Effects of climate change on flooding and water quality in a subtropical Australian catchment

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ABSTRACT

Anthropogenic changes over many decades, such as urbanisation, industrialisation, the introduction of livestock, loss of riparian vegetation, and adoption of fertilisers, have altered the natural characteristics of many rivers, exacerbating flooding and increasing nutrient and sediment loads. Anthropogenic climate change is expected to alter hydrological regimes throughout the world, causing increases in extreme precipitation, as well as altered temporal, seasonal and spatial patterns of rainfall. The hydrological extremes (e.g. floods and droughts) will impact water resources and water quality.

In recent decades research to address climate change impacts on flooding and water quality has increased. However, relatively little research on this topic has been published on Australian catchments and even less for subtropical regions compared to other regions of the world. The majority of the research has also been focused on large river systems, while comparatively little has considered small and mid-sized catchments (e.g., < 1000 km²).

Water quality problems and flooding are major issues for the coastal regions of southeast Queensland (SEQ). The International Panel for Climate Change (IPCC) has identified SEQ as one of the ‘hotspots’ for climate change in Australia and flooding and water quality issues are likely to be exacerbated in the future. Water quality in the Logan and Albert rivers is already particularly poor, with marked ongoing increases in sediment and nutrient loads since European settlement. In addition, the catchment is anticipated to be subject to substantial population growth, which may further exacerbate water quality issues, while increasing the number of residents and properties at risk of flooding. The issues of flooding are compounded by significant urban development located along the low-lying coastal floodplain. Sea level rise linked to climate change may act synergistically with inland hydrological changes to intensify flooding.

In this context, the primary aims of this research are to: (i) summarise understanding of the impacts of climate change on flooding in subtropical regions, (ii) identify the principal water quality issues in the subtropical Logan-Albert catchment of South East Queensland, (iii) and determine the impacts of climate change on high flows, flooding, and water quality in the Logan-Albert catchment. An improved understanding of the effects of climate change in subtropical Australia will benefit regional and local managers by allowing them to be better prepared for the range of future possible eventualities of
hydrological extremes, flooding, and water quality.

Effects of climate change on flooding in subtropical and tropical regions was assessed by a systematic evaluation of the literature which revealed adoption of a wide variety of methodologies for change impact assessments. The evaluation showed there was strong regional bias towards studies conducted in Asian catchments, while there was a paucity of research on catchments in Africa, Latin America, and particularly Australia, for which only one study was found. There was also an appreciable bias in the research towards studies conducted on large river systems, with little research conducted on smaller to mid-sized catchments similar in size to the Logan-Albert catchment. The impacts of climate change were shown to vary significantly across the various regions of the tropics and subtropics, with the most consistent increases in flooding predicted for South Asia, South East Asia, and the western Amazon. Results were more varied for Latin America and Africa, though there was a notable paucity of studies. Mitigating model uncertainty and improving data accessibility in subtropical regions were recognised as the principal issues faced by researchers.

An examination of long-term water quality monitoring data was conducted for the Logan and Albert estuaries and tributaries, to improve understanding of the drivers of water quality change. A seasonal Mann-Kendall test was applied at 15 sites to reveal spatial patterns of water quality change, while a Before-After Control-Impact (BACI) test was employed to assess the impacts of a recently constructed (Wyaralong) upstream dam on estuarine water quality. Significant decreases in nutrient concentrations and turbidity were observed at sites along the upper and middle Logan estuary, which was principally attributed to the construction of Wyaralong dam. Significant decreases in total phosphorus (TP) and nitrate concentrations along the lower Albert estuary were principally attributed to wetter conditions over the second half of the study period, which acted to dilute loads from a nearby wastewater treatment plant.

The impacts of climate change in the lower Logan-Albert catchment were examined through a novel coupled 1D-2D hydrodynamic model, which simulated flooding and inundation. The hydrological Nedbørfør-Afstrømnings Model (NAM) was employed to simulate the rainfall-runoff response under current and future climate conditions. An ensemble of 11 high-resolution dynamically downscaled climate models was applied with high (Representative Concentration Pathway 8.5 - RCP8.5) and intermediate (RCP4.5) emission scenarios. The climate models predicted an increase in the seasonal intensity of
precipitation in the 2020s, 2050s, and 2080s, relative to the baseline (1980-2010). Decreases were predicted for the winter and spring dry season and increases for the summer wet season. Predicted changes to the magnitude of mean and high flows in the three future periods largely followed the pattern predicted for precipitation, though decreases during the winter dry season were amplified, while increases in summer were diminished due to increased evaporation rates. There was considerable variation in the magnitude of predicted future flooding events, ranging from 5 to 100-year year average recurrence intervals (ARI). The largest events (100-year ARI) tended to increase by the 2080s, while smaller events (5-year ARI) tended to decrease. Floodplain inundation resulting from a 100-year ARI event increased in all future periods, and the inclusion of sea level rise near doubling floodplain inundation by the 2080s.

The same ensemble of climate models was applied with the Soil Water Assessment Tool (SWAT) catchment model to assess climate change impacts on total nitrogen (TN), TP, and total suspended sediment (TSS) loads in the 2020s, 2050s, and 2080s in the Logan and Albert rivers. Predicted decreases of streamflow from SWAT during the winter dry season were not as significant as those predicted from NAM, but similar changes were predicted for the remainder of the year by the two models. Changes to TN, TP, and TSS loads in the three future periods mostly reflected the pattern of change predicted for streamflow, with the largest decreases coinciding with the dry season. Compared with the baseline, decreases in TSS loads were 34.3 and 54.2% by the 2080s at the Logan and Albert rivers, respectively and were larger than decreases predicted for streamflow, TN and TP. Decreases to streamflow, however, may have the effect of increasing the relative importance of point load sources, which were found to be important drivers of estuarine water quality. Increased point loads in the future may therefore have the effect of increased in-stream pollutant concentrations. This is particularly important as point source contributions are typically dominated by dissolved inorganic nutrients that are more readily bioavailable than the organic and particulate nutrients associated with diffuse sources.

The outcomes of this Ph.D. study provide new insights into the potential impacts of climate change in a relatively unstudied region that has been identified as a hotspot for climate change. Flooding and changes in water quality from climate change are likely to be have substantial impacts throughout subtropical South East Queensland, especially when combined with pressure from rapidly growing human populations. Given these issues, mitigations measures may need to be employed to mitigate future flooding and
water quality issues.
Statement of Originality

This work has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Signed: 

Date: 07/04/2021

Rohan Eccles
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Acknowledgement of Published Paper

Section 9.1 of the Griffith University Code for the Responsible Conduct of Research (“Criteria for Authorship”), in accordance with Section 5 of the Australian Code for the Responsible Conduct of Research, states:

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- Acknowledge all those who have contributed to the research, facilities or materials but who do not qualify as authors, such as research assistants, technical staff, and advisors on cultural or community knowledge. Obtain
written consent to name individuals.

Included in this thesis are papers in Chapters 3, 4, 5, and 6 which are co-authored with other researchers. My contribution to each co-authored paper is outlined at the front of the relevant chapter. The bibliographic details for these papers are:

Chapter 3:


Chapter 4:


Chapter 5:


Chapter 6:

**ECCLES, R., ZHANG, H., HAMILTON, D., TRANCOSO, R. & SYKTUS, J. 2021.** Impacts of climate change on sediment and nutrient loads from a subtropical catchment. *(to be submitted to Science of the Total Environment)*.

Appropriate acknowledgements of those who contributed to the research but did not qualify as authors are included in each paper.
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Chapter 1: Introduction

1.1 Research Background
Rivers have historically played an integral role in the development of civilisation, providing water to sustain human life and agriculture, in addition to promoting commerce and transportation (Sadoff and Grey, 2002). Rivers continue to be an important economic, environmental, and social resource, supporting aquatic life, fisheries, recreational activities, agriculture, trade, and industry. However, over the last century, and even earlier in many cases, anthropogenic changes, including industrialisation, urbanisation, and the widespread adoption of fertilisers, have substantially altered the natural characteristics of the world’s rivers. These changes have had significant adverse effects on water balance, flooding, water quality, and biodiversity (Best, 2019, Acreman et al., 2020). Urbanisation has resulted in more impervious surfaces in catchments, which can exacerbate flooding (Miller and Hutchins, 2017). The adoption of fertilisers, degradation of native vegetation, and increased waste effluent have led to elevated nitrogen, phosphorus, and sediment loads to waterways (Galloway et al., 2004, Seitzinger et al., 2010), with excess levels of nutrients leading to eutrophication, algal blooms, deoxygenation, and the loss of aquatic life (Rabalais et al., 2009).

The Intergovernmental Panel on Climate Change (IPCC) provides a 95% level of certainty that climate change is a result of anthropogenic activities. Anthropogenically induced climate change is altering weather patterns across the globe, which has implications for water quality and flooding in many river systems. Over the last two centuries the rate of climate change has accelerated, with most of the observed changes occurring since the 1950s (Pachauri et al., 2014). Global greenhouse gas emissions, and by extension, temperatures, are likely to continue to rise throughout the 21st century, causing an intensification of the hydrological cycle (Giorgi et al., 2001, Walsh et al., 2004, Groisman et al., 2005). Consequently, more frequent and intense extreme precipitation events are expected over many parts of the world, resulting in possible increases to riverine flooding. Flooding and the export of nutrients and sediments are highly sensitive to climatic factors (Royer et al., 2006, Sinha and Michalak, 2016). Increased precipitation intensity elevates erosion rates and leads to increased nitrogen and phosphorus transport to rivers, degrading water quality (Kundzewicz et al., 2007, Whitehead et al., 2009).

Climate change has the potential to significantly increase the magnitude and frequency
of major flooding events. There has been a trend over the latter half of the 20th century towards more frequent extreme flood events (Milly et al., 2002) and studies on a global scale have indicated that this trend will continue over the 21st century for many parts of the world (Hirabayashi et al., 2013, Berghuijs et al., 2017, Gosling et al., 2017, Wiel et al., 2019). Spatiotemporal differences in climate change, however, lead to large variations in the hydrological response for various regions of the world (Hirabayashi et al., 2013). Therefore, it is vital that the hydrological response to climate change is assessed at regional scales corresponding to different climate zones. In recent decades there has been a marked increase in research addressing this topic, though there remains a paucity of research originating from some subtropical regions, including Australia (Eccles et al., 2019). Gu et al. (2020) predicted that climate change would lead to an increase in flood magnitude and volume in the tropical north of Australia using an ensemble of climate models, however, there was high uncertainty for these projections. By contrast, floods were predicted to decrease across the temperate south of Australia, with greater agreement amongst the model ensemble. In subtropical southeast Queensland (SEQ), Chen and Yu (2015) predicted little change in large flood magnitude for two small creeks by the 2030s using two climate models. However, studies based on a limited number of climate projections and using model predictions less than two decades into the future might not be representative of the future climate and therefore may not adequately inform preparedness for future flooding events.

Nutrient and sediment loads originating from diffuse sources are likewise highly sensitive to climatic factors (Royer et al., 2006, Sinha and Michalak, 2016), including in subtropical regions, where there are distinct seasonal climate patterns (Eccles et al., 2020). Climate change will alter the seasonality, variability, and intensity of precipitation, which may significantly impact nutrient and sediment loads originating from diffuse sources and, by extension, water quality in the receiving waters (Shrestha et al., 2012, Records et al., 2014, Boardman, 2015, Yang et al., 2017). In recent years there has been a marked increase in the number of studies assessing the effects of climate change, including in the temperature climate zones of Australia (Alam and Dutta, 2013, Dyer et al., 2014, Shrestha et al., 2016, Nguyen et al., 2017b, Nguyen et al., 2019), however, studies originating from subtropical regions of Australia are currently lacking.

The issues of water quality and flooding are substantial throughout the coastal regions of SEQ. The rivers and streams of SEQ have been altered significantly since the arrival of European settlement in 1823, which has resulted in degraded water quality (Neil, 1998,
Excessive nutrient and sediment loads from agricultural runoff and erosion are a major issue for many inland waterways (Healthy Land & Water, 2019). The Logan-Albert river system is the second largest in the region and is subject to severely degraded water quality, particularly along the estuarine reaches (Ecosystem Health Monitoring Program, 2019). It is estimated that phosphorus and nitrogen loads from the Logan-Albert river system have increased by a factor of 4.7 and 3.2, respectively, and sediment loads by a factor of 35 since European arrival (National Land and Water Resources Audit, 2001). Population in the catchment has increased rapidly over recent decades, which is expected to continue in the future, as an additional 200,000 residents are predicted to live in the Logan City area by 2036 compared to 2011 (Queensland Treasury, 2018). This population boom will have important implications for riverine water quality. Flooding is an even greater concern as the coastal regions of SEQ are some of the most flood prone in the country (Abbs et al., 2007). Additionally, SEQ has been identified as one of the ‘hotspots’ for climate change in Australia (Hennessy et al., 2007). The impacts of flooding are exacerbated by extensive urban development along the coastal floodplains, which has substantially increased the community’s exposure to flood damage from extreme events. The proximity of the floodplain to the coast also makes it susceptible to sea level rise, which may act synergistically with atmospheric climate change and storm surges to exacerbate flood events. As the population residing within the Logan-Albert catchment is projected to expand (Queensland Treasury, 2018), the number of residents at risk of flooding may increase further in the future.

Climate change impact studies are wide ranging and can involve a number of methodologies including both numerical and statistical modelling, with varying degrees of complexity and various advantages and limitations. These models provide simplifications of real-world systems and help to gain insights into the complex problems relating to flooding and water quality. Typically, these studies consist of a model chain outlined by Xu et al. (2005) involving; atmospheric climate projections derived from global circulation model (CGM) outputs under a specified emissions pathway, downscaling and bias correction to increase the resolution of outputs for a given region and to correct systematic errors, followed by hydrological/catchment/hydrodynamic model applications. Recently, high resolution daily climate projections have become available for Queensland from the Queensland Department of Environment and Science, under high and medium emissions scenarios (Syktus et al., 2020). Consequently, there is an opportunity to make use of these developments to quantify climate change impacts on
flooding and water quality in subtropical Australia, a region where studies are currently lacking. Given the current issues faced by managers relating to flooding and water quality, and the projections of future population growth, the Logan-Albert catchment is considered an appropriate site for this purpose.

Numerical modelling techniques are employed in this project in conjunction with high-resolution climate data. The overarching goal of this PhD study is to develop a range of numerical models to assess potential changes to flooding and water quality, respectively. The results are intended to benefit managers by allowing them to better understand and prepare for the range of future possibilities, improve capacity to adapt to the consequences of a future climate, and mitigate the impacts on the receiving environment. Additionally, the results may be used to help inform management of other catchments in the SEQ region, where some 3.6 million people live, and provide a framework which may be readily replicated for other catchments across the globe.

### 1.2 Research Objectives
The objective of this research was to study the impacts of climate change on flooding and water quality in a subtropical Australian river system and inform catchment managers on the likely consequences of this change. It is anticipated that this research will provide an improved understanding of climate change from a region where impact studies are lacking. The objectives of this study are as follows:

1. To understand the current available literature, techniques, and limitations for climate change impact studies in subtropical regions.

2. To understand the current hydrological conditions, and analyse the historical trends, patterns, and drivers of change for key water quality constituents in the Logan-Albert catchment, SEQ.

3. To develop a coupled river and floodplain model in the lower Logan-Albert catchment to investigate flooding and floodplain inundation and inform future floodplain planning by estimating the effects of atmospheric climate change, sea level rise, and storm surge on flooding.

4. To develop a mechanistic catchment water quality model to predict nutrient and sediment loads deriving from diffuse sources and quantify the predicted changes in loads and concentrations resulting from atmospheric climate change.
1.3 Research Scope

The purpose of this research was to develop individualised numerical models to assess the impacts of climate change on flooding and water quality. The application of these models was limited to the subtropical Logan-Albert catchment, which is subject to distinct seasonal climate patterns. It is necessary to calibrate the models to the historical conditions before useful predictions of the future can be made. The models are reliant on historical climate, streamflow, and water quality data for model calibration and validation. The models also rely on accurate historical river and climate monitoring data for future predictions.

The adopted approach makes use of high-resolution climate data available for Queensland. The approach was limited to using 11 GCMs (Syktus et al., 2020), which were downscaled using a regional Conformal-Cubic Atmospheric Model. Only the Representative Concentration Pathway 8.5 (RCP8.5) and RCP4.5 emission scenarios were considered, representing high and medium emission pathways, respectively. The scope of this research is limited to assessing the effects of climate change (including sea level rise), while the impacts of other anthropogenic factors (e.g., land use change, urbanisation, and wastewater treatment plant changes) are not considered in detail.

1.4 Research Design and Methodology

In order to achieve Objective 1, a systematic quantitative assessment of the literature relating to the impacts of climate change in subtropical and tropical regions was undertaken. This review involves quantitatively assessing the various methodologies and results from a wide range of studies. It informed research gaps in the field and highlighted the most appropriate methodologies for climate impact studies on extremes.

To understand the current conditions (Objective 2) rainfall and streamflow data were analysed across the catchment. Additionally, a number of statistical tests were performed on water quality monitoring data taken throughout the estuary. The statistical tests included Before-After Control-Impact tests and Generalised Additive Models to inform on the factors driving the change in water quality.

To achieve Objective 3, a coupled 1-D (one-dimensional) and 2-D hydrodynamic model was used for the lower Logan-Albert catchment to simulate streamflow and inundation in the channel and over the floodplain, linked to a hydrological model that evaluated the effects of atmospheric climate change on streamflow. The outputs of the hydrological model informed the inflow conditions that drove the hydrodynamic model. The effects of
sea level rise and storm surges on inundation resulting from a 1-in-100-year flood event were also considered. In order to achieve objective 4, a separate catchment/hydrological model was developed to investigate rainfall-runoff and nutrient and sediment loads derived from diffuse sources.

1.5 Research Significance and Novelty
The significance and novelty of this PhD research is highlighted in the following:

- The conceptualisation of a technique to disentangle drivers of water quality change from multiple anthropogenic and climate related sources in an estuary using 15 years of monthly water quality monitoring and climate data.

- The development of a coupled 1-D and 2-D hydrodynamic model to simulate inundation both in the river channel and across the floodplain in a computationally efficient manner.

- The application of hydrological/catchment models to assess climate change impacts in a subtropical Australian catchment, making this one of the first climate change-related assessments of floods in the region and the first assessment of water quality.

When assessing changes to flooding, the published literature typically only focusses on hydrological changes by comparing streamflow at certain locations before and after climate change. Few studies, however, evaluate the consequences of these changes on inundation downstream and fewer still consider the additional effects of sea level rise and storm surge on coastal inundation. The modelling approach adopted in this research addresses these issues through the implementation of a coupled 1-D and 2-D hydrodynamic model, making it one of few studies to consider compound flooding under climate change.

1.6 Thesis Outline
This thesis is composed of seven chapters. Chapter 1 introduces the background of the project and outlines the research objectives and scope. Chapter 2 describes the relevant literature related to the project. Chapter 3 evaluates predicted changes to floods in the subtropics and tropics due to climate change. Chapter 4 shows the results of data analysis with respect to water quality trends. Chapters 5 and 6 describe the impacts of climate change on flooding and water quality in the catchment, respectively. Chapter 7 presents
the research conclusions and highlights the directions for future research. Chapters 1, 2, and 7 are traditional thesis chapters, while Chapters 3, 4, 5, and 6 are reformatted peer-reviewed journal publications. As such, there may be some overlap in the introduction and the description of the study site among these chapters.

Chapter 2 introduces the study site in detail, including climate, water quality issues, land use, and major dams. A critical review is conducted of literature relating to nutrient cycling in rivers, climate change impacts on weather patterns in SEQ, and the effects of climate change on water quality globally.

Chapter 3 assesses the literature available on the impacts of climate change in tropical and subtropical regions using a quantitative literature review. The advantages and disadvantages of the different research methodologies are discussed, and the regional bias of research is investigated.

Chapter 4 describes the spatial and seasonal patterns of nutrients and turbidity in the Logan-Albert estuary and investigates the long-term trends for these water quality constituents. The impacts of the recently constructed Wyaralong Dam on downstream water quality are presented and the key factors influencing water quality in the estuary are outlined.

Chapter 5 investigates the impacts of climate change on mean, high, and extreme streamflow events from an ensemble of 11 high-resolution climate models using coupled hydrological and hydrodynamic models. The effects of a predicted change to a 1-in-100-year flood event on floodplain inundation are assessed for three future periods (2020s, 2050s, and 2080s). Additionally, the potential synergistic impacts of sea level rise and storm surges are considered.

Chapter 6 describes climate change impacts on total nitrogen, total phosphorus, and total suspended solids using the same ensemble of climate models applied in Chapter 5. The development of a physically based catchment hydrological/water quality model is described, and the results presented for the same three future periods used in Chapter 5.

Finally, Chapter 7 concludes this thesis by highlighting the key research findings, discussing the implications of these findings on flooding, water quality, and dam operation, and by examining the limitations of the project and the directions for future research.
Chapter 2: Literature Review

2.1 Logan-Albert Catchment

The Logan-Albert catchment, located south of Brisbane in SEQ covers approximately 3,862 km$^2$ (Figure 2.1), of which the Logan catchment covers around 3080 km$^2$ and the Albert 782 km$^2$. The Logan River rises along the McPherson Ranges by the New South Wales border and flows approximately 191 km in a north easterly direction before discharging into southern Moreton Bay, which is an ecologically significant Ramsar listed site. The Albert River rises by the Lamington National Park Mountains and flows in a predominately northerly direction for 102 km, after which it converges with the Logan River approximately 11.2 km from the river mouth. Other major tributaries in the catchment include Teviot Brook, Running Creek, Christmas Creek, Palen Creek, Burnett Creek, and Canungra Creek.

Moreton Bay experiences both microtidal (tidal range <2 m) and mesotidal (tidal range 2-4 m) conditions with a maximum tidal range of 2.8 m (Tibbetts et al., 1999). The tide affects the Logan River for approximately 60 km, and for approximately 35 km of Albert River, which begins at the confluence with the Logan (Matveev and Steven, 2014). Estuary depth varies from -13 m Australian Height Datum (AHD) in the lower estuary to almost 1 m AHD by the tidal boundaries. The maximum tidal range in the river is 2.2 m at the lower reaches, which reduces to 1.8 m in the upper reaches (Mirfenderesk and Tomlinson, 2006). The tidal regime of the estuary is predominantly semidiurnal, whereby high and low tides are experienced twice daily and are of roughly equal magnitudes. Flood current velocities (incoming tides) exceed those of ebb current velocities (outgoing tides) and flood tide durations are less than ebb tide durations (Mirfenderesk and Tomlinson, 2006). Typical flushing times range from 66 to 75 days (Dennison and Abal, 1999).
2.1.1 Climate

2.1.1.1 Precipitation

SEQ has a subtropical humid climate with high spatial and temporal precipitation variability (Abal et al., 2005). East coast low pressure systems, tropical cyclones, and thunderstorms bring regular precipitation to the region. A distinct wet season occurs during the summer months, while the dry season coincides with the winter months. Tropical cyclones impact the region infrequently, with an average recurrence interval of 0.26 per year coming within 200 km of Logan City (Environmental Risk Science and Audit, 2012). East coast lows, sometimes derived from ex-tropical cyclones, impact SEQ with much more regularity, bringing significant precipitation, often over the course of several days. The yearly occurrence of these events is exceedingly variable, with many
years recording zero instances and others having several, with a maximum of twelve east coast lows recorded during the 1978/79 summer. The long-term average recurrence interval for east coast lows in SEQ is 2.5 annually, which increases to 3.7 when considering the annual average since 1960 (Environmental Risk Science and Audit, 2012). Severe thunderstorms develop frequently from October through to April. They deliver heavy localised precipitation for short durations, which can result in localised flash flooding within the catchment (Environmental Risk Science and Audit, 2012).

Precipitation in the region is highly seasonal, causing many tributary streams in the catchment to run dry for much of the year. By contrast, in the wet season the rivers and streams often flow in ‘pulses’ after periods of heavy precipitation and high runoff (Abal et al., 2005). Year-to-year variability is also significant, with long periods of dryer or wetter conditions prevailing. Precipitation in wetter years can be twice that of dryer years (Bunn et al., 2007). The yearly precipitation totals are highly dependent on the El Niño Southern Oscillation (ENSO), which is the oscillating pressure difference between the south-eastern and south-western pacific (Syktus et al., 2003). This is typically measured quantitatively with the Southern Oscillation Index (SOI), which is the normalised pressure difference between Tahiti and Darwin (Troup, 1965). Negative SOI values usually denote El Niño episodes, associated with dryer conditions over eastern Australia, while positive SOI values are typical of La Niña episodes and are associated with increased precipitation (Wang and Hendon, 2007). Long-term trend analysis across eastern Australia has shown that mean annual precipitation has decreased significantly, particularly since the 1950s, with average decadal decreases of just under 55 mm per annum (Gallant et al., 2007). This trend has coincided with a tendency towards stronger El Niño conditions over the last few decades (Alexander et al., 2009).

There is also a high degree of spatial variability throughout SEQ, including in the Logan-Albert catchment. Generally, coastal and mountainous sub-catchments receive higher annual precipitation totals than the western regions mainly due to a mixture of onshore winds and adiabatic cooling (Abal et al., 2005). The eastern portions of the catchment receive on average 1000 to 1500 mm of precipitation annually (2002). Areas in the western catchment receive approximately 800 mm of precipitation yearly due to a minor rain shadow effect caused by Mount Tamborine and the Lamington National Park mountains. Precipitation along the southern Border Ranges is significant and variable, with areas closer to the coast and higher in elevation recording greater precipitation. Average annual precipitation varies between 1000 to 2000 mm in the Lamington National
Park, highlighting this variability (Figure 2.2).

Figure 2.2. Average annual precipitation over the Logan-Albert River catchment between 1961 and 1990 (Department of Natural Resources and Mines, 2002).

2.1.1.2 Temperature

The mean maximum and minimum temperatures for Logan City are 26.0°C and 15.1°C, respectively. Throughout the region, January is the hottest month with mean maximum and minimum temperatures of 29.8°C and 20.6°C observed at Logan, whereas July is the coolest with an average maximum and minimum temperature of 21.5°C and 8.8°C (Bureau of Meteorology, 2017a). The western portion of the catchment typically records slightly hotter and cooler average maximum and minimum temperatures, respectively. The average annual observed evaporation rate of 1550 mm from 1971-2000 is greater than the average annual precipitation total of 1135 mm for SEQ (Cobon et al., 2017), contributing to a net depletion of soil moisture. There has been a trend towards higher temperatures in the region, with an observed increase in the mean annual temperature of
0.4°C in the decade from 1997-2008 (Low Choy et al., 2010). Greater increases in temperature have been observed further inland compared to coastal areas, implying varying warming rates dependent on coastal proximity (Whetton et al., 2005).

2.1.1.3 Flooding

Flooding is the single largest cause of damage of all natural disasters in Australia, and within Australia the coastal plains of SEQ are the some of the most flood-prone regions in the country (Abbs et al., 2007). Extensive urban development along floodplains has left communities particularly susceptible to flooding during extreme precipitation events. Major flooding events in the Logan-Albert catchment have historically occurred after a period of extensive steady precipitation lasting several days, usually associated with low pressure systems or tropical cyclones. Such events have occurred in 1887, 1947, 1974, 1976, 1991, and more recently in 2013 and 2017 (Figure 2.3) (Bureau of Meteorology, 2017b). Severe storm events are usually not large enough to cause catchment-wide flooding. They do, however, cause localised flash flooding, hail, and wind damage throughout the catchment. Property damage during major flooding events is often extensive. It was estimated that in Logan catchment 6.7% of properties are at risk of flooding and 4% are at risk of over the floor inundation in the event of a 1-in-100-year flood (Middelmann, 2002).

![Figure 2.3. Historical flood record, separated into major, moderate, and minor floods at Waterford downstream of the Logan River (Bureau of Meteorology, 2017b).](image)

In January 1974 cyclone Wanda hit the catchment, bringing 5 days of heavy precipitation. A total of 825 mm of precipitation fell at Beenleigh, while 1340 mm fell at Mount Tamborine on the edge of catchment. The heaviest precipitation occurred over a 36-hour
period beginning 25 January, with 600 mm of precipitation falling on Beenleigh (Cameron McNamara & Partners, 1975). The Logan River and its tributaries rose rapidly, especially Teviot Brook, Scrubby and Slacks Creek, peaking at 21.35 m at Maclean Bridge. At the time, the catchment was mostly undeveloped and so relatively few properties were affected. Approximately, 150-200 houses were flooded, 10 of which were severely damaged and 2 washed away, mostly around the Waterford area (Cameron McNamara & Partners, 1975). In contrast, the March 2017 floods (the worst since 1974) were estimated to have flooded 250-300 homes.

![Image of floods](image.png)

*Figure 2.4. The Logan River at Waterford during the March 2017 flooding event (Queensland Fire and Emergency Services, 2017).*

2.1.2 Water Quality:
The Healthy Land & Water (2019) produced annual ‘report cards’ for SEQ’s waterways, assessing key water quality parameters. Water quality has improved slightly in the Logan and Albert catchments in recent years from ‘fair’ in 2016 to ‘fair’ and ‘good’ for the Logan and Albert catchment, respectively in 2020, however, estuarine water quality remains an issue. Major concerns for the estuary include elevated levels of turbidity; relating to sediment loads and high concentrations of nitrogen and phosphorus. The upper reaches of the river are characterised by poor riparian vegetation (Healthy Land & Water, 2019), which led to erosion and elevated sediment export. The decline of the ecologically significant Moreton Bay has been largely attributed to the increased nutrient and sediment
loads discharged into the bay from the region’s rivers (Olley et al., 2015). Abal and Dennison (1996) noted a decline in seagrass growth close to the Logan River mouth, which they attributed to the turbid waters and high nitrogen content. Seagrass was found to be more abundant with increasing distance (up to 23 km) from the river mouth, where nutrient concentrations and turbidity levels were lower. Matveev and Steven (2014) studied the effects of salinity, turbidity, and flow on fish biomass in the Logan River and reported that salinity and turbidity are important drivers in seasonal fish abundance. The primary water quality concerns for the Logan-Albert catchment relate to nitrogen and phosphorus loads from wastewater treatment plants, agricultural and urban runoff, and sediment loads related to erosion (South East Queensland Healthy Waterways Partnership, 2007, Healthy Land & Water, 2019).

2.1.2.1 Sediments

Total suspended solids (TSS) refers to the total matter suspended in the water column that can be trapped by a filter (Spellman, 2013) including, sediment, decaying organic matter, and sewage. TSS is an important water quality parameter, due to its influence on water density, light penetration, and nutrient availability. The Logan and Albert Rivers are characterised by relatively high TSS loads that lead to turbid waters. Mean annual loads have been estimated to be equal to 120 kt for the Logan River at Yarrabahappini and 45 kt for the Albert River at Bromfleet (Thomson et al., 2013). Sediment is the major component of TSS loads in the catchment and has seen a marked increase over the last two centuries. Neil (1998) estimated sediment loads to have increased in the order of 2 to 5 times compared to pre-European conditions, whereas the National Land and Water Resources Audit (2001) estimated that sediment loads have increased by a factor of 35 (Table 2.1). Erosion is the principal cause of sediment loads within the catchment, with land use, surface slope, precipitation intensity, and geology all influencing the rate of erosion. The introduction of domestic livestock, loss of riparian vegetation, and land use changes coinciding with the arrival of Europeans all contributed significantly to these increases (Neil, 1998, Abal et al., 2005).

Erosion is often split into two categories. Erosion in channels and river banks due to streamflow is known as gully erosion, while erosion derived from overland runoff from high intensity precipitation events is known as sheet erosion. Wallbrink (2004) estimated that gully erosion was the principle cause of fine sediments (<10 µm diameter) entering Moreton Bay, contributing to approximately 66% of total loads. Sheet erosion derived from cultivated and uncultivated land was estimated to contribute to 33% and 1% of loads,
respecitively. Olley et al. (2013) found similar results for sub catchments in the upper Brisbane River. Declining riparian vegetation was identified as a major contributing factor to elevated erosion rates (Olley et al., 2015). Olley et al. (2015) estimated sediment yield per unit area of a catchment in SEQ containing no remnant riparian vegetation to be 50 to 200 times greater than the yield from a catchment with fully vegetated channels.

Quantifying the principle sources and causes of erosion is an important step in managing catchment wide sediment loads. Douglas et al. (2003) investigated which rock formations contributed disproportionately to sediment loads entering Moreton Bay. They concluded the Marburg rock group contributed 60% of total sediment loads despite covering only 12% of the total area (principally within the Brisbane and Logan-Albert catchments), representing an enrichment factor of 5. The Lamington Group (southern Logan-Albert catchment), the Main Range Formation (Brisbane catchment), and Walloon Subgroup (Logan-Albert and Brisbane catchments) were all overrepresented with enrichment factors of around 2. These results are consistent with those of Bunn et al. (2007) who suggested that 60% of the sediment entering Moreton Bay originated from just 30% of the land in the Logan and Bremer (tributary to the Brisbane) catchments. These findings suggest that the Logan catchment is overrepresented in terms of sediment loads entering Moreton Bay. Hancock and Caitcheon (2010) investigated sediment sources during a major flow event in 2008 in the Logan-Albert catchment. They found approximately 70% of the sediment delivered to the Logan estuary during the event was derived from the Lamington Group rocks, covering the south-eastern part of the catchment.

Sediment loads fluctuate on a yearly and seasonal basis depending on streamflow and runoff volume with larger yields observed in wetter years and months (Garzon-Garcia et al., 2015, Olley et al., 2015). Abal et al. (2005) noted during an 11-year period, 42% of the TSS load entering Moreton Bay was delivered from just 1% of the time. This increased to 66% and 80% of the load for just 5% and 10% of time, respectively. Largest sediment loads occurred during flood events when runoff and streamflow was greatest allowing for more and heavier sediment particles to be transported downstream. In an average year the Logan River discharges around 190 kt of sediment into the Moreton Bay (Table 2.1), while total sediment yields are estimated at 0.47 t/ha/y for the catchment, almost 3 times greater than those of the Brisbane River (National Land and Water Resources Audit, 2001). Estimated residence time for sediments in the Logan River system is 0-9 years depending on conditions, with an average of 5 years (Olley et al., 2015).
Table 2.1. Comparison of average annual sediment and nutrient loads among major river systems in South East Queensland and Northern New South Wales (National Land and Water Resources Audit, 2001).

<table>
<thead>
<tr>
<th>Basin Area (km²)</th>
<th>Logan-Albert River</th>
<th>Brisbane River</th>
<th>Tweed River</th>
<th>Richmond River</th>
<th>Clarence River</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sediment export to coast (kt/y)</td>
<td>189</td>
<td>247</td>
<td>58</td>
<td>241</td>
<td>683</td>
</tr>
<tr>
<td>Sediment export to coast (t/ha/y)</td>
<td>0.47</td>
<td>0.18</td>
<td>0.55</td>
<td>0.36</td>
<td>0.31</td>
</tr>
<tr>
<td>Sediment ratio (Euro: pre-Euro)</td>
<td>35</td>
<td>37</td>
<td>16</td>
<td>32</td>
<td>198</td>
</tr>
<tr>
<td>Phosphorus export to coast (t/y)</td>
<td>265</td>
<td>685</td>
<td>46</td>
<td>235</td>
<td>624</td>
</tr>
<tr>
<td>Phosphorus export to coast (kg/ha/y)</td>
<td>0.64</td>
<td>0.50</td>
<td>0.42</td>
<td>0.33</td>
<td>0.28</td>
</tr>
<tr>
<td>Phosphorus ratio (Euro: pre-Euro)</td>
<td>4.7</td>
<td>5.3</td>
<td>1.8</td>
<td>2.9</td>
<td>3.8</td>
</tr>
<tr>
<td>Nitrogen export to coast (t/y)</td>
<td>1251</td>
<td>3162</td>
<td>499</td>
<td>1941</td>
<td>4799</td>
</tr>
<tr>
<td>Nitrogen export to coast (kg/ha/y)</td>
<td>3.01</td>
<td>2.33</td>
<td>4.58</td>
<td>2.77</td>
<td>2.16</td>
</tr>
<tr>
<td>Nitrogen ratio (Euro: pre-Euro)</td>
<td>3.2</td>
<td>2.7</td>
<td>1.4</td>
<td>2.3</td>
<td>2.0</td>
</tr>
</tbody>
</table>

The Logan estuary is highly turbid. The strong tidal currents keep sediments suspended within the water column and long sediment residence times (66-75 days) within the estuary exacerbate these conditions (Dennison and Abal, 1999). The Logan River is characterised by stronger flood tidal velocities than ebb tidal velocities potentially leading to a net transport of coarse sediment into the estuary (particularly sands). However, the ebb tide duration is longer than the flood tide duration, potentially causing a net transport of fine sediments out of the estuary as fine sediments are more influenced by tidal duration than velocity, while coarse sediments are more influenced by velocity (Mirfenderesk and Tomlinson, 2006). Combined with high sediment yields, these factors exacerbate the turbid nature of the Logan estuary.

2.1.2.2 Nutrients

Nutrients are chemical compounds that are essential to the health and wellbeing of waterways, providing the sustenance required for aquatic life (Ji, 2008). However, excessive concentrations of nutrients can lead to eutrophication, which may result in algal
biodiversity, a reduction in dissolved oxygen levels, and loss of aquatic life (US EPA, 2000). With the advent of fertilisers excessive nutrient levels have become one of the principal water quality issues globally. The US EPA (2000) estimates that nutrients contribute 25 to 50% of the total impairment of waterways within the United States. Nitrogen and phosphorus are the two most common nutrients in waterways. They occur as both organic and inorganic compounds, with inorganic compounds of greater concern for water managers, as they are more readily consumed for plant growth (Ji, 2008). Point sources such as sewage treatment plants, and non-point sources like agricultural runoff, all contribute to nutrient loads. Within the Logan-Albert catchment increased nitrogen and phosphorus loads over the last century are believed to have contributed considerably to the degradation of water quality (Abal and Dennison, 1996).

The Logan and Albert Rivers discharge large quantities of nutrients into Moreton Bay each year. Average annual nitrogen and phosphorus loads for the Logan River at Yarraville are 1200 t and 420 t, respectively, while, for the Albert River at Bromfield annual mean loads are 200 t and 86 t, respectively (Thomson et al., 2013). These measurements are larger than those presented by National Land and Water Resources Audit (2001) who reported total combined mean annual loads from the Logan-Albert River system of 1251 t for nitrogen and 265 t for phosphorus. The National Land and Water Resources Audit (2001) estimates that nitrogen and phosphorus loads have increased by a factor of 3.2 and 4.7 respectively, since European arrival (Table 2.1), while more recent findings by Thomson et al. (2013) indicate these figures may be understated. The majority of the increase in nutrient loads is thought to be the result of agricultural intensification since the 1960s and the widespread adoption of nitrogenous fertilisers (Neil, 1998, Tibbetts et al., 1999). There has been an observed increase (200 to 400%) in nitrate (NO$_3^-$) and phosphate (PO$_4^{3-}$) concentrations in the Logan River estuary since the 1950s for both the wet and dry seasons (Dennison and Abal, 1999). Bartley et al. (2012) observed a near perfect linear relationship between in-stream nitrate concentrations and the proportion of upstream land being fertilised for hundreds of sites along the eastern seaboard of Australia. Only around one-third of the fertiliser applied to cropping is retained by the crop, leaving two thirds as potential runoff into nearby waterways (Dennison and Abal, 1999).

Agricultural and urban activities throughout the catchment are the predominant non-point sources of nutrients entering the waterways. Agricultural runoff makes its way to streams and gullies where it is flushed out during large precipitation events. Garzon-Garcia et al.
(2015) carried out research on the effects of gully and channel erosion on the export of nitrogen and carbon in the Knapp Creek catchment upstream of the Logan River. They found that TSS export was the principal factor explaining nitrogen export followed by precipitation and flow, which indicates erosion controls nitrogen export for the Logan River. Olley et al. (2015) investigated the impacts of riparian vegetation on water quality in SEQ. They estimated that an un-vegetated stream would likely export between 25 and 60 times more phosphorus and between 1.6 and 4.1 times more nitrogen than a fully vegetated stream. They predicted nitrogen loads into Moreton Bay could be halved by completely repairing all remnant riparian vegetation along all channels in the region.

Wastewater treatment plants are the principal point source of nutrient loads into the Logan River system. Other point sources include landfills, aquaculture, boating and industry (Dennison and Abal, 1999). There are numerous sewage treatment plants within the Logan-Albert catchment (Table 2.3), many of which discharge directly into the river system. The total nitrogen, phosphorus, and volume of flow from these plants for the whole SEQ region can be seen in Table 2.2. The timing of peak nutrient loads correlates closely to that of TSS in the catchment. Largest loads are observed following large precipitation and flow events, whereas peak nutrient concentrations are observed during times of low flow as there is a build-up of in-stream nutrients, particularly from point sources (Meyer et al., 2005, Thomson et al., 2013, Garzon – Garcia et al., 2015). National Land and Water Resources Audit (2001) estimated the annual yield of nitrogen and phosphorus exported to the coast to be 3.01 kg/ha/y and 0.64 kg/ha/y respectively, some of the highest values in the region (Table 2.1). However, as more recent investigations by Thomson et al. (2013) have noted higher nutrient loads, it is possible these figures are underestimated.

<table>
<thead>
<tr>
<th>Variable</th>
<th>2010</th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
<th>2014</th>
<th>2015</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean flow (ML)</td>
<td>629</td>
<td>625</td>
<td>677</td>
<td>680</td>
<td>572</td>
<td>703</td>
</tr>
<tr>
<td>Total Nitrogen (tonne)</td>
<td>866</td>
<td>978</td>
<td>932</td>
<td>991</td>
<td>776</td>
<td>1282</td>
</tr>
<tr>
<td>Total Phosphorus (tonne)</td>
<td>514</td>
<td>542</td>
<td>522</td>
<td>522</td>
<td>553</td>
<td>582</td>
</tr>
</tbody>
</table>

Table 2.2. Volume and load of annual discharge from sewage treatment plants into waterways in South East Queensland (Queensland Government, 2016).
Table 2.3. List of operational sewage treatment plants within the Logan-Albert Catchment. Where AMTD is the adopted middle thread distance (the distance from the point of interest to the river mouth or junction with main river channel) and EP is the equivalent persons (volume unit, used in the design of sewage infrastructure) (Department of Environment and Heritage Protection (DEHP), 2015).

<table>
<thead>
<tr>
<th>Name</th>
<th>Proprietor</th>
<th>Peak Design</th>
<th>Discharge Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mt Cotton Sewage Treatment Plant</td>
<td>Redland City</td>
<td>10000-50000EP</td>
<td>Logan River 10.5 km AMTD</td>
</tr>
<tr>
<td>Loganholme Wastewater Treatment Plant</td>
<td>Logan Water</td>
<td>&gt;1000000EP</td>
<td>Logan River approximately 17 km AMTD</td>
</tr>
<tr>
<td>Jimboomba Sewage Treatment Plant</td>
<td>Logan Water</td>
<td>1500-4000EP</td>
<td>Irrigation of treated effluent to land</td>
</tr>
<tr>
<td>Flagstone Sewage Treatment Plant</td>
<td>Logan Water</td>
<td>1500-4000EP</td>
<td>Irrigation of treated effluent to land</td>
</tr>
<tr>
<td>Beaudesert Sewage Treatment Plant</td>
<td>Queensland Urban Utilities</td>
<td>4000-10000EP</td>
<td>Logan River approximately 105 km AMTD</td>
</tr>
<tr>
<td>Canungra Sewage Treatment Plant</td>
<td>Queensland Urban Utilities</td>
<td>1500-4000EP</td>
<td>Canungra Creek approximately 23 km AMTD</td>
</tr>
<tr>
<td>Koorabyn Sewage Treatment Plant</td>
<td>Queensland Urban Utilities</td>
<td>1500-4000EP</td>
<td>Released to creek via subsurface leaking from lagoon</td>
</tr>
<tr>
<td>Boonah Sewage Treatment Plant</td>
<td>Queensland Urban Utilities</td>
<td>1500-4000EP</td>
<td>Irrigation of treated effluent to land</td>
</tr>
<tr>
<td>Beenleigh Water Reclamation Facility</td>
<td>Logan Water</td>
<td>50000-100000EP</td>
<td>Albert River approximately 4 km AMTD</td>
</tr>
</tbody>
</table>

2.1.3 Land Use

Land use is an important factor that affects both flood propagation and water quality. Different land use types and practices allow for varying amounts of runoff to infiltrate the water table. Environments with low infiltration rates like urban settlements lead to greater quantities of runoff reaching the river system in less time, which translates to an earlier peak in the flood hydrograph (Bronstert et al., 2002). Land use practices pertaining to the use of fertilisers and the clearing of vegetation are important influences on water quality. Agricultural runoff contributes significantly to nutrient loads entering river systems, as large quantities of fertiliser are removed from farmland during precipitation events (Dennison and Abal, 1999). Changes in vegetation cover can lead to increased erosion and sediment export from the catchment.

SEQ is one of the fastest growing regions in Australia with a population of 3.4 million people and an annual growth rate of 1.7 percent, outpacing the remainder of the state (Queensland Government Statistician’s Office, 2017). This population growth has resulted in an ever-expanding urban footprint, comprising residential, industrial, and
service land types (Figure 2.5). The Logan City Council area has a population of approximately 319,000 persons as of June 2017, which is projected to grow to around 490,000 persons by 2036 (Queensland Treasury, 2018). The lower Logan catchment comprises large areas of sugarcane farming along the southern floodplains, while the Native Dog, Serpentine Creek, and Carbrook conservation areas extend over much of the northern floodplains with pockets of residential housing, golf courses, nurseries, and recreational areas also found (Department of Science Information Technology and Innovation, 2013). Logan City dominates the upper estuary, while further upstream land use transitions from urban residential to rural residential and rural living with agriculture present along the alluvial plains. The upper-middle catchment is dominated by agricultural grazing of unimproved native vegetation with irrigated cropping along the alluvial channels. Intensive dairies, poultry farms, horse studs, turf farms and hoop pine plantations can all be found in parts of the upper-middle catchment (Resilient Rivers Initiative, 2017). Protected National Parks and conservation areas including the Border Ranges, Mount Tamborine, Lamington National Park, and Springbrook National Park cover large areas of the upper catchment and remain in relatively pristine condition. Table 2.4 details the percentage area dedicated to different land use types in the catchment and the associated change in area over time (Department of Science Information Technology and Innovation, 2013).

Table 2.4. Percentage area of Logan catchment covered by different land use types for 2012 (Department of Science Information Technology and Innovation, 2013).

<table>
<thead>
<tr>
<th>Primary Land Use</th>
<th>1999 Percentage Area</th>
<th>2012 Percentage Area</th>
<th>Change in relative area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Native Vegetation Grazing</td>
<td>56.67%</td>
<td>55.00%</td>
<td>-1.68%</td>
</tr>
<tr>
<td>Conservation and Natural Environments</td>
<td>19.17%</td>
<td>18.95%</td>
<td>-0.21%</td>
</tr>
<tr>
<td>Urban Development</td>
<td>6.12%</td>
<td>9.55%</td>
<td>3.43%</td>
</tr>
<tr>
<td>Rural Residential and Rural Living Production from irrigated agriculture and plantations</td>
<td>10.22%</td>
<td>8.97%</td>
<td>-1.25%</td>
</tr>
<tr>
<td>Production from dryland agriculture and plantations</td>
<td>3.74%</td>
<td>3.46%</td>
<td>-0.29%</td>
</tr>
<tr>
<td>Water</td>
<td>1.37%</td>
<td>1.65%</td>
<td>0.28%</td>
</tr>
<tr>
<td>Intensive Horticulture and Animal Production</td>
<td>0.53%</td>
<td>0.60%</td>
<td>0.07%</td>
</tr>
</tbody>
</table>
2.1.4 Modified Features

Two major dams and a number of small weirs have been constructed along the Logan and Albert Rivers over recent decades to meet the region’s growing water needs and to reduce the impact of flooding (Figure 2.1). Most of these structures are situated along the Logan River and its tributaries, while the Albert River is largely unregulated, with only one weir situated close to Luscombe. Major dams include Maroon Dam and Wyaralong Dam, which are both located in the upper Logan catchment. Maroon Dam is a 34 m high earth and rockfill embankment located in upper Burnett Creek about 64 km southwest of Beaudesert. Completed in 1974 to permit the expansion of irrigation along Burnett Creek and the upper Logan River; it has a total capacity of 44,000 ML with a catchment size of 160 km². The operators have access to an outlet valve situated at the base of the dam capable of discharging water at a rate of 30 m³/s (Nutt, 1975). Maroon Dam is ungated, meaning that when the water level reaches 100 percent the operators have no control over the rate of spilling water. This type of dam helps to mitigate flooding by reducing the peak outflow during a flood event (South East Queensland Water, 2016a). Wyaralong Dam is a 48 m high roller compacted dam located along the Teviot Brook approximately 14 km northwest of Beaudesert (Deible et al., 2010). Constructed in 2011 to meet the region’s growing water demands, it has a total capacity of 103,000 ML and a catchment size of 546 km². Wyaralong Dam is ungated with two vertically submerged outlets valves facilitating the evacuation of up to 165 ML/day, providing Teviot Brook with a regular streamflow (Queensland Government, 2008, South East Queensland Water, 2016b).
2.2 Nutrient Cycles

Nitrogen and phosphorus species are transformed via nutrient cycles in terrestrial, aquatic, and atmospheric ecosystems (Ji, 2008). Both nitrogen and phosphorus cycles have been altered significantly in the last century by anthropogenic activities, which have greatly increased the rate of eutrophication in inland waters. Modelling these nutrient cycles in river systems requires a good understanding of the key transformation and transport processes.

2.2.1 Nitrogen Cycle

Gaseous nitrogen (N₂) is the most abundant component in the atmosphere, accounting for 78% of the total volume. However, unlike other forms of inorganic nitrogen N₂ is inert and does not degrade environmental quality, nor is it able to be taken up by plants directly unless associated with fixation (Follett and Hatfield, 2001, Ji, 2008). Nitrogen fixation is the process by which nitrogen fixing bacteria convert N₂ to ammonia (NH₃) and ammonium (NH₄⁺) to support plant growth (Ji, 2008). Large amounts of ammonia are also produced by anthropogenic activities. Synthetic fertiliser production using the Haber-Bosch process is the largest source of anthropogenic fixed nitrogen globally. The ammonia produced from this process is used in fertilisers, manufactured goods, animal feed, and explosives (Galloway et al., 2008). Other anthropogenic sources of nitrogen fixation come from the cultivation of leguminous crops and fossil fuel combustion (Follett and Hatfield, 2001). Together all anthropogenic sources are similar in magnitude to the natural rate of terrestrial nitrogen fixation (Canfield et al., 2010).

Ammonium is also produced from microbial decomposition of organic nitrogen found in organic matter or animal waste, in a process known as mineralisation or ammonification (Keeney and Olson, 1986). Ammonium may undergo nitrification in aerobic environments, through which ammonium is oxidised to nitrite (NO₂⁻) and then further to nitrate (NO₃⁻), which can be collectively referred to as NOₓ. Nitrification of ammonium in agricultural soils is a critical process for groundwater quality, as nitrates are highly soluble and mobile compared to ammonium. This leads to greater leakage of inorganic nitrogen from arable lands to creek and rivers (Schlesinger et al., 2006, Canfield et al., 2010).
Until recently, it was widely thought ammonium could only be oxidised under aerobic conditions (nitrification). However, anaerobic ammonium oxidation (anammox; Mulder et al., 1995) provides an alternative pathway to nitrification, through which ammonium and nitrate are converted into nitrogen gas under anaerobic conditions. This process is a nitrogen sink that can help mitigate the build-up of inorganic nitrogen in aquatic systems (McCarthy et al., 2016). In anoxic environments, microbes can reduce oxidised nitrogen and produce either ammonium, in a process called dissimilatory nitrate reduction to ammonium (DNRA), or more commonly nitrogen gas through denitrification (Canfield et al., 2010, Lam and Kuypers, 2011). Denitrification is the principal nitrogen sink in aquatic systems.

2.2.2 Phosphorus Cycle
Unlike nitrogen, phosphorus does not have a major atmospheric component and is instead mostly restricted to liquid and solid phases (Oelkers et al., 2008). Phosphorus is released from soils through the weathering of minerals and rocks (Filippelli, 2008). Its mobility is limited compared to other elements, and transportation is dominated by river flows despite its low solubility (Oelkers et al., 2008). In recent decades anthropogenic influences have significantly altered the natural phosphorus cycle. The world’s limited phosphorus reserves have been extensively mined for use in fertilisers, cattle feed, and industrial products (Elser and Bennett, 2011). Natural riverine phosphorus loads are thought to have doubled due to increased use of fertilisers, sewage effluent loads, and...
land use changes (Filippelli, 2008). In most freshwater systems, phosphorus is the limiting nutrient required for plant and algae growth (Webster et al., 2001), and as such concentrations can strongly influence eutrophication.

![Phosphorus Cycle Diagram](attachment:Phosphorus_Cycle.png)

Figure 2.7. Phosphorus cycle within an aquatic ecosystem (Ji, 2008).

In aquatic environments, phosphorus can be divided into inorganic and organic forms and further into particulate and dissolved components. Phosphate is an important component of phosphorus in riverine systems and occurs in several forms. Orthophosphate ($\text{PO}_4^{3-}$) constitutes the majority of all phosphates and is the compound most readily available for biological uptake and frequently used to represent total dissolved reactive phosphorus (Ji, 2008). Orthophosphate is commonly transported to rivers attached to sediments, which can be enriched in phosphorus due to the effects of farmland runoff and sewage effluent (Eager, 2017). In unpolluted waters, orthophosphate concentrations are typically negligible (Ji, 2008). Phosphates are highly surface-active and readily sorb to both suspended and bed sediment particles, which work to limit its bioavailability. This process is reversible however, and both absorption and desorption processes can occur simultaneously. If there is excess dissolved phosphorus in a river system, it may be sorbed to sediment particles, while when concentrations decrease, phosphorus may be released from these particles. This effectively dampens fluctuations of dissolved phosphorus in the water column, acting as a phosphate buffering system (Webster et al., 2001). Phosphate is also produced from the mineralisation of organic phosphorus found in organic matter.
Phosphorus can cycle repeatedly in aquatic systems until it is eventually removed from the system by either sedimentation or outflows (Ji, 2008). Although phosphorus can cycle very quickly within aquatic systems, the overall phosphorus cycle is considered slower than that of nitrogen due to the low mobility of phosphorus (Oelkers et al., 2008).

2.3 Climate Change

2.3.1 Framework for Climate Change Impact Studies
During the last two decades a large number of studies have been conducted to examine the potential impacts of climate change on river systems. These studies commonly follow a model chain outlined by Xu et al. (2005) consisting of the following: global circulation models (CGMs), downscaling and bias correction techniques, and hydrological, hydrodynamic, and water quality models, which are described below.

2.3.1.1 Global Circulation Models
GCMs are numerical models that simulate various climatic, earth, and oceanic physical processes on a global scale. They simulate the global response to changes in greenhouse gas concentrations and are the most advanced tools currently available to researchers for assessing the impacts of climate change on rivers. GCMs depict the global climate three dimensionally, running on course atmospheric resolutions (typically around 100-300 km), consisting of 20 to 50 vertical layers and are capable of modelling large-scale synoptic features (CSIRO and Bureau of Meteorology, 2015). The coarse resolution of these models is generally considered inadequate for analysis of individual river systems or regions, as local topographic features and dynamics are not well represented (Grotch and MacCracken, 1991, Fowler et al., 2007). There is also high uncertainty in climate projections from GCMs, and a wide range of predictions can be found for any given region. As such, it is widely recommended that an ensemble of GCMs be adopted with appropriate downscaling for climate change impact studies (Dankers and Feyen, 2009, Prudhomme and Davies, 2009, Teutschbein and Seibert, 2010, Veijalainen et al., 2010).

2.3.1.2 Emission Scenarios
Emission scenarios provide estimates of future greenhouse gas or radiative forcing pathways that are used to drive climate model simulations. The most commonly applied emission scenarios are given by the International Panel on Climate Change (IPCC) SRES (Special Report on Emission Scenarios; Nakicenovic et al., 2000) and the more recent RCP (Representative Concentration Pathways; Meinshausen et al., 2011). The SRES emission scenarios are based on socioeconomic storylines estimating future greenhouse
gas emissions based on economic growth, population growth, and technological development projections. The RCPs provide projections of greenhouse gas emissions and associated radiative forcing (atmospheric change in energy (W/m²)). In contrast to the SRES, RCPs do not directly link socioeconomic storylines and anthropogenic activities to these projections. However, efforts have been made to derive socioeconomic pathways consistent with all the RCPs (Burkett et al., 2014). Figure 2.8. Projected radiative forcing over the 21st century under emission scenarios from the SRES and RCP (Burkett et al., 2014). Figure 2.8 illustrates the radiative forcing of the various commonly applied emission scenarios over the 21st century.

2.3.1.3 Downscaling

GCMs run on a course resolution that is typically unable to represent local climatic features on a catchment scale (Fowler et al., 2007). Downscaling techniques are therefore required to bridge the gap between global-scale climate models and the regional and local-scale climate data required for impact assessments. This process can consist of dynamic downscaling using Regional Climate Models (RCMs) or statistical downscaling using empirical relationships between GCMs and local climate conditions (Prudhomme et al., 2002). Dynamic downscaling involves inputting GCM outputs as lateral boundary
conditions to drive an RCM, which is then resolved at a finer resolution (typically 10 to 50 km). The fine resolution of RCMs makes them suited to represent the climatic effects of local topographic features and land cover changes (Giorgi et al., 2001). The skill of the model is still strongly dependent on the skill of the GCM driving the model, as any biases are transferred between from the GCM to the RCM (Graham et al., 2007).

Statistical downscaling techniques provide a relatively simple, flexible, and computationally cheap alternative to the use of RCMs. The simplest of these techniques is the delta change approach, which in its most elementary form involves multiplying the relative percentage change in precipitation between a baseline and future climate run to an observational dataset. For temperature, the differences between baseline and future values are simply added to the observation dataset (Teutschbein and Seibert, 2012). Other statistical downscaling techniques include stochastic weather generators, weather typing schemes and regression models, each of which generates a time series of climate data (Fowler et al., 2007). Stochastic weather generators synthesise a time series of weather data for any length of time at a given location using the local statistical weather characteristics (Semenov et al., 1998, Wilks and Wilby, 1999, Hassan et al., 2014). Stochastic weather generators are also commonly applied for temporal downscaling of monthly data into more finely resolved data. Weather typing or classification schemes attempt to group the local climate into a number of different weather states based on their synoptic similarity (Wilby et al., 2004). The daily future climatic states, as simulated by the GCM are matched with their most similar corresponding weather states from the observational record and assigned an associated value or class of values for the variable in question (Trzaska and Schnarr, 2014). Regression models typically use transfer functions to represent the linear or non-linear relationship between the GCM-simulated climate and the local climate. Once a function is established, it can be applied to estimate future local conditions driven from GCM simulations of the future climate (Giorgi et al., 2001). A range of less common alternative methods may also be applied including: Canonical Correlation Analysis (CCA), Artificial Neural Networks (ANNs), and Singular Value Decomposition (Wilby et al., 2004, Trzaska and Schnarr, 2014). Some studies have described the overall skill difference between statistical and dynamic downscaling techniques as negligible (Wood et al., 2004, Ahmed et al., 2013).

2.3.1.4 Bias-correction

Downscaled GCM and RCM outputs usually have unacceptably high biases relative to observational datasets and thus bias-correction may be required prior to modelling (Wood
et al., 2004, Sillmann et al., 2013). These systematic errors commonly include an overestimation in the number of wet days, underestimation in precipitation intensity, and inadequate year-to-year variability in direct climate outputs (Ines and Hansen, 2006). A wide variety of bias-correction techniques may be employed to correct these biases with varying degrees of effectiveness. The most widely used bias-correction techniques include the delta-change (see above), scaling, and quantile mapping approaches. The scaling approach (in its simplest form) operates with monthly corrections derived from the difference between the control simulation and observed dataset. These ‘scaling factors’ are multiplied by the future simulated climate data to correct for biases (Teutschbein and Seibert, 2010). The basic approach of quantile mapping, also known as distribution mapping, is to correct the distribution of the simulated GCM/RCM current climate variables to match the distribution of the observed climate dataset. This is typically done by developing a transfer function to shift the simulated distribution to match the observed (Piani et al., 2010). The same transfer function is then applied to the future simulated climate as bias-correction. This method has been demonstrated to be more reliable in improving the projections of extreme events compared with other bias-correction techniques (Dobler et al., 2012, Teutschbein and Seibert, 2012).

2.3.2 Climate Projections for SEQ

Over the last two centuries the world’s climate has been altered at an ever-increasing pace, with most of the observed climatic changes having occurred since the 1950s (Pachauri et al., 2014). The IPCC is now 95% confident that climate change is the result of anthropogenic activities. Mean temperatures across Australia have risen by 1.4°C from 1910 to 2020 (Bureau of Meteorology, 2020). Trend analysis of mean and extreme climate data across Australia has suggested that the frequency and intensity of extreme events has increased more rapidly than the mean, with the most extreme of these events increasing at a faster rate than more moderate events (Alexander et al., 2007). Globally, there is predicted to be an increase in the most intense precipitation events under climate change conditions (Groisman et al., 2005).

The IPCC has identified SEQ as one of the ‘hotspots’ for climate change in Australia (Hennessy et al., 2007). Models have predicted increases in annual average temperatures, changes in annual precipitation, sea level rises, and an increase in extreme events for the region (Low Choy et al., 2010). GCM simulations tend towards a more El Niño like state under enhanced greenhouse gas emissions due to sea surface temperatures rising more in the eastern Pacific than the western Pacific (Walsh et al., 2004, Alexander et al., 2009).
Some modelling predicts more pronounced droughts due to the increased evaporation associated with elevated temperatures and the prolongation of El Niño events (Walsh et al., 2001). Increases in potential evaporation of up to 8% per degree Celsius of global warming have been predicted by Commonwealth Scientific and Industrial Research Organisation (CSIRO) models (Hughes, 2003). Suppiah et al. (2007) utilised the models of the IPCC (Hennessy et al., 2007) and predicted an increase in mean temperature of 0.5 °C to 1.5 °C by 2030 and 1 °C to 4 °C by 2070, depending on the emission scenario used. Increases in temperatures are likely to lead to an increase in the maximum precipitation intensity as it causes an intensification of the water cycle (Giorgi et al., 2001, Walsh et al., 2004).

Precipitation projections under climate change are more uncertain than temperature projections. The high natural spatial variability of precipitation, general poor resolution of climate models (which are unable capture many geographic features like mountain ranges), and the fact that precipitation may both increase or decrease under enhanced greenhouse gas emissions all reduce the accuracy of models (Whetton et al., 2005). Suppiah et al. (2007) predicted a decrease in annual precipitation of approximately 5% by 2030 and between 5-10% by 2070 in SEQ using multi-model ensembles. These results are similar to those of Cottrill (2009), who predicted decreases of 2-6% by 2031-2051 and 6-12% by 2081-2100 in annual precipitation. An intensification of the seasonality of precipitation is also expected, with increases in summer precipitation in the order of 5% by 2030 and 5-10% by 2070 predicted in addition to large decreases in autumn precipitation (Suppiah et al., 2007). Climate change is expected to bring a decrease in the number of wet days and an increase in the number of dry days in the region (Low Choy et al., 2010). An intensification in extreme precipitation events is also likely (Abbs et al., 2007). The frequency and intensity of 2-hour, 24-hour, and 72-hour extreme precipitation events are all predicted to increase, with a maximum intensity change of 40% predicted in some areas (Abbs et al., 2007, Low Choy et al., 2010).

While projections of cyclones are uncertain, it is likely that there will be an increase in the number of more intense (category 3-5) cyclones impacting the Queensland coast, but a decrease in the total number (Department of Climate Change, 2009). It is also likely that cyclones will track further south along the coast, and could impact the SEQ region with more regularity (Nguyen and Walsh, 2001). The magnitude of storm surges along the coast could also intensify as extreme winds associated with tropical cyclones and east coast lows increase with climate change (Department of Climate Change, 2009).
From 1901 to 2010 global mean sea levels rose by between 0.17 mm and 0.21 mm annually, with 75% of the observed rise occurring since 1970s (Pachauri et al., 2014). There is expected to be a continual rise in sea levels in the future. The fourth IPCC Assessment Report (AR4) projected mean sea levels to rise between 0.18 m to 0.59 m from 1990 to 2095 (Meehl et al., 2007). The more recent IPCC AR5 predicted rises from 0.26 m to 0.98 m from 1995 to 2090, depending on the emission scenario adopted (Church et al., 2013). These projections are larger than those in the AR4, as previous projections did not consider the contributions of melting land ice (Church et al., 2013). Rising sea levels and storm surges are expected to exacerbate flooding issues in the SEQ as the majority of the population lives along the coast plain. For instance, Abbs et al. (2000) predicted between 3% and 18% more dwellings and people would have likely been affected by cyclone Wanda (1974) if the event had occurred in 2050, with a sea level rise of 10 to 40 cm. There is expected to be a 0.5 m increase in the 1-in-100-year return period for maximum storm surge by the year 2050 for Cairns. Of this, 0.3 m is predicted to be caused by an intensification of cyclonic events and 0.2 m due to rising sea levels (Karim and Mimura, 2008).

2.3.3 Impacts of Climate Change on Water Quality
To date most of this research has focused on possible changes to the hydrological cycle and the associated impacts on water balance (Yang et al., 2017). However, it is increasingly evident that climate change will also have far-reaching consequences for riverine water quality (Jeppesen et al., 2011, Cho et al., 2016). Variations in streamflow, more intense precipitation, and increased water temperatures are likely to cause adverse water quality effects world-wide (Kundzewicz et al., 2007, Whitehead et al., 2009). Understanding the potential changes to riverine nutrient and sediment loads/concentrations can help engineers and decision makers assess future possible stressors and plan accordingly for the projected impacts of climate change (Records et al., 2014).

Modelling the effects of climate change on riverine water quality typically involves the use of one or a number of models. Hydrological models are required to simulate changes in river flow in response to changes in precipitation, temperature, and evapotranspiration as projected from climate models. Hydrological models can generally be split into three groups; lumped conceptual, semi-distributed conceptual, and distributed grid-based. Lumped models assume homogeneity of input and model parameters across the basin, and as such are typically reserved for small to medium sized basins (Koren et al., 1999).
Semi-distributed models lump meteorological variables and physical parameters into several sub-basins, while distributed models permit parameters to change on an individual grid basis, and therefore require significantly more data and time for calibration and validation (Jajarmizadeh et al., 2012). A range of water quality models may then be applied to assess the in-stream nutrient and sediment processes. Additional models may also be used to simulate terrestrial processes relevant to land management, nutrient processes, or sediment entrainment.

The effects of climate change are likely to induce significant changes in nutrient and sediment loads in riverine environments. Increasing temperatures would likely accelerate biogeochemical reaction rates and reduce soil moisture content. While changing annual and seasonal precipitation will alter the transport and entrainment of pollutants through altered streamflow and runoff. In recent years, the quantity of research assessing the impacts of climate change on nutrients and sediments in rivers has increased significantly, highlighting the significance of this work.

2.3.3.1 Nutrients

Studies suggest that climate change could result in either increased and decreased nitrogen loads in river catchments throughout the world. Temperature increases are one of the major changes expected under climate change, which will affect many aspects of nutrient cycles. Accelerated mineralisation rates as a result of temperature increases have been widely reported in the literature as a major contributing factor to increased nitrogen (Bouraoui et al., 2002, Whitehead et al., 2002, Andersen et al., 2006, Whitehead et al., 2006, Ahmadi et al., 2014, Huttunen et al., 2015) and phosphorus loading (Arheimer et al., 2012, Shrestha et al., 2012). Arheimer et al. (2005) predicted a 32% to 70% increase in nitrogen leaching rates from arable soils in a Swedish catchment by 2100 due to accelerated mineralisation rates and increased winter precipitation. Ducharme et al. (2007) estimated an increase in soil mineralisation rates due to climate change between 8% and 26% for the Seine River basin, which resulted in a 20% increase in nitrate leaching from agricultural soils and a 33% increase to in-stream nitrate concentrations by 2100. This increase in mineralisation was less than the 46% previously predicted by Rustad et al. (2001), which was thought to be due to decreased soil moisture content in the catchment. While it is widely acknowledged that mineralisation rates will increase under a warming climate, the consequences of these changes may be more complex. Some studies have suggested that increased mineralisation may result in long-term decreases in the organic matter pool, which may ultimately limit changes in mineralisation rates and could result
in reduced nitrogen losses in some instances (Jensen and Veihe, 2009, Molina-Navarro et al., 2018). Temperature rises can also be expected to be accompanied by accelerated rates of nitrification and denitrification in terrestrial and aquatic environments, which can work to counter increases in mineralisation and reduce in-stream nitrogen concentrations (Kaste et al., 2006). It is evident that temperature increases will accelerate many aspects of nutrient cycles, and may lead to increased or decreased nutrient loads, often depending on a range of complex interacting factors.

Changes in total precipitation, as well the seasonality and intensity of precipitation are expected to have major implications for nutrient concentrations and loads. Increased winter precipitation was the major contributing factor to predicted future increases in total nitrogen loads in the northern hemisphere (Ducharne et al., 2007, Wright et al., 2008, Martínková et al., 2011, Shrestha et al., 2012, Huttunen et al., 2015). Yang et al. (2017) conducted a sensitivity analysis of nitrogen loads and concentrations to projected changes in temperature and precipitation under climate for a subtropical southern Chinese catchment using a stochastic weather generator. They found that precipitation changes were highly influential on total nitrogen loads and somewhat influential on nitrogen concentrations, whereas temperature changes had no significant impact on either, contrasting previously mentioned studies. Changes in phosphorus loads also tend to follow projected changes in streamflow and precipitation (Chang, 2004, Jennings et al., 2009, Shrestha et al., 2012, Zhang et al., 2012, Records et al., 2014). However, phosphorus loads are more sensitive to changes in heavy erosion-inducing precipitation than annual precipitation changes, as loads are typically transported sorbed to sediments (Huttunen et al., 2015). This is evident from the similar rates of change observed for both phosphorus and sediment loads under climate change in some studies (e.g., Cho et al., 2016, Molina-Navarro et al., 2018). Changes in precipitation may also lead to changes in the atmospheric deposition of nitrogen (Hessen, 2013). Molina-Navarro et al. (2018) predicted a 7% and 14% increase in nitrate deposition by 2030 and 2060 respectively due to increased precipitation. While change in nutrient loadings typically follow changes in precipitation and streamflow, this is not always the case with nutrient concentrations. Rather, in-stream nutrient concentrations can show opposite signs of change to those of nutrient loads and may decrease with increased precipitation as rivers become diluted (Reder et al., 2013, Teutschbein et al., 2017). These studies suggest that nutrient loads tend to follow the sign of change in annual precipitation and streamflow, while nutrient concentrations may either increase or decrease with changes in precipitation.
Precipitation intensity can strongly influence phosphorus loads. The majority of the aforementioned studies have been conducted in temperature regions of Europe and North America and there is a need for further research throughout tropical and subtropical regions, where precipitation characteristics are inherently different.

More prolonged and pronounced droughts can be expected in many regions of the world under climate change, which will significantly influence in-stream pollutant concentrations (IPCC, 2014). This was demonstrated in a study by Wilby et al. (2006), who predicted a prolonged period of drought at the end of the century in a simulation of the Kennet River in the United Kingdom. This caused a build of nitrogen in the soil during the dry period, which, upon the first large precipitation event, leached into waterways causing excessive in-stream nitrogen concentrations. These findings suggest that drought events can be just as influential on water quality as extreme precipitation events. In drought prone regions of the world, the effects could be even greater and should therefore be explored further.

Climate model predictions of precipitation used for these studies are associated with large uncertainties, and as such, estimates of future nutrient loads should be treated with caution (Wilby et al., 2006, Arheimer et al., 2012, Teutschbein et al., 2017). Studies that make use of only one climate model may be particularly limited, as they only present results for one possible future climate. Instead, a range of climate models should be employed to ensure the results are representative of the range of plausible changes. While this mitigates inter-model uncertainty, intra-model uncertainty can also be significant. Hägg et al. (2014) utilised three different model runs of the same climate model and reported increased nitrogen loads ranging from 5-12% by 2100, depending on model run. These results demonstrate the high uncertainty of results not only between different climate models, but also between separate runs of the same climate model, especially for predictions in the end of the century.

A number of studies also considered the additional effects of changes in land use, agricultural management and policy, population, and consumption rates. Many reported that changes in land use were more influential in altering nutrient loads than predicted climate change (Reeder et al., 2013, Piniewski et al., 2014, Dimitriou and Mentzafou, 2016), while others reported climate change effects were more influential (Wu et al., 2012, Molina-Navarro et al., 2018). Hägg et al. (2014) noted that changes in consumption and population were the key drivers for projected increased loads in the southern
catchments of the Baltic Sea, while changes in climate were the key components in the northern catchments. These studies suggest that the relative changes in nutrient loads from land use and climate change are strongly dependent on the local climatic features, land use types, and assumptions made. A subset of the literature has examined the effects of mitigation techniques to reduce increased loads predicted under climate change. Adjustments in the application of fertilisers have been widely shown to be the most effective mitigation strategy for reducing nitrogen loads (Whitehead et al., 2006, Molina-Navarro et al., 2018, Yang et al., 2018). In contrast, phosphorus loads are best mitigated by improving ground cover and adding catch crops on agricultural land, which work to reduce erosion under heavy precipitation (Jeppesen et al., 2009, Piniewski et al., 2014, Huttunen et al., 2015). Reductions in point loads and the addition of vegetation filter strips were also shown to be effective remedial measures for phosphorus in other catchments (Ducharne et al., 2007, Yang et al., 2018).

2.3.3.2 Sediments

Soil erosion rates and, by extension, in-stream suspended sediment concentrations will be strongly affected by climate change, principally through changes to total precipitation and precipitation intensity. Field studies on hillslopes and cultivated lands have suggested that sediment transport occurs disproportionately during periods of extreme precipitation and flow (Romero et al., 2012, Boardman, 2015). At the catchment scale, it has been reported that the relative contribution of extreme events towards the total suspended sediment load is greatest as catchment size reduces (Gonzalez-Hidalgo et al., 2013), indicating small to medium sized catchments are more vulnerable to changes in precipitation intensity. Under climate change, as precipitation intensities are predicted to increase, the relative contribution from just a few extreme events towards sediment loads is expected to increase further (Nearing et al., 2004, Bussi et al., 2014). Coulthard et al. (2012) estimated the magnitude of 50-year return period precipitation events to be 1.28 times greater under a high emission scenario by 2100, resulting in sediment yields increasing by a factor of five. Pruski and Nearing (2002) reported a 0.85% increase in soil erosion for every 1% increase in precipitation while ignoring changes in precipitation intensity. However, when considering the additional effects of precipitation intensity, soil erosion rates increased by 1.7% for every 1% increase in precipitation. These studies highlight the importance of considering changes to precipitation intensity in climate studies. However, as climate models typically underestimate precipitation intensity, it would be advantageous to employ bias-correction to ensure these changes in extremes are accounted for.
Nunes et al. (2009) conducted a sensitivity analysis and reported that erosion rates were sensitive to changes in both storm intensity and mean annual precipitation. Similar results were found in an earlier study by Nearing et al. (2005) for two catchments in humid and arid climate zones. In comparison with these studies, Bussi et al. (2016) found that suspended sediment yield in the River Thames was more sensitive to changes in annual precipitation than changes in either extreme precipitation or temperature. Therefore, the relative importance of changes in total precipitation and precipitation intensity may potentially depend more on local catchment and climate characteristics. Changes in the seasonality of precipitation may also have significant impacts on sediment loads, affecting the wetting and drying cycle of a catchment and by extension the properties that effect erodibility and infiltration (Bussi et al., 2016).

Climate warming is expected to increase the rates of evapotranspiration, which would likely result in reduced soil moisture content. In a study on three German catchments, Routschek et al. (2014) reported that increased storm intensity would result in significant increases in soil loss by 2050. However, by 2100 soil loss was predicted to decrease, despite a continual increase in storm intensity due to a decline in initial soil moisture content, leading to less runoff. In this way, temperature increases may work to negate the effects of more intense precipitation. Increased temperatures may also increase plant biomass, particularly when considered with the additional fertilising effect of elevated CO₂ concentrations, which may work to reduce erosion. However, if temperature increases are excessive, plant growth may instead be inhibited by temperature stress and excessive evapotranspiration rates would reduce water supply (Nunes and Nearing, 2011). These changes in vegetation have a significant impact on the potential soil erosion within a catchment. Nunes et al. (2008) conducted a sensitivity analysis on vegetation cover and soil erosion under changes to temperatures, precipitation, and CO₂ emissions for two Portuguese catchments. They found increased temperatures and decreased precipitation resulted in declining wheat and vineyard biomass and in increased erosion from these land types. By contrast, in a later study, Nunes et al. (2013) predicted increased vegetation cover under climate change would mitigate the effects of increased storm intensity on soil erosion for two separate Portuguese catchments.

It has been widely reported that future climate induced land management changes are more influential to changes in soil erosion and sediment transport than direct changes from climate variability (Mullan et al., 2012, Mullan, 2013, Rankinen et al., 2013, Routschek et al., 2014, Paroissien et al., 2015, Simonneaux et al., 2015). Simonneaux et
al. (2015) predicted a maximum 250% increase in sediment yields for a Moroccan catchment considering only the effects of land use change, significantly greater than the 10% maximum increase predicted from climatic changes alone. Decreases in erosion rates were predicted for a northern Irish hillslope considering only the effects from downscaled climate change projections, whereas large increases and decreases were projected in scenarios considering land use and precipitation intensity changes, indicating the importance of both factors on the erosion regime (Mullan et al., 2012, Mullan, 2013). Changes in the sediment transport regime can extend beyond increased turbidity and water quality deterioration. Increased sediment transport to river systems, particularly of coarse sediments, may increase rates of bed-aggradation and reduce bankfull capacity. Lane et al. (2007) predicted inundation from a 1 in 0.5-year event to increase by 52.1% considering the effects of sedimentation and climate change for the River Wharfe in the United Kingdom by 2100. Comparatively, climate change alone was expected to result in a 21.6% increase in inundation. These results demonstrate how increased erosion rates from climate change may not only lead to degraded water quality but may exacerbate flooding.

2.3.3.3 Australian Case Studies

In comparison to Europe and North America, there have been relatively few studies conducted on Australian catchments assessing the impacts of climate change on nutrients and sediments (Table 2.5). Dyer et al. (2014) studied the Upper Murrumbidgee River in New South Wales reporting that river regulation had a greater negative effect on river health than the predicted effects of climate change. They estimated that the probability of total nitrogen concentrations exceeding regulatory guidelines fell between 0% and 24% under a 2 °C temperature rise. Nguyen et al. (2017b) projected minor increases in nitrate (2.8%) and phosphate (8.2%) concentrations under climate change conditions for the Millbrook catchment in South Australia, while Shrestha et al. (2017) projected decreases in nutrient loads for the nearby Onkaparinga catchment. Alam and Dutta (2013) studied changes to nutrient yields in the Latrobe River in Victoria by considering probable increases in temperatures and changes in annual streamflow. They reported that mean nitrate concentrations are likely to increase by 18% despite decreased streamflow, largely due to elevated temperatures accelerating biogeochemical processes. When subjected to a scenario of increased precipitation, mean nitrate concentrations were predicted to increase by 42%, while suspended sediment concentrations were predicted to increase by 4 and 12% under decreased and increased precipitation scenarios respectively. Wet and dry spatial analogue scenarios were used to assess the impacts of climate change on
sediment load in a small catchment in the Northern Territory (Hancock et al., 2017). Results indicated that sediment loads varied following changes in precipitation, with a near doubling of erosion rates under the wet scenario compared to the dry scenario. It is evident that the current literature in Australia is limited to studies mostly conducted in the southern temperature regions of the country. There is a lack of studies originating from subtropical regions and throughout Queensland in general. The results from the current literature in Australia is mixed, with predicted increases and decreases in nutrient and sediment loads under climate change reported.
<table>
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<th>Country, State, Catchment</th>
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<th>Downscaling and Bias-correction</th>
<th>Modelling Approach</th>
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<th>Key Findings</th>
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<tr>
<td>Australia, (VIC), Latrobe River</td>
<td>Applied projected changes in streamflow (A1F)</td>
<td>None</td>
<td>Used IISDHM hydrological model with nutrient equations adopted from INCA-N</td>
<td>None</td>
<td>Suspended solids and organic nitrogen concentrations increase with increases and decreases in streamflow largely due to temperature rises. Nitrate concentrations increase by 18 to 42% and suspended sediments levels by 4 to 12% with a 50% decrease and 20% increase in streamflow respectively by 2070.</td>
<td>Alam and Dutta (2013)</td>
</tr>
<tr>
<td>Australia, (NSW, ACT) Upper Murrumbidgee River</td>
<td>Ensemble of 15 GCMs for a 1°C and 2 °C rise in temperature (A1B)</td>
<td>Empirical daily scaling to downscale to a 5 km resolution</td>
<td>SIMHYD using streamflow indicators to assess potential changes in water quality</td>
<td>None</td>
<td>Between 0 to 24% chance that total nitrogen concentration would exceed regulatory guidelines with a 2 °C rise in depending on the sub catchment. No major change in the probability of total phosphorus exceeding the threshold.</td>
<td>Dyer et al. (2014)</td>
</tr>
<tr>
<td>Australia (NT) Corridor Creek</td>
<td>Used spatial analogue technique for sensitivity analysis considering a ‘wet’ and ‘dry’ scenario based on RCP 8.5.</td>
<td>None</td>
<td>CAESAR-Lisflood landscape and river evolution model.</td>
<td>None</td>
<td>Predicted increased and decreased erosion rates for the wet and dry scenarios respectively. Similar spatial erosion patterns were observed under all scenarios despite a near doubling of erosion rates under the wet scenario compared with the dry.</td>
<td>Hancock et al. (2017)</td>
</tr>
<tr>
<td>Australia, (SA), Millbrook Catchment</td>
<td>Ensemble of 6 GCMs (RCP 8.5 and RCP 4.5)</td>
<td>Nonhomogeneous Hidden Markov Modelling (NHMM) and stochastic weather generator for downscaling</td>
<td>SWAT applied for streamflow and nutrient modelling</td>
<td>Considered the conversion of 50% of pastoral land to either orchids or residential areas</td>
<td>Considering just climate change, phosphate and nitrate concentrations increased by 8.2 and 2.8% respectively under RCP 8.5 by 2045.</td>
<td>Nguyen et al. (2017b)</td>
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<tr>
<td>Australia, (SA), Onkaparinga Catchment</td>
<td>Ensemble of 6 GCMs (RCP 4.5 and RCP 8.5)</td>
<td>Nonhomogeneous Hidden Markov Modelling (NHMM) and stochastic weather generator for downscaling</td>
<td>SWAT applied for streamflow and nutrient modelling</td>
<td>Land use scenario consisting of a 70% increase in forested land and an 85% increase in urban area</td>
<td>Considering only climate change effects, total nitrogen and total phosphorus loading decreased by 18.4% and 22.9% for RCP 4.5 and by 24.3% and 29% under RCP 8.5 by 2070. With land use changes the decreases in nutrient loads were even larger.</td>
<td>Shrestha et al. (2017)</td>
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Chapter 3: A Review of the Effects of Climate Change on Riverine Flooding in Subtropical and Tropical Regions

Statement of contribution to co-authored published paper

This chapter includes a co-author paper. The bibliographic details of the co-authored paper, including all authors, are:


My contribution to the paper involved conducting the literature search, quantifying the results of the relevant papers, interpreting the results, and drafting the paper.

Signed: ________________ Date: 06/03/2021

Rohan Eccles

Countersigned: ________________ Date: 09/03/2021

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Principal Supervisor: Prof. David Hamilton (principal supervisor, Australian Rivers Institute)
Chapter 3: Impacts of Climate Change on Flooding in the Tropics and Subtropics

A Review of the Effects of Climate Change on Riverine Flooding in Subtropical and Tropical Regions

Abstract

Tropical and subtropical regions can be particularly severely affected by flooding. Climate change is expected to lead to more intense precipitation in many regions of the world, increasing the frequency and magnitude of flood events. This paper presents a review of studies assessing the impacts of climate change on riverine flooding in the world’s tropical and subtropical regions. A systematic quantitative approach was used to evaluate the literature. The majority of studies reported increases in flooding under climate change, with the most consistent increases predicted for South Asia, South East Asia, and the western Amazon. Results were more varied for Latin America and Africa where there was a notable paucity of studies. This review points to the need for further studies in these regions as well as in Australia, in small to mid-sized catchments, and in rapidly urbanising catchments in the developing world. Adoption of non-stationary flood analysis techniques and improved site-specific socioeconomic and environmental model scenarios were identified as important future directions for research. Data accessibility and mitigation of model uncertainty were recognised as the principal issues faced by researchers investigating the impacts of climate change on tropical and subtropical rivers.
Chapter 3: Impacts of Climate Change on Flooding in the Tropics and Subtropics

3.1 Introduction

Floods are one of the most costly and widespread climate related natural hazards (Jonkman, 2005). Between 1980 and 2009 it was estimated that floods led to the death of 539,000 people and adversely affected the lives of 2.8 billion people (Doocy et al., 2013), totalling US$654 billion worth of damage (adjusted for inflation) worldwide (Munich Re, 2017). Tropical and subtropical regions are often subjected to some of the worst flooding and this may be exacerbated under climate change. The United Nations International Strategy for Disaster Risk Reduction (2009) reports that the ten countries most prone to flooding are all located in tropical South and South East Asia, with countries in South America and Africa also widely affected. As there are a number of developing countries in the tropics and subtropics, the effects of flooding may be exacerbated due to poor infrastructure and healthcare. In Bangladesh for example, water-borne diseases are responsible for a greater number of flood related deaths than drownings (Jha et al., 2012).

The intensity of extreme precipitation events is predicted to increase throughout most parts of the world under climate change (Groisman et al., 2005), potentially leading to an increase in the magnitude of extreme flows. Despite a wide consensus of increased precipitation extremes under rising temperatures, several studies have suggested that this has not led to an increase in flooding, except in small catchments where flashy flows dominate (Wasko and Sharma, 2017, Sharma et al., 2018). However, trend analysis of extreme flooding events exceeding 100-year levels has shown a significant increase towards the second half of the twentieth century (Milly et al., 2002), while analysis of less extreme events has generally indicated a decreasing trend, particularly for large catchments (Do et al., 2017). Modelling on a global scale suggests the increasing trend of the most extreme floods may continue into the future (Hirabayashi et al., 2013). Changes in the magnitude of these extreme flooding events will have major implications for landholders, flood mitigation strategies, and infrastructure design. Quantifying these effects allows engineers and managers to consider changes to urban and infrastructure design standards based on a range of possible future eventualities and scenarios.

A large number of studies have been conducted using climate change projections to quantify the effects on riverine flooding. These studies typically follow a model chain outlined by Xu et al. (2005) consisting of the following, global circulation model (CGM) outputs, GCM downscaling and bias correction methodologies, and hydrological model applications. Selection of the most appropriate models and techniques for a given catchment can be challenging, as catchment size, topography, location, and climatic
conditions must all be taken into account. Changes to sea levels and anthropogenic activities (land use changes, urbanisation, water demand, and flood mitigation/control structures) may also be considered, adding further complexity to models. Each step in the modelling process involves assumptions, which inevitably cause some degree of error, and is compounded with each successive modelling step (Praskievicz and Chang, 2009). The mitigation and quantification of this model uncertainty is a major consideration in impact studies.

Review articles assessing the impacts of climate change on riverine flooding can be found on a global (Hunt and Watkiss, 2011, Kundzewicz et al., 2014), European (Kundzewicz et al., 2010, Madsen et al., 2014), and country-wide scale (Miller and Hutchins, 2017) but are lacking elsewhere. This paper aims to critically evaluate the current literature in the tropical and subtropical regions of the world and examine the factors that are unique to these climates. For this purpose, a systematic quantitative literature approach has been adopted (Pickering and Byrne, 2014) whereby articles have been coded into a customised database to quantitatively assess the literature. This is the first review of its kind conducted in tropical and subtropical regions and the first to adopt a quantitative approach.

To maintain a comparable standard of literature, ‘grey’ literature, including reports, conference papers, unpublished articles, theses, and book sections have been excluded from this review, rather only English language peer reviewed journal articles have been considered. Scopus and Web of Science were searched using a defined set of search terms. The inclusion criteria specified that articles must consider climate change scenarios, the use of hydrological modelling, and analysis of extreme river flows in either tropical or subtropical regions. A total of 134 peer reviewed journal articles were included in this review from an initial evaluation of 4711 (Figure 3.1). The multitude of papers included in this review allows for a more comprehensive analysis of the literature than that found in other similar reviews. A critical evaluation of the following aspects of the literature has been included: (i) the geographic distribution of studies, (ii) the chosen methodologies in terms of downscaling, bias correction, hydrological model choice, and analysis, (iii) the key findings of the literature and, (iv) the implications of these findings and future directions for research.
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Figure 3.1. PRISMA diagram (Moher et al., 2009) showing the number of papers included and excluded at each stage of the review process and the keywords used to find the relevant literature from the online databases.

3.2 Distribution of the Literature

An updated version of the Köppen Climate Classification (Peel et al., 2007) was used as the basis to delineate subtropical and tropical catchments (Figure 3.2). When river basins covered numerous climate zones, only when the majority of the catchment was within tropical or subtropical climates was it considered in this review. As such, studies on the lower Mississippi River were excluded, while those on the on the lower Yangtze were included. The literature was approximately evenly split between tropical and subtropical catchments, covering five continents and thirty-seven countries. Most of the research (59%) was published on Asian river basins, with the remainder published in Africa (13%), the Americas (12%), and on a global scale (16%). Figure 3.3 presents the number of studies included in this review on a per country basis, excluding those studies conducted on a global scale. Table A1 in the Appendix presents a detailed summary of the studies conducted in East Asia, Table A2 for those in South East Asia, Table A3 for South Asia, Table A4 for Africa, Table A5 for the Americas, and Table A6 for those studies conducted on a global scale.

It is evident from Figure 3.4 that there has been considerably more research published on Chinese, South Asian, and South East Asian rivers compared to other regions in the tropics/subtropics. The literature is also skewed towards studies of major river basins. Six major rivers including the Amazon, Niger, Ganges, Brahmaputra, Mekong, and Pearl River, are the focus of approximately 26% of all studies reviewed, each having an area
greater than 450,000 km$^2$. Most of the research has been conducted on similarly large river basins, while just under 4% of the literature was published on river basins less than 1,000 km$^2$ in area (Figure 3.4). This suggests that there is a need for further studies on smaller river basins as the flood-producing mechanisms are inherently different. Furthermore, studies are also required on heavily urbanising catchments in developing regions of the tropics and subtropics as they may be disproportionately affected by future flooding.

Figure 3.2. Regions in this study considered as tropical or subtropical (in blue) based on the Köppen Climate Classification devised by Peel et al. (2007).

Figure 3.3. Number of studies conducted by country in tropical and subtropical by regions. For rivers that were trans-boundary, only those countries that made up part of the study area and were in tropical or subtropical climates were considered.
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There is a marked shortage of literature focusing on parts of the Americas, Africa, and Australia. While the exclusion of non-English language journals in this review likely omitted a number of studies from Latin America and Africa, there is already low research output in these regions due to the difficulty of funding research. No studies were retrieved from Central America or the Caribbean, despite several studies being conducted in South America. This may relate to the small size of river basins in Central America and the Caribbean, as small river basins have been shown to receive considerably less research attention than larger basins (Figure 3.4). This assertion would seem to be supported in South America, as 5 of the 6 studies included in this review focussed on the Amazon River or its tributaries, while just one study was conducted elsewhere on the continent. In Africa there has been a similar disproportionate focus towards the Niger River, though the literature is overall much more evenly distributed across the continent. A paucity of studies originating from central Africa including the Congo River can also be noted. The scarcity of literature originating from tropical/subtropical northern Australia is perhaps most surprising, as a large portion of the country and population reside in tropical and subtropical zones. Here, research has focused on the temperate southwest (Evans and Schreider, 2002) and southeast (Schreider et al., 1996, Schreider et al., 2000), with only one study obtained for the tropical and subtropical northern regions. There is a clear need for further tropical and subtropical river basin research to be conducted throughout Australia, Latin America, and Africa.

Figure 3.4. Number of studies conducted by continent and region (left) and number of studies conducted by catchment size (right). For the catchment size plot, <10,000 is the range between 1,000 and 10,000 km$^2$, <100,000 is the range between 10,000 and 100,000 km$^2$, and <1,000,000 is the range between 100,000 and 1,000,000 km$^2$. 
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3.3 Research Methodologies Adopted in the Literature

3.3.1 Climate Models

The selection of GCMs, Regional Climate Models (RCMs), emission scenarios, downscaling techniques, bias correction techniques, and hydrological models all influence the outcome of climate impact studies. Various combinations and ensembles of these components have been applied throughout the reviewed literature. In total, ninety-nine different iterations of GCMs and numerous additional RCMs were used across all papers. This is somewhat unsurprising, given that the literature extends back approximately 17 years over which climate models have been continually updated and revised. There has been a steep upward trend in the number of studies conducted since 2010 with 90% of all reviewed literature published since this year and over half published since 2016 (Figure 3.5). This trend is most likely to continue as governments and researchers prioritise climate change impacts to assess past and future engineering design and planning.

Approximately 71% of the studies adopted an ensemble approach in which two or more climate models were employed to provide multiple projections as has been widely recommended (Dankers and Feyen, 2009, Prudhomme and Davies, 2009, Teutschbein and Seibert, 2010). The remaining 29% of the reviewed literature applied just a single climate model for assessing the impacts of climate change. This is considered a major limitation as results from these studies represent just a single plausible climate outcome that may not be representative of the likely effects of climate change.

Figure 3.5. Number of studies published and number of studies reporting use of a single or multiple GCM(s) by year.

![Graph showing number of studies published and use of single or multiple GCMs by year](image-url)
Several of the reviewed papers have reported that the largest source of uncertainty in the modelling process is from the GCM structure (Aich et al., 2014, Aich et al., 2016, Li et al., 2016a). Similar results have been found globally (Prudhomme et al., 2003, Kay et al., 2009), highlighting the importance of considering a range of climate models. Liu et al. (2013) reported that the relative uncertainty in predictions arising from the GCM structure was greater for projections in the mid to late century while statistical downscaling and emission scenario selections are greater sources for predictions in the 2020s. Similar results were reported by Shen et al. (2018), suggesting that as climate projections advance further from the baseline the divergence between model projections increases. Li et al. (2016a) found the uncertainty from GCM predictions to be spatially variable, with greater relative uncertainty in the subtropical regions to the south and east of China compared with the more arid north and west where the uncertainty from hydrological modelling was more pronounced. Similarly, Peclhivanidis et al. (2017) reported greater relative uncertainty from GCMs in the tropical and subtropical Niger and Ganges Basins compared to the Lena and Rhine Basins. Precipitation projections from GCMs in the deep tropics, particularly over Africa and South America have been shown to be the more uncertain than elsewhere in the world (Rowell, 2012). Vetter et al. (2015) concluded that the high uncertainty introduced from climate models in the upper Niger Basin was due to the local monsoonal climate in which river runoff responds principally to high precipitation driven by the GCMs.

3.3.2 Emission Scenarios

Over 43% of the studies employed emission scenarios from the International Panel on Climate Change (IPCC) Special Report on Emission Scenarios (SRES; Nakicenovic et al., 2000), while just under 50% used the more recent Representative Concentration Pathways (RCP; Meinshausen et al., 2011). The remaining (usually older studies) made use of alternative emission scenarios. Approximately 40% of the reviewed literature applied one emission scenario, 32% applied two, 13% applied three, and 12% applied four emission scenarios (Figure 3.6). Compared to climate models, emission scenarios introduce only minor uncertainty, especially for projections in the mid to late 21st century (Liu et al., 2013, Tian et al., 2016, Wang et al., 2017, Yuan et al., 2017).
3.3.3 Downscaling

GCMs run on a coarse resolution (typically 100-300 km) which make them unable to adequately represent local climatic features (Fowler et al., 2007), and as such, downscaling is often required. Both dynamic and statistical downscaling techniques have been widely applied throughout the literature. Approximately 35% of the studies reviewed adopted dynamic downscaling using RCMs while the remaining studies applied either statistical techniques or no downscaling at all. Bias correction is applied to correct systematic biases present in climate models including an overestimation in the number of wet days, underestimation in precipitation intensity, and inadequate year-to-year variability (Ines and Hansen, 2006). The most common bias correction approaches adopted in the literature include the delta change, quantile mapping, scaling, and a trend preserving technique proposed by Hempel et al. (2013), applied in 24, 22, 13, and 14% of studies, respectively. Numerous variations of these techniques were utilised in addition to a number of alternative approaches.

Yuan et al. (2017) conducted a thorough assessment of the relative contributions to uncertainty from the emission scenario, climate model, statistical downscaling/bias correction technique, hydrological model, and flood frequency distribution. They reported that statistical downscaling and bias correction were the predominant source of uncertainty for projections involving high flows and flooding events. Chen et al. (2013) concluded that uncertainty due to downscaling and bias correction was more significant for projections of extremes than mean flows. Dobler et al. (2012) found similar results for Europe and suggested applying a range of bias correction techniques to account for this uncertainty when conducting impact studies related to extreme events. These findings
highlight the importance of bias correction, especially for the modelling of flooding. In smaller to mid-sized catchments (where intense, short duration precipitation can be a major source of flooding), bias correction is especially important. Of the bias correction techniques adopted within the literature the quantile mapping approach appears the most suitable for flood impacts studies as it is best able to reduce systematic errors at high quantiles (Dobler et al., 2012, Chen et al., 2013).

3.3.4 Hydrological Models
Fifty-one different hydrological, rainfall-runoff and hydrodynamic models were applied across all studies. The most commonly used were the ‘Variable Infiltration Capacity’ (Liang, 1994), ‘Hydrologiska Byråns Vattenbalansavdelning’ (Bergstrom, 1976), and ‘Soil and Water Assessment Tool’ (Arnold et al., 1998) hydrological models, adopted in 16, 15, and 9% of the studies, respectively. A small subset of the research utilised hydrodynamic modelling for more accurate assessments of river flow, applying models such as SOBEK (e.g., Budiyono et al., 2016, Wei et al., 2016), MIKE 11 (e.g., Mirza, 2002, Mirza et al., 2003, Kure and Tebakari, 2012, Supharatid et al., 2016, Vo et al., 2016), HEC-RAS (Arunyanart et al., 2017, Shrestha and Lohpaisankrit, 2017), and FLO-2D (e.g., Mishra et al., 2017). Distributed grid-based models were adopted in 37% of literature and were most widely used for global and large-scale studies. Model resolution ranged from 0.5° (approximately 55 km; Gain et al., 2013, Dankers et al., 2014, Arnell and Gosling, 2016) to 200 m (e.g., Zhao et al., 2016). The remaining literature utilised semi distributed models, and in some cases, lumped models.

The potential uncertainty derived from hydrological modelling is often overlooked in the literature. While some studies have suggested that this uncertainty is significant and cannot simply be ignored (Tian et al., 2013, Tian et al., 2016), others have concluded that the relative uncertainty contributed from hydrological modelling is minor, especially when compared to GCM structure (Menzel et al., 2006, Kay et al., 2009, Teng et al., 2012b). Asadieh and Krakauer (2017) reported in their global study that the global hydrological models contributed more to uncertainty in streamflow changes than the GCMs. They therefore recommended that future studies adopt an ensemble of hydrological models in addition to an ensemble of GCMs.

3.3.5 Consideration of Dams
Many studies in this review were carried out on sizeable river basins regulated by many large dams and reservoirs. The Mekong River has seen major dam developments over
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recent years for hydropower and irrigation purposes, with many more in the planning phase. When all planned dams are complete the active storage capacity is expected to increase to 100 km$^3$ from the 5 km$^3$ initially available in 2010 (Johnston and Kummu, 2012). Given this significant increase, several studies have considered the combined effects of climate change with future damming in the Mekong (Lauri et al., 2012, Wang et al., 2017, Whitehead et al., 2019). Lauri et al. (2012) found an increase in the annual peak discharge downstream under climate change, but a decrease when considering additional effects of future dams. Wang et al. (2017) reported that while regulation would have a significant impact on upstream flooding, it would have only minor effects on flood peaks and frequency downstream. Other studies have chosen to ignore current and future dams altogether, instead focussing on the impacts of climate change as if the system were in its natural state (Kiem et al., 2008, Västilä et al., 2010, Phi Hoang et al., 2016).

Studies in South Asia have generally considered rivers as if they were unregulated, despite numerous large dams and irrigation schemes throughout the region. A shortage of available data throughout the region, as noted by Hopson and Webster (2010) may explain why dams are often overlooked. Nonetheless, Mohammed et al. (2018) argued that the effects of regulation were minimal during the flooding season for the Ganges River as most structures are intended for use primarily during the dry season and not as flood mitigation measures. Similarly, due to the large number of dams and a lack of knowledge of the operating procedures, studies along the Yangtze River have also neglected the impacts of the numerous large dams constructed over the last 50 years (Gu et al., 2014, Gu et al., 2018, Yu et al., 2018). However, again it has been argued that due to the high precipitation totals in the wet season these dams have little effect on the main channel discharge (Birkinshaw et al., 2017, Gu et al., 2018). By contrast, many studies in the Niger Basin have often considered the effects of major dams but not the effects of future planned dams (Aich et al., 2014, Aich et al., 2016, Thompson et al., 2016, 2017). This typically only involves the consideration of a few key structures that are sufficient to capture the effects of regulation, compared to the many hundreds or thousands of dams that would need to be considered throughout the Yangtze and the Ganges Basins.

3.3.6 Data accessibility
A subset of the literature discussed difficulties in obtaining high quality observational data for model setup, calibration, and validation. Obtaining suitable resolution in datasets for digital elevation models, land use, and bathymetry can be challenging in these regions, particularly for the analysis of small river systems. In parts of Africa, Asia, and the
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Americas there is often a lack of climate observations at sufficiently high spatial and temporal resolution to be effectively used for hydrological modelling and bias correction (Andersson et al., 2011). This was most evident for studies conducted in Africa where spatial coverage of meteorological and streamflow gauges was especially coarse. An array of reanalysed climate datasets, such as APHRODITE (Yatagai et al., 2012) and WATCH (Weedon et al., 2011) have thus been used within the literature to supplement the limited observational data. There are however, often large discrepancies in precipitation values between the various reanalysed datasets, especially in regions with poor gauge density such as much of Africa (Fekete et al., 2004).

Application of erroneous datasets for model calibration and bias correction may result in a biased hydrological model affecting flood estimates. Stream gauge networks are also limited throughout much of the tropics and subtropics, with historical records having neither the longevity nor consistency of similar gauges in Europe and North America. Model calibration and validation is thus more complicated and historical flood frequency analysis is less accurate with limited historical streamflow records. A lack of cross border cooperation in transboundary catchments, and delays between data collection and data availability in some countries further limits data accessibility (Artan et al., 2007). There is evidently a need to improve data accessibility and for continual improvements to be made to reanalysed datasets. Development of remote sensing technology may help to improve access to quality meteorological data in remote and poorly gauged regions, which would be beneficial to modellers.

3.3.7 Flood Analysis Techniques

Several techniques were adopted in the literature for the analysis of riverine flooding, of which, flood frequency analysis was the most commonly applied, being used in 53% of the studies. This involved comparisons between historical and future projected flood magnitudes for specified return periods. Of the studies using flood frequency analysis, 90% used the Annual Maxima (AM) series, whereby yearly flow maximums were used for flood estimation. The remaining literature utilised the Peak-Over-Threshold (POT) in which all statistically independent discharge values exceeding a selected threshold were analysed. This series is advantageous compared to the AM series as it allows for more data points to be analysed and ignores superfluous data that might have otherwise been included, a crucial advantage in highly variable climates. While the AM series dominates the literature, the POT series is potentially more appropriate for flood estimation, given the short timeframes considered (typically 20 or 30 years) for analysis of historical and
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future climates.

Traditional flood frequency analysis assumes stationarity, whereby the distribution of the flood frequency curves is assumed to be invariant for a given period (Prudhomme et al., 2003). However, due to continually changing climatic and hydraulic conditions (e.g., from land use, river infrastructure, and urbanisation changes), the assumption of stationarity may not always be reasonable, especially in cases where large man-made changes occur within a catchment during the time frame in question (Strupczewski et al., 2001). However, few studies have utilised non-stationary flood frequency techniques for flood impact assessments and this requires additional research attention.

Other studies have made comparisons between historic and future mean annual floods, high flows, and flood events derived from specific return period precipitation or storm events. Changes in high flows were assumed to be indicative of changes to flooding and was utilised in 26% of the reviewed papers. This method can be advantageous compared with flood frequency analysis as projections of high flows are more accurate than those of large flooding events (Aich et al., 2016). However, the rate of change predicted for high flows may not be the same as the rate of change for extreme flows, and as such, this method should only be used to provide an indication of flood changes.

3.3.8 Summary
There is evidently a wide array of possible approaches for assessing the impacts of climate change on extreme discharge. The choice of GCM/RCM, downscaling technique, bias correction, hydrological model, and analysis technique collectively affect the results. These choices can depend on a number of factors including computational power, budget, research domain, RCM availability, data accessibility, model familiarity, and topographic and climate variability within the spatial domain.

3.4 Key Findings
3.4.1 Asia
Both increases and decreases in extreme flows were predicted across the literature. There was a general consensus throughout Asia towards increased flooding under climate change. In South Asia increased flooding was projected for southern Nepal (Devkota and Gyawali, 2015, Mishra and Herath, 2015, Perera et al., 2015), Bangladesh (Mirza, 2002, Mirza et al., 2003, Masood and Takeuchi, 2016, Mohammed et al., 2018), various catchments in India (Jana et al., 2015, Mathison et al., 2015, Whitehead et al., 2018), the
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Mahanadi (Gosain et al., 2006, Asokan and Dutta, 2008, Jin et al., 2018b), the Ganges (Whitehead et al., 2015, Tsarouchi and Buytaert, 2018), and for the Brahmaputra River (Gain et al., 2011, Dutta and Ghosh, 2012, Gain et al., 2013, Mohammed et al., 2017a, Mohammed et al., 2017b, Philip et al., 2019). Contrasting some of these findings, Gosain et al. (2011) predicted minor decreases in high flows for the Ganges, Brahmaputra, Krishna, and Cauvery Rivers but increases for the remainder of the country. Pichuka et al. (2017) predicted a decrease in the number of small flood events, but an increase in the magnitude of larger floods for the Bhadra River, while Bothale and Katpatal (2017) reported uncertain changes for the upper Wardha River. Decreased flooding was predicted for the Wainganga River (Das and Umamahesh, 2017, 2018) and for two small catchments in south India (Mudbhatkal et al., 2017).

In South East Asia increases in flooding were projected for the Mekong (Kiem et al., 2008, Västilä et al., 2010, Lauri et al., 2012, Phi Hoang et al., 2016, Edangodage Duminda Pradeep et al., 2017, Wang et al., 2017, Whitehead et al., 2019), the Yang (Shrestha and Lohpaisankrit, 2017), the Trian (Dong et al., 2018), and for the Red River (Giuliani et al., 2016). Increases were also projected for catchments in Malaysia (Amin et al., 2017), the Philippines (Tolentino et al., 2016), and for the Ciliwung River in Indonesia (Emam et al., 2016, Mishra et al., 2017). Conversely, Budiyono et al. (2016) projected decreased flood risk for the Ciliwung River when considering only the effects of climate change, however, when combined with the effects of sea level rise and land use changes flood risk was predicted to increase considerably. Muis et al. (2015) reported an increase in the severity of floods over large parts of Indonesia with decreases projected for Java. For the Va Gia-Thu Bon catchment in Vietnam, Vo et al. (2016) predicted an increase in flooding, whilst Dang et al. (2017) reported uncertain changes. Similarly, for the Chao River in Thailand both increased flooding (Wichakul et al., 2015, Supharatid et al., 2016) and uncertain changes were reported (Hunukumbura and Tachikawa, 2012, Kure and Tebakari, 2012). Decreases to annual maximum flows have been predicted for the Lampao River in Thailand (Arunyanart et al., 2017).

Li et al. (2016a) projected flood magnitudes to increase throughout subtropical South China by 2100 despite a predicted decrease in annual precipitation, which was the result of a projected intensification of extreme precipitation. Increased extreme river flows were projected for Taiwan (Wei et al., 2016), the lower and middle Yangtze River (Gu et al., 2014, Ju et al., 2014, Gu et al., 2018, Yu et al., 2018), 5 river basins of Poyang Lake (Li et al., 2016b), and numerous smaller basins throughout China (Xu et al., 2011, Lu et al.,
In the Beijiang River both increased flooding (Wu et al., 2014, Wu et al., 2015) and uncertain changes were reported (Liu et al., 2017). Inconclusive results were also reported for the Lanjiang (Zhang et al., 2014) and the Jinhua Rivers (Tian et al., 2013). Although more recent studies found flood magnitudes were likely to increase for the Lanjiang River (Zhang et al., 2015) and decrease for the Jinhua River (Tian et al., 2016). Increased flooding was also widely predicted for the Pearl River in south China (Liu et al., 2012, Liu et al., 2013, Yuan et al., 2016). Liu et al. (2018) projected an increase in the occurrence of small flooding events in the catchment and a decrease in larger events. Whilst, Yuan et al. (2017) and Zhu et al. (2017) both reported uncertain changes for the Xijiang River, a major tributary of the Pearl River.

### 3.4.2 Africa

Aich et al. (2014) predicted increases in extreme flows for the upper Blue Nile in Ethiopia, uncertain changes for the Niger River, and no changes for the Oubangui River in central Africa. Other studies have predicted increased flooding for the Niger River (Aich et al., 2016, Andersson et al., 2017), whilst decreased or uncertain changes were predicted for the upper Niger Basin (Vetter et al., 2015, Thompson et al., 2016, 2017, Huang et al., 2018). Elsewhere in West Africa increased flooding was predicted for the Black Volta (Jin et al., 2018a) and the Ouémé River (Essou and Brissette, 2013). Bodian et al. (2018) predicted decreased high flows for the Gambia and uncertain changes for the Senegal River. In East Africa, Taye et al. (2011) reported an increase in the magnitude of 10-year flood events for the Nyando Basin in Kenya and uncertain changes for Lake Tana Basin. Likewise, Nawaz et al. (2010) projected uncertain changes for the upper Blue Nile. Increased flooding was predicted for the Nzoia River in Kenya (Githui et al., 2009) and the Kafue River in Zambia (Ngongondo et al., 2013), whereas decreases were projected for the Pungwe River in Mozambique and Zimbabwe (Andersson et al., 2011). For the Zambezi Basin, Fant et al. (2015) reported an increase in 50-year flood events for sections in Mozambique and Zambia and insignificant changes for Malawi and Zimbabwe.

### 3.4.3 Americas

In the upper Amazon River basin increased flooding was widely predicted (Guimberteau et al., 2013, Langerwisch et al., 2013, Mora et al., 2014, Sorribas et al., 2016, Zulkafli et al., 2016), while decreases or uncertain changes were forecasted for the lower Amazon basin (Guimberteau et al., 2013, Langerwisch et al., 2013, Sorribas et al., 2016). Increases were also predicted for the Upper Grande River in Brazil (Viola et al., 2015), the
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Apalachicola (Chen et al., 2014), San Jacinto (Muttiah and Wurbs, 2002), Yadkin-Pee Dee (Suttles et al., 2018), and Wolf Bay Basins (Wang et al., 2014) in the United States. Country-wide studies for the United States reported a likely increase in 100-year floods and high flows throughout the subtropical south east of the country (Naz et al., 2016, Wobus et al., 2017, Naz et al., 2018). Conversely, Risley et al. (2011) reported a likely decrease in high flows for the Flint River, while Zhao et al. (2016) and Chen et al. (2013) noted significant uncertainty in projections for the San Antonio and Chickasawhay River, respectively.

3.4.4 Global Studies

In addition to the studies completed on catchment, regional, and national scales, several global studies have been conducted. Arora and Boer (2001) reported that reductions in flood events throughout most of the tropical and subtropical world are likely with the exception of parts of the Indian subcontinent and Brazil. Voss et al. (2002) predicted increased 10-year flood magnitudes for all tropical and subtropical rivers assessed except for the Amazon River. Similar results were reported by Hirabayashi et al. (2008) who predicted increased 100-year flood magnitudes over much of the world, with the most consistent increases in Central Africa and South Asia. Okazaki et al. (2012) and Wiel et al. (2019) also reported likely increases in flooding throughout most of the tropics.

Falloon and Betts (2006) found 8 of the 10 rivers most affected by climate change to be in tropical or subtropical regions, while Alfieri et al. (2017) identified that 15 of the 20 most affected countries were in tropical or subtropical regions. However, most of these studies based their results on the outputs of a single GCM, applying no additional downscaling or bias correction and as such, their findings may not be representative of the likely effects of climate change.

Dankers et al. (2014) applied an ensemble of GCMs predicting flood peaks to increase throughout much of the tropics, with the most consistent increases for South and South East Asia. Other multi-model ensemble studies have also consistently predicted increases for South and South East Asia (Arnell, 2003, Hirabayashi et al., 2013, van Vliet et al., 2013, Koirala et al., 2014, Arnell and Gosling, 2016, Winsemius et al., 2016, Döll et al., 2018). Whilst the most consistent decreases are projected for parts of South and Central America (van Vliet et al., 2013, Koirala et al., 2014, Winsemius et al., 2016, Asadieh and Krakauer, 2017). Hirabayashi et al. (2013) predicted large flooding events to increase, especially in South and South East Asia, Eastern Africa, and the northern portion of the Andes Mountains. Krysanova et al. (2017) predicted mixed results and moderate
uncertainty for future high flow occurrences over many large tropical and subtropical rivers, with high flows predicted to increase only in the Ganges River, but with moderate certainty. Paltan et al. (2018) projected the largest increase in 100-year floods to occur over north India, east China, and the southern Amazon.

3.4.5 Summary
The majority of studies have predicted increases in extreme flows under climate change in both the tropics and subtropics. The percentage of studies predicting increases on a per country basis is presented in Figure 3.7. The most consistent changes were observed in South Asia, South East Asia, and the western Amazon, with over 70% of the reviewed literature projecting increased flooding in the future. Results from subtropical China and the United states were also highly consistent, with 67% and 70% of the literature predicting a future increase in riverine flooding, respectively. Mixed findings have been reported for most of Africa and most of South America, likely due to the small subset of literature reviewed from these regions and no consistent, meaningful conclusions can be drawn.

Figure 3.7. Percentage of studies (excluding studies conducted on a global scale) predicting increased river flooding on a per country basis in tropical and subtropical regions.

3.5 Implications and Future Directions

3.5.1 Implications
In order for research undertaken by the scientific community to be relevant to engineers and decision makers, it is essential that uncertainty is estimated and mitigated (Andersson et al., 2011, Aich et al., 2014). An important consideration in this is the propagation of uncertainty down the model chain that can lead to divergent outcomes for the same or
nearby catchments. Dankers et al. (2014) suggest approaching the issue of uncertainty from a risk management perspective, whereby even the most unlikely outcome that carries a high risk is considered. This precautionary approach is likely better adapted to decision makers. In doing so, the full range of plausible eventualities can be planned for and mitigated appropriately. Even so, the research processes adopted in the scientific literature are not always compatible with the legal and economic constraints placed on decision makers (Madsen et al., 2014). Any revisions made to design flood levels are likely to have a wide range of economic ramifications. Changes to the design and operation of hydraulic structures and key infrastructure can be very costly and changes to the delineation of flood hazard mapping will have consequences for insurance premiums affecting property owners. Increased pressure could be placed on water suppliers, as dams may have to operate under lower maximum storage to accommodate the increases in discharge associated with large flooding events.

Greater and more frequent floods would likely also exacerbate erosion processes, as sediment transport occurs disproportionately during extreme events (Romero et al., 2012, Gonzalez-Hidalgo et al., 2013, Boardman, 2015). This could cause greater pollutant and sediment loads in rivers, affecting downstream ecosystems. Accelerated erosion processes may result in channel sedimentation, instability, and river routing changes, which can work to undermine the stability of bridges, levees, and other flood control infrastructure. The entrainment and deposition of coarse sediments in river channels may work to reduce bankfull capacity, thereby raising flood levels under future events (e.g., Lane et al., 2007).

The additional effects of sea level rise and anthropogenic activities (e.g., hydraulic structures construction, land use changes, urbanisation) further complicates the issue. In some instances, these effects may be more pronounced than those of climate change (e.g., Budiyono et al., 2016, Zhao et al., 2016). The combination of these changes may be especially devastating in some developing nations of the tropics and subtropics. Bangladesh for instance, may be jointly affected by more intense cyclones (storm surges), increased extreme river flows, and sea level rises, all of which may exacerbate flooding. Adaptation strategies and emergency action plans are required to mitigate economic damage and fatalities from such events. These plans must be flexible and robust to account for the range of plausible scenarios and allow future adjustments to be made with advances in modelling (Mathison et al., 2013). Such plans may be more difficult to implement in the developing nations of the tropics/subtropics, as governments
understandably may not prioritise them over more immediate issues.

3.5.1 Future Directions

Continual improvements must be made to climate models, particularly in the modelling of land-surface processes if projections are to become more reliable (Okazaki et al., 2012). Increasing the availability of sub-daily climate model outputs would be advantageous especially for studies conducted on smaller catchments with flashier flows (Kiem et al., 2008). As it is widely agreed the largest source of uncertainty is from the GCM structure (Kay et al., 2009, Prudhomme and Davies, 2009), future research should extend the number of climate models in an ensemble modelling process. Results based on a limited number of scenarios may give a false indication of the direction of change under climate change conditions. Future studies are recommended to avoid overly simplistic bias correction techniques for precipitation, such as the delta change approach, as these methods are not well suited to the modelling of extremes. Rather a quantile mapping technique is recommended as it has been demonstrated to be more reliable in improving the projections of extreme events compared with other bias correction techniques (Dobler et al., 2012, Teutschbein and Seibert, 2012). Many studies have acknowledged the need to utilise multiple climate models, however, most studies utilise a single hydrological model and downscaling/bias correction technique. Ideally, an ensemble of hydrological models, downscaling, and bias correction techniques could be employed to better account for uncertainty, but this is a time-consuming process and may not always be feasible.

The majority of the reviewed literature has assumed the physical characteristics of the catchment remain the same throughout the study. However, land use, vegetation, and hydraulic structure changes all have significant impacts on the streamflow characteristics. Future studies could consider these changes through the development of site-specific socioeconomic and environmental scenarios. In many of these instances, the adoption of non-stationary flood frequency analysis techniques may be preferred over traditional stationary approaches, as they allow changes in the catchment characteristics to be considered.

The research considered in this review has been geographically limited, with minimal to no research found for large portions of Africa, Latin Americas, and Australia. There is a need for further studies in these regions and throughout the tropics/subtropics generally. The majority of the literature has assessed the effects of climate change on large river
systems and as such, additional studies on smaller to mid-sized catchments throughout the tropics are required, as the flood-producing mechanisms in these catchments are inherently different. Studies investigating flooding changes in heavily urbanising catchments in developing regions are also required. There is a need to improve the accessibility and quantity of observational data across much of the tropics. Limited historical records in stream gauge networks in the tropics/subtropics can lead to inaccurate flood frequency estimations, as they do not capture the full range of events. Enhancements in monitoring regimes are needed to improve modelling and our understanding of the extent of natural variability (Kundzewicz et al., 2008). Generally, there are limited available dynamically downscaled climate change projections for these regions compared to those in Europe (Andersson et al., 2011, Phi Hoang et al., 2016) and therefore, more RCM outputs should be made available throughout the tropics and subtropics.

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Chapter 4: Trends in Water Quality in a Subtropical Australian River-Estuary System: Responses to Damming, Climate Variability and Wastewater Discharges

Statement of contribution to co-authored published paper

This chapter includes a co-author paper. The bibliographic details of the co-authored paper, including all authors, are:


My contribution to the paper involved conducting the statistical analyses, interpreting the results, and drafting the paper.

Signed: ____________________________ Date: 06/03/2021

Rohan Eccles

Countersigned: ____________________________ Date: 09/03/2021

Principal Supervisor: Prof. Hong Zhang (principal supervisor, Griffith School of Engineering)

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Countersigned: ____________________________ Date: 10/03/21

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Trends in water quality in a subtropical Australian river-estuary system: responses to damming, climate variability and wastewater discharges

Abstract

The Logan-Albert estuary in southeast Queensland, Australia, has high biodiversity and supports multiple economic and recreational services. Elevated nutrient and sediment loads have been a longstanding management issue for the estuary. We investigated the spatial and seasonal patterns of nutrients and turbidity along the Logan-Albert estuary and assessed the effects of a recently constructed upstream dam. Nutrient concentrations and turbidity levels were analysed using 15 years of monitoring data from 19 water quality sites throughout the estuary. We hypothesised that the construction of Wyaralong Dam would act as a nutrient and sediment sink which may have positive effects on downstream water quality. Long-term trends of water quality constituents were evaluated using a non-parametric seasonal Mann-Kendall test and the effect of upstream impoundment was assessed with a Before-After Control-Impact (BACI) test. Nutrient concentrations and turbidity levels declined significantly with time in the upper Logan estuary and, to a lesser extent, in the lower Albert estuary. The general improvement of water quality in the upper Logan estuary was attributed to construction of the Wyaralong Dam. Significant decreases in concentrations of total phosphorus (TP) and oxidised nitrogen (NO$_3$-N) along the lower Albert were principally attributed to wetter conditions over the 15-year dataset, which diluted point-source loads from a nearby wastewater treatment plant (WWTP). Our results show that estuarine water quality changes can be highly dynamic with interactions amongst climate and management practices that necessitate long-term monitoring programs with good spatial coverage.


4.1 Introduction

Surface water pollution from elevated sediment and nutrient loads has become an important environmental issue, leading to eutrophication and decreased biodiversity (Rabalais et al., 2009). Levels of nutrients and sediment are often used as a proxy for river and estuary health, to assess the impacts of anthropogenic changes, and underpin the implementation of management strategies to mitigate adverse changes (Medeiros et al., 2011, Li et al., 2018). Limited understanding of the long-term trends and drivers of water quality change may lead to poor decision making about possible management strategies (Bertone et al., 2015). Disentangling these complex interactions between anthropogenic and natural drivers of change, which may act synergistically or antagonistically, remains a major challenge for managers, particularly in highly variable subtropical climates.

Over the last century, the seasonal regime of nutrient and sediment loads has been significantly altered in many rivers (Malmqvist and Rundle, 2002, Walling and Fang, 2003). Widespread deforestation, and agricultural and urban development are some of the principal factors which have led to excessive nutrient and sediment loads to downstream ecosystems (Malmqvist and Rundle, 2002). The effects of climate change, particularly changes in precipitation variability and intensity, may further increase loads (Nunes et al., 2009, Shrestha et al., 2017, Molina-Navarro et al., 2018). Conversely, the construction of dams and weirs, which alter natural flow patterns of rivers, can reduce downstream sediment and nutrient loads (Walling and Fang, 2003). Dams can effectively trap particulate nutrients and sediments, particularly in the early stages following construction (Friedl and Wüest, 2002, Medeiros et al., 2011, Zhang et al., 2013). Phosphorus adsorption to inorganic particles and denitrification within dams may also attenuate the export of nutrients. It has been argued that the impact of dams on downstream river flows and water quality may be greater in Australia than elsewhere in the world, due to greater climatic variability and highly variable flow regimes of Australian rivers (Harris, 2001).

Before-After Control-Impact (BACI) design is a statistically powerful design tool suitable for environmental impact studies where a particular causal factor may be implicated in an environmental change (Stewart-Oaten et al., 1986). It effectively separates the influence of natural variability from anthropogenic disturbances, providing that adequate data are collected, and the timing of the impact is known (Smokorowski and Randall, 2017). The BACI approach has been adopted for a range of environmental impact studies, including assessing the effects of reservoir removal and impoundment (Martina et al., 2013, Chang et al., 2017), stream morphology changes (Hughes and Quinn, 2014, Thompson et al.,
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Water quality measurements, taken predominantly on a monthly basis and available for numerous sites throughout the Logan-Albert estuary, were used in this study to investigate river-estuarine water quality, both spatially and temporally. The aims of this study were to (1) identify the mechanisms driving the spatial and seasonal patterns of nutrient concentrations and turbidity, (2) detect the long-term trends for these constituents, and (3) evaluate the effects of the recently constructed Wyaralong Dam on downstream water quality using the BACI design. We hypothesised that the construction of the upstream Wyaralong Dam would be detected as a positive impact for downstream water quality, superseding other negative environmental drivers relating to ongoing land use change, and dominating other possible drivers related to climate change and variability.

4.2 Study Site, Historical Data and Sample Collection

The study was focussed on the Logan-Albert river estuary (Figure 4.1), located south of Brisbane in southeast Queensland. The estuary supports a wide diversity of aquatic life and is important economically and recreationally. The system has a catchment area of approximately 3862 km², of which the Logan River catchment covers around 3080 km² and the Albert 782 km². The Logan and Albert Rivers rise along the McPherson ranges and converge approximately 11.1 km from the river mouth. The estuary discharge is to the Ramsar listed wetlands of southern Moreton Bay. The bay experiences semidiurnal microtidal (range <2 m) and mesotidal (range 2-4 m) conditions with a maximum range of 2.8 m (Tibbetts et al., 1999). The tidal influence extends approximately 60 km upstream on the Logan River and 35 km upstream of the Logan River confluence on the Albert River. Flood current velocities and duration exceed those of the ebb tide (Mirfenderesk and Tomlinson, 2006) and typical flushing times range from 66 to 75 days (Dennison and Abal, 1999).

The southeast Queensland region has experienced a significant deterioration in water quality since arrival of Europeans in 1823 (Olley et al., 2015) and the ecological decline of the major coastal receiving waters of Moreton Bay has been attributed to increased nutrient and sediment loads from the rivers in the region (Abal et al., 2005, Bunn et al., 2007). It is estimated that phosphorus and nitrogen loads from the Logan-Albert river system have increased by a factor of 4.7 and 3.2, respectively, and sediment loads by a factor of 35 since European arrival (National Land and Water Resources Audit, 2001). The Logan-Albert catchment has been identified by the Department of Infrastructure and
Transport (2013) as an area for major urban expansion, which may stress the already-degraded estuary system.

At the same time the effects of Wyaralong Dam, constructed upstream of the Logan River in 2010, have not yet been established. It was built to supplement the drinking water supplies for southeast Queensland following a major drought across south-eastern Australia in 2001-2009 (van Dijk et al., 2013). The dam has a storage capacity of 103,000 ML and a catchment of 546 km². Construction of the dam coincided with a change in the predominant meteorological conditions, from prolonged drought to wetter conditions culminating in major rainfall events in January 2011, January 2013, and April 2017, which led to the dam filling almost immediately after impoundment.

Figure 4.1. A) Location of the study area and major dams within the Logan-Albert catchment, B) location of catchment within Australia, C) location of Ecosystem Health Monitoring Program (EHMP) water quality monitoring sites, associated chainages from the river mouth, and the positions of the two major wastewater treatment plants (WWTPs) within the catchment.
Annual rainfall across the Logan-Albert catchment is spatially and temporally variable, ranging from 800 mm in the southwest to over 2000 mm in the south-eastern headwaters. A distinct wet season occurs in summer and a dry season in winter. Land use is dominated by native forest and scrub and by cattle grazing and pastoral lands in the upper to mid catchment, with irrigated cropping along the alluvial channels. Intensive dairies, poultry farms, horse studs, turf farms and hoop pine plantations occur in parts of the upper and middle catchment (DSITIA, 2014). Urban and rural residential developments are located across the lower catchment. Logan City, located along the upper estuary, is the largest population centre with approximately 319,000 residents (Queensland Treasury, 2018). Two major WWTPs are located close to this population centre and release effluent into the Logan and Albert estuaries at Chainage 17 and 15.1 km, respectively (Figure 4.1; DEHP, 2015). Treatment at the Logan WWTP involves either oxidation or biological nutrient removal through bioreactors followed by secondary clarifiers. At the Albert WWTP, biological nutrient removal is followed by clarification. The lower catchment comprises of large areas of sugarcane farming along the southern floodplains (Chainage 11.1 to 0 km).

Water quality monitoring data were obtained from the Ecosystem Health Monitoring Program (EHMP, 2007). EHMP conducts water quality sampling during ebb tides approximately 2 hours after high tide at twelve sites in the Logan estuary and seven in the Albert estuary (Figure 4.1.). Sampling was conducted from the river mouth to the extent of tidal influence, approximately 33 and 27 km upstream for the Logan and Albert estuaries, respectively. Water quality data were assessed between 2003 and 2018 for all sites. From 2003 to 2014, sampling was monthly, after which the sampling frequency was reduced to eight times annually, by excluding sampling in January, April, June and July.

Turbidity was measured with a YSI 6920 turbidity sensor (Yellow Springs Instruments, Ohio). Nutrient samples were taken just below the water surface, filtered on site, and transported on ice to the laboratory where they were kept frozen until analysis. Filtered samples were analysed for filterable reactive phosphorus (FRP), ammonium (NH₄-N), nitrate (NO₃-N), and nitrite (NO₂-N) using an automated LACHAT 8000QC flow injection analyser (FIA; American Public Health Association, 1998). Unfiltered samples were digested in an alkaline persulphate solution and analysed for TN and TP using the FIA, i.e., as FRP and NO₃-N following the digestion (American Public Health Association, 1998).
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The Queensland Department of Natural Resources, Mines and Energy regularly measures streamflow and water levels at several monitoring sites in the Logan-Albert catchment. River inflow from the Yarrahappini and Bromfleet stream gauges (ID: 145014A and 145102B) were applied in this study as they were closest to the tidal limit of the Logan-Albert estuary. Annual average loads of NH$_4$-N, TN and TP to the estuary from the two major WWTPs (Figure 4.1) were retrieved from the National Pollutant Inventory (NPI, 2019).

4.3 Methods

4.3.1 Data Pre-processing

A small number of measured nutrient concentrations were below the detection limit (~0.002 mg/L for NH$_4$-N (10% of samples), NO$_x$-N (5.2%), and FRP (0.18%), and 0.01 mg/L for TP (0.18%)). They were replaced using:

$$c_{ki} = d_k R_{ki}$$  \hspace{1cm} (4.1)

where $c_{ki}$ is the estimated concentration for the $k^{th}$ variable at the $i^{th}$ timestep, $d_k$ is the detection limit for variable $k$, and $R_{ki}$ is a uniformly distributed random number between 0.01 and 0.99 such that the mean of all censored values for each variable would be approximately half the detection limit. When sampling involved numerous measurements taken at the water surface for a single day, the averaged concentration was applied in these analyses. There were a small number of missing datapoints for some constituents at some locations but as this number was small (<4%) we chose to include all datapoints for these analyses.

4.3.2 Seasonal and Spatial Analysis

Monthly boxplots of TN and TP concentrations, turbidity, streamflow, salinity, and water temperature were calculated for the most upstream sampling sites: Logan (Chainage 33 km) and Albert (Chainage 27 km), where chainage is the adopted middle thread distance from the river mouth. Median monthly water quality values were calculated for salinity and all water quality constituents, at all sites. Median values were utilised instead of means to reduce the effects of extreme values. Similarly, median TN:TP, FRP:TP, and NO$_x$-N:TN mass ratio values were calculated for all sites and months. This analysis allowed for inferences to be made on whether the system may be N or P limited based on the Redfield molar element ratio of 16:1 for N:P or approximately 7:1 for mass. Mass ratios of TN:TP < 7 were inferred to be indicative of N limitation.
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4.3.3 Trend Analysis
Trends between 2003 and 2018 were evaluated with the seasonal Mann-Kendall test (Hirsch et al., 1982) for all constituents at all sites. This method has been widely adopted to assess monotonic trends in environmental time-series due to its robust nature and ability to consider non-normally distributed data, making it ideal for environmental and streamflow data (Li et al., 2018). A significance level of 0.01 was used in these tests to denote a highly significant trend. The results of the Mann-Kendall test were compared to those from a Generalised Additive Model (GAM) approach (Murphy et al., 2019). Details of the GAM methodology are given in Appendix B2. Optimal change points were detected for the timeseries using a minimalised cost function in MATLAB to investigate if their position through time coincided with the impoundment of Wyaralong Dam.

4.3.4 Impact Assessment
Delineating the effects of Wyaralong Dam on nutrient concentrations and turbidity from other effects was done by implementing a BACI design (Stewart-Oaten et al., 1986). This test controls for natural variability by comparing water quality samples at both control and impact sites taken at the same time (Smith, 2002). An ‘impact’ site was selected as the most upstream site along the Logan estuary (Chainage 33 km) where the effects of upstream impoundment are likely to be greatest. The upstream Albert estuary site (Chainage 27 km) was selected as the ‘control’. Both sites are located in similar along-river positions with similar degrees of saline intrusion (Figure 4.2 and 4.3). Samples taken at the control and impact sites were paired when sampling occurred on the same day or excluded when they did not. The differences between paired data points were calculated for the before and after impoundment periods as:

\[ D_{ik} = X_{iC_{k}} - X_{iI_{k}} = \mu + \eta_i + \epsilon_{ik} \]  \hspace{1cm} (4.2)

where \(D_{ik}\) is the difference between the before and after period \(i\), for the \(k^{th}\) paired value, \(X\) denotes the variable of interest, with \(C\) and \(I\) indicating either control or impact sites, \(\mu\) is the mean difference, \(\eta_i\) is the change in difference before and after impoundment, and \(\epsilon_{ik}\) is the error from these differences (Smith, 2002). The pre-impoundment period included all sampling that occurred before the diversion channel was plugged and the dam began to fill (December 2010) and the post-impoundment period included all sampling thereafter. The calculated differences \((D_{ik})\) are required to meet the assumption of additivity and independence. Additivity was tested by comparing a non-zero slope of the regression of differences \((D_{ik})\) against the mean observed value between impact and
control sites, while independence was evaluated using the Durbin Watson test (Stewart-Oaten et al., 1986, Smokorowski and Randall, 2017). All observation data were natural log transformed prior to performing the BACI test, to better meet the assumption of additivity. As the transformed water quality data used in this analysis did not all meet parametric conditions, the non-parametric Wilcoxon Rank Sum test was applied. We tested for a null hypothesis that there was no difference between each of the pre- and post-impoundment median water constituent values. This test is however limited in that any location-specific temporal difference between the two sites is interpreted as an impact, even if this is not the case (Underwood, 1992). Results must therefore be treated with some caution.

To evaluate the magnitude of change between the Before (pre-impoundment) and After (post-impoundment) groupings the Hodges-Lehmann estimator of step trend magnitude (Hodges Jr and Lehmann, 1963) and associated 95% confidence intervals were calculated for all sites and variables. The estimator was used to calculate the absolute and percentage changes in water quality constituents relative to the pre-impoundment period.

**4.4 Results**

**4.4.1 Seasonal and Spatial Patterns**

Inflows to the Logan and Albert estuaries showed clear seasonal trends. There was significant year-to-year variability for wet season flows (November to April) evident by the large interquartile ranges for these months, whereas dry season flows (May to October) were consistent throughout the study period, with smaller interquartile ranges (Figure 4.2). Median water temperatures in the upper estuaries peaked in summer at 27.2 °C (January) and were lowest in winter at 15.3 °C (July). Salinity levels typically remained low throughout most of the year, except for a discernible peak in concentrations at the end of the dry season/start of the wet season (October). At the upper Albert estuary site, TN, TP, and turbidity generally followed the seasonal patterns of streamflow, with higher levels recorded during the wet season. However, this seasonality was much less evident at the upper Logan estuary site. Instead, constituent concentrations at this location showed much greater year-to-year variation for all months compared to the Albert site, particularly during the dry season.

Longitudinal profiles of monthly median water quality values over the sampling period are shown in Figure 4.3. Salinity followed a similar seasonal pattern to that seen in Figure 4.2 throughout the estuary, with peak concentrations occurring at the end of the dry
season/start of the wet season and lowest concentrations coinciding with the end of the wet season. Values of TN, TP, and turbidity are similar to those in Figure 4.2, but the degree of seasonality is much more pronounced for TN and TP along the Albert estuary compared to the Logan. For NH$_4$-N concentrations the pattern is reversed, with higher values recorded during the dry season, especially at the sites in close proximity to the two major WWTPs located at Chainage 17 and 15.1 km along the Logan and Albert estuaries, respectively. Monitoring sites upstream of the WWTPs had higher FRP concentrations during wet-season months, while sites near to, and downstream of the WWTPs typically had higher concentrations during the dry season for both systems. Concentrations of NO$_x$-N did not show any clear seasonal patterns along the length of either estuary.

Annual median nutrient concentrations were highest along the lower reaches of the Albert between the WWTP site and the confluence with the Logan River (Chainage 13.1 to 14.9 km). Concentrations of TN and TP peaked further upstream along the Logan, around Chainage 23 km. In the Logan, peak concentrations of NH$_4$-N, NO$_x$-N, and FRP all coincided with the location of the WWTP at Chainage 17.4 km. There were large increases in annual median turbidity (68 NTU) in the middle part of the Logan estuary between Chainages 17.4 (42 NTU) and 23 km (110 NTU). For the Albert, turbidity was highest in the mid estuary, though levels were less than half of those in the upper Logan. Maximum concentrations of all constituents were lower along the Albert compared to the Logan.

Large differences in constituent values occurred seasonally. For example, in the middle Logan (Chainage 23 km) and Albert estuaries (Chainage 16.9 km) median turbidity ranged from 55.4 (August) to 190.5 NTU (January) and 23 (August) to 100.3 NTU (November), respectively. Similarly, large differences in NH$_4$-N concentrations occurred at sites closest to the two major WWTPs; 0.0235 (March) to 0.21 mg L$^{-1}$ (September) for the Logan (Chainage 17.4 km) and 0.0295 (March) to 0.12 mg L$^{-1}$ (August) for the Albert (Chainage 14.9 km), i.e., nearly an order of magnitude change at the site within the Logan but somewhat less at the site within the Albert.
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Figure 4.2. Seasonal distribution of monthly mean streamflow, rainfall, water temperature, salinity, TN, TP, and turbidity in the upper Logan estuary (Chainage 33 km) and the upper Albert estuary site (Chainage 27 km) between 2003 and 2018.
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Figure 4.3. Median values of key water quality constituents and salinity for all months along both estuaries during the sampling period (2003 – 2018) with increasing distance from the river mouth (Chainage 0 km). Black dashed lines show the locations of the two major WWTPs, blue points denote wet season months, red points show dry season months, and black solid lines show medians for all months.

Longitudinal profiles of TN:TP mass ratios (Figure 4.4) were approximately inversely related to longitudinal profiles of TN and TP concentrations (Figure 4.3), in that they were highest at the river mouth and steadily decreased to their lowest level around the location of maximum TN and TP concentrations. There was no clear seasonal pattern in TN:TP along the length of the Logan estuary, whereas along the Albert estuary ratios were greater during the dry season. This observation (for the upper estuary) suggests that TN is mobilised in greater relative quantities during the dry season and TP during the wet season in the Albert catchment. Both estuaries appear to be N-limited over their full length (based
on TN:TP < 7), with the greatest N limitation occurring upstream in the riverine part and the lowest downstream where mixing occurs with waters of oceanic origin. Maximum FRP:TP and NO\textsubscript{x}-N:TN ratios occurred around the location of the two WWTPs and FRP:TP ratios upstream of these WWTPs were considerably lower than those downstream. There was a noticeable seasonality of ratios near to and downstream of these WWTPs, with greater values recorded during the dry season.

Figure 4.4. Median TN to TP, NO\textsubscript{x}-N to TN, and FRP to TP mass ratios for the length of the Logan and Albert estuaries during the sampling period (2003 – 2018).

4.4.2 Trends

Long-term trends for TN, TP, and turbidity for the upper Logan and Albert estuaries and for sites near the WWTPs are presented in Figure 4.5. Significant (p<0.01) downward trends with time were identified (seasonal Mann-Kendall test) for TN at all sites and for TP at all sites except for the upper Albert estuary (Chainage 27 km). For turbidity, only the upper Logan estuary site had a significant downward trend over the study period. Calculated change points for TN (February to March 2012) and turbidity (February to July 2012) at all sites corresponded closely with when effects might have been expected from the impoundment of Wyaralong Dam (December 2010). While for TP the change points (January 2008 and November 2004) were seemingly unrelated to the opening of the dam.
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Figure 4.5. Trend analysis of TN, TP, and turbidity between 2003 and 2018 (Logan Chainage 33 and 17.4 km and Albert Chainage 27 and 14.9 km) using the seasonal Mann-Kendall test (Sen’s slope and significance level are provided for each plot). Vertical dashed black lines show the date of Wyaralong Dam impoundment, solid line shows the slope, and red circles show a change point determined from a cost minimised function.

Comparisons of the Sen’s slope showed a downward trend for TN at most sites during the study period (Table 4.1). Only sites located within 11 km of the river mouth did not have a significant decrease. Rather, sites near to the river mouth presented an opposing trend of increasing TN and turbidity, but none of the slopes were significant (p>0.01). In contrast to TN, only two locations along the upper Logan estuary (Chainage 29.3 and 33 km) had significant (p<0.01) declines in turbidity. Decreases in TP and NO$_x$-N concentrations were greatest along the upper and middle Logan estuary (Chainage 7.8 – 33 km) and along the lower Albert estuary (below Chainage 16.9 km). Sites along the upper Logan estuary (Chainage 15.6 – 33 km) had significant downward trends (p<0.01) for NH$_4$-N and FRP, while no sites along the Albert showed any change through time (p>0.01). Only the upstream Albert site (Chainage 27 km) showed a significant increase (p<0.01) in FRP:TP ratios and a significant decrease in TN:TP ratios during the study period. There were significant (p<0.01) decreases in NO$_x$-N:TN ratios with time at all sites along the middle and upper Logan estuary (Chainage 7.8 – 33km) except for the site nearest to the WWTP (Chainage 17.4 km). Only the most downstream site reported a significant (p<0.01) downward trend for the Albert estuary. Results from the GAM test (refer to Appendix B2) were similar to those from the seasonal Mann-Kendall test. The
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GAM results show significant downward trends at more sites than the Mann-Kendall test, especially for FRP (17 or 12 sites, depending on the number of selected for the analysis compared to 5 sites from the Mann-Kendall test).

Table 4.1. Trend analysis of all water quality constituents and mass ratios for all sites between 2003 and 2018 using the seasonal Mann-Kendall test. Sen’s slope values are shown (average yearly change of variable, where greater positive and negative values indicated more pronounced positive and negative trends, respectively). Green background colours denote decreasing trends and red increasing trends, darker backgrounds represent lower p-values, and bold values indicate significant (p<0.01) trends.

<table>
<thead>
<tr>
<th>Site (km)</th>
<th>TN</th>
<th>TP</th>
<th>Turbidity</th>
<th>NH₄-N</th>
<th>NO₂-N</th>
<th>FRP</th>
<th>TN/TP</th>
<th>FRP/TP</th>
<th>NO₃-N:TN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logan 0</td>
<td>0.005</td>
<td>0.001</td>
<td>0.050</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.002</td>
<td>-0.005</td>
<td>0.000</td>
</tr>
<tr>
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<td>0.000</td>
<td>0.193</td>
<td>0.000</td>
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<td>-0.003</td>
</tr>
<tr>
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<td>0.000</td>
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<td>0.000</td>
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<td>0.000</td>
<td>0.019</td>
<td>-0.002</td>
<td>-0.007</td>
</tr>
<tr>
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<td>-0.002</td>
<td>0.245</td>
<td>0.000</td>
<td>-0.010</td>
<td>-0.002</td>
<td>0.005</td>
<td>-0.001</td>
<td>-0.011</td>
</tr>
<tr>
<td>Logan 11.1</td>
<td>-0.018</td>
<td>-0.006</td>
<td>-0.164</td>
<td>-0.001</td>
<td>-0.015</td>
<td>-0.004</td>
<td>0.000</td>
<td>-0.003</td>
<td>-0.010</td>
</tr>
<tr>
<td>Logan 13.3</td>
<td>-0.023</td>
<td>-0.007</td>
<td>-0.318</td>
<td>-0.002</td>
<td>-0.017</td>
<td>-0.005</td>
<td>0.004</td>
<td>0.001</td>
<td>-0.009</td>
</tr>
<tr>
<td>Logan 15.6</td>
<td>-0.040</td>
<td>-0.014</td>
<td>0.014</td>
<td>-0.005</td>
<td>-0.030</td>
<td>-0.013</td>
<td>0.002</td>
<td>-0.007</td>
<td>-0.012</td>
</tr>
<tr>
<td>Logan 17.4</td>
<td>-0.053</td>
<td>-0.018</td>
<td>-0.470</td>
<td>-0.006</td>
<td>-0.038</td>
<td>-0.017</td>
<td>-0.027</td>
<td>-0.006</td>
<td>-0.011</td>
</tr>
<tr>
<td>Logan 23</td>
<td>-0.087</td>
<td>-0.035</td>
<td>-7.938</td>
<td>-0.003</td>
<td>-0.056</td>
<td>-0.022</td>
<td>0.008</td>
<td>-0.006</td>
<td>-0.020</td>
</tr>
<tr>
<td>Logan 26.3</td>
<td>-0.060</td>
<td>-0.027</td>
<td>-6.100</td>
<td>-0.001</td>
<td>-0.038</td>
<td>-0.015</td>
<td>0.029</td>
<td>-0.004</td>
<td>-0.024</td>
</tr>
<tr>
<td>Logan 29.3</td>
<td>-0.042</td>
<td>-0.020</td>
<td>-6.667</td>
<td>0.000</td>
<td>-0.028</td>
<td>-0.010</td>
<td>0.057</td>
<td>-0.004</td>
<td>-0.020</td>
</tr>
<tr>
<td>Logan 33</td>
<td>-0.034</td>
<td>-0.018</td>
<td>-7.550</td>
<td>0.000</td>
<td>-0.020</td>
<td>-0.007</td>
<td>0.040</td>
<td>0.000</td>
<td>-0.016</td>
</tr>
<tr>
<td>Albert 11.1</td>
<td>-0.021</td>
<td>-0.006</td>
<td>-0.333</td>
<td>-0.002</td>
<td>-0.016</td>
<td>-0.005</td>
<td>0.000</td>
<td>-0.002</td>
<td>-0.009</td>
</tr>
<tr>
<td>Albert 13.1</td>
<td>-0.030</td>
<td>-0.010</td>
<td>-0.429</td>
<td>-0.002</td>
<td>-0.023</td>
<td>-0.009</td>
<td>0.003</td>
<td>-0.003</td>
<td>-0.010</td>
</tr>
<tr>
<td>Albert 14.9</td>
<td>-0.035</td>
<td>-0.011</td>
<td>-0.944</td>
<td>-0.002</td>
<td>-0.023</td>
<td>-0.008</td>
<td>-0.005</td>
<td>0.000</td>
<td>-0.011</td>
</tr>
<tr>
<td>Albert 16.9</td>
<td>-0.027</td>
<td>-0.010</td>
<td>-1.067</td>
<td>-0.001</td>
<td>-0.015</td>
<td>-0.005</td>
<td>-0.016</td>
<td>0.000</td>
<td>-0.009</td>
</tr>
<tr>
<td>Albert 21</td>
<td>-0.020</td>
<td>-0.005</td>
<td>-1.600</td>
<td>0.000</td>
<td>-0.004</td>
<td>-0.001</td>
<td>-0.038</td>
<td>0.006</td>
<td>-0.002</td>
</tr>
<tr>
<td>Albert 23.1</td>
<td>-0.020</td>
<td>-0.003</td>
<td>-1.600</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.048</td>
<td>0.010</td>
<td>0.000</td>
</tr>
<tr>
<td>Albert 27</td>
<td>-0.019</td>
<td>-0.002</td>
<td>-1.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.002</td>
<td>-0.084</td>
<td>0.015</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Annual reported nutrient loads (TN, TP, and NH₄-N) released from the Logan WWTP site to the stream displayed a decreasing trend over the study period (Figure 4.6). For the Albert WWTP, only NH₄-N loads showed a decreasing trend, whereas TP loads remained mostly unchanged and TN loads increased. Over this same time period there was an increase in the monthly mean inflows along both rivers as evident by the positive Sen’s slope values, though not at significant levels (p>0.01; Figure 4.6). Interestingly, TN and TP concentrations showed significant (p<0.01) downward trends at the monitoring site (Chainage 14.9 km) closest to the WWTP in the Albert River despite loads either increasing or remaining unchanged, while NH₄-N concentrations did not change despite the reported decrease in loads (Table 4.1). All variables showed significant (p<0.01) decreases in concentration with time at the monitoring site (Chainage 17.4 km) closest to the WWTP on the Logan River.
Chapter 4: Analysis of Water Quality Trends

Figure 4.6. Monthly mean streamflow and trend using the seasonal Mann-Kendall test (Sen’s slope and significance level are shown) for flows entering (a) the Logan estuary from the Yarrahappani gauge and (b) the Albert estuary from the Bromfleet gauge. National Pollutant Inventory (NPI) yearly reported nutrient loads discharged to stream from the two wastewater treatment plants (WWTPs) situated along (c) the Logan estuary at Chainage 17 km and (d) the Albert estuary at Chainage 15.1 km.

4.4.3 Impact of Wyaralong Dam

Boxplots of key water quality variables for pre- and post-impoundment periods are shown for the upper Logan and Albert estuaries and sites near the WWTPs (Figure B1). Significant (p<0.01) differences in TN were found between these periods at all these sites. For TP and turbidity all sites except the upper Albert site (Chainage 27 km) and Logan WWTP site (Chainage 17.4 km) showed significant (p<0.01) decreases. The largest changes occurred at the upper Logan estuary site for TP and turbidity and at the WWTP site on the Logan estuary for TN.

Significant decreases (p<0.01) in the post-impoundment period were detected at the upper Logan (impact) site for turbidity, TP, FRP, and NO₃-N using the BACI test (Table 4.2). Mean values for all constituents decreased at the impact site between the pre- and post-impoundment periods, while at the control site mean values of TP and FRP both increased. The standard deviation of all water quality constituents at the impact site also decreased considerably after impoundment, whereas it increased for four of the six variables (TN, TP, turbidity, and FRP) at the control site (Table 4.2).

Differences between pre- and post-impoundment periods, as assessed with the Hodges-
Lehmann estimator and the corresponding percentage change in median values, are presented in Table 4.3 for both the control and impact sites. Turbidity showed the greatest decline post-impoundment (56.1% at the impact site and 33.3% at the control site). Large decreases in median values were also found for TP, NO$_x$-N, and FRP at the impact site (between 34.6 and 48.9%), whereas the changes were more modest at the control site (between 6.2 and 19.3%). For TN, decreases were similar at both sites (~27%). In contrast to all the other water quality constituents, NH$_4$-N concentrations decreased more at the control site than the impact site (26.1% compared to 0%).

Table 4.2. Monthly mean values with standard deviations in parentheses at the upper Logan and Albert estuary sites before and after impoundment. p-values are calculated from the BACI analysis using the Wilcoxon Rank Sum test and significant values are shown in bold.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Logan 33 km (impact)</th>
<th>Albert 27 km (control)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before</td>
<td>After</td>
<td>Before</td>
</tr>
<tr>
<td>TN (mg/L)</td>
<td>0.99 (0.44)</td>
<td>0.69 (0.27)</td>
<td>0.60 (0.35)</td>
</tr>
<tr>
<td>TP (mg/L)</td>
<td>0.352 (0.133)</td>
<td>0.209 (0.084)</td>
<td>0.183 (0.106)</td>
</tr>
<tr>
<td>Turbidity (NTU)</td>
<td>158.2 (128.2)</td>
<td>65.2 (41.7)</td>
<td>42.6 (50.8)</td>
</tr>
<tr>
<td>NH$_4$-N (mg/L)</td>
<td>0.018 (0.035)</td>
<td>0.013 (0.020)</td>
<td>0.030 (0.075)</td>
</tr>
<tr>
<td>FRP (mg/L)</td>
<td>0.148 (0.068)</td>
<td>0.096 (0.049)</td>
<td>0.084 (0.053)</td>
</tr>
<tr>
<td>NO$_x$-N (mg/L)</td>
<td>0.340 (0.283)</td>
<td>0.175 (0.174)</td>
<td>0.089 (0.127)</td>
</tr>
</tbody>
</table>

Table 4.3. Hodges-Lehmann estimators of nutrients (mgL$^{-1}$) and turbidity (NTU) for the Impact and Control sites and the associated percentage change (%) in parentheses using Before-After groupings. Negative values indicate a decrease in the median between the pre- and post-impoundment periods.

<table>
<thead>
<tr>
<th>Site</th>
<th>TN</th>
<th>TP</th>
<th>Turbidity</th>
<th>NH$_4$-N</th>
<th>NO$_x$-N</th>
<th>FRP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logan 33 km (Impact)</td>
<td>-0.25</td>
<td>-0.13</td>
<td>-76.9</td>
<td>0</td>
<td>-0.137</td>
<td>-0.045</td>
</tr>
<tr>
<td>Albert 27 km (Control)</td>
<td>-0.15</td>
<td>-0.01</td>
<td>-9.5</td>
<td>-0.003</td>
<td>-0.01</td>
<td>+0.014</td>
</tr>
</tbody>
</table>

Calculated Hodges-Lehman estimators and percentage changes relative to pre-impoundment medians of water quality variables are presented in Figure 4.7 for all sites. The largest decreases between the pre- and post-impoundment periods generally occurred along the upper and middle Logan estuary, while downstream sites showed little change. For the Albert estuary, the largest decreases in nutrients were downstream, close to the confluence with the Logan River. Turbidity decreased the most along the upper and middle sections of the Logan and Albert estuaries, respectively. The largest decreases in NH$_4$-N concentrations coincided with the locations of WWTPs for both estuaries. Relative changes to TP, FRP, turbidity, and NO$_x$-N were greatest in the upper Logan estuary and along the lower Albert estuary.
4.5 Discussion

4.5.1 Climate Variability

Disentangling the complex interactions between human modifications and multiple stressors in natural systems presents a considerable challenge for managers. In the Logan-Albert estuary, turbidity and total nutrient concentrations showed strong seasonal variation. Higher turbidity and TP concentrations in the wet season are likely to be linked to elevated gully and sheet erosion in catchments, with phosphorus adsorbed to the sediments transported into the channel (Webster et al., 2001). Increased erosion may also explain elevated TN concentrations in the wet season, as sediment has a component that is particulate nitrogen (Garzon-García et al., 2015). The highly seasonal rainfall regime in subtropical Australia ensures that the majority of nutrient and sediment loads are delivered from diffuse sources during the wet season, while nutrients tend to build-up on land during the dry season (Eyre, 1998, Abal et al., 2005).

The large increase in median turbidity in the mid Logan estuary between Chainages 17.4 km (42 NTU) and 23 km (110 NTU) is likely to reflect the location of an estuarine turbidity maximum (Figure 4.3). It is important to note, however, that there has been substantial urbanisation along these reaches during the study period, which may have
increased sediment loads and consequentially increased turbidity. Typically, the location of the estuarine turbidity maximum is largely dependent on the inflow conditions and tidal straining (Uncles et al., 2006, Toublanc et al., 2016). Mirfenderesk and Tomlinson (2006) showed strong tidal asymmetry in the Logan estuary, with flood currents exceeding those of ebb currents and longer low-water slack periods than high-water slack periods. Strong mixing processes and long periods of low flow lead to a predominantly well-mixed estuary for the much of the year. In well-mixed estuaries like the Logan, tidal straining resulting from tidal asymmetry is generally the major cause of estuarine circulation (Burchard and Schuttelaars, 2012). The mixing maintains elevated levels of sediments and nutrients in the water column, despite little replenishment of sediment from the catchment during the dry season.

In subtropical estuaries, flushing times during low flow periods tend to be very long (Eyre, 1998) and can lead to a build-up of in-stream nutrients and turbidity, particularly if there are important point-source contributions. The two WWTPs represent such point-sources, and NH$_4$-N concentrations rise considerably during the dry season when dilution of the WWTP discharge is reduced (Figure 4.3). Concentrations of NH$_4$-N in the upper Logan estuary were similar to those at the river mouth, indicating that diffuse source contributions were likely to be negligible during the dry season. The influence of the WWTPs is also evident on FRP concentrations, which typically peaked during the dry season at monitoring sites downstream of the WWTPs (Figure 4.3). FRP:TP and NO$_x$-N:TN ratios were greater downstream and near to the WWTP during the dry season when dilution from streamflow was reduced. This suggests that the WWTPs predominantly remove particulates and perform denitrification, leaving relatively high FRP in the absence of specific additional treatment (e.g., biological and/or chemical P removal).

High flow periods decrease flushing times and increase dilution from catchment sources, reducing the influence of the WWTPs (Paerl et al., 2006). However, high flow periods also bring significant diffuse loads and can change the nature of the estuary from well-mixed to partially mixed (Eyre, 1998), promoting flocculation at the freshwater-saltwater interface, which is seen to vary with the seasons (Figure 4.3). As high flows push the saltwater further downstream, upstream stations change from being largely estuarine to more closely reflecting the catchment runoff composition.

Weather cycles (e.g., El Niño or La Niña) and extreme events are major influences on water quality (Wetz and Yoskowitz, 2013), including in subtropical Australia. Over the 15-year duration of the study, the predominant weather changed from extended drought
to wetter conditions, which coincided with the impoundment of Wyaralong Dam in December 2010. Ideally, a flow adjustment technique could be adopted to remove the variance associated with streamflow and indicate whether changes in turbidity and nutrient concentrations were weather related. However, traditional techniques require a relationship between the water quality variable and discharge, and necessitate a stationary streamflow distribution (Hirsch et al., 1991), which due to the reservoir impoundment is not appropriate in this case. In recent years a number of techniques for trend analysis have been developed (e.g., Hirsch et al., 2010, Murphy et al., 2019), which include flow-normalisation techniques, and characterisation of non-linear changes and non-stationarity in time series data.

Several studies have shown that drought events result in improved water quality as runoff from agricultural lands is reduced (Burkholder et al., 2006, Palmer and Montagna, 2015). However, in this case a reverse trend occurred as nutrient concentrations decreased considerably at many sites along both estuaries during the latter, wetter phase of the study (Table 4.1). Improvements were greatest along the upper portions of the Logan estuary and the lower sections of the Albert close to the WWTP. While these changes correlated with the impoundment of Wyaralong Dam for the Logan estuary, no other major anthropogenic changes were identified in the Albert catchment during the study period. We therefore attribute this improvement principally to a change in climate. During the drought, low inflows and long residence times led to a build-up of nutrients in the estuary, mostly from the WWTP, while during wetter conditions these nutrients tended to be flushed from the system. Similar patterns have been noted for the Hudson (Howarth et al., 2000) and Neuse (Paerl et al., 2006) estuaries in the United States during drought events. Furthermore, prolonged drought allows for a build-up of nutrients within soils and can lead to a loss riparian vegetation that could mitigate nutrient losses to the aquatic system (Bond et al., 2008, Drewry et al., 2009). In drought-impacted catchments these factors can allow for larger quantities of sediments and nutrients to be transported during storm events.

4.5.2 Wastewater Discharges

During the study period effluent TN and TP loads from the Albert WWTP either increased or remained unchanged (Figure 4.6), though concentrations near to and downstream of the WWTP decreased significantly (p<0.01; Table 4.1). The elevated streamflow and increased flushing during the latter half of the study is considered to be a major factor contributing to reduced TN, TP, and NO₃-N concentrations in the lower Albert estuary.
Interestingly despite decreased effluent NH$_4$-N loads and increased streamflow, NH$_4$-N concentrations near to the WWTP did not decrease significantly (Table 4.1). This may be due to the tidal influence of the Logan estuary leading to a net influx of nutrients into the Albert. TN, TP and NH$_4$-N loads from the Logan WWTP all decreased during the study period (Figure 4.6), which in combination with elevated streamflow, is presumably the predominant cause of the significant ($p<0.01$) decreases in NH$_4$-N, TN, and TP concentrations in the mid estuary.

4.5.3 Damming

Our hypothesis was that the impoundment of Wyaralong Dam in December 2010 would have positive implications for downstream water quality. This hypothesis was validated using the BACI test, which showed significant ($p<0.01$) decreases for turbidity, TP, FRP, and NO$_x$-N at the upper Logan estuary site (impact) relative to the upper Albert site (control; Table 4.2). For TN, however, the relative change in concentration at the impact and control sites was of a similar magnitude (Table 4.3), which suggests that climatic factors had a greater effect on TN than dam impoundment. Additionally, no effect of impoundment was found on NH$_4$-N concentrations, which may be explained by the relatively low concentrations found at the impact site (Logan River Chainage 33 km) in the pre-impoundment period (Figure 4.3; concentrations at upstream sites are approximately an order of magnitude lower than those at sites near the WWTP), and the well oxidised state of the water in the upper estuary, which allows for rapid oxidisation of NH$_4$-N to nitrite and nitrate. The fact that both FRP and NO$_x$-N concentrations decreased significantly post-impoundment at the impact site suggests that longer residence times in the dam may have resulted in greater biological uptake by phytoplankton than would have otherwise occurred under the earlier natural stream conditions. The BACI design could be improved upon if multiple control sites were implemented as suggested by Underwood (1994), however, in this case data for additional control sites was not available.

In the São Francisco estuary, Medeiros et al. (2011) found similar improvements in downstream water quality due to the construction of several upstream dams. Jeong et al. (2014) reported that an estuary dam along the Geum River in Korea acted as a sink for both phosphate and ammonium, though water quality declined both above and below the reservoir during their study. In contrast, Baldwin et al. (2010) reported that there was net export of TN and TP, principally in the form of phytoplankton biomass, during a period of extreme drawdown from Lake Hume in southeast Australia, but the lake acted as a net...
sink of NO$_x$-N. Similarly, Westhorpe et al. (2015) investigated the effects of the Lake Copeton Dam, Australia, using a longitudinal profile of downstream sites, finding that the dam was a source of both nitrogen and phosphorus. They speculated that the release of water from the anaerobic zone of the lake elevated concentrations of NO$_x$-N and FRP downstream of the reservoir, with the additional NO$_x$-N likely arising from oxidation of NH$_4$-N.

Water can be released from any level of Wyaralong Dam, with releases of deeper waters likely to be avoided if there is a risk of anoxic water occurring immediately downstream of the dam. The studies by Baldwin et al. (2010) and Westhorpe et al. (2015) were conducted more than 40 years after construction of each reservoir to their respective studies, and the results may therefore reflect the reduced capacity of the reservoirs to trap sediments and particulate nutrients, as bottom sediments build-up and reservoir capacity diminishes. The Conowingo Dam upstream of Chesapeake Bay, for instance, has begun to export more sediment and phosphorus loads downstream due to reduced trapping capacity (Zhang et al., 2013, Zhang et al., 2016a). However, Wyaralong Dam, completed in 2010 to supplement the region's water supply is likely to initially have high capacity for sediment and nutrient trapping. Negative effects of dams arise from hindering migratory fish species and loss of riverine habitat and biodiversity. Globally, dam impoundment has been shown to decrease fish biodiversity (Liermann et al., 2012). In Australia, Kingsford (2000) showed dams have significant negative impacts on downstream floodplain wetlands, including reduced vegetation health and declines in bird, fish, and invertebrate populations. The Logan-Albert rivers discharge into southern Moreton Bay, which is an ecologically significant Ramsar-listed site. Impacts of the dam at this broader scale on local ecology requires further study and quantification.

4.5.4 Future Issues

Future climatic and land use changes projected for the southeast Queensland region (Suppiah et al., 2007, Low Choy et al., 2010) may negate any of the positive implications associated with the dam. The catchment is projected to urbanise significantly in the coming decades with an additional 200,000 residents predicted to live in the Logan City area by 2036 compared to 2011 (Queensland Treasury, 2018). Increased effluent from WWTPs and runoff from urban areas may result in further increases to in-stream concentrations, particularly during the low flow periods, and may necessitate WWTP upgrades or catchment offset schemes to accommodate the additional population. The duration and magnitude of low flow periods could extend in the future as more prolonged
and intense droughts are predicted with climate change for this region (Dai, 2013, Naumann et al., 2018). Effects of urbanisation and drought may therefore act synergistically to increase nutrient levels in the estuaries and cause eutrophication. Additionally, more intense precipitation (Groisman et al., 2005) and larger floods in subtropical regions (Eccles et al., 2019) will likely increase diffuse loads from storm events to the estuary. While, Wyaralong Dam currently appears to reduce loads of nutrients and sediments delivered to the downstream river and estuary of the Albert, if the trapping capacity of the dam decreases in the future then it may not continue to act as a sediment and nutrient sink.

In order to better determine changes to water quality a more targeted monitoring regime may be required with more finely resolved sampling around key sites (near to Dam and WWTPs). Monitoring in the freshwater sections of the river is sparser, both temporally and spatially, than in the estuary. Improved monitoring along freshwater reaches would allow for factors relating to land use and climate change to be more easily determined and detached from that of the estuary.

4.6 Conclusion

Determining the principal drivers of water quality is especially challenging for estuaries where there are complex interactions between climate, tide, and anthropogenic factors. The long-term monitoring of key water quality constituents at appropriate spatial coverage allows for improved understanding of the factors contributing to changes in estuarine water quality. Analysis of the long-term trends and patterns of key water quality constituents in the subtropical Logan-Albert estuary, Australia revealed distinct differences between the two estuaries, with higher values and greater variability along the Logan estuary. Water quality trends also showed large spatial variability throughout the estuary, with significant decreases along the upper Logan estuary and the lower Albert estuary over the duration of the study. Significant decreases in TP, FRP, NOx-N concentrations and turbidity in the upper Logan estuary were principally attributed to the impoundment of Wyaralong Dam, which acted as a nutrient and sediment sink. Significant decreases in nutrient concentrations along the lower Albert estuary were mostly attributed to wetter conditions over the study period, leading to increased dilution of a major point-source load from the WWTP. We demonstrated how to tease apart these factors but also found constraints from the multiple interacting factors that made it difficult to isolate any one cause and its effect. Improved coverage of water quality monitoring along freshwater reaches would allow future studies to more easily
differentiate between longer term climate variability and short-term changes relating to WWTP improvements and the development of Wyaralong Dam.

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Chapter 5: Impacts of Climate Change on Streamflow and Floodplain Inundation in a Coastal Subtropical Catchment

Statement of contribution to co-authored published paper

This chapter includes a co-author paper. The bibliographic details of the co-authored paper, including all authors, are:


My contribution to the paper involved conceptualisation, conducting the numerical modelling and statistical analyses, interpreting the results, and drafting the paper.

Signed: ___________________________ Date: 06/03/2021

Rohan Eccles

Countersigned: ___________________________ Date: 09/03/2021
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Corresponding author of paper: Mr. Jozef Syktus (Queensland Department of Environment and Science)
Impacts of climate change on streamflow and floodplain inundation in a coastal subtropical catchment

Abstract

Climate change is expected to significantly alter river hydrological regimes throughout the world, affecting water resources and the frequency of floods and droughts. The objectives of this study were to determine the impacts of climate change and sea level rise on streamflow and floodplain inundation in the subtropical Logan-Albert catchment, Australia. An ensemble of 11 high-resolution climate models forced under high (Representative Concentration Pathway 8.5 - RCP8.5) and intermediate-emission (RCP4.5) scenarios was applied. There was considerable variation from the model ensemble result in projections of major flooding events at 5 and 100-year average recurrence intervals (ARIs). The largest events (100-year ARI) tended towards an increase, whereas the smallest (5-year ARI) tended towards a decrease. Floodplain inundation from a 100-year ARI event increased in all simulations and inclusion of sea level rise resulted in increased floodplain inundation area nearly doubling by the end of the century, which has substantial implications for flood risk. Our study highlights the non-linear nature of climate change impacts on streamflow and floodplain inundation, demonstrating the need for a comprehensive assessment at the floodplain scale when informing preparedness for future flooding events.
5.1 Introduction

Climate change is expected to alter hydrological regimes throughout the world, with major implications for water resources and hydrological extremes (e.g., floods and droughts) (Blöschl et al., 2019). Flooding is one of the most costly and widespread climate-related natural disasters (Jönkman, 2005). It has major implications for landholders and urban infrastructure, and requires costly mitigation measures. Magnification of the variability of the hydrological cycle due to climate change is expected to result in greater frequency of extreme precipitation throughout most parts of the world (Groisman et al., 2005). Trends for the latter half of the 20th century indicate an increase in extreme flood events (Milly et al., 2002), while analysis of smaller floods has suggested a decreasing trend, particularly in larger catchments (Do et al., 2017). A number of studies on a global scale have shown that the trend of increasing flood magnitude for the most extreme events will continue over the 21st century for many regions of the world (Hirabayashi et al., 2013, Berghuijs et al., 2017, Gosling et al., 2017, Wiel et al., 2019).

In recent years there has been a marked increase in the number of studies assessing the impacts of climate change on flooding and high flow events at the regional and catchment scales (Liu et al., 2013, Li et al., 2016b, Phi Hoang et al., 2016, Tian et al., 2016, Gu et al., 2018, Jin et al., 2018b). These studies typically make use of a modelling framework outlined by Xu et al. (2005), consisting of global circulation model (GCM) outputs, downscaling, bias correction techniques, and hydrological model applications. Each step inevitably introduces some degree of error which is compounded sequentially, and different combinations of models and techniques can lead to some disparity in results (Praskievicz and Chang, 2009). GCMs are widely held as the largest source of uncertainty (Kay et al., 2009, De Niel et al., 2019) and it is recommended that an ensemble of climate models be used for hydrological projections (Prudhomme and Davies, 2009, Teutschbein and Seibert, 2010).

Due to spatiotemporal differences in climate change, the hydrological response varies substantially between regions of the world (Hirabayashi et al., 2013). It is therefore important that the impacts of climate change are evaluated across different regions. While there has been a marked increase in the number of studies on this subject, there remains a paucity of literature for many tropical and subtropical regions, including subtropical Australia (Eccles et al., 2019). Gu et al. (2020) reported uncertainty in response to flood magnitudes across subtropical and tropical Australia, however, most increases were concentrated in the tropical north and decreases in the temperate south. Chen and Yu
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(2015) found little change in large floods magnitudes for two subtropical southeast Queensland (SEQ) creeks by the 2030s using two climate models. However, studies based on a limited number of climate projections and predicting less than two decades into the future may not adequately inform preparedness for future flooding events.

The impacts of climate change on flooding may also be exacerbated by the nonlinear backflow effects of sea level rise in many coastal catchments, which has been found to be a major contributor to increased inundation (Västilä et al., 2010, Budiyono et al., 2016, Hamman et al., 2016), particularly under storm surge scenarios (Bilskie et al., 2014, Bilskie et al., 2016). Relatively few studies, however, have considered the combined effects of sea level rise and atmospheric climate change on riverine flooding, despite coastal zones being some of the most densely populated areas in the world (Neumann et al., 2015). However, studies are available that address other topics such as sediment transport (Huang et al., 2016). Such studies require an additional hydrodynamic model as part of the modelling framework, to simulate freshwater-marine interactions along estuaries and coastal floodplains (Västilä et al., 2010, Budiyono et al., 2016). Sea level rise will also have implications for coastal land cover, vegetation, and shoreline morphology (Saintilan and Rogers, 2009, Passeri et al., 2015, Bilskie et al., 2016), which may work to exacerbate flooding in coastal catchments.

Subtropical SEQ is one of the most flood-prone regions in Australia (Abbs et al., 2007) and has been identified as one of the ‘hotspots’ for climate change by the International Panel for Climate Change (IPCC, Hennessy et al., 2007). Urban development in the region is located along low-lying coastal floodplains. Sea level rise and altered streamflow conditions may therefore act synergistically to intensify flooding. The Logan-Albert catchment is the second largest catchment in the region and is anticipated to be subject to significant population growth (Queensland Treasury, 2018) potentially increasing population exposure to flood events, while land use changes may lead to more severe events.

This study implemented a modelling framework that integrated downscaled climate projections, hydrological modelling and coupled 1-D and 2-D hydrodynamic models to capture coastal inundation from floods. The aims were threefold: (i) to assess the hydrological response of a coastal subtropical catchment to future climate change; (ii) to examine how the projected changes in hydrology may impact floodplain inundation; and (iii) to evaluate the synergetic effects of atmospheric climate change and sea level rise on
floodplain inundation.

5.2 Methods

5.2.1 Study Area
The Logan-Albert catchment has an area of approximately 3862 km$^2$, of which the Logan covers around 3080 km$^2$ and the Albert 782 km$^2$ (Figure 5.1). The two major rivers of each catchment arise from the McPherson Range and converge 11 km from the coast. The climate is subtropical, with most precipitation in the summer (December to February) wet season and a dry season in winter (June to August). Major flooding events are usually associated with low-pressure systems or ex-tropical cyclones and commonly affect the region during the wet season. Precipitation over the catchment is also spatially variable, with >2000 mm yr$^{-1}$ in the south-eastern headwaters and <900 mm yr$^{-1}$ in the west.

![Figure 5.1. Logan-Albert catchment, showing major dams, built-up areas, major channels, rainfall and streamflow gauges used to calibrate the hydrological model.](image)
Land use in the upper and middle catchment is dominated by native forest cover and cattle grazing. Extensive sugarcane plantations are located along the southern floodplain near the river mouth (Figure C1). Logan City, located in the lower catchment south of Brisbane has a population of 319,000, which is projected to grow by about 50% to 490,000 by 2036 (Queensland Treasury, 2018). There are two major dams in the upper Logan catchment, which attenuate flood events arising from the upper catchment (Figure 5.1). Additionally, two major wastewater treatment plants (WWTPs) are located along the estuarine reaches of the Logan and Albert Rivers, respectively, and are reliant in part on some baseline levels of flushing to reduce their ecological impact.

5.2.2 Data
Bathymetry data (5 m horizontal resolution) of the lower Logan and Albert rivers was retrieved from Logan City Council and the Queensland Maritime Service. The data was incorporated into a digital elevation model (DEM) of the catchment obtained from Geoscience Australia (https://elevation.fsdf.org.au/) also consisting of a 5 m horizontal resolution. Land use and soil data for the region were obtained from the Queensland Government (http://qldspatial.information.qld.gov.au/catalogue/custom/index.page).

Daily synthetic pan evaporation data at 5 km spatial resolution was retrieved from the Scientific Information for Land Owners (SILO; Queensland Government, 2019) and converted to potential-evapotranspiration (PET) using a pan coefficient value of 0.7 (Allen et al., 1998). Daily observed rainfall data was obtained for 56 gauges across the catchment (Figure 5.1) from the Bureau of Meteorology (BOM; http://www.bom.gov.au/climate/data/). Thiessen polygons for all the rainfall gauges were developed, and missing values at each gauge were filled using an inverse distance weighting technique (De Silva et al., 2007).

Daily streamflow data for four stream gauges (ID: 145014A, 145102B, 145031A, and 145018A) was obtained from the Queensland Department of Natural Resources, Mines and Energy (DNRME, 2019). Daily dam discharge data was retrieved from the Queensland Government Bulk Water Supply Authority and downstream water level data for six gauges was obtained from the BOM (Figure 5.2). Hourly tidal data from the Russell Island tidal gauge, near the river mouth (Figure 5.1) was available after 2017 from the Queensland Maritime Service. The MIKE 21 Tidal Analysis and Prediction Module (DHI, 2017c) was used to calculate 69 tidal constituents based on the IOS method (Foreman, 1977), including 45 constituents of astronomical origin and 24 shallow water
constituents. Tidal constituents were then used to estimate tidal levels over the full calibration and validation periods. Effects of storm surge and other atmospheric driven components of tidal height were not included in this analysis.

Daily high-resolution climate projections from the fifth phase of the Coupled Model Intercomparison Project (CMIP5) multi-model database were obtained from the Queensland Department of Environment and Science (Syktus et al., 2020; Table C2). The climate models were dynamically downscaled by Syktus et al. (2020) to a 10-km spatial resolution over Queensland under the RCP8.5 and RCP4.5 scenarios using the regional Conformal-Cubic Atmospheric Model. These downscaled projections have been used to understand future climate risk and inform regional climate adaptation policy in Queensland (Trancoso et al., 2020). The RCP8.5 scenario represents a ‘high-emissions’ scenario with potentially the most significant changes to rainfall, representing a ‘worst-case’ scenario. It is important to consider high-emission pathways when informing natural hazards and disaster preparedness such as extreme floods to avoid neglecting the unknown future risk.

Precipitation and pan evaporation data were retrieved from the 11 climate models for the baseline (1980-2009) and three future periods representing the 2020s (2010-2039), 2050s (2040-2069), and the 2080s (2070-2099). Precipitation outputs were bias corrected by Syktus et al. (2020) using a quantile mapping technique (Piani et al., 2010). We adopted the same technique to bias correct pan evaporation outputs using historical synthetic pan evaporation data, after which the pan coefficient (0.7) was applied to convert values to PET. Sea level rise projections for the region under RCP8.5 and RCP4.5 were obtained from the Commonwealth Scientific and Industrial Research Organisation (CSIRO; Church et al., 2016).

5.2.3 Modelling
This study employed a modelling framework consisting of both hydrological and hydrodynamic models. First, the hydrological model was used to simulate daily streamflow from the Logan and Albert catchments, respectively. We then applied coupled 1-D and 2-D hydrodynamic models to estimate inundation along the coastal floodplain from an extreme event.

5.2.3.1 Hydrological Model
The deterministic, lumped, and conceptual Nedbør-Afstrømnings Model (NAM; DHI, 2019) was used to simulate river streamflow. NAM is a rainfall-runoff model, which
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requires inputs of precipitation and PET. The model accounts for moisture content in three separate storages, namely the surface, root zone, and groundwater. Catchment runoff is split into three conceptual components: overland flow, interflow, and baseflow (DHI, 2019). The NAM model has been applied to assess the effects of climate change on flooding for catchments in Kenya and Ethiopia (Taye et al., 2011), Thailand (Kure and Tebakari, 2012, Supharatid et al., 2016), and Belgium (Alam et al., 2014). The Logan-Albert catchment was split into four sub-catchments during model setup; one for each of the two major dams (Maroon and Wyaralong) and one for both the Logan and Albert Rivers at the Yarrahapini and Bromfleet stream gauges, respectively (Figure 5.1). A mean area weighting technique was adopted to calculate areal precipitation and PET for each sub-catchment. An initial one-year warmup period (2003) was designated in order to get the model operational.

We calibrated NAM during 2004-2014 against daily observed streamflow at the gauges shown in Figure 5.1 and validated NAM between 2015 and 2017. Model applications to dam sub-catchments were calibrated using the nearest available upstream gauge (Figure 5.1). As Wyaralong Dam was impounded mid-way through the calibration period (December 2010), two model runs were set up using the same parameter values for model calibration. One model did not consider the dam and ran until the date of impoundment and the other model, which did consider the dam, ran thereafter. Outputs of the first model run initialised the second model run and avoided an additional warmup period. In the calibration period prior to impoundment, simulated streamflow from the Wyaralong Dam sub catchment was used in the calibration of the downstream Yarrahapini gauge. After impoundment, measured dam discharge values were applied. Outputs from the two models were combined to assess the performance of the hydrological model during calibration. Model performance was evaluated at the Bromfleet and Yarrahapini gauges using the Nash-Sutcliffe efficiency (NSE), ratio of the root-mean-square error to the standard deviation of the observed data (RSR), and percentage bias (PBIAS).

5.2.3.2 Coupled 1-D and 2-D Hydrodynamic Model

MIKE HYDRO is a one-dimensional numerical river model that applies simplified equations of continuity and momentum (Saint-Venant equations) to simulate unsteady streamflow (DHI, 2019). As the model is one-dimensional, it is assumed that velocity and depth only vary in the longitudinal direction. It is also assumed that there is negligible variation in water density, that the bottom slope of the channel is small, and that the wave lengths are large compared to the water depth so that the streamflow direction is parallel
MIKE HYDRO was set up using measured streamflow from the Yarrahappini and Bromfleet gauges as upper boundary conditions and estimated tidal levels near the river mouth as lower boundary conditions (Figure 5.1). Outputs from the hydrological model were not applied as upstream boundary conditions. Cross sections were developed manually from the combined topography and bathymetry DEM and separated by distances ranging from 97 m to 1825 m, depending on stream morphology. Additional inflows along the principal channels from the ungauged creeks and streams were simulated with NAM using one-way coupling to MIKE HYDRO (Santiago-Collazo et al., 2019), with parameter values taken from the calibrated upstream basins. The hydrodynamic model domain encompassed the lower sections of both the Logan and Albert Rivers, where the effects of flooding are most consequential. This section of river is the most urbanised, bound by extensive floodplains near the river mouth, and is expected to undergo significant future population growth (Queensland Treasury, 2018). Additionally, the impacts of sea level rise will likely be greatest along the lower reaches of the river.

The lower Logan-Albert is bounded by extensive floodplains that inundate regularly during high flow events. This type of overland flow is not well suited to 1-D river modelling, so a 2-D overland flow model was also set up using MIKE 21. The MIKE 21 model is based on the Navier-Stokes equations for velocity, pressure, temperature, and density of river water, including the effect of viscosity. It has been widely applied for simulations of lakes, seas, rivers, estuaries, and floodplains (DHI, 2017b). We coupled together the two models in the form of a lateral link using MIKE FLOOD (Figure 5.2). In this way the 2-D overland model was only employed at times when the cross-sectional heights of the 1-D model were exceeded, saving on computation. This type of model coupling exercise has rarely been adopted in predicting climate change impacts on hydrology (Supharatid et al., 2016, Wu et al., 2017). The 2-D model consisted of a flexible mesh, allowing for improved resolution in regions of greatest interest and lower resolution in regions unlikely to be flooded or where topography varied little, although the minimum element area used in the model was relatively coarse at approximately 4000 m². Land use data for the region was used to estimate spatially variable overland Manning’s ‘n’ bed resistance values, while soil data was used to estimate spatially variable infiltration rates across the model domain (Te Chow, 1959, Hill et al., 2015). A mean areal PET was applied across the overland model based on historical data, which
was altered for model runs in the future to reflect climate change. Rainfall over the overland model was not considered as it had already been considered using the hydrological model input to the 1-D hydrodynamic model.

A two-stage procedure was used to calibrate the hydrodynamic model. The 1-D river model was first calibrated and validated between 2004 and 2017 using observed water levels at six downstream gauges shown in Figure 5.2. The calibration principally involved adjusting the Manning’s $n$ along the length of both rivers. We then coupled the calibrated 1-D river model with the 2-D overland model and calibrated and validated the combined model against 2017 and 2013 flood events, respectively. Only three of the six gauges (Carbrook, Logan Village, and Waterford) could be used for validation due to a lack of data of adequate quality in this period, whereas all gauges were used in calibration. The simulation period for these events extended over two months to include both normal and high flow conditions. Model performance was evaluated at the six downstream gauges shown in Figure 5.2 using the NSE, RSR, and PBIAS of the peak water level. In addition to the performance indicators, the maximum inundation extent from the 2017 flood event simulation was compared to the measured maximum flood extent.

5.2.4 Analyses
We considered the effects of climate change on flooding, high flows, and mean flows at the Yarrahappini and Bromfleet stream gauges (Figure 5.1). Flood magnitudes were
estimated using the Generalised Pareto Distribution and the Peak-Over-Threshold (POT) series, which consist of all statistically independent peaks that exceed a chosen threshold (Keast and Ellison, 2013). The POT series was considered advantageous over the more commonly adopted annual maxima as it allows for more data to be assessed, excludes data from years with no flooding and includes data from years with several floods (Keast and Ellison, 2013). We adopted a threshold that was exceeded on average 1.65 times annually (Stedinger and Foufoula-Georgiou, 1993) and followed a technique outlined by Lang et al. (1999) to ensure consecutive peaks met an assumption of independence:

\[ \theta < 5 \text{ days} + \log(A/2.59) \text{ or } X_{min} > (3/4) \min\{Q_1, Q_2\} \]  

(5.1)

where \( \theta \) is the minimum time difference between successive flood peaks (days), \( A \) is the catchment area (km\(^2\)), \( X_{min} \) is the minimum streamflow between two peaks (m\(^3\)/s), and \( Q_1 \) and \( Q_2 \) are the maximum daily streamflow of the two peaks (m\(^3\)/s). Relative changes to 5, 10, 25, 50, and 100-year average recurrence interval (ARI) flood events, high flows consisting of the top 10% (Q10), 5% (Q5), and 1% (Q1) of streamflow, and mean flows were calculated at each site for each climate model and for each of the future time periods (2020s, 2050s and 2080s) by comparing simulated future values to simulated baseline (1980-2009) values. We also considered changes to the seasonality of high and mean flows by determining monthly changes for each future time period relative to the values in the baseline.

Considering the effects of the dams during the calibration was important. However, when simulating the catchment response to the climate models we did not consider the impacts of the dams, similar to methods used in other studies (Phi Hoang et al., 2016, Gu et al., 2018, Mohammed et al., 2018). As we only considered relative changes between baseline and future periods from each of the climate models, the effects of the two dams within the model domain were assumed to be minor. This assumption would not hold if there were significant spatial variations in rainfall change or if differences in streamflow were assessed rather than relative changes.

Downstream changes to the maximum flood extent and to the inundated area under various water depths resulting from both changing streamflow and sea level rise were evaluated using the coupled hydrodynamic model. For this purpose, measured streamflow from a 2017 flood, which included the attenuating impacts of the dams, (~100-year ARI event; ex-tropical cyclone Debbie) was designated as a baseline event (DNRME, 2019). The measured baseline event was perturbed by the multi-model median predicted change.
to a 100-year ARI flood event for each of the future time periods. Simulated inflows from the downstream creeks and streams used in the baseline model run were likewise perturbed using this multi-model median change. These altered events represented estimates of the magnitude of a 100-year ARI flood and were used as upstream boundaries to drive the coupled hydrodynamic model, allowing for a comparison of the inundated area in each of the future periods relative to the inundated area from the baseline event. In addition to scenarios considering changes to streamflow, three additional scenarios were developed which considered the effects of sea level rise (Table 5.1) by varying the downstream boundary conditions based on projections for the region under RCP8.5 and RCP4.5. We applied a normalised nonlinearity index proposed by Bilskie et al. (2014) as a means to quantify the nonlinear changes to flooding from sea level rise.

Adopting predicted tidal levels as the coastal boundary neglected non-astronomic components of the tides, including storm surge although storm surges in the region are small (<1 m; Figure C3) compared to those reported in compound flood studies in the USA (Moftakhari et al., 2017, Moftakhari et al., 2019). An analysis of the dependence between non-tidal residuals (assumed to be indicative of storm surge) and streamflow events in the catchment (Section S3 of the Supplementary Materials) showed significant dependence between streamflow and non-tidal residuals (Figure C2). Additional scenarios were therefore analysed for the 2080s to combine non-tidal residuals from ex-tropical cyclone Debbie of 2017 with predicted tidal levels with and without the impacts of sea level rise.

<table>
<thead>
<tr>
<th>Time period considered</th>
<th>Sea Level Rise (compared to mean between 1986 and 2005)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RCP8.5</td>
</tr>
<tr>
<td>2010-2039</td>
<td>0.112 m</td>
</tr>
<tr>
<td>2040-2069</td>
<td>0.312 m</td>
</tr>
<tr>
<td>2070-2099</td>
<td>0.605 m</td>
</tr>
</tbody>
</table>

5.3 Results

5.3.1 Model Calibration and Validation

5.3.1.1 Hydrological Model

Simulated and observed streamflow at the Bromfleet and Yarrahapinni stream gauges during calibration and validation are shown in Figure 5.3. The NSE values for the
calibration and validation periods at the Bromfleet gauge were 0.872 and 0.944, respectively and 0.860 and 0.916 at the Yarrahappini gauge, respectively, indicating very good overall model performance (Moriasi et al., 2007). The performance of the model to simulate high flows was also assessed at these stations using the top 1% of streamflow, with NSE values of 0.823 and 0.936 obtained at the Bromfleet gauge and 0.812 and 0.897 at the Yarrahappini gauge during calibration and validation, respectively (Table 5.2).

![Figure 5.3. Comparison of observed and simulated hydrographs at the (a) Yarrahappini (Logan River) and (b) Bromfleet (Albert River) stream gauges for periods of calibration (2004-2014) and validation (2015-2017), which are separated by a grey vertical line.](image)

<table>
<thead>
<tr>
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<tbody>
<tr>
<td></td>
<td>NSE</td>
<td>RSR</td>
</tr>
<tr>
<td>Bromfleet (Albert River)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>0.872</td>
<td>0.357</td>
</tr>
<tr>
<td>High flows (1%)</td>
<td>0.823</td>
<td>0.417</td>
</tr>
<tr>
<td>Yarrahappini (Logan River)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>0.860</td>
<td>0.375</td>
</tr>
<tr>
<td>High flows (1%)</td>
<td>0.812</td>
<td>0.430</td>
</tr>
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</table>

5.3.1.2 Coupled 1-D and 2-D Hydrodynamic Model

The performance of the coupled hydrodynamic model was evaluated against major flooding events in 2017 and 2013 during calibration and validation, respectively. At the six downstream water level gauges, NSE values ranged between 0.938 and 0.973 during calibration. During validation only three of the gauges (Carbrook, Logan Village, and Waterford) were operational and the NSE ranged between 0.879 and 0.950 (Table 5.3).
There was a reasonable match between the simulated and observed flood peaks during both calibration (Figure 5.4) and validation, as the PBIAS of the peak water level never exceeded 10% at any gauge during calibration or validation (Table 5.3). The PBIAS of the peak water levels generally indicated a minor overestimation of the flood peak during calibration and an underestimation during validation. Such differences may relate to uncertainty in the measurement of large streamflow events or to changes in stream morphology that occur following large floods. The simulated flood extent can be seen in Figure 5.5 to be a good match to the observed flood extent, except for some parts of the lower floodplain where flood extent was underestimated, which may relate to inadequate resolution of the mesh (~ 4000 m²) for representing some of the changes in topography.

Table 5.3. Performance of the coupled hydrodynamic model during the calibration and validation periods at the downstream water level gauges along the Logan and Albert rivers. NSE = Nash-Sutcliffe efficiency, RSR = ratio of the root mean square error to the standard deviation of measured data (RSR) and PBIAS peak = percentage bias of the Peak water level.

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<tbody>
<tr>
<td></td>
<td>NSE</td>
<td>RSR</td>
</tr>
<tr>
<td>Beenleigh</td>
<td>0.939</td>
<td>0.248</td>
</tr>
<tr>
<td>Carbrook</td>
<td>0.950</td>
<td>0.223</td>
</tr>
<tr>
<td>Logan Village</td>
<td>0.973</td>
<td>0.163</td>
</tr>
<tr>
<td>Parklands</td>
<td>0.950</td>
<td>0.224</td>
</tr>
<tr>
<td>Waterford</td>
<td>0.951</td>
<td>0.222</td>
</tr>
<tr>
<td>Wolfdenene</td>
<td>0.954</td>
<td>0.215</td>
</tr>
</tbody>
</table>

Figure 5.4. Comparison between simulated and observed water level at the downstream gauges (refer to Figure 5.2 for locations) during the calibration period (2017).
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5.3.2 Changes to Precipitation and Potential-Evapotranspiration

Changes in average precipitation, PET, and the deficit (precipitation – PET) across the catchment under the RCP8.5 model ensemble are presented in Figure 5.6 for the three future time periods relative to the baseline (1980-2010). Precipitation in winter and spring was predicted to decrease in the future and this decrease became most apparent by the end of the century (2080s). Summer precipitation generally showed an opposing pattern of increase, which was also greatest by the 2080s. This pattern of change is more apparent when looking at the relative changes to precipitation (Figure C8). These changes represent an amplification of the seasonality of precipitation; a decrease during the winter dry season and an increase during the summer wet season. For the early century (2020s), there was little agreement on the directionality of change in precipitation for any season, with most climate models not indicating a clear increase or decrease. However, by the 2050s and 2080s there was widespread agreement in the model ensemble about the directionality of change in winter, spring, and summer, but not for autumn. Similar changes are noted under the RCP4.5 (Figure C9 and Figure C10) though the magnitude of the changes was smaller than under the RCP8.5. Interestingly, despite significant shifts in the projected distribution of precipitation for the different seasons, the multi-model median change to annual precipitation was predicted to vary only slightly (<4%) compared to the baseline for the three future time periods under both emission scenarios. Therefore, the precipitation increases in summer are projected to be large enough to offset decreases in winter and spring.

Figure 5.5. Maximum inundation extent from the coupled 1D-2D hydrodynamic model for the calibration (Baseline) period with an approximate 100-year ARI flood event resulting from ex-tropical cyclone Debbie (white lines show actual measured flood extent).
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The largest increases to PET occurred during summer and spring, while the smallest increases coincided with autumn and winter (Figure 5.6). Relative changes to the seasonal distribution of PET, however, were consistent across all seasons (Figure C8). By the 2080s under the RCP8.5 the largest increases to the multi-model median were predicted in spring (32.4%) and the smallest in autumn (27.7%). Annual PET assessed as the multi-model median increased by 4.9% for the 2020s, 17.1% for the 2050s, and 29.5% for the 2080s compared with more moderate increases under the RCP4.5 of 5.8%, 10.9%, and 14.6% for the three future periods, respectively.

![Figure 5.6. Multi-model ensemble (RCP8.5) changes in monthly mean (a) precipitation, (b) PET, and (c) deficit (P-PET) for the 2020s, 2050s, and 2080s with respect to the baseline (1980-2010). Boxplots show the multi-model median (middle line) and the interquartile range of model projections (25th and 75th percentiles).](image)

5.3.3 Hydrological Impacts of Climate Change

Projections of precipitation and PET from the climate model ensemble were used as inputs to run NAM. Changes to high and mean flows in each of the three future periods were evaluated relative to the baseline at the Yarrahappini (Logan River) and Bromfleet (Albert River) gauges, respectively (Figure 5.7). High and mean flows were predicted to decrease significantly in the future under RCP8.5 and these decreases became largest by the end of the century. By the 2050s and 2080s most of the climate models indicated decreased streamflow, whereas for the 2020s there was no clear indication on the sign of
change. Under RCP4.5, only by the 2080s did most of the climate models indicate decreased streamflow (Figure C11). Multi-model median changes to high flows ranged between -0.7 and 6.1% for the 2020s, -14.6 to -36% for the 2050s, and -15.1 to -51.7% for the 2080s under RCP8.5, depending on the site and streamflow quantile assessed. Changes were less extreme under RCP4.5; between 0.7 to -9.2% for the 2020s, 7.8 to -12.2% for the 2050s, and -8.2 to -24.8% by the 2080s. Different streamflow quantiles gave different magnitudes of change, with the largest decreases generally reported for Q10 flows and the smallest decreases for Q1 flows. Multi-model median decreases to Q1 flows ranged between -15.1 to -22.5% and between -46.2 and -49.1% for Q10 flows by the 2080s under RCP8.5, indicating that the relative change in the frequency of smaller flow events would decrease more than that of larger events.

Figure 5.7. Multi-model ensemble (RCP8.5) used for predicting relative changes to mean and high flows representing the top 10% (Q10), 5% (Q5), and 1% (Q1) of flows relative to the baseline period at the (a) Albert River at Bromfield and (b) Logan River at Yarrabahpini gauge. Boxplots show the multi-model median (middle line) and the interquartile range of model projections (25th and 75th percentiles).

Seasonal changes to high and mean flows under the RCP8.5 climate forcing largely reflected the changes for precipitation, with the largest decreases occurring during winter and spring months, and by the end of the century (Figure 5.8). Decreases in streamflow, however, were substantially greater during these months than decreases in precipitation. Multi-model median changes in high and mean flows were predicted to decrease by between -26.3 and -65% in winter, -26.1 and -78.7% in spring, and -22.7 and -30.7% in
autumn by the 2050s, depending on the site and streamflow quantile assessed, while in summer the comparable changes were between 1.9 and -13.8%. Multi-model median high and mean flows decreased further in winter and spring by the 2080s, varying between -52.6 and -83.7% in winter and between -59 and -93.4% in spring. For autumn these changes varied between -11 and -40.6% and in summer between 3 and -22%. It is important to note that historically, streamflow in winter and spring has been considerably lower than in summer, and therefore relative changes in these seasons can appear overly large compared with summer. Summer high and mean flows showed a lower probability of change, despite most climate models predicting an increase in summer precipitation by the 2080s (Figure 5.6). Projected changes under the RCP4.5 (Figure C12) followed the same seasonal pattern as for the RCP8.5 case, but with smaller decreases predicted during the winter and spring months on account of smaller decreases in precipitation and smaller increases in PET.

![Figure 5.8. Multi-model ensemble (RCP8.5) used for predicting relative changes to monthly high and mean flows (outliers removed) at the Albert River at Bromfleet and Logan River at Yarrahappini gauges. Boxplots show the multi-model median (middle line) and the interquartile range of model projections (25th and 75th percentiles).](image-url)
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Changes to the magnitude of different ARI flood events are shown in Figure 5.9 for RCP8.5 and in Figure C13 for RCP4.5. Generally, there was no clear agreement amongst the model ensemble on the sign (− or +) of change for smaller ARI events (5 and 10 year) in any of the future periods. For larger ARI events (50 and 100 year), however, most of the models predicted increased flood magnitude in all future periods, meaning that larger flood events were likely to increase more than smaller events. Multi-model median changes to the 100-year ARI flood event under the RCP8.5 were predicted to increase by 38.1% and 24.7% at the Albert and Logan Rivers, respectively, by the 2080s. In contrast, 5-year ARI flood events were predicted to change by 0.5% and -14.6%, respectively, in the same time period. A similar tendency was noted for high flows, where larger flows (Q1) generated smaller decreases than smaller flows (Q10; Figure 5.7). There was greater variability in the projections of larger ARI events than smaller events, evident by the size of the interquartile range. Somewhat surprisingly, there was generally greater variability in projections of future flood quantiles in the 2020s than in the 2050s and 2080s.

![Graph showing changes in flood magnitude](image)

*Figure 5.9. Multi-model ensemble (RCP8.5) of predicted relative changes to 5, 10, 25, 50, and 100-year ARI flood events relative to the baseline period (outliers removed) at (a) Albert River at Bromfleet and (b) Logan River at Yarraboppin gauges. Boxplots show the multi-model median (middle line) and the interquartile range of model projections (25th and 75th percentiles).*

5.3.4 Inundation Changes of Extreme Events

Multi-model median changes predicted for major (100-year ARI) flood events in each of the three future periods were used to perturb measured hydrographs from the baseline
flood event at the Yarrahappini and Bromfleet gauges (Figure 5.10; DNRME, 2019). Using the median change, flood magnitudes under the RCP8.5 were predicted to increase considerably for the Logan River by the 2020s (56.5%) and 2050s (57.3%), with lesser increases by the 2080s (38.1%). Increases were smaller for the Albert River; 41.5% by the 2020s, 40% by the 2050s, and 24.7% by the 2080s. Under the RCP4.5, increases were of a similar magnitude for the 2020s but were smaller for the 2050s and 2080s (Figure C14).

Changes to the maximum flood extent compared to the baseline flood extent were determined for the three future periods (RCP8.5) with and without the effects of sea level rise (Figure 5.11). In the 2080s the additional impacts of a storm surge event from 2017 were considered. Newly inundated areas are shown in red and green areas are flooded in the baseline but no longer flooded in the climate change scenario. The maximum flood extent increases substantially in all future period, with ~55% increase by the 2020s with and without sea level rise (Table 5.4). The effects of sea level rise were amplified by the 2050s and 2080s, increasing the predicted change in inundated area from 54% to 64% by the 2050s and from 33.4% to 60.2% by the 2080s. By the end of the century, sea level rise nearly doubles floodplain inundation increases that were predicted solely from atmospheric climate change, primarily affecting the downstream section of the floodplain (Figure C16). Considering the additional effects of storm surge resulted in only minor increases in flooding, from 60.2% to 63.8% inundation by the 2080s with sea level rise. In all scenarios the area of land inundated with more than 2 m of water also increased considerably (>52.6%). This increase was primarily along the upper estuarine reaches as a response to increased inflows rather than changes to sea level. The majority of the newly
inundated land was situated along the southern floodplains near the river mouth (particularly under sea level rise scenarios) and along the upper reaches of the Logan River (Figure 5.11).

<table>
<thead>
<tr>
<th>Inundation Depth (m)</th>
<th>Change in Inundation Extent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Increased Inundation</td>
</tr>
<tr>
<td>0.0001 - 0.1</td>
<td>Decreased Inundation</td>
</tr>
<tr>
<td>0.1 - 1</td>
<td></td>
</tr>
<tr>
<td>1 - 2</td>
<td></td>
</tr>
<tr>
<td>2 - 16</td>
<td></td>
</tr>
</tbody>
</table>

Figure 5.11. Predicted changes (RCP8.5) in the floodplain inundation area of the lower Logan-Albert catchment for different time periods with and without accounting for sea level rise (SLR). The additional effects of storm surge (SS) are considered for cases in the 2080s. Red and green areas indicate increases and decreases to the maximum flood extent relative to the baseline, while grey indicate non-wetted areas.
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Table 5.4. Comparison of changes (RCP8.5) to inundation area for various depths of, and change to, the maximum flood extent relative to the baseline scenario. SLR is sea level rise and SS is storm surge.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Area (km²) of inundation at various depth intervals (m)</th>
<th>Total inundation (km²)</th>
<th>Relative change to maximum flood extent (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>&lt; 0.1</td>
<td>0.1 - 1</td>
<td>1 - 2</td>
</tr>
<tr>
<td>Baseline</td>
<td>1.93</td>
<td>19.23</td>
<td>15.49</td>
</tr>
<tr>
<td>2020s no SLR</td>
<td>2.99</td>
<td>30.69</td>
<td>15.46</td>
</tr>
<tr>
<td>2020s SLR</td>
<td>2.98</td>
<td>31.39</td>
<td>15.67</td>
</tr>
<tr>
<td>2050s no SLR</td>
<td>2.92</td>
<td>30.84</td>
<td>15.22</td>
</tr>
<tr>
<td>2050s SLR</td>
<td>3.33</td>
<td>36.65</td>
<td>15.97</td>
</tr>
<tr>
<td>2080s no SLR</td>
<td>2.89</td>
<td>24.91</td>
<td>15.49</td>
</tr>
<tr>
<td>2080s SLR</td>
<td>2.77</td>
<td>39.94</td>
<td>17.52</td>
</tr>
<tr>
<td>2080s no SLR and SS</td>
<td>3.07</td>
<td>27.84</td>
<td>15.58</td>
</tr>
<tr>
<td>2080s SLR and SS</td>
<td>2.71</td>
<td>40.16</td>
<td>19.62</td>
</tr>
</tbody>
</table>

5.4 Discussion

5.4.1 Changes in Precipitation, PET, and Streamflow

Predicting changes in floods, high flows, and mean flows under climate change is crucial if informed adaptation strategies are to be implemented. The climate scenarios used in this study indicate that changes in precipitation are likely to vary seasonally, with increases predicted in summer and decreases in winter and spring. Increases in PET, which are strongly influenced by changes in temperature and humidity, are considerable by the 2050s and 2080s, with the largest increases predicted for summer and the smallest increases coinciding with winter. However, in terms of relative changes these increases show little seasonal variation (Figure C8). Increases in the deficit between precipitation and PET were greatest in spring, leading to some of the largest relative decreases in streamflow in this season (Figure 5.8). Teng et al. (2012a) showed that a 1% increase in PET led to a 1-2% reduction in streamflow across Australia, while a 1% increase in precipitation increased streamflow by 2-3%. We found seasonal changes to high and mean flows largely reflected the changes in precipitation, with the largest decreases occurring in winter and spring months (Figure 5.8). Decreases in streamflow, however, were substantially greater during these months than decreases in precipitation, while increased precipitation in summer did not necessarily lead to increased streamflow. This reflects the influence of elevated PET and by extension, lower soil moisture (in the root and surface zones of the hydrological model), which amplified decreases in streamflow during the subtropical winter dry season and diminished increases in the summer wet season as evident by the increase in the deficit (Figure 5.6).
Unlike high flows however, most models did not predict a decrease in major floods, indicating that increases in PET did not mitigate the size of different ARI flood events in the same way as was noted for high flows. The directionality of change in the different flood quantiles under climate change varied, with model predictions indicating both increases and decreases in the future (though larger events tended to increase). This outcome was in contrast to the widespread convergence among the models of decreased high and mean flows by the 2050s and 2080s. Predicted changes to flooding in the 2080s had smaller variability amongst the individual models than for the 2020s, evident as smaller differences in the interquartile range (Figure 5.9). This result is different from that of Liu et al. (2013) and Shen et al. (2018), who reported increased uncertainty for high and flooding flow predictions using GCM drivers extending further into the future. Our study also showed greater variability from the model ensemble of flood events of larger magnitude than smaller magnitude (Figure 5.9), which is consistent with the results of Liu et al. (2013), who noted greater uncertainty for more extreme flood events.

Considering changes to the multi-model median, there was predicted to be a slight decrease in the magnitude of smaller flood events (5-year ARI) by the 2080s and an increase of larger events (50 and 100-year ARI). This change indicates that different flood quantiles may have different rates of change, highlighting the importance of considering a range of flood magnitudes. Yin et al. (2018) and Essou and Brissette (2013) likewise reported different rates of change for different flood quantiles in subtropical China, and tropical West Africa, respectively. Predictions for the Logan-Albert catchment showed changes predicted for high flows differed substantially from flooding. A number of studies report changes in high flows to be indicative of changes to flooding (Aich et al., 2014, Li et al., 2016b, Asadieh and Krakauer, 2017), but our results suggest that high flows and flooding should be differentiated and high flows cannot always be relied upon to indicate the likely changes to flooding. This has important implications for cases in which infrastructure damage or design criteria are being considered as flooding, even at lower frequency, may have a disproportionate influence over high flows.

Assessing changes to high flows can be advantageous over flood frequency analysis, however, as predictions for high flows are more accurate than those for floods (Aich et al., 2016). We adopted a traditional flood frequency analysis technique using the Generalised Pareto Distribution and the POT series. In using traditional flood frequency analysis techniques, it was assumed that flow regimes were stationary around each of the time periods considered. Non-stationary techniques (e.g., Yin et al., 2018) would allow
consideration of continually changing climate and hydraulic conditions (e.g., from changes to river infrastructure, land use, or urbanisation – notably in our case from the Wyaralong Dam in the Logan catchment). However, in a study on the Wainganga River in India, Das and Umamahesh (2017) found only minor differences between stationary and non-stationary techniques when estimating the magnitude of larger ARI events.

5.4.2 Changes in Inundation from Extreme Events
The predicted inundation area from a 100-year ARI flood event increased significantly in all future periods under the RCP8.5. The effects of sea level rise were important, especially by the end of the century, when the change in inundation area nearly doubled. Comparatively few studies have considered the impacts of sea level rise when assessing changes in riverine flooding due to atmospheric climate change (Västilä et al., 2010, Budiyono et al., 2016, Hamman et al., 2016), despite coastal regions being some of the most densely populated in the world. Our results suggest the effects of sea level rise on flooding should not be ignored in coastal catchments and can be just as important as atmospheric changes. Similar findings have been reported for Jakarta (Budiyono et al., 2016), the Skagit River (Hamman et al., 2016), and the Mekong River (Västilä et al., 2010). The maximum inundation extent for the 2080s was less than that seen for the 2050s or 2020s when sea level rise was not considered, potentially relating to substantial increases in PET predicted by the end of the century. However, it is important to note that there is considerable uncertainty in these predictions, particularly for large magnitude flood events and as such, the inundation results should not be interpreted as deterministic. Multi-model median changes for the 2020s and 2050s were within the inter-quartile range of predictions for the 2080s (Figure 5.9), which indicates that 100-year ARI streamflow events in these periods may not necessarily be larger than those in the 2080s. The additional impacts of storm surge on inundation for the 2080s was relatively minor, particularly compared to that of sea level rise. This likely relates to the timing of the storm surge event used, which peaked two days prior to the peak of the streamflow event.

The issue of flooding could also be made worse in the catchment by increasing impervious area from urbanisation, as has been highlighted in previous studies (Budiyono et al., 2016, Zhao et al., 2016). As the Logan-Albert catchment is projected to undergo significant urbanisation and population growth in the future (~50% increase in population between 2017 and 2036; Queensland Treasury, 2018), further research could evaluate potential for land use change to affect flooding and risks to human lives and infrastructure. Particularly the impacts of urbanisation and the associated increases to impervious
surfaces. Climate change may also be associated with changes to in-stream and shoreline morphology (Bilskie et al., 2014, Passeri et al., 2015), which could exacerbate flooding. These changes are challenging to address without detailed stream and estuary geomorphological predictions. The unequivocal direction of inundation predictions from this study provides a solid basis, however, to inform the planning process about the vulnerability of areas subject to rapid urbanisation in the catchment floodplain.

5.4.3 Environmental and Water Supply Issues
The projected changes in high and mean flows will also have important consequences for water quality in the Logan-Albert catchment and other coastal catchments in the region. Nutrient and sediment loads have increased substantially since European arrival (Olley et al., 2015) and the estuarine reaches of the Logan-Albert River experience elevated concentrations of nutrients and high turbidity levels (Healthy Land & Water, 2019). Flushing times in subtropical Australian estuaries already tend to be very long, particularly during the winter dry season (Eyre, 1998), and can lead to a build-up of in-stream pollutants and sediments, as noted during the recent (2002-09) Millennium Drought (van Dijk et al., 2013, Eccles et al., 2020). There is projected to be an intensification in the seasonality of streamflow in the Logan-Albert river system, with large decreases in the dry season as well as increased extension of this season (Figure 5.8).

Low flushing rates for large portions of the year are likely to lead to a greater build-up of nutrients and sediments along the estuarine reaches, particularly in the region of WWTP outfalls. Due to urbanisation, two additional WWTPs are planned for the lower catchment that will necessitate offset schemes to ensure nutrient loads do not exceed guidelines. However, a majority of sediment and nutrient loads are delivered from diffuse sources during the wet season (Abal et al., 2005) and it is not known how projections for an intensification in the seasonality of precipitation and streamflow will affect diffuse loads and these offset schemes. Decreased flows and greater point source inputs are likely to become a growing issue during the dry season when catchment offset schemes would have less impact. Lower flows in the future may necessitate additional discharges from upstream dams to flush nutrients from the system. Additionally, nutrient loads from WWTPs are likely to consist of greater relative quantities of dissolved nutrients than particulates when compared with catchment sources, which are more bioavailable and may present additional management issues. The influence of these changes on both point and diffuse loads in the catchment is an area that requires further examination.
Lower mean flows and higher PET may also reduce water supplies throughout the region. Additionally, increases in the largest flooding events may require dams in the region to operate at lower maximum storage capacity to accommodate the large floods, diminishing long-term water reserves. A notable example is the 2011 flood event that occurred in the adjacent Brisbane River catchment, which led to significant dam releases, 18,000 properties inundated, and a class action lawsuit against the dam operators (Van den Honert and McAneney, 2011). The 2011 flood event has led to a more conservative approach to dam operating levels in order to avoid downstream damage, but with a potential trade off to water supply capacity.

5.4.4 Model Framework
A key feature of this study was the use of the coupled 1-D, 2-D hydrodynamic model, which was easily adaptable to represent regions of greater interest (e.g., urban areas, varying topography) in more detail than regions of little interest (e.g., un-inundated areas). When applying this coupled model, changes to the multi-model median were used to perturb a historical flood event rather than considering the full ensemble of climate models, which would have been difficult to do due to long computational run times. It is important to note that there is large uncertainty in the boundary conditions applied to run this model and the results should therefore be interpreted with this in mind. Additionally, only changes to major 100-year ARI events in the inundation model were considered, as smaller ARI events do not represent nearly as big of a risk to property or life. The coastal boundary conditions applied in this study included predicted tidal levels with no additional impacts of storm surge for most modelling scenarios except for use of a historical storm surge event for consideration of inundation in the 2080s. The magnitude of future storm surges could increase as more frequent and intense tropical cyclones are predicted to impact the region (Nguyen and Walsh, 2001, Department of Climate Change, 2009). Likewise, the nonlinear interactions between the different flood-causing mechanisms will change in the future as sea levels rise. This change may also alter the timing and magnitude of surge events. Future studies would be useful to examine details of interactions among these drivers.

This study was limited to two emissions scenarios (RCP8.5 and RCP4.5) and a single downscaling technique and hydrological model. It is widely accepted that the choice of GCM is the largest source of uncertainty in climate change impact studies (Kay et al., 2009, De Niel et al., 2019). An ensemble of 11 high-resolution dynamically downscaled climate models was therefore used in this study. The models were dynamically
downscaled using the Conformal-Cubic Atmospheric Model, and bias corrected using a quantile mapping approach, which has been shown to perform better in predicting extremes than other techniques (Dobler et al., 2012, Chen et al., 2013). The use of high-resolution (10-km spatial resolution) dynamically downscaled climate data was considered advantageous as the study catchment is relatively small (3862 km²), with significant heterogeneity in topography, land use and precipitation. Use of coarser climate model outputs, which may be suitable for larger catchments, may not adequately represent these local climatic drivers and features. For informing disaster preparedness, RCP8.5 is generally considered to be the most appropriate emissions scenario but for comparative purposes, results from RCP4.5 are presented in Section S4 of the Supplementary Materials. Future studies could consider a wider array of hydrological models as they are important additional sources of uncertainty in climate change impact studies (Wilby and Harris, 2006, Tian et al., 2016).

5.5 Conclusion
This study provides one of the first assessments of the impacts of climate change on high flows, flooding, and floodplain inundation of subtropical catchments. Hydrological modelling using an ensemble of climate models showed climate change was likely to cause greater seasonality of high and mean flows, with significant decreases in flow in winter and spring and highly variable changes in summer. The magnitude of large flooding events was predicted to vary significantly among climate models, although the multi-model median tended to show an increase in the magnitude of the largest events (100-year ARI) and a slight decrease or no change for smaller events (5-year ARI) in all future periods. These results highlight the importance of considering a range of flood quantiles in impact studies and show that changes in high flows should not necessarily be relied upon to inform the likely changes to flooding. The inundation area from a 100-year ARI flood was predicted to increase considerably in all future periods and increases in streamflow and sea level rise acted synergistically to increase floodplain inundation substantially by the 2050s and 2080s. For instance, when sea level rise was included in the modelling, the increase in floodplain inundation area was almost two-fold by the 2080s, which has important ramifications for flood risk. Our study highlights the nonlinear hydrological changes that result from climate change, the potential impacts on nutrient and sediments, and demonstrates the need for comprehensive assessments of floodplain inundation at the local scale to better inform preparedness for future flooding.
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Chapter 6: Impacts of Climate Change on Nutrient and Sediment Loads from a Subtropical Catchment

Statement of contribution to co-authored published paper

This chapter includes a co-author paper. The bibliographic details of the co-authored paper, including all authors, are:


My contribution to the paper involved conceptualisation, conducting the numerical modelling and statistical analyses, interpreting the results, and drafting the paper.

Signed: ___________________________ Date: 07/04/21

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Countersigned: ___________________________ Date: 07/04/21

Principal Supervisor: Prof. Hong Zhang (principal supervisor, Griffith School of Engineering)

Countersigned: ___________________________ Date: 07/04/21

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Countersigned: ___________________________ Date: 07/04/21

Corresponding author of paper: Dr. Ralph Trancoso (Queensland Department of Environment and Science)

Countersigned: ___________________________ Date: 07/04/21

Corresponding author of paper: Mr. Jozef Syktus (Queensland Department of Environment and Science)
Impacts of climate change on nutrient and sediment loads from a subtropical catchment

Abstract

Climate change is predicted to significantly alter hydrological cycles across the world, affecting runoff, streamflow, and pollutant loads from diffuse sources. The objectives of this study were to examine the impacts of climate change on streamflow, total nitrogen (TN), total phosphorus (TP), and total suspended sediment (TSS) loads in the subtropical Logan-Albert catchment, Queensland, Australia. The region is considered a ‘hotspot’ for environmental change due to projections of marked intensification of seasonal wet-dry cycles with climate warming and rapidly increasing populations. We calibrated the Surface Water Assessment Tool against event monitoring data in the Logan and Albert rivers, respectively. Hydrological and water quality effects of an ensemble of 11 dynamically downscaled high-resolution climate models was assessed with SWAT under high (Representative Concentration Pathway 8.5 – RCP8.5) and intermediate (RCP4.5) emission scenarios for the 2020s, 2050s, and 2080s relative to a climate baseline of 1980-2010. Streamflow decreased most in winter and spring and decreased least in summer under both RCP4.5 to RCP8.5. This followed the predicted seasonal changes for precipitation although decreases tended to be amplified due to increasing evaporative loss. Nutrient and sediment loads showed a similar pattern to streamflow, with the largest decreases predicted for the dry season under RCP8.5 by the 2080s. Annual TSS load decreased by 34.3 and 54.2%, TN load decreased by 29.8 and 30.5%, and TP load by 24.9 and 4.4% for the Logan and Albert sites, respectively. The results of this study indicate that for subtropical river-estuary systems, climate warming may lead to lower streamflow and contaminant loads, reduced flushing and greater relative importance of point source loads in urbanising catchments.
6.1 Introduction

Deterioration of surface water quality in rivers from elevated nutrient and sediment loads has become an important environmental issue. Excess loads can lead to a build-up of in-stream concentrations, potentially causing eutrophication and the loss of aquatic life and habitat (Rabalais et al., 2009). Anthropogenic changes, such as urbanisation, industrialisation, fertiliser applications, and loss of riparian vegetation have been the principal factors contributing to increased loads over recent decades (Galloway et al., 2004, Seitzinger et al., 2010). A decline in water quality in many rivers has necessitated management actions including catchment nutrient offset schemes, supported by detailed monitoring strategies (Behmel et al., 2016). The export of nutrients and sediments from diffuse sources is highly sensitive to climatic factors (Royer et al., 2006, Sinha and Michalak, 2016), including in subtropical areas where there are distinct seasonal climate patterns (Eccles et al., 2020). Climate change is expected to intensity hydrological variability in many parts of the world (Donat et al., 2016, Prein et al., 2017) and may alter seasonal rainfall patterns (Suppiah et al., 2007), affecting the timing and magnitude of nutrient and sediment delivery and potentially exacerbating water quality issues.

Catchment models serve as a useful tool to quantify the changes in hydrological systems and support short- and long-term management decisions to mitigate effects of climate change. The eco-hydrological SWAT model (Soil Water Assessment Tool; Arnold et al., 1998) has been widely applied to simulate streamflow and nutrient and sediment loads originating from diffuse sources (Abbaspour et al., 2015, Zhang et al., 2020) and has been increasingly used to assess climate change impacts on water quality (Shrestha et al., 2017, Me et al., 2018, Nguyen et al., 2019). Studies have shown climate change to have both positive and negative effects on receiving water quality, mostly due to projections of changes in climate (Sinha et al., 2017, Teutschbein et al., 2017, Yang et al., 2017). Due to spatiotemporal variations in climate change, the hydrological response to climate change varies substantially between different regions of the world (Hirabayashi et al., 2013). It is, therefore, important that the impacts of climate change are evaluated across different regions. There has been a marked increase in studies assessing this topic, including in temperate areas of Australia (Alam and Dutta, 2013, Dyer et al., 2014, Shrestha et al., 2016, Nguyen et al., 2017b, Nguyen et al., 2019), but there are few studies for subtropical Australia.

Subtropical southeast Queensland (SEQ) has experienced substantial declines in surface water quality since European arrival (Olley et al., 2015) and elevated nutrient and
sediment loads from catchments in this region have resulted in declines in the ecologically significant receiving waters of Moreton Bay (Abal et al., 2005, Bunn et al., 2007). Water quality in the Logan and Albert rivers is particularly poor compared with other rivers in the region, with sediment loads estimated to have increased by a factor of 35 since European arrival, while nitrogen and phosphorus loads have increased by a factor of 3.2 and 4.7, respectively (National Land and Water Resources Audit, 2001). Delivery of sediments and nutrients from diffuse sources varies significantly throughout the year. For instance, Abal et al. (2005) noted that during an 11-year period 42% of the total suspended solids (TSS) load entering Moreton Bay was delivered 1% of the time, increasing to 66% and 80% of the load for 5% and 10% of the time, respectively. The timing of peak nutrient loads correlates closely to those of TSS (Garzon-Garcia et al., 2015), indicating most nutrients are delivered in particulate form. However, peak concentrations often coincide with periods of low flows when there is reduced flushing, as there is a build-up of in-stream concentrations, particularly near to point sources, which usually release nutrients in dissolved form (Eccles et al., 2020).

The Logan-Albert river system is the second largest in the region discharging to Moreton Bay and is anticipated to be subject to considerable population growth (Queensland Treasury, 2018), potentially exacerbating water quality issues. Additionally, the region has been identified as one of the ‘hotspots’ for climate change by the International Panel for Climate Change (IPCC, Hennessy et al., 2007), although effects on water quality remain largely unexplored for this region. Quantifying the impacts of projected climate change on water quality is therefore vital to inform managers on the range of likely future eventualities and scenarios, and to plan mitigation and adaptation actions.

This study employed an ensemble of 11 high-resolution climate models run under the high (Representative Concentration Pathway 8.5 - RCP8.5) and intermediate (RCP4.5) emission scenarios to generate climate inputs to the SWAT catchment model for three different future periods. We sought to determine the effects of climate change on catchment water quantity and quality by evaluating changes to streamflow, total nitrogen (TN), total phosphorus (TP), and total suspended solids (TSS). We hypothesised that decreases in rainfall in the winter dry season would dominate changes in the annual flow pattern and that changes to nutrient and sediment loads would mostly follow this change.
6.2 Methodology

6.2.1 Study Area
The Logan-Albert catchment is the second largest in South East Queensland (SEQ), with an area of 3862 km², of which the Logan covers around 3080 km² and the Albert 782 km². Elevation ranges between 0 and 1370 m and annual precipitation varies between 900 mm in the western regions and up to 2000 mm in the south-eastern headwaters. The climate is subtropical with most precipitation falling in the summer (December to February) wet season, while winter (June to August) coincides with the dry season. Interannual variability is significant, with long periods of dryer or wetter conditions prevailing. Precipitation in wetter years can be twice that of dryer years (Bunn et al., 2007).

Land use in the catchment headwaters is dominated by native forest and scrub and by cattle grazing in the upper and middle catchment, with irrigated cropping along the alluvial channels. Logan City, located in the lower catchment to the south of Brisbane city, has a population of 319,000 and is the largest population centre. The city is projected to undergo significant population growth in the coming decades, reaching a population of 490,000 by 2036 (Queensland Treasury, 2018). This population is currently serviced by two major wastewater treatment plants (WWTPs), situated along the estuarine reaches of the Logan and Albert rivers, respectively. Operational licenses for WWTP discharges are reliant on riverine flow and tidal flushing to export nutrients into the adjacent coastal system. Two major dams are situated along the upper reaches of the Logan River and supply drinking and irrigation water (Figure 6.1). The catchment has been identified as an area for future major urban expansion (Department of Infrastructure and Transport, 2013), which may place additional stress on the already degraded system.

6.2.2 Data
The SWAT model requires topographical, soil, land use, and climate data to run. Digital elevation model (DEM) data consisting of a 5 m horizontal resolution was retrieved from Geoscience Australia (https://elevation.fsdf.org.au/). Land use and soil data were obtained from the Queensland Government Spatial Catalogue and the Australian Soil Resource Information System (ASRIS, http://www.asris.csiro.au/mapping/viewer.htm), respectively.

Daily gridded (~5 km) reanalysed climate data from 2003 to 2018 was obtained from the Scientific Information for Land Owners (SILO; Queensland Government, 2019). This included data on precipitation, minimum and maximum temperature, synthetic pan
evaporation, solar radiation, and relative humidity. Pan evaporation was converted to potential evapotranspiration (PET) using a pan coefficient value of 0.7 (Allen et al., 1998). Daily streamflow readings for two gauges (ID: 145014A and 145102B; Figure 6.1) were retrieved from the Queensland Department of Natural Resources, Mines and Energy (DNRME, 2019).

![Figure 6.1. Logan-Albert catchment, showing major land uses types designated for SWAT input, location of gauging stations, major channels, and major dams.](image)

Measured nutrient and sediment concentrations and loads from the Yarrahappini and Bromfleet gauges (ID: 145014A and 145102B; Figure 6.1) were obtained from the Queensland Department of Environment and Science (DES). Sampling was conducted during the rise, peak, and fall of events that occurred between 2006 and 2017 at the Yarrahappini site and for events between 2006 and 2015 at the Bromfleet site. Baseline sampling during moderate and low flows was not available at these gauges. TN was taken as the sum of total Kjeldahl nitrogen and oxidised nitrogen, TP was taken as the total Kjeldahl phosphorus following Bran and Luebbe (1990), and TSS was determined using a gravimetric method (Thomson et al., 2013).
6.2.3 SWAT Catchment Model

The physically based, semi-distributed, continuous SWAT catchment model (Arnold et al., 1998) was applied at a daily timestep to assess the effects of climate change on streamflow, sediment, and nutrient loads in the catchment. SWAT delineates the catchment into sub-catchments based on the drainage area of the tributary channels using DEM data. Sub-catchments are further organised into hydrological response units (HRUs), which represent unique combinations of land use, slope, and soil properties. The Soil Conservation Service curve number and variable storage coefficient methods were adopted in SWAT to calculate surface runoff and channel routing, respectively. Measured PET data from SILO was used in the SWAT model rather than one of the built-in methods in SWAT. Wyaralong and Maroon dam were incorporated in the model as storages and dam outflows were manually calibrated against daily dam release values.

Calibration of streamflow, TN, TP, and TSS loads was performed by SWAT-CUP using the SUFI-2 (Sequential Uncertainty Fitting version 2) at the Yarrahappini and Bromflett gauges. An initial manual parameterisation of the upstream sub-catchments following recommendations by Abbaspour et al. (2015) was conducted prior to this calibration, that resulted in initial regionalisation of the parameters. SUFI-2 estimates optimum parameter ranges and model uncertainty using P-factor and R-factor statistics (Abbaspour et al., 2007), which denote the percentage of observations that lie within the 95% probability distribution (95PPU) of all iterations and the thickness of the 95PPU envelope, respectively. Initial ranges for each parameter were defined based on adopted values in similar studies or from the default SWAT range. Parameter ranges were updated after each iteration of 500 simulations, which consists of 500 different combinations of parameters. Iterations were repeated until a sufficiently low R-factor was obtained, while still maximising the P-factor. Model performance was quantified in SUFI-2 using the Nash-Sutcliffe efficiency (NSE) objective function to minimise errors between observed and simulated values.

Streamflow was calibrated first, followed by TSS, and then both TN and TP as suggested by Santhi et al. (2001). After calibration of streamflow, the parameter ranges from the autocalibration were kept constant while the subsequent calibration of TSS was performed. Parameter ranges of streamflow and TSS were both kept constant for the calibration of TN and TP. Lastly, an iteration was performed on streamflow and all constituents and the best-fit parameter set determined based on the objective function (NSE). The model was calibrated against observed data from 2006 to 2014 and validated.
from 2015 to 2017. Due to a lack of water quality data over this time period in the Albert catchment, calibration of water quality variables was from 2006 to 2012 and validation from 2013 to 2015. The default range of parameter values and best-fit set are shown in Table D2 in the supplementary material. The ratio of the root mean square error to the standard deviation of the observed data (RSR), NSE, and percentage bias (PBIAS) were used to evaluate model performance of the best-fit set and compared to recommended values suggest by Moriasi et al. (2007). Visual inspections of the variability of the observed and simulated nutrient and sediment loads and concentrations were conducted using boxplots, which indicated if the model was able to reproduce the variability inherent in the observed event monitoring data. In addition, visual inspections were conducted of the simulated and observed relationships between streamflow and water quality constituents and between total suspended sediment and nutrients.

6.2.4 Climate Scenario Analysis
A total of 11 high-resolution climate projection datasets from the fifth phase of the Coupled Model Intercomparison Project (CMIP5) multi-model database were retrieved from the Queensland DES (Syktus et al., 2020; Table D1). The models were dynamically downscaled to a 10 km spatial resolution by Syktus et al. (2020) using the regional Conformal-Cubic Atmospheric Model and were run under the RCP8.5 and RCP4.5 emission scenarios, representing high and intermediate emission scenarios, respectively. These projections have been applied to assess future climate risk and inform regional adaption policies in Queensland (Trancoso et al., 2020, Eccles et al., 2021). Outputs of precipitation, solar radiation, minimum and maximum temperature, relative humidity, and pan evaporation were retrieved from the 11 climate models for the baseline (1980-2009) and three future periods representing the 2020s (2010-2039), 2050s (2040-2069), and the 2080s (2070-2099). Precipitation and temperature outputs were bias corrected by Syktus et al. (2020) using a quantile mapping technique (Piani et al., 2010). The same technique was applied to bias correct synthetic pan evaporation outputs from SILO, after which the pan coefficient (0.7) was applied to convert values to PET.

Catchment averaged precipitation and PET were calculated for each of the ensemble of 11 high-resolution climate models (Table D1) for the baseline period (1980-2010) and three future periods (2020s, 2050s, and 2080s) under both emission scenarios. Relative changes to catchment averaged precipitation and PET were evaluated for each month by comparing predicted future values to corresponding values in the baseline. Likewise, we considered the effects of climate change on streamflow, TSS, TN, and TP at the
Yarrahappini and Bromfleet stream gauges (Figure 6.1). Relative changes to the mean, 99th percentile (Q01), and 1st percentile (Q099) of streamflow were evaluated by comparing simulated future values in each of the three future periods to the simulated baseline values. Relative changes to mean and high (P01) quantiles of water quality constituents were also assessed. Changes to the seasonality of streamflow and water quality constituents were considered by determining monthly changes for each future period relative to the values in the baseline.

6.3 Results

6.3.1 Model Calibration and Validation

The performance statistics (RSR, NSE, and PBIAS) of the model for daily streamflow, TSS, TN, and TP are shown in Table 6.1, while the uncertainty statistics from the autocalibration procedure are presented in Table 6.2. NSE for streamflow was 0.607 and 0.862 during calibration and 0.727 and 0.791 during validation at the Logan and Albert sites, respectively, which is well above the satisfactory criteria recommended by Moriasi et al. (2007). Periods of low flow were generally overestimated by the SWAT model, particularly at Yarrahappini on the Logan River (Figure 6.2). Visual inspections of the variability in the observed event monitoring data and the corresponding simulated data indicated that SWAT was able to capture most of the variability in TSS, TN, and TP loads during calibration at the Yarrahappini and Bromfleet sites, though some of the largest events are not represented at the Yarrahappini site (Figure 6.3). Similar results are shown during the validation (Figure D1). Performance statistics, however, show unsatisfactory to satisfactory results for nutrient and sediment loads at the Yarrahappini site over the calibration period and unsatisfactory to very good results during validation (Table 6.1). At the Bromfleet site, unsatisfactory to very good results were obtained during calibration and unsatisfactory to good results during validation (Table 6.1).

The performance statistics of the model decreased in simulating concentrations of TSS and nutrients, and there was greater variability of both modelled and observed data. Concentrations of TSS and nutrients tended to be consistently underestimated at both sites (Figure 6.3). Visual inspections of the relationship between streamflow and concentrations of TSS, TN, and TP at both sites showed the model typically underestimated observed concentrations across all range of events (Figure 6.4). There was a reasonable match between the observed and simulated nutrient and sediment concentration, especially at the Bromfleet site (Figure 6.5), except during periods of low TSS concentration, when the model overpredicted TSS.
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Figure 6.2. Comparison of observed (blue) and simulated (red) streamflow discharge at the Logan River at Yarrahappini (top) and at the Albert River at Bromfleet (bottom) stream gauges for the calibration and validation periods.

Table 6.1. Statistical performance of SWAT for streamflow discharge, and sediment, and nutrient loads and concentrations during calibration and validation using the ratio of the root mean square error to the standard deviation of the observed data (RSR), Nash-Sutcliffe efficiency (NSE), and percentage bias (PBIAS). Performance was evaluated following Moriasi et al. (2007), where ‘a’ indicates unsatisfactory, ‘b’ indicates satisfactory, ‘c’ indicates good and ‘d’ indicates very good results.

<table>
<thead>
<tr>
<th>Modelling period</th>
<th>Stations</th>
<th>Performance criteria</th>
<th>Stream flow</th>
<th>Loads</th>
<th>Concentrations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration</td>
<td>Logan</td>
<td>RSR</td>
<td>0.62^b</td>
<td>0.844*</td>
<td>0.945*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NSE</td>
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<td>0.102*</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>59.209^a</td>
<td>62.956^b</td>
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<td></td>
<td>Albert</td>
<td>RSR</td>
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<td>0.428^d</td>
<td>0.432^d</td>
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<tr>
<td></td>
<td></td>
<td>NSE</td>
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<td>0.813^d</td>
<td>0.812^d</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PBIAS</td>
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<td>18.668^c</td>
<td>20.620^d</td>
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<tr>
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<td>0.924^a</td>
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<tr>
<td></td>
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<td>28.730^c</td>
<td>82.690^a</td>
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<td></td>
<td></td>
<td>NSE</td>
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<td>0.280^a</td>
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<tr>
<td></td>
<td></td>
<td>PBIAS</td>
<td>-37.226^a</td>
<td>30.777^b</td>
<td>26.246^c</td>
</tr>
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</table>

Table 6.2. Summary of uncertainty statistics for calibration and validation at the P-factor and R-factor statistics of SWAT on streamflow, sediment, and nutrient loads during model calibration and validation.
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<table>
<thead>
<tr>
<th>Stations</th>
<th>Performance criteria</th>
<th>Calibration period</th>
<th>Validation period</th>
</tr>
</thead>
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<tr>
<td></td>
<td></td>
<td>Streamflow</td>
<td>TSS</td>
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<td>Logan</td>
<td>P-factor</td>
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</tr>
<tr>
<td></td>
<td>R-factor</td>
<td>0.30</td>
<td>0.39</td>
</tr>
<tr>
<td>Albert</td>
<td>P-factor</td>
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<tr>
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<td>R-factor</td>
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</table>

Figure 6.3. Comparison of the variability present in the modelled and observed event monitoring data for loads and concentrations of TSS, TN, and TP during calibration at (a-f) Yarrahappini and (g-l) Bromfleet.

Figure 6.4. Relationship between streamflow and concentrations of (a) TSS, (b) TN, and (c) TP for observed (blue) and simulated (red) datasets for the Logan River at Yarrahappini and for (d) TSS, (e) TN, and (f) TP the Albert River at Bromfleet.
6.3.2 Changes to Precipitation and PET

Catchment averaged changes to precipitation and PET from the ensemble of climate models under RCP8.5 for the three future time periods, relative to the baseline, are presented in Figure 6.6. Decreases in winter and spring precipitation are predicted, with the largest decreases occurring by the 2080s. Precipitation in summer generally showed an opposing, increasing pattern, with the largest increases also occurring by the 2080s. These changes result in an amplification of the seasonality of precipitation, whereby during the winter dry season total precipitation decreases, while during the summer wet season it increases. During the 2020s, there was little agreement among the model ensemble on the directionality of change for precipitation, however, by the 2050s and the 2080s there was widespread agreement on the directionality of change in winter, spring, and summer, but not for autumn. Similar results occur for the RCP4.5 scenario (Figure D2), though the magnitude of the changes is smaller than those under the RCP8.5 scenario. Despite the variability of seasonal rainfall under different climate projections, multi-model median changes to annual precipitation were small (<4%) for the three future periods, indicating that the increases predicted for the summer wet season are sufficient to offset the decreases during the dry season. Changes predicted for PET are more consistent across the different seasons (Figure 6.6b). Annual PET is predicted to increase by 4.9% for the 2020s, 17.1% for the 2050s, and 29.5% for the 2080s, as assessed by the median values from the model ensemble. These values are larger than those of 5.8%, 10.9%, and 14.6%, respectively, for the three future periods under RCP4.5.
6.3.3 Effects of Climate Change on Streamflow

Changes to low, mean, and high flows were evaluated annually in each of the three future periods, relative to the baseline at the Yarrahappini (Logan River) and Bromfleet (Albert River) gauges, respectively (Figure 6.7). All streamflow quantiles were predicted to decrease in the future, and this decrease became most apparent by the end of the century. Most of the climate models predicted decreased streamflow by the 2050s and 2080s, whereas for the 2020s there was considerably less certainty in the directionality of change. A similar pattern was noted under RCP4.5 (Figure D4) though the magnitude of the decrease was generally less than that reported under RCP8.5 (Figure 6.7). Multi-model median changes to streamflow ranged between -1.7 and -16.2% for the 2020s, -8.8 and -40.5% for the 2050s, and -14.2 and -62.7% for the 2080s, depending on the streamflow quantile and river site assessed. These values were lower under RCP4.5 for the 2020s (-7.8 to -33.9%) and the 2050s (-6.3 to -48.3%), but decreases were smaller for the 2080s (-7.8 to -45.7%). The magnitude of the change varied for the different streamflow quantiles under both emission scenarios, with the largest decreases generally reported for low flow (Q99), while the decreases to mean flows and high flows (Q01) were less substantial.

Monthly relative changes to mean flows varied considerably throughout the year, with
the largest decreases coinciding with winter and spring for all future periods relative to the baseline. The greatest decreases occurred by the end of the century (Figure 6.8), largely reflecting the changes in precipitation (see Figure 6.6). However, decreases in streamflow were considerably greater than those for precipitation for all months, and increased precipitation in summer did not necessarily lead to an increase in streamflow. By the end of the century, multi-model median changes to mean flows are predicted to decrease by 24.4 and 17.8% in summer, 23.3 and 16.8% in autumn, 44.3 and 39.6% in winter, and 48.3 and 43.2% in spring for the Logan and Albert rivers, respectively. The RCP4.5 streamflow predictions generally followed the same seasonal patterns as the RCP8.5 predictions but with smaller decreases during the winter and spring months due to smaller decreases in precipitation and increases in PET.

Figure 6.7. Relative changes to simulated annual low (Q99), mean (QM), and high flows (Q01) from SWAT in the 2020s, 2050s, and 2080s relative to the baseline period from the ensemble of climate models under RCP8.5 at the (a) Yarrahappini and (b) Bromfleet gauges.
Figure 6.8. Relative changes to monthly simulated mean flows from SWAT in the 2020s, 2050s, and 2080s relative to the baseline period from the ensemble of climate models under RCP8.5 at the (a) Yarrahappini and (b) Bromfleet gauges.

6.3.4 Effects of Climate Change on Water Quality

Annual average TSS and TN loads were predicted to decrease at both sites in the three future periods under RCP8.5 (Figure 6.9). The largest decreases occurred by the 2080s and followed the same pattern of change as streamflow (Figure 6.7). Similar decreases were predicted for TP at the Yarrahappini (Logan River) site whereas changes in TP at the Bromfleet (Albert River) site were less certain, with several climate models predicting both increased and decreased loads in all future periods. Interestingly, predicted changes to TSS and TP loads appeared to be of a similar magnitude at Yarrahappini in the three future periods, but not at Bromfleet. Changes to high-quantile loads (P01) for TSS, TN, and TP followed the same pattern of change as the means, however, with larger decreases. By the end of the century, the annual median of TSS loads for the ensemble of models had decreased by 34.3 and 54.2% at the Logan and Albert sites, respectively (Table 6.3). This decrease was larger than that of TN and TP, which was 29.8 and 24.9%, respectively, at the Logan site and 30.4 and 4.3% at the Albert site. The decreases were generally smaller under RCP4.5, with TSS, TN, and TP loads decreasing by 25.3, 18.8, and 24%, respectively at Yarrahappini and changing by -52, -23.9, and 13%, respectively at Bromfleet (Figure D5).
Monthly relative changes to the TSS, TN and TP loads followed the seasonal pattern of change for streamflow in all future periods, where the largest decreases generally coincide with the winter and spring dry season and changes in the summer wet season are less certain (Figure 6.10). Multi-model median changes to mean loads were between -47.7 and -81.5% in winter and between -30.4 and -82.6% in spring, depending on the site and the constituent assessed by the 2080s (Table 6.3). The changes were more variable in summer (18.4 to -33.9%) and autumn (20.1 to -42.2%). Projected changes under RCP4.5 followed the same seasonal pattern of change as those for RCP8.5 (Figure D6), but with smaller decreases for winter and spring, in alignment with the smaller decreases in streamflow under this emissions pathway.

Figure 6.9. Relative changes to simulated annual average and high-quantile TSS, TN, and TP loads from SWAT in the 2020s, 2050s, and 2080s relative to the baseline period from the ensemble of climate models under RCP8.5 at the (a) Yarrahappini and (b) Bromfleet gauges.
Figure 6.10. Relative changes to simulated monthly average TSS, TN, and TP loads from SWAT in the 2020s, 2050s, and 2080s relative to the baseline period from the ensemble of climate models under RCP8.5 at the Yarrahappini (left) and Bromfleet (right) gauges.

Table 6.3. Predicted multi-model median change to streamflow (Q), total suspended solids (TSS), total phosphorus (TP), and total nitrogen (TN) at the Yarrahappini and Bromfleet sites by the 2080s under RCP8.5. Green colours indicate a decrease in loads, while red indicates an increase, with colour intensity showing the relative change.

<table>
<thead>
<tr>
<th>Month</th>
<th>Yarrahappini</th>
<th>Bromfleet</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q  TSS  TN  TP</td>
<td>Q  TSS  TN  TP</td>
</tr>
<tr>
<td>Jan</td>
<td>-30.7  -46.3  -31.9  -32.7</td>
<td>-30.4  -26.7  -4.4  -13.9</td>
</tr>
<tr>
<td>Feb</td>
<td>0.4   33.2   23.7   43.9</td>
<td>-11.2  21.2   37.0  119.7</td>
</tr>
<tr>
<td>Mar</td>
<td>-20.8  2.6   -18.5   -11.1</td>
<td>-13.4  -54.1  -48.8  18.8</td>
</tr>
<tr>
<td>Apr</td>
<td>-27.0  -63.8  -49.2  -40.6</td>
<td>-18.9  -82.8  -65.9  -65.9</td>
</tr>
<tr>
<td>May</td>
<td>-40.2  -43.2  -36.9  -38.0</td>
<td>-31.8  -81.8  -50.7  -49.6</td>
</tr>
<tr>
<td>Jun</td>
<td>-49.6  -56.2  -51.6  -56.0</td>
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</tr>
<tr>
<td>Jul</td>
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</tr>
<tr>
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</tr>
<tr>
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</tr>
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</tr>
<tr>
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<td>-46.7  -81.3  -72.2  -67.5</td>
</tr>
<tr>
<td>Dec</td>
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</tr>
<tr>
<td>Annual</td>
<td>-28.8  -34.3  -29.8  -24.9</td>
<td>-24.1  -54.2  -30.5  -4.4</td>
</tr>
</tbody>
</table>
6.4 Discussion

6.4.1 Changes to Precipitation, PET, and Streamflow
Projected changes to precipitation, PET, and streamflow under climate change will lead to changed sediment and nutrient regimes in river systems globally (Sinha et al., 2017, Teutschbein et al., 2017, Yang et al., 2017, Me et al., 2018). In the Logan-Albert catchment, the ensemble of climate models employed in this study indicated that precipitation was likely to vary seasonally in the future, with decreases predicted for winter and spring and increases in summer. Relative increases to PET were similar for all months of the year and had increased substantially by the 2050s and 2080s, although total increases in summer were larger than those in winter. Changes to streamflow largely followed the pattern of change predicted for precipitation, however, decreases were amplified during winter and spring and increases diminished in summer, reflecting the influence of elevated PET relative to the baseline. Subtropical regions typically already have high PET and highly seasonal rainfall, with distinct wet and dry seasons, and may therefore be particularly vulnerable to the further amplification of these factors.

In general, the SWAT model employed in this study overestimated low-flow events, especially at the Yarrahappini site (Figure 6.2). Similar results were noted by Shrestha et al. (2016) at the outlet of the Onkaparinga catchment, in temperate South Australia. SWAT has tended to underpredict streamflow in wet years and overpredict streamflow in dry years in Australian catchments (Das et al., 2013, Saha and Zeleke, 2015). Nguyen et al. (2017a) suggested that base-flow separation techniques in SUFI-2 can go some way to improving this shortcoming compared to traditional objective functions like the NSE, which can be skewed towards high flow events. Further studies specific to Australian conditions could test this technique to examine whether it improves predictions. Interestingly, the projected decreases to streamflow in winter and spring resulting from climate change in our study were less substantial than those derived from the conceptual Nedbør-Afstrømnings Model (NAM; DHI, 2019) hydrological model in the same catchment (Eccles et al., 2021), although projected changes in summer and winter were similar for the two models. This difference may relate to SWAT overestimating streamflow during low-flow periods, leading to lower predicted decreases during the dry season under climate change. These results highlight the importance of considering a range of hydrological models in climate change studies, as differing model structure can lead to varying results and requires careful interpretation.
6.4.2 Changes to Water Quality

Results from the SWAT model employed in this study to predict TSS, TN and TP loads and concentrations varied from unsatisfactory to very good during calibration and validation periods, according to recommended ranges for key performance statistics (Moriasi et al., 2007). However, these recommended ranges are intended to be applied to monthly simulation output, which have been shown to produce higher statistical performance than the daily simulations used in this study (Saha et al., 2014, Saha and Zeleke, 2015). In addition, the observed data used to calibrate and validate the model in this study consists of event monitoring data only. In subtropical SEQ the majority of diffuse loads are delivered from these events (Abal et al., 2005) and there is very high variability in the recorded measurements (Figure 6.3). No baseline monitoring data was available for typical low-flow or baseflow conditions, and therefore there was high variability in the observed data used to calibrate the model. Model performance may, therefore, may be moderate according to performance statistics (Table 6.2), but performance tends to be markedly poorer during high flow events (Me et al., 2015). Visual interpretation of the range of observed and modelled nutrient and sediment loads showed SWAT was able to capture the variability across the range of these events (Figure 6.3), although sediment and nutrient concentration were poorer and suggests some uncertainty in the directionality of change in predictions of these variables. For this reason, only changes to TSS, TN, and TP loads were considered in the climate change analyses, while changes to concentrations were not considered. It should be noted that models calibrated only to baseline monitoring data are likely to have similar, if not greater issues, as they lack the high-flow comparison to provide confidence in the model performance.

The predicted decreases in annual streamflow were accompanied by decreases in TSS, TN, and TP loads (Figure 6.9). Similar predictions of decreased streamflow and, by extension, nutrient loads have been described for catchments in temperate Australia (Shrestha et al., 2017, Nguyen et al., 2019), however, studies in subtropical Australian catchments are lacking. Changes to the seasonality of loads in our study also predominantly followed the pattern of change for streamflow, with the largest decreases noted in winter and spring and smallest changes coinciding with summer and was in line with our predicted hypothesis. Projected changes to TN and TSS loads were strongly correlated at the Logan River site relative to the Albert River site. This agrees with findings by Garzon-Garcia et al. (2015), who suggested that TSS export was the principal factor explaining nitrogen export, followed by rainfall and streamflow in the Knapp Creek
catchment, upstream of the Logan River. It should be noted that predicted changes to TSS, TN, and TP loads appeared to vary appreciably between the two sites, despite both being subject to similar patterns of change in terms of climate and streamflow conditions (Figure 6.8). The greatest differences related to TSS and TP, which are typically correlated with one another (Webster et al., 2001). This was the case for the Logan River, where TSS and TP showed moderate declines in loads (Figure 6.9). By contrast TSS loads were predicted to decrease considerably at the Albert River site, while changes to TP loads were uncertain. These differences may be explained by the independent calibration and parameterisation of the two catchments using the SWATCUP tool. Similar performance in the calibration and validation stages can be achieved through many different parameter combinations, in what has been termed parameter non-uniqueness (Abbaspour et al., 2007) or equifinality. This issue is pertinent because two different sets of parameter values can lead to similar results for a stationary climate (i.e., calibration and validation), but may lead to diverging outcomes under changing meteorological conditions (e.g., climate change).

Nutrient loads have increased considerably in the catchment following European settlement (Olley et al., 2015), which has led to high concentrations of turbidity and nutrients in the Logan-Albert estuary (Healthy Land & Water, 2019). While our predictions suggest diffuse loads may decrease, they are generally accompanied by similar levels of reduction in streamflow (Table 6.3). Low flushing rates (Eyre, 1998) and important point-source contributions can lead to a build-up of in-stream nutrient and sediment concentrations along the estuary, as occurred during the Millennium Drought (van Dijk et al., 2013, Eccles et al., 2020). This will increase the relative importance of point source inputs affecting water quality. Unless point source loads decrease by a similar level to those predicted for streamflow, there may be water quality issues associated with eutrophication along the Logan and Albert rivers, particularly during low-flow periods when flushing of nutrients is reduced. Predictions of future urbanisation may compound the issue, as Logan City is projected to grow by about 50% by 2036 compared to 2017 (Queensland Treasury, 2018), potentially increasing point pollutant loads. Two additional WWTPs are planned along the Logan River to accommodate for this population increase, which will likely require catchment nitrogen-offset schemes that would take a holistic approach to nutrient management in the Logan-Albert systems. Predictions of decreased loads noted in this study will have implications for such a scheme, as it will likely not achieve the same load reductions as noted under current conditions. Managers may
instead have to find alternative offsets programs or rely on WWTP upgrades.

6.4.3 Model Framework
This study employed an ensemble of 11 high-resolution dynamically downscaled climate models to assess climate change impacts. It was limited to considering high (RCP8.5) and intermediate (RCP4.5) emission scenarios, a single catchment model, and a single downscaling technique, all of which could bias (underestimate) the level of uncertainty. Climate models have been shown to be the largest source of uncertainty in climate impacts studies (Kay et al., 2009, De Niel et al., 2019). Nonetheless, it would be preferable if additional downscaling, bias correction, and catchment models could be employed to quantify this uncertainty. Differences between streamflow predictions using SWAT in this study and those using NAM (Eccles et al., 2021) highlight the importance of considering a range of models and techniques. Introducing additional ensembles of climate and hydrological models, as well as different downscaling/bias correction techniques can be time-consuming and costly and may not always be feasible.

Our study focused on the effects of a changing climate on streamflow and water quality using the SWAT catchment model. However, studies have shown that anthropogenic factors, notably land use change, can be just as influential on streamflow and water quality (Dimitriou and Mentzafou, 2016, Shrestha et al., 2017), including in catchments undergoing urbanisation (Nguyen et al., 2017b). The Logan-Albert catchment is expected to undergo significant urbanisation over coming decades (Queensland Treasury, 2018). There is a need for further research to evaluate the impacts of urbanisation on water quality under current and future climatic conditions. Additionally, agricultural practices and land uses will not remain stationary under a changing climate. In this study we assumed land use and cropping practices did not change. Future research could also examine the influences that a change in agricultural practices and land use types have on downstream water quality, particularly with changes in rainfall patterns and a warmer climate, which may render some current practices and crops unsuitable in the future (Fischer et al., 2005). Effluent from WWTP point sources has been shown to be an important driver of water quality change along the Logan and Albert estuaries (Eccles et al., 2020). Future research could extend the SWAT boundaries to consider the impacts of point source loads throughout the catchment on in-stream nutrient and sediment concentrations under current and future catchment conditions, particularly under scenarios of decreased streamflow. The application of 2-dimensional coupled hydraulic-water quality models may be useful to examine these processes in estuarine conditions.
6.5 Conclusion

This study provides one of the first assessments of the impacts of climate change on nutrient and sediment loads and concentrations in a subtropical Australian catchment. The distributed SWAT catchment model showed streamflow was likely to have greater seasonal variability in the future, reflecting changes to precipitation, with the largest changes occurring by the 2080s. Streamflow decreased most during winter and spring but less so in summer. Projections of nutrient and sediment loads generally followed the seasonal pattern of change noted for streamflow, with the largest decreases coinciding with winter and spring, as well as by the 2080s. Changes during summer were less certain in all future periods. These changes represent and amplification of the seasonality of precipitation, streamflow, and pollutant loads, which are already highly seasonal in subtropical river systems. This presents a significant issue for water managers from an environmental perspective as the relative importance of point source contributions is set to increase, particularly during the dry season when flows and diffuse pollutant loads decrease considerably. There is potential for significantly degraded water quality should point load contributions increase in the future as a result of population increases as predictions for reduced flows may mean there is insufficient baseline flushing to effectively flush nutrients from the system.

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7.1 Overview
This chapter describes the main outcomes and future directions resulting from the research. Section 7.2 reiterates the research objectives outcomes. Section 7.3 describes the implications of this research. Lastly, Section 7.4 discusses some of the limitations of the research and provides possible future research directions.

7.2 Research Objectives and Outcomes

7.2.1 Objectives
The four principal objectives of this research project were as follows:

1. To understand current techniques and limitations relating to climate change impact studies on a subtropical catchment.

2. To identify and understand historical hydrological and water quality drivers in a subtropical catchment (such as Logan-Albert catchment, South East Queensland (SEQ)).

3. To develop and apply a coupled river and floodplain model to investigate climate change impacts on flooding.

4. To development and implement a mechanistic catchment model to understand the effects of climate change on water quality.

The outcome of these objectives is an improved understanding of the effects of climate change on hydrology and water quality in a subtropical SEQ catchment. The work represents an impact assessment of climate change for a climate-vulnerable subtropical Australian catchment. Implementation of ensemble high-resolution climate models for the region allowed for a range of possible future climates to be accounted for. Assessments of the impacts of these changes on flooding and water quality were informed by analyses of the current catchment conditions, highlighting a number of issues relating to elevated nutrient and sediment loads. The modelling results from this project can be used to help inform future preparedness and adaptation strategies of local and regional water authorities and councils to changes in flooding and drought expected with future climate change.
7.2.2 Climate Change Impact Studies
The first stage of the project was to systematically quantify literature for climate change studies on flooding in subtropical and tropical regions. The results of the literature are described in Chapter 3. They are useful in informing which methodologies are best suited for hydrological impact assessments in SEQ. Furthermore, limitations and benefits of the most commonly adopted techniques are discussed and future directions for research in the field are identified. The results of the literature search helped inform the methodologies applied in the flood and water quality impact assessments presented in Chapter 5 and Chapter 6, respectively.

The review showed that the effects of climate change varied significantly across the regions of the tropics and subtropics, with the most consistent increases in flooding predicted for South Asia, South East Asia, and the western Amazon. There was a notable paucity of studies for regions in Africa, Latin America, and particularly in Australia where just one study was found, highlighting the need for more information from this country and from the identified regions generally. The majority of the research was conducted on large catchments and there was a need to further understand the effects of climate change on smaller to mid-sized catchments, such as the Logan-Albert (SEQ). It was noted that most of the research considered only the hydrological response to changing precipitation and evaporation, with relatively little research on flood propagation and even fewer studies on potential synergistic impacts of sea level rise.

7.2.3 Current Water Quality and Hydrological Conditions
Chapter 4 describes a comprehensive analysis of long-term water quality trends for the Logan-Albert estuary. Elevated sediment and nutrient loads were recognised as the principal issues facing water quality managers due to their potential to cause eutrophication and lead to decreases in biodiversity. Consequently, a better understanding of the spatial and seasonal patterns and long-term trends of turbidity and nutrient constituents was considered crucial in determining the principal drivers of water quality change. Consideration of the impacts of a recently (in 2010) constructed upstream dam on estuarine water quality was also vital to understand if changing water quality was from the dam, other anthropogenic, or climatic factors.

The application of the seasonal Mann-Kendall test at 15 water quality monitoring sites throughout the Logan-Albert estuary was used to reveal spatial trends among sites. A significant downward trend was observed for many of the water quality constituents along
the upper and middle Logan estuary and along the lower Albert estuary. Results from a Generalised Additive Model were similar to those of the seasonal Mann-Kendall test, providing additional independent validation of these findings. Significant improvements at the upstream Logan estuary site compared to the upstream Albert estuary site were principally attributed to the impoundment of Wyaralong Dam in the upper Logan catchment, which acted as a sediment and nutrient sink over the study period. Conversely, improvements in water quality along the lower Albert estuary, particularly reductions of total phosphorus and oxidised nitrogen, were predominantly attributed to wetter conditions over the second half of the study. Increase streamflow improved flushing from the system and effectively diluted point-source loads from a nearby wastewater treatment plant (WWTP). A combination of decreased effluent loads from the WWTP, wetter conditions, and dam impoundment contributed to water quality improvements along the middle Logan estuary. The results obtained from this analysis showed how estuarine water quality is highly dynamic, with interactions between climatic and anthropogenic factors necessitating long-term monitoring to disentangle the drivers.

7.2.4 Climate Change and Flooding
This study was focused on determining the likely impacts of climate change on flooding by applying numerical modelling techniques, and focusing on the variables of high flow, flood magnitude, and floodplain inundation. The impacts of sea level rise and storm surge events on floodplain inundation were also considered to more thoroughly include major drivers of flooding associated with climate change (see Chapter 3). A novel coupled 1D-2D hydrodynamic model was developed and linked to a hydrological model of the catchment. The methodology, calibration, and results of these models are described in Chapter 5.

Through the validated hydrological model, the impacts of changing precipitation and evaporation under high (Representative Concentration Pathway 8.5 - RCP8.5) and intermediate-emission (RCP4.5) scenarios from an ensemble of 11 climate models were analysed and discussed. Changes in three future periods representative of the 2020s, 2050s, and 2080s were assessed relative to a baseline period (1980-2010). The coupled model simulations indicated that there was likely to be an amplification in the seasonality of precipitation, with increases over the summer wet season and decreases coinciding with the dry season in winter and spring. The changes to high flows largely followed the pattern of change noted for precipitation. However, decreases to high flows were substantially greater during the dry season than those noted for precipitation, while
increases were diminished. This indicated the importance of rising temperatures and consequently increased evaporation in mitigating future high flows.

While there was a general model consensus towards decreased high flows, particularly by the 2050s and 2080s, the same consensus was not seen for changes to different average recurrence intervals (ARI) flood events. Rather, there was considerable variation of the model ensemble outputs for predictions of major flooding events ranging between 5 and 100-year ARIs. The largest flooding events tended to increase in magnitude in the future while the smallest tended to decrease. Multi-model changes to the magnitude of 100-year ARI flood events were used to predict future floodplain inundation. Floodplain inundation increased in all scenarios considered and the inclusion of sea level rise in the simulations resulted in a near doubling of the inundation area by the end of the century, highlighting the importance of including sea level rise in considerations of future flooding of coastal catchments. These findings have major implications for flood risk and show the need for comprehensive assessments at the floodplain scale, including sea level rise and storm surge considerations, when informing future flood preparedness.

7.2.5 Climate Change and Water Quality
This study focussed on determining the impacts of climate change on total suspended sediment (TSS), total nitrogen (TN), and total phosphorus (TP) loads. The Soil Water Assessment Tool (SWAT) catchment model was employed to simulate streamflow and diffuse pollutant loads in the upper and middle Logan and Albert catchments under current and future climate conditions. The methodology, calibration, and results of this study are presented in Chapter 6.

Through the validated SWAT model, the impacts of atmospheric climate change were evaluated and discussed using the same ensemble of 11 climate models applied in Chapter 5 under the RCP4.5 and RCP8.5 emission scenarios. Three future scenarios representative of the 2020s, 2050s, and 2080s were evaluated and compared to a baseline period (1980-2010). Model simulations showed that changes to streamflow were likely to follow the seasonal pattern of change predicted for precipitation in all future periods, with amplified decreases in the dry season and diminished increases in summer due to increased evaporation. These findings were similar to those from the hydrological model employed in Chapter 5, though predicted decreases in streamflow during the winter and spring dry season were less substantial using SWAT. These changes could have significant consequences for in-stream water quality, particularly downstream around point source
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contributions. A reduction of flows during low flow periods, may lead to point sources dominating and a build-up of concentrations in and around major point sources, such as WWTPs, as catchment flows may not be able to effectively dilute and flush these pollutants from the system. This is particularly concerning as point source inputs are often composed of more bioavailable dissolved forms of nutrients, which more readily cause eutrophication and other environmental issues.

Relative changes to TN, TP, and TSS loads reflected the pattern of change predicted for streamflow, with the largest decreases coinciding with the dry season and the smallest changes occurring during the wet season. By the 2080s annual TSS loads were predicted to decrease by 34.3 and 54.2% at the Logan and Albert rivers, respectively. By comparison TN loads decreased by 29.8 and 30.5%, while TP loads decreased by 24.9 and 4.4% at the two sites. These changes are largely in line with those predicted for streamflow and as such changes to in-stream concentration derived from diffuse sources is not likely to change significantly. As stated previously, these reductions imply a shift in the relative importance of loads to the system from diffuse to point sources, which may have important consequences for water quality.

7.2.6 Model Comparison

NAM is a conceptual hydrological model that divides catchments into sub catchments and lumps rainfall and rainfall-runoff parameters for each sub catchment. By contrast, SWAT is a physically based semi-distributed catchment model intended largely for water quality studies, though often used for studies on hydrology. This model splits catchments up into hydrological response units (HRUs), that represent various combinations of slope, land use, and soils and appropriately assigns rainfall-runoff parameters based on these HRUs. Gridded rainfall may be applied in the model that is not possible in NAM. The set-up, calibration, and validation of the SWAT model is considerably more involved than that of the NAM model as there are many times more parameters to be calibrated and much more input data required. Nonetheless, both models achieved generally good results in simulating streamflow during calibration and validation as noted in Chapter 5 and Chapter 6, though the performance of the NAM model was superior. As such, application of the NAM model is considered more appropriate for studies on hydrology in small to medium sized catchments due to its ease of use and performance. However, in larger catchments care should be taken when adopting NAM to ensure that there are adequate sub-catchments to correctly represent catchment features and precipitation variability. In-stream routing (attenuation) must also be considered more thoroughly in larger
catchments. The SWAT model is more appropriately adopted for studies on water quality or land use changes.

Due to the number of parameters that need to be calibrated many researchers choose to adopt auto-calibration schemes to automate the calibration process when using SWAT. A drawback of this, however, is that it can result in parameter non-uniqueness, whereby different parameter combinations can lead to similar model outcomes when run under the same period of record. This becomes an issue when ‘calibrated’ models are extrapolated beyond the period in which they were originally calibrated as the various combinations of parameter sets can lead to diverging model outcomes under changed climatic of catchment conditions. Researchers should be more wary of this issue, particularly when extrapolating calibrated models to assess climate change impacts.

### 7.3 Implications

In recent decades there has been a considerable increase globally in studies assessing climate change impacts on both flooding and water quality. However, studies in subtropical Australia are few or are limited in their scope. My research provides new insights into potential future flood dynamics in this relatively unstudied region. The impacts of climate change on flooding, low flow and water quality are likely to be considerable throughout SEQ, particularly when combined with the likely impacts from a growing population.

#### 7.3.1 Flooding

Climate change was widely shown to lead to increased flooding throughout most subtropical and tropical regions of the globe. The additional impacts of sea level rise and anthropogenic activities (e.g., construction of hydraulic structures, land use change, urbanisation) may further exacerbate flooding in many of these regions. These changes may in some cases act synergistically and could be devastating in many developing countries located in the tropics and subtropics, which already experience poor governance and rapidly growing populations. Ideally, adaptation strategies could be developed to mitigate the economic and social costs of predicted climate change. These plans ought to be flexible in order to consider the full range of possible eventualities and account for future advancements in climate modelling. However, such plans are unlikely to be implemented in many of the developing nations of the tropics and subtropics as they understandably prioritise more immediate short-term issues. Failure to plan now, however, may have drastic implications on the future livelihoods and economies of
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inhabitants in these regions.

In the Logan-Albert catchment, the predicted changes to flooding necessitate immediate consideration by managers and residents across the catchment and region. Extreme flood magnitudes were predicted to increase in the future, mostly along the lower southern floodplain, which is currently primarily used for sugarcane production. Increased inundation in this region may be especially large when the additional effects of sea level rise are factored in. More frequent inundation of this low-lying floodplain poses a risk to sugarcane growers, which is compounded by the likely increases in saline intrusion associated with rising sea levels and could lead to salinity contamination of coastal freshwater aquifers. These predicted changes raise questions over the long-term sustainability of sugarcane plantations along this low-lying coastal floodplain area.

An increase in the most extreme flood magnitudes is also likely to be associated with more frequent flooding of residential and commercial properties in parts of the catchment. This increase has implications for insurance premiums as well as potentially affecting property valuations. Significant urbanisation and population growth are predicted around Logan City, which may exacerbate flooding effects by increasing the impervious area and potentially the number of properties at risk. However, it is also important to note that the projections under climate change are not deterministic and that there is high uncertainty associated with these predictions. The uncertainty deriving from the ensemble of climate models was assessed in Chapter 5 and showed high uncertainty with projections of both increased and decreased flooding for the 2020s, 2050s, and 2080s. As such, it is also possible that flood magnitudes may decrease in the future.

7.3.2 Water Quality

The statistical analysis of water quality trends in the Logan-Albert estuary provides a useful technique to differentiate the various drivers of change. From the analysis described in Chapter 4 it is evident that periods of low flow are associated with degraded water quality, particularly at locations around the WWTPs. Climate change is predicted to lead to a decrease in precipitation in the dry season and decreased annual mean flow. Flow decreases will be largest during the dry season as is evident by the results in Chapter 5 and 6. The result may be a build-up of in-stream nutrient concentrations around point source such as WWTPs as natural inflows are unable to effectively dilute WWTP outputs. The relative importance of all point sources is likely to increase in the future as diffuse loads are predicted to decrease, particularly during the winter dry season. Point source
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loads may jointly increase on account of urbanisation and population increases, which will further increase the relative importance of these contributions. In addition, two new WWTPs are planned along the upper Logan estuary to accommodate for this population increase, potentially increasing effluent loads to the system. Increased effluent load and decreased flushing may therefore act synergistically in the future to exacerbate poor water quality along the Logan-Albert estuary and could increase the potential for further eutrophication.

7.3.3 Dam Operation

Increased magnitudes of the most extreme flood events in the future will also have important consequences for dam operation in the region, as they may necessitate operations at a lower maximum storage capacity to accommodate larger floods. This will, however, have negative implications on water supply by diminishing the long-term water reserves. Annual precipitation in the region is not predicted to change substantially under climate change, however, evaporation rates are predicted to increase considerably. This will lead to reduced inflows to the region’s dams and increased losses from evaporation, both of which will add stress to water supply. While annual precipitation is not predicted to change significantly, the seasonality of precipitation is likely to intensify. Greater inflows are therefore likely during the summer wet season, and lower inflows are predicted during the dry season of winter and spring. This intensification of seasonal flows may lead to excessive inflows and dam spillage in summer and a lack of supply in winter and spring. Additionally, future population growth predicted for the catchment and the wider region will require additional sources of water supply. Construction of new dams is often controversial, due to their environmental impacts and is also constrained as many natural water courses in the region are already utilised as water storages. As such, water suppliers may have to rely more so on non-traditional water supply methods, such as desalination and water reclamation, both of which are climate-resilient and have had infrastructure developed throughout the region during the 2009 Millennium Drought.

Water quality considerations are another factor that might potentially influence dam operation. Currently, Wyaralong Dam acts as a sink for nutrients and sediments, as is often the case when dams are relatively young. However, the efficiency of trapping sediment and nutrients is likely to decrease and in the long-term some sort of equilibrium is likely. Managers should therefore avoid assessing downstream water quality based on the current water quality of discharges from Wyaralong Dam. The dam does, however, have the potential to assist mitigation of the build-up of in-stream nutrient concentrations
around WWTPs during the dry season as previously discussed, by providing periodic flushing flows. The capacity to provide flushing flows will be a careful balance of implications on water supply and the balance of environmental and social considerations.

7.4 Future Research Directions
The climate change impact assessments described in this study made use of an ensemble of high-resolution dynamically downscaled climate outputs under two emission scenarios. These outputs allowed for uncertainty to be assessed from differences among climate models, which is widely held to be the largest source of uncertainty (Kay et al., 2009, Aich et al., 2016). However, only single downscaling, bias correction, and hydrological model approach was employed in this project. These steps in the model chain are also associated with uncertainty, though generally to a lesser degree. It would be preferable if additional downscaling techniques (e.g. statistical), bias correction techniques, and hydrological models were employed to assess the uncertainty associated with these individual procedures. Future research could consider these additional sources of uncertainty in a systematic way, similar to that carried out for climate models.

The impact studies presented in this project also considered the catchment to be stationary, whereby anthropogenic and geomorphic changes over the model simulation period are not considered. In reality, a wide variety of anthropogenic changes are likely to occur within the catchment that would influence both future flooding and water quality. For example, there is predicted to be considerable urbanisation over the next 20 years due to significant population growth around Logan City. Urbanisation is associated with an increase in impervious surfaces, which affects the timing and magnitude of flood peaks. Population increases may also lead to elevated effluent loads from WWTPs, impacting estuarine water quality. It would therefore be beneficial for future research to directly examine the impacts of predicted urbanisation on both flooding and water quality. For example, a sensitivity analysis of changing porosity in the urban catchment could be conducted. Agricultural practices and land uses will generally not remain stationary, but are even less likely to remain stationary under a changing climate. The SWAT catchment model employed in this project, however, assumed fertiliser application rates and land use did not change. Future research could also examine what influences these practices have on downstream water quality, particularly, as a changing climate may render some current agricultural practices and crops impractical in the future due to changes in temperature and water supply. It would also be of interest to examine the long-term feasibility of water takes (e.g. irrigation and bottle water) within the catchment given the
predicted changes to water supply.

This study also employed a stationary approach to flood frequency analysis, whereby the distribution of the flood frequency curves is assumed to be invariant for a given period. However, continually changing climatic and hydraulic conditions may render this assumption unreasonable, particularly if large scale anthropogenic changes need to be considered. Adoption of non-stationary flood frequency techniques may be more appropriate in these instances, particularly if changes to urbanisation and land use are to be considered.

It is also important to note that the SWAT catchment model domain covered only the upper and middle sections of the Logan and Albert catchments. Point source contributions and loads derived from downstream sources (where the majority of the population lives) were therefore not considered. Extending the catchment model downstream and including major WWTP point sources would allow for the predicted impacts of urbanisation on water quality to be assessed.

Currently, WWTP operators often make use of catchment offset schemes through remediation works of the upper catchment to offset effluent emissions from WWTP discharges downstream (May et al., 2017). There is an opportunity to assist such programs through the SWAT model developed in this project by identifying regions of high sediment/nutrient loads that may be suitable for remediation. However, it must be noted that WWTPs principally discharge more bioavailable dissolved forms of nutrients, while diffuse sources contain more particulates. As such, offsets of TN or TP may have to be an order or magnitude larger from diffuse sources to account for these differences and ensure similar environmental outcomes. Additionally, the impacts of climate change on the effectiveness of such offset schemes warrant further examination. Increased seasonality and reduced streamflow are predicted as a result of climate change. A decrease in streamflow is likely to reduce the benefits of these schemes as catchment loads are closely linked to streamflow. In addition, water quality around these WWTPs is poorest in the dry season when the benefit of reducing diffuse loads is largely inconsequential due to low rainfall and runoff. Further research is needed to examine the long-term viability of these nutrient offset programs giving a changing climate.

The climate change predictions described in this project will have a broad range of implications for dam operations in the region, but detailed assessment of dam operation was considered outside the scope of this research. There is a specific need to quantify the
combined effects of predicted population growth and climate change (rainfall and evaporation changes) on water security in the region, especially considering widespread predictions of more prolonged droughts in the future (Dai, 2013, Naumann et al., 2018). The impacts that predicted changes to extreme flood events will have on dam safety, operating levels, and flood mitigation also warrants further examination. Lastly, the ability of these dams to assist in providing periodic environmental flows to flush out excessive nutrients and prevent eutrophication requires further research.
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Appendices

This section presents supplementary materials for the preceding chapters and an additional publication which provided additional information to assist in understanding the results of this PhD research.

Appendix A
Supplementary materials for the Chapter 3 research article:


Appendix B
Supplementary materials for the Chapter 4 research article:


Appendix C
Supplementary materials for the Chapter 5 research article:


Appendix D
Supplementary materials for the Chapter 6 research article:

**ECCLES, R., ZHANG, H., HAMILTON, D., TRANCOSO, R. & SYKTUS, J.** 2021. Impacts of climate change on sediment and nutrient loads from a subtropical catchment. *(to be submitted to Science of the Total Environment).*

Appendix E
## Appendix A

### Appendix A1: List of Acronyms Used

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
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<tbody>
<tr>
<td>1K-FRM</td>
<td>1-Km distributed Flow Routing Model</td>
</tr>
<tr>
<td>BCC-CSM</td>
<td>Beijing Climate Centre-Climate System Model</td>
</tr>
<tr>
<td>BNU-ESM</td>
<td>Beijing Normal University-Earth System Model</td>
</tr>
<tr>
<td>BTOP</td>
<td>Block-wise use of TOPMODEL (TOPography based hydrological MODEL)</td>
</tr>
<tr>
<td>CaMa-Flood</td>
<td>Catchment-based Macro-scale Floodplain model</td>
</tr>
<tr>
<td>CCCma</td>
<td>Canadian Centre for Climate Modelling and Analysis</td>
</tr>
<tr>
<td>CCLM</td>
<td>Consortium for Small Scale Modelling-Limited-area Modelling</td>
</tr>
<tr>
<td>CCSM</td>
<td>Community Climate System Model</td>
</tr>
<tr>
<td>CGCM</td>
<td>Canadian Global Climate Model</td>
</tr>
<tr>
<td>CLIRUN</td>
<td>Climate Runoff Model</td>
</tr>
<tr>
<td>CSIRO-Mk</td>
<td>Commonwealth Scientific and Industrial Research Organisation</td>
</tr>
<tr>
<td>COSMO-CLM</td>
<td>Consortium for Small-scale MOdelling in CLimate Mode</td>
</tr>
<tr>
<td>CORDEX</td>
<td>Coordinated Regional Downscaling Experiment</td>
</tr>
<tr>
<td>DBH</td>
<td>Distributed Biosphere-Hydrological Model</td>
</tr>
<tr>
<td>DHSVM</td>
<td>Distributed Hydrology Soil Vegetation Model</td>
</tr>
<tr>
<td>ECHAM</td>
<td>European Center Hamburg</td>
</tr>
<tr>
<td>EIA3D</td>
<td>Environmental Impact Assessment 3D</td>
</tr>
<tr>
<td>GBHM</td>
<td>Geomorphology-Based Hydrological Model</td>
</tr>
<tr>
<td>GLOFRIS</td>
<td>Global Flood Risk with IMAGE Scenarios</td>
</tr>
<tr>
<td>GR4j</td>
<td>Génie Rural à 4 paramètres Journalier</td>
</tr>
<tr>
<td>HadAM</td>
<td>Hadley Centre Atmospheric Model</td>
</tr>
<tr>
<td>HadCM</td>
<td>Hadley Centre Climate Model</td>
</tr>
<tr>
<td>HadGEM</td>
<td>Hadley Centre Global Environmental Model</td>
</tr>
<tr>
<td>HadRM</td>
<td>Hadley Centre Regional Model</td>
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<tr>
<td>HBV</td>
<td>Hydrologiska Byråns Vattenbalansavdelning</td>
</tr>
<tr>
<td>HEC-HMS</td>
<td>Hydrologic Engineering Centre-Hydrologic Modelling System</td>
</tr>
<tr>
<td>HEC-RAS</td>
<td>Hydrologic Engineering Centre-River Analysis System</td>
</tr>
<tr>
<td>HMET5</td>
<td>Hydrology Model-École de Technologie Supérieure</td>
</tr>
<tr>
<td>HRM</td>
<td>Hadley Regional Model</td>
</tr>
<tr>
<td>HYPE</td>
<td>HYdrological Predictions for the Environment</td>
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<tr>
<td>HYMOD</td>
<td>HYdrological MODel</td>
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<tr>
<td>IGSM</td>
<td>Integrated Global Systems Model</td>
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<tr>
<td>IISDHM</td>
<td>IIS Distributed Hydrological Model</td>
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<tr>
<td>INCA</td>
<td>INtegrated CAtchment Model</td>
</tr>
<tr>
<td>JMA</td>
<td>Japanese Meteorological Agency</td>
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<tr>
<td>JULES</td>
<td>Joint UK Land Environment Simulator</td>
</tr>
<tr>
<td>LASH</td>
<td>Lavras Simulation of Hydrology</td>
</tr>
<tr>
<td>LPJml</td>
<td>Lund-Potsdam-Jena Managed Land</td>
</tr>
<tr>
<td>Mac-PDM</td>
<td>Macro-Scale-Probability Distributed Moisture Model</td>
</tr>
<tr>
<td>MATSIRO</td>
<td>Minimal Advanced Treatments of Surface Interaction and Runoff</td>
</tr>
<tr>
<td>MGB-IIP</td>
<td>Portuguese for Large Basins Model and Institute of Hydraulic Research</td>
</tr>
<tr>
<td>mHM</td>
<td>mesoscale Hydrologic Model</td>
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<tr>
<td>MIKE SHE</td>
<td>MIKE Système Hydrologique Européen</td>
</tr>
<tr>
<td>MIROC</td>
<td>Model for Interdisciplinary Research on Climate</td>
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<tr>
<td>MM5</td>
<td>Mesoscale Model5</td>
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<tr>
<td>MRI-AGCM</td>
<td>Meteorological Research Institute-Atmospheric General Circulation Model</td>
</tr>
<tr>
<td>MPI-HM</td>
<td>Max Planck Institute-Hydrology Model</td>
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<tr>
<td>NAM</td>
<td>Nedbør-Afstrømings-Model</td>
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<tr>
<td>NFS</td>
<td>Nile Forecast System</td>
</tr>
<tr>
<td>ORCHIDEE</td>
<td>Organised Carbon and Hydrology in Dynamic Ecosystems</td>
</tr>
<tr>
<td>PCR-GLOBWB</td>
<td>PCRaster Global Water Balance</td>
</tr>
<tr>
<td>PDHM</td>
<td>Parameter Distributed Hydrological Model</td>
</tr>
<tr>
<td>PERSISt</td>
<td>Pan-European Runoff Simulator for Solute Transport</td>
</tr>
<tr>
<td>PRECIS</td>
<td>Providing Regional Climates for Impact Studies</td>
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<tr>
<td>PRMS</td>
<td>Precipitation Runoff Modeling System</td>
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<tr>
<td>RCA</td>
<td>Rossby Centre regional Atmospheric Climate Model</td>
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<tr>
<td>RegCM</td>
<td>Regional Climate Model</td>
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<tr>
<td>RFM</td>
<td>River Flow Model</td>
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<tr>
<td>RISE</td>
<td>Rice Irrigation System Evaluation Model</td>
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<tr>
<td>RORB</td>
<td>Runoff Routing Model</td>
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<tr>
<td>RR1</td>
<td>Rainfall-Runoff-Inundation</td>
</tr>
<tr>
<td>SLURP</td>
<td>Semi-distributed Land Use-Based Runoff Processes</td>
</tr>
<tr>
<td>STREAM</td>
<td>Spatial Tools for River Basins Environmental Analysis and Management</td>
</tr>
<tr>
<td>SWAT</td>
<td>Soil and Water Assessment Tool</td>
</tr>
<tr>
<td>SWIM</td>
<td>Soil and Water Integrated Model</td>
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<tr>
<td>TOPMODEL</td>
<td>Topography based hydrological MODEL</td>
</tr>
<tr>
<td>TRIP</td>
<td>Total Runoff Integrating Pathways</td>
</tr>
<tr>
<td>VIC</td>
<td>Variable Infiltration Capacity</td>
</tr>
<tr>
<td>WaSIM</td>
<td>Water Balance Simulation Model</td>
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<td>WASMOD</td>
<td>Water and Snow Balancing System</td>
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<tr>
<td>WaterGAP3</td>
<td>Water a Global Assessment and Prognosis</td>
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<tr>
<td>WATLAC</td>
<td>Water Flow Model for Lake Catchments</td>
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<tr>
<td>WBM</td>
<td>Water Balance Model</td>
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<tr>
<td>WEHY</td>
<td>Watershed Environmental Hydrology</td>
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<tr>
<td>WRF</td>
<td>Weather Research and Forecasting Model</td>
</tr>
<tr>
<td>YHyM</td>
<td>University of Yamanashi Distributed Hydrological Model</td>
</tr>
<tr>
<td>XAJ</td>
<td>Xinanjiang Model</td>
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**Appendix A2: Tables A1-A6**

*Table A1. Climate change impact studies assessing flooding in East Asia.*

<table>
<thead>
<tr>
<th>Country / Region / Catchment</th>
<th>GCM / RCM (Climate Change Scenario)</th>
<th>Statistical / Dynamic Downscaling or Bias Correction Method</th>
<th>Hydrological Model and Approach</th>
<th>Flood Analysis Method</th>
<th>Key Findings for Future Climate Scenario</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>China 10 Major River Basins</td>
<td>Ensemble of 5 GCMs (RCP 2.6, RCP 8.5)</td>
<td>A trend preserving bias correction technique (Hempel et al., 2013)</td>
<td>DBH, H08, Mac-PDM, MATSIRO, MPI-HM, PCR-GLOBWB, VIC, WBM</td>
<td>Flood frequency analysis (AM with GEV distribution)</td>
<td>Increases in 5, 20, 30, and 50-year flooding events in subtropical South China despite decreases in annual rainfall by 2100.</td>
<td>(Li et al., 2016a)</td>
</tr>
<tr>
<td>China Qu River Basin</td>
<td>Ensemble of 4 GCMs (RCP 4.5, RCP 8.5)</td>
<td>Downscaling with LARS-WG to generate 50 years of daily data</td>
<td>GR4J (lumped conceptual rainfall-runoff model) and a 1-D hydraulic model</td>
<td>Flood frequency analysis (daily POT3 with Generalised Pareto distribution)</td>
<td>Increase in the magnitude of 20-year flood by 2050 for two sub-basins. Results for 50-year events are more uncertain, but still tend towards an increase.</td>
<td>(Gao et al., 2018)</td>
</tr>
<tr>
<td>China Huaihe River Basin</td>
<td>Ensemble of 16 GCMs downscaled with PRECIS RCM (A2, B2)</td>
<td>RCM outputs gridded to 50 km no bias correction</td>
<td>VIC (semi distributed hydrological mode)</td>
<td>Flood frequency analysis (daily AM with Pearson Type III distribution)</td>
<td>Flood frequency and flood magnitude increased under both emission scenarios by 30 to 40% for the 2030s.</td>
<td>(Lu et al., 2013)</td>
</tr>
<tr>
<td>China Upper Huai River Basin</td>
<td>CSIRO-Mk3.5 and CCCma-CGCM3.1 (A2, A1B, B1)</td>
<td>Stochastic weather generator, (LARS-WG) with delta change method</td>
<td>HBV (conceptual semi distributed rainfall-runoff model)</td>
<td>Copula approach to flood frequency analysis using AM series</td>
<td>Large increases in 50 and 100-year flood events with CSIRO-MK3.5 by 2100, while CCCma-CGCM3.1 projects uncertain changes. Declines in small 3-year flooding events for both GCMs.</td>
<td>(Kai et al., 2016)</td>
</tr>
<tr>
<td>China Beijiang River Basin</td>
<td>Ensemble of 24 GCMs (A1, RCP 2.6, RCP 4.5, RCP 8.5)</td>
<td>Stochastic weather generator run from weighted GCMs using Bayesian model averaging interpolated to a 0.25° grid</td>
<td>VIC (semi distributed hydrological mode)</td>
<td>Flood frequency analysis (daily AM with Pearson Type III distribution)</td>
<td>500-year flood events increase between 4.3 to 9.2% by 2050. 5000-year flood events increase by as much as 12.6% under RCP4.5.</td>
<td>(Wu et al., 2014)</td>
</tr>
<tr>
<td>China Beijiang River Basin</td>
<td>Ensemble of 5 GCMs (RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5)</td>
<td>A trend preserving bias correction technique (Hempel et al., 2013)</td>
<td>HBV-D (conceptual semi distributed rainfall-runoff model)</td>
<td>Analysis of daily high flows (Q5) and large flows exceeding POT3</td>
<td>Uncertain changes in high flows under a 1.5 and 2 °C temperature rise. Increase in magnitude of POT3 events leading to a 6 and 9% increase in 25 and 50-year floods.</td>
<td>(Liu et al., 2017)</td>
</tr>
<tr>
<td>China Upper Beijiang River Basin</td>
<td>Ensemble of 5 GCMs (RCP 2.6, RCP 4.5, RCP 8.5)</td>
<td>Equidistant quantile mapping approach (Li et al., 2010) with a stochastic weather generator for daily disaggregation</td>
<td>VIC (semi distributed hydrological model)</td>
<td>Flood frequency analysis (AM daily flows and AM 7-day flood volumes with Pearson Type III distribution)</td>
<td>Changes in 100-year 1-day flow events range from -11.3 to 91% and -1.2 to 74.7% by 2050 and 2080, respectively. Changes to 7-day flood volumes range from -16.8 to 80.1% and -2.9 to 71.8% by 2050 and 2080, respectively.</td>
<td>(Wu et al., 2015)</td>
</tr>
<tr>
<td>Region</td>
<td>Model Details</td>
<td>Application</td>
<td>Summary</td>
<td>Reference</td>
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<tr>
<td>China</td>
<td>HadCM3 downscaled with PRECIS RCM (A1B, A2, B2)</td>
<td>Flood frequency analysis (AM with Generalised Pareto distribution)</td>
<td>Uncertain changes to flood events across 6 sub-basins by 2040. Increase in small and decrease in large floods for main channel.</td>
<td>(Zhang et al., 2014)</td>
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<tr>
<td>Xin River Basin</td>
<td>2 GCMS dynamically downscaled with PRECIS RCM (A1B)</td>
<td>Comparison of large flows exceeding POT3</td>
<td>Peak flows increase between 12 to 144% at three stream gauges along the river by 2040, depending on the GCM and hydrologic model used.</td>
<td>(Zhang et al., 2015)</td>
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<tr>
<td>Jinhua River</td>
<td>HadCM3 downscaled with PRECIS RCM (A1B)</td>
<td>Flood frequency analysis (AM with GEV distribution)</td>
<td>Increase in large flooding events for 2 hydrologic models. Decrease in all flooding events for the XAJ hydrological model by 2040.</td>
<td>(Tian et al., 2013)</td>
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<td>Heshui River</td>
<td>Ensemble of 3 GCMS (RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5)</td>
<td>Flood frequency analysis (AM with GEV distribution)</td>
<td>Decreases in 10, 20, and 30-year flood events under all scenarios considered.</td>
<td>(Tian et al., 2016)</td>
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<tr>
<td>Yangtze River</td>
<td>Ensemble of 7 GCMS (A1B, A2, B1)</td>
<td>Flood frequency analysis (AM with GEV distribution)</td>
<td>5, 10, 25, 50, 100, and 200-year flood events increase for most projections. 200-year flood events increase by 12.9% by 2100.</td>
<td>(Qin and Lu, 2014)</td>
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<tr>
<td>Basin</td>
<td>ECHAM 5 dynamically downscaled with RegCM4.0-RCM (A1B)</td>
<td>Flood frequency analysis (daily, 7-day and 15-day AM with Pearson Type III distribution)</td>
<td>Current maximum daily floods with return periods of 50, 20, and 10 years will change to floods with return periods of 15, 7, and 3 years respectively by 2100.</td>
<td>(Gu et al., 2014)</td>
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<td>Yangtze River</td>
<td>HadGEM2-AO downscaled by 5 RCMs from the CORDEX (RCP 4.5, RCP 8.5)</td>
<td>Flood frequency analysis (AM 1-day flow and 5-day, and 15-day flood volumes with Pearson Type III distribution)</td>
<td>A mean increase in the magnitude of 2 to 50-year flood events at three stations assessed by 14.24% for 1-day flows, 12.79% for 5-day volume and 10.24% for 15-day volume by 2050.</td>
<td>(Gu et al., 2018)</td>
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<tr>
<td>Basin</td>
<td>Ensemble of 27 GCMS (RCP 4.5, RCP 8.5)</td>
<td>Flood frequency analysis (daily AM with no distribution assumed)</td>
<td>Magnitude of 5, 10, 15, and 30-year flood events increase in most sub-basins using the multi-model ensemble by 2100.</td>
<td>(Yu et al., 2018)</td>
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<td>Xiangxi River</td>
<td>Ensemble of 7 GCMS (A1B, A2, B1, B2)</td>
<td>Analysis of monthly high flows (Q5)</td>
<td>Increase in the magnitude of high flows between -3 and 41% under a 2 °C temperature rise for the various climate models.</td>
<td>(Xu et al., 2011)</td>
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<tr>
<td>Basin</td>
<td>Ensemble of 3 GCMS (RCP 2.6, RCP 4.5, RCP 8.5)</td>
<td>Analysis of daily high flows (Q10)</td>
<td>Most scenarios indicate a decrease in high flows exceeding Q10 for the 2020s, 2050s, and 2080s.</td>
<td>(Zhang et al., 2016b)</td>
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</table>
### Appendices

<table>
<thead>
<tr>
<th>Region</th>
<th>Ensemble Details</th>
<th>Methodology</th>
<th>Analysis/Outcome</th>
<th>Reference</th>
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<tr>
<td>China, Hanjiang River Basin</td>
<td>Ensemble of 20 GCMs (RCP 4.5, RCP 8.5)</td>
<td>Daily bias correction method for statistical downscaling (Chen et al., 2013)</td>
<td>Analysis of daily high flows (Q5)</td>
<td>(Shen et al., 2018)</td>
</tr>
<tr>
<td>China, Ganjiang River Basin</td>
<td>BNU-ESM and BCC-CSM1.1 (RCP 8.5)</td>
<td>Daily bias correction method for statistical downscaling (Chen et al., 2013)</td>
<td>Copula approach to flood frequency analysis using AM series</td>
<td>(Yin et al., 2018)</td>
</tr>
<tr>
<td>China, 5 Rivers Basins of Poyang Lake Catchment</td>
<td>COSMO-CLM RCM (RCP 2.6, RCP 4.5, RCP 8.5)</td>
<td>RCM output gridded to 0.5° with equidistant quantile mapping bias correction (Li et al., 2010)</td>
<td>Analysis of daily high flows (Q10) and comparison of daily flow duration curves</td>
<td>(Li et al., 2016b)</td>
</tr>
<tr>
<td>China, Pearl River Basin</td>
<td>Ensemble of 3 GCMs (A2, A1B, B1)</td>
<td>No bias correction</td>
<td>Flood frequency analysis (daily AM with Pearson Type III distribution)</td>
<td>(Liu et al., 2012)</td>
</tr>
<tr>
<td>China, Pearl River Basin</td>
<td>Ensemble of 4 GCMs and CCLM-RCM (A1B, A2, B1)</td>
<td>Daily percentile scaling approach and dynamic downscaling of one GCM with delta change approach</td>
<td>An increase in the 2, 5, 10, 20, and 50-year flood events.</td>
<td>(Liu et al., 2013)</td>
</tr>
<tr>
<td>China, Pearl River Basin</td>
<td>HadAM3H downscaled with PRECIS RCM (A1B)</td>
<td>RCM interpolated to 0.25° resolution with delta change and quantile mapping bias correction</td>
<td>Increases in 20-year flood events for all locations assessed under both bias correction techniques. Up to a 75% increase by 2040.</td>
<td>(Yuan et al., 2016)</td>
</tr>
<tr>
<td>China, Pearl River Basin</td>
<td>Ensemble of 5 GCMs (RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5)</td>
<td>A trend preserving bias correction technique (Hempen et al., 2013)</td>
<td>Comparison of large flows exceeding POT3</td>
<td>(Liu et al., 2018)</td>
</tr>
<tr>
<td>China, Xijiang River Basin</td>
<td>Ensemble of 4 GCMs (RCP 2.6, RCP 4.5, RCP 8.5)</td>
<td>4 downscaling techniques applied based on delta change and quantile mapping approaches</td>
<td>Flood frequency analysis (4 different distributions with AM daily streamflow)</td>
<td>(Yuan et al., 2017)</td>
</tr>
<tr>
<td>China, Xijiang River Basin</td>
<td>BCC-CSM1.1 downscaled with RegCM4 (RCP 4.5, RCP 8.5)</td>
<td>Downscaled to 0.5° grid with no bias correction</td>
<td>Uncertain results from the two hydrological models. Ensemble mean predicts decreases in small events and increases in large events.</td>
<td>(Zhu et al., 2017)</td>
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<tr>
<td>Taiwan, Tsengwen River Basin</td>
<td>MRI-AGCM dynamically downscaled from WRF</td>
<td>Quantile mapping approach bias correction (Su et al., 2016)</td>
<td>Compared magnitude of top typhoons events and impact on the operation of key structures</td>
<td>(Wei et al., 2016)</td>
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</tbody>
</table>
## Appendices

### Table A2. Climate change impact studies assessing flooding in South East Asia and Oceania.

<table>
<thead>
<tr>
<th>Country / Region / Catchment</th>
<th>GCM / RCM (Climate Change Scenario)</th>
<th>Statistical / Dynamic Downscaling or Bias Correction Method</th>
<th>Hydrological Model and Approach</th>
<th>Flood Analysis Method</th>
<th>Key Findings for Future Climate Scenario</th>
<th>Reference</th>
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<tbody>
<tr>
<td>South East Asia Mekong River Basins</td>
<td>High resolution MRI-AGCM 3.2S (RCP 8.5)</td>
<td>Bias correction (Inomata et al., 2011). Pampanga Basin downscaled with WRF to 5 km daily data</td>
<td>RRI (2D rainfall-runoff inundation model)</td>
<td>Change in flooding due to changes in 100-year rainfall events</td>
<td>Increase in extreme discharge and inundated area for the Solo, Chao Phraya, and Pampanga River Basins by 2100. Largest increase of 8% projected for the Pampanga River, Philippines.</td>
<td>(Iwami et al., 2017)</td>
</tr>
<tr>
<td>South East Asia Mekong River Basin</td>
<td>High resolution JMA AGCM (A1B)</td>
<td>Daily scaling approach</td>
<td>YHyM (grid based distributed hydrological model)</td>
<td>Analysis of daily high flows (Q10) and annual maxima flows</td>
<td>High flows increase by 10% across the whole basin by 2100. However, maximum flood magnitudes predicted to decrease.</td>
<td>(Kiem et al., 2008)</td>
</tr>
<tr>
<td>South East Asia Mekong River Basin</td>
<td>ECHAM4 dynamically downscaled with PRECIS RCM (A2)</td>
<td>RCM outputs gridded to 25km with a daily scaling bias correction approach</td>
<td>VIC (semi distributed hydrological model) coupled with EIA3D for the hydrodynamic modelling of the delta</td>
<td>Comparison of historical and future flooding events considering climate and sea level changes.</td>
<td>Flood duration, maximum flooded area, and flood height all increase by 2050 due to climate change. Sea level rise has minimal impact on peak flood heights.</td>
<td>(Västilä et al., 2010)</td>
</tr>
<tr>
<td>South East Asia Mekong River Basin</td>
<td>Ensemble of 5 GCMs (A1B, B1)</td>
<td>Delta change approach for downsampling to daily timeseries</td>
<td>VMod (distributed conceptual hydrological model)</td>
<td>Comparison of 5-day average annual maximum discharge</td>
<td>Flood peaks increase by 2-20% under A1B and 0-13% under B1 by 2041. Considering future dams leads to a -15-7% change for A1B and -15-0% change for B1.</td>
<td>(Lauri et al., 2012)</td>
</tr>
<tr>
<td>South East Asia Mekong River Basin</td>
<td>An ensemble of 5 GCMs (RCP 4.5, RCP 8.5)</td>
<td>Quantile mapping approach</td>
<td>VMod (distributed conceptual hydrological model)</td>
<td>Flood frequency analysis (daily AM with GEV distribution) and high flows, Q5</td>
<td>Increases in flood frequency (2 to 20-year return periods) at three locations assessed. Up to a 25% increase in high flows by 2065.</td>
<td>(Phi Hoang et al., 2016)</td>
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<tr>
<td>South East Asia Mekong River Basin</td>
<td>High resolution MRI-AGCM3-2S GC M (RCP 8.5)</td>
<td>A statistical bias correction method (Inomata et al., 2011)</td>
<td>Upstream hydrology with BTOP and RRI for downstream rainfall-runoff and inundation modelling</td>
<td>Comparison of inundation extent under future and historic climate conditions</td>
<td>Increase in inundation area by a factor between 1.24 and 1.35 by 2100. Downstream discharge increases by a factor between 1.16 and 1.25.</td>
<td>(Edangodage Duminda Pradeep et al., 2017)</td>
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<td>South East Asia Mekong River Basin</td>
<td>Ensemble of 5 GCMs (RCP 4.5, RCP 8.5)</td>
<td>A trend preserving bias correction technique (Hempel et al., 2013)</td>
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<td>Comparison of annual maxima flows and flows exceeding POT2</td>
<td>Increase in frequency of large floods by 2100, increases more downstream. Future planned dams reduce flooding upstream but have minimal effects downstream.</td>
<td>(Wang et al., 2017)</td>
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<tr>
<td>South East Asia Mekong River Basin</td>
<td>GFDL-CM downscaled with PRECIS RCM (RCP 4.5, RCP 8.5)</td>
<td>No bias correction</td>
<td>PERSiST (semi distributed conceptual rainfall-runoff model) and INCA for river modelling</td>
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<td>High flows increase between 4.2 and 12.7% by the 2050s and between 26.6 and 27.2% by the 2090s. Considering socio-economic changes and dam construction this changes to between 5.9 and 14.7% for</td>
<td>(Whitehead et al., 2019)</td>
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<td>Country</td>
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<td>Vietnam, Laos, China</td>
<td>Red River Basin</td>
<td>HadCM3 downscaled with PRECIS RCM (A1B)</td>
<td>Quantile mapping approach</td>
<td>HBV (conceptual semi distributed rainfall-runoff model)</td>
<td>Analysis of high flows (Q1 and Q10) Increase in Q1 high flows by 15.8 to 34.9% by 2100 over the Da, Thao, Lo, and Gam Rivers. (Giuliani et al., 2016)</td>
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<tr>
<td>Vietnam</td>
<td>Va Gia-Thu Bon River Basin</td>
<td>3 GCMs dynamically downscaled with the WRF-RCM (A2)</td>
<td>RCM output gridded to 30 km with delta change bias correction</td>
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<td>Flood frequency analysis (Combination of Gumbel and Exponential distributions) 100-year flood events increase from 50% to 150% for the 12 locations considered by 2100. Mountainous regions underwent the greatest increases in flood magnitudes (up to 200%). (Vo et al., 2016)</td>
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<tr>
<td>Vietnam</td>
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<td>Ensemble of 10 projections using 6 GCMs and 6 RCMs (A1B, A2)</td>
<td>Ensemble of 6 bias correction techniques</td>
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<td>Uncertain results with a large range of both positive and negative changes to 50-year flood events predicted by 2100 from the model ensemble. (Dang et al., 2017)</td>
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<td>Vietnam</td>
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<td>Flood frequency analysis (POT with Generalised Pareto distribution) Increase in magnitude of 50-year flood events by 30, 49, and 24% for the three gauges assessed by 2045. (Dong et al., 2018)</td>
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<td>Chao Phraya River Basin</td>
<td>High resolution MRI-AGCM3-1S GCM (A1B)</td>
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<td>Runoff projections from GCM directly applied to 1K-FRM river routing model</td>
<td>Annual maximum hourly discharge and flood frequency analysis (AM with Gumbel distribution) No clear increase in annual maximum flows or 10-year flood events in the downstream Chao Phraya River by 2040 and 2100. Increased flooding for some tributaries in the central north and southwest of the catchment. (Hunukumbura and Tachikawa, 2012)</td>
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<td>Thailand</td>
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<td>High resolution MRI-AGCM3-1S and AGCM3-2S GCM (A1B)</td>
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<td>Thailand</td>
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<td>High resolution MRI-AGCM3-2S GCM</td>
<td>Quantile mapping approach</td>
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<td>Thailand</td>
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<td>Comparison of flood hazard mapping Areas of west Bangkok will be more severely affected by flooding by 2050. (Supharatid et al., 2016)</td>
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<td>Thailand</td>
<td>Yang River Basin</td>
<td>Ensemble of 3 GCMs (RCP 4.5, RCP 8.5)</td>
<td>Delta change approach</td>
<td>BTOP for hydrological modelling and HEC-RAS for hydraulic routing</td>
<td>Increase in the magnitude of 100-year flood events between 36 and 55% by the 2080s. Expected to cause an additional 60 km² to be inundated.</td>
<td>(Shrestha and Lohpaisankrit, 2017)</td>
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<tr>
<td>Thailand</td>
<td>Lampao River Basin</td>
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<td>Downscaled using Statistical Downscaling Model (Wilby et al., 2002)</td>
<td>SWAT for hydrological modelling and HEC-RAS for hydraulic routing</td>
<td>30% decrease in the annual maximum daily flow by 2100.</td>
<td>(Arunyanart et al., 2017)</td>
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<td>Malaysia</td>
<td>Muda and Dungun River Basins</td>
<td>3 GCMs dynamically downscaled with MM5-RCM (A1B, A1F1, A2, B1)</td>
<td>RCM triple nested producing 6 km gridded data, no bias correction</td>
<td>WEHY (physically based hydrological model)</td>
<td>10 to 50% increase in 10, 20, 50, and 100-year flood events in both catchments from the 2030s to the 2080s.</td>
<td>(Amin et al., 2017)</td>
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<tr>
<td>Philippines</td>
<td>24 River Basins</td>
<td>3 GCMs (A1B, A2)</td>
<td>A generalised linear model approach</td>
<td>STREAM (spatially distributed rainfall-runoff model)</td>
<td>2, 10, and 100-year flood events increase significantly in the northern island of Luzon by 2050. Southern islands of Visayas and Mindanao predicted to have only moderate increases.</td>
<td>(Tolentino et al., 2016)</td>
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<td>Indonesia</td>
<td>Upper Ciliwung River Basin</td>
<td>MRI-CGCM3.2 (RCP 4.5)</td>
<td>Quantile mapping approach</td>
<td>HEC-HMS (physically based rainfall-runoff model)</td>
<td>Peak flows increase by up to 130% for the considered flood event by 2040.</td>
<td>(Emam et al., 2016)</td>
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<td>Indonesia</td>
<td>Ciliwung River Basin</td>
<td>3 GCMs (RCP 4.5, RCP 8.5)</td>
<td>Quantile mapping approach</td>
<td>HEC-HMS (physically based rainfall-runoff model) coupled with the FLO-2D hydrodynamic model</td>
<td>Change in flooding due to changes in 50-year 3-day rainfall events</td>
<td>(Mishra et al., 2017)</td>
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<tr>
<td>Indonesia</td>
<td>Jakarta Area</td>
<td>An ensemble of 40 projections from 5 GCMs (RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5)</td>
<td>A trend preserving bias correction technique (Hempel et al., 2013)</td>
<td>Sacramento (spatially lumped continuous rainfall runoff model) with SOBEK for hydrodynamic modelling</td>
<td>Flood hazard mapping from river flooding combined with sea level rise</td>
<td>(Budiyono et al., 2016)</td>
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<td>Indonesia</td>
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<td>Ensemble of 5 GCMs (RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5)</td>
<td>A trend preserving bias correction technique (Hempel et al., 2013) and delta change method</td>
<td>GLOFRIS and PCR-GLOBWB</td>
<td>Flood hazard due to climate change decreases by 46%. Flood risk increases by 14% due to sea level rise and by 126% due to land use changes in the catchment by 2030.</td>
<td>(Budiyono et al., 2016)</td>
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<tr>
<td>Australia</td>
<td>Oxley and Bulimba Creeks</td>
<td>GFDL-CM2.1 and CCAM RCM (A2)</td>
<td>Two bias correction techniques</td>
<td>RORB (nonlinear rainfall-runoff model)</td>
<td>Uncertain results as GFDL-CM2.1 predicts an increase in peak flows between 7-11% while CCAM predicts a decrease between 7-13% across the two catchments, by 2045.</td>
<td>(Chen and Yu, 2015)</td>
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### Table A3. Climate change impact studies assessing flooding in South Asia

<table>
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<tr>
<th>Country / Region / Catchment</th>
<th>GCM / RCM (Climate Change Scenario)</th>
<th>Statistical / Dynamic Downscaling or Bias Correction Method</th>
<th>Hydrological Model and Approach</th>
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<th>Key Findings for Future Climate Scenario</th>
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<td>Indian Subcontinent</td>
<td>HadCM3 and ECHAM5 downscaled with HadRM3 RCM</td>
<td>RCM outputs gridded to 25 km with no bias correction</td>
<td>TRIP (river routing model)</td>
<td>Analysis of monthly high flows (Q10)</td>
<td>All major rivers assessed project an increase in the occurrence of high flow events for the 2050s and 2080s, in some cases above a 100% increase.</td>
<td>(Mathison et al., 2015)</td>
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<tr>
<td>India and Bangladesh 5 Major River Basin</td>
<td>Ensemble of 3 GCMs downscaled with PRECIS RCM (RCP 8.5)</td>
<td>RCM output gridded to 25 km with no bias correction</td>
<td>PERSIST (semi distributed conceptual rainfall-runoff model) and INCA for river modelling</td>
<td>Analysis of daily high flows (Q5)</td>
<td>Increase in high flows between 5.9 and 35.2% for the 5 river basins by the 2050s and further increase between 14.7 and 97.7% by 2090s for the downscaled GFDL-CM3 projection.</td>
<td>(Whitehead et al., 2018)</td>
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<tr>
<td>Bangladesh Ganges, Brahmaputra, and Meghna Rivers</td>
<td>4 GCMs (2°, 4°, and 6° temperature increases)</td>
<td>No bias correction</td>
<td>MIKE 11 hydrodynamic model</td>
<td>Flood frequency analysis (daily AM with Gumbel distribution)</td>
<td>Mean peak flows increase by 0 to 45% in the Ganges, 0 to 17% in the Brahmaputra and 8 to 60% in the Meghna for all scenarios assessed.</td>
<td>(Mirza et al., 2002)</td>
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<tr>
<td>Bangladesh Ganges, Brahmaputra, and Meghna Rivers</td>
<td>4 GCMs (2°, 4°, and 6° temperature increases)</td>
<td>No bias correction</td>
<td>MIKE 11 hydrodynamic model</td>
<td>Comparison of mean annual maximum flows</td>
<td>Increase in magnitude of 100-year flood events by 27, 29 and 54% for the Ganges, 8, 24, and 63% for the Brahmaputra, 15, 38, and 81% for the Meghna under a 1.5, 2, and 4 °C temperature rise.</td>
<td>(Mirza et al., 2003)</td>
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<tr>
<td>Bangladesh Ganges, Brahmaputra, and Meghna Rivers</td>
<td>13 High resolution projections from EC-Earth3-HR and HadGEM3 (RCP 8.5)</td>
<td>A trend preserving bias correction technique (Hemel et al., 2013)</td>
<td>SWAT (physically based semi distributed continuous hydrological model)</td>
<td>Flood frequency analysis</td>
<td>Increase in magnitude of 100-year flood events by 27, 29 and 54% for the Ganges, 8, 24, and 63% for the Brahmaputra, 15, 38, and 81% for the Meghna under a 1.5, 2, and 4 °C temperature rise.</td>
<td>(Mohammed et al., 2018)</td>
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<tr>
<td>India and Bangladesh Ganges River Basin</td>
<td>Ensemble of 17 perturbations of HadCM3 downscaled with PRECIS RCM (A1B)</td>
<td>RCM output gridded to 25 km no bias correction</td>
<td>PERSIST (semi distributed rainfall-runoff model) and INCA for river modelling</td>
<td>Analysis of daily high flows (Q5)</td>
<td>High flows increase by 10-25% by 2060 and 30-60% by 2100.</td>
<td>(Whitehead et al., 2015)</td>
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<tr>
<td>India Upper Ganges River Basin</td>
<td>Ensemble of 21 GCMs (RCP 4.5, RCP 8.5)</td>
<td>Interpolated to 0.1° and delta change approach</td>
<td>JULES (land surface model)</td>
<td>Analysis of high flows (Q5)</td>
<td>Magnitude of high flows projected to increase by 41% and 60% under RCP 4.5 and 8.5, respectively by 2035. Increase of 42% and 63% considering land use change.</td>
<td>(Tsarouchi and Buytaert, 2018)</td>
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<tr>
<td>India and Bangladesh Brahmaputra River Basin</td>
<td>Weighted ensemble of 12 GCMs (A1B, A2)</td>
<td>No bias correction</td>
<td>PCR-GLOBWB (global gridded hydrological model)</td>
<td>Flood frequency analysis (AM with an ensemble of distributions)</td>
<td>A significant increase in flood magnitudes and frequency, with 100-year flood events predicted to be exceeded yearly by 2100.</td>
<td>(Gain et al., 2013)</td>
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<td>Analysis Details</td>
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<tr>
<td>India and Bangladesh</td>
<td>Weighted ensemble of 12 GCMs (A1B, A2)</td>
<td>No bias correction</td>
<td>Flood frequency analysis (AM, no distribution assumed) 10-year flood events increase from 82,000 m³/s to 140,000 m³/s. Current 10-year flood events will occur every 2 years by 2100. (Gain et al., 2011)</td>
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<td>Brahmaputra River Basin</td>
<td>EC-Earth and HadRM3P driven by HadAM3P</td>
<td>RCM outputs gridded to 50 km, no bias correction</td>
<td>Flood frequency analysis (daily AM series with GEV distribution) Probability of high discharge events 1.5 times more likely with a 2 °C temperature rise under climate change. (Philip et al., 2019)</td>
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<td>Bangladesh Brahmaputra River Basin</td>
<td>HadAM3H downscaled with PRECIS-RCM (A2)</td>
<td>RCM outputs gridded to 0.44° grid with a scaling approach for bias correction</td>
<td>Comparison of mean annual maximum flows and flood hazard mapping Median increases in monsoonal peak flows by 7.5, 19.3, and 21% at three locations by 2100. Significant increase in areas inundated. (Dutta and Ghosh, 2012, Ghosh and Dutta, 2012)</td>
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<td>India and Bangladesh</td>
<td>Ensemble of 11 projections using 8 GCMs, 3 RCMs from CORDEX (RCP 8.5)</td>
<td>RCM outputs gridded to 50 km, quantile mapping approach (Grillakis et al., 2013)</td>
<td>Flood frequency analysis (daily AM with Weibull distribution) Increase in the magnitude of 100-year flood events by 6% and 12% for a 1.5 °C and 2 °C temperature rise. Greater increases in lower return period events. (Mohammed et al., 2017b)</td>
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<tr>
<td>Brahmaputra River Basin</td>
<td>Ensemble of 11 projections using 8 GCMs, 3 RCMs from CORDEX (RCP 8.5)</td>
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<td>Monthly mean correction (delta change method)</td>
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<td>Meghna River Basin</td>
<td>PRECIS-RCM (A1B)</td>
<td>RCM output gridded to 50 km with no bias correction</td>
<td>Analysis of high flows (Q1) Majority of river basins had predicted increases in Q1 flows between 10-50%. Decreases in peak flows predicted for the Ganges, Krishna, Cauvery, and Brahmaputra Rivers by 2100. (Gosain et al., 2011)</td>
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<td>India and Bangladesh</td>
<td>HadRM2-RCM (greenhouse gas scenario)</td>
<td>RCM output gridded to 50 km with no bias correction</td>
<td>Comparison of mean annual maximum flows Increase in average maximum annual flows for the 2050s. (Gosain et al., 2006)</td>
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<td>Brahmaputra River Basin</td>
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<td>Simple downscaling based on Thiessen polygons</td>
<td>Comparison of top flow events in the wet season Increase in peak flows during the wet season under climate change by 2100. (Asokan and Dutta, 2008)</td>
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<td>India and Bangladesh</td>
<td>Ensemble of 3 GCMs downscaled with PRECIS RCM (RCP 8.5)</td>
<td>RCM outputs gridded to 25 km with a linear scaling bias correction method</td>
<td>Analysis of daily high flows (Q5) High flows increase between 5.7 and 18.6% by the 2050s and between 17.3 and 116.2% by the 2090s. (Jin et al., 2018b)</td>
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<td>Location</td>
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<td>India Upper Wardha River Basin</td>
<td>HadCM3 (A2, B2)</td>
<td>Downscaled</td>
<td>HEC-HMS (physically based rainfall-runoff model)</td>
<td>Analysis of monthly high flows (Q5)</td>
<td>Uncertain results, with an increase in high flows under the B2 emission scenario and decrease under the A2 scenario for the 2020s, 2050s, and 2080s.</td>
<td>(Bothale and Katpatal, 2017)</td>
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<td>India Wainganga River Basin</td>
<td>Ensemble of 6 GCMs downscaled through CORDEX (RCP 4.5, RCP 8.5)</td>
<td>RCM output gridded to 50 km with quantile mapping bias correction</td>
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<td>Decrease in 50, 75, and 100-year flood events under RCP 4.5 using a stationary approach and no change or slight increases under RCP 8.5 adopting a non-stationary approach by 2095.</td>
<td>(Das and U'mamahesh, 2017)</td>
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<tr>
<td>India Wainganga River Basin</td>
<td>Ensemble of 6 GCMs downscaled through CORDEX (RCP 4.5, RCP 8.5)</td>
<td>RCM output gridded to 50 km with quantile mapping bias correction</td>
<td>VIC (semi distributed hydrological model)</td>
<td>Flood frequency analysis (AM with GEV distribution) Bayesian approach for uncertainty analysis</td>
<td>Decrease in the magnitude of 2, 3, 5, 10, 20, 30, 50, 75 and 100-year flood events under RCP 4.5 using a stationary approach and no change or slight increases under RCP 8.5 adopting a non-stationary approach by 2095.</td>
<td>(Das and U'mamahesh, 2018)</td>
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<td>India Subamarekha River Basin</td>
<td>ECHAM4 downscaled with PRECIS RCM (A1B)</td>
<td>RCM outputs gridded to 50 km with no bias correction</td>
<td>HEC-HMS (physically based rainfall-runoff model)</td>
<td>Comparison of mean annual maximum flows</td>
<td>A 37 to 48.7% increase in the annual maximum flood predicted by 2030 for all sub-basins.</td>
<td>(Jana et al., 2015)</td>
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<td>India Bhadra River Basin</td>
<td>HadCM3 (RCP 4.5)</td>
<td>Downscaled</td>
<td>HEC-HMS (physically based rainfall-runoff model)</td>
<td>Comparison of frequency and mean magnitude of flood events</td>
<td>Number of smaller flood events is reduced, though the mean flood magnitude is increased by 2035. Number and magnitude of larger flooding events increases.</td>
<td>(Pichuka et al., 2017)</td>
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<td>India Malaprabha and Netravathi River Basins</td>
<td>EC-Earth downscaled with RCA4 (RCP 4.5)</td>
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<td>Decrease in high flows predicted for both catchments by 2070, with more substantial decreases predicted for the Netravathi than the Malaprabha River.</td>
<td>(Mudbhakatal et al., 2017)</td>
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<td>Nepal Bagmati River Basin</td>
<td>High resolution MIR-GCM (A1B)</td>
<td>Quantile mapping approach</td>
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<td>Flood frequency analysis (daily AM no distribution assumed)</td>
<td>Magnitude of 2, 5, 10, 25, 50, and 100-year flood events increase between 24 to 40% by 2100.</td>
<td>(Mishra and Herath, 2015)</td>
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<tr>
<td>Nepal West Rapti River Basin</td>
<td>High resolution MIR-AGCM 3.1S and 3.2S (A1B)</td>
<td>A statistical bias correction method (Inomata et al., 2011)</td>
<td>PDHM hydrological model with RRI for inundation modelling</td>
<td>Flood frequency analysis (daily POT with Gumbel distribution)</td>
<td>50-year flood events increase by 27 to 75% by 2040 and by 7 to 89% by 2100.</td>
<td>(Perera et al., 2015)</td>
</tr>
<tr>
<td>Nepal Koshi River Basin</td>
<td>2 GCMs dynamically downscaled with PRECIS RCM (A1B)</td>
<td>RCM outputs gridded to 25 km with quantile mapping bias correction</td>
<td>SWAT (physically based semi distributed continuous hydrological model)</td>
<td>Flood frequency analysis (daily AM with Pearson Type III distribution)</td>
<td>The magnitude of 2, 5, 10, 20, 50, 100, 500, 1000, and 10,000-year flood events increase significantly by 2060. 100-year flood events may double in magnitude.</td>
<td>(Devkota and Gyawali, 2015)</td>
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</tbody>
</table>
### Table A4. Climate change impact studies assessing flooding in Africa.

<table>
<thead>
<tr>
<th>Country / Region / Catchment</th>
<th>GCM / RCM (Climate Change Scenario)</th>
<th>Statistical / Dynamic Downscaling or Bias Correction Method</th>
<th>Hydrological Model and Approach</th>
<th>Flood Analysis Method</th>
<th>Key Findings for Future Climate Scenario</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Africa</strong></td>
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<tr>
<td>Niger, Upper Blue Nile, Limpopo, and Oubangui River Basins</td>
<td>Ensemble of 5 GCMs (RCP 2.6, RCP 8.5)</td>
<td>A trend preserving bias correction technique resampled to a 0.5° grid (Hempel et al., 2013)</td>
<td>SWIM (process based spatially semi distributed hydrological model)</td>
<td>Analysis of high flows (Q10)</td>
<td>Niger River high flow predictions vary from -50% to +305% change. Predictions for Upper Blue Nile are consistent with increases around 0-50%. No significant changes are predicted in the Oubangui River by 2100.</td>
<td>(Aich et al., 2014)</td>
</tr>
<tr>
<td>West Africa Niger River Basin</td>
<td>3 GCMs downscaled with RCA4-RCM from CORDEX (RCP 4.5, RCP 8.5)</td>
<td>Distribution based scaling bias correction</td>
<td>HYPE (semi distributed hydrological model)</td>
<td>Flood frequency analysis (AM with GEV distribution)</td>
<td>Consistent increases in the 100-year return period floods for large areas in Guinea, lower Nigeria, and the Benue River basin by 2100. Mostly uncertain results elsewhere.</td>
<td>(Andersson et al., 2017)</td>
</tr>
<tr>
<td>West Africa Niger River Basin</td>
<td>18 climate projections using 13 GCMs and 4 RCMs from CORDEX (RCP 4.5, RCP 8.5)</td>
<td>13 dynamically and 5 statistically downscaled projections (Hempel et al., 2013)</td>
<td>SWIM (process based spatially semi distributed hydrological model)</td>
<td>Flood frequency analysis (daily AM with GEV distribution)</td>
<td>Most scenarios indicate increases in 20-year flood events. Projected change ranges from -5% to +50% by 2050 when considering both land use and climate change effects.</td>
<td>(Aich et al., 2016)</td>
</tr>
<tr>
<td>West Africa Upper Niger River Basin</td>
<td>Ensemble of 5 GCMs (RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5)</td>
<td>A trend preserving bias correction technique (Hempel et al., 2013)</td>
<td>3 hydrological models (SWIM, HBV, and VIC)</td>
<td>Trends of future high flows (Q10)</td>
<td>Highly uncertain trends for the Upper Niger River with no clear indication of the direction of change by 2100.</td>
<td>(Vetter et al., 2015)</td>
</tr>
<tr>
<td>West Africa Upper Niger River Basin</td>
<td>Ensemble of 41 GCMs (RCP 4.5)</td>
<td>Delta change method</td>
<td>STELLA (semi distributed, conceptual hydrological model)</td>
<td>Analysis of monthly high flows (Q5) and peak flood extent</td>
<td>Most projections predict a decrease in the peak flood extent of the Inner Niger Delta under a 2°C temperature rise.</td>
<td>(Thompson et al., 2016)</td>
</tr>
<tr>
<td>West Africa Upper Niger River Basin</td>
<td>Ensemble of 4 GCMs (RCP 2.6, RCP 6.0)</td>
<td>A trend preserving bias correction technique (Hempel et al., 2013)</td>
<td>Ensemble of 3 hydrological models (SWIM, mHM, and VIC)</td>
<td>Flood frequency analysis (AM with GEV distribution) and comparison of POT2</td>
<td>Uncertain changes in high flows for the 2050s and 2080s across sub catchments. Ensemble mean indicates a decrease in the peak flood extent of the Inner Niger Delta.</td>
<td>(Huang et al., 2018)</td>
</tr>
<tr>
<td>West Africa Volta River Basin</td>
<td>Ensemble of 3 GCMs downscaled with RCA4 from CORDEX (RCP 8.5)</td>
<td>RCM outputs gridded to 50 km with a linear scaling bias correction method</td>
<td>PERSISt (semi distributed rainfall-runoff model) and INCA river model</td>
<td>Analysis of daily high flows (Q1, Q5, and Q10)</td>
<td>High flows in the Black Volta increase by 11% and 36% by the 2050s and 2090s, respectively considering both change and socio-economic changes.</td>
<td>(Jin et al., 2018a)</td>
</tr>
<tr>
<td>Region</td>
<td>Ensemble</td>
<td>Change Method</td>
<td>Model Used</td>
<td>Analysis Method</td>
<td>Results</td>
<td>References</td>
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<tr>
<td>West Africa</td>
<td>Ensemble of 6 GCMs (RCP 4.5, RCP 8.5)</td>
<td>Delta change method</td>
<td>GR4J (lumped conceptual rainfall-runoff model)</td>
<td>Comparison of maximum daily flows</td>
<td>Decrease in maximum daily flows for the Gambia River between 27 and 33% and uncertain changes for the Senegal River between -2 and 2% by 2050.</td>
<td>(Bodian et al., 2018)</td>
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<tr>
<td>Senegal and Gambia River Basins</td>
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<tr>
<td>Benin Ouémé River Basin</td>
<td>Ensemble of 65 climate projections from 24 GCMs (A2, B1, A1B)</td>
<td>Delta change method</td>
<td>HME TS (lumped conceptual hydrological model)</td>
<td>Flood frequency analysis (daily AM with Pearlson Type III distribution)</td>
<td>Slight increase in 20, 50, and 100-year flood events by 2065 and 2100. Flooding events with return periods less than 10 years predicted to decrease.</td>
<td>(Essou and Brissette, 2013)</td>
</tr>
<tr>
<td>Ethiopia Blue Nile Basin</td>
<td>Ensemble of 3 GCMs (A2, B2)</td>
<td>A stochastic weather generator with non-linear regression producing 20 km gridded data.</td>
<td>NFS (physically based distributed hydrological model)</td>
<td>Analysis of daily high flows (Q5 and Q1)</td>
<td>High flows (Q5) predicted to change between -43% to +15% by the 2080s.</td>
<td>(Nawaz et al., 2010)</td>
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<tr>
<td>Kenya and Ethiopia Nyando and Lake Tana Basins</td>
<td>Ensemble of 17 GCMs (A1B, B1)</td>
<td>Quantile perturbation downscaling approach</td>
<td>VHM and NAM (lumped conceptual hydrological models)</td>
<td>Flood frequency analysis (daily POT with no distribution assumed)</td>
<td>Increase in 10-year flood events by a factor of 1.2-3.8 for the Nyando Basin, Kenya. Uncertain results for Lake Tana Basin, Ethiopia by 2065.</td>
<td>(Taye et al., 2011)</td>
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<tr>
<td>Kenya Nzoia River Basin</td>
<td>Ensemble of 5 GCMs A2, B2)</td>
<td>No bias correction</td>
<td>SWAT (physically based semi distributed continuous hydrological model)</td>
<td>Comparison of events exceeding bankfull discharge</td>
<td>Increase in the frequency of flooding events by the 2020s and 2050s for all climate models. Greater increase under the A2 scenario and for the 2050s.</td>
<td>(Githui et al., 2009)</td>
</tr>
<tr>
<td>Southern Africa</td>
<td>HadRM3H applied with boundaries from HadAM3H and HadCM3 (A2)</td>
<td>RCM outputs gridded to 0.44°</td>
<td>Macroscale distributed hydrological model</td>
<td>Flood frequency analysis of monthly flows with (AM with GEV distribution)</td>
<td>Increase in 10-year monthly flood events for north Tanzania and south Kenya by 2100. Uncertain changes elsewhere in subtropical/tropical southern Africa.</td>
<td>(Arnell et al., 2003)</td>
</tr>
<tr>
<td>Mozambique and Zimbabwe Pungwe River Basin</td>
<td>CCSM3 and ECHAM4 dynamically downscaled with RCA3 (A2, B2)</td>
<td>Scaling approach adopted for analysis of extremes. Delta change for monthly water balance</td>
<td>HBV (conceptual semi distributed rainfall-runoff model)</td>
<td>Flood frequency analysis (daily AM with Gumbel distribution)</td>
<td>Decreases in 10, 100, and 1000-year flood events by 10-60% for the 2030s from 2 of 3 scenarios. ECHAM4 under A2 emission scenario predicted increases from 0-20%.</td>
<td>(Andersson et al., 2011)</td>
</tr>
<tr>
<td>Zambia Kafue River Basin</td>
<td>Ensemble of 3 GCMs (A2, B1)</td>
<td>No bias correction or downscaling</td>
<td>WASMOD-D (conceptual large-scale hydrological model)</td>
<td>Flood frequency analysis (daily POT, AM with Generalised Pareto and GEV distributions)</td>
<td>Increase in the 5, 10, 20, 50, and 100-year flood events, with greater increases predicted by 2050 than by 2100.</td>
<td>(Ngongondo et al., 2013)</td>
</tr>
<tr>
<td>East Africa Zambezi River Basin</td>
<td>Perturbations of the IGSM framework (Reilly et al., 2013)</td>
<td>Delta change method</td>
<td>CLIRUN-II (lumped hydrological model)</td>
<td>Flood frequency analysis of monthly flows</td>
<td>Increase in 50-year flood events for parts of the Zambezi in Mozambique and Zambia under a high emission scenario by 2050. Insignificant changes in Malawi and Zimbabwe.</td>
<td>(Fant et al., 2015)</td>
</tr>
</tbody>
</table>
Table A5. Climate change impact studies assessing flooding in the Americas.

<table>
<thead>
<tr>
<th>Country / Region / Catchment</th>
<th>GCM / RCM (Climate Change Scenario)</th>
<th>Statistical / Dynamic Downscaling or Bias Correction Method</th>
<th>Hydrological Model and Approach</th>
<th>Flood Analysis Method</th>
<th>Key Findings for Future Climate Scenario</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon Amazon River Basin</td>
<td>Ensemble of 8 GCMs (A1B, A2, B1)</td>
<td>Delta change method</td>
<td>ORCHIDEE (land surface model)</td>
<td>Analysis of daily high flows (Q10)</td>
<td>Increase in high flows for the north-western rivers (Amazonas and Negro Rivers), while decreases are projected for the southern and eastern regions.</td>
<td>(Guimberteau et al., 2013)</td>
</tr>
<tr>
<td>Amazon Peruvian Amazon River Basin</td>
<td>Ensemble of 18 GCMs (RCP 4.5, RCP 8.5)</td>
<td>Equidistant quantile mapping approach (Li et al., 2010)</td>
<td>JULES (land surface model)</td>
<td>Flood frequency analysis (AM with GEV distribution)</td>
<td>100-year return period floods increase by 12% under RCP 8.5, and 7.5% under RCP 4.5 by 2095.</td>
<td>(Zulkafli et al., 2016)</td>
</tr>
<tr>
<td>Amazon Amazon River Basin</td>
<td>Ensemble of 5 GCMs (RCP 8.5)</td>
<td>Quantile mapping and delta change approaches</td>
<td>MGB-IPH (large scaled distributed process based hydrological model)</td>
<td>Comparison of inundation extent under future and historic climate conditions</td>
<td>Maximum inundation extent increases by 18% in the Peruvian Amazon Basin, decreases in the lower Amazon, and no significant change predicted for the Bolivian Amazon by 2100.</td>
<td>(Sorribas et al., 2016)</td>
</tr>
<tr>
<td>Amazon Amazon River Basin</td>
<td>Ensemble of 24 GCMs (A1B)</td>
<td>An anomaly approach (Rammig et al., 2010) downscaled to daily data</td>
<td>LPJml (distributed large-scale vegetation and hydrological model)</td>
<td>Comparison of inundation extent under future and historic climate conditions</td>
<td>Consensus towards increased inundation in the western Amazon (60-100% of models) and no clear trend for the eastern Amazon by 2100.</td>
<td>(Langerwisch et al., 2013)</td>
</tr>
<tr>
<td>Ecuador Paute River Basin</td>
<td>Ensemble of 23 GCM and RCM runs (A1B, A2, B1)</td>
<td>Quantile perturbation downscaling approach</td>
<td>VHM (lumped conceptual rainfall-runoff model)</td>
<td>Comparison of maximum daily runoff</td>
<td>Increase in maximum runoff between 24 and 68% for the two sub catchments considered by 2065.</td>
<td>(Mora et al., 2014)</td>
</tr>
<tr>
<td>Brazil 4 Rivers in the Upper Grande River Basin</td>
<td>Perturbations of the HadCM3 dynamically downscaled with Eta-RCM (A1B)</td>
<td>RCM outputs gridded to 40 km no bias correction</td>
<td>LASH (deterministic, semi physical and distributed hydrological model)</td>
<td>Analysis of daily high flows (Q5 and Q10)</td>
<td>Increase in daily high flows (Q5) for all rivers assessed. Up to a 40% increase for the Aiuruoca River by 2100.</td>
<td>(Viola et al., 2015)</td>
</tr>
<tr>
<td>United States</td>
<td>Ensemble of 10 GCMs dynamically downscaled with RegCM4 (RCP 8.5)</td>
<td>Further downscaled with a quantile mapping approach to 4 km grids</td>
<td>VIC (semi distributed hydrological model)</td>
<td>Analysis of daily high flows (Q5)</td>
<td>Projects an increase in high runoff through most of the subtropical south east United States, generally between 5-20% by 2050.</td>
<td>(Naz et al., 2016)</td>
</tr>
<tr>
<td>United States</td>
<td>Ensemble of 29 GCMs (RCP 4.5, RCP 8.5)</td>
<td>Bias correction and spatial disaggregation technique (Wood et al., 2004)</td>
<td>VIC (semi distributed hydrological model)</td>
<td>Flood frequency analysis (daily AM series with GEV distribution)</td>
<td>Number of 100-year flood events expected to increase considerably across the United States, including the subtropical south east. Though region is predicted to be less affected than elsewhere.</td>
<td>(Wobus et al., 2017)</td>
</tr>
<tr>
<td>Country</td>
<td>Ensemble Methodology</td>
<td>Downscaling Techniques</td>
<td>Hydrological Model(s)</td>
<td>Analysis Type(s)</td>
<td>Result</td>
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<tr>
<td>United States</td>
<td>Ensemble of 10 GCMs dynamically downscaled with RegCM4 (RCP 8.5)</td>
<td>Further downscaled with a quantile mapping approach to 4 km grids</td>
<td>VIC (semi distributed hydrological model)</td>
<td>Flood frequency analysis (AM series with GEV distribution)</td>
<td>Increase in the magnitude of 100-year streamflow events in headwater basins across subtropical south-eastern US between 0 and 100% by 2050.</td>
<td>(Naz et al., 2018)</td>
</tr>
<tr>
<td>United States</td>
<td>CGCM1 and CGCM2 (IS92a)</td>
<td>Two downscaling techniques to capture spatial and temporal variations</td>
<td>SWAT (physically based semi distributed continuous hydrological model) and WRAP for reservoir modelling</td>
<td>Analysis of monthly high flows (Q5) and maximum floods</td>
<td>High and maximum flows increase between 5 and 10% by the 2050s under climate change.</td>
<td>(Mutiah and Wurbs, 2002)</td>
</tr>
<tr>
<td>United States San Jacinto River Basin</td>
<td>Ensemble of 5 GCMs (A1B, A2, B1)</td>
<td>Delta change method</td>
<td>PRMS (deterministic hydrological model)</td>
<td>Analysis of daily high flow and daily maximum flow trends (Q5)</td>
<td>High flows predicted to decrease between 1 and 30% by 2099 depending on the emission scenario. Greater decreases for annual maximum flows.</td>
<td>(Risley et al., 2011)</td>
</tr>
<tr>
<td>United States Flint River Basin</td>
<td>Ensemble of 4 GCMs projections using 3 GCMs and 2 RCMs (A2)</td>
<td>Delta change approach with daily disaggregation using WXGEN stochastic weather generator</td>
<td>SWAT (physically based semi distributed continuous hydrological model)</td>
<td>Analysis of daily high flows (Q10, Q5, and Q1)</td>
<td>High flows predicted to increase by approximately 30% by 2040 and by around 40% when considering the effects of changed land use.</td>
<td>(Wang et al., 2014)</td>
</tr>
<tr>
<td>United States Chickasawhay River Basin</td>
<td>Ensemble of 4 GCMs (A1B, A2, B1)</td>
<td>RCM output gridded to 50km with 6 empirical downsampling techniques</td>
<td>HSAMI (lumped conceptual hydrological model)</td>
<td>Comparison of changes in extreme discharge events</td>
<td>Large uncertainty from the ensemble of climate models and downscaling techniques by 2065. However, most scenarios indicate an increase in wet season flooding.</td>
<td>(Chen et al., 2013)</td>
</tr>
<tr>
<td>United States Wolf Bay Basin</td>
<td>Ensemble of 4 GCMs (A1B, A2, B1)</td>
<td>RCM outputs gridded to 50 km with delta change approach</td>
<td>SWAT (physically based semi distributed continuous hydrological model)</td>
<td>Change in flooding due to changes in 25-year 1-day rainfall events</td>
<td>Peak flows increase by 8 and 50% for the two RCMs used by 2070.</td>
<td>(Chen et al., 2014)</td>
</tr>
<tr>
<td>United States Apalachicola River Basin</td>
<td>2 RCMs, HRM3-HADCM3 and RCM3-GFDL</td>
<td>Delta change method</td>
<td>DHSVM (physically based distributed hydrological model)</td>
<td>Comparison of mean annual maximum flows</td>
<td>Uncertain changes to annual maximum flows due to climate change by 2100. Flows are likely to increase with greater urbanisation.</td>
<td>(Zhao et al., 2016)</td>
</tr>
<tr>
<td>United States San Antonio River Basin</td>
<td>Ensemble of 17 GCMs (RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5)</td>
<td>Delta change method</td>
<td>Multivariate AdaptiveConstructed Analogs downsampling to 4 km resolution (Abatzoglou and Brown, 2012)</td>
<td>Flood frequency analysis (AM series with the Log-Pearson Type III distribution)</td>
<td>Majority of scenarios predict increased magnitudes of 10 and 100-year flood events under the combined effects of climate change and urbanisation by 2070.</td>
<td>(Suttles et al., 2018)</td>
</tr>
</tbody>
</table>
### Table A6. Climate change impact studies assessing flooding on a global scale.

<table>
<thead>
<tr>
<th>Country / Region / Catchment</th>
<th>GCM / RCM (Climate Change Scenario)</th>
<th>Statistical / Dynamic Downscaling or Bias Correction Method</th>
<th>Hydrological Model and Approach</th>
<th>Flood Analysis Method</th>
<th>Key Findings for Future Climate Scenario</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>World, 23 Major River Basins</td>
<td>CGCM1 (IS92 forcing scenario)</td>
<td>No bias correction or downscaling</td>
<td>A grid based variable velocity algorithm for flow routing (Arora and Boer, 1999)</td>
<td>Flood frequency analysis (daily AM with GEV distribution)</td>
<td>Decreases in the 2, 5, 10, 25, and 50-year flood events by 2-30% for the Amazon, Yangtze, and Mekong Rivers. 10-20% increase for the Ganges. Mean annual floods decrease in the Congo, Parana, Nile, Zambezi, Indus, and Orinoco, but increase in the Tocantins and Brahmaputra by 2100. (Arora and Boer, 2001)</td>
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<tr>
<td>World 14 Major River Basins</td>
<td>ECHAM4 (IS92a forcing scenario)</td>
<td>No bias correction or downscaling</td>
<td>A grid based global hydrological discharge model (Hagemann and Dümenil, 1997)</td>
<td>Flood frequency analysis (10-day mean discharge using AM with GEV distribution)</td>
<td>Increases between 9-26% for 10-year flood events in the Congo, Parana, Nile, Yangtze, Ganges, and Brahmaputra. 6% decrease projected for the Amazon by 2090. (Voss et al., 2002)</td>
<td></td>
</tr>
<tr>
<td>World 9 Major River Basins</td>
<td>Ensemble of 3 GCMs</td>
<td>Pattern scaling for spatial distributions perturbed with a resampling approach</td>
<td>A simple distributed rainfall runoff scheme</td>
<td>Flood frequency analysis of monthly runoff (AM with Gamma distribution)</td>
<td>Increase in 50-year maximum runoff events for the Amazon, Parana, Lower Yangtze, and Mekong Rivers under rising temperatures. (Kleinen and Petschel-Held, 2007)</td>
<td></td>
</tr>
<tr>
<td>World 15 Major River Basins</td>
<td>MIROC5 (RCP 4.5, RCP 8.5)</td>
<td>No bias correction or downscaling</td>
<td>TRIP (river routing model)</td>
<td>Flood frequency analysis (daily AM with Gumbel distribution)</td>
<td>Massive flood occurrence increases approximately by a factor of 10 in Africa, 7 in Asia, 5 in South America, and only a slightly in North America by 2100. Flood risk increases more in the tropics. (Okazaki et al., 2012)</td>
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<tr>
<td>World 29 Major River Basins</td>
<td>Ensemble of 11 GCMs (RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5)</td>
<td>No bias correction or downscaling</td>
<td>CalMa-Flood (grid based global hydrological model)</td>
<td>Flood frequency analysis (daily AM with Gumbel distribution)</td>
<td>100-year flood events increase in the Parana, Amazon, Niger, Congo, Nile, Zambezi, Indus, Ganges, Brahmaputra, Mekong, and Yangtze, with no changes predicted for the Orinoco by 2100. Tropical and subtropical regions show a general increase in flood magnitudes. (Hirabayashi et al., 2013)</td>
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<tr>
<td>World 12 Major River Basins</td>
<td>An ensemble of 5 GCMs (RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5)</td>
<td>A trend preserving bias correction technique (Hempel et al., 2013)</td>
<td>9 hydrological models (ECOMAG, HBV, HYMOD, HYPE, mHM, SWAT, SWIM, VIC, and WaterGAP3)</td>
<td>Analysis of daily high flows (Q10)</td>
<td>High flows increase in the Ganges. Less certain increases are predicted for the Yangtze and Amazon, while results were uncertain for the Niger and Blue Nile by 2100. (Krysanova et al., 2017)</td>
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<tr>
<td>World 9 Major River Basins</td>
<td>Ensemble of 5 GCMs (RCP 8.5)</td>
<td>A trend preserving bias correction technique (Hempel et al., 2013)</td>
<td>Ensemble of 16 hydrological models</td>
<td>Analysis of daily high flows (Q5) and flood frequency analysis (AM, Gumbel distribution)</td>
<td>Increase in the magnitude of flood events for the Upper Amazon, Ganges, and Upper Niger Rivers for a 1, 2, and 3 °C temperature rise. More uncertain results for high flows. (Gosling et al., 2017)</td>
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<tr>
<td>Region</td>
<td>GCM Ensembles</td>
<td>Bias Correction</td>
<td>Hydrological Models</td>
<td>Analysis of High Flows</td>
<td>Prediction</td>
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<tr>
<td>World 5 Major River Basins</td>
<td>An ensemble of 5 GCMs (RCP 2.6, RCP 4.5, RCP 6.0, RCP 8.5)</td>
<td>A trend preserving bias correction technique (Hempel et al., 2013)</td>
<td>Ensemble of 5 hydrological models (HYPE, mHM, SWIM, VIC, and WaterGAP3)</td>
<td>Analysis of high flows (Q10 and Q1)</td>
<td>Increasing trend in high flows for the Ganges River under RCP 8.5 by 2100, while no clear changes are evident in the Niger River. (Pechlivanidis et al., 2017)</td>
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</tr>
<tr>
<td>World</td>
<td>HadGEM1 (A1B, A2)</td>
<td>Interpolation to 1° with no bias correction</td>
<td>TRIP (river routing model)</td>
<td>Comparison of monthly maximum flow values</td>
<td>8 of the 10 rivers showing the largest increase in maximum monthly river flows by 2100 are located in tropical and subtropical regions. (Falloon and Betts, 2006)</td>
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<tr>
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<td>MIROC (A1B)</td>
<td>No bias correction or downscaling</td>
<td>MATSIRO (spatially distributed land surface model) and TRIP (river routing model)</td>
<td>Flood frequency analysis (daily AM with Gumbel distribution)</td>
<td>Increase in 100-year flood events for large parts of South America, Africa, South, and South East Asia by 2100. Especially large flood increases for central Africa and South Asia. (Hirabayashi et al., 2008)</td>
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<tr>
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<td>Ensemble of 3 GCMs (A2, B1)</td>
<td>Quantile mapping approach</td>
<td>VIC (semi distributed hydrological model)</td>
<td>Analysis of daily high flows (Q5)</td>
<td>Increase in high flows for South and South East Asia, the Congo, and much of South America. Decrease for parts of Central America and northern South America. (van Vliet et al., 2013)</td>
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<tr>
<td>World</td>
<td>Ensemble of 5 GCMs (RCP 8.5)</td>
<td>A trend preserving bias correction technique (Hempel et al., 2013)</td>
<td>(LPJml, JULES, VIC, H08, Mac-PDM.09, WBm, MPI-HM, PCR-GLOBWB, and MATSIRO)</td>
<td>Flood frequency analysis (5-day running average using AM with GEV distribution)</td>
<td>Flood peaks increase throughout much of the tropics, particularly in South East and South Asia. Increases and decreases alike are predicted for large parts of tropical and subtropical Africa and South America by 2100. (Dankers et al., 2014)</td>
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<td>CaMa-Flood (grid based global hydrodynamic model)</td>
<td>Analysis of daily high flows (Q5)</td>
<td>Increase in high flows for East Africa, South Asia, South East Asia and the southern South America by 2100. Decrease for eastern Amazon and parts of Central America. (Koirala et al., 2014)</td>
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<td>Mac-PDM.09 (grid based global hydrological model)</td>
<td>Flood frequency analysis (daily AM with GEV distribution)</td>
<td>100-year flood events increase with high consistency across the models in tropical Africa, South, and South East Asia and much of South America under the A1B scenario by 2050. (Arnell and Gosling, 2016)</td>
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<td>GLOFRIS (global large-scale hydrologic flood model)</td>
<td>Flood frequency analysis (AM with Gumbel distribution)</td>
<td>Increase in 100-year flood events for western Amazon, West and East Africa, South and South East Asia by 2080. Decrease for parts of the southern Amazon and Central America. (Winsemius et al., 2016)</td>
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Appendices

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<th>World</th>
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<th>A trend preserving bias correction technique (Hempel et al., 2013)</th>
<th>Ensemble of 5 hydrological models (WBM, MacPDM, PCR-GLOBWB, DBH, and LPJmL)</th>
<th>Normalised analysis of daily high flows (Q5)</th>
<th>Increase in high flows for East Africa, South Asia, parts of Indonesia, and western Amazon over the 21st century. Decrease for Central America, southern US, and Brazil.</th>
<th>(Asadieh and Krakauer, 2017)</th>
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<td>Downscaled to 0.35° grid with no bias correction</td>
<td>LISFLOOD (hybrid rainfall-runoff model with river routing)</td>
<td>Flood frequency analysis (daily AM and POT with Gumbel distribution)</td>
<td>Increase in the occurrence of 100-year flood events globally under 1, 2, and 4 °C temperature rises. 15 of the 20 most affected countries within tropical and subtropical regions.</td>
<td>(Alfieri et al., 2017)</td>
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<td>Interpolation to 0.5° with no bias correction</td>
<td>TOPMODEL for hydrological modelling with RFM for river routing</td>
<td>Flood frequency analysis (AM with Gumbel distribution)</td>
<td>Increase in the occurrence of 100-year flood events throughout most of the tropics and subtropics for a 1.5 and 2 °C temperature rise. Largest increase for southern Amazon, subtropical China, and north India.</td>
<td>(Paltan et al., 2018)</td>
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<td>A trend preserving bias correction technique (Hempel et al., 2013)</td>
<td>2 large scale hydrological models (LPJmL and WaterGAP)</td>
<td>Annual maximum 7-day high flow</td>
<td>Increase in high flows for South and South East Asia and Central Africa under a 1.5 °C temperature rise. Additional increases for parts of South America with a 2 °C rise.</td>
<td>(Döll et al., 2018)</td>
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<td>EC-Earth (RCP 8.5)</td>
<td>Bilinear interpolation and correction of wet days and monthly total precipitation</td>
<td>PCR-GLOBWB (global distributed hydrological model)</td>
<td>Flood frequency analysis (AM series with GEV distribution) and an empirical estimation technique</td>
<td>Significant increase in 100-year flood events for South Asia, western Africa, western Amazon, and parts of South East Asia under a 2° rise in temperatures. Significant decreases for the White Nile, northern South America, and Central America.</td>
<td>(Wiel et al., 2019)</td>
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References


Appendix B

Appendix B1: Boxplots of TN, TP, and Turbidity at Key Monitoring Sites

Figure B1. Boxplots comparing the distribution of TN, TP, and turbidity in the pre- and post-impoundment periods and p-values from the Wilcoxon Rank-Sum test showing significant differences at upper Logan and Albert estuary sites (Chainage 33 and 27 km, respectively) and sites near to WWTPs (Chainage 17.4 and 14.9 km for Logan and Albert estuaries, respectively).
Appendices

Appendix B2: GAM Model

In addition to analysing trends using the seasonal Mann-Kendall test, a Generalised Additive Model (GAM) approach (Murphy et al., 2019) was applied using the ‘baytrends’ package in the R statistical software (Murphy et al., 2020), in which the GAMs are fit using the ‘mgcv’ package (Wood, 2019). The structure of the GAM is presented in ‘mgcv’ syntax below:

\[
\text{gam2: } \text{gam}(y \sim \text{cyear} + s(\text{cyear}, k = c(10,2/3)) + s(\text{doy}, bs = 'cc') + ti(\text{cyear},\text{doy},bs = ('tp','cc')), knots = list(\text{doy} = c(1,366)), select= \text{TRUE})
\]

Where: \(y\) is a response variable, \(\text{cyear}\) is the zero-centred date in decimal form, \(\text{doy}\) is the day of year, \(s()\) is a spline, \(ti()\) is a tensor product, \(k\) is the number of knots (either 10 or \(2/3 \times\) number of years), \(bs='tp'\) signifies a penalised thin plate regression, while \(bs='cc'\) signifies a cyclic penalized cubic regression spline (Murphy et al., 2019). The structure of the model allows for non-linear trends and seasonal cycles that can vary over time.

In addition, to the gam2 model, the gam4 model was considered, which considered inter-annual variations in streamflow. Streamflow data from the Yarrahappini and Bromfleet stream gauges (ID: 145014A and 145102B) were adopted in this analysis. Streamflow was averaged over a period \(n\) preceding day \((\text{flw\_sal})\), where \(n\) was determined by comparing correlation coefficients (Murphy et al., 2019).

\[
\text{gam4: } \text{gam}(y \sim \text{cyear} + s(\text{cyear}, k = c(10,1/3)) + s(\text{doy}, bs = 'cc') + ti(\text{cyear},\text{doy},bs = c('tp','cc')) + s(\text{flw\_sal}, k = c(10,2/3)) + ti(\text{flw\_sal},\text{doy},bs = c('tp','cc')) + ti(\text{flw\_sal}, \text{cyear},bs = c('tp','cc') + ti(\text{flw\_sal},\text{doy},\text{cyear}, bs = c('tp','cc','tp')), knots = list(\text{doy} = c(1,366)), select = \text{TRUE})
\]

Trends from GAM models were determined by evaluating the percentage change between the model estimates at beginning and end of the study period and the significance level of this change (Murphy et al., 2019). The number of years selected at the beginning and end of the period is an important consideration, though selection of the most appropriate number of years is not always clear. Too many years may underestimate a trend in the data, while too few years may be overly influenced by year-to-year variations in streamflow and water quality. This is a particular issue in subtropical Australia, where rivers are subject to highly variable flow and water quality regimes. As such, we chose to evaluate periods of 4 and 7 years at the beginning and end of the GAM models, the results for which are presented below.
### Table B1. Percentage change results based on the GAM (4-years). Green colours denote decreasing trends and red increasing. *Bold* values indicate significant (p<0.01) trends.

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<th>NO$_x$-N</th>
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### Table B2. Percentage change based on the GAM (7-years). Green colours denote decreasing trends and red increasing. *Bold* values indicate significant (p<0.01) trends.

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<th>NO$_x$-N</th>
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Appendices

Table B3. Percentage change results based on the GAM (4-years) with flow-adjusted. Green colours denote decreasing trends and red increasing. Bold values indicate significant (p<0.01) trends.

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Table B4. Percentage change results based on the GAM (7-years) with flow-adjusted. Green colours denote decreasing trends and red increasing. Bold values indicate significant (p<0.01) trends.

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Appendices

References


Appendices

Appendix C

Appendix C1: Catchment Information

Figure C1. Major land uses in the Logan-Albert catchment.
Table C1. List of Bureau of Meteorology rainfall stations adopted for the calibration and validation of the hydrological model.

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### Appendix C2: Climate Models

Table C2. Details of the 11 global circulation models from the fifth phase of the Coupled Model Intercomparison Project used in this study.

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Appendix C3: Storm Surge Analysis

Streamflow data was obtained from the Logan River at the Yarrahappini stream gauge (145014A) from the Queensland Department of Natural Resources, Mines and Energy. Non-tidal residuals (NTR), which are defined as the difference between the total water level and the astronomical tide and representative of storm surge, were obtained for the Brisbane Bar tidal gauge from the Queensland Maritime Service (https://www.msq.qld.gov.au/Tides/Open-data). Annual maximum values of streamflow and NTR were extracted from the record and paired to corresponding maximum values of NTR and streamflow, respectively, that occurred within a chosen time window of the annual maximum event. Here, \((Q_n, s_n)\) represents pairs of annual maximum streamflow and the corresponding max daily NTR that occurred within the time window. Conversely, \((S_n, q_n)\) represents annual maximum NTR and the corresponding max daily streamflow. \((Q_n^*, S_n^*)\) represents co-occurrence events where both the annual maximum streamflow and NTR occurred within the same time window. Dependence between the two sets of pairs \((Q_n, s_n)\) and \((S_n, q_n)\) was assessed using Kendall’s tau and Spearman Rank sum correlation coefficients under a range of time windows. Statistical output showed significant dependence for most time windows (Figure C2).

![Figure C2: Sensitivity of the dependence between storm surge and streamflow to the size of the sampling window as assessed with the Spearman Rank sum (top) and Kendall’s tau (bottom) correlation coefficients.](image)

*p represents the associated p-values.*
Pairs of \((Q_n, s_n)\), \((S_n, q_n)\), and \((Q^*_n, S^*_n)\) were plotted using a time window of three days (Figure C3). Levels of storm surge (NTR) are relatively low compared to levels reported by Moftakhari et al. (2017) and Moftakhari et al. (2019) for compound flood studies in American estuaries. The pairs of \((Q_n, s_n)\), \((S_n, q_n)\), and \((Q^*_n, S^*_n)\) were then converted into probability space as pseudo-observations using the R copula package (Hofert et al., 2014) as shown in Figure C4. There was a high number of co-occurrences in the record with 7 of the 19 years showing coincident annual maximum NTR and streamflow.

Figure C3. Paired values of streamflow and storm surge for 19 years of data.

Figure C4. Paired values transformed into probability space.
Appendices

A number of bivariate copulas were fitted to the pseudo observations using the R copula package. p-values for the Cramér-von Mises Goodness-of-fit test were compared for the different copula families. The Archimedean Frank Copula was found to be a significantly match the data (p<0.05). Figure C6 presents the pseudo observations and isolines for the Frank Copula, and the calculated joint probability isolines for the 80\textsuperscript{th}, 90\textsuperscript{th}, 96\textsuperscript{th}, and 98\textsuperscript{th} percentiles representing 5, 10, 25, and 50-year return periods, respectively. The Gamma distribution was found to best fit the univariate data series (Figure C5) and was applied to estimate the magnitude of streamflow and surge events corresponding to these probabilities. The joint probability return period under the OR hazard scenario (Moftakhari et al., 2017) was calculated from the copula as:

\[ T_{OR} = \frac{1}{1 - C_{XY}(P_x^*, P_y^*)} \]

where: \( C_{XY} \) is the copula modelling the joint random behaviour of the pair \((X, Y)\), \( X \) is streamflow and \( Y \) is storm surge (NTR). The bivariate OR hazard scenario corresponds to pairs of \((X, Y)\), where either \( X> x^* \), \( Y>y^* \), or both. Where \( x^* \) and \( y^* \) are given critical thresholds.

Figure C5. The Gamma distribution fit to the streamflow and storm surge data.

Figure C7 presents the return periods for the univariate and bivariate (OR) analyses. The OR return periods are significantly less than the univariate ones, indicating an increase in
the frequency of these events, but note that this scenario is considered to be overly conservative approach for evaluating the joint probability of a combined streamflow-surge event (Moftakhari et al., 2019).

Figure C6. Pseudo observation and isolines of the Frank Copula in probability space. The colourbar represents the joint probability values of the isolines.

Figure C7. Comparison of return periods from the univariate and bivariate analyses using the Frank Copula.
Appendices

Appendix C4: Results under RCP8.5 and RCP4.5

Figure C8. Multi-model ensemble (RCP8.5) relative changes to monthly mean (a) precipitation and (b) PET for the 2020s, 2050s, and 2080s with respect to the baseline (1980-2010). Boxplots show the multimodel median (middle line) and the interquartile range of model projections (25th and 75th percentiles).

Figure C9. Multi-model ensemble (RCP4.5) relative changes to monthly mean (a) precipitation and (b) PET for the 2020s, 2050s, and 2080s with respect to the baseline (1980-2010). Boxplots show the multimodel median (middle line) and the interquartile range of model projections (25th and 75th percentiles).
**Appendices**

*Figure C10. Multi-model ensemble (RCP4.5) changes in monthly mean (a) precipitation, (b) PET, and (c) deficit (P-PET) for the 2020s, 2050s, and 2080s with respect to the baseline (1980-2010). Boxplots show the multi-model median (middle line) and the interquartile range of model projections (25th and 75th percentiles).*

*Figure C11. Multi-model ensemble (RCP4.5) used for predicting relative changes to mean and high flows representing the top 10% (Q10), 5% (Q5), and 1% (Q1) of flows relative to the baseline period at the (a) Albert River at Bromfleet and (b) Logan River at Yarrabhippi gauge. Boxplots show the multi-model median (middle line) and the interquartile range of model projections (25th and 75th percentiles).*
Figure C12. Multi-model ensemble (RCP4.5) used for predicting relative changes to monthly high and mean flows (outliers removed) at the Albert River at Bromfleet and Logan River at Yarrahappini gauges. Boxplots show the multi-model median (middle line) and the interquartile range of model projections (25th and 75th percentiles).

Figure C13. Multi-model ensemble (RCP4.5) of predicted relative changes to 5, 10, 25, 50, and 100-year ARI flood events relative to the baseline period (outliers removed) at (a) Albert River at Bromfleet and (b) Logan River at Yarrahappini gauges. Boxplots show the multi-model median (middle line) and the interquartile range of model projections (25th and 75th percentiles).
Figure C14. Changes to the hourly hydrograph of a 100-year ARI measured flood event (2017 ex-tropical cyclone Debbie flood event) for the upper Logan and Albert Rivers using the simulated multi-model median (RCP4.5) change of a 100-year ARI flood event for each future period.

Table C3. Comparison of changes (RCP4.5) to inundation area for various depths of, and change to, the maximum flood extent relative to the baseline scenario. SLR is sea level rise and SS is storm surge.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Area (km$^2$) of inundation at various depth intervals (m)</th>
<th>Total inundation (km$^2$)</th>
<th>Relative change to maximum flood extent (%)</th>
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<tr>
<td></td>
<td>&lt; 0.1</td>
<td>0.1 - 1</td>
<td>1 - 2</td>
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<td>Baseline</td>
<td>1.93</td>
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<tr>
<td>2020s no SLR</td>
<td>2.94</td>
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<td>2020s SLR</td>
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<td>2050s no SLR</td>
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<td>2050s SLR</td>
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<td>38.34</td>
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Figure C.15. Predicted changes (RCP4.5) in the floodplain inundation area of the lower Logan-Albert catchment for different time periods with and without accounting for sea level rise (SLR). The additional effects of storm surge (SS) are considered for cases in the 2080s. Red and green areas indicate increases and decreases to the maximum flood extent relative to the baseline, while grey indicate non-wetted areas.
Figure C16. Normalised nonlinearity index (Bilskie et al., 2014) of maximum inundation under RCP4.5 (left) and RCP8.5 (right) comparing no sea level rise with predicted sea level rise in the 2020s (a and b), 2050s (c and d), and 2080s (e and f). Warm colours denote an amplification in water levels relative to sea level rise, cool colours indicate a de-amplification and white represents non-wetted areas.
Appendices

References


Appendices

Appendix D

Appendix D1: Climate Models Used

*Table D1. Details of the 11 global circulation models from the fifth phase of the Coupled Model Intercomparison Project used in this study.*

<table>
<thead>
<tr>
<th>GCM</th>
<th>Model Name</th>
<th>Institution Name</th>
<th>Country</th>
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<tr>
<td>ACCESS1.0</td>
<td>Australian Community Climate and Earth-System Simulator, version 1.0</td>
<td>CSIRO &amp; BOM</td>
<td>Australia</td>
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<td>CCSM4</td>
<td>Community Climate System Model, version 4</td>
<td>NCAR</td>
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<tr>
<td>CNRM-CM5</td>
<td>Centre National de Recherches Météorologiques Coupled Global Climate Model, version 5</td>
<td>CNRM-CERFACS</td>
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<tr>
<td>CSIRO-MK3.6</td>
<td>Commonwealth Scientific and Industrial Research Organisation Mark 3.6.0</td>
<td>CSIRO</td>
<td>Australia</td>
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<td>GFDL-CM3</td>
<td>Geophysical Fluid Dynamics Laboratory Climate Model, version 3</td>
<td>GFDL NOAA</td>
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<td>GFDL-ESM-2M</td>
<td>Geophysical Fluid Dynamics Laboratory Earth System Model with Modular Ocean Model, version 4 component</td>
<td>GFDL NOAA</td>
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<td>HadGEM2</td>
<td>Hadley Centre Global Environmental Model, version 2</td>
<td>Met Office Hadley Centre</td>
<td>UK</td>
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<td>MIROC5</td>
<td>Model for Interdisciplinary Research on Climate, version 5</td>
<td>AORI Japan</td>
<td>Japan</td>
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<td>MPI-ESM-LR</td>
<td>Max Planck Institute Earth System Model, low resolution</td>
<td>Max Planck Institute</td>
<td>Germany</td>
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<td>NorESM1-M</td>
<td>Norwegian Earth System Model, version 1 (intermediate resolution)</td>
<td>Norwegian Climate Centre</td>
<td>Norway</td>
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## Appendix D2: Catchment Information

### Table D2. Parameters used in the SWAT model.

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<tr>
<th>No.</th>
<th>Parameter</th>
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<th>Initial adjustment range</th>
<th>Fitted value</th>
<th>Yarrahappini</th>
<th>Bromfleet</th>
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<td>1</td>
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<td>(0 – 24)</td>
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<td>2.810</td>
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<tr>
<td>2</td>
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<td>Revap coefficient</td>
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<td>-0.033</td>
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<td>3</td>
<td>V_GW_SPLYLD.gw</td>
<td>Specific yield of the shallow aquifer for revap</td>
<td>(0 – 0.4)</td>
<td>0.207</td>
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<td>A_REVAPMN.gw</td>
<td>Threshold water level in shallow aquifer for revap</td>
<td>(-200 – 200)</td>
<td>290.024</td>
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<td>5</td>
<td>V_ALPHA_BF.gw</td>
<td>Baseflow recession constant</td>
<td>(0 – 1)</td>
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<td>6</td>
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<td>Threshold water level in shallow aquifer for baseflow</td>
<td>(-1500 – 1500)</td>
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<td>V_RCHRG_DP.gw</td>
<td>Aquifer percolation coefficient</td>
<td>(0 – 1)</td>
<td>0.640</td>
<td>0.534</td>
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<td>V_EP_CO.hru</td>
<td>Plant uptake compensation factor</td>
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<td>Soil evaporation compensation coefficient</td>
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<td>R_CN2 mgt</td>
<td>Curve number for moisture condition II</td>
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<td>R_SOL_K().sol</td>
<td>Saturated hydraulic conductivity</td>
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<td>R_SOL_AWC().sol</td>
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<td>(0 – 120)</td>
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<td>V_GW_DELAY.gw</td>
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<td>R_OV_N hru</td>
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<td>V_PRF_BSN.bsn</td>
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<td>1.112</td>
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<td>Minimum value for the cover and management factor for the land cover</td>
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## Table D2. Continued

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<th>No.</th>
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<th>Yarrahapini Fitted value</th>
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<th>Bromfleet Fitted value</th>
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<td>Rate constant for biological oxidization of nitrite-nitrogen to nitrate-nitrogen in the reach at 20 degrees</td>
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Appendix D3: Validation Results

Figure D1. Comparison of the variability present in the modelled and observed event monitoring data for loads and concentrations of TSS, TN, and TP during validation at (a-f) Yarrahappini and (g-l) Bromfleet.
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Appendix D4: Results under RCP4.5

Figure D2. Multi-model ensemble (RCP4.5) relative changes to monthly mean (a) precipitation and (b) PET for the 2020s, 2050s, and 2080s with respect to the baseline (1980-2010). Boxplots show the multi-model median (middle line) and the interquartile range of model projections (25th and 75th percentiles).

Figure D3. Relative changes to simulated annual low (Q99), mean (QM), and high flows (Q01) from SWAT in the 2020s, 2050s, and 2080s relative to the baseline period from the ensemble of climate models under RCP4.5 at the (a) Yarrahappini and (b) Bromfleet gauges.
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Figure D4. Relative changes to monthly simulated mean flows from SWAT in the 2020s, 2050s, and 2080s relative to the baseline period from the ensemble of climate models under RCP4.5 at the (a) Yarrahappini and (b) Bromfleet gauges.

Figure D5. Relative changes to simulated annual average and high-quantile TSS, TN, and TP loads from SWAT in the 2020s, 2050s, and 2080s relative to the baseline period from the ensemble of climate models under RCP4.5 at the (a) Yarrahappini and (b) Bromfleet gauges.
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Figure D.6. Relative changes to simulated monthly average TSS, TN, and TP loads from SWAT in the 2020s, 2050s, and 2080s relative to the baseline period from the ensemble of climate models under RCP4.5 at the Yarrahappini (left) and Bromfleet (right) gauges.

Table D.3. Predicted multi-model median change to streamflow (Q), total suspended solids (TSS), total phosphorus (TP), and total nitrogen (TN) at the Yarrahappini and Bromfleet sites by the 2080s under RCP8.5. Green colours indicate a decrease in loads, while red indicates an increase, with colour intensity showing the relative change.

<table>
<thead>
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<th></th>
<th></th>
<th></th>
<th>Bromfleet</th>
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Appendix E

Extreme event analysis of rainfall and streamflow in the Logan catchment

Abstract

Extreme event analysis of historical rainfall and streamflow data allow engineers and managers to predict the magnitudes of future extreme events, which are key parameters for infrastructure design and flood control. The frequency and magnitude of these events are most commonly evaluated using the Annual Maximum (AM) series as opposed to the less commonly applied Peak-Over-Threshold (POT) series. In the present study, the AM series with Generalised Extreme Value (GEV) distribution and POT series with Generalised Pareto (GP) distribution were applied to evaluate the intensity of extreme rainfall, while the POT series was applied to streamflow within the Logan-Albert Basin. Three techniques for threshold selection were applied to the POT series, including an automated threshold selection (ATS) proposed by Thompson et al. (2009) and a method based on the mean residual life (MRL) plot. The average recurrence intervals (ARI) curves were estimated for each site using all methods. All POT techniques produced reasonable results for streamflow, comparable to results obtained from previous studies. The AM series and POT series both produced reasonable results for precipitation in the catchment. The choice of threshold when using the POT series was shown to have an influence on the ARI curves produced. These results demonstrate the difference in peak magnitude flows between the two rivers and illustrate the degree of spatial rainfall variation across the catchment. This present study may be relevant to local government authorities, who make use of ARI curves for flood mitigation works and planning.
Appendices

E.1 Introduction

Flooding causes the most damage of any natural disaster in Australia, costing on average $377 million annually (Middelmann, 2009). The coastal regions of south-east Queensland (SEQ) are some of the most flood prone in the country (Department of Climate Change, 2009). Estimating the intensity and frequency of flooding events is important for urban planning and infrastructure design. Extreme event analysis is used to relate the magnitudes of extreme events to their predicted occurrence frequency through the use of probability distributions (Hamed and Rao, 1999). This allows for estimations of extreme events that extend beyond the historically measured record and improves estimations of events within the record (Nagy et al., 2017).

There are two principal methods for selecting data for extreme event analyses, namely, the annual maxima (AM) and peak-over-threshold (POT) techniques. The AM series consists of flood maxima extracted from each year of the historical record. The Australian Rainfall and Runoff (ARR) Guidelines identify two main advantages in using the AM series--the values in the series are likely to be statistically independent as only one event is retrieved annually, and the series is easily extracted with little ambiguity in the process (Ball et al., 2016). A drawback of this method is that in wet years some large events may be excluded, whilst in dry years insignificant events may be included which may have a disproportionate effect on the shape of the distribution (Ball et al., 2016).

The POT series is comprised of values in the dataset that exceed a chosen threshold. In some years several events may be included, whilst in other years there may be none at all. The POT series compares favourably with the AM series as insignificant events can be excluded, and significant events can be included that may not have been otherwise in AM. The POT series is especially useful in analysing sites with limited historical records, as it allows more data points to be assessed (Keast and Ellison, 2013). However, the AM approach remains more widely used than the POT due to complexities in selecting an appropriate threshold and issues in ensuring values in the dataset are statistically independent (Lang et al., 1999, Nagy et al., 2017). This study aims to compare the return levels and ARI curves produced from the AM series to those of the POT series using different threshold selection techniques within the Logan-Albert catchment.
E.2 Study Area and Data

The Logan-Albert catchment is located south of Brisbane in south-east Queensland, covering around 3,862 km² (Figure E1). The region is characterised by a subtropical humid climate with high spatial and temporal rainfall variability (Abal et al., 2005). Most of the rainfall in the region is associated with Australian east coast low-pressure systems, tropical cyclones, and thunderstorms. A distinct wet season occurs during the summer months and a dry season occurs during winter months. Year-to-year variability is also significant, with long periods of drier or wetter years often prevalent in the rainfall record. Rainfall in wetter years can be twice that of drier years (Bunn et al., 2007). Generally, the coastal and mountainous sub-catchments in the region receive higher annual rainfall (~1200 mm) than the mid-catchment region (~900 mm; Bureau of Meteorology, 2002), due to a mixture of onshore winds and adiabatic cooling (Abal et al., 2005).

Major flooding events in the Logan-Albert Catchment have historically occurred after extended periods of heavy rainfall, usually associated with low-pressure systems or tropical cyclones (Bureau of Meteorology, 2017). Tropical cyclones affect the region infrequently, with an average recurrence interval of 0.26 per year within 200 km of Logan City (Environmental Risk Science and Audit, 2012). East coast low-pressure systems, sometimes derived from ex-tropical cyclones, intersect SEQ with much more regularity, bringing significant rainfall, often over the course of several days. The occurrence of these events is exceedingly variable, with many years recording zero instances, and others having several, with a maximum of twelve east coast lows recorded during the 1978/79 summer. The long-term average recurrence interval for east coast lows in SEQ is 2.5 annually, which increases to 3.7 when considering the annual average since 1960 (Environmental Risk Science and Audit, 2012). Major flooding has occurred in the catchment in 1887, 1947, 1974, 1976, 1991, and more recently in 2013 and 2017.

Daily streamflow maxima were obtained from the Queensland Department of Environment and Management (DERM). Downstream gauges at Yarrahappini for the Logan River and Bromfleet for the Albert River (Figure E1) were used for analysis. The historical record extends back 48 years and 31 years, respectively, for these two sites. The datasets were for the most part complete and were therefore not supplemented. Daily total rainfall data were retrieved from the Bureau of Meteorology (BOM) for the Wilsons Peak, Beaudesert, and Rocky Point rainfall gauges representing the upper, middle, and lower catchment, respectively. The most recent 60 years of the historical record was taken from these gauges for analysis. Missing data were significant in these records, and thus the
nearest neighbouring rainfall gauges have been used to supplement the record.

Figure E1. Study area and location of streamflow and rainfall gauges

E.3 Extreme Event Analysis Methods

Both the AM and POT methodologies for extreme event analysis have been employed in this study. As threshold selection is a major consideration in the POT series, and there remains no clearly agreed guidelines for selecting an appropriate threshold (Lang et al., 1999), a number of selection techniques have been applied. The (ARR, 2016) states that typically, a threshold is selected such that it is exceeded on average 2-3 times annually (Ball et al., 2016). As such, the traditional POT method has been applied, with thresholds selected that were exceeded an average of three times (POT3), two times (POT2), and 1.65 times (POT1.65) annually for comparison. An alternative threshold selection technique described by Coles et al. (2001) based on the mean residual life plot (MRL) was also employed. In this technique, an appropriate threshold is chosen from the MRL plot at a point, beyond which the plot is approximately linear (e.g., Figure E2). However, this method is rather subjective and selection of an appropriate threshold from the plot is not always clear. An automated threshold selected technique (ATS) proposed by Thompson et al. (2009) for the analysis of extreme rainfall and wave events was also utilised. This technique overcomes subjectivity by automatically selecting an appropriate threshold from 300 values between the median and the 98th percentile of the dataset. The
method is based on standard maximum likelihood theory using the Generalised Pareto (GP) distribution. When assessing streamflow data, it is important to ensure the peaks selected in the POT series are statistically independent. For this purpose, a minimum 5-day lag between peaks was used as a criterion to ensure flood peaks were not a continuation of the same event.

There are many different probability distributions that can be used to describe extreme events. How to select an appropriate distribution for a given region is also vital and challenging. Rahman et al. (2013) studied flooding in catchments across Australia and identified the GP, Generalised Extreme Value (GEV), and log-Pearson 3 distributions to be the most suitable for flood frequency analysis. Rustomji et al. (2009) studied the flood variability across eastern Australia and concluded the GP distribution to be the most appropriate for modelling of flood frequency curves, whilst Lam et al. (2017) found the GP distribution to be the most suitable for catchments in SEQ. In this study the POT series was modelled with the GP distribution as it has been demonstrated in the literature to be suitable for catchments in SEQ and is also required for application of the ATS technique. Whilst, the AM series has been modelled with the GEV distribution, as it generally fits the AM series well (Ball et al., 2016).

![Figure E2. Example of the MRL plot for the Albert River at Bromfleet stream gauge and the selected threshold](image)

The maximum likelihood technique was used for estimation of the scale, shape, location (for GEV) parameters. Quantile and probability diagnostic plots were produced (Coles et
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al., 2001) to assess the suitability of the distributions. Return level plots were developed
for both stream gauges and all rainfall gauges using Eq. (E.1) for the GEV distribution
and Eq. (E.2) for the GP distribution (Coles et al., 2001). The extreme event analysis
techniques applied in this study have been summarised in Table E1 below

\[
Z_{ARI} = \mu - \frac{\sigma}{\xi} \left[ 1 - \left( -\ln \left( 1 - \frac{1}{n} \right) \right)^{-\xi} \right] \text{ for } \xi \neq 0 \quad (E.1)
\]

\[
Z_{ARI} = \mu + \frac{\sigma}{\xi} \left[ \left( \frac{n \times N}{Y} \right)^{\xi} - 1 \right] \text{ for } \xi \neq 0 \quad (E.2)
\]

where \( N \) is the number of events exceeding the chosen threshold, \( Y \) is the total years in
the historical record, \( \mu \) is the chosen threshold, and \( n \) is the ARI.

Table E1. Summary of extreme event analysis techniques used

<table>
<thead>
<tr>
<th>Method</th>
<th>Extreme analysis technique</th>
<th>Distribution function</th>
<th>Threshold selection technique</th>
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<tbody>
<tr>
<td>AM</td>
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<td>Annual Maximums</td>
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<td>POTx</td>
<td>POT</td>
<td>GP</td>
<td>Traditional Peak-Over-Threshold selection</td>
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<td>MRL</td>
<td>POT</td>
<td>GP</td>
<td>Mean residual life plot</td>
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<tr>
<td>ATS</td>
<td>POT</td>
<td>GP</td>
<td>Automatic threshold selection</td>
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</table>

E.4 Results

E.4.1 Streamflow

Return level plots for streamflow are presented in Figure E4 for all POT techniques used,
while quantile plots are presented in Figure E33. All techniques, using the range of
thresholds obtained somewhat similar results. The ARI curve produced from the MRL
technique at the Logan River can be seen to be significantly different from the curves
produced from the other two methods. It is possible this is the result of the large threshold
selected for this technique, removing small flood events and leading to large estimates at
small return levels. By contrast, the threshold selected from the POT3 technique at the
Albert River may have been too small, as the 100-year flood estimate from this technique
was significantly greater than the other techniques used. This may lead to the distribution
being skewed from the inclusion of too many small or non-flood related events. Selecting
a larger threshold would remove the superfluous data points and may produce improved
results. For this reason, return levels for the 25, 50, and 100-year events were calculated
for the POT2 and POT1.65 series for comparison, as shown in Table E2. For the Albert
River, it can be seen that the selection of a greater threshold from the POT2 and POT1.65 lead to results more in line with those obtained from the other techniques assessed. However, for the Logan River a change in the threshold from these methods is shown to have no significant effects on large flood estimates.

Estimations for large 25, 50, and 100-year events were nonetheless quite consistent, as seen in Table E2. For the Logan River 100-year ARI flood estimates ranged from 3966 m$^3$/s and 4215 m$^3$/s, while for the Albert River this extended from 2032 m$^3$/s to 2737 m$^3$/s. Previous flood frequency analysis of the Yarrahappini and Bromfleet gauges for the Logan and Albert Rivers estimated 100-year ARI flood magnitudes at 4836 m$^3$/s and 1935 m$^3$/s, respectively (Trapani, 2017). An additional earlier study by Cameron McNamara & Partners. (1975) estimated the 100-year ARI flood event at the Logan River at just under 5000 m$^3$/s. The results from this study show elevated estimates for the Albert River and lower estimates for the Logan River than those from previous studies.

The datasets used consist of 48 years of records for the Logan and 31 years for the Albert rivers and may not be sufficient for accurate estimates of large return level events. In addition, missing records from these gauges were not supplemented, which may have led to the exclusion of a number of flooding events. An assumption of stationarity was also made within this study, whereby the distribution of the flood frequency curves was assumed to be unchanging for length of analysis. In reality, changes to land use, the construction of additional hydraulic structures, and climatic changes may render this assumption somewhat unreasonable.

Flood magnitudes were larger in the Logan River than the Albert River as would be expected given the comparative size difference between the catchments. Generally, flood magnitudes were estimated to be approximately 80% greater in the Logan River than the Albert River at all return periods assessed. Overall, all POT techniques have shown that they may suitably be used for flood frequency analysis, provided that an appropriate threshold and independence criteria are selected.
Figure E3. Quantile Plots for the Logan River (left) and the Albert River (right) using the POT3, MRL, and Automatic methods with the GPD distribution

Table E2. Return level comparison between different modelling techniques at both rivers for large flooding events

<table>
<thead>
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<th>Technique</th>
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<th>Albert River**</th>
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<td>Threshold (m³/s)</td>
<td>25 year ARI (m³/s)</td>
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<tr>
<td>ATS + GP</td>
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<tr>
<td>MRL + GP</td>
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<td>3050</td>
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<tr>
<td>POT3 + GP</td>
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<tr>
<td>POT2 + GP</td>
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</tr>
<tr>
<td>POT1.65 + GP</td>
<td>167.5</td>
<td>2878</td>
</tr>
</tbody>
</table>

* Largest recorded flood event was 4700 m³/s
** Largest recorded flood event was 2378 m³/s
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Figure E4. Return level plots of the three main POT techniques used at the Logan River (left) and Albert River (right)

E.4.2 Rainfall

Return level plots for the three rainfall stations representing the upper, middle, and lower catchment are shown in Figure E5, while Table E3 and Table E4 present the selected threshold and calculated magnitudes of large magnitude rainfall events. The quantile plots and ARI curves for the automatic threshold selection technique are presented in Figure E6. The techniques assessed generally produced consistent estimations of large rainfall events at all rainfall stations. However, the AM series and ATS technique at Beaudesert, obtained rainfall estimates that were significant lower and greater than those obtained from the other techniques. For the AM series, this may be due to the high year-to-year variability in the rainfall record at this site, leading to the inclusion of insignificant events in the series from dry years, which could have skewed the distribution. While for the ATS technique the threshold selected may too low and include too many insignificant events, also leading to a skewed distribution. The datasets used for the rainfall analysis consisted of 60 years records, which may not be sufficient for estimations of 100-year events. Missing records for the rainfall record were supplemented from nearby stations, which likely lead to improved results.
### Table E3. Thresholds selected for the different techniques at three rainfall stations

<table>
<thead>
<tr>
<th>Modelling Technique</th>
<th>Wilsons Peak (mm)</th>
<th>Beaudesert (mm)</th>
<th>Rocky Point (mm)</th>
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<tr>
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<td>ATS + GP</td>
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<td>POT2 + GP</td>
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### Table E4. Return level comparison between different modelling techniques at three rainfall stations for large events

<table>
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<tr>
<th>Modelling Technique</th>
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<th>Beaudesert (middle)</th>
<th>Rocky Point (lower)</th>
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<td></td>
<td>25 year ARI (mm)</td>
<td>50 year ARI (mm)</td>
<td>100 year ARI (mm)</td>
</tr>
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<td>208.9</td>
<td>244.1</td>
<td>282.6</td>
</tr>
<tr>
<td>ATS + GP</td>
<td>220.1</td>
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<td>312.0</td>
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<tr>
<td>MRL + GP</td>
<td>206.1</td>
<td>239.1</td>
<td>274.6</td>
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<td>POT3 + GP</td>
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<tr>
<td>POT2 + GP</td>
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<td>245.2</td>
<td>285.5</td>
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### Figure E5. Return level plots for Wilsons Peak (top left), Beaudesert (top right), and Rocky Point (bottom)
The greatest 25, 50, and 100-year return period rainfall events were estimated at Beaudesert in the middle catchment, whilst the lowest were at Rocky Point in the lower catchment. The difference in magnitude of 100-year events between these sites varied from 50 mm to 150 mm per year, depending on the analysis technique used. These results are somewhat surprising given that the Beaudesert gauge receives the least annual rainfall of those assessed at approximately 900 mm compared to 1100 mm for Rocky Point and 1200 mm annually for Wilsons Peak. This highlights the high variability in rainfall at Beaudesert compared to the other sites.

Figure E6. Quantile and return level plots for Rocky Point (top), Beaudesert (middle), and Wilsons Peak (bottom) representing the lower, middle, and upper catchment respectively using the ATS method with the GP distribution
E.5 Conclusion

This study assessed four different methods of extreme event analysis for three rainfall datasets and two streamflow datasets within the Logan-Albert catchment. For streamflow, somewhat consistent return levels were produced for 25, 50, and 100-year events, depending on the technique applied. The POT series was considered suitable for assessing flood frequencies as it excluded insignificant events from analysis provided that an appropriate threshold and independence criteria were utilised. Threshold selection was influential in the return levels produced, with poorer results obtained from thresholds that were both too high and low. As such, it is recommended to apply and compare a range of thresholds when adopting the POT series for flood frequency analysis. There was good agreement between the different techniques used for extreme rainfall analysis in the catchment, with all methods presenting similar results. Threshold selection was also shown to be influential for rainfall estimates compared to streamflow.
Appendices

References


DEPARTMENT OF CLIMATE CHANGE 2009. Climate Change Risks to Australia's Coast, A first Pass National Assessment, Canberra, ACT.


Appendices


