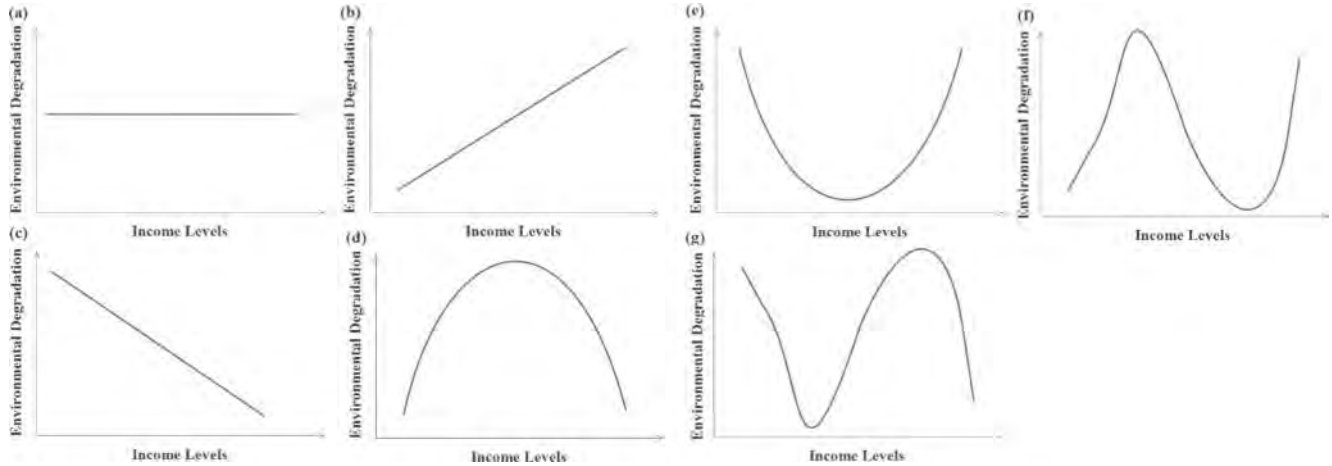
i. No relationship between x and y if $\beta_1 = \beta_2 = \beta_3 = 0$.
ii. A positive monotonic relationship between x and y if $\beta_1 > 0$, $\beta_2 = \beta_3 = 0$.
iii. A negative monotonic relationship between x and y if $\beta_1 < 0$, $\beta_2 = \beta_3 = 0$.
iv. Inversed-U shaped relationship between x and y if $\beta_1 > 0$, $\beta_2 < 0$, $\beta_3 = 0$.
v. U-shaped relationship between x and y if $\beta_1 < 0$, $\beta_2 > 0, \beta_3 = 0$.
vi. N-shaped relationship between x and y if $\beta_1 > 0$, $\beta_2 < 0, \beta_3 > 0$.
vii. Inversed-N-shaped relationship between x and y if $\beta_1 < 0$, $\beta_2 > 0$, $\beta_3 < 0$.

In a typical method for estimating the EKC hypothesis, the inclusion of a nonlinear term in a standard regression model leads to a conclusion of inversed-U shaped relationship if the nonlinear term is negative and significant with its turning point within the data series. Thus, the EKC hypothesis is valid if $\beta_1 > 0$, $\beta_2 < 0, \beta_3 = 0$ at a turning point calculated as $x^* = -0.5\,\beta_1/\beta_2$. Contrary to the aforementioned traditional method, Lind and Mehlum (2010) argue that the criteria are weak when "the true relationship is convex but monotone over relevant data values", as such, the quadratic specification produces erroneous turning point and U-shaped relationship. Lind and Mehlum (2010) reveal that:

> "*To test properly for the presence of a U-shape on some interval of values, there is a need to test the decreasing relationship at low values within the interval values and the increasing relationship at high values within the same interval. Thus, when the relationship increases at the left-hand side of the interval and/or decreases at the right-hand side, the traditional method of U-shape estimation is not suitable.*"

Against the backdrop, Lind and Mehlum (2010) provide the Utest algorithm used to test the presence of U-shaped, inverted U-shaped or

Box 3
The empirical specifications in Eq. (1), the relationship between environmental degradation and income level produces several interpretations.



(a) No relationship between x and y; (b) a positive monotonic relationship between x and y; (c) a negative monotonic relationship between x and y; (d) Inversed-U shaped relationship between x and y; (e) U-shaped relationship between x and y; (f) N-shaped relationship between x and y; and (g) Inversed-N-shaped relationship between x and y.

monotonic relationship on an interval. The Utest algorithm is applied after estimation commands which contain the level relationship of the independent variable and the nonlinear term based on the null hypothesis that the relationship is decreasing at the beginning of the interval and increasing at the end of the interval or vice versa. The Utest algorithm by default assumes the data range as the interval unless otherwise specified. The Fieller option within the algorithm can produce a Fieller interval for the turning point even for finite samples. The Utest has by far been applied by Dong et al. (2018a); Dong et al. (2018b); Sarkodie (2018); Sarkodie and Adams (2018); Sarkodie and Strezov (2018b), and among others.

4. Empirical findings

The empirical analysis of various studies is based on the adoption of data from different international and local databases, such as the World Development Indicators, by the World Bank (2016), FAO (2015) Statistical Yearbooks — World Food and Agriculture, Global Footprint Network (2017b) and others. Using the data on environmental indicators and economic indicators, authors employ the EKC hypothesis testing procedure using various econometric methods. Due to varied environmental indicators, the majority of the studies are categorized under atmospheric indicators, land indicators, oceans, seas, coasts and biodiversity indicators, and freshwater indicators (see Box 4). Table 1 presents a compilation of selected studies on the EKC hypothesis.

Box 4
Environmental related indicators for EKC hypothesis estimation in the existing literature.

Due to the broad concept of the EKC hypothesis and its applicability, environmental indicators used in most studies include:

- Atmospheric indicators,
- Land indicators,
- Oceans, seas, coasts and biodiversity indicators, and
- Freshwater indicators.

4.1. Atmospheric indicators

These indicators include greenhouse gas emissions and priority air pollutants. The greenhouse gas emissions encompass six main compounds, namely carbon dioxide, nitrous oxide, methane, perfluorocarbons, sulfur hexafluoride and hydrofluorocarbons, which directly affect climate change. Majority of studies are based on carbon dioxide emissions due to its major impact on global anthropogenic greenhouse gas emissions. Carbon dioxide emissions are mostly estimated from sectors that include energy, agricultural, forestry and land use, and industrial processes (DiSano, 2002). The priority air pollutants include the ambient concentration of particulate matter (PM_{10}, $PM_{2.5}$, suspended particulate matter (SPM) or black smoke), lead, sulfur dioxide, nitrogen dioxide, nitrogen monoxide, carbon monoxide, and volatile organic compounds including benzene. These data series are an indirect measure of urban population exposure to air pollution and the corresponding health outcomes. Thus, improvement in air quality leads to the promotion of sustainable human settlement. There are mix results on EKC hypothesis in the existing literature. Fodha and Zaghdoud (2010) found an inverted-U shaped relationship between sulfur dioxide and income levels, however, Stern and Common (2001) found no evidence in individual countries. Jalil and Mahmud (2009); Pao and Tsai (2011); Pao and Tsai (2010) support the validity of an inverted-U shaped relationship between carbon dioxide emissions and income levels in some countries, in contrast, Ozturk and Acaravci (2010) found no evidence of EKC.

4.2. Land indicators

Land indicators cover change in land use, land degradation, land area affected by desertification, arable and permanent cropland area, efficiency of fertilizer use, usage of agricultural pesticides, area under organic farming, ratio of land area covered by forests, forest trees damaged by defoliation, and area of forest under sustainable forest management. A continual decline in forest area and the degree of defoliation provide information for unsustainable forest management practices and health of the forest, which are critical to the eradication

Table 1
Compilation of studies on the EKC hypothesis.

Reference	Location	Period	Data series & method	Results & interpretation
Acaravci and Ozturk (2010)	19 European countries	1960–2005	Energy consumption, economic growth and CO_2 emissions using autoregressive distributed lag bounds test.	The EKC hypothesis is invalid, however, there is unidirectional causality from economic growth to CO_2 emissions. The study found a positive long-run relationship between CO_2 emissions and energy consumption.
Ahmad et al. (2016)	India	1971–2014	Energy consumption, economic growth and CO_2 emissions using autoregressive distributed lag and Granger causality test.	The EKC hypothesis is invalid India. The growth rate of CO_2 emissions is dependent on energy consumption. In a disaggregated level, coal energy source contributes more to pollution than natural gas energy source.
Alam et al. (2011)	India	1971–2006	Energy consumption, economic growth and CO_2 emissions using multivariate Toda and Yamamoto model, Impulse-Response and Granger causality test.	No EKC hypothesis. The study found a feedback hypothesis between to CO_2 emissions and energy consumption but no causal relationship between energy consumption and economic growth.
Antonakakis et al. (2017)	106 countries	1971–2011	Economic growth, energy consumption and CO_2 emissions using panel vector autoregression and Impulse-Response.	The EKC hypothesis is not valid. The study found a feedback hypothesis between energy consumption and economic growth.
Apergis and Payne (2009)	6 Central American countries	1971–2004	Energy consumption, economic growth and CO_2 emissions using a panel vector error correction model.	The EKC hypothesis is valid. There is a long-run relationship between energy consumption and CO_2 emissions. The Granger causality test reveals a unidirectional causality running from energy consumption to output and a bidirectional causality between CO_2 emissions and energy consumption.
Cole (2004)	OECD countries	1980–1997	Air pollutants, water pollutants, the share of manufacturing, exports, and trade openness using fixed and random effects.	Confirmed the EKC hypothesis in higher income countries. The inversed-U shaped relationship is somewhat associated with the demand for environmental regulation and increased investment in pollution abatement technologies.
Fei et al. (2011)	China	1985–2007	Energy consumption, economic growth and CO_2 emissions using ordinary least squares regression.	No EKC hypothesis. There is a long-run relationship between energy consumption and economic growth. The study revealed a positive impact of economic growth of pollution.
Fodha and Zaghdoud (2010)	Tunisia	1961–2004	CO_2 emissions, sulphur dioxide, and GDP using the vector error correction model.	The EKC hypothesis is valid between sulphur dioxide and GDP at a turning point of US$ 1200. A monotonic relationship between CO_2 emissions and GDP is revealed.
Heidari et al. (2015)	Five ASEAN countries	1980–2008	Energy consumption, economic growth and CO_2 emissions using panel smooth transition regression.	Invalid EKC hypothesis in ASEAN countries. Energy consumption increases CO_2 emissions even in regime changes compared to economic growth that increases CO_2 emissions in the first regime.
Hu et al. (2018)	25 developing countries	1996–2012	CO_2 emissions, GDP per capita, commercial services per capita, the share of renewable energy, size of renewable consumption per capita using fully-modified ordinary least squares & dynamic ordinary least squares regression.	No EKC hypothesis. The study found a positive impact of economic growth on renewable and vice versa. The negative role of renewable on CO_2 emissions was confirmed.
Jalil and Mahmud (2009)	China	1975–2005	Energy consumption, economic growth, trade and CO_2 emissions using autoregressive distributed lag bounds test.	The EKC hypothesis is valid. The Granger causality reveals a unidirectional causality running from economic growth to CO_2 emissions. The main determinants of CO_2 emissions are economic growth and energy consumption.
Jaunky (2011)	36 high-income countries	1980–2005	Economic growth and CO_2 emissions using generalized method of moments and vector error correction model.	The EKC hypothesis is valid. There is a unidirectional causality running from economic growth to CO_2 emissions.
Kais and Sami (2016)	58 countries	1990–2012	Energy consumption, economic growth and CO_2 emissions using generalized method of moments.	The study found the existence of the EKC hypothesis in 58 countries and confirm a positive long-run relationship between economic growth and CO_2 emissions.
Lean and Smyth (2010)	Five ASEAN countries	1980–2006	CO_2 emissions, energy consumption and per capita GDP using panel dynamic ordinary least squares regression.	The EKC hypothesis is valid. A unidirectional causality running from CO_2 emissions to energy consumption is valid in the short-run.
Narayan and Narayan (2010)	43 developing countries	1980–2004	Economic growth and CO_2 emissions using panel cointegration.	No EKC hypothesis. The study revealed that 15 of 43 countries decline pollution at long-run income levels.
Saboori et al. (2016)	Malaysia	1980–2009	Economic growth and CO_2 emissions using autoregressive distributed lag.	The EKC hypothesis is valid, thus, inverted U-shape between CO_2 emissions and economic growth. The study found a long-run equilibrium relationship between economic growth and CO_2 emissions.
Sarkodie (2018)	17 African countries	1971–2013	CO_2 emissions, birth rate, energy consumption, fertility rate, per capita GDP, agriculture, and ecological footprint using fixed and random effects, Utest, and Westerlund error-correction model.	Confirmed the validity of EKC hypothesis at a turning point of US$5702. A unidirectional causality running from economic development to environmental degradation was established.
Wang et al. (2016)	China	1990–2012	Energy consumption, economic growth and CO_2 emissions using vector error-correction, Impulse-Response and Granger causality test.	No EKC hypothesis. The study found a unidirectional causality running from energy consumption to CO_2 emissions and a feedback hypothesis between economic growth and energy consumption.

(continued on next page)

Table 1 (*continued*)

Reference	Location	Period	Data series & method	Results & interpretation
Yang and Zhao (2014)	India	1970–2008	Energy consumption, economic growth and CO_2 emissions using Granger causality test and directed acyclic graphs.	No EKC hypothesis. The study found a unidirectional causality running from energy consumption to CO_2 emissions and a feedback hypothesis between CO_2 emissions and economic growth.
York et al. (2003)	142 countries	1996	Human ecology, modernization and political economy variables using the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model.	Age-structure of the population has environmental impacts. Confirmed the validity of the EKC hypothesis. Institutional change improves ecological sustainability.
Zaman and Moemen (2017)	90 countries from low ($995 or less), middle-income ($996–12,055), and high-income ($12,056 or more) countries	1975–2015	Energy consumption, economic growth, service value added and CO_2 emissions using the generalized method of moments.	The study confirms the EKC hypothesis in low and middle-income countries. Increasing levels of energy consumption appear to facilitate the growth of environmental pollution. Service value added increases CO_2 emissions in the long term.

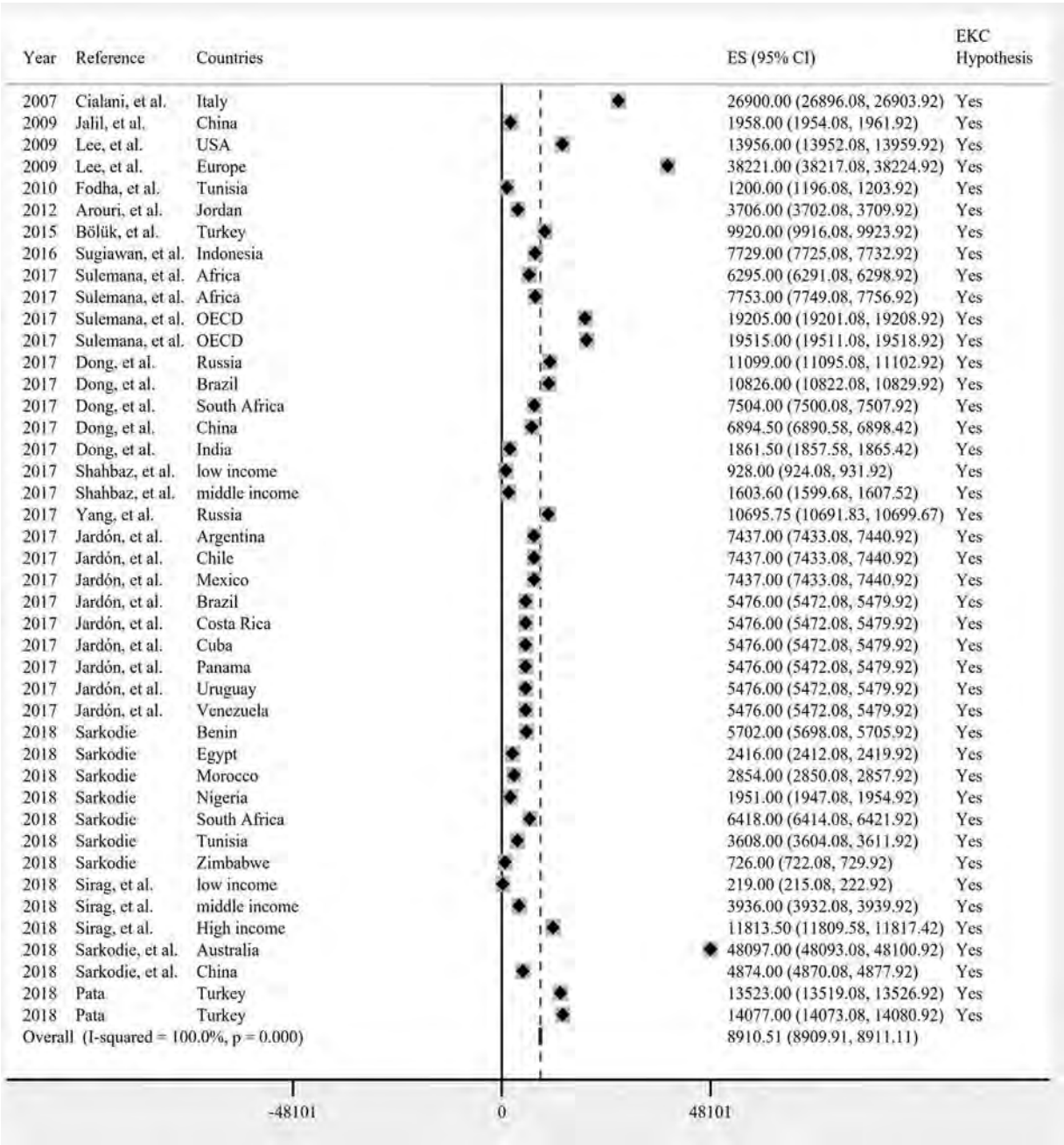


Fig. 2. Fixed effects meta-analytical method for valid EKC hypothesis. NB: The first value in the figure reveals the effect size (ES) while the values in the parenthesis represent the 95% confidence interval.

of extreme poverty, mitigating natural resource degradation and biodiversity loss (DiSano, 2002). The status of land use provides information on changes in land resources to enable sustainable land policy planning and management. The degree of land degradation and the severity of desertification affects sustainable agriculture and sustainable development. It is revealed that land degradation and desertification are the major causes of poverty in developing and least developing countries with an agrarian economy (DiSano, 2002). The intensive use of fertilizers is somewhat associated with loss of nutrients which may result in soil acidification, eutrophication of water bodies and nitrate contamination of water supply (Owusu et al., 2016). While pesticides improve agricultural productivity, its excessive use poses environmental and health challenges. Its accumulation in the soil and biota may affect groundwater and aquifers through leaching (Owusu and Asumadu-Sarkodie, 2016). Barbier and Burgess (2001) found an inversed-U shaped relationship between agricultural land expansion and economic development, which was different across countries. Chiu (2012) examined the nexus between deforestation and economic development in 52 countries and found an inverted-U shaped relationship at a turning point of US $ 3021 and US $ 3103 annual income levels. Stefano and Richard (2008) found no inversed-U shaped relationship between fertilizer consumption and income levels.

4.3. Oceans, seas, coasts, and biodiversity indicators

This indicator comprises of the share of population living in coastal areas, recreational water quality and aesthetics, the share of fish stocks within their safe biological limits, proportion if marine area protected, marine trophic index, the area of coral reef ecosystems and percentage live cover, proportion of protected terrestrial area per ecological region, effective management of protected areas, fragmentation of habitats, status of species, and the abundance of key species. The vulnerability to sea level rise and various coastal hazards is quantified to provide information about the drivers of coastal ecosystem pressure such as pollution loads land cover change. The violation of standards of recreational water quality poses health and economic risks for coastal dwellers and tourism. Thus, protected marine areas are critical to the conservation of biodiversity, recreation, cultural heritage and improve ecosystem

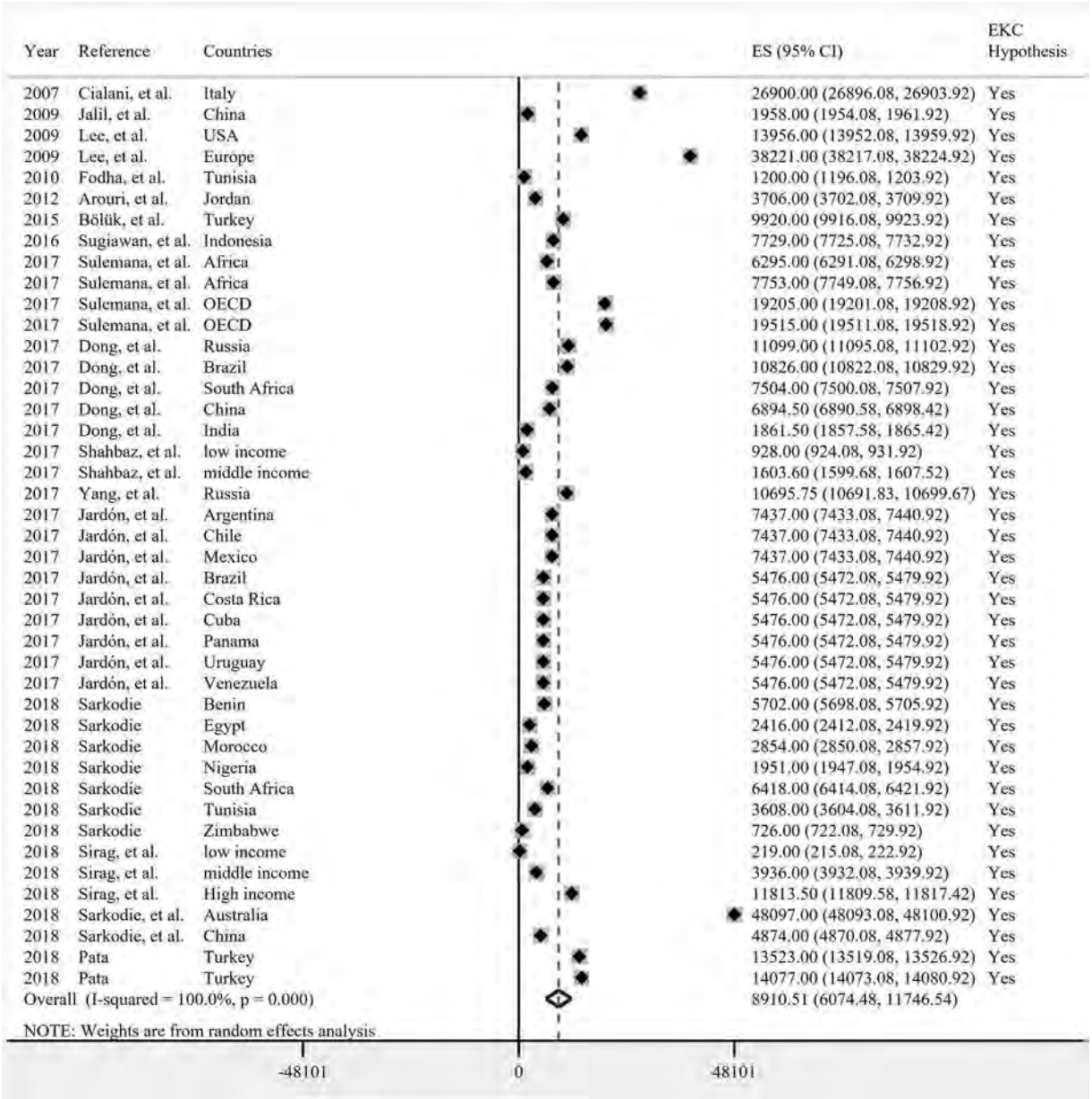


Fig. 3. Random effects meta-analytical method for valid EKC hypothesis.

diversity (DiSano, 2002). He et al. (2014) found an inverted-U shaped relationship between coastal ecosystem change and economic development in China. Mozumder and Berrens (2007) found no inverse-U shaped relationship between loss of biodiversity and economic development.

4.4. Freshwater indicators

Freshwater indicators encompass the use of total water resources, the intensity of water use per economic activity, the presence of fecal coliforms in freshwater, biological oxygen demand (BOD) in water bodies, and wastewater treatment (DiSano, 2002; United Nations, 2015). The extent of exploitation of the total renewable water resources to meet the water demand provides information on water scarcity and vulnerability to water shortage. Water scarcity tends to affect sustainability, pressuring economic and regional development which leads to biodiversity loss. The pressure of the economy on water resources shows progress in the implementation of integrated water resources management strategies (DiSano, 2002). The microbial quality of available water resources, the level of BOD in water resources and wastewater treatment strategies are essential to reduce morbidity and mortality of terrestrial and aquatic habitats, which the adverse effect poses a challenge to economic productivity and sustainable development (United Nations, 2015). Lee et al. (2010) found an inversed-U shaped relationship between BOD and economic development in America and Europe but invalid in Asia, Oceania, and Africa. Wong and Lewis (2013) found no inversed-U shaped relationship between water pollution and income levels in developing countries. Katz (2015) found an inversed-U shaped relationship between water demand and economic development in the US and OECD countries.

5. Meta-analysis of EKC

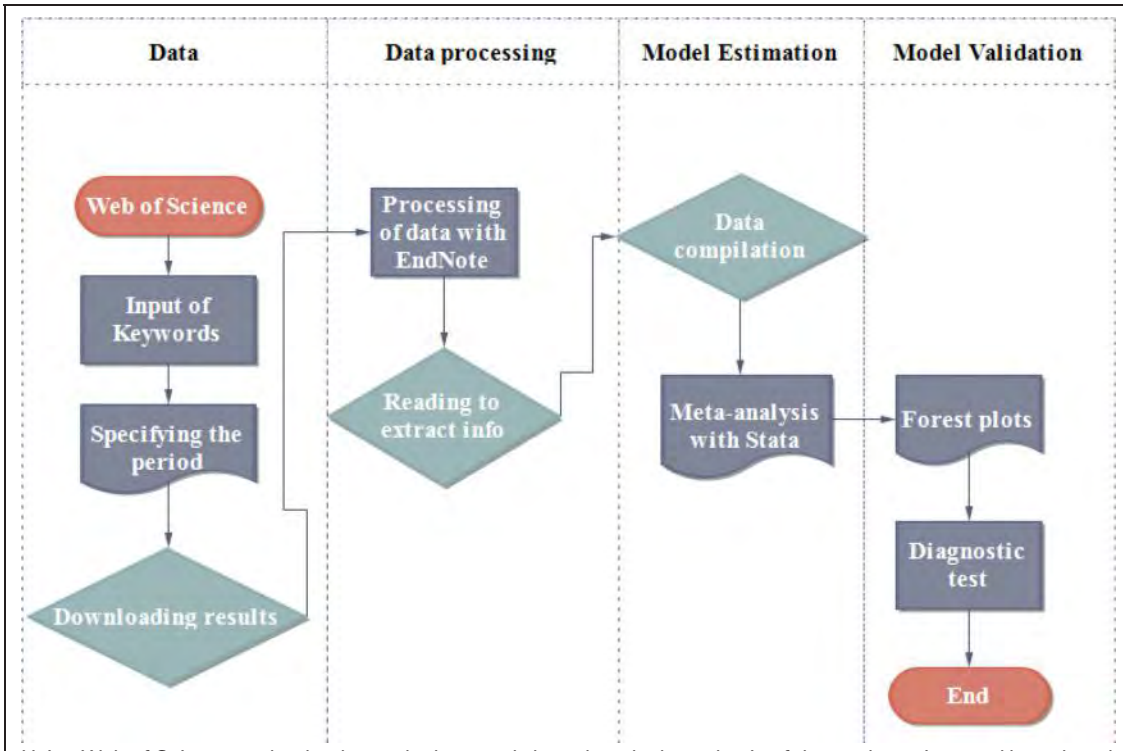
5.1. Background

The EKC hypothesis exists between environmental pressures and economic development at an expected turning point in income levels. However, the turning points vary depending on the selected pollutant and the estimation method employed. As such, there is a broad spectrum of outcome resulting in different interpretations. Hence, the use of meta-analysis is essential to synthesize results emanating from similar empirical studies to derive credible conclusions. This section examines the various turning points in EKC hypothesis based on the nexus between environmental pollution (GHG or CO_2 emissions) and economic growth using the fixed and random effects meta-analysis (Harris et al., 2008). The meta-analytic methods employed involves two stages in the model estimation, namely summary statistics of the selected studies and a weighted average of the information contained in the studies (fixed-effects meta-analytic method) or the incorporation of between-study variation (heterogeneity) estimate for weighting the information in the studies (random-effects meta-analytic method).

5.2. Synthesis of data

In order to quantitatively and qualitatively examine results of turning points in EKC hypothesis from existing literature, the study searches for: Topic: (Environmental Kuznets Curve) And Topic: (Turning Point) Or Title: (Environmental Kuznets Curve) And Title: (Turning Point) Or Topic: (EKC Hypothesis) And Topic: (Turning Point) Or Title: (EKC Hypothesis) And Topic: (Turning Point) Timespan: 2007–2018. Indexes: SCI-Expanded, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI,

Box 5
Schematic presentation showing the procedure for the meta-analysis.



Using Web of Science as the database, the keywords based on the hypothesis of the study are inputted based on the preferred period. The results from Web of Science are downloaded into RIS format compatible with EndNote software, with a subsequent data processing. Each of the entry is read and turning points and results of the EKC hypothesis extracted. Data are compiled to meet Stata requirements. Using the algorithm for meta-Analysis, the data is analyzed and results presented in Forest plots. Diagnostic tests are done to examine to validate the model.

CCR-Expanded, IC, in Web of Science database. The downloaded data were imported into EndNote, each article was read, and the required information extracted from the article. The initial search revealed 169 articles as of 2nd July 2018. Using the inclusion criteria of CO_2 emissions or GHG emissions as dependent variables and per capita GDP and squared per capita GDP in US$ with corresponding turning points, only 17 articles qualified, namely Cialani (2007), Jalil and Mahmud (2009), Fodha and Zaghdoud (2010), Lee et al. (2010), Wang et al. (2011), Arouri et al. (2012), Bölük and Mert (2015), Sugiawan and Managi (2016), Jardón et al. (2017), Dong et al. (2017), Shahbaz et al. (2017), Sulemana et al. (2017), Yang et al. (2017), Pata (2018), Sarkodie (2018), Sarkodie and Strezov (2018b), and Sirag et al. (2018). The results of the EKC hypothesis and their corresponding turning points are extracted from the individual article. For example, if one document studied and reported 20 countries, all the individual results are reported separately. The extracted results from the 17 documents revealed 43 results supporting the validity of the ECK hypothesis while 20 results reject the EKC hypothesis. The extracted data series are subsequently estimated using the meta-analytic methods (see Box 5).

5.3. Model estimation

For brevity, the mathematical representation of both fixed (Eq. (2)) and random (Eq. (3)) effects meta-analytic methods is expressed as (Harbord and Higgins, 2008):

$$y_i = \theta + \varepsilon_i, \text{where } \varepsilon_i \sim N(0, \sigma_i{}^2) \tag{2}$$

$$y_i = \theta + u_i + \varepsilon_i, \text{where } u_i \sim N(0, \tau^2) \text{ and } \varepsilon_i \sim N(0, \sigma_i{}^2) \tag{3}$$

The meta-analytic methods assume that individual study i of the total n studies provides an estimate, y_i, of the effect of interest with corresponding standard error σ_i for the estimation from each study and τ^2 denotes the between study variance estimated from the data series. The fixed-effects meta-analytic method assumes a single true effect size (ES) θ, while the random-effects meta-analytic method allows θ_i, the true effects to vary between studies and assumes they exhibits a "normal distribution around the mean effect" θ.

The percentage variation attributable to heterogeneity I^2 statistic is calculated as:

$$I^2 = 100\% \times \frac{(Q - df)}{Q} \tag{4}$$

where Q denotes Cochran's heterogeneity statistics and df denotes the degree of freedom. Higgins et al. (2003) suggest the following classifications for I^2 statistic: between 25%–50% represents low heterogeneity, between 50% and 75% denotes moderate heterogeneity while ≥75% represents high heterogeneity.

Figs. 2–5 present the forest plots from the fixed and random effects meta-analytic methods to synthesize the literature on EKC hypothesis. The diamond shape denotes the results from the individual studies showing the turning points of a specified geographical location, with their corresponding 95% confidence interval (CI) of the effect size. Both the fixed and random effects

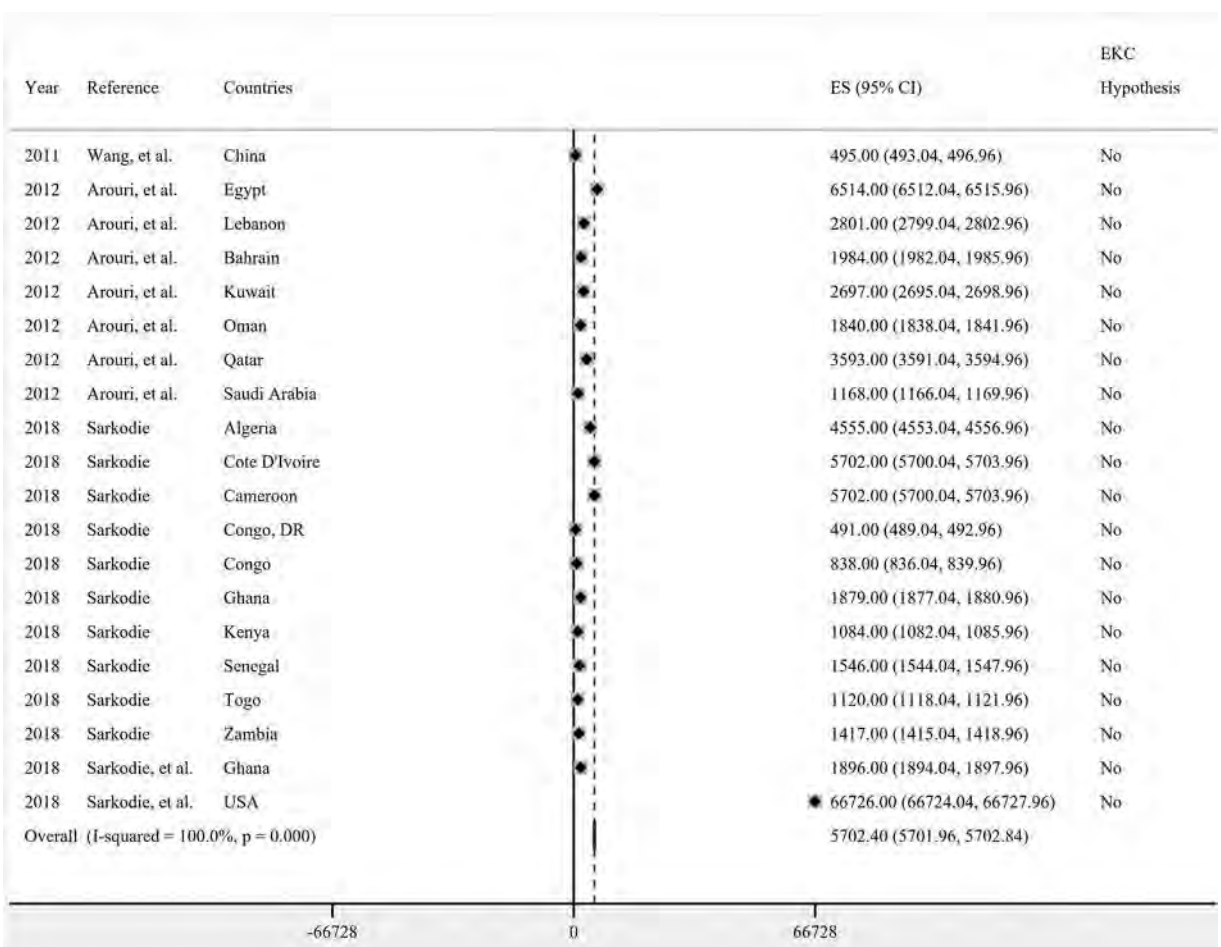


Fig. 4. Fixed effects meta-analytical method for invalid EKC hypothesis.

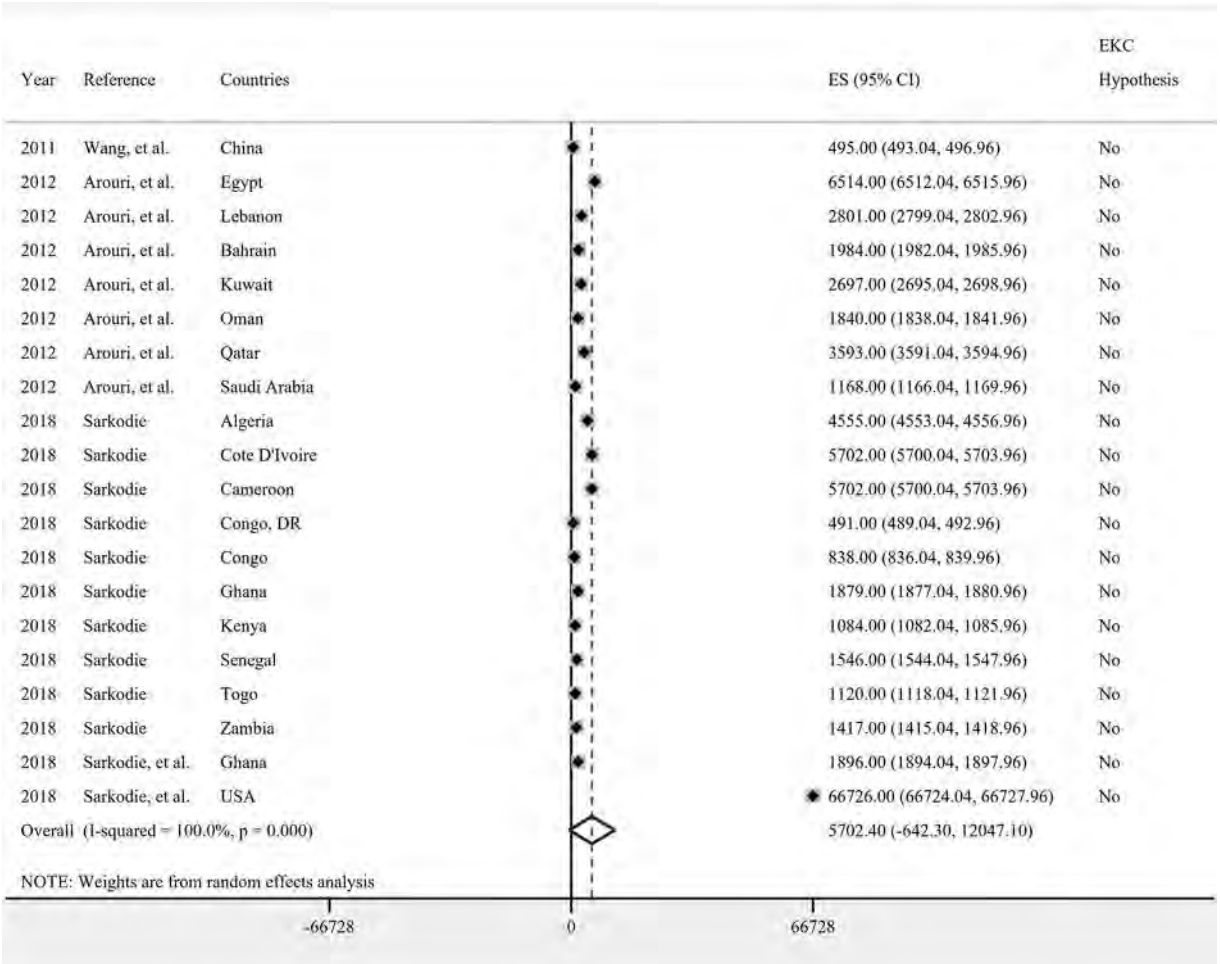


Fig. 5. Random effects meta-analytical method for invalid EKC hypothesis.

meta-analytic method for valid EKC hypothesis in Figs. 2–3 produce the same overall effect size even though different confidence intervals. The results reveal that the meta-analysis is statistically significant at 1% level with a borderline turning point of US$8910 GDP per capita and I^2 statistic value of 100%. The valid EKC hypothesis reveals a 100% variation attributable to heterogeneity, thus, in accordance with Higgins et al. (2003) classifications, a high heterogeneity exists between studies that validate the EKC hypothesis. The study further reveals that while low income and middle-income countries are below the US$ 8910 borderline, high income countries are above. In the same vein, the fixed and random effects of the meta-analytical method for invalid EKC hypothesis in Figs. 4–5 reveal the same I^2 statistical effect although at different confidence intervals. At 1% significance level, the study shows I^2 statistic value of 100% with at a turning point of US$ 5702. Majority of countries below the borderline are from middle-income countries while countries exhibiting extreme effect size are from high income countries.

To verify and validate the results of the meta-analysis, Table 2 presents the diagnostic test of the fixed and random effects meta-analytical methods. The heterogeneity chi-squared test validates the model by rejecting the null hypothesis of no differences in the turning points from the various studies. The possible explanation of the substantial differences in the turning point is due to the use of different econometric methods, the use of different data and time periods, thus, resulting in a broad spectrum of conflicting outcomes and policy implications (Dinda, 2004; Samuel and Owusu, 2017).

6. Bibliometric analysis

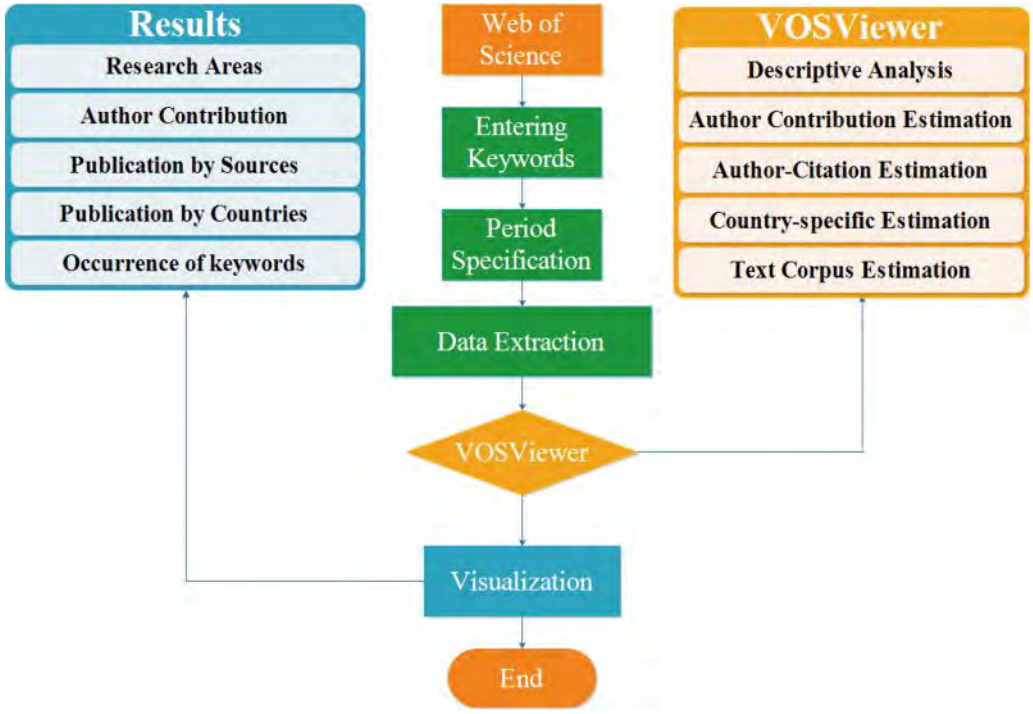
The bibliometric analysis employed in this study first starts with the problem definition, thus identifying the research area and defining the objectives of the scope of the study. In this study, an attempt is made to examine the broad knowledge of existing

Table 2
Diagnostic test of meta-analytical methods.

EKC hypothesis valid			
Fixed	ES	[95% conf. interval]	
I-V pooled ES	8910.51	8909.91	8911.105
Heterogeneity chi-squared	9.50E+08	(d.f. = 42)	p = 0.0000*
I-squared	100.00%	z = 29,215.05	p = 0.0000*
Random	ES	[95% conf. interval]	
D + L pooled	8910.51	6074.475	1.20E+04
Heterogeneity chi-squared	9.50E+08	(d.f. = 42)	p = 0.0000*
I-squared	100.00%	z = 6.16	p = 0.0000*
EKC hypothesis invalid			
Fixed	ES	[95% conf. interval]	
I-V pooled ES	5702.4	5701.962	5702.838
Heterogeneity chi-squared	4.00E+09	(d.f. = 19)	p = 0.0000*
I-squared	100.00%	z = 25,501.91	p = 0.0001*
Random	ES	[95% conf. interval]	
D + L pooled	5.70E+03	−642.298	1.20E+04
Heterogeneity chi-squared	4.00E+09	(d.f. = 19)	p = 0.0000*
I-squared	100.00%	z = 1.76	p = 0.0780**

* Denotes the significance of the null hypothesis at 1% level.
** Denotes the significance of the null hypothesis at 10% level.

Box 6
Procedure for the bibliometric analysis.



From the Web of Science database, the keywords and the period for the analysis is entered and search. Output data is downloaded and uploaded into VOSViewer software for bibliometric analysis. Using the linlog/modularity method of normalization and citations as the option for weights in the visualization scale, author contribution, author-document-citation, and text corpus are estimated. The results are then presented in visuals.

literature on the EKC hypothesis. To achieve the aim of the study, maps were created on trending scientific publications, scientific journals, authors contribution, the impact of research by countries, the impact of research by journals, popular keywords, citations count, and text corpus based on the network data extracted from Web of Science (see Box 6).

After defining the objectives, the study employs a search term for "Topic: (Environmental Kuznets Curve) Or Title: (Environmental Kuznets Curve) Or Topic: (EKC Hypothesis) Or Title: (EKC Hypothesis) Refined By: [Excluding] Publication Years: (2018) Timespan: All Years. Indexes: SCI-Expanded, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-Expanded, IC." in Web of Science database. Initial evaluation of the title and abstract are examined to identify potentially relevant papers for data collection The selected data comprised of the following information: "author(s)", "document title", "year", "source title", "volume-issue-pages", "citation count", "abstract", and "bibliographical information" The potential papers are then downloaded in a text file "txt" format for a subsequent analysis and synthesis using the bibliometric analysis through an inductive approach to iteratively refine the assessment framework.

VOSviewer software was then used to create visual maps based on the extracted data (Van Eck and Waltman, 2011). For brevity, the algorithms for the bibliometric analysis are available in Van Eck (2011).

6.1. Visualization of results

For interpretation of the maps, the density visualization was constructed in which the larger the number of keywords or publications by an author, the bigger and bolded the font and circular shape, and conversely, the smaller the number of keywords or publications by an author, the smaller the circular shape and the font (Van Eck and Waltman, 2011). It is important to note that the units may overlap which may not be visible if they have the same weight/density.

6.2. Descriptive analysis

The search terms for in Web of Science database showed 2341 publication records as shown in Fig. 6. The year 2017 had the highest number of publications (377 papers) on the Environmental Kuznets Curve hypothesis while the first publication on the topic occurred in

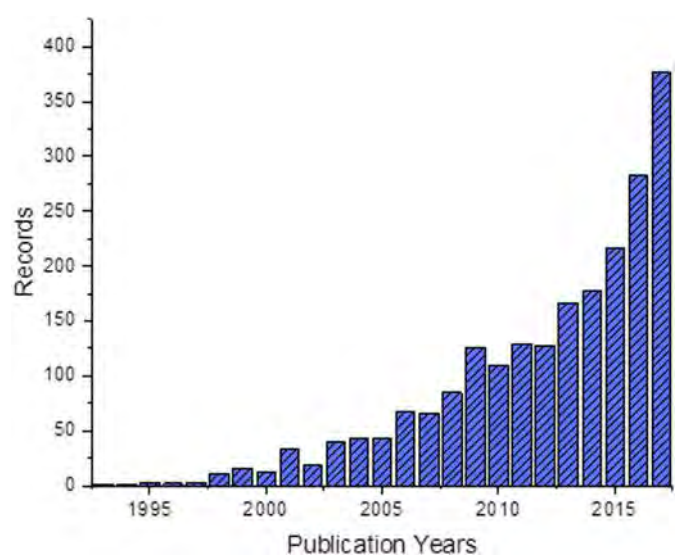


Fig. 6. Publication records on EKC hypothesis from Web of Science.

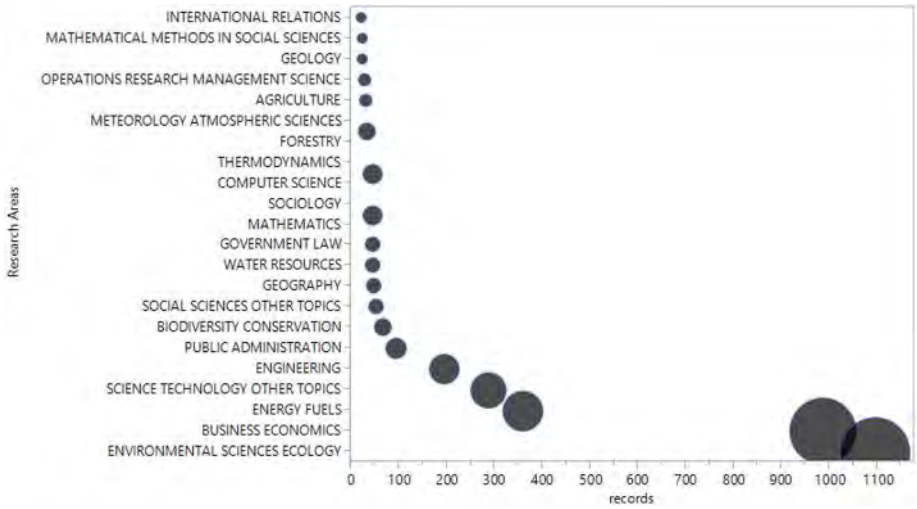


Fig. 7. Research areas on EKC hypothesis.

1993 (1 paper). However, research on the Environmental Kuznets Curve hypothesis has since experienced a significant increase. For the benefit of consistency and reliability, the data for subsequent analysis is truncated to 2017. Out of the 2164 publication records from 1993 to 2017, 1782 (82.35%) publications were articles, 232 (10.72%) publications were proceedings papers, 145 (6.70%) publications were reviews, 102 (4.71%) book chapters, 22 (1.02%) editorial materials, and 18 (0.83%). The bubble plot presented in Fig. 7 shows the top research areas that examine the EKC hypothesis, which include Environmental Sciences Ecology with 1093 (50.51%) publications, followed by Business Economics, Energy Fuels, Science Technology Other Topics, Engineering, Public Administration, Biodiversity Conservation, Social Sciences Other Topics, Geography, Water Resources, and Government Law. The results further reveal that the EKC hypothesis has received much attention in different research areas which include Mathematics, Sociology, Computer Science, Thermodynamics, Forestry, Meteorology Atmospheric Sciences, Agriculture, Operations Research Management Science, Geology, Mathematical Methods In Social Sciences, International Relations and others.

6.3. Author contribution

Authorship analysis was performed using the "author(s)" unit from the downloaded data and the full counting method from the VOSviewer computer software to create a map based on bibliographic data by selecting a threshold with a minimum of 5 documents of an author, which led to 25 thresholds. The 25 thresholds were analyzed using the association method of normalization and documents as the option for weights in the visualization scale. Fig. 8 presents a map of contributing authors with >5 publications on the Environmental Kuznets Curve hypothesis. According to the number of publications by each author, the largest number of publications (38) were authored by "Ozturk I" representing 1.76% of all selected publications, followed by "Shahbaz M" with 36 (1.66%) publications, "Managi S" with 25 (1.16%), "Mazzanti M" with 22 (1.02%) and others. The clusters in Fig. 8 reveal a strong evidence between the number of publications produced by an author on EKC hypothesis and co-authorship. Thus, the stronger the total link strength (i.e. scientific collaboration), the more authored publications.

Fig. 8. Author contribution by link strength.

6.4. Author-document citation relationship

Author-citation analysis was performed using the "author(s)" unit from the downloaded data to create a map based on citation data by selecting a threshold with a minimum of 100 citations of an author, which led to 50 thresholds. For each of the 50 authors, the number of citation links is calculated and the authors with the largest number of links are selected using the linlog/modularity method of normalization and citations as the option for weights in the visualization scale. Table 3 presents the top 50 most cited authors on EKC hypothesis. For brevity, Stern, D has a total of 2120 citations from 17 documents with a total link strength of 2. Ozturk, I has 1432 citations from 38 publications with 36 co-authorships, York, R has 1153 from 11 documents with 4 collaborations, Shahbaz, M has 1095 citations from 36 documents with 25 total link strength while Dinda, S has 1080 citations from 5 publications with no collaborators listed in this table. It is often assumed that the higher the number of publications an author has, the more likely citations, however, the case is different in this study. An observation from the total link strength in Table 3 shows that, while research collaboration may improve the number of scientific documents by an author, its citation impact may not be the impacted. Authors (i.e. Stern, D, Ozturk, I, Dinda, S, etc.) with an extensive literature review on the EKC hypothesis garnered more citations compared to original research articles.

Table 3
Top 50 most cited authors on EKC hypothesis.

Author	Publications	Citations	Total Link Strength[a]
Stern, D	17	2120	2
Ozturk, I	38	1432	36
York, R	11	1153	4
Shahbaz, M	36	1095	25
Dinda, S	5	1080	0
Dietz, T	5	965	4
Cole, M	12	843	1
Pao, HT	7	719	0
Saboori, B	11	501	5
Apergis, N	8	463	1
Wang, H	8	429	4
Al-Mulali, U	16	421	23
He, J	10	390	3
Managi, S	25	384	1
Neumayer, E	7	370	1
Martinez-Alier, J	5	365	0
Zaim, O	9	362	0
Mazzanti, M	22	358	11
Lean, HH	5	348	4
Martinez-Zarzoso, I	7	338	0
Zhang, X	9	301	8
Liu, Y	17	294	8
Roca, J	5	276	1
Padilla, E	7	256	1
Wang, Y	18	246	6
Jorgenson, AK	7	246	0
Wei, YM	7	239	5
Lin, B	11	235	0
Wagner, M	5	235	0
Zoboli, R	11	230	11
Hao, Y	15	210	7
Wang, S	17	209	12
Omri, A	6	206	0
Dogan, E	11	205	6
Farhani, S	6	204	5
Zhang, Y	12	185	3
Lindmark, M	6	175	2
Solarin, SA	11	172	17
Liddle, B	6	166	0
Katircioglu, ST	5	166	0
Wang, Z	6	165	2
Seker, F	6	158	5
Uddin, GS	6	148	5
Zhao, Y	7	144	6
Halkos, GE	12	140	10
Ahmed, K	11	137	7
Baek, J	6	137	0
Zaman, K	13	135	3
Liu, X	9	134	4
Tzeremes, NG	8	130	9
Kahn, ME	6	125	0
Chen, J	9	118	4
Kaivo-Oja, J	5	109	0
Berrens, R	5	103	10
Bohara, A	5	103	10
Gawande, K	5	103	10
Kander, A	6	102	2

[a] Total Link Strength signifies the number of co-authorship links with other authors based on available publications.

6.5. Source and country-wise analysis

Source publication analysis was done using the "source(s)" unit from the downloaded data to create a map based on citation data by choosing the top 25 journals that have published topics on EKC hypothesis. Fig. 9 presents a treemap of publications by journals. The top 5 journals that published manuscripts in Environmental Kuznets Curve hypothesis were Ecological Economics which published 183 (8.46%) documents, Energy Policy 103 (4.76%), Renewable Sustainable Energy Reviews 102 (4.71%), Environmental Science and Pollution Research 60 (2.77%) and Journal of Cleaner Production 50 (2.31%). Thus, it appears that literature on the Environmental Kuznets Curve has been sporadic, contrary to claims that the hypothesis has received much attention for over three decades.

Fig. 10 shows the country-wise publication analysis using the "country(ies)" unit from the downloaded data. For simplicity, the top 25 countries with the most published literature on EKC hypothesis are presented. The countries include; USA 499 (23.06%), Peoples R China 471 (21.77%), Turkey 130 (6.01%), England 124 (5.73%), Australia 120 (5.55%), Spain 112 (5.18%), France 109 (5.04%), Italy 100 (4.62%), Malaysia 97 (4.48%), Japan 89 (4.11%), India 69 (3.19%), Pakistan 67 (3.10%), Germany 64 (2.96%), Canada 59 (2.73%), Tunisia 57 (2.63%), Netherlands 56 (2.59%), Sweden 51 (2.36%), Greece 48 (2.22%), Taiwan 46 (2.13%), Switzerland 37 (1.71%), Austria 32 (1.48%), Iran 25 (1.16%), Brazil 24 (1.11%), South Africa 24 (1.11%), and Norway 23 (1.06%). Evidence from Fig. 10 reveals that studies on EKC hypothesis from low-middle and low-income countries are sporadic and limited.

6.6. Text corpus

The occurrence and importance of terms or text within the title and abstract were analyzed and apportioned with relevance scores. It is important to note in Fig. 11 that the round shape and bold text represents the weight of occurrences of text or terms. The highest occurring text include: China 249 occurrences (1.52), Economic Growth 231 occurrences (0.87), Evidence 230 occurrences (0.99), Environmental Kuznets Curve 203 occurrences (0.63), Country 184 occurrences (1.68), CO_2 Emission 182 occurrences (1.06), Energy Consumption 129 occurrences (1.08), Relationship 112 occurrences (0.45), Effect 97 occurrences (0.27), Impact 90 occurrences (0.66), Environment 74 occurrences (0.68), and Environmental Quality 63 occurrences (2.09). Due to the dominance of China in terms of global energy consumption, global crude oil imports, global coal consumption, global electricity consumption and global CO_2 emissions (Enerdata, 2017), it is not surprising that it emerged as the highest occurring term within the text corpus, because most studies are geared towards China to improve the current state of climate change impacts. The text corpus analysis reveals that the term "Environmental Quality" has the highest relevance score compared to the terms "Environmental Kuznets Curve", "CO_2 Emission", "Energy Consumption", "Economic Growth", and among others. This is because terms with a high relevance score appear to signify the specific topics covered in the text data. The majority of policy implication of studies on EKC hypothesis tends to improve the environmental quality.

Fig. 9. Publication by sources [constructed with Web of Science].

7. Conclusion

Due to the importance of the Environmental Kuznets Curve hypothesis for policy formulation, this study employed a systematic review of existing literature to investigate the EKC hypothesis using meta-analysis and bibliometric analysis. Though there are a large number of literature on the study, few have examined the turning point of income level at which the inverted-U shape hypothesis is validated. Using the meta-analysis, the study reveals a borderline turning point of US$8910 income level for studies that validate the inversed-U shaped relationship between environmental pollution and income levels. Studies with invalid EKC hypothesis, thus, U-shaped, monotone, N-shaped, have a borderline turning point of US$ 5702. Low income and middle-income countries are below the US$ 8910 and US$ 5702 thresholds while high-income countries are above. Due to differences in a period of study and econometric methods employed, the study confirms the validity of heterogeneity among turning point in studies on EKC hypothesis. The bibliometric analysis reveals that Ozturk, I published 38 articles, which is the largest number of publications on the EKC hypothesis, while Stern, D has the highest citations based on EKC publications. Review papers are the most cited publications on EKC hypothesis. The most dominant keyword is China while the most relevant keyword is Environmental quality. The empirical findings presented here reveal that most of the studies on the EKC hypothesis employ environmental indicators, such as atmospheric indicators, land indicators, oceans, seas, coasts and biodiversity indicators, and freshwater indicators. However, the most frequently applied topics on EKC hypothesis are based on atmospheric indicators. As such, future research should focus on the other environmental indicators.

7.1. Policy implications of EKC hypothesis

The environmental status of a country depends on many factors which include the size of the economy, the current state of technology, the sectoral economic structure, and demand for environmental-related services. Larger economies are characterized with rapid depletion of

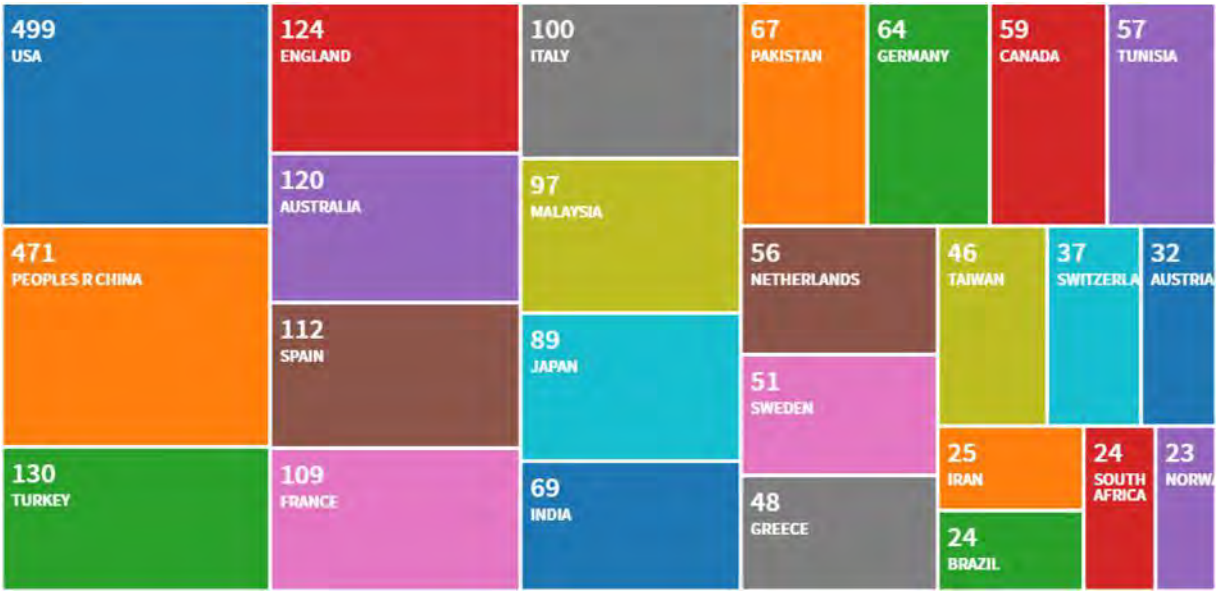


Fig. 10. Publication by countries [constructed with Web of Science].

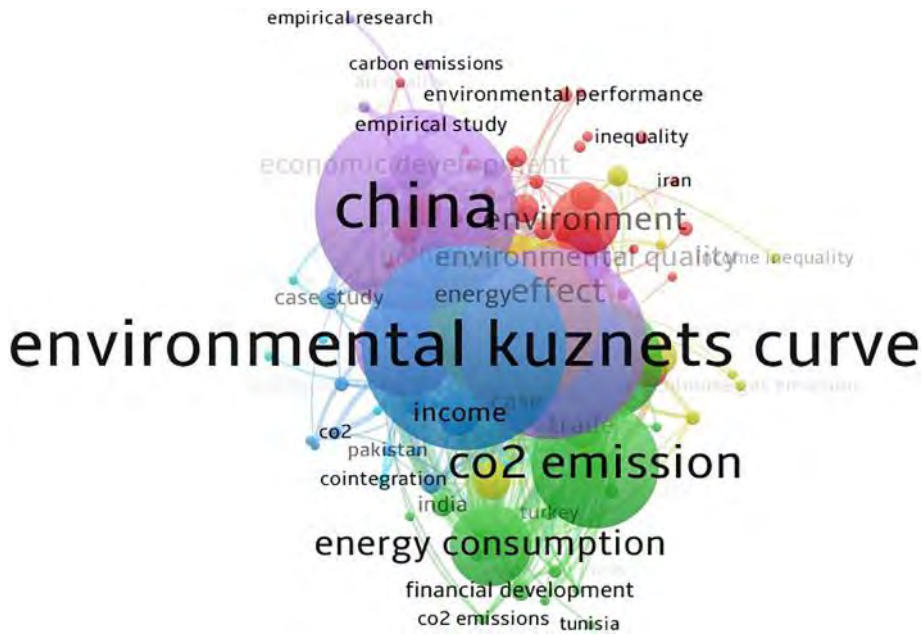


Fig. 11. Occurrence and relevance of keywords.

natural resource and higher pollution levels. Resource depletion and pollution levels are determined by the sectoral economic structure. While agrarian economies tend to exploit more natural resources, industrialized economies tend to suffer from urban pollution and congestion-related problems. The difference between agrarian and industrial economy is evident in the share of the industrial sector's contribution to a country's GDP. While the share of industrial GDP in middle-income countries is above one-third of GDP, the industry sector contribution to GDP in low-income countries is relatively smaller than the contribution of agriculture to the GDP (Panayotou, 1993). The industrial sector in low-income countries is dominated by agro-processing (i.e. the transformation of agriculture, fisheries, and forestry-related products into finished goods) and light assembling technologies. Factors affecting the industry in low-income countries include inadequate funding and financial instruments to support small and medium scale enterprises, lack of advanced technologies, high post-harvest losses, non-compliance to stringent industrial standards and regulations, and intermittency in raw material supply. Due to these factors, the relationship between environmental stress and industry-related GDP tends to be monotonic. Asumadu and Owusu (2016) and Sarkodie and Owusu (2017) found a strong relationship between agriculture and greenhouse gas emissions, which is in line with the IPCC report. According to the IPCC 5th Assessment report, the agricultural sector remains the second major contributor to global greenhouse gas emissions (IPCC, 2015). The industrial sector in middle-income countries is dominated by carbon-intensive and energy-intensive productions such as cement, chemicals, primary metals (heavy steel) and forest products (i.e. paper and pulp) among others. Due to cheaper production cost, lax environmental regulations and somewhat less-stringent industry standards, there is always an influx of carbon-intensive and energy-intensive industries from developed countries to middle-income countries. However, developing countries like China, Iran, India, Indonesia and South Africa have a comparative advantage in carbon-intensive production of goods and as such, increase the aggregate economic growth. Sarkodie and Strezov (2019) revealed that developing countries using their comparative advantage in exchange for modernized technological transfer, innovations, and partnership on clean energy technologies would reduce stress on natural resource and improve environmental sustainability, thus, reducing environmental pollution. The share of the industrial sector to GDP in higher income countries tends to reach a plateau state or somewhat decline, due to high production cost, stringent environmental regulations and compliance with industry standards. Due to this, there is a paradigm shift from carbon-intensive and energy-intensive manufacturing or primary metals, chemicals and forest products to less-energy intensive and carbon-intensive industries, such as food, transportation equipment; sophisticated and modernized technologies, such as green and clean energy technologies, electricals and electronic equipment, and services. As such, there is a reduction in energy intensity while improving energy efficiency. The structural change in economic development may be what explains the inversed-U shaped relationship between environmental deterioration and economic development.

The following recommendations emanate from the implications of the EKC hypothesis:

- Energy efficient economy requires an incorporation of clean and energy technologies in the energy mix including renewable energy, and cleaner fossil fuel energy technologies that adopt carbon, capture, and storage.
- Replacement of vintage and obsolesce energy technologies with innovative and modern energy technologies improve environmental quality.
- Enhanced global partnership, such as trade and foreign direct investment from developed countries that promote capacity building, and environmentally friendly and modern technological transfer in developing countries would help in the achievement of sustainable development.
- The mitigation of climate change and its impact requires an integration of climate change measures (awareness creation, capacity building, adaptation options and early warning signs) into national policies.
- Promoting sustainable industrialization that foster industry value addition, innovation, technological advancement, scientific research, and development is critical to the achievement of the SDGs.

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Declaration

There is no conflict of interest.

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Chapter Two: The Invisible Hand and EKC Hypothesis: What Are the Drivers of Environmental Degradation and Pollution In Africa?

Chapter Two presents the following research article:

- **Sarkodie, S.A.**, 2018. The Invisible Hand and EKC Hypothesis: What Are the Drivers of Environmental Degradation and Pollution In Africa? *Environmental Science and Pollution Research* 25, 21993–22022.

The study accounts for cross-sectional dependence in the Westerlund Error-Correction Model-based panel cointegration tests using the bootstrapping approach for 1,000 samples. The Utest method is used to validate the EKC hypothesis, alongside fixed- and random effect estimators, and panel causality test.

Pages 31-60 of this thesis have been removed as they contain published material. Please refer to the following citation for details of the article contained in these pages.

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Chapter Three: Effect of foreign direct investments, economic development and energy consumption on greenhouse gas emissions in developing countries.

Chapter Three presents the following research article:

- **Sarkodie, S.A.**, Strezov, V., 2019. Effect of foreign direct investments, economic development and energy consumption on greenhouse gas emissions in developing countries. *Science of The Total Environment* 646, 862-871.

The study employs the Driscoll-Kraay covariance estimator that does not restrict the limiting behavior of the panels and produces robust standard errors. We further account for distributional heterogeneity using panel quantile regression. Robust estimations are derived using an adaptive Markov Chain Monte Carlo optimization based on 1,000 draws.

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Effect of foreign direct investments, economic development and energy consumption on greenhouse gas emissions in developing countries

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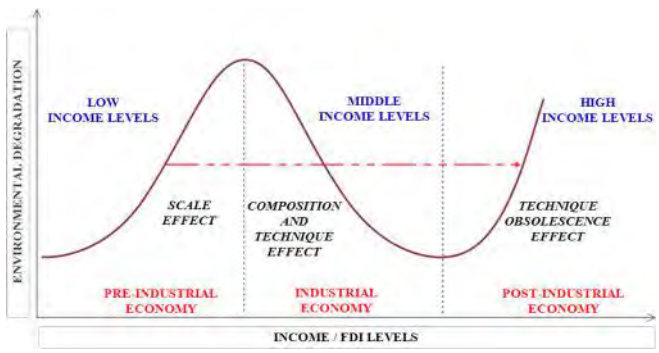
HIGHLIGHTS

- The environmental Kuznets curve hypothesis is valid for China and Indonesia.
- The pollution haven hypothesis is valid for China, India, Indonesia, Iran and South Africa.
- The study found a strong positive effect of energy consumption on CO_2 emissions.
- Foreign direct investment increases the level of CO_2 emissions in Indonesia.
- Clean and modern energy technologies will improve industrial-based pollution levels.

GRAPHICAL ABSTRACT



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ABSTRACT

In accordance with the Sustainable Development Goal 17 of improving global partnership for sustainable development, this study examined the effect of foreign direct investment inflows, economic development, and energy consumption on greenhouse gas emissions from 1982 to 2016 for the top five emitters of greenhouse gas emissions from fuel combustion in the developing countries, namely; China, India, Iran, Indonesia and South Africa. The study employed a panel data regression with Driscoll-Kraay standard errors, *U* test estimation approach and panel quantile regression with non-additive fixed-effects. The study found a strong positive effect of energy consumption on greenhouse gas emissions and confirmed the validity of the pollution haven hypothesis. The environmental Kuznets curve hypothesis is valid for China and Indonesia at a turning point of US$ 6014 and US$ 2999; second, a U-shape relationship is valid for India and South Africa at a turning point of US$ 1476 and US$ 7573. Foreign direct investment inflows with clean technological transfer and improvement in labour and environmental management practices will help developing countries to achieve the sustainable development goals. Mitigation of greenhouse gas emissions depends on enhanced energy efficiency, adoption of clean and modern energy technologies, such as renewable energy, nuclear, and the utilization of carbon capture and storage for fossil fuel and biomass energy generation processes.

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1. Introduction

The pollution haven hypothesis postulates that dirty industries migrate from high-income countries to low and middle-income countries through the trading of goods and foreign direct investment. Foreign direct investment (FDI) inflows remain one of the main sources of

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external funding for developing countries, yet, the relocation of carbon-intensive and energy-intensive industries from jurisdictions with more stringent environmental regulation to weak locales results in pollution haven. The transfer, dissemination, and diffusion of FDI inflows with polluting technologies, goods, and services to developing countries become the most important part of the challenge to achieve the sustainable development goals (SDGs). On the contrary, the environmental Kuznets curve (EKC) hypothesis postulates that the initial growth of a country's economic development leads to gradual deterioration of environmental quality and improves environmental conditions after reaching a threshold in economic development (Grossman and Krueger, 1991). Thus, both the pollution haven hypothesis and the EKC hypothesis are important policy derivatives for developing countries. Considering the importance of climate change mitigation and its impacts, as accentuated in SDG 13, the effect of FDI inflows, economic development, and energy consumption on greenhouse gas emissions in developing countries needs further attention to be able to alleviate the impacts.

Studies on pollution haven hypothesis (Zakarya et al. (2015) Behera and Dash, 2017; Solarin et al. (2017) Sun et al. (2017), support the validity of this hypothesis. Solarin et al. (2017) validated the pollution haven hypothesis for Ghana using the autoregressive distributed lag (ARDL) bounds testing approach. Sun et al. (2017) examined the impact of FDI inflows, economic growth, energy use, economic freedom, urbanization, financial development, and trade openness on CO_2 emissions using the autoregressive distributed lag model. The study confirmed the validity of the pollution haven hypothesis in China and that the positive effect of FDI inflows stems from the large contribution of manufacturing, mining and electricity shifted from the developed countries. Using the fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares regression, Behera and Dash (2017) found a positive impact of FDI inflows and energy consumption on CO_2 emissions in 17 south and southeast Asian countries, thus, confirming the pollution haven hypothesis. Zakarya et al. (2015) found a long-run effect of FDI inflows and energy consumption on CO_2 emissions in Brazil, Russia, India, and China, thus, validating the pollution haven hypothesis via panel causality and FMOLS regression. On the contrary, studies like Zhu et al. (2016) and Zhang and Zhou (2016), rejected the pollution haven hypothesis. Zhu et al. (2016) employed panel quantile regression to examine the heterogeneous effect of FDI inflows, economic growth, and energy consumption on CO_2 emissions in Indonesia, Malaysia, Philippines, Singapore, and Thailand from 1981 to 2011. The study found insufficient support for the pollution haven hypothesis but rather found the halo effect hypothesis in high emission countries. Zhang and Zhou (2016) argue that FDI inflows of modern technologies contribute to CO_2 emissions reduction in China rather than environmental deterioration. Dasgupta et al. (1999, 2001) and Dean et al. (2004) revealed that developing countries depend on sophisticated technology transfer through FDI inflows from developed countries as their primary source of acquiring technology. Hence, clean and upgrading from vintage to modern technologies help in the reduction of emission levels.

The EKC hypothesis posits that the initial stages of economic development are characterized by high emission levels and environmental stress, however, as the economy grows and reaching a specific turning of income level, pollution levels decline (Grossman and Krueger, 1991). Panayotou (1993) argued that the initial stages of economic development increase the natural resource extraction leading to an increase in waste generation. However, at higher levels of economic development, the improvements in technology, stringent environmental regulations and a structural change in the economy from pollution-intensive industries to services and information declines environmental deterioration (Grossman and Krueger, 1991; Panayotou, 1993; Sarkodie, 2018). A number of recent studies on the EKC hypothesis (Lau et al. (2014); Al-Mulali and Ozturk (2016) Abdallh and Abugamos (2017) Sarkodie (2018) Sarkodie and Strezov (2018) support this hypothesis while Özokcu and Özdemir (2017) and Zoundi (2017) reject the validity of the EKC hypothesis. The opposing arguments on both the pollution haven and the EKC hypothesis due to the mixed outcomes in existing literature prompt on the need for further empirically tests of the validity of both hypotheses by examining the effect of FDI inflows, economic development, and energy consumption on GHG emissions.

The aim of this study is to investigate both pollution haven and EKC hypotheses to determine the effect of foreign direct investments, economic development, and energy consumption on greenhouse gas emissions in developing countries. The study selects the top five greenhouse gas emitting developing countries, namely China, India, Iran, Indonesia and South Africa. Contrary to existing literature, which adopts econometric methods that have challenges with cross-sectional dependence and issues when the time dimension becomes large, this study employs the Driscoll-Kraay covariance estimator that does not restrict the limiting behaviour of the panels and produces robust standard errors. As most of the results from previous studies neglect the distributional heterogeneity which may adversely impact the findings, this study considers distributional heterogeneity using panel quantile regression. The study employs Powell (2016) estimator with non-additive fixed-effects and non-separable disturbance term in the panel quantile estimation, which can correct the additive fixed-effects and separate disturbance terms when panel quantile regression is employed in the analysis. In order to produce robust estimations, the panel quantile regression is estimated using an adaptive Markov Chain Monte Carlo optimization based on 1000 draws. The study contributes to the global debate on greenhouse gas emissions from the top five emitters of carbon emissions from fuel combustion in developing countries by assessing the determinants of disaggregate greenhouse gas emissions throughout the quantiles.

2. Materials and methods

2.1. Data

To meet the outlined objectives, the study employs data from the World Development Indicators (World Bank, 2016) from 1982 to 2016 for the top five emitters of greenhouse gas emissions from fuel combustion in developing countries, namely; China, India, Iran, Indonesia and South Africa. The selection of the five countries stems from the Global Energy Statistical Yearbook 2018 ranking on CO_2 intensity by Enerdata (2017). Five study variables, Foreign direct investment net inflows (FDI), GDP per capita (GDPP), CO_2 emissions (CO_2E), total greenhouse gas emissions (GHG) and Energy use (ENE) are adopted in the study, as presented in Table 1. The World Bank defines FDI inflows as the inward direct investment to the indigenous economy made by foreigners (World Bank, 2016). GDP per capita is an indicator which measures the total economic output reflecting the changes in the production of goods and service excluding the cost of social and environmental production and consumption (Disano, 2002). CO_2 emissions measure anthropogenic emissions from fossil fuel energy combustion, industrial processes like cement manufacturing, and agricultural, forestry and land-use (World Bank, 2016). GHG emissions measure the six main GHG namely CO_2 emissions, methane, sulphur hexafluoride, nitrous oxide, hydrofluorocarbons, and perfluorocarbons. Thus, the data on non-CO_2 greenhouse gas emissions (NCO_2E) is extracted by deducting CO_2 emissions from the total greenhouse gas emissions to derive the data series. Energy use is an indicator which measures the primary energy consumption before end-use (World Bank, 2016). The selection of the data is based on the United Nations' Indicators of Sustainable Development: Guidelines and Methodology and the Sustainable Development Goals (SDGs) (United Nations, 2015). Due to the availability of data, missing data points are filled with Microsoft Excel interpolation method by aggregating duplicates using average at 99.99% confidence interval presented in Appendix A.

2.2. Panel regression

To examine the pollution haven hypothesis, the study employs a panel data regression with Driscoll-Kraay standard errors for coefficients estimated by the fixed-effects estimator. Cross-sectional dependence is one of the challenges in panel data settings, thus, yielding inconsistent estimates. Unlike standard techniques, Driscoll and Kraay (1998) algorithm accounts for cross-sectional dependence which results in a consistent and robust estimated standard errors. The Driscoll-Kraay algorithm assumes that the error structure is heteroskedastic, autocorrelated up to some lag and correlated between the groups in the panel. The Driscoll-Kraay estimator is a non-parametric technique which is more flexible without any restriction imposed on limiting behaviour of the number of panels and more useful when the time dimension becomes larger, thus, the estimator is based on large T asymptotics. The Driscoll-Kraay covariance estimator is capable of handling missing values and applicable in balanced and unbalanced panel data. The study takes the absolute of all negative values to prevent missing data after logarithmic transformation.

This study employs Driscoll-Kraay standard errors for pooled ordinary least squares (OLS) estimation by considering a linear model expressed as:

$$y_{i,t} = x'_{i,t}\beta + \varepsilon_{i,t}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T \tag{1}$$

where $y_{i,\,t}$ is the dependent variable (CO_2E| NCO_2E) and is a scalar, $x_{i,\,t}$ denotes the independent variables (FDI, FDI^2, FDI^3, GDPP, $GDPP^2$, $GDPP^3$ and ENE) with a $(K+1)\times 1$ vector, whose first element is 1, and β denotes the unknown coefficients with $(K+1)\times 1$ vector, i denotes the individual/cross-sectional units at time t.

Stacking all the observation, the formulation is expressed as:

$$\begin{aligned} y &= \left[y_{1,t_{1,1}}, \ldots, y_{1,T_1}\ y_{2,t_{2,1}}, \ldots, y_{N,T_N}\right]' \text{ and } X \\ &= \left[x_{1,t_{1,1}}, \ldots, x_{1,T_1}\ x_{2,t_{2,1}}, \ldots, x_{N,T_N}\right]' \end{aligned} \tag{2}$$

This is assumed that $x_{i,\,t}$ are uncorrelated with the scalar error term $\varepsilon_{i\,s}$ for all s, t (strong exogeneity). Nevertheless, $\varepsilon_{i,\,t}$ can exhibit heteroscedasticity, autocorrelation and cross-sectional dependence. Based on the outlined assumptions, β can be consistently estimated by OLS regression which results in (Hoechle, 2007):

$$\hat{\beta} = (X'X)^{-1}X'y \tag{3}$$

For brevity, the coefficient estimates of the Driscoll-Kraay standard errors are derived as a "square roots ($\hat{S}_T$) of the diagonal elements of the asymptotic covariance matrix" expressed as (Driscoll and Kraay, 1998):

$$V\left(\hat{\beta}\right) = (X'X)^{-1}\hat{S}_T\,(X'X)^{-1} \tag{4}$$

After the estimation of the panel regression, the study employs the U test algorithm by Lind and Mehlum (2010) to test the EKC and pollution haven hypothesis in individual countries.

Table 1
Description of variables.

Series	Series name	Units
FDI	Foreign direct investment, net inflows	Current US$
GDPP	GDP per capita	Current US$
CO_2E	CO_2 emissions	kt
GHG	Total greenhouse gas emissions	kt of CO_2 equivalent
ENE	Energy use	kg of oil equivalent per capita

2.3. Quantile regression for panel data

This subsection introduces panel quantile regression estimator by Powell (2016) with non-additive fixed-effects and maintains the non-separable disturbance term related with quantile estimation in panel data settings. It is contrary to other panel quantile regression estimators (Zhu et al., 2016) with additive fixed-effects and separable disturbance term incorporated into the quantile estimation, with the assumption that time-varying components only affect the variability of parameters.

The distribution of the outcome variable $Y_{i,\,t}$ is estimated using the quantile panel regression for treatment variables $D_{i,\,t}$. To maintain the non-separable disturbance term usually linked with panel quantile estimation, the study employs non-additive fixed-effects to model the outcome, expressed as:

$$Y_{i,t} = D'_{i,t}\beta(U^*{}_{i,t}), \qquad U^*{}_{i,t} \sim U(0,1) \tag{5}$$

where $D_{i,\,t}'\beta(\tau)$ strictly increases in quantile τ, $U^*{}_{i,t}$ denotes the function of the disturbance terms and proneness for the outcome. The structural quantile function for Eq. (5) is expressed as:

$$S_Y(\tau/d) = d'\beta(\tau), \qquad \tau\in(0,1) \tag{6}$$

The structural quantile function explains the quantile of the latent outcome variable $Y_d = d'\beta(U^*)$ for randomly selected U^*~$U(0,1)$ and a fixed potential value of the treatment effect d.

Based on the above algorithm, the study specifies the panel quantile regression to test the effect of FDI and per capita GDP on carbon dioxide emissions and greenhouse gas emissions as:

$$\begin{aligned} (CO_2E|NCO_2E)_{i,t}(\tau|\alpha_i, \delta_t, x_{i,t}) = {} & \alpha_i + \delta_t + \beta_{1,\tau}FDI_{i,t} + \beta_{2,\tau}FDI^2{}_{i,t} \\ & + \beta_{3,\tau}FDI^3{}_{i,t} + \beta_{4,\tau}GDPP_{i,t} \\ & + \beta_{5,\tau}GDPP^2{}_{i,t} + \beta_{6,\tau}GDPP^3{}_{i,t} \\ & + \beta_{7,\tau}ENE_{i,t} \end{aligned} \tag{7}$$

where, α_i denotes the non-adaptive fixed-effects, x denotes the matrix of the independent variables at individual countries i and time t. In order to improve the results of the panel quantile regression, the study performs a numerical optimization via adaptive Markov chain Monte Carlo sampling using a multivariate normal proposal distribution by Baker (2014).

The study specifies the cointegrating relationship as:

$$\begin{aligned} (CO_2E|NCO_2E)_{i,t} = {} & \gamma_i + \beta_1 FDI_{i,t} + \beta_2 FDI^2{}_{i,t} + \beta_3 FDI^3{}_{i,t} + \beta_4 GDPP_{i,t} \\ & + \beta_5 GDPP^2{}_{i,t} + \beta_6 GDPP^3{}_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{8}$$

where γ_i denotes the panel-specific fixed-effects, $\beta_1, \ldots, \beta_6$ denote the cointegrating parameters which are the same across the panel, and ε

Table 2
Panel unit root tests.

	lnFDI	$lnCO_2E$	$lnNCO_2E$	lnGDPP	lnENE
Level					
Breitung	1.3509	6.6682	1.5927	4.8141	6.3624
p-Value	0.9116	1.0000	0.9444	1.0000	1.0000
IPS	−1.4531	1.9348	1.8576	4.2605	4.3570
p-Value	0.0731	0.9735	0.9684	1.0000	1.0000
Hadri	36.8638	47.3130	21.9341	42.9495	46.4008
p-Value	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]
1st diff					
Breitung	−4.1102	−6.5870	−6.8856	−6.4326	−4.0060
p-Value	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]
IPS	−8.0031	−6.1878	−7.2197	−5.6604	−6.7919
p-Value	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]
Hadri	−1.7984	−1.0196	−1.9159	0.8258	0.9721
p-Value	0.9639	0.8461	0.9723	0.2045	0.1655

[a] Rejection of the null hypothesis at 1% significance level.

Table 3
Results of Kao test for cointegration.

Kao test statistic	CO_2E		NCO_2E	
	−14.8016	0.0000[a]	−13.4722	0.0000[a]
Modified Dickey-Fuller t	−7.2251	0.0000[a]	−4.2012	0.0000[a]
Dickey-Fuller t	−4.8266	0.0000[a]	−3.3882	0.0004[a]
Augmented Dickey-Fuller t	−14.6411	0.0000[a]	−11.3254	0.0000[a]
Unadjusted modified Dickey-Fuller	−7.2173	0.0000[a]	−4.0505	0.0000[a]
Unadjusted Dickey-Fuller t	−14.8016	0.0000[a]	−13.4722	0.0000[a]

[a] Denotes the rejection of the null hypothesis of no cointegration at 1% significance level.

represents the white noise. The Kao cointegration test employs Bartlett Kernel for an automatic lag selection and proposes five test statistics namely, modified Dickey-Fuller t, Dickey-Fuller t, augmented Dickey-Fuller t, unadjusted modified Dickey-Fuller, and unadjusted Dickey-Fuller t.

3. Results

3.1. Panel unit root & cointegration test

Prior to the estimation of the panel data regression with Driscoll-Kraay standard errors for coefficients and panel quantile regression, the study performs three variety of tests for stationarity in a strongly balanced panel data series. The variety of tests includes Breitung (1999), Im-Pesaran-Shin (IPS) (Pesaran et al., 2003) and Hadri (2000) Lagrange multiplier (LM). Both Breitung and IPS tests have the same null hypothesis that all the data series contain a unit root while Hadri LM test has the null hypothesis that all the panel data series are stationary. Breitung (1999) test transforms the data series before the regression to make the standard t statistics usable. Even though the IPS test (Pesaran et al., 2003) does not require a strongly balanced panel like Breitung and Hadri LM tests it allows each panel to have its own rho_i. Hadri (2000) LM test conducts an alternative test to provide strong evidence to reject the null hypothesis. The test assumes that the error terms in the model are normally distributed and is more appropriate for panel data series with a large period (T) and moderate to small cross-sectional units (N). Evidence from Table 2 reveals that the null hypothesis of unit root by the IPS and Breitung tests cannot be rejected at level but rejected at first difference. The null hypothesis of stationarity by the Hadri LM test cannot be rejected at level but rejected at first difference. Thus, all the three tests reveal that the data series under investigation are integrated of order one.

With evidence that the data series are integrated of order one, the study proceeds to test the long-run effect of FDI, squared of FDI, cubic of FDI, GDPP, squared of GDPP and cubic of GDPP on CO_2E and NCO_2E emissions using the Kao (1999) test for cointegration. Table 3 reveals that the null hypothesis of no cointegration is rejected at 1% significance level for all five test statistics under the two models.

3.2. Driscoll-Kraay panel regression

To enable comparison, the study first estimates the panel regression with Driscoll-Kraay standard errors. Table 4 presents the results of the level-log panel data with Driscoll-Kraay standard errors estimated by fixed-effect regression and average marginal effects for post-estimation. The results reveal that all the coefficients in the pollution haven hypothesis and EKC hypothesis are significant at 1% level.

The nexus between per capita GDP and CO_2/non-CO_2 GHG emissions are presented in Table 4. In both scenarios of CO_2 and non-CO_2 GHG emissions, economic development is initially positive, thus, increases CO_2 and non-CO_2 GHG emissions by 270,000 kt and 308,000 kt of CO_2 equivalent but decreases by 39,278 kt and 42,978 kt of CO_2 equivalent after reaching a turning point in economic development, and accelerates by 1876 kt and 1975 kt of CO_2 equivalent afterwards. Hence, the Driscoll-Kraay panel regression supports the EKC hypothesis for all the selected countries.

The initial effect of FDI on CO_2 emissions is positive and becomes negative at the first turning point ($lnFDI^2$) of development after reaching an extreme point but becomes positive at the second turning point ($lnFDI^3$) of development. Quantitatively, the initial impact of FDI increases CO_2 emissions by 265,000 kt, thus, confirming the pollution haven hypothesis. However, CO_2 emissions decline by 13,772 kt at the first turning point and increases by 236 kt thereafter. This means that the pollution haven hypothesis affects the shape of the EKC (Dinda, 2004). Similarly, FDI accelerates non-CO_2 GHG emissions by 60,791 kt of CO_2 equivalent until it reaches a threshold, then declines by 3070 kt of CO_2 equivalent and accelerates by 51 kt of CO_2 equivalent afterward, hence, the initial positive effect confirms the pollution haven hypothesis.

A positive impact of energy use on CO_2 emissions and non-CO_2 GHG emissions is evidenced in Table 4. 1% increase in energy use propels CO_2 emissions and non-CO_2 GHG emissions by 14,640 kt and 3327 kt of CO_2 equivalent.

To verify and validate the results of the Driscoll-Kraay panel regression, the study employs the average marginal effects as a post-estimation technique. The corresponding results of the average marginal effects are presented in columns 6–9 of Table 4. The post-

Table 4
Results of panel data regression and average marginal effects.

	Coef.	Drisc/Kraay std. err.	t	P > t	dy/dx	Std. err.	z	P > z
CO_2E								
lnGDPP	270,000	139,000	1.94	0.0610	270,000	139,000	1.94	0.0520
$lnGDPP^2$	−39,278	18,909	−2.08	0.0450	−39,278	18,909	−2.08	0.0380
$lnGDPP^3$	1876	855	2.19	0.0350	1876	855	2.19	0.0280
lnFDI	265,000	34,652	7.64	0.0000	265,000	34,652	7.64	0.0000
$lnFDI^2$	−13,772	1687	−8.16	0.0000	−13,772	1687	−8.16	0.0000
$lnFDI^3$	236	27	8.69	0.0000	236	27	8.69	0.0000
lnENE	14,640	3060	4.78	0.0000	14,640	3060	4.78	0.0000
_cons	−2,370,000	444,000	−5.35	0.0000	R-squared	0.92	Prob > F	0.0000
NCO_2E								
lnGDPP	308,000	90,094	3.42	0.0020	308,000	90,094	3.42	0.0010
$lnGDPP^2$	−42,978	12,456	−3.45	0.0020	−42,978	12,456	−3.45	0.0010
$lnGDPP^3$	1975	569	3.47	0.0010	1975	569	3.47	0.0010
lnFDI	60,791	13,860	4.39	0.0000	60,791	13,860	4.39	0.0000
$lnFDI^2$	−3070	680	−4.52	0.0000	−3070	680	−4.52	0.0000
$lnFDI^3$	51	11	4.64	0.0000	51	11	4.64	0.0000
lnENE	3327	1822	1.83	0.0770	3327	1822	1.83	0.0680
_cons	−1,130,000	282,000	−4.02	0.0000	R-squared	0.29	Prob > F	0.0000

Table 5
U test estimation results.

Country		CO_2E-GDPP		CO_2E -FDI		NCO_2E -GDPP		NCO_2E -FDI	
		Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
China	Interval	203.3349	8123.181	4.30E + 08	2.91E + 11	203	8123	4.30E + 08	2.91E + 11
	Slope	0.0006	−0.0002	1.31E − 11	−2.70E − 12	1.89E − 04	2.13E − 05	6.71E − 12	−1.66E − 12
	t-Value	14.1947	−4.4986	17.8293	−3.0833			8.1789	−1.6772
	P > t	2.18E − 16	0.0000	1.93E − 19	0.0020			0.0000	0.0512
		Turns[a]	6014	**Turns**	2.41E + 11	**Turns**	9126	**Turns**	2.33e + 11
		Shape[b]	Inverse U shape	**Shape**	Inverse U shape	**Shape**	Monotone	**Shape**	Inverse U shape
India	Interval	271.3336	1709.592	5,640,000	4.45E + 10	2.71E + 02	1.71E + 03	5.64E + 06	4.45E + 10
	Slope	0.0023	−0.0004	7.09E − 11	−2.00E − 11	1.23E-03	−1.64E − 03	3.20E − 11	−4.43E − 11
	t-Value	6.5755	−1.0916	5.9385	−1.4061	6.2867	−6.6996	5.20E + 00	−5.76E + 00
	P > t	6.79E − 08	0.1412	4.65E − 07	0.0843	0.0000	0.0000	0.0000	0.0000
		Turns	1476	**Turns**	3.47E + 10	**Turns**	889	**Turns**	1.86e + 10
		Shape	U shape	**Shape**	Inverse U shape	**Shape**	Inverse U shape	**Shape**	Inverse U shape
Indonesia	Interval	471	3688	−4.55E + 09	2.51E + 10	4.71E + 02	3.69E + 03	1.45E + 08	2.51E + 10
	Slope	0.0011	−0.0003	6.29E − 11	2.32E − 11	0.0003	−0.0011	0.0000	0.0000
	t-Value	7.1031	−1.9177			0.6782	−2.5032		
	P > t	0.0000	0.0317			0.2510	0.0086		
		Turns	2999	**Turns**	4.25E + 10	**Turns**	1153	**Turns**	−1.43e + 11
		Shape	Inverse U shape	**Shape**	Monotone	**Shape**	U shape	**Shape**	Monotone
Iran	Interval	1081	7833	−3.62E + 08	4.66E + 09	1.08E + 03	7.83E + 03	2.00E + 06	4.66E + 09
	Slope	0.0001	0.0002	6.41E − 10	−2.49E − 10	8.93E − 05	2.88E − 04	0.0000	0.0000
	t-Value			6.0527	−1.8032			3.0777	−0.1657
	P > t			3.29E − 07	0.0400			0.0020	0.4347
		Turns	−4456	**Turns**	3.25E + 09	**Turns**	−1955	**Turns**	4.31e + 09
		Shape	Monotone	**Shape**	Inverse U shape	**Shape**	Monotone	**Shape**	U shape
South Africa	Interval	2052	7976	−4.53E + 08	9.89E + 09	2.05E + 03	7.98E + 03	3.36E + 06	9.89E + 09
	Slope	0.0002	0.0000	1.16E − 10	−5.73E − 11	1.50E − 04	2.95E − 04	5.81E − 10	−6.13E-10
	t-Value	5.2522	−0.3378	4.5952	−1.7379			3.28E + 00	−2.50E + 00
	P > t	3.74E − 06	0.3688	0.0000	0.0455			0.0012	0.0086
		Turns	7573	**Turns**	6.47E + 09	**Turns**	−4102	**Turns**	4.81e + 09
		Shape	U shape	**Shape**	Inverse U shape	**Shape**	Monotone	**Shape**	Inverse U shape

NB: **CO_2-GDPP** represents the relationship between CO_2 emissions, per capita GDP and the square of per capita GDP; **NCO_2-GDPP** represents the relationship between non-CO_2 GHG emissions, per capita GDP and the square of per capita GDP; **CO_2-FDI** represents the relationship between CO_2 emissions, FDI inflows and the square of FDI inflows; **NCO_2-FDI** represents the relationship between non-CO_2 GHG emissions, FDI inflows and the square of FDI inflows.

[a] Denotes turning point.

[b] Denotes interpretation.

estimation technique estimates and reports statistics based on a fitted model where some or all of the covariates are fixed. The results of the average marginal effects produce the same results as the Driscoll-Kraay panel regression but with robust p-values, thus, confirming the initial outcome at 1% significance level.

3.3. U test estimation

After examining the Driscoll-Kraay panel regression, the study examines both the pollution haven and EKC hypothesis in the individual countries using the *U* test estimation algorithm by Lind and Mehlum (2010) to corroborate the empirical results of the panel regression. Table 5 presents the results of the *U* test estimation. The nexus between CO_2 emissions and economic development on a per capita basis reveals three outcomes.

First, based on a 5% significance level, the inverse U-shape hypothesis is valid for China and Indonesia at a turning point of US$ 6014 and US $ 2999; second, a U-shape relationship is valid for India and South Africa at a turning point of US$ 1476 and US$ 7573 and third, a monotone relationship exists between CO_2 emissions and economic development for Iran at a turning point of US$ −4456, signifying economic recession or impacts related to international economic sanctions. The nexus between non-CO_2 GHG emissions and economic development reveals three outcomes namely; inverse U-shape, U-shape, and monotonic shape presented in columns 7–8 of Table 5. The inverse U-shape hypothesis is valid for India at a turning point of US$ 889; the U-shape hypothesis is valid for Indonesia at a turning point of US$ 1153 while a monotonic relationship is valid for China, Iran, and South Africa at a turning point of US$ 9126, US$ −1955, and US$ −4102.

The relationship between CO_2 emissions and foreign direct investment inflows reveals two outcomes in Table 5. First, an inverse U-shape nexus between CO_2 emissions and FDI is valid for China, India, Iran, and South Africa at a turning point of FDI inflows of US$ 241 billion, US$ 34.7 billion, US$ 3.25 billion and US$ 6.47 billion, respectively, while monotonic relationship between CO_2 emissions and FDI is revealed for Indonesia at a turning of FDI inflows of US$ 42.5 billion. The results in Table 5 confirm the validity of an inverse U-shape relationship between non-CO_2 GHG emissions and FDI for China, India, and South Africa at a turning of FDI inflows of US$ 233 billion, US$ 18.6 billion, and US$ 4.81 billion, while Iran and Indonesia exhibit a U-shaped relationship and monotonic shape at a turning point of US$ 4.31 billion and −US$ 143 billion. The negative turning point exhibited by Indonesia denotes a larger disinvestment capital by foreign investors compared to the value of capital newly invested in the economy.

3.4. Panel quantile regression

This section employs a panel quantile regression estimator developed by Powell (2016) to address the limitation[1] of the Driscoll-Kraay panel regression and existing fixed-effect quantile estimators. The distributional and heterogeneous effect of FDI, GDPP, and ENE on CO_2 and non-CO_2 GHG emissions were examined with the panel quantile regression estimator and presented in Tables 6–7. The panel quantile results are reported for 5th, 10th, …, 90th and 95th percentiles of the conditional CO_2 emissions and non-CO_2 GHG emissions.

The results in Tables 6–7 reveal that the impact of treatment variables on CO_2 and non-CO_2 GHG emissions are heterogeneous and statistically significant at 1% level. The lnGDPP column of Table 6 shows that the economic development increases CO_2 emissions in the 5th to 70th

[1] Individual fixed-effects included in the model change the interpretation of the estimation coefficient on the explanatory variables.

Table 6
Panel quantile results with CO_2E as dependent variable.

Quantile	Model	lnGDPP	$lnGDPP^2$	$lnGDPP^3$	lnFDI	$lnFDI^2$	$lnFDI^3$	lnENE
5	Coef	212,000	−33,252	1640	367,000	−18,827	320	10,846
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
10	Coef	147,000	−23,904	1204	433,000	−22,112	374	10,260
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
20	Coef	145,000	−23,952	1213	382,000	−19,589	333	11,206
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
30	Coef	111,000	−19,387	1016	394,000	−20,246	345	10,637
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
40	Coef	78,390	−14,763	793	381,000	−19,603	335	11,702
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	Coef	96,519	−17,769	946	302,000	−15,948	279	12,263
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
60	Coef	37,624	−10,701	680	275,000	−14,755	261	11,716
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
70	Coef	85,735	−16,755	928	295,000	−15,652	275	11,243
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
80	Coef	−18,641	−2591	298	237,000	−12,953	234	10,236
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
90	Coef	−287,000	35,719	−1471	245,000	−13,300	239	4392
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
95	Coef	285,000	−46,402	2386	267,000	−14,502	260	7124
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

quantiles, declines in the 80th to 90th quantiles and accelerates at 95th quantile. In the $lnGDPP^2$ column of Table 6, CO_2 emissions decrease with increasing economic growth from the 5th to 80th quantiles, but, accelerate in the 90th quantile and decline thereafter (95th quantile). However, the aggregated weight of the economic impact on CO_2 emissions is negative. In $lnGDPP^3$ column of Table 6, CO_2 emissions are positive with income levels from the 5th to 80th quantiles but decline in the 90th quantile and accelerate in the 95th quantile.

On the contrary, the relationship between non-CO_2 GHG emissions and income level in Table 7 becomes homogeneously positive in the 5th to 80th quantiles of lnGDPP; homogeneously negative in the 5th to 80th quantiles of $lnGDPP^2$ and homogeneously positive in the 5th to 80th quantiles of $lnGDPP^3$. The effect of income levels on non-CO_2 GHG emissions turns insignificant above 80th quantile. Notwithstanding, the aggregate effect of economic development on non-CO_2 GHG emissions agrees with results in Table 4.

Tables 6–7 reveal that the quest to improve income levels in low-income countries increases greenhouse gas emissions at the initial stages of economic development, however, CO_2 emissions decline in the middle to high-income countries at a specific turning point in economic development, accentuated in Table 5 of the *U* test estimation. The results support the validity of the EKC hypothesis in the five countries and agree with the previous studies (Sarkodie (2018); Sarkodie and Strezov (2018).

In columns 6–8 of Table 6, the nexus between CO_2 emissions and FDI is homogeneously positive from the 5th to 95th quantiles but becomes homogeneously negative at the second polynomial of FDI and becomes homogeneously positive at the third polynomial of FDI. Thus, the results corroborate the validity of the pollution haven hypothesis expounded in Tables 4–5. The relationship between non-CO_2 GHG emissions and FDI shows a different scenario. The effect of FDI on non-CO_2 GHG emissions is homogeneously positive from the 5th to 80th quantiles and turns negative and insignificant afterward. Similarly, the impact of FDI on non-CO_2 GHG emissions turns negative in $lnFDI^2$ and positive in $lnFDI^3$ from the 5th to 80th quantiles and becomes insignificant thereafter. The influx of foreign direct investment affects the anthropogenic

Table 7
Panel quantile results with NCO_2E as dependent variable.

Quantile	Model	lnGDPP	$lnGDPP^2$	$lnGDPP^3$	lnFDI	$lnFDI^2$	$lnFDI^3$	lnENE
5	Coef	139,000	−21,598	1062	82,481	−4270	73	3139
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
10	Coef	89,978	−14,310	708	91,383	−4710	81	2031
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
20	Coef	116,000	−17,575	844	87,553	−4531	78	1426
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
30	Coef	128,000	−19,047	903	102,000	−5234	89	1550
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
40	Coef	98,273	−15,117	734	80,680	−4215	73	1459
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	Coef	77,116	−12,114	592	59,923	−3231	58	1251
	p-Value	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
60	Coef	29,724	−5589	295	71,034	−3733	65	1204
	p-Value	0.0240	0.0040	0.0020	0.0000	0.0000	0.0000	0.0010
70	Coef	106,000	−16,702	828	66,168	−3596	65	265
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5860
80	Coef	154,000	−23,360	1135	56,894	−3199	59	221
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.6450
90	Coef	3.78E + 20	−4.62E + 19	1.89E + 18	−9.75E + 19	4.01E + 18	−5.35E + 16	−1.29E + 19
	p-Value	0.8310	0.8400	0.8480	0.6910	0.6910	0.6940	0.7470
95	Coef	8.69E + 17	−1.41E + 17	7.33E + 15	−8.19E + 17	4.13E + 16	−6.88E + 14	2.31E + 16
	p-Value	0.6860	0.6260	0.5720	0.3590	0.3590	0.3580	0.3270

emission levels due to the displacement effect in developing countries. Pollution-intensive industries migrate to developing countries with lax environmental regulations and cheaper cost of production, as such, the levels of greenhouse gas emissions increase (Dasgupta et al., 1999, 2001; Dean et al., 2004). Hence, developing countries have a comparative advantage in pollution-intensive and energy-intensive goods compared to developed countries. The study further reveals that the effect of foreign direct investment inflows is more severe on CO_2 emissions compared to non-CO_2 GHG emissions, demonstrating that domestic investments and initiatives have a greater contribution to the non-CO_2 emissions.

Table 6 shows a strong positive effect of energy consumption on CO_2 emissions. The positive effect becomes insignificant from the 70th to 80th quantiles, turns insignificant negative in the 90th quantile and turns insignificant positive thereafter. The study is in line with Jayanthakumaran et al. (2012), Shahbaz et al. (2013), Wang et al. (2016) and Sarkodie (2018) who found a strong relationship between energy consumption and CO_2 emissions in China, India, Indonesia and South Africa. Various studies argue that the eagerness of developing countries to improve economic development adjures them to be reliant on fossil fuel energy technologies. Table 7 reveals that the effect of energy consumption on non-CO_2 emissions is weak. This may be because the non-CO_2 emissions depend on other processes, such as waste management, food production, and manufacturing.

To test the robustness of the results, the study employs average marginal effects as a post-estimation technique. The marginal effects examine and report changes in the response for alteration in some or all the covariates fixed at different values based on a fitted model. The results reveal that the estimated coefficients and p-values are in line with the output of the average marginal effects, thus, validating the models. Figs. 1–2 present the stability plots for the 5th quantile, 50th quantile and 95th quantile and show that these line plots fall within the red spikes which denote the 95% confidence interval, thus, confirming the robustness of the panel quantile regression models.

4. Discussion

The results of the study can be summarized in a diagrammatic format presented in Fig. 3 as a pictorial interpretation of the EKC and pollution haven hypothesis presented in all the models applied in this study. Using the second and third-degree polynomial of GDPP and FDI, the study presents the results in three scenarios.

All the models reveal a positive coefficient of per capita GDP in low-income levels coupled with its negative coefficient in the second-degree polynomial, providing evidence to support the EKC hypothesis for the selected developing countries. According to the EKC hypothesis, low echelons of a country's development is characterized by a low intensity and quantity of environmental deterioration. This is due to the limited impacts of economic development on the natural resource base (Panayotou, 1993; Sarkodie, 2018), thus, leading to a vast ecological reserve. The individual *U* test estimation reveals that CO_2 and GHG emissions for Iran and South Africa in Table 5, to some extent, follow a monotonic relation with income level, thus, confirming the scale effect, which is contrary to Sarkodie (2018). As economic development intensifies, the extraction of natural resources, such as oil, natural gas, coal, the mineral ores and agricultural productivity increases. Economic development propels industrialization, thus adding value to the extracted natural resources, and intensifies agricultural output leading to increasing rate of natural resource depletion, while exceeding the regenerative natural resource capacity (i.e. ecological deficit), and the quantity and toxicity of waste generation increases (Sarkodie and Strezov, 2018). Due to the middle-income status of Iran and South Africa, a composition and technique economic effect was expected but it appears that their economies depend on carbon-intensive industries and fossil fuels to maintain their economic status. As presented in Table 5, the country-wise estimation, based on the nexus between CO_2 emissions and economic development, reveals that the inverse U-shape hypothesis is valid for China (is in line with Dong et al. (2018)) and Indonesia at a turning point of US$ 6014 and US$ 2999, on a per capita basis. However, based on the relationship between non-CO_2 GHG emissions and economic development, the inverse U-shape hypothesis is only valid for India at a turning point of US$ 889. At higher levels of economic development, as presented in Fig. 3, environmental awareness creation, enforcement of environmental laws, policies and regulations, high environmental expenditure, advancement in technology and structural change towards energy-intensive and carbon-intensive industries and services result in a gradual decline in environmental deterioration (Panayotou, 1993).

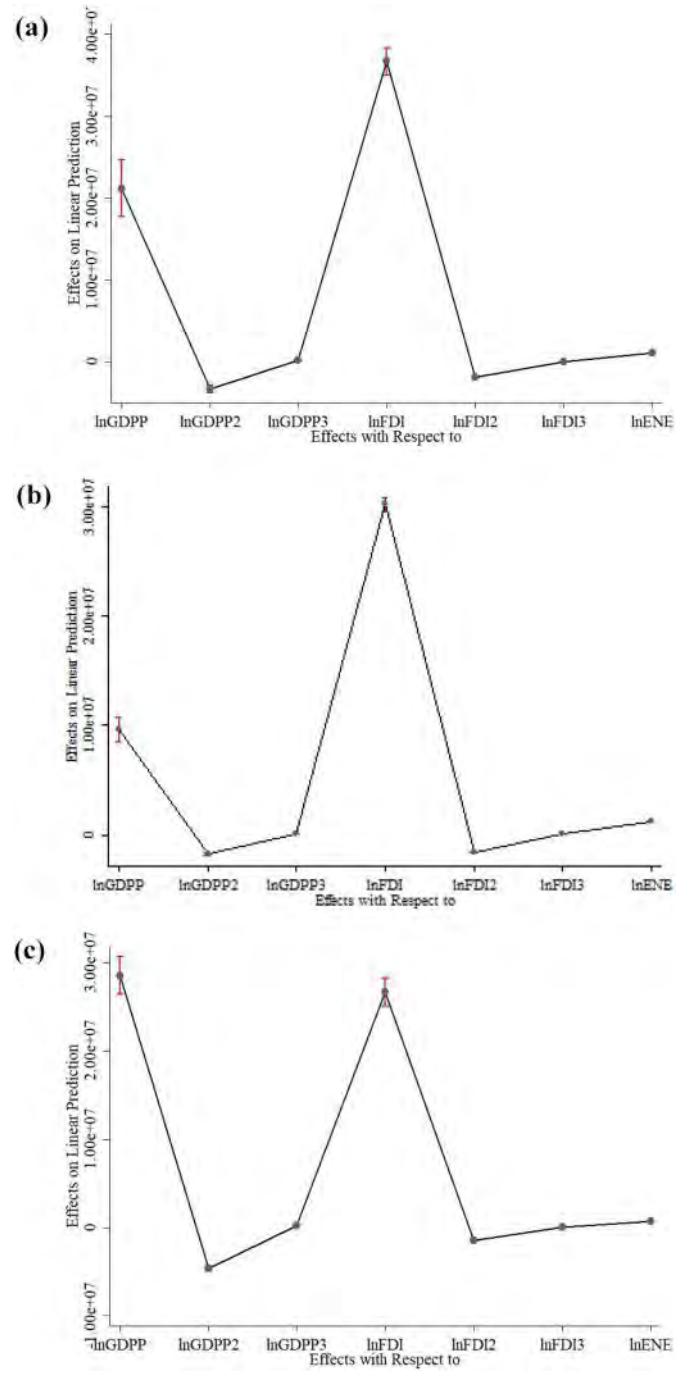

Fig. 1. Stability of panel quantile with CO_2E as the dependent variable (a) 5th quantile (b) 50th quantile and (c) 95th quantile. NB: The red spikes denote the 95% Confidence Interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

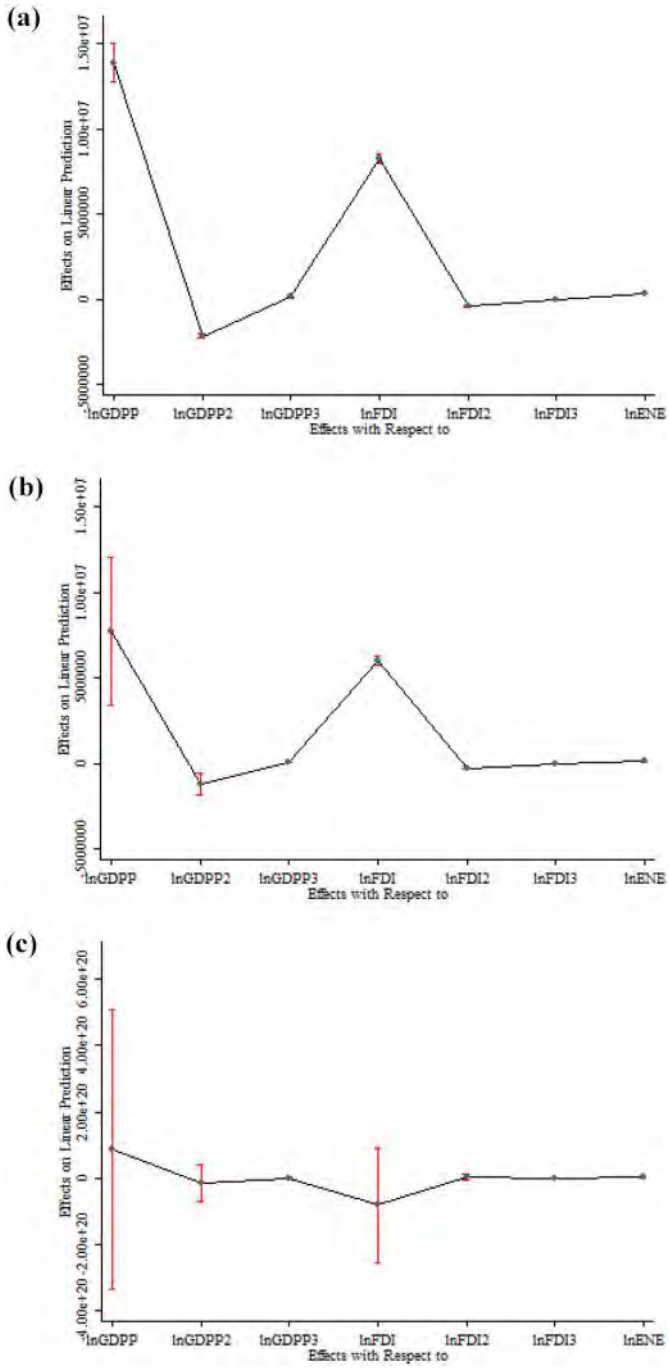

Fig. 2. Stability of panel quantile with NCO_2E as the dependent variable (a) 5th quantile (b) 50th quantile and (c) 95th quantile. NB: The red spikes denote the 95% Confidence Interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The panel quantile regression reveals that the heterogeneous effect of FDI on CO_2 and non-CO_2 GHG emissions still support the results of aggregate effect reported in Driscoll-Kraay panel regression and *U* test estimation. Contrary to Zhu et al. (2016), who found evidence of halo effect, the positive coefficient of FDI in all the models is significant and sufficient to support the pollution haven hypothesis in the five countries. The hypothesis posits that countries with weak environmental regulations attract polluting industries from countries with stringent environmental regulations. Due to stringent environmental regulations, the cost of the key inputs for products with pollution-intensive production increases, thus reducing the country's comparative advantage in those products. Propelling the transfer of pollution-intensive production to pollution haven countries is evidenced in the study. Since foreign direct investment inflows are a key source of external funding for developing countries, the study reveals that at a turning point of foreign investment inflows of US$ 241 billion, US$ 34.7 billion, US$ 3.25 billion and US$ 6.47 billion for China, India, Iran, and South Africa cause CO_2 emissions to decline. However, at a turning of foreign investment inflows of US$ 42.5 billion, the level of CO_2 emissions in Indonesia continue to rise unabated. In contrast, a country-wise effect of FDI on non-CO_2 GHG emissions reveals that at a turning point of foreign investment inflows of 233 billion, US$ 18.6 billion, and US$ 4.81 billion for China, India, and South Africa, greenhouse gas emissions excluding CO_2 emissions decline. A U-shaped relationship and monotonic shape at a turning point of US$ 4.31 billion and −US$ 143 billion were valid for Iran and Indonesia. In terms of per capita consideration, the turning point of FDI in China is US$ 174.81 (~2.15% of GDP) for CO_2 emissions and US$ 169 (~2.08% of GDP) for non-CO_2 GHG emissions; India is US$ 26.21 (~1.53% of GDP) for CO_2 emissions and US$ 14.05 (~0.82% of GDP) for non-CO_2 GHG emissions; Iran is US$ 40.48 (~0.78% of GDP) for CO_2 emissions and US$ 53.69 (~1.03% of GDP) for non-CO_2 GHG emissions; South Africa is US$ 115.50 (~2.19% of GDP) for CO_2 emissions and US$ 85.87 (~1.63% of GDP) for non-CO_2 GHG emissions; and Indonesia is US$ 162.76 (~4.56% of GDP) for CO_2 emissions and US$ -547.65 (~−15.34% of GDP) for non-CO_2 GHG emissions. The decline of CO_2 and non-CO_2 GHG emissions can be due to an improved investment climate, technological transfer, growth in the private sector, improved labour and managerial skills, and implementation of the sustainable development goals. While investments in Iran are impacted by economic sanctions, the negative turning point exhibited by Indonesia denotes a larger disinvestment capital by foreign investors compared to the value of capital newly invested in the economy, hence, affecting climate investment. Overall, the results show that the pollution haven hypothesis influences the shape of the EKC, which is in line with Dinda (2004).

The study reveals a strong positive effect of energy consumption on CO_2 emissions and a weak effect on non-CO_2 GHG emissions. This is because China, India, Indonesia, Iran and South Africa are industrial economies and depend mostly on fossil fuel energy technologies for energy-intensive foreign direct investment inflows and carbon-intensive industries to drive their economic development. The outcome of this study is in line with the Intergovernmental Panel on Climate Change (IPCC) 5th assessment report (IPCC, 2014). According to the IPCC report, energy consumption contributes to 34.6% of the global GHG by economic sectors. The rate of the emissions was due to higher energy demand coupled with a rapid economic development and an increase in the share of fossil fuels, especially coal. Thus, energy-related emissions reduction includes a paradigm shift from fossil fuel, the incorporation of clean and renewable energy technologies like renewables, nuclear power, and carbon capture and storage, improving energy efficiency, and among others (Owusu and Asumadu, 2016; Sarkodie and Adom, 2018), leading to a decarbonized electricity generation. Liobikienė and Butkus (2018); Sarkodie and Adams (2018) revealed that the promotion of higher energy efficiency, specifically in upper-middle-income countries is the most important climate policy opportunity that helps to mitigate GHG emissions.

5. Conclusion

The study examined the effect of foreign direct investment inflows, economic development, and energy consumption on disaggregate greenhouse gas emissions. The study employed data spanning from 1982 to 2016 for the top five emitters of carbon emissions from fuel combustion in the developing countries. The study revealed a strong positive effect of economic development on CO_2 emissions, thus, confirms the validity of the EKC hypothesis. The panel quantile regression showed a distributional and heterogeneous effect of FDI, GDPP and ENE on greenhouse gas emissions, however, the aggregate effect

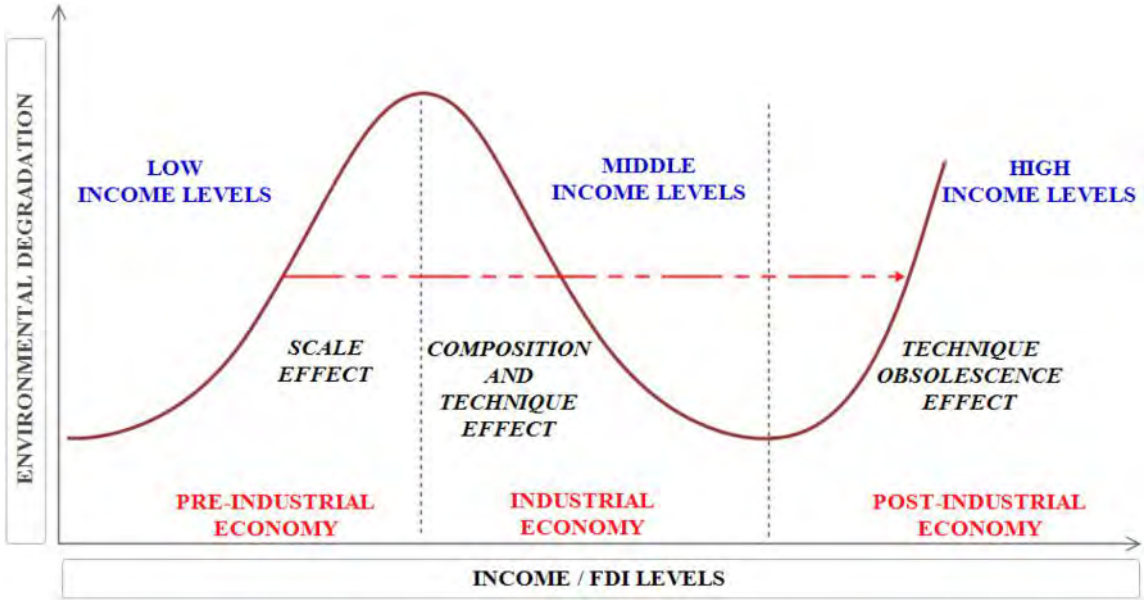

Fig. 3. Schematic representation of the EKC and pollution haven hypothesis.

confirmed the validity of the pollution haven hypothesis. Even though foreign direct investment inflows are considered a major source of external funding which improves the economic development of a country and grows the private sector. The study revealed that foreign direct investment inflows increase CO_2 emissions in the top five emitters of carbon emissions from fuel combustion from developing countries. In the process of globalization and the urge to improve economic development, many least developing and developing countries are eager to attract foreign direct investment inflows with polluting industries by engaging in an inefficient competition, such as weakening their environmental standards yet have poor environmental management systems and modern technologies to streamline polluting trends. The study revealed that there is more room for improvement as greenhouse gas emissions appear to decline at a sustained increase in foreign direct investment inflows.

The inverse U-shape hypothesis was for China, India, Iran, and South Africa at a turning point of foreign investment inflows of US$ 241 billion, US$ 34.7 billion, US$ 3.25 billion and US$ 6.47 billion. This means that foreign direct investment inflows with clean technological transfer and improvement in labour and environmental management practices will help developing countries in the achievement of the sustainable development goals. As a policy implication, there is a need for a global partnership that ensures promotion, transfer, and dissemination of clean and modern technologies in developing countries that will assist in the achievement of a long-term sustainability. Energy consumption has a strong positive effect on CO_2 emissions, as evidenced in the study. Deterioration of the environment stems from the overdependence on fossil fuel energy technologies to meet the growing energy demand for residential and commercial purposes. Pollution haven in developing countries also propels the adoption of fossil fuel energy technologies rather than renewables in order to accumulate low production cost of goods and services from energy-intensive and carbon-intensive industries. Therefore, a reduction of CO_2 emissions and environmental pollution will depend on enhanced energy efficiency, behavioural changes in political institutions that adopts inefficient competitive advantage to lure FDI inflows with polluting technologies, the adoption of clean and modern energy technologies such as renewables, nuclear power plants, the adoption of carbon capture and storage for fossil fuel and biomass energy generation processes.

While this study employed FDI inflows, future studies can possibly examine the role of international trade in pollution levels using both EKC and the pollution haven hypothesis. This will in effect help to understand the dynamics of the factors that determine the shape of the EKC.

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Declaration

There is no conflict of interest.

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Chapter Four: Empirical study of the Environmental Kuznets curve and Environmental Sustainability curve hypothesis for Australia, China, Ghana and USA.

Chapter Four presents the following research article:

- **Sarkodie, S.A.**, Strezov, V., 2018. Empirical study of the Environmental Kuznets curve and Environmental Sustainability curve hypothesis for Australia, China, Ghana and USA. *Journal of Cleaner Production* 201, 98-110.

The study for the first time examines the empirical relationship between environmental sustainability and economic growth nexus, environmental sustainability and energy consumption nexus, and environmental sustainability and CO_2 emissions nexus.

Journal of Cleaner Production 201 (2018) 98–110

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Empirical study of the Environmental Kuznets curve and Environmental Sustainability curve hypothesis for Australia, China, Ghana and USA

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ABSTRACT

This study examines Environmental Kuznets and Environmental Sustainability curve hypotheses for Australia, China, Ghana and the USA from 1971 to 2013 in order to examine the factors contributing to adverse greenhouse gas emission and economic impacts relative to their development. The study revealed that the decline of carbon dioxide emissions in developed countries can be attributed to a paradigm shift and structural change from high-energy intensive and carbon-intensive industries to services and information-intensive industries. The increasing levels of carbon dioxide emissions in developing and least developing countries can be attributed to the economy driven by agriculture, transport and services. Environmental policies and regulations in developing and least developing countries are weaker compared to developed countries, as such, they become a haven for high-energy and carbon-intensive industries. The high awareness of environmental sustainability, technological advancement, stringent environmental regulations and policies in developed countries result in a decline in energy intensity and a decline in carbon dioxide emissions. The Environmental Sustainability Curve hypothesis shows that the affecting factors include economic growth, energy consumption patterns and carbon dioxide emissions. The study reveals electric power consumption as the main contributor of energy intensity in the selected countries. Decoupling economic growth from electric power consumption and improving energy efficiency in China, Ghana, Australia, and the USA will enhance energy security and decline the economic related dynamics and activities on the environment.

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1. Introduction

Climate change has become a central theme among major players in environmental and energy development cooperation, such as the United Nations Framework Convention on Climate Change (UNFCC). The recent COP-21 enlightened the need to bilaterally help to combat or mitigate climate change and its impact as accentuated in the thirteenth Sustainable Development Goal (United Nations, 2015).

According to the International Panel on Climate Change (IPCC), of the total 49 Gt carbon dioxide emissions equivalent in 2010, electricity and heat production contributes 25%, followed by agricultural, forestry and land use (24%), industrialization (21%), transportation (14%), other energy (9.6%) and buildings (6.4%), (IPCC, 2016). Thus, energy sector dynamics remain the major contributor to anthropogenic carbon dioxide emissions. To halt the extreme global average temperature to below 2 °C, countries are expected to adopt mitigation options that reduce greenhouse gas emissions and enhance sinks and reservoirs through environmental sustainability, socio-economic capacity, availability and accessibility of information, and technological advancement (UNFCC, 2017).

The seminal work of Grossman and Krueger (1991), in line with sustainable development, has set the center-stage for the EKC hypothesis. Fig. 1 shows a schematic of the inverted U-Shaped hypothesis representing the initial work of Grossman and Krueger (1991). Three main categories, namely scale, composition, and technique were expounded in their study. Firstly, on the scale effect, Grossman and Krueger (1991) argued that the exponential increase in economic development of pre-industrial economies, typically low-income levels, triggers the generation of more

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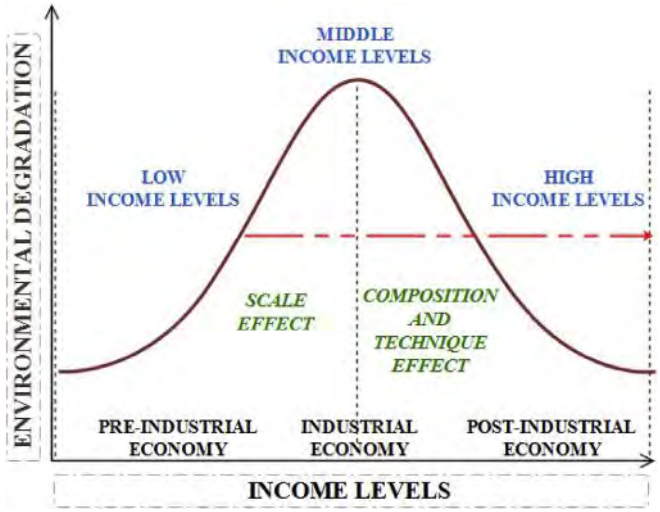

Fig. 1. Schematic of Inversed U-Shaped EKC hypothesis [Source: Authors].

environmental pollutants which are detrimental to the environment. Thus, economic development comes along with increasing energy demand in the form of combusting conventional sources of energy, such as oil, coal and natural gas, for electricity production in homes and industries. The output of such growth in the economy propels environmental degradation and vice versa. To empirically understand the role of economic sectoral related emissions, several studies have examined the causal mechanism, short-run and long-run equilibrium relationships, and variance decomposition to study the impulse-response mechanisms for policy direction. For example, Stern and Van Dijk (2017) investigated the role of economic development in increasing particulate matter ($PM_{2.5}$), a hazardous pollutant with dangerous health implications among 151 countries. Their study found a small positive effect of the role played by economic development in atmospheric concentrations of $PM_{2.5}$. A current study on Africa reveals that the EKC hypothesis is not valid in Ghana, but rather shows a monotonic relationship between pollution and income levels (Sarkodie, 2018). While preventing externalities of cross-boundary atmospheric concentrations, the study cast doubt on the validity of the inverted U-shaped (EKC) hypothesis, meaning that increasing economic development does not affect carbon dioxide emissions. Zaman and Moemen (2017) found a positive relationship between sectoral growth and CO_2 emissions in 90 countries. Thus, economic development driven by carbon-intensive industrialization exacerbates GHG emissions and environmental degradation due to the overreliance on conventional energy sources, which seems cheaper compared to green and renewable energy sources. The IPCC report shows that the economic-sector-related greenhouse gas emissions is dominated by energy consumption, especially from fossil fuels (oil, coal and natural gas) (IPCC, 2016).

Secondly, the composition effect involves industrial economies, typically middle-income level countries focusing on natural resources that have a comparative advantage over other competing neighbours and have weak environmental policies and regulations. The environmental implications of this action depend on whether there was a shift from pre-industrial economy to industrial economy or vice versa. For example, developed countries with stringent environmental policies based on the polluter-pays principle, or environmental regulations, such as carbon taxes and emission abatement programs, transfer their energy-intensive or pollution-intensive production sectors to other countries with weak or flexible environmental policies and regulations. Farhani and Ozturk (2015) examined the role of financial development and trade openness on CO_2 emissions coupled with economic development in Tunisia. Their study confirmed the validity of the Pollution Haven Hypothesis. Due to the weak environmental, economic and industrial policies and regulation, major carbon intensive trade or industries are shifted from developed countries to conceal the cost of paying high externalities. He and Yao (2017) examined the validity of the Pollution Haven and EKC hypothesis in 29 provinces in China. The study found an inverted U shape between economic growth and emissions from dust and soot, but SO_2 emissions exhibited a positive monotonic trend with economic development. On the other hand, SO_2, dust and soot exhibited a positive relationship with foreign direct investment, thus confirming the Pollution Haven hypothesis in two regimes. The study suggests that besides this finding, China is experiencing a fast pace economic development due to the transfer of "dirty" industrial production from developed countries, thus, exacerbating CO_2 emissions. This empirical evidence contradicts the EKC hypothesis, where China, at its current state of economic development should have experienced a decline in CO_2 emissions with a shift to a cleaner environment, but not the case (He and Yao, 2017).

Thirdly, the technique effect encompasses a change in regime from the business as usual to an efficient regime where pollution per unit of economic development is not monotonic. This occurs in industrial economies and typically high-income level countries. A paradigm shift from traditional and pollution-intensive technologies to modern technologies that improve environmental quality while propelling economic development is visible in the technique effect. As awareness of sustainable development and concerns about the urgency of environmental degradation increases, developed countries with high-income levels tend to adopt cleaner environment as an expression of their high standard of living and increased national wealth (Grossman and Krueger, 1991). As a result, stringent environmental policies and stricter laws and regulations on the cleaner environment are enforced as economic development increases, leading to a progressive decline in environmental degradation. For example, Lorente and Álvarez-Herranz (2016) examined the effect of energy innovation and energy regulating policies on greenhouse gas emissions coupled with economic development in 17 OECD countries. The study found a diminishing effect of GHG emissions when conventional sources of energy (oil, coal and gas) are replaced by renewable energy sources (solar, wind, hydro, etc.) alongside stringent energy and environmental policies over time, which confirmed the validity of the technical effect of the EKC hypothesis. Nassani et al. (2017) revealed that the incorporation of renewable energy sources in the energy portfolio reduce fossil-fuel energy consumption, nitrous oxide emissions and greenhouse gas emissions. A study by Zaman and Moemen (2017) found an inverted-U shape relationship between economic development and CO_2 emissions in 90 countries, however, the relationship between economic growth and carbon dioxide emissions exhibited a flat shape in high-income countries, like Australia, USA, United Kingdom, among others. This suggested that most high-income countries have attained a levelized status in economic development, where it seems not to affect pollution. This can be attributed to the advancement in technology and innovation in economic intensive sectors in high-income countries compared to developing and least developed countries.

While there are numerous empirical studies on EKC hypothesis for individual countries, there is a lack of correlation between the EKC and Environmental Sustainability curve (ESuC) hypotheses for different countries relative to their economic development. The objectives of this study are to examine the factors underpinning the Environmental Kuznets curve (EKC) and the ESuC hypotheses relative to the energy intensity and greenhouse gas emissions for a

selected range of countries, which include Australia, China, Ghana and the USA. This study first empirically and structurally tests the validity of the EKC hypothesis in the selected countries. Second, contrary to previous studies on the EKC hypothesis (Sarkodie, 2018; Sarkodie and Strezov, 2018; Shahbaz et al., 2013; Sinha et al., 2017; Stern, 2017), this study examines the empirical relationship between environmental sustainability and economic growth nexus, environmental sustainability and energy consumption nexus, and environmental sustainability and CO_2 emissions nexus. Third, the study examines the factors that contribute to energy intensity, which are critical to achieving the Sustainable Development Goals.

The remainder of the study comprises of Methodology, Results and Discussion, and Conclusion.

2. Methods

2.1. Data and variable definition

The study used the annual time series data spanning from 1971 to 2013 for Australia, China, Ghana, and the US, from the World Development Indicators database (World Bank, 2016) and the Global Footprint Network (Global Footprint Network, 2017). The period of the data spans over four decades, as such presents the trend of historical events of the selected variables and because there is sufficient data available during this time range to conduct the study. These four countries were selected for the study because of two reasons. Firstly, they represent different geographical contribution to mitigating climate change and its impact. Secondly, the four countries have different types of economies, while the US is the largest economy and the largest energy user per capita, China is the country with a developing economy achieving the largest economic growth and energy use growth per annum, Ghana represents a typical African developing nation aspiring to achieve high economic growth rates and is a low energy user, and Australia is a developed economy largely reliant on fossil fuels. Table 1 presents the ten variables used in the model estimation. The selection of the variables was based on the indicators of Sustainable Development: Guidelines and Methodologies by the United Nations (Economic, 2007).

Table 1
Variable definition.

Indicator Name	Indicator Code
Biocapacity[a] (gha/person)	BCAP
CO2 emissions (ktoe)	CO2
Ecological Footprint[b] (gha/person)	EF
Electric power consumption (kWh per capita)	ENEFI
Energy imports, net (% of energy use)	EGIMP
Energy use (kg of oil equivalent per capita)	EGCOM
GDP per capita (current US$)	PGDP
Household final consumption expenditure (current US$)	HCONE
Urban population growth (annual %)	URBGR
Energy Intensity (kg of oil equivalent per current US$)	ENEI

[a] "The capacity of ecosystems to regenerate what people demand from those surfaces. Life, including human life, competes for space. The biocapacity of a surface represents its ability to renew what people demand. Biocapacity is, therefore, the ecosystems' capacity to produce biological materials used by people and to absorb waste material generated by humans, under current management schemes and extraction technologies. Biocapacity can change from year to year due to climate, management, and proportion considered useful inputs to the human economy. In the National Footprint Accounts, biocapacity is calculated by multiplying the physical area by the yield factor and the appropriate equivalence factor. Biocapacity is expressed in global hectares" Global Footprint Network (2017). National Footprint Accounts, Ecological Footprint. Retrieved from http://data.footprintnetwork.org.

[b] "A measure of how much area of biologically productive land and water an individual, population, or activity requires to produce all the resources it consumes and to absorb the waste it generates, using prevailing technology and resource management practices. The Ecological Footprint is usually measured in global hectares. Because trade is global, an individual or country's Footprint includes land or sea from all over the world. Without further specification, Ecological Footprint generally refers to the Ecological Footprint of consumption. Ecological Footprint is often referred to in short form as Footprint" Global Footprint Network (2017).

2.2. Model estimation

In order to examine the validity of the EKC hypothesis, the relationship between biocapacity and the predictor variables, and investigate the underlying factors of energy intensity, the study follows a linear relationship expressed in equations (1)–(3):

$$CO_2 = f(PGDP) \tag{1}$$

$$ENEI = f(HCONE,\ ENEFI,\ EGIMP,\ BCAP,\ EF,\ URBGR) \tag{2}$$

$$BCAP = f(PGDP,\ CO2,\ EGCOM) \tag{3}$$

Where CO_2 denotes carbon dioxide emissions, *PGDP* represents economic growth, *ENEI* denotes energy intensity calculated as energy per unit of economic growth, *HCONE* represents household final consumption expenditure, *ENEFI* denotes electric power consumption, *EGIMP* denotes energy imports, *BCAP* denotes biocapacity, *EF* denotes ecological footprint, *URBGR* denotes urban population growth, *EGCOM* denotes energy consumption.

The model specification of equation (1) follows the *U* test relationship by Lind and Mehlum (2010) employed in the study to test the validity of the EKC hypothesis. The *U* test relationship incorporates the standard quadratic term approach in a linear model expressed as:

$$CO_{2i} = \alpha + \beta^{*}PGDP_i + \gamma^{*}(PGDP)^2{}_i + \xi z_i + \varepsilon_i,\ i = 1,\ 2, \ldots, n \tag{4}$$

CO_2 is regressed on *PGDP* and $PGDP^2$, where α denotes the constant, β, γ and ξ represent the coefficients of the slope, z denotes a vector of the controlled variable, and ε is the error term. The presence of a U-shape infers that $\beta + 2\gamma PGDP_l < 0$ and $\beta + 2\gamma PGDP_h > 0$. The algorithm by Lind and Mehlum (2010) improves the previous quadratic equation to include a confidence interval for the estimated turning point using Fieller (1954) procedure. For brevity, the extended standard quadratic term approach in a linear model is available in Lind and Mehlum (2010).

The model specification of equation (2) follows the Pooled Mean Group Autoregressive Distributed Lag (PMG/ARDL) estimation. The ARDL model is a standard least squares regression that incorporates the lags of the response and predictor variables as regressors. However, the ARDL model is problematic in panel data with individual effect caused by the correlation between the error term and the mean differenced regressors, resulting in bias for small sample observations *T* and large cross-sectional units *N*. The inappropriateness of the dynamic panel Generalized Method of Moments (GMM) (Arellano and Bond, 1991) in large sample observations *T*. This study employs the PMG estimator by Pesaran et al. (1999), which is a favourable candidate. The PMG/ARDL adjusts the ARDL model for time series data from panel data settings which allows the intercepts, short-run equilibrium relationship coefficients, and the cointegrating terms to diverge across the cross-sectional units.

The PMG model can be expressed as:

$$\Delta y_{i,\ t} = \phi_i EC_{i,\ t} + \sum_{j=0}^{q-1} \Delta X_{i,\ t-j'}\ \beta_{i,\ t} + \sum_{j=1}^{p-1} \lambda_{i,\ j'} \Delta y_{i,\ t-j'} + \varepsilon_{i,\ t} \tag{5}$$

$$EC_{i,\ t} = y_{i,\ t-1} - X_{i,\ t'}\theta \tag{6}$$

Where, Δ is the difference operator, y is the dependent variable of interest, X is the independent variables (HCONE, ENEFI, EGIMP, BCAP, EF, URBGR), ϕ denotes the adjustment coefficient, EC is the error correction of individual countries i at time t, q and p are number of lags in each cross-sectional unit (it is assumed that q and p are the same for individual cross-sectional units), θ denotes the long-run coefficient and ε denotes the error term. For brevity, the log-likelihood function with respect to the long-run and adjustment coefficients is detailed in Pesaran et al. (1999).

In accordance with the Sustainable Development Goals 1 and 7 thus, ending poverty and ensuring "*access to affordable, reliable and sustainable modern energy for all*" (United Nations, 2015), the role played by household consumption expenditure in energy access and utilization is examined in this work. According to the indicators of Sustainable Development: Guidelines and Methodologies by the United Nations (Economic, 2007), access to energy is one of the core indicators of poverty, thus, the structural relationship between energy intensity and final household consumption expenditure is tested in this work. To test for the structural relationship, a bivariate model is developed following a second-degree polynomial fit. The bivariate model is expressed as:

$$ENEI_{i,t} = \alpha_{i,t} + \psi^{*}HCONE_{i,\ t} + \zeta^{*}(HCONE)^{2}_{i,t} + \varepsilon_{i,t} \tag{7}$$

For the model specification in equation (3), this study tests the structural relationship between environmental sustainability (BCAP) and economic development; energy consumption and carbon dioxide emissions using a bivariate model founded on the third-degree polynomial fit equation expressed as:

$$\begin{aligned} BCAP_{i,t} = {} & \alpha_{i,t} + \psi^{*}(PGDP|CO2|EGCOM)_{i,t} \\ & + \zeta^{*}(PGDP|CO2|EGCOM)^{2}_{i,\ t} \\ & + \phi^{*}(PGDP|CO2|EGCOM)^{3}_{i,\ t} + \varepsilon_{i,\ t} \end{aligned} \tag{8}$$

Where α is the intercept, ψ, ζ and ϕ are the slope coefficients and ε denotes the error term of individual countries i at time t.

Sarkodie (2018) reveals that panel data models may suffer from bias inferences and misleading results if cross-sectional dependence in the error term is not considered. It is believed to arise from unobserved components and common factors that become part of the error term. Based on this, the study employs cross-sectional dependence tests as a residual diagnostic tool to examine the cross-sectional independence of the disturbances in the model. Even though cross-sectional dependence tests are necessary for large N and small T sample data, however, the literature shows that cross-sectional dependence is evidential in panel regression models (De Hoyos and Sarafidis, 2006). As part of the cross-sectional tests, the study employs the test statistics described by Breusch-Pagan LM, Pesaran Scaled LM, Pesaran CD (Pesaran, 2004), Baltagi, Feng, and Kao Bias-Corrected Scaled LM (Baltagi et al., 2012).

Finally, the direction of causality was tested using Dumitrescu Hurlin Panel Causality Tests (Dumitrescu and Hurlin, 2012) based on the following bivariate regression equation:

$$y_{i,t} = \alpha_{0i} + \alpha_{1i}y_{i,t-1} + \alpha_{li}y_{i,t-1} + \beta_{1i}x_{i,t-1} + \ldots + \beta_{1i}x_{i,t-1} + \varepsilon_{i,t} \tag{9.1}$$

$$x_{i,t} = \alpha_{0i} + \alpha_{1i}x_{i,t-1} + \alpha_{li}x_{i,t-1} + \beta_{1i}y_{i,t-1} + \ldots + \beta_{1i}y_{i,t-1} + \varepsilon_{i,t} \tag{9.2}$$

$$\alpha_{0i} \neq \alpha_{0j}, \alpha_{1i} \neq \alpha_{1j}, \ldots,\ \alpha_{li} \neq \alpha_{lj},\ \forall i,j \tag{9.3}$$

$$\beta_{1i} \neq \beta_{1j}, \ldots, \beta_{li} \neq \beta_{lj}, \forall i,j \tag{9.4}$$

Where, y is the dependent variable, x is the independent variable, α_{0i} denotes the individual effect assumed to have a fixed time dimension, the autoregressive parameters and slope coefficients in (9.3) and (9.4) differ across cross-sections, i denotes cross-sectional units at time dimension t. Dumitrescu and Hurlin Panel Non-causality Tests is based on the null hypothesis that, for example, BCAP does not homogeneously cause PGDP. Unlike other causality tests, Dumitrescu Hurlin Panel Non-causality test calculates the standard Granger causality test for individual cross-sectional units and takes the average test statistic represented by the Wbar statistic. The test assumes that the individual residuals and cross-sectional units are independent and normally distributed. The panel causality test is used to investigate the ability of lagged values of one variable in forecasting another in the panel setting.

3. Results and discussion

3.1. Descriptive analysis

Understanding the characteristics of variables under investigation is critical to the adoption of estimation techniques in econometrics. Appendix A presents the descriptive statistical analysis of the variables under investigation from 1971 to 2013. The mean biocapacity of Australia is 20.5 gha/person compared to a mean ecological footprint of 9.3 gha/person. Ghana has a mean biocapacity of 1.5 gha/person compared to a mean ecological footprint of 1.4 gha/person. Thus, the positive difference between biocapacity and ecological footprint equals the ecological reserve. This means that Australia and Ghana exploit less natural resources than the ecosystem can reproduce. Contrary, the mean biocapacity of China is 0.85 gha/person compared to a mean ecological footprint of 1.8 gha/person. The USA has a mean biocapacity of 4.3 gha/person compared to a mean ecological footprint of 10 gha/person. Hence, the negative difference between biocapacity and ecological footprint equals the ecological deficit. This indicates that China and USA exploit more available natural resources than the ecosystem can reproduce. It is important to note that the biocapacity and ecological footprint of Ghana and China are below the global average of 2.1 gha/person and 2.7 gha/person in the same period (Global Footprint Network, 2017). A visual inspection of the variables confirms that both China and the USA have ecological deficit meaning that future generations must rely on other countries to meet their ecological needs. However, statistical inferences cannot be made without inferential statistics, hence, our model estimation solves this controversy.

The level of CO_2 in Australia is between 152,775 ktoe to 394,793 ktoe and a numerical mean of 277,865 ktoe. The median value of 277,398 ktoe is closely related to the mean. China, on the other hand, has the level of CO_2 between 876,633 ktoe to 10,249,463 ktoe with a mean of 3,555,935 ktoe and a median 2,695,982 ktoe. The level of CO_2 in Ghana is between 2296 ktoe to 14,620 ktoe and a numerical mean and median value of 5387 ktoe and 3982 ktoe. The level of CO_2 in the USA is between 4,306,748 ktoe to 5,795,162 ktoe and a numerical and median mean of 5,040,388 ktoe and 4,955,081 ktoe. However, except for Australia, all the CO_2 levels from the considered countries are positively skewed, yet, China and Ghana

exhibit a leptokurtic distribution of CO_2. Meaning that the level of risk of China and Ghana are more than Australia and USA since relatively small changes with regards to readiness and adaptation occur. Thus, this descriptive evidence sets the pace to examine and verify the reasons why China and Ghana are more vulnerable to CO2 emission levels compared to Australia and the USA.

Urban population growth plays a critical role in climate change agenda in terms of risk, readiness and lives and livelihoods towards climate change adaptation options. The average urban population growth in Australia and USA is approximately 1.5% compared to about 4% in China and Ghana, however, the urban population growth of Ghana and Australia exhibits a leptokurtic distribution compared to China and USA. This means that the cities in Ghana and Australia are more susceptible to climate change-related hazards compared to USA and China. Hence, the risk, readiness and lives and livelihoods in these countries require a statistical scrutiny.

Macroeconomic performance of countries is essential in achieving the Sustainable Development Goals by 2030. The average per capita GDP in Australia, China, Ghana and the USA are around US$ 22,129, US$ 1,233, US$ 540, and US$ 27,109, respectively. Thus, on an average, a daily per capita GDP in Australia, China, Ghana and the USA is US$ 60.6/day (i.e. US$ 22,129/365 days), US$ 3.4/day, US$ 1.5/day and US$ 74.3/day. Based on the per capita GDP, only Ghana is below the poverty line of US$ 1.90/day, as suggested by the United Nations (2015). In corroboration, the Human Development Index Report pegs the population living below the poverty line in Ghana around 25.2% and 1.9% in China (UNDP, 2016). However, except for the USA, the per capita GDP exhibits a leptokurtic distribution in the remaining countries, thus, Australia, China, and Ghana are vulnerable to changes in economic development which may impact environmental sustainability. The household final consumption expenditure, which translates into the market value of goods and services procured by households, follows the same line with per capita GDP. This variable is critical in assessing environmental sustainability and pollution because, with reference to the EKC hypothesis, it is believed that a reduction in CO_2 emissions is due to the willingness of the population to pay for a cleaner environment. Thus, the ability to make great changes in goods and services are essential in energy efficiency, conservation, and a cleaner environment. However, the descriptive statistics show that Australia, China, and Ghana are not likely to make changes with regards to purchasing goods and services. The confirmation of the descriptive statistics requires some inferential statistics to ascertain the veracity of the outcome.

Energy intensity is pivotal in environmental sustainability due to the quantification of required energy translated into a unit output. Thus, in accordance with the EKC hypothesis, higher income countries have a declined energy intensity compared to low and middle-income countries, translating into energy efficiency (see Fig. 1). The mean energy intensity of Australia and USA at 0.36 and 0.44 kg of oil equivalent per current US$, are lower compared to 1.91 and 0.88 kg of oil equivalent per current US$ for China and Ghana respectively. The energy intensity of Australia and USA exhibits a leptokurtic distribution compared to China and Ghana. Thus, energy intensity is critical to GHG emissions in Australia and the USA, due to less frequent changes in the level of disaggregation in the energy mix, however, this is not conclusive. However, the electric power consumption of China and Ghana exhibits a leptokurtic distribution compared to Australia and the USA. Thus, the level of risk in electric power consumption is higher in China and Ghana. The average energy import as a share of energy consumption for Australia, China, Ghana and the US is around −85%, 0.5%, 23% and 19%. Meaning that Australia is an energy independent country with sufficient energy to utilize and export the remainder to neighbouring countries. However, energy import as a share of energy consumption for China and Ghana exhibits a leptokurtic distribution, hence, are at high risk of energy-related crisis. On the contrary, energy consumption for the USA and China exhibits a leptokurtic distribution, meaning that they are less frequently to make small changes in the disaggregation levels of energy consumption.

3.2. Panel unit root test

After examining the characteristics of the data series using descriptive statistics, the study tested for the presence of unit root (non-stationarity) in the panel data series, which implies that any shock on the data series will have a permanent effect. As such, three-panel unit root tests were employed, namely, ADF - Fisher Chi-square (Choi, 2001) Breitung unit-root tests (Breitung, 2001) and cross-sectionally augmented Dickey Fuller (CADF), a second generational panel unit root test by Pesaran et al. (2003). ADF - Fisher Chi-square (Choi, 2001) conducts individual panel unit root test before combining the p-values using the inverse-normal, inverse-chi-square and inverse-logit alterations to produce an overall test under the null hypothesis of the presence of a unit root. The ADF - Fisher Chi-square does not require a strongly balanced panel data like Breitung unit-root test (Breitung, 2001). On the contrary, Breitung unit-root test (Breitung, 2001) requires a strongly balanced panel data by assuming that, "all panels have a common autoregressive parameter", under the null hypothesis that all series contain a unit root. Significantly, the Breitung unit-root test has more power in heterogeneous panel data series and considerably more powerful compared to other panel unit root tests like Hadri LM stationarity test, Fisher-type tests (PP and ADF), Im-Pesaran-Shin test, Levin-Lin-Chu test and Harris-Tzavalis test (Breitung, 2001). For the CADF unit root test, a *t*-test is estimated for the unit roots in heterogeneous panel with cross-sectional dependence. Table 2 presents the results of the panel unit root tests. Both ADF - Fisher Chi-square and Breitung unit-root tests show that the null hypothesis of a unit root at level cannot be rejected at 5% significance level but rejected at first difference. The CADF test in Table 2 reveals that the null hypothesis of non-stationary data series is rejected at first difference. Meaning that the variables under observation are integrated of order one, I(1).

3.3. PMG/ARDL regression analysis

Having met the precondition that all variables are either I(0) or I(1) or I(0) and I(1), we proceed to the estimation of the PMG/ARDL regression using a maximum of two dependent lags and maximum of two lags for the dynamic regressors selected automatically by the Akaike Information Criterion (AIC). The final selected model from the four evaluated models is ARDL(1, 2, 2, 2, 2, 2, 2).

Using the selected model from the ARDL regression analysis, the ARDL F-Bounds cointegration test is performed, as presented in Table 3. In accordance with Pesaran et al. (2001), Wald test restrictions are applied to achieve the F-statistic tests, which are compared to the asymptomatic critical value bounds for F-statistic tests proposed by Pesaran et al. (2001). Table 3 reveals that the F-statistic is above the upper bounds I(1) at 10%, 5%, 2.5% and 1%, thus, the null hypothesis of no cointegration is rejected, meaning that the response and predictor variables in the PMG/ARDL regression model are cointegrated.

Next, the study examines the long-run and short-run equilibrium relationship of the energy intensity model. In accordance with the requirement of the PMG/ARDL regression analysis results presented in Tables 4 and 5, the error correction term [ECT(-1)] is negative and significant at 5% level, thus, the disequilibria of the preceding years are corrected to the current years with the

Table 2
Unit root test.

Variables	ADF - Fisher Chi-square		Breitung unit-root test		Pesaran's CADF test	
	Level	1st Difference	Level	1st Difference	Level	1st Difference
	t-Stat	t-Stat	lambda	lambda	t-bar	t-bar
BCAP	0.5481*	0.0000*	1.7589	−5.8292*	−2.3720	−5.3990*
CO_2	1.9342	48.8674*	5.2128	−5.3120*	−1.1650	−3.0950*
EF	0.6962	0.0001*	4.7673	−5.7041*	−1.1610	−4.0950*
EGCOM	0.5354	0.0001*	3.7116	−4.9687*	−1.8100	−3.5230*
EGIMP	0.6289	0.9963*	1.9157	−7.0708*	0.9880	−4.4550*
ENEFI	0.3274	0.0034*	4.6047	−4.3963*	−0.1650	−4.1950*
ENEI	0.7463	0.0000*	3.4465	−2.6335*	−2.3960	2.8050*
HCONE	0.1689	0.7435*	7.9821	−2.7505*	−0.0030	−2.5620*
PENE	0.0391	0.9992*	4.7896	−5.4403*	−0.2050	−3.3810*
PGDP	1.0000	0.9516*	7.2484	−3.5267*	0.0600	−3.3940*
URBGR	0.0000	0.1109*	−1.3366	−3.2072*	−2.1900	−3.0340*

*rejection of the null hypothesis at 5% significance level.

Table 3
ARDL bounds test.

Test Statistic	Value	Prob.	k	10%		5%		2.5%		1%	
F-statistic	5.92	0.0000	6	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
Chi-square	35.52	0.0000		2.53	3.59	2.87	4.00	3.19	4.38	3.60	4.90

Table 4
PMG/ARDL regression analysis.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Overall Long Run Relationship				
HCONE	−0.1099	0.1431	−0.7680	0.4442
ENEFI	0.3512	0.1349	2.6025	0.0106*
EGIMP	−0.2938	0.0827	−3.5548	0.0006*
BCAP	−0.2867	0.0757	−3.7863	0.0003*
EF	0.0966	0.0865	1.1171	0.2665
URBGR	−0.0036	0.0470	−0.0763	0.9394
Overall Short Run Relationship				
ECT(-1)	−0.3191	0.1212	−2.6332	0.0097*
ΔHCONE	−0.5466	0.1664	−3.2848	0.0014*
ΔENEFI	0.4311	0.4019	1.0727	0.2858
ΔEGIMP	0.1743	0.0833	2.0926	0.0388**
ΔBCAP	−0.0693	0.2263	−0.3061	0.7601
ΔEF	−0.0800	0.0405	−1.9727	0.0511***
ΔURBGR	0.0293	0.0567	0.5175	0.6059
C	26.5595	15.5041	1.7131	0.0896***
@TREND	−0.6359	0.4426	−1.4369	0.1537
Cross-Section Dependence Test				
Test	Statistic	d.f.	Prob.	
Breusch-Pagan LM	176.0894	6	0.0000*	
Pesaran scaled LM	49.1006		0.0000*	
Bias-corrected scaled LM	49.0518		0.0000*	
Pesaran CD	13.1609		0.0000*	

*, **,*** Denotes, 1%, 5% and 10% significance level.

corresponding speed of adjustments. The overall long-run relationship for Australia, China, Ghana, and the USA suggests that a percentage increase in electric power consumption increases energy intensity by 0.35%. The results may have two sides, depending on the source of energy utilized in power plants and combined heat and power production. Fossil fuels dominate the energy mix of Australia, China, and the USA compared to Ghana where their major source of energy comes from renewable energy, mainly hydropower (Sarkodie and Owusu, 2016). China, USA, and Australia are part of the top five countries by primary energy production accounting for 42% of the world's overall primary energy production estimated at 505.61 quadrillion Btu in 2015, which is also reflected in their total primary energy consumption (Knoema, 2015). However, increasing energy import and biocapacity decreases energy intensity by almost 0.29% in the long-run. On the contrary, energy import has a positive impact on energy intensity in the short-run. This means that the immediate effect of energy import is imminent in every economy, but a stabilized economy in the post-industrial stage is not affected by the fluctuations in energy imports in the long-run. In addition, evidence from the overall short-run relationship shows that increasing household final consumption expenditure and ecological degradation has a negative immediate effect on energy intensity. Taking the individual cross-sectional units in perspective, Table 5 reveals that, except for China, 1% increase in household final consumption expenditure decreases energy intensity by 0.99% in Ghana, 0.56% in the USA and 0.20% in Australia. 1% increase in electric power consumption increases energy intensity in USA and Ghana by 0.07% and 0.06%, a unit increase in the same, decreases energy intensity by 0.04% in Australia but insignificant in China. The short-run equilibrium relationship reveals that all four countries agree on the impact of energy import on energy intensity, in that, a unit increase in energy import increases energy intensity by 0.35% in China, 0.28% in Ghana, 0.04% in the USA and 0.02% in Australia. Split results with regards to biocapacity are evident, an increase in biocapacity increases energy intensity in Australia and China by 0.23% and 0.22%, while an increase in biocapacity decreases energy intensity in Ghana and USA by 0.73% and 0.01%. However, an increase in ecological footprint in Australia and Ghana decrease energy intensity by 0.11% and 0.15% while ecological footprint increases energy intensity in the USA by 0.04% and insignificant in China. In the short-run, a unit rise in urban population growth increases energy intensity by 0.17% and 0.07% in China and Ghana, however, an increase in urban population decreases energy intensity by 0.10% and 0.02% in Australia and USA. As a diagnostic test, the study examined the cross-sectional dependence of the residuals. It is revealed in Table 4 that the null hypothesis of no cross-section dependence (correlation) is rejected at 1% significance level. This suggests that there is a common factor, correlation or homogeneous causality underlying the impact of household final consumption expenditure, electric power consumption, energy import, biocapacity, ecological footprint, and population growth on energy intensity.

Table 5
Cross-sectional short-run estimation.

Variable	AUS				CHN			
	Coefficient	Std. Error	t-Statistic	Prob.	Coefficient	Std. Error	t-Statistic	Prob.
ECT(-1)	−0.2183	0.0014	−155.0115	0.0000*	−0.6343	0.0193	−32.8653	0.0001*
ΔHCONE	−0.2018	0.0091	−22.1045	0.0002*	−0.4328	0.3994	−1.0836	0.3579
ΔHCONE(-1)	0.0821	0.0075	10.8793	0.0017*	1.0665	0.4019	2.6535	0.0768**
ΔENEFI	−0.0434	0.0160	−2.7084	0.0733**	1.6343	0.8201	1.9928	0.1403
ΔENEFI(-1)	0.3466	0.0177	19.5560	0.0003*	0.3229	0.7640	0.4226	0.7010
ΔEGIMP	0.0235	0.0034	6.9408	0.0061*	0.3514	0.0145	24.3181	0.0002*
ΔEGIMP(-1)	−0.0171	0.0032	−5.3919	0.0125*	0.2049	0.0160	12.8049	0.0010*
ΔBCAP	0.2375	0.0019	122.9728	0.0000*	0.2212	0.0063	34.9155	0.0001*
ΔBCAP(-1)	0.1333	0.0020	65.6276	0.0000*	0.0640	0.0055	11.5647	0.0014*
ΔEF	−0.1052	0.0006	−184.3655	0.0000*	−0.1054	0.2113	−0.4988	0.6522
ΔEF(-1)	−0.0559	0.0004	−124.6793	0.0000*	−0.5207	0.2618	−1.9889	0.1408
ΔURBGR	−0.0981	0.0006	−173.4329	0.0000*	0.1647	0.0038	43.4342	0.0000*
ΔURBGR(-1)	−0.0325	0.0005	−59.3919	0.0000*	−0.0304	0.0044	−6.8466	0.0064*
C	16.9028	23.1021	0.7317	0.5173	70.9341	239.1677	0.2966	0.7861
@TREND	−0.5222	0.0327	−15.9682	0.0005*	−1.9143	0.1820	−10.5160	0.0018*
Variable	GHA				USA			
	Coefficient	Std. Error	t-Statistic	Prob.	Coefficient	Std. Error	t-Statistic	Prob.
ECT(-1)	−0.3598	0.0059	−61.2685	0.0000*	−0.0640	0.0001	−1026.6600	0.0000*
ΔHCONE	−0.9941	0.0261	−38.0822	0.0000*	−0.5576	0.0135	−41.3452	0.0000*
ΔHCONE(-1)	−0.2906	0.0214	−13.5618	0.0009*	0.2804	0.0137	20.4668	0.0003*
ΔENEFI	0.0626	0.0036	17.5032	0.0004*	0.0710	0.0012	61.5234	0.0000*
ΔENEFI(-1)	−0.0710	0.0040	−17.8920	0.0004*	0.0200	0.0009	21.8440	0.0002*
ΔEGIMP	0.2812	0.0063	44.6649	0.0000*	0.0412	0.0001	276.6643	0.0000*
ΔEGIMP(-1)	0.2053	0.0065	31.3533	0.0001*	0.0080	0.0002	43.1487	0.0000*
ΔBCAP	−0.7270	0.0977	−7.4387	0.0050*	−0.0089	0.0002	−57.7176	0.0000*
ΔBCAP(-1)	−0.8319	0.1312	−6.3415	0.0079*	0.0134	0.0001	104.0165	0.0000*
ΔEF	−0.1472	0.0204	−7.2312	0.0055*	0.0380	0.0002	204.1389	0.0000*
ΔEF(-1)	0.3716	0.0239	15.5231	0.0006*	−0.0029	0.0001	−19.8855	0.0003*
ΔURBGR	0.0700	0.0245	2.8573	0.0647**	−0.0192	0.0001	−177.5057	0.0000*
ΔURBGR(-1)	−0.1928	0.0202	−9.5519	0.0024*	0.0220	0.0001	247.5569	0.0000*
C	19.6768	91.6857	0.2146	0.8438	−1.2759	0.7970	−1.6009	0.2077
@TREND	−0.1653	0.0394	−4.2005	0.0246**	0.0581	0.0019	30.9780	0.0001*

*, ** denotes 1% and 10% significance level.

3.4. Testing the EKC hypothesis

Many studies have examined the EKC Hypothesis arriving at different conclusions based on the economic technique employed. This study employed the Utest algorithm to test the validity of the EKC hypothesis, thus, the nexus between greenhouse gas emissions and economic development. The bivariate model is used to examine the structural relationship between emissions and per capita GDP in Australia, China, Ghana, and the US. Table 6 presents the results of the EKC hypothesis while Fig. 2 depicts the structural examination of the same. Table 6 reveals that the EKC hypothesis is valid for Australia and China but invalid for Ghana and the US.

In Australia, the validity of the EKC hypothesis occurs between US$3493 and US$67,792 at a turning point of US$48,097 [lower than the turning point of US$63,322.3 by Shuai et al. (2017), which can be attributed to the period of the dataset] depicted in Fig. 2, thus, confirming the status of Australia as a developed country. The results contradict the work of Shahbaz et al. (2017) in relation to the validity of the EKC hypothesis. Australia is in the post-industrial state with a paradigm shift and structural change from high-energy intensive and carbon-intensive industries to services and information-intensive industries coupled with a high awareness of environmental sustainability, technological advancement, stringent environmental regulations and policies resulting in a decline in energy intensity and a decline in GHG emissions and environmental degradation.

In China, the turning of US$4874 occurs between US$119 and US$7078 confirming China's status as a Middle-Income country. The turning point estimated in this work is consistent with Grossman and Krueger (1995) who found US$4053 in 1995 but inconsistent with Wang et al. (2011) who found a U-shape relationship between CO_2 emissions and income level. The disparity can be attributed to the short period (1995–2007) of data used for their study. The inversed-U shape means that China is an industrial economy exhibiting signs of composite and technique effect, however, the structural view seems different from Australia. Compared to Australia, China is still managing energy-intensive and carbon-intensive industries coupled with technological and

Table 6
Investigation of the EKC hypothesis.

Country	Interval		Extreme point	Structure	Interpretation
	Lower bound	Upper bound			
AUS	3493	67,792	48,097	Inverted U shape	EKC hypothesis valid
CHN	119	7078	4874	Inverted U shape	EKC hypothesis valid
GHA	233	1814	1896	Monotone	EKC hypothesis Invalid
USA	5623	52,787	66,726	Inverted N-Shape	Reject EKC hypothesis

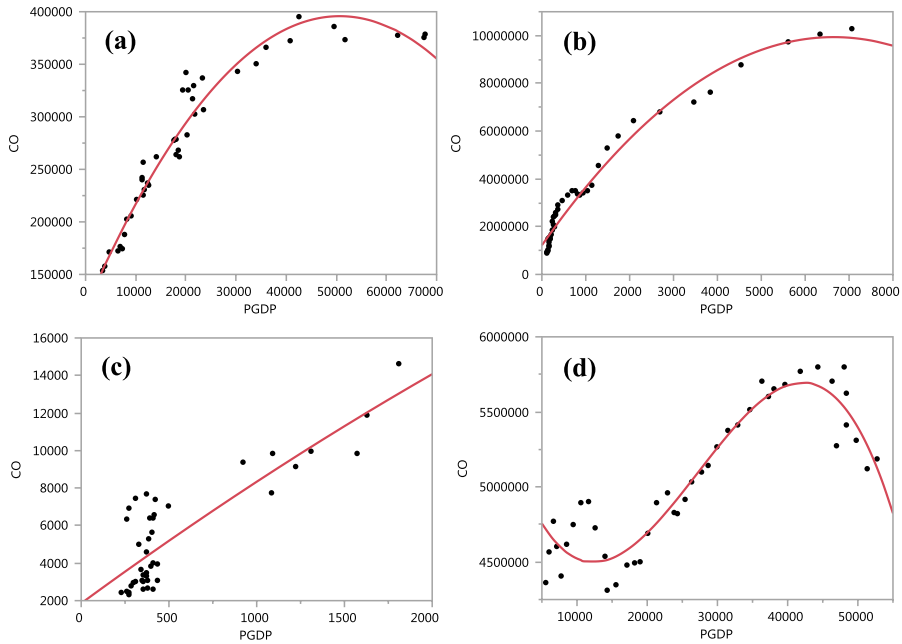

Fig. 2. Investigation of the EKC hypothesis (a) Australia (b) China (c) Ghana (d) USA.

environmental awareness, but, environmental policies and regulations are weak compared to Australia, as such, China has become a haven for high-energy and carbon-intensive industries from developed countries. China's results accord with the development of most of the provinces from the polluting industrial economy to a less polluting service economy (Diao et al., 2009). The results are, in part, consistent with Diao et al. (2009), who argues that the inversed-U shape of China's economy is dependent on the income levels of urban residents who are willing to pay for a cleaner environment compared to the countryside residents with low-income levels characterized by consistent environmental deterioration. The inversed-U shape of China's economy is consistent with Riti et al. (2017) and can further be attributed to the legislation of the Promotion of Cleaner Production and Promoting Cycle Economy in Industry Law enacted and strictly enforced in some Provinces, leading to a further reduction in pollution (Diao et al., 2009). Riti et al. (2017) argue that structural changes such as renewable energy policies and among others are essential in China for the mitigation of climate change and its impact.

The situation is different in Ghana, in that, the validity of the EKC hypothesis is rejected between US$233 and US$1814 at a turning point of US$1896 depicted in Fig. 2. The results are in line with Sarkodie (2018) thus, the relationship between CO_2 emissions and economic development exhibits a characteristic of a monotonic shape, meaning that Ghana is still in the pre-industrial economy with much dependency on agriculture (i.e. agrarian economy). While Lin et al. (2016) rejected the validity of the EKC hypothesis in Africa, a recent study by Sarkodie (2018) confirmed the existence of the EKC hypothesis in Africa. Ghana attained a Middle-Income status of US$1000 in 2015 through the Development Agenda for Economic Growth and Poverty Reduction Strategy by the Government of Ghana, however, Ghana has challenges in the creation of decent jobs and expanding the labour force (Owusu and Samuel, 2016). Other factors impeding economic development include limited research and development, limited innovation and modern technologies, and poor energy infrastructure which allows the availability and accessibility of affordable and modern energy. Compared to China and Australia, Ghana has not attained a full-fledged industrial economy, however, the growth of Ghana's economy is driven by, among other things, agriculture, services, and transport. Even though CO_2 emissions in the aforementioned countries is way higher than Ghana, yet, there has been an increasing trend of CO_2 emission within the past decades. This is due to an accelerated economic development characterized by the intensification of agriculture and resource extraction, such as gold mining, timber logging, etc., leading to increasing levels of waste generation and toxicity (Panayotou, 1993; Samuel and Owusu, 2017).

The validity of the EKC hypothesis is rejected in the US, with income levels between US$5623 and US$52,787 at a turning point of US$66,726 depicted in Fig. 2, thus, confirming the status of the US as a developed country. However, the shape follows an inverted N-shape hypothesis contrary to Australia and China. The results are consistent with Dogan and Ozturk (2017), thus, an inverted N-shape relationship occurs when the nexus between CO_2 emissions and economic development is initially negative but becomes positive once the given extremum point of economic development is reached, up until CO_2 emissions becomes negative again. Thus, high-income levels decrease the level of CO_2 emissions in the initial stages of the economy when the threshold of income level is attained. The process continues with a monotonic increase between CO_2 emissions and high income to the second stage where an achievement of a threshold in income level decreases CO_2 emissions thereafter. The return of the upward trend of CO_2 emissions between the initial stage and the second stage of the US economy may be linked with the exhaustion of technological advancement and innovation, and the relaxation of stringent pollution policies and regulations. However, the current decline in CO_2 emissions is in part attributed to the legislation of the Clean Air Act (EPA, 1990) which deems to reduce acid rain, urban air pollution, toxic air emissions and the stratospheric ozone depletion, through modern science and innovation.

3.5. Factors affecting sustainability

The limitation of obtaining a representative time series variable

for sustainability makes the quantification of environmental sustainability difficult. In this work, the relationship between environmental sustainability and economic development, energy consumption, and carbon dioxide emissions are examined using a bivariate estimation technique based on a third-degree polynomial fit. The results of the study are presented in Appendix B and Figs. 3–5. In this study, the hypothesis is labeled as Environmental Sustainability Curve (ESuC) hypothesis, which is the opposite of the EKC hypothesis. Thus, instead of the inversed-U shape, a U-shape is expected for the ESuC hypothesis to be valid with $\psi < 0$, $\zeta > 0$ and $\phi = 0$ (i.e. representing β_1, β_2 and β_3).

Fig. 3 shows that Australia in part fulfils $\psi < 0$, $\zeta > 0$ and $\phi = 0$ (U-shape), thus, environmental sustainability decreases with increasing economic development in the first phase until it reaches a threshold income level of about US$60,000 at the second phase before environmental sustainability begins to rise thereafter. Australia exhibits a weak ESuC hypothesis. For China, it is observed that $\psi > 0$, $\zeta < 0$ and $\phi = 0$ (inversed-U shape), meaning that environmental sustainability increases with increasing economic development up until the turning point in the income level of about US$6000 before a decline in environmental sustainability in the second phase of development. However, the scenario is different in Ghana, in that, $\psi < 0$, $\zeta > 0$ and $\phi < 0$ (inverted-N shape), meaning that environmental sustainability decreases with increasing economic development to a threshold income level of US$750 in the first phase of development. Subsequently, environmental sustainability begins to rise with increasing economic development up until a threshold income level of US$1500 in the second phase followed by a decline in environmental sustainability with increasing economic development thereafter. The US exhibits $\psi < 0$, $\zeta > 0$ and $\phi < 0$ (flat inverted-N shape), thus, USA follows the same part as Ghana but not prominent in terms of structure. The flat inverted-N shape indicates that environmental sustainability decreases in the US with increasing economic development to a turning point of an income level of about US$20,000 in the first phase of development. Afterward, environmental sustainability sees a little rise with increasing economic development up to a turning point of US$40,000 in the second phase with a subsequent decline in environmental sustainability with increasing economic development afterward (see Appendix B).

Fig. 4 depicts the structural relationship between environmental sustainability and energy consumption. The threshold value is revealed in the output estimation and in accordance with EKC studies, presented as a supplementary data in Appendix B. Fig. 4 shows that Australia in part fulfils $\psi < 0$, $\zeta < 0$ and $\phi = 0$ (decreasing monotone), meaning that environmental sustainability decreases with increasing energy consumption in the first phase until a threshold energy consumption level of about 5000 kg of oil equivalent per capita at the second phase with a continuous decline thereafter. China follows $\psi > 0$, $\zeta > 0$ and $\phi < 0$ (inverted-N shape type 1), thus, environmental sustainability increases with increasing energy consumption up until a turning point of about 2000 kg of oil equivalent per capita before a decline in environmental sustainability in the second phase of energy consumption. Ghana follows $\psi > 0$, $\zeta < 0$ and $\phi < 0$ (inverted-N shape type 2), meaning that, environmental sustainability decreases initially but increases with increasing energy consumption to a threshold consumption level of 375 kg of oil equivalent per capita in the second phase and decline thereafter. The USA exhibits $\psi < 0$, $\zeta > 0$ and $\phi > 0$ (N shape with broad peaks), consequently, environmental sustainability decreases initially and accelerates with increasing energy consumption to a turning point of about 7500 kg of oil equivalent per capita in the first phase of consumption. There is a decline thereafter to the second phase of a turning point of around 8100 kg of oil equivalent per capita, with an exponential increase afterwards (see Appendix B).

Fig. 5 shows the structural relationship between environmental sustainability and carbon dioxide emissions. In Fig. 5, Australia exhibits $\psi < 0$, $\zeta < 0$ and $\phi < 0$ (decreasing bulge monotone), meaning that environmental sustainability decreases with increasing carbon dioxide emissions in the first phase, second phase and beyond with a threshold pollution level of 277,864 kt at

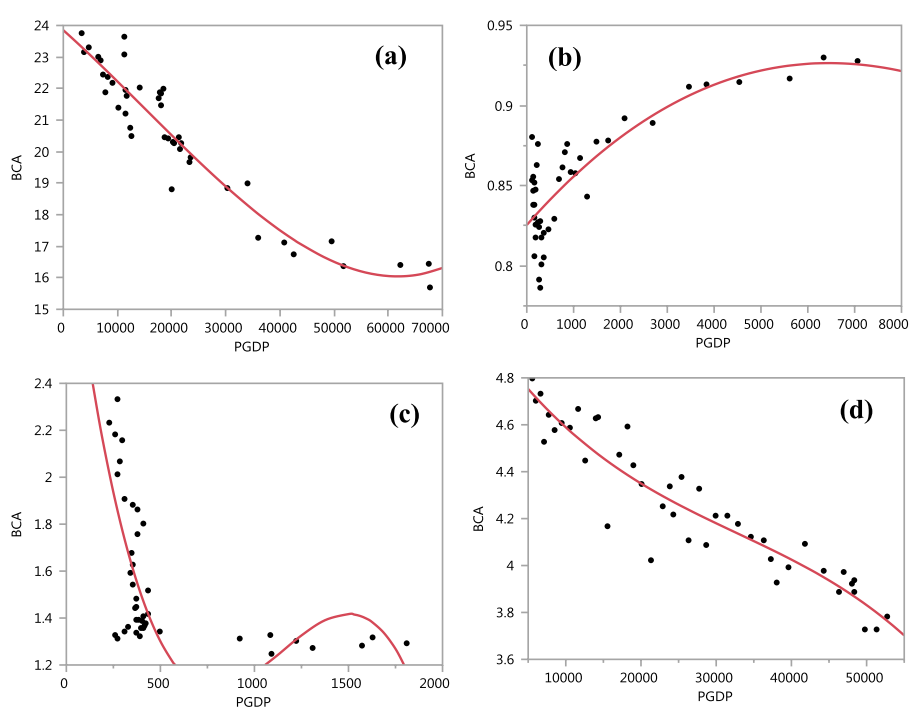

Fig. 3. Relationship between environmental sustainability and economic development (a) Australia (b) China (c) Ghana (d) USA.

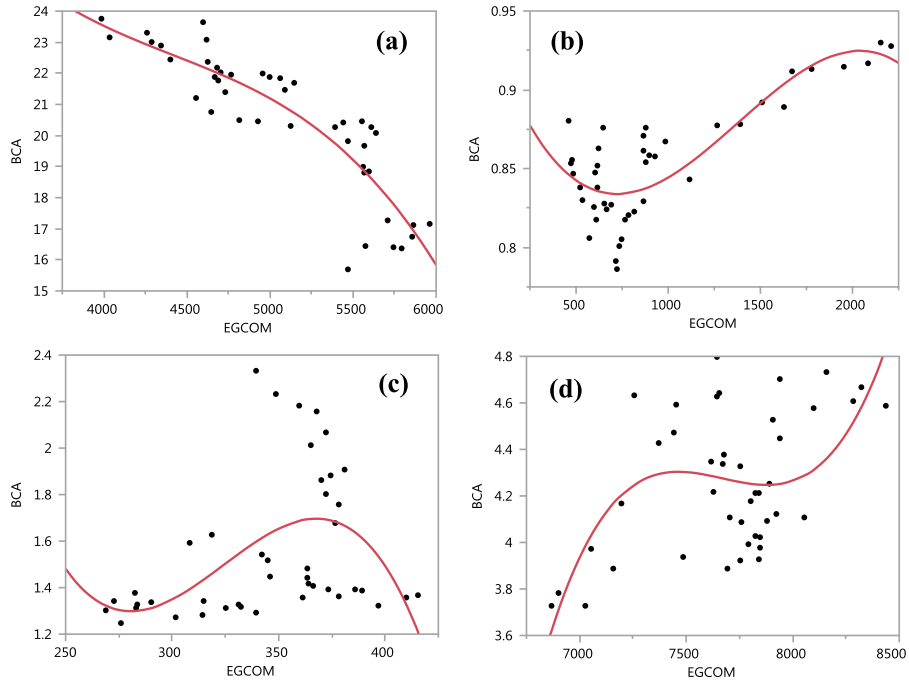

Fig. 4. Relationship between environmental sustainability and energy consumption (a) Australia (b) China (c) Ghana (d) USA.

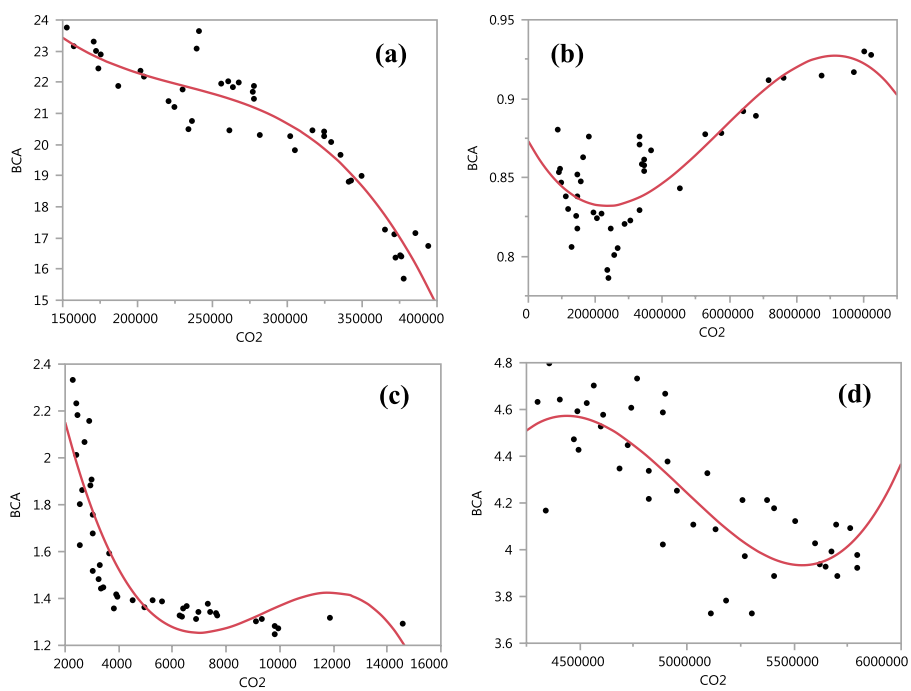

Fig. 5. Relationship between environmental sustainability and carbon dioxide emissions (a) Australia (b) China (c) Ghana (d) USA.

the second phase. China follows $\psi > 0$, $\zeta > 0$ and $\phi < 0$ (inverted-N shape type 1), hence, environmental sustainability increases at low levels of pollution then decreases at the first phase up until a turning point of about 2,000,000 kt when environmental sustainability increases with increasing emissions until a threshold pollution level of 8,500,000 kt in the second phase before depreciation sets in. Ghana follows $\psi < 0$, $\zeta > 0$ and $\phi < 0$ (inverted-N shape type 2), thus, environmental sustainability begins at a high level with low levels of carbon dioxide emissions until it reaches the depression stage at a little rise in emissions with a threshold level of 6000 kt, then rises thereafter to the peak stage of 12,000 kt threshold pollution level and decline afterwards. The US exhibits $\psi < 0$, $\zeta > 0$ and $\phi > 0$ (N shape with broad depression), meaning that, environmental sustainability is higher at low pollution levels until a threshold level of 4,500,000 kt and declines with increasing emissions to the depression stage at a turning point of 5,500,000 kt before environmental sustainability rises thereafter (see Appendix B).

The ESuC hypothesis in part shows that, inter alia, the factors affecting environmental sustainability include economic growth, energy consumption patterns and carbon dioxide emissions. The ESuC hypothesis reveals that at high levels of economic development, evidenced in Australia and USA, the intensity and quantity of environmental sustainability is in part, attributed to the impacts of maintaining economic activities at the expense of the natural resources. However, the acceleration of economic development intensifies the exploitation of the natural resources and agricultural activities which further deteriorates environmental sustainability as evidenced in Ghana (an agrarian economy). At higher levels of economic development, as evidenced in Australia but not in the USA, there is a paradigm shift from a more natural-resource-intensive economy to services and information-intensive economy which contributed to a rise in environmental sustainability. The relationship between environmental sustainability and carbon dioxide emissions is positive in the US due to technological obsolescence. The case is different in China, where a technological advancement and decoupling economic development from the use of natural resources would improve environmental sustainability.

Energy consumption is seen to play a major role in environmental sustainability, as outlined in the Sustainable Development Goals. ESuC hypothesis reveals that structural changes in the energy mix from conventional sources of energy, such as coal, oil, and gas to renewable energy technologies play a vital role in environmental sustainability. Even though fossil fuels are cheaper and more reliable compared to renewable energy technologies, its over-exploitation affects environmental sustainability, as evidenced in Australia. A paradigm shift from energy-intensive manufacturing industries to less-energy intensive industries reduces the energy demand, thus reducing utilization which in turn reduces the impact on the environment.

Table 7
Panel non-Causality Test.

Null Hypothesis:	W-Stat.	Zbar-Stat.	Prob.
PENE ⇏ BCAP	4.7227	4.7239	0.0000*
BCAP ⇏ PENE	0.8075	−0.3175	0.7509
URBGR ⇏ BCAP	0.4430	−0.7868	0.4314
BCAP ⇏ URBGR	1.7197	0.8571	0.3914
HCONE ⇏ BCAP	11.4872	13.4342	0.0000*
BCAP ⇏ HCONE	1.3819	0.4222	0.6729
PGDP ⇏ BCAP	13.1736	15.6056	0.0000*
BCAP ⇏ PGDP	2.1120	1.3622	0.1731
EF ⇏ BCAP	6.6052	7.1479	0.0000*
BCAP ⇏ EF	2.9286	2.4137	0.0158**
URBGR ⇏ PENE	1.0859	0.0410	0.9673
PENE ⇏ URBGR	1.1511	0.1250	0.9005
HCONE ⇏ PENE	2.3386	1.6541	0.0981***
PENE ⇏ HCONE	3.3106	2.9057	0.0037*
PGDP ⇏ PENE	2.6277	2.0263	0.0427**
PENE ⇏ PGDP	4.6791	4.6677	0.0000*
EF ⇏ PENE	2.5818	1.9672	0.0492**
PENE ⇏ EF	2.7343	2.1635	0.0305**
HCONE ⇏ URBGR	2.0819	1.3234	0.1857
URBGR ⇏ HCONE	0.4854	−0.7322	0.4640
PGDP ⇏ URBGR	1.9127	1.1056	0.2689
URBGR ⇏ PGDP	0.1164	−1.2073	0.2273
EF ⇏ URBGR	1.8777	1.0606	0.2889
URBGR ⇏ EF	2.1268	1.3813	0.1672
PGDP ⇏ HCONE	4.5594	4.5136	0.0000*
HCONE ⇏ PGDP	2.2312	1.5157	0.1296
EF ⇏ HCONE	2.4133	1.7503	0.0801***
HCONE ⇏ EF	2.1754	1.4439	0.1488
EF ⇏ PGDP	3.6570	3.3517	0.0008*
PGDP ⇏ EF	1.9447	1.1468	0.2515

NB: ⇏ denotes: Does not homogeneously cause; ⇒ denotes unidirectional causality, ⇆ denotes bidirectional causality and *, **, *** denotes 1,5,10% significance level.

3.6. Panel non-causality

The direction of causality using Dumitrescu Hurlin Panel non-Causality test is presented in Table 7. The results show that the null hypothesis[1] when X does not homogeneously cause Y is rejected at 1%, 5%, and 10% significance levels. Table 7 reveals a unidirectional causality running from PGDP ⇒ BCAP, thus, the structural changes, implementation and the adjustment of economic policies alter environmental sustainability. A unidirectional causality is revealed running from PGDP ⇒ HCONE, as expected, as alteration of economic development affects household final consumption expenditure. There is also a unidirectional causality running from PENE ⇒ BCAP. The results of the panel non-causality test reveal that the implementation of policies which reduce the energy sector dynamics, such as energy conservation and management, will reduce environmental sustainability by substituting fossil fuels with renewable energy technologies in the energy mix. A unidirectional causality running from HCONE ⇒ BCAP means that financial policies that reduce household final consumption expenditure affect environmental sustainability. In addition, there is a unidirectional causality running from EF ⇒ HCONE and EF ⇒ PGDP, hence, the implementation of stringent policies that reduce the exploitation of the natural resources directly affect both economic development and household final consumption expenditure.

Moreover, Table 7 reveals a bidirectional causality between EF ⇆ BCAP, HCONE ⇆ PENE, PGDP ⇆ PENE, and EF ⇆ PENE, respectively. Thus, there is a feedback hypothesis between ecological footprint and environmental sustainability, household final consumption expenditure and energy sector dynamics, economic growth and energy sector dynamics, and, ecological footprint and energy sector dynamics. This reveals that a systemic change in ecological footprint affects environmental sustainability and vice versa, an alteration in the household final consumption expenditure and economic growth affect the energy sector dynamics either positively or negatively, while a structural change in the ecosystem (ecological footprint) affects energy sector dynamics, and vice versa.

4. Conclusion and policy implications

4.1. Conclusion

This study examined the underlying factors of energy intensity, the validity of the EKC hypothesis, and tested the environmental sustainability hypothesis. With a data spanning from 1971 to 2013, the study employed the PMG/ARDL panel regression estimator, Utest regression, a bivariate model, and Panel non-causality test, in Australia, China, Ghana, and the US. The empirical evidence from

[1] Energy dynamics (PENE) does not homogeneously cause environmental sustainability, household final consumption expenditure does not homogeneously cause environmental sustainability, economic growth does not homogeneously cause environmental sustainability, ecological footprint does not homogeneously cause environmental sustainability, environmental sustainability does not homogeneously cause ecological footprint, household final consumption expenditure does not homogeneously cause energy sector dynamics, energy sector dynamics does not homogeneously cause household final consumption expenditure, economic growth does not homogeneously cause energy sector dynamics, energy sector dynamics does not homogeneously cause economic growth, ecological footprint does not homogeneously cause energy sector dynamics, energy sector dynamics does not homogeneously cause ecological footprint, economic growth does not homogeneously cause household final consumption expenditure, ecological footprint does not homogeneously cause household final consumption expenditure, and ecological footprint does not homogeneously cause economic growth, is rejected at 1%, 5% and 10% significance levels.

the PMG/ARDL panel regression analysis suggests a strong long-run equilibrium relationship running from household final consumption expenditure, electric power consumption, energy import, biocapacity, ecological footprint, and population growth to energy intensity, at 32% speed of adjusting the previous disequilibrium to an equilibrium state. To eliminate spurious regression and bias inferences coupled with the problems of cross-sectional dependency, this study diagnosed the panel model for non-cross-sectional dependence. The empirical evidence supports the results, hence, there is a common factor in the four countries underpinning the impact of the regressors on energy intensity. The overall long-run relationship of the panel regression reveals electric power consumption as the main contributor of energy intensity in Australia, China, Ghana, and the USA. The declining trends in electric power consumption relative to economic development indicate the capacity of a country's economy to improve energy efficiency. Thus, high-income countries, like Australia and the USA, can reduce their electric power consumption with a growing income level compared to middle-income and low-income countries like China and Ghana. Decoupling economic development from electric power consumption is the way to achieving target 7.3 of the Sustainable Development Goal 7, which seeks to double the global rate of energy efficiency improvements in member countries by 2030. As such, improving energy efficiency in China, Ghana, Australia, and the USA enhances energy security and declines the economic related dynamics and activities on the environment.

The empirical results confirmed the validity of the EKC hypothesis in Australia and China. In Australia, a turning point of US$48,097 between the income levels of US$3493 and US$67,792 compared to a turning of US$4874 between the income levels of US$119 and US$7078 in China is evident. On the contrary, Ghana exhibits a monotone with income levels between US$233 and US$1814 whiles the USA follows an inverted N-shape hypothesis between the income levels of US$5623 and US$52,787 at a turning point of US$66,726.

Based on the definition of Sustainable Development in the Brundtland Report, this study adopted biocapacity as a proxy for environmental sustainability. The study tested the Environmental Sustainability Curve (ESuC) hypothesis to examine the relationship between environmental sustainability and economic development, energy consumption, and carbon dioxide emissions. The ESuC hypothesis revealed that at high levels of economic development, evidenced in Australia and USA, the rate of environmental sustainability is in part attributed to the impacts of maintaining economic activity at expense of the natural resources. The structural change in the energy mix from conventional sources of energy, such as coal, oil, and gas, to renewable energy technologies, plays a vital role in environmental sustainability. Hence, a paradigm shift from energy-intensive manufacturing industries to less-energy intensive industries reduces the burden on the energy demand, thus reducing utilization which in turn reduces environmental stress. The panel non-causality test reveals a unidirectional causality running from economic growth to environmental sustainability and household final consumption expenditure. Moreover, there was evidence of bidirectional causality between ecological footprint and environmental sustainability, household final consumption expenditure and energy sector dynamics, economic growth and energy sector dynamics, and ecological footprint and energy sector dynamics. The existence of a bidirectional causality appears to be on the tangent of biological mutualism, thus, each variable benefit from the other.

4.2. Policy implications

The policy implications of the results reveal that: first, there's a paradigm shift and structural change from high-energy intensive and carbon-intensive industries to services and information-intensive industries in Australia and USA. There is a high awareness of environmental sustainability, technological advancement, stringent environmental regulations and policies resulting in a decline in energy intensity and a decline in CO_2 emissions and environmental degradation.

Second, China is still managing energy-intensive and carbon-intensive industries coupled with technological and environmental awareness, thus, reflecting on the EKC hypothesis. Environmental policies and regulations in China are weaker compared to Australia and the USA, as such, China has become a haven for high-energy and carbon-intensive industries from developed countries. China's results accord with the development of most of the provinces from polluting industrial economy to a less polluting service economy. The inversed-U shape of China's CO_2 emissions relative to economic development is dependent on the income levels of urban residents who are willing to pay for a cleaner environment compared to the countryside residents with low-income levels characterized by consistent environmental deterioration. Even though some Provinces in China have legislated the Promotion of Cleaner Production and Promoting Cycle Economy in Industry Law, the legislation must be improved, adopted and strictly enforced in the remaining Provinces in order to facilitate further reduction in CO_2 emissions.

Third, Ghana and some other developing and least developing countries have not attained a full-fledged industrial economy, thus, their economy is driven by, among other things, agriculture, transport, and services. IPCC report classifies agriculture, forestry, and land-use as the second contributor of greenhouse gas emissions, it is therefore recommended that agrarian economies adopt sustainable agriculture coupled with technological advancement and scientific innovations to reduce further deterioration of the environment. As revealed by the empirical result, CO_2 emissions decline in the USA, however, without improving research and development, science and innovation, the USA may enter the state of technical obsolescence where the already existing technology may not be useful to deal with the immediate situation. As such, increasing the level of innovation, science and technology are key for high-income countries in the same category as the USA.

Future studies should aim at expanding on the Environmental Sustainability Curve in order to ascertain the key determinants in other regions.

Declaration

There is no conflict of interest.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jclepro.2018.08.039.

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Chapter Five: Assessment of contribution of Australia's energy production to CO_2 emissions and environmental degradation using statistical dynamic approach.

Chapter Five presents the following research article:

- **Sarkodie, S.A.**, Strezov, V., 2018. Assessment of contribution of Australia's energy production to CO2 emissions and environmental degradation using statistical dynamic approach. *Science of The Total Environment* 639, 888-899.

The study employs the statistically inspired modification of partial least squares capable of eliminating multicollinearity problems reported in previous literature. The study undertakes sustainability sensitivity analysis capable of estimating how environmental pollution and degradation can be minimized while increasing economic development and energy security.

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Assessment of contribution of Australia's energy production to CO_2 emissions and environmental degradation using statistical dynamic approach

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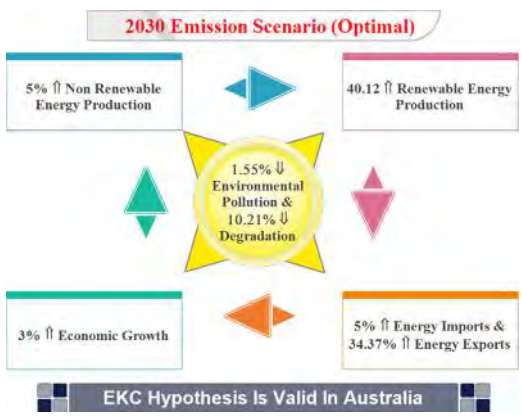
HIGHLIGHTS

- The study validates the Environmental Kuznets curve hypothesis.
- Environmental pollution depends on the share of disaggregate energy sources.
- Renewable energy plays a vital role in environmental sustainability.
- Structural change in economic growth is critical to climate change mitigation.
- Emission reduction target can be met by reducing fossil fuels and energy imports.

GRAPHICAL ABSTRACT



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ABSTRACT

Energy production remains the major emitter of atmospheric emissions, thus, in accordance with Australia's Emissions Projections by 2030, this study analyzed the impact of Australia's energy portfolio on environmental degradation and CO_2 emissions using locally compiled data on disaggregate energy production, energy imports and exports spanning from 1974 to 2013. This study employed the fully modified ordinary least squares, dynamic ordinary least squares, and canonical cointegrating regression estimators; statistically inspired modification of partial least squares regression analysis with a subsequent sustainability sensitivity analysis. The validity of the environmental Kuznets curve hypothesis proposes a paradigm shift from energy-intensive and carbon-intensive industries to less-energy-intensive and green energy industries and its related services, leading to a structural change in the economy. Thus, decoupling energy services provide better interpretation of the role of the energy sector portfolio in environmental degradation and CO_2 emissions assessment. The sensitivity analysis revealed that nonrenewable energy production above 10% and energy imports above 5% will dampen the goals for the 2030 emission reduction target. Increasing the share of renewable energy penetration in the energy portfolio decreases the level of CO_2 emissions, while increasing the share of non-renewable energy sources in the energy mix increases the level of atmospheric emissions, thus increasing climate change and their impacts.

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1. Introduction

Mitigating climate change and its impact while ensuring access to affordable modern energy has become a global challenge. The availability, accessibility and utilization of energy play a critical role in modern economic growth. Economic productivity is powered by energy production and consumption, a situation that distinguishes developed, developing and least developed countries. Energy drives almost all the sustainable development goals, ranging from poverty eradication, wellbeing, jobs and economic growth, food and water supply, industrialization, responsible production and consumption, and climate change mitigation (Owusu and Asumadu-Sarkodie, 2016; United Nations, 2015). However, the adverse effect of energy production and consumption on environmental pollution and degradation requires an empirical investigation.

There is a pool of studies on the role played by economic development in the acceleration of environmental pollution. The seminal work of Grossman and Krueger (Grossman and Krueger, 1991) on environmental Kuznets curve (EKC) hypothesis motivated the modern research on environmental pollution-economic growth nexus. The notion of EKC hypothesis supports the "*grow first clean later*" development strategy which postulates that the initial stages of economic development through industrialization and urban growth increases the consumption of natural resources to meet the growing demand, thus depleting the biocapacity leading to the ecological deficit and environmental deterioration.

The aftermath of Grossman and Krueger's work has motivated several studies on EKC hypothesis using both time series and panel data techniques, however, there are limited studies available in testing the EKC hypothesis in Australia. For example, Balaguer and Cantavella (2018) examined the role of education in Australia's EKC hypothesis with an autoregressive distributed lag approach from 1950 to 2014. The study revealed that education has a potential effect on environmental pollution contrary to economic growth in environmental policy formulation and implementation. Stern (2017) investigated adequacy of the EKC hypothesis model in Australia after 25 years and concluded that economic growth contributes to Australia's environmental pollution. The robustness of the econometric method was found to play a vital role. Similarly, Moosa (2017) examined the validity of the EKC hypothesis in Australia and found that without proper econometric method, the validity of the EKC hypothesis is rejected. The use of sensitivity analysis which validates the existence of EKC hypothesis in Australia was proposed. Shahbaz et al. (2017) found a long-run equilibrium relationship between energy consumption, population growth and globalization with environmental pollution. Their study confirmed a unidirectional causality from energy consumption to environmental pollution. It appears that none of the studies in Australia examined the role of energy sector dynamics on CO_2 emissions and degradation.

The relationship between economic growth, CO_2 emissions and energy consumption has been a subject of a number of studies summarized in Appendix A. These studies can be divided into three categories, namely the pollution-economic growth nexus, the pollution-energy-growth nexus, and the pollution-energy dynamics-growth nexus. The relationship between economic growth and environmental pollution produces two-sides for policymakers which is vital in developing the economies. As much as governments want to grow their economy without limitations, the other constraint is maintaining environmental sustainability, which has become a global target. Many studies have confirmed that the economic development has a positive monotonic relationship with environmental pollution (Acaravci and Ozturk, 2010; Narayan and Narayan, 2010; Saboori et al., 2016; Sarkodie and Owusu, 2016a; Sarkodie and Owusu, 2016b). The scale effect can be examined by using the EKC hypothesis pathway or the direction of causality in the pollution-economic growth nexus.

Beside the scale effect, many studies on the pollution-economic growth nexus either follow the growth hypothesis, conservation hypothesis, neutrality hypothesis or the feedback hypothesis. The growth hypothesis postulates that the direction of causality moves from environmental pollution to economic development but not vice versa, meaning that policy implementations that propel environmental quality will affect economic growth (Bastola and Sapkota, 2015). The conservation hypothesis postulates that environmental quality depends on economic growth, meaning that environmental sustainability options, such as carbon capture and sequestration technologies in carbon-intensive resources, afforestation, etc. can only be driven by wealth and willingness to pay for a quality environment. In this case, the conservation hypothesis supports the EKC hypothesis, but only economic reliant countries can be in this category. For instance, as part of Australia's Emissions Projections by 2030, measures have been instituted to reduce deforestation compared to historical trends (Commonwealth of Australia, 2016). Several studies confirm the unidirectional causality running from economic growth to environmental pollution (Sarkodie and Owusu, 2016c). The neutrality hypothesis suggests no relationship between environmental pollution and economic growth. Improving economic growth has no effect on environmental quality. The feedback hypothesis suggests that the nexus between environmental pollution and economic growth is complimentary. Accordingly, there is a bi-directional causality between economic development and environmental quality and vice versa (Chang, 2010; Sarkodie and Owusu, 2017b).

The second strand of studies focuses on the pollution-energy-growth nexus. The role of energy consumption and economic development cannot be underestimated in environmental pollution and sustainability. A decline in the trend of energy consumption in relation to economic development indicates that a country's economy can improve its energy efficiency (Chiu, 2017; Salahuddin and Gow, 2014).

The final strand of studies focuses on the pollution-energy dynamics-growth nexus. The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report reveals that provision of energy services or energy consumption in the form of heat and electricity is the highest contributor to greenhouse gas emissions compared to agriculture, forestry and land-use, transportation, and others (IPCC, 2016). The IPCC data reveal that fossil fuel energy generation in 2010 remained the highest contributor of carbon dioxide emissions with 39% increase in concentrations above the pre-industrial levels (IPCC, 2011).

The investigation of existing literature reveals the evidence of the role of energy consumption (aggregate or disaggregate) and economic growth on environmental pollution. However, there are several identified limitations in the current state of knowledge, as outlined below:

- The existing literature reveals a mixed outcome on the role of energy consumption and economic growth on environmental pollution, depending on the econometric method, the country of the study, the duration of the data and the source of data.
- Most of the reviewed studies employ synthetic data rather than locally compiled data which provides the true account of the trend exhibited by the data series.
- Most of the employed econometric methods, such as fully modified ordinary least squares (FMOLS), dynamic ordinary least squares (DOLS), autoregressive distributed lag (ARDL), vector error correction model (VECM), and vector autoregressive (VAR) for single countries are unable to reveal the variable importance and eliminate multicollinearity, which is problematic in energy-growth-pollution nexus reported in several studies.
- Majority of literature focuses on aggregate energy consumption rather than disaggregate energy consumption.
- To the best of our knowledge, none of the studies under consideration examined the role of disaggregate energy production in sustainable development.

- None of the reviewed literature considers the role of energy services such as energy imports and exports, which are critical for assessment of environmental pollution and sustainable development. According to the IPCC (2011) Fifth Assessment Report on renewable energy and climate change, the share of imports in the total primary energy consumption, energy imports and exports are critical indicators for the assessment of energy security in sustainable development.

The study aims to contribute to furthering the existing knowledge by, first, using locally compiled data inventory on energy and its related services to ascertain the real evidence of the role of disaggregate energy production, energy imports, energy exports and economic development in environmental pollution and degradation in Australia. Secondly, this study employs the statistically inspired modification of partial least squares capable of eliminating multicollinearity problems reported in previous literature. This method reveals the significance of data series prior to model estimation, which is absent in other econometric methods like autoregressive distributed lag, fully modified and dynamic ordinary least squares regression, and among others reported in the literature. Third, this study undertakes sustainability sensitivity analysis capable of estimating how environmental pollution and degradation can be minimized while increasing economic development and energy security. Finally, this study reveals the structural implications of the environmental pollution and degradation using the environmental Kuznets curve hypothesis that stimulates policy implication and provides information and policy guidance to help Australia's transformation towards achieving the Sustainable Development Goals by 2030.

Based on the economy-wide emission reduction targets by the Annex I parties in the climate change convention, Australia is expected to reduce its emissions by 5–15% by 2020 compared to the 2000 levels, to stabilize greenhouse gas concentrations at 450 ppm in the atmosphere (Secretariat, 2014). This study in accordance with Australia's Emissions Projections by 2030, focuses on Australia to examine how its energy portfolio contributes to CO_2 emissions and environmental degradation through modern econometric methods and provide a sensitivity analysis on how adjustments can be made towards the achievement of a decarbonized economy while meeting the emission targets.

2. Methods

To examine the environmental impacts of Australia's energy portfolio, this study employs data on carbon dioxide emissions [CO_2, (kt)] and economic growth per capita [RGDP, (current LCU)] from the World Bank (2016b) Development Indicators, data series on ecological footprint [EF, (Consumption per capita)] adopted from the Global Footprint Network (2017b) while data on renewable energy [RENE, (Petajoules)], nonrenewable energy [NRENE, (Petajoules)], energy imports [ENEE, (Petajoules)] and exports [ENEI, (Petajoules)] are derived from the Department of Industry Innovation and Science (2016) data on energy. Ecological footprint is defined as, "a measure of how much area of biologically productive land and water an individual, population, or activity requires to produce all the resources it consumes and to absorb the waste it generates, using prevailing technology and resource management practices" (Global Footprint Network, 2017a). In this study, ecological footprint is represented as a proxy for environmental degradation, as recommended by Al-Mulali et al. (2015). Table 1 presents the variables and data series description used in this study. The data series on renewable energy comprises of biomass (wood, wood waste, bagasse, and other waste), biogas, biofuels (ethanol and biodiesel), hydropower, wind, solar photovoltaics (PV) and solar water heater. Nonrenewable energy comprises of oil, natural gas, brown coal and black coal. Energy exports include coal, natural gas, refined products, liquid petroleum gas and crude oil. Energy imports include coke, natural gas, refined products, liquid petroleum gas and crude oil.

Table 1
Data description.

Variable	Description	Unit
EF	Ecological Footprint	Consumption per capita
NRENE	Nonrenewable	Petajoules
RENE	Renewables	Petajoules
ENEE	Energy Exports	Petajoules
ENEI	Energy Imports	Petajoules
RGDP	GDP per capita	current LCU
CO2	CO2 emissions	kt

This study adopted disaggregate energy production rather than aggregate energy consumption presented in previous studies, to investigate the Australian energy sector dynamics, because Australia's energy consumption embodies national energy production and energy imports for energy conversion activities which include petroleum refining and electricity generation among others, and excludes fuels supplied to ships and aircraft for international transportation. Decoupling energy services, such as energy imports, provides better interpretation to the role of energy-related services in assessment of environmental degradation and CO_2 emissions. On the other hand, energy production entails energy produced prior to energy consumption, conversion or transformation and related losses before utilization.

The relationship between ecological footprint (*EF*) and carbon dioxide emissions (CO_2) as dependent variables versus nonrenewable energy (*NRENE*), renewable energy (*RENE*), per capita (*RGDP*), squared of per GDP ($RGDP^2$), energy imports (*ENEI*), energy exports (*ENEE*) can be expressed as:

$$CO_2 = f(RENE, NRENE, RGDP, ENEE, ENEI) \tag{1}$$

$$CO_2/EF = f\left(RENE, NRENE, RGDP, RGDP^2, ENEE, ENEI\right) \tag{2}$$

The empirical specification of Eq. (1) follows the fully-modified ordinary least squares (FMOLS), dynamic ordinary least squares (DOLS) and canonical cointegrating regression (CCR) pathway expressed as:

$$CO_{2t} = \beta_0 + \beta_1 RENE_t + \beta_2 NRENE_t + \beta_3 RGDP_t + \beta_4 ENEE_t + \beta_5 ENEI_t + \varepsilon_t \tag{3}$$

where β_0 denotes the intercept, $\beta_1, \ldots, \beta_5$ denote the slope coefficients, and ε denotes the error term at time *t*.

To estimate the FMOLS regression, this study employs the FMOLS estimator by Phillips and Hansen (1990) expressed as:

$$\hat{\theta} = \begin{bmatrix} \beta \\ \hat{\gamma}_1 \end{bmatrix} = \left\langle \sum_{t=2}^{T} Z_t Z_t' \right\rangle^{-1} \left\langle \sum_{t=2}^{T} Z_t\, y_t^{+} - T \begin{bmatrix} \lambda_{1\,2}^{+} \\ 0 \end{bmatrix} \right\rangle \tag{4}$$

To estimate the CCR, this study employs the CCR estimator by Park (1992) expressed as:

$$\hat{\theta} = \begin{bmatrix} \beta \\ \hat{\gamma}_1 \end{bmatrix} = \left\langle \sum_{t=1}^{T} Z_t^{*}\, Z_t^{*\prime} \right\rangle^{-1} \sum_{t=1}^{T} Z_t^{*} y_t^{*} \tag{5}$$

where β cointegrating equation coefficient, $\lambda_{1\,2}^{+}$ is the estimated bias correction term, X_t is the levels regression, y_t^{+} is the modified dependent variable, $Z_t = (X_t, D_t)'$ for FMOLS, $Z_t^{*} = (Z_t^{*\prime}, D_1{}_t)'$ for CCR denotes the regressors, *D* denotes the deterministic trend, at sample size *T* and time *t*. FMOLS is based on a semi-parametric correction, thus, the FMOLS estimator is based on symmetric and one sided long-run covariance matrices of the residuals necessary to eliminate the challenges associated with the cointegrating equation and the stochastic regressor innovations in a long-run correlation (Phillips and Hansen, 1990). On the contrary, the CCR estimator eliminates the challenges associated with the cointegrating equation and the stochastic regressor innovations in a long-run correlation using the least squares of the stationary transformed data series (Park, 1992).

To estimate the DOLS regression, this study employs the DOLS estimator by Saikkonen (1992); Stock and Watson (1993) expressed as:

$$y_t = X_t\beta + D_1\gamma_1 + \sum_{j=-q}^{\tau} \Delta X_{t+j}\delta + v_{1\,t} \tag{6}$$

where y is the dependent variables, X denotes the cointegrating independent variables, β long-run cointegrating equation coefficient, D denotes the deterministic trend, δ denotes the short-run dynamic coefficient, Δ denotes the difference operator, τ denotes the leads, q denotes the lags, v denotes the residual variance at time t. The advantage of using the DOLS estimator is to eliminate the feedback mechanism evident in the cointegrating system through the augmentation of the cointegration regression with lags and leads resulting in an orthogonal error term of the cointegrating equation thus, making it an efficient estimator (Saikkonen, 1992; Stock and Watson, 1993).

To fulfill the requirements of the FMOLS, DOLS, and CCR, this study first tests the cointegration between data series using the Hansen's Instability Test (Hansen, 1992) based on the null hypothesis of cointegration, thus a fulfillment of this condition means there is evidence of parameter stability.

The FMOLS and CCR estimator adjusted the sample to 1975–2013 and employed a constant as the cointegrating equation deterministic while regressor equations were estimated using differences. On the contrary, the DOLS estimator adjusted the sample to 1975–2010 and employed constant and trend as the cointegrating equation deterministic with fixed leads of three and zero lags specification. However, all the three estimators employed Prewhitening with three lags from an automatic selection using Akaike Information Criterion at a maximum of three lags and Bartlett kernel, Integer Newey-West of 4 fixed bandwidths for the long-run covariance estimation. It is important to note that the squared of per capita GDP in these models was excluded due to issues with collinearity.

The partial least squares (PLS) regression is a multivariate method with a range of advantages over the principal component analysis because the PLS is insensitive to the usual multicollinearity between independent variables. Importantly, the PLS reveals the variable importance of projection of data series, which is a disadvantage of the econometric methods (Samuel and Owusu, 2017). Moreover, PLS prediction is better than the principal component analysis and econometric methods but not with the neural network (Sarkodie and Owusu, 2016c) using Monte Carlo Simulation. The PLS model assumes that the causal relationship is driven by linear combinations of observed predictor variables known as latent variables or factors. The main aim of the PLS is to produce score values from few eigenvectors of the predictor variables, which are summarized in the variance of the predictor variables that are highly correlated with the dependent variables. For brevity, the PLS model consists of both the outer relation and the inner relation. The former results from the decomposition of the eigenstructure X and Y matrices while, the later links the scores for X and Y matrices through a regression expressed as:

$$X = TP^T + E \tag{7}$$

$$Y = UQ^T + F \tag{8}$$

$$U = BT \tag{9}$$

where X is an $n \times m$ matrix of the predictors, Y is an $n \times p$ matrix of the responses, n denotes the samples, m and p denote the variables, T and U are $n \times l$ matrices which represent projections of X and Y (−scores), P and Q are $l \times m$ orthogonal loading matrices, P^T and Q^T denote the transposed P and Q matrices, E ($n \times m$ matrices) and F ($n \times p$ matrices) represent the error term, while, B is the regression coefficient with $n \times n$ matrices. The relation of X is achieved by the decomposition of X into T (scores) and P (loadings) matrices as shown in Eq. (7). The relation of Y is achieved by decomposition of Y into U (scores) and Q (loadings) matrices as shown in Eq. (8). Thus, the aim of the PLS model is to reduce the norm of F residual matrix while still achieving a correlation between X and Y. However, the inner relation of Eq. (9) is weak, thus requires a better algorithm that increases the predictive power of the response variable. Literature shows that the statistically inspired modification of partial least squares (SIMPLS) is superior to PLS (Li, 2006) or the nonlinear iterative partial least squares (Sarkodie and Owusu, 2017a). The empirical specification of Eq. (2) follows a modified partial least square known as SIMPLS by Boulesteix and Strimmer (2007); De Jong (1993); Wise (2004) expressed below:

$$\text{Assumption}: X = X_0, Y = Y_0 \; and \; t = X_0 w \tag{10}$$

where, $X = X_0$ denotes the centered and scaled matrices of the predictor variables ($RENE, NRENE, RGDP, RGDP^2, ENEE, ENEI$) and $Y = Y_0$ is the centered and scaled matrix of the response variables (CO_2/EF), t and w are the score vector and its corresponding weight vector. X_0 and Y_0 of the centered and scaled matrices of the predictor and response variables are predicted by the PLS method in Eqs. (7–9) through a regression on t.

$$\hat{X}_0/\hat{Y}_0 = tp'/tc', \;\; \text{where } p' = \frac{t'X_0}{t't} \text{ and } c' = \frac{t'Y_0}{t't} \tag{11}$$

where, X-loading and Y-loading are vectors p and c; the specific linear combination, $t = X_0 w$ expressed in Eq. (10) has $t = t'u$ as the maximum covariance, and $u = Y_0 q$ as the response linear combination with X-weight and Y-weight (w and q) "*proportional to the first left and right singular vectors of the covariance matrix* $X_0' Y_0$" (Sarkodie and Owusu, 2017a). The cross-product matrix, $X_0' Y_0$ is deflated recurrently for the required factors (latent variables) if necessary. The elaborated algorithm is available in Boulesteix and Strimmer (2007); De Jong (1993); Wise (2004).

A SIMPLS model depends on the selection of an optimal number of factors. There is an option to select all factors available during the SIMPLS model estimation, however, the resultant factors may not be optimal to predict the response variables. As such, using a cross-validation method to automate the optimal factor selection was employed. This study used the leave-one-out cross-validation method that prevents overfitting and selects the optimal components by a repetitive leave-out option for a single observation.

Available literature shows that the leave-one-out cross-validation method known as Van der Voet T^2 reports an "*almost unbiased estimator of the generalization properties of the statistical models*" (Cawley and Talbot, 2004; Sarkodie and Owusu, 2017a). The Van der Voet T^2 cross-validation method is a randomization test used to cross-calibrate and simulates the optimal number of latent variables required for the SIMPLS model. The Van der Voet T^2 cross-validation method employs the root mean predicted residual error sum of squares (PRESS) as an indicator for selecting the optimal factors for the model, using the null hypothesis that "*the squared residuals for both models have the same distribution*" (Sarkodie and Owusu, 2017a). The PRESS calculates a value with a minimizing number of factors using the response variables and predictor variables by the estimated SIMPLS model with one Van der Voet T^2 cross-validation method.

3. Results

3.1. Descriptive analysis

Table 2 presents the descriptive statistical analysis of the data series under examination. The descriptive statistical analysis is essential to ascertain the characteristics exhibited by the investigated variables. For the selected period of the data (1974–2013), the minimum carbon dioxide emissions of 172,356 kt occurred in 1974 while its maxima occurred in 2009 at 394,793 kt with an average of 286,673 kt over the

Table 2
Description statistical analysis.

Statistic	CO_2	EF	ENEE	ENEI	NRENE	RENE	RGDP	$RGDP^2$
Mean	286,673	9.3817	10,423.9	1064.42	8440.47	249.3357	29080.3	1.18E + 09
Median	277,946	9.5047	9505.6	911.75	7797.35	250.95	25631.7	6.57E + 08
Maximum	394,793	11.3135	22,989.9	2288.98	16,101.9	338.013	65941.1	4.35E + 09
Minimum	172,356	7.5785	2657.8	345	3487.2	194.4	4389.27	19,265,722
Std. Dev.	66,305	0.8651	5707.02	594.442	3642.76	38.1747	18524.4	1.29E + 09
Skewness	−0.0458	0.0012	0.3341	0.7526	0.3671	0.253	0.5211	1.2045
Kurtosis	1.8616	2.6416	2.071	2.338	2.001	2.0816	2.1774	3.258
Jarque-Bera	2.174	0.2141	2.1826	4.5065	2.5619	1.8326	2.938	9.7824
Probability	0.3372	0.8985	0.3358	0.1051	0.2778	0.4000	0.2302	0.0075*
Correlation								
CO_2	1							
EF	0.5299	1						
ENEE	0.9719	0.5235	1					
ENEI	0.9088	0.4959	0.9445	1				
NRENE	0.9747	0.5304	0.9986	0.9563	1			
RENE	0.8891	0.4516	0.9232	0.8714	0.9194	1		
RGDP	0.9666	0.5330	0.9900	0.968	0.9942	0.8972	1	
$RGDP^2$	0.8828	0.4639	0.9400	0.9732	0.9479	0.8257	0.9685	1
Unit root								
PP								
Level	−2.4640	4.5780	−0.0390	3.0380	1.8180	3.5880	5.8230	−1.1510
Prob	0.1245	1.0000	0.9552	1.0000	0.9984	1.0000	1.0000	0.6944
1st Diff	−8.5700	−9.8910	−7.9940	−7.8100	−6.6250	−10.0430	−7.0350	−8.4610
Prob	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*

* Rejection of the null hypothesis, at 5% significance level.

investigated period. The minimum ecological footprint of 7.58 consumption per capita occurred in 1982 while its maxima occurred in 2003 at 11.31 per capita with a mean of 9.38 per capita. In terms of energy-related services, the minimum exportation of energy occurred in 1975 accounting for 2658 petajoules while its maxima occurred in 2013 at 22,990 petajoules and an average of 10,424 petajoules. The minimum imported energy of 345 petajoules occurred in 1985 while its maxima occurred in 2013 at 2288.98 petajoules and an average of 1064.42 petajoules. The minimum renewable energy produced in Australia occurred in 1979 at 194 petajoules while the maximum production occurred in 2013 at 338 petajoules with an average production of 249 petajoules. The maximum renewable energy production was complimented with growth in wind, solar and bagasse even though there was a decline in hydropower due to rainfall variability (Department of Industry, 2016). The minimum nonrenewable energy produced in Australia occurred in 1974 at 3487 petajoules while the maximum production occurred in 2013 at 16,102 petajoules with an average production of 8440 petajoules. The variation in the production patterns is due to the addition of new coal mining sites to existing energy systems and population increase, thus, increasing energy demand and supply. The minimum economic growth expressed as per capita GDP of AU$ 4389 occurred in 1974 while the maximum per capita GDP of AU$ 65,941 occurred in 2013 with an average per capita GDP of AU$ 29,080.

The skewness statistic reveals that except carbon dioxide emissions, all the remaining data series have a long right tail, thus, positively skewed, however, the kurtosis statistic shows that except the squared of per capita GDP, all the data series exhibit a platykurtic distribution. The Jarque Bera test of the normal distribution as the null hypothesis reveals that, except the squared of per capita GDP, all the data series exhibit a normal distribution at 5% significance level.

The correlation analysis reveals that energy imports and exports, renewable and nonrenewable energy production and economic growth have a strong relationship i.e. as it approaches 1, with carbon dioxide emissions however, there is a weak relationship between ecological footprint and the independent variables.

As a precondition of FMOLS, DOLS, and CCR methods, the data series should be integrated of order one and cointegration prior to the application of the methods. This study employs Phillips-Perron (PP) (Phillips and Perron, 1988) unit root test to examine the integration order of the variables. The PP unit root test in Table 2 reveals that the null hypothesis of a unit root cannot be rejected at level but rejected at first difference, thus, the data series under investigation are integrated of order one.

3.2. FMOLS, DOLS and CCR estimation results

Hansen (Hansen, 1992) proposed the use of Lagrange Multiplier test (Lc) statistic for estimating the parameter instability shown in Table 3. The Hansen's Instability test reveals that the null hypothesis of cointegration cannot be rejected [Lc = 0.7736 at p-value >5% (i.e. 0.1038)].

The predictive power of FMOLS, DOLS, and CCR are 97.8%, 99.8% and 97.8%, respectively, thus, the predictive power of DOLS outweighs both FMOLS and CCR. The DOLS estimator in Table 3 reveals that 1% increase in RENE decreases CO_2 emissions by 0.74%, while 1% increase in NRENE, ENEI and RGDP increase CO_2 emissions by 2.3%, 0.3% and 0.24%, respectively. Dogan and Ozturk (2017) found similar outcomes, however, the only difference is that they considered the role of renewable and nonrenewable energy consumption rather than production.

3.3. SIMPLS model

3.3.1. Estimation results

To corroborate the FMOLS, CCR and DOLS results, this study employed the SIMPLS multivariate method to estimate two models, namely (1) pollution-energy related service-disaggregate energy production and growth nexus and (2) environmental degradation-energy related service-disaggregate energy production and growth nexus by following the environmental Kuznets curve hypothesis pathway.

Table 4 presents the results of the cross-validation method for factor selection. The table reveals a minimum root mean PRESS of 0.6612 corresponding to 5 factors as the minimizing number of components, which are selected as the optimal components for the SIMPLS model estimation. Using the 5 factors, the next step of the SIMPLS model is to analyze the Variable Importance of Projection (VIP) using the approximation of VIP >0.80 (Sarkodie and Owusu, 2017a). The VIP

Table 3
FMOLS, DOLS and CCR estimation results.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FMOLS				
ENEE	−0.1478	0.0621	−2.3806	0.0232
ENEI	0.0151	0.0180	0.8424	0.4056
NRENE	0.1576	0.0872	1.8079	0.0797
RENE	−0.1435	0.0362	−3.9631	0.0004
RGDP	0.3639	0.0256	14.2081	0.0000
C	9.5044	0.2834	33.5390	0.0000
R-sq	0.9795	Adj. R-sq	0.9764	
DOLS				
ENEE	−0.0826	0.1486	−0.5562	0.5917
ENEI	0.3031	0.0407	7.4416	0.0000
NRENE	2.3099	0.2858	8.0830	0.0000
RENE	−0.7382	0.0589	−12.5353	0.0000
RGDP	0.2352	0.0308	7.6477	0.0000
C	−6.3769	1.3066	−4.8805	0.0009
@TREND	−0.0798	0.0047	−16.8304	0.0000
R-sq	0.9980	Adj. R-sq	0.9921	
CCR				
ENEE	−0.0098	0.0715	−0.1366	0.8921
ENEI	0.0480	0.0205	2.3454	0.0252
NRENE	0.0186	0.1072	0.1736	0.8632
RENE	−0.1638	0.0409	−4.0082	0.0003
RGDP	0.3124	0.0189	16.5206	0.0000
C	9.9008	0.3461	28.6102	0.0000
R-sq	0.9796	Adj. R-sq	0.9765	
Cointegration test - Hansen parameter instability				
Lc statistic	Stochastic Trends (m)	Deterministic Trends (k)	Excluded Trends (p2)	Prob.*
0.7736	5	0	0	0.1038

estimation is essential to determine the viable candidates for the model. Thus, contrary to unit root test employed by other econometric methods, like FMOLS, DOLS and CCR, to test for first order integration of data series, the PLS models require data series to have a VIP >0.8 on the metric scale, lower than the optimum scale suggests that the data series is not viable for the model estimation, thus, affects the predictive power of the SIMPLS model. Table 5 reveals that all the data series considered in the SIMPLS model are >0.8. Another revelation from Table 5 is that NRENE, ENEE, RGDP and RGDP2 have VIP >1 meaning that the aforementioned data series are highly influential in the model while RENE and ENEI have VIP <1 thus, are moderately influential in the SIMPLS model estimation.

After fulfilling the minimum requirement of the VIP, the next step is the estimation of the relationship between environmental pollution/environmental degradation, energy-related services, disaggregate energy production and economic development while testing for the validity of the EKC hypothesis in Australia. Table 6 presents the results of the SIMPLS model estimation with the corresponding coefficients of the data series. Contrary to the inability of FMOLS, DOLS, and CCR to tame collinearity in the model, thus eliminating RGDP2, SIMPLS corrected the infractions making it possible to estimate the validity of the EKC hypothesis. Both CO_2 emissions and EF estimation results are presented in Table 6. The results reveal that 1% increase in nonrenewable energy production increases EF by 0.26% and CO_2 emissions by 0.47%. Increasing energy imports by 1% increase EF by 0.37% and CO_2 emissions by 0.15%. On the contrary, 1% increase in renewable energy production declines EF by 0.34% and CO_2 emissions by 0.15%. Growing energy exports by 1% decrease EF by 0.99% and CO_2 emissions by 0.16%. On economic development, the results reveal that RGDP is positive while $RGDP^2$ is negative thus, validating the EKC hypothesis in Australia. The economic growth per capita increases Australia's EF and CO_2 emissions by 0.88% and 0.81% and declines thereafter (i.e. -0.5*RGDP/RGDP2) which is contrary to Shahbaz et al. (2017) who revealed no evidence of a U-shaped relationship between CO_2 emissions and economic growth. The diagnostic plots in Fig. 1(a) shows the normal quantile plots of the residuals. The graphical representation shows that the SIMPLS model is normally distributed thus, confirming the independence of the residuals. Table 7 shows that the predictive power of SIMPLS method for CO_2 emissions and EF model is 98% and 35%, respectively. Thus, 98% of variations were explained by the independent variables for the CO_2 emissions

Table 4
Selection of factors and cross-validation test.

№ of factors	Root mean PRESS	Plot	van der Voet T²	Prob > van der Voet T²
0	1.0256		22.2581	<.0001*
1	0.6853		7.3409	<.0001*
2	0.6920		5.2416	0.0420*
3	0.6763		4.1836	0.0750
4	0.6637		2.3361	0.3030
5	0.6612		0.0000	1.0000
6	0.6753		9.7043	0.0030*

Each of the dotted lines represents 0.2 unit.
* 5% significance level.

Table 5
Results of variable importance.

X	VIP	Graphical view
NRENE	1.0160	
RENE	0.9262	
ENEE	1.0199	
ENEI	0.9650	
RGDP	1.0507	
$RGDP^2$	1.0171	

The blue line represents the required VIP of 0.80.

while 35% of variations were explained by the independent variables for the EF model reviewed in Fig. 1(b).

4. Discussion

4.1. Sustainability sensitivity analysis

In the final step of this study, different scenarios are examined that can minimize CO_2 emissions and ecological footprint (EF) while increasing economic development and maintaining an optimal level of nonrenewable energy production and energy-related services. Fig. 2 presents eight different scenarios of sustainability sensitivity analysis. The prediction profiler is used in the SIMPLS model to examine the sensitivity of dynamic changes in the independent variables under investigation. The purple triangle in Fig. 2 denotes the sensitivity indicator which shows the direction of the corresponding value of the partial derivative of the profile function with reference to the current value. It is important to note that the scale of the sensitivity analysis plot is based on 100% points.

To make the scenarios parallel with the sustainable goals by 2030, this study projected Australia's energy demand, non-renewable and renewable energy production, and energy imports and exports using the historical data. Based on the forecasted data, this study estimates the percentage changes from 2014 to 2030. The output is used to estimate the sensitivity of the nexus between CO_2 emissions and ecological footprint, disaggregate energy production and energy-related services.

In Appendix B, the forecast reveals that energy consumption in Australia will reduce by 3.3% in 2030, a reflection of the decline of energy imports in 2030 by 10.4%. On the contrary, energy exports will increase by 34.37% coupled with an increase in renewable and non-renewable energy production by 14.55% and 71.65%, respectively. Thus, Australia's energy consumption in 2030 will be 50.12% of energy production excluding the 35.63% of energy imports by 2030. Using the forecasted changes in Australia's energy sector, the sensitivity of the future changes in CO_2 emissions and environmental degradation, expressed as ecological footprint (EF), can be quantified.

Fig. 2(a) reveals that CO_2 and EF will increase by 2.56% and 21.15% in 2030 assuming no change (business as usual) in NRENE, RENE, ENEE, ENEI and RGDP. Thus, the current energy portfolio coupled with economic development deteriorates the environment and declines environmental quality. As such, other seven scenarios are proposed to examine the sensitivity of the aforementioned variables in the attainment of sustainable development by 2030.

It is assumed in Fig. 2(b) that Australia's energy demand (50.12% of energy production) in 2030 will be met using only fossil fuel energy sources (50.12%) at an economic growth of 3% as proposed by World Bank. Fig. 2(b) reveals that, depending on only fossil fuels, the energy sources will increase CO_2 emissions by 31.55% and EF by 37.79%. On the contrary, Fig. 2(c) assumes that the 2030 energy demand (50.12% of energy production) will be met by only renewable energy sources (50.12%) and all other variables remain constant at an economic growth of 3%. The results show that CO_2 will decline by 1.05%, while EF will increase by 12.47%.

In Fig. 2(d), this study assumes that the 2030 energy demand (50.12% of energy production) will be dependent on fossil fuels (50.12%) coupled with energy exports (34.37%) at 3% economic growth, while all other variables remain constant. The results reveal that this scenario will increase CO_2 by 26.24% and EF will increase by 9.69%.

Fig. 2(e) assumes the energy demand (50.12% of energy production) by 2030 will be met by only renewable energy sources (50.12%) coupled with energy exports (34.37%) in 2030 to ensure 3% annual economic growth. The results reveal that contrary to Fig. 2(d), CO_2 and EF will decline by 6.36% and 15.63%, thus, confirming the empirical results by FMOLS, DOLS, CCR, and SIMPLS models that energy exports and renewable energy sources play a critical role in pollution reduction and sustainable environment evidenced in the Sustainable Development Goal 7.

In Fig. 2(f), it is assumed that Australia's energy demand (50.12% of energy production) in 2030 will be met by renewable energy sources (14.49%) coupled with energy exports (34.37%) and energy imports (35.63%) at 3% economic growth. The results show that CO_2 and EF will increase by 4.74% and 5.01%. This is because Australia's energy import is characterized by only fossil fuels, thus, if the percentage of energy

Table 6
Model coefficients estimation.

Coefficient	EF	Graphical view	CO_2	Graphical view
Intercept	0.0000		0.0000	
NRENE	0.2594		0.4693	
RENE	−0.3410		−0.1481	
ENEE	−0.9909		−0.1455	
ENEI	0.3726		0.1492	
RGDP	2.6878		1.5841	
$RGDP^2$	−1.5347		−0.9825	

Each of the dotted lines represents the length of the coefficient plot.

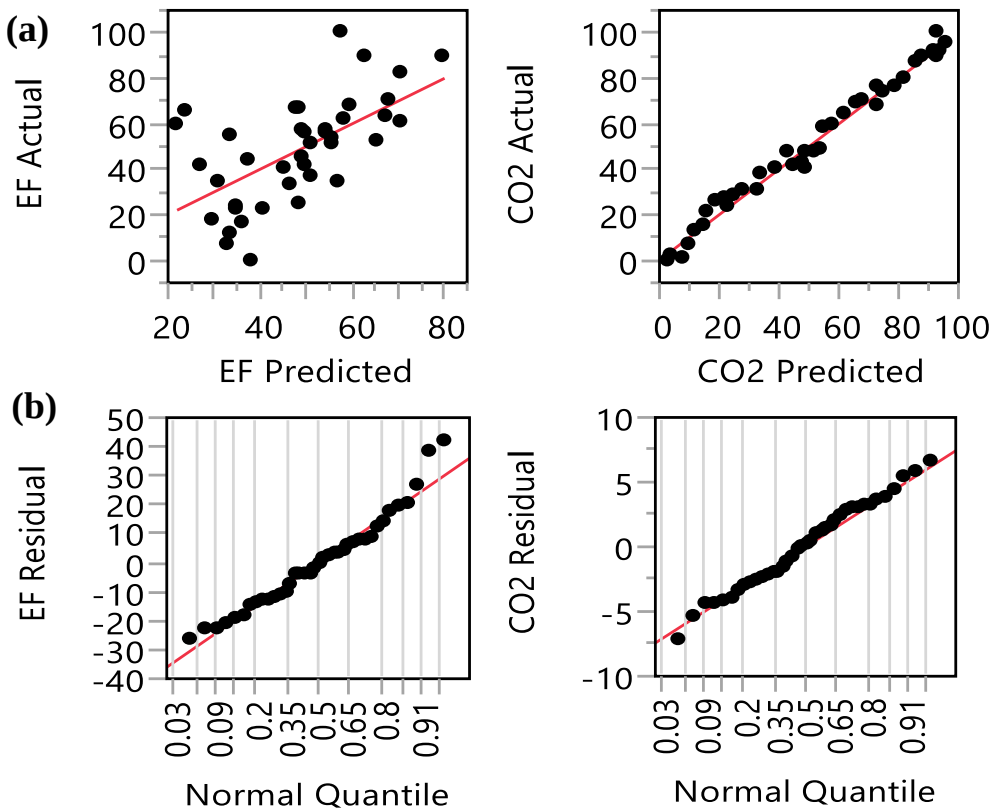

Fig. 1. Diagnostics Plots: (a) Actual by Predicted Plot and (b) Residual Normal Quantile Plot of the SIMPLS model.

imports outweighs renewable energy sources, pollution and degradation will still increase. Fig. 2(g) assumes that Australia's energy demand (50.12% of energy production) in 2030 will be met by renewable energy sources (35.63%) coupled with energy exports (34.37) and energy imports (14.49%) at 3% economic growth. Evidence from Fig. 2(g) reveals that CO_2 and EF will decline by 1.85% and 7.23% when renewable energy sources outweigh energy imports.

Finally, in Fig. 2(h), this study considers all variables in the assumption that fossil fuel energy sources and energy imports are increased by 5% each at 3% economic growth with 40.12% renewable energy sources penetration coupled with 34.37% energy exports. This study reveals that CO_2 and EF will decline by 1.55% and 10.21%.

A decline in CO_2 emissions and EF is dependent on a <5% increase in fossil fuel energy production while economic growth is pegged below 3%. In other words, countries that appear to depend on fossil fuel energy-driven economy will have difficulty to reduce the impacts on environmental quality and sustainability.

This study clearly shows that increasing fossil fuel energy production above 5% coupled with an increase in economic development above 3% accelerates CO_2 emissions and EF, leading to poor environmental quality while reducing environmental sustainability. Decoupling the double burden (i.e. fossil fuel energy production and economic growth) and pegging the rates below the proposed levels will accelerate Australia's effort to achieving the emission target by 2030.

In accordance with Australia's annual GDP growth rate of about 2.6% in 2016 by World Bank (World Bank, 2016a), Fig. 2(h) may be selected as the optimal scenario for environmental sustainability policies. Based on the 2.6% economic growth in 2016, it is assumed that Australia's GDP will increase to around 3%, as such, the decline in CO_2 emissions and EF from the energy sector is dependent on the reduction of the share of fossil fuel energy production while increasing the share of renewable energy production. The share of oil (i.e. crude oil, LPG and refined products) dominated Australia's energy consumption by an increased to 2237 PJ (37.8%), followed by coal consumption at 1908 PJ (32.2%), natural gas at 1431 (24.2%) and renewable energy consumption at 343 PJ (5.8%) (Department of Industry, 2016). It also means that declining CO_2 emissions and EF will not affect economic growth since energy exports will increase to about 20%. In 2014–2015, Australia's energy export increased from 12,509 PJ to 13,088 PJ supported by production growth of coal, natural gas, oil and LPG, and refined products, which constitute almost two-thirds of energy production (Department of Industry, 2016). It appears that Australia's energy production is gradually becoming export-oriented. Thus, trading of fossil fuels rather than utilization in Australia is one of the identified approaches to maintain the economic growth while reducing the domestic environmental impacts.

Table 7
Model comparison summary.

Variable	% variation explained for cumulative X	% variation explained for cumulative Y	Number of VIP > 0.8
CO2	99.99	98.40	6
EF	97.36	34.61	6
Overall	99.99	67.70	6

NB: X denotes independent variables & Y denotes the dependent variables.

4.2. Comparative assessment of the employed econometric models

This study revealed an agreement between the three estimators (FMOLS, DOLS, and CCR), SIMPLS regression and the sensitivity analysis. The coefficients of FMOLS, DOLS and CCR and the SIMPLS regression

showed the same direction for all variables, however, the significance level differs between the models. In terms of predictability, DOLS outweighs FMOLS, CCR and SIMPLS estimation methods, however, in terms of interpretability and versatility for policy formulation, the SIMPLS estimation model is still beneficial. The following evidence emanates from the estimation methods:

- The SIMPLS model revealed that renewable and non-renewable energy production, and energy exports and imports are important variables for estimating CO_2 emissions and EF in Australia.
- Energy-related services are essential in the determination and abatement of CO_2 emissions in Australia. Thus, energy imports worsen CO_2 emissions while energy exports improve environmental quality since major polluting energy sources are exported to other countries, such as China.
- The role of economic development in Australia cannot be underestimated. This study reveals that any structural change in economic growth in the lives of the populace plays a critical role in CO_2 emissions and sustainability. Decoupling energy production from economic growth is seen to be essential in improving energy efficiency while reducing CO_2 emissions and EF.
- Representing energy production rather than consumption in a disaggregated form has provided a more meaningful interpretation of environmental pollution in Australia. Thus, increasing renewable energy penetration into Australia's energy portfolio decreases the

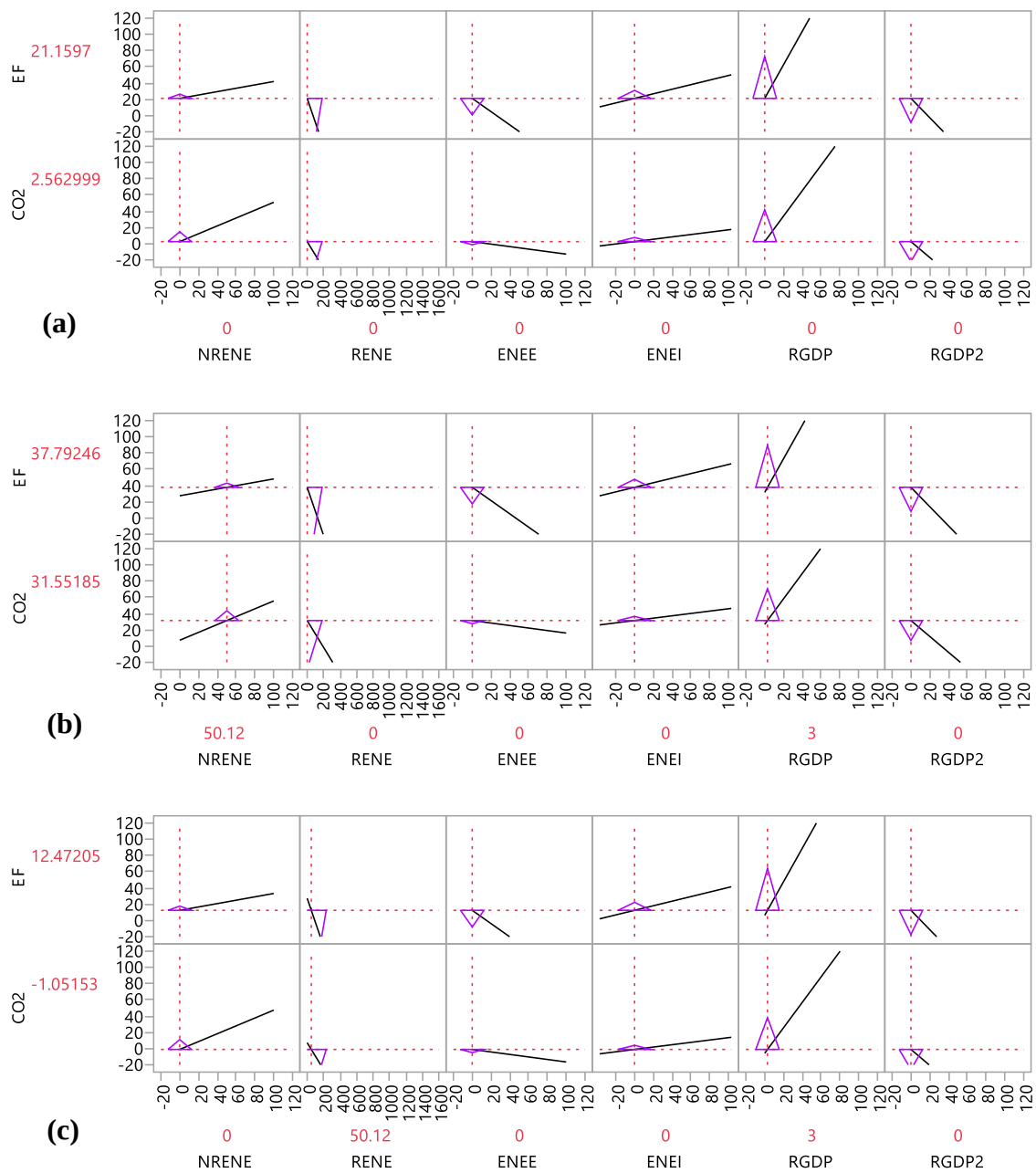

Fig. 2. Sensitivity Analysis: Minimizing Environmental Degradation/Pollution Using (a) Scenario 1 (b) Scenario 2 (c) Scenario 3 (d) Scenario 4 (e) Scenario 5 (f) Scenario 6 (g) Scenario 7 (h) Scenario 8 The purple triangle denotes the sensitivity indicator which shows the direction of the corresponding value of the partial derivative of the profile function with reference to the current value. The values in red are the output of the sensitivity analysis expressed in percentages. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

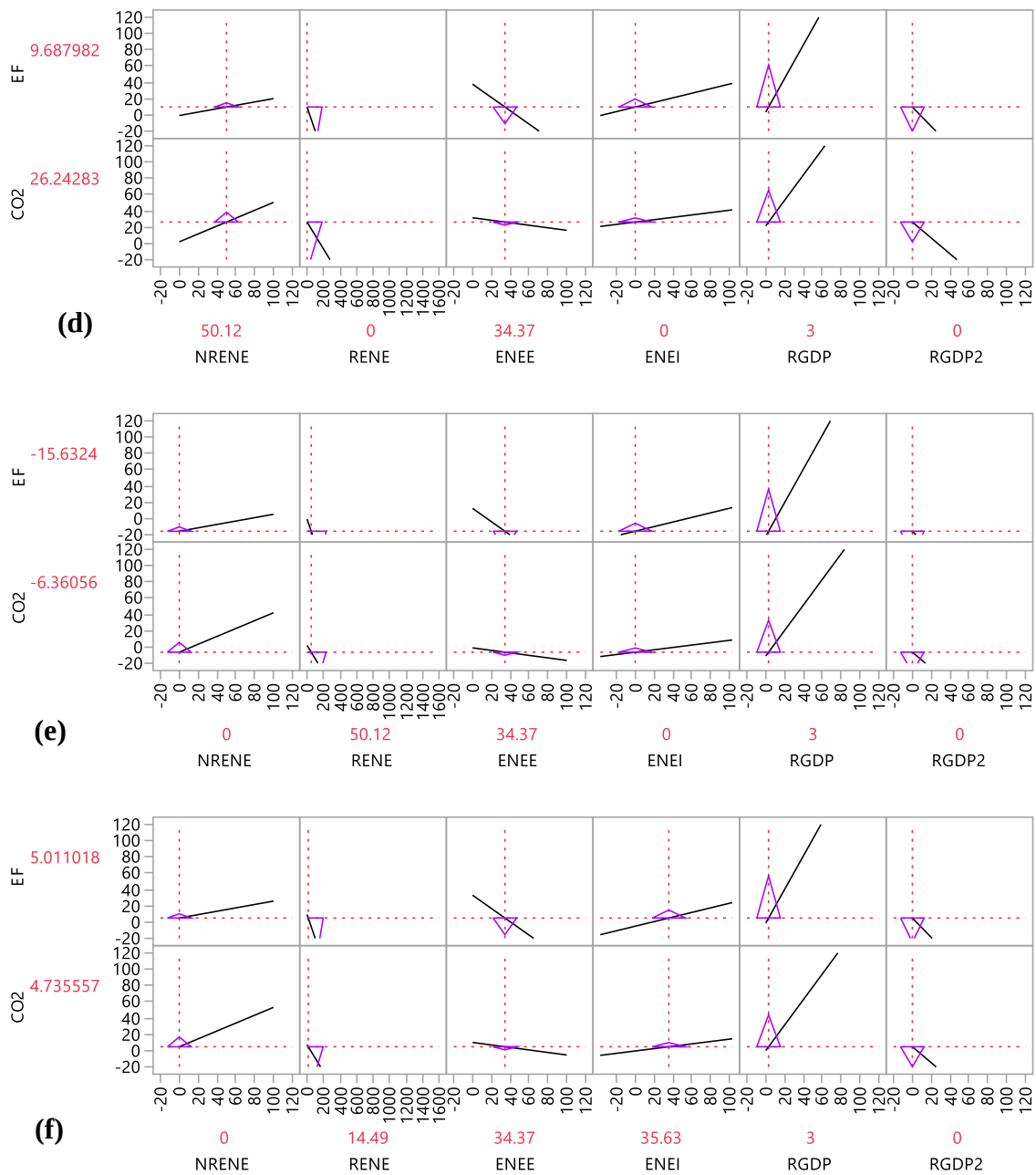

Fig. 2 (*continued*).

levels of CO_2 emissions. On the contrary, increasing the share of non-renewable energy sources in the energy mix increases the levels of atmospheric emissions, thus increasing climate change and its impacts.

The policy implications of the sensitivity analysis are that renewable energy production and energy exports hold the key to the reduction of CO_2 emissions and EF, which contrasts with Australia's current energy portfolio. Renewable energy production accounts for only 2% of the total energy production compared to fossil-fuel energy production which dominates the energy mix (Department of Industry, 2016).

Australia's energy imports comprise of commodities, such as oil and LPG, refined petroleum, natural gas, and coke, which all appear to be nonrenewable energy sources, therefore, increasing the rate of nonrenewable energy import affects the attainment of a clean environment. The sensitivity analysis revealed that nonrenewable energy production above 10% and energy imports above 5% will dampen the goals for the 2030 emission reduction strategies instituted in Australia.

Even though Australia is well endowed with brown coal, black coal, natural gas and uranium, the benefits of incorporating additional renewable energy sources rather than nonrenewable energy sources include increased energy security and diversification of energy supply and reduced natural resource depletion.

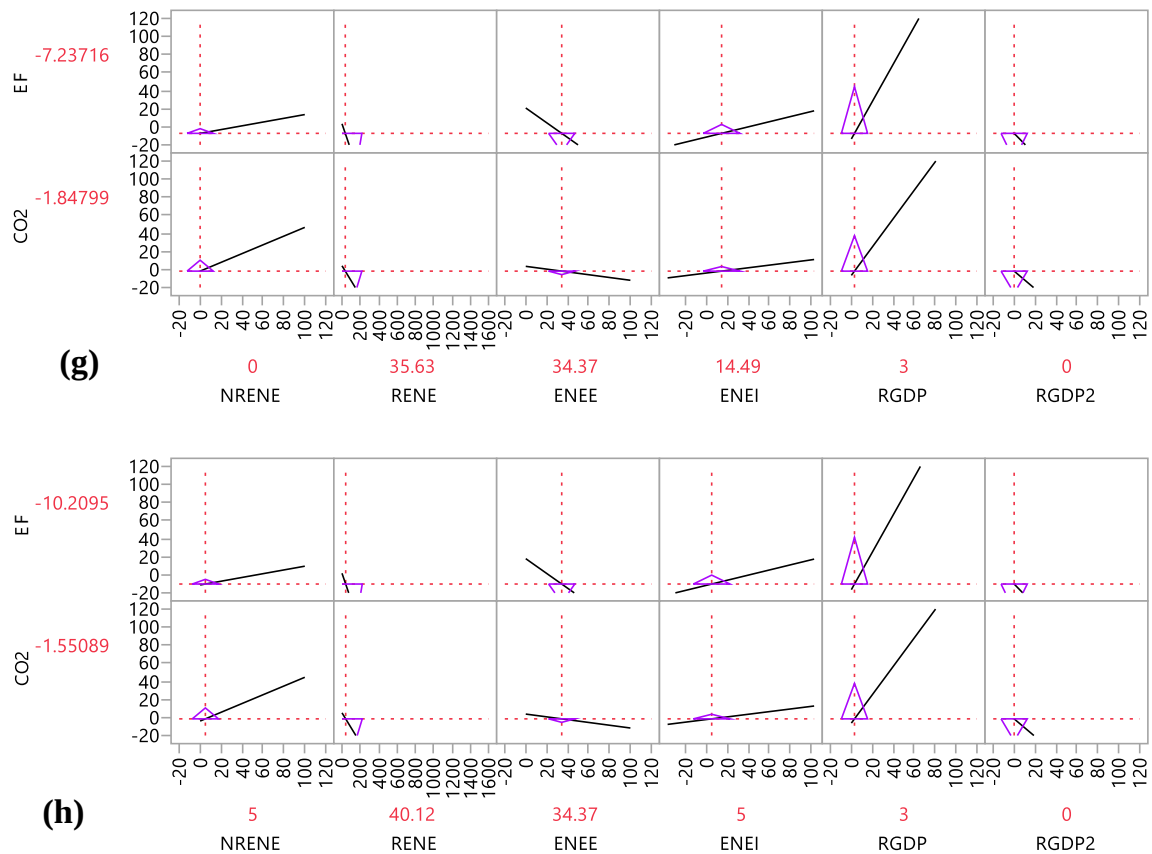

Fig. 2 (*continued*).

5. Conclusion

In this study, the role of Australia's energy portfolio on environmental pollution and environmental degradation expressed as ecological footprint was investigated using locally available data from 1974 to 2013 by applying FMOLS, DOLS and CCR, and SIMPLS regression with a subsequent sensitivity analysis. Contrary to previous studies that employed aggregate energy consumption, this study adopted disaggregate energy production, because in this case energy production is broader (i.e. energy conversion and losses inclusive) and excludes energy imports compared to energy consumption, thus providing the actual empirical evidence necessary for policy formulation and adjustments.

This study revealed that energy-related services, such as energy imports and exports, are essential in the determination and abatement of CO_2 emissions in Australia. Energy imports worsen CO_2 emissions while energy exports improve environmental quality since major polluting energy sources are exported to other countries. Decoupling energy services provide better interpretation of the role of energy sector portfolio in CO_2 emissions and ecological footprint assessment. This study revealed that any structural change in economic growth in the lives of the populace plays a critical role in environmental sustainability. Decoupling energy production from economic growth is essential to improve energy efficiency while reducing CO_2 emissions and environmental degradation. Increasing the share of renewable energy penetration in Australia's energy portfolio decreases the levels of CO_2 emissions, while increasing the share of non-renewable energy sources in the energy mix increases the levels of atmospheric emissions, thus increasing climate change and its impacts. The validity of the EKC hypothesis in Australia means that structural changes in the economy result from a paradigm shift from energy-intensive and carbon-intensive industries to less-energy-intensive and green energy industries and their related services. Finally, this study revealed that Australia's energy portfolio contributes to CO_2 emissions and environmental degradation. As such, structural adjustments are required towards the achievement of a decarbonized economy while meeting the emission targets. The share of renewable energy production in the energy mix needs to be given a priority over non-renewable energy sources and should increase from the current 2% to at least 50%, based on the sensitivity analysis, in order to promote sustainable development, which is in accordance to the sustainable development goals by 2030.

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Declaration

There is no conflict of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.05.204.

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Chapter Six: Renewable energy, nuclear energy, and environmental pollution: Accounting for political institutional quality in South Africa.

Chapter Six presents the following research article:

- **Sarkodie, S.A.**, Adams, S., 2018. Renewable energy, nuclear energy, and environmental pollution: Accounting for political institutional quality in South Africa. Sci. Total Environ. 643, 1590-1601.

We do a comparative analysis of the effect of nuclear energy, renewable and non-renewable energy on carbon emissions. Second, we examine the independent and moderating role urbanization on the energy-environmental pollution association. Third, the political economy of the energy-environmental pollution link is investigated. Finally, we employ a more robust technique; ARDL bounds testing procedure by using critical values and approximate p-values based on response surface regression and CUSUM test for detecting structural breaks.

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Renewable energy, nuclear energy, and environmental pollution: Accounting for political institutional quality in South Africa

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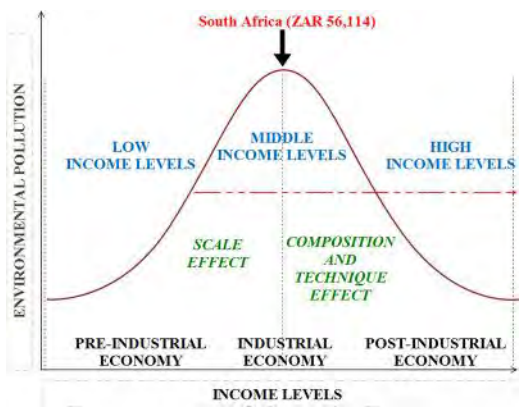
HIGHLIGHTS

- The EKC hypothesis is valid in South Africa at a turning point of ZAR 56,114.
- 1% increase in fossil fuel will increase CO_2 emissions by 10,436 kt in the long term.
- 1% increase in renewable energy decreases CO_2 emissions by 2865 kt in the long-run.
- Aggregate energy consumption and economic growth intensify environmental pollution.
- Political institutional quality declines environmental pollution by 0.1% in the long-run.

GRAPHICAL ABSTRACT



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ABSTRACT

This study examined the impact of disaggregate and aggregate energy, economic development, urbanization and political institutional quality on environmental pollution using a time series data spanning from 1971 to 2017. The study employed response surface regressions, structural break cumulative sum (CUSUM) test based on recursive residuals and ordinary least squares (OLS) residuals for parameter stability en route to estimating the autoregressive distributed lag (ARDL) regression. The environmental Kuznets curve (EKC) hypothesis is valid in South Africa with an extreme point of ZAR 56,114 which occurred in 2011. Evidence from the study reveals that political institutional quality plays a huge role in the social, governance and economic readiness to mitigate climate change and its impact. Structural adjustment in disaggregate and aggregate energy consumption, economic growth, and political institutional quality play a critical role in environmental quality. Fossil-fuel rich countries require diversification of the energy portfolio by incorporating renewable energy sources which will promote environmental sustainability and improve air quality while reducing their economy's vulnerability to price volatility. A paradigm shift from energy and carbon-intensive industries to a service-oriented economy will cause a structural economic change thus, aiding in the mitigation of climate change and its impacts.
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1. Introduction

Modernization with its associated changing lifestyles and the need for reliable modern energy access is expected to require energy supply

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to be at least doubled from 2016 to 2030. The situation is worsened by energy-sector bottlenecks and power shortages which cost the African region 2–4% of GDP annually, which undermines growth, jobs, and investment. The Africa Progress Panel (APP) (2016) estimates that some 600 million people on the continent do not have access to electricity, a figure that will require $55bn per year in investment by 2030 to fix. It is not surprising that more than 2.7 billion people – 38% of the world's population – are estimated to rely on the traditional use of solid biomass for cooking mostly in Asia and Sub-Sahara Africa (WEO, 2016). Renewable energy and the application of nuclear energy technology have acquired a reputation among policymakers as cost-effective and environmentally friendly sources of energy.

To mitigate the continuous problem of sustainable energy supply, the South African government has committed itself to pursue renewable energies (RE) vigorously as a viable alternative to traditional sources such as fossil fuels. It was in 2003 that renewable energy became prominent in South African policy document, where it outlined the strategic intention for RE for the next decade (Weideman et al., 2017). In the light of this, the South African government formed the Renewable Energy Independent Power Producers Procurement Programme (the REI4P), an extensive initiative infrastructure to install 17.8 GW of electricity generation capacity from renewables – wind, solar, biomass, biogas and hydropower to reduce carbon emissions over the period 2012–2030 (Walwyn and Brent, 2015).

South Africa is the seventh largest exporter of coal and among the top emitters of fossil fuel related emissions, as nearly 90% of its energy (42.8 GW) is produced from coal (Baker, 2017; Nakumuryango and Inglesi-Lotz, 2016). Appreciating the contribution of coal-generated energy to the rising issues of global climate change, the South African government recognized the need to achieve a sustainable energy mix by developing renewable energy source. To deepen this resolve, it developed an integrated Resource plan in 2010 to promote RE and more recently, the Renewable Energy Independent Power Producer Procurement Programme (REIPPPP) in 2014. The result of these initiatives and particularly the grid-connected RE auctions have seen grid prices fall, as one of the lowest in the world with solar PV prices as low as USc 6.4/kWh and the cheapest wind at USc 4.7/kWh (Eberhard and Kåberger, 2016). It is noteworthy that South Africa's renewable energy industry has faced challenges including resistance by the electricity utility Eskom (State monopoly), which is embroiled with scandals of state capture and corruption, as well as the ability of Eskom's transmission grid to integrate renewable energy generation (Baker, 2017).

Additionally, with climate change being regarded as one of the most pressing global problems, nuclear energy has found its way into policy roundtables all over the world (Lenzen, 2008). The World Nuclear Performance Report (2017) indicates that over 9GWe nuclear capacity came online in 2016, which is the largest increase in the last quarter of a century. The amount of electricity supplied by nuclear power globally increased from 35 TWh to 2476 TWh, and there are plans to increase electricity supply by nuclear energy to 25% of the world's electricity by 2050. Currently, the only nuclear power plant operational in sub-Saharan Africa is in South Africa which accounts for 5% of the electricity generating capacity. Government has a strong commitment to the future of nuclear energy, with firm plans for further 1300 MWe in the face of significant financial constraints (World Nuclear Association, 2017).

With the impetus for renewables, the big question is how has this impacted on the environment? This is the question the study seeks to answer. It is important to mention that to date; many studies have examined the effect of renewable and nuclear energy on economic growth but not much on how they impact carbon emissions. Thus, the study fills this is gap, because the few available literature have yielded mixed results (Apergis et al., 2010; Saidi and Mbarek, 2016). This suggests that country-specific studies could help shed more light on the scope of the study.

To achieve the research objective and provide consistent estimates, the study further considers two other variables (urbanization and political institutional quality), which the literature suggests have an impact on the environment. However, there are no empirical studies to examine the importance of the indicators to provide evidence for policy formulation. Accordingly, to reduce the problem of omitted variable bias, we control for the urbanization process. The study examines how institutional environment moderates the energy-environment degradation link. In achieving the research objective, we contribute to the literature in three main ways. First, we do a comparative analysis of the effect of nuclear energy, renewable and non-renewable energy on carbon emissions. Second, we examine the independent and moderating role urbanization on the energy-environmental pollution association. Third, the political economy of the energy-environmental pollution link is investigated. Finally, we employ a more robust technique; ARDL bounds testing procedure by using critical values and approximate p-values based on response surface regression and CUSUM test for detecting structural breaks over the period 1971–2017.

The rest of the paper is organized as follows: Literature review, Methodology, Results and discussion, and Conclusion.

2. Literature review

The literature on the energy – environmental degradation link is vast with no consistent results. There are two strands of the energy – environmental degradation literature; the first focuses on the overall energy and the second, examines the differential effects of the components (renewable versus nonrenewable). For example, Dogan and Seker (2016a) examine the energy consumption, urbanization and carbon dioxide emissions link for the USA over the period 1960–2010 and show that in the long run, energy consumption and urbanization increase environmental degradation. Similarly, Franco et al. (2017) in a study of India over 110 years (1901–2011) find that urbanization improves the quality of life of people while promoting economic growth; however, it also increases energy consumption and has a significant impact on carbon dioxide emissions. Martínez-Zarzoso and Maruotti (2011) show that the effect of urbanization is moderated by the level of development. The authors find that urbanization demonstrates a very different impact on emissions for low, lower-middle-income and upper-middle income countries. Liddle (2014) in a review of macro-level studies on urbanization and population dynamics find that urban density has a negative effect on carbon emissions.

Decomposing the energy variable into renewable and nonrenewable energy, Shafiei and Salim (2014), Dogan and Seker (2016a), Dogan and Seker (2016b) and Jebli et al. (2016) find that non-renewable energy consumption raises CO_2 emissions while renewable energy consumption reduces CO_2 emissions in OECD countries. Al-Mulali et al. (2015) find that non-renewable energy consumption enhances CO_2 emissions, while renewable energy consumption has no effects on CO_2 emissions in Vietnam. In another study of Kenya over the period 1980–2012 based on ARDL, Al-Mulali et al. (2016) report that renewable energy reduces CO_2 emissions while non-renewable energy, and urbanization increase environmental pollution. In a regional study of 25 SSA, Zoundi (2017) shows a negative effect of renewable energy on carbon emissions. Nonetheless, the impact of renewable energy is outweighed by primary energy consumption in both the short and long run. Investigating the relationship for developing countries based on panel econometric analysis of annual data from 1990 to 2012, Paramati et al. (2017) show that renewable energy consumption positively contributes to economic output and environmental quality. Accordingly, the authors recommend that policymakers initiate effective policies to promote more renewable energy generation. Controlling for cross-sectional dependence, using the cross-sectionally augmented Dickey Fuller (CADF) and cross-sectional augmented Im, Pesaran and Shin (CIPS) tests, Irfan and Shaw (2017) find that renewable energy decreases carbon emissions, while nonrenewable energy increase emissions in the EKC

model for the top countries listed in the Renewable Energy Country Attractiveness Index.

Some studies provide results contrary to those discussed above. For example, Apergis et al. (2010) examine the causal relationship between CO_2 emissions, nuclear energy consumption, renewable energy consumption, and economic growth for a group of 19 developed and developing countries for the period 1984–2007 using a panel error correction model. The long-run estimates indicate that there is a statistically significant negative association between nuclear energy consumption and emissions, but a statistically significant positive relationship between emissions and renewable energy consumption. The authors conclude that renewable energy does not contribute to the reduction of carbon emissions. This may be due to the lack of adequate storage technology to overcome intermittent supply problems as a result, electricity producers must rely on emission generating energy sources to meet peak load demand. This is also in line with the findings of Menyah and Wolde-Rufael (2010) for the US that renewable energy did not contribute to carbon emissions reduction.

Additionally, some studies do not show differential effects between renewable and nonrenewable energy on carbon emissions. Farhani and Shahbaz (2014) analyze the case for Middle East and North Africa (MENA) countries by applying the fully modified ordinary least squares (FMOLS) and the dynamic ordinary least squares (DOLS) on data from 1980 to 2009 and conclude that both renewable and non-renewable energy increases the level of emissions. Mert and Bölük (2016) investigate the case of 16 European Union (EU) countries over the 1990–2008 period using OLS and fixed effects and find that both renewable and nonrenewable energy consumption contributes to environmental degradation though renewable energy contributes around 1/2 less per unit of energy in terms of GHG (greenhouse gas) emissions. In a related study of the MENA region from 1980 to 2009, based on Breitung IPS and Pedroni cointegration techniques, Bilgili et al. (2016) demonstrate that both renewable and nonrenewable energy contribute to carbon dioxide emissions.

Some other studies, however, report that renewable energy has a positive impact on the environment only when it has reached a certain minimum threshold. According to Chiu and Chang (2009), renewable energy supply must account for 8.39% of total energy supply before any impact on mitigating CO_2 emissions could be observed. Indeed, the results show that below the threshold, renewable energy contributes to environmental degradation. Heal (2009) and Forsberg (2009) claim that renewable energy may not reduce emissions because of the intermittent nature of its output and the lack of adequate storage technology for renewable energy. Threshold effects have also been reported for urbanization. For example, Irfan and Shaw (2017) examined three Asian countries (India, Pakistan, and Bangladesh) over the period 1978–2011 using fixed effects to show support for the Kuznets curve. More importantly, the results suggest that there exists a threshold below which increases in urbanization increases carbon emissions but after the threshold is reached, further urbanization leads to a fall in carbon dioxide emissions.

Bhattacharya et al. (2017) extend the literature by discussing the role of institutions (economic freedom) in the energy consumption and environment relationship using various econometric tools including GMM and FMOLS for 85 developed and developing countries over the period 1991–2012. The results of the study show that both renewable energy and institutions have a positive influence on growth and environmental quality. Al-Mulali et al. (2015) used FMOLS to show that energy consumption, urbanization, trade openness and industrial development increase environmental damage while political stability lessens it in the long run for MENA countries over the period 1996–2012. Adams et al. (2016a, 2016b) report that both the regime type and regime stability matter in explaining environmental outcomes. Similarly, Adams and Klobodu (2017) argue that though democracy matters, democratic consolidation is more important in explaining environmental policy outcomes. This study contributes to the debate by examining how both political and economic institutions affect the energy-carbon dioxide relationship. The methodology for achieving the objectives is discussed next.

3. Methodology

3.1. Data

To meet the objectives, the study employs time series data from the World Bank Development Indicators (World Bank, 2016), U.S. Energy Information Administration (EIA, 2017), and University of Gothenburg (UoG, 2017). The eight data series include Urban population (URB), CO_2 emissions (CO_2E), Energy use (EGUSE), Political institutional quality (PIQ), Renewable energy (RENE), Fossil Fuel energy (NRENE), GDP per capita (GDPPC) and Nuclear Electricity Net Generation (NUC), presented in Table 1. The selection of the variables is motivated by the Sustainable Development Goals by 2030.

Due to data availability, the missing data within the series were filled using the seasonal algorithm (exponential smoothing) which accounts additive error, additive trend and additive seasonality (AAA) based on a 99.99% confidence interval available in Microsoft Excel. Thus, the period of the data used for the empirical analysis spans from 1971 to 2017, using South Africa as a case study.

Fig. 1 shows the trend and the graphical representation of the data series under study. From observation, it appears that CO_2 emissions, GDP per capita and urbanization exhibit an increasing trend compared to the other data series. One may be attempted to believe that there are issues of structural breaks by just observing the pictorial view of the data series. As such, issues related to structural breaks would be discussed exhaustively in the subsequent sections of the study.

To better understand the characteristics of the data series prior to estimating the model, the study descriptively analyzes the study variables presented in Table 2. Based on the available data, the averages of the variables are quantified as: CO_2 emissions, 348,274 kt; energy use, 2450 kg of oil equivalent per capita; GDP per capita, 22,495 South African Rand (ZAR); fossil fuel energy, 87%; nuclear electricity generation, 8%; political institutional quality, 0.40 relative factor scores; renewable energy, 17%, and urbanization, 22,369,184 people.

Table 2 reveals that except CO_2E, EGUSE, NRENE, and NUC, all the remaining variables are positively skewed. However, only NUC has excess kurtosis exceeding 3 thus, exhibiting a leptokurtic distribution. The Jarque-Bera test of normal distribution reveals that all the variables are normally distributed in their raw values except for GDPPC, and PIQ.

The test of association using correlation reveals that while all the variables have a positive relationship with CO_2 emissions except for fossil fuel energy, however, in reality, sounds deceptive. Meaning that the descriptive statistics are unable to examine causation, thus, requires inferential statistics to empirically examine the causal nexus between CO_2 emissions used as a proxy for environmental pollution and the predictor variables under study.

Table 1
Variable definition.

Series name	Abbreviation
Urban population	URB
CO_2 emissions (kt)	CO_2E
Energy use (kg of oil equivalent per capita)	EGUSE
Political institutional quality (relative factor scores)	PIQ
Renewable energy (%)	RENE
Fossil Fuel energy (%)	NRENE
GDP per capita (current LCU)	GDPPC
Nuclear Electricity Net Generation (billion kWh)	NUC

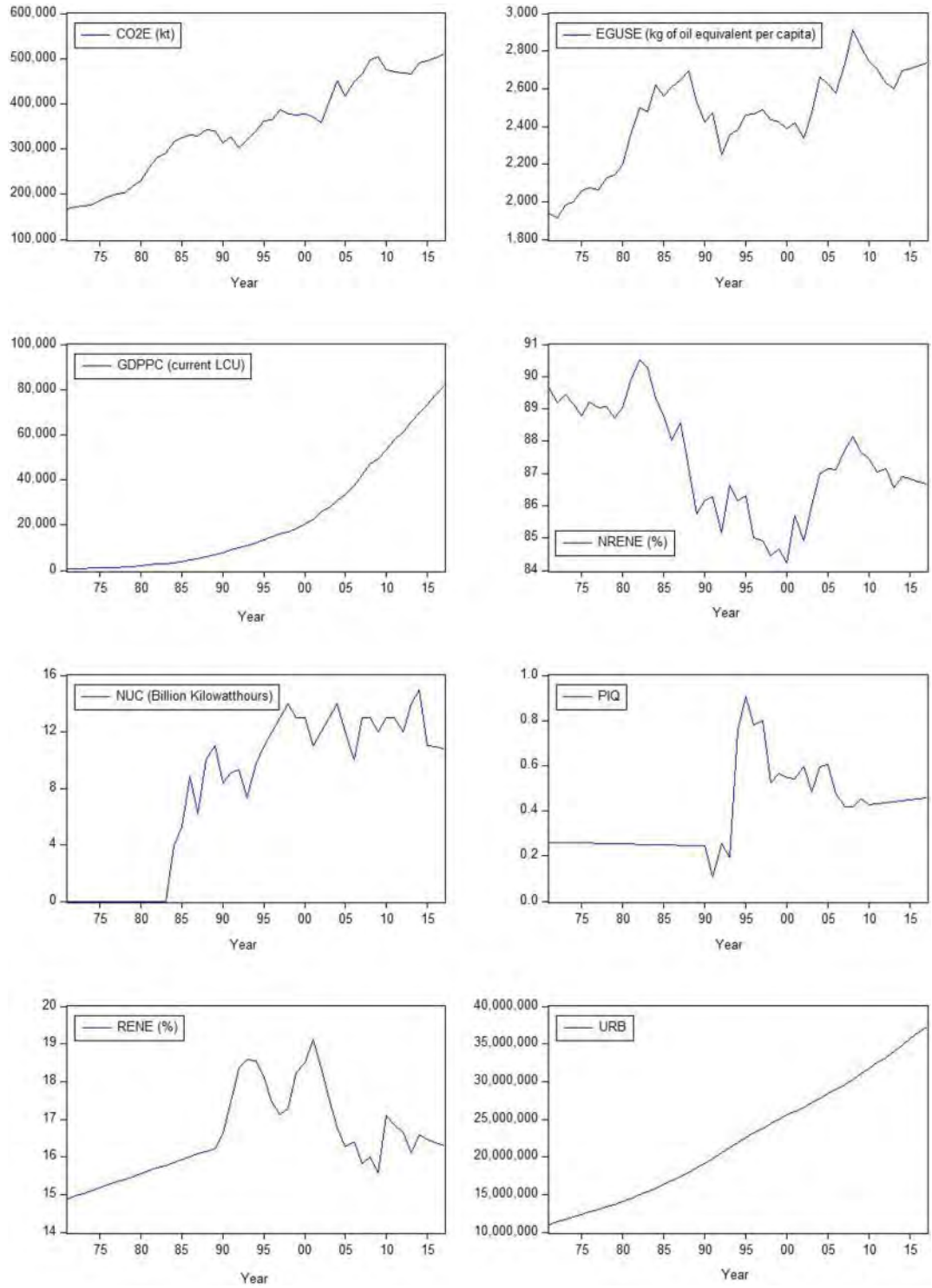

Fig. 1. The trend of data series. Legend: Urban population (URB), CO_2 emissions (CO_2E), Energy use (EGUSE), Political institutional quality (PIQ), Renewable energy (RENE), Fossil Fuel energy (NRENE), GDP per capita (GDPPC) and Nuclear Electricity Net Generation (NUC).

3.2. Model estimation

The study employs three relationship models with ARDL specification following the work of Asumadu-Sarkodie and Owusu (2016) expressed as a linear function below:

$$CO_2E_t = f\left(LRENE_t, LNRENE_t, LGDPPC_t, LGDPPC^2{}_t, LPIQ_t\right) \quad (1)$$

$$CO_2E_t = f\left(LRENE_t, LNRENE_t, LNUC_t, LGDPPC_t, LGDPPC^2{}_t, LPIQ_t\right) \quad (2)$$

$$LCO_2E_t = f(LEGUSE_t, LURB_t, LGDPPC_t, LPIQ_t) \quad (3)$$

Model 1–2 in Eqs. (1)–(2) is based on a level-log regression using the EKC hypothesis pathway contrary to Model 3. Moreover, Model 1–2 represents the disaggregation energy consumption while Model 3

Table 2
Descriptive statistical analysis.

Statistic	CO_2E	EGUSE	GDPPC	NRENE	NUC	PIQ	RENE	URB
Mean	348,273.7	2449.502	22,495	87.3676	7.9733	0.3960	16.5117	22,369,184
Median	343,055.2	2471.021	12,038.97	87.1497	10.0000	0.4180	16.2683	21,903,210
Maximum	509,548.4	2913.13	81,693.47	90.5063	15.0000	0.9028	19.1214	37,338,489
Minimum	168,568.3	1912.971	619.304	84.2434	0.0000	0.1066	14.8817	11,060,997
Std. dev.	105,814.8	253.4518	24,531.69	1.6717	5.4451	0.1805	1.1277	7,948,592
Skewness	−0.170204	−0.527874	1.052538	−0.0309	−0.5648	0.9135	0.6344	0.245333
Kurtosis	1.967159	2.417412	2.806119	2.0339	1.6731	3.2470	2.4141	1.816373
Jarque-Bera	2.316001	2.847446	8.751666	1.8353	5.9471	6.6559	3.8253	3.215047
Probability	0.314114	0.240816	0.012578[a]	0.3995	0.0511	0.0359[a]	0.1477	0.200383

Correlation**	CO_2E	EGUSE	GDPPC	NRENE	NUC	PIQ	RENE	URB
CO_2E	1							
EGUSE	0.9037	1						
GDPPC	0.8726	0.6765	1					
NRENE	−0.5181	−0.3005	−0.3299	1				
NUC	0.8780	0.7341	0.6665	−0.8106	1			
PIQ	0.5055	0.3034	0.3661	−0.6147	0.6308	1		
RENE	0.3949	0.2435	0.1645	−0.8196	0.6353	0.5522	1	
URB	0.9593	0.7626	0.9465	−0.5578	0.8488	0.5349	0.4189	1

[a] Rejection of the null hypothesis of normal distribution.
** Denotes 5% significance level.

represents the aggregated energy consumption. The adoption of disaggregate and aggregate energy consumption is in line with Sarkodie and Strezov (2018), they argue that the former presents valuable results in terms of interpretation. The empirical specification of Model 1–3 based on the autoregressive distributed lag (ARDL) regression is quantified as:

$$\begin{aligned}\Delta CO_{2t} = {} & \alpha_0 + \delta_1 CO_{2t-1} + \delta_2 LRENE_{t-1} + \delta_3 LNRENE_{t-1} \\ & + \delta_4 LGDPPC_{t-1} + \delta_5 LGDPPC^2{}_{t-1} + \delta_5 LPIQ_{t-1} \\ & + \sum_{i=1}^{p} \beta_{1j}\Delta CO_{2t-i} + \sum_{i=0}^{p} \beta_{2j}\Delta LRENE_{t-i} \\ & + \sum_{i=0}^{p} \beta_{3j}\Delta LNRENE_{t-i} + \sum_{i=0}^{p} \beta_{4j}\Delta LGDPPC_{t-i} \\ & + \sum_{i=0}^{p} \beta_{5j}\Delta LGDPPC^2{}_{t-i} + \sum_{i=0}^{p} \beta_{6j}\Delta LPIQ_{t-i} + \varepsilon_t \end{aligned} \tag{4}$$

$$\begin{aligned}\Delta CO_{2t} = {} & \alpha_0 + \delta_1 CO_{2t-1} + \delta_2 LRENE_{t-1} + \delta_3 LNRENE_{t-1} + \delta_4 LNUC_{t-1} \\ & + \delta_5 LGDPPC_{t-1} + \delta_6 LGDPPC^2{}_{t-1} + \delta_7 LPIQ_{t-1} \\ & + \sum_{i=1}^{p} \beta_{1j}\Delta CO_{2t-i} + \sum_{i=0}^{p} \beta_{2j}\Delta LRENE_{t-i} \\ & + \sum_{i=0}^{p} \beta_{3j}\Delta LNRENE_{t-i} + \sum_{i=0}^{p} \beta_{4j}\Delta LNUC_{t-i} \\ & + \sum_{i=0}^{p} \beta_{5j}\Delta LGDPPC_{t-i} + \sum_{i=0}^{p} \beta_{6j}\Delta LGDPPC^2{}_{t-i} \\ & + \sum_{i=0}^{p} \beta_{7j}\Delta LPIQ_{t-i} + \varepsilon_t \end{aligned} \tag{5}$$

$$\begin{aligned}\Delta LCO_{2t} = {} & \alpha_0 + \delta_1 LCO_{2t-1} + \delta_2 LEGUSE_{t-1} + \delta_3 LURB_{t-1} \\ & + \delta_4 LGDPPC_{t-1} + \delta_5 LPIQ_{t-1} + \sum_{i=1}^{p} \beta_{1j}\Delta LCO_{2t-i} \\ & + \sum_{i=0}^{p} \beta_{2j}\Delta LEGUSE_{t-i} + \sum_{i=0}^{p} \beta_{3j}\Delta LURB_{t-i} \\ & + \sum_{i=0}^{p} \beta_{4j}\Delta LGDPPC_{t-i} + \sum_{i=0}^{p} \beta_{5j}\Delta LPIQ_{t-i} + \varepsilon_t \end{aligned} \tag{6}$$

where LCO_2, $LEGUSE$, $LRENE$, $LNRENE$, $LNUC$, $LGDPPC$, $LURB$, and $LPIQ$ denote the logarithmic transformation of CO_2 emissions, Energy use, Renewable energy, Fossil Fuel energy, Nuclear Electricity Net Generation, GDP per capita and Political institutional quality, the intercept is denoted by α, p is the lag order, Δ is the first difference operator, and the error term is represented as ε at time t. The ARDL regression model is used to estimate and test the level relationship between the response variable and the regressors. Importantly, ARDL model is suitable for small sample size and multiple predictors can have different lag orders.

The study employs Pesaran et al. (2001) bounds test for levels relationship where the approximate p-value and critical values for the F-tests and t-statistics are derived from Kripfganz and Schneider (2018) response surface regressions. The Null hypothesis of no co-integration between response and regressors is rejected if the approximate p-value and critical values for the F-tests and t-statistics are above the upper bound critical values.

The study analyzes the parameter stability of the time series regression by examining the existence of structural break over a period of time, in order to prevent spurious regression. We employ the cumulative sum tests namely; CUSUM test based on recursive residuals and OLS residuals for parameter stability expressed mathematically as (Brown et al., 1975):

$$C_t{}^{rec} = \frac{1}{\hat{\sigma}} \sum_{j=k+1}^{j=t} e_j{}^{rec} \tag{7}$$

where $C_t{}^{rec}$ denotes the limiting distribution of the sequence, k represents variables, t denotes time, $e_t{}^{rec}$ represents recursive residuals and variance $\hat{\sigma}^2 = \{1/(T-k)\} \sum_{k+1}^{T} (e_t{}^{rec} - e_t{}^{-rec})^2$.

$$C_t{}^{ols} = \frac{1}{\hat{\sigma}\sqrt{T}} \sum_{j=k+1}^{j=T} e_j{}^{ols} \tag{8}$$

where $C_t{}^{ols}$ denotes the limiting distribution of the sequence, k represents variables, t denotes time, $e_t{}^{ols}$ represents ols residuals and variance $\hat{\sigma}^2 = \{1/(T-k)\} \sum_{k+1}^{T} (e_t{}^{ols} - e_t{}^{-ols})^2$.

4. Results and discussion

4.1. Unit root

After examining the characteristics of the data series, the study employs the Phillips-Perron test to examine the presence of unit root among the data series. Contrary to the Augmented Dickey-Fuller unit root test that uses supplementary lags of the first difference data series, the Phillips-Perron (Phillips and Perron, 1988) unit root test accounts

Table 3
Phillips-Perron unit root test.

Variable	Intercept				Intercept & trend				None			
	Level	Prob	1st diff	Prob	Level	Prob	1st diff	Prob	Level	Prob	1st diff	Prob
CO_2E	−0.8185	0.8043	−6.8058	0.0000	−2.6217	0.2730	−6.7452	0.0000	2.5198	0.9966	−5.8943	0.0000
EGUSE	−1.8486	0.3530	−6.4746	0.0000	−2.2048	0.4757	−6.4953	0.0000	1.1356	0.9315	−6.2844	0.0000
GDPPC	9.0960	1.0000	−0.7592	0.8208	2.0978	1.0000	−4.4413	0.0049	11.4269	1.0000	0.1711	0.7311
NRENE	−1.6729	0.4380	−7.5025	0.0000	−1.6774	0.7453	−7.4641	0.0000	−0.7329	0.3936	−7.5249	0.0000
NUC	−1.4539	0.5477	−7.7865	0.0000	−1.5476	0.7980	−7.8404	0.0000	0.1364	0.7207	−7.7103	0.0000
PIQ	−2.1200	0.2380	−6.9745	0.0000	−2.4766	0.3377	−6.8995	0.0000	−0.6090	0.4481	−7.0423	0.0000
RENE	−1.9746	0.2966	−4.9835	0.0002	−1.7010	0.7348	−5.0843	0.0008	0.2602	0.7572	−5.0422	0.0000
URB	5.7959	1.0000	−0.7197	0.8313	−1.2951	0.8768	−1.7838	0.6960	18.8792	1.0000	1.8875	0.9845

for serial correlation by implementing Newey-West standard errors, as such produces more accurate unit root tests. Table 3 presents the results of Phillips-Perron unit root test in three different options namely; intercept, intercept and trend, and none. Table 3 reveals that the null hypothesis that the variables under investigation contain unit root at level cannot be rejected at 5% significance level in intercept, intercept and trend, and none. On the contrary, except GDPPC and URB, the null hypothesis that the variables unit root at first difference is rejected at 5% significance level in intercept, intercept and trend, and none. Meaning that the variables are integrated of order zero [I(0)] and order one [I(1)], except GDPPC and URB.

Contrary to other econometric techniques, the proposed ARDL by Pesaran and Shin (1998) does not require all variables to be I(1) or I(0) and I(1). However, as a precondition, the dependent variable must be non-stationary and none of the data series must be I(2) in normal conditions and in the structural break. Pesaran and Shin (1998) revealed that the ARDL bounds cointegration among the data series can have a different number of lag terms.

4.2. Structural break

In order to overcome challenges related with structural breaks in the time series variables, the study employed the cumulative sum test for parameter stability by Brown et al. (1975) to ascertain the stability of coefficients in the time series regression over time. All the two tests namely; the cumulative sum of recursive residuals and the cumulative sum of OLS residuals are analyzed in the study due to the advantage each has over the other. According to Ploberger and Krämer (1992), the cumulative sum of recursive residuals has the advantage to detect parameter instability that occurs in the early periods of the sample data. On the contrary, the cumulative sum of OLS residuals has an advantage of detecting the parameter instability for breaks in the later periods of the sample data. Thus, combining both tests is essential in the study. Another advantage of the cumulative sum test for parameter stability is that it prepares data series to be free from structural breaks prior to model estimation and produces CUSUM plots with corresponding test statistics to support the test output. Table 4 presents the results of the structural break test statistic with their corresponding plots depicted in Figs. 2–3. Figs. 2–3 show that the plotted cusum is within the 95% confidence band. Additionally, Table 4 reveals that the test statistics for all the three models using both cumulative sum test are smaller than the 1%, 5% and 10% critical values as such, cannot reject the null hypothesis that all the parameters are stable over time using the data series. Thus, the estimated models have no issues of structural break.

Table 4
Test of structural break.

Models	Statistic	Test statistic	1% critical	5% critical	10% critical
			Value	Value	Value
Model 1	ols	0.6720	1.6276	1.3581	1.2240
Model 1	recursive	0.8364	1.1430	0.9479	0.8500
Model 2	ols	0.5789	1.6276	1.3581	1.2240
Model 2	recursive	0.4495	1.1430	0.9479	0.8500
Model 3	ols	0.8459	1.6276	1.3581	1.2240
Model 3	recursive	0.6810	1.1430	0.9479	0.8500

4.3. Cointegration

The study examines the existence of a level relationship between the response and predictor variables via the famous Pesaran et al. (2001) bounds test procedure by using critical values and approximate p-values based on response surface regression from Kripfganz and Schneider (2018).

The Kripfganz and Schneider (2018) pathway to Pesaran et al. (2001) bounds test is more beneficial to estimate the upper and lower bound critical values in conditions were all long-run data series are either integrated of order zero, I(0) or order one, I(1). Moreover, the response surface estimates provide accurate finite sample critical value bounds for an unlimited number of short-run coefficients.

For brevity, the approximate p-values by Kripfganz and Schneider (2018) can be mathematically presented as:

$$F^{-1}(p) = \sum_{i=0}^{n} \varnothing_i \left\lfloor \hat{Q}(p) \right\rfloor^i + e \tag{9}$$

$$\hat{p} = F\left(\sum_{i=0}^{n} \hat{\varnothing}_i \tau^i\right) \tag{10}$$

where $F^{-1}(p)$ denotes the inverse cumulative distribution function applied under standard asymptotics, $\hat{Q}(p)$ denotes the predicted p-quantile, e denotes the error term, n denotes the higher order term, $\hat{\varnothing}_i$ denotes the estimated coefficients from Eq. (9) and $\hat{p}$ is the corresponding approximate p-value from the observed value of the test statistic τ.

Table 5 presents the ARDL bounds test for cointegration. The results in Table 5 reveals that the F-statistics and t-statistics of the three models are more extreme than the critical values for the upper bound, I(1) and corroborated by Kripfganz and Schneider (2018) approximate p-values, thus, rejecting the null hypothesis of no level relationship. In other words, the response variable and the predictor variables in the three models are cointegrated. Meaning that a more parsimonious ARDL model can be estimated following Pesaran and Shin (1998).

4.4. Long- and short-run equilibrium relationship

After rejecting the null hypothesis of no level relationship, the next step is to examine the long- and short-run equilibrium relationship between CO_2 emissions and the regressors using the ARDL model with optimal lag selection using Akaike Information Criterion of pure autoregressive processes.

Using the optimal lag in the levels regression, the estimated long- and short- run equilibrium relationship are based on ARDL(1,0,0,0,1,0) for model 1, ARDL(1,0,1,0,0,1,0) for model 2, and ARDL(1,1,1,1,1) for model 3, respectively. The long-run coefficients in Model 1 are

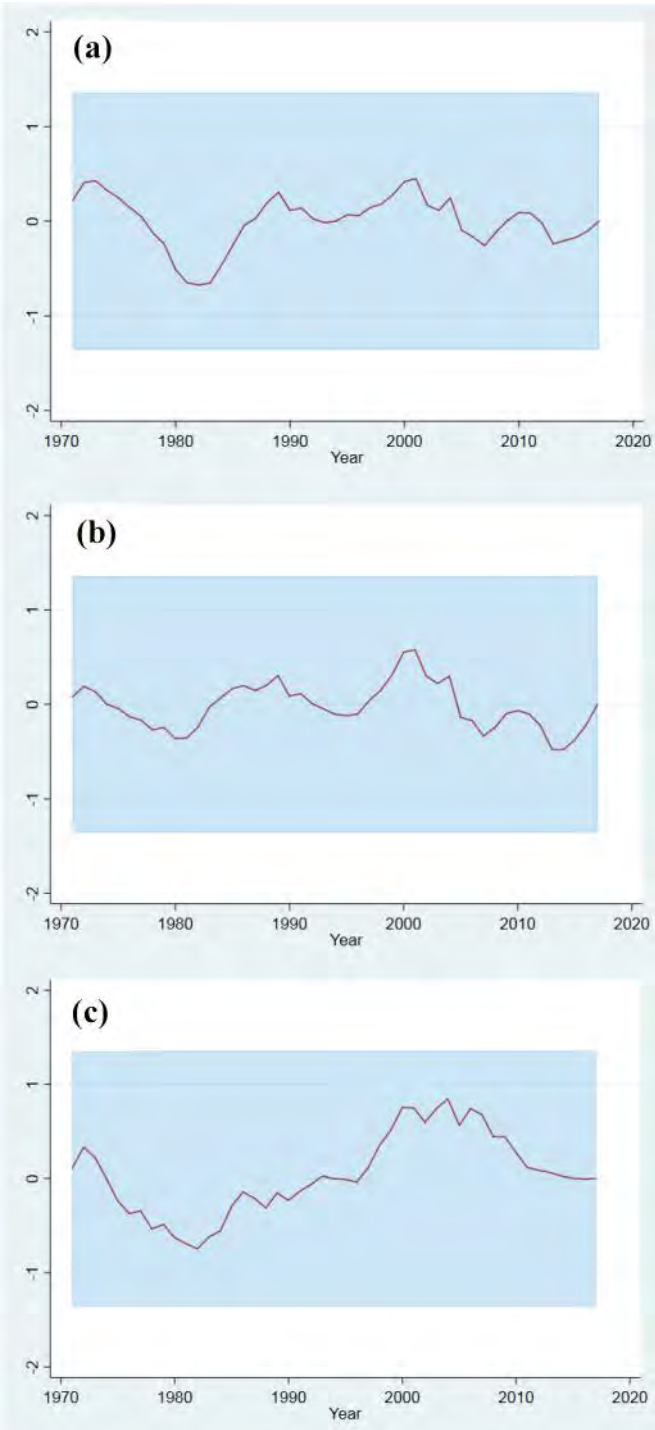

Fig. 2. Recursive CUSUM plot for structural break: (a) Model 1 (b) Model 2 and (c) Model 3.

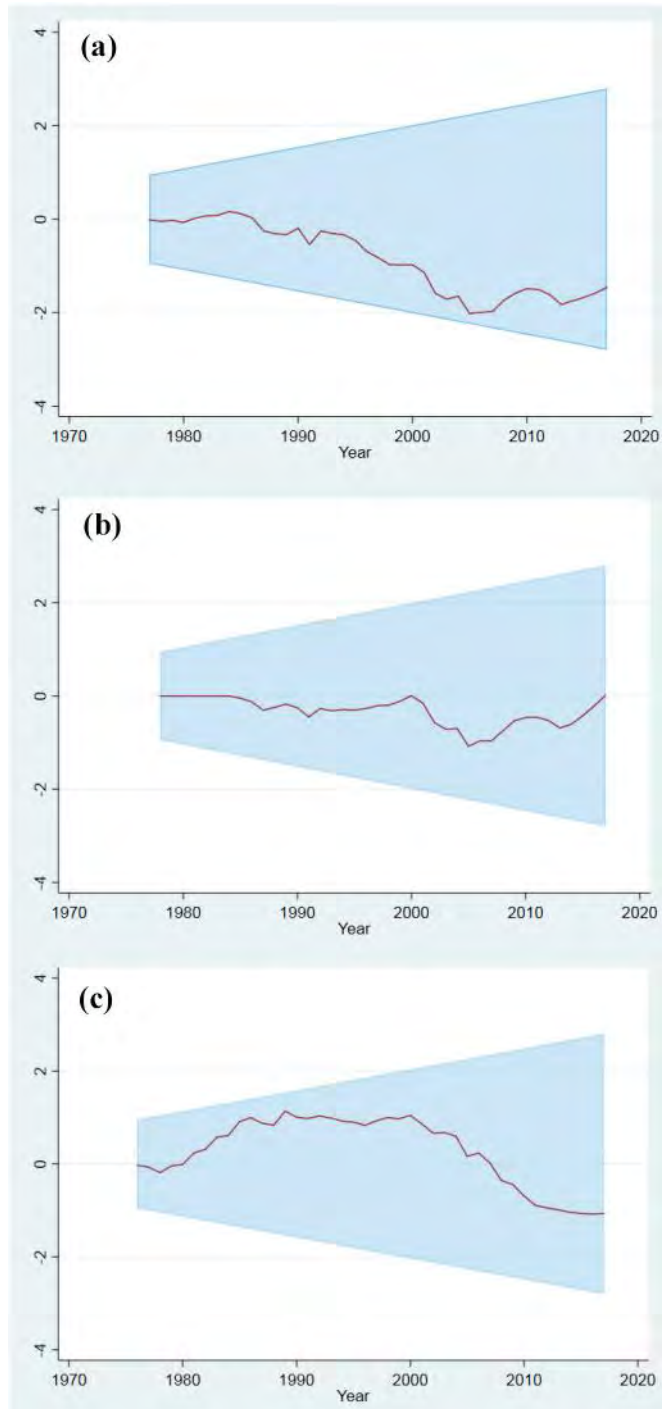

Fig. 3. OLS CUSUM Plot for structural break: (a) Model 1 (b) Model 2 and (c) Model 3.

expressed in time t (estimated in first difference form) while the long-run coefficients in Models 2 and 3 are expressed in $t-1$. Thus, reflecting in the error correction with the levels regressors. Even though both parameterizations produce identical coefficients except for the first first-difference term of each long-run independent variable.

The results of the ARDL regression for Model 1–3 are presented in Table 6. Models 1 and 2 are a level-log (i.e. $\beta/100$ in explaining coefficients) regression which shows the nexus between environmental pollution (CO_2E), disaggregate energy consumption (LRENE and LNRENE), economic growth (LGDPPC) and political institutional quality (LPIQ). The results show that disaggregate energy sources provide a detailed assessment of the effect of renewables and fossil fuel on environmental pollution.

Model 1 reveals that the error correction [ECT$(-1) = -0.65$] is negative and statistically significant at 1%. Thus, confirming a long-run relationship running from disaggregate energy consumption, economic development and political institutional quality to environmental pollution. The error correction term reveals a 65% speed of adjustment in correcting deviations from the long-run equilibrium level of environmental pollution during the first-year after short-term shocks.

Model 1 reveals that a 1% increase in the share of renewable energy declines environmental pollution by 3288 kt while a percentage increase in the share of fossil fuel in the energy mix increases

Table 5
ARDL bounds test.

Bounds	10%		5%		1%		p-Value		F/t statistic
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
F (Model 1)	2.48	3.69	2.98	4.32	4.13	5.79	0.00	0.00	7.01
t (Model 1)	−2.56	−3.87	−2.90	−4.28	−3.60	−5.09	0.00	0.00	−5.59
F (Model 2)	2.35	3.62	2.81	4.24	3.91	5.70	0.00	0.00	8.29
t (Model 2)	−2.53	−4.01	−2.88	−4.44	−3.60	−5.31	0.00	0.00	−6.83
F (Model 3)	2.60	3.82	3.13	4.51	4.38	6.09	0.00	0.03	5.17
t (Model 3)	−2.53	−3.64	−2.88	−4.04	−3.57	−4.83	0.00	0.01	−4.82

environmental pollution by 8913 kt. The outcome is in line with Mohiuddin et al. (2016) which shows that electricity generation from oil, natural gas, and oil contributes to environmental degradation.

The sign of per capita GDP (LGDPPC) is positive while the sign of the squared per capita GDP ($LGDPPC^2$) is negative and both exhibiting statistical significance at 1%, which suggest that, in the long-run, environmental pollution will increase by 13% (*i.e.* $-0.5 * \frac{LGDPPC}{LGDPPC^2}$) at the initial stage of economic development and decreases thereafter with increasing economic productivity. Thus, validating the EKC hypothesis in South Africa.

The nexus between environmental pollution and political institutional quality is negative yet insignificant in Model 1.

In the business as usual scenario, the short-run equilibrium relationship in Model 1 reveals that disaggregate energy consumption, economic development, and political institutional quality will reduce environmental pollution by 27,901 kt in the short-term.

Table 6
ARDL regression with long- and short-run equilibrium relationship.

	$\Delta L/CO_2E$	Coef.	Std. err.	t	p > t
Model 1					
ADJ	ECT(−1)	−0.6457	0.1154541	−5.59	0.0000*
LR	LRENE	−328,847.9	92,462.24	−3.56	0.0010*
	LNRENE	891,285	346,892.3	2.57	0.0140**
	LGDPPC	276,410.6	53,250.63	5.19	0.0000*
	$LGDPPC^2$	−10,641.29	2823.255	−3.77	0.0010*
	LPIQ	−9641.346	9496.722	−1.02	0.3170
SR	_cons	−2,790,194	1,035,229	−2.7	0.011**
Model 2					
ADJ	ECT(−1)	−0.7819	0.1145	−6.8300	0.0000*
LR	LRENE	−286,501	75,388	−3.8000	0.0010*
	LNUC	15,970	9503	1.6800	0.1020
	LNRENE	1,043,614	314,461	3.3200	0.0020*
	LGDPPC	208,125	62,517	3.3300	0.0020*
	$LGDPPC^2$	−7447	3156	−2.3600	0.0240**
	LPIQ	−7018	7134	−0.9800	0.3320
SR	ΔLRENE	−224,006	67,909	−3.3000	0.0020*
	ΔLNUC	25,551	8438	3.0300	0.0050*
	ΔLNRENE	815,967	247,321	3.3000	0.0020*
	ΔLGDPPC	162,726	50,790	3.2000	0.0030*
	$\Delta LGDPPC^2$	−12,654	5460	−2.3200	0.0270**
	ΔLPIQ	−5487	5472	−1.0000	0.3230
	_cons	−3,741,482	1,137,020	−3.2900	0.0020*
Model 3					
ADJ	ECT(−1)	−0.7315	0.1518	−4.8200	0.0000*
LR	LEGUSE	1.2570	0.1256	10.0100	0.0000*
	LGDPPC	0.2446	0.0994	2.4600	0.0190**
	LURB	−0.4551	0.3955	−1.1500	0.2570
	LPIQ	−0.0610	0.0199	−3.0700	0.0040*
SR	ΔLEGUSE	1.0869	0.1246	8.7300	0.0000*
	ΔLGDPPC	−0.0156	0.1252	−0.1200	0.9010
	ΔLURB	1.4711	1.6858	0.8700	0.3890
	ΔLPIQ	−0.0229	0.0155	−1.4800	0.1470
	_cons	6.1181	4.5906	1.3300	0.1910

NB: ADJ = speed of adjustment; LR = long-run and; SR = short-run.
* Rejection of the null hypothesis at 1% significance level.
** Rejection of the null hypothesis at 5% significance level.

Model 2 reveals a long-run relationship running from renewable energy consumption, fossil fuel energy consumption, nuclear energy generation, economic development and political institutional quality to environmental pollution; as the speed of adjustment [ECT(−1) = −0.78] is negative and statistically significant at 1%. The error correction term shows a 78% speed in correcting disequilibrium from the long-run equilibrium level of environmental pollution during the first-year to equilibrium after short-term shocks.

Evidence from Model 2 shows that a 1% increase in the renewable energy penetration decreases environmental pollution by 2865 kt in the long-run. It is important to note that a mere incorporation of renewable energy sources doesn't mean environmental sustainability if the generation and deployment of renewables are not done sustainably.

A 1% increase in fossil fuel energy penetration will propel environmental pollution by 10,436 kt in the long term, which is in line with (Sarkodie and Owusu, 2017a). According to their study, the overdependence on fossil fuel energy technologies thwarts efforts towards achieving a sustainable development. On the contrary, decoupling nuclear energy generation from fossil fuel yields no significant results in the long-term.

Per capita GDP (LGDPPC) is positive and significant at 1% whereas the sign of the squared per capita GDP ($LGDPPC^2$) is negative and statistically significant at 5%. The evidence shows that environmental pollution will increase by 14% in the long-run at the early stages of economic productivity but declines after achieving the required turning point in economic development. Accordingly, confirming the EKC hypothesis in the long-run revealed in Model 1.

In the same manner in Model 1, Model 2, the relationship between environmental pollution and political institutional quality is negative and insignificant.

The short-run equilibrium relationship in Model 2 reveals that the incorporation of renewable energy technologies in the energy portfolio will decline pollution by 2240 kt in the short-term. Thus, complementing the role of renewable energy in both long and short-term.

On the contrary, conventional sources of energy like coal, oil and natural gas will exacerbate environmental pollution by 8160 kt in the short-run. Accordingly, accentuating the aggravating impact of fossil fuels on atmospheric emissions.

The short-run equilibrium relationship in Model 2 further confirms the validity of the EKC hypothesis; this means pollution will accelerate by 6% parallelly with economic growth till it reaches the turning point of economic development then declines thereafter in the short term.

Even though nuclear energy is sustainable but nonrenewable, the short-run relationship between pollution and nuclear energy generation reveals that nuclear energy intensifies environmental pollution by 256 kt. Pollution from nuclear energy may be associated with the emission of radioactive substances and nuclear waste management (handling and disposal). It appears that the impact of nuclear energy on environmental pollution is lower compared to typical fossil fuel energy technologies like coal, oil, and gas (Owusu and Asumadu-Sarkodie, 2016). The short-run equilibrium relationship in Model 2 further reveals that the nexus between pollution and political institutional quality is negative and insignificant.

Business as usual in terms of renewable energy, fossil fuel, nuclear energy generation, economic growth and political institutional quality will decline environmental pollution by 37,415 kt in the short-term.

After examining the impact of disaggregated energy on environmental pollution, Model 3 presents the nexus between aggregate energy consumption, economic development, urbanization and political institutional quality. The estimation of Model 3 is based on a log-log regression presented in Table 6.

The results of Model 3 shows that the error correction [ECT(−1) = −0.73] is negative and statistically significant at 1%, hence, confirming a long-run relationship running from energy consumption, economic growth, urbanization and political institutional quality to environmental pollution. Model 3 shows a 73% speed of adjusting disequilibrium from the long-run level of environmental pollution to equilibrium during the first-year after short-term shocks.

The long-run equilibrium relationship in Model 3 shows that a 1% increase in aggregate energy consumption and economic development will intensify environmental pollution by 1.3% and 0.2%, confirming the work of Sarkodie and Owusu (2017c). They argued that aggregate energy consumption and economic growth work together, as such, exhibits a feedback effect. It appears that the parallel effect of energy consumption and economic development on environmental pollution is valid for developing countries. For energy efficiency to occur, it is expected that as economic growth increases, energy consumption should decline, but contrariwise in South Africa. On the contrary, while urbanization has no significant effect in both long- and short-run, political institutional quality declines environmental pollution by 0.1% in the long-run.

The short-run equilibrium relationship in Model 3 further confirms that aggregate energy consumption increases environmental pollution by 1.1% in the short-term, which is in line with (Sarkodie and Owusu, 2017b).

The study corroborates the validity of the EKC hypothesis using the Utest estimation by Lind and Mehlum (2010). The Utest estimation method is used to test for the presence of a U-shaped or inverted U-shaped relationship between a predictor variable and the response variable on an interval. The only condition of the Utest estimation is to have a level explanatory variable and a non-linear, quadratic or inverse term. Using the level of per capita GDP and the squared of per capita, the overall test shows the presence of an Inverted U-shape presented in Table 7. Thus, the results of the Utest confirms the validity of the EKC hypothesis in the disaggregate energy consumption model shown in Table 6. The Utest further reveals that the turning point of environmental pollution with respect to per capita income level occurs at ZAR 56,114 which corresponds to the year 2011 in the time series data.

In other to prevent spurious and bias inferences, the study employs diagnostic tests to examine the independence of the residuals in the three ARDL models. Table 8 reveals that the three ARDL models are free from 1st order autocorrelation (Durbin-Watson test), has no ARCH effects for higher order autocorrelation (ARCH LM test), has no serial correlation (Breusch Godfrey LM test), has a constant variance free from heteroskedasticity issues (Breusch-Pagan/Cook-Weisberg test), and has no omitted variables (Ramsey RESET test). Finally, the study examines the stability of the three ARDL models using the CUSUM and CUSUM Squared Plots depicted in Figs. 4–5. The cumulative sums (CUSUM) of the recursive residuals and CUSUM Squared Plots from the ARDL regression show that the plots are within the 95% confidence band graphs, hence, confirming the stability of the ARDL models.

Table 7
Verification and validation of EKC hypothesis.

	Lower bound	Upper bound	Extreme point
Interval	619	81,693	56,114
t-Value	8.7437	−3.1577	3.1600
p > t	0.0000	0.0014	0.0014

Table 8
Model verification and validation.

LM test	lags(p)	chi^2	df	Prob > chi^2
Model 1	1	0.0040	1	0.9491
Model 2	1	0.0000	1	0.9857
Model 3	1	3.1740	1	0.0748
Breusch-Godfrey LM test	**lags(p)**	**chi^2**	**df**	**Prob > chi^2**
Model 1	1	1.617	1	0.2036
Model 2	1	1.316	1	0.2513
Model 3	1	2.801	1	0.0942
Breusch-Pagan/Cook-Weisberg test				
Model 1	$chi^2(1)$	0.3500	Prob > chi^2	0.5559
Model 2	$chi^2(1)$	1.9100	Prob > chi^2	0.1673
Model 3	$chi^2(1)$	0.9400	Prob > chi^2	0.3318
Ramsey RESET test				
Model 1	F(3,32)	0.4500	Prob > F	0.7195
Model 2	F(3,30)	0.3600	Prob > F	0.7853
Model 3	F(3,33)	0.0500	Prob > F	0.9835
Durbin-Watson				
Model 1	d-Statistic(8,43)			2.2427
Model 2	d-Statistic(10,43)			2.2092
Model 3	d-Statistic(10,46)			2.1812

The study applies diagnostic tests to examine the independence of the residuals.

4.5. Discussion

The results of the empirical analysis from the nexus between disaggregate energy consumption and environmental pollution speak volumes on policy strategies that can help reduce environmental pollution without reducing access to energy as accentuated in the sustainable development goals.

Every large scale or commercial deployment of energy technologies always come with environmental trade-offs (IPCC, 2011). Yet, the long-term effect of renewable energy technologies improves environmental quality. The study revealed that the share of renewable energy declines environmental pollution while fossil fuel energy sources exacerbate pollution. Fossil fuel energy consumption takes center stage in South Africa's energy portfolio and is mainly dominated by coal and lignite. The 2017 Global Energy Statistics reveals that South Africa is the 6th in the world and 1st in Africa in terms of coal and lignite consumption and further ranks 2nd in terms of CO_2 intensity in the world (Enerdata, 2017).

However, substituting the finite and scare fossil fuel energy sources with renewable energy sources will not only ensure environmental quality but leads to energy-dependent economic emancipation. Since renewable energy sources are localized and cannot be traded internationally compared to fossil fuels, the utilization of the ubiquitous renewable energy sources reduces the dependency on fossil fuel importation thus, leading to energy security and economic productivity. Owusu and Asumadu-Sarkodie (2016) revealed that renewable energy has a direct relationship with sustainable development, due to its enormous opportunities which include energy access, social and economic development, reduction of environmental and health impacts.

Even though nuclear energy is a clean source of energy but unsustainable depending on the generation processes involved. The empirical study shows that nuclear energy promotes environmental pollution in South Africa in the short term. Perhaps, its associated pollution may be due to the technologies used to decommission and decontaminate past strategic nuclear facilities, and the improper nuclear waste disposal management practices.

Due to the small ratio of renewable energy penetration in the energy mix compared to fossil fuel energy sources, the aggregate energy

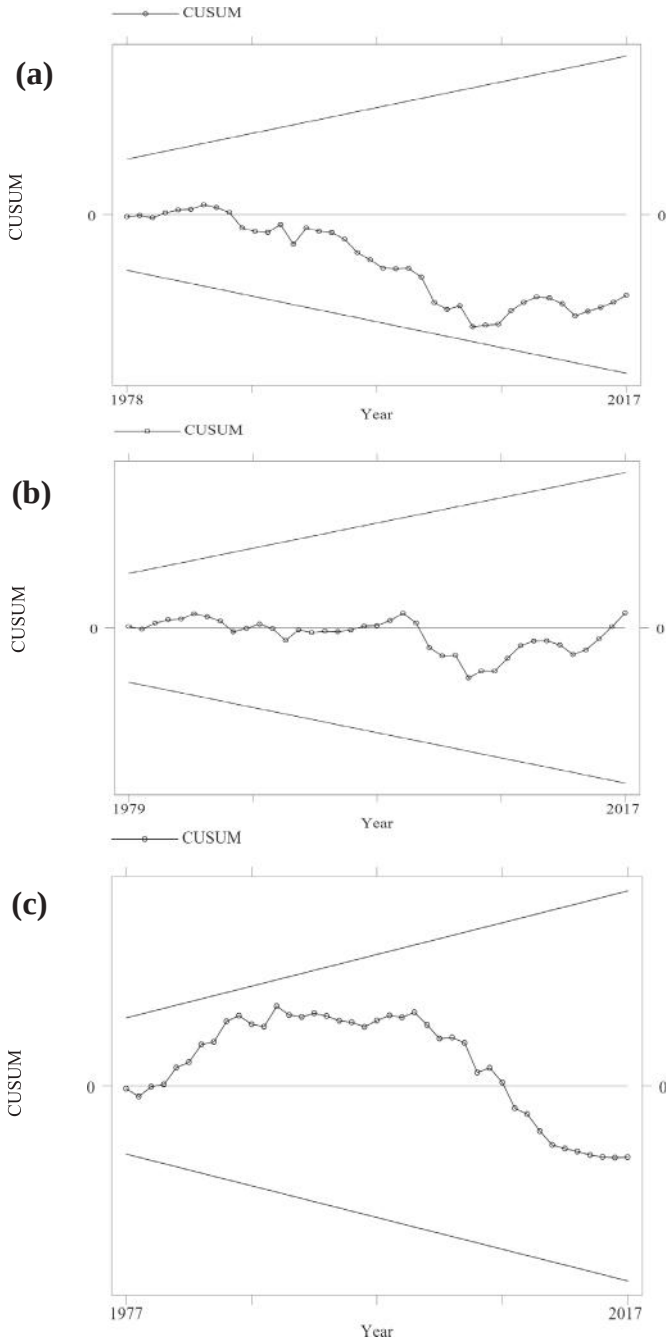

Fig. 4. (a) Model 1 (b) Model 2 and (c) Model 3: CUSUM plot for ARDL regression.

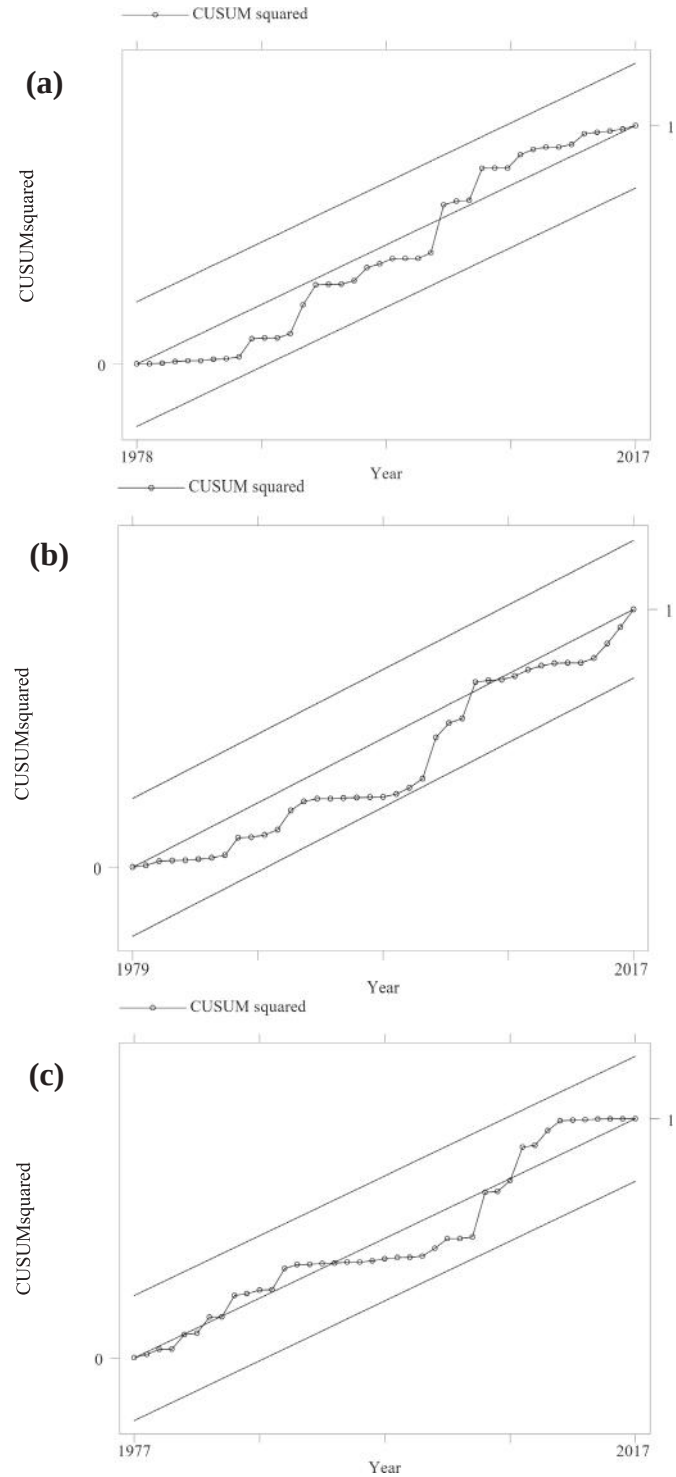

Fig. 5. (a) Model 1 (b) Model 2 and (c) Model 3: CUSUM squared plot for ARDL regression.

consumption accelerates environmental pollution. The IPCC reports show that energy consumption (heat and electricity) and its related services remain the highest contributor to greenhouse gas emissions.

Urbanization plays a weak or insignificant role in environmental pollution, perhaps due to enhanced economic activities in South Africa evidenced in the per capita GDP. However, urban concentrations are still one of the critical sensitivity indicators of vulnerability to climate change. Owusu et al. (2016); Asumadu-Sarkodie et al. (2015) revealed that an uncontrolled urban concentration in developing countries causes congestion and pressurizes available water resources, urban hydrology, and hydraulics leading to flooding and among others.

The study confirms the validity of the EKC hypothesis in South Africa, at a turning point of ZAR 56,114. The EKC hypothesis postulates that developing economies pollute more to grow their economy then clean later after attaining a specific turning point in economic development. It is therefore expected that environmental pollution will decline in South Africa at ZAR 56,114 while boosting economic productivity and decreasing energy intensity thus, an indication of energy efficiency.

Obviously, strong institutions and political leadership with the capacity to plan and manage policies and investments that support climate-smart development are an essential building block of low carbon, climate resilient societies (Foresight Africa (2017)). Political institutional quality plays a huge role in the social, governance and economic readiness to mitigate climate change and its impact. Hence, stringent social, governance and economic reforms and policies are

required by quality political institutions before adaptation options can be effected. As it stands, South Africa has a low climate change vulnerability with the readiness, however, adaptation options for climate change are still challenging.

5. Conclusion

To increase the global debate on climate change mitigation, the study examined the impact of disaggregate and aggregate energy, economic development, urbanization and political institutional quality on environmental pollution, from 1971 to 2017 with a case study in South Africa. South Africa remains Africa's economic giant, and the second most carbon-intensive country in the world due to their rich fossil fuel energy sources. However, their commitment to climate change mitigation and its impacts motivates its selection for the study. The EKC hypothesis is valid in South Africa and it was attained in 2011 at a turning point of ZAR 56,114. Evidence from the study shows that political institutional quality plays a huge role in the social, governance and economic readiness to mitigate climate change and its impact.

South Africa is a fossil-fuel-rich country in Africa, however, diversification of the energy portfolio by incorporating renewable energy sources will promote air quality and environmental sustainability while reducing their economy's vulnerability to price volatility. Based on the policy implications of the effect of disaggregate and aggregate energy consumption, economic growth, and political institutional quality on environmental pollution, the study proposes, first, a paradigm shift from energy and carbon-intensive industries to a service-oriented economy which will cause a structural economic change thus, aiding in the mitigation of climate change and its impacts. Second, there is a need for technological advancement in manufacturing industries and power sectors that employ advanced technologies such as carbon capture and storage, among others in other to promote energy efficiency. Finally, a structural economic change depends on the willingness by the Government to promote policies to decarbonize the economy and provide the conducive political environment that promotes clean and modernized energy, thus, promoting environmental quality. Renewable energy investment has a competitive disadvantage compared to fossil fuel and nuclear energy. For renewable energy technology to be attractive, it requires deployment policies that mutually include technological development (research and development, innovation and technological advancement), industry development (higher performance, affordable cost, and higher quality) and market development (available and accessible markets).

The study proposes a future research that examines the effect of research and development and renewable energy financing and policies on pollution reduction.

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Chapter Seven: Economic, social and governance adaptation readiness for mitigation of climate change vulnerability: evidence from 192 countries.

Chapter Seven presents the following research article:

- **Sarkodie, S.A.**, Strezov, V., 2019. Economic, social and governance adaptation readiness for mitigation of climate change vulnerability: Evidence from 192 countries. *Science of The Total Environment* 656, 150-164.

The study for the first time examines the impact of aggregate and disaggregate adaptation readiness on climate change vulnerability using spatial analysis and panel quantile regression model accounting for heterogeneity and unconditional distribution across quantiles.

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Economic, social and governance adaptation readiness for mitigation of climate change vulnerability: Evidence from 192 countries

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HIGHLIGHTS

- Scandinavian countries have low vulnerability and high climate change readiness.
- African countries have high climate sensitivity and low adaptive capacity.
- Climate change adaptation actions mitigate climate vulnerability.
- Economic, governance and social interventions are critical to climate stress reduction.

GRAPHICAL ABSTRACT

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ABSTRACT

Adaptation strategies have become critical in climate change mitigation and impact reduction, to safeguard population and the ecosystem from irreparable damage. While developed countries have integrated adaptation plans and policies into their developmental agenda, developing countries are facilitating or yet to initiate adaptation policies in their development. This study examines the nexus between climate change vulnerability and adaptation readiness in 192 UN countries using mapping and panel data models. The study reveals Africa as the most vulnerable continent to climate change with high sensitivity, high exposure, and low adaptive capacity. Developed countries, including Norway, Switzerland, Canada, Sweden, United Kingdom, Finland, France, Spain, and Germany, are less vulnerable to climate change due to strong economic, governance and social adaptation readiness. International commitment from developed countries to developing countries is essential to strengthen their resilience, economic readiness and adaptive capacity to climate-related events.

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1. Introduction

Changes in climatic conditions have impacted natural and human systems around the globe, due to human interferences with the climatic system within the past decades (IPCC, 2014b). Impacts of the climate-related extreme events (heat waves, floods, droughts, wildfires,

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cyclones, etc.) include ecosystem alterations, disruption of water supply, interruption of food production, damage to settlements and infrastructure and increase in morbidity and mortality, (Field et al., 2014). These hazards occur and have impacts due to lack of social, economic and governance readiness to combat climatic events. However, historical experience proves that societies have adjusted to and have adopted successful adaptation strategies for climate, climate variability and extreme events (IPCC, 2014b). There are several adaptation experiences across the globe embedded in adaptation planning processes. In Africa, governance systems for adaptation are being initiated [disaster risk management (Van Niekerk, 2006), changes in infrastructure and technology, public health measures and ecosystem-based strategies are reducing climate change vulnerability] (Noble et al., 2014). In Asia, climate change adaptation actions incorporated into development planning, early warning systems, integrated water resource management, and integrated coastal zone management are being facilitated (IPCC, 2014b; Noble et al., 2014). In Australia, adaptation planning for sea level rise, drought, and reduced water availability are being implemented (Kiem, 2013). In the Arctic regions, the deployment of adaptive co-management options and infrastructure for communications in some communities are being executed (IPCC, 2014b; Plummer and Baird, 2013). In North, Central and South America, governments are implementing ecosystem-based adaptation (Vignola et al., 2013), adaptation assessment and planning, long-term energy and public infrastructural investments (Easterly and Serven, 2003), integrated water resource management, climate forecasts and resilient crop varieties (Lin, 2011) in the agricultural sector (IPCC, 2014b). In Europe, adaptation planning has been incorporated into environmental protection, coastal management (Pickaver et al., 2004), water resource management, land planning, agricultural risk management (Bielza et al., 2007) and disaster risk management (Fekete et al., 2014), while adaptation policies are being developed (IPCC, 2014b). International cooperation appears to facilitate adaptation readiness to climate change, as evidenced in the sustainable development goals (United Nations, 2015).

Numerous studies have examined the immediate and underlying drivers of climate change (Martin and Saikawa, 2017; Raftery et al., 2017; Sarkodie, 2018), however, studies on vulnerability and adaptation readiness are limited. A recent study by Watson et al. (2013) examined the vulnerability and conservation of species, focusing on biodiversity loss without accounting for other climate-sensitive and vulnerable sectors. Most adaptation assessments have been limited to impacts (Hansen and Stone, 2015), exposure, sensitivity (Miller et al., 2018) and vulnerability, with limited studies examining the effects of adaptation actions (IPCC, 2014b). In contrast, this study for the first time examines the impact of aggregate and disaggregate adaptation readiness on climate change vulnerability using spatial analysis and panel quantile regression model, while accounting for heterogeneity and unconditional distribution across quantiles.

Evidence from the study reveals a decline in climate change vulnerability at a positive economic, governance and social adaptation readiness. While there are global efforts and partnerships to combat climate change and its impact, developed countries appear to have low sensitivity, exposure and high adaptive capacity to climate-related events compared to developing countries.

2. Methods

2.1. Data

Due to the complexity of climate change and its related services, this study employs a wide range of variables and indicators capable of modeling climate change mitigation and adaptation options. Data series for the model estimation is retrieved from ND-GAIN (2018b). Figs. 1 and 2 present the fundamentals and indicators of vulnerability to climate change and the components and indicators of readiness to mitigate climate change. The selection of the 45 indicators used to examine vulnerability to climate change and readiness to mitigate climate change is in accordance with the 17 Sustainable Development Goals by 2030 and the United Nations' indicators of sustainable development: guidelines and methodologies (DiSano, 2002). For easier comparison between countries prior to the economic model estimation, the data series are converted into scores ranging from 0 to 1 following the scaling formula by ND-GAIN (2018b), expressed as:

$$Score = \left\langle Direction - \frac{Raw\ Data - Reference\ Point}{Baseline\ Maximum - Baseline\ Minimum} \right\rangle \tag{1}$$

where *Direction* has two parameters namely; 0 for scoring vulnerability indicators and 1 for scoring readiness indicators. In this case, a vulnerability score of 1 denotes worse state (higher vulnerability to climate change) while a readiness score of 1 denotes a better state (higher readiness to mitigate climate change). As shown in Fig. 1, Climate Vulnerability comprises of 36 indicators from 6 sectors, such as food, water, health, ecosystem services, human habitat and infrastructure. Out of the 36 indicators of vulnerability from the six sectors, 12 indicators each were categorizations under; Exposure, Sensitivity and Adaptive Capacity. On the contrary, readiness to mitigate climate change in Fig. 2 covers 9 indicators under three components, namely economic, governance and social readiness.

The availability of high-quality data series for the model estimation limited the period of the study from 1995 to 2016 conducted in 192 countries under the United Nations. The adoption of a time series data to construct a panel data of 192 countries helps track historical changes and trend of country-specific climate vulnerability and adaptation readiness.

2.2. Study design

This study builds an econometric model based on the linear relationship between vulnerability and readiness expressed with Eq. (2):

$$Vulnerability = f\langle Readiness \rangle \tag{2}$$

The disaggregate effect of readiness on climate change vulnerability is expressed with Eq. (3) as:

$$Vulnerability = f\langle economic, governance, social \rangle \tag{3}$$

Prior to the model estimation, the study first performs a series of unit root tests to examine the stationarity of the panel data set. Both first and second generational unit root tests such as Breitung (Breitung, 1999), Im-Pesaran-Shin (IPS) (Pesaran et al., 2003) and Pesaran's Cross-sectionally Augmented Dickey-Fuller (CADF) (Pesaran, 2007) are employed. The study control for cross-sectional dependence using Pesaran's CADF, an issue which is problematic in panel data settings. At this point, the common factors can have different effects across different cross-sectional units and reduce unobserved common factors required in the model. The first generational unit root tests (Breitung and IPS) follow a simplified first-order autoregressive panel data model expressed as:

$$y_{i,t} = \rho_i y_{i,t-1} + \overset{\text{ẽ}}{z}_{i,t}\gamma_i + \epsilon_{i,t} \quad i = 1, \ldots, N; t = 1, \ldots, T \tag{4}$$

where y denotes the observations in the panel, $\epsilon_{i,\,t}$ is mean zero regression error term, $\acute{z}_{i,t}\gamma_i$ denotes the fixed effects (panel-specific means), i represents index panels, and t denotes index time. Thus, the generalized null hypothesis $\rho_i = 1$ versus the alternative hypothesis $\rho_i < 1$. Contrary to the first generation unit root tests based on "deviation from the estimated common factors", Pesaran's CADF (Pesaran, 2007) is based on an augmentation with the cross-sectional means of lagged levels and first-difference of the individual units. The results of the panel unit root tests are presented in Table 1, which confirms the stationary process of the

SECTOR	Food	Water	Health	Ecosystem Services	Human Habitat	Infrastructure
Exposure Component	Projected change of cereal yields	Projected change of annual runoff	Projected change of deaths from climate change induced diseases	Projected change of biome distribution	Projected change of warm period	Projected change of hydropower generation capacity
Exposure Component	Projected population change	Projected change of annual groundwater recharge	Projected change of length of transmission season of vector-borne diseases	Projected change of marine biodiversity	Projected change of flood hazard	Projection of Sea Level Rise impacts
Sensitivity Component	Food import dependency	Fresh water withdrawal rate	Slum population	Dependency on natural capital	Urban concentration	Dependency on imported energy
Sensitivity Component	Rural Population	Water dependency ratio	Dependency on external resource for health services	Ecological footprint	Age dependency ratio	Population living under 5m above sea level
Adaptive Capacity Component	Agriculture capacity (Fertilizer, Irrigation, Pesticide, Tractor use)	Access to reliable drinking water	Medical staffs (physicians, nurses and midwives)	Protected biomes	Quality of trade and transport-related infrastructure	Electricity access
Adaptive Capacity Component	Child malnutrition	Dam capacity	Access to improved sanitation facilities	Engagement in International environmental conventions	Paved roads	Disaster preparedness

Fig. 1. The fundamentals and indicators of vulnerability to climate change. NB: categorized into exposure, sensitivity and adaptive capacity.

data series at first-difference, thus, variables are integrated of order one [I (1)].

After satisfying the preconditions of the stationary process at first-difference, the study examines the cointegration of the variables using panel data cointegration tests namely Pedroni (Pedroni, 2004) and Westerlund (Westerlund, 2005). Testing for cointegration of the data series is necessary to ascertain the long-run equilibrium relationship of the I (1) data series under the null hypothesis of no cointegration. The specification of the cointegrating relationship between vulnerability, the disaggregate effect of readiness (economic, governance and social) and readiness are expressed as:

$$vulnerability_{i,t} = \gamma_i + \beta_{1,i} economic_{i,t} + \beta_{2,i} governance_{i,t} + \beta_{3,i} social_{i,t} + \epsilon_{i,t} \quad (5)$$

$$vulnerability_{i,t} = \gamma_i + \beta_{1,i} readiness_{i,t} + \epsilon_{i,t} \quad (6)$$

where γ_i represents the panel specific average (fixed-effects), $\beta_{1,\,i}$, ..., $\beta_{3,\,i}$ denotes the panel specific cointegrating parameters, and $\epsilon_{i,\,t}$ is the white noise. Pedroni cointegration produces three statistics, such as modified Phillips-Perron t, Phillips-Perron t, augmented Dickey-Fuller t employ a Bartlett kernel with 4 lags for serial correlation adjustment process. In contrast, Westerlund cointegration produces a variance ratio test statistic with a panel-specific autoregressive parameter. The results from both Pedroni and Westerlund cointegration tests presented in Table 2 reject the null hypothesis of no cointegration at 1% significance level with or without panel-specific time trends. Accordingly, cointegrating relationships between vulnerability, the disaggregate effect of readiness and readiness were confirmed in Table 2.

2.3. Model estimation

The study estimates 15 econometric models with their empirical results presented in Table 3. The specification of Models 1[a]–2[a] follows Pesaran's Pooled Mean-Group (PMG) model useful for large N and T panel data samples expressed as:

$$\Delta y_{i,t} = \varphi \times (y_{i,t-1} + \beta_{i,t}) + \Delta y_{i,t-1} a_1 + \ldots + y_{i,t-p} a_p + \Delta x_{i,t} b_1 + \ldots + \Delta x_{i,t-q} b_q + \varepsilon_{i,t} \quad (7)$$

where y is the dependent variable (vulnerability), x represents the independent variables (economic, governance, social and readiness), φ denotes the error correction speed of adjustment parameter, β represents a $k \times 1$ vector of the parameters, $a_1, \ldots, a_p$ and $b_1, \ldots, b_q$ are the p and q parameters to be estimated, $x_{i,\,t}$ denotes a $1 \times k$ vector of covariates, $i = (1,\ldots,N)$ represents the individual cross-sectional units, $t = (1,\ldots,T_i)$ is the time period, and $\varepsilon_{i,\,t}$ represents the white noise. The PMG model is useful for constraining the long-run effects and beta coefficient equally across all cross-sectional units, however, the short-run coefficient can differ across all cross-sectional units.

The empirical specification of Models 3[b]–4[b] presented in Table 3 follows a pooled ordinary least squares (OLS) regression with Driscoll and Kraay (1998) standard errors. Contrary to the PMG model, Driscoll-Kraay standard errors estimator is a nonparametric technique capable of handling missing values, balanced or unbalanced panel data and

Economic Readiness	Governance Readiness	Social Readiness
Doing business	Political stability and non-violence	Social inequality
	Control of corruption	ICT infrastructure
	Rule of law	Education
	Regulatory quality	Innovation

Fig. 2. Components and indicators of readiness to mitigate climate change and its impacts.

produces robust standard errors when T dimension becomes large (Sarkodie and Strezov, 2019). Importantly, the model has no restrictions on the limiting behavior of the number of cross-sectional units (Driscoll and Kraay, 1998).

Standard panel data regression techniques are limited to mean effects of variables resulting in under- or over- specification and estimation of parameters and relevant coefficients which affect important causal relationships (Sarkodie and Strezov, 2019; Zhu et al., 2016). Contrary to the traditional panel data regression incapable of estimating conditional distribution of climate change indicators in large panel data samples with large cross-sectional units, this study adopts a panel quantile regression technique, which is robust to unobserved country-specific heterogeneity, outliers, and conditional distributions. For brevity, the panel quantile function with unconditional quantile treatment effect and a consistent generalized quantile regression estimator can be expressed as:

$$Q_{vulnerability_{i,t}}(\tau|\alpha_i, x_{i,t}) = \alpha_i + \beta_{1,\tau} economic_{i,t} + \beta_{2,\tau} governance_{i,t} + \beta_{3,\tau} social_{i,t} \quad (8)$$

Table 1
Panel unit root tests.

Variable	Breitung		IPS		Pesaran's CADF	
	Level	1st diff.	Level	1st diff.	Level	1st diff.
Vulnerability	14.897	−27.711*	3.842	−28.069*	−2.365	−3.448*
Economic	8.100	−33.545*	18.937	−24.456*	−1.578	−3.078*
Governance	−0.445	−37.510*	2.019	−26.830*	−2.167	−2.986*
Social	24.623	−21.026*	18.235	−19.668*	−2.311	−2.862*
Readiness	9.353	−34.423*	10.229	−26.715*	−1.967	−3.088*

* $p < 0.01$, the rejection of the null hypothesis at 1% significance level.

where τ denotes τth quantile, α_i represents the non-additive fixed effect, $\beta_{1,\tau}, \ldots, \beta_{3,\tau}$ are the coefficients to be estimated, i indexes cross-sectional units, and t indexes time. τ used in the model estimation ranges from 5th to 95th quantile, corresponding to Models 5c–15c presented in Table 3.

2.4. Model validation

To improve the estimation and calculation of the panel quantile regression standard errors, the study applies adaptive Markov Chain Monte Carlo optimization method expounded in Chernozhukov and Hong (2003). The estimated models are validated using marginal effects post-estimation technique with corresponding plots presented in Figs. 3–7. The plots of the marginal effect of estimated models are within the 95% confidence interval, thus, validating the independence of the residuals and the stability of the panel data regression models.

The nexus between vulnerability to climate change and adaptation readiness is corroborated using nonlinear prediction models, such as Lorentzian Peak, Gaussian Peak, and Exponential 3P.

Lorentzian Peak Prediction Model can be expressed as:

$$\frac{a_{i,t} \times {b_{i,t}}^2}{\left(\left(Readiness_{i,t} - c_{i,t}\right)^2 + {b_{i,t}}^2\right)} \quad (9)$$

where a is the peak value, b is the growth rate and c represents the critical point.

Gaussian Peak Prediction Model can be expressed as:

$$a_{i,t} \times \exp\left(-\left(0.5 \times \left(\frac{Readiness_{i,t} - b_{i,t}}{c_{i,t}}\right)^2\right)\right) \quad (10)$$

where a is the peak value, b is the critical point and c represents the growth rate.

Exponential 3P Prediction Model can be expressed as:

$$a_{i,t} \times b_{i,t} \times \exp\left(c_{i,t} \times Readiness_{i,t}\right) \quad (11)$$

where a denotes asymptote, b is the scale and c represents the growth rate.

The plot of the nonlinear prediction models is depicted in Fig. 8 with its corresponding parameter estimates presented in Table 4.

2.5. Data availability

Data supporting the findings of this study are publicly available and accessible at ND-GAIN.[1]

3. Results and discussion

To understand the propensity of climate change hazards and impacts on human society, the study presents a choropleth map showing the geographical mean of disaggregate vulnerability indicators of climate change presented in Fig. 9. On a scale of 0–1, the highest mean value (1) in Fig. 9 represents '*worse*' status of a country's disaggregate vulnerability indicator. The intensity of the colors corresponds to the statistical mean differences across geographic regions.

Disaggregate vulnerability indicators include exposure, sensitivity and adaptive capacity to climate change. Exposure measures future climate change stress on human society and its related services. The choropleth map reveals that northern Africa, Europe and some parts of Asia have low exposure to climate change compared to the high

[1] https://gain.nd.edu/our-work/country-index/download-data/.

Table 2
Panel data cointegration tests.

Cointegration	EGS				Readiness			
	No trend		Trend		No trend		Trend	
	Statistic	p-Value	Statistic	p-Value	Statistic	p-Value	Statistic	p-Value
Pedroni								
Modified Phillips-Perron t	6.632	0.000	8.551	0.000	3.538	0.000	4.920	0.000
Phillips-Perron t	−7.006	0.000	−8.164	0.000	−2.906	0.002	−4.340	0.000
Augmented Dickey-Fuller t	−8.191	0.000	−9.641	0.000	−2.735	0.003	−5.910	0.000
Westerlund								
Variance ratio	−2.756	0.003	−2.707	0.003	1.871	0.031	−2.452	0.007

EGS = economic, governance and social.

Table 3
Effects of economic, governance, social and readiness on climate vulnerability. Different model results are presented in each column, with their corresponding standard error in [ ].

	Model 1[a]	Model 2[a]	Model 3[b]	Model 4[b]	Model 5[c]	Model 6[c]	Model 7[c]	Model 8[c]	Model 9[c]	Model 10[c]	Model 11[c]	Model 12[c]	Model 13[c]	Model 14[c]	Model 15[c]
ECT (−1)	−0.153*	−0.180*													
	[0.014]	[0.017]													
Economic		−0.039*		−0.154*	−0.042*	−0.017*	−0.112*	−0.083*	−0.157*	−0.221*	−0.194*	−0.146*	−0.203*	−0.159*	−0.253*
		[0.007]		[0.010]	[0.008]	[0.005]	[0.014]	[0.003]	[0.001]	[0.004]	[0.003]	[0.017]	[0.002]	[0.006]	[0.017]
Governance		0.022*		−0.096*	−0.143*	−0.087*	−0.051*	−0.092*	−0.118*	−0.015*	−0.066*	−0.059*	−0.142*	−0.171*	−0.057*
		[0.005]		[0.010]	[0.008]	[0.009]	[0.004]	[0.004]	[0.002]	[0.003]	[0.009]	[0.020]	[0.002]	[0.006]	[0.010]
Social		−0.132*		−0.226*	−0.075*	−0.109*	−0.122*	−0.199*	−0.191*	−0.209*	−0.237*	−0.180*	−0.179*	−0.179*	−0.367*
		[0.003]		[0.002]	[0.010]	[0.041]	[0.011]	[0.006]	[0.001]	[0.003]	[0.009]	[0.031]	[0.001]	[0.003]	[0.030]
Readiness	−0.087*		−0.464*												
	[0.007]		[0.003]												
_cons			0.634*	0.624*											
			[0.001]	[0.003]											
R^2			0.53	0.57											
MAR					0.146	0.400	0.154	0.042	0.057	0.048	0.230	0.181	0.106	0.207	0.057

MAR = mean acceptance rate. Models 5–15 represents 5th to 95th quantiles used in the model estimation.
* $p < 0.01$, rejection of the null hypothesis at 1% significance level.
[a] Regression with Driscoll-Kraay standard errors.
[b] Regression with Pooled Mean-Group estimator.
[c] Quantile regression for panel data with adaptive MCMC optimization.

exposure levels scattered in Africa and few Asian countries (Fig. 9(a)). The highly exposed countries include Niger, India, Myanmar, Zambia, Angola, North Korea, Sudan, Chad, and Burkina Faso, while countries with low exposure include Mongolia, Czech Republic, Jordan, Libya, Turkmenistan, Uzbekistan, Kazakhstan, Morocco, Algeria, and Tunisia [N = 4224, Mean = 0.44 and Std Dev = 0.08]. The resulting global distribution is largely affected by the projected[2] change in cereal yield (an indicator of hunger), expected[3] change in population, projected change in annual groundwater recharge, expected change in climate change induced diseases and deaths, projected change in vector-borne diseases based on the length of transmission season, predictable change in biome distribution, expected change in marine biodiversity, expected change in hydropower generation capacity (Conway et al., 2015; IPCC, 2014b), projected change in warm, cold periods, impacts of sea level rise and flood hazards. Sensitivity measures the degree to which sectoral dependence by the society is affected by climate change and its impacts. Fig. 9(b) shows that Africa and Asia have a relatively high sensitivity to climate change compared to the low levels in Australia, Europe, North and South America. The highly sensitive countries include Guinea-Bissau, Niger, Chad, Sudan, Mauritania, Uganda, Benin, Uzbekistan, Tajikistan, and Egypt, while countries with low sensitivity include Australia, Canada, Iceland, Russia, Colombia, Norway, Sweden, France, United Kingdom, and Argentina [N = 3762, Mean = 0.40, and Std Dev = 0.10]. The global distribution of the sensitivity component is affected by the dependency on food import, rural population, the rate of freshwater withdrawal, water-dependency ratio (Conway et al., 2015; Owusu and Asumadu, 2016), slum population, dependency on outward resources for health services, natural capital dependency, ecological footprint, urban concentration, age-dependency ratio, dependency on energy imports, and population living five meters above sea level. Adaptive capacity measures a society's ability to mitigate possible damage and willingness to respond to the adverse effect of climate events. Adaptive capacity is relatively low in Africa compared to Asia, but high in Australia, Europe, North and South America, as depicted in Fig. 9(c). Countries with low adaptive capacity include Somalia, Chad, Democratic Republic of Congo, Niger, Eritrea, Papua New Guinea, Afghanistan, Guinea-Bissau, Madagascar, and Liberia, while countries with high adaptive capacity include Italy, Norway, Japan, Finland, United Kingdom, Austria, Netherlands, France, New Zealand, and USA [N = 3960, Mean = 0.51, and Std Dev = 0.17]. The resulting geographical distribution of adaptive capacity is largely influenced by agriculture capacity, child malnutrition, accessibility to reliable drinking water, dam capacity, medical staffs, accessibility to improved sanitation conditions and facilities, protected biomes, international engagement in environmental conventions, quality of trade and transport-related infrastructure and services, paved roads, access to electricity and disaster preparedness (ND-GAIN, 2018a; United Nations, 2015).

[2] "The projected change is calculated based on the percentage change from the baseline projection of the annual average of the actual variable (1980–2009) to the future projections (2040–2069) in line with the Representative Concentration Pathways (RCPs) 4.5 emission scenario" (ND-GAIN, 2018a).

[3] "The expected change is based on the percentage change from the baseline variable in 2010 to the average predicted between 2020 and 2050" (World Bank, 2018).

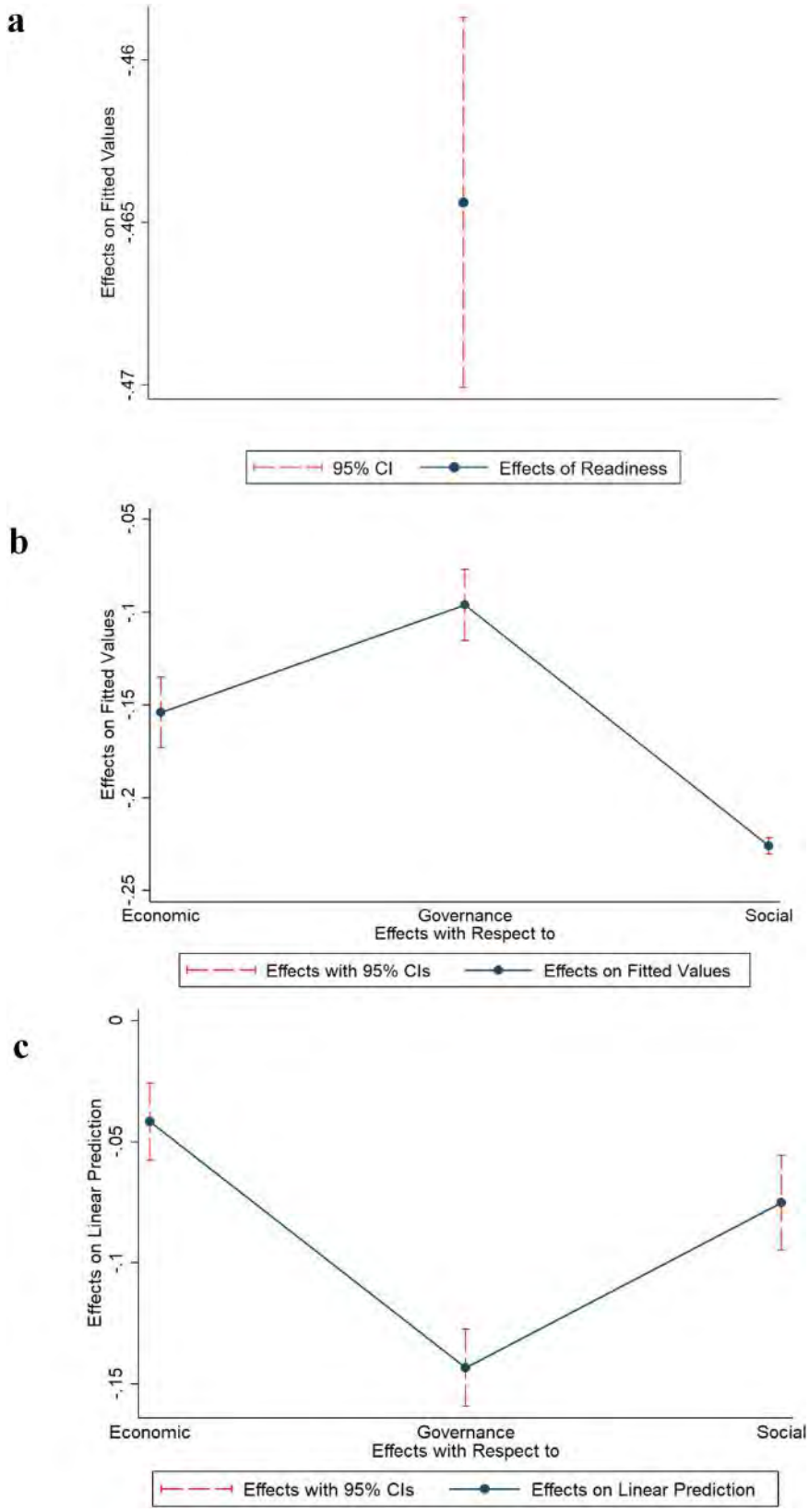

Fig. 3. Diagnostic Test (a) Model 1[a], (b) Model 2[a], and (c) Model 5[c].

Fig. 10 presents a choropleth map showing the geographical mean of disaggregated adaptation readiness of climate change indicators. The indicator comprises economic, governance and social readiness to mitigate climate change. On a scale of 0–1, the lowest mean value (0) in Fig. 10 represents '*better*' status of a country's disaggregate readiness indicator. The intensity of the colors corresponds to the statistical average differences across geographic regions.

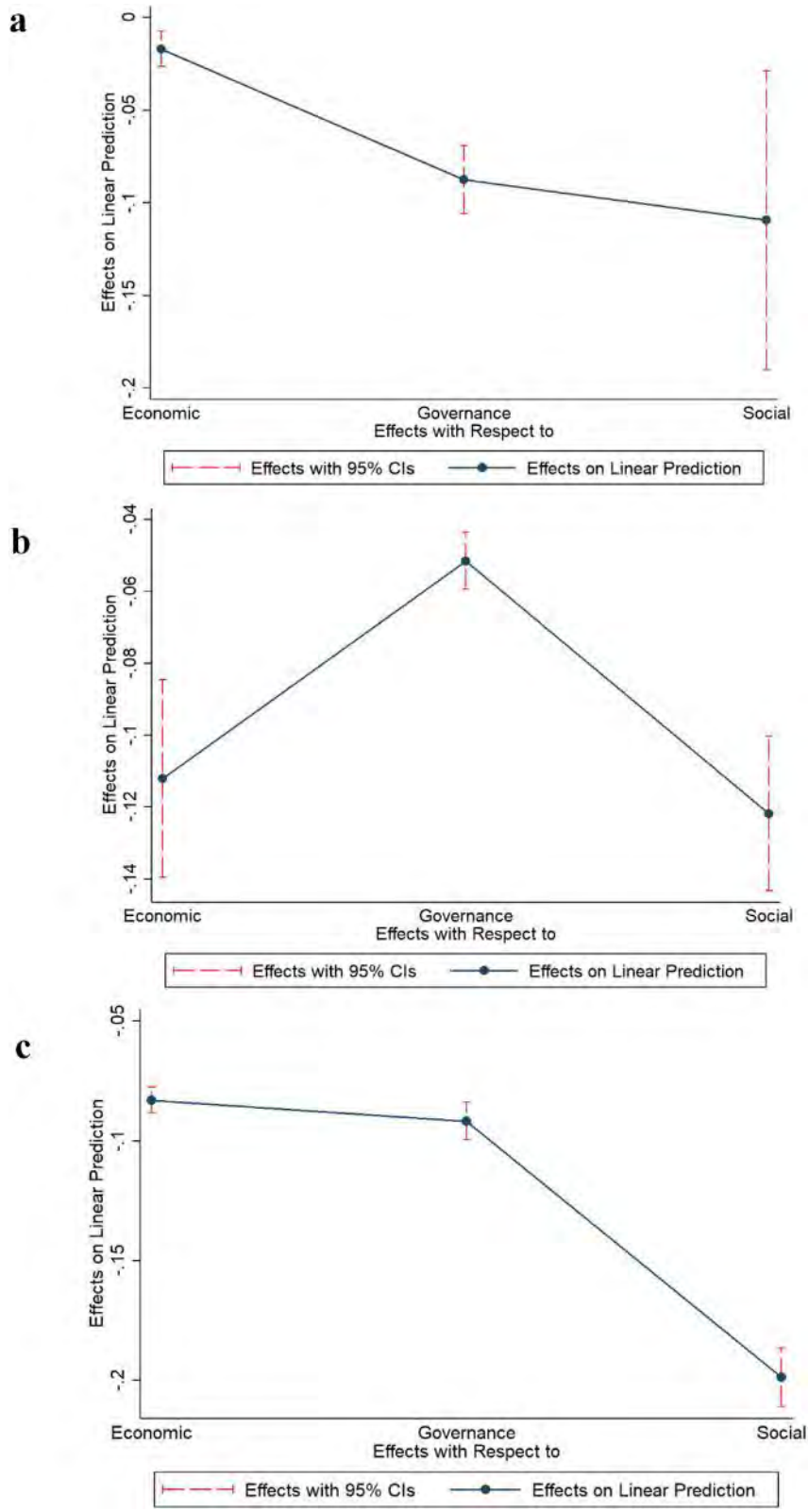

Fig. 4. Diagnostic Test (a) Model 6^{c}, (b) Model 7^{c}, and (c) Model 8^{c}.

Economic readiness measures investment that enables capital mobilization from the private sector. Fig. 10(a) shows that, while Australia, Europe, North, and South America have relatively high economic readiness, Africa and Asia have a low economic readiness to mitigate climate change and its impacts. Countries with high economic readiness include Norway, New Zealand, USA, Iceland, Australia, Finland, United Kingdom, Ireland, Canada, and Estonia, while countries with low economic readiness include Democratic Republic of Congo, Central African Republic,

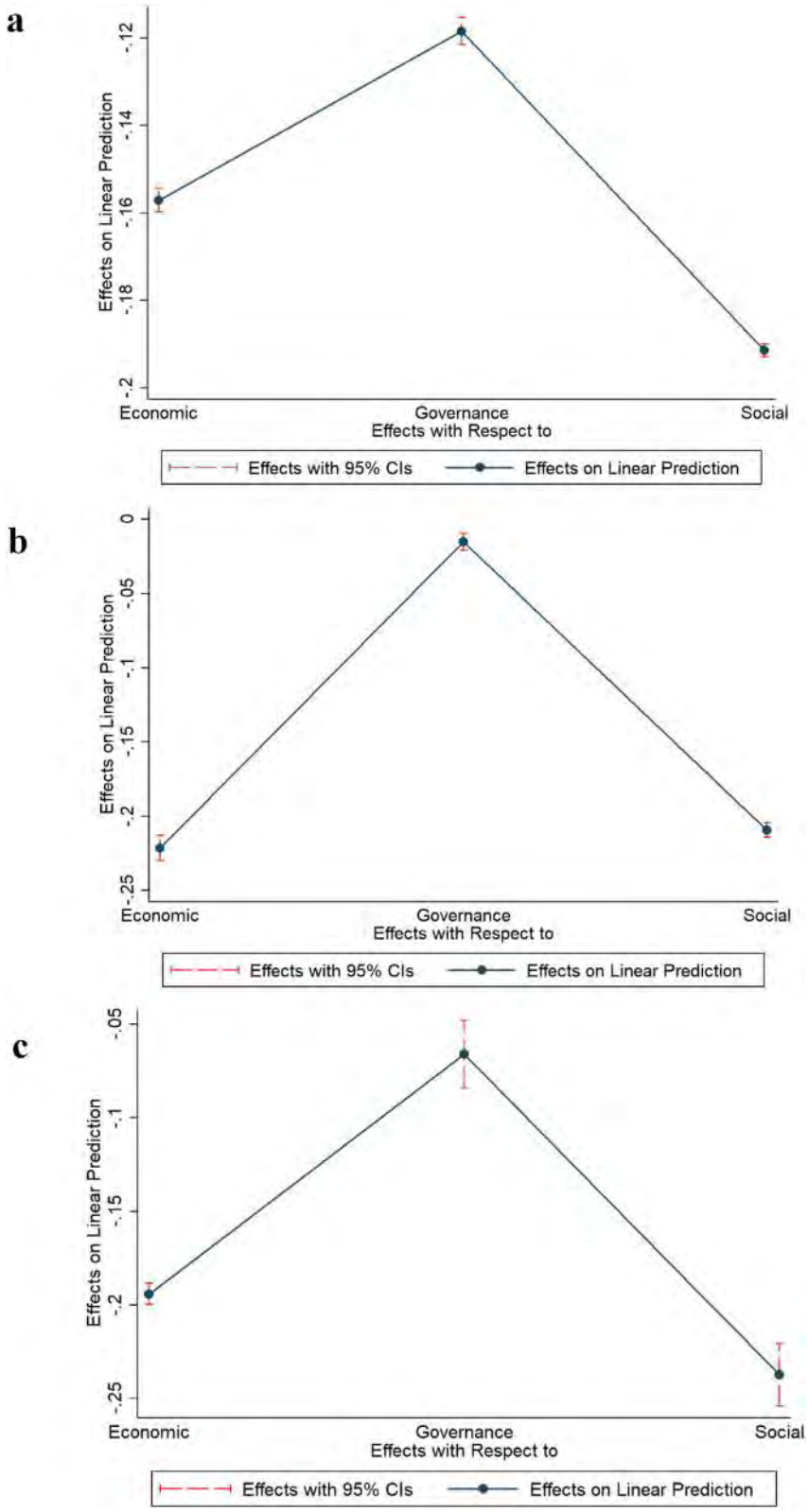

Fig. 5. Diagnostic Test (a) Model 9[c], (b) Model 10[c], and (c) Model 11[c].

Chad, Eritrea, Myanmar, Venezuela, Côte D'Ivoire, Senegal, Benin, and Burkina Faso [N = 3916, Mean = 0.39 and Std Dev = 0.17]. The spatial distribution of economic readiness is affected by the ease of doing business which includes business start-up, acquisition of construction permits, payment of taxes, transboundary trade, access to electricity, property registration, access to credit, investors protection, contract enforcement and resolving insolvency. Governance readiness involves societal stability and institutional quality for investment risks. Governance

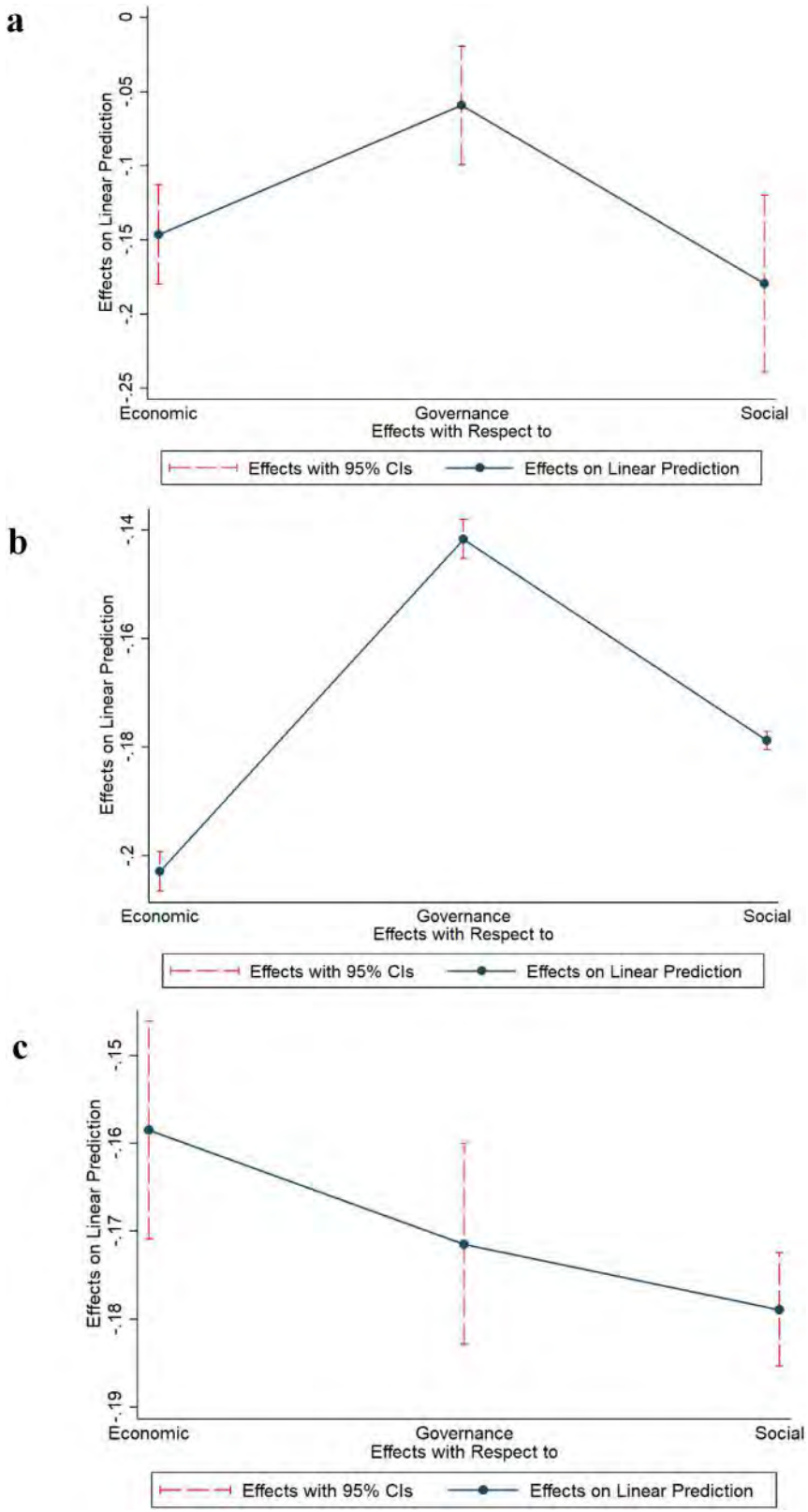

Fig. 6. Diagnostic Test (a) Model 12[c], (b) Model 13[c], and (c) Model 14[c].

readiness appears relatively high in Australia, parts of Europe, North and South America, while a moderate to low governance readiness exists in Africa, Asia and some parts of Europe, as depicted in Fig. 10(b). Top ten countries with high governance readiness include Finland, New Zealand, Denmark, Sweden, Norway, Netherlands, Switzerland, Australia, Canada and Iceland, and countries with low governance

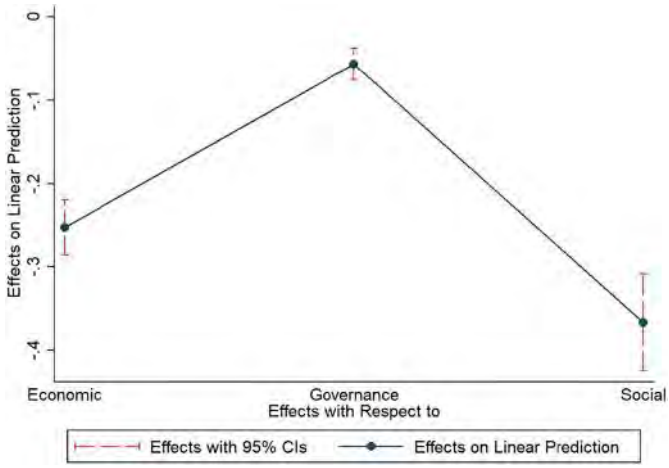

Fig. 7. Diagnostic Test Model 15[c].

Table 4
Parameter estimates of nonlinear prediction model showing the relationship between vulnerability and readiness.

Parameter	Lorentzian Peak	Gaussian Peak	Parameter	Exponential 3P
Peak value	2.191*	23629548*	Asymptote	−1.486*
	[1.876]	[2.1711e+9]		[0.027]
Growth rate	0.718*	−5.418*	Growth rate	−1.652*
	[0.228]	[13.978]		[0.158]
Critical point	−1.033*	−31.919*	Scale	0.57*
	[0.316]	[166.828]		[0.019]
Error measures				
AICc	−10,369.37	−10,355.50		−10,372.70
BIC	−10,344.22	−10,330.35		−10,347.55
SSE	17.212	17.272		17.197
MSE	0.004	0.004		0.004
RMSE	0.066	0.066		0.066
R-square	0.543	0.542		0.544

* $p < 0.05$, the rejection of the null hypothesis at 5% significance level.

readiness include Somalia, Afghanistan, Iraq, Sudan, Myanmar, North Korea, Zimbabwe, Angola, Liberia, and Chad [N = 4136, Mean = 0.50 and Std Dev = 0.18]. The geographical distribution of governance readiness is fairly attributed to political stability, non-violence, level, and control of corruption, regulatory quality (policy formulation and implementation), and the rule of law (law enforcement, policing and property rights). Social readiness encompasses social conditions that promote investment productivity and enable effective and equitable use of investment. Fig. 10(c) reveals a high level of social readiness in Australia, part of Europe, North and South America while low social readiness is evident in Africa, Asia and part of Europe. Countries with relatively high social readiness include South Korea, Finland, Denmark, Norway, Sweden, New Zealand, Austria, Germany, USA, and France. Countries with low social readiness include Eritrea, Zimbabwe, Equatorial Guinea, Lesotho, Papua New Guinea, Myanmar, Botswana, Zambia, Honduras, and Guatemala [N = 4048, Mean = 0.31 and Std Dev = 0.16]. The distribution of social readiness mainly depends on social inequality (income inequality), ICT infrastructure, education, and innovation (science, research, and development expenditure).

Fig. 11 presents a choropleth map showing the geographical mean of vulnerability and adaptation readiness indicators of climate change. Contrary to the disaggregated indicators presented in Figs. 9 and 10, aggregated indicators categorized under vulnerability and adaptation readiness are mapped. On a scale of 0–1, the lowest mean value (0) in

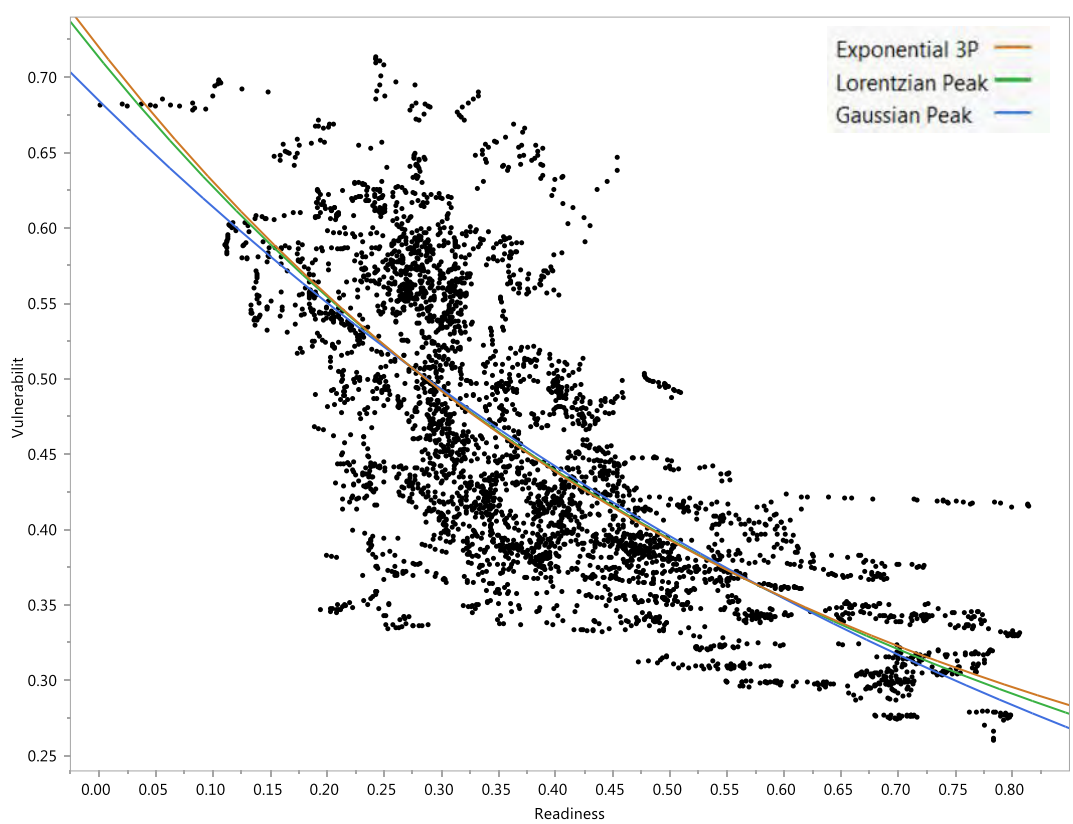

Fig. 8. Nonlinear prediction models showing the nexus between vulnerability and readiness.

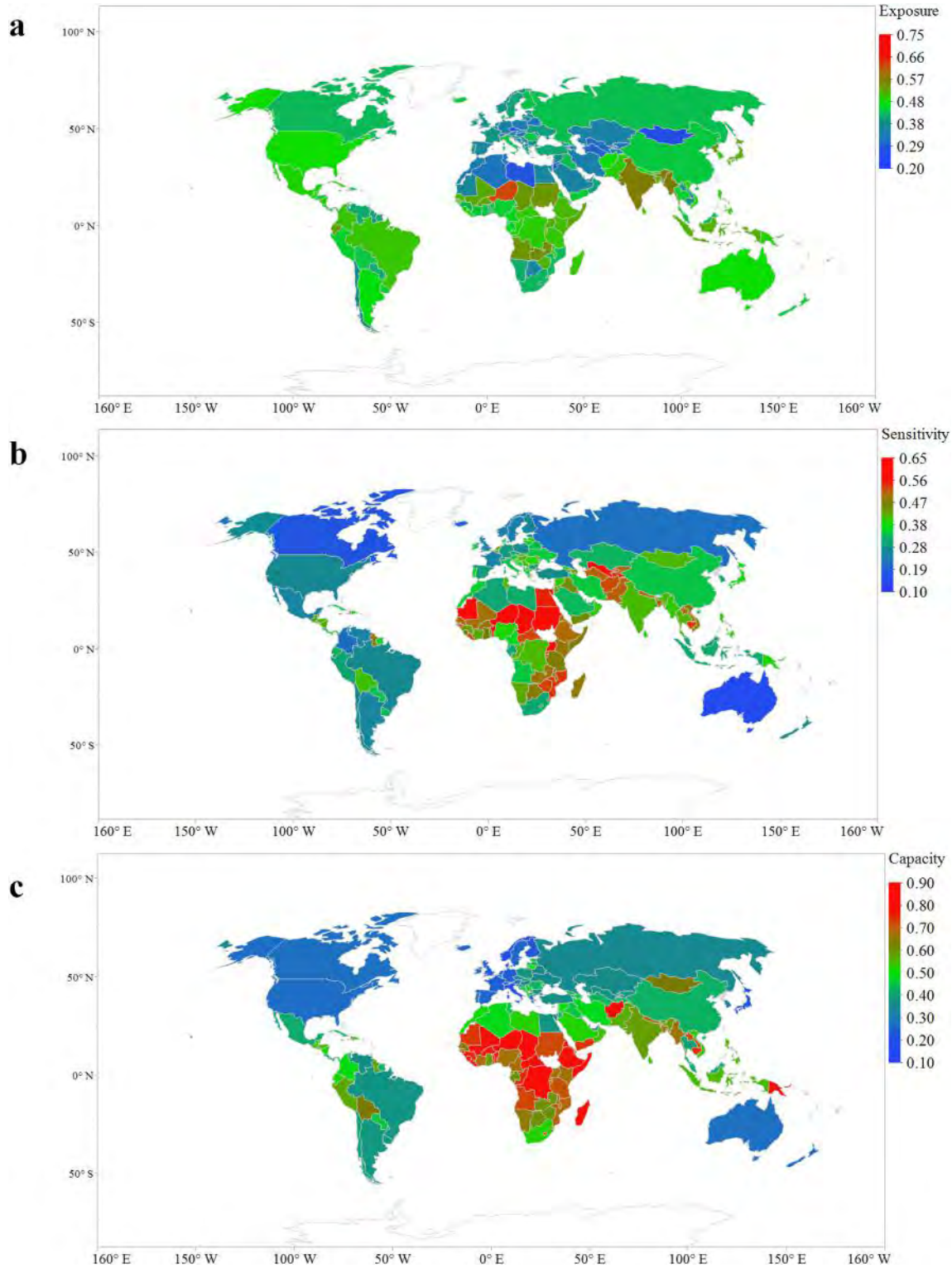

Fig. 9. Choropleth map showing the geographical mean of disaggregate vulnerability indicators of climate change. (a) Exposure [mean range: 0.20–0.75]; (b) sensitivity [mean range: 0.10–0.65]; (c) capacity [mean range: 0.10–0.90].

Fig. 11 represents '*worse*' status of a country's vulnerability while the highest mean value (1) denotes '*better*' status of a country's readiness. The intensity of the colors denotes the statistical mean differences across geographic regions.

Vulnerability measures the propensity of the society negatively affected by climate change and its impacts. While Australia, part of Europe, North, and South America have low vulnerability to climate change, Sub-Saharan Africa is highly vulnerable to climate change hazards, as revealed in Fig. 11(a). Countries with high vulnerability to climate change include Niger, Somalia, Chad, Guinea-Bissau, Liberia, Mali, Sudan, Eritrea, Afghanistan, and Burkina Faso, while countries with very low vulnerability include Norway, Switzerland, Australia,

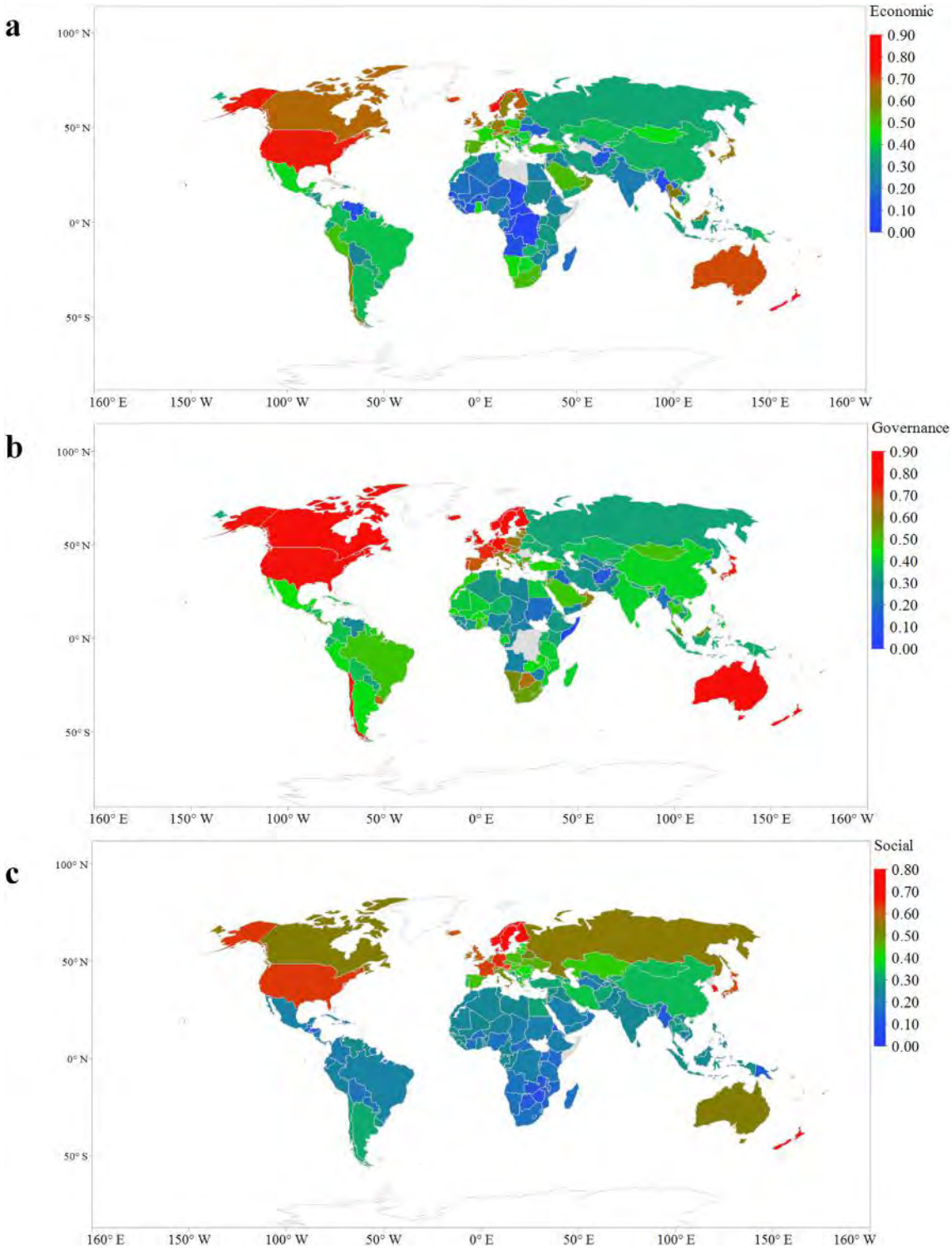

Fig. 10. Choropleth map showing geographical mean of disaggregate adaptation readiness indicators of climate change. (a) Economic [mean range: 0.00–0.90]; (b) governance [mean range: 0.00–0.90]; (c) social [mean range: 0.00–0.80].

Canada, Sweden, United Kingdom, Finland, France, Spain, and Germany [N = 3982, Mean = 0.45 and Std Dev = 0.10]. Readiness involves social and governance willingness to mitigate climate change and the efficient use of investments for adaptation actions. Fig. 11(b) shows that adaptation readiness is relatively high in Australia, Europe, North and South America, contrary to Sub-Saharan Africa. Specifically, countries with high adaptation readiness to mitigate climate change include New Zealand, Norway, Finland, Denmark, Sweden, USA, Iceland, Austria, United Kingdom, and Switzerland, while countries with very low readiness include Somalia, Democratic Republic of Congo, Myanmar, Central African Republic, Eritrea, Chad, Côte D'Ivoire, Afghanistan, Venezuela, and Congo [N = 4202, Mean = 0.40 and Std Dev = 0.15].

The results of the spatial mapping appear to coincide with the Intergovernmental Panel on Climate Change (IPCC) 5th Assessment Report

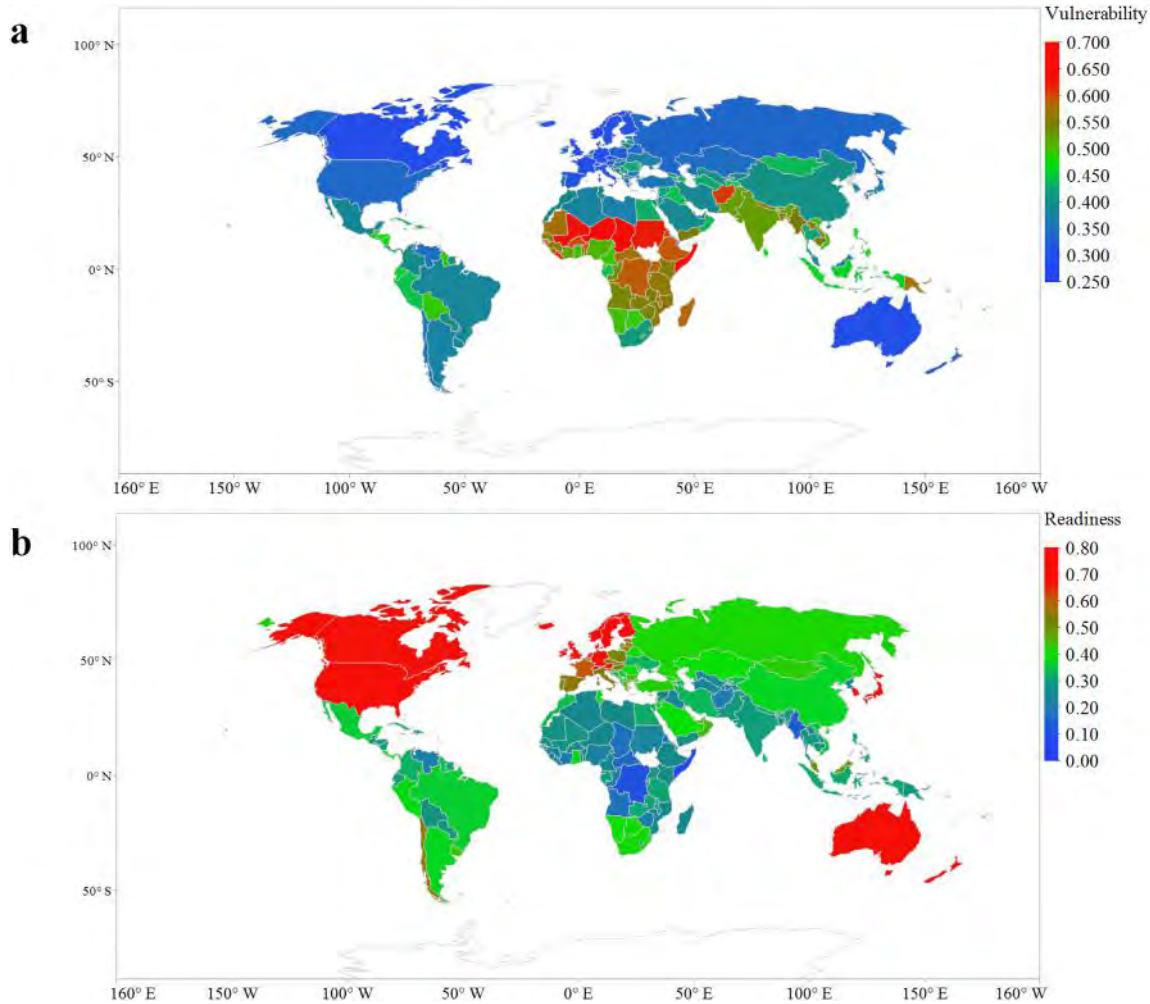

Fig. 11. Choropleth map showing geographical mean of vulnerability and adaptation readiness indicators of climate change. (a) Vulnerability [mean range: 0.25–0.70]; (b) readiness [mean range: 0.00–0.80].

on impacts, adaptation, and vulnerability, which states that Africa is one of the most vulnerable continents to climate variability and climate change. According to the IPCC report, a weak adaptive capacity due to social, economic and governance challenges exacerbates Africa's vulnerability to climate change (IPCC, 2014a).

Fig. 12 illustrates a negative relationship between vulnerability to climate change and adaptation readiness. The baseline results are corroborated by both nonparametric: Spearman's ρ estimation results (Appendix A) and the panel regression results in Table 3. Due to the complexities in examining climate change-related variables, six econometric methods with different parameters were employed to test the validity of the baseline results (Fig. 12). Table 3 reveals that the nexus between vulnerability and readiness yields an error correction of 15% (Model 1[a]) while the relationship between vulnerability, economic, governance, and social readiness yields an error correction of 18% (Model 2[a]). Meaning that the individual effects of adaptation readiness, including economic, governance and social readiness, are more productive in adjusting the previous disequilibrium in climate change vulnerability to near stability in 192 countries. Almost all the 15 models in Table 3 support the role of economic, social and governance adaptation readiness in reducing global climate change vulnerability. Developed countries have low-vulnerability to climate change and its impacts compared to developing and least developed countries, as revealed in the choropleth maps. Hence, socio-economic development and good governance play complementary roles in climate change, provided they incorporate adaptation strategies, such as poverty alleviation [Sustainable Development Goal (SDG) 1], hunger eradication (SDG 2), better nutrition and health (SDG 3), better education (SDG 4), gender equality (SDG 5), clean water and proper sanitation (SDG 6), clean and modern energy (SDG 7), better jobs, enhanced economic growth and reduced income inequality (SDG 8, 10), sustainable cities, communities and industrialization, innovation and better infrastructures (SDG 9, 11), sustainable production and consumption (SDG 12), ecosystem conservation and management (SDG 13–15), and strong and quality institutions coupled with global partnership (SDG 16–17) (United Nations, 2015).

4. Conclusion and policy recommendations

As a contribution to the global targets for combating climate change and its adverse impacts, this study shifts the focus from impact assessment and assessing determinants to the assessment of adaptation actions. The study empirically tests the nexus between climate change vulnerability and adaptation readiness using a panel data of 192 UN countries from 1995 to 2016. Choropleth maps were produced to examine the geographical distribution of climate-related variables. The study employed Pooled Mean Group model estimator, pooled ordinary least squares regression with Driscoll and Kraay standard errors, and panel quantile regression technique with adaptive Markov Chain Monte Carlo optimization method to control for cross-sectional dependence,

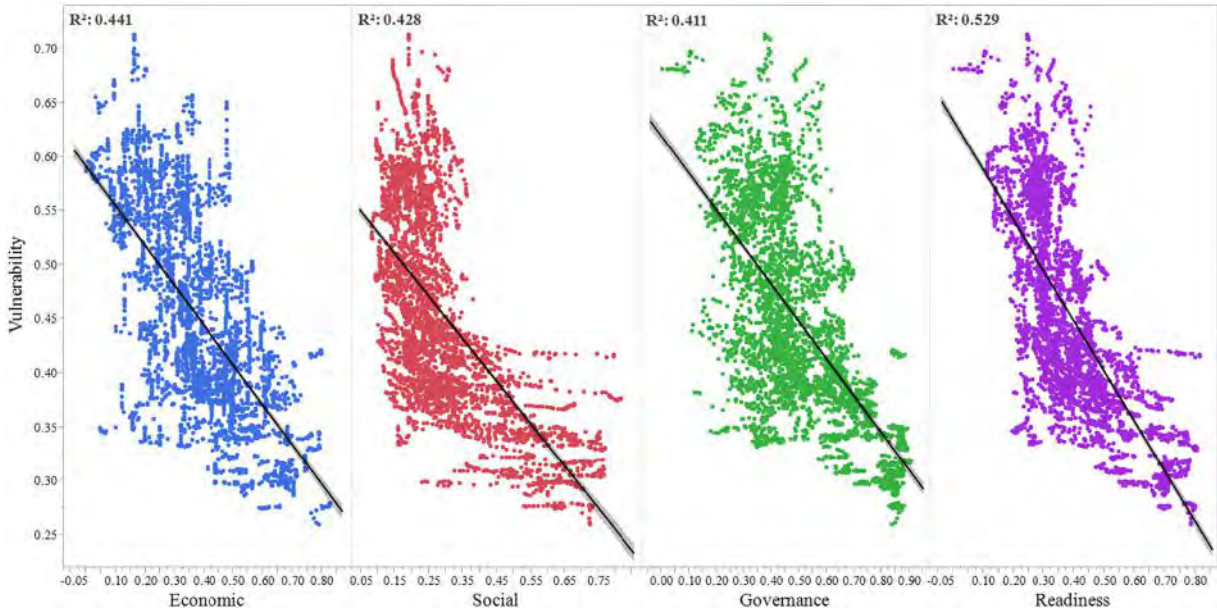

Fig. 12. Vulnerability to climate change versus economic, social, governance, and readiness for climate change mitigation.

heterogeneity, and unconditional distribution across quantiles. The nonlinearity of the model was further tested using nonlinear prediction models, such as Lorentzian Peak, Gaussian Peak, and Exponential 3P. Empirical results from most of the estimating methods, including the Spearman's ρ modeling results, corroborate the contribution of economic, governance and social adaptation readiness in reducing climate change vulnerability.

The study reveals that six sectors, namely food, water, health, ecosystem, human habitat, and infrastructure are vulnerable to climate change. The impact of climate change on food security and food production systems affects cereal yield (maize, rice, and wheat), which contributes to two-thirds of global food consumption (FAO, 2018). This leads to the dependency on food imports if a country's agriculture adaptive capacity is low coupled with a higher food demand due to future changes in population growth. Thus, climate change affects food availability, accessibility, utilization and price stability. The effect of climate change on water resources due to rainfall and temperature variability affects annual runoff, groundwater recharge, freshwater withdrawal rates, and accessibility to reliable drinking water. Climate change is expected to exacerbate health problems and climate-change-induced mortality from water-borne, air-borne, food-borne and vector-borne diseases. Hence, climate-change-induced morbidity and mortality have a high prevalence in developing countries with low-income levels (IPCC, 2014b). Climate change affects terrestrial biome and marine biodiversity due to human pressures and temperature variability. The over-exploitation of available natural resources above its regenerative capacity (biocapacity) at the initial stages of economic development affects the ecological footprint leading to an ecological deficit. The impact of climate change on human habitat has resulted in natural disasters, such as flooding, drought, earthquake, volcanic eruptions, mass movement, and extreme temperatures. Infrastructure capacity in many developing countries has come under threat due to climate change. Hydropower generation capacity has declined in many climate-sensitive regions due to rainfall variability. Sea level rise and storm surge have impacted many settlements and the population living under 5-meter above sea level.

The empirical results reveal that although Africa produces less anthropogenic greenhouse gas emissions, the continent is highly exposed and vulnerable to climate variability and climate-related events due to their dependence on climate-sensitive sectors, such as agriculture and hydropower for energy generation. While economic, governance and social commitment is high and proactive in developed countries like New Zealand, Norway, Finland, Denmark, Sweden, USA, Iceland, Austria, United Kingdom and Switzerland, developing countries, such as Somalia, Democratic Republic of Congo, Myanmar, Central African Republic, Eritrea, Chad, Côte D'Ivoire, Afghanistan, Venezuela and Congo have low adaptive capacity due to limited and sporadic economic, governance and social commitment to climate change adaptation. The policy implications of the study reveal the following requirements for each region:

In Africa — early warning systems and mapping climate change vulnerability; sustainable urban development; agricultural and technological adaptation responses, such as irrigation, climate stress-tolerant crops, and integrated water and land planning.

In Australasia — coastal flood risk management systems, early warning systems, water, and fishing stress reduction.

In Asia — integrated water resource management, early warning systems, urban planning, and sustainable cities, and disaster preparedness.

In North, Central & South America — wetland conservation, integrated water resource management, flood management systems, early heat warning systems, urban planning, and sustainable cities, and the development of drought and temperature resistant crop varieties.

In Europe — wildfire management systems, reduction of air pollution, integrated water resource management, flood management systems, early warning systems, and urban planning and sustainable cities.

This study demonstrates that policymakers need to build the capacity of developing countries and adopt the three-arm of adaptation readiness to mitigate climate change and its impacts.

Declaration

There is no conflict of interest.

Acknowledgment

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.11.349.

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Discussion and Conclusion

This thesis examined the drivers, policies, and measures that affect greenhouse gas emissions using modern econometric methods in 192 UN countries. Data series were selected based on the following Sustainable Development Goals (SDGs):

SDG 1 - 2 — Eradicate extreme poverty and hunger, ensuring food security (the availability, accessibility, healthy and nutritious food) and sustainable agricultural production.

SDG 3 - 5 — Promote healthy living and wellbeing, access to education and gender equality.

SDG 6 - 7 — Access to clean and sustainable water resources, and accessibility to affordable and modern energy technologies.

SDG 8 - 11 — Ensure decent jobs, economic development, innovation, industrialization, reduced inter and intra inequalities, modern infrastructure, and sustainable cities and settlements.

SDG 12 - 13 — Ensure sustainable production and consumption patterns while mitigating climate change and its impacts.

SDG 14 - 15 — Conservation of marine and terrestrial ecosystem through the prevention of biodiversity loss.

SDG 16 - 17 — Ensure institutional quality and strengthen the global partnership for sustainable development.

According to the Intergovernmental Panel on Climate Change (IPCC) 5th Assessment Report, GHG emissions are affected by immediate drivers, underlying factors and policies and measures, as explained in the introduction section. Thus, to examine the policy implications of the trio-interconnection, this thesis examined the EKC hypothesis, Pollution haven hypothesis, Environmental Sustainability hypothesis, determinants of environmental degradation and energy consumption.

Chapter One: This review article investigated the previous studies on the EKC hypothesis and collated bibliographic records to examine the past, present and future implications of the EKC hypothesis. Apart from the traditional qualitative assessment for literature review, this paper employed two quantitative methodologies namely bibliometric and meta-analytic statistics to track the historical trend in existing literature. The EKC hypothesis postulates that a country's initial economic development is characterized by increased levels of environmental related pollution due to over-exploitation of available natural resources, increased material footprint and waste production. The above scenario is applicable to developing countries dependent on agrarian economy. On the contrary, in an industrialized economy, the EKC hypothesizes that environmental related pollution and contamination begins to decline when a country's economic development reaches a turning point with a substantial increased in income levels. The population gradually become aware of environmental pollution, calls for environmental sustainability and are willing to pay for clean environment. However, the review article reveals that the shape of the EKC is on an extent influenced by income elasticity of environmental quality, scale, composition and technique effects, and international trade. The empirical findings show that environmental indicators employed

for testing the EKC hypothesis via econometric methods include atmospheric indicators, land indicators, oceans, seas, coasts and biodiversity indicators, and freshwater indicators. However, the majority of the existing literature on EKC hypothesis is skewed towards atmospheric related indicators. The very few literature on EKC that examines the turning point of income level reveals a borderline turning point of US$8,910 income level for studies that validate the inverted-U shaped relationship between environmental pollution and income levels. On the contrary, studies with invalid EKC hypothesis, thus, U-shaped, monotone, N-shaped, have a borderline turning point of US$ 5,702. Low income and middle-income countries are found below the US$ 8,910 and US$ 5,702 thresholds while high-income countries are found above the borderline income level. Thus, the meta-analytic method validates heterogeneity among turning point in studies on EKC hypothesis. The lack of cohesion between existing literature on EKC hypothesis can be attributed to differences in study periods, data preprocessing, econometric methods employed and among others. A country's environmental quality standing is hinged on several factors which include the size of the economy, the state of art or vintage technologies, the sectoral economic structure, and demand for environmental-related services. Larger economies appear to have higher pollution levels and rapid depletion of the natural resource due to the sectoral economic structure. Whereas agrarian and industrialized economies tend to exploit more natural resources and suffer from congestion-linked problems and urban pollution.

Chapter Two: With evidence from the review article in Chapter One, this research article examined the current state of environmental degradation and pollution in 17 countries in Africa by testing the validity of the EKC hypothesis. Though Africa contributes less to

anthropogenic GHG emissions yet, the most vulnerable continent to climate change and its impacts. The empirical findings revealed that environmental degradation and pollution in Africa are in part driven by immediate and underlying factors ranging from socio-economic, demography, agricultural, forest and land-use, and energy consumption patterns. While the nexus between environmental degradation and economic development exhibits a U shape at a turning point of US$ 7,958 GDP per capita, the relationship between environmental pollution and economic development validates the EKC hypothesis in Africa at a turning point of US$ 5,702 GDP per capita. Income inequality (gap between the rich and the poor) is seen to dominate the majority of sub-Saharan African countries except for South Africa (>US$ 800), all the countries have their lower bound income between US$ 100-400 per capita. Yet, these same countries including South Africa have their upper bound income between US$ 1,000-9,000 per capita. The cost of living by some households in Africa, excluding South Africa (US$ 2.47/day, thus, 900/365) is between US$ 0.27/day - US$ 1.10/day using the lower bound income scenario compared to the upper bound income between US$ 2.74/day - US$ 24.70/day. Thus, the majority of families in Africa except South Africa live below the poverty line of US$ 1.90/day in accordance with SDG (1). In other words, multidimensional poverty is synonymous with environmental pollution. This explains why the majority of households in Africa depends on traditional sources like fuelwood and charcoal for heating and cooking purposes. Therefore, governmental and NGOs policies that help poverty alleviation, is one step towards reducing climate change and its impact among the most vulnerable people, especially women and children in Africa. The empirical findings further suggest that energy consumption, food production, economic growth, permanent

crop, agricultural land, environmental pollution, birth rate, and fertility rate are the main drivers of environmental degradation and pollution in Africa.

Chapter Three: Contrary to Chapter two which studied the EKC hypothesis is developing countries with an agrarian economy, Chapter three examines both Pollution haven hypothesis and EKC hypothesis in the top five developing economies with high GHG emissions, namely China, India, Iran, Indonesia, and South Africa. The pollution haven hypothesis suggests that energy and carbon intensity industries in developed countries migrate to low and middle-income countries with laxed environmental policies and regulations through international trading of goods, technology, innovation, services, and foreign direct investment. Though the inflows of foreign direct investment remain the backbone of external funding for developing countries, however, the transfer of dirty industries from jurisdictions with more severe environmental regulations to weak countries results in pollution haven. The study found a strong positive effect of foreign direct investment and economic development on GHG emissions, hence, validating the pollution haven and EKC hypotheses. The need to improve economic development is the main target of many least developing and developing countries. These countries are eager to attract foreign direct investment from developed countries with carbon-intensive industries, therefore, engages in inefficient competition by weakening their environmental standards coupled with poor environmental management systems and vintage technologies which increases pollution trends. On the contrary, the inflows of foreign direct investment with transfer clean technologies and innovation, improvement in labor capital and sustainable environmental management practices will assist developing countries to achieve the sustainable development goals. Energy consumption has a strong

positive effect on CO_2 emissions, as evidenced in the study. Pollution haven in developing countries similarly drives the adoption of fossil fuel energy technologies rather than renewables to accumulate low production cost of goods and services from energy and carbon-intensive industries. Consequently, the reduction of CO_2 emissions is dependent on enhanced energy efficiency, adoption of clean and modern energy technologies such as renewables, nuclear power plants, and the implementation of carbon capture and storage for fossil fuel and biomass energy generation processes.

Chapter Four: This paper examined the EKC and Environmental Sustainability hypotheses in four countries namely Ghana, China, Australia and USA with characteristics of pre-industry economy, industrial economy and post-industry economy. Electric power consumption is revealed as the main contributor of energy intensity in Australia, China, Ghana, and the USA. The declining trends in electric power consumption proportionate to economic growth indicate a country's economic capacity to improve energy efficiency. Therefore, post-industrialized economies like Australia and the USA can reduce their electric power consumption with a growing income level in relation to middle- and low-income countries like China and Ghana. Decoupling economic growth from electric power consumption will help double the global rate of energy efficiency improvements in member countries by 2030. Meaning that improvements in energy efficiency enhances energy security and declines the economic impact on the environment. The Environmental Sustainability Curve hypothesis revealed that at high levels of economic development, the intensity of environmental sustainability is in part attributed to the impacts of maintaining economic activities at the expense of the available and regenerative capacity of natural resources. A structural change in the energy

portfolio from fossil fuel energy technologies to clean and renewable energy technologies accelerates the agenda to achieving environmental sustainability. Thus, reducing environmental stress requires an economic shift from energy- and carbon-intensive manufacturing industries to less-polluting industries that reduce energy demand and utilization.

Chapter Five: This paper examined how energy portfolio contributes to CO_2 emissions and environmental degradation in accordance with Australia's Emissions Projections by 2030. Using modern econometric methods, the study provides a sensitivity analysis on how adjustments in immediate drivers can be made towards achieving a decarbonized economy while meeting the emission targets. Australia is expected to reduce its emissions by 5-15% by 2020 and stabilize GHG concentrations at 450 ppm in the atmosphere, as expounded in the Annex I parties of the climate change convention. Evidence from the study revealed that energy imports and exports are essential in the determination and abatement of CO_2 emissions in Australia. While energy imports worsen CO_2 emissions, energy exports improve environmental quality since major polluting energy sources are exported to other countries. Australia's energy portfolio contributes to CO_2 emissions and environmental degradation. As such, structural adjustments are essential to achieving a decarbonized economy while meeting the emission targets. To promote sustainable development, the sensitivity analysis reveals that the share of renewable energy production in the energy portfolio must be increased from the current 2% to at least 50%. Decoupling energy production from economic growth is essential to improve energy efficiency while reducing CO_2 emissions and environmental degradation. The EKC hypothesis was validated, meaning that, structural change in Australia's economy results

from a shift from energy- and carbon-intensive industries to less-energy-intensive and green energy industries and their related services. Increasing the share of renewable energy penetration in Australia's energy portfolio decreases the level of CO_2 emissions, while increasing the share of non-renewable energy sources in the energy mix increases the level of atmospheric emissions, hence, increasing climate change and its impacts.

Chapter Six: This paper utilizes both immediate drivers and underlying factors of GHG emissions expounded in the introductory section. While South Africa is ranked as the second most carbon-intensive country in the world due to its fossil fuel rich energy sources, it remains Africa's economic giant. The confirmed the validity of the EKC hypothesis in South Africa and political institutional quality plays a critical role in adaptation readiness to mitigate climate change and its impact. Diversification of the energy mix by incorporating renewable energy sources will promote air quality and environmental sustainability while reducing economic vulnerability to price volatility. The study reveals that technological advancement in manufacturing industries and power sectors are essential to promote energy efficiency. Government's resolve to promote policies that decarbonize the economy and provide a conducive political climate that promotes clean and modernized energy would promote environmental quality and a structural change in the economy. Though renewable energy investment has a competitive disadvantage compared to fossil fuel and nuclear energy, however, attractive renewable energy technology requires deployment policies that mutually include technological development, industry development, and market development.

Chapter Seven: This paper investigated the impact of adaptation readiness on climate change vulnerability using a panel of 192 UN countries. The empirical results reveal that

although Africa produces less anthropogenic GHG emissions, the continent is highly exposed and vulnerable to climate variability and climate-related events due to their dependence on climate-sensitive sectors, such as agriculture and hydropower for energy generation. Majority of African countries are agrarian economy and depend heavily on the agricultural sector for almost 28% of its economic revenue while 65% of the working population are dependent on the agricultural sector for their daily livelihoods. Due to low adaptive capacity, high financial and technological constraints, changes in weather patterns such as rainfall variability and higher temperatures affect food production leading to extreme poverty, hunger, rural-urban migration and social instability, which are already happening. While economic, governance and social commitment is high and proactive in the developed countries New Zealand, Norway, Finland, Denmark, Sweden, USA, Iceland, Austria, United Kingdom and Switzerland, developing countries, such as Somalia, Democratic Republic of Congo, Myanmar, Central African Republic, Eritrea, Chad, Côte D'Ivoire, Afghanistan, Venezuela and Congo have low adaptive capacity due to limited and sporadic economic, governance and social commitment to climate change adaptation. Six sectors, specifically food, water, health, ecosystem, human habitat, and infrastructure are vulnerable to climate change variability across the globe. For example, climate change affects food availability, accessibility, utilization and price stability — the impact of climate change on food security and food production systems affects cereal yield, leading to the dependency on food imports. The effect of climate change on water resources due to rainfall and temperature variability affect annual runoff, groundwater recharge, freshwater withdrawal rates, and accessibility to reliable drinking water. Climate change exacerbates health problems and climate-change-induced mortality from

water-borne, air-borne, food-borne and vector-borne diseases. Thus, climate-change-induced morbidity and mortality have a high prevalence in developing countries with low-income levels. The terrestrial biome and marine biodiversity are affected by climate change due to human pressures and temperature variability. The over-exploitation of available natural resources above its regenerative capacity at the initial stages of economic development affects the ecological footprint leading to an ecological deficit. The impact of climate change on human habitat has resulted in natural disasters such as flooding, drought, earthquake, volcanic eruptions, mass movement, and extreme temperatures. Infrastructure capacity in many developing countries has come under threat due to climate change. Hydropower generation capacity has declined in many climate-sensitive regions due to rainfall variability while sea level rise and storm surge have impacted many settlements and the population living under 5-meter. Policies and measures that help in the mitigation of climate change include awareness creation, economic incentives, non-climate policies, planning, direct regulations, provision of information, and research and development.

Appendices

This section compiles journal articles co-authored during the PhD Candidature, which are in line with the thesis topic of assessing the drivers of greenhouse gas emissions.

In Appendix 1 — Publication Eight, the article assessed the drivers of energy consumption in Kenya using the nonlinear iterative partial least squares (NIPALS) estimation approach capable of preserving important variables and controlling for multicollinearity. Consistent with existing literature, the study found population, economic development and climate change to trigger energy consumption.

In Appendix 2 — Publication Nine, the study investigated the role of energy and financial development in examining the environmental Kuznets curve hypothesis using ecological footprint as an environmental indicator. Using both augmented mean group estimator and heterogeneous panel causality approach, the study confirmed the validity of the EKC hypothesis in 11 newly industrialized economies. Economic development was found to play a complementary role in both climate change and environmental sustainability.

In Appendix 3 — Publication Ten, the study examined the asymmetric behaviour of energy consumption using a trio model namely Markov-switching dynamic regression, neural network and NIPALS estimation technique. The study demonstrated that unobserved variables such as machineries for agricultural mechanization, foreign direct investment, greenhouse gas emissions, industrialization, and fisheries production spur energy consumption. On the contrary, electric power and distribution losses were found to decline energy consumption. Foreign direct investments in the form of green and renewable energy sources and technology transfer are essential to improving energy efficiency and climate reduction.

In Appendix 4 — Publication Eleven, the study explored the nexus between energy consumption, carbon dioxide emissions, and economic growth in South Africa using Bayer and Hanck cointegration and Kripfganz and Schneider critical and approximate p-

values for bounds testing procedure. Inverted-U shaped relationship was found between energy consumption and economic development, signifying less intensification of energy consumption at higher levels of economic growth (i.e. energy efficiency).

In Appendix 5 — Publication Twelve, the study examined the relationship between CO_2 emissions, resource rent, renewable and nonrenewable energy in 16-EU countries using panel pooled mean group-autoregressive distributed lag model. The study demonstrated that the overdependence on natural resources without conservation and management options affects environmental sustainability. In line with previous studies, the empirical results confirmed the role of economic development and fossil fuel energy technologies in environmental pollution. Hence, environmentally friendly policies such as increasing the share of renewable energy technologies in the global energy mix, are useful to mitigating climate change and its impacts.

In Appendix 6 — Publication Thirteen, the study employed a novel dynamic ARDL simulations to develop conceptual tools for decision making on environmental sustainability. Biomass energy consumption was found to support Australia's transition towards a decarbonized economy. The study validated an inversed-U shaped relationship between energy consumption and economic development —denoting a decline in energy intensity while increasing energy efficiency.

Appendix 1 — Publication Eight: Determinants of energy consumption in Kenya: A NIPALS approach

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Determinants of energy consumption in Kenya: A NIPALS approach

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ABSTRACT

This study examines the drivers of aggregate energy consumption, fossil fuel and electricity consumption in Kenya using the nonlinear iterative partial least squares (NIPALS) method. The results show the importance of price, population density, urbanization, and renewable energies from hydro sources in promoting energy demand reductions. On the contrary, higher income and climate change are likely to cause a backfire in energy consumption. Though population growth increases the consumption of other energy types, it shows opposite effect on electricity consumption, which is possibly explained as a substitution to other energy types in the presence of a fragile electrical system. These results have important implications for the design of energy conservation and efficiency policies in Kenya.
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1. Introduction

The achievement of the Sustainable Development Goals (SDG) is central to the eradication of poverty in Africa. In this regard, social, health and economic factors that propel the development process are strongly required [1]. For example, to reduce poverty, important economic interventions that ensure the provision of decent jobs, access to good health care, education, and reliable energy supply, and etcetera are very important [1,2]. However, in the case of Kenya, while the supply of energy is limited, demand for energy continues to increase due to economic growth, industrialization, and urbanization. This has widened the demand-supply gap in the energy sector, which coupled with the high intermittency in hydro that constitutes a major source of supply, has occasionally caused power crisis in the country [3–6]. Moreover, the situation in the energy sector has also increased the country's dependence on imported fuel [7]. In 2017, about 79 million kWh of energy out of the total production of 9 billion kWh was imported [3].

Consequently, this has increased the cost of energy in the country. For example, the levelized cost of electricity (US$ 0.15/kWh) in Kenya is almost four times higher than that in South Africa (US$ 0.04/kWh) [4]. Obviously, this from the perspective of production and consumption is problematic. Thus, while businesses in Kenya are likely to be less competitive due to higher energy cost, residential consumers may have limited access to energy, which is an important requirement for the attainment of the SDGs. With a total population of about 47 million [2015 est. [5]], only 15% of the population has access to electricity, albeit there are attempts by the government to increase this to at least 50% before 2022 [6]. In the case of Kenya, understanding the drivers of energy demand from various sources is important for the design of appropriate energy conservation and efficiency programmes. This is because efficiency and conservation improvement will improve energy usage, reduce energy import dependence and hence the feed-in inflation into consumer prices, and reduce the investment in additional generation plant capacity. Despite the significance of the issue, empirical studies on the drivers of the different energy sources are lacking in the case of Kenya. Motivated by this, the aim of the current study is to study the problem of determinants of demand for total energy consumption, fossil fuel consumption, and electricity consumption

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in Kenya.

There are several studies that have investigated the drivers of total energy consumption in Africa [7–9] and in Kenya [10–12], however, no study applies the nonlinear iterative partial least squares (NIPALS) technique to investigate the drivers of energy consumption. Keho [12] applied a panel regression method to investigate the drivers of aggregate energy consumption in sub-Saharan Africa that included Kenya. Onuonga [11] tested the causal relationship between commercial energy consumption and gross domestic income in Kenya. Also, Onuonga, Etyang [10] estimated manufacturing energy demand in Kenya. These studies focused on the determinants of either one energy type, and therefore do not provide the grounds to compare the influence of factors across the different energy sources. The only exception is the study by Kolawole, Adesola [13] that used panel-based regression to study the drivers of energy demand for the different fuel types in sub-Saharan Africa (including Kenya). However, this study only provided group estimates with no evidence on country-level analysis. Also, as a commonality, the present literature on energy demand, particularly in the case of Kenya, does not explicitly handle the issue of multicollinearity (i.e. the correlation between or among regressors) and the statistical determination of variable importance prior to model estimation [14]. The possible cause could be that the econometric methods employed in these studies do not have an inherent mechanism that makes it possible to handle the issue of variable importance and multicollinearity. Therefore, these studies risk including an unimportant variable in the model which is a potential source of multicollinearity and hence creates parameter identification issues. Consequently, results obtained could be biased.

This article makes the following contributions to the literature, particularly in the case of Kenya. First, the study investigates the drivers of total energy consumption, fossil fuel consumption, and electricity consumption. This makes it possible to compare elasticities of demand across the different energy sources analyzed. Second, this article applies the NIPALS technique to investigate the drivers of energy consumption. NIPALS provide the following advantages over other traditional econometric techniques: (1) it has an inherently built mechanism that provides formal detection of variable importance before proceeding to the main estimation and (2) it explicitly handles the issue of multicollinearity. Thus, in the case of the former, NIPALS minimizes the problem of including unimportant variables in the model, while in the case of latter minimizes the problem of parameter identification issues.

The remainder of the study is as follows. Section 2 is the literature review. Section 3 provides a discussion of the energy situation in Kenya. Section 4 is the method and data. Section 5 discusses the main findings of the study. Section 6 concludes with a policy recommendation.

2. Literature review

This section reviews the empirical literature. The section is in two parts. The first part reviews work on the energy consumption – economic growth nexus. The section part reviews the literature on the drivers of energy consumption.

2.1. Energy consumption-economic growth nexus

There are several studies that have tested the energy consumption-economic growth nexus. From these studies, four relationships have been identified: (1) unidirectional causality from energy consumption to economic growth, (2) unidirectional causality from economic growth to energy consumption, (3) bidirectional causality or feedback effect between energy consumption and economic growth, and (4) neutral or no relationship between energy consumption and economic growth. The first relationship implies that energy is a vital input into the growth process of economies. Therefore, reduction in energy consumption achieved via energy conservation and not energy efficiency would be detrimental to economic growth. The second relationship indicates that energy conservation policies would not affect economic growth. The feedback hypothesis suggests that both economic growth and energy consumption matter to each other. Lastly, the neutral hypothesis implies that energy can be disconnected from economic growth. Generally, there is no consensus on which of the above relationships is true even for the same country study. This is understandable since behavioral changes over time can alter the demand and production patterns which may redefine the structure of the economy.

Ouedraogo [15] tested the long-run relationship between energy consumption and economic growth in fifteen (15) West African countries. The result showed (1) a unidirectional causality (both in short- and long-run) from GDP to energy consumption and (2) a unidirectional causality from electricity consumption to GDP, in the long–run. Amar [16] tested a similar hypothesis for 22 African countries that included Kenya. The result confirmed a positive income effect on economic growth and a unidirectional causality from GDP to energy consumption. Asongu, El Montasser [17] studied the case of 24 African countries. They found an evidence of weak causality from energy consumption to economic growth in the short-run and not in the long-run. Studies in Kenya [11] and Benin [18] revealed a unidirectional causality from economic growth to energy consumption. Asumadu and Owusu [19] examined the causal relationships between energy, carbon dioxide emissions, and macroeconomic factors in Ghana. Their study found that shocks in energy consumption are mainly due to financial development. Moreover, the study found a bidirectional causality between energy consumption, financial development, industrialization, and population in Ghana. Owusu and Samuel [20] confirmed the validity of the feedback hypothesis in Ghana between economic development and electricity consumption. In contrast, Asumadu and Owusu [21] revealed a unidirectional causality from GDP to electricity consumption in Ghana.

Salahuddin, Gow [22] investigated the relationship between carbon dioxide emissions, financial development, economic growth, electricity consumption in the Gulf countries from 1980 to 2012. Their study found a positive effect of economic growth and electricity consumption on carbon dioxide emissions and a unidirectional causality from electricity consumption to economic growth. Jammazi and Aloui [23] also found a unidirectional causality from energy consumption to carbon dioxide emissions and a bidirectional causality between energy consumption and economic growth in the Gulf countries from 1980 to 2013.

2.2. Drivers of energy consumption

The other generation of studies provides an econometric investigation into the drivers of energy consumption. These include both studies on energy intensity and energy consumption. A study by Adom [9] concluded that large imports, fewer exports, and de-industrialization have caused energy intensity to fall in South Africa. A study in Nigeria concluded that industrialization has a positive impact on energy intensity while foreign direct inflows and trade openness have a negative effect on energy intensity [8]. A similar study by Adom [24] revealed a significant role of price, income, trade openness, and foreign direct inflows in explaining energy intensity in Algeria. Aboagye and Alagidede [25] considered the sample of sub-Saharan African countries. They found that while price and trade openness reduce energy intensity, industry and

service output increase it. Adom and Amuakwa-Mensah [26] also examined the drivers of energy intensity in East Africa (including Kenya). Their result showed that openness in trade, foreign direct inflows, and industry structure play significant roles in explaining energy intensity in East Africa.

Keho [12] rather focused on the drivers of energy consumption for selected African countries. The study found significant roles in economic growth, industrial output, population, and urbanization. Kolawole, Adesola [13] examined disaggregate energy demand (electricity, diesel, petrol, kerosene, solid biomass, and liquefied petroleum gas consumption) in sub-Saharan Africa. The results confirmed the significant roles of income, urbanization, population and economic structure in explaining energy demand in sub-Saharan Africa. Onuonga, Etyang [10] investigated the drivers of manufacturing energy demand in Kenya. They confirmed the significant roles played by price and technology (showing a negative effect) and income (showing a positive effect). Mensah, Marbuah [27] examined the drivers of the different fuel types in Ghana. Their result also revealed the important roles of price, income and demographic factors.

2.3. Literature gap

Few studies have examined the drivers of energy demand of different types. In the case of Kenya, the evidence is lacking. Second, traditional econometric methods such as ARDL, VECM, and VAR [39–41] do not have inherently mechanism that first tests for variable importance before proceeding to the final estimation. Within these methods, researchers follow either the general-to-specific modelling or specific-to-general modelling approaches to arrive at the final model. Therefore, there is the risk of including an unimportant variable in the model which may affect the biasedness of the results. Few studies have discussed the issue of regressor importance [14,42]. Moreover, explicit explanation about how to handle multicollinearity issues especially with single equation regression is sparse in the energy demand literature in Africa [38]. This article makes the following contributions to energy demand studies in Kenya: (1) it investigates the determinants of demand for the different energy sources in Kenya and (2) it applies the NIPAL approach by Wold, Sjöström [28] as the econometric method. NIPALS relative to other econometric methods provides (1) an inherent measure of variable importance and (2) deals with multicollinearity issues.

3. The energy situation in Kenya

The energy situation in Kenya, comparable to other countries in Africa, is precarious. There are supply limitations and a continuous rise in demand. This imbalance between demand and supply has often culminated in shortages and power blackouts. Kenya's energy mix like other sub-Saharan African countries is dominated by wood fuel. The composition is about 68% for wood fuel and other biomass, 22% for petroleum, and 9% for electricity. Eighty percent (80%) of Kenya's population relies on fuelwood for cooking and heating purposes, which constitutes a demand of 30 million tons/year. Yet, due to the expansion of agricultural land and population density, only 15 million tons/year can be supplied as fuelwood, with a yearly deficit of 20 million tons [6,29]. This vacuum has propelled illegal means of meeting the supply of fuelwood, leading to high rates of deforestation and adverse environmental related problems like droughts, desertification, famine, and land degradation.

Electricity in Kenya is generated mainly from fossil fuel and hydropower. Even though hydropower accounts for 50% (761 MW) of Kenya's energy generation mix, the poor rainfall patterns and drought in the country make hydropower less reliable. It has therefore been forecasted to lose its relevance and supply only 5% (1039 MW) of the energy generation mix by 2031 [30]. Notwithstanding, there is a hydropower potential of about 1500 MW and 3000 MW small, mini and micro hydropower yet to be exploited [6]. The intermittent rainfall patterns and drought resulted in a 9% decline in Kenya's hydropower generation which led to the inclusion of oil-fired power plants to play a supplementary role in energy generation. 33% of Kenya's generation energy mix comes from oil sources with plans in place to build more oil-fired power plants [6]. Further, there are plans underway for Kenya to adopt coal in their energy mix because of the newly discovered 400 million tons of coal mine in the Mui basin [29]. The discovery is a "*blessing and a curse*" in disguise. Even though it will boost their energy production to meet the growing energy demand, the negative environmental impacts (i.e. carbon dioxide emissions) are predicted to be enormous. It is, therefore, necessary for the country to adopt the clean coal technology (carbon capture and sequestration) even if it intends to exploit the potential resource.

The reliance on fossil fuel for the generation due to the intermittency in hydropower supply has increased the country's energy import expenditure. Kenya spends over 40% of its foreign exchange earnings on the importation of crude oil and other petroleum products [6]. Presently, 100% of Kenya's petroleum requirements for the growing automobile fleet and industrial activities are imported. Kenya's crude oil imports have risen from 4.5 million to 6 million tons, thus, 130,000 barrels/day. Diesel imports account for 55–60% while gasoline accounts for 35–40%. To boost the oil imports while dodging bottlenecks, a new "US$500 million floating oil import jetty and 800,000 tons of storage facility" has been completed in Mombasa [31]. The consumption of LPG has increased from 40,000 to 80,000 metric tons per year within the last decades. As a result, only 30,000 metric tons per year of LPG is produced by the Kenya Petroleum Refinery while 50,000 metric tons per year of LPG is imported to meet the demand. However, recent developments in the energy sector are fast-tracking the upgrade of the Petroleum Refinery to produce 115,000 metric tons of LPG to reduce the cost of imports [32].

An alternative energy source to remedy the energy situation in Kenya is to develop and use renewable energies. Kenya has the most viable commercial solar photovoltaic market in among the other developing countries. It has an installed capacity of about 4 MW and an annual PV sale of between 25,000–30,000 PV modules. Estimated 200,000 households have access to affordable solar home systems. It is estimated that the grid-connected PV systems covering 3% of the area (15–20 km^2) in Nairobi could generate 3801 GWh/year of electrical energy. There is a 40 MW off-grid solar potential still untapped that can supply 4 million rural households in Kenya with electricity [6]. Kenya is currently the home of Africa's largest wind farm (Lake Turkana wind farm) of about 310 MW, 300–500 installed windpumps as of 2007 and a further 900 MW of wind energy under development. Kenya is the world's 8th largest geothermal energy producer accounting for 7 GW of the 15 GW in entire Africa [29]. Kenya's Rift Valley has an estimated potential of over 2000 MW of geothermal energy while the national potential is estimated 7000–10,000 MW. Geothermal energy has been identified by the Least Cost Power Development Plan, Kenya, as a cost-effective power option to ease the financial burden and solve the recent energy crisis. Efforts have been put in place by the Geothermal Development Company to fast-track the development of geothermal energy resource potential [33].

Aside from the supply-side options, there are energy demand management options that the country can also exploit to salvage the energy situation in the country. Several energy conservation options have been put in place by the Kenya Power for home users to achieve power supply efficiency and maximize productivity

Table 1
Variable definition.

Indicator Name	Indicator Code	Unit
Population density	POPDN	people per sq. km of land area
Population growth	POPGR	annual %
GNI per capita	GNIP	constant 2010 US$
Fossil fuel energy consumption	FFCOM	% of total
Energy use	EGCOM	kg of oil equivalent per capita
Electric power consumption	ELECOM	kWh per capita
Electricity production from hydroelectric sources	ELCHYRO	% of total
Electricity production from renewable sources, excluding hydroelectric	ELCRE	kWh
Urban population	URB	% of total
Real Oil Prices	ROP	US$/bbl
CO_2 emissions	CO2	kt

while cutting off wastage in existing energy resources. A few of the options include: the use of compact fluorescent lamps, LED lighting, electronic ballasts, timers, motion sensors and photo sensors to turn security lights on and off, house design that maximizes natural sunlight during the day, dimming switches, using pressure cookers, electric kettles rather than cookers, toasters rather than grill, 150 W medium-sized refrigerators, etc. [34].

4. Methodology

4.1. Data

The study employs time series variables from the World Development Indicators [5] and BP Statistical Review of World Energy that covers the period 1971–2014. The variables include Population density, Population growth, GNI per capita, Fossil fuel energy consumption, total Energy use, Electric power consumption, Electricity production from hydroelectric sources, Electricity production from renewable sources, excluding hydroelectric, urban population, Real Oil Prices, and CO_2 emissions. Table 1 contains information on how the variables are measured.

Energy use involves the use of the primary energy prior to transformation into other end-use fuels. Carbon dioxide emissions have received global attention due to its short-term and long-term effects on the environment such as changes in weather patterns and air quality. Kenya's hydropower has suffered the effect of climate change variability leading to poor rainfall patterns, which has affected the energy sector adversely. Fossil fuel energy consumption includes oil, natural gas, and coal. Electricity production from oil sources (Thermal energy) in Kenya's energy mix plays an auxiliary role to make up for the shortfalls in hydropower generation. Thus, crude oil prices are critical to the efficiency of thermal power plants. Notwithstanding, Kenya is making progress in renewable energy by the incorporation of solar (4 MW commercial) and wind (310 MW) energies to the energy portfolio [29]. Against the backdrop, the selection of the variables in the study is founded on the primary contribution of energy sources to Kenya's energy portfolio and the socio-economic energy-related dynamics. Logarithm transformation has been applied to all the data variables to have a normal distribution thereby reducing skewness.

4.2. Model assessment

This study models energy consumption as a function of population density, carbon dioxide emissions, population growth, gross national income per capita, electricity production from hydro, electricity production from renewables excluding hydro, urbanization rate, and the real price of oil. Mathematically, this is depicted in Equation (1).

$$\begin{aligned}\mathrm{ELECOM}_t|\mathrm{EGCOM}_t|\mathrm{FFCOM}_t = \beta_0 &+ \beta_1\mathrm{POPDN}_t + \beta_2\mathrm{CO2}_t \\ &+ \beta_3\mathrm{POPGR}_t + \beta_4\mathrm{GNIP}_t \\ &+ \beta_5\mathrm{ELCHYRO}_t + \beta_6\mathrm{ELCRE}_t \\ &+ \beta_7\mathrm{URB}_t + \beta_8\mathrm{ROP}_t + \varepsilon_t, \qquad (1)\end{aligned}$$

where β_0 represents the constant, $\beta_1, \ldots, \beta_8$ denote the coefficients of the independent variables in year t and ε designates the error term. The empirical model is first motivated by the theory of demand in neoclassical economics, which postulates a relationship between demand for a product and the price of the product and income of the consumer. The inclusion of the other variables is strongly motivated by their general importance as revealed in the general literature ([12,13,27], *inter alia*). In contrast to the current empirical literature, this study performs an initial statistical test about the relevance of each regressor before proceeding to the final model estimation. Through this approach, the present study provides an explicit handling of the problem of multicollinearity.

4.3. NIPALS algorithm

The NIPALS regression begins with the selection of factors that have a minimum root mean predicted residual sum of squares (PRESS) using the leave-one-out validation method. This method employs the van der Voet test (T^2), a randomization test that compares the residuals of the predicted series with different models and selects the number of factors with the fewest residuals insignificantly larger compared to the model residuals with the minimum PRESS [35]. This multivariate analysis method is employed due to its numerical accuracy in results and prediction compared to other decomposition of covariance techniques [36,37]. En route to model estimation, the original data variables [$\boldsymbol{X}$ (predictors) and $\boldsymbol{Y}$ (response)] are preprocessed to have a zero mean and a standard deviation of one (thus, scaled and centered). In other words, this transformation deals with potential problems of a unit root in the variables. The NIPALS algorithm is initiated with a "guess value" for y-scores $\boldsymbol{u}$ and respectively calculates the properties of the model in the following steps by Wold, Sjöström [28]:

$$\boldsymbol{u}_{start} = some\ \boldsymbol{y}_j \qquad (2)$$

$$w^T = u^T X \big/ u^T u \qquad (3)$$

$$w^T_{new} = w^T_{old} \big/ w^T_{old} \qquad (4)$$

$$t = Xw \big/ w^T w \qquad (5)$$

$$q^T = t^T Y \big/ t^T t \qquad (6)$$

$$q^T_{new} = q^T_{old} \big/ q^T_{old} \qquad (7)$$

$$u = Yq \big/ q^T q \qquad (8)$$

X-loadings is calculated and normalized once convergence has been reached from the algorithm in two successive cycles without a change in $\boldsymbol{t}$ as:

$$P^T = t^T X \Big/ t^T t \text{ and } P^T_{old} \Big/ P^T_{old} \tag{9}$$

The orthogonal values of x-score are obtained by using the new values of $\boldsymbol{p}$ in an extra loop expressed as:

$$t^T = Xp \Big/ p^T p \tag{10}$$

Where p is the loading factor, t represents the x-scores, y represents a single response of the jth variable, w denotes the weights of the predictors and q denotes the weights of the response.

Next, the NIPALS regression employs the "Variable Importance in the Projection" (VIP) as an indicator for the predictors modelling power. This is expressed as:

$$VIP_j = \sqrt{N \sum_{j=1}^{k} \frac{SS_c \left(\frac{w_{cj}}{w_{cj}^2} \right)}{\sum_{c=1}^{k} SS_c}} \tag{11}$$

Where N denotes the number of predictor variables, k represents the number of partial least square dimensions extracted, w_{cj} represents the weight of the variables (j) for partial least square dimensions (c) and SS_c denotes the sum of squares explained by the partial least square dimensions (c). The VIP is a very essential indicator for selecting viable and influential variables for further analysis. Based on the accepted cut-off available in the literature [[38–41]], the less influential variables with VIP values lower than 0.8 were excluded from the energy consumption model. Aside from the VIP, the study employs the leave-one-out cross-validation technique for training and validation of the energy consumption model. Finally, diagnostic tests are applied to the NIPALS regression model to examine the stability and the reliability of the model to make unbiased statistical inferences.

5. Results and discussion

5.1. Determination of regressor importance

Table 2 shows the OLS estimation of energy consumption. It shows that the models are best-fit, with corresponding r-squared values of 89, 90 and 96%, respectively. A closer look at the fossil fuel energy demand model shows that population density, urbanization, and real oil prices are not significant (>10%) at the individual relationship level. Nonetheless, increases in population growth, gross national income, and carbon dioxide emissions cause an increase in fossil fuel energy consumption by 1.5%, 1.2%, and 1.3%, respectively. On the contrary, as expected, electricity production from hydropower sources and electricity production from renewable energy excluding hydropower reduces fossil fuel energy consumption by 1.1% and 0.6% respectively.

In the energy consumption model, population density, population growth, urbanization and carbon dioxide emissions are not statistically significant at the individual relationship. However, gross national income per capita and electricity production from renewable energy excluding hydropower increase energy consumption by 10.5% and 13.5% while an increase in real oil prices and electricity production from hydropower sources decreases energy consumption by 4% and 3.2%.

Results from the electricity consumption model show that population growth, urbanization, and real oil prices are not significant at the individual relationship level. However, a percentage rise in population density, gross national income per capita, electricity from hydropower, and electricity from renewable energy sources excluding hydro increase electricity consumption by 20.7%, 4.9%, 6.3%, and 3.5%, respectively.

The variance inflation factor analysis of the energy demand model reveals evidence of multicollinearity (rule of thumb: VIF<10) among the variables. As such, the application of OLS will produce bias results. This problem motivates the study to employ the NIPALS regression that deals with issues related to strong collinearity and variables that are not integrated of order 1. NIPALS is a type of partial least of squares regression that, "fits linear models based on linear combinations, called factors of the independent variables" which are derived via the "maximization of the covariance" between the predictor and the response variables [37] and making use of their correlations to make known the causal "latent" structures.

Fig. 1 shows that the minimum root mean PRESS is 0.4038 and the minimizing number of factors is 6. After confirming the number of optimal factors, the study proceeds to examine the variable importance of projection (VIP) to select the variables that are important (VIP>0.8). Fig. 2 reveals that all the variables are important in explaining fossil fuel, energy, and electricity consumption in Kenya. Using the classification by Eriksson, Johansson [39], the study categorises the important variables based on "highly influential" $(VIP > 1)$ and "moderately influential" $(0.8 < VIP < 1)$. Table 3 reveals that gross national income per capita, real oil prices, and electricity from hydropower sources are highly influential,

Table 2
Results of the linear regression model.

Term	FFCOM					EGCOM					ELECOM				
	Coef	SE Coef	T-Value	P-Value	VIF	Coef	SE Coef	T-Value	P-Value	VIF	Coef	SE Coef	T-Value	P-Value	VIF
Constant	17.8400	0.1170	152.1700	0.0000		452.1990	0.7600	594.9100	0.0000		120.0750	0.7290	164.6100	0.0000	
POPDN	0.2900	1.9400	0.1500	0.8830	266.2600	−16.5000	12.5000	−1.3200	0.1970	266.2600	20.7000	12.0000	1.7200	0.0950	266.2600
POPGR	1.4920	0.7030	2.1200	0.0410	35.1400	1.9700	4.5600	0.4300	0.6680	35.1400	6.0100	4.3700	1.3700	0.1780	35.1400
GNIP	1.1880	0.3800	3.1300	0.0040	10.2600	10.5000	2.4600	4.2600	0.0000	10.2600	4.9000	2.3600	2.0700	0.0460	10.2600
ELCHYRO	−1.1310	0.2200	−5.1400	0.0000	3.4400	−3.1900	1.4300	−2.2400	0.0320	3.4400	6.3000	1.3700	4.6000	0.0000	3.4400
ELCRE	−0.5590	0.3120	−1.7900	0.0820	6.9000	13.5300	2.0200	6.7000	0.0000	6.9000	3.5300	1.9400	1.8200	0.0770	6.9000
URB	−2.3600	1.4100	−1.6800	0.1030	141.4400	−3.2700	9.1400	−0.3600	0.7230	141.4400	−3.7600	8.7800	−0.4300	0.6710	141.4400
ROP	−0.1580	0.2290	−0.6900	0.4970	3.7400	−4.0000	1.4900	−2.6900	0.0110	3.7400	−1.7400	1.4300	−1.2200	0.2300	3.7400
CO2	1.3020	0.4480	2.9000	0.0060	14.3000	3.6800	2.9100	1.2700	0.2140	14.3000	3.0300	2.7900	1.0900	0.2850	14.3000
Source	DF	Adj SS	Adj MS	F-Value	P-Value	DF	Adj SS	Adj MS	F-Value	P-Value	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	8	173.051	21.6313	35.77	0.0000	8	7889.26	986.16	38.79	0.0000	8	17727	2215.87	94.65	0.0000
Error	35	21.166	0.6048	S	R-sq	35	889.77	25.42	S	R-sq	35	819.4	23.41	S	R-sq
Total	43	194.217		0.7777	89.10%	43	8779.04		5.0420	89.86%	43	18546.4		4.8386	95.58%

Source: Author's computation.

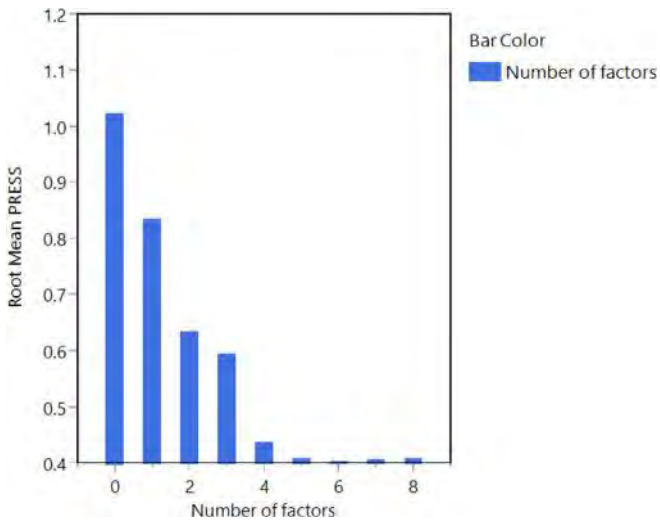

Fig. 1. Factors of the NIPALS model.
Source: Author's computation.

Table 3
Classification of variable importance.

X	VIP	Plot	Classifications
POPDN	0.8721		Moderately influential
POPGR	0.9131		Moderately influential
GNIP	1.1097		Highly influential
ELCHYRO	1.1793		Highly influential
ELCRE	0.9404		Moderately influential
URB	0.9513		Moderately influential
ROP	1.1558		Highly influential
CO2	0.8113		Moderately influential

Source: Author's computation

while carbon dioxide emissions, population density, population growth, electricity from renewable energy sources excluding hydropower and urbanization are moderately influential variables in explaining the fossil fuel, energy, and electricity consumption.

5.2. Drivers of energy consumption

Next, we examine the drivers of the different energy consumption types. Table 4 shows the sensitivity analysis of the different models with their corresponding coefficient of estimation. Table 4 reveals that both the fossil fuel and energy consumption models follow the same pattern contrary to the trend exhibited by the electricity consumption model. In the fossil fuel and energy consumption models, population growth, gross national income per capita, electricity from renewable energy sources excluding hydropower and carbon dioxide emissions are above the threshold line, signifying their positive monotonic effect on fossil fuel and energy consumption. However, in the electricity consumption model, all the variables are above the threshold except for population growth and real oil prices.

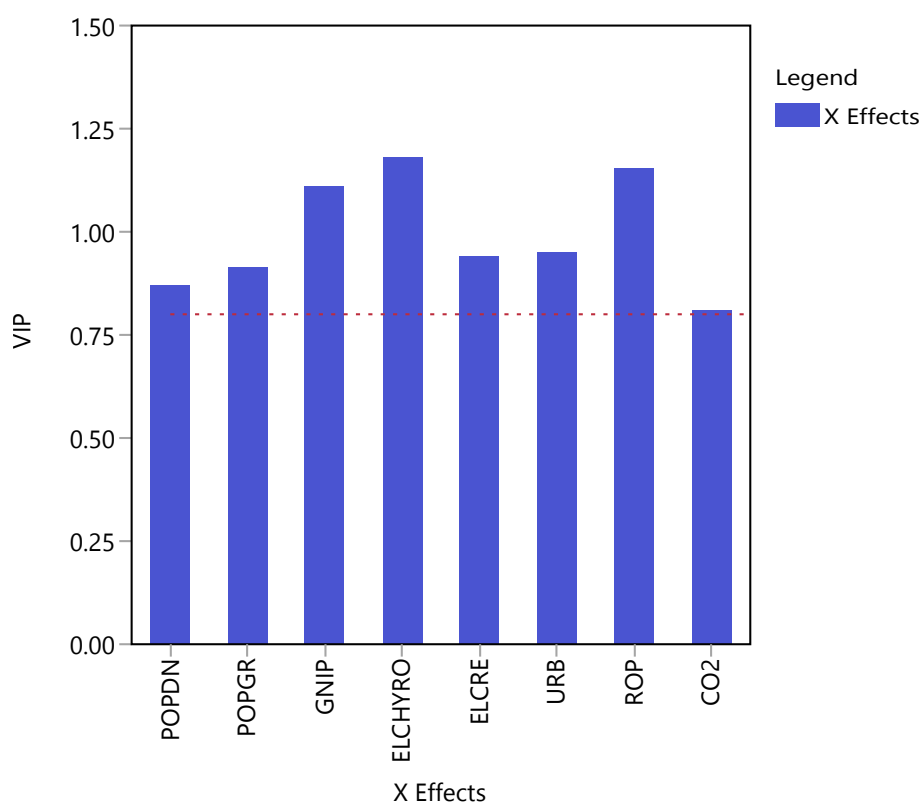

Fig. 2. Variable Importance Plot.
Source: Author's computation.

Table 4
NIPALS estimation results.

Coefficient	FFCOM	FFCOM	EGCOM	EGCOM	ELECOM	ELECOM
Intercept	0.0000		0.0000		0.0000	
POPDN	−0.6215		−0.6981		0.1077	
POPGR	0.4084		0.4605		−0.0769	
GNIP	0.4964		0.6796		0.2209	
ELCHYRO	−0.4703		−0.1561		0.3743	
ELCRE	0.1140		1.1380		0.5182	
URB	−0.7854		−0.9646		0.1081	
ROP	−0.0556		−0.3370		−0.0528	
CO2	0.5560		0.4939		0.1029	

The coefficients of the trio consumption model presented in Table 4 agree on 4 situations. First, an increase in gross national income per capita increases fossil fuel, energy consumption and electricity consumption by 0.5%, 0.7%, and 0.2%, respectively. This confirms the empirical finding that higher income creates more scale effects than technical effects resulting in the use of more energy-consuming appliances ([12,13,27], *inter alia*). Though some energy efficiency investments are expected when income increases, the positive effect of income implies that in the case of Kenya, economic growth that translates into higher income is likely to raise the levels of energy demand.

Second, an increase in carbon dioxide emissions increases fossil fuel, energy consumption and electricity consumption by 0.6%, 0.5%, and 0.1%. This implies that climate change induced by higher atmospheric greenhouse gas accumulation will cause a backfire in energy consumption since more energy may be needed for cooling and heating.

Third, an increase in electricity from renewable sources excluding hydropower increases fossil fuel, energy consumption and electricity consumption by 0.1%, 1.1%, and 0.5%. The positive effect of renewables on aggregate energy consumption and electricity consumption could be explained from the economies of scale perspective. Optimal renewable energy mixes provide more sustainable energy sources, and this increases the supply of energy in the country. Since energy cannot be stored, consumption levels increase. Also, renewable energies have the potential to reduce the price of energy below the equilibrium level [42]. The reduction in prices causes a resurgence in energy use. The positive effect of renewable energy on fossil fuel contrasts with our a priori expectation. One would expect more renewables to displace the consumption of fossil fuels in Kenya. However, in the case of Kenya, we can provide the following possible explanation, which could be debated though. Most of the renewable energy sources employed in Kenya have challenges with regards to seasonal variability. As such, fossil fuel energy sources are used as backup generators to play auxiliary roles during the intermittency of weather patterns. The penetration of renewable energy sources (solar, wind and geothermal energy) play a crucial role in Kenya's energy demand.

Fourth, an increase in real oil price reduces fossil fuel, energy consumption, and electricity consumption by 0.06%, 0.3%, and 0.05%, respectively. This confirms the findings in the empirical literature that the government can use taxes on energy prices to stimulate energy efficiency and energy conservation practices.

Further results from Table 4 show that fossil fuel and energy consumption models agree on the remaining outcomes. First, an increase in population density will decrease fossil fuel and energy consumption by 0.6% and 0.7% but increase electricity consumption by 0.1%. The result suggests that, in the case of Kenya, we are likely to experience economies of scale in aggregate energy consumption and fossil fuel consumption when the population density increases. This makes sense since higher population density implies reduced travel times and a higher use of bicycles and other traditional means of travels as cities become closer to each other and business centers.

Second, an increase in population growth will increase fossil fuel and energy consumption by 0.4% and 0.5% but decrease electricity consumption by 0.08%. This implies that higher population causes scale effect and raises the energy consumption levels of aggregate and fossil fuel. The result for electricity contrasts with our a priori expectation. However, a possible explanation (which is debatable though) could be that higher population increases the demand load in the short-run and where the electrical system remains very fragile, frequent power outages might increase (as in the case of Kenya). Electricity thus becomes an unsustainable energy source and consumers may switch to other types in the future, which would result in lower electricity consumption in the long-run. Thus, the negative effect of population on electricity consumption in the case of Kenya should be interpreted loosely to mean a substitution away from electricity to other energy types due to the unreliable nature of the electrical system in Kenya.

Third, an increase in urbanization will decrease fossil fuel and energy consumption by 0.8% and 1.0% but increase electricity consumption by 0.1%. This confirms the earlier claim that, in the case of Kenya, the concentration of people in small places provide economies of scale, and this helps to reduce energy consumption levels in the country. However, this is more so for aggregate energy consumption and fossil fuel and not electricity consumption.

Finally, an increase in electricity from hydropower will decrease fossil fuel and energy consumption by 0.5% and 0.2% but increase electricity consumption by 0.4%. The negative relationship between fossil fuel and hydropower supply is expected. It signifies the substitution that exists between both fuels. Generating electricity from hydropower is cheaper than from oil sources. Therefore, an increase in the generation of power from hydro source will decrease the reliance on fossil fuel. However, the overall effect on

total energy consumption depends on the shares of fossil and electricity in total energy consumption and the magnitude of the decline in fossil as hydropower increases electricity consumption. As it is in the case of Kenya, wood fuel and other biomass constitute about 68%, while petroleum and electricity constitute about 22% and 9%, respectively. Thus, a smaller increase in hydro that causes an equal or lesser decline in fossil fuel will not decrease total energy consumption. However, a greater degree of substitution that leads to significant decline in fossil fuel may decrease total energy consumption.

5.3. Model evaluation

Finally, we examine the model fit. The two goodness of fit estimations [(MAPE = 3.05%; 0.74%; 2.81%) and (RMSD = 0.11; 0.69; 0.62)] revealed that the estimated models are best-fit. This is also evident in Figs. 3–5, which shows that the predicted model tracks the actual movements in the actual data. The fitted model can explain about 89.1% of the variation in the dependent variables. Fig. 6 shows the plot of the model residuals. The residual values are scattered randomly about zero showing the independence of the residuals. The Normal Quantile plot confirms that the residuals are normally distributed.

6. Concluding remarks

This study examined the drivers of aggregate energy consumption, fossil fuel and electricity consumption in Kenya. Given the continuous increase in the demand-supply gap in the energy sector, an investigation into the drivers of demand is critical for the design of energy efficiency and energy conservation policies. To do this, we applied the NIPALS approach which deals with the problem of multicollinearity. The data period covers 1971–2014. The following results emerged from the study.

Crude oil price showed a consistently negative effect on total energy consumption, fossil fuel consumption, and electricity consumption. The negative price effect suggests that, in the case of Kenya, the government can use taxes on the prices of these energy types to promote energy conservation and energy efficiency practices. In other words, the policy by the government to subsidize the price of energy may compromise energy efficiency and conservation improvements. It is estimated that a 3% reduction in Kenya's peak energy demand saves the country US$48,355,950 in expanding generation capacity and US$9,671,190 in annual fuel costs. Therefore, energy conservation and efficiency are critical to improve the efficiency of Kenya's Power and make energy cheaper

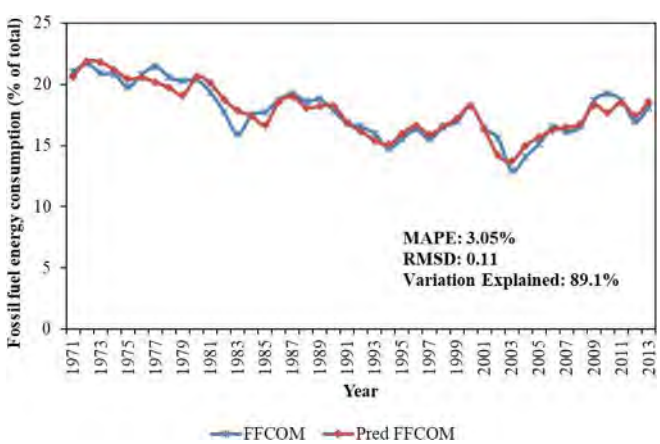

Fig. 3. The plot of fitted and actual values – fossil fuel consumption.

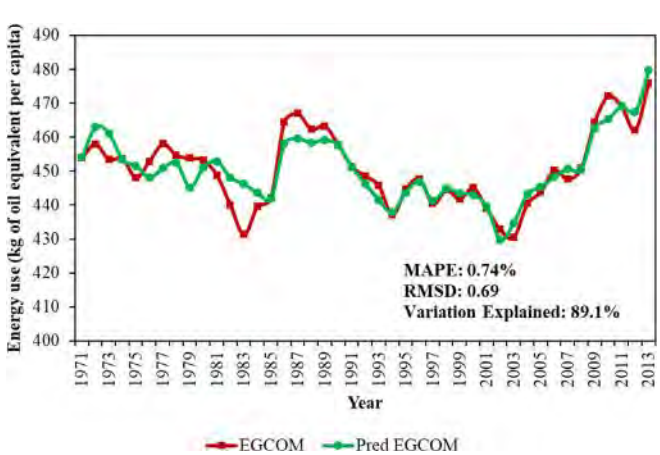

Fig. 4. The plot of fitted and actual values –total energy consumption.

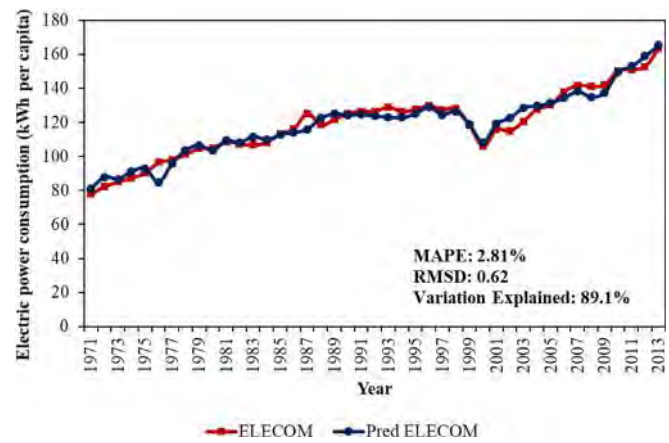

Fig. 5. The plot of fitted and actual values –Electricity consumption.

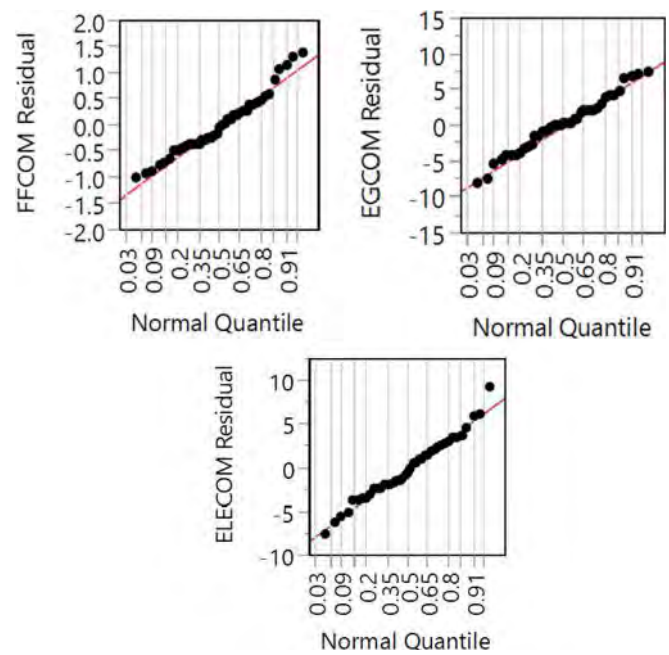

Fig. 6. Diagnostic Plots for Testing Residual Normal Quantile.
Source: Author's computation.

for end-users.

Population density and urbanization reduce aggregate and fossil fuel energy consumption and not electricity. This implies that, in the case of Kenya, the concentration of people in smaller places is likely to generate economies of scale for aggregate energy consumption and fossil fuel consumption. However, this is largely dependent on the social and economic infrastructure that has been developed. To benefit from these economies of scale, the government should significantly improve the economic infrastructure as well as the social infrastructure in major cities in the country.

Further, increasing the share of electricity from hydro reduces fossil fuel and hence aggregate energy consumption. Thus, increasing the share of hydro in total electricity generation might help conserve energy or improve energy efficiency. However, for other renewables that excludes hydro, the effect is positive, and this could be explained as due to economies of scale and lower energy prices associated with other renewable energy sources. Both income and carbon dioxide emissions exert positive effects on energy consumption. The latter implies that measures to improve the environmental quality would prevent possible backfire in energy consumption caused by climate change. More ambitious measures like creating a green bank that supports green investment in the country could help improve the environment greatly.

The positive effect of population on total energy and fossil fuel consumption suggests that measures like population control as well as energy demand management initiatives could help mitigate the scale effect associated with population. Although, as shown in the study, for a vulnerable electrical system, a similar policy prescription might not be useful to attain lower consumption levels since there would be a substitution away from electricity to other energy types.

Declaration

There is no conflict of interest.

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Nomenclature

Abbreviations

ARDL	Autoregressive Distributed Lag
DOLS	Dynamic Ordinary Least Squares
DPD	Dynamic Panel Data
FMOLS	Fully Modified Ordinary Least Squares
GMM	Generalized Method of Moments
LCB	Lower Confidence Bound
LPG	Liquid Petroleum Gas
MAE	Mean Absolute Error
MAPE	Mean absolute percentage error
MASE	Mean Absolute Scaled Error
NIPALS	Nonlinear Iterative Partial Least Squares
PV	photovoltaic
QREG	Quantile Regression
RMSD	Root mean square deviation
RMSE	Root Mean Squared Error
SMAPE	Symmetric Absolute Mean Percentage Error
UCB	Upper Confidence Bound
VAR	Vector Autoregression
VECM	Vector Error Correction Model
VIF	variance inflation factor

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Appendix 2 — Publication Nine: Investigation of environmental Kuznets curve for ecological footprint: The role of energy and financial development

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Investigation of environmental Kuznets curve for ecological footprint: The role of energy and financial development

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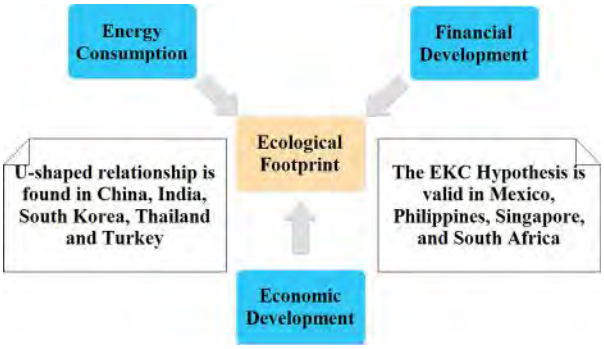
HIGHLIGHTS

- This study examines the validity of environmental Kuznets curve hypothesis.
- There is bidirectional causality between economic growth and ecological footprint.
- The study found a unidirectional causality from economic growth to energy consumption.

GRAPHICAL ABSTRACT



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ABSTRACT

Climate change has become a global phenomenon due to its threat to sustainable development. However, economic development plays a complementary role in both climate change and sustainability. Thus, the environmental Kuznets curve hypothesis is critical to climate change policy formulation and development strategies. Accordingly, this study examined the validity of environmental Kuznets curve hypothesis by investigating the relationship between economic growth, energy consumption, financial development, and ecological footprint for the period from 1977 to 2013 in 11 newly industrialized countries. For this purpose, the study employed both augmented mean group (AMG) estimator and heterogeneous panel causality method which are suitable for dependent and heterogeneous panels. The results of the estimator show that there is an inverted U-shaped relationship between economic growth and ecological footprint. According to the causality test results, it is concluded that there is bi-directional causality between economic growth and ecological footprint.
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1. Introduction

In recent decades, increasing visible signs of climate change and global warming have contributed to raising the awareness of

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environmental degradation (Ipcc, 2014). Similarly, the effect of economic activities on environmental degradation has become one of the most attractive topics for researchers. In this regard, the environmental Kuznets curve hypothesis is the most examined hypothesis which explains the relationship between income level and environmental pollution. According to the EKC hypothesis, environmental degradation is increased with the first stages of economic growth to a certain point, and after turning point, the economic development leads to environmental improvements, thus, an inverted U-shaped relationship between economic growth and environmental degradation (Panayotou, 1993).

Most of the studies on the relationship between economic growth and pollution have focused on utilizing carbon dioxide emissions as an indicator of environmental degradation (Salahuddin et al., 2015; Wang et al., 2016). However, carbon dioxide emissions is a portion of environmental degradation. In recent years, the ecological footprint of Wackernagel and Rees (1998) is accepted as the more comprehensive indicator to determine the degree of environmental degradation because it considers cropland, grazing land, fishing grounds, forestland, carbon footprint, and built-up land. Based on the above reasons, the main aim of this study is to examine the effect of economic growth and other possible predictors (energy consumption and financial development) on the ecological footprint for the period 1977–2013 in 11 newly industrialized countries namely South Korea, Singapore, Brazil, China, Turkey, Thailand, Malaysia, Mexico, India, South Africa and Philippines.

The developmental dynamics of the 11 newly industrialized countries make them viable candidates to be studied, to understand their role in ecological footprints and provide more insight into climate change mitigation. The contributions of this study to the existing literature are as follows; first, this is the first study to examine the relationship between economic growth and ecological footprint in newly industrialized countries. Second, as an estimation of a bivariate empirical model may lead to unreliable results, this study uses a multivariate empirical model using energy consumption and financial development as explanatory variables. Third, unlike previous studies, the methodologies used in this study consider cross-sectional dependency and country-specific heterogeneity among countries. Moreover, the empirical findings of each country can be separated using a parameter estimator and causality procedure, therefore, the obtained results will be more policy-oriented.

2. Literature review

There are several studies on the EKC hypothesis in many developed, developing and least developed economies. However, there are different outcomes leading to different policy implications. This suggests the complexity of the EKC hypothesis based on methodologies, the period of the data, and the geographical dynamics. Two categories of previous research are discussed (Table 1).

The first strand of studies examines environmental pollution, energy consumption, and macroeconomic nexus using both time series and panel data. Remuzgo and Sarabia (2015) revealed a decline of global carbon dioxide emissions by 22% due to economic development. Wang et al. (2016) revealed that shocks in carbon dioxide emissions have a small effect on GDP and energy consumption. In China, energy intensity was revealed as the main contributor to carbon dioxide emissions (Ouyang and Lin, 2015). In USA, China, Japan and India, Azam et al. (2016) confirmed a positive relationship between carbon dioxide emissions and economic growth. In Senegal, Sarkodie and Owusu (2017) revealed an increase in carbon dioxide emissions from the effect of energy consumption, financial development, and industrialization while urbanization and GDP reduce carbon dioxide emissions in the long-term. In Nigeria, it was evident that industrialization had no effect on carbon dioxide emission (Lin et al., 2015). In Sri Lanka, there was evidence of a long-run equilibrium relationship, a bidirectional causality between industrialization and energy consumption, and unidirectional causality from carbon dioxide emissions to energy consumption (Sarkodie and Owusu, 2016). In Pakistan, Mohiuddin et al. (2016a) showed evidence of long-run relationship and a unidirectional causality from energy consumption to carbon dioxide emissions. In Malaysia, there was evidence of a unidirectional causality from energy consumption to carbon dioxide emissions (Gul et al., 2015). Jammazi and Aloui (2015) confirmed a bidirectional causality between electricity consumption and economic growth and Salahuddin et al. (2015) a unidirectional causality from electricity consumption to carbon dioxide emissions.

The second strand of studies investigates the environmental Kuznets curve hypothesis. For example, Saidi and Mbarek (2016) tested the validity of EKC in 19 countries from 1990 to 2013 using the ARDL method. Their study found no proof of EKC in the 19 emerging economies. Baek (2015) found no existence of the EKC hypothesis in the 12 nuclear energy intense countries, however, nuclear energy reduces carbon dioxide emissions in the long-run. Apergis and Ozturk (2015) revealed the existence of EKC in the Asian countries while Osabuohien et al. (2014); Sarkodie (2018) validated the existence of EKC in Africa. Tiwari et al. (2013) confirmed the existence of EKC in both long run and short run equilibrium relationship in India. Shahbaz et al. (2012) confirmed the presence of EKC in a long run equilibrium relationship in Pakistan. Hamit-Haggar (2012) revealed the presence of EKC in a long run relationship and a unidirectional causality from energy consumption to greenhouse gas emissions. Pao and Tsai (2011) validated the EKC and found a bidirectional causality between foreign direct investment and carbon dioxide emissions. Nasir and Rehman (2011) revealed a positive effect of energy consumption and foreign trade on carbon dioxide emissions and confirmed the validity of the EKC. Acaravci and Ozturk (2010) revealed a long-run equilibrium relationship running from energy consumption and economic growth on carbon dioxide emissions and validated the presence of EKC in Denmark and Italy.

It is important to note that the above-mentioned literature employs a single environmental pollution indicator (carbon dioxide emissions) to examine the EKC hypothesis which is limited to consumption-based approach making it difficult to understand the dynamics of environmental pressures since available biocapacity is not considered. Significantly, the country's biocapacity affects the outcome of the EKC hypothesis. The analysis of the ecological footprint of emerging economies is critical to mitigating climate change and its impact.

3. Data and methodology

To examine the validity of environmental Kuznets curve (EKC) hypothesis, the annual data for the period 1977 to 2013 is investigated for 11 newly industrialized countries: Brazil, China, India, Malaysia, Mexico, Philippines, Singapore, South Africa, South Korea, Thailand, and Turkey. The 11 newly industrialized countries can be categorized under Very High Human Development, High Human Development and Medium Human Development based on the 2016 Human Development Index (HDI) report. Very High Human Development includes South Korea and Singapore, High Human Development includes Brazil, China, Turkey, Thailand, Malaysia and Mexico, and the Medium Human Development includes India, South Africa, and Philippines (UNDP, 2016).

According to the HDI report, Singapore, a population of 5.6 million population is ranked 5th with HDI = 0.925, exports and imports account for 326.1% of GDP, environmental sustainability stands at 9.4 t of carbon dioxide emissions per capita, a Multidimensional Poverty Index (MPI) not applicable and an Income/Composition of Resources of $78,162 Gross national income (GNI) per capita (UNDP, 2016). Singapore's energy consumption was 47,513.8 GWh of electricity in 2015, comprising of 42.3% industrial related, 36.8% commerce and services, 15% household consumption, 5.1% transport and 0.6% others. Energy imports (173.7 Mtoe) in 2015 were 65.3% petroleum products, 28.5% crude oil, 6% natural gas, 0.4% coal and peat and 0.1% others.

Table 1
Summary of literature review.

Reference	Period	Study area	Variables	Method	Interpretations
Environmental pollution-energy consumption-macroeconomic nexus					
Wang et al. (2016)	1990–2012	China	CO_2, EC and GDP	VECM	Shocks in CO_2 has a small effect on EC and GDP
Azam et al. (2016)	1971–2013	USA, China, India and Japan	CO_2, TO, EC and HC	FMOLS	Positive relationship between CO_2 and GDP in USA, China and Japan
Salahuddin et al. (2015)	1980–2012	GCC countries	CO_2, EC, FD and GDP	DOLS, FMOLS and DFE	Insignificant short-run and a positive relationship between CO_2 and EC
Sarkodie and Owusu (2017)	1980–2011	Senegal	CO_2, EC, FD, IND, URB and GDP	NIPALS	EC, FD and IND increase CO_2 while URB and GDP reduces CO_2 in the long-term.
Jammazi and Aloui (2015)	1980–2013	GCC countries	CO_2, EC and GDP	Wavelet approaches	Bidirectional causality between EC and GDP, and unidirectional causality from EC to CO_2.
Remuzgo and Sarabia (2015)	1990–2010	World data	CO_2, EI, P and GDP	Decomposition	Global CO_2 declined by 22% from 1990 to 2010
Mohiuddin et al. (2016b)	1971–2013	Pakistan	CO_2, EI, P and GDP	VECM	Evidence of long-run relationship and unidirectional causality from EC to CO_2
Ouyang and Lin (2015)	1991–2010	China	GHG, CO_2, EI, P and GDP	LMDI and cointegration	EI is main contributor of CO_2
Lin et al. (2015)	1908–2011	Nigeria	CO_2, EI, P, IND and GDP	VECM	Inverse significant relationship between IND and CO_2
Sarkodie and Owusu (2016)	1971–2012	Sri Lanka	CO_2, EC, FD, IND and GDP	ARDL and Neural Network	Evidence of long-run, Bidirectional causality between IND and EC and unidirectional causality from CO_2 to EC
Gul et al. (2015)	1975–2013	Malaysia	CO_2, and EC	MEBM	Unidirectional causality from EC to CO_2
EKC hypothesis testing					
Saidi and Mbarek (2016)	1990–2013	19 emerging economies	CO_2, INC, TO, FD and URB	ARDL	No existence of EKC
Baek (2015)	1980–2009	12 countries	CO_2, EC, NUE and GDP	DOLS and FMOLS	No existence of EKC and nuclear energy reduces CO_2
Apergis and Ozturk (2015)	1990–2011	Asian countries	CO_2, LN, P, IND and GDP	GMM	Existence of EKC
Osabuohien et al. (2014)	1995–2010	African countries	CO_2, EC, P and GDP	Panel DOLS	Existence of EKC
Tiwari et al. (2013)	1966–2011	India	CO_2, CC, TO and GDP	ARDL	Existence of EKC
Shahbaz et al. (2012)	1971–2009	Pakistan	CO_2, EC, TO and GDP	ARDL	Existence of EKC
Hamit-Haggar (2012)	1990–2007	Canada	GHG, EC and GDP	FMOLS and cointegration	Existence of EKC and a unidirectional causality from EC to GHG
Pao and Tsai (2011)	1992–2007	BRIC	CO_2, EC, FDI and GDP	VECM and Granger causality	Existence of EKC and a bidirectional causality between FDI and CO_2
Nasir and Rehman (2011)	1972–2008	Pakistan	CO_2, FT, EC and INC	VECM	Existence of EKC and a positive effect of FT and EC on CO_2
Acaravci and Ozturk (2010)	1960–2005	Europe	CO_2, EC and GDP	ARDL	Long-run relationship and existence of EKC in Denmark and Italy

Energy exports (92 Mtoe) in 2015 were 98.8% petroleum products and 1.2% crude oil (Authority EM, 2016).

South Korea is ranked 18th (HDI = 0.901), has a population of 50.3 million, exports and imports constitute 84.8% of GDP, environmental sustainability stands at 11.8 t of carbon dioxide emissions per capita, an MPI not applicable and an Income/Composition of Resources of $34,541 GNI per capita (UNDP, 2016). South Korea ranks seventh in refined crude oil products production (141 Mt) and ranks tenth in electricity production (546 TWh) (Enerdata, 2017). South Korea's electricity generation of 546 TWh comprises of 39% coal, 31% nuclear energy, 19% natural gas, 6% crude oil, 4% other renewable energy sources and 1% hydroelectric power. South Korea produced only 1.9 million short tonnes in 2015 compared to its 146 million short tonnes consumed thus, importation of coal has increased in the last few years to meet the demand deficit. Moreover, there was the importation of crude oil (2.8 million barrels/day) and liquefied petroleum gas (1.6 trillion cubic feet) in 2015 due to the growing demand (EIA, 2017).

Malaysia is ranked 59th (HDI = 0.789), has a population of 30.3 million, exports and imports account for 134.4% of GDP, environmental sustainability stands at 8.0 t of carbon dioxide emissions per capita, MPI not applicable and an Income/Composition of Resources of $24,620 GNI per capita (UNDP, 2016). Malaysia ranks tenth in natural gas production (67 bcm) (Enerdata, 2017). Malaysia's primary energy production comprises of 40,113 ktoe natural gas, 26,765 ktoe crude oil, 15,357 ktoe coal and coke, 6699 ktoe petroleum products, 3038 ktoe hydropower, 300 ktoe biodiesel, 181 ktoe biomass, 63 ktoe solar PV and 12 Mbiogas (MEIH, 2014).

Turkey is ranked 71st (HDI = 0.767), has a population of 78.7 million, exports and imports constitute 58.8% of GDP, environmental sustainability stands at 4.2 t of carbon dioxide emissions per capita, MPI not applicable and an Income/Composition of Resources of $18,705 GNI per capita (UNDP, 2016). Turkey's electricity demand was 264 TWh in 2015 however, it is projected to reach 416 TWh in 2023. Currently, the primary energy demand is 125 Mtoe comprising of 35% natural gas, 28.5% coal energy, 27% oil, 7% hydropower generation and 2.5% from other renewable energy sources. The primary energy demand is projected to reach 218 Mtoe in 2023. Turkey's 99% of natural gas (48.4 bcm) and 86% of crude oil (25 million tonnes) consumed are imported (MFA, 2016).

Mexico is ranked 77th (HDI = 0.762), has a population of 127.0 million, exports and imports account for 72.8% of GDP, environmental sustainability stands at 3.9 t of carbon dioxide emissions per capita, MPI is 0.024 and an Income/Composition of Resources of $16,383 GNI per capita (UNDP, 2016). Mexico ranks tenth in crude oil production (127 Mt) (Enerdata, 2017) and its primary energy portfolio (188 Mtoe) comprises of 51% crude oil, 32% natural gas, 7% coal, 5% bioenergy, 4% other renewable energy sources (geothermal, solar PV and wind energy) and 1% nuclear energy (IEA, 2016).

Brazil is ranked 79th (HDI = 0.754), 207.8 million population, exports, and imports constitute 27.4% of GDP, environmental sustainability stands at 2.5 t of carbon dioxide emissions per capita, MPI is 0.010 and an Income/Composition of Resources of $14,145 GNI per capita (UNDP, 2016). Brazil ranks tenth in the global carbon dioxide emissions from fuel consumption (455 MtCO2) (Enerdata, 2017), ranks eighth in electricity production (586 TWh), eighth in refined crude oil products production (107 Mt), ninth in crude oil production (129 Mt) and third in the share of renewables in electricity production (73.5%) (Enerdata, 2017). Brazil's renewables including biofuel consumption increased by 157%, consumption of hydropower increased by 43%, gas consumption increased by 44%, oil consumption increased by 21%, nuclear energy

consumption increased by 113% and coal consumption decreased by 4% (BP, 2016).

Thailand is ranked 87th (HDI = 0.740), 68.0 million population, exports, and imports account for 131.9% of GDP, environmental sustainability stands at 4.5 t carbon dioxide emissions per capita, MPI is 0.004 and an Income/Composition of Resources of $14,519 GNI per capita (UNDP, 2016). Thailand's installed capacity as of December 2015 was 38,815 MW comprising 67% from natural gas, 5% from renewables and 28% from other sources. Consumption of imported coal amounted to 21.9 million tonnes thus, 5% increases compared to previous years due to the expansion of industrial sector consumption for production. Natural gas consumption increased by 2% thus, 4746 million cubic feet/day (EPPO, 2016).

China is ranked 90th (HDI = 0.738), 1376.0 million population, exports, and imports constitute 41.2% of GDP, environmental sustainability stands at 7.6 t carbon dioxide emissions per capita, MPI is 0.023 and an Income/Composition of Resources of $13,345 GNI per capita (UNDP, 2016). China is classified as the first of the top 5 emitters of global greenhouse gas emissions (CDIAC, 2017), ranks first in electricity production (5682 TWh), ranks first in the global carbon dioxide emissions from fuel consumption (8948 $MtCO_2$), second in refined crude oil products production (512 Mt), first in coal and lignite production (3538 Mt), ranks fourth in crude oil production (216 Mt) and has the highest energy consumption of 3101 Mtoe (Enerdata, 2017).

Philippines is ranked 116th (HDI = 0.682), 100.7 million population, exports, and imports account for 60.8% of GDP, 1.0 t carbon dioxide emissions per capita, MPI is 0.033 and an Income/Composition of Resources of $8395 GNI per capita (UNDP, 2016). Philippines economy has shifted from agrarian to industrialization with the last decade. Its primary energy demand comes from non-renewable energy sources such as oil and gas and renewable energy sources like geothermal, biomass, hydropower, wind, solar and biofuel. As at 2011, energy consumption constituted 31% oil, 22% from geothermal, 20% from coal, 12% from biomass, 6% from hydropower and 1% from wind, solar and biofuel (Energypedia, 2016).

South Africa is ranked 119th (HDI = 0.666), 207.8 million population, exports and imports constitute 62.8% of GDP, 8.9 t carbon dioxide emissions per capita, MPI is 0.041 and an Income/Composition of Resources of $12,087 GNI per capita (UNDP, 2016). South Africa has an installed capacity of 44,175 MW from which coal-fired plants constitutes 92.6%, 5.7% nuclear energy, 1.2% pumped, 0.5% hydroelectric power and 0.1% from gas turbine generation. Electricity consumption comprises of industrial activities (40.9%), residential use (36.8%), commercial use (11.4%), Transportation (2.7%) and others (8.1%). Renewable energy is projected to contribute 18.2 GW to the gross energy production (8.4 GW wind, 8.4 GW solar, 1 GW concentrated solar power and 0.4 biomass) (USEA, 2017). South Africa ranks seventh in the global coal and lignite production (248 Mt) and the highest in Africa (Enerdata, 2017).

India is ranked 131st (HDI = 0.624), 1311.1 million population, exports, and imports account for 48.8% of GDP, 1.6 t carbon dioxide emissions per capita, MPI is 0.282 and an Income/Composition of Resources of $5663 GNI per capita (UNDP, 2016). India is one of the top emitters of global greenhouse gas emissions (CDIAC, 2017), ranks third in electricity production (1368 TWh), ranks fourth in refined crude oil products production (239 Mt), third in coal and lignite production (764 Mt) and ranks third in the global carbon dioxide emissions from fuel consumption (2166 MtCO2) (Enerdata, 2017). India has an installed capacity of 329,204.53 MW from which 194,402.88 MW comes from coal, 25,329.38 MW from gas, 837.63 MW from diesel-fired plants, 6780 MW is from nuclear energy, hydropower constitutes 44,594.42 MW, and 57,260.23 MW are from newly exploited renewable energy technologies (4379.86 MW from small hydropower, 32,279.77 MW from wind energy, 8188.70 MW from biomass cogeneration, 130.08 MW from waste to energy and 12,288.83 MW from solar energy) (CEA, 2017).

Following the studies of Halicioglu (2009), Tamazian and Rao (2010), environmental pollution is described as a function of real GDP, the square of real GDP, energy consumption and financial development. The panel version of the empirical model can be written as follows;

$$\ln EF_{it} = \varphi_0 + \varphi_1 \ \ln Y_{it} + \varphi_2 \ \ln Y_{it}^2 + \varphi_3 \ \ln EC_{it} + \varphi_4 \ \ln FD_{it} + \mu_{it} \quad (1)$$

where t, i and μ_{it} refer to a period, cross-section and residual term, respectively. In addition, *lnEF* is log of ecological footprint, *lnY* (lnY^2) is log of real GDP per capita (log of the square of real GDP), *lnEC* is energy consumption per capita and *lnFD* is the credit of private sector to GDP ratio. The real GDP per capita is measured in millions of constant 2010 US dollars and energy consumption per capita is measured in kg of oil equivalent. The data of *Y*, *EC* and *FD* is obtained from World Development Indicators (World Bank, 2016), and the data of *EF* is retrieved from Global Footprint Network (Global Footprint Network, 2017).

The 1970's oil crises, the 2007 global financial crisis, and the Kyoto protocol show there is a high degree of integration on economic, financial and environmental indicators in the world. Based on this reason, this study first examines the existence of cross-sectional dependence among countries using by LM test of Breusch and Pagan (1980), CD_{LM} and CD test of Pesaran (2004) and LM_{adj} test of Pesaran et al. (2008). In addition, slope homogeneity is examined with $\Delta\sim$ and $\Delta\sim_{adj}$ test of Pesaran and Yamagata (2008).

This study uses the Augmented Mean Group (AMG) estimator developed by Eberhardt and Bond (2009), Bond and Eberhardt (2013) to consider the cross-sectional dependence and country-specific heterogeneity among countries. The other advantage of using this methodology is that it allows the examination of the parameters of non-stationary variables. Therefore, any pre-testing procedure (unit root or cointegration) is not required to use this approach. In the first step of the testing procedure, the main panel model (Eq. (1)) is estimated with the first-differenced form and *T-1* period dummy as follows;

$$\Delta EF_{it} = \gamma_1 \Delta Y_{it} + \gamma_2 \Delta Y^2{}_{it} + \gamma_3 \Delta EC_{it} + \gamma_4 \Delta FD_{it} + \textstyle\sum_{t=2}^{T} p_t(\Delta D_t) + u_{it} \quad (2)$$

where ΔD_t is first differences *T-1* period dummies; p_t is the parameters of period dummies. In the second step, estimated p_t parameters are converted to φ_t variable which indicates a common dynamic process as follows:

$$\Delta EF_{it} = \gamma_1 \Delta Y_{it} + \gamma_2 \Delta Y^2{}_{it} + \gamma_3 \Delta EC_{it} + \gamma_4 FD_{it} + d_i(\varphi_t) + u_{it} \quad (3)$$

$$\Delta EF_{it} - \varphi_t = \gamma_1 \Delta Y_{it} + \gamma_2 \Delta Y^2{}_{it} + \gamma_3 \Delta EC_{it} + \gamma_4 FD_{it} + u_{it} \quad (4)$$

The group-specific regression model is first adapted with φ_t and then the mean values of group-specific model parameters are computed. For instance, the parameter of economic growth (γ_1) can be computed as $\gamma_{1,\,AMG} = 1/N\sum_{i=1}^{N}\gamma_{1,\,i}$.

To examine the causal connections between variables, this study uses heterogeneous panel causality of Dumitrescu and Hurlin (2012). This methodology is a modified version of Granger causality and adapted to heterogeneous panel data. In addition, the Monte Carlo simulations show that this methodology gives consistent results under cross-sectional dependency. The computation of the statistic is as following;

$$W_{N,T}^{HNC} = \frac{1}{N}\sum_{i=1}^{N} W_{i,t} \quad (5)$$

$$Z_{N,T}^{HNC} = \sqrt{\frac{N}{2K}}\left(W_{N,T}^{HNC} - K\right) \rightarrow N(0,1) \quad (6)$$

where $W_{i,\,t}$ is the Wald statistic and $W_{N,\,T}^{HNC}$ statistic is obtained with averaging each Wald statistics for cross-sections. In the testing procedure,

the null hypothesis of "there is no homogeneous causality" is tested against the alternative hypothesis that the causal relationships are heterogeneous.

4. Results and discussion

In the first step of the analysis, the cross-sectional dependence and country-specific heterogeneity were examined, and the empirical findings are shown in Table 2. According to the results, the null hypothesis that there is no cross-sectional dependence among countries is rejected for all tests. This means a shock that occurs in one of sample country may spill-over to the other countries. In addition, the homogeneity test results show that there is a country-specific heterogeneity among countries.

In the second step of our analysis, the effect of real GDP, square of real GDP, energy consumption and financial development on ecological footprint is investigated with AMG estimator. According to the results presented in Table 3, the coefficient of real GDP is positive and the coefficient of the square of real GDP is negative in Mexico, the Philippines, Singapore, and South Africa. However, the coefficient of real GDP is negative and the coefficient of the square of real GDP is positive in China, India, South Korea, Thailand, and Turkey. Therefore, an inverted U-shaped relationship is found in Mexico, Philippines, Singapore, and South Africa. Meaning that income levels increase environmental degradation at the initial stages of economic development but declines after attaining a specific turning point of income level. Sarkodie (2018) revealed that the decline in environmental pollution versus economic development can be attributed to a structural change in economic growth and technological advancement. According to Sarkodie and Strezov (2019a), as income levels increases, environmental awareness increases, thus, driving the populace to demand clean environment resulting in the enforcement of environmental laws, policies, and regulations which in turn reduces environmental pollution. On the other hand, a U-shaped relationship is supported in China, India, South Korea, Thailand, and Turkey. This results may be attributed to vintage and obsolesce energy technologies that influence economic productivity. Sarkodie and Strezov (2019b) revealed that the U-shape relationship occurs when energy intensity increases per economic outcome, thus, reducing energy efficiency. Apart from this, since China, India, South Korea, Thailand, and Turkey are industrialized countries, pollution haven hypothesis may have influenced the shape of the EKC hypothesis as revealed by Sarkodie and Strezov (2019a, 2019b). According to (Dinda, 2004); Sarkodie and Strezov (2019a), developed countries with stringent environmental policies and regulations transfer their dirty technologies to developing countries with lax environmental laws, hence, adding to their pollution stock. In addition, an increase in energy consumption leads to an increase in environmental degradation in China, India, Mexico, Singapore, and Thailand, which is in line with Sarkodie and Adams (2018). Sarkodie and Adams (2018) revealed that while clean and renewable energy technologies promote a clean environment, fossil fuel energy technologies increases environmental pollution. However, the negative coefficient of financial development on environmental degradation is found in China and Malaysia. When the group panel estimation results are evaluated, the inverted U-shaped EKC hypothesis is confirmed in newly industrialized countries.

Table 2
Cross-sectional dependence and slope homogeneity.

	Statistic	*p*-Values
Cross-sectional dependence		
LM	161.604***	0.000
CD_{LM}	10.164***	0.000
CD	5.679***	0.000
LM_{adj}	28.913***	0.000
Homogeneity		
$\hat{\Delta}$	27.130***	0.000
$\hat{\Delta}_{adj}$	28.682***	0.000

*** Indicates significance at 1% level.

Table 3
AMG estimation results.

	lnY	lnY^2	lnEC	lnFD
Brazil	0.905	−0.031	0.357	−0.002
	[6.418]	[0.351]	[0.310]	[0.018]
China	−0.211**	0.029***	0.518***	−0.095**
	[0.104]	[0.008]	[0.059]	[0.038]
India	−0.853***	0.072***	0.662***	−0.014
	[0.323]	[0.024]	[0.134]	[0.041]
Malaysia	2.267	−0.063	−0.044	−0.145**
	[2.771]	[0.156]	[0.171]	[0.059]
Mexico	53.611*	−2.904*	0.877**	−0.046
	[29.420]	[1.642]	[0.389]	[0.051]
Philippines	28.515***	−1.907***	0.056	0.070
	[6.858]	[0.458]	[0.283]	[0.051]
Singapore	5.722**	−0.197*	0.354***	0.428**
	[2.530]	[0.106]	[0.126]	[0.173]
South Africa	42.754*	−2.381*	−0.073	0.029
	[22.845]	[1.297]	[0.102]	[0.051]
South Korea	−3.020***	0.223***	0.110	−0.036
	[0.554]	[0.036]	[0.177]	[0.048]
Thailand	−1.664*	0.141**	0.266**	0.019
	[0.935]	[0.064]	[0.114]	[0.046]
Turkey	−5.418*	0.331*	0.408	0.003
	[3.216]	[0.175]	[0.260]	[0.030]
PANEL	11.146*	−0.607*	0.828***	0.019
	[6.201]	[0.355]	[0.282]	[0.044]

Note: *, ** and *** indicates statistical significance at 10, 5 and 1% level, respectively. Numbers in brackets are standard errors.

In the third step of the analysis, the causal relationship between ecological footprint, economic growth, energy consumption, and financial development is examined with heterogeneous panel causality method. The results are illustrated in Table 4. Accordingly, there is a bi-directional causality between economic growth and ecological footprint, thus, confirming the feedback hypothesis. Economic development in industrialized economies accelerates natural resource extraction and exploitation, as such reduces the biocapacity of the environment while increasing the ecological footprint (Panayotou, 1993). However, if sustainable and management options are integrated into production and consumption, the rate of natural resource depletion and environmental stress declines, hence, allowing resources to regenerate (United Nations, 2015). Unidirectional causal relationships are found from energy consumption to ecological footprint, from ecological footprint to financial development, from economic growth to energy consumption and from economic growth to financial development. Most of the newly industrialized countries depend on the conventional form of energy sources such as coal, oil and gas. However, unlike the renewable energy technologies that are ubiquitous and sustainable, fossil fuel energy technologies are finite and unsustainable, as such, its exploitation increases the ecological footprint (Owusu and Asumadu, 2016). A unidirectional causality from economic growth to energy consumption confirms the conservation hypothesis (Inglesi-Lotz and Pouris, 2016). Meaning that economic growth drives energy consumption patterns rather than the opposite. As such, energy conservation options in the 11 newly industrialized countries will have no effect on economic development.

5. Conclusions and policy implications

This study aims to examine the relationship between ecological footprint, economic growth, energy consumption and financial development in 11 newly industrialized countries. For this purpose, the annual period from 1977 to 2013 is investigated using the augmented mean group estimator and heterogeneous panel causality method. Because both methods are suitable to investigate the relationship between

Table 4
Heterogeneous panel causality test results.

	Wald Stat.	*p*-Value
lnY⇏ lnEF	7.725***	0.000
lnEF⇏ lnY	5.245**	0.022
lnEC ⇏ lnEF	6.218***	0.000
lnEF⇏ lnEC	4.447	0.169
lnFD⇏ lnEF	3.440	0.820
lnEF⇏ lnFD	5.229**	0.023
lnEC ⇏ lnY	3.307	0.938
lnY⇏ lnEC	4.969**	0.049
lnFD⇏ lnY	1.904	0.129
lnY⇏ lnFD	5.989***	0.001
lnFD⇏ lnEC	2.521	0.414
lnEC ⇏ lnFD	2.482	0.389

Note: *, ** and *** indicates statistical significance at 10, 5 and 1% level, respectively. Numbers in brackets are standard errors.

variables in the case of cross-sectional dependence and country-specific heterogeneity, we first test the dependence and slope homogeneity among the countries.

According to the augmented mean group estimator results, it is concluded that an inverted U-shaped environmental Kuznets curve hypothesis is supported by the panel of newly industrialized countries. It is important to note that increased levels of energy use lead to an increase in ecological footprint for these countries. When the estimator results of each country were evaluated, we found an inverted U-shaped EKC hypothesis valid in Mexico, Philippines, Singapore, and South Africa while a U-shaped relationship is found in China, India, South Korea, Thailand, and Turkey. In addition, increased energy consumption leads to an increase in environmental degradation in China, India, Mexico, Singapore, and Thailand. However, the negative coefficient of financial development on environmental degradation is found in China and Malaysia. Causality test results show that there is evidence of a bi-directional causality link between economic growth and ecological footprint. Finally, we found one-way causality running from energy consumption to ecological footprint, from ecological footprint to financial development, from economic growth to energy consumption and from economic growth to financial development.

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Declaration

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Appendix 3 — Publication Ten: Does energy consumption follow asymmetric behavior? An assessment of Ghana's energy sector dynamics

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Does energy consumption follow asymmetric behavior? An assessment of Ghana's energy sector dynamics

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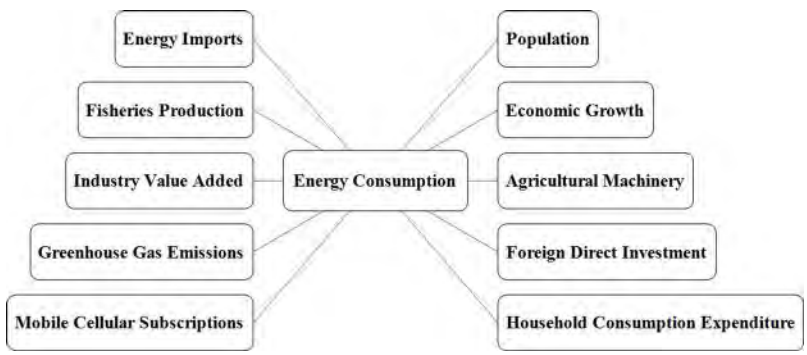
HIGHLIGHTS

- Does energy evolves in different states by transitioning over a finite set of states?
- We ascertain if energy consumption follow an asymmetric behavior.
- We examine the unobserved factors underpinning energy crisis in Ghana.
- Markov-switching, NIPALS regression, and neural network analysis are used.

GRAPHICAL ABSTRACT



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ABSTRACT

The study answered the following questions: First, does energy evolves in different regimes by transitioning over a finite set of unobserved states? Second, does energy consumption follow an asymmetric behavior over "energy boom" and energy scarcity? and, Third, are there unobserved factors underpinning energy crisis? We employed Markov-switching dynamic regression to examine the asymmetric effect, NIPALS regression to examine energy determinants and neural network analysis for prediction. The neural network model suggests a 99% prediction of energy consumption by the predictor variables. It was evident that energy consumption evolves in two states by transitioning over a finite set of unobserved states. The 11.6% growth in energy consumption is expected to occur in 4.1 years while energy crisis is expected to last for 3.7 years. Technological advancement and the development of green energy through foreign direct investment are essential to improve energy sector portfolio.
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1. Introduction

Energy production and consumption remain the largest contributor of anthropogenic carbon dioxide emissions, as such, mitigation option requires measures that promote energy efficiency and the substitution of conventional energy sources with renewable energy technologies (Owusu and Asumadu, 2016; Sarkodie and Strezov, 2018). While the Sustainable Development Goal Seven seeks to ensure the availability and accessibility of clean and modern energy technologies (United Nations, 2015), the underlying factors that propel energy consumption levels should not be underestimated.

The determination of factors affecting energy consumption and economic growth has been a topical subject of many studies, since the 1970s. However, the existing evidence on the nexus between economic growth and energy consumption has been inconclusive. Yet, an understanding of the determinants of energy consumption and its modeling in emerging economies is important. Studies on the relationship between energy consumption and economic growth have been found to be very complex due to the four possible impact scenarios, namely (Inglesi-Lotz and Pouris, 2016; Sarkodie and Adom, 2018): growth, conservative, feedback and neutrality hypotheses.

The growth hypothesis postulates a unidirectional causality from energy consumption to economic growth. This implies that energy saving policies may hinder growth because such an economy is dependent on energy to grow. Second, the conservative hypothesis refers to a unidirectional causality from economic growth to energy consumption. Here, energy-saving policies may have little or no negative effects on growth (Destek and Sarkodie, 2019). However, if the causal relationship from energy consumption to growth is positive, the adoption of energy-saving policies can lead to a decline in growth and employment. Conversely, if the causal relationship from economic growth to energy consumption is negative, the use of energy saving policies can lead to an increase in output. The feedback hypothesis refers to a bidirectional causality between energy consumption and economic growth. Thus, energy conservation policies can restrict the economy and vice versa. The neutrality hypothesis argues that there is no causal relationship between energy consumption and economic growth. Accordingly, reducing energy consumption is ineffective for economic growth.

The lack of consensus evidence in energy-growth correlation is primarily due to the omission of other potential determinants in the modeling of energy demand function (Chang, 2015). As such, we propose using econometric methods that allow for the consideration of an asymmetric effect and viable data series in studying the causal factors of energy consumption.

The aim of the study is to answer the following questions: First, does energy evolves in a different state (regime) by transitioning over a finite set of unobserved states? Second, does energy consumption follow an asymmetric behavior over "energy boom" and energy scarcity? Third, are there unobserved factors underpinning energy crisis? and Fourth, what are the probabilities that a country will experience "energy boom" or "energy crisis"?

To the best of our knowledge, no study in existing literature considers trio dynamic models that minimize the complexities of available models in the literature. First, this study overcomes multicollinearity, a problem with time series variables by using both NIPALS and neural network models. Second, the study controls for structural breaks and discontinuous shifts in regression regimes at an unknown point using the Markov-switching dynamic regression. The Markov-switching dynamic regression has been widely used in financial economics (Hamilton, 1989), political (Jones et al., 2010) and health sciences (Martínez-Beneito et al., 2008) but has not been applied in energy economics. Importantly, the Markov-switching dynamic regression can easily switch the states according to the Markov process; the speed of adjustment/correction is quick after a change of state and has the ability to deal with a high number of variable observations. Third, the study draws attention to unobserved variables that play a critical role in energy demand-side management and energy conservation while examining the predictive power of trio models, thus, providing new evidence with policy implications.

The remainder of the study consists of section two "*Literature Review*", section three "*Methodology*", section four "*Results and Discussion*", and section five "*Conclusion*".

Nomenclature

3G	Third Generation of Broadband Cellular Network Technology
4G	Fourth Generation of Broadband Cellular Network Technology
ARDL	Autoregressive Distributed Lag
GSM	Global System for Mobile communication
ICT	Information and Communication Technology
LMDI	Logarithmic Mean Divisia Index
MAD	Mean Absolute Deviation
MAPE	Mean Absolute Percentage Error
NEPAD	New Partnership for Africa's Development
NIPALS	Nonlinear Iterative Partial Least Squares
OECD	Organisation for Economic Co-Operation and Development
RSME	Root Mean Square Error
SSE	Error Sum of Squares
VECM	Vector Error Correction Model
VIP	Variable Importance of Projection

2. Literature review

An investigation of the causal nexus between economic activities and energy consumption and Greenhouse gas emissions has been studied in several empirical works. According to Sarkodie and Owusu (2016), the majority of the existing literature can be categorized into three; the first category of research, examines the causal effect of environmental pollution, energy consumption, and macroeconomic variables by testing the validity of the environmental Kuznets curve hypothesis.

Using fixed effects model and the method of least square generalized linear regression in China between 1995 and 2010, Zhang and Lin (2012), illustrated that the demographic intensities, GDP, industrial production, and energy consumption have an impact on CO_2 emissions. Ahmed et al. (2016) examined the causal effect of carbon dioxide emissions, GDP, and energy consumption in Brazil, South Africa, China and India using a panel data spanning from 1970 to 2013 using the fully modified least squares method. Their results confirmed the validity of the environmental Kuznets curve hypothesis and found evidence of bidirectional causality between carbon dioxide emissions and energy consumption.

According to (Sarkodie and Owusu, 2016) the second category of research examines the causal effect of environmental pollution, energy consumption, and macroeconomic variables without testing the validity of the environmental Kuznets curve hypothesis. Employing a multivariate co-integration analysis, ARDL and vector error correction modeling techniques to investigate in Ghana for the period 1971–2013, Asumadu and Owusu (2016b) examined the relationship between carbon dioxide emissions, GDP, energy consumption and population. Their results suggested the existence of mutual causality between Ghana's energy consumption and GDP.

Another study by Owusu and Samuel (2016) investigated the relationship between carbon dioxide emissions, energy consumption, population and GDP in Ghana using VECM technique for the period 1980–2012. Their findings suggested that the continuous increase in population growth within the study period has resulted in a substantial increase in energy demand and CO_2 emissions in Ghana. A bidirectional causality was observed between carbon dioxide emissions and energy consumption.

In the same way, Mohiuddin et al. (2016) examined the relationship between carbon dioxide emissions, energy consumption (EC), GDP, and electricity production from oil, coal and natural gas, in Pakistan from

1971 to 2013 and found evidence of long-run equilibrium relationship running from EC, electricity production from coal, electricity production from natural gas, electricity production from oil and GDP to carbon dioxide emissions.

The third category of research according to (Sarkodie and Owusu, 2016) examines the causal effect of environmental pollution and agricultural variables. Using Chinese official statistical data, Zou et al. (2015), investigated the emissions of greenhouse gases from agricultural irrigation to inform strategies for reasonable use of water resources and emission reduction. The study found out that the total carbon dioxide equivalent (CO_2-e) emission from agricultural irrigation is 36.72–54.16 Mt. Emissions from energy activities in irrigation (including water pumping and conveyance) account for 50%–70% of total emissions from energy activities in the agriculture sector. Groundwater pumping was the biggest emission source, accounting for 60.97% of total irrigation emissions.

Similarly using the LMDI technique, Li et al. (2014) investigated agricultural CO_2 emissions in China from 1994 to 2011. Their findings suggested that economic development acts to increase CO_2 emissions significantly whiles Agricultural subsidy acts to reduce CO_2 emissions effectively.

The fourth category of research (Faucheux and Nicolaï, 2011; Hamdi et al., 2014; Moyer and Hughes, 2012) examines the causal effect of energy consumption, CO_2 emission, and information communication technology usage. Employing panel unit root test accounting for the presence of cross-sectional dependence, a panel cointegration test, the Pooled Mean Group regression technique and Dumitrescu-Hurlin causality test, Salahuddin and Alam (2016) examined the short- and long-run effects of ICT use and economic growth on electricity consumption using OECD panel data for the period of 1985 to 2012. Their findings suggested electricity consumption in both the short- and the long-run had a direct relationship to the use of ICT and economic growth. In a similar study using data for a period of 1985–2012 in Australia, Salahuddin and Alam (2015) examines the short- and long-run effects of Internet usage and economic growth on electricity. Their results indicated the presence of a unidirectional between Internet usage to economic growth and electricity consumption.

Examining the trend of worldwide electricity consumption Van Heddeghem et al. (2014) and showed that three key ICT categories, namely, communication networks, personal computers, and data centers, has increased in 2012 from its level in 2007 due to increase in electricity consumption.

The majority of the aforementioned literature assured the existence of a closed-form relationship between energy consumption and macroeconomic factors mostly, focusing on a casualty with less than three variables. As a contribution to literature, an attempt is made to investigate the causal relationship between energy consumption, agricultural machinery, foreign direct investment net inflows, economic growth, total greenhouse gas emissions, industrialization, total fisheries production, net energy imports, electric power transmission and distribution losses, household final consumption expenditure, mobile cellular subscriptions, and population using time series data from 1971 to 2014 in Ghana.

3. Methodology

3.1. Data

To conduct an assessment of energy consumption in Ghana, the study employs data from 1971 to 2014 from the World Bank World Development Indicator database (World Bank, 2016). Twelve data variables are used in the study namely; Total greenhouse gas emissions (kt of CO_2 equivalent), Energy consumption (kg of oil equivalent per capita), GDP (current LCU), Mobile cellular subscriptions, Population, Total fisheries production (metric tons), Industry, value added (current US$) as a proxy for industrialization, Household final consumption expenditure (current LCU), Foreign direct investment, net inflows (% of GDP), Energy imports, net (% of energy use), Agricultural machinery and Electric power transmission and distribution losses (% of output) presented in Table 1. Energy use employed as a proxy for energy consumption is defined by the World Bank as "*the use of primary energy before transformation to other end-use fuels, which is equal to indigenous production plus imports and stocks change, minus exports and fuels supplied to ships and aircraft engaged in international transport*" (World Bank, 2016). Fig. 1 presents the trend of the study variables. A visual assessment of Fig. 1 shows that the trend of the variables exhibits some unexplainable behaviors and complexities that can only be ascertained through a dynamic regression model elaborated in the subsequent section.

3.2. Model estimation

3.2.1. Markov-switching dynamic regression

The Markov-switching dynamic regression model was initiated by Goldfeld and Quandt (1973); Quandt (1972) and was first employed by Hamilton (1989) in economics to examine the observed asymmetric behavior in the growth rate of GDP. The Markov-switching dynamic regression model is "rich enough" to capture the dynamic and switching behavior of macroeconomic and energy-related variables thus, allows quick adjustment/correction of the state classification measures (Hamilton, 1989; Zhu et al., 2017).

The general specification of the Markov-switching dynamic regression model is expressed as:

$$Y_t = \varphi_s + X_t\alpha + Z_t\beta_s + \varepsilon_s \tag{1}$$

where Y_t is the dependent variable, φ_s is the "state-dependent" intercept, X_t and Z_t represent exogenous variables in a vector form, α represents the "state-invariant" coefficients, β_s is the "state-dependent" coefficients and ε_s represents the independent and identically distributed normal error with a "state-dependent" variance σ_s^2 and a zero mean.

The two-state Markov state-switching model considers that the response of the independent variables' return to structural energy consumption shocks is dependent on the state (S_t) at time (t). S_t denotes an observable two-state and 1st order Markov process. The transition probability of the two-state is expressed in a matrix as:

$$P = \begin{pmatrix} p11 & p21 \\ p12 & p22 \end{pmatrix} \tag{2}$$

where $p_{ij} = P(S_t = j|S_{t-1} = i)$, by means of $\sum_{j=1}^{2} p_{ij} = 1, i\ (i = 1,2)$ denotes the number of states involved in the Markov process.

3.2.2. Neural network

The neural network is a function of some hidden nodes derived from the non-linear functions of the original inputted variables.

Table 1
Data variable description.

Variable name	Variable code
Total greenhouse gas emissions (kt of CO_2 equivalent)	GHG
Energy consumption (kg of oil equivalent per capita)	ENUS
GDP (current LCU)	GDP
Mobile cellular subscriptions	MCS
Population	POP
Total fisheries production (metric tons)	TFP
Industry, value added (current US$)	INA
Household final consumption expenditure (current LCU)	HFICE
Foreign direct investment, net inflows (% of GDP)	FDIN
Energy imports, net (% of energy use)	EGIM
Agricultural machinery	AGM
Electric power transmission and distribution losses (% of output)	EPTDL

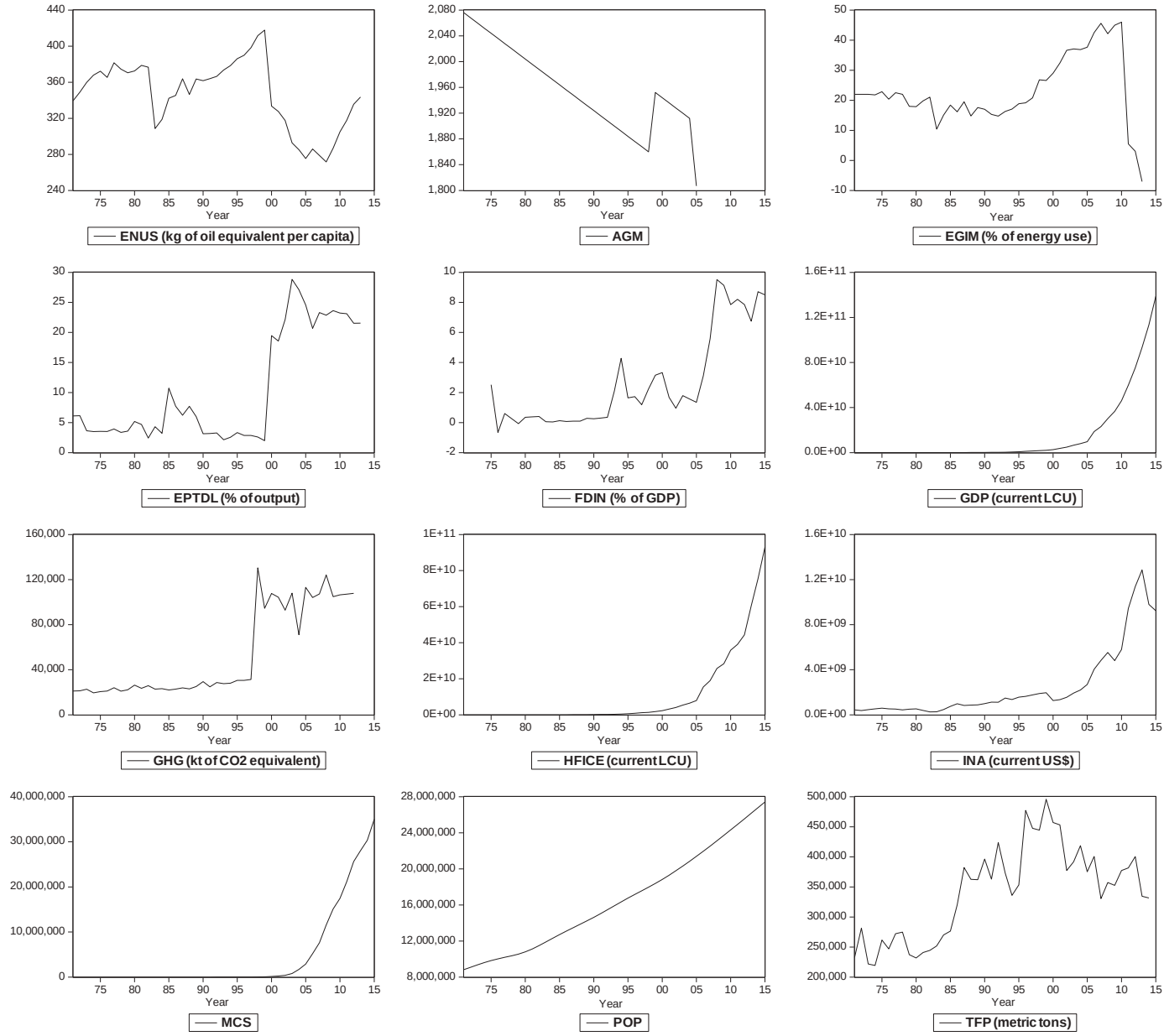

Fig. 1. Trend of variables.

A one-layer feed-forward neural network employed in the study is expressed as:

$$PredENUS = f\left(\varepsilon_o + \sum_{j=1}^{k} \boldsymbol{h}\left(\varphi_j + \sum_{i=1}^{n} X_i w_{ij}\right)\varepsilon_j\right) \tag{3}$$

where *PredENUS* is the predicted values of energy consumption representing the neural network output, $f(.)$ is the non-linear transfer function of the independent variables (inputs) X_i, $h(.)$ is the hidden layer activation function applied to the nodes with corresponding biases of the hidden layer φ_j, w_{ij} denotes the weight from the input layer to the hidden layer, ε_o and ε_j represent the output biases and the weight values from the hidden layer to the output layer.

3.2.3. NIPALS regression

The Nonlinear Iterative Partial Least Squares (NIPALS) regression analysis by Sarkodie and Adom (2018); Wold et al. (2001) begins with the centering and scaling of the dependent variable (Y) and independent variables (X). The next step involves the initialization of $u = Y$ with a subsequent repetition of Eqs. (4)–(9) to reach convergence thus,

$$w = X'u/(u'/u) \tag{4}$$

$$w := w/\|w\| \tag{5}$$

$$t = Xw \tag{6}$$

$$c = Y't/(t'/t) \tag{7}$$

$$c := c/\|c\| \tag{8}$$

$$u = Yc \tag{9}$$

where w and c are the X and Y loadings with a unit norm thus, c is a 1×1 unit vector converging in a single NIPALS iteration while t and u are the X and Y scores.

Subsequently, X and Y are regressed on t and u as:

$$p = X't/(t'/t) \tag{10}$$

$$q = Y'u/(u'/u) \tag{11}$$

The next step is a deflation of the matrices of X and Y expressed as:

$$X := X - tp' \tag{12}$$

$$Y := Y - tc' \tag{13}$$

The deflation of the matrices is repeated d times gathering the vectors (t, p, u, q) into matrices to produce a preferred factorization into X and Y scores **T** and **U**, X and Y loadings **P** and **Q**, weights of X and Y **W** and **C** derived by gathering **w** and **c** vectors into $n \times d$ and $m \times d$ matrices and output errors/residuals **E** and **F** expressed as:

$$X = TP' + E \tag{14}$$

$$Y = UQ' + F \tag{15}$$

To predict Y from X, the matrix of the regression coefficient (B) is expressed as:

$$B = W \times C' \tag{16}$$

Therefore, the final NIPALS regression is given as:

$$\hat{Y} = XB^* + (\mu_Y - \mu_X B^*) \tag{17}$$

where

$$B^* = \Sigma_X{}^{-1} B \Sigma_{Y'} E^* = E \Sigma_{X'} \tag{18}$$

4. Results and discussion

4.1. Descriptive analysis

This section begins with a descriptive statistical analysis of the study variables presented in Table 2. The average energy consumption within the last four decades was almost 347 kg of oil equivalent per capita, a minimum and maximum consumption of 272 and 418 kg of oil equivalent per capita. Total greenhouse gas emissions experienced a rise from 19,454 kt of CO_2 equivalent to 130,473 kt of CO_2 equivalent with an average of 45,194 kt of CO_2 equivalent. Economic growth grew from almost GH₵ 250,000 in 1971 to GH₵ 113 billion in 2014 with a mean of GH₵ 12.3 billion. Mobile cellular subscriptions (i.e. MTN, Vodafone, Tigo, Airtel, and Expresso) has experienced a significant growth in the communication industry from zero in 1971 to 30,360,771 in 2014 at an average of 3,826,884 subscriptions. It is important to note that mobile cellular subscription is employed as a proxy for assessing the trend of mobile phone usage in Ghana. There has been an exponential growth in population, from 8,827,273 to 26,786,598 in 2014 at an average growth of 16,307,944 people. Since Ghana is an agrarian country, the use of agricultural machinery grew from 1807 tractors to 2, 076 tractors, with a mean of 1957 tractors and the total fisheries production appreciated from at least 219,327 metric tons to a maximum of 495,683 metric tons at an average of 341,821 metric tons. The economic value of industrialization has increased from US$ 252,000,000 to US$ 12,900,000,000 with a mean of US$ 2,380,000,000. There has been a huge increase in household final consumption expenditure from GH₵ 193,500 to GH₵ 75.5 billion with a mean of GH₵ 8.64 billion. Foreign direct investment net inflows grew from −1% of GDP to 10% of GDP at a mean of 2%. Ghana's net energy imports grew from −7% of energy use to 40% of energy use, with an average of 23% of energy use. Electric power transmission and distribution losses grew from 2% of output to 29% of output, with an average of 10% of output energy production. Table 2 reveals that except for energy consumption, the remaining variables are positively skewed. Apart from EGIM, FDIN, GDP, HFICE, INA, and MCS, the remaining variables exhibit a platykurtic distribution. It is further revealed that only ENUS, AGM, EGIM and TFP are normally distributed hence, the application of a logarithmic transformation to the study variables. The correlation analysis reveals that except AGM, FDIN, and TFP, the remaining variables have a negative relationship with energy consumption. However, due to the limitation of correlation as a descriptive analysis and its inability to determine the causal factors, the study proceeds with inferential statistical analysis.

4.2. Unit root test

According to Perron (1989), unit roots and structural breaks have a close relationship, thus, traditional unit root tests are "*biased towards false unit root null when the data are trend stationary with a structural*

Table 2
Descriptive statistical analysis.

Statistic	ENUS	AGM	EGIM	EPTDL	FDIN	GDP	GHG	HFICE	INA	MCS	POP	TFP
Mean	347	1957	23	10	2	12,300,000,000	53,508	8,640,000,000	2,380,000,000	3,826,884	16,307,944	341,821
Median	360	1948	21	5	1	334,000,000	27,815	275,000,000	1,190,000,000	1071	15,689,386	355,305
Maximum	418	2076	46	29	10	113,000,000,000	130,473	75,500,000,000	12,900,000,000	30,360,771	26,786,598	495,683
Minimum	272	1807	−7	2	−1	250,000	19,454	193,500	252,000,000	0	8,827,273	219,327
Std. Dev.	38	66	12	9	3	26,300,000,000	40,160	17,400,000,000	3,080,000,000	8,255,112	5,399,093	76,964
Skewness	−0.4048	0.0252	0.2317	0.7448	1.1955	2.5042	0.6903	2.3418	2.0955	2.1368	0.3432	0.0209
Kurtosis	2.2932	2.3680	3.2326	1.7977	3.0377	8.5307	1.6243	7.8792	6.5000	6.2290	1.9109	1.9782
Jarque-Bera	2.0693	0.5863	0.4816	6.5649	9.5298	102.0677	6.6476	83.8612	54.6592	52.5978	3.0385	1.9173
Probability	0.3553	0.7459	0.7860	0.0375[a]	0.0085[a]	0.0000[a]	0.0360[a]	0.0000[a]	0.0000[a]	0.0000[a]	0.2189	0.3834
Correlation	347	1957	23	10	2	12,300,000,000	53,508	8,640,000,000	2,380,000,000	3,826,884	16,307,944	341,821
ENUS	1											
AGM	0.1420	1										
EGIM	−0.4579	−0.2795	1									
EPTDL	−0.8121	−0.2866	0.8336	1								
FDIN	0.1392	−0.3927	0.3901	0.1809	1							
GDP	−0.6687	−0.5217	0.8882	0.883	0.3257	1						
GHG	−0.3163	−0.4708	0.8281	0.6683	0.5188	0.7622	1					
HFICE	−0.6686	−0.5175	0.8917	0.8856	0.3272	0.9998	0.7678	1				
INA	−0.2143	−0.8340	0.6515	0.5335	0.5676	0.7826	0.7129	0.7812	1			
MCS	−0.6724	−0.4713	0.6926	0.725	0.142	0.8995	0.5265	0.8954	0.6507	1		
POP	−0.3531	−0.8179	0.6831	0.6561	0.5621	0.7973	0.7856	0.7992	0.9255	0.5744	1	
TFP	0.0389	−0.7153	0.3993	0.2929	0.5241	0.4365	0.6024	0.4403	0.7746	0.2030	0.8279	1

[a] Rejection of the Null hypothesis of Normal distribution at 5% significance level.

break". Hence, the study employs Vogelsang and Perron (1998) and Zivot and Andrews (2002) unit root tests for structural breaks. Both tests presented in Table 3 reveals that all the data series are stationary at first difference, therefore, integrated of order one [I(1)]. Zivot and Andrews unit root test in Fig. 2 reveals two prominent regimes after/before/between the break dates.

The structural break test provides a series of information that needs to be examined. Agricultural machinery observed a minimum breakpoint in 2006 due to a decline in the investment in tractors by the Government, however, the trend changed during a regime change.

Industrialization observed a minimum breakpoint in 2006 due to the rise of the agricultural and services sectors' contribution to the GDP therefore much attention was focused on the two. However, industrialization took a rising turn at the commencement of mining crude oil in 2010, quadrupling the share of the industrial sector in Ghana's economic growth (Ackah et al., 2014).

Total fisheries production experienced a minimum breakpoint in 1986 due to a decline of outboard motors that serve as an important feature in canoe fishing. The decline of outboard motors was due to the exponential increase in the price of purchasing, running (price of premix fuel) and maintenance (Wayo Seini, 1995).

The mobile industry began in 1992 in Ghana with over 100% mobile penetration rate, thus, the reason why mobile cellular subscriptions experienced a minimum breakpoint in 1992 (AMGOO, 2014).

Household final consumption expenditure, GDP, and foreign direct investment net inflows observed a minimum breakpoint in 1978 due to the 1978 coup d'état that made Ghana ungovernable. This action led to civil unrest, the dismissal of 1000 public employees, about eighty strike actions taken by civil servants and a declaration of a state of emergency, thus, affecting the country's economic policies including household income (Photius, 2011). In addition, the inflation rate increased to over 92% per year in 1978, affecting both economic growth and foreign direct investment net inflows (Aryeetey et al., 2000).

The total greenhouse gas emissions had a minimum breakpoint in 1998, which was due to the introduction of the forestry development master plan in 1996 that promotes sustainable forest harvesting. The policy made Ghana a net sink due to the high echelons of carbon capture sequestration in the land use, land-use change, and forestry sector. In addition, there was a reduction in energy consumption in 1998 compared to other years, hence, increasing the net greenhouse gas removals (MLNR, 2012).

The net energy import observed a minimum breakpoint in 2007 due to an increase in Ghana's current account deficit from 6.9% in 2006 to 8.6% in 2007, resulting in a trade deficit caused by a higher than expected oil import bill (OECD, 2008). As such, the import cover declined in 2007. Ghana discovered its first indigenous oil and gas in the Jubilee fields in 2007 which saved Ghana US $1000,000 per day on the importation of fuel for thermal power generation (USAID, 2016).

Energy consumption observed a minimum breakpoint in 2000 due to the poor energy sector policies and poor economic state, which turned the country into a highly indebted poor country in 2001. This propelled households to spend relatively small of their expenditure on energy due to high electricity tariffs and prices of petroleum products while salaries and wages remained stagnant (ESMAP, 2006). Electric power transmission and distribution losses experienced a minimum breakpoint in 2000 due to the introduction of a customer base of about 120,000 by the Northern Electricity Department. The distribution system consisted of 8000 km of sub-transmission lines, 22 bulk supply points, 30,000 km distribution networks and 1800 MVA installed transformer capacity which was very efficient leading to a reduction in transmission and distribution losses but however dwindled in the subsequent years (ESMAP, 2006).

The minimum breakpoint in population occurred in 1986 which was due to a decline in fertility rate as a result of the earlier introduction of contraceptives, an increase in under-5 infant mortality rate of 155 per

Table 3
Zivot-Andrews and Vogelsang and Perron Breakpoint Unit Root Test.

Variable	Zivot-Andrews Unit Root Test									Vogelsang and Perron Breakpoint Unit Root Test							
	Level				1st difference					Level				1st difference			
	BD	5% (−4.8/−4.42/−5.08)			BD	5% (−4.8/−4.42/−5.08)				Intercept		Both		Intercept		Both	
	I/T/B	Intercept	Trend	Both	I/T/B	Intercept	Trend	Both		T-Statistic	Prob	T-Statistic	Prob	T-Statistic	Prob	T-Statistic	Prob
AGM	2006/2001/2006	−476.149	−3.425	−402.779	2006/2007/2006	−6.974	−6.756	−10.506		−0.6269	≥0.50	−2.3194	>0.99	−583.7652	<0.01	−576.6685	<0.01
EGIM	2007/2007/2007	−1.249	−3.268	−3.773	2008/2005/2010	−6.462	−6.332	−7.076		−1.5665	>0.99	−1.6612	>0.99	−6.4037	<0.01	−6.3733	<0.01
ENUS	2000/2007/2000	−4.39	−1.994	−3.817	2006/2004/2000	−6.446	−6.412	−8.276		−1.7003	>0.99	−2.1678	>0.99	−7.1421	<0.01	−7.2557	<0.01
EPTDL	2000/1994/2000	−7.62	−3.075	−6.848	2000/2002/2000	−8.253	−8.024	−9.369		−3.092	<0.10	−3.374	<0.10	−10.8199	<0.01	−10.6852	<0.01
FDIN	1978/1984/1977	−3.103	−3.582	−3.887	1987/1994/1987	−6.319	−5.744	−6.283		−1.0768	≥0.50	−2.0194	≥0.50	−5.692	<0.01	−6.6877	<0.01
GDP	1978/1987/1983	−3.157	−4.87	−5.133	1978/1979/1977	−6.896	−7.43	−7.899		−1.4878	≥0.50	−0.7256	>0.90	−5.8905	<0.01	−6.3077	<0.01
GHG	1998/1986/1983	−16.443	−3.14	−4.359	2000/1999/1998	−9.799	−9.494	−10.216		−2.2368	>0.99	−4.2133	<0.025	−6.2801	<0.01	−5.6891	<0.01
HFICE	1978/1987/1998	−3.183	−4.378	−16.374	1978/1979/1977	−7.022	−7.452	−7.722		−1.7283	>0.41	−0.5719	>0.90	−5.9161	<0.01	−6.4708	<0.01
INA	2006/1982/1981	−3.808	−4.194	−4.183	1984/1987/1983	−5.838	−5.361	−6.16		−0.2445	≥0.50	−3.4588	<0.05	−5.453	<0.01	−5.4624	<0.01
MCS	1992/1979/1992	−6.699	−2.07	−13.516	1992/1993/1992	−7.022	−5.897	−7.99		−5.7968	<0.01	−3.5356	<0.10	−32.4316	<0.01	−36.5975	<0.01
POP	1986/1991/1986	−7.423	−8.172	−7.505	1991/1980/1978	−2.454	−4.244	−4.1		−4.8497	>0.10	−3.1525	>0.80	−7.734	<0.01	−8.2349	<0.01
TFP	1986/1999/1996	−4.184	−4.184	−4.558	2000/1987/1988	−8.907	−8.91	−9.046		−4.3873	>0.05	−4.213	>0.25	−9.5847	<0.01	−9.3623	<0.01

NB: I = Intercept, T = Trend, B=Both (Intercept & Trend), BD = Break Date.

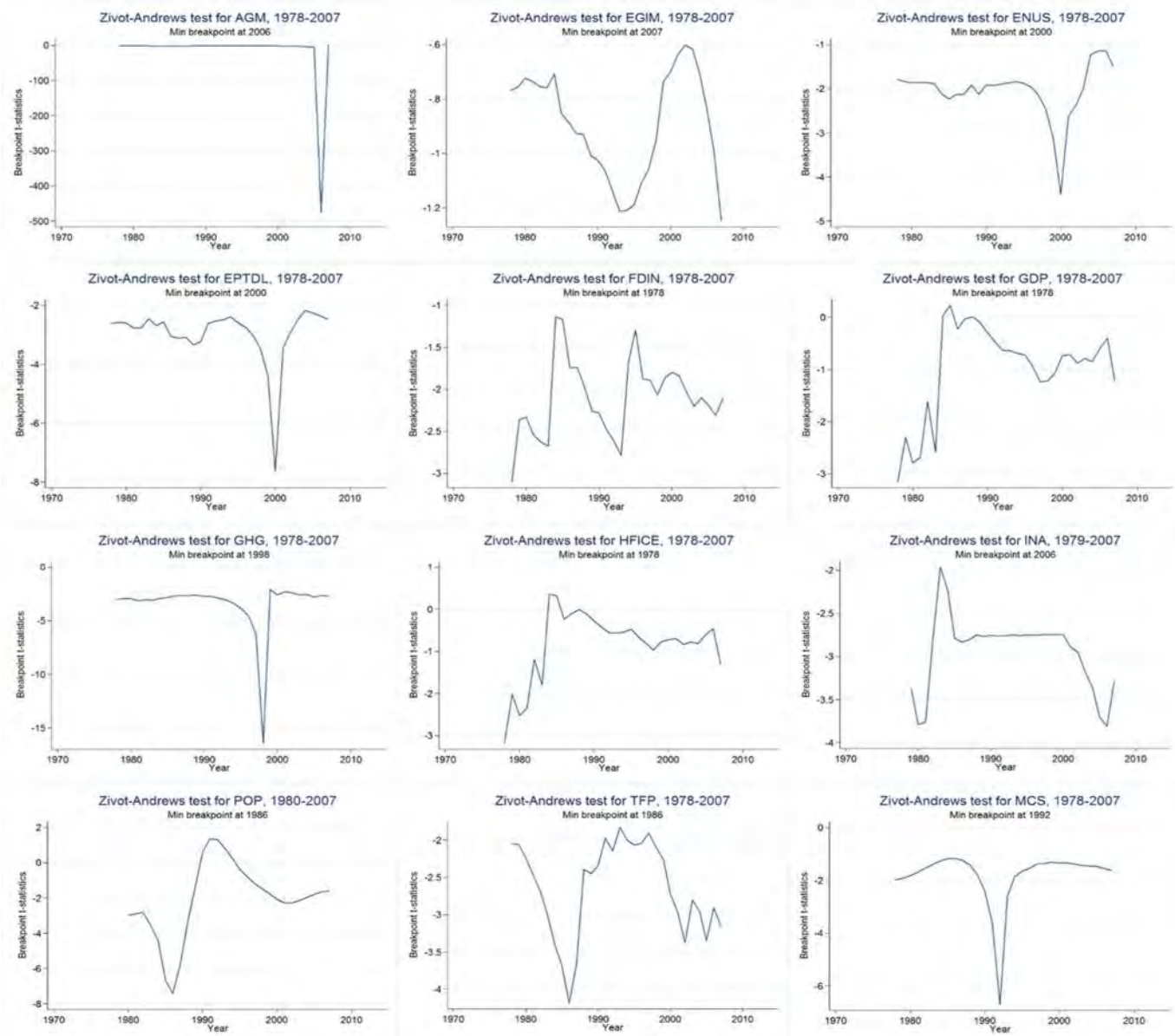

Fig. 2. Structural break using Zivot-Andrews Unit Root Test.

1000 live births and a decline in the proportion of married women (UN, 2001).

The structural breaks have policy implications but requires a methodology (revealed in the subsequent sections) capable of explaining the two regimes in order to prevent speculative assumptions.

4.3. Asymmetric effect of predictors on energy consumption

Table 4 shows the linear regression analysis of the study. The linear regression is employed as a baseline result to examine the impact of the predictor variables on energy consumption without the switching effect. Table 4 reveals that only net energy imports and electric power transmission and distribution losses are significant at 5% level. To test the asymmetric effect of the predictor variables on energy consumption, the study estimates the Markov-switching dynamic regression which considers the switching effect. The results of the Markov-switching dynamic regression in Table 5 shows statistical significance for all the predictor variables. Essentially, the linear regression and the Markov-switching dynamic regression have the same sign (i.e. negative/positive) and significant at 5% level. Table 5 shows that

Table 4
Linear regression analysis.

Source	SS	df	MS	Number of obs	44
				F(11, 32)	15.82
Model	0.4586	11	0.0417	Prob > F	0.0000
Residual	0.0843	32	0.0026	R-squared	0.8447
				Adj R-squared	0.7913
Total	0.5429	43	0.0126	Root MSE	0.0513

ENUS	Coef.	Std. Err.	t	P > t	[95% Conf. Interval]	
AGM	0.0130	0.0069	1.89	0.0670	−0.0010	0.0270
EGIM	−0.0520	0.0247	−2.11	0.0430	−0.1023	−0.0017
EPTDL	−0.0808	0.0180	−4.49	0.0000	−0.1174	−0.0442
FDIN	0.0353	0.0175	2.02	0.0510	−0.0002	0.0709
GDP	0.1391	0.2666	0.52	0.6060	−0.4040	0.6822
GHG	0.0499	0.0337	1.48	0.1480	−0.0186	0.1185
HFICE	−0.0732	0.2549	−0.29	0.7760	−0.5924	0.4460
INA	0.0503	0.0451	1.11	0.2730	−0.0416	0.1422
MCS	−0.0078	0.0063	−1.23	0.2260	−0.0207	0.0051
POP	−0.9794	0.7216	−1.36	0.1840	−2.4492	0.4905
TFP	0.1014	0.0785	1.29	0.2050	−0.0584	0.2612
_cons	18.1719	10.6136	1.71	0.0970	−3.4474	39.7911

Table 5
Markov-switching dynamic regression.

	Variable	Coef.	Std. Err.	z	P > z
ENUS	AGM	0.0097	0.0024	4.1000	0.0000
	EGIM	−0.0231	0.0086	−2.6900	0.0070
	EPTDL	−0.0815	0.0061	−13.3500	0.0000
	FDIN	0.0347	0.0059	5.8800	0.0000
	GDP	0.2973	0.0917	3.2400	0.0010
	GHG	0.0336	0.0116	2.9000	0.0040
	HFICE	−0.2636	0.0875	−3.0100	0.0030
	INA	0.0310	0.0153	2.0200	0.0430
	MCS	−0.0098	0.0022	−4.5100	0.0000
	POP	−0.4742	0.2412	−1.9700	0.0490
	TFP	0.0541	0.0272	1.9900	0.0470
State 1	_cons	11.4730	3.5443	3.2400	0.0010
State 2	_cons	11.5625	3.5436	3.2600	0.0010
	sigma	0.0175	0.0019		

agricultural machinery, foreign direct investment net inflows, economic growth, total greenhouse gas emissions, industrialization and total fisheries production have a positive effect on energy consumption while net energy imports, electric power transmission, and distribution losses, household final consumption expenditure, mobile cellular subscriptions, and population have a negative effect on energy consumption. In this study, state 1 is classified as "*energy crisis*" with high volatility while state 2 is classified as "*energy boom*" with low volatility. The output in Table 4 shows that energy consumption will grow by 11.6% during the energy boom periods while growth will decline by 0.1% during the period of energy crisis (11.5%). Table 6 presents the post-estimation of Markov-switching dynamic regression. The expected duration and the transition probability of entry into the two states are estimated. The output in Table 6 reveals that 11.6% growth in energy consumption is expected to occur in 4.1 years while energy crisis is expected to last for 3.7 years. Further evidence shows a 73% probability (p11) of remaining in 3.7 years of energy crisis while there is a 75% chance of staying in 4.1 years of energy boom (p22). The probability (p12) of switching from energy crisis to energy boom is 27%, and the probability (p21) of changing from an energy boom to energy crisis is 25%. The predictive power of state 1 and state 2 on energy consumption is examined as a sensitivity analysis presented in Fig. 3. We employ MAPE and R-square as error and predictive power metrics. Fig. 3 (a) reveals that state 1 has a MAPE of 0.91% while state 2 has a MAPE of 0.86% (Appendix A). We select state 2 with minimum MAPE to examine its predictive power presented in Fig. 3(b). It is evident that the predictor variables in state 2 explain 81% (i.e. $R^2 = 0.81$) of observed dynamics in Energy consumption.

4.4. Neural network estimation

This section examines the predictive power of the neural network model via a causal relationship between energy consumption, agricultural machinery, foreign direct investment net inflows, economic growth, total greenhouse gas emissions, industrialization, total fisheries production, net energy imports, electric power transmission and distribution losses, household final consumption expenditure, mobile cellular subscriptions and population. Fig. 4 shows the exact input-output diagram of the model that employs one layer. The study employs a TanH activation function [i.e. TanH {(TanH $= e^{2x} - 1/e^{2x} + 1$) where x is a linear combination of the predictors} which is a sigmoid function that converts a value between −1 and 1 (see Appendix A)] at the nodes of the hidden layer. The resultant Predicted ENUS equation using a one-layered feedforward network with three hidden nodes is presented as:

$$PredENUS = 5.5510 + -0.1194* : H1_1 + -0.1140* : H1_2 + 0.3825* : H1_3 \quad (19)$$

where, the output equations based on the hidden layer from the model are expressed as:

$$\begin{aligned} H1_1 : \mathrm{TanH}(0.5 * (&112.3534 + -0.3939* : \mathrm{AGM} + -1.8115* : \mathrm{EGIM} \\ &+ -0.2193* : \mathrm{EPTDL} + -1.2334* : \mathrm{FDIN} + 0.2788* : \mathrm{GDP} \\ &+ 1.2323* : \mathrm{GHG} + 0.9370* : \mathrm{HFICE} + 0.5512* : \mathrm{INA} \\ &+ -0.2972* : \mathrm{MCS} + -3.3136* : \mathrm{POP} + -7.7411* : \mathrm{TFP})) \end{aligned} \quad (20)$$

$$\begin{aligned} H1_2 : \mathrm{TanH}(0.5 * (&145.9786 + -0.0661* : \mathrm{AGM} + -2.2040* : \mathrm{EGIM} \\ &+ -0.7693* : \mathrm{EPTDL} + 0.1199* : \mathrm{FDIN} + -0.2646* : \mathrm{GDP} \\ &+ -2.9475* : \mathrm{GHG} + -0.2758* : \mathrm{HFICE} + -1.9081* : \mathrm{INA} \\ &+ -0.4148* : \mathrm{MCS} + -4.8500* : \mathrm{POP} + 2.2950* : \mathrm{TFP})) \end{aligned} \quad (21)$$

$$\begin{aligned} H1_3 : \mathrm{TanH}(0.5 * ((&-160.7658) + -0.0542* : \mathrm{AGM} + -0.4877* : \mathrm{EGIM} \\ &+ -0.4435* : \mathrm{EPTDL} + -0.0613* : \mathrm{FDIN} + 0.7052* : \mathrm{GDP} \\ &+ -0.5345* : \mathrm{GHG} + -0.3905* : \mathrm{HFICE} + 0.2477* : \mathrm{INA} \\ &+ -0.9188* : \mathrm{MCS} + 10.2696* : \mathrm{POP} + -0.2103* : \mathrm{TFP})) \end{aligned} \quad (22)$$

Thus, $H1_1$, $H1_2$ and $H1_3$ are the hidden nodes from the one-layered feedforward neural network model.

Fig. 5 presents the training and validation plots of the neural network model while the corresponding goodness of fit estimates are displayed in Table 7. Due to the flexibility of the neural network model, there may arise problems related to overfitting data, which will, in turn, predict future observations poorly. This temptation of overfitting is prevented via the application of a "penalty" on the parameters of the model and the assessment of the predictive power of the model using an independent dataset for validation. Fig. 5 reveals evidence of 35 observations for the training set and 9 observations for the validation set. This study employs the K-Fold validation method advantaged in the efficient use of a small sample dataset and produces accurate predictions. The output results in Table 7 shows that the training and validation set predict energy consumption at almost 99% R-Squared value, 0.01 RSME value, 0.01 MAD value, 0.01 SSE value and 0.16% MAPE value (Appendix A). The predictive power and error metrics confirm the relationship between energy consumption and the predictor variables.

4.5. Determinants of energy consumption

To examine the determinants of energy consumption, the study employs the NIPALS regression analysis. NIPALS regression is a powerful multivariate analysis that is superior to other conventional econometric methods in terms of accuracy, predictability and variable projections. The model allows for the imputation of missing data using their means. The NIPALS regression analysis begins with the selection of a viable model using the number of factors available. Appendix B presents a model comparison summary. The output in Appendix B shows that the

Table 6
Post estimation of Markov-switching dynamic regression.

Post estimation	Estimate	Std. Err.	[95% Conf. Interval]	
Expected duration				
State 1	3.7299	1.3439	2.0402	8.1644
State 2	4.0710	1.4814	2.1931	8.9044
Transition probabilities				
p11	0.7319	0.0966	0.5099	0.8775
p12	0.2681	0.0966	0.1225	0.4901
p21	0.2456	0.0894	0.1123	0.4560
p22	0.7544	0.0894	0.5440	0.8877

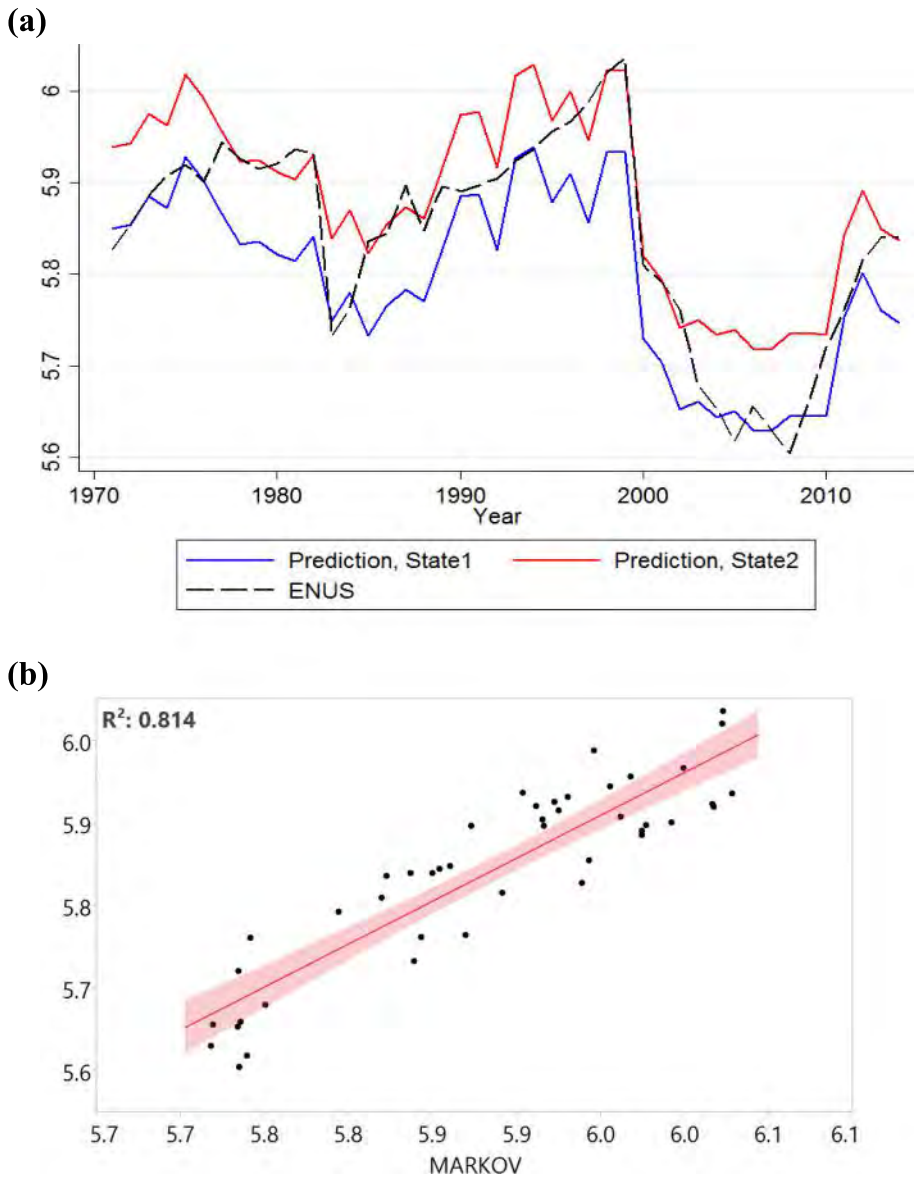

Fig. 3. (a) Prediction of ENUS by states (b) Markov-switching dynamic regression model.

model with the asterisk (*) is superior compared to the others, accordingly, selected for further analysis. The selected model has a corresponding number of factors in Appendix C required for coefficient estimation. Appendix C shows that almost all the variables have VIP greater than or equal to 0.8, a requirement for selecting important variables (Samuel and Owusu, 2017). The variables can be classified into two categories based on their VIP value; EPTDL, EGIM, and TFP are highly important variables (VIP > 1) while the remaining predictor variables are moderately important variable thus, 0.8 ≤ VIP ≤ 1. Now, we estimate the coefficient of the regression analysis using the 11 factors presented in Appendix D and its corresponding output in Appendix B.

The NIPALS estimated coefficients in Table 8 have the same sign as the linear regression (Table 4) and the Markov-switching dynamic regression (Table 5) analysis, hence, confirming the validity of the coefficients in explaining the relationship between the response and the predictor variables. The output in Table 8 reveals that a 1% increase in agricultural machinery, foreign direct investment net inflows, economic growth, total greenhouse gas emissions, industrialization, and total fisheries production increases energy consumption by 0.35%, 0.47%, 5.00%, 0.32%, 0.47%, and 0.21%. In contrast, net energy imports, electric power transmission and distribution losses, household final consumption expenditure, mobile cellular subscriptions, and population decreases energy consumption by 0.30%, 0.65%, 2.62%, 0.49%, and 2.93%. The next step is to examine the independence of the residuals and the predictive power of the NIPALS regression. Appendix E shows a diagnostic plot of the residuals while Fig. 6 depicts the NIPALS Prediction Plot. The residual normal quantile plot shows that the residuals of the model are normally distributed. We examine the prediction error using MAPE. The error metric reveals a MAPE of 0.64% (Appendix A). Fig. 6 shows that the predictor variables can explain about 85% of the dynamics in energy consumption.

The Markov-switching dynamic regression shows that linear regression is incapable of examining the relationship between energy consumption and the predictors in the presence of structural breaks. Using the linear regression as a baseline and the NIPALS regression as a validation method for the study, the Markov-switching dynamic regression showed the asymmetric effect of the predictors on energy consumption. It was evident in Table 5 and Table 8 that agricultural machinery, foreign direct investment net inflows, economic growth, total greenhouse gas emissions, industrialization, and total fisheries production have a positive effect on energy consumption. It is positive in the sense of increasing the demand for energy consumption.

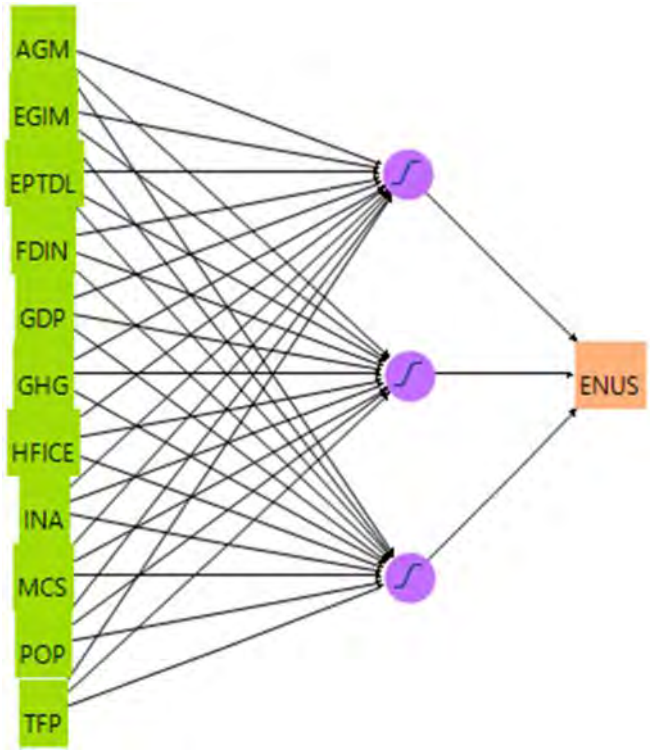

Fig. 4. One-layered feedforward neural network model for energy consumption.

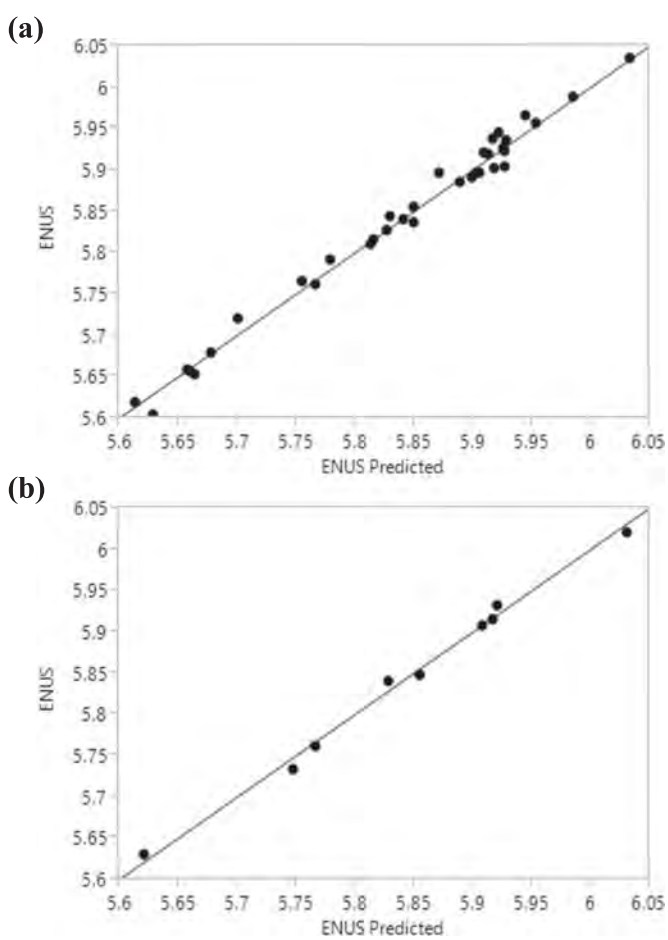

Fig. 5. Model: (a) training and (b) validation.

Table 7
The goodness of fit estimation of the model.

ENUS	Training	Validation
Measures	Value	Value
RSquare	0.9881	0.9931
RMSE	0.0121	0.0093
MAD	0.0093	0.0081
-LogLikelihood	−104.8593	−29.3045
SSE	0.0051	0.0008
Sum Freq	35	9

Agricultural machineries are dependent on fuel for its operations in medium and large-scale agricultural production. Therefore, as large-scale agricultural production enhances, agricultural machineries evolves, hence, increasing energy demand (fossil fuels). Our study is supported by Kuang et al. (2017), they found a relationship between agricultural mechanization and energy consumption in China. Their study concluded that energy consumption and efficient agricultural mechanization are strongly linked with agricultural economic growth.

As of 2010, fisheries production accounted for 7.3% of the agricultural GDP in Ghana (Asumadu and Owusu, 2016a). Thus, Government invests more to boost the sustainable production through the provision of subsidies on premix fuel. Fisheries production impact energy consumption in the sense of premix fuels used to operate outboard motors for canoe fishing. Tyedmers (2004) argues that energy in the form of fuel is used directly in fishing vessels for vessel propulsion. In large-scale fishing, high-intensity lamp batteries, onboard processing, automated jigging machines, refrigeration, freezing, vessel construction, and maintenance are all powered by diesel-fueled generators, therefore, increasing energy consumption (Tyedmers, 2004).

Contrary to the work of Adom (2015) that suggests a negative effect of Foreign direct investment net inflows on energy intensity in South Africa, Sadorsky (2010) confirms our results, thus, a positive effect of Foreign direct investment net inflows on energy consumption (Sadorsky, 2010). Foreign direct investment net inflows play a critical role in Ghana's energy consumption. Legislation and structural frameworks that provide an enabling environment to attract foreign investors give Ghana a comparative advantage over other Sub-Saharan African countries in terms of foreign investments (Sarkodie and Strezov, 2019). The multi-party democracy system, the rule of law, good governance (i.e. "first country to be reviewed under the Africa Peer Review Mechanism of NEPAD".), peaceful socio-political environment, outstanding hospitality and personal security, the availability of export free zone territory, access to tariff-free exports to the USA via the Africa Growth and Opportunity Act, the vast ongoing oil exploration, endowed natural resources, and among others entice foreign direct investment to the energy sector (CGA, 2017). For example, a compact was signed in 2014 between Ghana and the Millennium Challenge

Table 8
Model coefficients for centred and scaled data.

Coefficient	ENUS	Plot
Intercept	0.0000	
AGM	0.3579	
EGIM	−0.3045	
EPTDL	−0.6534	
FDIN	0.4725	
GDP	5.0147	
GHG	0.3252	
HFICE	−2.6233	
INA	0.4684	
MCS	−0.4919	
POP	−2.9376	
TFP	0.2107	

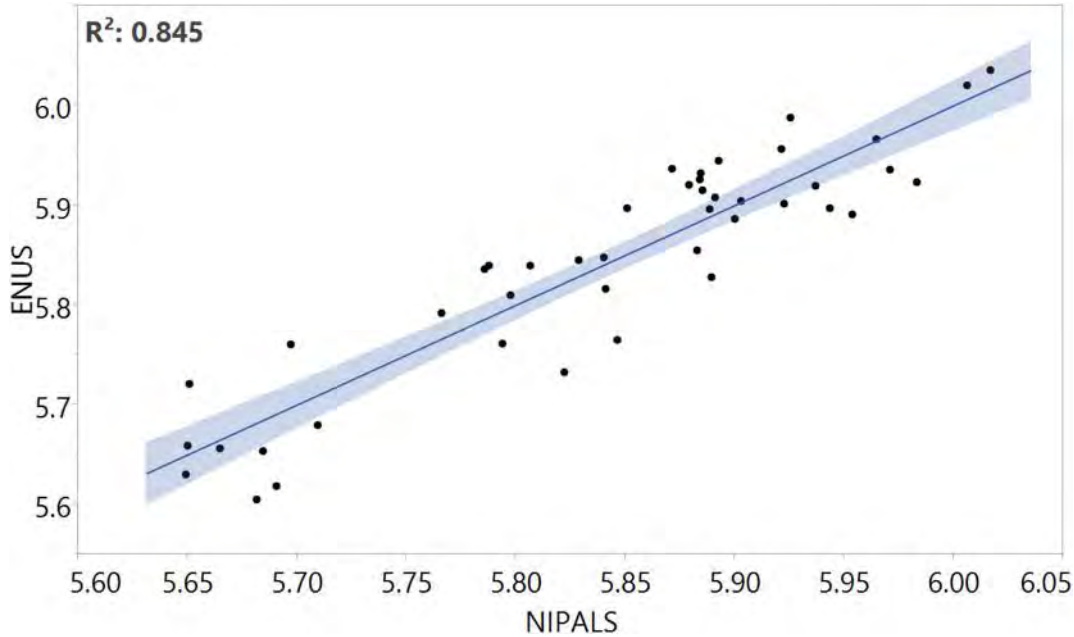

Fig. 6. NIPALS Prediction Plot.

Corporation for an investment of US$ 498.2 million to enable the renovation of Ghana's energy sector (i.e. electricity production, distribution, and accessibility to clean energy) and to motivate foreign and private investment (USAID, 2017). Foreign direct investment net inflows mediate in either the expansion of Ghana's energy sector or widening the energy demand, which increases energy consumption. Sadorsky (2010) argues that financial development is a sign of prosperity and economic growth that strengthens customer and business confidence thereby increasing the economic demand for energy-intensive goods.

Economic growth has a positive effect on energy consumption with corresponding positive foreign direct investment net inflows. Developed countries with sustained and high economic growth rates can institute policies and measures that enable access to constant electricity while developing and least developing countries stand a risk of energy supply interruptions due to inconsistent economic growth, which Ghana is not an exception (DiSano, 2002). The positive effect of the total greenhouse gas emissions on energy consumption means that environmental policies and renewable energy policies are put into effect to repeal and replace fossil fuel energy sources with green energy while meeting the energy demand.

The positive effect of industrialization means it stimulates energy consumption. Ghana's peak demand has been increasing due to loads emanating from the industrial and commercial sectors. The upstream activities of Ghana's petroleum sector involve the production and refining of crude oil and other petroleum products to meet the needs of the industrial sector. For example, there has been a development of the West Africa gas pipeline to feed industries with fuel (CGA, 2017; Owusu and Sarkodie, 2016).

In contrast, Table 5 and Table 8 revealed a negative effect of energy imports, electric power transmission, and distribution losses, household final consumption expenditure, mobile cellular subscriptions, and population on energy consumption. The study expected a positive effect of energy imports, household final consumption expenditure, mobile cellular subscriptions, and population on energy consumption. However, the results proved otherwise, but surprisingly, all the three regressions have the same sign which means the models have no misspecification problem. Theoretically, as energy imports, household final consumption expenditure, population, and mobile cellular subscriptions increases, it is expected that energy demand which translates into consumption will increase. As household consumption expenditure increases, members of the household are able to afford energy-intensive goods and services thus, consuming more energy. However, the negative effect of household consumption expenditure maybe due to energy efficiency and conservation practices such as using green energy technologies and services that reduce energy consumption. Increasing population becomes burdensome on the peak energy demand, thus, increasing energy demand and consumption. Social media like Facebook, WhatsApp, Snap Chat, Instagram and among others propel the use of mobile phones in Ghana. The use of 4G, 3G, and wireless networks in mobile phones drain more battery compared to GSM, as such, the frequency of charging mobile phones increases, thus, affecting electricity demand. It is reported that base stations in cellular networks account for over 50% of energy consumption in mobile phones (Han and Ansari, 2013). It is in this regard that mobile cellular subscription is an important factor in assessing the determinants of energy consumption. Increasing levels of electric power transmission and distribution losses reduce energy consumption, which affects energy efficiency and conservation.

5. Conclusion

This study examined the asymmetric behavior of energy consumption by assessing Ghana's energy sector dynamics. Using a time series data from 1971 to 2014, the study employed Markov-switching dynamic regression to examine the asymmetric effect, NIPALS regression to examine the determinants of energy consumption and neural network analysis for prediction.

Using Vogelsang and Perron, and Zivot and Andrews unit root tests for structural breaks, the study revealed some historical information that has policy implications but required a methodology that could explain the two regimes exhibited in the structural break plots. While the linear regression used as a baseline of the study had limitations, the Markov-switching dynamic regression revealed the presence of asymmetric effect in the presence of structural breaks.

It was evident in both Markov-switching and NIPALS regression that agricultural machinery, foreign direct investment net inflows, economic growth, total greenhouse gas emissions, industrialization, and total fisheries production have a significant positive effect on energy consumption. However, both models showed a significant negative effect of energy imports, electric power transmission, and distribution losses,

household final consumption expenditure, mobile cellular subscriptions, and population on energy consumption.

The study revealed that energy consumption evolves in two different states (energy boom and energy scarcity) by transitioning over a finite set of unobserved states. Energy consumption is expected to grow by 11.6% during the energy boom periods while growth will decline by 0.1% during energy crisis (11.5%). The expected duration and the transition probability of entry into the two states show that 11.6% growth in energy consumption is expected to occur in 4.1 years while energy crisis is expected to last for 3.7 years. There is 73% probability of staying in energy crisis for 3.7 years while the chance of staying in 4.1 years of energy boom is 75%. The probability of switching from energy crisis to energy boom is 27%, while the probability of changing from an energy boom to energy crisis is 25%.

The NIPALS regression revealed unobserved or unreported factors like electric power transmission, and distribution losses, and mobile cellular subscriptions underpinning energy crisis. There was evidence of continuous shift in the regression from agricultural machinery, foreign direct investment net inflows, economic growth, total greenhouse gas emissions, industrialization, total fisheries production, net energy imports, electric power transmission and distribution losses, household final consumption expenditure, mobile cellular subscriptions, and population to energy consumption at a known point.

Even though the neural network is disadvantaged in terms of interpretability yet revealed an accurate prediction of energy consumption compared to the Markov-switching dynamic and the NIPALS regression models. The neural network model suggests a 99% relationship between energy consumption and the predictors.

As a policy implication, there is the need for improved and sustainable agricultural mechanization systems in Ghana to enhance the efficient use of energy while increasing agricultural productivity. As foreign direct investment net inflows propel technological advancement and the development of green energy and energy efficiency, is essential for the Government of Ghana to improve the renewable energy policy that will provide more incentives and bolster foreign and private investment into the energy sector. There is the need for sustained and high economic growth rates in Ghana through the institution of financial policies and measures that increases financial development, which will help the development and access to constant electricity thereby increasing productivity.

Future research should aim at expanding the scope of the study to include the role of research development and income inequality on energy consumption.

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Declaration

There is no conflict of interest.

Appendices A–E. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2018.10.147.

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Appendix 4 — Publication Eleven: Another look at the relationship between energy consumption, carbon dioxide emissions, and economic growth in South Africa

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Another look at the relationship between energy consumption, carbon dioxide emissions, and economic growth in South Africa

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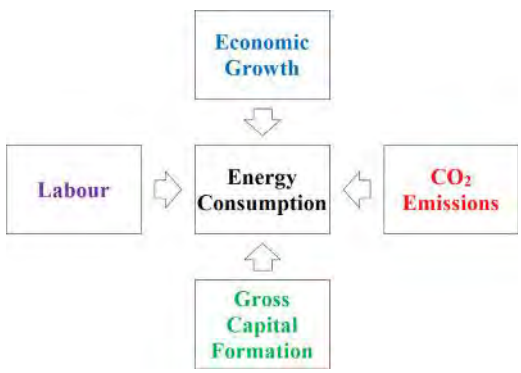
HIGHLIGHTS

- A unidirectional causality is observed from energy consumption to CO_2 emissions.
- The results validate the energy-induced growth hypothesis in South Africa
- Economic growth and carbon dioxide emission exhibits an inverse relationship.
- Decoupling economic growth from energy use needed to achieve energy efficiency

GRAPHICAL ABSTRACT



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ABSTRACT

This study explores the energy use and economic growth nexus from 1960 to 2016 in South Africa while accounting for capital, labour, and carbon dioxide emissions. We applied Bayer and Hanck (2013) combined cointegration approach, Pesaran et al. (2001) bounds test and Kripfganz and Schneider (2018) critical values and approximate *p*-values. The empirical evidence finds support for a long-run equilibrium relationship among investigated variables. The Granger causality test indicates one-way causality from energy use to economic growth, validating the energy-led growth hypothesis. Our study found an inverted U-shaped pattern between energy use and economic growth in the long run. This finding suggests that at a higher level of economic development there is less intensification of energy consumption, hence, signifying a decline in energy intensity while validating energy efficiency in South Africa.

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1. Introduction

The pioneering study on the linkage between energy consumption and economic growth by Kraft and Kraft (1978) conducted for the

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United States was an invitation for several other studies to take place in different countries and blocs of countries(Emir and Bekun, 2018; Akadiri et al., 2018; Asumadu-Sarkodie and Owusu, 2017; Wada, 2017; Tang et al., 2013; Sadorsky, 2010; Apergis and Payne, 2009). The discussion of this topic is still heated in the energy economics literature, as much attention has been placed on the outcomes by energy practitioners and government administrators, particularly since it has been observed that economies with higher energy production and consumption have higher per capita incomes (Owusu and Asumadu, 2016). Thus, it is pertinent for government administrators and all stakeholders to understand the dynamic interaction between the variables under investigation for them to engage in effective and robust energy and environmental policy construction.

Thus far, the energy literature has produced four well-established strands based on causality flows (Inglesi-Lotz and Pouris, 2016; Sarkodie and Adom, 2018; Sarkodie et al., 2019). The first strand involves the energy led-growth hypothesis. This divide in the literature asserts that economic growth is premised on increased energy consumption (inter alia Damette and Seghir, 2013; Ghali and El-Sakka, 2004). The second strand or group consists of the conservative hypothesis (Baranzini et al., 2013; Jamil and Eatzaz, 2010), in which economic activities are said to drive higher energy consumption. The third strand is represented by what is known as feedback causality, in which causality is observed to be running from both sides (Lee et al., 2008; Tang and Tan, 2013). Finally, the fourth strand centres on the neutrality hypothesis (Halicioglu, 2009; Soytas and Sari, 2006), in which there is no causality in either direction from economic growth and energy consumption.[1]

There exist well-documented studies in the energy economics literature, which have been done mostly on developed economies in the past decades. However, little or no studies regarding the theme for the case involving Sub-Saharan Africa (SSA). Thus, this current study seeks to fill this identified gap by focusing on South Africa. The attention has become necessary given the central role the country plays in Africa. To the best of our knowledge, only Balcilar et al. (2010) and Menyah and Wolde-Rufael (2010) have investigated this relationship in South Africa. The statistics from the South Africa Department of Energy and Minerals (DEM, 2016) provides ample evidence that the South African economy is energy driven. Its energy sector accounts for 15% of the nation's economic output, with coal ranking as the top contributor in the energy mix. Further statistics from the World Bank (2018) shows that approximately 70% of the nation's aggregate energy supply is extracted from coal, while its coal-fired power plant stations account for 93% of its electricity production. Over-dependence on coal by the South African economy has translated into intense levels of carbon emissions (Winkler, 2007). South Africa is reputed to be the 7th largest greenhouse gas emitter in the world.

Following the studies of Odhiambo (2009) and Ziramba (2009) for the case of South Africa, the current study extends the extant literature by investigating the long run and causality interaction between the considered variables while accounting for capital, labour, and the dynamics of carbon dioxide emissions in a multivariate framework in order to avoid omitted variable bias. We also extend the frontier of knowledge by examining the long-run and causality linkage between energy consumption-growth nexus for the South Africa economy. Our study's novelty/contribution also relies on the adoption of recent time series econometrics methodologies that account for a possible structural break, something previous studies fail to address. Our study uses the unit root test reputed to account for a single structural break advanced by Zivot and Andrews (1992) to investigate the stationarity traits of the series under review. An ADRL bound testing is employed for cointegration analysis while modeling for possible break years. The newly advanced combined cointegration by Bayer and Hanck (2013) is applied to affirm cointegration results over the investigated period. Subsequently, causality analysis is conducted via Granger causality methodology.

The rest of this study is structured as: Section 2 renders brief insights into the South African energy sector and CO_2 emissions. Section 3 focuses on sources of data and methodological procedure applied. Section 4 presents the study findings and discussion. Concluding remarks and policy implication(s) are presented in Section 5.

2. An overview of energy sector dynamics in South Africa

South Africa has dynamic geographical features, with a coastline that stretches more than 2500 km (1600 miles). South Africa is bordered by Namibia on its western coast, while southwards around the tip of Africa and to the north, it is bordered by Mozambique. South Africa is reputed to have a rapidly emerging economy with strengths in natural resources, energy, and the financial sector.

The South African economy is said to depend on its abundant coal resources. The recent statistics show that electricity mostly generated by using coal sources (almost 90% of the country's power), followed by nuclear (5.2%) and natural gas (3.2%). Furthermore, electricity needs for South Africa were expected to be more than 56,000 MW by 2030 (DOE, 2016). According to statistics from the Energy Council (WEC, 2016), South Africa is the 6th largest producer of coal in the world, and its energy production is primarily driven by coal. South Africa has a well-organized energy production and supply system. Regardless of its endowment in coal energy production and importation, the nation has limited crude oil and natural gas. The country also possesses some degree of renewable energy sources. A report from the DEM (2016) affirms that the nation's rich sunshine is currently being exploited for possible electricity power generation for both industrial and residential consumption. The contribution of South Africa's energy sector to the national output (i.e., GDP) is placed at 15%, which account for approximately 250,000 employment opportunities for South Africa's citizenry (Beg et al., 2002).[2]

2.1. An overview of CO_2 emissions in South Africa

South Africa has a very interesting dynamic energy sector with a huge reliance on coal production for her energy needs. There has been a rise in its energy demand that has triggered carbon dioxide emissions directly and indirectly. This is substantiated as CO_2 emissions grow at the same pace if not more than its energy consumption and economic growth in recent times (See Fig. 1).

Statistics from U.S energy information administration reveals that South Africa is reputed as most intensive carbon emission non-oil producing developing country (EIA, 2010). South Africa accounts for 42% of Africa's emissions alone, which stretches more than the entire sub-Saharan Africa put together and 1% of the world's emissions. This is derived from her huge coal operation in the economy that drives CO_2 emissions (Nasr et al., 2015; Shahbaz et al., 2013a, 2013b; EIA, 2010). Fig. 1 provides the dynamics of economic growth, energy use and CO_2 emissions level of South Africa. Fig. 1 shows a strong evidence of economic progress and a rise in energy use and CO_2 level as their trend increases. Meaning that the higher the economic growth and energy use, the higher environmental degradation in South Africa. Thus, there were some giant strides to mitigate the menace that threatens environmental sustainability. Among such strides is seen in South Africa's membership as a signatory to the Kyoto protocol and the Paris agreement. Fossil fuel-based energy sources still dominate South Africa's energy sector portfolio, hence, increases energy intensity, and challenges of environmental degradation. DOE (2016) report suggests that about 18,000 MW of renewable energy in South Africa's energy mix would reduce CO_2 emissions by 34% by 2020 as a part of its commitment to the Paris agreement.

[1] For brevity of space, the interested reader can consult the studies of Ozturk, I. for a detail survey on the energy-growth literature.

[2] For brevity, interested readers can consult the following website for details on the South African energy dynamic: https://www.indexmundi.com/south_africa/#Energy

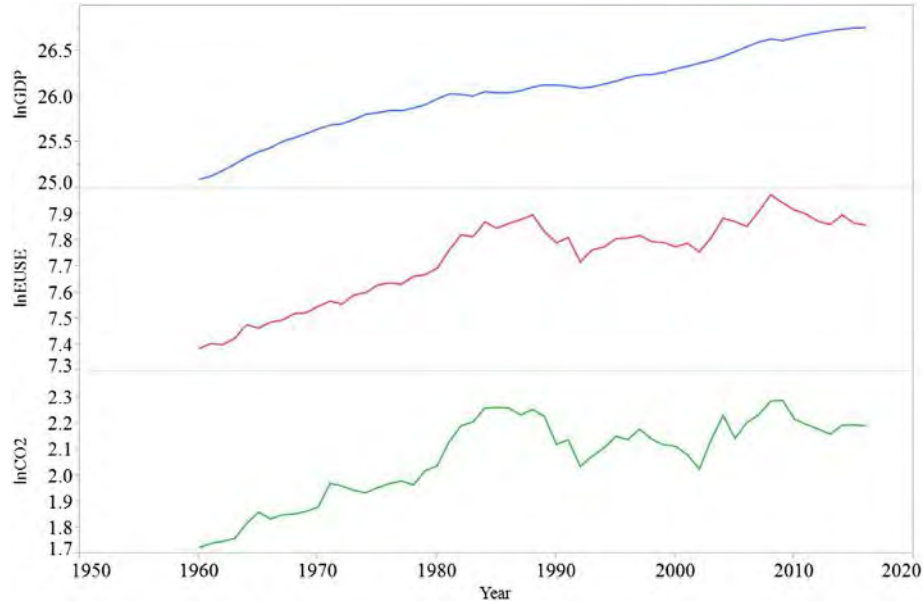

Fig. 1. Dynamics of economic growth, energy use and CO_2 emission in South Africa.

3. Materials and methods

To examine long- and short-run interactions between economic growth (RGDP), use of energy (EU), gross capital formation (K), labour (L), and carbon dioxide emissions (CO_2) in South Africa, data for the above-mentioned variables were collated from the WorldBank Indicators (www.databank.worldbank.org), with the exception of labour. The labour data was obtained from the Conference Board of Canada (2018). The selection of the variables is based on the Sustainable Development Goals (SDGs) 7,8,9 and 13 (United Nations, 2015). Energy use — Access to energy and its related services plays a critical role in economic development, thus, sustainable development (SDG 7). Economic growth — A sustained economic development relies on improved labour productivity and access to financial services (SDG 8). Labour/Gross capital formation — Improvements in employment, labour productivity, and manufacturing output depend on renewed investments needed to build strong infrastructures, thus, improving industrial share economic development (SDG 9). Carbon dioxide emissions — Climate change mitigation depends on responsible consumption and production option of energy and its related services (SDG 13). Annual frequency data from 1960 to 2016 was used to examine the interactions among the interested variables. The investigated variables were used in their logarithmic form to minimize problems with heteroscedasticity. RGDP and CO_2 are used as proxies for economic growth and environmental degradation, respectively. RGDP and gross capital formation (K) are measured in constant 2010 USD, CO_2 is measured in metric tons per capita, and EU is measured in kg of oil equivalent per capita. The functional relationship for this study is expressed as (Soytas and Sari, 2009):

$$\mathrm{EU} = f\left(\mathrm{RGDP}, \mathrm{RGDP}^2, \mathrm{K}, \mathrm{L}, \mathrm{CO}_2\right) \tag{1}$$

$$\mathrm{CO}_2 = f\left(\mathrm{RGDP}, \mathrm{EU}, \mathrm{K}\right) \tag{2}$$

$$lnEU_t = \alpha + \beta_1 lnRGDP_t + \beta_2 lnRGDP_t{}^2 + \beta_3\ \ln L_t + \beta_4 lnK_t + \beta_5 lnC02_t + \varepsilon_t \tag{3}$$

$$\ln \mathrm{CO}_{2t} = \alpha + \beta_1 lnRGDP_t + \beta_2\ \ln \mathrm{EU} + \beta_3\ \ln K_t + \varepsilon_t \tag{4}$$

where α is a constant term, and the β's are slope parameters which need to be estimated.

To examine for possible long-run interactions among these variables, BH (2013) combined cointegration technique was employed, and the results were confirmed using Pesaran et al. (2001) Bounds testing technique. Furthermore, short-run interactions among the variables under consideration were also investigated.

The stationarity properties of the series were examined prior to the cointegration test. Therefore, we employed the conventional ADF and PP unit root tests. However, these tests do not consider structural breaks. Thus, to account for a possible structural break, ZA (1992) test was employed. Once we had the information on the order of integration of the series, an attempt is made to examine the presence of a cointegration among the variables by employing the more recent BH (2013) test and Bounds testing approach. Bayer and Hanck's (2013) cointegration technique combine the tests of Engle and Granger (1987) and Johansen (1991), the error correction F-test of Boswijk (1994), and the error correction *t*-test of Banerjee et al. (1998). Bayer and Hanck's (2013) technique depends on the same order of integration of the series, i.e., all variables are integrated order one, and jointly determines test statistics for the listed techniques. The BH test has a null hypothesis of no cointegration against an alternative of cointegration among variables. The Fisher's equation is provided below.

$$EG{-}JOH = -2\left[\mathrm{In}(P_{EG}) + (P_{JOH})\right] \tag{5}$$

$$EG{-}JOH{-}BO{-}BDM = -2\left[\mathrm{In}\left((P_{EG}) + (P_{JOH}) + (P_{BO}) + (P_{BDM}\right)\right. \tag{6}$$

where pEG, pJOH, pBO, and pBDM represent the significance levels for the Engle and Granger (1987), Johansen (1991), Boswijk (1994), and Banerjee et al. (1998) cointegration tests, respectively. Thus, if the computed Fisher (1932) statistic is greater than the critical values provided by the BH (2013) combined cointegration statistics, the hypothesis of non-convergence is rejected.

To confirm the consistency and robustness of the results, the bounds testing approach was employed in the presence of structural breaks. This approach describes a dynamic unrestricted error model by using a linear transformation that joins together the long run and short-run dynamics without losing any information for the long run (Pesaran et al., 2001). A dynamic unrestricted error model presented

below:

$$\Delta lnEU_t = \theta_1 + \theta_2 lnRGDP + \theta_3\ \ln RGDP^2_{t-1} + \theta_4\ \ln K_{t-1} + \theta_5\ \ln L_{t-1} + \sum_{j=1}^{p}\theta_j \Delta lnEU_{t-j} + \sum_{k=0}^{q}\theta_k \Delta lnRGDP_{t-k} + \sum_{l=0}^{r}\theta_l \Delta lnRGDP^2_{t-l} + \sum_{m=0}^{s}\theta_m \Delta lnK_{t-m} + \sum_{n=0}^{t}\theta_n \Delta lnL_{t-n} + \mu t \quad (7)$$

$$\Delta lnCO_{2t} = \theta_1 + \theta_2\ \ln RGDP + \theta_3\ \ln EU_{t-1} + \theta_4\ \ln K_{t-1} + \sum_{j=1}^{p}\theta_j \Delta lnCO_{2t-j} + \sum_{k=0}^{q}\theta_k \Delta lnRGDP_{t-k} + \sum_{l=0}^{r}\theta_l \Delta lnK_{t-l} + \sum_{m=0}^{s}\theta_m \Delta lnK_{t-m} + \mu t \quad (8)$$

"where" Δ and μ represent the first difference operator and the normally distributed residual term, respectively. After that, to examine the cointegration relationship between investigated variables, the Wald test was employed by imposing limitations on the estimated coefficients. If the calculated F-statistic exceeds the upper level, then the hypothesis of no cointegration among variables is rejected. Furthermore, our study's fitted model was subjected to diagnostic and robustness checks, including normality, heteroscedasticity, and autocorrelation tests. Also, model stability was confirmed using the Cumulative Sum (CUSUM) and Cumulative Sum of Squares (CUSUMsq) tests. Finally, we applied the causality test to examine the directions of flow of the dynamic causal link among the investigated variables.

4. Results and empirical findings

To scrutinize the stationarity of the data series (Appendix A) as a precondition of the cointegration method, the study employs ADF and PP unit root tests to check the stationary properties. Table 1 reports the outcomes of these tests and their order of integration while accounting for a possible structural break.[3] However, in the presence of a structural break in the series, ADF and PP unit root tests are weak; the result is biased and gives spurious results in terms of the non-rejection of the unit root hypothesis (Shahbaz et al., 2013a, 2013b). Therefore, the ZA (1992) unit root test was employed to define the breakpoint. All test statistics support the claim that all variables have unit root in their level form and integrated order one.

Since all the variables are stationary at their first differences, the BH (2013) combined cointegration test was employed to test the cointegration among the variables. Table 2 presents the results and demonstrates that the calculated Fisher statistics for EG-JOH, as well as for EG-JOH-BO-BDM, for EU, RGDP, RGDP^2, K, L, and CO_2 are consistently greater than the critical value at a 1% significance level. Therefore, we can infer that the series EU, RGDP, RGDP^2, K, L, and CO_2 are cointegrated and a long run interaction exists among the variables over the investigated period. Furthermore, the ARDL bounds testing result validates BH (2013) conclusion and discovers long-run relationships between the variables at the 1% level of significance. The right-hand column of Table 2 presents the residual diagnostic check for the model. The fitted model is free from both serial correlation and heteroscedasticity and it's properly specified. The CUSUM and CUSUMsq plots were found between the 95% confidence interval, thus, our model meets the stability conditions.

Tables 3 reports the Pesaran et al. (2001) bounds test and Kripfganz and Schneider (2018) critical values and approximate *p*-values test results. The test further validates the existence of a level long-run relationship among the study variables. This was attained with both F-statistic and T-statistical greater than the upper bounds for all statistical significance level as well as the *p*-value with K = 2 as the number of parameters in the fitted model. The choice of the critical values rest on its uniqueness to provide more robust and reliable outcomes in the presence of small finite sample size Kripfganz and Schneider, 2018.

The long- and short-run dynamic impacts of RGDP, RGDP^2, K, L, and CO_2 on EU are presented in Table 4. The cointegration coefficient is statistically significant at the 1% significance level, which verifies the established long-run equilibrium among the variables. Our fitted model is robust with an error correction term of approximately 16% of the speed of adjustment to its cointegration path with the contribution of all the explanatory variables. Interestingly, our analysis found an inverted U-shaped relationship between EU and RGDP in the long run, thus, corroborates Sarkodie and Strezov (2018). That is, a 1% increase in economic activities and the square term of RGDP give rise to magnitudes of 15.2% and −0.28%, respectively. However, this hypothesis is not significant in the short-run. Energy use plays a critical role in economic growth; however, the energy-intensive economy is tantamount to pollution-intensification, which contributes negatively to environmental sustainability. The inverted U-shaped relationship between EU and RGDP implies that at a higher threshold level of economic growth, there is less intensification of energy use. The decline in energy intensity at higher development may be attributed to improvements in energy sector efficiency, structural changes in the economy and change in

Table 1
Unit root tests results.

Variables	ADF	PP	ZA unit root test	
	t-statistics	T-statistics	T-statistics	Time break
Panel A: level				
LnRGDP	−3.2826	−2.8756	−3.6053(1)	2005
LnRGDP^2	−3.1836	−2.7683	−3.5365(1)	2005
LnEU	−1.5659	−1.5548	−4.1484(0)	1989
LnK	−2.5164	−2.1299	−4.5058(1)	1985
LnL	−1.9412	−2.1027	−4.0524(0)	1987
LnCO_2	−1.9311	−1.9822	−4.0419(0)	1990
Panel B: Δ				
LnRGDP	−4.5868*	−4.6307*	−6.2114(0)*	1994
LnRGDP^2	−4.6072*	−4.6523*	−6.1903(0)*	1994
LnEU	−7.6523*	−7.6548*	−8.3256(0)*	2003
LnK	−5.7784*	−5.9456*	−7.1826(1)*	1994
LnL	−6.8072*	−6.8968*	−7.8831(0)*	1992
LnCO_2	−7.3071*	−7.3070*	−7.9337(0)*	2003

Source: Authors' computations.
Note: The Mackinnon (1996) one-sided *p*-value is reported. Models with intercept and trend were reported for ADF and PP test statistics. ( ) indicate the lag lengths of the variables. Δ represents first difference.
* 1% significance level.

Table 2
The results of Bayer and Hanck (2013) cointegration analysis.

Estimated models	EG-JOH	EG-JOH-BO-BDM	Cointegration remark	
EU = f (RGDP,RGDP2,K,L,CO_2)	69.0775***	92.1235*	Yes	
Bounds testing results		Diagnostic test		
Estimated models	F-statistics	χ^2white	χ^2LM test	χ^2RESET
EU = f (RGDP,RGDP^2,K,L,CO_2)	4.9941*	0.5260	0.2707	0.9776
	Critical values			
	Lower bounds 1(0)	Upper bounds 1 (1)		
1%	3.41	4.68		
5%	2.62	3.79		
10%	2.26	3.35		

Source: Authors' computations.
Note: Critical values for EG-JOH at 1% and 5% are 15.701 and 10.419, respectively, while, for EG-JOH-BO-BDM, they are 29.850 and 19.888, respectively. Lag length is based on the minimum value of the Akaike Criterion.
* 1% significance level.
** 5% significance level.

[3] For brevity, visual plots of the series show possible structural breaks. The graphs can be made available on request.

Table 3
Pesaran et al. (2001) bounds test and Kripfganz and Schneider (2018) critical values and approximate *p*-values.

$lnCO_2$	K = 2	10%	5%			1%		*p*-value	
		I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
F	10.9260	2.8200	3.9400	3.3990	4.6410	4.7250	6.2170	0.0000	0.0000
t	−6.2080	−2.5510	−3.4350	−2.8790	−3.8000	−3.5330	−4.5140	0.0000	0.0000

Source: Authors Computation.

energy consumption patterns. Sarkodie and Strezov (2018) argued that a structural change in the economy, by moving from energy-intensive production patterns to less energy and pollution-intensive production reduces energy intensity while improving energy efficiency. Even though fossil fuel energy technologies dominate the energy portfolio in South Africa, however, a recent study (Sarkodie and Adams, 2018) reveals that the incorporation of renewable energy and clean energy technologies like nuclear energy into South Africa's energy mix have contributed immensely to energy efficiency and the decline of environmental pollution. Change in consumption patterns due to behavioural and lifestyle changes may account for the reduction in energy demand in higher economic development. It is argued that higher economic development translating into higher household income levels motivates the acquisition and the replacement of outmoded energy consuming appliances with less and energy efficient appliances — energy conservation options, hence, improving energy efficiency (Sarkodie and Adom, 2018).

Contrary to Apergis and Payne (2009) who found a positive impact of capital and labour on energy usage in Central America, our empirical results demonstrate that labour and capital have a negative effect on energy use in the long run, while labour has a positive effect on energy use in the short run. We find that a 1% increase in labour demand will cause a 0.33% decrease in energy consumption in the long-run. Along with this, a 1% rise in capital formation will cause a 0.09% reduction in energy consumption in the long run, while it will cause a 0.04% increase in the short run. The initial positive shocks in energy consumption are expected in the initial or short-term effects of gross capital formation and labour. A shift from unemployment state to an employed state is often characterized by the 'wobbling effect'. As usual, people tend to utilize all the lost opportunities during the unemployed condition, as such, reflects in energy consumption behaviour and lifestyle. However, in the long-run, as labour effect stabilizes, and income level grows, the willingness to pay for cleaner and modern energy appliances due to self-actualization leads to a reduction in energy consumption, reflecting in energy efficiency. The long-run negative effect of gross capital formation implies the acquisition of less pollution, less disposal, and energy conservative assets such as machineries, equipment, infrastructures, agricultural-related cultivated assets, and among others. As investments in clean, modern and energy efficient tangible and intangible assets increases, economic productivity per energy consumption decreases, thus, reducing energy intensity while improving energy efficiency.

In the case of CO_2, a positive-significant relationship occurs between CO_2 and energy consumption both in the long run and short run. Our results are in line with Sarkodie (2018); Sarkodie and Adom (2018); Wang et al. (2018), who argues that a positive effect of carbon dioxide emission on energy use. This implies that "climate change induced by higher atmospheric greenhouse gas accumulation will cause a backfire in energy use, since more energy may be needed for heating and cooling purposes" as posited by Sarkodie and Adom (2018). This finding is of significance for government administrators and environmental specialists.

Table 5 below render the short and long run dynamics for the current study with a fast pace of adjustment of 90%, which is statistically significant at 1% level to equilibrium path with the contribution of other regressors. This is an indication of a workable mechanism. The fitted carbon function model reveals that economic growth (GDP) and carbon dioxide emission exhibits an inverse relationship. This suggests that a 1% increase in economic activities in South Africa decreases CO_2 emission by 0.25% in the long run while statistically insignificant in the short-run. This is insightful, as it indicates that South Africa's economic growth does not increase CO_2 emissions, given the country's antecedent in greenhouse gas emissions flaring over the years. The outcome further implies that South Africa has initiated compliance with global partnership and international practices in its economic dealings. Contrary to the inverse association observed between GDP and CO_2, energy use and CO_2 exhibit a positive correlation in both long- and short-run. Our results are corroborated by Kais and Sami (2016) with evidence from 58 countries, Alam et al. (2016) with evidence from Brazil, India, China, and Indonesia. This implies that an increase in energy consumption triggers carbon dioxide emissions in South Africa. Thus, government and energy stakeholders are encouraged to promote cleaner energy sources like solar, wind, hydro, bioenergy, and nuclear energy consumption. Renewable and green energy

Table 4
ARDL results for energy consumption model.

Dependent variable = lnEU			
Variable	Coefficient	Std. error	T.stat.
Long-run results			
Constant	−194.086	52.5030	−3.6967
lnRGDP	15.2060*	3.9747	3.8257
$lnRGDP^2$	−0.2879*	0.0770	−3.7408
lnK	−0.0868	0.0781	−1.1110
lnL	−0.3335**	0.1306	−2.5539
$lnCO_2$	0.9528*	0.0939	10.1520
Short-run results			
ECT(−1)	−0.15946*	0.2578	−6.1853
ΔlnEU(−1)	0.3630***	0.1894	1.9170
ΔlnRGDP	12.3393	15.7410	0.7839
$\Delta lnRGDP^2$	−0.2231	0.2998	−0.7442
ΔlnK	0.0428	0.0389	1.0978
ΔlnL	−0.8160*	0.2097	−3.8922
$\Delta lnCO_2$	0.9324*	0.0965	9.6596

Source: Authors' computations.
* 0.01 significance level.
** 0.05 significance level.
*** 0.10 significance level.

Table 5
Long- and short-run analysis for CO_2 emission.

	$\Delta lnCO_2$	Coef.	Std. Err.	t	P > t
ADJ					
	ECT (−1)	−0.9011	0.1452	−6.2100	0.0000
LR					
	lnGDP	−0.2445	0.0469	−5.2100	0.0000
	lnEUSE	1.3200	0.0691	19.0900	0.0000
	lnK	0.0882	0.0273	3.2300	0.0020
SR					
	ΔlnGDP	−0.3792	0.2337	−1.6200	0.1110
	ΔlnEUSE	1.0832	0.1085	9.9800	0.0000
	ΔlnK	0.0673	0.0499	1.3500	0.1840
	_cons	−3.5098	0.7004	−5.0100	0.0000

Source: Authors' computations.

technologies have been proven to be more environmentally friendly and support ecosystem rejuvenation compared to conventional energy sources (Owusu and Asumadu, 2016). To account for the role of capital in carbon function modeling, the study examined the nexus between CO_2 emissions and capital formation. The results reveal a significant positive relationship between CO_2 emissions and capital formation in the long-run relative to the insignificant short-term effect.

The Granger causality test is applied to test the directional flow of the causal relationships among variables. Table 6 provides the empirical findings of this analysis. The results affirm that there is a one-way causality running from energy use, labour, and CO_2 emissions to economic growth. The results are in line with Spetan (2016), Bhattacharya et al. (2016), Fotourehchi (2017), and Khobai and Le Roux (2017). Energy consumption and labour remain the building blocks of economic development. In accordance with SDG 7 and 8, improving energy production and consumption patterns and increasing labour productivity are critical to a sustainable economic development (United Nations, 2015). The one-way causality running from energy use to CO_2 emissions is supported by Shahbaz et al. (2012) and Balsalobre-Lorente et al. (2018). This validates the energy-induced growth hypothesis for the case of South Africa. Sarkodie and Adams (2018) revealed that South Africa's energy portfolio is dominated by fossil fuel energy technologies especially coal power plants, as such, increases atmospheric CO_2 emissions during combustion processes. Furthermore, unidirectional causality is also seen from energy use to labour and CO_2 emissions as well as from CO_2 emissions to labour. Feedback causality is found between capital formation and CO_2 emissions.

5. Conclusion

This study investigated the causal link between energy use and economic growth, a topical topic in energy and economics literature. Due to the lack of consensus on causality direction of the scope of the study, we draw attention to the theme by accounting for the contribution of capital, labour, and CO_2 emissions to energy use in the case of South Africa. The empirical analyses for this study span from 1960 to 2016 on an annual basis. Empirical findings reveal a long-run equilibrium relationship among the investigated variables using BH (2013) combined cointegration test and confirmed by Pesaran et al.'s (2001) bounds testing approach. This implies that the joint contributions of CO_2 emissions, economic growth, capital formation, and labour spur an increase in South Africa's energy consumption.

The causal analysis between energy use and economic growth reveals a unidirectional causality. Thus, the results validate the energy-induced growth hypothesis. This means that energy conservative policy/strategies will harm the initial economic development in South Africa, which is instructive for government administrators. Interestingly, our analysis investigated an inverted U-shaped relationship between energy consumption and economic growth in the long run. This relationship implies that at a higher threshold level of economic activities, there is less intensification of energy use. The unidirectional causality observed from energy use to CO_2 emissions is of concern to environmental policymakers, giving the global awareness of the need for renewable and cleaner energy sources. This is a warning sign for South Africa to strengthen its commitment to the Kyoto Protocol and the Paris Agreement.

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Table 6
Results of Granger causality analysis.

Null hypothesis:	Causality	F-Statistic	Prob.
LNRGDP ≠> LNEU	EU → RGDP	1.81597	0.1835
LNEU ≠> LNRGDP		8.79044*	0.0045
$LNRGDP^2$ ≠> LNEU	EU → $RGDP^2$	1.72000	0.1953
LNEU ≠> $LNRGDP^2$		8.83279*	0.0044
LNK ≠> LNEU	K ≠ EU	2.28493	0.1366
LNEU ≠> LNK		0.77138	0.3838
LNL ≠> LNEU	EU → L	0.00382	0.9510
LNEU ≠> LNL		9.56867*	0.0032
$LNCO_2$ ≠> LNEU	EU → CO_2	0.06587	0.7984
LNEU ≠> $LNCO_2$		4.71200**	0.0345
$LNRGDP^2$ ≠> LNRGDP	RGDP ↔ $RGDP^2$	4.79262**	0.0330
LNRGDP ≠> $LNRGDP^2$		4.57682**	0.0370
LNK ≠> LNRGDP	RGDP ≠ K	0.26207	0.6108
LNRGDP ≠> LNK		1.41572	0.2394
LNL ≠> LNRGDP	L → RGDP	2.86355***	0.0965
LNRGDP ≠> LNL		2.42588	0.1253
$LNCO_2$ ≠> LNRGDP	CO2 → RGDP	9.79703*	0.0028
LNRGDP ≠> $LNCO_2$		2.06006	0.1571
LNK ≠> $LNRGDP^2$	K ≠ $RGDP^2$	0.21032	0.6484
$LNRGDP^2$ ≠> LNK		1.50390	0.2255
LNL ≠> $LNRGDP^2$	L ≠ $RGDP^2$	2.64300	0.1099
$LNRGDP^2$ ≠> LNL		2.39874	0.1274
$LNCO_2$ ≠> $LNRGDP^2$	CO_2 → $RGDP^2$	9.75773*	0.0029
$LNRGDP^2$ ≠> $LNCO_2$		1.99460	0.1637
LNL ≠> LNK	L ≠ K	2.14337	0.1491
LNK ≠> LNL		0.02119	0.8848
$LNCO_2$ ≠> LNK	K ↔ CO_2	3.19973***	0.0794
LNK ≠> $LNCO_2$		3.03314***	0.0874
$LNCO_2$ ≠> LNL	CO2 → L	7.17081*	0.0098
LNL ≠> $LNCO_2$		0.14473	0.7051

Note: ≠ represents no Granger causality, → symbolized unidirectional causality, and ↔ represents feedback causality. ≠> symbolized 'does not granger cause'.
* 0.01 significance level.
** 0.05 significance level.
*** 0.10 significance level.

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Declaration

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Appendix 5 — Publication Twelve: Toward a sustainable environment: Nexus between CO_2 emissions, resource rent, renewable and nonrenewable energy in 16-EU countries

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Toward a sustainable environment: Nexus between CO_2 emissions, resource rent, renewable and nonrenewable energy in 16-EU countries

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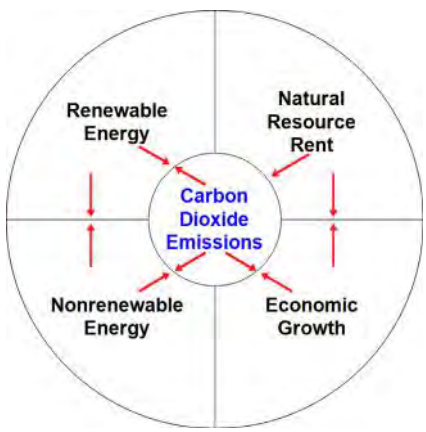
HIGHLIGHTS

- Renewable energy consumption improves environmental quality in 16 EU countries.
- Feedback causality observed between natural resources rent and economic growth.
- Long-term risk of natural resource rent affecting environmental sustainability.
- Economic growth influences carbon dioxide emissions in EU-16 countries.
- Fossil fuels exert more distortion on environmental sustainability.

GRAPHICAL ABSTRACT



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ABSTRACT

The study investigates the long-run and causal interaction between, renewable energy consumption, nonrenewable energy consumption, and economic growth in a carbon function. The current study incorporates natural resources rent to the model as an additional variable. Empirical evidence is based on a balanced panel data between annual periods of 1996–2014 for selected EU-16 countries. The Kao test reveals a cointegration between carbon dioxide emissions, economic growth, natural resources rent, renewable, and nonrenewable energy consumption. The Panel Pooled Mean Group-Autoregressive Auto regressive distributive lag model (PMG-ARDL) suggests a positive significant relationship between the countries' natural resource rent and CO_2 emissions in the long-run. Implying that the overdependence on natural resource rent affects environmental sustainability of the panel countries if conservation and management options are ignored. Our study affirms that nonrenewable energy consumption and economic growth increase carbon emission flaring while renewable energy consumption declines CO_2 emissions. The panel causality analysis reveals a feedback mechanism between economic growth, renewable, and nonrenewable energy consumption. We further observed a feedback causality between natural resources rent and economic growth. Effective policy implications could be drawn toward modern and environmentally friendly energy sources, especially in attaining the Sustainable Development Goals.

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1. Introduction

One of the most pertinent environmental turmoils of the past decades is global warming, which characterizes the global climate change. Through the contribution of labor, capital resources and other production inputs, increased human activities are largely responsible for the growth in the world's economy (Owusu and Asumadu, 2016). However, competition for natural resources and sustainability among organisms, especially human, has been linked to environmental degradation. So far, carbon emissions remain the largest contributor to declining environmental sustainability. The concentration of carbon dioxide (CO_2) emission has reportedly increased by about 45% in the last 130 years (Carbon Footprint, 2018). In addition to the emission of carbon dioxide from plants, animals and other sources, the common by-product of energy source usage has largely been attributed to carbon emissions. Unfortunately, CO_2 emissions remain unfriendly to environmental sustainability and constitute a focal factor in the global debate on climate change. Hence, the concept of mitigating carbon dioxide emissions which largely constitute the anthropogenic greenhouse gas (GHG) (about 81% of greenhouse gases), has consistently become a priority of the world's advanced economies (Owusu and Asumadu-Sarkodie, 2016). This is because CO_2 emissions have persistently remained the world's most threatening issue facing the natural ecosystem and human development. Anthropogenic CO_2 emissions trap heat in the atmosphere, thereby increasing the global temperature. According to the Intergovernmental Panel on Climate Change (IPCC, 2014) 5th assessment report, the gaseous emission has undesirably increased from 9434.4 million tons in 1961 to 34,649.4 million tons in 2011.

In this context, the British Petroleum (BP) Statistical Review of World Energy (British Petroleum, 2018) noted that carbon dioxide emissions increased from 29,714.2 million tons in 2009 to 33,444.0 million tons in 2017. Despite the Paris Agreement of 2015[1] and the strong drive towards reducing carbon emission by member countries, the BP report indicates that the global carbon dioxide emissions have increased by 1.6% between 2006 and 2017. Importantly, between the said periods, the growth rate of carbon dioxide emissions in the European region, which is second to the Middle East countries is about 2.5% (British Petroleum, 2018). Hence, the continent has consistently been at the forefront of the push against climate change. Even after witnessing the attainment of its commitment within the first period (2008–2012) of the Kyoto Protocol, subsequent targets were set to accommodate a shift in the decomposition factors of CO_2 emission in the region. The dynamics that have impacted the changes associated with the level of energy-related carbon dioxide emissions have been identified in extant literature. Some of these driving forces previously mentioned includes: economic growth (Apergis et al., 2010; Sarkodie and Owusu, 2016a; Bekun et al., 2019); fossil fuel or nonrenewable energy component (Khoshnevis Yazdi and Shakouri, 2017; Nguyen and Kakinaka, 2019); renewable energy component (Inglesi-Lotz and Dogan, 2018; Khoshnevis Yazdi and Ghorchi Beygi, 2018), and other notable factors (Al-mulali, 2012; Sarkodie and Owusu, 2016b). And, specifically in the EU-28, resource rent (of the natural resource) which is the total revenue earned from the extraction of the natural resource, is expected to determine both the economic growth and carbon abatement policy of the region.

However, the diversity in economies and its dynamics in existing literature continues to establish the link between natural resources and the economic indicators (Ahmed et al., 2016; Badeeb et al., 2017; Balsalobre-Lorente et al., 2018; Ben-Salha et al., 2018; Satti et al., 2014; Shahbaz et al., 2018). In a panel investigation of five European (EU-5) countries, Balsalobre-Lorente et al. (2018) found that natural resources, economic growth, and renewable electricity are significant determinants of CO_2. As such, the study examined the environmental Kuznets curve (EKC) hypothesis in the observed countries for the period 1985–2016. In specifics, the relationship between economic growth and CO_2 is found to exhibit N-shape. The empirical results indicate that natural resources abundance, renewable electricity consumption, and energy innovation inhibit environmental degradation. On the other hand, the interaction between renewable electricity consumption and economic growth is found to worsen environmental pollution. For the case of the United States (US), Shahbaz et al. (2018) applied Bayer and Hank cointegration test and vector error correction model (VECM) to detect the direction of causality for financial development, education and resource rent. The empirical evidence of the investigation which spans for the period 1960–2016 suggests a positive and statistical relationship between resource rent and financial development. A similar trend is observed between education and financial development, education is found to exert a positive impact.

The current study hypothesized the underpinning of the dynamic nexus of resource rent, renewable and nonrenewable energy with carbon dioxide emissions of the 16 EU countries (Austria, Belgium, Bulgaria, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherland, Portugal, Spain, Sweden, and United Kingdom) over the period 1996–2014. Although previous literature reveals a similar scope of the study, however, this study contributes to existing literature in a few notable areas. First, contrary to previous attempts, the study further incorporates resource rent to the existing and pre-determined CO_2 emissions model. The addition of the variable would help investigate the contribution of the earnings from natural resources of the selected regions to their CO_2 abatement drive and policies. Second, the uniqueness of this study is reflected in the adopted estimation approach to investigate the concept among EU countries. As observed, the investigation considered sixteen selected EU countries which comprise accordingly to the availability of the main examined variables, especially renewable energy consumption. Last, the study jointly examines the short- and long- run relationships by utilizing the Pooled Mean Group/Autoregressive Distributed Lag (PMG-ARDL) and Granger causality associated with the estimated model.

The remainder of the study is organized as follows: Section 2 outlines the methodology employed in the study. Results and Discussion are presented in Section 3 and Section 4 offers concluding remarks that include policy implication of the study.

2. Materials and methods

The rising prices of fossil energy resources and the efficient use of energy account for the high convergence of energy transition among the European countries. The energy transition policy is being advocated among these countries because of higher emission levels associated with the inefficient use of energy. In the European Union (EU), the adoption of 2001/77/EC (European Union 2001) and 2003/30/EC (European Union 2003) directives[2] has further paved way for the development of renewable energy sources. To further enhance the economic, social and environmental sustainability of the regional countries, a mandatory target and regulative framework are aimed to pave way for the adoption of renewable energy by the member states in 2020 (the EU Directive 2009/406/EC). In the region, it is reported that renewable energy is now cost-competitive and efficient even as fossil fuels imports is reduced by 16 billion Euros by early 2017. The dynamics of the natural resource rent, renewables and nonrenewable relative to carbon dioxide emissions of the European Union is further represented in Fig. 1.

[1] More details relating to the Paris Agreement of 2015 is contained is available at: https://unfccc.int/process/conferences/pastconferences/paris-climate-change-conference-november-2015/paris-agreement.

[2] The directives of the European Union of renewable energy are contained in https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:32009L0028.

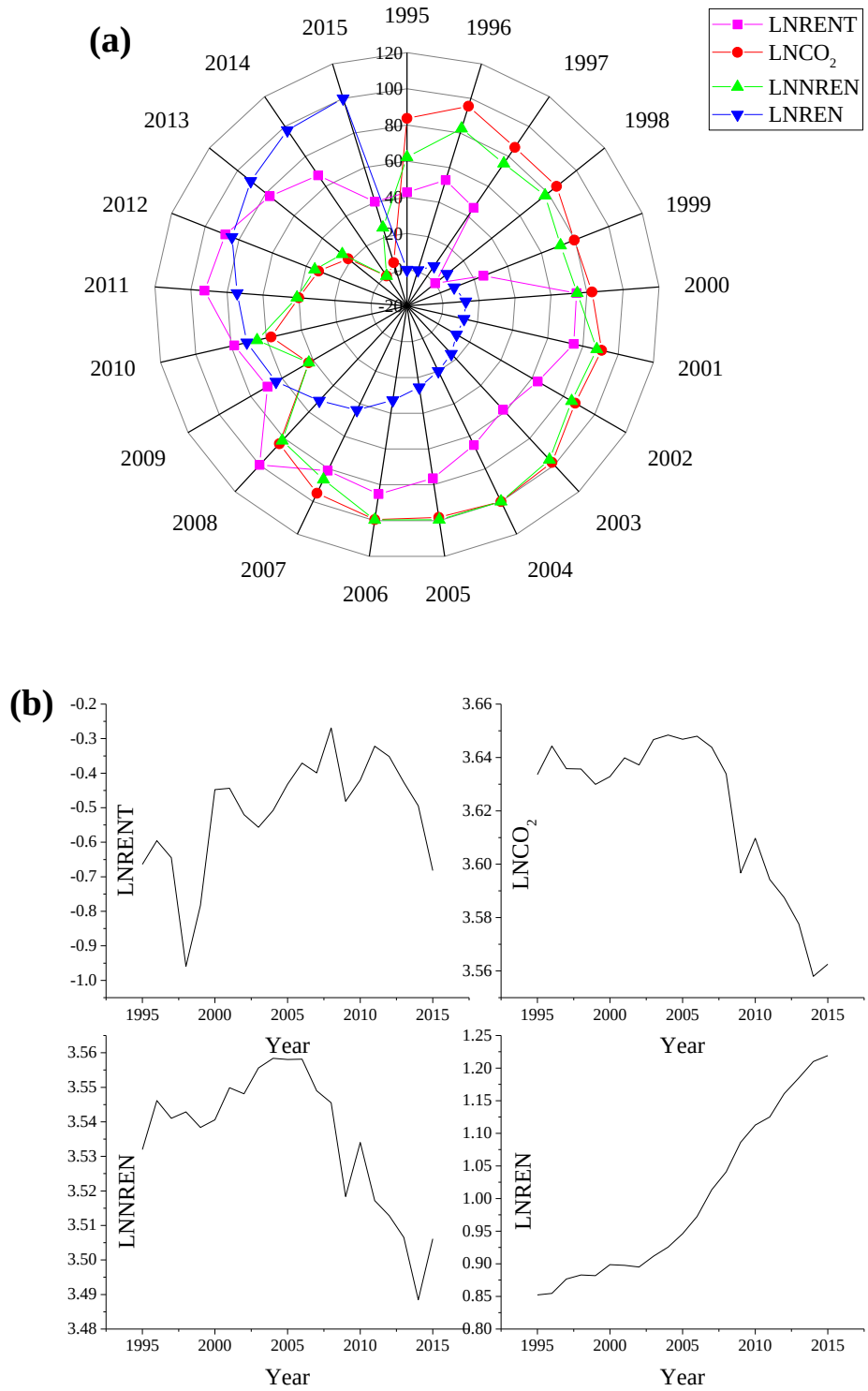

Fig. 1. The movement pattern (a) and relative magnitude (b) of the series. NB: The plot shows the dynamics of the natural resource rent, renewables and nonrenewable relative to carbon dioxide emissions of the European Union.

2.1. Data

Our study employs balanced and periodically annual data 1996–2014 for the estimated series. The estimation model uses carbon dioxide emissions (CO_2) (the kilotons of the burning of solid, liquid and gas fossil fuels, gas flaring, and the manufacture of cement) as the dependent variable. The explanatory variables employed are: Real Gross Domestic Product (*GDP*) per capita (measured in constant 2010 USD), the renewable energy consumption (*REN*) as the share of renewables in the total final energy consumption, energy use (non-renewables denoted as *NREN*) is the kilogram of oil equivalent per capita which is measured in the form of primary energy source before transformation into other end-use, and the resource rent (*RENT*) is the total natural resources rents. In the estimation model, the unobserved factors are controlled for by real *GDP* per capita. The World Bank (2017) Development Indicator is the source of the aforementioned data series. Data

Table 1
Data description.
Source: Authors compilation.

Variable name	Code	Unit	Source
Carbon dioxide emissions	CO_2	kt	WDI
Real gross domestic product	GDP	Constant 2010 USD	WDI
Total natural rent	RENT	% of GDP	WDI
Renewable energy consumption	REN	% share of renewables in the total final energy consumption	WDI
Nonrenewable energy consumption	NREN	kg of oil equivalent per capita	WDI

NB: WDI = world development indicators, world bank database.
Real Gross Domestic Product (*GDP*) per capita (measured in constant 2010 USD), the renewable energy consumption (*REN*) as the share of renewables in the total final energy consumption, energy use (non-renewables denoted as *NREN*) is the kilogram of oil equivalent per capita which is measured in the form of primary energy source before transformation into other end-use, and the resource rent (*RENT*) is the total natural resources rents.

availability (especially for renewable energy) is largely responsible for both the restricted period of the data series and the selection of the estimated countries. See Table 1 for a summary of data description.

2.2. Model estimation

While a good number of studies have jointly observed the nexus of non-renewable and renewable energy with carbon dioxide emissions (Inglesi-Lotz and Dogan, 2018; Khoshnevis Yazdi and Shakouri, 2017; Nguyen and Kakinaka, 2019), the current studies have applied the concept for selected European Union countries. Additionally, our model uniquely incorporated resource rent (*rent*) to replace trade openness and urbanization in the study of Khoshnevis Yazdi and Shakouri (2017) such that:

$$CO_2 = f(GDP, RENT, REN, NREN) \tag{1}$$

$$lnCO_{2i,t} = \alpha + \beta_1 lnGDP_{i,t} + \beta_2 lnRENT_{i,t} + \beta_3 lnREN_{i,t} + \beta_4 lnNREN_{i,t} + \varepsilon_{i,t} \tag{2}$$

For the data series to have a constant variance, the study applies a logarithmic transformation. Here, $lnCO_{2i,\ t}$ against $lnGDP_{i,\ t}$, $lnRENT_{i,\ t}$, $lnREN_{i,\ t}$, and $lnNREN_{i,\ t}$ denote the logarithmic transformed dependent variable versus the independent variables, α represents the intercept term, $\beta's$ are the partial slope coefficients, and $\varepsilon_{i,\ t}$ is the stochastic term.

Due to bias triggered by the correlation between the mean-differenced independent variables and the white noise term, standard ARDL estimation models are incapable of controlling for bias especially in panel data models with individual effects. As such, a combination of PMG estimator by Pesaran et al. (1999) and ARDL model provide a solution to the challenge contrary to the inappropriate dynamic panel generalized method of moments (GMM) estimators (Sarkodie and Strezov, 2018b).

Contrary to existing panel data models available in Destek and Sarkodie (2019), Sarkodie (2018), and Sarkodie and Strezov (2019b), this study follows the PMG-ARDL pathway utilized in Sarkodie and Strezov (2018b), expressed as:

$$\Delta\ \ln y_{i,t} = \phi_i ECT_{i,t} + \sum_{j=0}^{q-1} \Delta\ \ln X_{i,t-j}\beta_{i,j} + \sum_{j=1}^{p-1} \psi_{i,j^*}\ \Delta\ \ln y_{i,t-j} + \varepsilon_{i,t} \tag{3}$$

$$ECT_{i,t} = y_{i,t-1} - X_{it}\theta \tag{4}$$

where, y is the dependent variable (CO_2), X represents the regressors (*GDP*, *RENT*, *REN*, *NREN*) with same number of lags q across individual cross-sectional units i in time t, Δ denotes the difference operator, ϕ represents the adjustment coefficient, θ denotes the long-run coefficient that produces β and ψ estimates after reaching convergence, and ε represents the error term.

This study follows 3 paths for its empirical analysis. (i) Stationarity test by fisher ADF and Pesaran et al. (2003) unit root test (ii) cointegration analysis and long-run regression advanced by Pesaran et al. (1999) and (iii) Causality analysis through Dumitrescu and Hurlin (2012). However, preliminary estimation of descriptive statistics and correlation analysis were conducted.

3. Results and discussion

The summary statistics are reported in Table 2. This is necessary to ascertain the basic measure of central tendency and dispersion of the variables and how they fare over the investigated period (1996–2014). Table 2 shows that carbon dioxide has a minimum value of 86,759 kt from the start-up years with a maximum of 13,6985 kt over the period under consideration while real income has highest (maximum) of over $11,000 and a minimum of $8000 plus. All interest variables under consideration are negatively skewed except for total natural resource rent and non-renewable energy consumption. The current study is conducted for sample size panel of 304 observations with all series not normally distributed with the exemption of carbon dioxide that is normally distributed given the failure to reject the null hypothesis of normality.

In addition to the summary statistical analysis, we conducted a correlation matrix analysis to explore the relationship between the variables under review as resented in Table 3. A significant positive relationship is observed between carbon dioxide emissions and real GDP for the sampled period. However, for the case of total resource rent, an inverse statistically significant synergy is seen with carbon dioxide emissions while for renewable energy consumption and carbon dioxide emissions a negative statistical association is observed which is desirable for the sampled countries. This implies that renewable energy sources mitigate against carbon dioxide emissions. For nonrenewable energy consumption as *apriori* expectation, a positive significant relationship is observed. It is noteworthy that correlation coefficients estimation analysis is not sufficient on its own to validate any outcome. It's on the above premise that this study proceeds to conduct econometric analysis that is more reliable and consistent to either validate or refute the objectives of this study.

Stationarity test is pertinent in econometrics analysis to circumvent spurious regression trap. Table 4 renders the unit root analysis, we observed that all variables of interest are first difference stationary except for natural resource rent that is stationary even at 1% significance level. Thus, the general conclusion is that all series are mixed order integrated as reported by both ADF-Fisher unit root test and Im Pesaran Shin unit root test.

Subsequently, our study examined the long run relationship between the variables. According to Kao residual cointegration test, there exist long-run (equilibrium relationship) between carbon dioxide emissions, economic growth, renewable energy consumption, nonrenewable consumption and natural rent over the period considered.

Table 2
Descriptive statistics for EU-16 countries under review.
Source: Authors computation.

	$LNCO_2$	LNGDP	RENT	LNREN	NREN
Mean	11.5586	10.4157	0.4113	2.1639	3732.953
Median	11.1885	10.5681	0.1546	2.1872	3587.883
Maximum	13.6985	11.0215	2.8391	3.9109	7134.854
Minimum	8.6759	8.2296	0.0006	−0.1592	1687.785
Std. Dev.	1.1898	0.5461	0.5478	1.0028	1260.710
Skewness	−0.1641	−2.3939	2.1155	−0.2943	0.6882
Kurtosis	2.7402	8.9928	7.6723	2.3155	2.6694
Jarque-Bera	2.2192	745.2860	503.2614	10.32476	25.3858
Probability	0.3297	0.0000***	0.0000***	0.0057***	0.0003***
Observations	304	304	304	304	304

NB: *** denotes rejection of the null hypothesis at 1% significance level.

Table 3
Correlation matrix analysis.
Source: Authors computation.

	$LNCO_2$	LNGDP	RENT	LNREN	NREN
$LNCO_2$	1.0000				
T-statistic	–				
Prob.	–				
LNGDP	0.1813	1.0000			
T-statistic	3.2040	–			
Prob.	0.0015**	–			
RENT	−0.1345	−0.3869	1.0000		
T-statistic	−2.3590	−7.2934	–		
Prob.	0.0190**	0.0000***	–		
LNREN	−0.2502	0.0199	0.1026	1.0000	
T-statistic	−4.4914	0.3468	1.7932	–	
Prob.	0.0000***	0.7290	0.0739*	–	
LNNREN	0.1516	0.5054	−0.0401	0.1218	1.0000
T-statistic	2.6650	10.1791	−0.6979	2.1329	–
Prob.	0.0081***	0.0000***	0.4857	0.0337**	–

We conduct a correlation matrix analysis to explore the relationship between the variables under review.
Note: ***, **, * represents 0.01, 0.05 and 0.10 rejection level respectively.

Thus, we proceed to investigate the magnitude of cointegration as reported in Table 5 via PMG-ARDL. The results show a robust estimation with a convergence speed of 7% by the contribution of other regressors toward their equilibrium path. The current study observes a positive significant relationship between carbon emissions and economic growth. As a 1% increase in economic activities birth a corresponding 1.15% increase in carbon dioxide emission (environmental degradation) in the long run. This is in line with the scale effect, thus, our study affirms a positive linear relationship between economic growth and environmental degradation (Shahbaz et al., 2017). This finding is indicative to environmental administrator/policy makers in the region to curtail CO_2 emissions. Similarly, in the short run linear positive relationship exit between economic growth and CO_2 though not statistically significant. Regarding natural rent, there exist an inverse relationship with CO_2 emissions for the sampled region in the short run. Contrary, we observe a positive relationship between natural resource rent and CO_2 emissions in the long run. This is desirable as the exploration of natural resources triggers economic growth directly and subsequently spurs increased CO_2 emissions. Regarding renewable energy consumption in both the long and short run, there exist a statistical inverse relationship with CO_2. This result is interesting to energy and environmental economists as 1% increase in the consumption of renewable energy sources leads to 0.18% decrease in the long run and 0.13% decrease of environmental pollution in the short run in the selected European Union countries investigated. This result is laudable and the possible explanation could be that most EU countries are signatory to the Kyoto protocol agreement to decrease CO_2 emissions. This position is advocated in the recent studies of Alola and Alola (2018); Emir and Bekun (2018). For the case of nonrenewable energy consumption, we observe a positive and statistically significant relationship in both the short and long run. This is in line with previous studies that nonrenewable energy

Table 4
Unit root results.

	ADF-Fisher		Im, Pesaran Shin	
	Level	Δ	Level	Δ
LNRGDP	23.613	73.311***	1.154	−4.175***
LNREN	24.350	69.770***	1.023	−3.848***
LNNREN	17.475	82.909***	3.841	−5.296***
LNRENT	73.012***	155.620***	−3.997***	−11.289***
$LNCO_2$	19.862	92.568***	2.550	−5.765***

Note: *** represents 0.01 rejection level respectively while Δ denotes first difference. Stationarity test is pertinent in econometrics analysis to circumvent spurious regression trap. We observe that all variables of interest are first difference stationary except for natural resource rent that is stationary even at 1% significance level.

Table 5
Pooled mean group with dynamic autoregressive distributed lag [PMG-ARDL(1,1,1,1,1)].

Model: $lnCO_2$ = f(LNGDP, LNRENT, LNREN, LNNREN)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
Long run				
LNGDP	1.1536***	0.2313	4.9877	0.0000
LNRENT	0.0740***	0.0252	2.9410	0.0036
LNREN	−0.1805***	0.0427	−4.2388	0.0000
LNNREN	0.8819***	0.1589	5.5469	0.0000
Short run				
ECT(−1)	−0.0700***	0.0241	−2.9041	0.0041
LNGDP	0.0130	0.0542	0.2406	0.8101
LNRENT	−0.0007	0.0069	−0.0980	0.9220
LNREN	−0.1284***	0.0467	−2.7513	0.0065
LNNREN	1.1228***	0.0931	12.0575	0.0000
Constant	−0.4772***	0.1575	−3.0282	0.0028
Kao residual cointegration test				
ADF			−2.4593	0.0070
Residual variance			0.000671	
HAC variance			0.000705	

Note: number of observations = 288, information criterion-Akaike information criterion (AIC), maximum lag 1 as suggested by AIC and most parsimonious.
Note: *** denotes 0.01 rejection level respectively.

sources like coal and oil consumption increases CO_2 emission and by extension deplets environmental quality.

In Fig. 2, the diagnostic test of confidence ellipse is captured with the stability points centralized within the ellipse. Hence, it implies that the estimation model presents a significant confidence level.

Table 6 finally reports the Dumitrescu and Hurlin panel causality test. The panel causality test employed in this study allows the examination of the Granger non-causality from independent variable to the dependent variable in a heterogeneous panel setting following the procedure outlined by Dumitrescu and Hurlin (2012). We observe a bidirectional causality between CO_2 emissions and GDP. This implies industrial activities increase economic growth while the structural dynamics of the economy accelerate carbon dioxide emissions. In other words, a feedback mechanism exists between environmental deterioration and economic development in EU countries. Hence, a structural change from energy and carbon-intensive economy to a decarbonized economy and services are essential to mitigate climate change and its impacts (Sarkodie and Strezov, 2019a). A feedback mechanism is also observed between: renewable energy and carbon dioxide emissions, nonrenewable energy and carbon dioxide emissions, renewable energy and economic growth, nonrenewable energy and economic growth, natural resource rent and economic growth, and nonrenewable and renewable energy. Both nonrenewable and renewable energy are observed to trigger carbon dioxide emissions and vice versa. Thus, countries increase the penetration of renewable energy technologies in their energy mix when fossil fuel energy consumption accelerates carbon dioxide emissions leading to extreme climate change related events. In another scenario, both nonrenewable and renewable energy triggers economic development and contrariwise. Contrary to the challenges associated with renewable energy technologies, Owusu and Asumadu (2016) noted in the comparison between renewable and fossil fuel energy technologies that, "*renewable energy reduces energy imports and contribute to the diversification of supply options and reduce an economy's vulnerability to price volatility and presents opportunities to enhance energy security*". The role of natural resource rent is key to most economies in the world. Thus, the current study traces feedback causality from natural resource rent and economic growth. As the exploration of a nation's natural resources births economic growth. However, Destek and Sarkodie (2019) reported that the overexploitation of the available natural resources affects a country's biocapacity (ability for the natural resources to regenerate) while increasing the ecological footprint, leading to an ecological deficit. As such, a shift from vintage

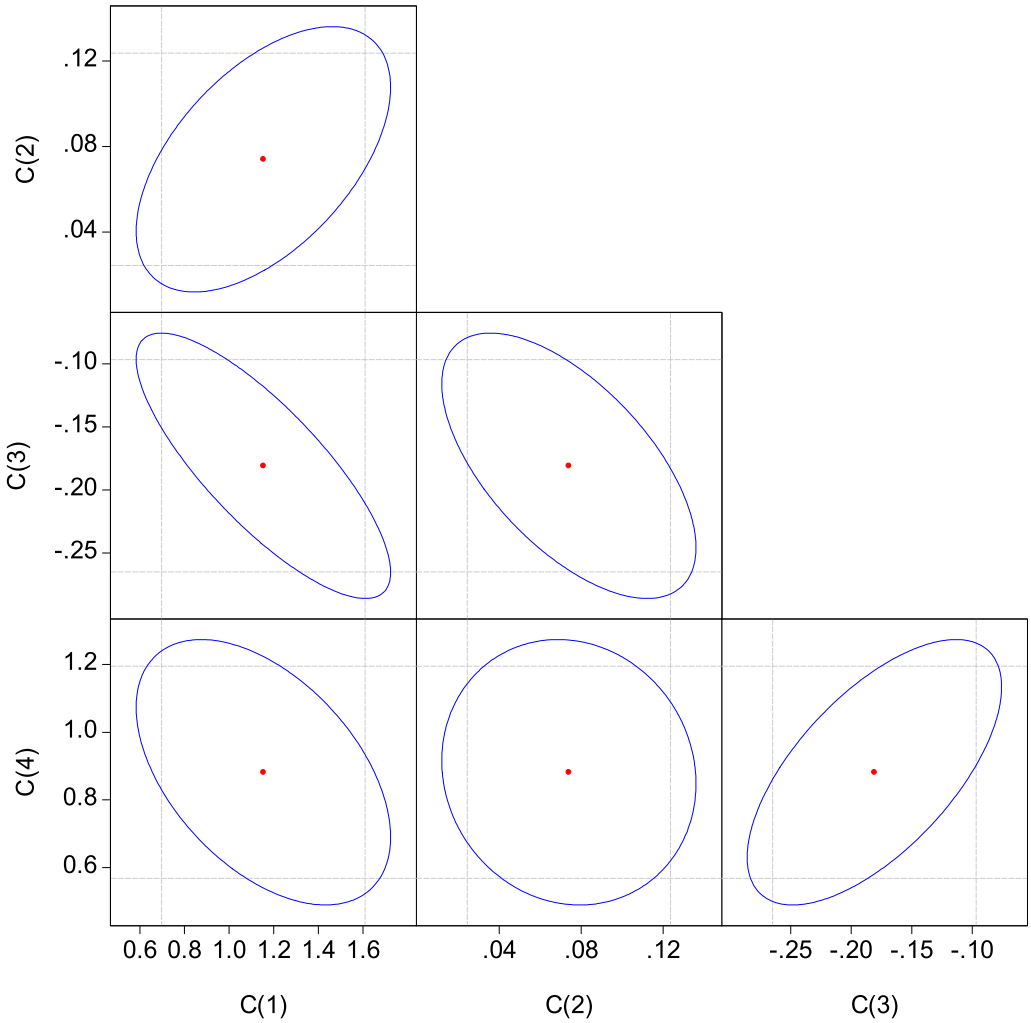

Fig. 2. Coefficient diagnostic with confidence interval. NB: The diagnostic test of confidence ellipse is captured with the stability points centralized within the ellipse. Hence, it implies that the estimation model presents a significant confidence level.

technologies that utilize more natural resources to modern technologies that incorporates recycling, reusing, innovation, value-addition and artificial resources that replace natural resources will improve economic development while reducing environmental degradation. Nonrenewable and renewable energy exhibit a mutualistic mechanism in EU countries. Meaning that the incorporation of either of the energy

Table 6
Dumitrescu and Hurlin Panel causality test.

Null Hypothesis:	W-Stat.	Prob.	Causality
LNGDP does not homogeneously cause $LNCO_2$	4.19340^{***}	0.0000	$CO_2 \leftrightarrow GDP$
$LNCO_2$ does not homogeneously cause LNGDP	3.02356^{***}	0.0000	
LNREN does not homogeneously cause $LNCO_2$	10.4189^{***}	0.0000	$REN \leftrightarrow CO_2$
$LNCO_2$ does not homogeneously cause LNREN	4.17975^{***}	0.0000	
LNNREN does not homogeneously cause $LNCO_2$	5.49765^{***}	0.0000	$NREN \leftrightarrow CO_2$
$LNCO_2$ does not homogeneously cause LNNREN	6.52856^{***}	0.0000	
LNRENT does not homogeneously cause $LNCO_2$	4.55141^{***}	0.0000	$RENT \rightarrow CO_2$
$LNCO_2$ does not homogeneously cause LNRENT	0.51074	0.1623	$CO_2 \neq RENT$
LNREN does not homogeneously cause LNGDP	4.72473^{***}	0.0000	$REN \leftrightarrow GDP$
LNGDP does not homogeneously cause LNREN	4.00907^{***}	0.0000	
LNNREN does not homogeneously cause LNGDP	3.18038^{***}	0.0000	$NREN \leftrightarrow GDP$
LNGDP does not homogeneously cause LNNREN	6.37251^{***}	0.0000	
LNRRENT does not homogeneously cause LNGDP	5.01345^{***}	0.0000	$RENT \leftrightarrow GDP$
LNGDP does not homogeneously cause LNRENT	3.21713^{***}	0.0000	
LNNREN does not homogeneously cause LNREN	3.41013^{***}	0.0000	$NREN \leftrightarrow REN$
LNREN does not homogeneously cause LNNREN	10.4324^{***}	0.0000	
LNRENT does not homogeneously cause LNREN	2.36213^{**}	0.0087	$RENT \rightarrow REN$
LNREN does not homogeneously cause LNRENT	1.87917	0.1150	$REN \neq RENT$
LNRENT does not homogeneously cause LNNREN	6.1562^{***}	0.0000	$RENT \rightarrow NREN$
LNNREN does not homogeneously cause LNRENT	0.6908	0.3143	$NREN \neq RENT$

Source: Authors computation
Note: ***, **, * depict 0.01,0.05 and 0.10 rejection level respectively. Where ≠, → and ↔ represent No Granger causality, one-way causality and bi-directional causality, respectively.

sources into a country's energy portfolio depends on each other to achieve a sustainable production and utilization. While most renewable energy technologies have intermittency and stability issues, fossil fuel energy technologies, on the other hand, has carbon-intensive issues. Hence, Sarkodie and Strezov (2018a) proposed a strategic combination of both energy sources essential to achieving universal access to modern and affordable energy services while mitigating climate change and its impacts. The study found a one-way causality running from natural resources rent to carbon dioxide emissions, natural resources rent to renewable and nonrenewable energy. Meaning that the availability of natural resources propels both renewable and nonrenewable energy consumption. In contrast, overdependence on natural resource rent triggers environmentally pollution in a natural resource dependent economy. As such, diversification and structural change in economic development is required to achieve a sustainable environment.

4. Conclusion

The energy economics literature has well-documented studies on the relationship between renewable energy consumption, nonrenewable consumption, and economic growth with respect to environmental degradation. This study extends the literature by incorporation of natural resource rent in a carbon function for selected 16 European countries (Austria, Belgium, Bulgaria, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherland, Portugal, Spain, Sweden, and United Kingdom) over the period 1996–2014. We employed the PMG-ARDL approach to examine the long-run equilibrium relationship between carbon dioxide emissions, economic growth, natural resources rent, renewable, and nonrenewable energy consumption. While a negative and significant long and short run equilibrium relationship is observed between CO_2 and renewable energy consumption, economic growth, natural resources rent, and nonrenewable energy consumption are shown to exert more distortion on environmental sustainability. The plausible explanation to this milestone is credited to the commitment of each EU country to carbon reduction and cleaner environment by increasing the share of renewable energy in the energy portfolio. More so, most of the countries examined are signatory to the Kyoto protocol and Paris agreement. Nonetheless, there is still a need to maintain the current momentum in the light of awakening global consciousness toward the attainment of a sustainable environment. In view of this, further studies on the scope should include more countries to capture a large contextual view.

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Declaration

There is no conflict of interest.

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Appendix 6 — Publication Thirteen: Environmental sustainability assessment using dynamic Autoregressive-Distributed Lag simulations—Nexus between greenhouse gas emissions, biomass energy, food and economic growth

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Environmental sustainability assessment using dynamic Autoregressive-Distributed Lag simulations—Nexus between greenhouse gas emissions, biomass energy, food and economic growth

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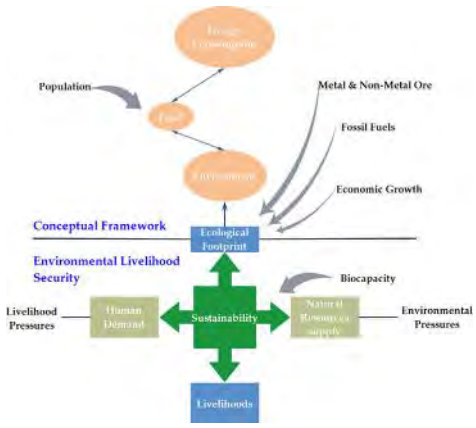
HIGHLIGHTS

- This study assessed the overarching nexus between environment and economic policy.
- We employed novel dynamic simulations of Autoregressive-Distributed Lag models.
- Evidence shows a shock in food production affects long term energy consumption.
- Modernized biomass energy consumption supports the reduction of GHG emissions.
- Economic development declines energy intensity and improves energy efficiency.

GRAPHICAL ABSTRACT



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ABSTRACT

Increasing population demand has triggered the enhancement of food production, energy consumption and economic development, however, its impact on climate change has become a global concern. This study applied a novel environmental sustainability assessment tool using dynamic Autoregressive-Distributed Lag (ARDL) simulations for model estimation of the relationships between greenhouse gas (GHG) emissions, energy, biomass, food and economic growth for Australia using data spanning from 1970 to 2017. The study found an inversed-U shaped relationship between energy consumption and income level, showing a decarbonized and services economy, hence, improved energy efficiency. While energy consumption increases emissions by 0.4 to 2.8%, biomass consumption supports Australia's transition to a decarbonized economy by reducing GHG emissions by 0.13% and shifts the demand for fossil fuel. Food and energy consumption underpin socio-economic development and vice versa. However, food waste from production and consumption increases ecological footprint, implying a lost opportunity to improve food security and reduce environmental pressure from agricultural production. There is no single path to achieving

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environmental sustainability, nonetheless, the integrated approach applied in this study reveals conceptual tools which are applicable for decision making.

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1. Introduction

The world population is expected to reach 9.7 billion by 2050, an increase of approximately 3 billion from today. Global wealth, especially in developing countries, has been increasing particularly in the last twenty years as a result of the industrial revolution and technological enhancement. However, the challenges for sustainable development are associated with anthropogenic induced climate change, environmental pollution and resource depletion. Countries are now trying to reduce their emission levels while at the same time improving sustainable development (United Nations, 2017).

Carbon dioxide (CO_2) is one of the primary GHG compounds, which is responsible for global warming and climate change. It is evident that over 60% of the GHG effect originates from CO_2 followed by methane which contributes around 20% (IPCC, 2014). Combustion of fossil related fuels is responsible for over 40% of the GHG emissions. It is reported that CO_2 emissions from the combustion of natural gas, coal and oil have been increasing since the industrial revolution, and it is expected to reach 40.4 Gt CO_2 in 2030 (Stanyeland, 2007).

There are several international protocols and frameworks to reduce CO_2 emissions. As a result, the Australian government has approved its commitment to reducing GHG emissions by up to 50% in the next 50 years (Commonwealth of Australia, 2016). Besides CO_2 emissions, sustainable economic development is also affected by food and energy production. Unsustainable production of food and energy can lead to exhaustion of natural resources which in turn reduces economic growth by aggravating ecosystem degradation without increasing either energy or food security (Biggs et al., 2015).

Society plays a pivotal role in the complex and meta-coupled global change system through the demand for water, food and energy (Bieber et al., 2018; Narayan and Smyth, 2005; Sarkodie and Strezov, 2018a). Thus, a surge in the growth of societies drives the tradeoff between resources in the form of coal, natural gas, hydroenergy, food and oil, which accelerates the global climate change. A "nexus" is a sustainability-driven concept that explicitly integrates the resource domains (i.e. biomass, food, energy, and among others) that past policies managed in isolation (Hoff, 2011).

Biomass is one of the renewable energy sources with increased importance, as energy policy and strategies of countries are focusing significantly on renewable sources of energy for their sustainable development (Owusu and Asumadu, 2016). It is the major source of energy in many developing countries providing around 35% of their energy demand (Demirbas et al., 2009), which raises the global consumption to 13%. Most developing countries directly use biomass as firewood for cooking and heating purposes. Major sources of biomass are wastes derived from the forest, agriculture and municipal origin with an annual global capacity of more than 13 billion metric tonnes (Müller et al., 2015) which is equivalent to 108 Gtoe, almost ten times the world's current energy demand (Weldekidan et al., 2018). Wood waste contributes to the majority of biomass energy, reaching up to 64% while municipal and agricultural wastes constitute 24% and 5%, respectively (Demirbaş, 2001).

Biomass is a CO_2 neutral source of energy, hence efficient utilization of this source through the adoption of improved conversion technologies to biofuels can bring sustainable economic development. Biofuel is a useful energy carrier obtained from biomass resources, such as forest and agricultural residues, municipal waste and energy crops, and can be used as heating, electricity and transportation fuels. Biofuels that can replace fossil fuels and petrochemicals can be produced from biomass through thermochemical, biochemical or physicochemical processes. Producing biofuels in a sustainable way can mitigate GHG emissions and offer an alternative solution to a number of environmental problems. For example, biofuels can be used as transportation fuels in vehicles and reduce CO_2 emissions by 19% and CO by 70% (Demirbas et al., 2009). Studies indicate that there are currently over a billion vehicles around the world. This number is expected to double by 2050, resulting in a higher amount of GHG emissions to the environment (Zahedi et al., 2019). The application of biofuels for transportation purposes alone can reduce a significant amount of CO_2 emissions.

Biomass energy development in Australia has been suggested as a potential cost-effective option for environmental improvements, such as soil salinity, water quality, soil protection and other benefits (Schuck et al., 2004). Only a handful of studies connect biomass energy consumption and economic growth, even though over 70% of the populace depends exclusively on biomass energy (Martins, 2018). A recent review study underpins two distinct strands of analysis (Endo et al., 2017): first, studies highlighting the strength of the interdependencies of water, food and energy under a given economic development scenario; second, those that report the cause of the intensified dependencies. Feng et al. (2016) conceptualized the latter and found a nonlinear relationship between biomass energy and population dynamics of the coupled system. Bildirici (2016) and Bildirici and Özaksoy (2018) found a short-run causal link country-level biomass energy consumption and economic growth, confirming the conservation hypothesis for Australia, Belgium, Finland and Japan, and the feedback hypothesis for the UK, France and the US. Sustainable growth is threatened due to the significant feedback effects of biomass use, gross domestic product and emissions within the West African sub-region (Adewuyi and Awodumi, 2017).

Food production system, CO_2 emissions, and economic growth have not been left out in this study. According to the IPCC report, agriculture, forestry and land use are the second contributors to anthropogenic GHG emissions after energy production (IPCC, 2014). While food security is essential for economic development, unsustainable production, management and consumption patterns negate environmental sustainability by altering ecosystems and ecological processes (Mwampamba et al., 2018; United Nations, 2015). Poor agricultural waste management, such as crop residue burning and cereal production increase atmospheric emissions by at least 1% and 1.38% respectively, while 1% of machinery use decreases emission by 0.09% (Asumadu-Sarkodie and Owusu, 2017). It is critical to minimize the trade-offs while maximizing the synergies in the use of natural resources for food and energy production while achieving environmental sustainability. Sustainable development policies can be achieved through the analysis of the combined impacts of the sub-sectors under policy uncertainties.

Despite a growing body of literature, the "nexus" concept remains unclear from econometrics perspective. Studies have informed numerous policies by linking economic growth, resource demand, and emissions (as a proxy for environmental degradation), which may lead to erroneous conclusions due to the interconnectedness of resource use (Soimakallio, 2012). The importance of biomass energy development in Australia requires an explicit understanding of its impact on emissions. This study contributes to the advocacy for

integrated policy options on sustainable growth by providing a clear link between sectoral energy and food consumption, and the growth pathways in Australia, which is ignored due to model limitations and data availability.

This study adopts novel dynamic simulations of ARDL model capable of examining the effect of the counterfactual changes in regressors on the response variable, which improves the complex nature and difficulty in the interpretation of the existing ARDL model. Secondly, this study develops five conceptual tools capable of accelerating Australia's agenda towards achieving sustainable development. Finally, the study contributes to the global debate on environmental sustainability by assessing the overarching nexus between the environment and economic policy.

2. Materials and method

2.1. Data

Table 1 presents the description of thirteen data series used in the model estimation. The thirteen variables spanning between 1970 and 2017 include food production index, energy use, CO_2 emissions, total greenhouse gas emissions, GDP, GDP per capita, adjusted savings: natural resources depletion, biomass extraction, fossil fuels extraction, metal ores extraction, non-metallic minerals extraction, biocapacity, and ecological footprint. The selection of the data series is based on the United Nations' indicators for sustainable development (DiSano, 2002). To examine the characteristics of the variables, the study examines the descriptive statistical analysis presented in Table 2. Prior to the model estimation, a logarithmic transformation was applied to give the data series a constant variance.

The ARDL model with dynamic simulations proposed by Jordan and Philips (2018) follows the standard pathway expressed as:

$$\begin{aligned}\Delta(y)_t = {} & \alpha_0 + \theta_0(y)_{t-1} + \theta_1(x_1)_{t-1} + \ldots + \theta_k(x_k)_{t-1} \\ & + \textstyle\sum_{i=1}^{p}\alpha_i\Delta(y)_{t-1} + \sum_{j=0}^{q_1}\beta_{1j}\Delta(x_1)_{t-j} + \ldots \\ & + \textstyle\sum_{j=0}^{q_k}\beta_{kj}\Delta(x_k)_{t-j} + \varepsilon_t \end{aligned} \tag{1}$$

where a change in the dependent variable (y) is a function of the intercept (α_0), all the independent variables at $t-1$ in levels to a maximum of p and q_k lags in their first-differences (Δ) with error term (ε) in time t. The ARDL bounds testing procedure for a level relationship by Pesaran et al. (2001) is examined using Kripfganz and Schneider (2018) critical values and approximate p-values based on response surface regressions. To reject the null hypothesis of no level relationship [$H_0 = \theta_0 + \theta_1 + \ldots + \theta_k = 0$], the F-statistic from the jointly zero estimation of all parameters on the independent variables in level and the lagged dependent variable coefficient must be above the upper bound critical values [I(1)], coupled with statistically significant approximate p-values.

Based on the empirical specification expressed in Eq. (1), the error correction forms of the 7 ARDL-bounds models are estimated as:

MODEL 1:

$$\begin{aligned}\Delta\ \ln(ENERGY)_t = {} & \alpha_0 + \theta_0\ \ln(ENERGY)_{t-1} + \beta_1\Delta\ \ln(FOOD)_t \\ & + \theta_1\ \ln(FOOD)_{t-1} + \beta_2\Delta\ \ln(NATRES)_t \\ & + \theta_2\ \ln(NATRES)_{t-1} + \beta_3\Delta\ \ln(CO_2E)_t \\ & + \theta_3\ \ln(CO_2E)_{t-1} + \beta_4\Delta\ \ln(PCGDP)_t \\ & + \theta_4\ \ln(PCGDP)_{t-1} + \beta_5\Delta\ \ln\left(PCGDP^2\right)_t \\ & + \theta_5\ \ln\left(PCGDP^2\right)_{t-1} \end{aligned} \tag{2}$$

MODEL 2:

$$\begin{aligned}\Delta\ \ln(GHG)_t = {} & \alpha_0 + \theta_0\ \ln(GHG)_{t-1} + \beta_1\Delta\ \ln(BIOMAS)_t \\ & + \theta_1\ \ln(BIOMAS)_{t-1} + \beta_2\Delta\ \ln(FOSSIL)_t \\ & + \theta_2\ \ln(FOSSIL)_{t-1} + \beta_3\Delta\ \ln(MORES)_t \\ & + \theta_3\ \ln(MORES)_{t-1} + \beta_4\Delta\ \ln(NMMIN)_t \\ & + \theta_4\ \ln(NMMIN)_{t-1} + \beta_5\Delta\ \ln(GDP)_t \\ & + \theta_5\ \ln(GDP)_{t-1} \end{aligned} \tag{3}$$

MODEL 3:

$$\begin{aligned}\Delta\ \ln(GHG)_t = {} & \alpha_0 + \theta_0\ \ln(GHG)_{t-1} + \beta_1\Delta\ \ln(ENERGY)_t \\ & + \theta_1\ \ln(ENERGY)_{t-1} + \beta_2\Delta\ \ln(NATRES)_t \\ & + \theta_2\ \ln(NATRES)_{t-1} + \beta_3\Delta\ \ln(BCAPA)_t \\ & + \theta_3\ \ln(BCAPA)_{t-1} + \beta_4\Delta\ \ln(EFCONS)_t \\ & + \theta_4\ \ln(EFCONS)_{t-1} + \beta_5\Delta\ \ln(GDP)_t \\ & + \theta_5\ \ln(GDP)_{t-1} \end{aligned} \tag{4}$$

MODEL 4:

$$\begin{aligned}\Delta\ \ln(CO_2E)_t = {} & \alpha_0 + \theta_0\ \ln(CO_2E)_{t-1} + \beta_1\Delta\ \ln(ENERGY)_t \\ & + \theta_1\ \ln(ENERGY)_{t-1} + \beta_2\Delta\ \ln(NATRES)_t \\ & + \theta_2\ \ln(NATRES)_{t-1} + \beta_3\Delta\ \ln(GDP)_t \\ & + \theta_3\ \ln(GDP)_{t-1} \end{aligned} \tag{5}$$

Table 1
Description of data series.

Abbreviation	Series description	Unit	Source
FOOD	Food production index	Index, 2004–2006 = 100	World Bank (2018)
ENERGY	Energy use	kg of oil equivalent per capita	World Bank (2018)
CO_2E	CO_2 emissions	kt	World Bank (2018)
GHG	Total greenhouse gas emissions	kt of CO_2 equivalent	World Bank (2018)
GDP	GDP	Current US$	World Bank (2018)
PCGDP	GDP per capita	Current US$	World Bank (2018)
NATRES	Adjusted savings: natural resources depletion	% of GNI	World Bank (2018)
BIOMAS	Biomass	tons	Materials Flow (2017)
FOSSIL	Fossil fuels	tons	Materials Flow (2017)
MORES	Metal ores	tons	Materials Flow (2017)
NMMIN	Non-metallic minerals	tons	Materials Flow (2017)
BCAPA	Biocapacity	gha	Global Footprint Network (2017)
EFCONS	Ecological footprint	gha	Global Footprint Network (2017)

Table 2
Descriptive statistics.

Statistic	BCAPA	BIOMAS	CO_2E	EFCONS	ENERGY	FOOD	FOSSIL	GDP	GHG	MORES	NATRES	NMMIN	PCGDP
Mean	3.18E+08	1.78E+08	277,716.7	1.43E+08	5066.54	79.93915	2.98E+08	4.99E+11	638,003.2	4.53E+08	1.8355	1.69E+08	24,514.29
Median	3.17E+08	1.68E+08	277,397.5	1.36E+08	5075.649	74.63	2.71E+08	3.25E+11	482,298.3	3.77E+08	1.7148	1.71E+08	18,697.01
Maximum	3.37E+08	2.34E+08	394,792.9	1.98E+08	5964.666	109.72	5.98E+08	1.57E+12	1,241,516	1.24E+09	4.1945	2.37E+08	67,990.29
Minimum	2.93E+08	1.10E+08	147,618.8	1.01E+08	3989.63	50.67	78,873,820	4.13E+10	314,446.1	99,932,549	0.4616	1.05E+08	3299.037
Std. Dev.	10,047,698	40,835,205	75,158.48	2.76E+07	553.5617	18.8317	1.55E+08	4.59E+11	302,683.1	3.15E+08	0.9605	3.33E+07	18,785.92
Skewness	−0.0301	0.0199	−0.0566	0.4509	−0.2159	0.1521	0.3005	1.1245	0.7132	1.0121	0.7044	−0.1882	1.0104
Kurtosis	2.6772	1.4855	1.8519	1.9837	1.9058	1.5451	1.8888	2.9242	1.8849	3.1696	2.6561	2.2265	2.7995
Jarque-Bera	0.2022	4.5904	2.4957	3.4613	2.6522	4.3266	3.1921	10.1267	5.8737	8.2518	4.1180	1.4799	8.2473
Probability	0.9039	0.1007	0.2871	0.1772	0.2655	0.1149	0.2027	0.0063***	0.0530**	0.0161**	0.1276	0.4771	0.0162**
Observations	45	48	45	45	46	47	48	48	43	48	47	48	48

***, ** denote significance at 1, and 5% level.

MODEL 5:

$$\begin{aligned}\Delta\ \ln(FOOD)_t = {} & \alpha_0 + \theta_0\ \ln(FOOD)_{t-1} + \beta_1\Delta\ \ln(ENERGY)_t \\ & + \theta_1\ \ln(ENERGY)_{t-1} + \beta_2\Delta\ \ln(GHG)_t \\ & + \theta_2\ \ln(GHG)_{t-1} + \beta_3\Delta\ \ln(EFCONS)_t \\ & + \theta_3\ \ln(EFCONS)_{t-1} + \beta_4\Delta\ \ln(GDP)_t \\ & + \theta_4\ \ln(GDP)_{t-1}\end{aligned} \tag{6}$$

MODEL 6:

$$\begin{aligned}\Delta\ \ln(EFCONS)_t = {} & \alpha_0 + \theta_0\ \ln(EFCONS)_{t-1} + \beta_1\Delta\ \ln(BIOMAS)_t \\ & + \theta_1\ \ln(BIOMAS)_{t-1} + \beta_2\Delta\ \ln(FOSSIL)_t \\ & + \theta_2\ \ln(FOSSIL)_{t-1} + \beta_3\Delta\ \ln(MORES)_t \\ & + \theta_3\ \ln(MORES)_{t-1} + \beta_4\Delta\ \ln(NMMIN)_t \\ & + \theta_4\ \ln(NMMIN)_{t-1} + \beta_5\Delta\ \ln(GDP)_t \\ & + \theta_5\ \ln(GDP)_{t-1} + \beta_6\Delta\ \ln(FOOD)_t \\ & + \theta_6\ \ln(FOOD)_{t-1}\end{aligned} \tag{7}$$

MODEL 7:

$$\begin{aligned}\Delta\ \ln(BCAPA)_t = {} & \alpha_0 + \theta_0\ \ln(BCAPA)_{t-1} + \beta_1\Delta\ \ln(ENERGY)_t \\ & + \theta_1\ \ln(ENERGY)_{t-1} + \beta_2\Delta\ \ln(NATRES)_t \\ & + \theta_2\ \ln(NATRES)_{t-1} + \beta_3\Delta\ \ln(GDP)_t \\ & + \theta_3\ \ln(GDP)_{t-1}\end{aligned} \tag{8}$$

3. Results and discussion

3.1. Unit root

The initial step of testing the level relationships between the dependent variables and their regressors is to ensure that the data series, especially the dependent variables are integrated of order one, I(1). Second, all the regressors must not be integrated of order one or exhibit seasonal unit roots. To meet the requirement, the study employed three unit root tests such as Phillip-Perron (PPERRON), Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) to examine the order of integration of the variables. Table 3 presents the results of PPERRON, ADF and KPSS unit root tests. While PPERRON and ADF are tested under the null hypothesis of a unit root, KPSS, on the other hand, has a null hypothesis of stationarity. Evidence from Table 3 reveals that at 1% significance level, the null hypothesis of a unit root (PPERRON and ADF) or stationarity (KPSS) cannot be rejected at level in almost all the variables, however, rejected at first-difference. Hence, all the data series are integrated of order one and potential candidates for ARDL bounds cointegration.

3.2. Cointegration

After meeting the pre-requirements, the next step is to examine the level relationships exhibited by the proposed models. The data series are said to be integrated of order one if the current state of the variables is a function of all past stochastic shocks plus to some extent, new innovations. While short-run perturbations may cause disequilibrium of the series, this disequilibrium is corrected over time as the series moves backwards to a stable long-run relationship (Jordan and Philips,

Table 3
Unit root tests.

Data series	KPSS		ADF		PPERRON	
	Level	1st Diff.	Level	1st Diff.	Level	1st Diff.
BIOMAS	0.2550	0.0220***	−1.5530	−11.4170***	−1.3020	−11.8700***
FOSSIL	0.8160	0.0199***	1.6980	−7.8730***	2.6130	−7.9080***
MORES	0.8600	0.1930***	5.0650	−3.5520***	4.4250	−3.4940***
NMMIN	0.1740	0.0189***	−1.6860	−10.5510***	−1.5370	−10.7620***
BCAPA	0.2970	0.0172***	−4.0850***	−10.4860***	−4.1170***	−11.9430***
EFCONS	0.4760	0.0607***	−1.6020	−7.5880***	−1.4950	−7.7580***
FOOD	0.2170	0.0246***	−1.2440	−10.0850***	−1.0110	−10.6450***
ENERGY	0.3580	0.0620***	−1.7130	−6.9940***	−1.7290	−6.9840***
CO_2E	0.1320	0.0992***	−1.6190	−5.8200***	−1.5730	−5.8620***
GHG	0.3380	0.0764***	−1.4930	−9.7290***	−1.4210	−9.1500***
GDP	0.8800	0.0834***	0.4240	−4.8010***	0.1340	−4.7780***
PCGDP	0.7470	0.0861***	−0.1760	−4.9980***	−0.3740	−4.9680***
NATRES	0.3960	0.0551***	−2.5210	−7.3270***	−2.4650	−7.4440***

*** Denotes the rejection of the null hypothesis of unit root at 1% significance level.

Table 4
ARDL bounds cointegration test.

Models	Statistic		10%		5%		1%		p-Value	
			I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
lnGHG = f (lnBIOMAS lnFOSSIL lnMORES lnNMMIN lnGDP)	F	11.29	2.44	3.88	2.98	4.64	4.30	6.49	0.0000	0.0000
lnFOOD = f (lnENERGY lnGDP lnGHG lnEFCONS)	F	6.92	2.64	3.91	3.21	4.64	4.56	6.39	0.0010	0.0060
$lnCO_2E$ = f (lnENERGY lnGDP lnNATRES)	F	10.63	2.83	4.12	3.47	4.95	5.01	6.91	0.0000	0.0010
lnGHG = f (lnENERGY lnGDP lnNATRES lnBCAPA lnEFCONS)	F	6.64	2.47	3.80	2.99	4.50	4.25	6.19	0.0010	0.0070
lnEFCONS = f (lnBIOMAS lnFOSSIL lnMORES lnNMMIN lnFOOD lnGDP)	F	5.25	2.35	3.65	2.82	4.29	3.94	5.80	0.0020	0.0180
lnENERGY = f (lnFOOD lnNATRES $lnCO_2E$ lnPCGDP $lnPCGDP^2$)	F	10.34	2.44	3.80	2.96	4.50	4.19	6.18	0.0000	0.0000
lnBCAPA = f (lnNATRES lnGDP lnENERGY)	F	9.26	2.88	4.05	3.51	4.83	4.99	6.64	0.0000	0.0010

NB: The null hypothesis of no level relationship is rejected when the F-statistic is above the 10%, 5% and 1% upper bound critical values, corroborated by the p-value.

2018). Such series exhibits a cointegrating relationship. However, since not all relationships between I(1) data series appear to validate the presence of cointegration, it becomes essential to test the validity of a cointegrating relationship. Table 4 presents the results of the ARDL bounds cointegration test using response surface regression with accurate critical values and approximate p-values proposed by Kripfganz and Schneider (2018). The ARDL bounds cointegration test reveals that the F-statistic values of all variables in level and the lagged dependent variable coefficient in the estimated models are above the upper bound critical values [I(1)], corroborated by statistically significant approximate p-values. Thus, validating the cointegrating relationships between I(1) variables in all the 7 estimated models.

3.3. Dynamic stimulated ARDL models

Contrary to the complexities of existing ARDL models in examining the effect of short- and long-run in complex model specifications, Jordan and Philips (2018) introduced a novel dynamic stimulated ARDL model capable of estimating, stimulating and automatically plotting predictions of counterfactual change in one regressor on the dependent variable while holding other regressors constant. To apply the dynamic stimulated ARDL technique, the data series for the model estimation should be integrated of order one and cointegrated, for which the variables in this work meet the requirements. The dynamic ARDL error correction algorithm utilized for the 7 models adopts 5000 simulations of the vector of parameters from a multivariate normal distribution. Table 5 presents the results of the dynamic stimulated ARDL error correction models.

The study further examined the effect of counterfactual change in regressors on the dependent variables using graphical representations depicted in Figs. 1–8. Sustainable livelihoods play a critical role in achieving the sustainable development goals outlined by the United Nations. This study presents the different forms of interaction that reveal the various determinants of sustainable livelihoods.

3.3.1. Energy-food-emission-income level nexus

Table 5 column 2 reveals a negative and statistically significant error correction of −0.24—representing 24% speed of correcting the previous disequilibrium over time as the variables move backwards to a stable long-run relationship. The coefficient on food is positive in the long-run and negative in the short-run, but insignificant to make statistical inferences. Though the nexus between energy and food is a conceptual tool critical for achieving sustainable development (Biggs et al., 2015), yet this study provides statistically insignificant results to support previous studies. The study found a positive short-run relationship between energy consumption and CO_2 emissions but insignificant negative relationship in the long-run. The results are in line with Bekun et al. (2019b); Sarkodie and Adom (2018) for South Africa and Kenya. The short-term effect of CO_2 emissions spurs energy consumption for cooling and heating purposes due to the abnormal change in the global average temperatures. Climate change and socio-economic development were found to increase the intensity of energy-food nexus in South Africa (Conway et al., 2015). An increase in natural resources depletion, which comprises of forest, energy and mineral depletion is found to significantly decline energy consumption in the long-run but insignificant in the short-run. Increasing levels of natural resources depletion affect environmental livelihood security due to an imbalance between natural resource supply and human demand. Hence, environmental livelihood insecurity affects energy security, leads to livelihood pressures and hampers sustainability. Growth in income level is observed to have a positive effect on energy consumption in the long-run. To examine the role of income level on energy efficiency, the study included the square of income level in the model. While the coefficient of income level is positive, the square of income level is found to have a significant negative coefficient, signifying an inversed-U shaped relationship. While growth in income level intensifies energy consumption (growth hypothesis), intensive energy utilization declines after reaching a turning point of income level, hence, translating into energy efficiency due to a decline in energy intensity. The results are in line with Rajbhandari and Zhang (2018) for 56 countries. They found a negative effect of income on energy intensity in the lower, middle- and higher-income countries. Thus, growth in income levels in Australia triggers energy efficiency—sustainable utilization of energy and its related services. Fig. 1 depicts the impulse-response plot of food-energy nexus and income-energy nexus. Fig. 1(a) shows that a +1 shock at 10th scenario time appears negative in the short-run but increases eventually and turns positive with over 1 predicted value in the long-run. Contrary, −1 shock produces a positive effect in the short-run but turns negative and declines over time in the long-run. Food production, such as residues of crops and livestock are a great source of biomass energy generation (biofuels, biopower, and traditional fuels like charcoal and wood fuel). Hence, a shock in food production affects long term energy consumption. While a positive shock in income levels intensifies energy access and utilization, a negative shock affects energy access and consumption, meaning that energy security is dependent on income.

3.3.2. Climate change-natural resource-biomass-economic growth nexus

Model 2 (Table 5 column 3), model 3 (Table 5 column 4) and model 4 (Table 5 column 6) show ~56%|~58%|~24% speed of adjusting past disequilibrium in emissions to equilibrium following a stable long-run relationship. The coefficient on lnGDP in Model 2–3 is negative and statistically significant in both short- and long-run. The empirical evidence signifies a negative relationship between GHG emissions and economic development in both short-term and long-term. Thus, the increasing levels of Australia's dominant services economy promotes environmental sustainability. In line with a similar result in the US (Bilgili, 2012), a long-run negative relationship is observed between GHG emissions and biomass energy consumption. The possible explanation is the sustainable management of biomass fuel sources for the full life cycle, which ensures the re-absorption of produced CO_2 emissions to the feedstock supply chain. Australia's lignocellulose supply comes from agricultural residues, organic municipal and agro-industrial waste, wastewater, wood waste and animal residues

Table 5
Results of dynamic stimulated ARDL models.

Variable	$\Delta lnENERGY_t$ (Model 1)	$\Delta lnGHG_t$ (Model 2)	$\Delta lnGHG_t$ (Model 3)	$\Delta lnCO_2E_t$ (Model 4)	$\Delta lnFOOD_t$ (Model 5)	$\Delta lnEFCONS_t$ (Model 6)	$\Delta lnBCAPA_t$ (Model 7)
$\Delta lnENERGY_t$			1.2385	0.8978***	−0.0286		−0.1816
			(0.8757)	(0.1594)	(0.5062)		(0.1937)
$lnENERGY_{t-1}$	−0.2389[a]***		2.8212***	0.3580**	0.4560		0.2069
	(0.1160)		(0.9910)	(0.1383)	(0.4973)		(0.1432)
$\Delta lnGHG_{t-1}$					0.1176		
					(0.0813)		
$lnGHG_{t-1}$		−0.5630[a]***	−0.5751[a]***		−0.0260		
		(0.1075)	(0.1354)		(0.0637)		
$\Delta lnFOOD_t$	−0.0489					0.8143***	
	(0.0459)					(0.2698)	
$lnFOOD_{t-1}$	0.0270				−0.4565[a]***	0.6607*	
	(0.0459)				(0.1545)	(0.3675)	
$\Delta lnBIOMAS_t$		0.0016				−0.0038	
		(0.2220)				(0.1688)	
$lnBIOMAS_{t-1}$		−0.1329***				−0.4114	
		(0.2548)				(0.3046)	
$\Delta lnNATRES_t$	0.0068		−0.1214*	−0.0172			−0.0074
	(0.0097)		(0.0685)	(0.0123)			(0.0153)
$lnNATRES_{t-1}$	−0.0133*		−0.0983**	0.0012			−0.0293***
	(0.0076)		(0.0480)	(0.0083)			(0.0106)
$\Delta lnFOSSIL_t$		−0.1329				−0.0203	
		(0.4768)				(0.2832)	
$lnFOSSIL_{t-1}$		−0.3142				−0.0677	
		(0.2452)				(0.1512)	
$\Delta lnCO_2E_t$	0.5021***						
	(0.0957)						
$lnCO_2E_{t-1}$	−0.0191			−0.2351[a]**			
	(0.0697)			(0.0883)			
$\Delta lnBCAPA_t$			0.7719				
			(0.8111)				
$lnBCAPA_{t-1}$			1.4499*				−0.8750[a]***
			(0.8427)				(0.1642)
$\Delta lnGDP_t$		−0.3977*	−0.0965	0.0352	−0.2279*	0.3481***	−0.0629
		(0.2050)	(0.2376)	(0.0400)	(0.1187)	(0.1177)	(0.0479)
$lnGDP_{t-1}$		−0.2325*	−0.2259**	0.0243	0.0451	−0.0785	−0.0279
		(0.1182)	(0.1019)	(0.0199)	(0.0454)	(0.0613)	(0.0192)
$\Delta lnPCGDP_t$	0.0828						
	(0.3821)						
$lnPCGDP_{t-1}$	0.2420**						
	(0.1023)						
$\Delta lnPCGDP_t^2$	−0.0015						
	(0.0192)						
$lnPCGDP_{t-1}^2$	−0.0105**						
	(0.0048)						
$\Delta lnEFCONS_t$			−0.1016		0.5149***		
			(0.3713)		(0.1506)		
$lnEFCONS_{t-1}$			0.7304**		0.1524	−0.3611[a]***	
			(0.2967)		(0.1356)	(0.1248)	
$\Delta lnMORES_t$		−0.0461				0.0889	
		(0.3356)				(0.1956)	
$lnMORES_{t-1}$		0.4624**				0.0593	
		(0.2040)				(0.1220)	
$\Delta lnNMMIN_t$		0.6714**				0.2540	
		(0.2872)				(0.1813)	
$lnNMMIN_{t-1}$		0.4809				0.4187*	
		(0.3888)				(0.2415)	
Constant	0.7993	−18.3749***	−52.4789***	−0.7394	−5.5829*	5.9645	16.1264***
	(0.6279)	(5.8324)	(16.7268)	(0.5694)	(3.2705)	(4.4392)	(2.9698)
N	44	42	42	42	39	44	42
Sims	5000	5000	5000	5000	5000	5000	5000
Prob > F	0.0001***	0.0002***	0.0054***	0.0000***	0.0029***	0.0021***	0.0008***
R^2	0.66	0.65	0.54	0.61	0.54	0.60	0.49
Diagnostics							
$\chi^2_{LM-ARCH}$	0.80	0.10	0.02	0.96	1.32	0.39	3.32*
χ^2_{LM-B-G}	0.79	2.08	6.78***	0.06	2.69	0.44	10.94***

***, **, * denote significance at 1, 5, and 10%; [a] denotes the speed of adjustment; parenthesis ( ) denotes the standard error; Sims represents the number of simulations; $\chi^2_{LM-ARCH}$ represents the LM test for autoregressive conditional heteroskedasticity (ARCH); and χ^2_{LM-B-G} is the Breusch-Godfrey LM test for autocorrelation.

(Bioenergy Australia, 2018). Hence, biomass energy consumption supports a transition to a decarbonized economy by reducing GHG emissions while shifting the demand for fossil fuel energy and its related products.

While no significant outcome is observed between fossil fuels and GHG emissions, other disaggregate natural resources extraction such as metal ores and non-metallic minerals have a positive impact on GHG emissions in the long-run and short-run, respectively. Visible

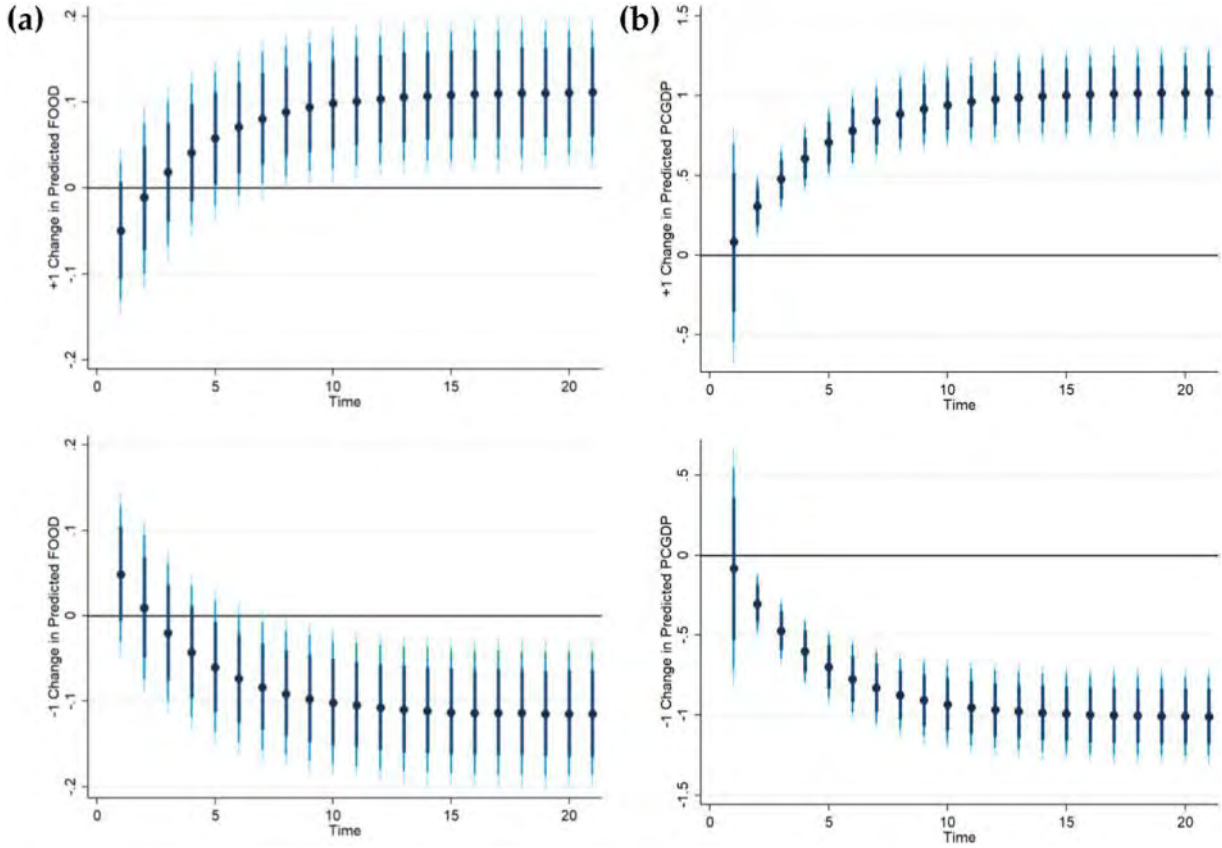

Fig. 1. (a) Model 1: change (±1%) in predicted FOOD on ENERGY (b) Model 1: change in predicted PCGDP on ENERGY. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

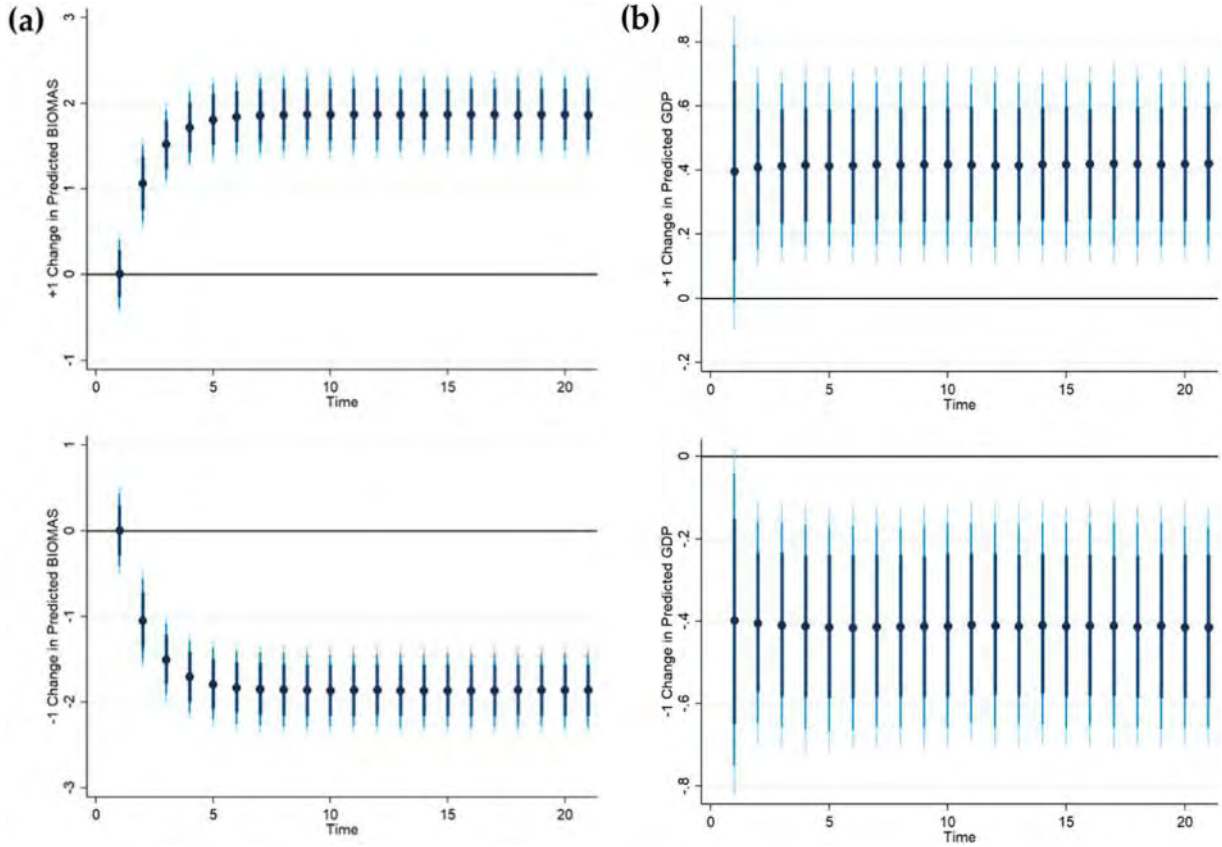

Fig. 2. (a) Model 2: change (±1%) in predicted BIOMAS on GHG (b) Model 2: change in predicted GDP on GHG. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

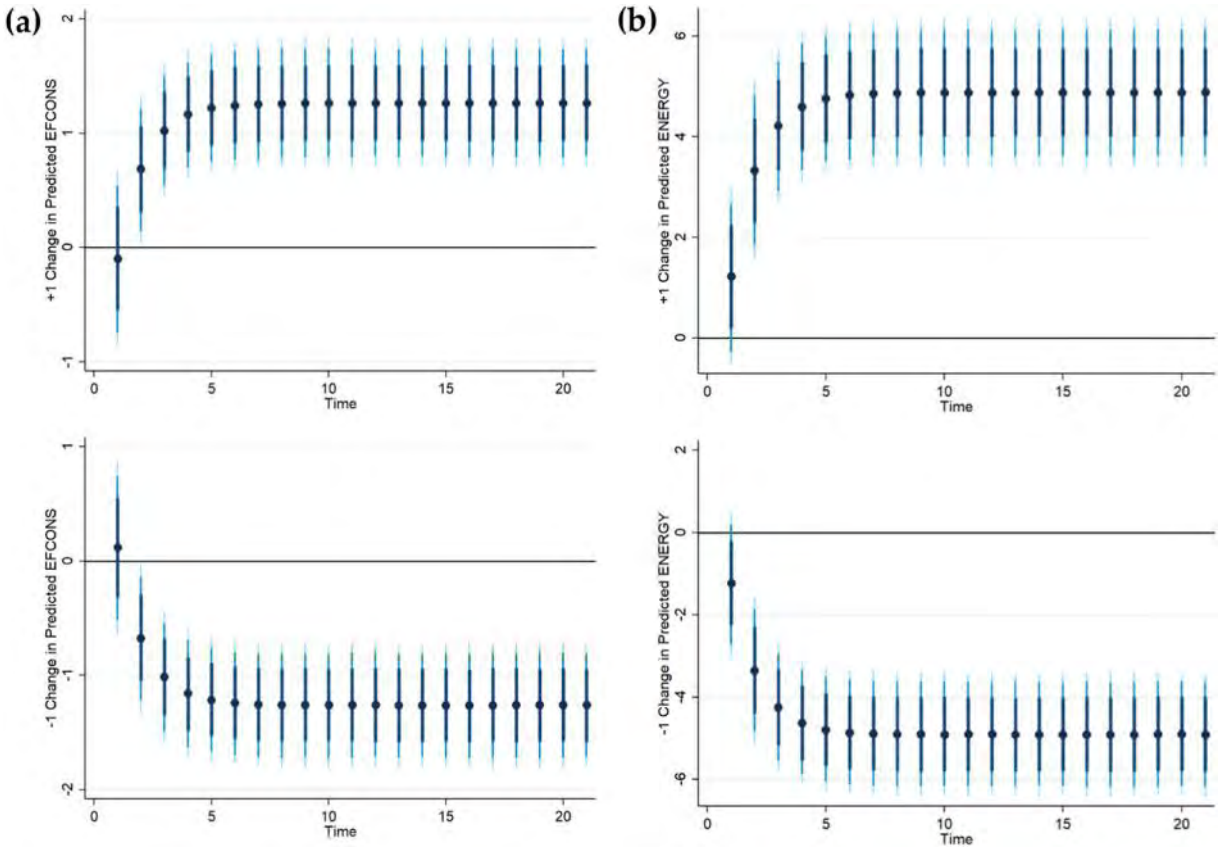

Fig. 3. (a) Model 3: change (±1%) in predicted EFCONS on GHG (b) Model 3: change in predicted ENERGY on GHG. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

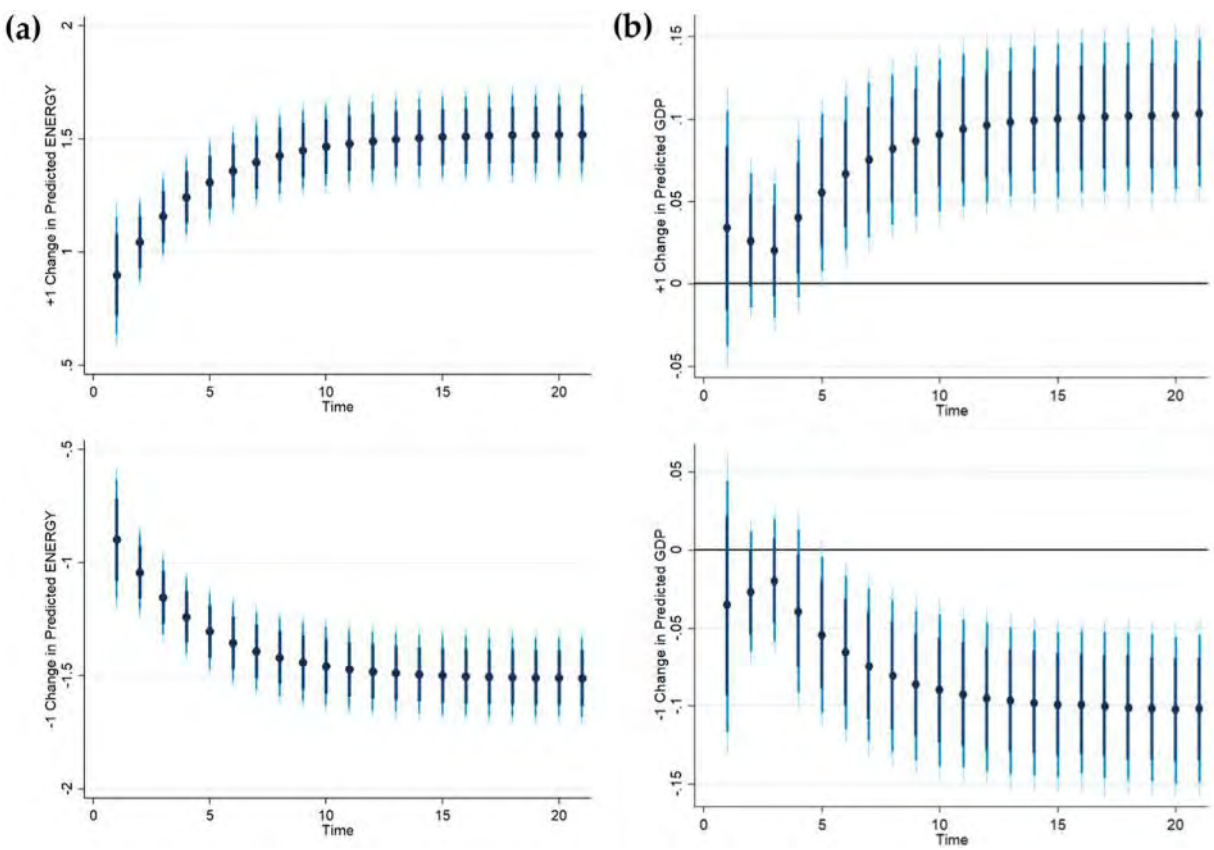

Fig. 4. (a) Model 4: change (±1%) in predicted ENERGY on CO_2E (b) Model 4: change in predicted GDP on CO_2E. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

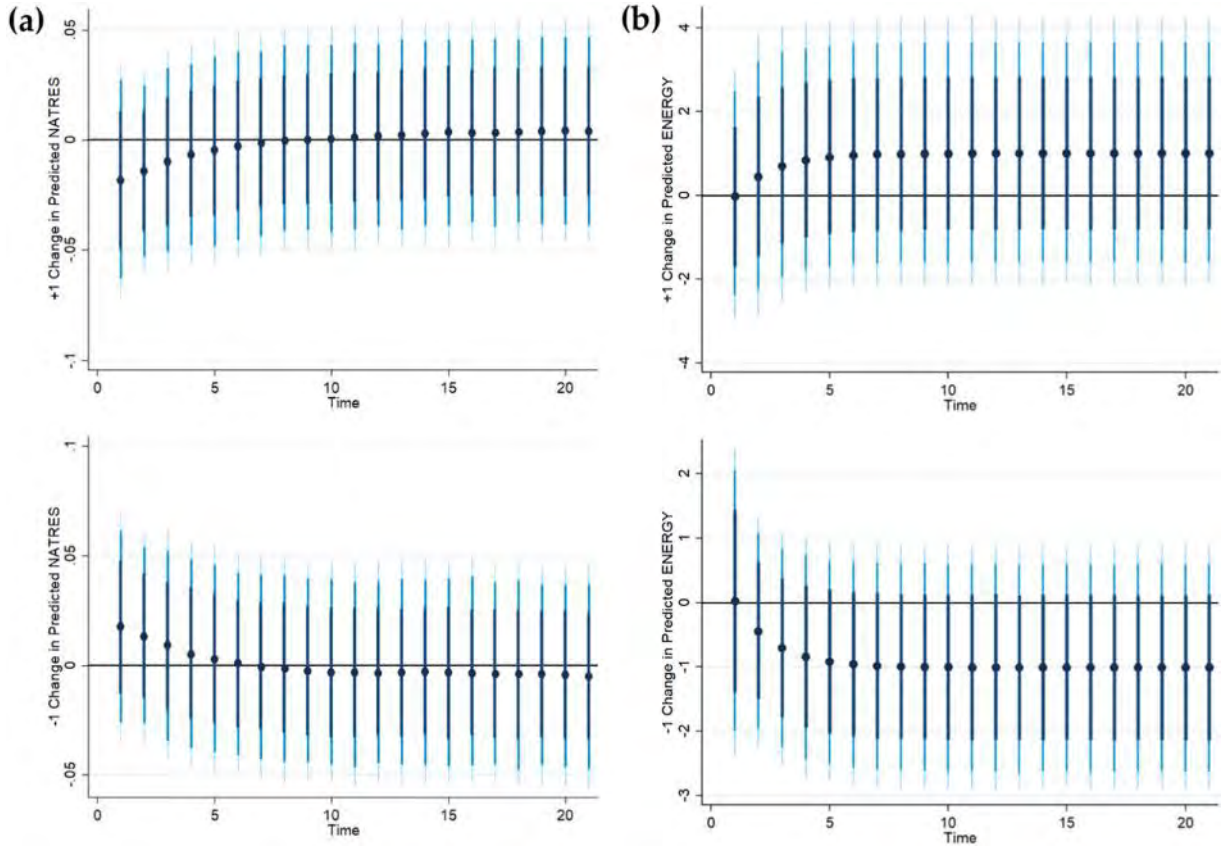

Fig. 5. (a) Model 4: change (±1%) in predicted NATRES on CO_2E (b) Model 5: change in predicted ENERGY on FOOD. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

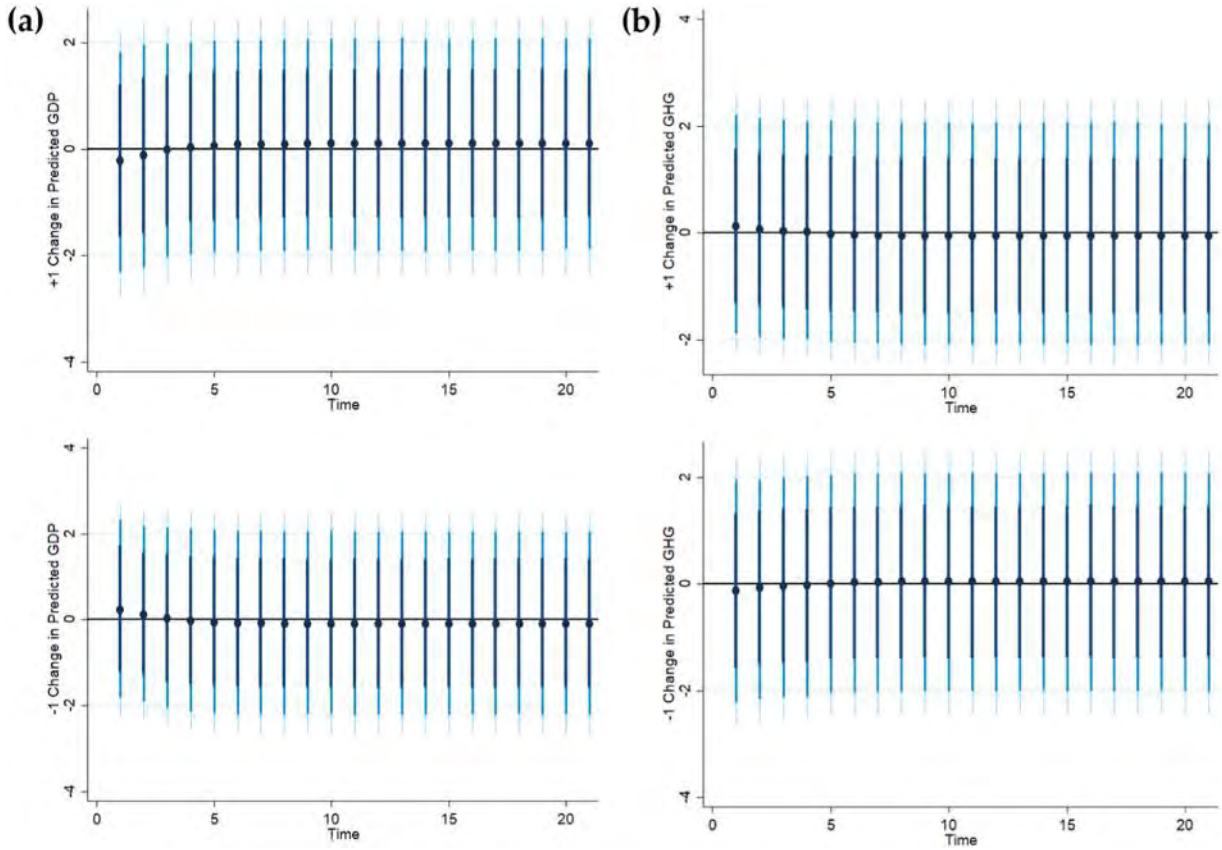

Fig. 6. (a) Model 5: change (±1%) in predicted GDP on FOOD (b) Model 5: change in predicted GHG on FOOD. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

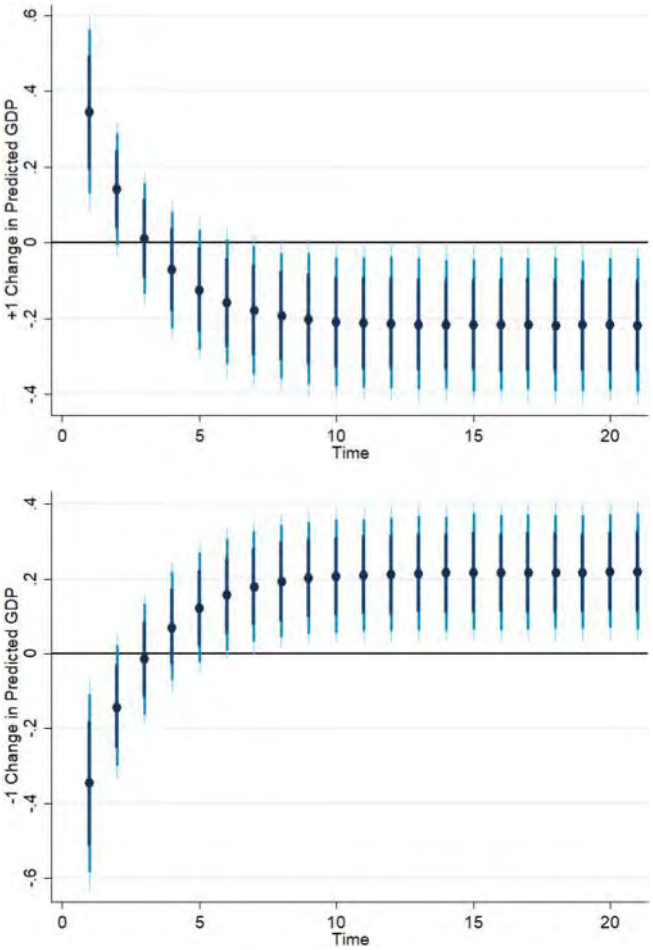

Fig. 7. Model 6: Change (±1%) in predicted GDP on EFCONS. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

signs of GHG emissions are evident during mining, processing, smelting and refining of metal ores. Nevertheless, a lifecycle analysis (Norgate and Haque, 2010) on the contribution of mining and mineral processing to GHG emissions revealed that Australia's mining sector performs better in environmental management compared to the global standard. The success story can be attributed to the introduction of "Enduring Value"—Australia's mineral industry framework for sustainable development.

Fig. 2 presents an impulse-response plot of biomass-GHG nexus and economic growth-GHG nexus. Positive or negative shock in biomass extraction and consumption can either negate or affirm GHG emissions benefits. While a positive shock immediately escalates GHG emissions in the short-term, the response stabilizes in the long-term. However, GHG emissions respond immediately to a negative shock in biomass energy consumption but flatten in the long-run. The increasing levels of GHG emissions can be attributed to the non-vanishing life-cycle emissions originating from the use of fossil fuels during pre-planting, planting, regrowth, harvesting and post-harvesting cycles, and potential agricultural, forestry, land-use and management related emissions (Bruckner et al., 2015; Tilman et al., 2009). According to the Intergovernmental Panel on Climate Change (IPCC) 5th Assessment Report, "the direct emissions from biogenic feedstock combustion largely corresponds to the amount of atmospheric CO_2 sequestrated via the growth cycle of bioenergy production" (Bruckner et al., 2015). Other factors affecting biomass lifecycle emissions include inter alia, feedstock type, location, scale and technologies used in biomass production (Owusu and Asumadu, 2016). For example, the direct use of food crops for energy generation rather than lignocellulosic biomass contributes indirectly to emissions. Both positive and negative future shocks in GDP have relatively no change on GHG emissions, evidenced in Fig. 2(b). The possible explanation may be due to the structural change in economic development, by shifting from carbon-and energy-intensive economy to a decarbonized and services economy, corroborated by Sarkodie and Strezov (2018b); and Sarkodie and Strezov (2018a).

In models 3–4, a positive relationship between GHG/CO_2 emissions and energy consumption was observed, which is consistent with Shahbaz et al. (2017). Australia's reliance on fossil fuel technologies to meet the growing energy demand intensifies GHG emissions rather than negating it. Fig. 3 shows the change in predicted ecological footprint and energy consumption on GHG emissions. A graphical observation reveals a positive response of GHG emissions to a positive shock in both ecological footprint and energy consumption. On the contrary, a negative shock in ecological footprint and energy consumption triggers a negative response in GHG emissions but stabilizes in the long-run. The IPCC 5th Assessment Report revealed electricity and heat production as the major contributors to global anthropogenic GHG emissions. According to Sarkodie and Strezov (2018a), renewable energy sources (wind, solar, hydro, and biomass) contribute only 2% to Australia's energy mix, hence, restructuring of the energy portfolio to increase the share of clean and modern energy technologies is essential to mitigate GHG emissions. The indicator for ecological footprint measures the required biologically productive land and water needed to produce all the resources for consumption and using existing technologies and resource management practices to absorb waste generated (Global Footprint Network, 2017). Hence, ecological footprint, an indicator of environmental degradation, was found to intensify GHG emission in the long-run if overexploited. Limiting the ecological deficit in Australia is required to prevent the liquidation of ecological assets while promoting environmental sustainability.

The impulse-response between energy/economic growth against CO_2 emissions is presented in Fig. 4. A positive shock in energy consumption increases GHG emissions while a negative shock declines GHG emissions. In the same way, a positive shock in economic growth increases GHG emissions after $t = 3$ but reduces anthropogenic GHG emissions in the long-run after $t = 3$. Energy consumption and economic development are essential to achieving sustainable development. However, carbonized and energy-intensive economy due to fossil fuel energy production and utilization result in environmental pressures, depletion of natural resources and creating pollution, hence, increasing GHG emissions. Decoupling economic development from energy consumption and a structural change in the economy, by decarbonization and switching from energy-intensive production to energy-efficient and service economy are pragmatic steps to attaining the 2030 emission targets. Fig. 5(a) reveals that natural resources depletion has a relatively low impact on GHG emissions. Similar studies found a strong positive relationship between natural resources and GHG emissions in 16 European Union countries (Bekun et al., 2019a). A positive shock in natural resources depletion causes a small increase in emissions after $t = 10$ while a negative shock causes a small decline in GHG emissions. Australia is on the verge of achieving a sustainable production and consumption pattern by declining domestic material intensity of the economy and adopting modern technologies needed to produce goods and services. A decline in natural resources depletion is essential to environmental protection and natural resource conservation, thus, achieving environmental sustainability (DiSano, 2002).

3.3.3. Food-energy-economic growth-climate change nexus

In a growing population seeking answers to meet its energy demand, food challenges and economic development, reduction in GHG emissions cannot be ignored. This study adopted food-energy-economic growth-climate change nexus as a conceptual tool to understand the

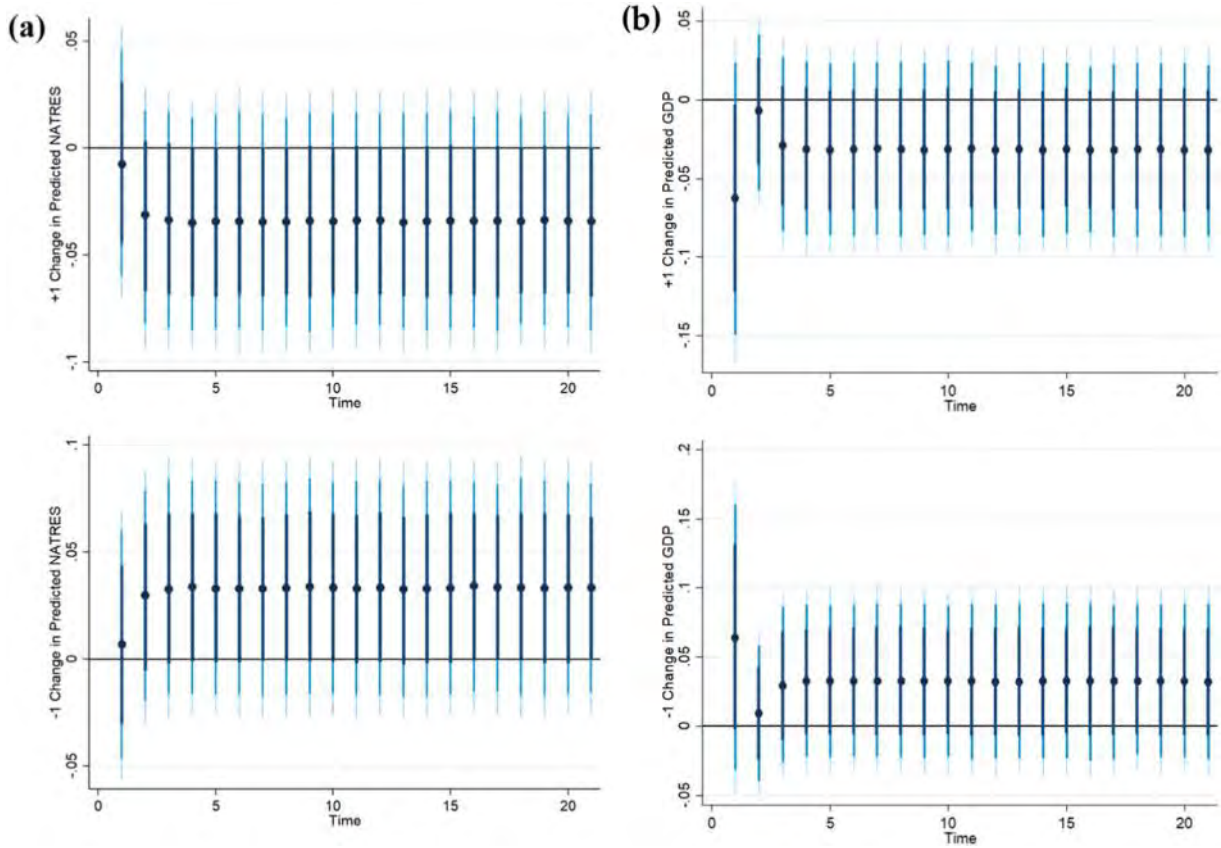

Fig. 8. (a) Model 7: change (±1%) in predicted NATRES on BCAPA (b) Model 7: change in predicted GDP on BCAPA. NB: Dots represent average predicted value while dark blue to light blue lines denote 75, 90 and 95% confidence interval. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

existing dynamics in Australia. Table 5 column 6 reveals a negative and statistically significant error correction of −0.46—representing ~46% speed of adjusting the previous disequilibrium over time as the variables move backwards to a stable long-run relationship. The empirical results show no significant impact of energy/GHG emission on food production in both short- and long-run. On the contrary, economic growth has a negative effect on food production while ecological footprint exhibits a positive impact on food in the short-run. Fig. 5(b) shows that a positive shock in energy increases food after $t = 1$ but the impact stabilizes after $t = 7$. Nevertheless, a negative shock in energy declines food production in the long-run. Energy plays a dominant role in agricultural mechanization used in food production. The role of energy, as a driver of agricultural mechanization improves planting, cultivation, harvesting, food processing and transportation, thus, increases agricultural productivity and ensures a sustainable food security. Fig. 6 depicts the impulse-response between GHG emissions/economic growth versus food production. It is evident in Fig. 6 that a positive shock in economic growth has a relatively low positive impact on food production while a negative shock declines food production. Sustained and inclusive economic growth increases a population's income level and purchasing power, causing an increase in varieties and demand for food, thus, increasing food production. While increasing income level is essential in achieving human development, behavioural changes due to high income trigger the nutritional transition to more affluent food consumption patterns (Gerbens-Leenes et al., 2010), hence, expanding food production at the cost of the natural environment (FAO, 2017). In contrast, Fig. 6(b) shows that a positive shock in GHG emissions declines food production whereas a negative shock adds a little increase to food production. Increasing levels of anthropogenic GHG emissions affect the average global temperature and rainfall patterns, as such, climate-dependent sectors, such as food production, are vulnerable to climate change impacts.

3.3.4. Ecological footprint-biomass-food-fossil fuel nexus

Table 5 column 7 reveals a 36% speed of adjusting past imbalances to equilibrium following a stable long-run relationship between response and regressors. The nexus between ecological footprint and food production produces a positive effect in both short- and long-run. Population growth has become the main driver of food production in order to meet population demand. However, food choices and consumption patterns have the potential of increasing food production, hence increasing the ecological footprint. For example, a transition from locally available food to imported food products due to affluent lifestyle increases the energy used for pre-harvesting, harvesting and post-harvesting operations. Processed foods utilize a large amount of water, energy and materials for production, packaging, refrigerating, and transportation, in addition to waste generation. Meat production and consumption account for 21% of global carbon footprint, while cereal production and consumption contribute about one-third of food waste, as well as GHG emissions (FAO, 2013; Owusu and Asumadu-Sarkodie, 2017). According to FAO (2013), "one-third of food produced from human utilization is lost or wasted annually, leading to both economic and environmental costs. Food wasted signifies a lost opportunity of improving food security and reduce environmental stress from agricultural production". No significant results were found between ecological footprint, biomass, fossil fuel, metal ore, and non-metallic mineral extraction. However, the role of material consumption and footprint in the capitalization of Australia's economy and environmental sustainability cannot be ignored (United Nations, 2015), perhaps, the

polluting natural resources extracted are exported to developing countries in the form of exports and foreign direct investments (DIIS, 2016).

Fig. 7 presents the impulse-response between economic growth and ecological footprint. A positive shock in economic growth decreases ecological footprint while a negative shock increases ecological footprint in the long-run. Recent studies in Qatar and Industrialized countries revealed a feedback mechanism between economic development and ecological footprint (Charfeddine, 2017; Destek and Sarkodie, 2019) while another study in 27 countries found a unidirectional causality running from economic development to ecological footprint (Uddin et al., 2017). Uddin et al. (2017) accentuated the importance of economic development yet its insufficiency in safeguarding the environment and improving sustainability. Nevertheless, it appears Australia's economic structure depends more on services and less on natural resource extraction and material consumption, as such, improvements and sustained economic growth reduce ecological footprint, therefore, reducing environmental degradation.

3.3.5. Biocapacity-energy-economic growth-natural resource nexus

The impulse-response between economic growth and natural resources depletion versus biocapacity are presented in Fig. 8. A positive shock in natural resources depletion declines biocapacity while a negative shock improves biocapacity. In addition, a positive shock in economic growth declines biocapacity while a negative shock improves biocapacity in the long-run. The above observations are in accordance with the achievement of environmental sustainability. The exploitation

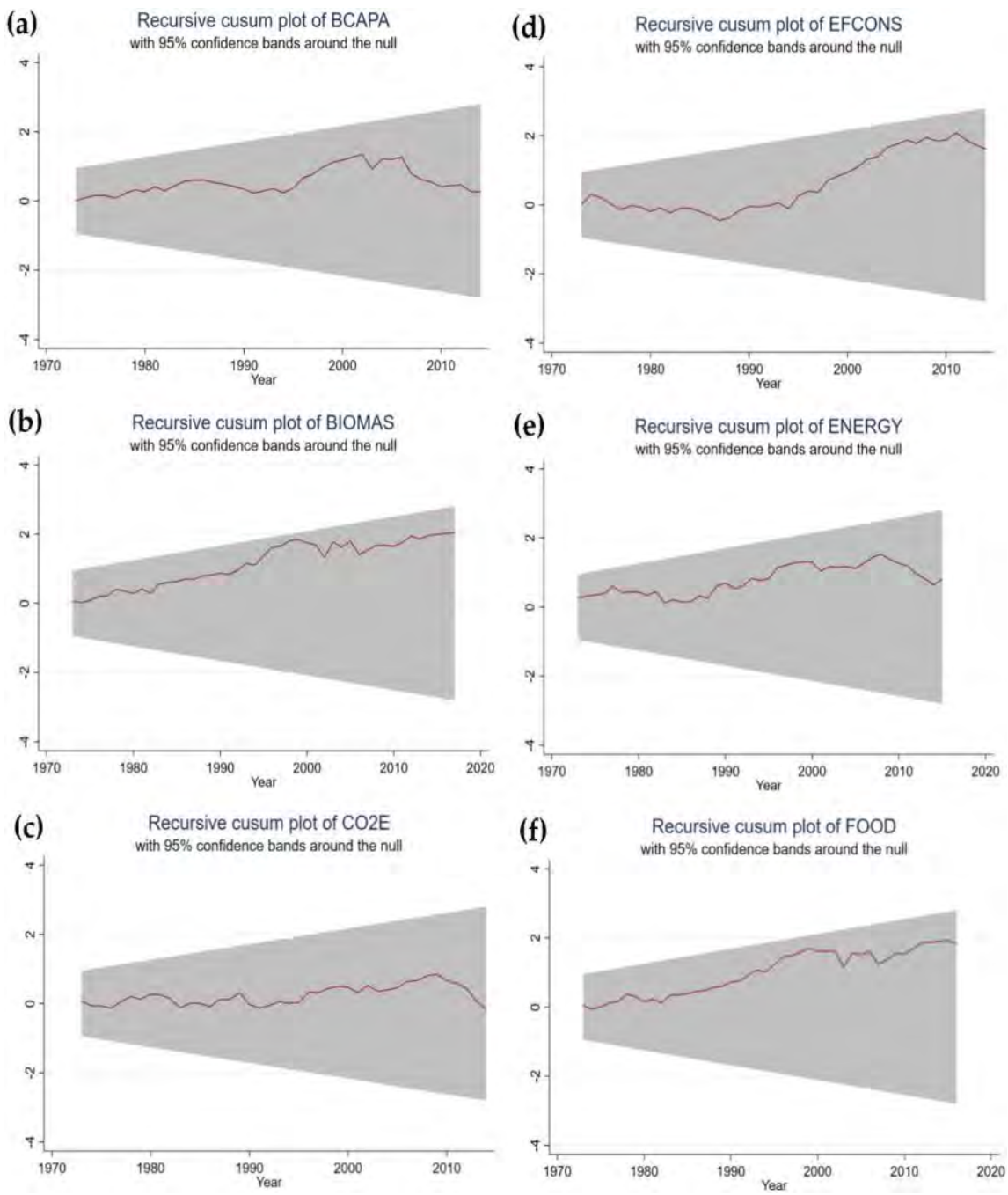

Fig. 9. Recursive cusum plot (a) BCAPA (b) BIOMAS (c) CO_2E (d) EFCONS (e) ENERGY (f) FOOD. NB: The recursive cusum plots within the 95% confidence bands confirm the stability of the estimated models.

of natural resources without sustainable and conservation management practices hampers ecosystems' ability to regenerate itself to support material demand for economic development. Australia's material footprint has increased from 611 million tons in 1996 to 967 million tons in 2015 at a growth rate of 2.74% per annum (UNEP, 2018). The sustainable growth and development entail reduced natural resources depletion, material footprint, the use of toxic materials, and minimizing generated waste and pollutants from cradle-to-grave (United Nations, 2015). Australia's economic growth versus biocapacity negates the theory of environmental sustainability due to the decline of ecosystems' capacity to regenerate itself, hence, leading to an ecological deficit. Corroborated by Sarkodie and Strezov (2018b), the study revealed a U-shape relationship between biocapacity and economic growth, and a unidirectional causality running from economic development to biocapacity, hence, demonstrating that economic development decreases environmental sustainability in Australia. As a policy implication, decoupling economic development from natural resource extraction and consumption patterns improve environmental sustainability and sustainable development.

3.3.6. Model validation

The estimated models were verified using the diagnostic tests in Table 5 and Figs. 9–10 to examine residual independence. To improve the coefficients and achieve robust standard errors, 5000 dynamic

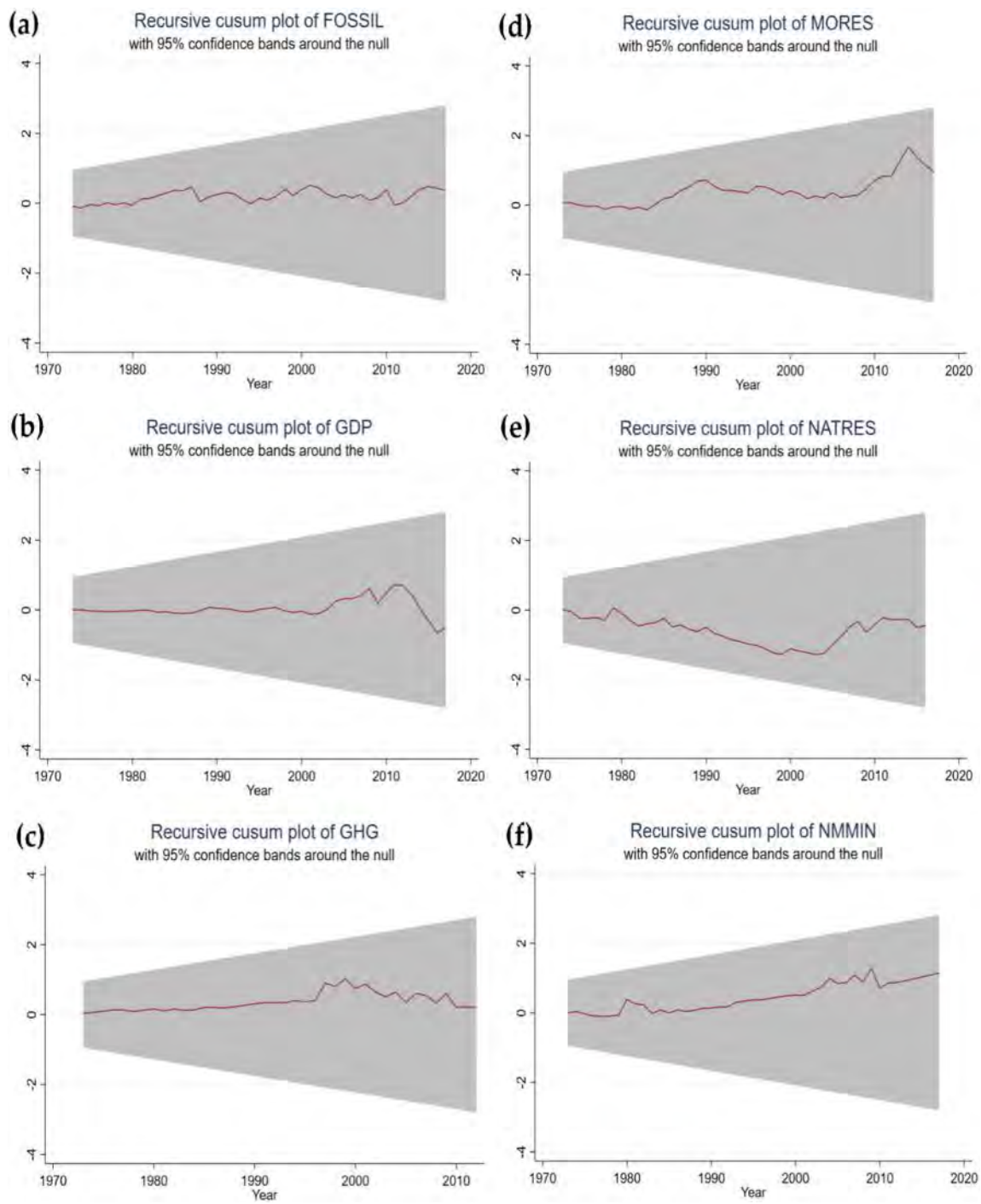

Fig. 10. Recursive cusum plot (a) FOSSIL (b) GDP (c) GHG (d) MORES (e) NATRES (f) NMMIN. NB: The recursive cusum plots within the 95% confidence bands confirm the stability of the estimated models.

simulations were estimated. The diagnostic tests include Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity; and Breusch-Godfrey LM test for autocorrelation. Results revealed that, except models 3 and 7, the remaining models have no ARCH effect and no issues with autocorrelation. In time-series regression analysis, it is assumed that the coefficients are stable over time. This study applied a CUSUM test to check for structural breaks in the residuals. The work tested the assumption on whether the time series brusquely changes in ways not predicted by the estimated model (Ploberger and Krämer, 1992). The parameter stability of the models is examined using cumulative sum test presented in Figs. 9–10. Evidence from the recursive cusum plot shows that all the data series utilized in the 7 models are within the 95% confidence band, hence, confirming the stability of the estimated models.

4. Conclusion

The complexities of climate change and its impacts require a multifaceted approach to examine the dynamics and interactions with the environment. Using Australia's data as a case study, novel dynamic ARDL simulations were used in this work to examine the interaction between environment and economic policy indicators. Food and energy consumption underpin socio-economic development by improving food security, health and nutrition, income levels, and among others. This study found no significant short and long-run relationship between food and energy consumption. Nevertheless, both positive and shock in food production has a long-term effect on energy consumption. On the contrary, the study found a positive relationship between food and ecological footprint. Food production and its associated services from cradle-to-grave have significant environmental externalities due to the use of energy, natural resources and its related GHG emissions. As such, improvements in sustainable development require sustainable and modern agricultural practices throughout the lifecycle. An inversed-U shaped relationship was found between energy consumption and income level. While growth in income levels intensifies energy consumption, intensive energy utilization declines after reaching a turning point of income level, signifying energy efficiency due to a decline in energy intensity. Australia's energy intensity has declined over the last 30 years due to a structural change in the economy—a paradigm shift from an energy-intensive economy to a decarbonized and services economy, hence, improving energy efficiency. To support the premise, a negative relationship between GHG emissions and economic development is revealed in both short- and long-term, meaning that Australia's economic development is on the pathway to achieving environmental sustainability. Lifecycle emissions of bioenergy sources are problematic in achieving sustainable energy consumption and production patterns. Yet, a negative long-run relationship was observed between GHG emissions and biomass energy consumption. Thus, biomass energy supports a transition to a decarbonized economy by reducing GHG emissions while shifting the demand for fossil fuel energy and its related products. Natural resources depletion was observed to increase ecological footprint as well as increasing GHG emissions. Consequently, limiting Australia's ecological deficit and natural resources exploitation is essential to preventing the liquidation of ecological assets while promoting environmental sustainability.

Policy implications, such as sustainable and conservation management practices for natural resources extraction are required to improve Australia's biocapacity for economic development. Decoupling economic development from natural resource extraction and consumption patterns improve environmental sustainability and sustainable development. Increasing the penetration of renewable energy technologies in the energy mix would reduce energy-related GHG emissions.

An extended discussion on the relationship between food and energy consumption as promoters of socio-economic development with the subsidiary effect of food waste from production and consumption are essential scenarios for the case of the EU. As such, future research should endeavor to identify the efforts needed to reduce the rate of food waste.

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Declaration

There is no conflict of interest.

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Appendix 7 — Supplementary Material for Chapter Two

Appendix A: ND-GAIN Matrix

Kenya

VIEW PROFILE

ND-GAIN Country Index rank

152

Score: 38.9

Trend: ↑

Vulnerability 0.533

Readiness 0.312

Benin

VIEW PROFILE

ND-GAIN Country Index rank

151

Score: 39.4

Trend: ↑

Vulnerability 0.573

Readiness 0.360

Nigeria

VIEW PROFILE

ND-GAIN Country Index rank

144

Score: 40.1

Trend: ↑

Vulnerability 0.480

Readiness 0.282

Côte d'Ivoire

VIEW PROFILE

ND-GAIN Country Index rank

138

Score: 41.5

Trend: ↑

Vulnerability 0.499

Readiness 0.329

Cameroon

VIEW PROFILE

ND-GAIN Country Index rank

138

Score: 41.5

Trend: ↑

Vulnerability 0.484

Readiness 0.313

Zambia

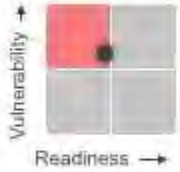
VIEW PROFILE

ND-GAIN Country Index rank

133

Score: 41.9

Trend: ↑



Vulnerability 0.538

Readiness 0.376

Senegal

VIEW PROFILE

ND-GAIN Country Index rank

132

Score: 42.5

Trend: ↑

Vulnerability 0.519

Readiness 0.368

Algeria

VIEW PROFILE

ND-GAIN Country Index rank

114

Score: 47.0

Trend: ↑

Vulnerability 0.403

Readiness 0.344

Ghana

VIEW PROFILE

ND-GAIN Country Index rank

105

Score: 49.1

Trend: ↑

Vulnerability 0.472

Readiness 0.453

Egypt

VIEW PROFILE

ND-GAIN Country Index rank

101

Score: 49.6

Trend: =

Vulnerability 0.407

Readiness 0.400

Morocco

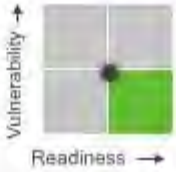
VIEW PROFILE

ND-GAIN Country Index rank

90

Score: 52.6

Trend: ↑



Vulnerability 0.393

Readiness 0.445

South Africa

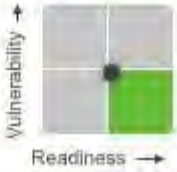
VIEW PROFILE

ND-GAIN Country Index rank

85

Score: 53.3

Trend: =



Vulnerability 0.390

Readiness 0.455

Tunisia

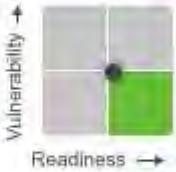
VIEW PROFILE

ND-GAIN Country Index rank

82

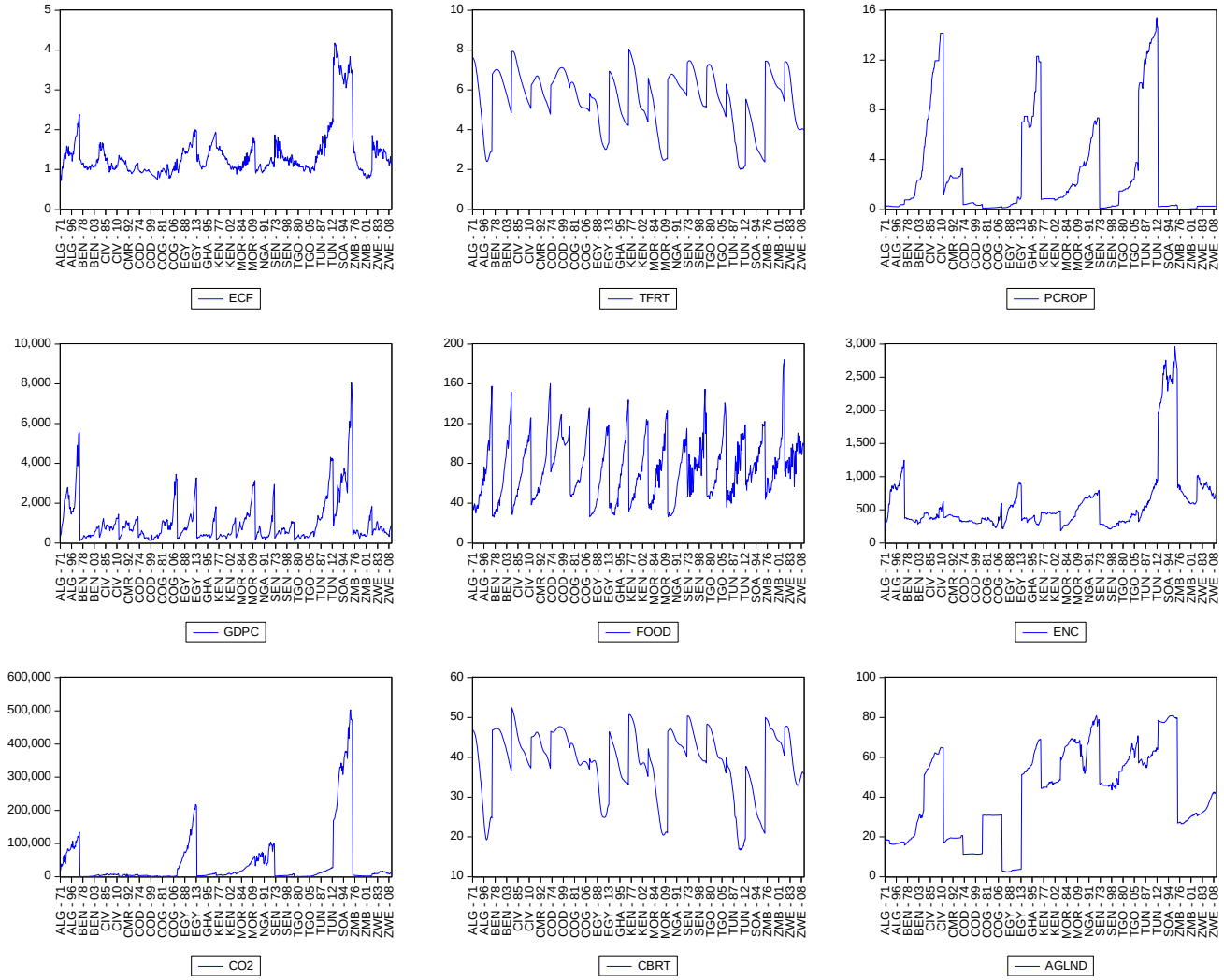
Score: 53.8

Trend: ↓



Vulnerability 0.398

Readiness 0.474



Appendix B. The trend of data variables in Africa

Appendix C. Descriptive Analysis

Statistics	TFRT	PCROP	GDPC	FOOD	ENC	ECF	CO2	CBRT	AGLND
Mean	5.5123	2.7819	1044.8040	74.6531	605.5504	1.3742	39642.5500	38.9295	41.9936
Median	5.7720	0.8434	663.2055	72.7800	425.1814	1.1889	6222.8990	40.2420	45.4475
Maximum	8.0510	15.4094	8049.9540	184.3700	2963.3630	4.1771	503262.7000	52.4590	80.9205
Minimum	2.0000	0.0148	100.6932	26.0700	180.2704	0.7236	260.3570	16.7000	2.4459
Std. Dev.	1.4694	3.9734	1109.9240	30.0954	513.5380	0.6238	85046.5500	8.3099	22.3336
Skewness	-0.6723	1.6533	2.6622	0.4904	2.9270	2.6253	3.3480	-0.9381	-0.0484
Kurtosis	2.6251	4.4975	11.8685	2.8801	11.4694	10.0202	14.5606	3.0992	1.8510
Jarque-Bera	59.3515	401.3252	3259.0240	29.7434	3228.5860	2340.7480	5436.3370	107.5269	40.4942
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Appendix 8 — Supplementary Material for Chapter Three

Appendix A. Data Management of Variables

Variables	China	India	Indonesia	Iran	South Africa
FDI	N/A	N/A	N/A	Absolute values	Absolute values
GDPP	N/A	N/A	N/A	1991-1992 generated	N/A
CO_2E	2015-2016 generated	2015-2016 generated	2015-2016 generated	2015-2016 generated	2015-2016 generated
GHG	2013-2016 generated	2013-2016 generated	2013-2016 generated	2008-2016 generated	1984-1989; 2008-2016 generated
ENE	2015-2016 generated	2015-2016 generated	2015-2016 generated	2015-2016 generated	2015-2016 generated

Missing data were ***generated*** using Excel forecasting technique based on 99.99% Confidence Interval

Appendix 9 — Supplementary Material for Chapter Four

Appendix A: Descriptive Analysis

Descriptive Analysis Australia

Statistics	BCAP	CO2	EF	EGCOM	EGIMP	ENEFI	ENEI	HCONE	PGDP	URBGR
Mean	20.4852	277865	9.2877	5075	-85.2585	8143	0.3581	2.42E+11	22129	1.5323
Median	20.7197	277398	9.4819	5062	-92.1329	8550	0.2791	1.86E+11	18249	1.4427
Maximum	23.7380	394793	11.3135	5965	-4.3356	10973	1.1423	8.57E+11	67792	3.7724
Minimum	15.6668	152775	7.5518	3990	-172.4383	3752	0.0807	2.44E+10	3493	0.7924
Std. Dev.	2.2437	71734	0.9081	547	46.6348	2304	0.2382	2.17E+11	16824	0.4895
Skewness	-0.6434	-0.0573	0.0298	-0.1476	0.1776	-0.4191	1.5545	1.4485	1.3956	2.4911
Kurtosis	2.3755	1.8554	2.4792	1.8728	1.8567	1.8189	5.3882	4.2601	4.1569	11.7455

Descriptive Analysis China

Statistics	BCAP	CO2	EF	EGCOM	EGIMP	ENEFI	ENEI	HCONE	PGDP	URBGR
Mean	0.8538	3555935	1.8480	958	0.5491	1015	1.9128	6.26E+11	1233	3.7745
Median	0.8527	2695982	1.5501	767	-1.1662	605	2.0884	1.93E+11	366	4.0083
Maximum	0.9298	10249463	3.5948	2214	14.7565	3773	3.9461	3.55E+12	7078	5.2957
Minimum	0.7858	876633	1.0718	465	-7.5437	152	0.3128	5.13E+10	119	1.7058
Std. Dev.	0.0370	2644796	0.7327	496	5.8108	1004	1.1297	8.63E+11	1764	0.9251
Skewness	0.3126	1.2410	1.1126	1.2975	1.0303	1.3773	0.0867	2.0253	2.0309	-0.6270
Kurtosis	2.4053	3.4910	3.0545	3.4737	3.0725	3.7661	1.6260	6.3001	6.1490	2.7714

Descriptive Analysis Ghana

Statistics	BCAP	CO2	EF	EGCOM	EGIMP	ENEFI	ENEI	HCONE	PGDP	URBGR
Mean	1.5483	5387	1.3719	346	22.9593	318	0.8753	7.86E+09	540	3.9985
Median	1.3884	3982	1.2804	360	20.7839	332	0.9665	4.74E+09	380	4.0559
Maximum	2.3299	14620	1.9405	416	45.9080	426	1.5005	3.09E+10	1814	5.3478
Minimum	1.2451	2296	1.0079	269	-7.4934	93	0.1873	1.58E+09	233	2.3279
Std. Dev.	0.3058	2976	0.2940	39	11.5395	73	0.3591	7.90E+09	407	0.7030
Skewness	1.1705	1.0777	0.5414	-0.4379	0.2045	-0.9825	-0.7225	1.6759	1.9111	-0.5995
Kurtosis	3.0772	3.6179	1.9127	2.2451	3.2739	3.8851	2.6002	4.3279	5.3438	3.0937

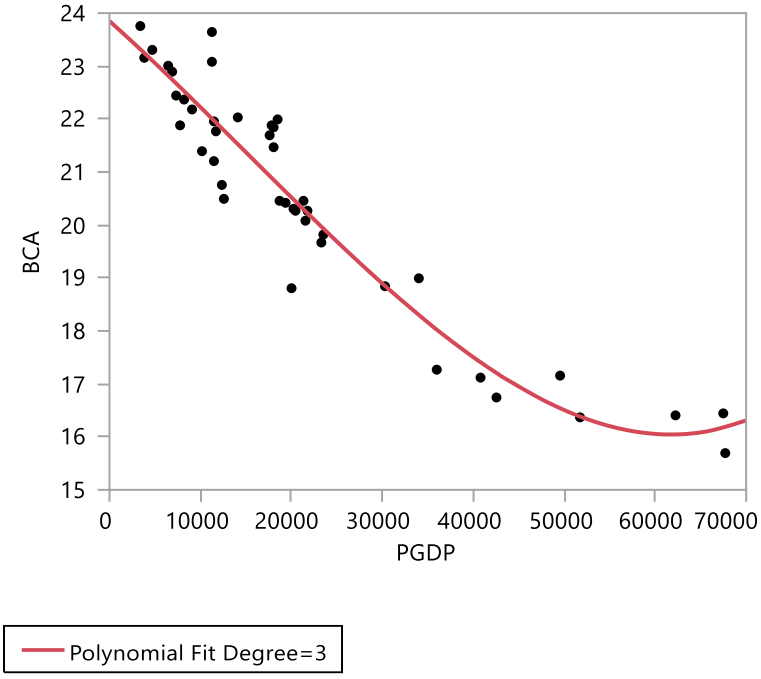
Descriptive Analysis USA

Statistics	BCAP	CO2	EF	EGCOM	EGIMP	ENEFI	ENEI	HCONE	PGDP	URBGR
Mean	4.2529	5040388	10.0440	7697	18.7439	11510	0.4386	4.96E+12	27109	1.2379
Median	4.2112	4955081	10.0735	7758	18.5741	12134	0.3012	4.22E+12	25493	1.1359
Maximum	4.7941	5795162	11.1396	8438	29.6592	13705	1.3594	1.14E+13	52787	1.9086
Minimum	3.7245	4306748	8.4039	6869	9.0487	7517	0.1308	7.01E+11	5623	0.9084
Std. Dev.	0.3019	463669	0.6626	360	5.8401	1893	0.3423	3.37E+12	14859	0.2852
Skewness	0.0691	0.1441	-0.7180	-0.4695	0.2219	-0.4976	1.3649	0.4466	0.1945	1.0781
Kurtosis	1.8480	1.7691	3.0407	3.0942	2.0101	1.8488	3.7316	1.8792	1.7542	2.8117

Appendix B: Biocapacity Structural Relationship

ECONOMIC GROWTH

Bivariate Fit of BCAP By PGDP Country=AUS



Polynomial Fit Degree=3

BCAP = 23.860354 - 0.0001671*PGDP + 5.574e-10*(PGDP-22128.9)^2 + 2.613e-14*(PGDP-22128.9)^3

Summary of Fit

RSquare	0.910908
RSquare Adj	0.904054

Root Mean Square Error	0.694976
Mean of Response	20.48522
Observations (or Sum Wgts)	43

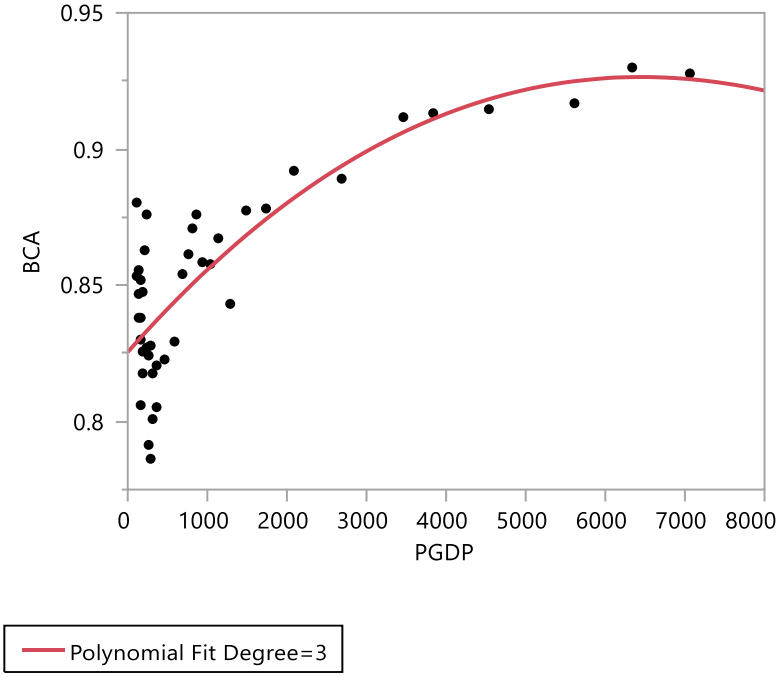
Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	3	192.59179	64.1973	132.9160
Error	39	18.83666	0.4830	**Prob > F**
C. Total	42	211.42844		<.0001*

Parameter Estimates

Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**
Intercept	23.860354	0.291407	81.88	<.0001*
PGDP	-0.000167	1.229e-5	-13.60	<.0001*
(PGDP-22128.9)^2	5.574e-10	8.01e-10	0.70	0.4904
(PGDP-22128.9)^3	2.613e-14	2.04e-14	1.28	0.2074

Bivariate Fit of BCAP By PGDP Country=CHN



Polynomial Fit Degree=3

BCAP = 0.829881 + 2.5965e-5*PGDP - 2.84e-9*(PGDP-1233.22)^2 + 4.499e-14*(PGDP-1233.22)^3

Summary of Fit

RSquare	0.6831

RSquare Adj	0.658723
Root Mean Square Error	0.021641
Mean of Response	0.853751
Observations (or Sum Wgts)	43

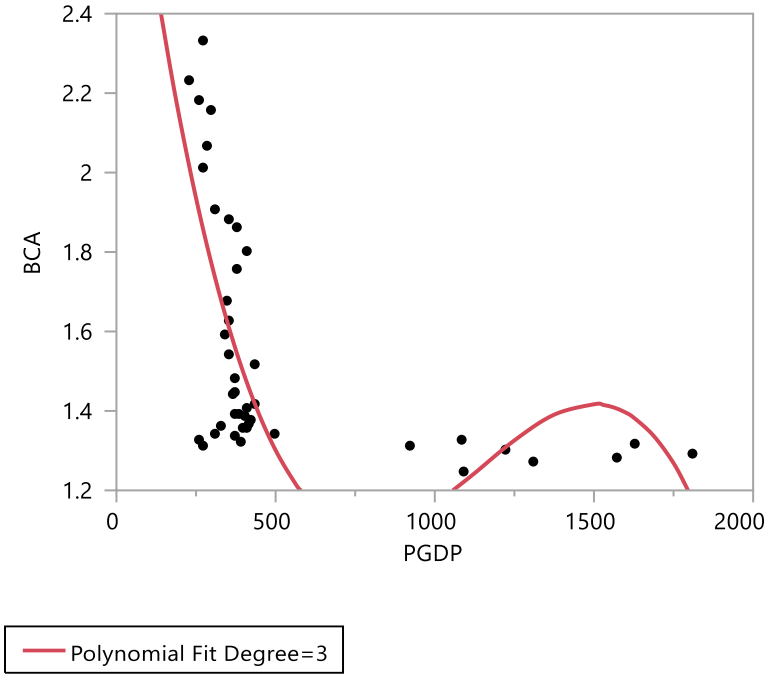
Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	3	0.03937079	0.013124	28.0224
Error	39	0.01826467	0.000468	**Prob > F**
C. Total	42	0.05763545		<.0001*

Parameter Estimates

Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**
Intercept	0.829881	0.004987	166.40	<.0001*
PGDP	2.5965e-5	4.492e-6	5.78	<.0001*
(PGDP-1233.22)^2	-2.84e-9	3.677e-9	-0.77	0.4445
(PGDP-1233.22)^3	4.499e-14	5.87e-13	0.08	0.9393

Bivariate Fit of BCAP By PGDP Country=GHA



Polynomial Fit Degree=3

BCAP = 1.9418791 - 0.0012926*PGDP + 3.256e-6*(PGDP-539.774)^2 - 1.7941e-9*(PGDP-539.774)^3

Summary of Fit

RSquare	0.446724
RSquare Adj	0.404164
Root Mean Square Error	0.236034
Mean of Response	1.548326
Observations (or Sum Wgts)	43

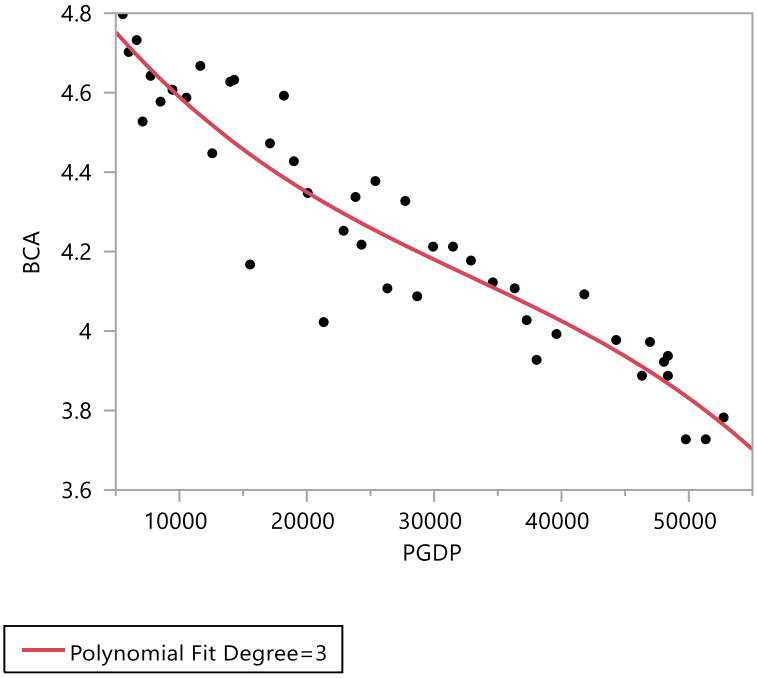
Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	3	1.7543273	0.584776	10.4964
Error	39	2.1727679	0.055712	**Prob > F**
C. Total	42	3.9270951		<.0001*

Parameter Estimates

Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**
Intercept	1.9418791	0.090674	21.42	<.0001*
PGDP	-0.001293	0.000256	-5.05	<.0001*
(PGDP-539.774)^2	3.256e-6	8.837e-7	3.68	0.0007*
(PGDP-539.774)^3	-1.794e-9	6.05e-10	-2.96	0.0052*

Bivariate Fit of BCAP By PGDP Country=USA



Polynomial Fit Degree=3

BCAP = 4.6583357 - 1.5981e-5*PGDP + 1.547e-10*(PGDP-27109.4)^2 - 9.104e-15*(PGDP-27109.4)^3

Summary of Fit

RSquare	0.88236
RSquare Adj	0.873311
Root Mean Square Error	0.107446
Mean of Response	4.252866
Observations (or Sum Wgts)	43

Analysis of Variance

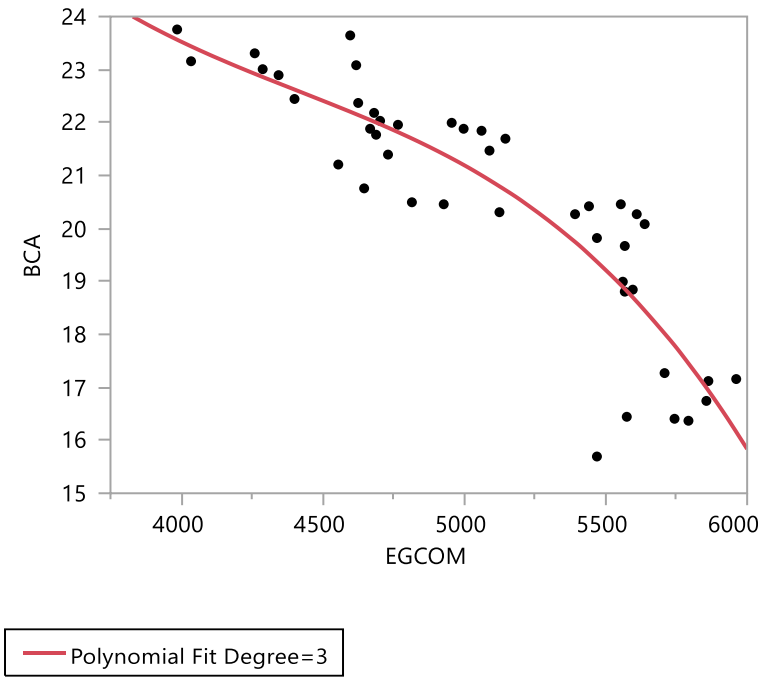
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	3	3.3770695	1.12569	97.5070
Error	39	0.4502435	0.01154	**Prob > F**
C. Total	42	3.8273131		<.0001*

Parameter Estimates

Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**
Intercept	4.6583357	0.087913	52.99	<.0001*
PGDP	-0.000016	3.095e-6	-5.16	<.0001*
(PGDP-27109.4)^2	1.547e-10	9.52e-11	1.63	0.1121
(PGDP-27109.4)^3	-9.1e-15	7.84e-15	-1.16	0.2526

ENERGY CONSUMPTION

Bivariate Fit of BCAP By EGCOM Country=AUS



Polynomial Fit Degree=3

BCAP = 37.27961 - 0.0032153*EGCOM - 1.7079e-6*(EGCOM-5074.5)^2 - 8.698e-10*(EGCOM-5074.5)^3

Summary of Fit

RSquare	0.782966
RSquare Adj	0.766271
Root Mean Square Error	1.08471
Mean of Response	20.48522
Observations (or Sum Wgts)	43

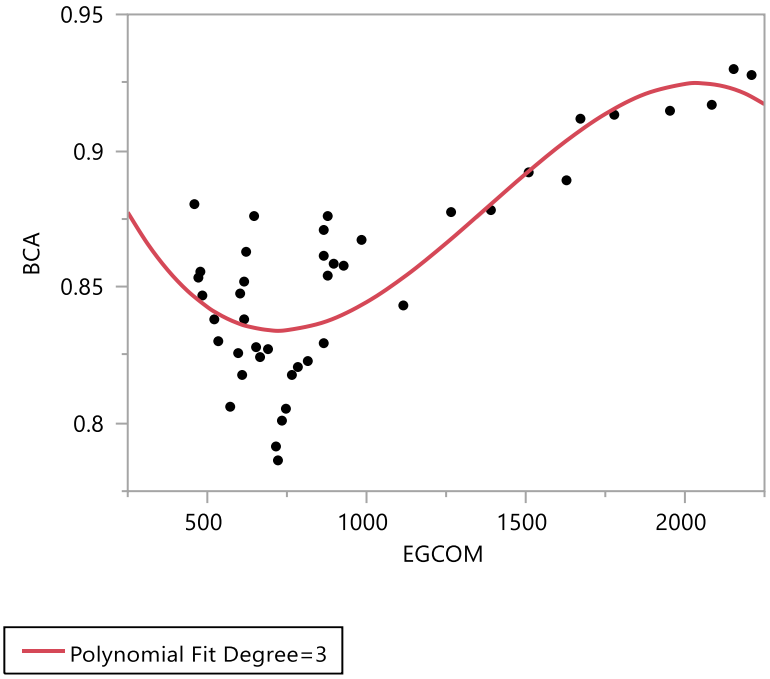
Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	3	165.54120	55.1804	46.8983
Error	39	45.88724	1.1766	**Prob > F**
C. Total	42	211.42844		<.0001*

Parameter Estimates

Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**
Intercept	37.27961	3.211979	11.61	<.0001*
EGCOM	-0.003215	0.000643	-5.00	<.0001*
(EGCOM-5074.5)^2	-1.708e-6	7.201e-7	-2.37	0.0227*
(EGCOM-5074.5)^3	-8.7e-10	1.085e-9	-0.80	0.4276

Bivariate Fit of BCAP By EGCOM Country=CHN



Polynomial Fit Degree=3

BCAP = 0.7836361 + 6.0581e-5*EGCOM + 1.008e-7*(EGCOM-957.509)^2 - 7.933e-11*(EGCOM-957.509)^3

Summary of Fit

RSquare	0.684543
RSquare Adj	0.660277
Root Mean Square Error	0.021591
Mean of Response	0.853751
Observations (or Sum Wgts)	43

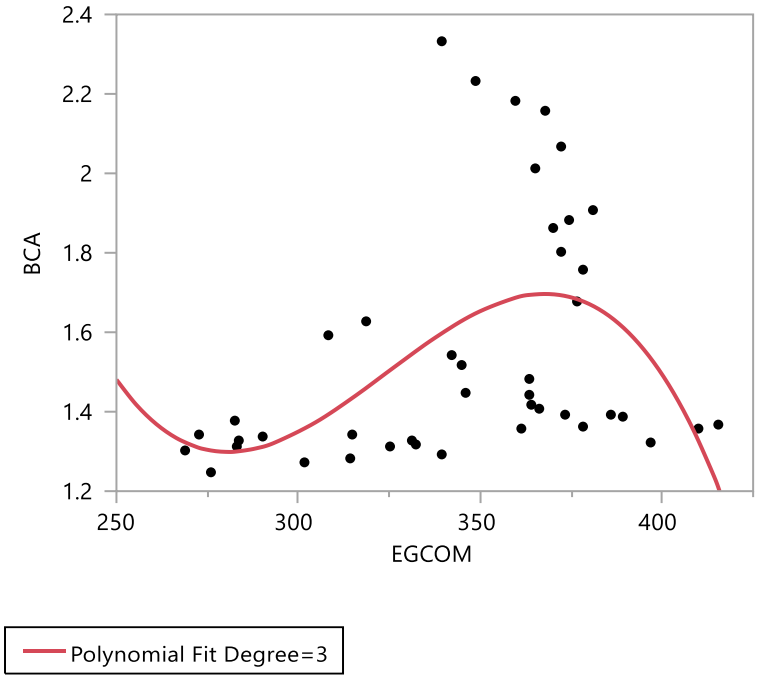
Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	3	0.03945394	0.013151	28.2100
Error	39	0.01818152	0.000466	**Prob > F**
C. Total	42	0.05763545		<.0001*

Parameter Estimates

Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**
Intercept	0.7836361	0.012848	60.99	<.0001*
EGCOM	6.0581e-5	1.366e-5	4.43	<.0001*
(EGCOM-957.509)^2	1.008e-7	3.397e-8	2.97	0.0051*
(EGCOM-957.509)^3	-7.93e-11	3.11e-11	-2.55	0.0149*

Bivariate Fit of BCAP By EGCOM Country=GHA



Polynomial Fit Degree=3

BCAP = -0.162148 + 0.005192*EGCOM - 7.7074e-5*(EGCOM-345.608)^2 - 0.0000012*(EGCOM-345.608)^3

Summary of Fit

RSquare	0.268223
RSquare Adj	0.211932
Root Mean Square Error	0.271452
Mean of Response	1.548326
Observations (or Sum Wgts)	43

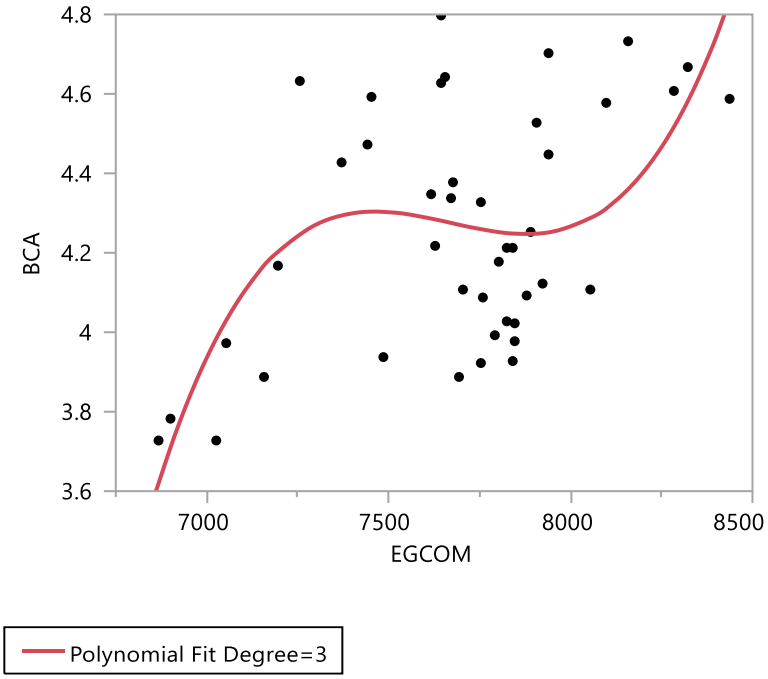
Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	3	1.0533370	0.351112	4.7650
Error	39	2.8737582	0.073686	**Prob > F**
C. Total	42	3.9270951		0.0063*

Parameter Estimates

Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**
Intercept	-0.162148	0.852092	-0.19	0.8501
EGCOM	0.005192	0.00242	2.15	0.0382*
(EGCOM-345.608)^2	-0.000077	2.814e-5	-2.74	0.0092*
(EGCOM-345.608)^3	-1.201e-6	6.732e-7	-1.78	0.0823

Bivariate Fit of BCAP By EGCOM Country=USA



Polynomial Fit Degree=3

BCAP = 5.8141734 - 0.0002006*EGCOM + 1.2837e-7*(EGCOM-7697.12)^2 + 1.5836e-9*(EGCOM-7697.12)^3

Summary of Fit

RSquare	0.357165
RSquare Adj	0.307716
Root Mean Square Error	0.251168
Mean of Response	4.252866
Observations (or Sum Wgts)	43

Analysis of Variance

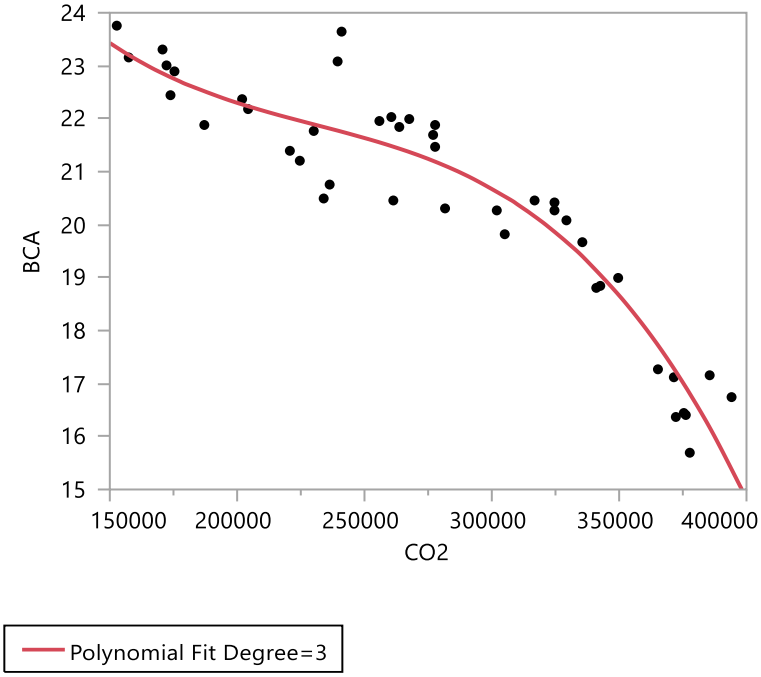
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	3	1.3669819	0.455661	7.2229
Error	39	2.4603312	0.063085	**Prob > F**
C. Total	42	3.8273131		0.0006*

Parameter Estimates

Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**
Intercept	5.8141734	1.835828	3.17	0.0030*
EGCOM	-0.000201	0.000237	-0.85	0.4032
(EGCOM-7697.12)^2	1.2837e-7	2.294e-7	0.56	0.5790
(EGCOM-7697.12)^3	1.5836e-9	5.58e-10	2.84	0.0072*

CARBON DIOXIDE EMISSIONS

Bivariate Fit of BCAP By CO2 Country=AUS



Polynomial Fit Degree=3
BCAP = 26.555844 - 1.9321e-5*CO2 - 1.438e-10*(CO2-277864)^2 - 1.015e-15*(CO2-277864)^3

Summary of Fit

RSquare	0.900467
RSquare Adj	0.89281
Root Mean Square Error	0.734571
Mean of Response	20.48522
Observations (or Sum Wgts)	43

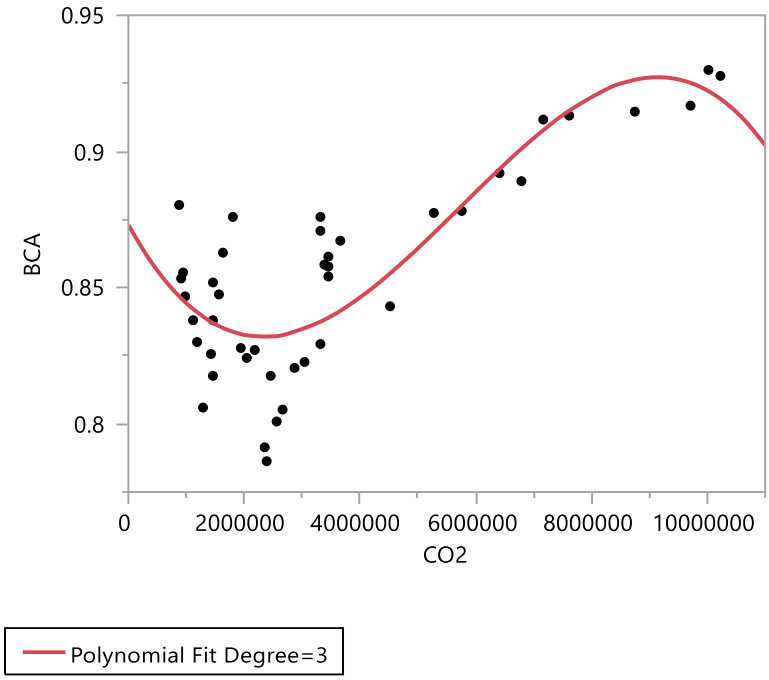
Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	3	190.38427	63.4614	117.6095
Error	39	21.04417	0.5396	**Prob > F**
C. Total	42	211.42844		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	26.555844	1.134933	23.40	<.0001*
CO2	-1.932e-5	4.11e-6	-4.70	<.0001*
(CO2-277864)^2	-1.44e-10	2.5e-11	-5.76	<.0001*
(CO2-277864)^3	-1.02e-15	4.1e-16	-2.48	0.0176*

Bivariate Fit of BCAP By CO2 Country=CHN



Polynomial Fit Degree=3

BCAP = 0.796224 + 1.2364e-8*CO2 + 3.934e-15*(CO2-3555935)^2 - 6.01e-22*(CO2-3555935)^3

Summary of Fit

RSquare	0.694818
RSquare Adj	0.671343
Root Mean Square Error	0.021237
Mean of Response	0.853751
Observations (or Sum Wgts)	43

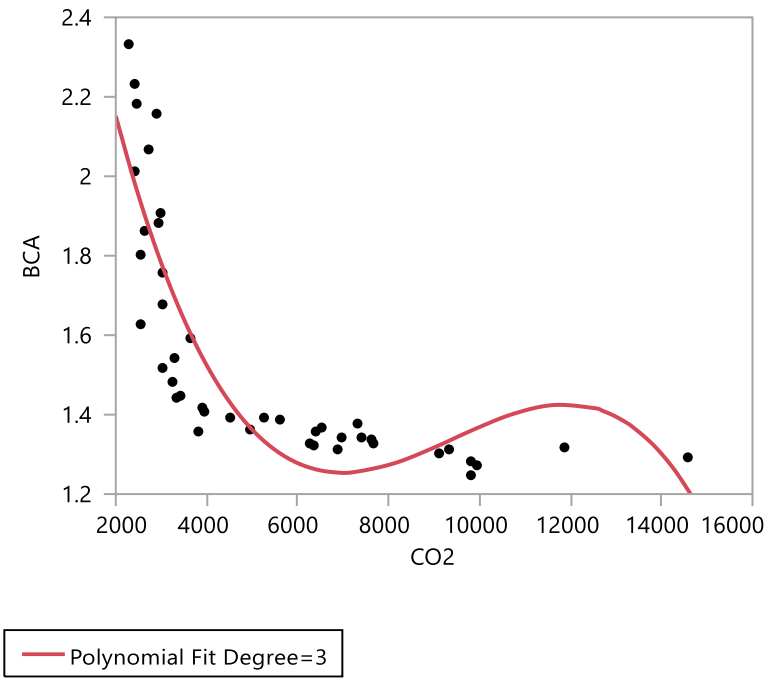
Analysis of Variance

Parameter Estimates

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	0.04004617	0.013349	29.5976
Error	39	0.01758928	0.000451	**Prob > F**
C. Total	42	0.05763545		<.0001*

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.796224	0.009612	82.84	<.0001*
CO2	1.2364e-8	2.475e-9	5.00	<.0001*
(CO2-3555935)^2	3.934e-15	1.1e-15	3.58	0.0009*
(CO2-3555935)^3	-6.01e-22	1.95e-22	-3.09	0.0037*

Bivariate Fit of BCAP By CO2 Country=GHA



Polynomial Fit Degree=3

BCAP = 1.8129757 - 9.1285e-5*CO2 + 3.553e-8*(CO2-5387.16)^2 - 2.925e-12*(CO2-5387.16)^3

Summary of Fit

RSquare	0.760562
RSquare Adj	0.742144
Root Mean Square Error	0.155274
Mean of Response	1.548326

Observations (or Sum Wgts) 43

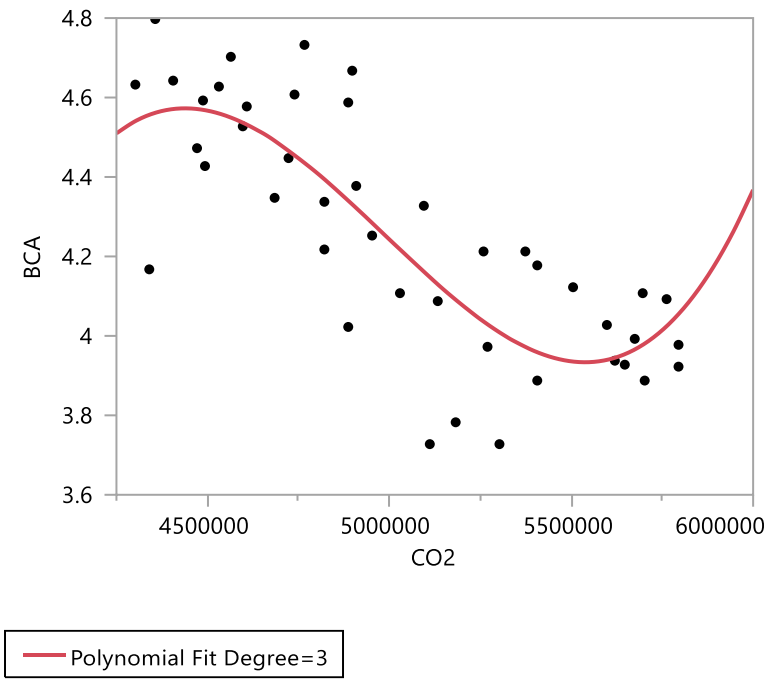
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	2.9867996	0.995600	41.2938
Error	39	0.9402956	0.024110	**Prob > F**
C. Total	42	3.9270951		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	1.8129757	0.075224	24.10	<.0001*
CO2	-9.129e-5	1.173e-5	-7.78	<.0001*
(CO2-5387.16)^2	3.553e-8	6.013e-9	5.91	<.0001*
(CO2-5387.16)^3	-2.93e-12	7.11e-13	-4.12	0.0002*

Bivariate Fit of BCAP By CO2 Country=USA



Polynomial Fit Degree=3

BCAP = 8.5642619 - 8.6428e-7*CO2 + 1.504e-13*(CO2-5040388)^2 + 9.623e-19*(CO2-5040388)^3

Summary of Fit

RSquare	0.645109
RSquare Adj	0.61781
Root Mean Square Error	0.186622

Mean of Response	4.252866
Observations (or Sum Wgts)	43

Analysis of Variance

Source	**DF**	**Sum of Squares**	**Mean Square**	**F Ratio**
Model	3	2.4690343	0.823011	23.6310
Error	39	1.3582788	0.034828	**Prob > F**
C. Total	42	3.8273131		<.0001*

Parameter Estimates

Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**
Intercept	8.5642619	0.832245	10.29	<.0001*
CO_2	-8.643e-7	1.656e-7	-5.22	<.0001*
$(CO_2\text{-}5040388)^2$	1.504e-13	1.58e-13	0.95	0.3465
$(CO_2\text{-}5040388)^3$	9.623e-19	4.16e-19	2.31	0.0260*

Appendix 10 — Supplementary Material for Chapter Five

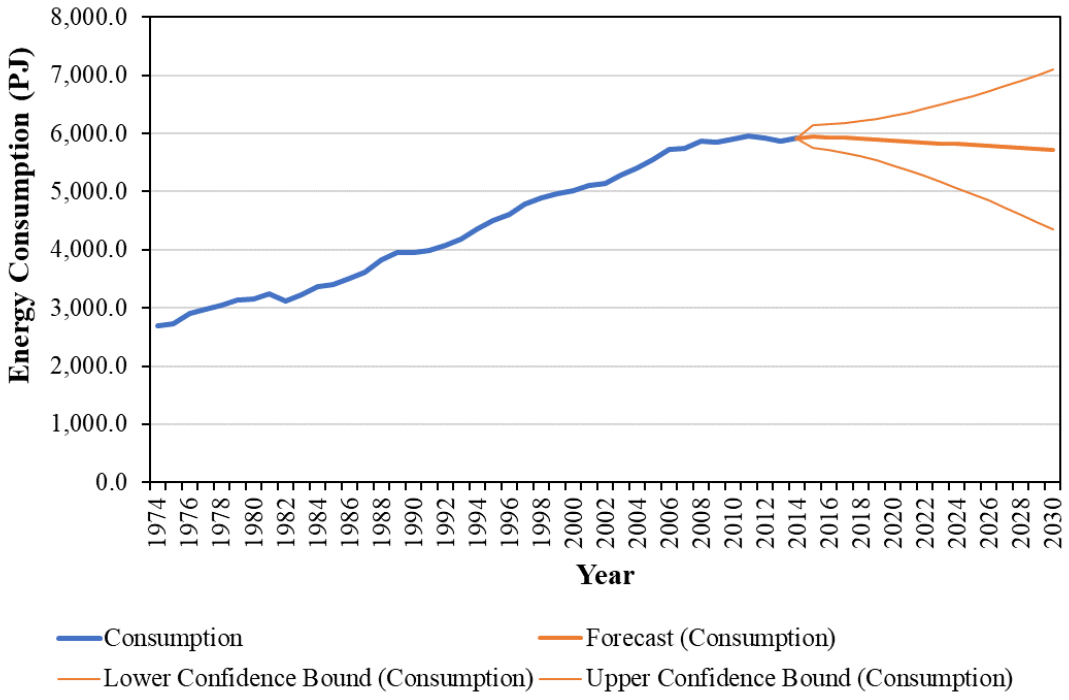
Appendix A. Summary of selected literature dealing with assessment of economic growth, CO_2 emissions and energy consumption.

Reference	Period	Country	Variables & Method	Outcome
Acaravci and Ozturk (2010)	1960-2005	19 European countries	Energy consumption, economic growth and CO_2 emissions using ARDL bounds test.	They found a positive long-run relationship between CO_2 emissions and energy consumption. The existence of EKC hypothesis was invalid, however, there was unidirectional causality from economic growth to CO_2 emissions.
Ahmad et al. (2016)	1971-2014	India	Energy consumption, economic growth and CO_2 emissions using autoregressive distributed lag and Granger causality test.	Their study confirmed the validity of the EKC hypothesis in India. The growth rate of CO_2 emissions is dependent on energy consumption. In a disaggregated level, coal energy source contributes more to pollution than natural gas energy source.
Alam et al. (2011)	1971-2006	India	Energy consumption, economic growth and CO_2 emissions using multivariate Toda and Yamamoto model, Impulse-Response and Granger causality test.	The study found a feedback hypothesis between to CO_2 emissions and energy consumption but no causal relationship between energy consumption and economic growth.

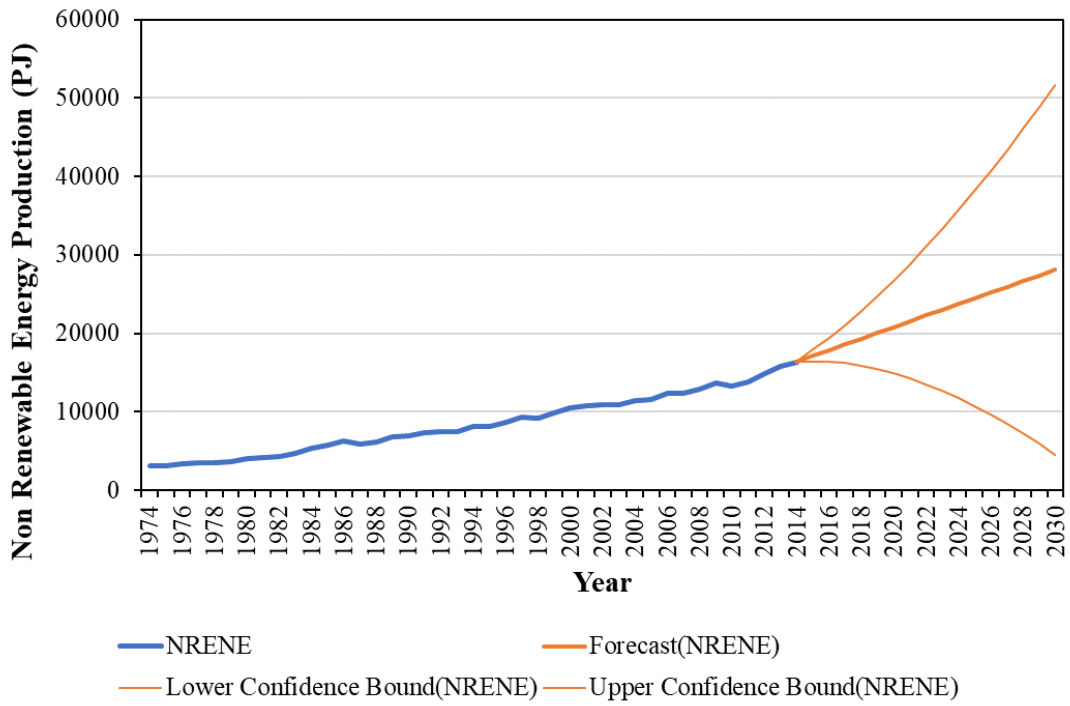
Antonakakis et al. (2017)	1971-2011	106 countries	Economic growth, energy consumption and CO_2 emissions using panel vector autoregression and Impulse-Response.	The study found a feedback hypothesis between energy consumption and economic growth. The EKC hypothesis is not valid.
Fei et al. (2011)	1985-2007	China	Energy consumption, economic growth and CO_2 emissions using ordinary least squares regression.	There was a long-run relationship between energy consumption and economic growth. The study revealed a positive impact of economic growth of pollution.
Heidari et al. (2015)	1980-2008	Five ASEAN countries	Energy consumption, economic growth and CO_2 emissions using panel smooth transition regression.	The study confirmed the invalidity of the EKC hypothesis in ASEAN countries. Energy consumption was found to increase CO_2 emissions even in regime changes compared to economic growth that increases CO_2 emissions in the first regime.
Hu et al. (2018)	1996-2012	25 developing countries	CO_2 emissions, GDP per capita, commercial services per capita, the share of RENE, size of RENE consumption per capita Using FMOLS & DOLS	The study found a positive impact of economic growth on RENE and vice versa. The negative role of RENE on CO_2 emissions was confirmed.
Jaunky (2011)	1980-2005	36 high-income countries	Economic growth and CO_2 emissions using generalized method of moments and vector error correction model.	The EKC hypothesis was validated in the study while there was a unidirectional causality running from economic growth to CO_2 emissions.

Kais and Sami (2016)	1990-2012	58 countries	Energy consumption, economic growth and CO_2 emissions using generalized method of moments.	The study found the existence of EKC hypothesis in 58 countries and confirm a positive long-run relationship between economic growth and CO_2 emissions.
Narayan and Narayan (2010)	1980-2004	43 developing countries	Economic growth and CO_2 emissions using panel cointegration.	The study revealed that 15 of 43 countries decline pollution at long-run income levels.
Saboori et al. (2016)	1980-2009	Malaysia	Economic growth and CO_2 emissions using autoregressive distributed lag.	The study found a long-run equilibrium relationship between economic growth and CO_2 emissions. The EKC hypothesis was validated, thus, inverted U-shape between CO_2 emissions and economic growth.
Wang et al. (2016)	1990-2012	China	Energy consumption, economic growth and CO_2 emissions using VECM, Impulse-Response and Granger causality test.	The study found a unidirectional causality running from energy consumption to CO_2 emissions and a feedback hypothesis between to economic growth and energy consumption.
Yang and Zhao (2014)	1970-2008	India	Energy consumption, economic growth and CO_2 emissions using Granger causality test and directed acyclic graphs.	The study found a unidirectional causality running from energy consumption to CO_2 emissions and a feedback hypothesis between CO_2 emissions and economic growth.
Zaman and Moemen (2017)	1975-2015	25 countries low	Energy consumption, economic growth,	The study confirmed the existence of the EKC hypothesis in low and

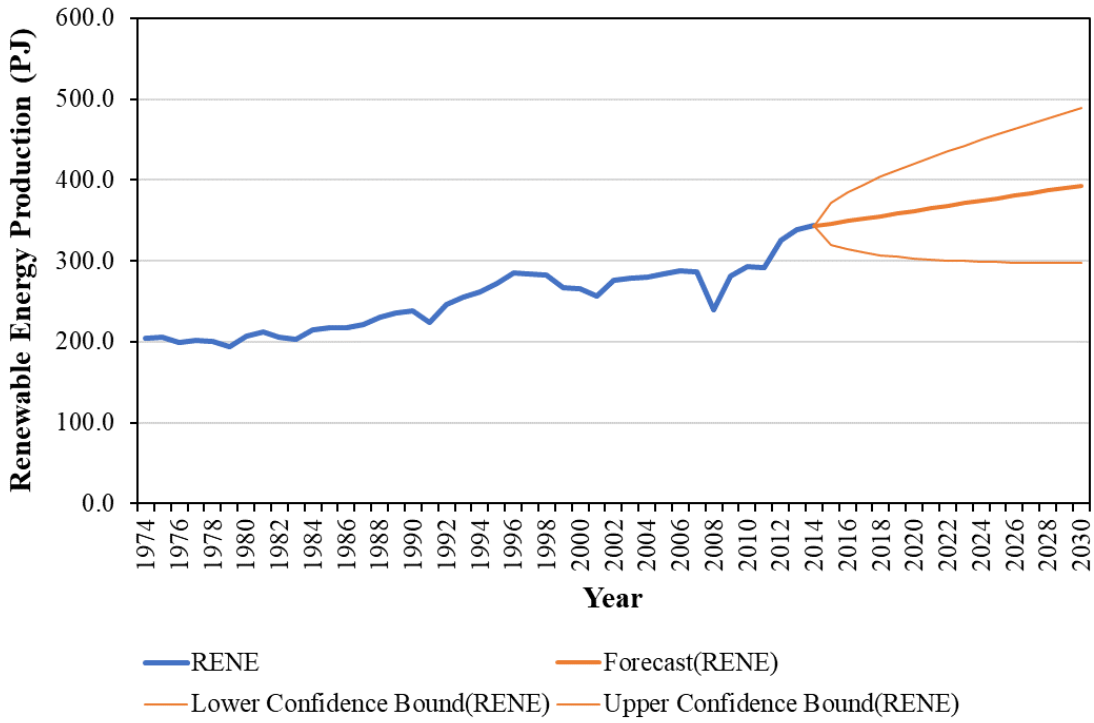
	income countries, 42 lower middle and upper middle income countries, and 23 high income countries	service value added and CO_2 emissions using the generalized method of moments (GMM).	middle-income countries. Increasing levels of energy consumption appear to facilitate the growth of environmental pollution. Service value added increases CO_2 emissions in the long term.



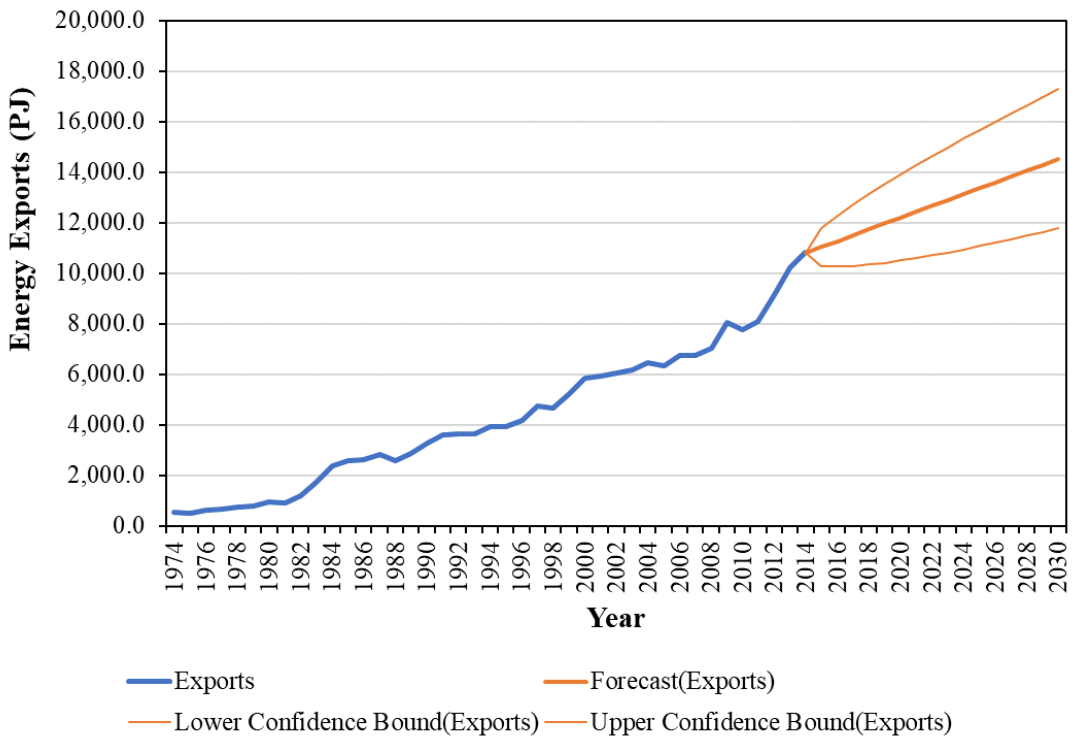
Appendix B. Energy Consumption Forecast



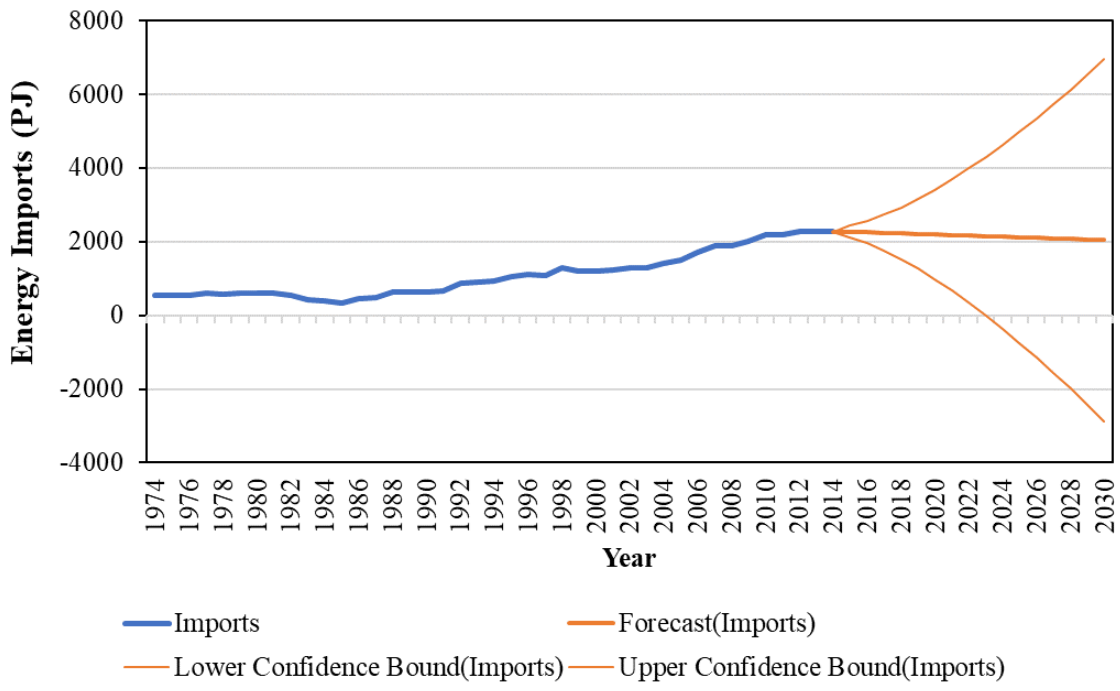
Appendix C. Non-Renewable Energy Production Forecast



Appendix D. Renewable Energy Production Forecast



Appendix E. Energy Export Forecast



Appendix F. Energy Import Forecast

Appendix 11 — Supplementary Material for Chapter Seven

Appendix A. Nonparametric: Spearman's ρ Estimation Results

Variable	by Variable	Spearman ρ	Prob>|ρ|	Plot
Exposure	Capacity	0.484	<.0001*	
Sensitivity	Capacity	0.607	<.0001*	
Sensitivity	Exposure	0.245	<.0001*	
Vulnerability	Capacity	0.907	<.0001*	
Vulnerability	Exposure	0.637	<.0001*	
Vulnerability	Sensitivity	0.745	<.0001*	
Economic	Capacity	-0.700	<.0001*	
Economic	Exposure	-0.296	<.0001*	
Economic	Sensitivity	-0.517	<.0001*	
Economic	Vulnerability	-0.658	<.0001*	
Governance	Capacity	-0.654	<.0001*	
Governance	Exposure	-0.296	<.0001*	
Governance	Sensitivity	-0.471	<.0001*	
Governance	Vulnerability	-0.623	<.0001*	
Governance	Economic	0.801	<.0001*	
Social	Capacity	-0.674	<.0001*	
Social	Exposure	-0.377	<.0001*	
Social	Sensitivity	-0.442	<.0001*	
Social	Vulnerability	-0.663	<.0001*	
Social	Economic	0.480	<.0001*	
Social	Governance	0.468	<.0001*	
Readiness	Capacity	-0.775	<.0001*	
Readiness	Exposure	-0.359	<.0001*	
Readiness	Sensitivity	-0.566	<.0001*	
Readiness	Vulnerability	-0.742	<.0001*	
Readiness	Economic	0.904	<.0001*	

Readiness	Governance	0.911	<.0001*
Readiness	Social	0.673	<.0001*

Appendix B. Short-Run Equilibrium Relationship

	Model 1(a)	Model 2(a)
Economic		0.009
		0.006
Governance		-0.007
		0.005
Social		-0.034
		0.026
Readiness	-0.002	
	0.008	
_cons	0.076	0.093*
	0.008	0.010

* (*P < 0.01*) denotes the rejection of the null hypothesis at 1% significance level

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