ENVIRONMENTAL PREDICTIVE MODELS FOR SHARK ATTACKS IN AUSTRALIAN WATERS

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DECLARATION

This work has not previously been submitted for a higher degree to any other university or

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ABSTRACT

Shark attacks tend to generate disproportionate public concern and, often, calls for enhanced mitigation. However, lethal shark control measures are undesirable and a pressing challenge is to develop non-lethal mitigation strategies. This requires an improved understanding of the drivers of shark attacks. In this study, the relationships between shark attacks in Australia (1915–2015) and environmental variables were explored. Attack data from the Australian Shark Attack File and corresponding environmental data were collated, analysed, and modelled. A K-means cluster analysis revealed two attack temporal periods: 1915–1970 and 1970–2015. White shark attacks in the 1970–2015 period showed the strongest correlation with environmental variables. To identify environmental predictors of white shark attacks, a series of models were fitted, and cross-validated, using presence (attack) and randomly-generated pseudo-absence (no attack) data. The most influential variables were location (river distance, latitude, and longitude), recent rainfall, and SST anomaly. SST anomaly on non-attack dates (mean range +0.5°C to +0.7°C) was significantly (P<0.05) higher than on attack dates (mean +0.2°C). This suggests that with warmer SSTs, white sharks may seek cooler inshore locations potentially bringing them closer to humans. Warning the public of shark attack conditions may decrease attack risk without further affecting marine life.

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1. INTRODUCTION

Shark attacks

Australia has an iconic 'beach culture' that sees thousands of people entering its coastal waters daily to participate in water-based activities (James, 2000; Short, 2007; Short and Woodroffe, 2009). Occasionally, however, humans are attacked, sometimes fatally, by dangerous shark species. Shark attack events are traumatic and usually have severe consequences for those involved (Curtis *et al.*, 2012). In Australia, by far the largest number of serious attacks have been attributed to three species, white sharks (*Carcharodon carcharias*), tiger sharks (*Galeocerdo cuvier*) and bull sharks (*Carcharhinus leucas*) (Chapman and McPhee, 2016) and these three species are the main focus of this thesis.

Shark attacks have been recorded in Australia since the 1700's, although the quality and completeness of the records dating back that far are variable (West, 2011). In an effort to standardise the reporting of shark attacks in Australia, the Australian Shark Attack File (ASAF) was established in 1984 (West, 2011). A report on attacks in 1990, suggested that shark attacks per decade had slowly declined and remained relatively stable after shark management practices were introduced around Sydney in the 1930s (West, 1996).

Over recent years, shark attacks have increased in frequency, worldwide. Australia is one of the global 'hotspots' for shark attacks, recording the highest number of fatalities each year (Chapman and McPhee, 2016). Shark attacks generate disproportionate media and public interest, leading to calls for policy makers to implement more effective mitigation strategies (Neff, 2012; Gibbs and Warren, 2014; Catlin *et al.*, 2014). These management strategies often involve lethal shark control measures (Dudley, 1997).

Shark attack mitigation strategies

Over the last 80 years, successive Australian state governments have implemented a range of shark attack mitigation strategies to address public concerns (Dudley, 1997; Neff, 2012; Meeuwig and Ferreira, 2014). Strategies include the NSW Shark Meshing (Bather Protection) Program (NSMP) introduced in 1937, the Queensland Drumline and Meshing Program introduced in 1962 (Dudley, 1997; Reid *et al.*, 2011), the 2014 Western Australia Bait and Kill policy (House, 2014), and the latest 2016–17 meshing trial on the far north coast of NSW (NSW Fisheries, 2016). Similar management measures have been used in other parts of the world that experience frequent incidents of shark attack, for example the South African KwaZulu-Natal gill-net program (Cliff and Dudley, 2011).

Most existing attack mitigation strategies rely on nets and/or drumlines to reduce the abundance of large, potentially dangerous sharks close to popular beaches (Dudley, 1997; Curtis *et al.*, 2012). However, these strategies may also affect non-target species, some of which are critically endangered, e.g. grey nurse sharks (Reid *et al.*, 2011). With high public concern about the environmental impacts of lethal control measures, several government agencies, academic institutions and private enterprises are investigating non-lethal shark attack mitigation strategies, such as aerial surveillance, drones, smart drumlines, eco-barriers, shark shields, and many others (Neff and Yang, 2013; Kock and O'Riain, 2015; Gibbs and Warren, 2015).

Contributing factors to shark attacks

With improved knowledge and understanding of shark attacks, there is a higher possibility of effective mitigation (Weltz *et al.*, 2013). Chapman and McPhee (2016) suggested, that shark attacks are unlikely to be random events, but rather influenced by a set of conditions that increases the probability of an attack (Chapman and McPhee, 2016). Numerous studies have attributed multiple potential contributing factors to shark attacks and the recently increased frequency of shark attacks. These include the increase in human population, increased popularity of water-based sports, changes in shark abundance, anomalous water conditions, environmental cues, reductions in prey availability, and sharks mistakenly identifying humans as prey items (Wetherbee *et al.*, 1994; McCosker and Lea, 1996; Burgess and Callahan, 1996; Carrier *et al.*, 2010; West 2011; Amin *et al.*, 2012; McPhee 2014; Chapman and McPhee, 2016).

It has been suggested that the steady increase in the number of shark attacks globally is correlated to the increase in human population, and in particular, the increased popularity of water sports such as surfing (Wetherbee *et al.*, 1994; West, 2011; Curtis *et al.*, 2012; Burgess, 2015). However, a decline in white shark attacks in Australia from 1876—1992 was not consistent with an increasing human population, but may have been due to a declining white shark population (West, 1996). In Australia, an increase in white shark attacks has only occurred over the last twenty years (West, 1996; West, 2011), suggesting that other factors may have contributed to changing trends in shark attacks.

Geographical location and specific environmental conditions have been suggested as factors that may increase the risk of shark attacks. Globally, most attacks by white sharks have occurred at the surface of the water, in summer, and in clear waters that are less than 20°C (Burgess and Callahan, 1996). In Western Australia, more white shark attacks have occurred offshore in winter and spring, and in waters that were below 20°C (WA Fisheries, 2012). Coastal rivers and river mouths are shark

feeding and breeding areas, and may be high-risk areas for shark attacks (Pillans and Franklin, 2004; ASAF, 2016). Internationally, bull shark attacks have occurred predominantly near estuaries and river mouths (Chapman and McPhee, 2016). Similarly, in California USA, white shark attacks mostly occurred near river mouths and harbours, and in all months of the year (McCosker and Lea, 2006).

On the east coast of Australia, it has been found through tagging data obtained from other juvenile white sharks, that most white shark attacks have occurred at locations where juvenile white sharks appeared to be in transit rather than in areas where juveniles took residency (Werry et al., 2012). In South Australia, northern NSW, and southern QLD, white shark attacks have occurred in higher numbers during spring, when the waters are the coolest (West, 2011; Werry et al., 2012). In contrast, attacks by bull sharks have occurred more frequently in the Sydney region over the summer when waters are warmer (West, 2011). Despite the foregoing generalisations, the relationship(s) between geographic location, environmental conditions (if any) and shark attacks in Australia are poorly understood.

It has been suggested that more shark attacks on humans occur during periods of warmer oceanic waters characterised by an El Niño event (McCosker and Lea, 1996). However, in California in 1974, the year when one of the highest number of white shark attacks was recorded fell within a 'coldwater' period of the strong 1973–1976 La Nina event (McCosker and Lea, 1996), and fewer attacks occurred during the extreme 1997–1998 ENSO (El Niño/Southern Oscillation) oceanographic warming event (McCosker and Lea, 2006). However, the exceptionally strong climatic El Niño event in 1997–98 was correlated to a substantial increase in shark attacks along the South African coastline (Chapman and McPhee, 2016). The contrast between South Africa and California suggests that a more extensive analysis is needed in order to understand the local climatic conditions and how they might influence the frequency of shark attacks.

Shark attacks on humans are quite rare events and this lack of data complicates a statistically robust analysis of shark attack circumstances. However, the environmental conditions influencing attacks by sharks on their natural prey, such as pinnipeds (white sharks) (McCosker and Lea, 1996; McCosker and Lea, 2006), or turtles and dugong (tiger sharks) (Clua *et al.*, 2014), may help to understand shark attacks on humans. If certain environmental conditions make it more likely that sharks will be in a specific area and/or more likely to be actively hunting prey, the potential for a negative interaction with a human may be increased. It has also been suggested that some attacks on humans may have occurred because a white shark has mistaken a human for a pinniped (McCosker and Lea, 1996; McCosker and Lea, 2006).

The frequency and success of predation on pinnipeds has been found to be influenced by environmental factors (Pyle *et al.*, 1996; Fallows *et al.*, 2016). White sharks prey on pinnipeds throughout the entire day in South Africa, but with a higher success rate in low light levels, (i.e. at dawn and dusk) (Hammerschlag *et al.*, 2006). White sharks also appear to exploit the sun when hunting seals, by positioning the sun behind them in both the morning and afternoon, suggesting that white sharks make behavioural adjustments when hunting to exploit fluctuating local environmental conditions (Huveneers *et al.*, 2015). The frequency of white shark attacks on pinnipeds in California increased with swell height, decreased water clarity, and upwelling the previous day (Pyle *et al.*, 1996). Lunar illumination also influenced shark behaviour (Pyle *et al.*, 1996). Similarly, at Seal Island in South Africa, attack frequency increased in winter, during high tides, under low light levels, and at sea depths of 26–30 m (Hammerschlag *et al.*, 2006). Also in South Africa, Fallows *et al.* (2016), found white shark success in killing Cape fur seals decreased with the Full Moon compared to the New Moon.

Stomach samples taken from tiger sharks indicate that sea turtles and dugongs are common prey items (Heithaus, 2001), and that in certain areas tiger sharks specialise on large air-breathing prey (Fitzpatrick *et al.*, 2012). Perhaps, unsurprisingly, the circumstances of many attacks by tiger sharks on humans are consistent with a typical predatory response to a potential surface prey item, such as a turtle or dugong (Clua *et al.*, 2014).

A multitude of factors may influence shark behaviour and, therefore, alter the risk of shark attacks on humans. These include anomalous water conditions, environmental cues, prey availability, anthropogenic environmental changes, and sharks mistakenly identifying humans for other prey items (McCosker and Lea, 1996; Clua et al., 2014; Chapman and McPhee, 2016). Nonetheless, a broader analysis of the environmental factors and oceanographic processes that may influence shark movements and the risk of shark attack is still needed (Pyle et al., 1996; McCosker and Lea, 1996; McCosker and Lea, 2006; Towner et al., 2013; Weltz et al., 2013; Chapman and McPhee, 2016).

Shark ecology, biology, and migratory behaviours

In recent years, there has been a concerted effort to improve understanding of shark presence, movement patterns, and behaviour, which may assist in minimising the risk of attacks (Curtis et al., 2012; Towner et al., 2013; Weltz et al., 2013; Meeuwig and Ferreira, 2014). Distributions and migratory pathways of animals are often linked to prey availability, thermal tolerances, mating/breeding, and predator evasion (Bruce et al., 2006; Speed et al., 2010). Environmental cues

such as changes in water temperature influence animal movements and behaviour (Speed et al., 2010; Towner et al., 2013). Some shark species are now known to undertake lengthy migrations (Block *et al.*, 2011; Heupel *et al.*, 2015). The factors affecting these movements are thought to be similar to other predators and include, but are not limited to, prey availability, mating, breeding, and the thermal physiological optimum for that animal. (Speed *et al.*, 2010).

Tiger sharks

Tiger sharks utilise a wide variety of habitats ranging from shallow atoll lagoons to deep reefs and open-oceans, and may provide important trophic links between these habitats (Meyer *et al.*, 2010). The presence of tiger sharks appears linked to warmer sea surface temperatures (SST > 19°C), prey availability, and shallower habitats (Heithaus *et al.*, 2007). Large tiger sharks must consume approximately 3.7% of their body weight per day, which corresponds to eight kg per day for a typical 200 kg adult tiger shark (Hammerschlag *et al.*, 2012a). Adults appear to engage in long-distance foraging migrations in order to meet their energy requirements (Papastamatiou *et al.*, 2013), while sub-adults may display year-round residency (Werry *et al.*, 2014). Their presence is often correlated with the abundance of prey, such as dugongs, albatross, and sea turtles (Heithaus, 2001; Heithaus *et al.*, 2005; Heithaus *et al.*, 2007; Fitzpatrick *et al.*, 2012).

Bull sharks

Bull sharks have a widespread distribution in both tropical and warm temperate waters with optimum temperatures in the range 23°C—33°C (Carlson *et al.*, 2010; Smoothey *et al.*, 2016). Their presence in an area has previously been found to be highly related to SST (Smoothey *et al.*, 2016). Bull sharks are thought to be predominately a coastal zone species (Carlson *et al.*, 2010) and their ability to osmoregulate in both salt and fresh water (Hammerschlag, 2006), allows for the species to inhabit an array of shallow freshwater and marine ecosystems (Heupel and Simpfendorfer, 2008; Carlson *et al.*, 2010; Smoothey *et al.*, 2016). Their preference for these ecosystems is likely driven by a high abundance of teleost prey (Hammerschlag *et al.*, 2012b). Additionally, reproduction, e.g. pupping, appears to regulate their movements south (Espinoza *et al.*, 2016).

White sharks

White sharks are a highly migratory species and are commonly segregated spatially, by sex, age, and size (Burgess *et al.*, 2014). Worldwide, mature white sharks and adolescents (sub-adults) spend a portion of their time congregated around coastal aggregation sites (with a peak between August and January in the northern hemisphere), primarily within the vicinity of pinniped rookeries (Jorgensen *et al.*, 2009; Jorgensen *et al.*, 2012). White sharks are known to make lengthy migrations

across cool temperate ocean basins, e.g. from Australia to New Zealand, South Africa to Western Australia, and from California to Hawaii (Jorgensen *et al.*, 2009; Duffy *et al.*, 2012; Bradford *et al.*, 2012). Foraging is unlikely the primary purpose of these offshore migrations, as when sharks were in productive nearshore habitats, they consumed food at double the rate when compared to their consumption rate offshore (Carlisle *et al.*, 2012). Based on data from pop-up archival transmitting (PAT) tags, Jorgensen *et al.* (2012) were unable to ascertain definitively whether white sharks embarked on offshore migrations for mating or foraging, but their behaviour resembled that of lekmating systems in other organisms, such as the shortfin mako (Mucientes *et al.*, 2009).

Globally, SST, seasonal inter-annual variation, and lunar phase appear to influence the ecology and movements of white sharks. Catch rates of white sharks in the KwaZulu-Natal shark nets were higher in years of negative SST anomalies, as white sharks, or perhaps their prey, appear to favour cooler waters in events of upwelling (Cliff *et al.*, 1989). In Florida, white sharks are mostly encountered between January and April, mid-winter to early spring in continental shelf waters ranging 18.8–21.6°C (Adams *et al.*, 1994). In California, white sharks are sighted in greater abundance in autumn, with increased sightings in the New Moon phase (Pyle., *et al*, 1996). Similarly, in South Africa, a higher number of white sharks are reported in False Bay in SSTs between 14–18°C and during New Moon phases (Weltz *et al.*, 2013), and around Seal Island in winter (Fallows *et al.*, 2012).

In Australia, larger white sharks move into waters in greater numbers when temperatures are at an optimum range 14–18°C, with the two sexes having differing optimum thermal ranges (Robbins, 2007). For example, female white sharks were recorded in greater abundance when temperatures ranged 15.7–18.1° C, while males were recorded in greater abundance in temperatures of 14.3–17.8° C (Robbins, 2007). In addition to shark physiology, SST may be an indirect environmental cue for prey availability, given that global spatiotemporal patterns of white shark distribution correlate with high pinniped, squid, and finfish (e.g. tuna) abundance (Pyle *et al.*, 1996; Robbins, 2007; Jorgensen *et al.*, 2009; Jorgensen *et al.*, 2012; Fallows *et al.*, 2012; Carlisle *et al.*, 2012).

The distribution of bull, white, and tiger sharks in Australian waters

The size and location of the Australian continent means that its coastal waters encompass a range of oceanographic and climatic conditions, and a correspondingly diverse range of biogeographic regions (Steffen, 2009). Depending on spatial and temporal variables, these water bodies range in SST from 10°C to 30°C (BoM, 2016). Bull, white, and tiger sharks are present in Australian waters year-round, and collectively inhabit a wide range of marine and brackish habitats including estuaries, beaches, mangroves, open oceans, bays, rivers, and reefs (Figure 1) (Last and Stevens,

2009). Each species occupies different ecological niches in defined geographical regions (Last and Stevens, 2009), which therefore exposes water users to differing relative risks, depending on their location (McPhee, 2014).



Figure 1: Maps of Australia, a. highlights in green the distribution of bull sharks, b. highlights in orange the distribution of tiger sharks and c. demonstrates in blue the distribution of white sharks in Australian waters.

Bull sharks are distributed between southwestern Western Australia, around the northern coastline, and down along the east coast, to southern New South Wales (Last and Stevens, 2009). They are predominately a coastal zone species (Carlson *et al.*, 2010) with many individuals displaying yearlong residency among the Great Barrier Reef (GBR) (Heupel *et al.*, 2015). Bull sharks have a peak in abundance from Brisbane to the GBR in September to December (Heupel *et al.*, 2015; Espinoza *et al.*, 2016). However, lengthy migrations do occur and are predominately made by large juveniles and adult bull sharks (Heupel *et al.*, 2015), with mature females moving south to the Sydney region in the warmer months (February – April) (Espinoza *et al.*, 2016). Tagging data and catch records of bull sharks from the NSMP suggest substantial seasonality, with sharks mostly caught in the summer and autumn months in and around Sydney Harbour, indicating higher abundance in the Sydney region when the SST is greater than 22°C (Reid *et al.*, 2011; Heupel *et al.*, 2015; Smoothey *et al.*, 2016).

Tiger sharks are keystone predators in many Australian marine ecosystems e.g. Shark Bay in Western Australia (Heithaus, 2001). They inhabit both coastal and offshore tropical/sub-tropical waters, from southwestern Western Australia, around the tropical north, and south to the southern coast of New South Wales (Last and Stevens, 2009). Catch rates of tiger sharks in the NSMP are lower in the cooler water months (September-December), perhaps indicating that their presence in these waters can be linked to SST (Reid *et al.*, 2011). Mature females migrate inshore along the east coast, near Queensland in the summer months (Simpfendorfer, 1992). In Shark Bay, Western Australia, the seasonal abundance of tiger sharks frequently correlates with both SST and the foraging patterns of dugongs, one of their main prey items in this location (Heithaus, 2001; Wirsing and Ripple, 2010). Dugongs were found to occupy shallower waters in June, when the abundance

of tiger sharks was relatively low and deeper channels in January when the abundance of tiger sharks was greater, suggesting that dugongs may seek to minimise predation risk by foraging in deeper waters (Wirsing and Ripple, 2010).

The geographical distribution of the white shark in Australian waters differs from that of bull and tiger sharks (Last and Stevens, 2009). White sharks are apex predators (Myers *et al.*, 2007) and have been sighted in all coastal areas in Australia, with the exception of the Northern Territory (Paterson, 1990). They are found in anti-tropical, cool temperate waters (Last and Stevens, 2009), and are frequently reported to have a wide and uneven distribution (Bruce, 1992; Bruce *et al.*, 2006; Blower *et al.*, 2012). White sharks display seasonal aggregations in large numbers at specific locations in temperate waters, e.g. Neptune Islands, South Australia (Paterson, 1990; Bruce *et al.*, 2006; Last and Stevens, 2009).

Juvenile white sharks are temporary seasonal residents in certain locations around Australia, e.g. Port Stephens, NSW and Corner Inlet, Victoria (Bruce *et al.*, 2006; Bradford *et al.*, 2012). It has been suggested that white sharks prefer SSTs between 18°C–20°C (Bruce *et al.*, 2006; Bradford *et al.*, 2012) and catch data from the NSMP does show a peak in white sharks caught in the nets in spring (September to December), correlating with cooler SST (Reid *et al.*, 2011). Juvenile white sharks are hypothesised to make seasonal movements, following common routes or 'highways', and have been documented moving north of NSW (northward along the east coast) between winter and spring, and then south in late spring and early summer (Bruce *et al.*, 2006). Juvenile white sharks in Australian waters are ordinarily found inshore, among rocky reefs, or within shallow coastal bays, confined to shelf waters, and generally in areas between five and one-hundred meters deep (Bruce, 2008; Werry *et al.*, 2012; Bradford *et al.*, 2012).

Study objectives

Current literature suggests that bull, white, and tiger sharks make migratory movements along Australia's coastline that correlate with changing SST (Bruce *et al.*, 2006; Heithaus *et al.*, 2007; Speed *et al.*, 2010; Espinoza *et al.*, 2016). The established relationships that exist between shark movements and their environment suggest a level of predictability regarding movements and/or presence (Bruce *et al.*, 2006; Bruce and Bradford, 2012; Weltz *et al.*, 2013; Towner *et al.*, 2013; Espinoza *et al.*, 2016). However, the links, if any, between environmental factors and the likelihood of shark attacks are still poorly understood. Determining the predictability of these linkages has the potential to inform management and develop strategies that may reduce the risk of shark attacks (Pyle *et al.*, 1996; Weltz *et al.*, 2013; Towner *et al.*, 2013; Chapman and McPhee, 2016).

This thesis is an investigation of the relationship between the incidence of shark attack and environmental variables. Specifically, the aims of this study were to 1) Review and identify patterns of shark attacks in Australian waters; 2) Identify correlations between the incidence of shark attack and regional environmental conditions, and 3) Generate predictive models for shark attacks based on identified environmental factors. Identifying ecological drivers of shark movements and behaviours that may increase the likelihood of a potentially negative encounter between a human and a shark may assist decisions makers in developing shark attack mitigation strategies that enhance the protection of human life, without further affecting the marine ecosystem.

2. METHODS

2.1 Study Area

This study encompassed the borders of Australia's Exclusive Economic Zone (EEZ), which includes all waters 200 nautical miles from the coastline. This includes all Australian fringing coastal states and territories, Territorial Seas, as well as small offshore islands, such as Lord Howe. Australia's coastline is 59,700 kilometres long (including island coastlines), lies between latitudes 9° and 44°S, and longitudes 112°E and 159°E, and encompasses an array of climatic regions from the tropics to cool temperate areas (Short and Woodroffe, 2009).

2.2 Data Collection

2.2.1 Australian Shark Attack File

Shark attack data were obtained from the Australian Shark Attack File (ASAF), which is curated by the Taronga Conservation Society Australia, and affiliated with the International Shark Attack File (ISAF) (West, 2011). The ASAF aims to standardise the reporting of shark attacks in Australia, as well as compile historical shark attack data from a variety of sources (West, 2011). The database is dynamic, and continually researched and updated. It is recognised internationally as Australia's most accurate and comprehensive shark attack database (WA Fisheries, 2012). There are over 100 data fields for each attack, including variables such as species, location, victim activity, and date. However, environmental parameters—such as SST—are incomplete, and so for this study further data collection was therefore required.

The ASAF database was interrogated to obtain all shark attack data from 1915–2015. There were 835 shark attacks over this period, with wobbegongs (*Orectolobidae*) accounting for 20% of these attacks. However, only sharks that have caused fatalities (i.e. bull, white, and tiger sharks) were included in the analysis, as they pose the most threat to human life.

Given the circumstances of an attack, shark identification can sometimes be problematic. Where an accurate identification of the species responsible for the attack—either through visual identification during the incident or a direct examination of the bite wound afterwards—was inconclusive, the ASAF records the species as that most likely to have been responsible. This is established using various factors such as, the location of the attack (river/reef/coast etc.) and the description obtained from the witnesses/victim, expert opinions, as well as similarities to previous incidents (West, 2011, WA Fisheries, 2012). In many cases, the identification of shark species is generic; for instance, many attacks are attributed to 'whalers' as not all attacks thought to be made by bull sharks could be

positively identified as such (West, 2011). In this study, all attacks attributed to bull sharks or 'whalers' were categorised as whaler shark attacks. Any other attacks where the species responsible could not be determined or predicted with a degree of certainty were excluded from the analysis.

In total, there were 531 attacks attributed to tiger, white, and whaler sharks between 1915 and 2015, which were included for analysis. The exclusion of the further 99 attacks was due to speculation regarding the species involved in the attack, as well as due to missing environmental data for some of the attacks. Of these attacks, the original ASAF data fields retained for analysis were date, season, species, location (beach/river), and attack severity.

2.2.2 Shark attack location

The ASAF lists location and site description for each attack. Using Google Earth (Google, USA), latitude and longitude points were recorded for the nearest water body described.

2.2.3 Pseudo-absence points

The shark attack data represent a 'presence only' dataset, and, therefore, only represent the environmental conditions on attacks days. In order to identify the environmental drivers of the months when attacks occurred, the background environment needed to be included in the predictive modelling. This was achieved through the use of pseudo-absence points (Chefaoui and Lobo, 2008; Brodie *et al.*, 2015). However, the primary issue with this approach is that geographical location and the number of points is not robustly assessed (Warton and Shepherd, 2010). To compensate for this, and as well as avoid issues with model interpretation and implementation (Warton and Shepherd, 2010), pseudo-absence points were selected randomly within similar spatial and temporal boundaries of the attack (presence) locations (Phillips *et al.*, 2009; Warton and Shepherd, 2010; Brodie *et al.*, 2015). A total of 4500 pseudo-absence points were generated using the R package *spatialEco* (Evans, 2016). These random points were generated within the EEZ of Australia. Subsequently, a random date between 1915 and 2015 was allocated to each point, by generating a random date in Excel 2016 (Microsoft). If a subsequent check determined that an attack had in fact occurred in that location and on that date, a new random date was generated.

2.2.4 River distance

Given that previous studies have linked rivers, lakes, harbours, and/or embayments that are open to the sea and both shark presence and shark attacks (see above), the distance (in km) from each attack location (latitude and longitude) to the nearest river was calculated. The rivers that were included on the Geoscience Australia base layer in ArcGIS version 10.2 (ESRI, California) were used for the analysis. Distance from river was calculated using the latitude and longitude of each attack

and the coordinates of the closest river mouth, i.e. where the river meets the sea. Attacks that occurred within a river were given a distance to river of 0 km.

2.2.5 Human population

To assess whether the increase in shark attacks over recent years might be correlated with human population growth and the increase in popularity of water based activities (e.g. West, 2011), human population data were incorporated into the analysis. No reliable water-activity usage data dates back to 1915; therefore, total human population numbers (1915–2015) were obtained from the Australian Bureau of Statistics (ABS, 2016) for the analysis.

2.2.6 Environmental Data

Sea Surface Temperature (SST) and SST anomaly

SST data were collected from the Centre for Environmental Data Analysis (CEDA). This was the most comprehensive SST dataset available over the 101 year time frame, i.e. the Met Office HadISST 1.1 dataset (Hadley Centre for Climate Prediction and Research, 2006) which provided monthly SST records in 1° area grids. Weekly recordings would have been preferred; however, monthly data is all that exists for the entire data set dating back to 1915.

SST data were obtained for each attack (presence) or non-attack (pseudo-absence) location (1° resolution). The long-term mean SST was also calculated for each location in the same month over the 101 year period. Using the observed monthly SST and the long-term mean, the SST anomaly was calculated for each of the attack or non-attack data points. In order to compare and highlight trends of changing SST's over the years, annual SST anomaly data were calculated for the entire study area from 1915–2015. Annual anomaly data for the oceans surrounding Australia were obtained from the National Oceanic and Atmospheric Administration (NOAA) database (NOAA, 2016).

Post 1994 SST Temperature data and corresponding spatial maps

There is a detailed time series available from the Integrated Marine Observing System (IMOS) Data Portal (http://imos.aodn.org.au/imos/) starting in 1994. Six day average SST and SST anomaly measurements were obtained from the satellite-derived SST (MODIS-Aqua). Mean SST for each attack was calculated as the mean over a 100 km² area centred over the attack location, over 6 days, starting 3 days before the attack, and ending 2 days after the attack.

SST anomaly data were also calculated using the same temporal and spatial parameters. SST anomaly was calculated as the temperature difference between SST and the long-term mean SST (1994–2015).

Rainfall

Rainfall amounts around the time of each attack were obtained from the Bureau of Meteorology (BoM), Australia (BoM, 2016). For each data point (attack or non-attack), the nearest rainfall stations were identified and the total and long-term mean monthly rainfall were recorded (in mm). Rainfall anomaly was calculated as the monthly mean rainfall minus the long-term (1915–2015) mean rainfall for the same month.

2.3 Data analysis

2.3.1 Cluster analysis

In years where a large number of attacks occurred (e.g. 2009, 2012), there has been a tendency to refer to these incidences collectively as attack 'clusters' (Sprivulis, 2014). Statistically, clustering is a formal analytical method where data are partitioned into subsets through validated algorithms (Han et al., 2011). A K-means cluster analysis is one of the most popular and simple clustering algorithms (Jain, 2010). The algorithm assigns each data point to a cluster subset, via similarities (Jain, 2010; Han et al., 2011). In order to determine if shark attacks that appear temporally close are separate temporal attack 'clusters' the data were partitioned statistically. Using the function kmeans in the software program R (CoreTeam, 2014), shark attack data were entered as a continuous string of frequencies and dates over the 101 year period. The cluster analysis partitioned the data into two subgroups; attacks that occurred between 1915 and 1970 (Cluster 1 or period 1), and attacks that occurred between 1970 and 2015 (Cluster 2 or period 2). A K-means cluster analysis was only used as a method to split the data temporally. Attack clusters are not being redefined in this study and it is important to note that attack clusters would need a spatio-temporal analysis to identify shark attack clusters.

2.3.2 Shark attacks and long-term population/social trends

Given that not only the human population has increased, but also the number of people engaged in water-based activities, a yearly trend was calculated to account for these social changes. Annual social trends were determined by fitting a polynomial curve to the shark attack yearly sum plot, which was weighted for human population. Population was weighted using the attack rate mean, where the total annual population in millions (e.g. 5.6 was used for a human population of 5,600,000) was divided by the yearly attack sum (e.g. 5). Any year that was one standard deviation above the long term attack mean was considered a high attack year, and any year that was considered one standard deviation below, was considered a low attack year.

2.4 Environmental predictive models

2.4.1 Environmental covariates

To avoid problems with collinearity among variables used in the modelling, environmental variables for all data points (presence and pseudo-absence) were tested for covariation using Pearson's rank correlation coefficient and pair plots (Zuur *et al.*, 2007). Covariates were removed where the reported Pearson's rank correlation coefficients were > 0.5 and < -0.5 (Brodie *et al.*, 2015).

2.4.2 The explanatory model

Models were created in an attempt to predict the probability of a shark attack occurring under certain environmental conditions. To fit and 'train' the model, 80% of the presence (attack) data were used, along with ten times that amount of randomly generated pseudo-absence (non-attack) data, based on previous approaches with this type of modelling (Chefaoui and Lobo, 2008). Generalised Linear Models (GLM) were fitted to four datasets or subsets: 1) attacks by all species (whaler, white, and tiger sharks) for the entire dataset (1915–2015); 2) attacks by all species in Cluster 2 (1970–2015; arising from the cluster analysis); 3) attacks by each individual species (white shark, whaler shark, and tiger shark) (1915–2015); and 4) attacks by white sharks in Cluster 2 (1970–2015). Attacks by whaler sharks and tiger sharks were only modelled for the entire period (1915–2015), and not the later Cluster 2 epoch (1970–2015) like white sharks, due to small sample sizes and large variance. As the response variable was count data, a binomial distribution with a logistic link function was selected for the subsequent modelling (Zuur et al., 2007).

Model explanatory variables were selected for the GLMs using the forward-backward stepwise logistic regression method, where the most significant (P<0.05) variables that also decreased the Akaike Information Criterion (AIC) were retained and used to build the final model (Chefaoui and Lobo, 2008), because stepwise regression can be prone to overfitting the data. One way to test for model performance and accuracy is through cross validation (Hilbert, 2004). To avoid overfitting, the model fits were validated using AIC scores, such that if the addition of an environmental variable did not decrease the AIC by more than five points, that variable was dropped from the model (Zuur et al., 2009).

After examining the distribution of the residuals obtained from the tiger and whaler shark attack GLMs, other statistical models were investigated. When models require a more flexible regression and error structure the best practice is to use additive models, e.g. Generalised Additive Models (GAMs) (Zuur *et al.*, 2009). GAMs allow for a more flexible non-linear relationship between the

response variable and multiple explanatory variables. GAMs are a more simple and intuitive model, and are somewhat easier to interpret (Zuur *et al.*, 2007). Given this, GAMs were subsequently run on all original GLMs. The same methods that were used to fit the GLMs were used to fit the GAMs. The only changes in the methodology were that GAMs were run using the *gam* function in the 'mgcv' package of R, and that explanatory variables were smoothed (Wood, 2006).

Smoothing of the variables gives a line of best fit that is non-linear. However, smoothing is liable to cause overfitting in GAM's, and in order to avoid overfitting explanatory variables were smoothed using a penalised regression spline smoother (Brodie *et al.*, 2015). This allowed for the smoothness of the line to be controlled based on Generalised Cross Validaton (GCV). If the estimated degree of freedom (edf) was close to one, this indicated that the smoothing had generated a fit of linearity (Zuur *et al.*, 2009), and any variables that had an edf of 1 were not smoothed in the final model (Brodie *et al.*, 2015). The final model was chosen based on the set of variables with the lowest AIC (Ryan *et al.*, 2015).

2.4.3 Interpreting the model

The spatial patterns of shark attacks were displayed using their geographical locations. Attacks were plotted as XY coordinates in ArcGIS version 10.2 (ESRI, California) for each species, on a map of Australia. Additionally, geographical and environmental model explanatory variables for each shark attack model were discussed and plotted. By visually demonstrating the relationships between the variables and attacks, highlighted higher attack risk parameters.

2.4.4 Model evaluation

Evaluation of the predictive ability of each model was assessed using cross-validation. This involved randomly partitioning the data into two groups: the model fit subgroup consisted of 80% of the data, and the test subgroup consisted of the remaining 20% of the data. The test subgroup was not used to fit the model, but as a cross validation tool to test the predictability of the model fit. The tested subgroup had a 1:1 ratio of presence to pseudo-absence data.

The predictive power for each model was assessed in two ways. Firstly, the trained and tested models were assessed using the function *evaluate* in the R 'dismo' package (Hijmans *et al.*, 2013), and the mean Area Under the receiver-operating Curve (AUC) was calculated and retained for each model (Hijmans, 2012). An AUC score of 0.5 from a possible range of 0–1 indicates a prediction as good as random, and an AUC score >0.75 is considered to have a good predictive power (Brodie *et al.*, 2015).

The AUC score and overall model fit was tested by predicting the probability of an attack from the test (20%) dataset subgroup. The models prediction of an attack (probability) was then compared to the test subgroup attack or non-attack data, in order to assess the accuracy of the predictions. Predictability was recorded as a mean percentage and was calculated subtracting the probability of an attack from 1 (predicted vs observed).

2.4.5 White sharks and SST anomalies.

Temporal analysis of SST anomalies

To determine if the observed SST anomalies on an attack day were consistent or abnormal for that region, a temporal analysis was undertaken. Importantly, standardising month and location in such an analysis removes any potential seasonal and spatial variation. Therefore, monthly SST anomaly at each attack location was recorded, as well as the SST anomaly for the same month in both the year before and the year after. An ANOVA was used to compare the SST anomalies in the attack year, the year before and the year after.

Spatial comparisons of SST anomalies

In order to characterise the background environmental conditions of attacks, and determine whether attacks occurred in differing SSTs, a spatial analysis was also undertaken. The annual mean SST anomalies of Australia's surrounding coastal waters were calculated for each year between 1915 and 2015, as well as the white shark attacks annual mean SST anomalies. Australia's coastal waters mean SST anomalies were compared with ANOVA to the white sharks annual mean SST anomalies. This was also plotted in order to display the relationships between shark attacks SST anomalies and the surrounding waters SST anomalies.

A spatial case study – Far North Coast of NSW

Some 15% of all white shark attacks have occurred on the far north coast of NSW, i.e. Ballina shire, Lennox Head, and the Byron Bay region since 1970, and so this region was selected for a spatial comparison of SST anomalies. Standardising the temporal scale for the analysis removes temporal variation and, therefore, only compares SST anomalies on a regional scale. Using ANOVA, the monthly SST anomaly for each attack location, to the SST anomaly 100 km north of the attack, and 100km south of the attack were compared. SST anomalies at the attack location, and north and south were collected for the same month of the attack but two years previous, whilst ensuring no attack had happened within those sample months. Running the same spatial analysis in non-attack years (two years previous) established whether there was a difference in SST anomalies between the different geographical locations.

3. RESULTS

3.1 Data analysis

3.1.1 Shark attacks in Australian waters between 1915 and 2015

There has been a total of 835 shark attacks (attributed to 12 different species of shark) in Australian waters between 1915 and 2015. One in every four of these attacks was fatal, and three species of shark were responsible for those fatal attacks, white sharks, tiger sharks, and whaler sharks. Of the 835 attacks, 75% (630) were attributed to whaler, white, and tiger sharks, of which 531 cases were used for analysis in this study. White sharks were responsible for 45% (237) of these attacks, followed by tiger sharks 30% (160), and whaler sharks 25% (134).

3.1.2 Frequency of shark attacks over time

Since the mid 1970's there has been an increase in the mean number of shark attacks per year, and the year-on-year variability in attack counts (Figure 2). The *k-means* cluster analysis supported this, partitioning the data into two temporal clusters: attacks that occurred from 1915–1970 (Cluster 1) and attacks that happened from 1970–2015 (Cluster 2) (Figure 2). The two clusters were significantly different (ANOVA, P = 0.01, $t_{df} = 1$) in both the mean number of attacks per year, as well as the variance in attacks (Cluster 1 $\overline{x} = 4.25$ s² = 7.94, Cluster 2 $\overline{x} = 6.5$ s² = 24.26).

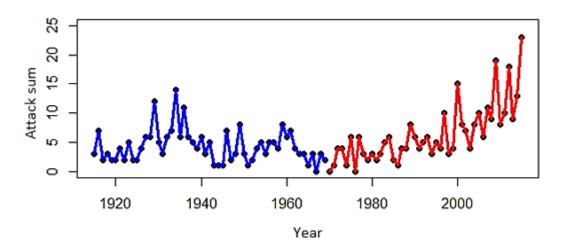


Figure 2. Number of shark attacks per year for whaler, white, and tiger sharks combined from 1915–2015. Cluster 1 is represented by the blue line, which highlights attacks occurring from 1915–1970. The red line represents Cluster 2, attacks occurring from 1970–2015.

The different cluster groups were also dominated by different species (Figure 3). Tiger and whaler sharks were responsible for most of the attacks in Cluster 1 (1915–1970), while Cluster 2 (1970–2015) was dominated by white shark attacks. Of the 250 attacks that have occurred between 1970 and 2015, 72% (180) were attributed to white sharks. Overall, white sharks have increased in the

number of attacks (Cluster 1 Σ = 57, and Cluster 2 Σ = 180), particularly since 2000 (2000–2015 Σ =124), with greater annual variability (Cluster 1 s² = 1.16, and Cluster 2 s² = 16.43).

The number of attacks by white sharks was significantly different between Cluster 1 (1915—1970) and Cluster 2 (1970—2015) (ANOVA, P< 0.001, t_{df} = 1), with more attacks occurring per year in Cluster 2 (Cluster 1 \overline{x} =1.03 s² = 1.16, Cluster 2 \overline{x} =3.91 s² = 16.43). The number of attacks by whaler sharks have remained consistent over the years, with no significant difference in frequency between the two clusters (ANOVA, P=0.34, Cluster 1 Σ = 56, \overline{x} =1.21 s² = 1.26 and Cluster 2 Σ = 47, \overline{x} =1.46 s² = 2.03). However, the number of attacks by tiger sharks have decreased significantly with fewer attacks in Cluster 2 than Cluster 1 (ANOVA, P<0.001, Cluster 1 Σ = 116, \overline{x} =2.07 s² = 3.30 and Cluster 2 Σ = 47, \overline{x} =1 s² = 1.17).

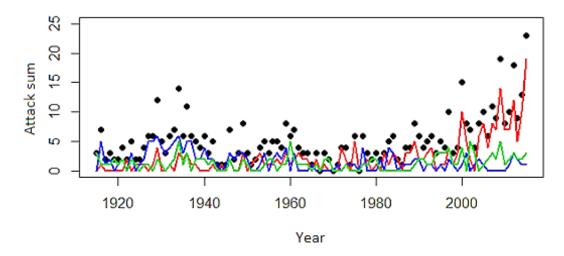


Figure 3. Number of attacks per year by whaler, white, and tiger sharks species combined from 1915 to 2015 (black points). Attacks by individual species are also shown: white sharks (red line), tiger sharks (blue line), and whaler sharks (green line). Note the marked increase in attacks by white sharks (but not other species) since 2000.

3.1.3 Shark attack trends

When the attack data were fitted with yearly trends, there was still an overall increase in shark attacks, as well as high year-to-year variability (Figure 4). The years that were considered high attack years in Cluster 1 were; 1929, 1932–37, 1940, 1946, 1949, 1954, 1956–57, 1959–61, and high years in Cluster 2 include; 1975, 1977, 1989, 1997, 2000, 2009, 2012, and 2015. Years that had higher attack numbers occurred less frequently in Cluster 2 (Σ =8) than in Cluster 1 (Σ =16). The presence of distinct high and low attack years (Figure 4) suggests that factors other than population growth may be affecting the overall increase and annual-variation in the total number of shark attacks. Because of this finding, subsequent modelling was performed on the data in an attempt to identify any environmental factors that may explain the overall increase in attacks and fluctuations between years.

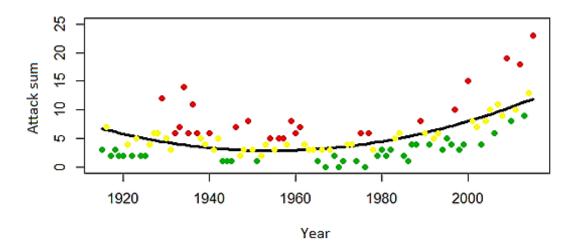


Figure 4. Total number of attacks attributed to whaler, white, and tiger sharks per year, fitted with a polynomial curve to account for population and yearly social changes over time. Data point's one standard deviation (SD) above the curve (red filled circles) were considered high years and data points one SD below the curve (green filled circles) were considered a low year. Yellow points indicate the years that fall within a 95% confidence interval of the fitted trend line.

3.2 Environmental predictive models for shark attacks

3.2.1 Environmental covariates

The covariates retained for model selection (highlighted with an asterisk (*) in Appendix 1, Table 2) were month, distance to river, latitude, longitude, SST anomaly, and total monthly rainfall. SST and average SST were removed due to their strong correlation with latitude. Mean rainfall and rain anomaly were also removed as a result of a strong correlation with total rainfall, and season was removed due to the correlation with month. Additionally, year had an equal mean with no significant (P>0.05) difference between presence and pseudo-absence data points.

3.2.2 Model fits

Both GLMs and GAMs were fitted to the attack data. The final models were: 1) GLM of attacks by all of whaler, white, and tiger sharks in Cluster 2 (1970—2015); 2) GLM of attacks by white sharks in Cluster 2 (1970—2015); 3) GAM of attacks by whaler sharks from 1915-2015; and 4) GAM of attacks by tiger sharks (1915-2015).

The ability of most of the models to predict the probability of an attack was good based on AUC values (Table 1). The white shark attack Cluster 2 (1970–2015) model AUC was 0.86, whaler, white, and tiger sharks attack Cluster 2 (1970–2015) model AUC was 0.83, and the whaler (1915–2015) model AUC was 0.9 which indicated good predictive power for these models. However, the tiger shark (1915–2015) model AUC was 0.6, which does not indicate good predictive power, given that a value close to 0.5 indicates a chance or random performance. The ability of the models to predict attack and non-attack data points was also assessed on the tested group's residuals, which was the predicted values (model) vs. the observed values (tested subgroup).

Table 1. Summary of models predicting attacks for whaler, white, and tiger sharks combined and individual species of sharks from the environmental variables.

Model	Year	Test	Variables	Р	AIC	AUC	Р%
Combined	1970-	GLM					
Final model	2015		riverdist * raintot * month * lon	0.001	1031	0.86	69.41
Final model -1			riverdist * raintot * month + lon		1093		
White sharks	1970-	GLM					
Final model	2015		riverdist * lon * lat * raintot + sstanom	0.015	502	0.83	66.67
Final model -1			riverdist * lon * lat * raintot		520		
Whaler sharks	1915-	GAM					
Final model	2015		s(riverdist) + s(lon) + s(lat) + s(raintot) + s(month)	0.001	363	0.90	79.54
Final model -1			s(riverdist) + s(lon) + s(lat) + s(raintot)		395		
Tiger sharks	1915-	GAM					
Final model	2015		s(riverdist) + s(lon) + s(lat) + s(raintot)	0.001	547	0.69	35.78
Final model -1			s(riverdist) + s(lon) + s(lat) +		582		

Column one displays the model descriptor, the final model, and then the final model minus the last variable added (Final model -1). Timeframe of the data used is listed in year. Test identifies the type of model, e.g. Generalised Linear Model (GLM), or Generalised Additive Model (GAM). The explanatory variables are listed in the column 'Variables', and presented how the model was fitted including all slopes and interactions. The s written in front of the covariate represents a smoothing factor was used in the final model. P-values comparing the two last models are listed in the column p. All models listed have the AIC for each model fit, which were used to avoid overfitting. Model validation is provided; Area Under the receiver-operating Curve (AUC), with the correctly predicted percentage recorded as P%.

Whaler, white, and tiger shark attacks

Shark attacks attributed to whaler, white, and tiger sharks have occurred around most of the Australian coastline, with the highest frequency of attacks recorded on the east coast, between Sydney and Brisbane (Figure 5). The species responsible for each attack largely reflects the natural geographical distribution of that species, e.g. white shark attacks occur mostly in temperate and cool-temperate waters south of the Tropic of Capricorn.

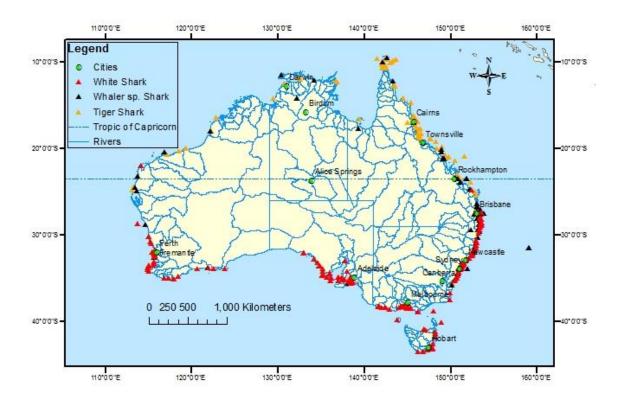


Figure 5. The distribution of whaler, white, and tiger shark attacks in Australian waters between 1915 and 2015. Red represents white shark attacks, orange tiger shark attacks and black whaler sharks attacks. Attacks follow the natural distributions of the species attributed to the attack.

Whaler, white, and tiger shark attacks between 1970 and 2015

Whaler, white, and tiger sharks model indicated that attacks were recorded more frequently in warmer months between October and April along the east coast of Australia. These attacks also occurred close to rivers. Of the 250 attacks, 48% (120) occurred within 10km of the nearest river, as well as within the river itself. Most attacks were recorded in months when the total rainfall was less than 100mm (Figure 6). The model predicted that the probability of an attack by whaler, white, and tiger sharks increases within 10 km of a river, along the east coast, in warmer months with a total monthly rainfall of less than 100 mm. However, the probability of an attack changes with each differing parameter of the interacting environmental variables.

Based on these explanatory variables, the model correctly predicted 69.41% of the test (20%) subset data for all shark attacks in Cluster 2. However, the model was more efficient at predicting absence (non-attack) points, rather than attack points. The model predicted 10% of the tested attacks to have a probability of zero, indicating that one in every ten attacks was/is unable to be predicted.

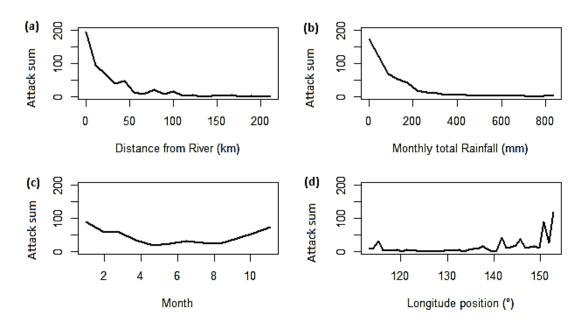


Figure 6. The relationship between whaler, white, and tiger shark attacks combined and the explanatory environmental variables; (a) Distance from River, (b) Monthly total Rainfall, (c) Month, and (d) Longitude. Shark attacks in Cluster 2 (1970—2015) occur in greater numbers in warmer months along the east coast of Australia, within a 10 km radius to the closest river, and with a monthly total rainfall of <100 mm.

White Shark attacks between 1970 and 2015

The Cluster 2 (1970–2015) white shark attack GLM retained most of the explanatory variables, which suggests a strong relationship exists between geographical location, environmental conditions and white shark attacks (Table 1). Most retained covariates increased the predictability of an attack in a non-linear fashion, and, therefore, could not be modelled by the additive marginal effects alone. Rather, river distance, latitude, longitude and total monthly rainfall interacted with each other on different levels/intercepts, thus increasing probability of an attack based on the combination of these factors. The final model was significantly (P=0.02) influenced by SST anomaly, when compared to the previous model (Table 1).

White shark attacks in Cluster 2 (1970—2015) occurred in greater numbers along the east (NSW) and central south coasts (SA) of Australia. On average they were recorded within 19.94 km of the nearest river, with a total monthly rainfall of <100 mm (Figure 7). White shark attacks mostly occurred during positive SST anomalies (\overline{x} = +0.19°C). The probability of an attack by a white shark is therefore higher within 20 km of a river, south of the Tropic of Capricorn, in months where total rainfall was less than 100 mm and within positive SST anomalies.

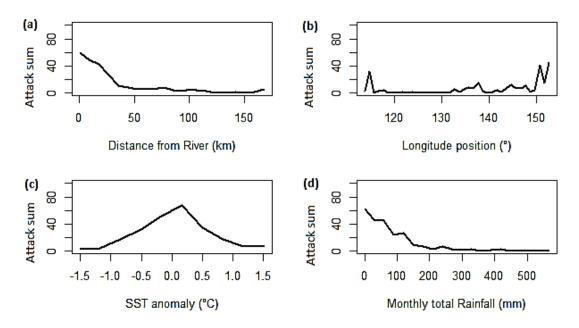


Figure 7. The relationship between white shark attacks and the explanatory environmental variables; (a) Distance from River, (b) Longitude, (c) SST Anomaly, and (d) Monthly total Rainfall. White shark attacks in Cluster 2 (1970–2015) occur in greater numbers along the east, and south west coast of Australia, in positive SST anomalies (x = +0.19°C), within a 40km radius to the closest river (x = 19.94), and with a monthly total rainfall of <100mm.

When this model was cross-validated on the test subgroup, it correctly predicted 66.67% of both presence and absence points (Figure 8). The model was better at predicting absence (non-attack) data points than attack data points. Nevertheless, the explanatory variables predicted the probability of an attack at greater than 0.8 for a third of the actual attacks that did occur. However, five actual attacks were given a probability of less than 0.2.

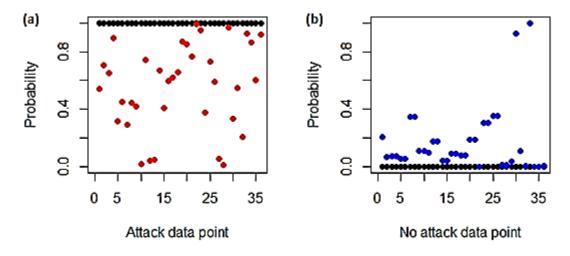


Figure 8. Prediction plot of the GLM model of attacks by white sharks in Cluster 2 (1970–2015). (a) Presence or attack data (red dots), (b) pseudo-absence or non-attack data (blue dots). In each graph, the Y-axis represents the predicted probability value of a particular attack or non-attack based on the fitted environmental predictors. Filled black circles in each graph represent the observed values (attack or no attack having a value of 1 or 0, respectively).

Whaler shark attacks between 1915 and 2015

Whaler shark attack data were modelled using a GAM (Table 1). The model displayed a strong relationship between attacks, geographical location, and seasonality when covariates were smoothed in order to account for non-linear relationships (see Appendix 1, Figure 16). Whaler shark attacks increased and peaked within 10 km from a river (\overline{x} = 13.92 km), between latitudes -35°S and -20°S (Figure 9). The explanatory power of the model increased significantly (P<0.001) with the addition of month and rainfall (Table 1). Attacks were recorded more frequently in the summer months, showing a rapid increase from October to December followed by a decrease in March, with a total monthly rainfall of approx. 100 mm. The model predicts that the probability of an attack by a whaler shark was greater within 10 km of a river, between Sydney and Brisbane, in warmer months with a total rainfall of less than 100 mm.

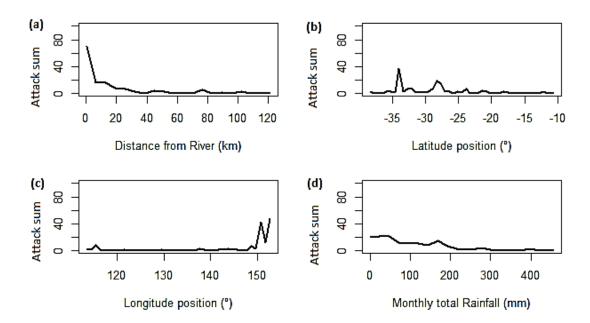


Figure 9. The relationship between whaler shark attacks and explanatory environmental variables; (a) Distance from River, (b) Latitude, (c) Longitude, and (d) Monthly total Rainfall. Most whaler shark attacks occurred on the east coast of Australia, around Sydney, with an additional peak on the far north coast of NSW, within a 5km radius to the closest river, and with a monthly total rainfall of <100mm.

The model fit correctly predicted 79.54% of tested data (see Appendix 1, Figure 17). However, 75% of the attacks were predicted based on the geographical location. Additionally, the model predicted one non-attack data point with a probability of 0.5, given the data point's season and geographical location.

Tiger shark attacks between 1915 and 2015

Attacks by tiger sharks were modelled using a GAM and have a relationship predominately with geographical location (Table 1). The retained smoothed covariates for the final model were: distance from river, longitude, latitude, and total monthly rainfall (Appendix 1, Figure 18).

The GAM highlighted that tiger shark attacks were likely to occur on the coastline, with a higher likelihood of an attack occurring further away from rivers (\bar{x} = 43.08 km), particularly at offshore locations (Figure 10). The longitude and latitude effect confirms this, with attacks increasing on northeast coasts in reef locations. The effect of rain (higher rainfall in the tropics), further supports the geographical relationship with tiger shark attacks (total rainfall prior to an attack was <200 mm). The model predicts that the probability of an attack by a tiger shark was higher in offshore locations amongst reefs.

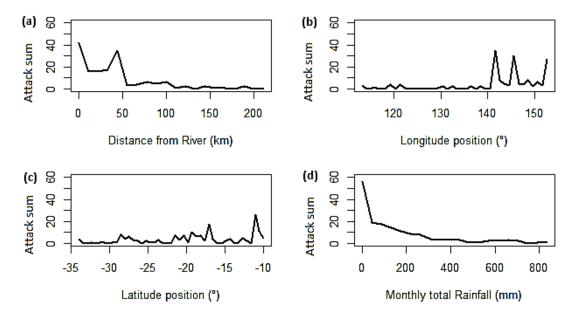


Figure 10. The relationship between tiger shark attacks and explanatory environmental variables; (a) Distance from River, (b) Longitude, (c) Latitude, and (d) Monthly total Rainfall. Tiger shark attacks tend to occur offshore on the north east coast of Australia, within a 50km radius of the closest river, and with a monthly total rainfall of <200mm.

As the AUC score indicates, the GAM for tiger shark attacks performs poorly when predicting attack incidents (see Appendix 1, Figure 19). The model correctly predicted only 25% of the non-attack test data, and predicted several attacks to have a probability of zero. Based on the identified significant predictor variables, the model was unable to adequately predict the probability of tiger shark attacks.

3.3 White shark attacks relationship with SST anomalies

3.3.1 Temporal analysis of SST anomalies

The predictive models identified SST anomaly as a significant (P=0.04) explanatory variable for white shark attacks in Cluster 2 (1970–2015). To investigate the relationship between attacks and SST changes, anomalies were examined on a finer scale (Appendix 2, Table 3). White shark attacks occurred in a significantly (ANOVA, P=0.02) lower SST anomaly ($\overline{x} = +0.19$ °C), when compared to the SST anomaly of the year before and year after ($\overline{x} = +0.52$ °C) (Figure 11).

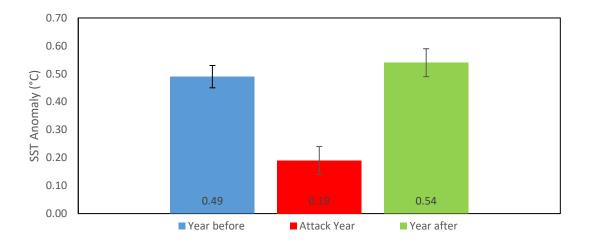


Figure 11. Temporal comparisons of monthly recorded Cluster 2 (1970—2015) white shark attacks SST anomaly data. Values shown are mean and ± 1 standard error of the mean SST anomalies for the year before (blue) and the year after the attack (green) compared to the year of the attack (red), at the same location, and in the same month. Note that white shark attacks occurred in lower SST anomalies than both the year before or the after.

3.3.2 Spatial scale analysis of SST anomalies

The oceans around Australia have warmed by an overall mean of +0.9°C, since 1915. During this period, white shark attacks occurred in significantly less positive (ANOVA, P=0.04, t_{df} = 1) SST anomalies (\overline{x} = +0.19°C), compared to the average ocean SST anomaly (\overline{x} = +0.50°C) (Figure 12).

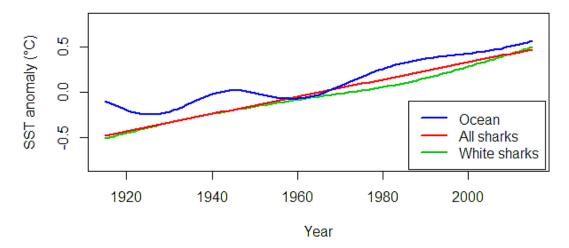


Figure 12. Smooth spline lines plot comparing SST anomalies. The blue line represents the mean Australian oceans SST anomaly between 1915 and 2015. The red line is the mean SST anomaly of all shark attacks, and the green line represents white shark attacks mean SST anomaly. Overall, white shark attacks occur in less positive SST anomalies than the mean ocean SST anomaly.

3.3.3 Spatial scale analysis of SST anomalies - A Case Study

Since 1970, 15% of all white shark attacks have occurred on the Far North Coast (FNC) of NSW, Australia (latitude - 28°S) (Figure 13). When the FNC's white shark attack's SST anomalies were compared to those both 100km north and 100km south of the attack locations, there was a significant difference between them (ANOVA, P = 0.02). In attack months the mean SST anomaly for the FNC was +0.20°C, while the mean SST anomaly north of the attack was +0.75°C and for south of the attack was +0.64°C. Thus, waters surrounding the attack locations were warmer (combined north and south mean +0.5°C), indicating that white shark attacks occurred in relatively cooler waters (Figure 14). For non-attack years there was no significant difference (P = 0.07) between the mean SST anomalies for the location where the attack had occurred at another time (mean = +0.3°C), and north (mean = +0.5°C) or south (mean = +0.4°C).

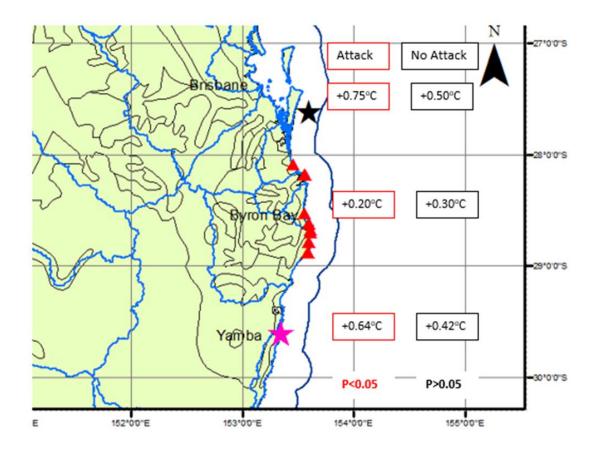


Figure 13. A map of the Far North Coast (FNC) of NSW. Black star symbolises testing location 100km north of the attacks. Red Triangles represent attacks along the FNC, and the Pink star symbolises the testing location 100km south of the location. The red squares on the map represent the average SST anomaly for that region in attack years, and the black squares represent SST anomalies recorded for non-attack years.

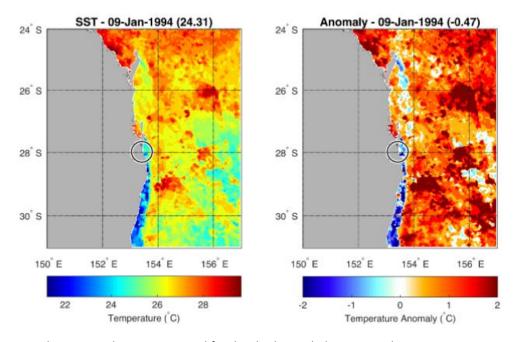


Figure 14. A SST and SST anomaly map generated for the shark attack that occurred on NSW FNC in January 1994. The black circle represents the attack location, which recorded an average SST anomaly measurement for a 100km² radius, which was compared to the grid 100km above and below the circle. These maps show the cooler pocket of water that occurred along the coastline, and the temperature difference, north, south and offshore, suggesting that attacks may be more likely when relatively cooler pockets of water occur in inshore locations.

4. DISCUSSION

Environmental predictive models for shark attacks

All shark attacks analysed in the present study occurred within the natural geographical range of the three species deemed responsible (Last and Stevens, 2009). Through the use of predictive models, geographical parameters and other environmental variables such as rainfall and SST anomaly were correlated with the likelihood of an attack. Given the geographical differences in the distribution of whaler, white, and tiger sharks, attack trends were modelled separately for each individual species rather than collectively.

White shark attacks

The occurrence of white shark attacks displayed the strongest relationship with environmental conditions. Geographical location, monthly total rainfall, and SST anomaly all had a significant interacting relationship. The multidimensional nature of the model highlights the complex relationship that likely exists between attacks and these environmental variables. However, the model may be useful for predicting climatic conditions under which the probability of an attack by a white shark is higher.

White shark attacks were recorded within the shark's natural distribution, south of the Tropic of Capricorn, in cool/temperate waters (Last and Stevens, 2009), with a mean SST of 19.57°C. The results of this study are consistent with the incidence of white shark attacks globally, which have generally occurred in clear waters, less than 20°C, nearshore, and in all months (Burgess and Callahan, 1996; Levine, 1996; West, 1996).

SST anomalies had a significant effect on the probability of a white shark attack. This was evident when comparing SSTs of attack locations to pseudo absence points, the temporal differences (year before/year after) analysis, and the spatial differences analysis (SST anomalies on the FNC of NSW). Essentially, attacks by white sharks occurred more frequently in locations that were significantly cooler than the surrounding waters. This finding reflects observations of predation attempts by white sharks on pinnipeds, which occurred more frequently and had a higher rate of success following the upwelling of cooler water at the attack location (Pyle *et al.*, 1996).

SST anomalies are relative, as they were calculated using the long-term average over the study period from 1915 to 2015, and within this timeframe SSTs have increased by 0.9°C (BoM, 2014). Thus, attacks still appear to occur when there is a positive temperature anomaly. However, rather than thinking of the SST anomaly as being positive or negative (relative to the long term average,

the absolute value of which will change depending on the range of years used to calculate it) it should be interpreted as a temperature difference relative to surrounding locations.

Given that the oceans around Australia are warming, all being equal we would expect to see temperatures increase from the year before, to attack year, then to the year after. However, the attack year was cooler than both the year before and the year after. This indicates that attacks occur when the waters are cooler, similar to reports of white shark attacks in California occurring in cooler water periods (McCosker and Lea, 1996). These findings also reflect catches of white sharks in the KwaZulu-Natal nets, which occurred at a higher frequency in years when water was cooler (Cliff *et al.*, 1989), and with white shark abundance in Gansbaai, South Africa, which were more common in cooler years (Towner *et al.*, 2013).

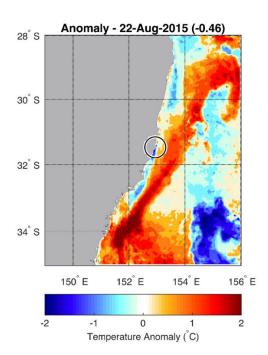
Cooler SSTs in Australian oceans are related to climatic changes, ENSO events, seasons, geographical location, and oceanographic processes. Year-to-year ENSO variability generates either cooler or warmer SSTs (IMOS, 2016). Mean SSTs around the coastline of Australia vary with season, spring recording the coolest temperatures, and autumn the warmest (IMOS, 2016). Moreover, these changes in SST are influenced by oceanographic processes such as wind strength and direction, as well as, strengthening boundary currents e.g. the western boundary current - the East Australian Current (EAC), the poleward moving current on the west (Leeuwin Current), and their eddy effects (Waite et al., 2007; Suthers et al., 2011; Everett et al., 2014; Carroll et al., 2016). The eastern, southern, and western coasts of Australia are all affected by seasonal upwelling events (Waite et al., 2007; Everett et al., 2014). Upwelling results in cooler, nutrient-rich water being brought to the surface, which has a higher concentration of chlorophyll-a, thus generating increased prey availability to marine predators such as sharks (Waite et al., 2007). The strongest upwelling events are usually recorded in summer, although they can occur at other times throughout the year (Oke and Middleton, 2001).

SST is one of the most important environmental variables determining the geographical distribution of sharks (Knip *et al.*, 2010) and is an environmental cue that is often linked to the movements and distribution patterns of many marine species including potential prey of sharks (Block *et al.*, 2011; Towner *et al.*, 2013; Weltz *et al.*, 2013; Hobday *et al.*, 2015; Brodie *et al.*, 2015; Carroll *et al.*, 2016). It has been suggested that migration movements by white sharks are influenced by SST, as they are known to move into areas only when SSTs falls within an optimal range (Cliff *et al.*, 1989; Adams *et al.*, 1994; Pyle *et al.*, 1996; Reid *et al.*, 2011; Bruce and Bradford, 2012; Werry *et al.*, 2012; Towner *et al.*, 2013; Weltz *et al.*, 2013;). It is unclear whether the preference for specific SSTs by white sharks

is driven by the sharks' physiological requirements or whether the sharks are following prey that may also use temperature cues, for example to find food. Given that white sharks are endothermic and are able to regulate their internal temperature (Goldman, 1997), it may be that SST preferences are related to foraging behaviour, as it is known that several prey items of white sharks, such as albacore and bluefin tuna show distinct SST preferences during migration (Dufour *et al.*, 2010).

Using a finer scale analysis, the case study on the FNC of NSW further confirmed that white shark attacks occur in locations that are cooler relative to surrounding waters. Other marine predators also use thermal cues. Little penguins seek out areas with relatively lower SSTs, possibly due to prey availability, as forage fish are vulnerable to rising SSTs (Carroll *et al.*, 2016). Bluefin tuna, a prey item of white sharks, were caught in higher numbers in areas with negative sea surface height anomalies and cooler SSTs (Teo and Block, 2010). One of the white shark's major prey items, pinnipeds, also forage in areas that are influenced by SST, for example Australian fur seal individuals selected regions for foraging where SSTs range was 16.0–16.8°C (Arnould and Kirkwood, 2007).

Seasonal upwelling occurs at specific locations, as does the aggregation of white sharks (Bruce and Bradford, 2012). Cooler upwelled water conditions have been previously found to favour juvenile white sharks, due to prey availability (Cliff *et al.*, 1996). Consistent with this, is the presence of a juvenile white shark nursery at Port Stephens in NSW (Bruce, 2008), which experiences large upwelling events (Oke and Middleton, 2001; Bruce and Bradford, 2012). This location and other surrounding locations are coincident with several shark attacks that occurred during these oceanographic events (Figure 15). This suggests that further research on the influence of ocean processes on shark presence, behaviour, and movement patterns is needed.



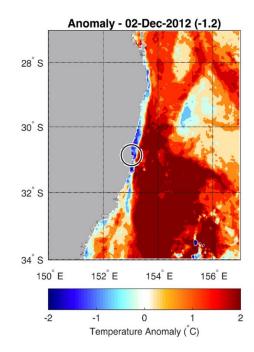


Figure 15. SST anomaly maps generated for the shark attacks that occurred in Port Macquarie in December 2012 (left panel) and August 2015 (right panel). The circle is centred on the attack location, and describes an area of 100km². This was compared to the 100km² immediately above and below the circle. These maps show the cooler pocket of water that occurs along the coastline, and the temperature difference, north, south and offshore, suggesting that attacks are occurring in cooler inshore locations.

The predictability of the model used to fit the white shark attack data was considered high based on the AUC score. However, in large part this score reflects the fact that the model was very good at predicting non-attack days, although it still predicted a number of attacks with reasonable probabilities. Further improvements in the accuracy and predictability of the white shark attack model will require a restriction of the geographical extent of the data included in the modelling, as many of the pseudo-absence points were in offshore locations and this will likely have biased the success of the model in predicting non-attack days. Moreover, future studies could incorporate weekly SST data, international white shark attacks, other oceanographic processes (e.g. upwelling events), predator-prey interactions, and additional measures of shark presence, e.g. meshing catch data or tagged shark data.

Whaler shark attacks

A GAM was used to predict the probability of a whaler shark attack based on explanatory variables. Significant identified environmental predictors for whaler shark attacks were river distance, latitude, longitude, and monthly total rainfall, which indicated the importance of seasonal factors and geographical location on the probability of an attack.

The geographical factors identified for whaler attacks were consistent with their ecology. Attacks are more likely to occur within 10 km of a river, which coincides with their preferred habitat, the

coastal zone (Carlson *et al.*, 2010). The probability of a bull shark capture in Sydney Harbour increases exponentially when water temperatures are above 23°C (Smoothey *et al.*, 2016), which is consistent with the findings of this study in that the probability of an attack increased in southerly locations, such as Sydney, in the summer and autumn months. Given the correlation between location and SST it might be assumed that the probability of an attack increases with warmer temperatures. However, this interpretation must be taken with caution as bull sharks migrate southwards in the summer months (Espinoza *et al.*, 2016). This suggests that month and location are the strongest environmental predictors, and SST alone cannot predict the probability of a whaler shark attack/presence, a conclusion also supported by the low/high AIC score of the GAM fit.

The ability of the fitted model to predict a whaler shark attack was relatively good. However, the probability of an attack was based on seasonal and geographical covariates alone, which is likely to produce a high number of false positives and thus limit the practicality of this model as an attack mitigation tool. For example the model would indicate a high probability of an attack on any day between December and April in Sydney Harbour, yet such an attack is in fact a relatively rare occurrence. To further improve the accuracy and predictability of the model, future research could potentially include the effects of oceanographic processes, chlorophyll-a levels, predator-prey interactions, and energetic requirements in cooler waters/breeding periods.

Tiger shark attacks

A GAM was used to predict the probability of a tiger shark attack based on explanatory covariates. River distance, latitude, longitude, and monthly total rainfall were all significant identified explanatory variables for tiger shark attacks and, again indicate the importance of geographical location on the probability of attacks. Tiger shark attack probability increased further north and east on offshore reef locations. The location of attacks were consistent with the distribution of this species (Last and Stevens, 2009). Given that latitude correlates strongly with SST, it suggests that tiger sharks have thermal preferences and indicates that their presence can be linked to SSTs (Reid et al., 2011).

The accuracy of predictions for tiger shark attacks were poor. The model demonstrated a significant relationship to geographical location, and therefore, when an attack occurred outside this geographical range it was given a low probability score, essentially a false negative. These predictions indicate that tiger shark attacks cannot be adequately modelled or predicted based on the existing attack data. To improve the accuracy and predictability of the model, future research

should include the effects of oceanographic processes, anomalous SSTs, chlorophyll-a levels, migration, habitat usage patterns, and predator-prey interactions.

Shark attack and environmental data

This study was the first of its kind to predict the probability of a shark attack based on environmental conditions. Previous modelling approaches have determined the probability of shark presence based on environmental conditions (Towner *et al.*, 2013; Weltz *et al.*, 2013), identified oceanic habitats for pelagic fish (Brodie *et al.*, 2015), predicted distribution patterns of whale sharks (Sequeira *et al.*, 2012; Sequeira *et al.*, 2014), and predicted the probability of shark catch in differing SSTs (Smoothey *et al.*, 2016). The results from this study must be interpreted with caution due to the small sample size, variability of habitats around Australia, the complexities of the models, and the particular environmental parameters used.

In order to maximise sample size, attack data going back as far as 1915 were analysed. However, because of the limited availability of environmental data over this period, SST data was restricted to monthly 1° grid samples. The mean monthly SSTs recorded at this scale limited the resolution of temperature for smaller bodies of water, e.g. areas of cooler water arising from upwelling events, and for shorter time scales. Future studies may be able to utilise SST data at a finer temporal and spatial resolution, e.g. daily/weekly records at 1x1km grid – available since 1994 (IMOS).

Distance from river is a complex variable for a number of reasons. Any point along the coastline of Australia is on average 22km from the closest river. Thus, most attacks occurred close to rivers because rivers were common and close to each other. However, when the average distance of attacks to a river was 10km or less, which was the case for whaler sharks, river location may play a role in the predictability of attacks, as river distance was a significant explanatory variable for all species. Distance from river increased the probability of an attack when in a certain geographical location For example proximity to a river between Sydney and Brisbane increased the chance of an attack by a whaler shark, while increased distance from a river on the north east coast of Australia increased the chance of an attack by a tiger shark.

The significance of distance from river as an explanatory factor may be influenced by the pseudoabsence points, as they were randomly generated within the geographical envelope defined by the furthest attack from the coastline, for all species. Hence, more pseudo-absence points were located further away from the coastline than most of the attacks. In future work, pseudo-absence points with restricted geographical range will be generated to address this bias in the model. Rainfall and SST anomaly relationships were unaffected by the current approach to selection of pseudo-absence data points as they were calculated within the same grid as if the point was located on the coastline.

Shark attacks where the species responsible has likely been misidentified or implied based on circumstantial evidence, e.g. a white shark recorded as a whaler, may have resulted in reduced confidence in the models. It is believed that juvenile white shark attacks are often confused with bull shark attacks (Bruce, 1992). Additionally, the whaler shark model potentially incorporates attacks by a range of whaler and other species, not necessarily just bull sharks, which may have also affected the relationship with environmental conditions given their differing ecologies and life histories. Curating the data in the ASAF in an attempt to remove records where species identification was uncertain should have reduced these types of errors in the modelling but may not have been perfect.

Factors contributing to the increase in shark attacks

Australia is a global 'hotspot' for shark attacks (Chapman and McPhee, 2016). Shark attacks have increased markedly since the 1970s and show significant inter-annual variation in attack rate, both of which are trends that are reflected globally (McPhee, 2014). Both in Australia and worldwide, the increase in attacks has been attributed to white sharks (McPhee, 2014). It has been suggested that the global increase in shark attacks is related to human population growth, shark population growth, increased participation in water-based activities, and other contributing factors, e.g. environmental influences (West, 2011; Chapman and McPhee 2016).

Human population and water based activities

Given that many have suggested that the increase in shark attacks over recent years has been attributed to the increase in the human population (Wetherbee *et al.*, 1994; West, 2011), and the increase in water-based activities, this study has attempted to account for this. A yearly social trend line was fitted to the annual total of shark attacks, in order to see if attacks were related to population (Figure 4). Similar to McPhee (2014), and Chapman and McPhee (2016), human population alone was found to be an insufficient explanatory factor.

It has been proposed that an increase in participation in water-based activities, e.g. surfing, as well as the availability of wetsuits that have made it possible for humans to participate in water-based activities for a longer period of time, as well as year-round, have potentially increased our exposure to sharks and thus resulted in the increase in attacks (West, 2011; Clua *et al.*, 2014; Chapman and McPhee, 2016). However, as shark attacks fluctuate each year even when accounting for these yearly trends (increase in water sports, wetsuit usage, and water-based activities), it is considered

unlikely that the increase in participation in water-based activities is the sole contributing factor to shark attacks (McPhee 2014).

Shark abundance

Yearly trends such as the variation in shark abundance were considered when classifying annual abnormal shark attack numbers. As previously mentioned, human population and social trends were also considered. However, there was still an overall increase in shark attacks in Australian waters since 1970.

Since the instalment of the NSMP, there has been a reported decline in white sharks being caught in the nets, although, the catch rate of white sharks has recently been found to slightly increase over the past two decades, with present catch rates being similar to that in the 1980's. This is perhaps a result of the species receiving national protection under the Commonwealth's *Environment Protection and Biodiversity Conservation Act 1999* (Reid *et al.*, 2011). The recent incline suggests that perhaps the juvenile white shark population may be starting to show signs of recovery along the coast of NSW. However, the white shark catch rate since the early 1990's, remains less than the catch rate when the nets were first installed in 1937 (Reid *et al.*, 2011) and so it seems unlikely that the increase in shark attacks since 1970 reflects increasing white shark abundance (Chapman and McPhee, 2016)

Tiger shark attacks have declined over the 101 year period studied, with a significant difference in the number of attacks between Cluster 1 (1915—1970) and Cluster 2 (1970—2015). This could be correlated to shark abundance or shark control programs, as the overall number of tiger sharks caught in shark control programs have declined over time, (Holmes *et al.*, 2012; Reid *et al.*, 2011). Declining trends in annual catch rates of tiger sharks in Queensland and NSW may reflect the state of the local population, or indicate a spatio-temporal shift in tiger shark abundance (Holmes *et al.*, 2012; Reid *et al.*, 2011).

Whaler shark attacks were consistent over the 101 year study period with no difference in the number of attacks between Cluster 1 (1915—1970) and Cluster 2 (1970—2015). However, whaler shark data from the NSMP significantly declined by 75% since 1950 in the annual catch rate, possibly indicating a significant decline in the population (Reid *et al.*, 2011). Given the coexisting nature between the two, there is question if shark populations contribute to shark attack numbers. However, the extent of geographical movement and habitat usage patterns of large sharks complicates our ability to monitor populations and, therefore, it is inconclusive if attacks are related to shark abundance.

Shark attack clusters

Years in which a large number of attacks have occurred, have been referred to as 'attack clusters' (Neff and Hueter, 2013; Sprivulis, 2014). However, the *k-means* statistical cluster analysis from this study only partitioned the dataset into two temporal periods: attacks that occurred from 1915—1970 (Cluster 1) and attacks that occurred from 1970—2015 (Cluster 2). This result suggests that high attack years are not distinct temporal clusters, but instead represent either random variability or a latent relationship with specific environmental factors. White sharks dominated all the eight high attack years since 1970 and are a species for which movements and behaviours are influenced by environmental factors.

High attack years and the relationship to climatic conditions

One of the strongest ENSO El Niño events occurred between 1997–1998, causing increased ocean warming (Hoegh-Guldberg, 1999; Jin *et al.*, 2003). The South African eastern boundary Agulhas Current system was positively and significantly correlated to SST in the KwaZulu-Natal area, which recorded a positive SST anomaly during the 97-98 ENSO event (Rouault *et al.*, 2010), as well as a decreased catch rate of white sharks in the shark nets (Dudley and Simpfendorfer, 2006). However, the southern west coast of South Africa is significantly negatively correlated with the eastern boundary current (Rouault *et al.*, 2010), and affected by the upwelling system generated from the Benguela current (Nelson, 1992). This suggests that the warming ocean on the east and perhaps the upwelling processes on the south-west may have influenced the decreased catch rate in KwaZulu-Natal and the increased attack rate southwest of South Africa in 1998 (Chapman and McPhee, 2016).

Much of southeast Australia has experienced rainfall substantially below the long-term average since 1997 (Timbal and Jones, 2008). To coincide with this climatic pattern strong El Niño events were experienced in Australia in 1982-1983, 1997-1998, 2009-2010 and again in 2015-2016 (NOAA, 2016). Similar to South Africa, Australia also saw a high number of attacks during the 1997-1998 El Niño event, and then again in 2009 and 2015. However, the 1982 El Niño event did not results in a high number of attacks in Australia, similar to the situation in California (McCosker and Lea, 1996). Over the last thirty years in strong El Niño events, Australia have coincided with a greater number of shark attacks. However, this has not been the case in South Africa (Chapman and McPhee, 2016). Australia has also recorded high attacks years in 2000 and 2012, which were not El Niño events, although these years experienced strengthened boundary currents influencing SSTs and Chl-a levels (IMOS, 2016).

The media called the 2008—2009 summer season the 'Sydney Shark Summer' (Powell, 2015). Australia documented the second highest number of shark attacks on record in 2009. Simultaneously, Australia was exposed to an array of climatic conditions and weather extremes (Chapman and McPhee, 2016). The country was affected by abnormally high temperatures and lower than average rainfall (National Climate Centre, 2009), which is consistent with previous studies of environmental conditions in high attack years (McCosker and Lea, 1996). NSW had a major heat wave, with 2009 being the warmest year on record (National Climate Centre, 2009; Chapman and McPhee, 2016). The state also documented 16 of the 19 attacks that occurred in Australia, with 70% of those attacks recorded within the first 3.5 months.

The strong western boundary current, the EAC, pushed warm waters down the coast in the summer of 2009. At the EAC separation point an anti-cyclonic eddy was formed generating an upwelling event in the late summer. This upwelling event brought cool-nutrient-rich waters to inshore areas around the Sydney region (IMOS, 2009; Suthers, 2015). The inshore SST was notably cooler than surrounding waters and recorded an increased chlorophyll-a level for several weeks after the event (IMOS, 2009). This persistent oceanographic process occurred within the same spatial and temporal scales as the recorded shark attacks. As outlined earlier, elsewhere higher attack numbers, catch rates, and predation success on pinnipeds have been linked to 'colder-water' periods. The oceanographic process that occurred in the late summer of 2009 may therefore have been a direct contributor to the higher frequency of attacks.

Warm outer shelf waters driven by strong boundary currents, and cooler inshore SSTs, are possibly an environmental cue used by white sharks, or their prey, to move closer in to shore. This was demonstrated in the spatial analysis used in this study. Oceanographic processes potentially reduce the foraging area of white sharks or their prey, into narrow cooler inshore shelf waters. The compression of white sharks into a smaller area closer to shore may heighten the risk of an attack on a human.

Australia also experienced a high number of attacks in 2012 but the temporal and spatial pattern of the attacks was different to the 2009 event. The majority of attacks occurred in winter from Western Australia to southeast Tasmania/Victoria. The Leeuwin current was strong during winter and resulted in several eddies around the coast, which generated a mixing of cold and warm water. This mixing generates nutrients, thus increasing prey availability (IMOS, 2016). The southern shelf in 2012 also experienced very strong current speeds and along-shelf flow (IMOS, 2016). The chlorophyll-a deep within these currents was found to be a significant indicator of the total water

column productivity within the region (Waite *et al.*, 2007). However, whether these unusually strong currents and increased prey availability along the shelf are related to higher shark attack numbers is uncertain.

Australia recorded the highest number of attacks ever in 2015. On average attacks that occurred in 2015 were consistent with previous findings and the present study's findings that white shark attacks occurred in waters 0.5°C cooler than surrounding water temperatures. The relationship between white shark distribution and SST is complex (Towner *et al.*, 2013). White sharks of different mass/size are likely to have different thermal physiological requirements, as well as differing prey items, both of which may influence their movement patterns (Hussey *et al.*, 2012). In years of warmer ocean SST, the presence and sexual ratio of sharks has been found to be altered at known aggregation sites (Robbins, 2007). This raises questions as to whether sharks and/or their prey are actively seeking out cooler waters in those warmer years, given their absence from known aggregation areas.

World-wide, 2015 was also the highest attack year on record (Burgess, 2015). In order to determine if high attack years in 'shark attack hot spots' are correlated, it is recommended that shark attacks be investigated on a global level. A larger sample size could then be used to investigate the environmental drivers of global shark attacks, and potentially identify the general climatic conditions or environmental cues for high attack years. Further long-term research is needed correlating oceanographic influences to shark movements, predator-prey interactions, and behaviours (Suthers *et al.*, 2011). Greater knowledge of large predatory shark's movement and habitat usage patterns, improves the accuracy of predicting attacks, and in turn leads to increased human safety (Weltz *et al.*, 2013).

Summary/Conclusion

Shark attacks are infrequent events that result in disproportionate attention and often trigger the implementation of enhanced management strategies. Non-lethal mitigation strategies that do not impact marine life are preferred by the majority of stakeholders and this has resulted in an expansion of research that aims at understanding shark movements and behaviours, with the aim of decreasing the risk of sharks to ocean users. Previous research has shown a level of predictability in regards to shark movements and presence given particular environmental cues. To this end, environmental predictors for shark attacks were investigated and identified.

Tiger shark attack probability increases offshore in tropical locations amongst reefs. The probability of a whaler shark attack is higher along the coast when the animal is migrating to and from Sydney

in warmer months (December to April). White shark attacks had the highest predictability and strongest relationship to environmental variables. The identified environmental predictors suggested that white sharks might seek out specific cooler inshore locations that may bring them into closer contact with humans. Variations in climatic conditions appear to coincide with the interannual variation in white shark attacks, suggesting that attack risk may be higher in some years than in others. To identify higher risk years for shark attacks further research is needed investigating the influence of oceanographic processes on shark movements and behaviour.

Decision makers could use identified explanatory variables (location, time of year, and SST anomaly) to increase public awareness on shark attack conditions. A 'higher risk day' warning system could eventuate from the findings of this study and build upon current shark attack mitigation strategies. Warning the public of shark attack conditions could potentially decrease the risk of an attack without further affecting marine life.

5. APPENDIX

5.1. Appendix 1: The model fit

Table 2. Summary of environmental/geographical covariates relevant to the 531 shark attacks used in the present study. The observed range is provided for each of the species, where T refers to Tiger shark, W to White shark and B to Whaler shark, mean values in brackets (x), and * symbolises the environmental covariate retained for model usage.

Covariates	Description	Units	Range
Month*	Calendar months of the year		January – December
Season	Temperate seasonal patterns		Summer, Autumn,
			Winter, Spring
Year*	1915 -2015		1915 – 2015
Activity	Boat related, SCUBA diver, Shallow water,		
	snorkelling, spearfishing, surfing& swimming		
Species*	Shark species involved in attack	Sum	W: 237
			T: 160
			B: 134
SST	Sea Surface Temperature, calculated monthly	°C	T: 18.66 – 29. 94 (26.27)
	from In-situ sea surface observations and		W: 10.59 – 27.51 (19.57)
	satellite derived estimates by Met office		B: 16.14 – 29.27 (23.56)
	Hadley Centre in the UK, in 1° area grid		
SST average	SST, monthly calculated long term (101 years)	°C	T: 19.10 – 29.86 (26.31)
	average for each 1° area grid		W: 10.89 – 27.06 (19.38)
			B: 15.84 – 28.82 (23.54)
SST anomaly*	Difference between the observed SST, and	°C	T: -1.50 – 1.41 (-0.04)
	the long term average recorded SST		W: -1.51 – 1.85 (0.23)
	(Anomaly = Observed – Average)	0 /	B: -1.32 – 2.05 (0.01)
Latitude*	Angular distance of a place north or south of	0,	T: -34.059.40
	the earth's equator		W: -43.5721.95
		0/	B: -38.439.95
Longitude*	Angular distance of a place east or west of	0,	T: 113.10 – 153.7
	the Greenwich meridian		W: 113.8 – 153.6
Diver	Coloulated distance between data resint and	I/ ma	B: 113.40 – 153.8
River distance*	Calculated distance between data point and the closest river	Km	T: 10.78 – 221.88 (43.08)
distance	the closest river		W: 0.10 – 177.31 (19.94) B:0.10 – 16.16 (13.92)
Rain total *	Total monthly rainfall for a given location,	Mm	T: 0 – 878.3 (163)
Raili total	complied by BOM	IVIIII	W: 0 – 597.8 (88.25)
	complied by BOW		B: 0 – 481.20 (105.9)
Rain average	The long term monthly average for each	Mm	T: 26.07 – 486 (135.62)
	location	IVIIII	W: 39.40 – 635 (84.38)
	location		B: 10 – 360 (105.8)
Rain anomaly	Difference between the observed monthly	Mm	T: -285.3 – 488.9 (27.36)
am anomary	rainfall, and the long term average recorded	141111	W: -580 – 422 (3.87)
	monthly rainfall		B: -188.8 – 273 (0.10)
	monany rannan		D. 100.0 273 (0.10)

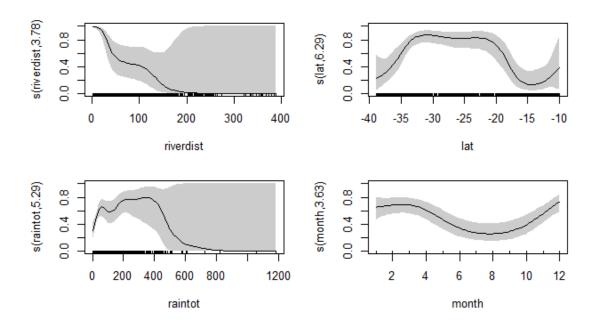


Figure 16. Fitted GAM plots for each smoothed predictor for whaler shark attacks between 1915 and 2015. Left to right, top to bottom: Distance from river (km), with edf written on the y axis label, latitude (°`), total monthly rainfall (mm), and month. Shaded grey area represents 95% confidence intervals and whiskers on the x-axis indicate the presence and pseudo-absence data. The y-axis labels are the plots covariate and the smoother factor's contribution in brackets. The y-axis (0-1) indicates probability of attack influenced by the environmental covariate.

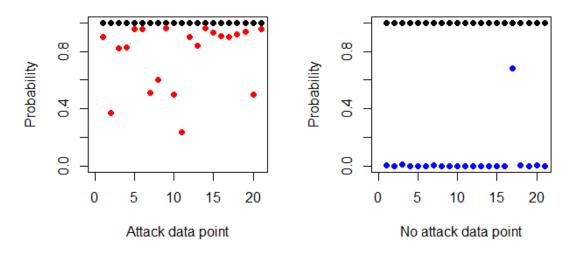


Figure 17. The predicted probability of a whaler shark attack occurring given the environmental covariates in the GAM model fit. X axis represents tested data (attack/no attack). Y-axis represents probability of an attack (red attack and blue dots no attack) based on the fitted environmental predictors (distance from river, latitude, month, and monthly total rainfall).

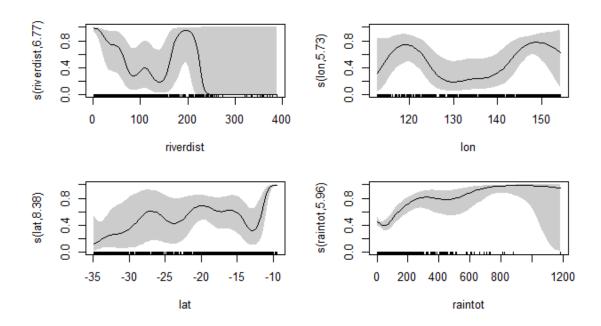


Figure 18. Tiger shark attack fitted GAM plots for each smoothed predictor between 1915 and 2015. Left to right, top to bottom: Distance from river (km), with edf written on the y axis label, longitude (°`), latitude (°`), and total monthly rainfall (mm). Shaded grey area represents 95% confidence intervals and whiskers on the x-axis indicate the presence and pseudo-absence data. The y-axis labels are the plots covariate and the smoother factor's contribution in brackets. The y-axis (0-1) indicates probability of attack influenced by the environmental covariate.

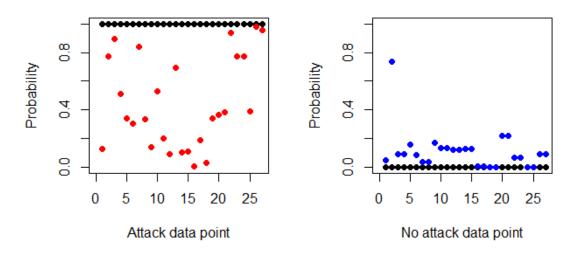


Figure 19. The predicted probability of a tiger shark occurring given the environmental covariates in the GAM model fit. Black dots represent test subgroup (attack/no attack) Y-axis represents probability of an attack (red) and/or no attack (blue) based on the fitted environmental predictors (distance from river, latitude, longitude, and monthly total rainfall).

5.2 Appendix 2: Shark attacks relationship with environmental covariate's

Table 3. Temporal comparisons of monthly-recorded shark attack SST anomaly data. Comparing SST anomalies from the year before and after the attack to the month of the attack, at the same location. -Year mean represents year before, and +Year mean, year after the attack. Significant groups highlighted with (*).

Species	Cluster	P value	<year average</year 	>Year average	Attack average
All species	All years	P = 0.23	+0.13°C	+0.15°C	+0.10°C
Tiger	All years	P = 0.63	-0.02°C	-0.02°C	-0.04°C
White	All years	P = 0.22	+0.30°C	+0.31°C	+0.23°C
Whaler	All years	P = 0.86	-0.01°C	+0.06°C	+0.01°C
All species	1	P = 0.82	-0.21°C	-0.22°C	-0.21°C
Tiger	1	P = 0.42	-0.12°C	-0.12°C	-0.16°C
White	1	P = 0.35	-0.28°C	-0.28°C	-0.17°C
Whaler	1	P = 0.90	-0.32°C	-0.33°C	-0.32°C
All species*	2	P = 0.04	+0.40°C	+0.44°C	+0.29°C
Tiger	2	P = 0.81	+0.23°C	+0.23°C	+0.25°C
White*	2	P = 0.02	+0.49°C	+054.°C	+0.19°C
Whaler	2	P = 0.70	+0.31°C	+0.45°C	+0.35°C

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