THE IMPACT OF CLIMATE CHANGE ON THE HYDROLOGY OF THE HALDA BASIN, SOUTHEASTERN BANGLADESH

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SUMMARY

Water security is one of the most challenging issues of the 21st century. Developing countries, including Bangladesh, are particularly vulnerable to climate change due to their low capacity for adaptation and mitigation, high population density and poverty. Climate change has already impacted water security in Bangladesh in many ways, mostly in the form of coastal and inland flooding due to higher monsoon precipitation and runoff, increased salinity and reduced flow during the dry season. Thus, this goal of this thesis is to identify current impacts of climate change on the Halda River Basin, southeastern Bangladesh, and assess potential future consequences of climate and land use change on river discharge. Meteorological records from this region indicate that temperature has increased by 0.4-0.6°C per decade since 1980 and 2013, although there has been no trend in mean or total precipitation. A Soil and Water Assessment Tool (SWAT) was used to simulate the catchment dynamics of a data-poor, monsoon driven, small river basin, and to serve as a baseline for scenario modelling. The model showed good agreement with gauge flow data, except during peak flows. The SWAT model was then used to predict the future impact of climate and land use changes, individually and combined, on streamflow in the Halda Basin. Result indicated a likely net gain in streamflow until at least 2060. Future shifts in temperature and precipitation of the Halda River will have broad ranging consequences. Hence, I also explored seasonal and annual relationships between carp spawn production and key climate and hydrological variables (temperature, precipitation and water discharge), finding that temperature plays the dominant role in determining spawn production over different time scales. However, precipitation and water discharge also influence spawn production on seasonal time-scales. The outcomes

of this research could be used in designing management and planning tools to facilitate climate change adaptation.

Contents

DECLARATION

I, Farzana Raihan, hereby declare that the work in this thesis entitled "*The Impact of Climate Change on the Hydrology of the Halda Basin, Southeastern Bangladesh*" submitted to the Department of Biological Sciences, Macquarie University, Sydney, for the award of a Doctor of Philosophy Degree is my original research work. This work has not been submitted in any other form, for a higher degree at any other university or institution.

SIGN …………………………………………………………..

FARZANA RAIHAN

JULY 2017

CHAPTER DECLARATION

This thesis is structured and written to conform to the “thesis by publication” format. It is organized into six chapters: an introductory chapter, four data chapters and a conclusion chapter. The titles of and my contribution to each chapter are as follows:

Chapter 1: Introduction.

I reviewed the literature, identified knowledge gaps and completed the writing, with feedback from Dr Linda Beaumont and Dr Maina Mbui.

Chapter 2: Detection of recent changes in climate using meteorological data from southeastern Bangladesh (Published in *Journal of Climatological and Weather Forecasting*, DOI: 10.4172/2332-2594.1000127).

The research idea was perceived by myself. I undertook the analyses with technical assistance from Dr. Guangqi Li and feedback from Professor Sandy Harrison. Dr Li and Professor Harrison also aided with interpretation of the results. I undertook the writing, with feedback from Dr Li and Professor Harrison.

Chapter 3: Simulating streamflow in the upper Halda Basin, southeastern Bangladesh using SWAT model.

I perceived the idea and undertook all analyses. I wrote the chapter with editorial assistance from Professor Sandy Harrison, Dr Linda Beaumont, Dr Maina Mbui and Professor A.K.M. Saiful Islam.

Chapter 4: Combine impact of changes in climate and land use under RCP scenarios on streamflow in the Halda Basin, southeastern Bangladesh.

I perceived with Dr Maina Mbui. I undertook all analyses with input from Dr Linda Beaumont and Dr Maina Mbui. Professor Shahidul Islam and Professor Saiful Islam provided technical assistance for bias correction of climate data. I wrote the chapter with editorial assistance from Dr Linda Beaumont and Dr Maina Mbui.

Chapter 5: Impacts of climate variation on spawn production of Indian major carps in the Halda Basin, Bangladesh.

I perceived the idea. Professor Niamul Naser provided data and Mr. Amit Roy provided technical assistance with ARDL model analysis. Mr Roy and Monir Uddin Ahmed helped with interpretation of the results. I wrote the chapter with feedback from Amit Roy, Dr Linda Beaumont and Dr Maina Mbui.

Chapter 6: Conclusion

I wrote this chapter with feedback from Dr Linda Beaumont and Dr Maina Mbui.

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I would like to remember my father and father-in-law who left this domain during my PhD candidature. I also would like to express my deepest gratitude to my mother for her constant support and prayers, in particular after the demise of my father.

Those to whom I personally owe and dedicate this thesis, are my husband, **Munim Joarder**, and my daughter **Nashita**. I would like to thank my husband for being

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DEDICATION

*In memory of my wonderful father "**A.K.M. Mofizur Rahman**",*
who will truly be missed but never forgotten…
*to my great **mother**, for her endless prayers,*
*to my elder daughter "**Nushfiqua Wardah Nashita**"*
for her patience and tremendous support,
*to my understanding **husband***
for his moral, financial support and unconditional love.

CHAPTER 1: INTRODUCTION

Climate change is expected to alter the spatial and temporal distribution of water resources around the world (Huntington, 2006). For many regions, there is compelling evidence that the redistribution of water will pose serious challenges to the supply of fresh water for drinking, irrigation and industrial sectors (Sathaye et al., 2006). Thus, there is an essential need to understand future hydrological changes at scales relevant to decision making. Yet, quantifying the potential impacts of climate change on local hydrology remains a challenge. Information about water-related impacts of climate change in many geographic regions is sparse, particularly in developing countries. This necessitates the use of hydrological models to estimate the changes in streamflow likely to occur as a result of climate change. From this perspective, the objective of my dissertation is to identify current conditions, causes and consequences of climate change on the hydrology of the Halda River Basin in southeastern Bangladesh. This research will facilitate future endeavors to address the optimal allocation of water resources. Importantly, this research has direct policy implications in the widely debated areas of reliable climate adaptation strategies and water policy.

20th-21st Century Climate Change

Climate change has been defined by the Intergovernmental Panel on Climate Change (IPCC) as:

> *"A change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer. Climate Change may be due to natural internal processes or external forcings…and persistent anthropogenic changes in the composition of the atmosphere or in land use". (IPCC 2007)*

Reports by the Intergovernmental Panel on Climate Change (IPCC, 2007) have demonstrated that, mostly due to anthropogenically-driven increases greenhouse gases, the earth's climate is changing. Since the start of the industrial revolution in ~ 1750, CO_2 concentrations have risen 280 ppm (Widdicombe et al., 2013). Recent annual greenhouse gas (GHG) emissions (i.e. from 2000 to 2010) have increased on average 1.0 Gt carbon dioxide ($GtCO_2$) compared to 0.4 Gt over the period 1970 to 2000 (IPCC, 2014). Driving this increase in GHGs are human activities including burning of fossil fuels, land clearance and expansion of agriculture. As a result, the global mean annual temperature has increased by ~ 0.85°C (0.65-1.06°C). Presently, more than 80% of this heat has been absorbed by the oceans (IPCC, 2007). Thermal expansion combined with melting of glaciers has resulted in an average global sea level rise of 8 ± 0.5 mm per year from 1961 to 2003 (IPCC, 2007). Furthermore, observed trends from 1900 to 2005 indicate a significant increase in precipitation over eastern parts of North and South America, northern Europe, and northern and central Asia, whilst drying has been observed in Sahel, Mediterranean, Southern Africa and parts of Southern Asia (Haji, 2011).

Climate change and its effects on water resources

Water is indispensable for life. Climatic variability is one of the most significant determinants that has threatened the availability and sustainability of water resources (Woldeamlak et al., 2007). Forecasting the impacts of climate change on hydrological cycles and related variables is crucial for water resource planning and management over time and space. Climate change is expected to affect the hydrological cycle through changes in precipitation, temperature, evapotranspiration, runoff, streamflow and groundwater supplies, with consequences on societies, economies and the environment (House et al., 2016).

Rising human populations and the ever-increasing pace of economic development will enhance demands for fresh water, further eroding the availability of water resources (IPCC, 2007). Though the global water balance is governed by the changes in climatic conditions, at the catchment scale hydrological changes are mostly attributed to non-climatic factors such as population growth, economic development, urbanization and land use (Jiménez Cisneros et al., 2014; Kundzewicz et al., 2008).

Multiple interacting factors within the earth system influence hydrological cycles over time and space. For example, elevated concentrations of atmospheric CO_2 directly impact plant transpiration, potentially resulting in higher water loss (Luo et al., 2013). Drier soils accelerated by longer droughts can lead to shifts in vegetation growth patterns, affecting catchment runoff of precipitation. Additionally, ground water may be affected via changes in water percolation and consequently altering the contribution of base flow, thus influencing water availability (Haji, 2011). Water scarcity may be intensified by various stressors including organic and inorganic pollution and land use changes with subsequent threats to river ecology (Navarro-Ortega et al., 2015). For instance, reduced stream flow combined with higher stream temperature will have consequences for aquatic ecosystems, e.g., resulting in shifts in habitat suitability for native species and range changes as well as alterations to the timing of life cycle events (Harvey et al., 2006; Luo et al., 2013).

Based on data from the World Resources Institute (WRI), Bangash (2014) argued that the world's water systems face challenging pressures. More than a billion people currently live in water scarce regions and could experience water scarcity by 2025 (Bangash, 2014). Warmer temperatures have led to significant changes in the seasonal timing of runoff in many mountain areas during the past half century (Westerling et al., 2006). In the U.S and Canada, spring snow packs have been melting earlier in most mountain areas while winter precipitation has increased (Miller and Yates, 2006). It is evident that climate change is increasing water resource stress in some regions of the world where runoff is decline (such as Mediterranean Europe, Central and South America, and Southern Africa) whereas in other water-stressed parts of the world, particularly Southern and Eastern Asia, climate change may increase runoff (Arnell, 2004; Jha, 2010). These increases tend to appear during the wet season and the extra water may not be available during the dry season (Pervez and Henebry, 2015; Trenberth, 2011).

Many hydro-climate studies have been carried out using Global Climate Model (GCMs) and Representative Concentration Pathways (RCPs) to derive future projections (Tan et al., 2014; Zhang et al., 2016) or to assess the impacts of climate change on the hydrological cycle (Agrawal et al., 2014; Guo et al., 2008; Hallema et al., 2014; Niedda et al., 2014). Ho et al. (2016) stated that under the RCP 4.5, Tocantins-Araguaia (Brazil) will experience a large decline in streamflow during the dry season over the period of 2071-2100. Based on GCM output, annual rainfall and maximum temperature of Kelantan River Basin of Malaysia is projected to increase by 1.2%-8.7% and 0.6-2.1°C, respectively (Tan et al., 2017). Based on an ensemble of six GCMs and three RCPs, Ouyang et al. (2015) reported a likely decrease in future stream flow in the Huangnizhuang Catchment, China. GCMs also indicate that the Central Asian region may experience considerably higher levels of warming compared to the global average (Gan et al., 2015). This region has been identified as a "hot spot" of climate change where the impact on water resources is projected to be substantial (Unger-Shayesteh et al., 2013). For instance, increases in temperature of 1-3°C are projected to increase average streamflow by 10-40%, while other regions may face streamflow decreases by 10-30% (Muller, 2007). Gan et al. (2015) reported that small scale natural climate fluctuations have had large impacts on glaciers over the past 10,000 years, providing further evidence that changes in climate can impact the hydrological environment (Ludwig et al., 2014).

Due to relative coarse horizontal resolution of GCMs, regional climate models (RCMs), which are run at higher spatial resolutions, can be used to evaluate the possible magnitude of climate change and to simulate the impact of climate extremes on catchment hydrology at the regional scale. The increasing availability of climatic outputs from global and regional climate models provides the potential for exploring model uncertainties in predicting future climate through ensembles outputs (Manning et al., 2009).

Bangladesh Climate and Impacts on its Water Resources

As with other developing countries in South Asia, Bangladesh is very prone to hydro meteorological and geological hazards due to its geographical location (Dastagir, 2015; Mirza, 2002). Bangladesh is a mostly flat, deltaic, monsoon-drenched land at the confluence of the great Himalayan rivers (the Ganges, Brahmaputra and Meghna - GBM) and comprises an area of 147,570km^2 (Safiullah, 2007). The World Risk Report (2012), which operationalized risk as an interaction between exposure to natural hazards and the vulnerability of societies, ranked Bangladesh fifth out of 173 countries (Joarder and Miller, 2013). Only Vanuata, Tonga, The Philippines and Guatemala were ranked above Bangladesh as global risk hotspots (United Nations University Institute for Environment and Human Security et al., 2012). Based on the International Disaster Database 2010, Joarder and Miller (2013) reported that forty-five million people were made homeless in 1998, and thirty-five million in 2004, due to the devastating floods with an estimated combined death toll of 3000-7600. Further, environmental degradation such as river bank erosion has placed an estimated one million people at risk of losing their homes, and should be moved to other areas (Joarder and Miller, 2013).

Bangladesh is projected to experience mean annual and seasonal temperature rises of between 2 and 4.7°C by the end of this century coupled with changes in seasonal rainfall patterns (Christensen et al., 2007). The increasing temperature will cause higher evapotranspiration, further elevating demands for water withdrawal via irrigation (Shahid, 2011). Recently, the distribution of rainfall has been highly inconsistent, demonstrating an increasingly uneven distribution (Ahsan et al., 2010). Rising temperature combined with irregular rainfall patterns have already induced droughts, causing negative impacts on crops (Ahmed, 2006). Sarwar et al. (2014) projected that low rainfall during the monsoon and excessive rainfall in the post monsoon season is likely to bring agricultural drought and cause flash floods. The melting of the Himalayan glaciers is projected to lead to rapid increases in the spatial extent and magnitude of floods (Dewan, 2015), as well as potential increases in drought frequency in the dry season, although large uncertainties remain (Kundzewicz et al., 2008). Greater frequency and intensity of floods has been forecasted to have substantial impacts on food production (Douglas, 2009), while sea level rises of 15-38 cm, which may occur by 2050, are projected to displaced ~35 million people around the Bay of Bengal (Revi, 2008). River water from the melting Himalayan glaciers in the north and an encroaching Bay of Bengal in the south pose myriad risks in the form of floods, droughts, riverbank erosion, salinity intrusion, water logging and cyclonic storm surges (Alam, 2017; Dastagir, 2015). The societal exposure to such risks is further triggered by Bangladesh's very high population density, with population growth resulting in greater demand for food and water for irrigation (Kirby et al., 2013). To address this issue, developing watershed management tool based on hydrological simulation using appropriate modelling is an urgent issue.

Therefore, a comprehensive model is required that can be used to investigate the impact of climate change on river hydrology such as water availability and future water yield. Previous modelling studies undertaken in many different environments show that simulated climate change impacts vary significantly depending on the model used as well as emission scenarios (Yan et al., 2015). Considering these requirements, the open source code of SWAT models was selected due to its advantages compared to other catchment-scale raster-based models, such as MIKE-SHE (Refsgaard and Storm, 1995), TOPMODEL (Beven and Kirkby, 1979) or WASIM (Schulla, 1997) (Rathjens and Oppelt, 2012). SWAT has been demonstrated to simulate very large basins with minimal data input (e.g., digital elevation model, soil and land use map and weather data) in the Indian subcontinent (Bharati et al.,2016; Narsimlu et al., 2013), and without consuming large amounts of time or computational resources (Mango et al., 2011). Though data in Bangladesh are scarce, there are number of organizations that collect and maintain some hydro-meteorological data (e.g. BWDB, WARPO, SRDI, CEGIS and IWM). As such, SWAT was used to assess the impacts of climate change on the hydrology of the

Halda Basin, Southeastern, Bangladesh, to facilitate long term planning at national and regional levels.

Why study the Halda Basin?

The fisheries sector provides a significant source of income and food to Bangladesh, contributing 3.69% to the Gross Domestic Product (GDP) and 2.5% of total export earnings (Hossain, 2015). Bangladesh ranks third in the world in terms of inland fish production, after China and India (Ghose, 2014). In Bangladesh, fish is a usual counterpart to rice in the national diet giving rise to the proverb "*Maache-Bhate Bengali*" ("*a Bengali is made up of fish and rice*") (Ghose, 2014). Approximately 60% of Bangladeshi people's daily animal protein intake comes from fish supplements (Alam et al., 2013). The culture and consumption of fish therefore has important implications for national income and food security.

The inland water resources in Bangladesh offer major potential for the development of freshwater capture fisheries (Shamsuzzaman et al., 2017). However, fish production from capture fisheries in Bangladesh has faced several challenges over the last three decades as a result of degradation and loss of fish habitat, obstruction of fish migration routes by dams, embankments and water control structures, and siltation of water bodies by natural processes (Hossain, 2015), which in turn have affected the breeding and spawning of many native species (Shamsuzzaman et al., 2017). According to Matin (2013) one third of 230 rivers in Bangladesh are under threat of physical disappearance owing to sedimentation caused by reductions in water flow due to upstream water diversion.

The Halda River, Bangladesh, is facing major threats due to the disturbed natural flow. The 81 km river is fed by several hilly streams in the Chittagong District of Bangladesh and flows through Fatickchari, Hathazari and Raozan Upzilas and Chittagong Kotwali Thana, before discharging into the Karnaphuli River approximately 35 km from the Bay of Bengal (Akter and Ali, 2012; Patra and Azadi, 1985).

The Halda River catchment plays a substantial role in the ecological health and economy of southeastern Bangladesh. The total value of tangible resources has been estimated as $US 20.5 million per annum (Kabir et al., 2013). The river is the only natural breeding ground for Indian major carp (*Catla catla, Labeo rohita, Cirrhinus mrigala, and Labeo calbasu*) and, hence, the only suitable place where fisherman can collect fertilized eggs from fish populations that are mostly disease resistant, free from inbreeding, and have the ability to survive under stressful conditions (Kabir et al., 2013). However, in recent years the Halda River has experienced rapid deterioration of the breeding condition of carp, water quality and aquatic life, due to various manmade and natural drivers.

Given the ecological and economic importance of the Halda Basin, there is an urgent need to investigate the potential impact of climate change on the hydrology of the basin. The goal of this thesis was to identify recent climate trends across the Halda Basin, and assess potential future consequences of climate and land use change on streamflow. This thesis is written in the format of "thesis by publication", with four data chapters either already published or in preparation for publication, in addition to an introductory chapter (Chapter One) and a conclusion (Chapter Six). Briefly, in Chapter Two I undertook an examination of meteorological records from south-eastern Bangladesh to determine whether there are coherent trends in climate over recent decades. In Chapter Three, I used a Soil and Water Assessment Tool (SWAT) to understand the catchment dynamics of a data-poor, monsoon driven, small river basin, and to serve as a baseline for scenario modelling. Chapter Four built upon Chapter Three, and used the SWAT model to explore the future impact of climate and land use changes, individually and combined, on streamflow in the Halda Basin. In Chapter Five, I explored consequence of alterations in streamflow by assessing the seasonal and annual relationships between carp spawn production and key climate and hydrological variables (temperature, precipitation and streamflow). Chapter Six provides a conclusion to this thesis. Within that chapter, I reiterate the main findings of my thesis, its limitations, and outline future research directions.

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CHAPTER 2: DETECTION OF RECENT CHANGES IN CLIMATE USING METEOROLOGICAL DATA FROM SOUTHEASTERN BANGLADESH

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Abstract

Analysis of meteorological records from four stations (Chittagong, Cox's Bazar, Rangamati, Sitakunda) in southeastern Bangladesh show coherent changes in climate over the past three decades. Mean maximum daily temperatures have increased between 1980 and 2013 by ca 0.4 to 0.6°C per decade, with changes of comparable magnitude in individual seasons. The increase in mean maximum daily temperature is associated with decreased cloud cover and wind speed, particularly in the pre- and post-monsoon seasons. During these two seasons, the correlation between changes in maximum temperature and clouds is between -0.5 and -0.7; the correlation with wind speed is weaker although similar values are obtained in some seasons. Changes in mean daily minimum (and hence mean) temperature differ between the northern and southern part of the basin: northern stations show a decrease in mean daily minimum temperature during the post-monsoon season of between 0.2 and 0.5°C per decade while southern stations show an increase of ca 0.1 to 0.4°C per decade during the pre-monsoon and monsoon seasons. In contrast to the significant changes in temperature, there is no trend in mean or total precipitation at any station. However, there is a significant increase in the number of rain days at the northern sites during the monsoon season, with an increase per decade of 3 days in Sitakunda and 7 days

at Rangamati. These climate changes could have a significant impact on the hydrology of the Halda Basin, which supplies water to Chittagong and is the major pisciculture centre in Bangladesh.

Introduction

Global average temperature has increased by 0.85°C (0.6-1.05°C) during the post-industrial period (1880-2012) with an increase over the most recent decade (2003-2012) of ca 0.78°C (0.72-0.85°C) [1, 2] and it is extremely likely that more than half of the observed increased in the latter part of the 20th century is anthropogenic [3]. The increase in global temperature is reflected at a regional scale across much of Asia [4-8]. Changes in mean temperature are accompanied by an increase in minimum temperature and in the frequency of extreme temperatures and heatwaves in many regions, including Asia [7, 2]. Increases in global temperature are expected to lead to increases in precipitation [9]. Although increases in precipitation over mid-latitude land areas have been detected during the latter part of the 20th century [2], it is more difficult to detect changes in monsoon regions where high-quality records are shorter and the impact of short-term climate variability is large. Nevertheless, several studies have suggested that monsoon precipitation is increasing in parts of Asia [10, 11].

Bangladesh is a predominantly agricultural country, and hence likely to be very sensitive to changes in climate. It has been predicted that Bangladesh could lose up to 17% of its land area and 30% of its food production as a result of the impacts of anticipated climate changes by 2050, while Hertel et al. [12] have suggested that Bangladesh will experience a 15% net increase in poverty by 2030 as a result of climate change. From this perspective, the Halda River Basin in southeastern Bangladesh, is particularly important because it is the major spawning ground for Indian major carp and sustains pisciculture in Bangladesh [13]. Fish constitute ca 63% of the daily protein consumption in Bangladesh and pisciculture is responsible for 5-6% of the nation’s gross domestic product [13].

There have been several studies on the detection of climate changes in Bangladesh [14-26]; but the focus has largely been on individual climate variables and there has been little attempt to determine how changes in e.g. mean temperature are related to or influence other aspects of the regional climate. Furthermore, these studies have focused on the country as a whole rather than on areas that are most important from an agricultural point of view. In this study, we examine meteorological records from southeastern Bangladesh to determine whether there are coherent trends in climate over recent decades, taking the opportunity to extend the analyses to cover the period to 2013. In addition to individual temperature and precipitation trends that have been the focus of previous analyses of the climate of Bangladesh, we also explore trends in related climate variables (humidity, cloud cover, wind speed) in order to explain the mechanisms underpinning the changes in temperature and precipitation.

Study Area and Methods

Southeastern Bangladesh has a typical tropical monsoon climate, with most of the rainfall occurring during the monsoon season from June to September. The seasonal cycle of temperature is mediated by the monsoon, with lowest temperatures in January (ca 16-20° C) but highest temperatures (ca 38-40° C) in April just before the onset of the monsoon.

Daily data on maximum and minimum daytime temperature, precipitation, relative humidity, cloud cover and wind speed are available from four meteorological stations in southeastern Bangladesh: Chittagong, Sitakunda, Rangamati and Cox's Bazar (Figure 1, Table 1). Mean daily temperature was derived as the average of maximum and minimum daytime temperature, and diurnal temperature range as the difference between these variables. Sunshine data was only available for 3 of the stations, and thus is not used in our analyses. The records cover the period of 1980 to 2013, except in the case of Chittagong. The Chittagong station was moved in 2003. To avoid problems of inhomogeneity, analyses were performed on data from the interval 1980 to 2002 only for this station. The climate of southeastern Bangladesh has three distinct seasons: the pre-monsoon season is from March through May; the monsoon season is June through September; and the post-monsoon season is October through February. Monthly, seasonal and annual averages were calculated for all the climate variables. No attempt was made to infill missing values of the daily observations, and the averages were only calculated for those months, seasons or years for which there were no missing values. The number of observations used therefore varies between variables and stations (Table 1).

Linear regression between climate index and year number was used to determine whether there were trends in the observations [e.g. 27, 28]. The significance of the trends was determined using a t-test, with a 95% cut-off for significance (i.e. the probability of accepting the null hypothesis of no change is <0.05). A 95% cut-off, rather than a 99% cut-off, was used because of the comparatively short length of the records examined. The r^2 value provides a measure of the goodness-of-fit of the relationships, and is lower when there is a large scatter around the regression line. It will always be close to zero when there is no significant trend. The slope coefficients from the regressions were then used to estimate the magnitude of the change, over the length of the record, expressed as change per decade.

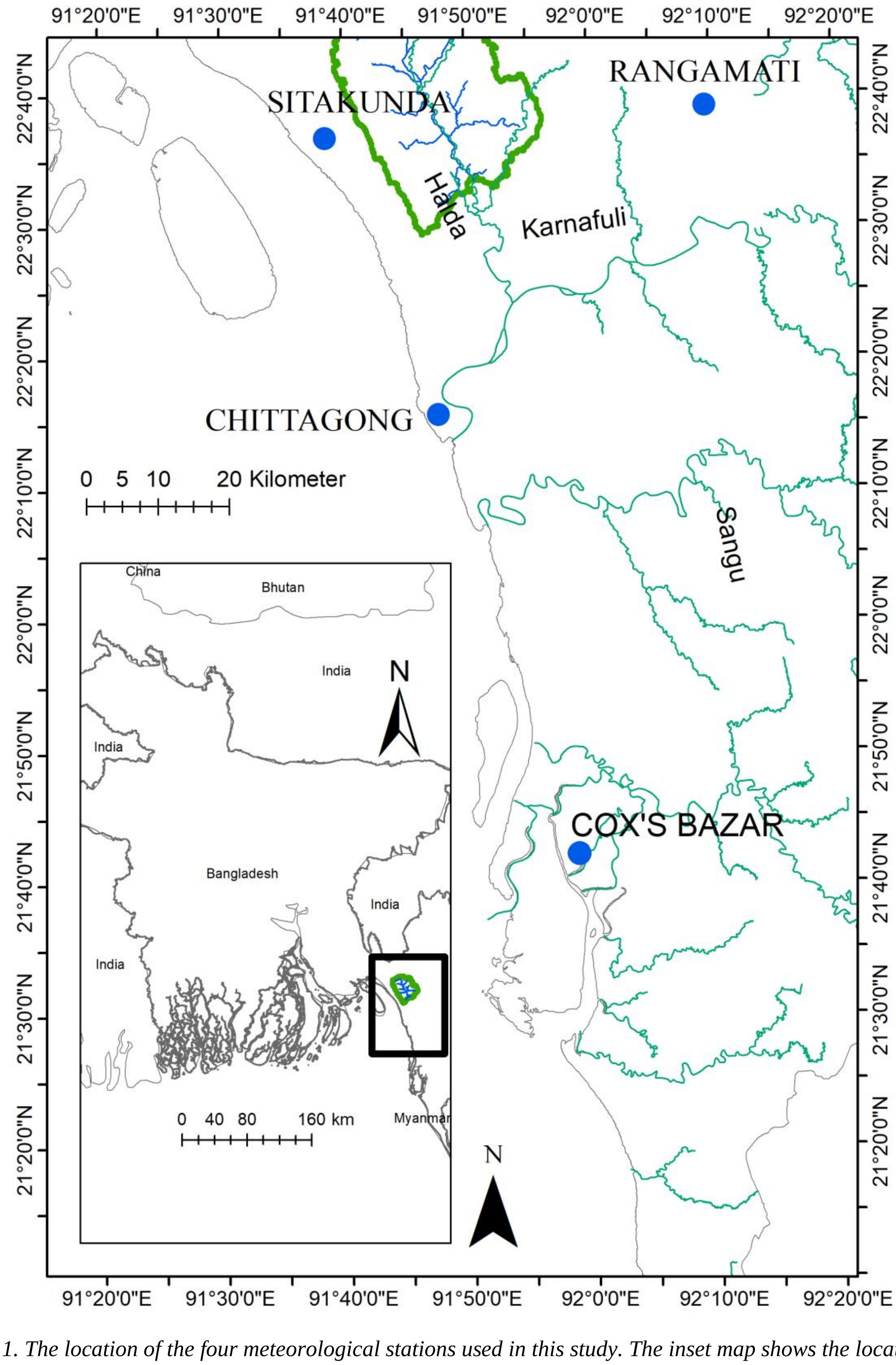

Figure 1. The location of the four meteorological stations used in this study. The inset map shows the location of the Halda Basin (in box) within Bangladesh, and the regional context of Bangladesh.

Table 1. Information about the meteorological stations collected from Bangladesh Meteorological Department(BMD). Latitude (Lat) and longitude (Long) are given in decimal degrees, elevation (Elev) in meters. Averages were only calculated for periods (months, seasons, years) when there were no missing daily observations, and therefore the number of intervals used in these calculations varies by site and by variable. The number of monthly observations within the pre-monsoon (Pre), monsoon (Mon) and post-monsoon (Post) seasons for each site and variable is given.

Station	**Lat (°N)**	**Long (°E)**	**Elevation (m)**	**Period covered**	**No of monthly observations**																	
					Maximum temperature (°C)			**Minimum temperature (°C)**			**Precipitation (mm)**			**Cloud (tenths)**			**Wind speed (km per hr)**			**Humidity (%)**		
					Pre	**Mon**	**Post**	**Pre**	**Mon**	**Post**	**Pre**	**Mon**	**Post**	**Pre**	**Mon**	**Post**	**Pre**	**Mon**	**Post**	**Pre**	**Mon**	**Post**
Cox's Bazar	21.45	91.97	2	1980-2013	83	106	136	84	122	154	86	127	108	99	131	164	99	132	165	99	131	164
Chittagong	22.22	91.80	6	1980-2002	55	79	102	60	82	100	58	86	82	65	88	109	66	88	110	65	88	109
Rangamati	22.63	92.15	69	1980-2013	87	125	161	98	133	164	90	130	113	98	132	163	99	132	165	98	132	163
Sitakunda	22.63	91.70	7	1980-2013	98	125	162	94	126	161	94	128	107	99	132	165	99	132	165	102	136	170

Results

All of the stations show a significant increase in maximum daily temperature (Figure 2) in the annual mean over the interval of observations. This positive trend is present in all seasons (and most individual months) at Cox's Bazar, Rangamati and Sitakunda (Table 2, Table 3). A positive trend (i.e. an increase in maximum daily temperature over the interval with observations) is also seen in every season at Chittagong, but is only significant for the monsoon and post-monsoon seasons, and for the month of April during the pre-monsoon season. The lack of significance in the pre-monsoon season overall probably reflects the shortness of the length of record (22 years) for this station. The increase in maximum daily temperature is less marked in the monsoon season than in either the pre- or post-monsoon seasons, with values in the range of 0.4 to 0.6°C per decade compared to a range of 0.5-0.7 °C per decade in the pre-monsoon and 0.5 to 1.1°C per decade in the post-monsoon interval (absolute values per decade calculated from slope coefficients given in Table 2).

Although the recent change in maximum daily temperature is coherent at all four stations, the trends in minimum daily temperature differ between the southern (Cox's Bazar, Chittagong) and northern (Sitakunda, Rangamati) stations (Figure 3). There is a significant increase in minimum daily temperature at Cox's Bazar, both in annual average and in the pre-monsoon season. Minimum daily temperatures also increase during the monsoon and post-monsoon seasons, but the trend is not statistically significant although the trend for some individual months (August in the monsoon, October in the post-monsoon season) within each season is significant. The increase in both maximum and minimum daily temperature results in an overall increase in mean daily temperature at Cox's Bazar, which is significant in annual, and pre-monsoon and post-monsoon season, and positive though not significant in the monsoon season (Figure 4). Increases in minimum daily temperature are also recorded at Chittagong; although a positive trend is seen in all seasons, the trend is only significant during the monsoon season (Figure 3). Again, the increase in both maximum and minimum daily temperature results

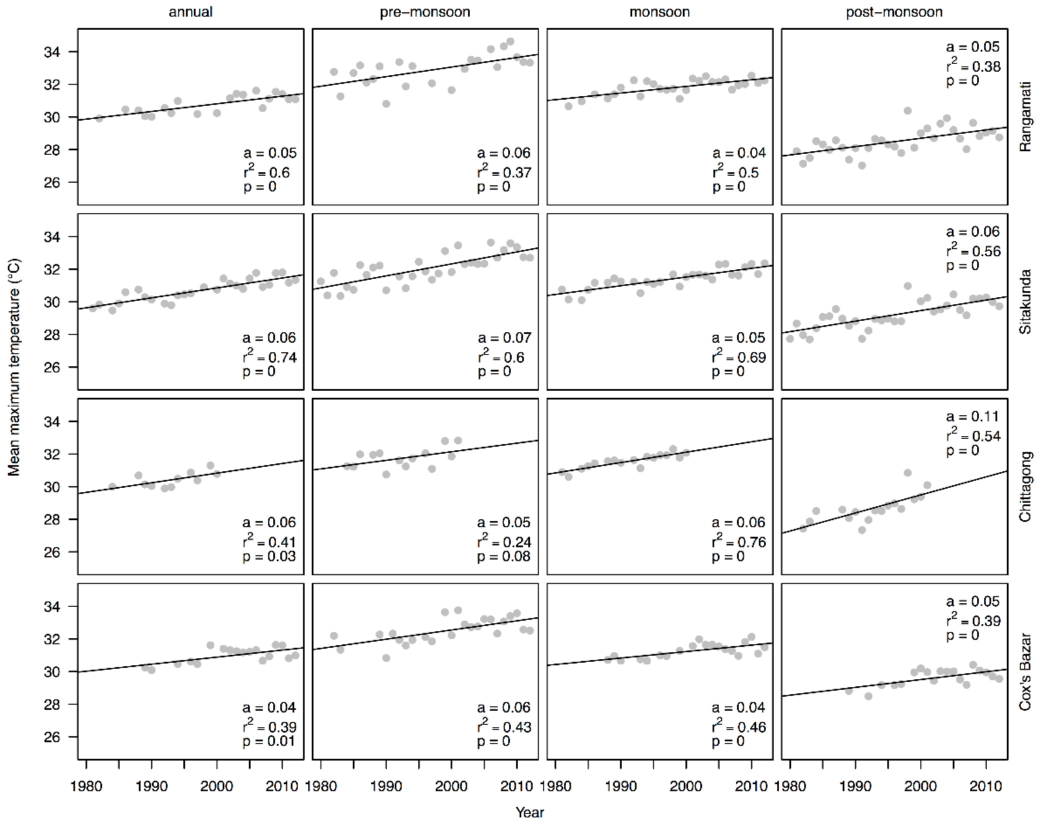

Figure 2. Annual and seasonal trends in maximum daily temperature at each of the four meteorological stations.

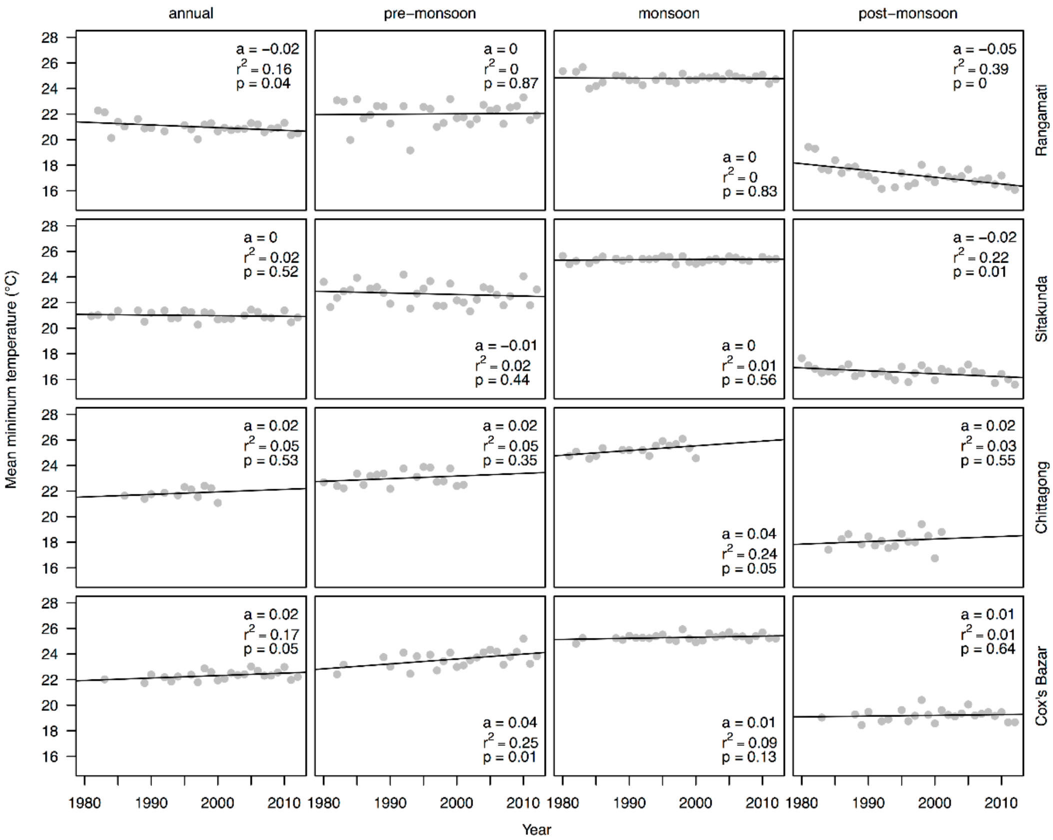

Figure 3. Annual and seasonal trends in minimum daily temperature at each of the four meteorological stations.

Table 2. Observed trends in annual and seasonal climate at individual meteorological stations. The values given are the slope coefficients from the linear regression; values in bold are significant (i.e. show a trend) at the 95% confidence level.

Station	Variables	Code	Annual	Pre-monsoon	Monsoon	Post-monsoon
Cox's Bazar	Mean daily temperature (°C)	Tmean	**0.02**	**0.02**	**0.01**	0.01
	Maximum daily temperature (°C)	Tmax	**0.04**	**0.06**	**0.04**	**0.05**
	Minimum daily temperature (°C)	Tmin	**0.02**	**0.04**	0.01	0.01
	Diurnal temperature range (°C)	DTR	**0.03**	**0.03**	**0.05**	**0.03**
	Maximum daily precipitation (mm)	Pmax	**2.41**	**2.32**	**2.25**	0.32
	Mean daily precipitation on rain days (mm)	Pmean	0.08	**0.40**	0.04	0.02
	Total precipitation (mm)	Ptot	12.41	**8.13**	6.90	-1.88
	Number of rain days	Pwet	0.03	0.02	0.10	-0.09
	Cloud cover (tenths)	Cloud	-0.01	-0.01	0.00	-0.01
	Humidity (%)	Hum	-0.02	-0.05	**-0.04**	0.00
	Wind speed (km per hr)	Wind	**-0.04**	**-0.05**	-0.03	**-0.04**
Chittagong	Mean daily temperature (°C)	Tmean	**0.03**	0.02	**0.03**	**0.04**
	Maximum daily temperature (°C)	Tmax	**0.06**	0.05	**0.06**	**0.11**
	Minimum daily temperature (°C)	Tmin	0.02	0.02	0.04	0.02
	Diurnal temperature range (°C)	DTR	**0.03**	0.03	0.01	**0.05**
	Maximum daily precipitation (mm)	Pmax	**-7.39**	2.04	**-7.46**	2.33
	Mean daily precipitation on rain days (mm)	Pmean	0.10	0.38	0.01	0.15
	Total precipitation (mm)	Ptot	7.31	3.37	0.81	4.31
	Number of rain days	Pwet	-0.10	-0.31	-0.08	0.19
	Cloud cover (tenths)	Cloud	0.02	0.00	0.01	0.02
	Humidity (%)	Hum	**0.12**	0.07	0.02	**0.18**
	Wind speed (km per hr)	Wind	**-0.11**	**-0.18**	**-0.12**	**-0.06**
Rangamati	Mean daily temperature (°C)	Tmean	-0.01	0.00	0.00	**-0.03**
	Maximum daily temperature (°C)	Tmax	**0.05**	**0.06**	**0.04**	**0.05**
	Minimum daily temperature (°C)	Tmin	**-0.02**	0.00	0.00	**-0.05**
	Diurnal temperature range (°C)	DTR	**0.08**	**0.06**	**0.05**	**0.10**
	Maximum daily precipitation (mm)	Pmax	-0.32	-0.32	0.31	0.30
	Mean daily precipitation on rain days (mm)	Pmean	-0.08	-0.18	-0.07	-0.01
	Total precipitation (mm)	Ptot	6.84	-1.72	9.52	1.23
	Number of rain days	Pwet	**0.90**	0.14	**0.72**	0.13
	Cloud cover (tenths)	Cloud	**-0.02**	-0.01	0.00	**-0.03**
	Humidity (%)	Hum	**0.07**	0.02	0.03	**0.13**
	Wind speed (km per hr)	Wind	-0.02	-0.01	**-0.03**	0.00
Sitakunda	Mean daily temperature (°C)	Tmean	**-0.03**	-0.02	-0.01	**-0.06**

	Maximum daily temperature (°C)	Tmax	**0.06**	**0.07**	**0.05**	**0.06**
	Minimum daily temperature (°C)	Tmin	0.00	-0.01	0.00	**-0.02**
	Diurnal temperature range (°C)	DTR	**0.07**	**0.08**	**0.05**	**0.09**
	Maximum daily precipitation (mm)	Pmax	-0.32	-0.24	1.26	-1.15
	Mean daily precipitation on rain days (mm)	Pmean	-0.02	-0.04	0.20	-0.29
	Total precipitation (mm)	Ptot	9.20	-0.41	**23.30**	-4.62
	Number of rain days	Pwet	0.40	0.07	**0.29**	0.02
	Cloud cover (tenths)	Cloud	**-0.01**	**-0.02**	-0.01	**-0.02**
	Humidity (%)	Hum	**0.27**	**0.18**	**0.17**	**0.39**
	Wind speed (km per hr)	Wind	**-0.05**	**-0.06**	**-0.05**	**-0.04**

Table 3: Observed trends in monthly climate at individual meteorological stations. The values given are the slope coefficients from the linear regression; values in bold are significant (i.e. show a trend) at the 95% confidence level.

Station	Variables	Code	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Cox's Bazar	Mean daily temperature (°C)	Tmean	0.00	0.02	0.02	0.03	0.00	**0.03**	0.01	0.01	0.00	0.01	0.01	0.02
	Maximum daily temperature (°C)	Tmax	**0.04**	**0.08**	**0.08**	**0.05**	**0.04**	**0.06**	0.03	**0.05**	**0.04**	**0.04**	**0.05**	**0.04**
	Minimum daily temperature (°C)	Tmin	0.02	0.03	**0.05**	0.03	0.01	0.02	0.01	**0.01**	0.01	**0.02**	0.01	0.04
	Diurnal temperature range (°C)	DTR	0.01	**0.05**	0.02	**0.03**	**0.03**	**0.05**	**0.04**	**0.05**	**0.04**	0.02	0.03	0.01
	Maximum daily precipitation (mm)	Pmax	-0.10	-0.17	0.18	0.18	**2.16**	1.80	1.25	1.22	0.06	**1.62**	-1.44	-0.34
	Mean daily precipitation on rain days (mm)	Pmean	-0.02	0.37	0.08	-0.05	**0.49**	0.08	0.21	0.15	0.00	0.27	**-0.72**	-0.10
	Total precipitation (mm)	Ptot	-0.08	-0.30	-0.32	-1.20	**8.37**	-0.60	4.42	5.78	2.40	3.61	-2.46	-0.22
	Number of rain days	Pwet	-0.01	-0.05	-0.04	-0.06	0.11	-0.06	-0.03	0.09	**0.12**	0.10	-0.02	-0.02
	Cloud cover (tenths)	Cloud	-0.01	-0.02	-0.01	-0.02	0.01	-0.01	0.00	0.01	0.01	0.01	-0.02	0.00
	Humidity (%)	Hum	0.04	-0.07	-0.05	-0.07	-0.02	**-0.12**	-0.05	-0.03	0.03	0.07	0.02	0.06
	Wind speed (km/hr)	Wind	**-0.05**	**-0.03**	**-0.05**	**-0.05**	**-0.05**	-0.04	**-0.05**	-0.03	-0.02	-0.03	**-0.06**	**-0.06**
Chittagong	Mean daily temperature (°C)	Tmean	-0.01	0.04	0.04	0.05	0.01	**0.04**	**0.03**	**0.03**	0.02	**0.04**	0.05	0.04
	Maximum daily temperature (°C)	Tmax	0.04	0.08	0.08	**0.11**	0.01	**0.07**	**0.05**	0.03	**0.05**	**0.07**	**0.08**	**0.10**
	Minimum daily temperature (°C)	Tmin	-0.04	0.03	0.00	0.04	0.04	0.04	0.03	**0.04**	0.02	0.04	0.06	-0.01
	Diurnal temperature range (°C)	DTR	**0.07**	0.04	0.06	0.03	-0.01	0.01	0.02	0.00	0.02	0.01	0.03	**0.07**

	Maximum daily precipitation (mm)	Pmax	0.18	0.83	-0.25	-0.74	2.10	-3.91	-4.79	-1.89	-0.45	3.06	0.49	0.15
	Mean daily precipitation on rain days (mm)	Pmean	0.30	0.68	0.00	-0.06	0.72	-0.23	-0.15	-0.05	-0.08	0.37	-0.51	0.60
	Total precipitation (mm)	Ptot	0.22	1.44	-0.22	-4.86	8.44	-2.30	-7.97	-1.16	0.56	4.35	0.91	0.47
	Number of rain days	Pwet	0.00	0.01	-0.09	-0.24	0.03	-0.02	-0.14	-0.06	0.12	0.24	0.08	-0.02
	Cloud cover (tenths)	Cloud	0.01	0.02	-0.02	**-0.04**	**0.06**	-0.01	0.01	0.01	0.02	**0.07**	0.03	0.00
	Humidity (%)	Hum	**0.27**	**0.29**	0.09	0.01	0.12	-0.01	-0.01	0.03	0.06	0.13	**0.32**	**0.20**
	Wind speed (km/hr)	Wind	**-0.11**	**-0.14**	**-0.11**	**-0.31**	-0.12	**-0.13**	**-0.15**	**-0.14**	-0.06	-0.04	-0.06	-0.01
Rangamati	Mean daily temperature (°C)	Tmean	**-0.05**	-0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.00	-0.01	**-0.03**	**-0.05**
	Maximum daily temperature (°C)	Tmax	**0.04**	**0.08**	**0.09**	**0.07**	0.04	**0.04**	**0.05**	**0.05**	**0.05**	**0.04**	**0.05**	**0.05**
	Minimum daily temperature (°C)	Tmin	**-0.08**	**-0.06**	-0.03	0.00	0.00	0.01	0.00	0.00	-0.01	-0.02	**-0.06**	**-0.07**
	Diurnal temperature range (°C)	DTR	**0.12**	**0.15**	**0.10**	**0.06**	**0.03**	**0.04**	**0.04**	**0.05**	**0.06**	**0.06**	**0.10**	**0.11**
	Maximum daily precipitation (mm)	Pmax	0.10	-0.75	-0.05	-0.69	-0.06	1.76	0.21	**-2.45**	0.60	0.48	-0.59	-0.18
	Mean daily precipitation on rain days (mm))	Pmean	0.01	-0.50	-0.24	-0.20	-0.18	0.23	-0.22	-0.27	-0.11	0.02	-0.15	-0.35
	Total precipitation (mm)	Ptot	0.13	-1.26	-0.39	-1.84	0.62	6.42	-1.85	-2.30	2.23	2.78	-0.99	-0.05
	Number of rain days	Pwet	0.01	-0.07	0.01	-0.02	0.15	0.09	**0.14**	**0.18**	**0.20**	**0.16**	0.00	0.01
	Cloud cover (tenths)	Cloud	-0.02	**-0.03**	-0.01	**-0.03**	0.01	0.00	0.00	0.00	0.00	0.00	**-0.06**	**-0.04**
	Humidity (%)	Hum	**0.17**	-0.07	-0.09	0.02	0.06	0.04	0.00	0.04	**0.06**	**0.15**	**0.18**	**0.19**

	Wind speed (km/hr)	Wind	0.02	0.01	0.00	-0.03	-0.01	-0.01	-0.03	**-0.06**	**-0.03**	**-0.03**	**-0.02**	0.00
Sitakunda	Mean daily temperature (°C)	Tmean	**-0.08**	**-0.05**	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	**-0.02**	**-0.03**	**-0.05**	**-0.07**
	Maximum daily temperature (°C)	Tmax	**0.05**	**0.09**	**0.09**	**0.07**	**0.06**	**0.05**	**0.06**	**0.05**	**0.05**	**0.07**	**0.06**	**0.05**
	Minimum daily temperature (°C)	Tmin	**-0.05**	-0.03	-0.02	-0.02	0.00	0.00	0.01	0.00	0.00	0.00	-0.01	-0.02
	Diurnal temperature range (°C)	DTR	**0.10**	**0.14**	**0.10**	**0.09**	**0.05**	**0.05**	**0.05**	**0.05**	**0.06**	**0.06**	**0.08**	**0.07**
	Maximum daily precipitation (mm)	Pmax	0.10	-0.18	-0.70	-0.64	0.37	1.08	1.05	1.79	1.06	-0.11	-0.90	-0.23
	Mean daily precipitation on rain days (mm)	Pmean	0.01	0.06	-0.53	-0.14	0.06	0.22	0.06	0.12	-0.08	-0.24	-0.71	-0.39
	Total precipitation (mm)	Ptot	0.14	-0.25	-1.60	-2.32	3.52	4.25	2.45	4.73	2.88	-0.72	-1.64	-0.20
	Number of rain days	Pwet	0.01	-0.04	-0.02	-0.05	0.13	0.01	0.05	0.08	**0.17**	0.10	0.00	0.00
	Cloud cover (tenths)	Cloud	-0.01	-0.02	-0.02	**-0.04**	-0.01	-0.01	-0.01	0.00	0.00	0.00	-0.03	-0.02
	Humidity (%)	Hum	**0.47**	**0.28**	0.17	**0.18**	**0.19**	**0.18**	**0.12**	**0.16**	**0.21**	**0.31**	**0.42**	**0.52**
	Wind speed (km/hr)	Wind	-0.04	-0.02	-0.04	**-0.09**	**-0.05**	**-0.05**	**-0.06**	**-0.06**	**-0.05**	**-0.03**	**-0.05**	**-0.04**

in an overall increase in mean daily temperature at the Chittagong station, in all seasons although the trend is only significant for the monsoon and post-monsoon seasons (Figure 4).

In contrast to the two southern stations, both Rangamati and Sitakunda show no significant changes in minimum daily temperature during the pre-monsoon and monsoon seasons (Figure 3). However, they both show a significant decrease in minimum daily temperature during the post-monsoon season. This change is larger than the increase in maximum daily temperature, and as a result the mean daily temperature during the post-monsoon season is reduced by 0.3°C per decade at Rangamati and 0.6°C per decade at Sitakunda (in contrast to the increase in mean daily temperature of 0.1°C per decade at Cox's Bazar and 0.4°C per decade at Chittagong).

There is a significant increase in diurnal temperature range, annually and in all seasons in Cox's Bazar, Rangamati and Sitakunda (Figure 5). There is also an increase in diurnal temperature range at Chittagong, but the trend is only significant in the post-monsoon season. The increase in the diurnal temperature range in the northern sites (Sitakunda, Rangamati) reflects the fact that minimum daily temperature is decreasing while maximum daily temperature is increasing. However, the increase in the diurnal temperature range in the southern sites (Cox's Bazar, Chittagong) reflects the fact that the increase in maximum daily temperature is larger than the increase in minimum daily temperature. Thus, the coherent response in diurnal temperature range across the region results from two different causes.

The recent trends in temperature are relatively coherent, but changes in precipitation are less coherent. There are no discernible trends in precipitation in any season at Chittagong, which may reflect the shortness of this record. However, there are changes in precipitation during the monsoon season at Sitakunda and Rangamati (Figure 6). At Sitakunda, there is a significant increase in total precipitation during the monsoon season, which is associated with a significant increase in the number of rain days (Figure 6). Maximum daily precipitation

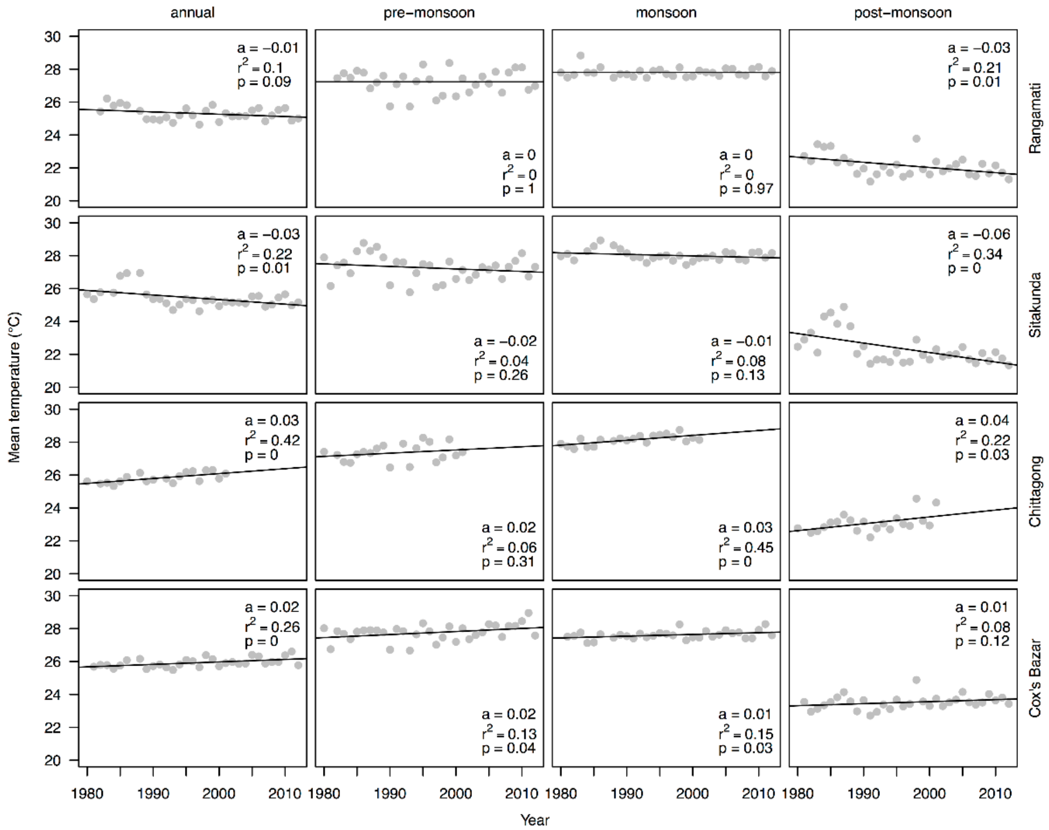

Figure 4. Annual and seasonal trends in mean daily temperature at each of the four meteorological stations.

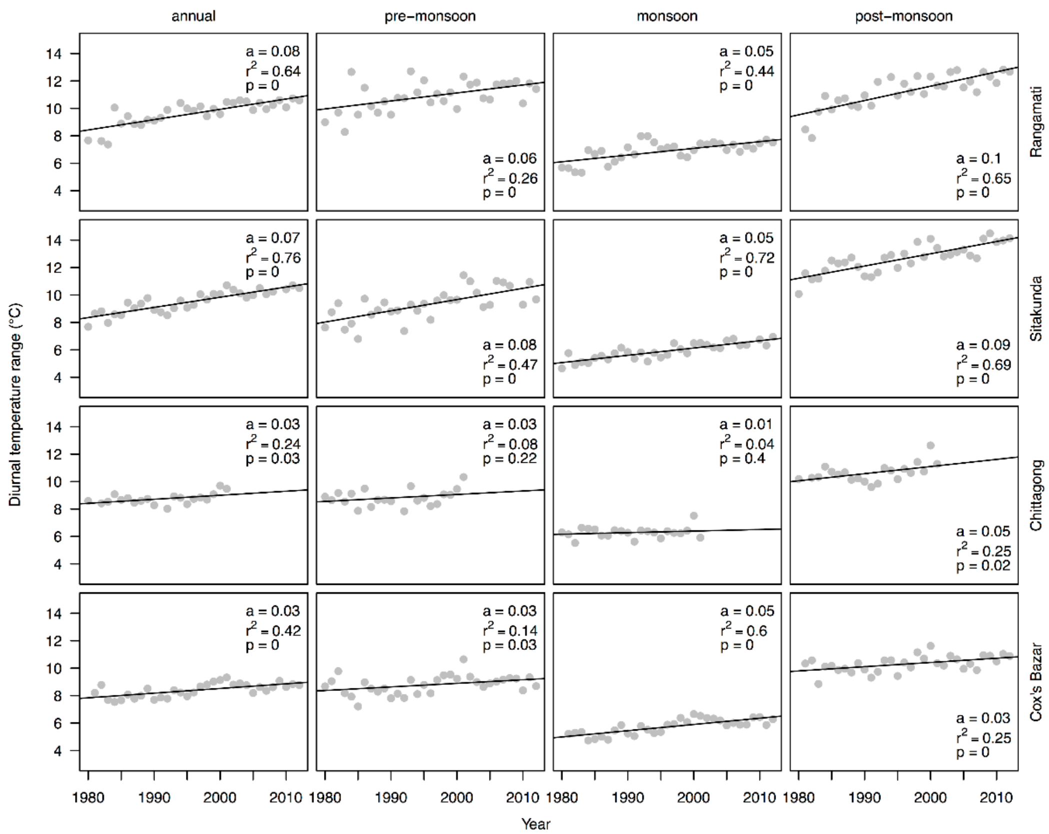

Figure 5. Annual and seasonal trends in diurnal temperature range at each of the four meteorological stations.

Table 4. Summary of correlations between temperature variables and related climate variables for individual seasons, where the pre-monsoon season is defined as March through May, the monsoon season as June through September, and the post-monsoon season October through February. Numbers in bold are significant at the 95% level.

Station	Season	Variables	Diurnal temperature range (°C)	Maximum daily precipitation (mm)	Mean daily precipitation on rain days (mm)	Total precipitation (mm)	Number of rain days	Wind speed (km/hr)	Cloud cover (tenths)	Humidity (%)
Cox's Bazar	Pre-monsoon	Mean daily temperature (°C)	0.1	0.05	0.06	-0.23	**-0.45**	-0.26	-0.34	**-0.37**
		Maximum daily temperature (°C)	**0.57**	0.32	0.34	0.09	-0.21	-0.34	**-0.62**	-0.39
		Minimum daily temperature (°C)	-0.34	0.37	**0.48**	0.14	-0.25	-0.24	-0.01	-0.01
	Monsoon	Mean daily temperature (°C)	**0.36**	0.18	-0.05	-0.14	-0.2	-0.18	-0.11	**-0.47**
		Maximum daily temperature (°C)	**0.89**	0.13	-0.22	-0.22	0	**-0.5**	**-0.46**	0.02
		Minimum daily temperature (°C)	0.13	-0.02	**-0.44**	**-0.42**	0	0.06	-0.16	-0.33
	Post-monsoon	Mean daily temperature (°C)	0.28	-0.19	-0.08	-0.25	-0.27	-0.09	**-0.49**	-0.23
		Maximum daily temperature (°C)	**0.63**	-0.09	-0.17	-0.4	-0.33	**-0.65**	**-0.72**	-0.22
		Minimum daily temperature (°C)	-0.13	-0.09	-0.06	-0.15	-0.12	0.04	-0.18	0.07
Chittagong	Pre-monsoon	Mean daily temperature (°C)	-0.2	0.24	0.03	-0.41	**-0.62**	0.15	**-0.46**	-0.13
		Maximum daily temperature (°C)	0.44	0.15	0.16	-0.21	-0.42	-0.22	**-0.71**	-0.43
		Minimum daily temperature (°C)	**-0.48**	0.32	0.19	-0.19	**-0.6**	0.23	-0.22	0.28
	Monsoon	Mean daily temperature (°C)	0.11	-0.23	0.17	0.03	-0.44	-0.41	-0.12	-0.03
		Maximum daily temperature (°C)	0.43	-0.22	0.38	0.15	**-0.56**	-0.39	0.05	0.11
		Minimum daily temperature (°C)	-0.46	-0.11	0.35	0.17	-0.47	-0.06	-0.08	0.01

	Post-monsoon	Mean daily temperature (°C)	0.42	-0.1	-0.09	-0.19	-0.09	0.06	-0.08	-0.05
		Maximum daily temperature (°C)	**0.68**	0.15	0.09	-0.15	-0.21	-0.06	-0.15	0.09
		Minimum daily temperature (°C)	-0.26	-0.47	-0.18	-0.07	0.12	0.09	0.15	-0.03
Rangamati	Pre-monsoon	Mean daily temperature (°C)	0	-0.16	-0.04	**-0.48**	**-0.68**	0.25	-0.31	**-0.65**
		Maximum daily temperature (°C)	**0.59**	**-0.51**	**-0.43**	**-0.59**	**-0.48**	-0.26	**-0.64**	**-0.56**
		Minimum daily temperature (°C)	**-0.53**	-0.04	-0.18	**-0.4**	**-0.46**	0.24	0.06	-0.21
	Monsoon	Mean daily temperature (°C)	-0.14	0.21	0.07	-0.27	**-0.47**	0.28	-0.09	**-0.57**
		Maximum daily temperature (°C)	**0.71**	-0.1	-0.35	-0.15	**0.43**	**-0.52**	**-0.44**	-0.31
		Minimum daily temperature (°C)	**-0.58**	0.27	0.13	0.04	-0.08	**0.54**	-0.33	-0.09
	Post-monsoon	Mean daily temperature (°C)	-0.33	**-0.41**	-0.16	**-0.36**	**-0.43**	0.35	0.25	**-0.57**
		Maximum daily temperature (°C)	**0.76**	-0.26	-0.29	**-0.37**	-0.22	0	**-0.71**	0.13
		Minimum daily temperature (°C)	**-0.77**	**-0.36**	-0.16	-0.32	**-0.37**	**0.54**	**0.42**	-0.34
Sitakunda	Pre-monsoon	Mean daily temperature (°C)	-0.32	-0.17	-0.33	**-0.54**	**-0.5**	**0.59**	-0.06	**-0.55**
		Maximum daily temperature (°C)	**0.73**	-0.2	-0.2	**-0.4**	-0.33	-0.26	**-0.63**	0.14
		Minimum daily temperature (°C)	**-0.63**	-0.15	-0.33	**-0.49**	**-0.51**	**0.52**	0.13	-0.12
	Monsoon	Mean daily temperature (°C)	-0.04	0.12	-0.08	-0.1	-0.1	**0.46**	-0.06	**-0.69**
		Maximum daily temperature (°C)	**0.95**	-0.09	-0.03	0	0.01	**-0.37**	-0.36	**0.47**
		Minimum daily temperature (°C)	-0.07	-0.11	-0.26	-0.22	0	-0.12	-0.21	0

	Post-monsoon	Mean daily temperature (°C)	-0.27	0.01	0.06	-0.14	**-0.39**	**0.58**	0.16	**-0.78**
		Maximum daily temperature (°C)	**0.89**	-0.25	-0.32	**-0.37**	-0.22	-0.21	**-0.5**	**0.52**
		Minimum daily temperature (°C)	**-0.57**	0.04	-0.01	-0.05	-0.13	0.28	0.14	-0.29

during the monsoon season also shows an increase, but this is not significant (p = 0.26) and there is no discernible trend in mean precipitation on rain days. There is also a significant increase in the number of rain days during the monsoon season at Rangamati, although this is not accompanied by significant trends in other precipitation characteristics. Although total precipitation increases at Cox’s Bazar during the monsoon season, the trend is not significant. However, there is a significant increase in mean daily precipitation on rain days during the pre-monsoon season, largely driven by a significant increase (in mean and maximum precipitation on rain days and in total precipitation) during the month of May. The change in total precipitation during the monsoon season at Sitakunda is 233 mm per decade and the change in the pre-monsoon season at Cox’s Bazar is 81 mm per decade. As might be expected, the increases in precipitation at Rangamati and Cox’s Bazar are strongly correlated with increases in relative humidity (Table 4). However, the relationship between relative humidity and precipitation is also positive at the other stations, even when the change in precipitation is not significant. Overall, the emerging pattern is towards increased monsoon rainfall, although the way this is expressed and the exact timing differ between stations.

There are no discernible or consistent trends in cloud cover during the monsoon season at any station, despite the apparently significant changes in either total precipitation or the number of rain days. However, there are decreases in cloud cover during the pre- and post-monsoon seasons. The decrease in cloud cover at Sitakunda is significant for both seasons (Table 2). There is a decrease in cloud cover in both seasons at Rangamati, but the decrease is only significant during the post-monsoon season. Cloud cover also appears to decrease during both seasons at Cox’s Bazar, although the changes are not statistically significant. The reduction in cloud cover is significantly correlated (Table 4) with an increase in maximum daily temperature (although not with minimum or mean daily temperature) at all three sites, suggesting that changes in cloud cover contribute to the strong observed increase in maximum daily temperature.

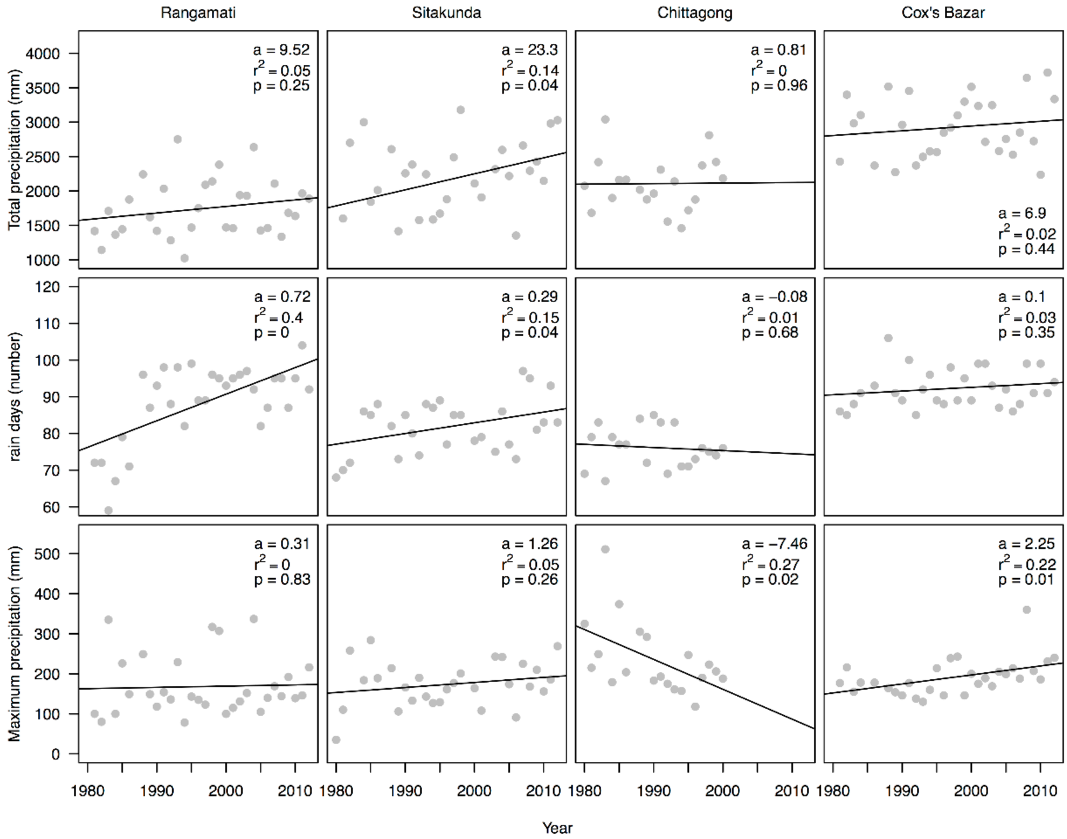

Figure 6. Total precipitation, number of rain days and maximum daily rainfall during the monsoon season at each of the four meteorological stations. Only number of rain days shows any significant trends.

The analyses indicate a general decrease in wind speed across this region. At Sitakunda and Chittagong, the decrease in wind speed is significant in all three seasons (Table 2). Although wind speeds decrease in all three seasons at Cox's Bazaar, the trends are only significant in the pre- and post-monsoon seasons. On the other hand, there is no significant change in wind speed during these two seasons at Rangamati, but a strong decrease (by 0.3 km/hr per decade) during the monsoon season. The change in wind speed is significantly negatively correlated with changes in maximum temperatures (Table 4) suggesting that decreased wind speed is potentially contributing to the observed increases in maximum daily temperatures.

Discussion and conclusions

There is a significant increase in maximum daily temperature in southeastern Bangladesh over the past three decades. This trend is seen throughout the year, although the largest changes occur outside the monsoon season. The trends in minimum daily temperature and in mean temperature are different between the northern and southern parts of the region, with a decrease in both minimum and mean daily temperature in the north (Sitakunda, Rangamati) and an increase in both in the south (Cox's Bazar, Chittagong). The diurnal temperature range has increased at all stations, but this reflects the fact that maximum and minimum daily temperatures show opposite tendencies in the northern stations while in the southern stations the increase is due to larger increases in maximum than in minimum daily temperatures. Our results are broadly consistent with earlier analyses of temperature changes in Bangladesh [e.g. 20, 25]. Islam [20] found an overall increase of maximum daily temperature in southeastern Bangladesh between 1948-2007, and also identified the contrast between northern and southern stations in the region in terms of the trend in minimum temperature. The reconstructed sign and magnitude of the annual change in these variables are comparable for Cox's Bazar (0.26°C versus 0.2°C per decade in our study), Chittagong (0.16°C versus 0.3°C per decade in our study) and Rangamati (-0.11°C versus -0.1°C per decade in our study), despite the fact that the analyses cover different periods of time. There is, however, a discrepancy in the direction of the observed trend in mean annual temperature at Sitakunda, which is positive (0.19°C per decade) according to Islam [20] but negative (-0.3°C per decade) according to our analyses. Further diagnosis is required to determine whether this is a reflection of differences in seasonal patterns or a function of the time interval used. Shahid et al. [25] found a year-round increase in diurnal temperature range at three stations from southeastern Bangladesh (Chittagong, Cox's Bazar, Rangamati) over the period 1961-2008. The rates are comparable to those obtained here (0.17 versus 0.3 in our study for Chittagong, 0.28 versus 0.3 at Cox's Bazar, 0.44 versus 0.8 in Rangamati) and confirm that there is a distinct gradient in the magnitude of the trend between northern and southern stations. More detailed comparisons with earlier studies cannot be made because neither Islam [20] nor Shahid et al. [25] diagnose the relationships between seasonal changes in different components of the temperature regime.

The difficulty in identifying statistically robust trends in precipitation is a common theme of previous analyses [21-24, 26] and also in this study. However, we have shown that there is a significant increase in total precipitation and the number of rain days during the monsoon season at Sitakunda, in the number of rain days during the monsoon season at Rangamati, while evidence of an increase in mean daily precipitation on rain days in May at Cox's Bazar suggests an earlier onset of the monsoon season there. Ahasan et al. [21] suggested that, while there was little or no change in rainfall during the monsoon season, there was a trend towards increased precipitation in the pre-monsoon season for Bangladesh as a whole between 1961 and 2010. Shahid [23] also found a significant increase in mean rainfall during the pre-monsoon season at Chittagong and a marginally significant increase at Cox's Bazar, consistent with our findings. In a second paper, Shahid [22] also showed similarly significant trends for the northern stations (Rangamati, Sitakunda) during the pre-monsoon season. Analyses based on the interval 1958-2007 suggest that the number of rain days per year has increased at Cox's

Bazar Shahid [24], but unfortunately these analyses did not examine the records from Sitakunda and Rangamati – which show a statistically significant increase in the number of rain days during the monsoon season in our analyses. We are limited in our ability to compare the magnitude of the trends in precipitation characteristics because the earlier studies use different stations (or numbers of stations), examine different intervals of time, and focus on different precipitation variables. Nevertheless, all of the analyses suggest that there are changes in precipitation that could have an important influence on the hydrological regimes of southeastern Bangladesh.

There are significant decreases in cloud cover and wind speed during the pre- and post-monsoon seasons in southeastern Bangladesh over the past three decades. These changes are closely correlated with changes in temperature, and particularly maximum daily temperature. This suggests that the observed increases in maximum daily temperature during the pre- and post-monsoon seasons can, at least partly, be explained by reduced cloud cover and reduced wind speed – both of which will led to enhanced surface heating. There is no change in either cloud cover or wind speed during the monsoon season at any of the stations. The absence of a discernible change in cloud cover and wind speed may reflect the fact that precipitation changes during the monsoon season are small (or hard to detect).

This analysis is based on meteorological records covering the interval from 1980 onwards, chosen in order to focus on the time corresponding to the most marked global warming. It is more difficult to identify statistically significant trends from short records. Nevertheless, significant trends exist in multiple seasonal climate variables. We suspect that similar trends at different sites, or similar trends in different seasons at a given site, or coherent trends between different climate variables, are real even when they are not statistically significant. For example, it seems likely that the positive but non-significant trend in maximum daily temperature in the pre-monsoon season at Chittagong is a real feature of the climate, given that similarly positive but significant trends are found in this season at other stations and that similarly positive and significant trends are found in the other seasons at Chittagong itself. Similarly, it seems likely that monsoon precipitation is increasing across the whole of southeastern Bangladesh, even though the indicators that register a significant change are different at the different stations: change in total precipitation during the monsoon season at Sitakunda, a lengthening of the monsoon season at Cox's Bazar, and an increase in the number of rain days at Rangamati. Nevertheless, changes in all of the precipitation-related variables are coherent across the four stations even when they are not significant. Thus, the relatively short length of the records analyzed in this study is not a drawback to detecting climate changes across the region.

The observed trends in temperature and precipitation are small but, if these changes continue in the future, they are likely to have significant impacts on water resources in southeastern Bangladesh. Diagnosing whether the overall impacts on water availability, river flows and the incidence of flooding will be positive or negative requires forward modelling of the system [e.g. 29, 30]. Our analyses identify both the need for such modelling and provide calibration data sets that make it feasible. There is already considerable concern about water availability and water quality in southeastern Bangladesh [31, 32], and thus an assessment of how these have been affected by recent climate changes and how they will be affected in the near-term future is a matter of some urgency.

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CHAPTER 3: SIMULATING STREAMFLOW IN THE UPPER HALDA BASIN OF SOUTHEASTERN BANGLADESH USING SWAT MODEL

Abstract

Most catchments in tropical regions are ungauged and data deficient, complicating the simulation of water quantity and quality. Yet, developing and testing hydrological models in data poor regions is vital to support water resource management decisions. Here, I used the Soil and Water Assessment Tool (SWAT) to predict stream runoff in Halda Basin, southeastern Bangladesh. While the calibrated model's performance was satisfactory (R^2 = 0.80, NSE = 0.71), the model was unable to track the extreme low flow peaks. Adjusting the ground water parameter manually revealed ground water delay, base-flow alpha factor and curve number as the sensitive parameters influencing model performance. Overall, this study provides understanding of the catchment dynamics of a data-poor, monsoon driven, small river basin, and could serve as a baseline for scenario modelling.

Introduction

The impact of climate change on water resources has become a global concern (Githui et al., 2009). Changes in hydrological variables, such as evapotranspiration, soil moisture, water temperature, stream flow volume, timing and magnitude of runoff, and the frequency and severity of floods, will in turn affect plant growth, sediment loads and nutrient fluxes, with further impacts on water resources (Zhang et al., 2007). Climate change is expected to alter the risk of hydrological extremes, and may contribute to water scarcity by reducing the quantity available for human use and increasing water demand in the near future (Lehner et al., 2006). Alterations to water supply and demand may also pose a substantial threat to global communities in terms of food security (Hanjra and Qureshi, 2010; Alcamo et al., 2007; Barnett et al., 2005; Döll and Siebert, 2002; Spash, 2007).

Climate change is an additional complication for water resource management in South Asian countries, where its short and long term impacts can be measured across almost every sector of the economy (Shaw et al., 2013). This is particularly the case in Bangladesh, which has already experienced major impacts of climate change on hydrology, mostly in the form of coastal and inland flooding due to extreme monsoon-influenced precipitation and runoff, increased salinity and reduced flow during the dry season (Agrawala et al., 2003). Changes in the quantity or quality of water increases the vulnerability of rural communities and creates problems for the allocation of water to sectors such as energy and agriculture (WWAP, 2012). Environmental modifications and declines in water quality have placed pressure on fisheries in Bangladesh, threatening biodiversity and livelihoods.

The Halda River catchment plays a significant role in maintaining the ecological health and the economy of southeastern Bangladesh. The river and its associated canals are the main source of water for crop irrigation throughout the basin, with an estimated 347–583 giga-litres of water extracted annually for use in agriculture (MoFL, 2016). The total value of tangible resources derived from the catchment has been estimated at $US 20.5 million per annum (Kabir et al., 2013). Moreover, surface water from the basin serves as the primary source of drinking water for the city of Chittagong (Zuthi et al., 2009).

The river is also the major spawning ground for Indian major carp (*Catlacatla spp.*, *Labeorohita spp.*, *Cirrhimus mrigala,* and *Labeo calbasu*). Indeed, it is the only location in Bangladesh from which fisherman can collect fertilized eggs from fish populations that are mostly disease resistant, free from inbreeding, and have the ability to survive under stressful conditions (Kabir et al., 2013).

The Halda River Basin receives ~ 2800 mm of rainfall per annum, most of which falls during the monsoon (June–September). Over the past three decades, the southern regions of the basin have experienced a significant increase in total precipitation, total number of rain days, and maximum daily temperature (Raihan et al., 2015).

In addition to the direct impacts of climate change, catchment hydrology is also being impacted through direct human pressures. These include conversion of forests into cultivated land, and canalization of the oxbows that once formed the main breeding grounds for carp (Akter and Ali, 2012). Understanding the impacts of climate change and direct human pressures is essential for the development of a watershed management decision support tool for the Halda Basin.

Several types of hydrological models for simulating catchment dynamics exist. However, SWAT (Soil and Water Assessment Tool) (Arnold et al., 1998), a physically-based semi-distributed model, is better suited for data scarce regions compared to other commonly used models such as MIKE-SHE (Refsgaard and Storm, 1995), TOPMODEL (Beven and Kirkby, 1979) or WASIM (Schulla and Jasper, 2007). Developed by the USDA Agricultural Research Service, SWAT has demonstrated strength in simulating catchment hydrology taking into account climate, land management practices on water, sediment and agriculture chemicals in large, complex watersheds (Neitsch et al., 2002). The development of a watershed management tool for the Halda Basin is vital for identifying key hydrological processes influencing water availability, and for evaluating how these may change in the future. In this study, I establish baseline hydrological conditions for the Halda Basin, using the SWAT modelling framework, in order to provide a basis for future water resource management and monitoring.

Materials and Methods

Study area

Running approximately 81 km, the Halda River (Figure 1) originates in the Chittagong Hill Tracts in southeastern Bangladesh and eventually flows into the Karnaphuli River. The seasonal cycle of temperature across the basin is arbitrated by the monsoon, and typically December and January are the coldest months (ca 16–20 °C) whereas May–August are the warmest (ca 38–40 °C). Annual average rainfall is ~2800 mm, with most rainfall occurring during the summer monsoon (June–September) (the climatology of this basin is shown in Figure 2). Downstream of Panchpukuria Station the river is affected by tidal action, while upstream from here river flow varies from 4 m PWD (Public Works Datum) in the dry, to 10 m PWD in the rainy season. During the monsoon, the river experiences frequent flash floods due to heavy rainfall.

Soils throughout the river basin are deep and flat, with topsoil texture ranging from loam to clay (Alam et al., 2006). Soil permeability is rapid with low moisture holding capacity. The leading land use in the basin is agriculture, and the natural land cover is predominantly tropical evergreen, and deciduous forests and shrubs (Alam et al., 2006).

SWAT Model

SWAT is a physically-based, semi-distributed, computationally efficient model that is run on a daily time step (Arnold et al., 1998; Srinivasan et al., 1998).

SWAT subdivides a basin into sub-basins, then into hydrological response units (HRU) which represent unique combinations of soil and land use properties. The HRUs characterize percentages of each sub-basin and are not linked or spatially connected in the SWAT simulation (Arnold, 2012). Surface runoff is estimated at the sub-basin level and routed via a specified channel network to the associated reach and watershed outlet. I configured the computing of flow routing in the river channels to apply the variable storage routing methods developed by

Williams (1969). This method provides a simulating hydrograph with short time steps. Due to the lack of information on solar radiation, I configured the model to apply Hargreaves method (Hargreaves et al., 1985) of estimating potential evapotranspiration (PET).

Input Data

SWAT requires as input data, elevation, land-use, soil and climate (temperature and precipitation) data.

Elevation

I used the Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER) derived digital elevation model (DEM) downloaded from (http://gdem.ersdac.jspacesystems.or.jp/search.jsp). ASTER DEM is served at 30m spatial (horizontal) resolution.

Land Use Data

Land use data were derived from the 1 km resolution Global Land Cover 2000 data set (GLC2000: http://geodata.grid.unep.ch/options.php). The data were reclassified based on the SWAT land cover/plant growth database (Appendix Table A1). "Shrub cover evergreen" was converted to "Range-brush" (RNGE), as the dominant vegetation is native grass. "Shrub cover deciduous" was converted to "Range-brush" (RNGB) for areas where the vegetation type is characterized by woody stems. The class "Cultivated managed area" was categorized as "Agricultural land close grown" (AGRC), as this corresponds to the area used for annual crop production. Finally, "Mosaic cropland/tree cover" was categorized as "Agricultural land generic" (AGRL), as I assumed that cultivated crops grow under natural rain fed conditions and utilize little or no irrigated water.

Soil Data

Data on soil type were extracted from a local soil database developed by WARPO (Water Resource Planning Organization, Bangladesh) which was originally prepared by Bangladesh Soil Research Institute (SRDI) based on the Reconnaissance Soil Survey (RSS) using aerial interpretation and field survey. In this database, soil classification is based on physiographic condition and geologic origin of the parent material. Soil properties information was interpreted from the 1km resolution of FAO (Food and Agriculture Organization) database. Three major classes of soil (acrisols, cambisols and gleysols) are present in the Halda Basin (Appendix Table A2).

Slope Class

A slope map was derived from the DEM. Slope was estimated as the maximum rate of change between each cell and its eight neighbours (%). The mapped slopes were aggregated into five classes (0–3%, nearly level; 3–6%, very gentle; 6–9%, moderate; 9–27%, moderate to steep; and > 27%, steep) using the percentage function in ArcGIS 10.1 (ESRI, 2012) 3D Analyst.

Weather Data

Daily weather data (precipitation, maximum/minimum temperature) for the Sitakunda Meteorological Station (22.63◦N and 91.70◦ E) were obtained from the Bangladesh Meteorological Department (BMD). These data span the period 1980–2013, although data for ~170 days are missing. I also obtained rainfall data from a second source, the Global National Center for Environmental Prediction (NCEP) Climate Forecast Reanalysis (CFSR) data (http://globalweather.tamu.edu) at ~38 km resolution, to compare hydrological predictions.

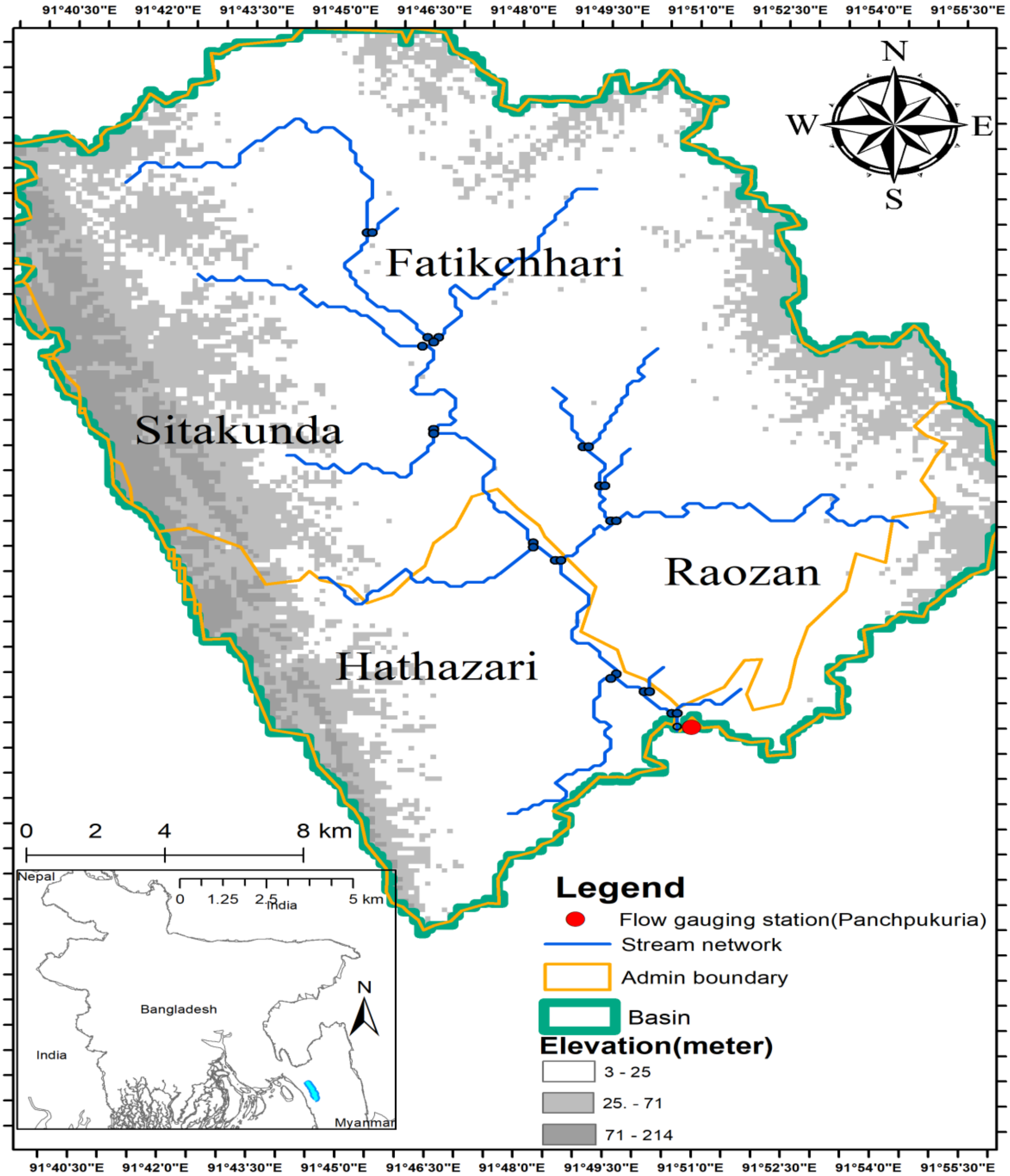


Figure 1: Location of the study area. The map showing the stream network of the Halda Basin within Bangladesh (inbox with highlight).

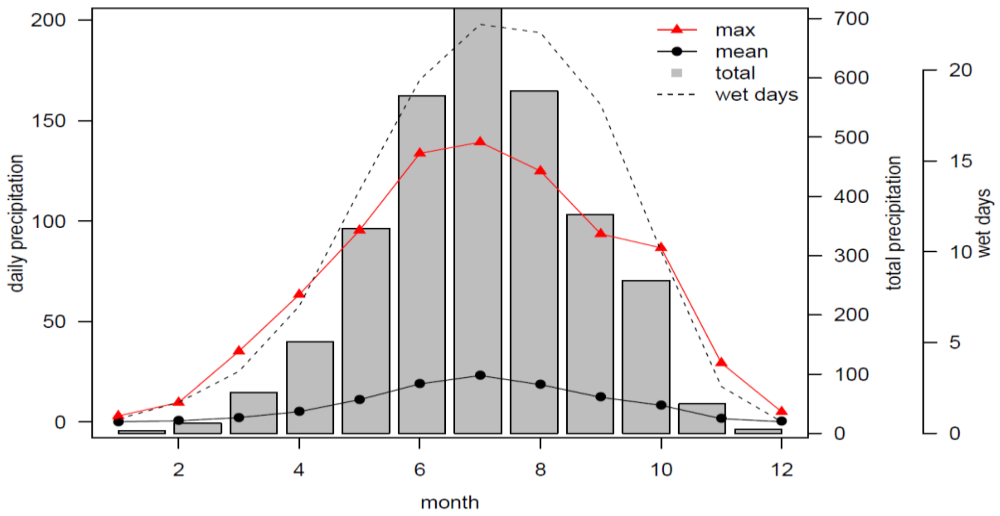


Figure 2: Maximum and mean distribution for daily precipitation, and total monthly precipitation, across the Halda River Basin, Bangladesh. The dash line represents the number of wet days.

River Discharge

Monthly flow data from the Panchpukaria Hydrometric Station (Station ID: 119.1) were used for model calibration and validation. Daily data were collected from the BWDB (Bangladesh Water Development Board) for the period of 1980–2004 (data were unavailable after 2004). These data were not complete: ~ 5% was missing for the period 1980–1994, and ~10% from 1995–2004. However, within the latter period discharge was measured twice each month. I used a rating curve to calculate daily discharge and monthly averages from these data.

Model setup

The ArcGIS 10.1 interface of SWAT (ArcSWAT version 2012) was used to derive the parameters controlling hydrologic processes in the Halda River Basin. Generally, the observed stream network differs in several respects from that generated automatically from the DEM, which could reflect the different resolutions of data sources used for the DEM or artificial modification of the river course (Reddy and Reddy, 2015). To define the correct location of the drainage network, I applied DEM based watershed delineation methods. In this research first, I digitized the stream network of the basin from Google Earth (August 13th, 2014). The ASTER

DEM grid of the study area was loaded into the SWAT model. Here Burn-in option was used to improve streams hydrographic segmentation and sub basin boundary delineation. Then digital stream network was imported and superimposed it onto the DEM. In SWAT, the definition of the stream reach and sub-basins was performed automatically by filling sinks and calculating the flow direction and flow accumulation grids. The total drainage area was 569 km^2, divided into 25 sub-basins and further subdivided into 482 HRUs, to characterize the dominant land use and soil types within each sub-basin. There was no attempt to limit the number of HRUs by imposing minimum thresholds for the percentages of land cover, soil or slope type required to be present. I defined the rainfall distribution setting on the SWAT platform as ‘skewed normal’, based on the rainfall distribution of the study area.

The model was run at a monthly time step from January 1980 to December 2004, with the first five years of simulation considered a spin-up period for stabilizing the model. The period 1985–1994 was used for the model calibration as there were less missing data. In addition, this period experienced two major flood years (1988, 1991) and two drought years (1989, 1994), which allowed us to evaluate the model’s ability to simulate extreme flow events associated with the monsoon-driven climate. The interval from 1995–2004 was used for model validation.

Calibration and Uncertainty Analysis

To explore model calibration and uncertainty, I tested three alternate models, here referred to as the ‘uncalibrated’, ‘auto-calibrated’ and ‘manually-calibrated’ models. The uncalibrated model utilized the default parameter values in SWAT. The auto-calibration model utilized the Sequential Uncertainty Fitting (SUFI-2) interface of SWATCUP (Table 1) to estimate optimal coefficients for model parameters (Abbaspour, 2007). For this model, I set the objective function to bR^2 (where R^2 is multiplied by the coefficient of the regression line between the measured and simulated data *b*) and the Nash–Sutcliffe efficiency (NSE), which places more emphasis on extreme events than an average flow (Malagò et al., 2015).

Table 1: Parameter sensitivity analysis using SWATCUP algorithm. Sensitive variables are defined as those with P < 0.05 ranges used in SUFI-2 algorithm (values in bold).

No.	**Parameter Name**	**Fitted Value**	**Min value**	**Max value**	**P-value**
1	R__CN2.mgt	-0.30	-2	2	**0.00**
2	V__ALPHA_BF.gw	0.12	0	1	**0.02**
3	V__GW_DELAY.gw	5.62	5	20	**0.01**
4	V__GWQMN.gw	1622.16	1600	1700	**0.04**
5	V__GW_REVAP.gw	0.12	0.01	0.16	0.34
6	V__REVAPMN.gw	384.16	0	500	0.25
7	V__ESCO.bsn	0.39	0.3	0.5	0.95
8	V__SURLAG.bsn	3.24	0	24	0.81
9	R__SOL_AWC(..).sol	0.76	0	1	0.44
10	R__SOL_K(..).sol	7.02	0	11	**0.05**
11	V__RCHRG_DP.gw	0.01	0	0.4	**0.01**

Parameter uncertainty was quantified using 95% prediction uncertainty (95PPU), which achieved by calculating 2.5% and 97.5% levels of the cumulative distribution of the output variable (Abbaspour, 2007, Van Griensven et al., 2006). The goodness of calibration was quantified using two indices, the P and R factor. The P factor denotes the proportion of observed data within the 95PPU. For discharge, P > 0.70 was recommended by Abbaspour (2007). The R factor defines the average width of the 95PPU band divided by the standard deviation (a value < 1.5 is recommended) of the corresponding measured variable, and ranges from 0–infinity (Abbaspour, 2007). Calibration performance was further assessed using the coefficient of determination (R^2), the slope of the regression line between measured and predicted flow (bR^2), Nash–Sutcliffe efficiency (NSE) and Percent Bias (PBIAS). NSE indicates how closely the measured and simulated values fit a 1:1 line, and range from -∞ –1 (Nash and Sutcliffe 1970). Higher NSE values indicate better model performance. PBIAS measures the average tendency of the simulated data to be larger or smaller than their measured values. Positive and negative values indicate under- and over-estimation, respectively.

The manually calibrated model was based on a calibration by adjusting the parameter coefficients (Neitsch et al., 2002) using values derived from the literature that were applied for other regions (Table 2).

Table 2: Allowable ranges of parameters used in SWAT manual adjustment, as suggested by Arabi et al. (2007), Cibin et al. (2010), Ghaffari et al. (2010), Wu et al. (2012)

No	Parameter	Allowable range	Fitted value	Unit
1	R__CN2.mgt	35-98	55.37	fraction
2	V__ALPHA_BF.gw	0-1	0.06	days
3	V__GW_DELAY.gw	0-500	10	days
4	V__GWQMN.gw	0-5000	1800	mm
5	V__GW_REVAP.gw	0.02-0.2	0.01	n/a
6	V__REVAPMN.gw	0-500	300	mm
7	V__ESCO.bsn	0-1	0.5	fraction
8	V__RCHRG_DP.gw	0-1	0.02	Fraction

Results

I tested two different rainfall datasets by comparing outputs from models that were run with a) BMD and b) CFSR. I found that the latter performed marginally (R^2 = 0.52, NSE = 0.51). Further, hydrograph comparisons indicated that this model did not represent the actual precipitation pattern in the CFSR dataset due to excessive (> 3400 mm) average rainfall and the underestimation and overestimation during the calibration and validation periods respectively (See Appendix Figure A1 & A2). To minimize the uncertainty associated with capturing precipitation pattern, I used BMD data set for hydrological simulations.

Table 3: Criteria for evaluating accuracy of calibration and validation periods of monthly discharge for the Halda Basin, Bangladesh using BMD data

Model Evaluation Period	**Model Performance**			
	Nash-Sutclieffe Efficiency (NSE)	Coefficient of determination (R^2)	Modified coefficient of determination (bR^2)	Percent bias (PBIAS) %
Calibration (1985–1994)	0.72	0.73	0.60	4.8
Validation (1995–2004)	0.71	0.80	0.80	-20.4

Performance of the Uncalibrated and Auto-calibrated Models

When river-flow simulations based on the uncalibrated model were tested against the measured runoff, an R^2 of 0.68 and the NSE 0.67 were obtained, suggesting a low fit (Figure 3a). Auto-calibration resulted in a slight improvement (R^2 = 0.73 and NSE = 0.72) (Figure 3b). The P factor indicated that 83% of the measured data were within model prediction uncertainty (95PPU) while the R factor was 0.60, indicating acceptable accuracy of the model calibration (Figure 4). Model performance was similar in both the validation and calibration periods.

The performance of the auto-calibrated model (R^2 = 0.80, NSE = 0.71; Figure 3d) was higher for the validation period than that of the uncalibrated model (R^2 = 0.76 and NSE = 0.50; Figure 3c). The P and R factors were 0.80 and 0.74, respectively, suggesting good performance of the model during validation. Thus, overall the auto-calibrated model demonstrated improved performance during the calibration and validation periods in terms of hydrographic response.

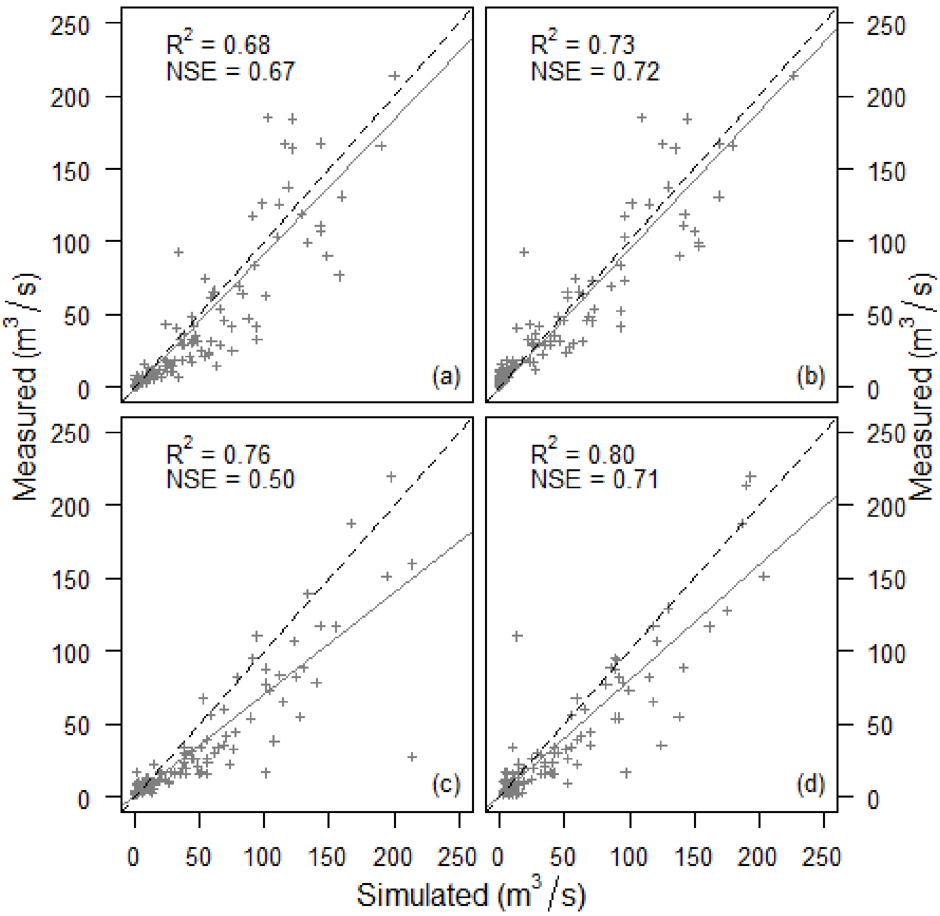


Figure 3: Simulated versus measured monthly runoff across the Halda basin, Bangladesh, before and after auto calibration. Simulations were conducted with SWAT.The dashed line shows 1:1 line and the grey solid line is the regression line. The interval 1985–1994 was used for auto calibration and the model was applied to the period 1995–2004 without further modification. The plots show results for the period 1985–1994 (a) before calibration and (b) after calibration, and for the period 1995–2004 (c) validation without modification and (d) validation with modification from the calibrated model.

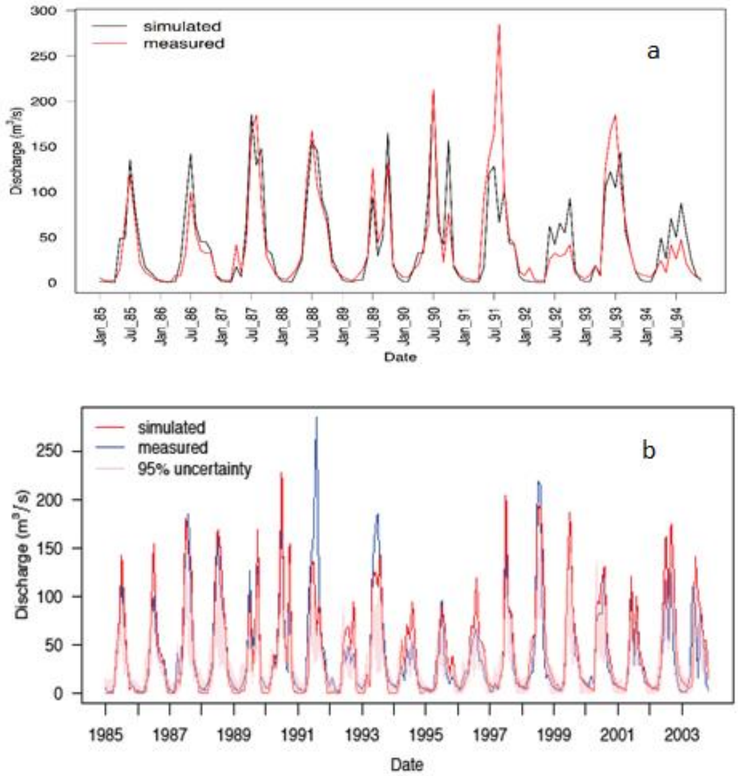


Figure 4: (a) Monthly and (b) yearly time series of simulated (red) and measured (blue) runoff from 1985–2004. The 95% uncertainty limit of the model is shown in pink shading. The interval 1985–1994 was used for auto calibration. The model was applied to the period 1995–2004 as validation without modification.

The high R^2 and NSE of the calibration and validation data indicate that the auto-calibrated model adequately captured the stream flow of the basin (Table 3). However, in some cases this model did not simulate peak flows correctly during the calibration period. Furthermore, the positive bias (PBIAS = 4.8%) in the calibration period indicates that flow was underestimated, while the negative bias (PBIAS = -20.4%) in the validation period indicates a flow was overestimated (Figure 4).

Better performance was also obtained in the month-to-month seasonal hydrograph: the auto-calibrated model appears to accurately simulate flow in both the pre-monsoon season during March–May ($R^2 = 0.60$) and post-monsoon season during October–February ($R^2 = 0.87$) (Figure 5). However, model performance was lower during the monsoon (July–September) ($R^2 = 0.44$).

The auto-calibrated model reasonably reproduced the observed discharge quantity and monthly trends, except for the years 1988, 1991, 1993, 1998, where the simulated discharge failed to capture the extreme peak flow (Figure 6). During these years, the model underestimated extreme events and peak flows. This is likely because of missing rainfall data during periods of devastating floods in 1988, 1993 and 1998, and the 1991 tropical cyclone that occurred in the study area.

The performance metrics give the impression that the auto-calibrated model performed well during the calibration period and slightly better in the validation period. Also, the reasonable evaluation metric is a reflection of the model accurately reproducing the seasonal cycle. The behaviour of the strong seasonal cycle in runoff across the Halda Basin largely reflects the observed pattern of precipitation. To test the models' ability to capture inter-annual variability in monthly flow, I detrended and compared simulated and measured discharge (See Appendix Figure A3). Comparisons showed a relatively low correlation between measured and simulated flows (See Appendix Figure A2(b), R^2 values vary between 0.19 and 0.28, depending on the model and time used). Thus, the reasonable performance of the uncalibrated and the auto-calibrated model largely reflects the imprint of seasonality on the simulations rather than the ability of the model to capture inter-annual variability in monthly flows.

Performance of the Manually Adjusted Model

A number of parameters influence stream flow (Table 1) including: Curve number (CN2.mgt); GW_DELAY (ground water delay time); threshold depths for base flow (GWQMN); Baseflow alpha factor (Alpha-BF); Re-evaporation (REVAPMN); Groundwater revap coefficient (GW_REVAP); SOL_AWC (available water capacity of the soil layer); ESCO (soil evaporation compensation factor); SURLAG (surface runoff lag coefficient); SOL_K (saturated hydraulic conductivity); and RCHRG_DP (deep aquifer percolation fraction). From the results of the SUFI-2 algorithm (Table 1) CN2.mgt, GW_DELAY, RCHRG_DP and Alpha-BF, were the most sensitive parameters.

Evaluation of Parameterization by Surface Response

Using the SWAT checker tools (White et al., 2014), the simulated value of the curve number for moisture condition was found to be 79.22. This indicates a huge volume of runoff and ought to be most sensitive parameter. In order to better match the flows, the surface runoff parameter, i.e. curve number (CN2.mgt) was decreased by 30%. This improved agreement between the measured and simulated hydrograph, decreasing runoff and increasing infiltration, base flow and recharge. I reduced the ESCO value from the default of 0.95 to 0.5, which indicated that more water was being extracted from the upper soil. This led to more evaporative demand, reducing the high water yield and increased evapotranspiration.

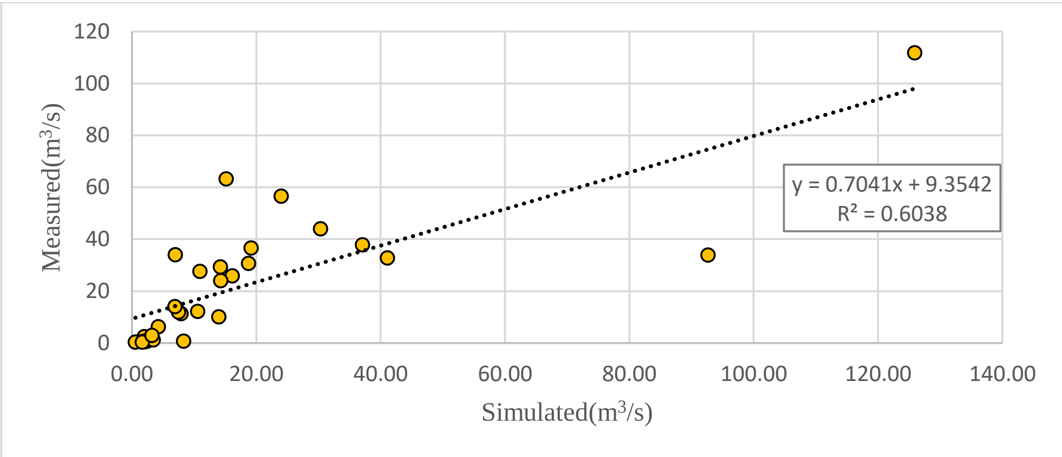
Evaluation of Parameterization by Sub Surface Response

To obtain a higher base flow, I altered REVAPMN to 300, and decreased ALPHA_BF to 0.06, which better reflected the slow drainage and high storage in the basin's shallow aquifer. Reducing GW_DELAY from 31 to 10 days permitted a better approach for the periods of low flow (See Appendix Figure A4).

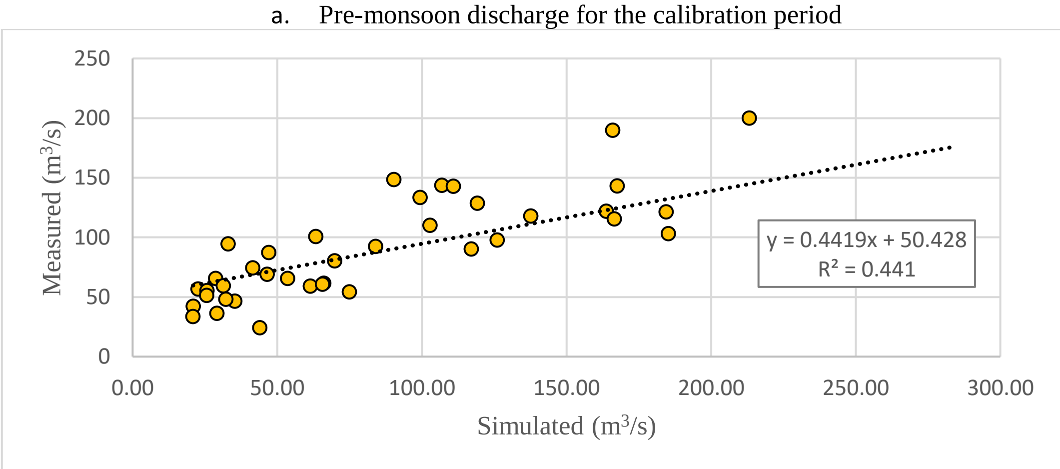
Results indicate that increasing GW_REVAP by 0.01, altering GWQMN to 1800 and reducing RCHRG_DP by 0.02 strongly influenced the base flow calculations (See Appendix Figure A4). Manual calibration marginally improved model performance (NSE = 0.73), compared to the auto-calibration (NSE = 0.72) using the SUFI-2 algorithm.

Output of Water Balance dynamics displayed by SWAT checker

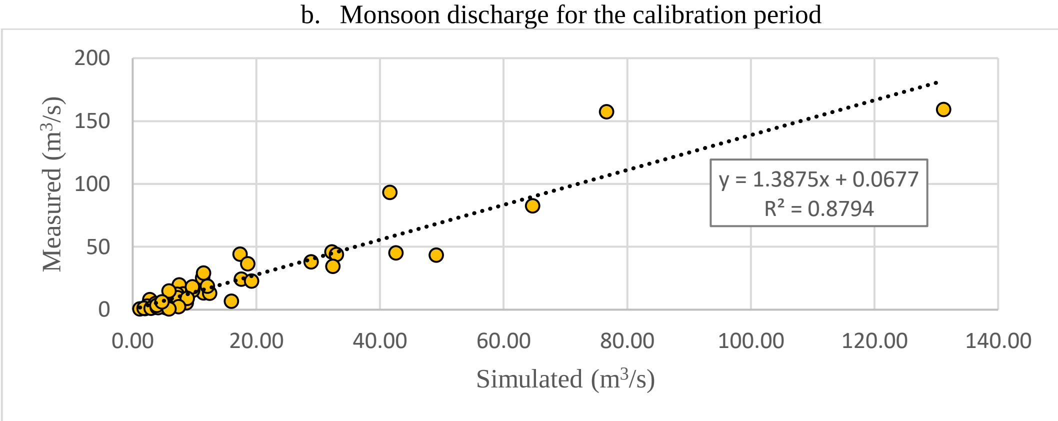
Using SWAT checker (White et al., 2014), the uncalibrated total water balance results for the Halda River Basin indicated 3,196 mm of rainfall during the calibration period 1985–1994, from which 529 mm (17%) was lost through evapotranspiration. In this simulation, Surface Runoff and the precipitation ratio were high (0.69), indicating excessive runoff. Adjusting the parameter manually reduced this ratio to 0.40.



a. Pre-monsoon discharge for the calibration period



b. Monsoon discharge for the calibration period



c. Post-monsoon discharge for the calibration period

Figure 5: Plots showing correlation between simulated and measured discharge during the calibration period (1985–1994) for (a) the pre-monsoon season (March–May), (b) the monsoon season (June–September) and (c) the post-monsoon season (October–February).

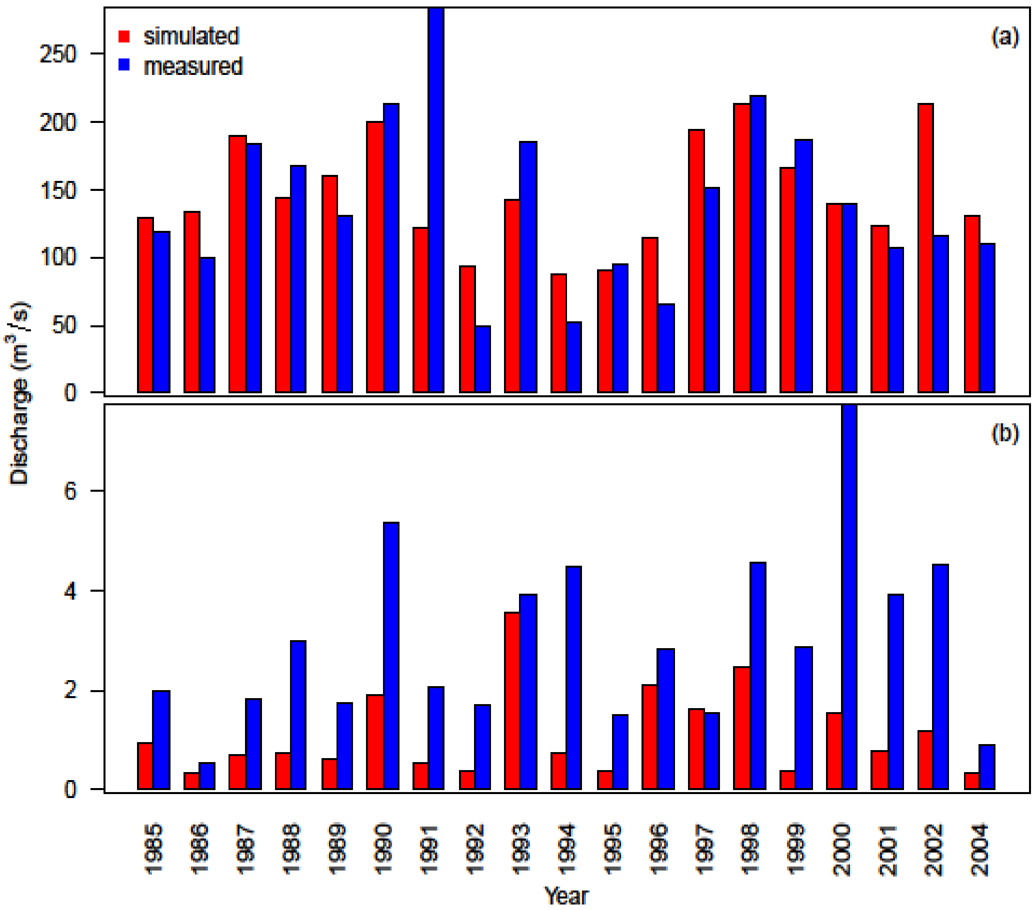


Figure 6: Bar plot showing maximum ***(a)*** *and minimum* ***(b)*** *value in a year of simulated and measured monthly runoff for the period of 1985–2004 from the uncalibrated model. The interval 1985–1994 was applied for autocalibration and the model was used for validation without furthur modification during 1994–2004.*

The ratio of streamflow and total rainfall was 0.81 in the uncalibrated model, which decreased to 0.78 after manual calibration. The ratio of base flow to total flow prior to and after modification was 0.31 and 0.65, respectively. This increased the performance of the manually calibrated model (R^2 = 0.73, NSE = 0.73). A tabular representation of the water balance ratio is shown in Appendix Table A3.

Discussion

This study simulated water balance in Halda Basin and investigated performance and parameter sensitivity of the SWAT modelling platform configured for a small basin in South-eastern

Bangladesh. Performance metrics of the auto-calibrated model indicated that the model adequately simulated monthly runoff, despite under- and over-estimating river flow during the calibration and validation periods, respectively. However, the auto-calibrated model generally underestimated runoff during peak flows, potentially due to uncertainties associated with the rainfall data and the runoff generation process (Conan et al., 2003).

Given the importance of rainfall in hydrologic processes, I compared models calibrated with rainfall data from two sources, and found that those based on Bangladesh Meteorological Data (BMD) performed better than those using the Climate Forecast Reanalysis (CFSR) gridded rainfall data. A number of studies have also found that CFSR data overestimates precipitation, hence resulting in higher than normal river flow peaks (Dile and Srinivasan, 2014; Faramarzi et al., 2015; Roth and Lemann, 2015). This may be because CFSR data do not accurately represent precipitation seasonality (Roth and Lemann, 2015) and its weather simulations compare poorly with conventional weather data (Dile and Srinivasan, 2014).

Using a limited number of precipitation stations may misrepresent the actual precipitation patterns of the watershed. This is also addressed by Narsimlu et al. (2015) who argued that using one-gauge station for a larger basin, such as the Kunwari River Basin (6821 km^2), is not only insufficient, but also introduces model uncertainties. Halda Basin is however, a comparatively smaller basin and is impacted minimally by having only a single rainfall gauge. Though, the basin has not experienced a significant change to annual or seasonal patterns in precipitation over the period 1980-2013 for all station (Raihan et al., 2015) but during the monsoon season, the northern sites of the basin experience a substantial increase in the number of rain days, ranging from 3 days per decade in Sitakunda to 7 days per decade at Rangamati. In contrast, southern parts of the basin have experienced a lengthening of the monsoon season, with a north-south gradient in the magnitude of the trend (Raihan et al., 2015). In the current study, I employed traditional thiessen polygons, which minimized potential drawbacks of there being few weather stations within the study area.

Model uncertainties in model simulations could also result from the use of a coarse-scale (1km) gridded global soil dataset. It is well-known that hydrological responses to storms are largely influenced by the soil water content (Medici et al., 2008). In this study, I found that the peak flow was underestimated, which implies that too much rainfall is being soaked up by the soil. Further, inaccurate estimations of soil parameters that control the hydrologic conditions of the soil profile influenced this underestimation of peak flow. According to Peterson and Hamlett (1998), SWAT may be unable to simulate the base flow due to the soil characteristics, which restrict water flow and root penetration. Hence, low base flow underestimated the period of low flow and in turn biased the performance of PBIAS (4.8%). Pervez and Henebry (2015) also found SWAT to under-estimate stream flows for the calibration period (PBIAS = 3.3%). This was a result of high uncertainty during the low flow season, in particular during the pre-monsoon season in the Brahmaputra Basin in Bangladesh. Studies have also found that precipitation in regions of the Halda Basin, i.e., Sitakunda and Rangamati, is likely to decrease in the pre- and post- monsoon, thereby enhancing the dry period (Raihan et al. 2015).

Halda Basin experiences lowest flow during the pre-monsoon season (March–May) due to high evapotranspiration and low rainfall. The correlation between simulated and measured flow for this period ($R^2 = 0.60$) is mainly attributed to low stream flow due to lower rainfall and the dry hydrologic conditions. Low flow is also experienced during the post-monsoon season (October–February) and shows a strong correlation ($R^2 = 0.87$) between simulated and measured flow, indicating that the auto-calibrated model simulates the hydrological conditions of the basin during low flow fairly well. Thus, the overall extent of disagreement between measured and simulated flow is attributed to differences in model performance during particular seasons. Rostamian et al. (2008) argued that uncertainties are high during low flow seasons because SWAT is unable to simulate ground water flow. This could also be influenced by the long base flow recession which cannot be measured by the local gauge station.

Difficulties in achieving satisfactory results during low flow conditions have been reported in other studies (Sudheer et al., 2007; Leisenring and Moradkhani, 2012). However, flooding, riverbank erosion and sedimentation of the downstream reservoir generally incorporates peak flows (Dile et al., 2016). In my study, floods and droughts have occurred frequently in recent decades. The auto-calibration also revealed that the measured peak values in the major flooding years 1988, 1991 and 1993 did not fall under the 95PPU band due to the model under-predicting extreme events. This may be due to the selection of bR^2 as the objective function of the model calibration (which is unbiased towards peak flows). This underestimation is consistent with the findings of Pervez and Henebry (2015) for the Brahmaputra Basin in Bangladesh, where some peak flow months were under-predicted, mainly for periods of observed higher flows. Similarly, studies for other basins have reported that SWAT may under-predict higher flow due to difficulties simulating extreme events (Chu and Shirmohammadi, 2004;1 Tolson and Shoemaker, 2007).

Strong seasonal cycles with high rainfall events could be the main driver for the simulated peak flow. Chu and Shirmohammadi (2004) noted that SWAT was unable to simulate the base flow during extremely wet years, whereas Wu and Johnston (2007) posited that the long temporal lag enhances the underestimation of base flow by SWAT throughout the dry years. As a result, models have a tendency to underestimate flow in the wet season and overestimate it in the dry season. Probable reasons for these discrepancies may be related to other parameters that govern flow through the shallow and deep aquifers simulated by the model. Furthermore, insufficient knowledge of groundwater processes in the model structure may result in model uncertainty. Therefore, I manually parameterized groundwater storage and dynamics using semi-intuitive trial and error process for the calibration period, 1985–1994.

In order to obtain a better hydrograph, GW_DELAY was decreased to 10 days, resulting in good agreement with the measured flow, but reflected lower sensitivity during auto-calibration. Schmalz et al. (2008) also argued that changing this parameter from the default value of 0 to 50 days allowed for a better fit during low flow and changed the discharge significantly. Although GW_DELAY reflects the time lag for percolation to enter the shallow aquifer, its lack of sensitivity considers the higher water infiltration rate and steeper slopes (Me et al., 2015). It is apparent from this study that decreasing CN2.mgt by 30% resulted in high sensitivity of the discharge and improved the underestimation of simulated base flow. However, I noticed difficulties while attempting to increase the peak flow during the storm event, as surface runoff occurs over the entire period. Decreasing ESCO increased the soil depth to compensate the water deficit from lower to upper layers and caused higher soil ET (Malagò et al., 2015). However, the lack of lower sensitivity of ESCO, where $p = 0.95$, indicated high and seasonally consistent rainfall in this study, as well as the findings of Me et al. (2015). This contrasts to Guse et al. (2014), who found ESCO to be the most sensitive parameter for a lowland catchment, and pointed out that ground water parameters (such as RCHRG_DP, GW_DELAY and ALPHA_BF) are highly sensitive to simulating quick flow. In this study, however, RCHRG_DP ($p = 0.01$) and GW_DELAY ($p = 0.01$) were sensitive to the base flow. This contradiction may be due to less forest cover and flatter topography (Me et al., 2015).

Very little improvement was achieved by the model parameterization, as most parameters revealed similar hydrograph response behaviour patterns. This may be due to lack of information concerning ground water processes and aquifer systems. In particular, natural and man-made water retention features such as dams and reservoirs, wetlands and water impoundments, are highly relevant to the hydrological regime. Incorporating these features into a model generally leads to a more accurate simulation of base and peak flow (Schmalz et al., 2008). This demonstrates that the inclusion of complete and good quality data (specifically, high resolution gridded data for rainfall; fine resolution of soil data; and land use data) is vital for achieving a good model calibration.

Based on the results, it appears that the GLC 2000 dataset may not accurately represent land cover during the calibration period (1985-1995). Therefore, this land use dataset is not ideal for quantifying the impacts of vegetation on stream flow, which would affect SWAT output. It is worth noting that results from the performance metrics for the validation period (R^2 = 0.80, NSE = 0.71) are very similar to the calibration period (R^2 = 0.73, NSE = 0.72). This may be because land use values more clearly approximate the validation period. However, I was unable to consider the impacts of landuse/landcover changes, such as effects of unplanned urbanization, conversion of unvegetated to vegetated cover and agricultural practices, which can alter surface runoff generation and soil erosion, thereby affecting hydrological processes throughout the catchment. For example, Mango et al. (2011) showed that conversion of forest to agriculture or grassland lead to a decrease in dry season flows and increased peak flows. Similarly, Guo et al. (2008) noted that forest destruction increased the potential for, as well as enhanced, drought impacts. I note that since 1960, the forest resources of Bangladesh have been reduced significantly as a result of deforestation (Haque and Karmakar, 2009), driven by the demand for food and fodder. According to FAO, approximately 2000 ha of forest cover in Bangladesh was lost between 2000–2005. This has caused drastic deforestation, particularly in the southeast region (Rasul et al., 2004), increasing soil erosion and accelerating land degradation.

Another factor that may modify the measured runoff is human intervention in the hydrological network, e.g. through canalization, construction of dams, sluices and reservoirs, wetlands and other water impoundments, and through water abstraction or diversion for irrigation. A large part of the upper Halda Basin can have very low flows or may even dry up during the dry season because of upstream water retention through construction of rubber dams (Kabir et al., 2013). In addition, at the confluence of the Halda-Karnafuli Rivers, there is an embankment (Kaptai Dam) with a reservoir (Kaptai Lake) positioned ~ 50 km upstream (Akter and Ali, 2012). Recently, the water level of the reservoir decreased tremendously, particular during the pre-monsoon season (Akter and Ali, 2012). Drainage and siltation, monsoon flood and additional siltation through hill erosion is now a common problem in this river zone. However, other studies have shown that upstream dam construction and diversion of streams for irrigation can also lead to poor model performance (see e.g. Schmalz et al., 2008; Setegn et al., 2010). Small-scale natural features such as wetlands and ponds can also influence upstream water retention and could help to explain the mismatch between simulated and measured high and low flows.

An additional source of uncertainty could be the 30 m ASTER DEM used in this study. Errors in this DEM may have resulted in lower slope estimates that reduce simulated peak flow. Since the watershed area directly influences surface runoff volume, a larger error in the watershed delineation may produce subsequent errors in the expected model output. Hence, Chaubey et al. (2005) suggested using use a finer resolution to minimize model uncertainty. For example, the use of a high resolution SPOT or Lidar derived DEM in conjunction with multi–spectral images may generate better land use information and improve model predictions.

Conclusion

I used a semi-distributed process-based hydrological model, SWAT, to understand the hydrological process of water balance in the Halda Basin, south-eastern Bangladesh. For the auto-calibrated model, calibration (R2 = 0.73, NSE = 0.72) and validation (R2 = 0.80, NSE = 0.71) using gauged flow data suggested fairly good agreement, except during peak flows. The auto-calibrated model largely captured the strong seasonal cycle of precipitation in this basin. However, the weakest elements of this model lay in its inability to adequately capture the contribution of ground water to stream flow and its underestimation of extreme precipitation events. Assigning sensitive model parameterizations and use of higher resolution input data may improve the application of the SWAT model to monsoon-driven data poor catchments. Future work should evaluate the relative importance of climate and land use changes in influencing the hydrology of the Halda Basin.

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Appendix

List of Appendices:

Table A1: Land use type reclassification into SWAT land use classes

Grid code	GLC2000 Land use class	LU SWAT CODE	Area (%)
11	Shrub cover evergreen	RNGE (Range-brush)	38.61
12	Shrub cover deciduous	RNGB (Range-brush)	11.78
16	Cultivated managed area	AGRC (Agricultural land close grown)	41.13
17	Mosaic cropland /Tree cover	AGRL (Agricultural land generic)	9.48

Table A2: Soil types and their assigned properties used in the model

Soil type	Hydrography	Texture	Maximum rooting depth (mm)	Available water capacity (mm H_2O/mm soil)	Moist bulk density (mg/m^3)	Clay (%)	Silt (%)	Sand (%)
Gleysol	C	Loam	1000	0.18	1.38	23	40	37
Cambisol	B	Loam	1000	0.12	1.41	20	39	41
Acrisol	B	Sandy loam	1000	0.14	1.58	10	12	78

Table A3: Summary of water balance ratio

Water balance Ratios	Before Calibration	After Calibration
Streamflow/Precipitation	0.81	0.78
Base flow/Total flow	0.31	0.65
Surface runoff/Total flow	0.69	0.40
Percolation/Precipitation	0.27	0.50
Deep recharge/Precipitation	0.01	0.03
ET/Precipitation	0.17	0.18

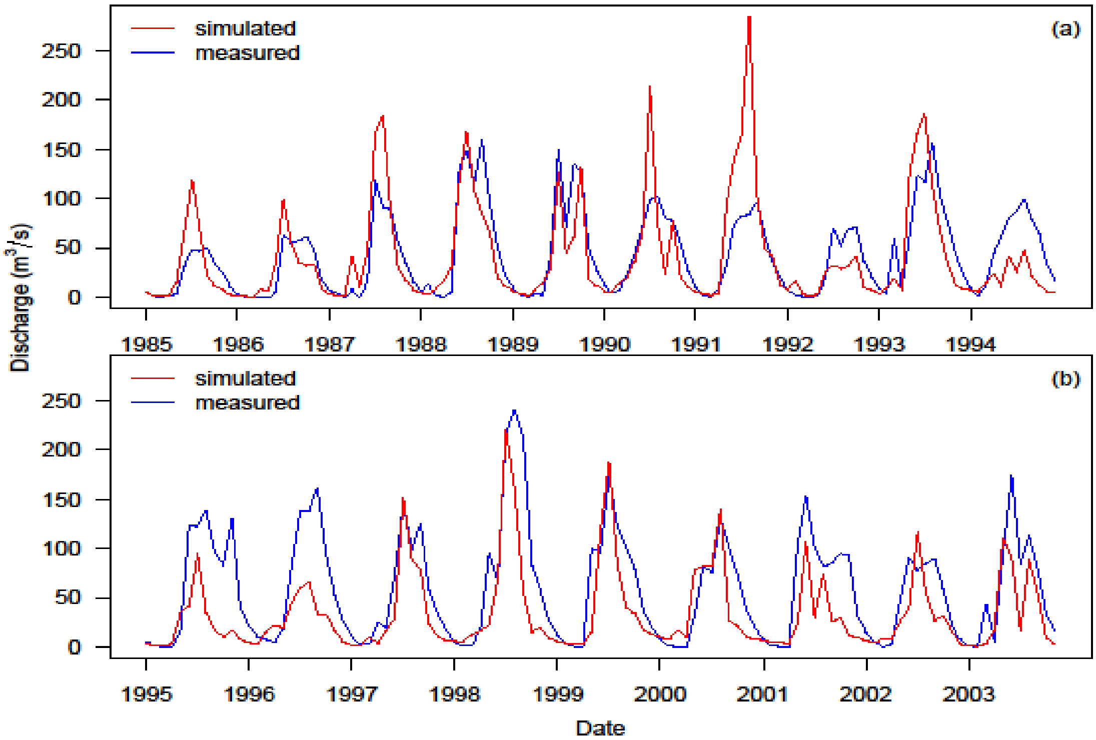


Figure A1: Monthly simulated and measured stream flow(m^3/s) over modelling period using CFSR climate data.

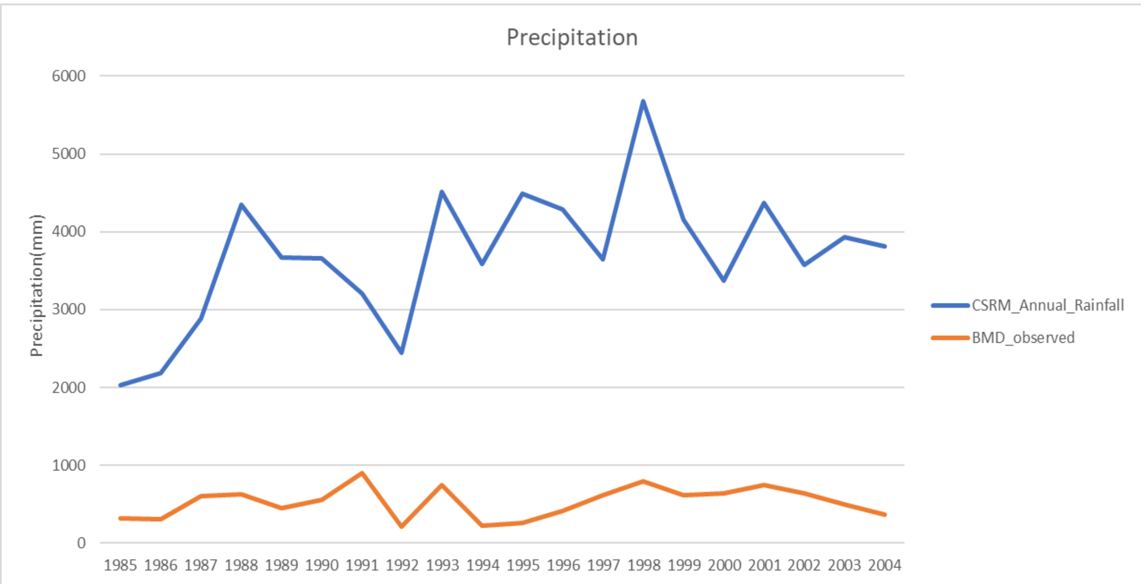
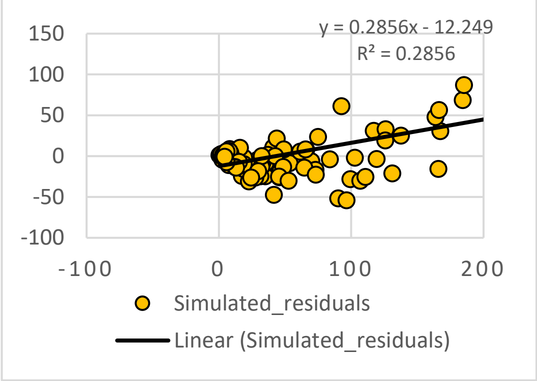
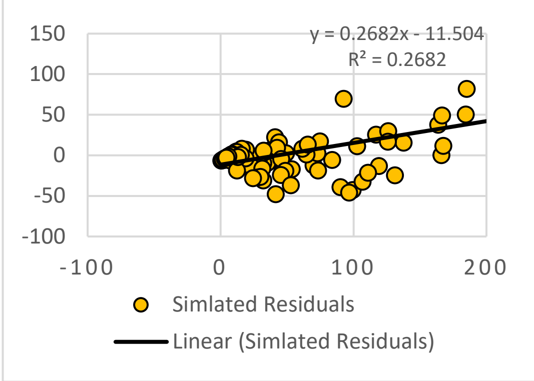


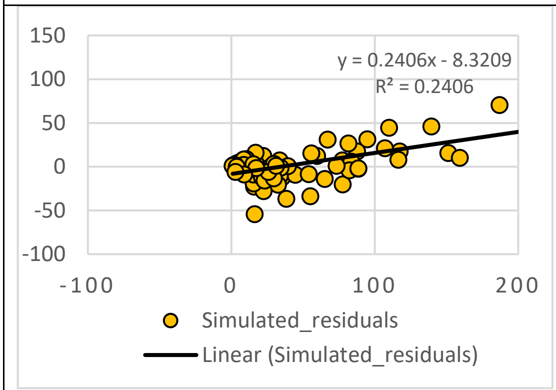
Figure A2: Comparison in time between BMD and CFSR climate data



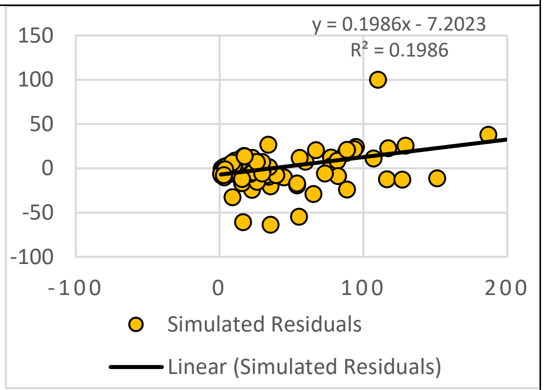
a. Before auto-calibration (1985–1994)



b. After auto-calibration (1985–1994)



c. Validation without modification (1995-1994)



d. Validation with modification (1995–2004)

Figure A3: Plots showing residuals from the seasonally detrended measured and simulated monthly, to show the impact of the seasonal cycle on model performance. The interval 1985–1994 was used for autocalibration, and the model was applied to the period 1995–2004 without further modification. The plots show results for the period 1985–1994 (a) before calibration and (b) after calibration, and for the period 1995–2004 (c) validation without modification and (d) validation with modification from the calibrated model.

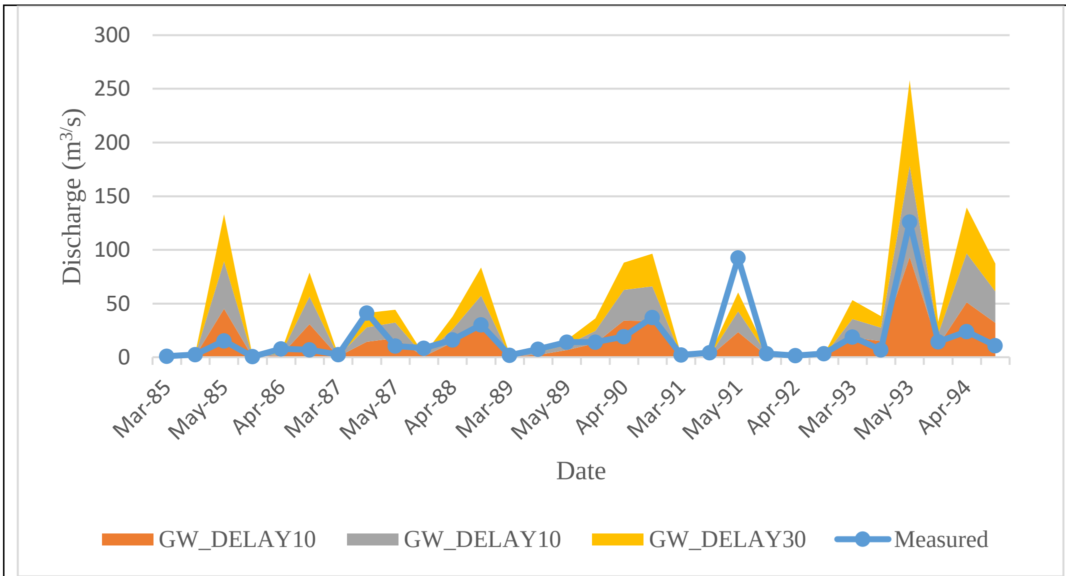


Figure A4: Comparison of parameterization of ground water delay (GW_DELAY) after manual calibration for the period 1985–1994.

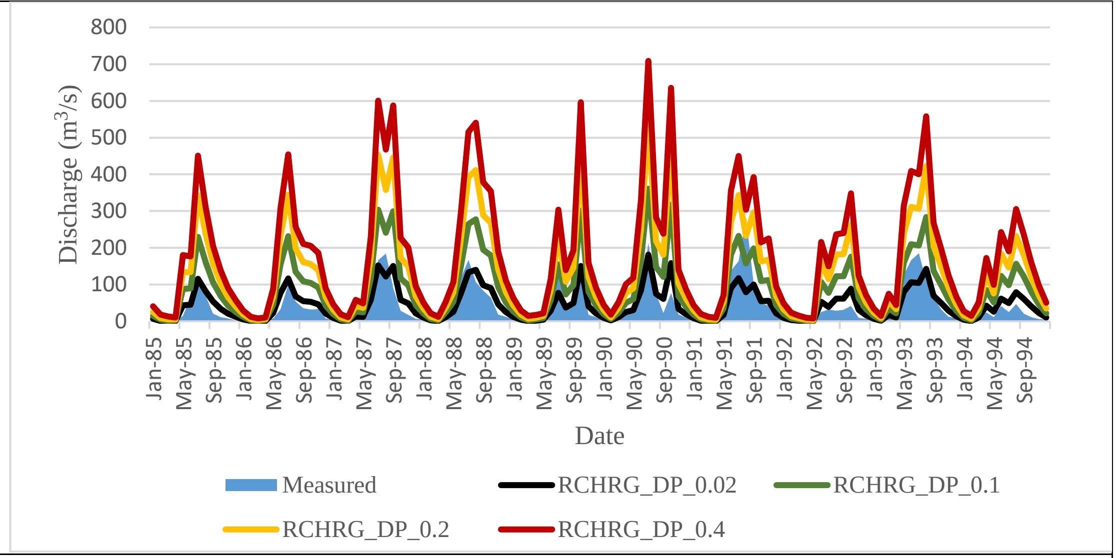


Figure A5: Comparison of parameterization of aquifer percolation coefficient (RCHRG_DP) after manual calibration for the period 1985–1994.

CHAPTER 4: COMBINED IMPACTS OF FUTURE CLIMATE AND LAND USE CHANGES ON STREAM FLOW IN THE UPPER HALDA BASIN, BANGLADESH

Abstract

Water resource management and land use changes are intrinsically linked and have received extensive attention in their prospective modelling domains. In this study, a SWAT model associated with a Land Cover Model (LCM) model is used to simulate streamflow in the Halda Basin under future land use and climate scenarios, and to assess the separate and combined impacts of both types of change on projections of future streamflow. Despite uncertainties in future projections, this study indicates that the Halda Basin is expected to become warmer in future, with more precipitation during the dry season but less in the monsoon. By the 2060s, maximum temperature is projected to be up to 1.6°C warmer than the baseline period. Minimum temperature is also projected to increase across the 21st century, although at a lower rate than maximum temperature. Simulations also show that climate change is likely to increase future streamflow in the Halda River. Monthly streamflow changes were influenced mainly by the variability in precipitation. Results shows that the simple LCMs projected decreases in the area of grassland along with cultivated land, at the expense of artificial surfaces. Combined, future climate and land use changes are projected to result in increases in annual streamflow, although results indicate that climate change is likely to be a greater driver of changes in streamflow than land use changes.

Introduction

Water security is one of the most challenging issues of the 21st century (Simonovic, 2003), with global warming resulting in an intensification of the hydrological cycle (IPCC, 2013) shifting the timing and distribution of freshwater resources (Kundzewicz *et al.*, 2008). Indeed, recent changes in the balance between precipitation, runoff and evapotranspiration have been attributed to anthropogenic climate change (Zhang et al., 2012).

Developing countries are particularly vulnerable to adverse effects of climate changes, due to their low capacity for adaptation and mitigation, high population density and poverty. This includes Bangladesh, one of the most densely populated countries in the world. The rapid population growth and economic development of this country has resulted in excessive withdrawal of freshwater supplies causing water scarcity issues. This, in turn, has aggravated food shortages leading to adverse impacts on human and ecosystem health (Gain and Wada, 2014). Additionally, Bangladesh experiences strong climate variability with alternate periods of floods or drought which exacerbate water crises. As such, more effective monitoring of fresh water dynamics is vital for the management of river basins and reconciliation of water availability and demand.

Since hydrologic conditions differ from place to place, the influence of climate change on local hydrological processes will be expected to vary between neighborhoods even under the same climate scenarios (Zhang *et al.*, 2007). Hence, quantifying the impacts of climate change on water resources and understanding links to climate variability and anthropogenic pressure has emerged as a major area of research (Papa *et al.*, 2015).

Water resource management and land use changes are intrinsically linked. Water resources are dependent on vegetation state and function, which is affected by environmental change (Ukkola, 2015). Approximately 40% of the earth's land surface has been altered by humans, substantially reducing the world's natural vegetation cover by clearing woody vegetation for the expansion of cropland and pasture (Sterling and Ducharne, 2008). In addition, land use activities (such as farming, grazing, logging, tree planting and urbanization) alter hydrological process, exerting impacts on the hydrological cycle by transforming water flow pathways and, therefore, have the potential to affect water resource management (Chhabra *et al.*, 2006; Stonestrom *et al.*, 2009). Generally, runoff increases with the growth of built up areas and decline of natural vegetation, whereas higher water demand and corresponding water withdrawal results in decreases to runoff (Arnold and Gibbons, 1996; Foley *et al.*, 2005; Wijesekara *et al.*, 2012).

To date, numerous studies have assessed the impact of land use changes on water resources (Aichele, 2005; Tang *et al.*, 2005; White and Greer, 2006). However, comparatively few studies have assessed the combined effects of climate and land use changes on hydrology (Guo *et al.*, 2008; Ma *et al.*, 2009; Tu, 2009). As such, determining the relative contribution of these two drivers to changes in hydrological cycles is an important challenge for researchers and policy makers (Ma *et al.*, 2009).

The recent integration of Soil and Water Assessment Tools (SWAT) with land use simulation models (Dixon and Earls, 2012; Shi *et al.*, 2011; Wilson and Weng, 2011) provides an approach to assessing the impact of alternate land use and land cover (LULC) scenarios on hydrology. Furthermore, SWAT has demonstrated its capability in different parts of the world to assess the impacts of land use changes (e.g., Ghaffari *et al.*, 2010; Miller *et al.*, 2002), climate change (e.g., Jha, 2010; Liu *et al.*, 2011) or both simultaneously (e.g., Kim *et al.*, 2013; Li *et al.*, 2009; Mango *et al.*, 2011; Tu, 2009). But in Bangladesh little work has been undertaken on the use of hydrological models to develop management plans for river basins. The Halda Basin, southeastern Bangladesh, is an ecologically sensitive area that has experienced rapid deterioration of water quality and aquatic life. Over the past three decades, the southern region of this basin has experienced a significant increase in total precipitation, total number of rain days, and maximum daily temperature (Raihan *et al.*, 2015). Additionally, the catchment hydrology of this region is being impacted through different man-made interventions (Akter and Ali, 2012).

Here, I apply the SWAT model to simulate streamflow in the Halda Basin under future land use and climate scenarios, and assessed the separate and combined impacts of these scenarios on projections of future streamflow.

Study area and Data

Study area

Halda Basin (Figure 1), located in southeastern of Bangladesh, is one of the most important river basins in Chittagong, and is fed by several hilly streams starting at its origin and 12 tributaries located in the downstream reaches. The basin is a primary spawning ground for Indian major carps (Kibria, 2011), and a key source of drinking water in the surrounding region. The Halda River is currently experiencing substantial alterations to its flow pattern due to the construction of a rubber dam, rapid urbanization and industrialization, and increases in agriculture within the basin (MoFL, 2016). Subsequently, its rate of water discharge has declined, particularly in the dry season. To date, no scientific study has been conducted to investigate the impact of future climate and land use changes on the Halda Basin.

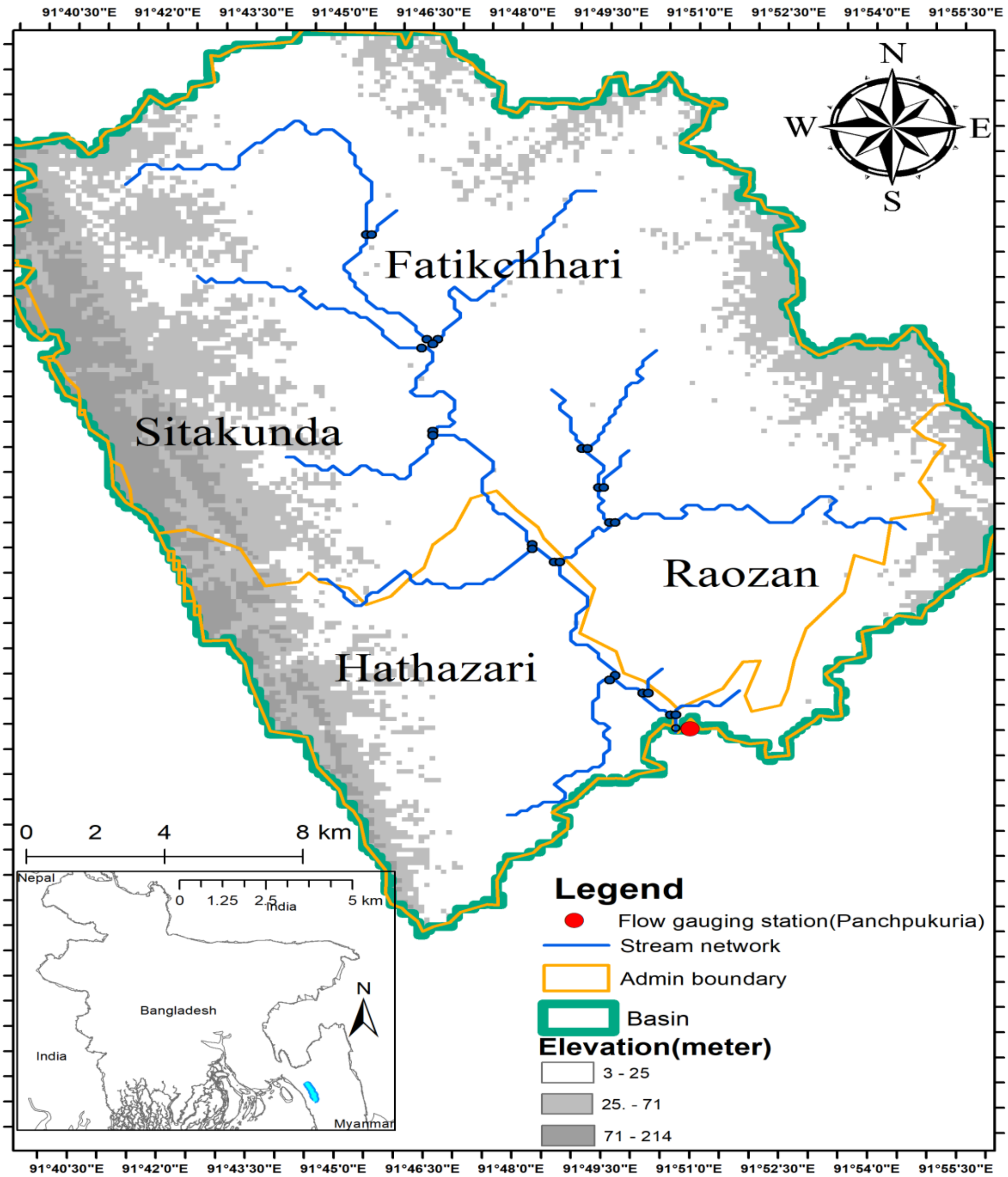


Figure 1: Location of the study area. The inset map shows the stream network of the Halda Basin. Map of Bangladesh in context to South Asia is shown in the index.

Data sources and methods

Imminent environmental change is anticipated to alter the global hydrological cycle, with consequences for the regional distribution of fresh water supplies. Regional precipitation and temperature projections however, differ largely between models, making future water resource projections highly ambiguous. Therefore, I used future climate scenarios from two representative concentration pathways (RCP 4.5 and 8.5) and five regional climate models (RCM) (Table 1). RCP 4.5 is an intermediate scenario where radiative forcing (RF) stabilizes at 4.5 W m^{-2} by 2100, and atmospheric CO_2 concentration reaches 576 ppm (ensemble average) by 2080, after which it stabilizes (Clarke *et al.*, 2007). RCP 8.5 is an extreme trajectory where RF reaches 8.5 Wm^{-2} and atmospheric CO_2 concentration 1231 ppm by 2100 (Riahi *et al.*, 2007).

A five-member ensemble of projected daily precipitation (*prec*) and daily maximum/minimum temperature (*tmax* and *tmin*, respectively) data was collected from the Coordinated Regional Climate Downscaling Experiment (CORDEX) South Asia domain database (http://cccr.tropmet.res.in/home/ftp_data.jsp). CORDEX is a program sponsored by the World Climate Research Program (WCRP) to produce an improved generation of regional climate change projections. CORDEX contains high resolution data between 1971 and 2100 with a grid resolution of 0.5° latitude x 0.5° longitude. Projections were generated by a combination of global climate model (GCM) and RCM output. Although data from 11 climate models are included in CORDEX, I selected only five based on data availability and homogeneity (Table 1).

After downloading the RCMs, I corrected for bias before analyzing projected precipitation and temperature. The reference dataset used for bias correction was a hybrid dataset of Watch Forcing Data (WFD) (Weedon *et al.*, 2010) and Watch Forcing Data methodology applied to ERA Interim data (WFDFI) (Weedon *et al.*, 2014). These RCM experiments are listed in Table 1.

Table 1: List of Regional Climate Models (RCMs) and of their associated Global Climate Models (GCMs) used in this study.

Institute	Name	GCM	RCM	Reference
Commonwealth Scientific and Industrial Research Organisation, Australia	Australian Community Climate and Earth System simulator	ACCESS1.0	CCAM-1391M	(Bi *et al.*, 2013)
National Centre for Atmospheric Research	The Community Climate System Model	CCSM4.0	CCAM-1391M	(Gent *et al.*, 2011)
National Centre for Meteorological Research	Coupled Global Climate Model Version-5	CNRM-CM5	CCAM-1391M	(Voldoire *et al.*, 2013)
Max Planck Institute for Meteorology	Max Planck Institute for Meteorology-Earth System Model	MPI-ESM-LR	CCAM-1391M	(Giorgetta *et al.*, 2013)
Irish Centre for High-End Computing, EC-Earth Consortium	Irish Centre for High End Computing	ICHEC-EC-EARTH	RCA4	(Samuelsson *et al.*, 2011)

Bias Correction of the RCM outputs

Numerous bias correction methods have been developed and improved for local climate studies (Jakob Themessl *et al.*, 2011) to reduce uncertainty from different climate models (Chen *et al.*, 2011; Johnson and Sharma, 2012). These methods range from simple scaling to more sophisticated approaches (Teutschbein and Seibert, 2012). For this study, I used the delta method for temperature (Hay *et al.*, 2000) and quantile mapping (QM) (Sun *et al.*, 2011; Wood *et al.*, 2004) for precipitation. For bias correction, the reference period 1981–2010 was considered.

In the delta method, the climate change signal (i.e. the delta or anomaly) is applied to the baseline climate to simulate future time periods based on the use of a change factor (Hay *et al.*, 2000). In this approach, daily variability is assumed to be of the same magnitude in the future and reference periods. The advantage of the delta method is that it is relatively straight-forward to apply and can be applied to the full range of available non-stochastic variables (i.e. temperature). However, it cannot be applied to non-normal distributions, i.e. daily precipitation, and cannot account for changes in the length of dry and wet spells or extreme events (Trzaska and Schnarr, 2014).

To ensure realistic daily and inter-annual variability, QM was used for daily precipitation (Jakob Themessl *et al.*, 2011). QM has been successfully used for hydrologic and many other climate variables to adjust the distribution of modeled data (Sun *et al.*, 2011; Wood *et al.*, 2004). QM mostly accounts for all statistical moments (i.e. standard deviation or percentile rather than only corrected daily mean values) and can remove the systematic bias in the simulation (Teutschbein and Seibert, 2012).

Projection of Landcover change

I obtained the landcover maps for the years 2000 and 2010 from Global Landcover Dataset (www.globeland30.org). The main land-use types of the two time periods were: Cultivated land, Forest, Grassland, Waterbodies, and Artificial surfaces. I used the Land Change Modeler (LCM) module in TerraSet application (Clark Labs 2016) to analyze land use changes that occurred between 2000 and 2010, and to forecast future land uses for the periods 2020, 2040 and 2060. LCM consists of a transition potential sub-model (to assess drivers of land use changes over the baseline period) and a change prediction model (a multi-layer Perception Markov Chain Model (MLP_ Markov) (Figure 2). Initially, the net gain and loss of each land cover category across the two historical time periods was assessed.

In LCM, constraints are the criteria that bound the development of built up land use. Physical constraints can be existing built up area, water bodies, road network etc. Here in land projections we considered slope, distance to roads and railways, and population growth as potential drivers of any changes for the transition sub-model. Next, the change prediction model forecasted the allocation of land cover for each of the future time periods. This approach is summarized in the flow chart in Figure 2.

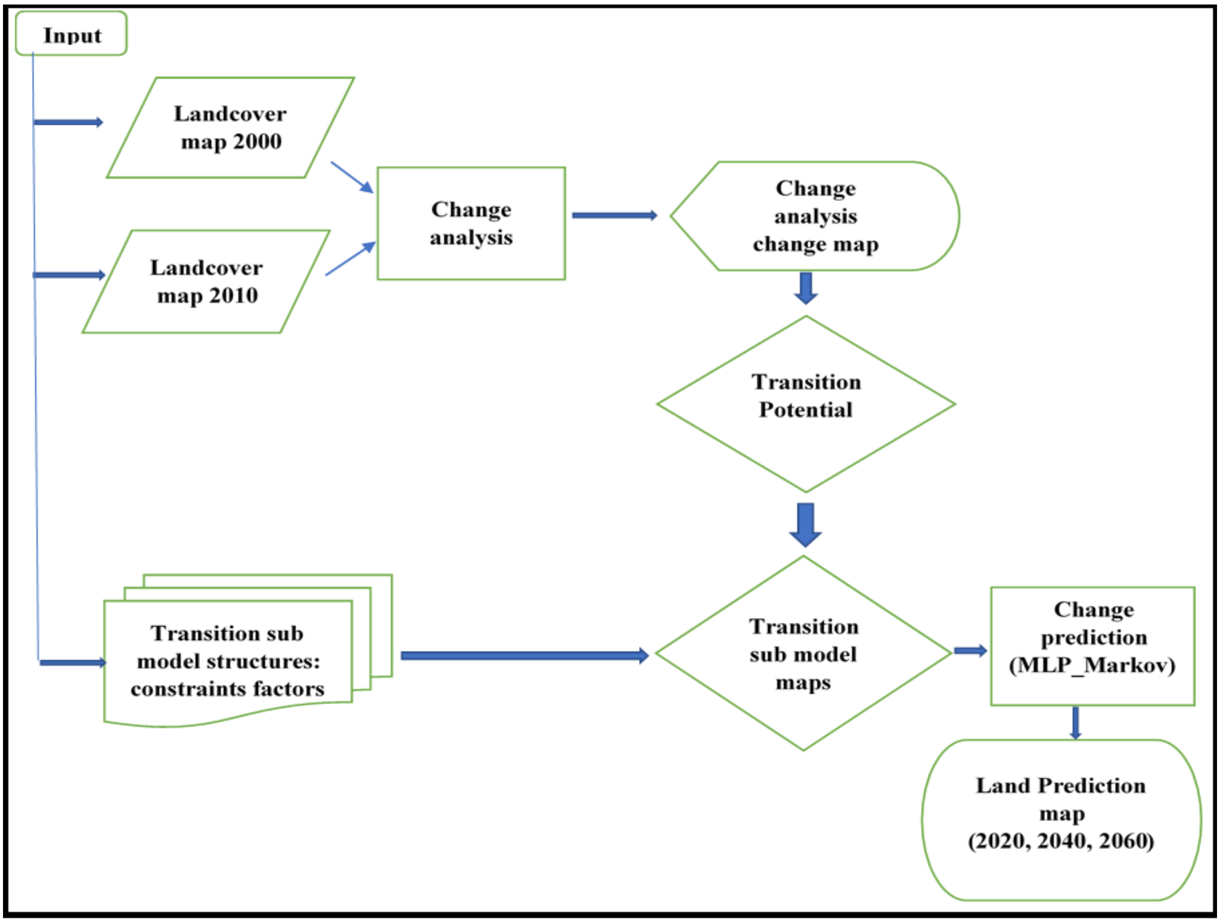


Figure 2: Schematic diagram of the Land Change Model used to forecast future land use across the Halda Basin, Bangladesh.

Hydrological modeling

In this study, the Soil and Water Assessment Tool (SWAT, Arnold et al., 1998) was used to assess the impact of climate and land use changes on water resources across the Halda Basin. In a previous study, I assessed the suitability of the SWAT model for simulating stream flow in this basin (Chapter 3). Since details of the model set up and data input were discussed in Chapter 3, here I provide only a summary of the approach. The ArcGIS v10.1 interface of SWAT (ArcSWAT version, 2012) was used to derive the parameters controlling hydrologic processes in the Halda River Basin. The basic input data required for SWAT are elevation, soil map, land use/landcover map, and weather data (see Table 2). The total drainage area of the basin (569 km^2) was divided into 25 sub-basins and 482 Hydrological Response Units (HRUs).

Table 2: Data used in the SWAT model in this study

Input Data	Scale/Resolution	Sources
DEM (Digital Elevation Model)	30 m	ASTER http://asterweb.jpl.nasa.gov/gdem-wist.asp
SOIL	1km	Water Resource Planning Organization, Bangladesh (WARPO).
LANDUSE	1km	GLC2000 http://geodata.grid.unep.ch/options.php
WEATHER (Daily precipitation, maximum and minimum temperature)	0.44°(~50km)	(http://cccr.tropmet.res.in/home/ftp_data.jsp)

For simulating future discharge, the SWAT model was run at daily steps from 2006 to 2070 with RCP 4.5 and 8.5 scenarios of bias corrected daily *tmax* and *tmin* and p*rec* data. To determine the relative importance of climate and land use change and their combined effect on streamflow, I generated two sets of simulations: a) a climate change-only simulation (CC) and b) and climate and land use change simulation (CC+LUC). I then calculated the ratio of streamflow from the CC simulation compared to the CC+LUC simulation to calculate the portion of streamflow arising from land use change only.

Linear regression between simulated streamflow's and year was undertaken to determine whether there were trends in the simulated data (Blender *et al.*, 2003). I used a 95% cutoff for significance, i.e. the probability of accepting the null hypothesis of no change is < 0.05.

Results and Discussion

Future temperature and precipitation changes

The change in mean daily *tmax* and *tmin* for the period 2006 to 2070, relative to 1986 to 2005, was calculated for all five RCM experiments under the RCP 4.5 and 8.5 scenarios (Figure 3). Monthly *tmax* is projected to increase across all months under both RCPs. By the 2060s, *tmax* is projected to be 0.95°C and 2.3°C warmer than the baseline period under RCP 4.5 and 8.5, respectively (Table 3). Although the increase under RCP 4.5 is relatively consistent across all months, under the higher emission pathway (RCP 8.5) winter temperature (December-February) is projected to increase slightly faster.

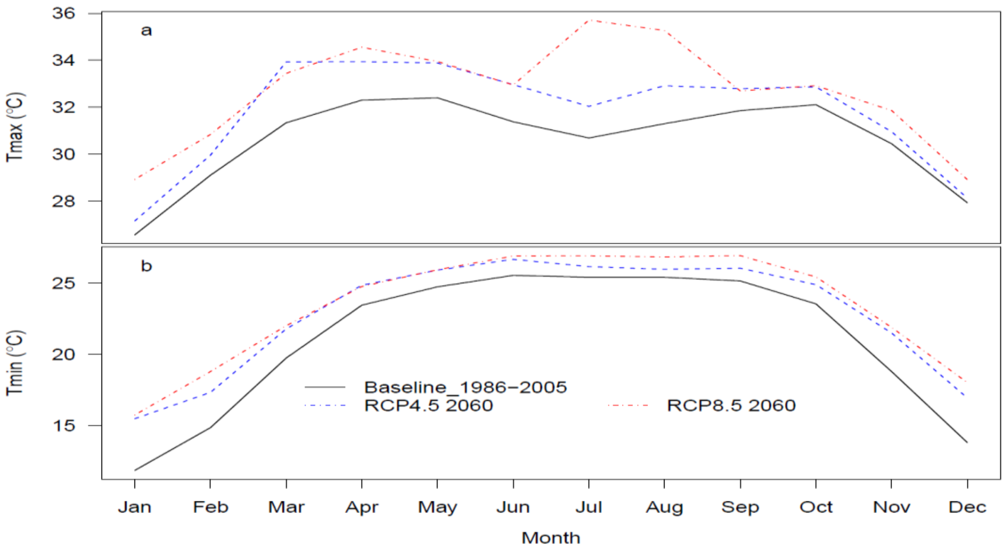


Figure 3: Mean monthly multi-model future temperature projection for RCP4.5 and 8.5 scenarios.

Tmin is also projected to increase across the 21st century, although at a lower rate than *tmax*. By the 2060s, *tmin* across the Halda Basin is likely to be 0.95-1.3°C warmer than the baseline period (Table 3). Rates of increase are relatively uniform across all months under both RCPs.

The analysis of the decadal mean air temperature shows interdecadal variability (Table 3). *Tmax* is projected to increase most rapidly from the baseline to the 2030s under RCP 4.5, to 1.5°C above the baseline. In contrast, *tmin* is projected to continue to rise until at least the 2060s. Under RCP 8.5 both *tmin* and *tmax* are projected to continue rising until at least the 2060s. Similar findings were also projected by Schewe and Levermann (2012), i.e. that Southeast Asia will face an increase in temperature through to the late 21st century, which will cause frequent changes and shifts to monsoon precipitation.

Table 3: Inter-decadal variability of temperature changes (°C) relative to the baseline 1986-2005, for RCP4.5 and RCP 8.5 scenarios. Results are based on the average of a five-member regional climate model ensemble.

Decade	Tmax4.5 (mean) (°C)	Tmin4.5 (mean) (°C)	Change Tmax4.5 (°C)	Change Tmin4.5 (°C)	Tmax8.5 (mean) (°C)	Tmin8.5 (mean) (°C)	Change Tmax8.5 (°C)	Change Tmin8.5 (°C)
Baseline	30.6	21.0	NA	NA	NA	NA	NA	NA
2010-2019	31.0	22.0	0.4	0.9	30.7	22.1	0.1	1.1
2020-2029	32.0	22.0	1.4	1.0	31.1	22.2	0.5	1.1
2030-2039	32.1	22.0	1.5	0.9	31.5	22.2	0.9	1.2
2040-2049	31.5	22.0	0.9	0.9	31.7	22.3	1.1	1.2
2050-2059	31.7	22.0	1.0	0.9	32.3	22.3	1.6	1.3
2060-2069	31.6	22.0	1.0	0.9	32.9	22.3	2.3	1.3

Annual precipitation during the baseline period averaged 3225 mm p.a. (± 609 mm). Precipitation over the monsoon period (June-September) averaged 565 mm (± 128 mm) per month. In contrast, during winter (December-February), the driest part of the year, total precipitation over the baseline period averaged 13 mm per month (± 12 mm).

Averaged across the five RCMs, annual precipitation for both RCP scenarios is projected to decrease ~231 mm from the baseline (269 mm), although there is some variability in projections for the monsoon period (Figure 4). Future declines in precipitation were also reported by Islam (2009) who used PRECIS RCM to model temperature and rainfall scenarios in Bangladesh.

By the 2060s, annual precipitation is projected to decline ~234 mm compared to the baseline period (i.e. 13% decrease) (Table 4). Precipitation during the monsoon period (June-September) is projected to be an average 16% per month lower than the baseline monsoon (565 mm). Conversely, precipitation is projected to increase ~108% (14 mm) during the dry months relative to the baseline. These results are consistent with other studies in Bangladesh. Pervez and Henebry (2015) reported projected increases in precipitation from dry months (November through January) by 2075, in the Brahmaputra Basin, Bangladesh. Similarly, Rajib *et al.* (2011)

argued that dry months will experience higher increases in precipitation compared to the monsoon period. My results also indicate that while the quantity of annual precipitation may decline, the overall number of wet days (if > 0.9 mm) is projected to increase (baseline = 133; 2060s, RCP 4.5 = 200, RCP 8.5 = 286).

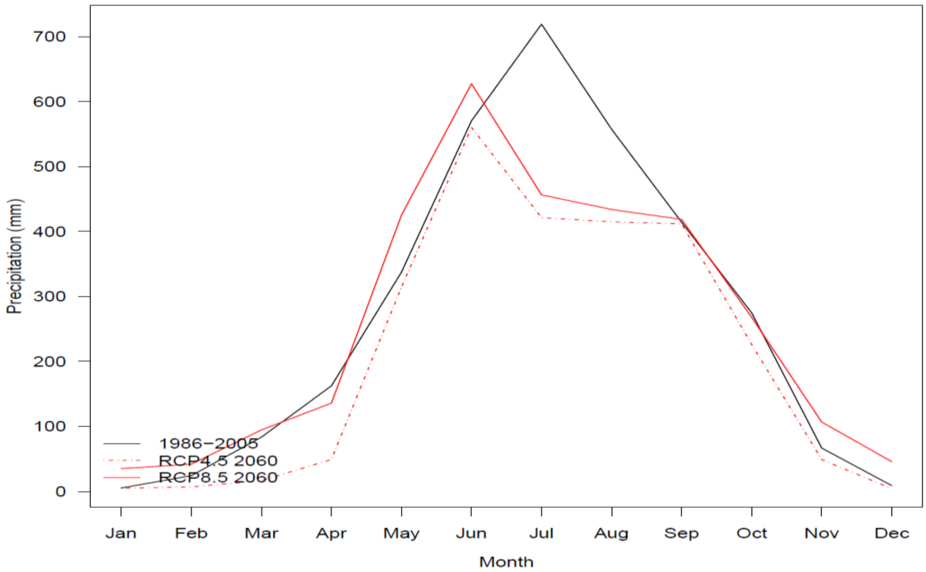


Figure 4: Projected mean monthly precipitation for 2060-2069 compared to the average of baseline 1986-2005.

Table 4: Inter-decadal changes in monthly precipitation compared to the baseline period 1986-2005.

Descriptive statistics	**Baseline**	**2010-2019 (mm)**	**2020-2029 (mm)**	**2030-2039 (mm)**	**2040-2049 (mm)**	**2050-2059 (mm)**	**2060-2069 (mm)**
Mean	268.7	235.5	226.8	227.0	234.2	237.8	234.2
Median	218.6	230.8	223.4	223.4	235.4	239.0	233.1
Maximum	719	256.3	258.6	255.3	252.1	251.9	245.1
Minimum	5.4	213.8	216.4	201.5	213.3	219.0	225.4
Std. Dev.	249.7	15.8	12.1	16.7	12.3	11.9	6.7

Impact of climate change on streamflow

Annual, monthly and seasonal streamflow was calculated for the period 2006-2070 under both RCPs, while retaining land use conditions for the year 2000 (Figure 5). Averaged annual streamflow across the Halda River Basin is projected to increase during the 21st century, compared to the baseline period 1986-2005 (562 m^3/sec). Based on changes in climate projected under RCP 4.5, simulated results indicate that annual streamflow will continue to increase through to at least 2060 (i.e. ~ 674 m^3/sec). While RCP 8.5 simulates a major increase in annual streamflow by 2020 (i.e. from 562 m^3/sec to 673 m^3/sec), a decline is projected to occur at some point between 2020 and 2040, and continue until at least 2060 (643 m^3/sec).

Considerable differences for monthly streamflow trends were found. The greatest increase in monthly streamflow for the 2060s is projected to occur in February (16 m^3/sec for RCP 4.5 and 12 m^3/sec for RCP 8.5, representing a 633% and 469% increase under these scenarios respectively (Figure 5), relative to the baseline of 2.2 m^3/sec). In contrast, July is projected to have the greatest decline, i.e. -21% (97 m^3/sec) and -24% (94 m^3/sec) for RCP 4.5 and 8.5, respectively. On a seasonal basis, these represent an increase in streamflow during the dry season of 134% and 110% for RCP 4.5 and 8.5, respectively, by 2060. In contrast, streamflow during the monsoon season is projected to decline by -8% (RCP 4.5) to -13% (RCP 8.5). These results are contrary to other hydrological studies for this region (e.g., Imerzeel 2008, 2010, 2014). This could be because the resolution of the RCM is too coarse for a small basin, and therefore does not capture the behavior of land atmosphere dynamics. Further uncertainties could be associated with local scale patterns in downscaling or bias in the modelled precipitation (Akhtar et al., 2009)

Masood *et al.* (2015) also argued that future changes of hydrological variables are larger in the dry season (likely because small absolutely changes during the dry season convert to large proportional changes). These results of increasing streamflow in dry months are also consistent with the simulations for the Brahmaputra River Basin reported by Pervez and

Henebry (2015) and Alam *et al.* (2016). To summarize, SWAT models indicate that, as a result of changes in precipitation, the Halda Basin will experience lower streamflow in monsoon, thus reducing flood potential in the wet season.

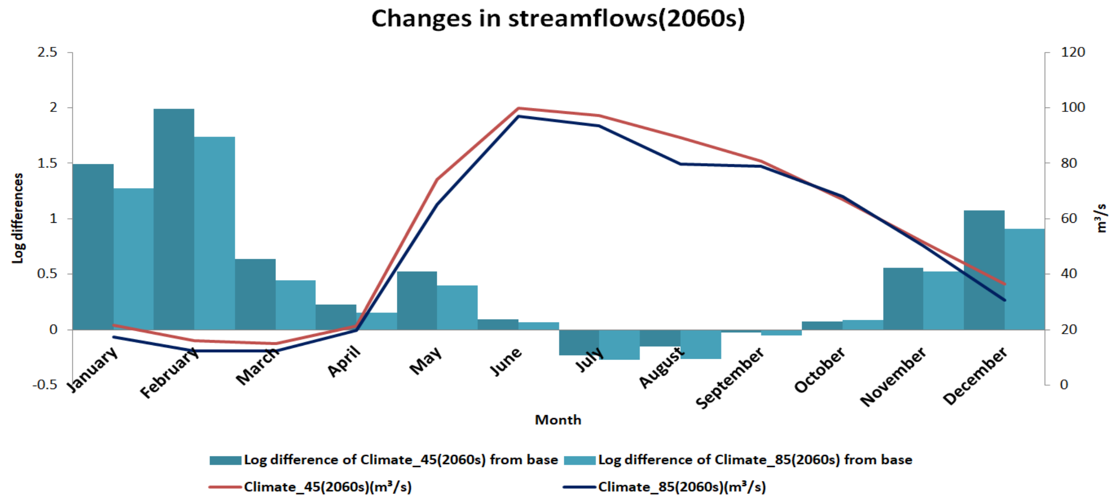


Figure 5: Projected changes in monthly streamflow under RCP 4.5 and 8.5 climate scenarios for the decade 2060-2069. Logarithmic differences represent the change from the base line (1986-2005).

Climate scenarios for this study were derived from five regionally downscaled RCMs and can show substantial variation across projections of precipitation. As such, streamflow may also vary depending upon which alternate future eventuates. Correlations of streamflow and year based on data from individual RCMs can highlight some of these between-model differences (Figure 6). Indeed, there are substantial differences among some of these models, which could result in very different outcomes in terms of streamflow, depending on which ‘future’ eventuates. For instance, CSSM_4.5 for the pre-monsoon season has a period of very little change in streamflow spanning almost 30 years, followed by an abrupt increase around 2040. In contrast, IHEC4.5 has substantial inter-annual variability up until around 2050, after which there is much less variability in both the monsoon and pre-monsoon periods. IHEC 8.5 has several years with anomalously high pre-monsoon streamflow. Most of the models produce year to year variability.

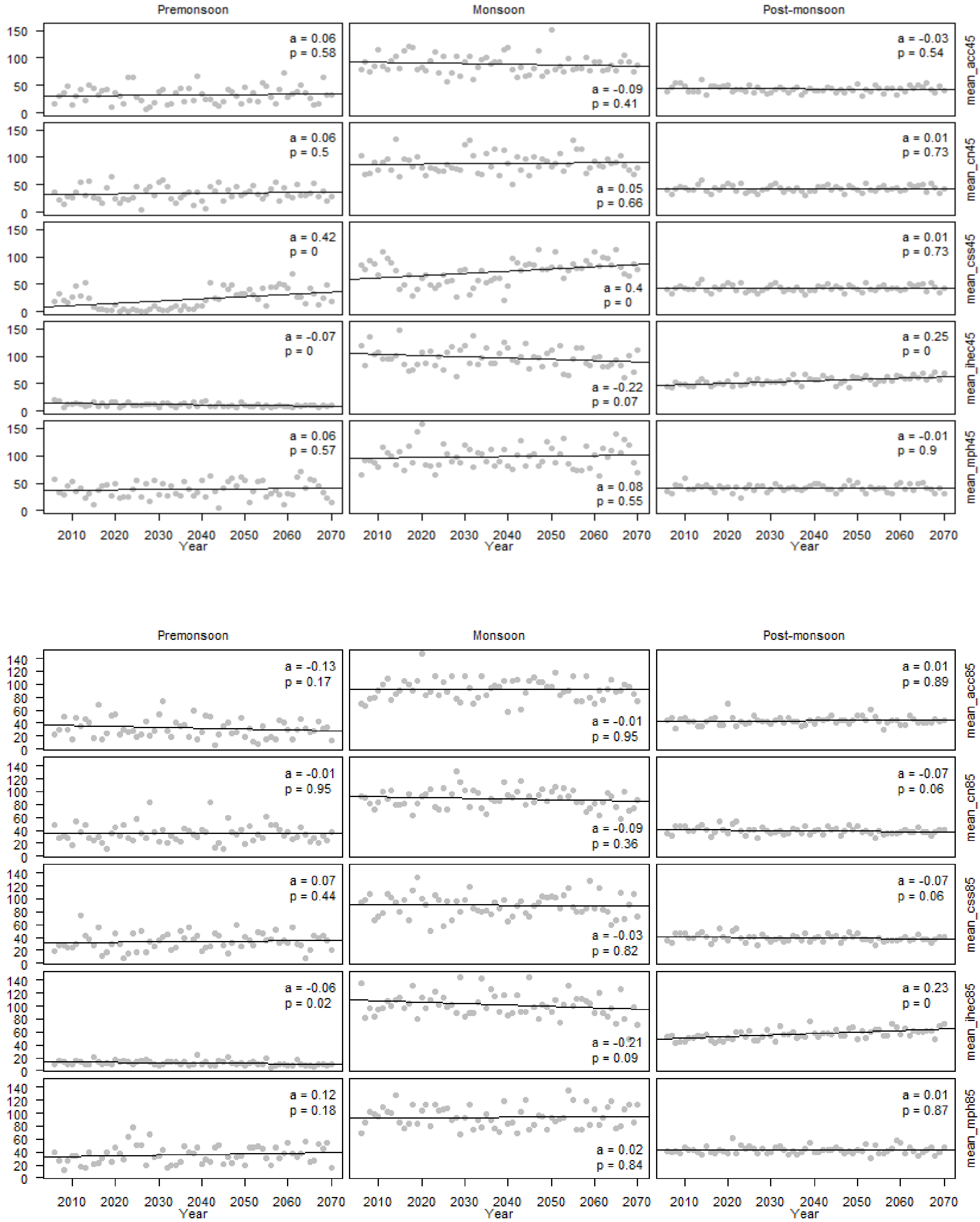


Figure 6: Trends in stream flow for the future periods under RCP 4.5 (top) and RCP 8.5 (bottom) scenarios showing pre-monsoon (Mar-May) and monsoon season (Jun-Sep) and Post monsoon (Oct-Feb).

Impact of land use changes

The Halda River Basin covers 569 km^2. Across this area, the primary LULC category as of 2000 was cultivated land (311 km^2), followed by forest (176 km^2), artificial surfaces (64.5 km^2), followed by grassland (16.1 km^2) and waterbodies (0.6 km^2) (Table 7).

Table 7: Land use change in Halda River basin between 2000 and 2010, and the area projected for each land use category for 2020, 2040 and 2060

Land type	2000 (km^2)	2010 (km^2)	Change (%)	2020 (km^2)	2040 (km^2)	2060 (km^2)
Artificial surfaces	64.5	106	64.2	136.4	175.3	197.6
Cultivated land	311.3	273.7	-12.1	242.9	203.9	181.5
Forest	175.6	174.1	-0.9	174.1	173.8	173.8
Grass	16.1	14.1	-12.8	14.6	15	15
Waterbody	0.6	0.4	-38.7	0.4	0.4	0.4

During the period 2000 to 2010, substantial changes in LULC took place across the Halda Basin. Generally, the trend was conversion of grassland to forest and of grassland, cultivated land to settlement or artificial surfaces and forest (Figure 7). The changes were mainly caused by government reforestation policy, which led to spatial shifts in forests (with little overall increase in area) and decreases in grassland and cultivated land. The key changes and transitions were mostly found in artificial surfaces from cultivated land and grassland and vice versa. Indeed, artificial surfaces increased from 64.5 km^2 in 2000 to 106.0 km^2 in 2010.

Using the LCM, I created a map of the areas of land that underwent transitions. Different constants or time dependent driver variables, such as slope, distance from road, railways, population, were added as the transition sub-model. Multi-layer Perception Markov Chain Model (MLP Markov) was offset by gains elsewhere (via conversion of previously cultivated or built up areas), resulting in a net change of -0.03%. Cultivated land lost 15.20% to forests and artificial surfaces, and gained 4.04%, with a net change -3.65%. I then used these changes to projected future land use and land cover maps for the years 2020, 2040 and 2060 (Table 7; Figure 8).

This model suggests that artificial surfaces will continue to expand at the expense of other land cover categories. Due to urbanization and industrial development, the percentage of artificial surfaces is projected to increase 206% (from 64.5 km^2 in 2000 to 197.6 km^2 in 2060) whereas cultivated land is projected to decline 42% (2000: 311.3 km^2; 2060: 181.5 km^2) and waterbodies 35% by the year 2060.

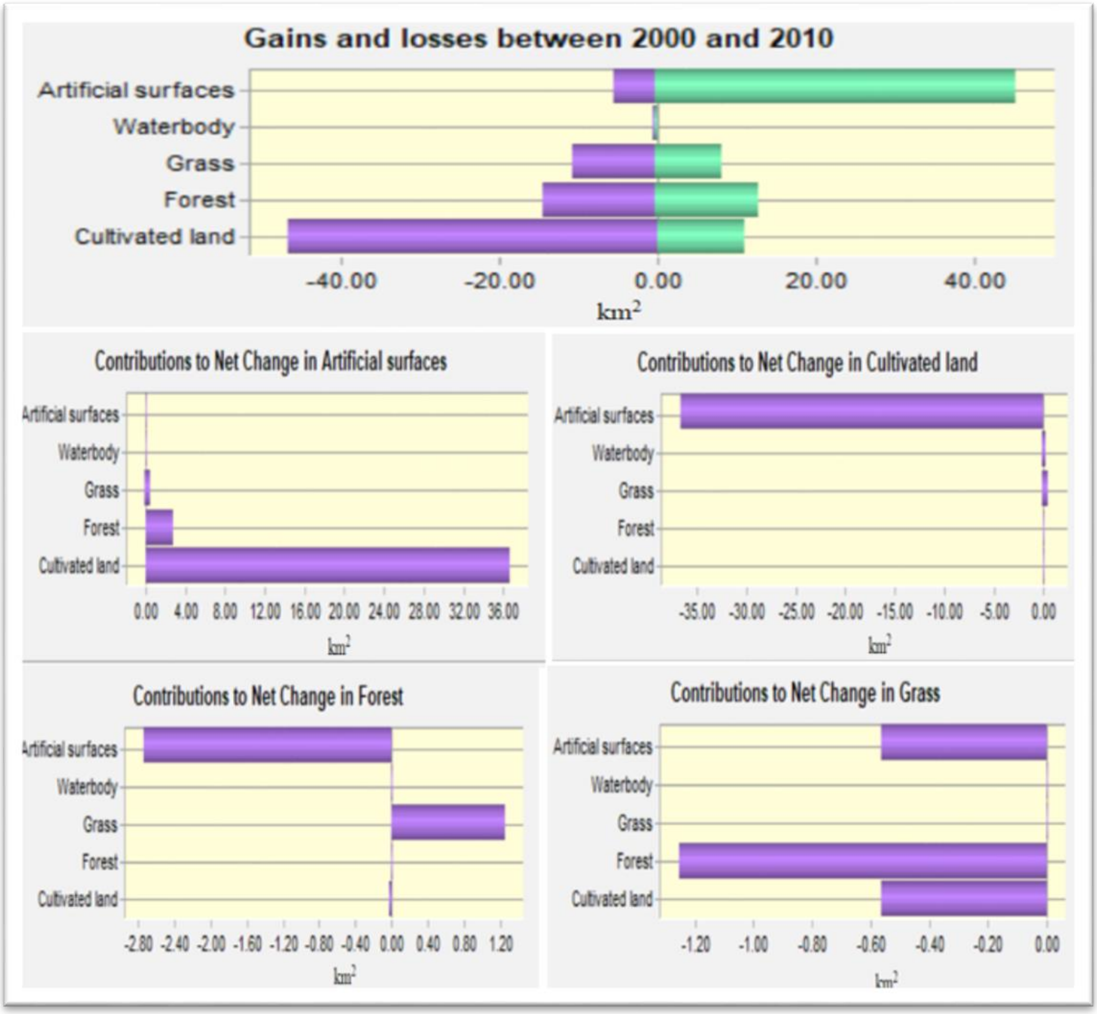


Figure 7: Gains and losses of land use /cover types between 2000 and 2010 across the Halda River Basin.

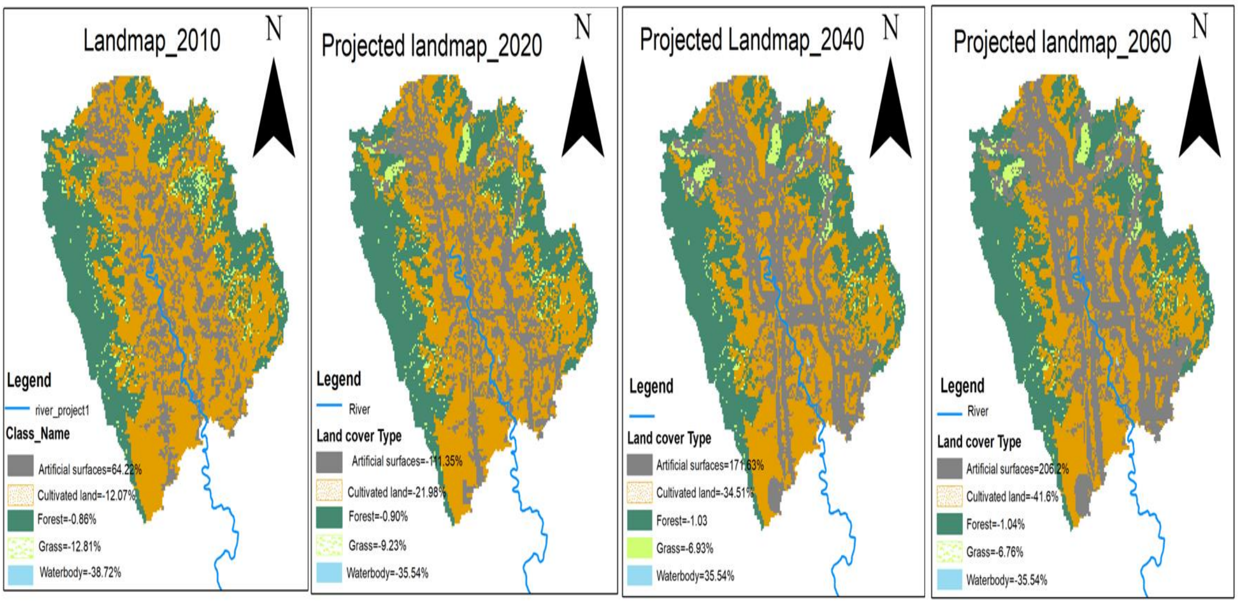


Figure 8: Future land use/landcover maps arranged from 2010 to 2060.

Combined effects of climate and land use change

The combined impacts of climate and land use changes on streamflow for the future periods are shown in Figure 9. The results indicate that under RCP 4.5, streamflow is likely to decline between the baseline and 2020s by ~3%, and then increase for the later time periods (2040s: ~14%, 2060s: ~14%) (Table 8). Streamflow in the wet season is projected to decline across the three future time periods, although dry season streamflow is projected to more than double. While similar patterns are also projected for the wet and dry season under RCP 8.5, annual streamflow is projected to be 13 and 16 % above the baseline by the 2020s (633 m^3/sec) and 2060s (654 m^3/sec) respectively.

Table 8: Simulated annual and seasonal changes in streamflow across the Halda River Basin, for the future periods (2020s,2040s and 2060s) under RCP 4.5 and 8.5 scenarios. Two simulations were run, one considering climate change only and a second considering both climate and projected land cover changes. Values for streamflow and the ratio are presented in m^3/sec and presented as median from the five climate models. Here ± denotes standard deviation. Values for streamflow associated with changes in land use only where then calculated as the ratio of the CC to CC/LULC simulations.

	Streamflow (m^3/sec)	**Baseline**	**2020 (4.5)**	**2040 (4.5)**	**2060 (4.5)**	**2020 (8.5)**	**2040 (8.5)**	**2060 (8.5)**
Baseline								
	Annual	562 (±119)						
	Wet Season	400 (±17)						
	Dry Season	47 (±13)						
Climate change simulation								
	Annual		596 (±43)	620(±38)	674 (±37)	673 (±50)	659 (±46)	643 (±45)
	Wet Season		355 (±11)	349 (±10)	367 (±9)	365 (±11)	358 (±10)	349 (±9)
	Dry Season		103 (±14)	101 (±14)	110 (±15)	105 (±14)	103 (±16)	98 (±16)
Climate & Land use change simulation								
	Annual		544 (±21)	639 (±58)	641 (±59)	633 (±66)	647 (±58)	654 (±50)
	Wet Season		360 (±10)	353 (±10)	360 (±9)	371 (±11)	356 (±9)	348 (±10)
	Dry Season		103 (±14)	101 (±14)	105 (±16)	105 (±14)	103 (±16)	98 (±16)
Land use only	Annual		1.1	0.97	1.05	1.06	1.02	0.98
	Wet Season		0.99	0.99	1.01	0.98	1	1
	Dry Season		1	1	1.04	1	1	1

By 2060, streamflow for the dry month of February is projected to increase 600% (16 m^3/sec) and 452% (12 m^3/sec) under the RCP 4.5 and 8.5 scenarios, respectively, compared to the baseline. Streamflow for the entire dry season is projected to increase to 110 m^3/sec under RCP 4.5 and 98 m^3/sec under RCP 8.5, relative to the baseline (47 m^3/sec). In contrast, streamflow during the monsoon is projected to decline from the baseline of 400 m^3/sec to 367 or 349 m^3/sec under RCP 4.5 and 8.5, respectively.

Hence the result implies that higher precipitation and streamflow during the dry period will be beneficial to farmers. For example, a key crop in this region is Boro Rice, which has high water demands. Currently during the dry period from December to March, approximately 80 to 135 million cubic meter of water needs to be withdrawn from the Halda Basin for cultivating Boro Rice and for winter vegetation (MoFL, 2016).

These results demonstrate that under the combined impact of climate and land use change, streamflow will likely increase in the long term under both RCP scenarios. However, in the near term (i.e. from the baseline to the 2020s), streamflow is projected to decline under RCP 4.5 scenarios. This contrasts substantially with the considerable increase in streamflow projected under RCP 8.5 for the 2020s, and illustrates that very different water management actions may be required to reduce risks associated with this uncertainty.

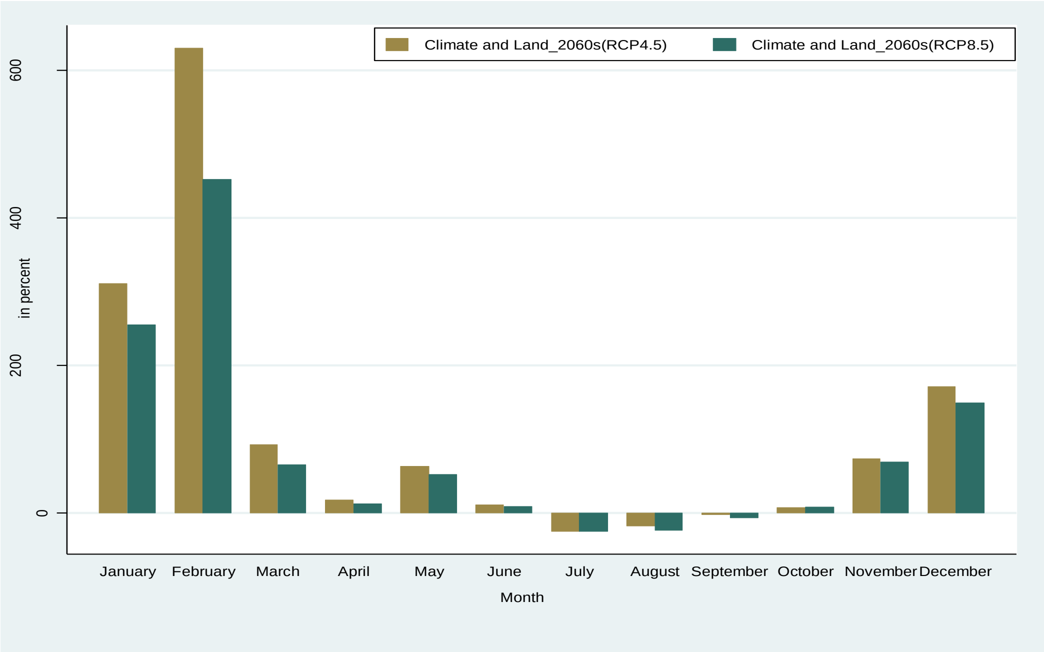


Figure 9: Projected changes in monthly streamflow under RCP 4.5 and 8.5 climate scenarios for 2060s relative to the baseline period (1986-2005).

Changes in Streamflow Resulting from Land Use Changes

To assess the change in streamflow from the impact of projected land cover change (LULC) only, the proportional change in streamflow from the combined simulation compared to the climate change only simulation was calculated. The results indicate that annual streamflow will fluctuate across three time periods (2020s, 2040s and 2060s) (Table 8). Under RCP4.5, streamflow is projected to increase by 10% in 2020, decline slightly by 2040 then increase at a rate 5% by 2060. Under RCP 8.5, it is projected to increase 6% by 2020 then decline slightly for the later period 2040s and 2060s. Streamflow during both the wet and dry season are projected to remain very similar to baseline levels. A possible driver of the decline in streamflow may be increased forest cover in hydrologically sensitive areas (e.g. on steep slopes) as a result of targeted afforestation (Figure 7) and the decline in rainfall during the wet months. This change in streamflow may be due to the effects of land use conversion such as conversion of grassland to forest, as vegetation within forests can draw moisture from soil (by large evapotranspiration) faster than short rooted plants (Ma *et al.*, 2009). Natural and man-made water retention features such as dams and reservoirs, wetlands and water impoundments, are highly relevant to the hydrological regime. A large part of the upper Halda Basin can have very low flows or may even dry up during the dry season because of upstream water retention through construction of rubber dams (Kabir *et al.*, 2013). Kim *et al.* (2013) reported that increases in streamflow resulting from urban growth and larger areas of impervious surfaces, however the model in this chapter projected reductions in streamflow even though artificial surfaces increase. Probable reasons for these discrepancies may be related to other parameters that govern flow through the shallow and deep aquifers.

Therefore, it is assumed that the changes in LULC (primarily artificial surfaces and forest cover) in near future resulting slight decline in flow during the same period across wet and dry season. The simulated land use change does not appear to impact highly on river flow. Perhaps the simulated land use change is not sufficient to impact on river flow and more LULC change would need to occur for the impact to be reflected in the flow amount.

Conclusion

The contribution of separate and combined impacts of climate and LULC changes on streamflow in the Halda Basin were evaluated using a SWAT model associated with an LCM model, and two future scenarios using five RCM experiments. Multi climate model comparison showed substantial interannual variation in projections of future precipitation regimes. As such, streamflow may also vary depending upon which alternate future eventuates and most of the changes across time intervals are within the standard deviation band of the multiple RCMs. Despite uncertainties in future projections, this study indicates that the Halda Basin is expected to become warmer in future, with more precipitation during the dry season but less in the monsoon. Simulations also show that climate change is likely to increase future streamflow in the Halda River. Monthly streamflow changes were influenced mainly by the variability in precipitation. Simple LCMs projected decreases in the area of grassland along with cultivated land at the expense of artificial surfaces. Combined, future climate and land use changes are projected to result in increases in annual streamflow, although results indicate that climate change is likely to be a greater driver of changes in streamflow than land use changes. However, there is considerable variation between RCP 4.5 and 8.5 and across the time periods. Further, much of the variation is projected for the near future, indicating that adaptation plans will need to span very different scenarios.

Understanding the changes in streamflow caused by separate and combined impacts of future climate and land use changes provides information to stakeholders and policy makers, and will facilitate effective decision making with regards to implementing land and water resources planning and management.

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CHAPTER 5: IMPACTS OF CLIMATE VARIATION ON SPAWN PRODUCTION OF INDIAN MAJOR CARPS IN THE HALDA BASIN, BANGLADESH

Abstract

Bangladesh is the world's fourth largest producer of fish, and is one of the most vulnerable countries to climate change impacts. The Halda Basin, in southeastern Bangladesh, is the only region in the country where Indian major carp spawn naturally and from where fertilized eggs can be collected. This paper examines the impact of climate change on spawn production in Halda Basin. Using an Autoregressive Distributed Lag (ARDL) model bounds testing approach I investigated the short-run dynamics and long-run relationship between spawn production and major climatic variables (temperature, precipitation and streamflow) for the period 1985-2013. I found that temperature plays the dominant role in determining spawn production both in the short-run and long-run. A 1% increase in temperature leads to a > 6% rise in spawn production (i.e. increasing spawn production from an average 239 kg to 252 kg) in the long-run, and a 4% rise in the short-run. This indicates that future moderate temperature increases may have a favorable impact on spawn production in the Halda River.

Introduction

The country of Bangladesh is a low riparian delta. It is enveloped by the Ganges (or Padma), Brahmaputra, Jumna and Meghna River Basins, which descend from the Himalayas and branch into more than 720 middle and small rivers and tributaries (BFRI, 2007) before flowing into the Bay of Bengal. This environment is highly supportive of the spawning of fish, and Bangladesh is the world's fourth largest producer of fish, yielding 3.6% of global supplies

(FAO, 2016). The total fishing estate of Bangladesh comprises of 32,477 km^2 of inshore fishing area (IFA) along with 84,846 km^2 of bay shelf economic area zoned Offshore Fishing Area (OFA). The fisheries and aquaculture sector in Bangladesh employs almost 17.80 million people annually (including 1.40 million women) which represents almost 11% of the country's population (BER, 2016). Fisheries and aquaculture is the second largest export earning sector of Bangladesh recording 2.1% of total export earnings in 2014 (EPB, 2014), contributing to 3.65% of country's total GDP and 23.78% of agricultural GDP in 2015 (BBS, 2016).

In addition to the economy, fisheries and aquaculture contributes significantly towards food security and nutrition, with fish accounting for more than 59% of the total animal protein consumption in Bangladesh (WFC, 2015). The per capita fish intake, however, is only 53 grams/day (FRSS, 2016), which is relatively poor compared to the world's three top fish producers, China, India and Vietnam.

Fish production in Bangladesh has increased almost five-fold over the last three decades, and more than double in the last seven years, due to dissemination of improved technology packages and supportive extension services at the fisheries level (FRSS, 2016). However, such growth has led to environmental concerns. According to the Department of Fisheries of the Government of Bangladesh (2014), inland waters capture fishery production has been declining since the mid-1980s as a result of habitat degradation arising from flood control measures undertaken by the government.

The ecological system which supports fisheries is very sensitive to climate variability (Orr et al., 2005; Fernandes et al., 2013; Merilä, 2016) and it is being rapidly impacted by climate change (NAS, 2009; Dulvy et al., 2011). Fisheries are dynamic systems and are already exposed to a diverse range of direct and indirect climate threats (Handisyde et al., 2006; De Silva and Soto, 2009). According to Brander (2007), climate change driven-threats to fish production may arise from *"(i) stress due to increased temperature and oxygen demand and decreased pH, (ii) uncertain future water supply, (iii) extreme weather events, (iv) increased* *frequency of diseases and toxic events, (v) sea level rise and conflict of interest with coastal defenses, and (vi) an uncertain future supply of fishmeal and oils from capture fisheries*" (Figure 1). Moreover, river water flow responds to changes in precipitation regimes and may ultimately affect the flow and quality of freshwater inputs to marine and coastal fish habitats (Graham and Harrod, 2009). In addition, climate change can alter water salinity, which will ultimately effect spawn production. For instance, increases in salinity in tropical oceans (Freeman, 2017) could impact adjunct rivers or estuaries, altering microorganism communities and ecosystem characteristics and thereby impacting plankton and fish species (Schallenberg et al., 2003; Brierley and Kingsford 2009).

Most importantly, food security of South Asia will be severely affected by the middle of the 21th century (WFC,2009). This is particularly the case for Bangladesh which *is the most vulnerable country worldwide*, partly because its fisheries sector is located in the tropical and subtropical belts where the carrying capacity and productivity of the aquatic environment may diminish (Cochrane, 2009; Lam et al., 2012; Merino et al., 2012; IPCC 2014; Havens, 2016).

Since 1880, global mean annual temperature has increased ~0.85 [0.65-1.06] °C, and if current greenhouse emission rates continue, is likely to rise 2.6-4.8°C by 2081-2100 (relative to 1986-2005) (IPCC, 2014). Biological responses to this change have been observed in freshwater and marine realms, and include changes in physiology (e.g. productivity), phenology and the geographic range of species, and has resulted in shifts at the community and ecosystem level (Barange et al., 2014; Poloczanska et al., 2013). Similarly, there is substantial evidence that climate change is affecting important biological processes, negatively impacting primary production and the distribution of fishstock (Freeman 2017).

The characteristics of spawning and successful reproduction of marine and freshwater organisms are strongly influenced by variability in aquatic conditions (Feiner et al., 2016). Thus, spawning and reproduction are closely related to the influences of climate and hydrological variability. According to Barange and Perry (2009), "*Spawning times and locations have evolved to match prevailing physical (such as temperature, salinity, currents) and biological (such as food) conditions that maximize the chances for a larva to survive to become a reproducing adult or at the very least to minimize potential disruptions caused by unpredictable climate events ... such as temperature...".* Temperature affects species' physiology and ecology. It is a dominant driver of the reproductive cycle of fishes and strongly influences the age of sexual maturity, with warmer conditions leading to earlier maturity (Pörtner 2010; Dey et al., 2016). Climate change is likely to induce strong selection on the timing of spawning in river ecosystems, and will influence the size of eggs and consequent size of larvae (Crozier et al., 2008). In addition, reproduction of fish in inland waters depends strongly on the combination of contrasting processes such as water flows, stratification and nitrification as well as human water use (Welcomme et al., 2010; Bakker 2016). Thus, changes to the watercourse river system will have flow-on consequences for the growth, body size, distribution and abundance of fishes and other taxa (Simpson et al., 2011; Cheung et al., 2013).

Climate change may have some positive impacts on aquaculture. For instance, warmer temperature and longer growing seasons may enhance fish yield (Barange and Perry, 2009). The intensification of hydrological cycles will also influence limnological processes via increased runoff, discharge rates, flooding area and dry season water levels, thereby boosting productivity across all trophic levels (Portner and Peck, 2010; Dey et al., 2016). Appendix I summarizes potential impacts of climate change on fish and aquaculture. The combination of these proximate positive and negative impacts results in emergent ecological responses which include alterations in species distributions, biodiversity, microevolutionary processes and productivity (Harley et al., 2006).

Bangladesh has the third highest diversity of fish species in Asia (after China and India) with about 800 species in fresh and marine waters (Hussain and Mazid, 2001). Of these, four species of Indian major carps are commercially important: catla (*Catla catla*), roho labeo or rui (*Labeo rohita*), kalibaush (*L. calbasu*) and mrigel (*Cirrhinus mrigala*). IWM (2012) classified the Indian major carps in Bangladesh into five stocks based on the differences in their spawning grounds, spawning seasons and geographic distribution: i) Brhamaputra-Jamuna, ii) Upper Padma (Ganga), iii) Upper Meghna (Barak River), iv) Halda (with Karnaphuli and Sangu) and Kaptai. The first three stocks spawn in the upstream reaches of rivers within the Indian territory while the remaining two stocks spawn in the downstream reaches within the Bangladesh territory (Azadi, 1996). Three of the four Indian major carps are found in the Halda River: *C. catla*, *L. rohita* and *C. mrigala*. Importantly, Halda is the only river in Bangladesh where these carp spawn naturally. Declines in water temperature, dissolved oxygen and hydrogen ion concentration provide the physicochemical factors necessary for the major carps to spawn (Tsai, 1981). The fertilized eggs are collected for human consumption making this river highly important to the heritage of Bangladesh (Kabir et al., 2013).

Given the importance of production of fish spawn in Halda, and the potential impact of climate changes on fisheries, this study aims to explore the dynamic relationship between spawn production and key climate and hydrological variables in the Halda River Basin. The goal is to examine casual relationships between spawn production and key three variables: temperature, precipitation and stream flow.

Methods & Materials

Study area

Halda River (22° 24´ to 22° 54´ N and 91° 48´ to 91° 53´ E) originates in the hilly streams of Halda Chora at Ramgor of Khagrachari Hill District, in southeastern Bangladesh. The River is 81 kilometers long, and ranges from 35 to 210 meters wide. It flows through the Fatickchari, Hathazari and Rouzan Upzilas of Chittagong District and then confluences with the Karnaphuli River ~35 km from the Bay of Bengal (Figure 2).

According to Arshad-Ul-Alam and Azadi (2016), 83 species of finfish (belonging to 13 orders, 35 families and 69 genera, and including three exotic species), are found in the Halda River. There are also 10 species of shellfish from three families and three genera. Major carps in the Halda River begin spawning from late March to June in oxbow-bends (U-shaped curve in a stream), when the tide is at its highest level (which ranges from two meters during neap tide to four meters during spring tide, in downstream reaches). Upstream at Panchpukuria, water level varies from four to 10 meters in dry and rainy seasons, respectively, during full and new moons (Ali et al., 1974). Heavy rain over two to three days (1.0-2.88 cm) during full and new moons reduces water temperature to 25-28^{0}C, triggering the carp to spawn (Azadi, 2011; Patra and Azadi, 1985). Furthermore, current flow during this period, of 16.5-85 cm/sec, is sufficient to prevent the demersal carp eggs from being damaged by bacteria and fungus or suffocating (Patra and Azadi, 1985).

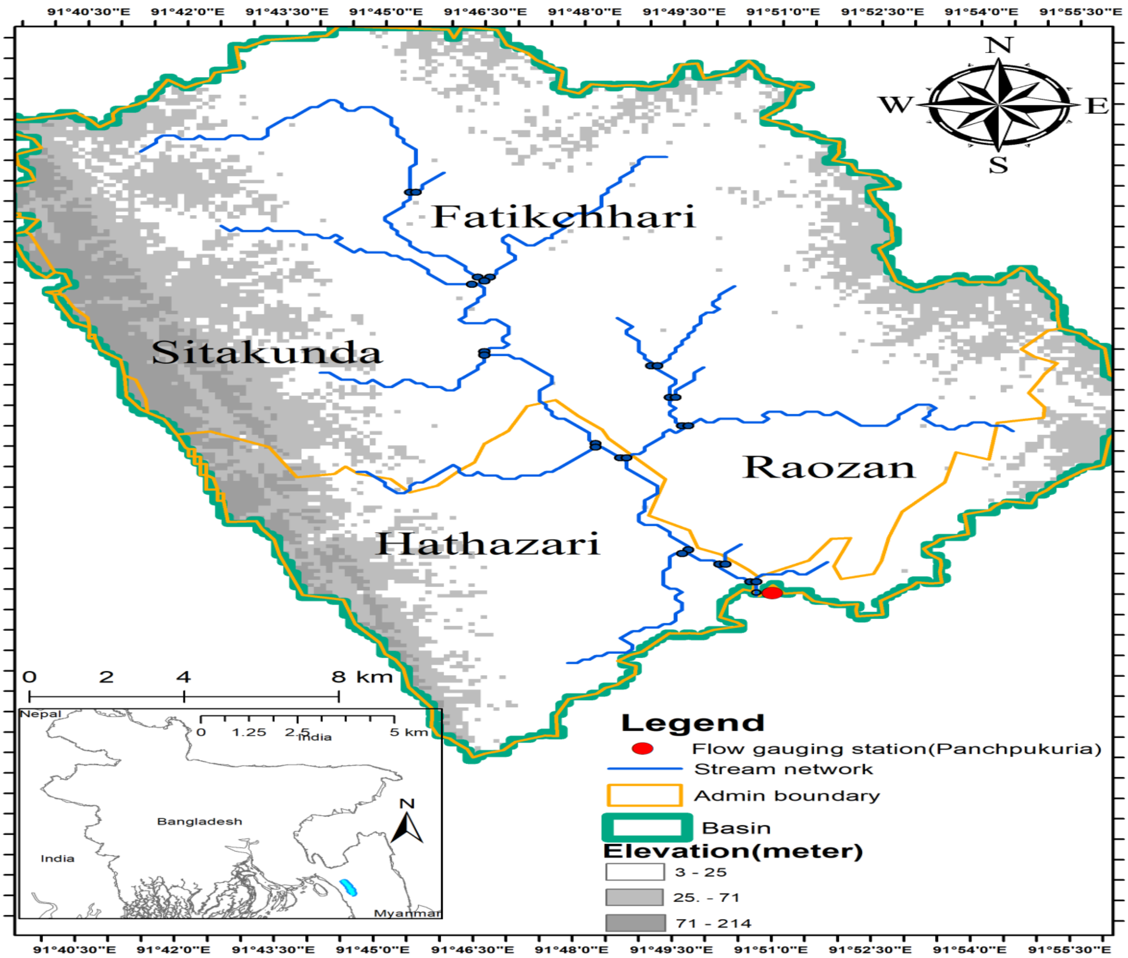

Figure 2: Map of the Halda Basin within Bangladesh(inbox).

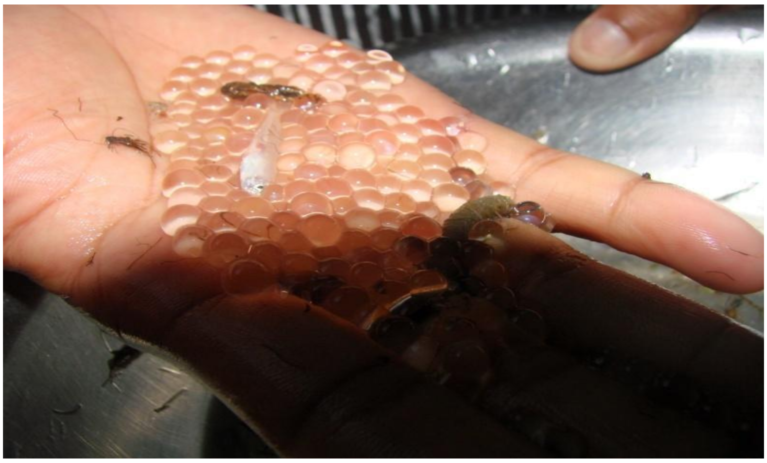

Figure 3. Spawn collected from Halda River. Source: IWM (2012)

Model

The effect of climate change is not geographically or temporally homogeneous (FAO, 2009), and may impact spawn production via multiple pathways (Figure 4).

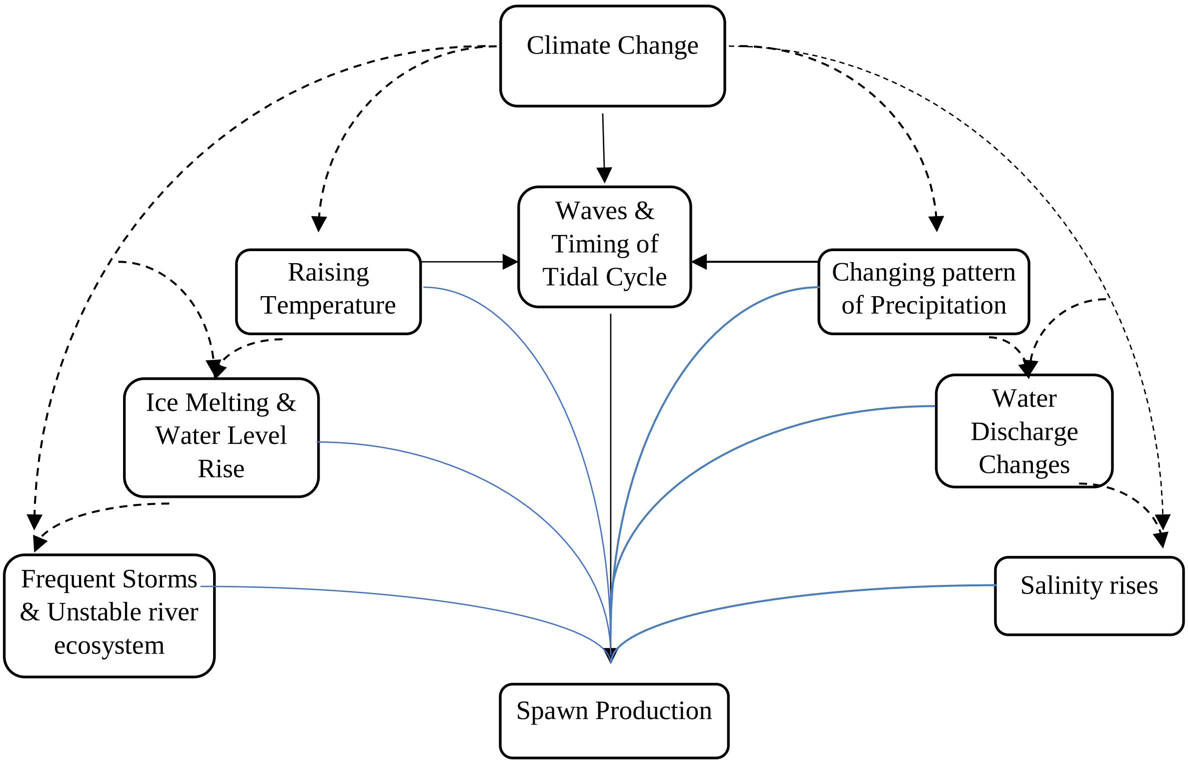

Figure 4: Pathways by which climate change may affect spawn production

Thus, spawn production ($Spawn_t$) can be expressed as a function of variation in climatic and hydrological variables:

$$Spawn_t \;=\; f(Temp_t, Prep_t, Water_t) \qquad (1)$$

where *Temp*, *Prep* and *Water* represent *temperature*, *precipitation* and *streamflow* in the river, respectively. In statistical form,

$$Spawn_t = \alpha + \beta_o Temp_t + \beta_1 Prep_t + \beta_2 Water_t + \epsilon_t \qquad (2)$$

where α is an intercept coefficient and ϵ denotes an error term and *t* is a time index. These variables are in natural logarithmic form in order to remove the heterogeneity of the data and to measure the percentage of change in spawn delivery with respect to climate variables.

Although the expected signs of the parameters β_o, β_1 and β_2 are positive, these may be altered due to climatic variations.

Estimation Steps and Techniques

Unit Root Test

Non-stationarity is a common property of time series data and arises when statistical properties such as the mean and variance are not constant over time (Engle and Granger, 1987; Johansen 1988; Phillips and Hansen, 1990). To test that my data were stationary, I used the Augmented Dickey–Fuller (ADF) test which can be written without deterministic trend:

$$\Delta Spawn_t \;= s_0 + s_1 Spawn_{t-1} + \sum_{i=1}^{n} s_i Spawn_{t-i} + \mu_{st} \quad (3)$$

$$\Delta Temp_t \;= h_0 + h_1 Temp_{t-1} + \sum_{i=1}^{n} h_i Temp_{t-i} + \mu_{ht} \quad (4)$$

$$\Delta Prep_t \;= p_0 + p_1 Prep_{t-1} + \sum_{i=1}^{n} \rho_i Prep_{t-i} + \mu_{pt} \quad (5)$$

$$\Delta Water_t \;= w_0 + w_1 Water_{t-1} + \sum_{i=1}^{n} \omega_i Water_{t-i} + \mu_{wt} \quad (6)$$

and with deterministic trend:

$$\Delta Spawn_t \;= s_0 + s_1 Spawn_{t-1} + \sum_{i=1}^{n} s_i Spawn_{t-i} + \delta t + \mu_{st} \quad (7)$$

$$\Delta Temp_t \;= h_0 + h_1 Temp_{t-1} + \sum_{i=1}^{n} \hbar_i Temp_{t-i} + \delta t + \mu_{ht} \quad (8)$$

$$\Delta Prep_t \;= p_0 + p_1 Prep_{t-1} + \sum_{i=1}^{n} \rho_i Prep_{t-i} + \delta t + \mu_{pt} \quad (9)$$

$$\Delta Water_t \;= w_0 + w_1 Water_{t-1} + \sum_{i=1}^{n} \omega_i Water_{t-i} + \delta t + \mu_{wt} \quad (10)$$

where $s_0, h_0, p_0\ and\ w_0$ are constant, $s_{1,} h_1, p_1 and\ w_1$ and $s_i, \hbar_i, \rho_i$ and ω_i are the model coefficients, 'δ' denotes the time trend in the estimation procedure, and $\mu_{st,}\ \mu_{ht},\ \mu_{pt}\ and \mu_{wt}$ are the distributed random error terms with mean (0) and constant variance (σ). Δ is the first difference operator. Based on the above equations a unit root test can be executed. If two time-series data are nonstationary at level and are stationarity at first difference, then they are said to be integrated of order one $I(1)$, that is, they share a long run relationship. However, if the stationary test indicates *I(1)* at level, the variables are not cointegrated.

The Cointegration Rank Test

The basic idea behind cointegration is that if, in the long-term (i.e. relationship between the variables over 15-20 years) two or more series move closely together, even though the series themselves are trended, the difference between them is constant (Hall and Henry, 1989). Non-existence of cointegration suggests that such variables have no long-run relationship: in principle they can wander arbitrarily far from each other (Dickey et. al., 1991). I employed the maximum likelihood (ML) test procedure established by Johansen and Juselius (1990) and Johansen (1991), where $Spawn_t$ is an n×1 vector of variables that are integrated of order commonly denoted (1) and t is an n×1 vector of time. Johansen's methodology takes its starting point in the vector auto regression (VAR) of order P.

$$\Delta Spawn_t = \mu + \Pi Spawn_{t-1} + \sum_{i-1}^{\rho-1} \tau_i \, \Delta Spawn_t + \mu_{st} \qquad (11)$$

Where $\Pi = \sum_{i=1}^{\rho} A_i - I$ and $\tau_i = -\sum_{j+1}^{\rho} A_j$.

To determine the number of co-integration vectors, Johansen (1988; 1989) and Johansen and Juselius (1990) suggested two statistical tests. The first of these is the trace test. It tests the null hypothesis that the number of distinct cointegrating vectors is less than or equal to q against a general unrestricted alternative q = r. The test is calculated as follows:

$$\lambda \, trace \, (r) = -T \sum_{i=r+1} \ln\left(1 - \hat{\lambda}_t\right) \qquad (12)$$

where, T is the number of usable observations, and the $\hat{\lambda}_i$ are the estimated eigenvalues from the matrix. The second statistical test is the maximum eigenvalue test (max) that is calculated as:

$$\lambda \max(r, r+1) = -T \ln(1 - \lambda r + 1) \tag{13}$$

This is a test of the null hypothesis, that there is r of co-integrating vectors, against the alternative that there is r + 1 co-integrating vectors.

Autoregressive Distributed Lag (ARDL) Model

For this study, I employed the Autoregressive Distributed Lag model (ARDL) developed by Pesaran and Shin (1999) and Pesaran et al. (2001). ARDL is able to estimate the long and short-run parameters of the model simultaneously. Moreover, it can be applied when the variables are in different order on integration. Maximum lags in the model are determined by the number of lags (m, n, o, p, q) selected by the Akaike Information Criterion (AIC) of the ARDL specification.

$$\begin{aligned}\Delta Spawn_t \; &= s_0 + s_1 Spawn_{t-1} + h_1 Temp_{t-1} + p_1 Prep_{t-1} + w_1 Water_{\,t-1} \\ &\quad + \sum_{i=1}^{n} \mathscr{s}_i \Delta Spawn_{t-i} + \sum_{i=1}^{n} \mathscr{h}_i Temp_{t-i} + \sum_{i=1}^{n} \mathscr{p}_i Prep_{t-i} \\ &\quad + \sum_{i=1}^{n} \omega_i Water_{\,t-i} + \mu_{st}\end{aligned}$$

$$\begin{aligned}\Delta Temp_t \; &= h_0 + s_1 Spawn_{t-1} + h_1 Temp_{t-1} + p_1 Prep_{t-1} + w_1 Water_{\,t-1} \\ &\quad + \sum_{i=1}^{n} \mathscr{h}_i Temp_{t-i} + \sum_{i=1}^{n} \mathscr{s}_i \Delta Spawn_{t-i} + \sum_{i=1}^{n} \mathscr{p}_i Prep_{t-i} \\ &\quad + \sum_{i=1}^{n} \omega_i Water_{\,t-i} + \mu_{ht}\end{aligned}$$

$$\Delta Prep_t \;= p_0 + s_1 Spawn_{t-1} + h_1 Temp_{t-1} + p_1 Prep_{t-1} + w_1 Water_{\ t-1} + \sum_{i=1}^{n} \wp_i Prep_{t-i} + \sum_{i=1}^{n} \hbar_i Temp_{t-i} + \sum_{i=1}^{n} \mathcal{s}_i \Delta Spawn_{t-i} + \sum_{i=1}^{n} \omega_i Water_{\ t-i} + \mu_{pt}$$

$$\Delta Water_t \;= w_0 + s_1 Spawn_{t-1} + h_1 Temp_{t-1} + p_1 Prep_{t-1} + w_1 Water_{\ t-1} + \sum_{i=1}^{n} \omega_i Water_{\ t-i} + \sum_{i=1}^{n} \wp_i Prep_{t-i} + \sum_{i=1}^{n} \hbar_i Temp_{t-i} + \sum_{i=1}^{n} \mathcal{s}_i \Delta Spawn_{t-i} + \mu_{wt} \tag{14}$$

The ARDL bound test developed by Pesaran et al., (2001) is used to examine the effect of the variables on the right to those on the left, both in the short and long run. The variables $s_{1,} h_1, p_1 and\ w_1$ represent the long run dynamics of the model, while $\mathcal{s}_i, \hbar_i, \rho_i\ and\ \omega_i$ represent the short run dynamics. The null hypothesis of above equation is $s_1 = h_1 = p_1 = \ w_1$ and is tested against the alternative hypothesis $s_1 \neq h_1 \neq p_1 \neq \ w_1$ using the F-statistic.

Error Correction Model (ECM)

Following the estimation of the ARDL (m, n, o, p, q) specification (where m, n, o, p, q represents lag length for each variable) and calculation of the long-run multipliers, the short-run dynamics are estimated by obtaining the error correction coefficient from the verified long-run model. The estimated ECM term should have a negative sign and be statically significant. Generally, the estimated value of the ECM term will indicate the speed of adjustment to long run equilibrium in response to the disequilibrium caused by short run shocks of the previous period. The short run relation model including the ECM term, which expressed the speed of convergence can be express as follow:

$$\Delta Spawn_t = s_0 + \lambda_{Spawn}\mathrm{E}_{t-1} + \sum_{i=1}^{n} s_i \Delta Spawn_{t-i} + \sum_{i=1}^{n} h_i Temp_{t-i} + \sum_{i=1}^{n} p_i Prep_{t-i} + \sum_{i=1}^{n} \omega_i Water_{\,t-i} + \mu_{st}$$

$$\Delta Temp_t = h_0 + \lambda_{Temp}\,\mathrm{E}_{t-1} + \sum_{i=1}^{n} h_i Temp_{t-i} + \sum_{i=1}^{n} s_i \Delta Spawn_{t-i} + \sum_{i=1}^{n} p_i Prep_{t-i} + \sum_{i=1}^{n} \omega_i Water_{\,t-i} + \mu_{ht}$$

$$\Delta Prep_t = p_0 + +\lambda_{Prep} + \sum_{i=1}^{n} p_i Prep_{t-i} + \sum_{i=1}^{n} h_i Temp_{t-i} + \sum_{i=1}^{n} s_i \Delta Spawn_{t-i} + \sum_{i=1}^{n} \omega_i Water_{\,t-i} + \mu_{pt}$$

$$\Delta Water_t = w_0 + \lambda_{Water} + \sum_{i=1}^{n} \omega_i Water_{\,t-i} + \sum_{i=1}^{n} p_i Prep_{t-i} + \sum_{i=1}^{n} h_i Temp_{t-i} + \sum_{i=1}^{n} s_i \Delta Spawn_{t-i} + \mu_{wt} \quad (15)$$

E_{t-1} is the ECM term and λ indicates the speed of adjustment between short-run and long-run. After the long run and short run relationship between both variables is identified, the impulse response functions can be generated to assess the stability between the estimated series.

Granger-Causality

In the case of nonstationary and cointegrated data set, Vector Error Correction Model (VECM) Granger non-causality/block exogeneity tests can be employed to find causality. Granger causality tests are conducted to determine whether the current and lagged values of one variable affect another. The non-significance of both the *t* and Wald F-statistics in the ECM implies that the dependent variable is weakly exogenous. Granger causality of the dependent variables is tested as by a simple t-test or by a joint Wald F-test.

$$\Delta Spawn_t = a_{11}(L)\Delta Spawn_{t-1} + a_{12}(L)\Delta Temp_{t-1} + a_{13}(L)\Delta Prep_{t-1} + a_{14}(L)\Delta Water_{t-1} + \lambda_{Spawn}\mathrm{E}_{t-1} + \mu_{1t}$$

$$\Delta Temp_t = a_{21}(L)\Delta Temp_{t-1} + a_{22}(L)\Delta Spawn_{t-1} + a_{23}(L)\Delta Prep_{t-1} + a_{24}(L)\Delta Water_{t-1} + \lambda_{Temp}\,\mathrm{E}_{t-1} + \mu_{2t}$$

$$\Delta Prep_t = a_{31}(L)\Delta Prep_{t-1} + a_{32}(L)\Delta Temp_{t-1} + a_{33}(L)\Delta Spawn_{t-1} + a_{34}(L)\Delta Water_{t-1} + \lambda_{Prep}\,\mathrm{E}_{t-1} + \mu_{3t}$$

$$\Delta Water_t = a_{41}(L)\Delta Water_{t-1} + a_{42}(L)\Delta Prep_{t-1} + a_{43}(L)\Delta Temp_{t-1} + a_{44}(L)\Delta Spawn_{t-1} + \lambda_{Water}\mathrm{E}_{t-1} + \mu_{4t} \quad (16)$$

Data

To test the effect of climate change on spawn production, March-June monthly spawn data were obtained as a secondary data from the Department of Fisheries (DoF) of the Government of Bangladesh (GoB) for the period 1985 to 2014. These data represent collections from local markets. I aggregated these monthly data. Monthly temperature and precipitation were obtained from the Department of Meteorology (DoM) of the GoB for 1985 to 2013 (DoM, 2013). Moreover, monthly water discharge data were obtained from the Bangladesh Water Development Board for 1985 to 2014 (BWDB, 2014). Since all the variables cover the period of 1985 to 2013, these analyses spanned 29 years. Moreover, as the spawning season spans the months March to June, the estimations consisted of (29 × 4) 116 sample periods. It is worthwhile to mention that since river water temperature data were not available, I used surface temperature data from Sitakundu, the closest station (using thiessen polygon) area of the Halda Basin, as a proxy of water temperature. All the definition, sources and descriptive statistics of variables are presented in (Table 1 and Table 2) and estimations and calculations are carried out by EViews 9.

Table 1: Definition and Sources of Data

Variables	Definition	Source
Spawn	Quantity of fish spawn monthly caught in the Halda Basin measured in kilogram (Kg)	Department of Fisheries, Government of Bangladesh
Temperature	Mean monthly surface temperature at Sitakundo measured in Celsius (°C) and calculated by the authors from daily mean temperature data. Generally, favorable temperature ranges from 22-31°C (Patra and Azadi, 1985).	Department of Meteorology, Government of Bangladesh
Precipitation	Monthly precipitation at Sitakundu measured in millimeters (mm) and calculated by the authors by summing daily precipitation data. Generally spawning occurred during or after heavy rainfall (10-30 mm) and thunderstorms (Patra and Azadi, 1985). Early water flow in April in the upper reaches influenced downstream migration of the brood and stimulated optimal conditions for breeding (MoFL, 2016).	Department of Meteorology, Government of Bangladesh
Streamflow	Level of water discharged in Halda Basin at Panchpukuria station, measured in m^3/s. The possible habitat for carps has been found in river depths ranging from 1.5 to 4.5m (Akhter and Ali., 2012).	Bangladesh Water Development Board, Government of Bangladesh

Empirical Analysis and Results

Descriptive Statistics

Table 2: Descriptive Statistics of Model Variables in logarithmic scale

Variables	Spawn (kg)	Temperature(^{0}C)	Precipitation(mm)	River Water Discharge(m^3/s)
Mean	4.05	3.31	5.19	2.5
Median	3.93	3.33	5.54	2.78
Maximum	8.6	3.41	8.23	5.35
Minimum	0	2.93	0	-2.76
Std. Dev.	1.62	0.07	1.47	1.68
Nos. of Observations	116	116	116	116

Records of monthly mean spawn production from 1986 onwards indicated that April is consistently the most productive month (Figure 5). Average spawn production was high during the period 1991-1995. The river water discharge due to flood of 1991 may have temporarily enhanced spawning ground conditions in 1991-92 which causing a peak in spawn production in that period. Spawn production rapidly declined in subsequent years due to withdrawn of water from the upstream area, destruction of brood fish, cutting river band and obstacles of sluice gate. Although from 2011 onwards it has remained relatively stable might be due to strict surveillance enforced by the Department of Fisheries (MOFL, 2016).

However, data for the 2014-2015 season indicates that a decline in spawn production (Table 3), with 107 kg of spawn collected compared to an average of 613 kg over 2011-2014.

Table: 3 Annual Carp Spawn/Fertilized Egg Collected from Halda Basin 2014-15/ N.B: These data, from FRSS, show the number of people, nets and boats engaged in collection of spawn, the quantity of spawn collected and the value of the collected spawn. Similar data for previous years were not available. Source: FRSS (2016, page 53).

No. Savers	**No. People engaged**	**No. Nets used**	**No. Boats used**	**Spawn Collected**	**Sale Value**
283	*1256*	*594*	*588*	*107 Kg*	US$ *618/kg*

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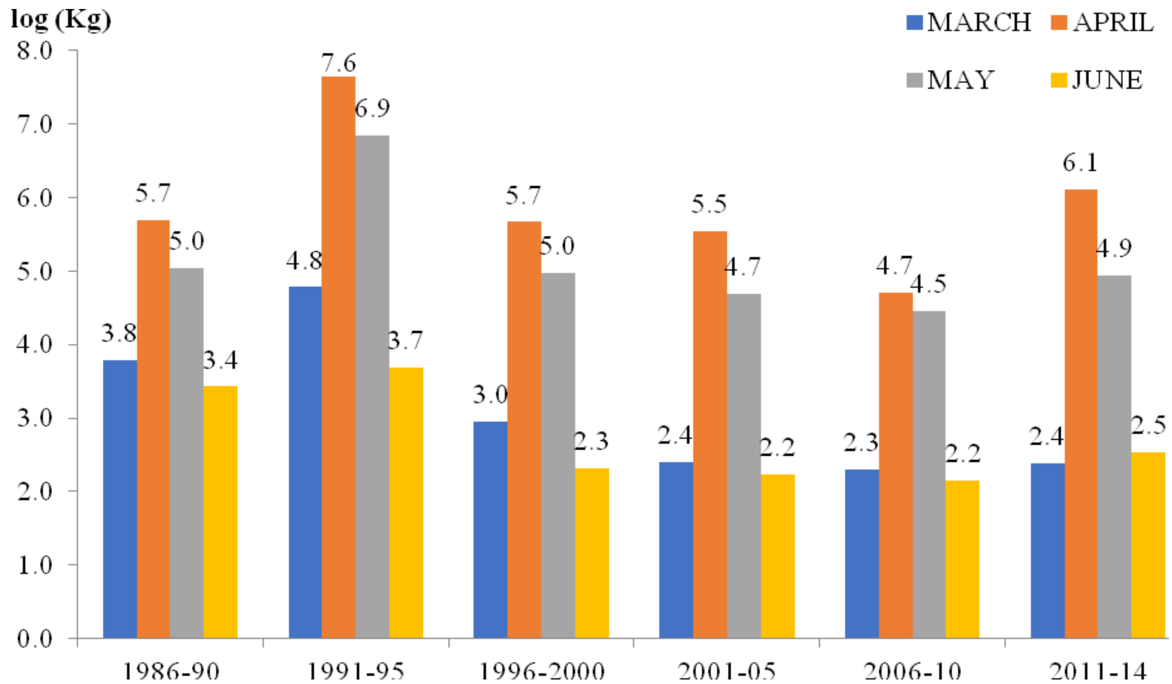

Figure 5: Spawn Production in Halda in 5 year average log scale. Source: Authors calculation is based on FRSS (2016).

Correlation Matrix

Temperature and precipitation are positively corrected with spawn production, explaining 26% and 8% of variation in spawning, respectively (Table 4); however, river water discharge i.e. streamflow is negatively correlated (R = -0.10) with spawning at 1% level of significance. Moreover, temperature, precipitation and streamflow are positively correlated with each other at 1% level of significance.

*Table 4: Correlation Matrix (coefficient of correlation between Spawn and climate variables). N.B: *** represents 1% level of significance*.

Variables	Spawn	Temp	Prep	Water
Spawn	1.00			
Temp	0.26***	1.00		
Prep	0.08***	0.24***		
Water	-0.10***	0.12***	0.43***	1.00

Unit Root Test result

I used Augmented Dickey Fuller (ADF) tests to assess the stationarity of the variables. The hypothesis was the series has a unit root. I found that the four variables (spawn, temperature, precipitation, streamflow) are non-stationary at a 1% level of significance for both the cases of trend and no-trend (Table 5). Thus, I cannot reject the null hypothesis of a unit root in the time-series. For instance, in the case of Spawn, the ADF value without trend is -2.05, which is > the Mackinnon critical value of -2.89 at a 5% level of significance, so it rejects the Ho of unit root. Thus Spawn is nonstationary at level.

*Table 5: ADF Test of Stationarity. N.B: *, ** and *** denote 10%, 5% and 1% level of significance respectively. Δ donates first difference of the variables.*

	Variables	**Constant, No Trend**			**Constant, Linear Trend**		
		Level	**Δ**	**Decision**	**Level**	**Δ**	**Decision**
Augmented Dickey-Fuller Unit Root Test Ho= Variable has a unit root	Spawn	-2.05	-5.41***	I(1)	-2.61	-5.43***	I(1)
	Temp	-2.84*	-9.35***	I(1)	-2.94	-9.14***	I(1)
	Prep	-1.64	-7.20***	I(1)	-1.71	-7.29***	I(1)
	Water	-1.98	-4.31***	I(1)	-2.41	-4.41***	I(1)
Mackinnon critical values	1% level	-3.49			-4.05		
	5% level	-2.89			-3.45		
	10% level	-2.58			-3.15		

In the case of ΔSpawn, ADF value without trend is -5.41, i.e. less than the Mackinnon critical values -3.49 at 1% level of significance, so it fails to reject the Ho of unit root. Thus ΔSpawn is stationary at Δ. Similarly, all variables were found statistically significant ($p < 0.001$) at first difference (Δ) level. Hence, I rejected the Ho that the variables have a unit root at Δ and conclude that they are all stationary at Δ, which implies that all of the variables are integrated of order *I(1)*.

Autoregressive Distributed Lag (ARDL)

Overall, the results are somewhat inconclusive since temperature was found stationary at 10% level of significance. For conclusive decision making, Auto Regressive Distributed Lag (ARDL) modeling and bounds testing was designed by Pesaran and Shin (1999) and Pesaran et al. (2001). This model has a number of features that may give it some advantages over conventional cointegration testing, including that it can be used with a mixture of I(0) and I(1) data. Vis-a-vis different variables can be assigned different lag-lengths as they entered into the model. Thus, cointegration relationships among the variables spawn, temp, prep and water were examined using the newly developed ARDL bound testing procedure based on the Akaike Information Criterion (AIC) (Table 6).

*Table 6: Cointegration Test [based on AIC]. N.B: *, ** and *** denote 10%, 5% and 1% level of significance respectively. Ho: No long-run relationship exists. F statistics are here significant at the 1% level except in case of model 4. All of the models assume no trend.*

Model	**ARDL**	**Dependent variable**	**Forcing variables**	**F Statistic**	**Critical Value Bounds at 1% Level**		**Cointegration**
					I(0)	I(1)	
1	1,1,1,1	*Spawn*	*Temp, Prep, Water*	12.50***	4.29	5.61	Present
2	2, 0, 2, 2	*Temp*	*Spawn, Prep, Water*	27.37***	4.29	5.61	Present
3	1, 3, 0, 1	*Prep*	*Spawn, Temp, Water*	21.31***	4.29	5.61	Present
4	2, 2, 2, 2	*Water*	*Spawn, Temp, Prep*	48.63***	4.29	5.61	Present

F-statistics exceeded the critical values at 1% level of significance (Table 4), hence it can be concluded that there is evidence of a long-run relationship among the four time-series. Moreover, results suggested that bi-directional long-run relationships among spawn, temp, prep and water exist. We verified these findings using a cointegration rank test.

Cointegration Rank Test

Having found *I(1)* in section 3.4, I then checked the rank of cointegration among the variables. Employing the Johansen and Juselius (1990) multivariate cointegration test following maximum eigenvalue statistics and trace statistics, it was found that both the variables were cointegrated at 5% level of significance at rank one (1).

Table 7: Unrestricted Cointegration Rank Test. Both Trace test and Max-eigenvalue test indicates 1 cointegrating equation(s) at 5% level of significance.

Hypothesized No. of CE(s)	**Trace**				**Maximum Eigenvalue**			
	Eigen value	Trace Statistic	0.05 Critical Value	P-values	Eigen value	Max-Eigen Statistic	0.05 Critical Value	P-values
None	0.2	56.6	47.9	0.0	0.2	28.0	27.6	0.0
At most 1	0.2	28.7	29.8	0.1	0.2	19.1	21.1	0.1
At most 2	0.1	9.6	15.5	0.3	0.1	9.0	14.3	0.3
At most 3	0.0	0.5	3.8	0.5	0.0	0.5	3.8	0.5

Both the Trace test and Max-eigenvalue were 56.65 and 27.97, respectively, which exceed the 5% critical value (Table 7); accordingly, the hypothesis of "no cointegrating equation" can be rejected. These tests suggested that there is at least 1 cointegration equation among the variables under study which confirms that there is long-run relationship among the variables.

Long run Impact Analysis

After verifying the existence of long run relationships among the variables under study, I estimated the impact of the climate variables on spawn production (Table 8).

*Table 8: Estimated Long Run Coefficients using the ARDL Approach based on AIC. N.B: *, ** and *** indicates 10%, 5% and 1% level of significance respectively. Standard errors are reported in parenthesis.*

Model / **Variable**	**Autoregressive Distributed Lag (ARDL) (1, 1, 1, 1)**	**Fully Modified Ordinary Least Squares (FMOLS)**	**Dynamic Ordinary Least Squares (DOLS)**	**Canonical Cointegrating Regression (CCR)**
Temp	6.79*** (1.36)	5.29*** (0.48)	8.44*** (1.85)	6.67*** (1.82)
Prep	0.17* (0.10)	0.11*** (0.03)	0.2034 (0.11)	0.13 (0.10)
Water	-0.13 (0.09)	-0.28*** (0.03)	-0.30** (0.14)	-0.40*** (0.10)
Long-run variance	-	0.21	3.30	0.79

AIC selected an ARDL (1, 1, 1, 1) model for this analysis. I also present results for the Fully Modified Ordinary Least Squares (FMOLS) developed by Phillips and Hansen (1990), Dynamic Ordinary Least Squares (DOLS) introduced by Phillips and Loretan (1991), Saikkonen (1991), and Stock and Watson (1993) and Canonical Cointegrating Regression (CCR) by Park's (1992) suggested by previous authors (Hermes and Lensink, 2003; Ahmed et al. 2015) for extension and robustness of our findings. These three estimators are known to be asymptotically equivalent and efficient in the presence of a serial correlation in the error term and/or a correlation between the regressors and cointegration errors known *second-order bias* (Hayakawa and Kurozumi 2006). Results from these tests indicated that temperature has a positive and significant effect on spawn production in the long run (Table 8). Since variables are in logarithm form, we can easily interpret them in the form of elasticity. Results suggested that, irrespective of model variations, a *1% increase in temperature will lead to more than 5% rise in spawn production in the long run in Halda Basin.* Since the model is in logarithmic form, it is not straightforward to calculate the forecast by taking antilog. Using the methodology proposed by Wooldridge (2015), the error variance must first be calculated, follow by the forecasted value. For instance, if we held fixed precipitation and streamflow at their average values, then in the long-run 1% rise in average temperature will increase the spawn production on average from 239 to 252 kg. However, the significance of the impact of the precipitation and streamflow varied over the alternate models. The negative sign of water-discharged conforms to Miah's (2015) observation that the level of water variation has an adverse effect on spawn production. Most of the models suggested that a 1% increase in the streamflow will lead to decline of < 0.4% in spawn production in the long run in Halda Basin. Moreover, 1% increase in precipitation will lead to > 0.1% rise in spawn production in the long run. Since the FMOL model produces lower variance, it can be taken as the best fitted model among three long run extension models of DOLS, FMOL and CCR. Therefore, it can be concluded that precipitation has a positive effect and streamflow has a negative impact on spawn production in the long run. Further, temperature plays the dominant role in driving spawn dynamics while other variables showed mixed results.

Short Run Effects Analysis

ARDL (1, 1, 1, 1) which was selected using AIC, showed the short-run coefficients of each of the regressors (Table 9). The three variables, temperature, precipitation and streamflow, and their one period lag significantly affect the short-run dynamics of spawn. For instance, the model shows that 1% increases in temperature during the month increased spawn production by 3.99% while 1% increases in temperature in the previous month decreased spawn production by 4.42%. That is, variation in contemporary month temperature has a positive effect on spawn production while variation in temperature in the previous month has negative effect. This indicates that a hot summer period which precedes the pre-monsoon has a negative effect on spawn production. Moreover, it was found that increases in precipitation during March and the previous month decreased spawn production by 0.15% while decreases in streamflow during March and the previous month decreased spawn production by 0.4% to 0.9%. Thus, precipitation and streamflow have a negative effect on spawn production in the short run. This is perhaps due to the fact that pre-monsoon precipitation takes place with storms, cyclones and consequent flooding in the Halda Basin, which creates an unfavorable environment for spawn production. Moreover, the ECM is -0.95 which is negative and less than 1, confirming the short run converge of the model.

*Table 9: Short Run Effects Analysis: Error Correction Model (ECM). N.B: *, ** and *** denote 10%, 5% and 1% level of significance respectively*

ARDL (1, 1,1, 1)		**$\Delta Temp_t$**	**$\Delta Temp_{t-1}$**	**$\Delta Prep_t$**	**$\Delta Prep_{t-1}$**	**$\Delta Water_t$**	**$\Delta Water_{t-1}$**	**E_{t-1}**
Coefficient		3.99*	-4.42**	-0.15*	-0.15***	-0.24***	-0.41***	-0.95***
t-value		2.07	-2.35	-2.68	-2.78	-2.47	-4.46	-10.69
p-value		0.07	0.02	0.09	0.00	0.01	0.00	0.00
F-statistic	18.89			R^2=0.55		Adjusted R^2=0.53		
p-value	0.00							

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Responses of spawn production due to variations in the climate and hydrological variables in the short run are displayed in the impulse response functions (IRF) below (Figure 6).

Figure 6 (a)

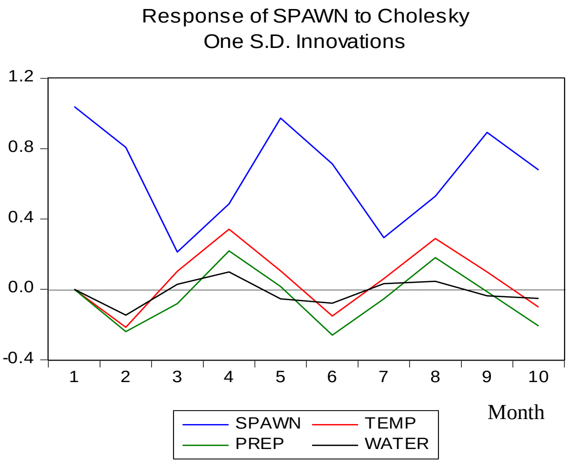

Figure 6 (b)

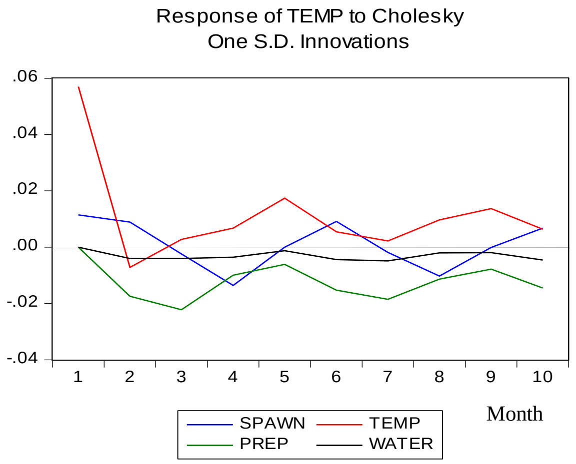

Figure 6 (c)

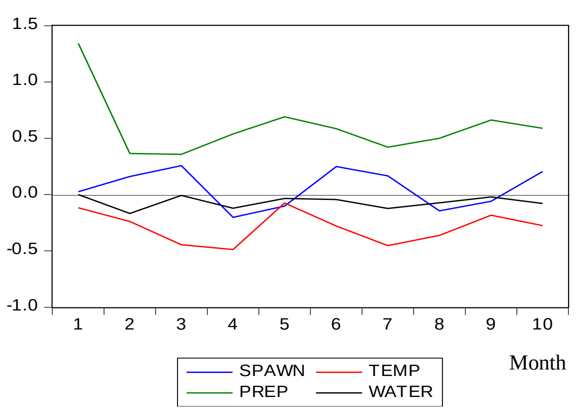

Figure 6 (d)

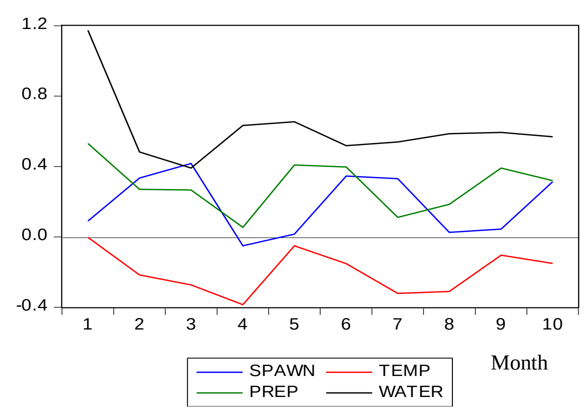

Figure 6: Impulse Response Functions. The vertical axis indicates the $\pm$0.2 standard deviation of innovation and the horizontal axis represents the time period (i.e. month).

Impulse response function depicts the dynamic output for the given input signal (called impulse), that is, the reaction of a dynamic system in response to some external change (Pesaran et al. 1998). Figure 6 exhibits the response of spawn production, temperature, precipitation and water discharge to a one-standard deviation structural innovation. The results are shown by the solid lines. Figure in upper left-hand corner Figure 6(a) shows the response of spawn production to an expansionary shock from temperature, precipitation, water discharge and the spawn production by itself. Figure 6(b), 6(c) and 6(d) represent the responses of temperature, precipitation and water to the other variables respectively. Figure 6(a) shows the impulses from temperature, precipitation and water discharge to spawn production and the results show the cyclical patterns. The spawn production decreases in the very short-run (in April) and then again increases up to June and the cycle continues. It suggests that spawn production declines in the very first stage of pre-monsoon and then increases in the subsequent periods. However, short-run forecast is very complex using the ARDL bound testing approach as it does not consider long-run variance. Using the vector error correction (VECM) approach, the short-run forecast has been calculated for a short-term horizon which resembles the impulse-response results as, in the short-run, the spawn production has been reduced from the average level when the model considers the effects of the forcing variables. VECM analysis suggests that in the short-run spawn production will decrease from 131Kgs to 85 Kgs on average which resembles the IRF's results. Other figures show the impulse-response between the variables.

Temporal Granger Causality

Wald Chi-square Block Exogeneity tests were executed to determine temporal Granger Causality to examine the seasonal or short run causality among the variables (Table 10). It was found that the change in (Δ) temperature, precipitation and streamflow have a direct casual effect on spawn production in the short run. Precipitation and temperature have bi-directional causal relationships suggesting that changes in temperature affect changes in precipitation levels and vice-versa. Moreover, both of these variables affect streamflow levels; however, streamflow has no effect on either temperature or precipitation.

*Table 10: Temporal Granger Causality/Block Exogeneity Wald Tests N.B: Δ to be read as "change in" here. *, ** and *** indicates 10%, 5% and 1% level of significance respectively*

Ho	Wald χ^2	P-values	Outcome
ΔTemp does not Granger Cause ΔSpawn	7.10**	0.03	Ho rejected
Δ Prep does not Granger Cause ΔSpawn	5.38*	0.07	Ho rejected
Δ Water does not Granger Cause ΔSpawn	3.90***	0.01	Ho rejected
ΔSpawn does not Granger Cause ΔTemp	4.53	0.10	Ho not rejected
Δ Prep does not Granger Cause ΔTemp	9.62***	0.01	Ho rejected
Δ Water does not Granger Cause ΔTemp	2.36	0.31	Ho not rejected
ΔSpawn does not Granger Cause Δ Prep	17.01***	0.00	Ho rejected
ΔTemp does not Granger Cause Δ Prep	13.89***	0.00	Ho rejected
Δ Water does not Granger Cause Δ Prep	1.18	0.56	Ho not rejected
ΔSpawn does not Granger Cause Δ Water	26.85***	0.00	Ho rejected
ΔTemp does not Granger Cause Δ Water	5.64*	0.06	Ho rejected
Δ Prep does not Granger Cause Δ Water	10.04 ***	0.01	Ho rejected

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Conclusion and Policy Recommendations

Bangladesh, the fourth largest producer of world fish, is one of the most vulnerable countries to climate change impacts. Halda Basin is the only tidal river in Bangladesh where Indian major carp spawn naturally and, hence, from where fertilized eggs can be collected. In this regard, this chapter examined the impact of climatic variables on spawn production in the short-run and long-run in Halda Basin. An ARDL bound testing approach was employed to investigate the short-run and long-run dynamic relationship between spawn production and major climate variables of temperature and precipitation vis-a-vis hydrological variables of streamflow in the Halda Basin. This time-series spanned 116 spawning months from March-June 1985 to 2013. I then tested the casual effect of temperature, precipitation and streamflow on spawn production.

From this study, I found statistically valid evidence that temperature plays the key role in carp spawn production in both the short-run and long-run. The analysis suggested that a 1% increase in the temperature would increase fish spawn > 6% in the long run as well as almost 4% in the short run. This implies that climate change may have a favorable effect on spawn production in the Halda Basin. However, precipitation and streamflow showed mixed results. While a rise in precipitation may reduce fish spawn in the short-run, it may boost spawning in the long-run.

However, streamflow has negative consequences on fish spawning in both the short and long run. This may be because low flow and sedimentation on the river bed may damage eggs. In addition to temporal effects, I have found a statistically robust casual effect of temperature, precipitation and streamflow on fish spawning. However, a limitation of this study is the lack of the data on physical factors (such as water depth, current, waves, water temperature and humidity) and chemical factors including pH, Dissolved oxygen (DO), which are environmental requirements for spawning. This paves a new avenue for further research incorporating these parameters.

To conclude, I recommend that appropriate steps be taken to maximize natural water flow during March-June spawning period and maintain water quality in the Halda Basin by reducing pollution, siltation and salinity intrusion.

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Appendix

Appendix I: The Threat to Fisheries and Aquaculture from Climate Change

Drivers	Biophysical Effects	Implications for fisheries and aquaculture
Changes in sea surface temperature	More frequent harmful algal blooms; Less dissolved oxygen; Increased incidence of disease and parasites; Altered local ecosystems with changes in competitors, predators and invasive species; Changes in plankton composition.	For aquaculture, changes in infrastructure and operating costs from worsened infestations of fouling organisms, pests, nuisance species and/or predators. For capture fisheries, impacts on the abundance and species composition of fish stocks.
	Longer growing seasons; Lower natural mortality in winter; Enhanced metabolic and growth rates.	Potential for increased production and profit, especially for aquaculture.
	Enhanced primary productivity	Potential benefits for aquaculture and fisheries but perhaps offset by changed species composition.
	Changes in timing and success of migrations, spawning and peak abundance, as well as in sex ratios.	Potential loss of species or shift in composition in capture fisheries; Impacts on seed availability for aquaculture.
	Change in the location and size of suitable range for particular species.	Aquaculture opportunities both lost and gained. Potential species loss and altered species composition for capture fisheries.
Higher inland water temperatures	Increased stratification and reduced mixing of water in lakes, reducing primary productivity and ultimately food supplies for fish species.	Reductions in fish stocks.
	Raised metabolic rates increase feeding rates and growth if water quality, dissolved oxygen levels, and food supply are adequate, otherwise possibly reducing feeding and growth. Potential for enhanced primary productivity	Possibly enhanced fish stocks for capture fisheries or else reduced growth where the food supply does not increase sufficiently in line with temperature. Possible benefits for aquaculture, especially intensive and semi-intensive pond systems.
	Shift in the location and size of the potential range for a given species.	Aquaculture opportunities both lost and gained. Potential loss of species and alteration of species composition for capture fisheries.
	Reduced water quality, especially in terms of dissolved oxygen; Changes in the range and abundance of pathogens,	Altered stocks and species composition in capture fisheries; For aquaculture, altered culture species and possibly worsened losses to disease (and so

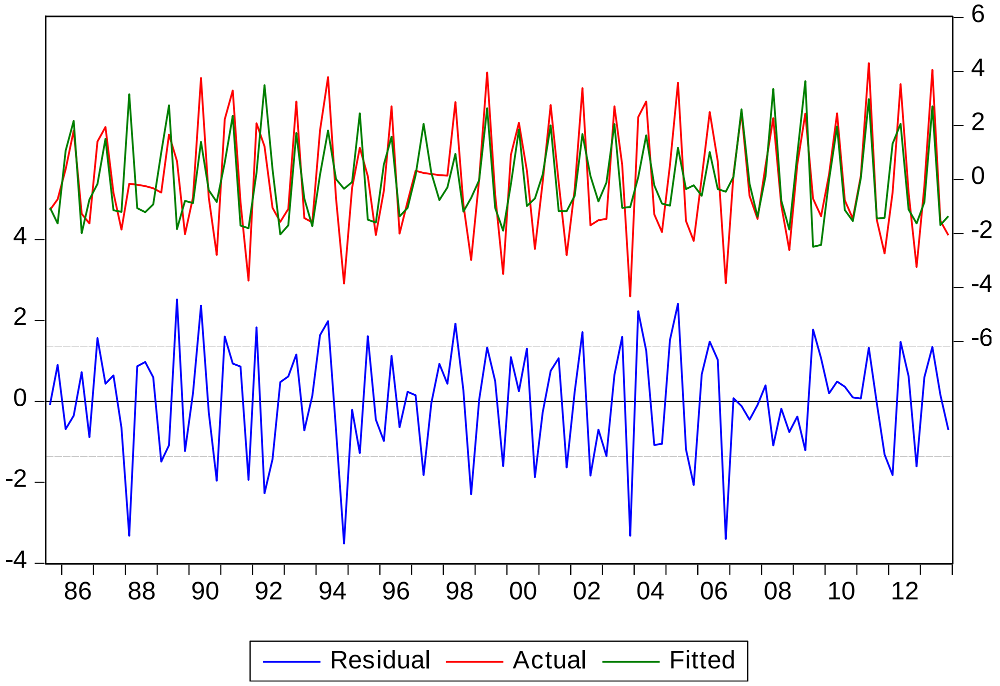
	predators and competitors; Invasive species introduced.	higher operating costs) and possibly higher capital costs for aeration equipment or deeper ponds.
	Changes in timing and success of migrations, spawning and peak abundance.	Potential loss of species or shift in composition for capture fisheries; Impacts on seed availability for aquaculture.
Changes in precipitation and water availability	Changes in fish migration and recruitment patterns and so in recruitment success.	Altered abundance and composition of wild stock. Impacts on seed availability for aquaculture.
	Lower water availability for aquaculture. Lower water quality causing more disease. Increased competition with other water users. Altered and reduced freshwater supplies with greater risk of drought.	Higher costs of maintaining pond water levels and from stock loss. Reduced production capacity. Conflict with other water users. Change of culture species.
	Changes in lake and river levels and the overall extent and movement patterns of surface water.	Altered distribution, composition and abundance of fish stocks. Fishers forced to migrate more and expend more effort
Increase in frequency and/or intensity of storms	Large waves and storm surges. Inland flooding from intense precipitation. Salinity changes. Introduction of disease or predators into aquaculture facilities during flooding episodes.	Loss of aquaculture stock and damage to or loss of aquaculture facilities and fishing gear. Impacts on wild fish recruitment and stocks. Higher direct risk to fishers; capital costs needed to design cage moorings, pond walls, jetties, etc. that can withstand storms; and insurance costs.
Drought	Lower water quality and availability for aquaculture. Salinity changes.	Loss of wild and cultured stock. Increased production costs. Loss of opportunity as production is limited.
	Changes in lake water levels and river flows.	Reduced wild fish stocks, intensified competition for fishing areas and more migration by fishers.

Source: World Fish Centre, Policy brief

Appendix II: Spawning Environment in the Halda River

Parameter	Values	References
Turbidity	300 ppm to 2150 ppm	Patra and Azadi 1985
Seechi disk transparency	10-13 cm	Azadi 2007
Level of pH Hydrogen	7.0-8.2 alkaline	Azadi 2007
Acidic water	6.2-6.8	Azadi 2011
Conductivity	39.19 to 135.94 μ-mhos	Azadi 2011
Dissolved Oxygen (DO)	3.2-6.67 mg/l	Azadi 1996

Appendix III: Residual Plot of Spawn Estimation



CHAPTER 6: CONCLUSION

Climate change and its impacts on water resources has become a global concern, and generates an additional level of insecurity to many South Asian countries. These countries already face a variety of water-related challenges such as floods in the monsoon season, water scarcity in summer, sedimentation and river bank erosion in flood plain areas, drainage congestion in low lying areas, as well as ecological degradation. These threats are particularly significant for Bangladesh.

Despite growing efforts to quantify freshwater availability and the vulnerability of this sector to natural hazards, there has been less focus on climate change impacts on hydrology at a scale relevant for management. In particular, there has been limited use of hydrological models for basin-wide assessments for Bangladesh. Fisheries and water resource sectors in southeastern Bangladesh are highly sensitive to changes in climate. Therefore, my thesis seeks to help fill this knowledge gap and should be of interest to resource managers, planners and policy makers involved with the formulation of regional adaptation strategies.

From this perspective, the first chapter of my thesis provided an assessment of the magnitude of climate change trends across southeastern Bangladesh. The remainder of the thesis explored current and future understanding of the hydrological process of water balance in the Halda Basin, with the goal to support water resource management decisions. In the final data chapter, an investigation of both short run and long run relationships between spawn production of Indian major carp and key climate and hydrological variables was undertaken using an ARDL bound testing approach.

Major Findings and limitations

In Chapter Two, I examined meteorological records from the past three decades across southeastern Bangladesh and demonstrated that there have been detectable changes to temperature and precipitation over this period. In addition, I explored trends in related climate variables, including cloud cover and wind speed, to address the mechanisms underpinning the observed changes over the past three decades.

Between 1980 and 2013, mean maximum daily temperature increased by 0.4 to 0.6°C per decade, with changes of comparable magnitude in individual seasons. The increase in mean maximum daily temperature was associated with decreased cloud cover and wind speed, particularly in the pre and post-monsoon seasons. In contrast to the significant changes in temperature, no trends in mean or total precipitation was found at any station in this region. However, there were a significant increase in the number of rain days during the monsoon season.

In Chapter Three, I used a semi-distributed process-based hydrological model, SWAT, to understand the hydrological process of water balance in the Halda Basin, southeastern Bangladesh, using readily available data. Calibration (NSE = 0.72, R^2 = 0.73) and validation (NSE = 0.71, R^2 = 0.80) of the model performance showed good agreement with the simulated and measured stream flows except during peak flows. However, although model performance was acceptable based on the evaluation criteria used, there remain uncertainties that prevent the model accurately simulating the observed data. The satisfactory performance of the model largely depended on the strong seasonal cycle in the Halda Basin.

The results presented in this thesis are specific to the Halda Basin and hydrological model used, and are based on the basin average. However, average changes do not necessarily reflect changes in variability and in extreme events (Masood et al., 2015). As such, developing and testing alternate hydrological models for other data poor regions is vital to support water resource management decisions. Further, future research on climate change, along with land use changes, should be considered to obtain better hydrological output for models of the Halda Basin. Consequently, future studies may benefit from greater scrutiny and selection of high quality data to enable hydrological processes to be represented more accurately, to improve model performance, and help to avoid arbitrary adjustment of model parameters.

In Chapter Four, I examined the relative impacts of land use and climate change on hydrology in the Halda Basin. Simulations suggested that streamflow may vary depending upon which alternate future eventuates. Although uncertainties exist in future projections, climate model projections indicate that precipitation will be lower in the monsoon season but may increase in the dry season. By the 2060s, maximum temperature is projected to be up to 1.6°C warmer than the baseline period. Minimum temperature is also projected to increase across the 21st century, although at a lower rate than maximum temperature. The relative change in precipitation is projected to be greater during the dry months compared to the monsoon months. These shifts in precipitation are also reflected in simulations of future streamflow, which was projected to increase from a baseline 562 m^3/sec p.a. to 643-674 m^3/sec, depending upon the emission scenario. Under the combined impact of land use and climate changes, models suggested that annual streamflow for the 2060s will be 1.14-1.16 times greater than the baseline. Furthermore, although increases to streamflow were projected for the dry period, declines were projected for the monsoon season. This implies a strong need to adapt rainfall-dependent activities and formulate environmental friendly policies.

Land use change may lead to declines in streamflow for 2060 for both wet and dry season. Projected changes in future land use did not appear to impact highly on streamflow. It must be noted that there remains considerable uncertainty about the future land use scenarios, and this is an area that requires further research. Additionally, the question of how and to what degree changes in land/and climate affect hydrology should be explored using alternate hydrological modelling platforms. Further considerations should be given to base flow estimations. For example, the relationship between base flow and precipitation should be explored to provide a more accurate representation of the physical behavior of this basin. Use of high resolution data, particularly for land use, as well as local land use/landcover data is recommended to develop more realistic estimates of land use changes. Similarly, additional drivers of change should be explored to effectively determine spatial changes in land cover. In addition, the uncertainty associated with climate change scenarios and regional climate model outputs needs to be considered when developing future water polices. Overall, this study helps to understand and visualize how future land use and climate change may interact to alter streamflow. It will assist stakeholders and policy makers to develop alternate adaptation plans for the future distribution of water. It also promotes the assessment of implications of climate vulnerability in view of sustainable water resource management.

In Chapter Five, I used an Autoregressive Distributed Lag (ARDL) Model bound testing approach to investigate the short-run dynamics and long-run relationship between Indian major carp spawn production and key climate variables: temperature and precipitation vis-a-vis the hydrological variable (river water discharge or streamflow). The results indicate that temperature plays the dominant positive role in determining spawn production both in the short-run and long-run. A 1% increase in temperature leads to more than a 6% rise in spawn production in the long-run, while this drops to 4% in the short-run. However, other climate variables - precipitation and streamflow - showed mixed results. For example, streamflow has negative consequences in fish spawning in both the short and long run. Hence, ecological niche modelling to assess species' potential distributions and migration routes under future climate scenarios would aid with identifying key spawning grounds for restoration.

Policy Implications and Future Directions

While this thesis did not directly evaluate the influence of policy on water resources management and climate strategies, it contains relevant policy implications. From a policy perspective, the implications of Chapter Two and Four may aid those who are currently working with climate issues. Several studies have sought to assess recent trends in climate elsewhere across Bangladesh, focusing primarily on shifts in mean annual temperature and total precipitation (Ahmed, 2003; Islam, 2009; Ahsan et al., 2010; Shahid, 2010; Hasan et al., 2014). In general, the climate variability of Bangladesh and the lack of long-term data has hampered efforts to identify recent trends, and Raihan et al. (2015) was the first assessment of climate trends across Halda Basin. However, over the last decade there has been a concerted effort by the Bangladeshi Government to assess recent trends in climate change and implications of future changes. Future research needs to explore trends in other climate variables, beyond temperature and precipitation, to enable a thorough exploration of the mechanisms underpinning wet and dry season trends (e.g. humidity, cloud cover, wind speed). With respect to projections of future climate, variation across the output of the five regional climate models used in Chapter Four highlights the need for impacts assessors to explore a range of climate scenarios in order to develop reliable forecasts of future conditions, and to develop adaptation plans accordingly.

With the support of development partners (e.g. United Nations Environmental Program [UNDP], World Bank, the United Kingdom's Department for International Development [DFID], The Danish Development Organization [DANIDA], the Japan International Cooperation Agency [JICA] the Bangladesh Government has invested ~$US 10 billion over the last 35 years to reduce the vulnerability of diverse sectors (e.g. flood management schemes, coastal polders, cyclone and flood shelters, and the infrastructure development of roads and highways above flood level) to natural disasters (Molla, 2016). In addition, the country is awash with many initiatives and projects related to climate change adaptation and mitigation. To further build the capacity and resilience of the country to meet the challenges of climate change, a 10-year (2009-2018) Bangladesh Climate Change Action Plan has been developed by the government, in conjunction with non-government organizations, research organizations and the private sectors (Ahmed, 2004; UO-Oxfam, 2008; Rahman et al., 2010).

In 2005, Ministry of Government and Forest (MoGF) Bangladesh, presented a set of adaptation measures - NAPA (National Adaptation Program of Action). The theme of Project No-3 highlighted capacity building programs such as: an integrated approach to climate change in planning; designing of infrastructure; conflict management and land water zoning for water management institutions (Huq and Rabbani, 2011). Huq and Rabbani (2011) argued that existing water policies in Bangladesh are partly integrated with environmental issues such as agriculture and sanitation. Sustainability issues of climate change are not yet considered to be a regular part of the water management sector. The Government of Bangladesh instituted the National Water Act 2013 (Government of Bangladesh, 2013) after the National Water Policy (NWPO, 1999) based on integrated surface-ground water development and more robust systems of water distribution and protection. However, as yet there is no adequate indication of how the government will address the key issues such as land grabbing, river encroachment and the establishment of treatment plants for industrial effluent (Ngai Weng et al., 2016). Therefore, integrating climate change policy into surface-ground water planning is crucial to attaining sustainable water resources management and implementation of IWRM (Integrated Water Resource Management) (Rouillard et al., 2014). Moreover, engineers, other policy makers within the water management sector as well as those involved with water governance should undergo training climate change science and adaptation.

Over recent years a number of government departments have been involved with initiatives associated with the management of the Halda Basin, either directly or indirectly. For example, the Department of Environment (DoE) has undertaken work to restore the ecology of the river (MoFL, 2016). The Department of Agricultural Extension (DAE) along with the Local Government and Engineering Department (LGED) constructed a rubber dam at Bhujpur in Chittagong in 2012, to provide irrigation water to adjacent agricultural lands, while the

Bangladesh Water Development Board (BWDB) has removed oxbow bends from sections of the river to reduce exposure to floods. However, while these initiatives have been beneficial to some sectors, they have negatively impacted the breeding capacity of fish and the hatching of fish eggs (MoFL, 2016). In addition, the presence of a paper mill and tannery power plants located around Halda have resulted in the discharge of chemical wastes into the river without proper treatment, which has further impacted the ecology of the river and biology of fish (Akter and Ali., 2012). As such, to reduce the risk of maladaptation, future water management policies must carefully weigh up potential negative impacts that actions may have on other sectors. Indeed, given the decline in the quality of the Halda River in recent years, and the negative impact on the spawning of Indian major carp, judicious intervention from the government and other policy makers will be crucial to the sustainability of these fish and their associated industries. Thus, there is scope for policy intervention on the part of governments in Bangladesh to stimulate spawn production using aquaculture development such as through the development of fishery nursery structures adjacent to the existing regulator at Halda Basin, as suggested by IWM (2012).

In view of the above, policy makers' attention might be drawn to the recommendations below, based on MoFL (2016) and IWM (2012):

- Restoration of the Garduara loop and management of existing loop.
- Relocation of brickfields along the river bank, as the extraction of raw material (soil) from the river bed contributes to river bank erosion, while water withdrawal for brick manufacturing reduces flow during drier months.
- Industries utilizing the Halda River for irrigation should be encouraged to fulfil their water requirements via other sources, for instance rain water harvest, use of groundwater sources through deep/shallow tube wells.

- The ban on fishing within the protected reaches of the Halda River during March to June should be properly monitored.
- An environmental impact assessment needs to be conducted on the impact of existing infrastructure on fish habitat.
- High water demand crops should be cultivated phase by phase or minimized if water availability cannot be ensured.
- Sluice gates already constructed in the river and connecting canals should be renovated and rendered fully operational.

To conclude, the Halda River Basin is of considerable economic, ecological and cultural value to southeastern Bangladesh. Provisioning services across the basin are estimated to be worth $US 21.5 million p.a. (Kabir et al., 2015). The river supports a host of industries associated with egg and fry collection and fisheries, is a key source for drinking and irrigation water, and provides a means for transportation. As such, sustainable use of the river is vital to the surrounding human population. Yet communities utilizing the river have shown concern for its future state (Kabir et al., 2015). My research indicates that climate change will alter future precipitation and streamflow across the Basin. Further refinement of my models will assist with developing adaptation plans to increase the resilience of both natural and human-managed sectors throughout the Basin.

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