Impact of environmental water delivery and climate change on floodplain vegetation: a case study of a connected floodplain-lakes system

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Abstract

River floodplains are one of the most dynamic and diverse ecosystems in the world, renowned for their remarkable biodiversity and productivity. They provide a wealth of ecosystem services, benefiting both the natural environment and human communities. Nevertheless, they face the looming threats of degradation and loss, primarily due to river regulation and the impact of climate change. Among the vulnerable components of floodplain ecosystems, vegetation stands out as significantly affected, especially in semi-arid and arid regions.

Environmental water is strategically deployed to rejuvenate floodplains in many countries. This intervention aims to create more natural flooding patterns, utilizing water resources to restore floodplain ecosystems, sustain vegetation health, and support animal breeding. My research is centered on floodplain vegetation.

Government monitoring programs have demonstrated that environmental water has yielded a variety of positive outcomes for floodplain components. However, these monitoring programs mostly rely on ground-based methods, which are time intensive and require considerable resources. The emergence of remote sensing datasets offers a promising avenue for assessing long-term effects of both degrading and restorative processes in floodplain ecosystems. Leveraging these extensive datasets and linking them to environmental water presents a novel challenge. To make informed decisions about the quantity and timing of environmental water delivery in the context of climate change, accurate models are needed to predict how vegetation will respond to watering events. This becomes even more complex in semi-arid floodplains, where plant abundance can vary significantly.

The primary objective of this thesis is to investigate the spatiotemporal impacts of environmental water on floodplain vegetation. Additionally, it seeks to assess various environmental water allocation scenarios under different climate projections for the future. These findings aim to provide insights into future management strategies and the preservation of vegetation in a changing climate.

This research focuses on a connected floodplain-lakes system in south-eastern Australia – the Hattah Lakes floodplain in north-western Victoria. This region, designated as a Ramsar site, comprises a complex system of more than 20 semi-permanent wetlands. Three specific research questions were addressed.

Research Question 1 delves into the spatiotemporal impact of environmental water on floodplain vegetation and how it differs from the effects of natural floods. This study utilizes the Normalized Difference Vegetation Index (NDVI) derived from 30 years of Landsat imagery datasets to represent vegetation dynamics. A Generalized Additive Mixed Model (GAMM) was developed to analyze vegetation responses to watering events and climatic factors. The findings reveal significant spatial and temporal variation in the influence of environmental water and natural floods on floodplain vegetation. While vegetation in most areas of Hattah Lakes is improved by natural floods within one month of inundation, positive responses to environmental water occur 1 to 3 months after inundation and exhibit more constrained spatial patterns.

Research Question 2 aimed to extract the quantitative influence of environmental water volume and lag time on fringing vegetation of floodplain lakes and assess the effectiveness of the current environmental watering strategy. Random Forest regression (RF) models identified the monthly total of environmental water volume three months prior to vegetation sampling as a more important factor than natural floods in shaping fringing vegetation condition. Notably, the volume of environmental water from three months prior exerts a positive influence on NDVI until reaching a specific threshold. Significant enhancements in floodplain vegetation have been observed under the current environmental water strategy, particularly since the implementation of permanent pumping infrastructure to the floodplain in 2013.

Research Question 3 is dedicated to assessing whether environmental water can offset the influence of future climate change on floodplain vegetation. Utilizing Long Short-term Memory (LSTM) networks, I forecasted NDVI values from 2016 to 2045 across 16 different climate models and scenarios, and under 3 distinct environmental water allocation scenarios. NDVI exhibited improved performance when environmental water was allocated, as compared to scenarios without environmental water, and this was consistent across all climate patterns.

More importantly, the results showed that all three environmental water allocation scenarios have the potential to effectively mitigate the impacts of future climate change across the 30-year time frame of the predictions.

The combined findings of all research demonstrate that environmental water allocation is an effective approach to enhance vegetation condition on the floodplains of a highly regulated river system. This conclusion is based on assessments of past observations and analyses of future projections under a changing climate. However, results from Research Questions 2 and 3 suggest the increased utilization of infrastructure to reduce the spatial heterogeneity of environmental water outcomes observed across the system. Collectively, the results presented in this thesis offer valuable technical support to environmental water management efforts aimed at restoring and sustaining vegetation health in the face of future climate uncertainty.

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Zusammenfassung

Flussauenlandschaften gehören zu den dynamischsten und vielfältigsten Ökosystemen der Welt und zeichnen sich durch eine bemerkenswerte Biodiversität und Produktivität aus. Sie erbringen eine Fülle von Ökosystemleistungen, die sowohl der Natur als auch den menschlichen Gemeinschaften zugutekommen. Sie sind jedoch zunehmend von Degradation und Verlust gefährdet, vor allem aufgrund der Flussregulierung und der Auswirkungen des Klimawandels. Besonders betroffen ist die Vegetation, die zu den verwundbarsten Komponenten der Flussauenlandschaften gehört, insbesondere in semi-ariden und ariden Regionen.

Umweltwasser wird in vielen Ländern strategisch zur Wiederherstellung von Überschwemmungsgebieten eingesetzt. Die Maßnahmen zielen darauf ab, natürlichere Überschwemmungsmuster zu schaffen, mit Nutzung der Wasser Ressourcen die Auenökosysteme wiederherzustellen, die Vegetationsgesundheit zu erhalten und die Tierzucht zu unterstützen. Meine Forschung fokussiert sich auf die Auenvegetation.

Staatliche Überwachungsprogramme haben gezeigt, dass Umweltwasser eine Vielzahl von positiven Ergebnissen für die Auenkomponenten erbracht hat. Diese Überwachungsprogramme basieren jedoch meist auf bodengestützten Methoden, die zeitintensiv sind und erhebliche Ressourcen erfordern. Die neue Fernerkundungsdatensätze bieten eine vielversprechende Möglichkeit, um die langfristigen Auswirkungen von sowohl degradierenden als auch restaurativen Prozessen in Überschwemmungsökosystemen zu bewerten. Die Nutzung dieser umfangreichen Datensätze und ihre Verknüpfung mit dem Umweltwasser stellt eine neue Herausforderung dar. Um fundierte Entscheidungen über die Menge und den Zeitpunkt der Wasserzufuhr im Zusammenhang mit dem Klimawandel zu treffen, sind genaue Modelle erforderlich, um vorherzusagen, wie die Vegetation auf Bewässerungsereignisse reagieren wird. Dies wird in semi-ariden Auenlandschaften noch komplexer, wo der Pflanzenreichtum erheblich variieren kann.

Das Hauptziel dieser Arbeit besteht darin, die raum-zeitlichen Auswirkungen von Umweltwasser auf die Auenvegetation zu untersuchen. Darüber hinaus sollen verschiedene Szenarien der Umweltwasserverteilung für die Zukunft im Rahmen unterschiedlicher Klimaprognosen bewertet werden. Diese Ergebnisse sollen Einblicke für die zukünftige Managementstrategien und den Erhalt der Vegetation in einem sich wandelnden Klima liefern.

Diese Forschung konzentriert sich auf ein verbundenes Auen-Seen-System im Südosten Australiens - die Hattah Lakes Aue im Nordwesten von Victoria. Diese als Ramsar-Gebiet ausgewiesene Region umfasst ein komplexes System von mehr als 20 semi-permanenten Feuchtgebieten. Drei spezifische Forschungsthemen wurden behandelt.

Forschungsfrage 1 befasst sich mit den raum-zeitlichen Auswirkungen von Umweltwasser auf die Auenvegetation und wie sie sich von den Auswirkungen natürlicher Überschwemmungen unterscheiden. In dieser Studie wurde der Normalized Difference Vegetation Index (NDVI) verwendet, der aus 30 Jahren Landsat-Bilddatensätzen abgeleitet wurde, um die Vegetationsdynamik darzustellen. Ein Generalized Additive Mixed Model (GAMM) wurde entwickelt, um die Vegetationsreaktionen auf Bewässerungsereignisse und klimatische Faktoren zu analysieren. Die Ergebnisse zeigen eine signifikante räumliche und zeitliche Variation im Einfluss von Umweltwasser und natürlichen Überschwemmungen auf die Auenvegetation. Während sich die Vegetation in den meisten Gebieten der Hattah Lakes durch natürliche Überschwemmungen innerhalb eines Monats nach der Überschwemmung verbesserte, traten positive Reaktionen auf Umweltwasser 1 bis 3 Monate nach der Überflutung auf und wiesen eingeschränktere räumliche Muster auf.

Forschungsfrage 2 zielte darauf ab, zu quantifizieren, wie sich Umweltwassermenge und -zeitverzögerung auf die Ufervegetation von Auenseen auswirken, und die Wirksamkeit der aktuellen Umweltwasserstrategie zu bewerten. Bei der Gestaltung des Zustands der Ufervegetation wurde es durch Random Forest Regression (RF) Modelle identifiziert, dass die monatliche Gesamtwassermenge von Umweltwasser drei Monate vor der Vegetationsprobenahme einer wichtigere Faktor als natürliche Überschwemmungen war. Bemerkenswert ist, dass das Volumen des

Umweltwassers aus drei Monaten zuvor einen positiven Einfluss auf den NDVI ausübte, bis ein bestimmter Schwellenwert erreicht wurde. Im Rahmen der aktuellen Umweltwasserstrategie wurden signifikante Verbesserungen der Auenvegetation beobachtet, insbesondere seit der Implementierung einer permanenten Pumpinfrastruktur in die Auen im Jahr 2013.

Forschungsfrage 3 widmet sich der Beurteilung, ob Umweltwasser den Einfluss des Klimawandels auf die Auenvegetation ausgleichen kann. Unter Verwendung von Long Short-term Memory (LSTM) Netzwerken wurden die NDVI-Werte von 2016 bis 2045 für 16 verschiedene Klimamodelle und -szenarien sowie jeweils unter drei unterschiedlichen Szenarien der Umweltwasserverteilung prognostiziert. Der NDVI zeigte eine verbesserte Leistung, wenn Umweltwasser zugeteilt wurde, im Vergleich zu Szenarien ohne Umweltwasser, und dies war bei allen Klimamodellen gleich. Wichtiger noch, die Ergebnisse zeigten, dass alle drei Szenarien der Umweltwasserverteilung das Potenzial hatten, die Auswirkungen des Klimawandels über den 30-Jahres-Zeitraum der Vorhersagen wirksam abzumildern.

Die kombinierten Ergebnisse aller Forschungen zeigen, dass die Umweltwasserverteilung ein wirksamer Ansatz ist, um den Vegetationszustand in den Überschwemmungsgebieten eines stark regulierten Flusssystems zu verbessern. Diese Schlussfolgerung basiert auf den Bewertungen vergangener Beobachtungen und den Analysen zukünftiger Prognosen unter einem sich ändernden Klima. Die Ergebnisse aus den Forschungsfragen 2 und 3 legen jedoch eine erhöhte Nutzung der Infrastruktur nahe, um die räumliche Heterogenität der beobachteten Umweltwasserereignissen im gesamten System zu reduzieren. Zusammenfassend bieten die in dieser Arbeit präsentierten Ergebnisse eine wertvolle technische Unterstützung fürs Umweltwassermanagement, um die Vegetationsgesundheit angesichts der zukünftigen Klimaunsicherheit wiederherzustellen und zu erhalten.

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Declaration

I, Chunying Wu, declare that this thesis titled, ‘Impact of environmental water delivery and climate change on floodplain vegetation: a case study of a connected floodplain-lakes system’ and the work presented in it are my own. I confirm that:

1) The thesis comprises only my original work towards the Doctor of Philosophy except where indicated in the preface;
2) Due acknowledgement has been made in the text to all other material used; and
3) The thesis is less than the maximum word limit in length (80000 words), exclusive of tables, maps, bibliographies, and appendices as approved by the Research Higher Degrees Committee.

Chunying Wu

19/10/2023

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Preface

This thesis represents original research of me (Chunying Wu) conducted during my Ph.D. candidature at the University of Melbourne, Australia (my main university) and Karlsruhe Institute of Technology, Germany (my partner university). The thesis includes three research chapters: Chapter 3 has been published in an international journal, Chapter 4 has been submitted to an international journal and Chapter 5 has been finished to journal submission standard and will be submitted soon after the dissertation submission. I have contributed over 85% of the work including conceptualization, methodology, modelling and validation, analysis, completing drafts of original manuscripts, coordination of co-authors and responsibility for edits. My supervisors offered help as co-authors with guidance in framework design, result analysis and edits to manuscripts. In each of these chapters, the pronoun 'we' is employed to acknowledge the contributions of coauthors. All work was undertaken after my enrollment in this degree program, and none of it was submitted for any other qualifications. This thesis was produced without the involvement of third-party editorial assistance. The details of each chapter are shown as follows.

Chapter 3 has been published in *Remote Sensing* on 2 February 2022.

- Wu, C., Webb, J.A. and Stewardson, M.J., 2022. Modelling impacts of environmental water on vegetation of a semi-arid floodplain–lakes system using 30-year Landsat data. *Remote Sensing*, 14(3), Article 708 (15pp).

Chapter 4 has been published in *Ecohydrology* in March 2024.

- Wu, C., Webb, J.A. and Stewardson, M.J., Assessment of environmental water strategies for improving fringing vegetation health by modelling vegetation condition in a lakes-connected floodplain. *Ecohydrology,* p.e2644.

Chapter 5 has been completed to journal submission standard and will be submitted to *Remote Sensing*.

- Wu, C., Webb, J.A. Assessing the potential of environmental water to mitigate effects of future climate change on floodplain vegetation. *Remote Sensing* (to be submitted)

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Secondly, I would like to express my gratitude to my committee chair, Prof. Dr. Dongryeol Ryu. Your research advice has been very helpful in guiding my doctoral progress, and I've gained valuable insights from each review meeting.

Simultaneously, I would like to thank the German committee members, Prof. Dr. Franz Nestmann and Prof. Dr. Andreas Fink, for their guidance and suggestions during committee meetings.

Thirdly, I wish to convey my gratitude to the University of Melbourne, Karlsruhe Institute of Technology, and the Climate-Energy College, which facilitated my joint-PhD program. Thank you for offering me this precious opportunity to pursue a doctorate at two outstanding universities, engaging in research that I'm passionate about, and experiencing an exciting life as an international student.

Fourthly, I want to thank my colleagues at the University of Melbourne's Water Group and Karlsruhe Institute of Technology. You've made my international student life less lonely and have contributed to my interdisciplinary knowledge.

Fifth, I want to express my appreciation for the staffs who supported me during my PhD journey, particularly Emma Payne, for helping me adjust to the University of Melbourne when I first arrived, and Petra Van Nieuwenhoven, for assisting with my visa documents for Germany and addressing questions about the joint PhD program. I would also like to express my heartfelt gratitude to Dr. Andreas Schenk of KIT for his invaluable assistance during my research and throughout my exchange program at KIT.

I would like to thank everyone who has helped me during my doctoral studies. Your presence has enriched and colored my life, making it unforgettable.

Lastly, I would like to offer my heartfelt thanks to my family. To my parents, thank you for unconditionally supporting my academic pursuits and encouraging me when I lost confidence, reminding me that you are my unwavering support. To my husband, thank you for your companionship during my studies abroad, providing me with a sense of home in a foreign land.

Finally, I want to express my deepest gratitude to my soon-to-be-born baby, who has given me tremendous strength and motivation to successfully complete my thesis. May you grow up happily and let us continue to thrive together.

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Chapter 1 . Introduction

1.1 Background & Problem Statement

River floodplains stand out as one of Earth's most diverse and ever-changing ecosystems (Moxham et al, 2019). Floodplains are defined as “areas that are periodically inundated by the lateral overflow of rivers or lakes, as well as by direct precipitation or groundwater; characteristic community structures are created due to the resulting physicochemical environment” (Junk, 1989). Floodplain ecosystems are characterized by shifting dynamics of surface water and groundwater interactions, in which the resident plants and animals have evolved remarkable adaptations to cope with highly variable flows and landscape morphologies (Caruso et al, 2013; Thoms, 2003). Due to their rich biodiversity and productivity, floodplains play a significant role in both ecology and the economy. (Cunningham, 2008; Tockner & Stanford, 2002). River floodplains serve various functions that can sometimes conflict for space, including roles such as water conveyance and storage during peak discharge, biological habitats, agricultural production, and recreational areas (van Iersel et al, 2018).

Nevertheless, these ecosystems face the threat of deterioration and potential loss as a result of escalating human populations, river regulation, and the effects of climate change (Overton & Doody, 2008; Tockner & Stanford, 2002). River damming is one of the primary human interventions affecting freshwater environments globally. Reductions in overbank flows over years or decades lead to severe cumulative ecological repercussions (Rood et al, 2005). Meanwhile, alterations in climate and resulting adjustments in local and catchment-wide hydrological behaviors are likely to influence hydrological conditions within floodplains (Thompson et al, 2017a).

Floodplain vegetation plays a pivotal role in these ecosystems, and is known for its substantial influence on flood management, aquatic habitats, and various ecosystem services (Li et al, 2020). Flooding serves as a principal catalyst for enhancing the productivity of floodplain vegetation (Thapa et al, 2016b; Tockner

& Stanford, 2002). Hence, the variability and unpredictability of flooding exert an influence on the productivity and distribution of vegetation (Casanova, 2005; Thapa et al, 2016a). Floodplain vegetation experiences spatial and temporal dynamics that are shaped by both physical disturbances and environmental stressors (Shafroth et al, 2002). Floodplain vegetation is a primary target in floodplain restoration efforts. Preserving floodplain integrity and restoring deteriorated floodplain vegetation form important parts of the framework of semi-arid floodplain river management initiatives (Thapa et al, 2019).

To rejuvenate floodplain ecosystems, alleviate the repercussions of river regulation, and uphold environmental well-being, numerous environmental water delivery initiatives have been deployed globally (Anderson et al, 2019; Beesley et al, 2014; Gilvear et al, 2017). Environmental water has been delivered into floodplains to simulate natural flood occurrences (Beesley et al, 2014; O'Donnell, 2017). Considering the benefits for vegetation is a crucial factor when deciding on environmental water releases. One of the important long-term goals of environmental water programs is to enhance the diversity and abundance of native water-dependent vegetation on floodplains (Moxham et al, 2019).

Environmental water has achieved a range of beneficial outcomes for native fish, water birds, vegetation and water quality on floodplains (Docker & Johnson, 2017; Wood et al, 2016). However, these monitoring programs are based on ground-based monitoring methods, which requires a lot of manpower and material resources. These methods constrain the capacity of predictive models due to their reliance on the spatially and temporally limited monitoring data. This is especially the case in semi-arid floodplains and wetlands, because plant abundances in these areas varies widely, and vegetation growth can be slow but is highly impacted by seasonal conditions under climate change (IPCC, 2014b). Optimal decisions about how much environmental water to pump, and when, need accurate predictions of how vegetation might respond to the watering events (Moxham et al, 2019; Nagler et al, 2018a). Therefore, an understanding of long-term response of floodplain vegetation to environmental water and climate change is important for environmental water management and maintaining or restoring floodplain ecosystem health.

1.2 Case study - Hattah Lakes Floodplain system

The study area selected for this research is the Hattah Lakes floodplain, situated in Northwestern Victoria, Southeastern Australia (Figure 1.1). This region constitutes a complex floodplain system, with more than 20 permanent and semi-permanent lakes in the system. This area holds immense ecological significance and has been designated as a Ramsar wetland site with exceptional ecological value (Butcher & Hale, 2011).

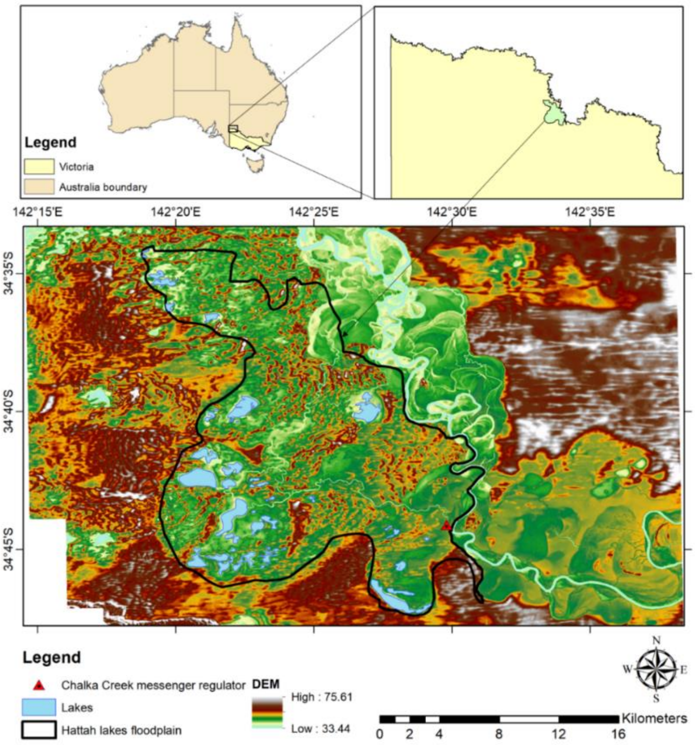

Figure 1.1 Location of study area – Hattah Lakes

In the Hattah Lakes system, while the lakes maintain water for extended periods due to their ability to capture and hold peak river flows, the surrounding floodplains experience only temporary inundation and quickly revert to dry land as the river levels decrease (MDBA, 2012b). The ecological dynamics of the Hattah Lakes floodplain communities are profoundly shaped by the patterns of flooding they experience (MDBA, 2012b), and an important threat to the floodplain communities in Hattah Lakes is the disruption of water regimes (Wood et al, 2016). The environmental health of the floodplain ecosystem and its habitat value for both fauna and flora have diminished because of the reduced connectivity between the Hattah Lakes and the Murray River, coupled with water extraction for agriculture, industry, and urban use, as well as severe drought over the past decade (Kenny et al, 2017). Selected as one of The Living Murray's "icon" sites in Australia (Wood et al, 2016), environmental water has been delivered into Hattah Lakes since 2005 to maintain animal breeding and vegetation health. Environmental water was delivered through Chalka Creek regulator from 2013 (Figure 1.2).

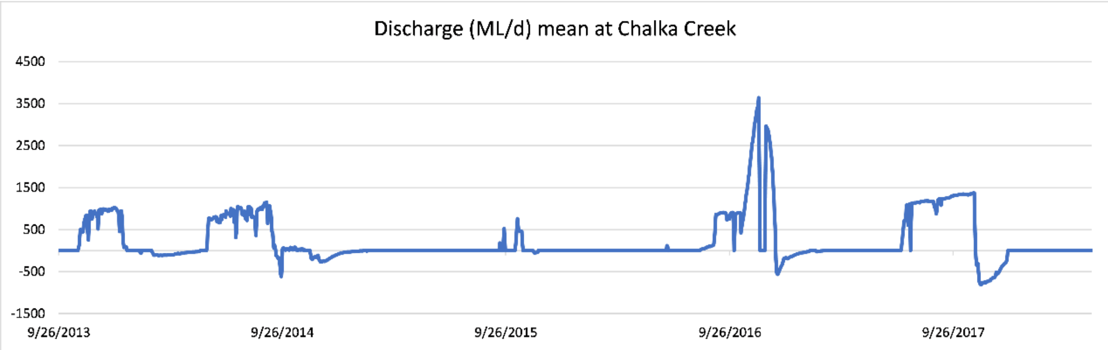

Figure 1.2 Mean discharge records at Chalka Creek representing environmental water volume delivered into the Hattah Lakes system

River Red Gum trees are one of the dominant vegetation around the lakes in the Hattah Lakes system. The reduction in flooding has resulted in the decline and reduced vigor of riparian Red Gums and changes in tree distributions (DSE, 2003). The following two images (Figure 1.3) depict the condition of the Hattah Lakes floodplain in 1996 and 2004, captured by Landsat 5. The 2004 image clearly shows the impact of drought, with noticeably poorer vegetation conditions compared to the healthier state observed in 1996.Figure 1.4 shows climatic and Vegetative Dynamics (NDVI extracted from Landsat images) during the 1993 Floods and 2014 Environmental water events in Hattah Lakes.

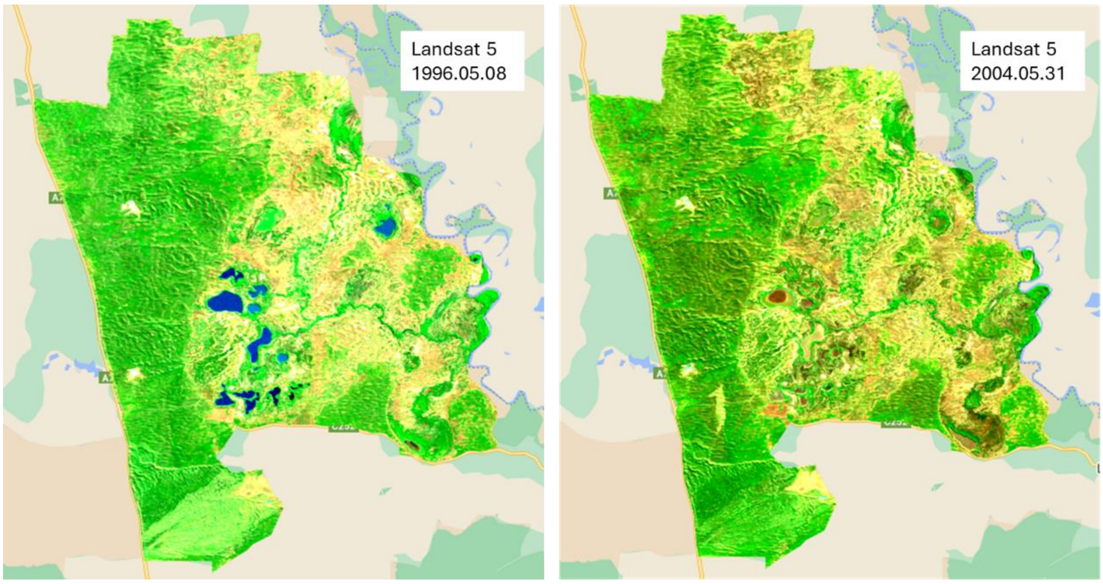

Figure 1.3 Hattah Lakes floodplain in 1996 and 2004 displayed as Landsat 5 TM (bands 7,4,2 as RGB)

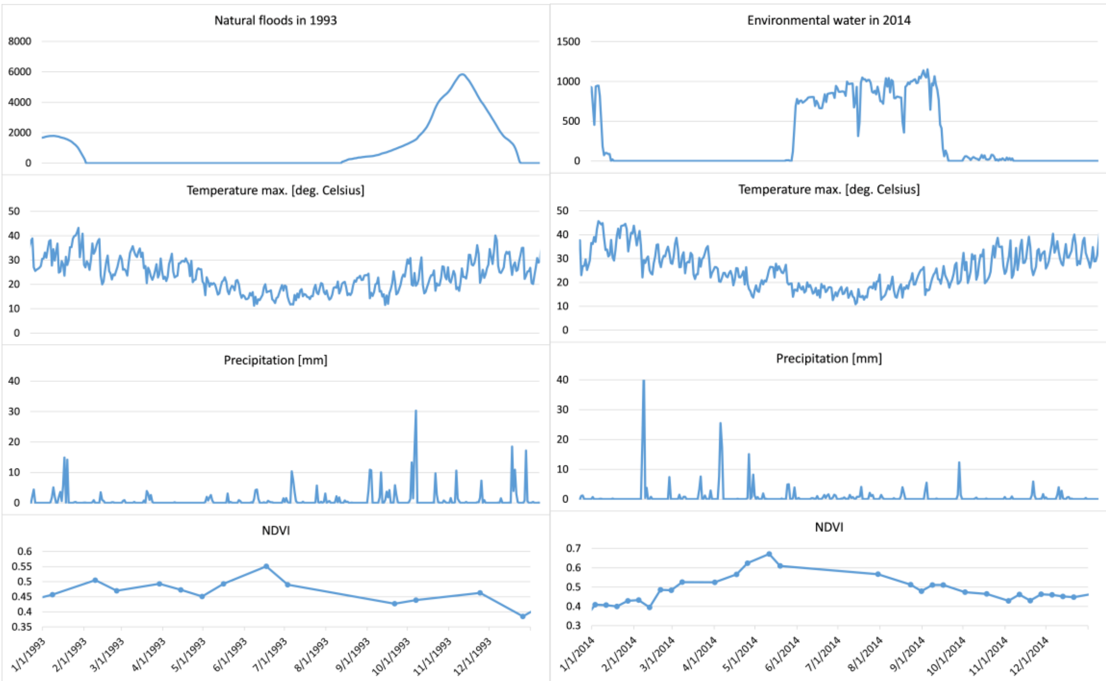

Figure 1.4 Climatic and Vegetative Dynamics (NDVI extracted from Landsat images) During the 1993 Floods(left) and 2014 Environmental water events (right) in Hattah Lakes

1.3 Research objectives

The overarching objective of this thesis is to explore the spatiotemporal effects of environmental water on floodplain vegetation, considering both historical trends and anticipated future changes in climate. This investigation relies on extensive, long-term monitoring of vegetation conditions. In addition, the study seeks to evaluate environmental water management strategies to address the challenges posed by diverse future climate scenarios, thus providing advice to environmental water managers in the effective administration of environmental water resources amidst the uncertainties of a changing climate. The specific three objectives are:

Research objective 1: to investigate the qualitative impact of environmental water on floodplain vegetation and determine its capacity to emulate the influence of natural floods.

Research objective 2: to quantitatively assess the influence of environmental water volume and lag time on the fringing vegetation of floodplain lakes and evaluate the efficacy of existing environmental watering strategies.

Research objective 3: to examine whether environmental water can mitigate the impacts of future climate change on floodplain vegetation and evaluate environmental water allocation strategies to aid vegetation under future climate uncertainties.

The amalgamation of all three research objectives collectively provides essential technical support for decision-makings in environmental water management, with the overarching goal of maintaining the health of floodplain vegetation amidst the challenges posed by future climate uncertainty.

1.4 Thesis structure

This thesis comprises six chapters. Chapter 2 provides a comprehensive literature review on four primary topics closely related to the core theme of the thesis. Chapters 3 through 5 represent the major research components of the thesis, each presenting a journal paper that addresses one of the three research objectives listed above. Finally, Chapter 6 serves as the concluding section, offering a comprehensive discussion and conclusion that amalgamates the findings presented throughout the thesis and provides overarching recommendations for the field of environmental water management.

Chapter 2 . Literature review

2.1 Floodplains and environmental water

2.1.1 Floodplains and disturbance

Floodplains rank among the Earth's most dynamic ecosystems (Kingsford, 2000). A floodplain is a flat or gradually sloping expanse of land located alongside a river, stream, or other watercourse, which is prone to periodic inundation (Junk, 1989). These floodplains take shape through the gradual accumulation of sediments transported by flowing water over extended periods (Junk, 1989). As a key component of ecosystems, floodplains are extremely valuable, embodying a wide range of functions. These include flood control, water quality enhancement, biodiversity conservation, support for agriculture and fisheries, recreational amenities, and the natural regulation of water resources (Krause et al, 2007; Petsch et al, 2022; Wu & Chen, 2020). River flows are pivotal for revitalizing floodplain habitats, and there has been a growing interest in flow management for this purpose in recent years (Hughes & Rood, 2003).

While providing a plethora of environmental services, river floodplain ecosystems face severe threats, particularly in arid and semi-arid regions (Petsch et al, 2022), including river regulation and climate change (Baldwin & Mitchell, 2000). As a result of the escalating human activities occurring over the past century, significant and dramatic alterations have taken place in the size, morphology, and ecological dynamics of numerous wetlands and floodplains around the world (Ye et al, 2019). The flooding and drying patterns of numerous floodplain systems have undergone significant alterations due to river regulation. Rivers are dammed for agricultural, domestic, and industrial purposes; causing far-reaching impacts on downstream river and floodplain ecosystems, and ultimately resulting in severe cumulative ecological consequences (Northcott et al, 2007; Steinfeld & Kingsford, 2013). Moreover, the anticipated impact of climate change is expected to bring further modifications to the flow regimes of both regulated and unregulated rivers (Baldwin & Mitchell, 2000), which will further affect floodplains.

Riverine fauna and flora are subject to similar pressures and challenges as those faced by floodplains (Kingsford, 2000). The loss of connectivity to the river results in a transformation of aquatic systems into terrestrial ecosystems, affecting aquatic plants, microbes and sedentary animals (Kingsford, 2000; Pace et al, 2021). Vegetation communities represent a vital component within riparian and floodplain ecosystems (Catelotti et al, 2015). Although floodplain vegetation plays a critical role in supporting ecosystem function and values, there is a concerning global trend of dieback in floodplain forests and woodlands (Wallace et al, 2020). Floodplain vegetation is profoundly affected by the flow patterns of the parent river, particularly in arid and semi-arid regions susceptible to the floodplain disturbances described above (Colloff et al, 2010; Jensen & Walker, 2017).

The conservation of floodplain vegetation is of growing importance. However, the state of knowledge regarding the ecology and flow dependence of floodplain vegetation poor. The tolerance levels of these key species to stress factors are not well comprehended, and as a result, the impacts of modified flow patterns on floodplain vegetation have yet to be sufficiently quantified (Colloff et al, 2010; Moxham et al, 2019).

2.1.2 Environmental water for floodplain environments

The use of environmental water flows has emerged as a measure for the global restoration and conservation of floodplains. Environmental flows are formally defined as controlled water releases originating from water management infrastructure, such as dams, with the primary objective of preserving ecosystem functionality and providing important ecosystem services (Horne et al, 2017a; Richter et al, 2006; Schlatter et al, 2017). Globally, governments are responding to the challenges posed by flow-related risks to freshwater ecosystems by implementing environmental water management strategies (John et al, 2020b). Broadly defined, environmental water provision entails ensuring the availability of water with appropriate quality, quantity, and timing to sustain ecological objectives and associated community values (Horne et al, 2017c).

In Australia, environmental water aims to mimic key components of the natural flooding regime and has specific objectives, ranging from enhancing water quality and the well-being of particular species to more comprehensive goals, such as the overall enhancement of ecosystem functionality (Arthington et al, 2009; Beesley et al, 2014; Jensen & Walker, 2017). The Australian government has obtained water allocations designated for the environment with the aim of reinstating more natural hydrological patterns and enhancing the overall ecosystem integrity of floodplain wetlands (Reid & Brooks, 2000). Plant communities and native fishes are common targets of environmental flow programs (Beesley et al, 2014). In practical implementations, environmental water delivery to wetlands is determined based on ecological objectives, seasonal conditions, and water availability. The process involves assessing the needs of specific wetlands, deciding on the timing and volume of water to be delivered, and ensuring that the water supports the desired ecological outcomes, such as maintaining habitats, supporting biodiversity, and promoting healthy ecosystems. The decisions are made in consultation with stakeholders and experts to ensure that the water is used effectively and sustainably (VEWH, 2015).

Environmental water monitoring and management have gained emerging attention all over the world. Many plans are designed based on monitoring of vegetation, fish and bird response to environmental water (Wood et al, 2018). However, the scarcity of scientific knowledge regarding the anticipated results of different environmental water delivery scenarios poses a significant obstacle to the restoration and preservation of ecosystems (Colloff et al, 2010). Management options are inherently complex due to factors such as the spatial scale over which environmental water is delivered, the diffuse nature of the impacts, and the frequent involvement of multiple stakeholders (Horne et al, 2017b).

2.2 Monitoring vegetation health

Monitoring vegetation enables the assessment of alterations including shifts in species abundance and diversity, the emergence of threats, alterations in vegetation coverage, stressors, or overall changes in the condition of vegetation communities (Lawley et al, 2016). The traditional approach to monitoring vegetation condition has focused on ground-based methods (Gibbons & Freudenberger, 2006). However, such data sets are both spatially and temporally limited. The growing need for broader-scale and longer-term information has led to the adoption of remote sensing-based techniques (Wallace et al, 2006). The following sections discuss these two vegetation monitoring methods.

2.2.1 Ground-based monitoring methods

Ground-based monitoring techniques for vegetation have a rich history of application and continue to be widely employed today (Lawley et al, 2016; Wood et al, 2016). The majority of ground-based assessments use quadrats to gather comprehensive data on the composition, structure, and functional characteristics of the selected site (Lawley et al, 2016). These methods involve the documentation and categorization of plant species (Wheeler & Meier, 2000), offering a nuanced understanding of species' capabilities concerning various stressors, disturbances, adaptation mechanisms, plant fitness, and vegetation resilience (Lausch et al, 2018). In Australia, the government employs ground-based monitoring to assess vegetation condition and investigate the effectiveness of environmental water management (Wood et al, 2018).

Ground-based approaches require a substantial allocation of human resources and materials. Although they provide extensive and specific understanding of vegetation, they have inherent spatial and temporal limitations because of the nature of the data collected and by focusing on taxonomic units (Soberón, 2007). When it comes to drawing comprehensive conclusions, their ability is constrained because ground-based mapping is predominantly limited to point samples or small areas (Lausch et al, 2018). Furthermore, these methods are expensive for sustained, long-term monitoring and cannot offer continuous data over time.

2.2.2 Remote sensing-based methods

As the demand for extensive and enduring monitoring grows, remote sensing approaches have become more widely used for evaluating vegetation health. Satellite remote sensing imagery offers distinct capability because it is regular, spatially comprehensive, and has consistent coverage. This makes it invaluable for supplying data to supplement and refine ground-based assessments (Wallace et al, 2006).

Much research has concentrated on the assessment of vegetation health through indicators such as vegetation moisture, biochemical characteristics of plants, including chlorophyll levels and other leaf pigments (Valentini et al, 1994; Wang et al, 2019). Another vital aspect, primary productivity (Fay et al, 2009; Ye et al, 2019), has been extensively estimated through remote sensing. These measurements are seldom obtained through conventional site-based assessments, introducing a fresh perspective to vegetation condition monitoring (Lawley et al, 2016).

Satellite vegetation index (VI) products derived from remote sensing images are widely applied to characterize vegetation cover and vegetation canopy greenness (Jiang et al, 2008). The Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) are two useful indices of vegetation health. While there are additional vegetation indices available, these two indices are the most commonly used for forecasting and assessing vegetation conditions (Nagler et al, 2018b; Yu et al, 2022).

NDVI is derived from the ratio of near-infrared spectral and red spectral wavelengths reflected by vegetation (Pettorelli et al, 2005; Tucker, 1979). NDVI is widely used and highly correlated with vegetation distribution, phenology and productivity (Pettorelli et al, 2005). But NDVI has some shortcomings related to soil background brightness, making it sensitive to attenuation and scattering by atmospheric aerosols. It is also prone to saturation in high vegetation biomass areas (Jiang et al, 2008).

$$\text{NDVI} = \frac{NIR-RED}{NIR+RED}, \text{ Equation 2.1}$$

EVI was developed to solve the problem of sensitivity in high biomass areas through de-coupling of the canopy background signal and reduction of atmospheric influences (Huete, 2002). The formula is as follows, in which NIR, RED and BLUE are Landsat surface reflectance measurements for corresponding bands. G is a gain factor and equals 2.5. C1, C2 and L are coefficients for correcting the aerosol effects on canopy reflectance, and soil background signal, and they are equal to 6, 7.5 and 1, respectively (Huete, 2002; Li et al, 2017). There is also a variant EVI2 that does not use the blue band, which is designed to make the index less sensitive to atmospheric conditions.

$$\mathrm{EVI} = \mathrm{G}\frac{NIR-RED}{NIR+C1*RED-C2*BLUE+L}, \text{ Equation 2.2}$$

2.3 Effect of river regulation and climate change on floodplain vegetation

Floodplain vegetation is a significant component of floodplain ecosystems. This PhD research concentrates on floodplain vegetation, and the following two sections will explore current research pertaining to the impact of river regulation and climate change on floodplain vegetation.

2.3.1 River regulation

Research on the effects of river regulation on riparian and floodplain vegetation has been conducted all over the world. Prolonged exposure to adverse conditions such as water stress can result in impacts upon vegetation health (Yousef et al, 2019). The identification of effects of regulation on riparian vegetation necessitates the acquisition of three distinct types of data: pre-regulation vegetation and channel conditions, the transient response subsequent to changes in flow and sediment supply, and the composition of new vegetation after the adjustment period (Johnson, 1998).

River regulation elicits diverse and variable responses across different aspects of vegetation (Nilsson et al, 1997), and manifests different rates of adjustment. Anticipated shorter readjustment periods, typically occurring within a decade following river regulation, pertain to sediment load, hydrology, floodplain vegetation, and water quality. In contrast, channel substrate, aquatic plants, channel morphology, and benthic invertebrates are projected to undergo a more protracted readjustment process, spanning from 5 to more than 100 years (Petts, 1984).

The impacts of dams on floodplain erosion and deposition processes, floodplain evolution, and riparian vegetation are notably complex (Marren et al, 2014). The construction of dams, resulting in reduced water level fluctuations, induces significant alterations in the spatial distribution of floodplain plant species and their overall composition (Leyer, 2005). Both species richness and composition have been found to be significantly disrupted, primarily attributed to the modification of hydrological regimes and the disruption of longitudinal flow patterns (Auble et al, 1994; Nilsson & Berggren, 2000).

It is noteworthy that Riparian communities located within semi-arid and low-altitude regions tend to show greater sensitivity to water regulation, primarily attributed to their flatter terrain, where minor flow alterations can have far-reaching effects across extensive areas (Nilsson & Berggren, 2000). In semi-arid regions, vegetation is more dependent on river flow than on rainfall for sustenance. Higher evaporation rates and lower rainfall increase the reliance on river flows.

2.3.2 Effects of changing climate

Generally, vegetation growth is predominantly influenced by external climatic factors, including temperature, precipitation, and solar radiation (Wu et al, 2015). To date, the majority of studies have concentrated on examining vegetation response to distinct climate parameters, including temperature and precipitation (de Jong et al, 2013; Ren et al, 2022), time-lag effects (Wu et al, 2015), drought (Wilhite et al, 2014), and sensitivity to water availability and turbidity (Seddon et al, 2016). Recent research has shown a growing body of evidence indicating that vegetation responses to climate exhibit a discernible time lag (Wu et al, 2015). This makes vegetation response to climate complicated, and antecedent conditions such as drought will affect vegetation growth in the current and subsequent years (Thoma et al, 2016). Interactions between vegetation and climate are characterized by nonlinearity and complexity. Warmer temperatures generally promote plant growth by enhancing metabolic processes and lengthening the growing season. However, this positive effect has limits. Once temperatures exceed a certain threshold, the rate of evapotranspiration can surpass the ability of plants to take up water, especially if soil moisture is limited. This can lead to increased vapor pressure deficit, where the atmosphere's demand for water exceeds the supply, stressing plants and potentially reducing greenness (Lobell & Gourdji, 2012). Accumulated heat is critical for the timing of crop development, including ripening. For many crops, there is an optimal temperature range that maximizes growth (Lobell & Gourdji, 2012). Rainfall is a key driver of greenness, particularly in arid and semi-arid regions. Moderate increases in rainfall generally lead to higher soil moisture, which supports plant growth. However, at high levels of rainfall, the benefits may diminish. Excessive rainfall can lead to waterlogged soils, reducing oxygen availability to plant roots and leading to reduced growth or even root death (Liu et al, 2022). Consequently, the connection between vegetation and climate variables remains a subject of intense debate, making it challenging to simulate and quantify the individual contributions of specific climate factors (Kong et al, 2017).

Vegetation responses to climatic factors exhibit geographic differences around the world. Studies have identified temperature as the primary limiting factor for vegetation growth at high latitudes in the Northern Hemisphere (Xiao & Moody, 2008) and Western Europe (Afuye et al, 2021). For example, temperature was identified as the pivotal determinant of vegetation greenness in high latitudes within the regions of North America and Siberia, particularly during spring and autumn (Kong et al, 2017). In Central Asia, South America, and Southern Africa, the reduction in precipitation and increase in temperatures have shown correlations with decreased vegetation vigor (Afuye et al, 2021; Kogan et al, 2011).

The biodiversity of vegetation is susceptible to alterations in climate (Mantyka-Pringle et al, 2013). The adverse effects of vegetation loss and fragmentation have been particularly pronounced in regions that experience high temperatures during the warmest months and decreasing rainfall. Furthermore, these impacts have exhibited variations across different vegetation types.

Similar to the effects of river regulation, prior research has demonstrated that vegetation vigor is expected to continue declining under predicted temperature and rainfall conditions in arid or semi-arid regions (Afuye et al, 2021; Brown et al, 2012; Fu & Burgher, 2015).

2.4 Effect of environmental water and natural flooding on floodplain vegetation

In semi-arid floodplain ecosystems, vegetation is constrained by water availability. In the context of floodplains, the effects of both environmental water and natural flooding can be characterized by the extent of inundation. The impacts of environmental water and natural floods exhibit distinct patterns due to variations in inundation mechanisms. The following sections delineate the specific research on each influence and the modelling methodologies previously employed.

2.4.1 Influence of natural floods

The 'flood pulse concept' acknowledges that the flow of water, including its variability, serves as the primary driver of ecological processes within floodplains (Junk, 1989). High-flow pulses in temperate regions are also significant for preserving the ecological integrity of floodplains (Caruso et al, 2013). Floodplain inundation stimulates vegetation productivity responses, following an adaptive cycle characterized by wetting, wet, drying, and dry stages (Thapa et al, 2019). Vegetation growth vigor and biomass exhibit an initial rapid increase in response to a flood pulse. Subsequently, this vigor wanes during the senescence phase, eventually leading to dormancy during the inter-flood dry period (Mohammadi et al, 2017; Powell et al, 2014).

Different flood characteristics can play crucial roles in the natural functioning of floodplain ecosystems. These include flood magnitude, duration, frequency, volume, timing, rates of change, and the temporal interval since the last flood event (Caruso et al, 2013; Poff et al, 1997).

Diverse vegetation types exhibit distinct responses to inundation by natural floods. Floodplain tree species, such as *Eucalyptus coolabah*, are characterized by their low transpiration rates, enabling them to endure conditions of limited soil moisture during exceptionally arid periods under reduced natural floods (Doody et al, 2015). Numerous grasses and shrubs inhabiting arid and semi-arid floodplains fall into the category of ephemerals, persisting in a dormant form during dry periods. In contrast, perennial grasses display rapid responses to increased water availability, exhibiting rapid growth during substantial resource pulses to increase biomass, set seeds, and replenish storage organs upon exposure to wet conditions (Thapa et al, 2019). Natural flood events prompt a swift response from vegetation, particularly annual grasses and forbs, which can be sustained for extended periods by the soil moisture resulting from the infiltration of floodwaters into the floodplain (Capon, 2005; Stammel et al, 2021).

Flooding serves as a fundamental driver of plant productivity within floodplains, with vegetation exhibiting improved condition following rainfall or flooding events, reaching peak condition after the floodwaters recede. This phenomenon contributes to functional landscape heterogeneity and illustrates the classification of dryland floodplains as boom-bust ecosystems (Parsons & Thoms, 2013). Sims & Colloff (2012) quantified the response of floodplain vegetation to flooding events by assessing NDVI within the Paroo River wetland ecosystem in Australia in comparison to the adjacent terrestrial area. Their findings revealed that NDVI increased by up to 19% above non-flood levels, persisting for a duration of 13 months following the recession of floodwaters. The combined impact of both precipitation and flooding has also been identified as a significant factor influencing vegetation variation within floodplains (Broich et al, 2018).

2.4.2 Influence of environmental water

In contrast to the extensive research on the influence of natural floods, there is relatively limited study of the effects of environmental water on floodplain vegetation. Modelling floodplain vegetation responses to inform environmental watering outcomes presents a formidable challenge (Moxham et al, 2019). Improved vegetation condition based on site-specific monitoring has been reported, but these have tend to be of a limited scale and short-term (Chen et al, 2021b).

Nonetheless, positive effects of environmental water on floodplain vegetation have been documented in studies conducted worldwide. Restoration of riparian vegetation, the germination of new vegetation (Miller et al, 2013), and increasing vegetation greenness (IBWC, 2014) have been observed after watering events occurred in the United States (Docker & Johnson, 2017). In Australia, several monitoring projects are in place to assess ecological responses to environmental water. As part of 'The Living Murray' program, watering events have yielded numerous positive ecological outcomes, including enhancements in the vitality of river red gum communities, favorable responses from moira grass, and increased productivity in both within the Chowilla anabranch and downstream in the river Murray (MDBA, 2015a). Inundation-dependent vegetation communities exhibited improved conditions following the application of Commonwealth environmental water (Gawne et al, 2019). In China, ecological water has been redirected to the lower reaches of the Tarim River, resulting in a notable increase of the water table near the riverbank by 2 to 4 meters. This has significantly enhanced groundwater conditions in the lower reaches and has led to a remarkable recovery of vegetation (Deng et al, 2014).

The impacts of watering events on vegetation diversity may vary and exhibit spatial differences with regard to the local canopy conditions. The consequences of environmental water allocation on vegetation diversity may exhibit spatial variations concerning canopy structure and temporal fluctuations linked to prior conditions (Capon et al, 2017; Howell & Benson, 2000). Hence, it is essential to consider spatial factors and antecedent conditions when assessing and analyzing the impacts of environmental water.

2.4.3 Modelling methods

There is currently no standardized method for assessing the necessity or relative priority of environmental water to achieve desired tree condition outcomes (Wallace et al, 2020). Modelling and predicting ecological outcomes represent a formidable scientific challenge within the field of water management. The development of robust ecosystem models, grounded in scientifically established connections between flow patterns and vegetation reactions, plays a crucial role in facilitating the adaptive management of environmental water in Australia (Colloff et al, 2010). Models that explicitly delineate the connections between hydrological parameters and vegetation can serve as valuable tools for managers to evaluate vegetation responses across various water management scenarios (Canham et al, 2021). However, it should be noted that when any environmental assessment process relies heavily on models that lack empirical verification, there exists a significant risk that assumptions founded on subjective judgments may result in biased assessments (Lyons et al, 2022).

Current modelling approaches for vegetation response can be categorized into two broad classes: traditional statistical methods and machine learning methods. Specific traditional modelling methods include multiple linear regression models (Shafroth et al, 2002; Wu et al, 2015), multivariate regression models incorporating breakpoint methods (Broich et al, 2018), combinations of climate and water balance models (Thoma et al, 2016), generalized additive models

(GAMs) incorporating year, month, and spatial group data (Pace et al, 2021), and generalized linear models (GLM) (Norman et al, 2014).

However, many of the above approaches employed traditional ground-based monitoring methods. The analysis of information from remote sensing images remains a challenge for applying traditional statistical methods (Yu et al, 2022). This challenge is mainly because of the large number of data points and the presence of spatial autocorrelation within the images (Figure 1.4). Machine learning methods represent an alternative approach for addressing this challenge in prediction. Artificial neural networks (ANNs) have been employed for predicting vegetation changes (Kang et al, 2016; Smith & Jin, 2014; Zhou & Yang, 2008). More specifically, long short-term memory (LSTM) neural network models have been developed to simulate NDVI under varying ecological water scenarios, demonstrating strong performance (Wang et al, 2022).

Enhancing a models' ability to assess the effect of individual watering events is particularly crucial in the context of proactive environmental water management (John et al, 2020b). When modelling vegetation response, a thorough understanding of how various pressures interact with watering practices to influence floodplain vegetation responses is necessary for the prioritization of environmental water allocation and the establishment of suitable watering schedules to attain desired vegetation outcomes (Capon et al, 2017).

2.5 Research gaps and questions

2.5.1 Research gaps

Based on the above review of literature, three research gaps were identified:

1) Long-term effects of environmental water on floodplain vegetation have not been described because of a lack of longer-term datasets. A lack of effective response monitoring of environmental flows is common around the world (Gwinn et al, 2016; Moxham et al, 2019).
2) Few studies investigate spatiotemporal variation in floodplain vegetation response to climate change and environmental water delivery. Even fewer consider both directly and indirectly observed water balance factors (Thoma et al, 2016).

3) Previous research has not explored the impact of distinct environmental water scenarios on vegetation health within the context of varying future climate projections. An emphasis on addressing future climate uncertainties and investigating strategies for environmental water allocation would offer valuable insights to inform future management practices.

2.5.2 Research questions

The overall aim of this thesis is to study spatiotemporal effects of environmental water on floodplain vegetation under climate change and to formulate management strategies under different climate scenarios. We hypothesized that 1) environmental water delivery has a positive effect on the health of floodplain vegetation, distinct from the effects of natural floods; 2) The volume and timing of environmental water delivery significantly affect the improvement of floodplain vegetation health; and 3) Environmental water can partially or fully offset the negative effects of future climate change on floodplain vegetation health. Specific research questions relate to the detailed research objectives identified in Section 1.2, as well as the knowledge gaps identified above, and include:

1) What is the effect of environmental water delivery on floodplain vegetation productivity or health? Is it different from the influence of natural floods?

This question is designed to address the knowledge gap 1 (Section 2.5.1). There are three problems to be solved in this question. Firstly, remote sensing indices that can represent long-term vegetation condition and health need to be chosen. Secondly, a method is needed to distinguish the influences of environmental water from those of precipitation and natural floods. Finally, a suitable mathematical method to model vegetation response to environmental water is needed.

2) How can we assess current environmental watering strategies? Does volume and timing affect the improvement in vegetation health?

This question is linked to research gap 2 presented above. For a more comprehensive examination of the mechanisms underlying vegetation responses to environmental water, it is necessary to assess how vegetation responds to variations in both the volume and timing of environmental water delivery. To address this, the study will employ machine-learning techniques to model the long-term condition of vegetation, considering climate, natural flood volume, and environmental water volume as key factors. Additionally, the study will assess the effectiveness of current environmental water strategies using the trained model.

3) Can environmental water offset the influence of future climate change on floodplain vegetation?

This research question is associated with the third research gap outlined above. Floodplain vegetation is confronted with increasing pressures due to the uncertainties associated with future climate conditions. To inform future environmental water management and the preservation of floodplain vegetation health in the face of impending climate change, it is imperative to investigate the potential of different environmental water scenarios to mitigate the adverse impacts of future climatic shifts on floodplain vegetation.

Chapter 3 . Modelling Impacts of Environmental Water on Vegetation of a Semi-Arid Floodplain–Lakes System Using 30-Year Landsat Data

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3.1 Abstract

River floodplains are among the most dynamic and diverse ecosystems on the planet. They are at risk of degradation due to river regulation and climate change. Environmental water has been delivered to floodplains to maintain environmental health by mimicking natural floods. It is important to understand the long-term effects of environmental water to floodplain vegetation to support its management. This study used Normalized Differences Vegetation index (NDVI) from the 30-year Landsat datasets of the Hattah Lakes floodplain in Australia to investigate the drivers of vegetation dynamics. We developed generalized additive mixed models (GAMM) to model responses of vegetation to environmental water, natural floods, precipitation, temperature, and distance to water across multiple spatial and temporal scales. We found the effect of environmental water on floodplain vegetation to be quite different from that of natural floods in both space and time. Vegetation in most areas of Hattah Lakes will respond to natural floods within one month of flooding, while positive responses to environmental water occur 1 to 3 months after inundation and are more restricted spatially. For environmental water planning, managers need to be aware of these differences. The implementation of new infrastructure to transport or retain environmental water on floodplains needs to be planned carefully, with continuous monitoring of rainfall and natural floods. Whilst

environmental floods do not mimic the effect of natural floods, they do provide some positive benefits that can partially offset effects of reduced natural floods.

3.2 Introduction

River floodplains are among the most diverse, dynamic and vulnerable ecosystems on the earth (Moxham et al, 2019). They are important to ecology and the economy because of the ecosystem services they provide, including water purification, biodiversity, sediment retention, carbon sequestration, and tourism (Cunningham, 2008; Salem et al, 2020; Tockner & Stanford, 2002; Wu & Chen, 2020). However, they are at risk of degradation and destruction due to increasing human populations, river regulation and climate change (Overton & Doody, 2008; Tockner & Stanford, 2002).

Wetland inundation regimes have been altered because of water resource management, such as the construction of dams or locks, leading to a decline in riverine ecosystem health (Frazier & Page, 2006). Surface flow reductions, agricultural expansion and groundwater mining have cause declines in woody vegetation populations and seedling establishment in western North America, Europe, and Asia (Schlatter et al, 2017). In Australia, due to water resources regulation and climate change, wetlands in semi-arid floodplains and their hydrological connectivity with main river channels are under increasing pressure (Karim et al, 2015). For example, anthropogenic influences on river systems combined with the 'Millennium Drought' from 1997 to 2009 led to severe declines in vegetation condition across the floodplains of the Murray-Darling Basin (Doody et al, 2014; Leblanc et al, 2012).

Environmental flows are defined as the volumes of water maintained in rivers to protect and enhance the ecological functions of floodplain, riverine and wetland ecosystems (Sims & Colloff, 2012). In this study, environmental water is mainly referred as environmental flow. To restore floodplain ecosystems, mitigate the impact of river regulation and maintain environmental health, increasing numbers of environmental water delivery programs have been implemented around the world (Galat et al, 1998; Stewardson & Guarino, 2018). These now include engineering-based approaches including inundating floodplains by pumping into canals and then controlling water delivery with regulators to mimic flood events (Bond et al, 2014; O'Donnell, 2017). In the Missouri River, USA, flooding was managed and controlled to mainly benefit migrant waterbirds when the annual natural flooding did not occur (Galat et al, 1998). Similar infrastructure projects are also proposed to increase seasonal wetland flooding in Poyang Lake wetland, China, which has experienced reduced flooding since the construction of the Three Gorges Dam (Bond et al, 2014). In Australia's Murray-Darling basin, environmental water has been pumped into many wetlands such as Chowilla floodplain and Hattah Lakes floodplain to improve the health of vegetation and restore habitat (Stewardson & Guarino, 2018). These examples notwithstanding, using artificial engineering methods to provide water to floodplain is relatively a new practice (Bond et al, 2014).

The response of vegetation is one important consideration when determining environmental water releases, and improving the richness and abundance of water dependent native vegetation is a common long-term management objective of environmental flow programs (Moxham et al, 2019). Designing environmental water programmers and requirements to achieve ecological goals for floodplain ecosystems is challenging because of their complex plant communities. Field experiments, ecological modelling and remote sensing technology have been used to detect vegetation response to floods or environmental flows (Broich et al, 2018; Thapa et al, 2019). Short-term benefits of a large-scale environmental flow event have been evaluated using a multi-taxon Bayesian hierarchical model based on a single environmental flow event and limited field data (Moxham et al, 2019). However, long-term effects of environmental flows on floodplain vegetation have not been described because of a lack of longer-term datasets (Gwinn et al, 2016; Moxham et al, 2019). Therefore, long-term effects of environmental water on floodplain ecosystems need to be monitored and modeled to better manage environmental water (Nagler et al, 2018a).

To address this research gap, this paper focuses on modelling vegetation response to environmental water based on 30-year Landsat datasets in Hattah Lakes, Australia. Most environmental water programs are based on the assumption that environmental water can be used to mimic natural floods (Bond et al, 2014; MDBA, 2017). Therefore, comparing the impact of natural floods and environmental water to see if environmental water can achieve the same goal of natural floods is a key objective of this research. The influence of climate factors including precipitation and temperature, lag time are also considered in the modelling. We developed a generalized additive mixed model, combining continuous and categorized data, which is a first attempt in this type of research. The spatial responses of vegetation were then summarized according to different vegetation classes. We conclude by giving technical support and suggestions for government and management to make decisions regarding environmental water release strategies.

3.3 Materials and Methods

3.3.1 Study Area

The Hattah Lakes floodplain, located in north-western Victoria, south-east Australia (34°41´14´´S, 142°22´54´´E), is a semi-arid connected floodplain-lakes system. As part of the floodplain of the Murray River, Hattah Lakes covers an area of ca. 480 square kilometers (Vilizzi et al, 2013) and floodplain is composed of more than 20 semi-permanent wetlands, including 12 Ramsar-listed wetlands (Figure 3.1). With an average rainfall of about 250mm, Hattah Lakes is generally only inundated when the Murray River reaches moderately high flows. These semi-permanent shallow lakes (0.4–2.8m retained water depth) are important habitats for the floodplain biota (Vilizzi et al, 2013).

The ecological value of Hattah lakes has been affected by river regulation. Discharge at Euston Weir (~70 kilometers upstream of Hattah Lakes) has been reduced by ~50% of natural levels as a result of water extraction in the upstream regions of the Murray River and its tributaries. For Hattah Lakes, these changes have reduced flood frequency and duration by 57% and 65%, respectively. Flood timing has also been delayed from August to September or October (Vilizzi et al, 2013). Therefore, most water bodies in Hattah Lakes receive reduced inflow and only maintain wet status for a very short time due to regulation. Between 1996 and 2010, natural floods occurred only in 1996 and 2010, but they would have occurred at least seven times under natural inundation conditions (Vilizzi et al, 2013).

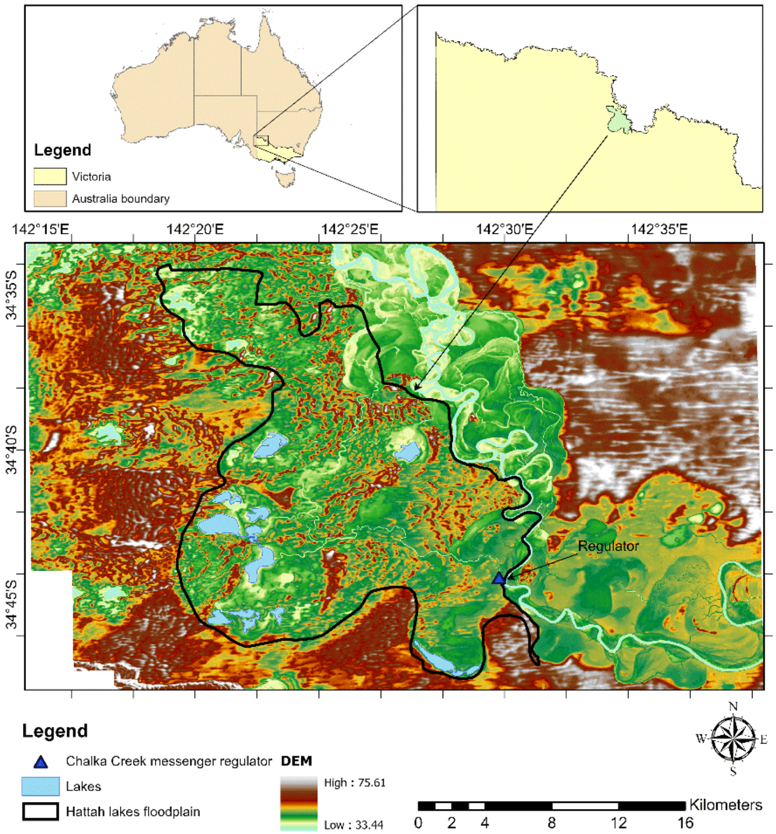


Figure 3.1 Location and elevation of study area. The floodplain boundary used in this research is extracted from interim Biogeographic Regionalization for Australia version 7 (IBRA7).

Environmental water was first pumped into Hattah Lakes in 2005 with the purpose of restoring and improving the health of River Red Gum (*Eucalyptus camaldulensis*) forests threatened by the below-average rainfall during the Millennium Drought. Tree condition was improved by the environmental watering between 2006 and 2010, but the restored area was relatively limited and other trees in Hattah Lakes remained in poor condition (Wood et al, 2016). After 2010 and 2011, the condition of River Red Gum greatly improved following above-average precipitation and natural floods. As a result of increasing water availability following high rainfall, flooding events in 2010 and 2011 improved most River Red Gums in Hattah Lakes. At the same time, excess water may recharged groundwater in this region (Wood et al, 2016). Low rainfall occurred following this wet season in the Hattah lakes. Between 2013 and 2017, environmental water has been delivered to Hattah Lakes five times through the Chalka Creek regulator (marked as a triangle in Figure 3.1) (Wood et al, 2018).

3.3.2 Datasets

3.3.2.1 Remote sensing data

A 30-year Landsat dataset from 1988 to 2018 was used in this study. Landsat 4,5,7,8 surface reflectance Tier 1 data were accessed through the Google Earth Engine (GEE). The temporal resolution of the dataset is 16-days. These remotely sensed images meet geometric and radiometric quality requirements and have been atmospherically corrected within GEE. We removed pixels with clouds and cloud shadows using the 'pixel_qa' band from the pixel quality information, and repaired Landsat 7 Scan Line Corrector (SLC)-off error using the morphological mean filter method in GEE. Values were interpolated from the previous and following images to fill the pixel gaps.

Two vegetation indices were calculated based on the Landsat data. Normalized Difference Vegetation Index (NDVI) is derived from the ratio of near-infrared spectral (NIR) and red spectral (RED) wavelengths reflected by vegetation (Pettorelli et al, 2005; Tucker, 1979). NDVI has been widely used in research and is strongly related to vegetation distribution, phenology, and productivity (Pettorelli et al, 2005; Robinson et al, 2017). We compared NDVI and the Enhanced Vegetation Index (EVI) (Jiang et al, 2008) to compare their effectiveness in representing vegetation condition of the study area. We found that EVI values were generally low over semi-arid sites. In contrast, NDVI shows variation among years and has different patterns for different Ecological Vegetation Classes (EVCs; explained below in section 2.3.4.) (Figure 3.2 and Figure 3.3). Together, these show that NDVI is appropriate to be used to represent vegetation condition in Hattah Lakes.

$$\mathrm{NDVI} = \frac{NIR-RED}{NIR+RED}\text{ , Equation 3.1}$$

The modified Normalized Difference Water Index (mNDWI) was calculated from green spectral (GREEN) data and MIR spectral data and was used to delineate open water. MIR refers to the middle infrared band, such as the TM band 5 (Xu, 2007).

$$\text{MNDWI} = \frac{GREEN-MIR}{GREEN+MIR}, \text{Equation 3.2}$$

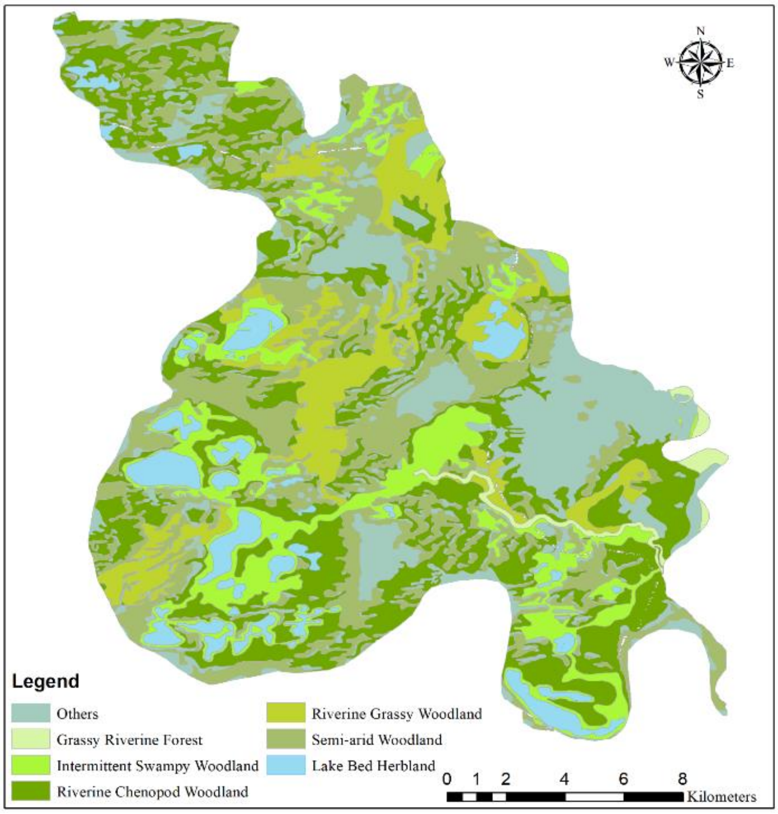


Figure 3.2 Main ecological vegetation classes in Hattah Lakes.

The distance to water for each pixel was derived from the mNDWI. Surface water was identified as areas with mNDWI greater than 0. Then Euclidean distance to the nearest water pixel was obtained for each pixel and each date using the "ee. Image.distance" function in GEE.

3.3.2.2 Climate data

The AWAPer package (Peterson et al, 2019) was used to extract daily maximum temperature and precipitation data for Hattah Lakes with a spatial resolution of approximately 5 km. The climate data have been developed through the Bureau of Meteorology's Australian Water Availability Project (Jones, 2009). To match dates of the remote sensing imagery, we calculated maximum temperature on the date the image was taken and accumulated precipitation data for the 16 days before the date.

3.3.2.3 Hydrological data

Natural flood records and environmental water records for the Hattah Lakes floodplain were derived from discharge data at Euston Weir and the Chalka Creek regulator. A commence-to-flow threshold of 36700ML/day was applied to delineate the occurrence of a natural flood (Wood et al, 2016). Records of environmental flow inputs have been recorded at the Chalka Creek regulator since 2013, and from pumping records prior to then.

3.3.3 Model Design and Evaluation

3.3.3.1 Predictor variables and response variable

Table 3.1 shows the predictor variables used in this study, including distance to water, precipitation and temperature, all of which are 30-year spatial data. Hydrological variables include concurrent water, water in period 01 and water in period 02. These were categorized as “NN”, “NY”, “YN”, “YY”, representing whether environmental water (first letter) or natural floods (second letter) occur or not in the corresponding period and in what combination. The response variable in this model is NDVI, representing vegetation condition.

Table 3.1 Description of predictor variables used in the model.

Model terms	Description
day of year	To represent vegetation phenology
distance to water	Euclidean distance to the nearest water based on mNDWI dataset
precipitation	16 days accumulated precipitation
temperature	Max temperature over the 16-day period
Concurrent water	Environmental water or natural floods occurs or not within one month prior to the image date
water in period 01	Environmental water or natural floods occurs or not 1 to 3 months prior
water in period 02	Environmental water or natural floods occurs or not 4 to 12 months prior

3.3.3.2 Generalized additive mixed models (GAMMs)

Generalized additive mixed models (GAMMs) were applied in this study to assess the relationships between NDVI and the multiple independent variables. This approach was selected because it can deal with autocorrelated data likely in time-series. GAMMs can not only model the nonlinear relationship between response variables and explanatory variables, but also include random effects similar to generalized linear mixed models (Speelman et al, 2018; Wood, 2017). Recently, GAMMs have been increasingly used in the studies of ecology, environments, and linguistics to extract temporal trends or model complex relationships (Mellor & Cey, 2015).

An autoregressive-moving average (ARMA) correlation structure was selected to model temporal autocorrelation of the time-series data. The model structure used in this research takes the following form.

$$g(\mu_t) = \sum_{i=1}^{m} s_i(X_{ti}) + \sum_{i=1}^{n} X_{ti}\beta_i + ARMA(p,q), \text{ Equation 3.3}$$

$$ARMA(p,q) = \sum_{j=1}^{p} \varphi_j (g(y_{t-j}) - (\sum_{i=1}^{m} s_i(X_{t-j,i}) + \sum_{i=1}^{n} X_{t-j,i}\beta_i)) + \sum_{j=1}^{q} \theta_j (g(y_{t-j}) - g(\mu_{t-j})), \text{Equation 3.4}$$

In this equation, $g(\mu_t)$ is the response variable, and g is the link function; $s_i(X_{ti})$ are smoothing parts of the explanatory variables nonlinearly related to the response variable; $X_{ti}\beta_i$ are the linear components of the model, including parameters for linear variables and intercept; $ARMA(p,q)$ is a correlation structure for modelling temporal autocorrelation. After considering the relationships between dependent and independent variables, the variables "day of year" and "distance to water" were modelled using smooth functions, while others were considered as linear terms.

This model was implemented using the "gamm" function from the mgcv package in R. Restricted Maximum Likelihood (REML) estimation was used to estimate parameters for this model (Wood, 2004). Thin plate regression splines (Wood, 2003) were utilized for smooth terms; they out-perform traditional cubic regression splines but are computationally intensive.

3.3.3.3 Per pixel model

GAMMs were applied independently to each individual pixel of the Hattah Lakes floodplain. Because resolution of Landsat data is 30 meters, we resampled the climate data to 30-meter resolution. Therefore, the size of pixel is 30 × 30 meters and in total we obtained 343956 pixels for the Hattah Lakes floodplain. To perform model simulation across all pixels, the High Performance Computing system SPARTAN (Lafayette et al, 2016) at the University of Melbourne was used to improve the computation time. The function "future_map" in furrr package (Vaughan & Dancho, 2018) in R was used to parallelize computations.

3.3.3.4 Model evaluation

Before modelling, a variance inflation factor (VIF) test was conducted to check for multicollinearity between the predictor variables. This was done using vif() function from the car package in R. The VIF scores were all less than 1.4. This shows that multicollinearity is not a problem among those predictor variables, and it is not considered further in the results. To evaluate modelling results, we used the adjusted R2 statistic. The partial autocorrelation function (PACF) was also used to test if autocorrelation in the model was removed.

The results were evaluated and analyzed by looking at the distribution of REML estimates of the regression coefficients across the set of per-pixel models, stratifying by EVCs (Figure 3.2). EVCs are the principal units used to classify native vegetation and plan land-use and management in Victoria (Parkes et al, 2003; Peake et al, 2011). They are distinguished through a combination of floristic, life form and ecological characteristics, and through an inferred fidelity to particular environmental attributes (Peake et al, 2011). EVCs were obtained from Victorian Department of Environment, Land, Water & Planning (https://discover.data.vic.gov.au/dataset/native-vegetation-modelled-2005-ecological-vegetation-classes-with-bioregional-conservation-sta, last accessed on 28/12/2021).

3.4 Results

3.4.1 Vegetation Composition and Changes in NDVI

Hattah Lakes is mainly covered by five main EVCs (Figure 3.2). To illustrate how NDVI changes from 1988 to 2018, yearly NDVI was calculated in four typical years with ten-year interval (Figure 3.3).

NDVI shows the lowest value in 2008, coincident with the millennium drought in Australia. The millennium drought occurred from 1997 to 2009, affecting most of southern Australia (Broich et al, 2018). *Semi-arid woodland*, composed of non-eucalypt woodland, has a relatively lower value of NDVI. The mean NDVI value of *Grassy riverine forest*, which are mainly River Red Gum forests, is higher than other classes. This type of vegetation occurs along Chalka creek, through which environmental water is delivered to the water bodies in Hattah Lakes. *Riverine* *chenopod woodland*, *riverine grassy woodland* and *intermittent swampy woodland* have similar NDVI values in each year.

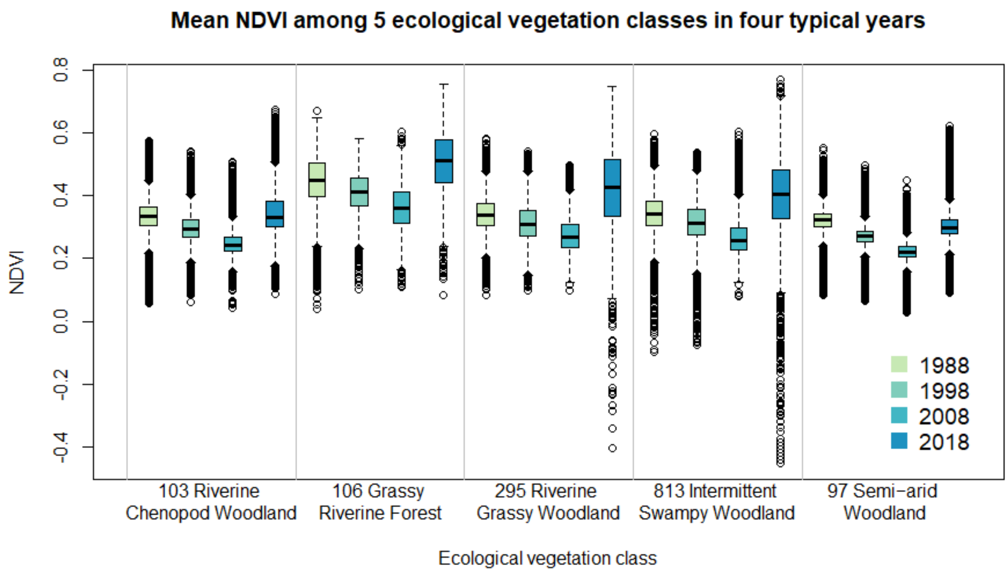


Figure 3.3 Mean NDVI for five vegetation EVCs, showing various among four typical years.

3.4.2 Vegetation Responses to Natural Floods and Environmental Water

Coefficients of natural floods and environmental water are summarized by the percentage of negative and positive regression parameter estimates across all of Hattah Lakes (Table 3.2). More than 85% of the pixels of *semi-arid woodland*, *riverine chenopod woodland* and *grassy riverine forest* positively responded to natural floods occurring within one month of the survey date ('concurrent'). The other two types of vegetation also positively respond to concurrent natural floods, but with a smaller percentage of pixels (76% and 79%). Apart from grassy riverine forest, more than 60% of the pixels of other EVCs have on-average slightly negative responses (i.e., positive response rate is < 50%) to natural floods occurring 1 to 3 months prior to the survey and have positive responses to natural floods occurring 4 to 12 months previously.

Table 3.2 Percentages of positive coefficient of watering events for five vegetation classes in Hattah Lakes.

	97 Semi-arid Woodland	*103 Riverine Chenopod Woodland*	*106 Grassy Riverine Forest*	*295 Riverine Grassy Woodland*	*813 Intermittent Swampy Woodland*
concurrent natural flood	95%	91%	85%	79%	76%
Natural flood in period 1	40%	35%	64%	35%	33%
Natural flood in period 2	77%	67%	75%	61%	68%
current env water	21%	22%	9%	24%	21%
Env water in period 1	72%	61%	85%	60%	57%
Env water in period 2	73%	68%	61%	63%	68%
Both occur in period 2 [1]	83%	74%	55%	70%	66%

[1] ’Both’ refers to both Natural floods and Environmental water occurring within the same period.

Unlike natural floods, environmental water appears to have a negative influence on vegetation in more than 76% pixels in the month after delivery (concurrent). However, over half the pixels for each EVC show a positive response to environmental water with a lag time more than 1 month (periods 1 and 2). This phenomenon is most apparent in *semi-arid woodland*, where the percentage shifts from more 70% negative during the 'concurrent' period to more than 70% positive when lag time is greater than one month (Table 3.2).

To further explore spatial influence patterns of natural floods and environmental water, we classified pixels into eight classes according to positive and negative value of coefficients (Table 3.3). If effects of watering events within one month are positive, then no matter how the effects change with lag time, we describe them as vegetation increasing immediately. If vegetation responds positively to watering events happening 1 to 3 months previously, but negatively to concurrent events, we consider them as vegetation increasing with 1 to 3 months lag time. Other classes are described in the same way (Table 3.3).

Vegetation in most areas of Hattah Lakes will respond to natural floods immediately within one month (Figure 3.4a). In the southwestern part of Hattah Lakes, some *riverine grassy woodland* responds to natural floods with a lag time of 1 to 3 months. In some fringing areas around Lake Lockie (red area in Figure 3.4a), NDVI only increases with natural floods that occurred 4 to 12 months previously.

Compared to natural floods, the impacts of environmental water are more spatially complex (Figure 3.4). Environmental water can help vegetation condition immediately in the northern Hattah Lakes floodplain (green area in Figure 3.4b), while vegetation over most of Hattah lakes will positively respond to environmental water occurring 1 to 3 months prior. *Intermittent swampy woodland* (area with green slash in Figure 3.4b) shows different patterns, in that environmental water occurring 4 to 12 months earlier has a positive impact. There are only a few pixels classified as class eight (negative response), which means that neither environmental water nor natural floods will improve vegetation health within 1 year of the event.

Table 3.3 Classification of influence patterns of watering events (+ represents positive influence, while - influences negative influence.)

Class of Influence	<1 Month	1 Month to 3 Months	4 Months to 12 Months	Description
1	+	−	−	Increase immediately
2	+	+	−	Increase immediately
3	+	−	+	Increase immediately
4	+	+	+	Increase immediately
5	−	+	+	1 to 3 months lag
6	−	+	−	1 to 3 months lag
7	−	−	+	4 to 12 months lag
8	−	−	−	Negative response

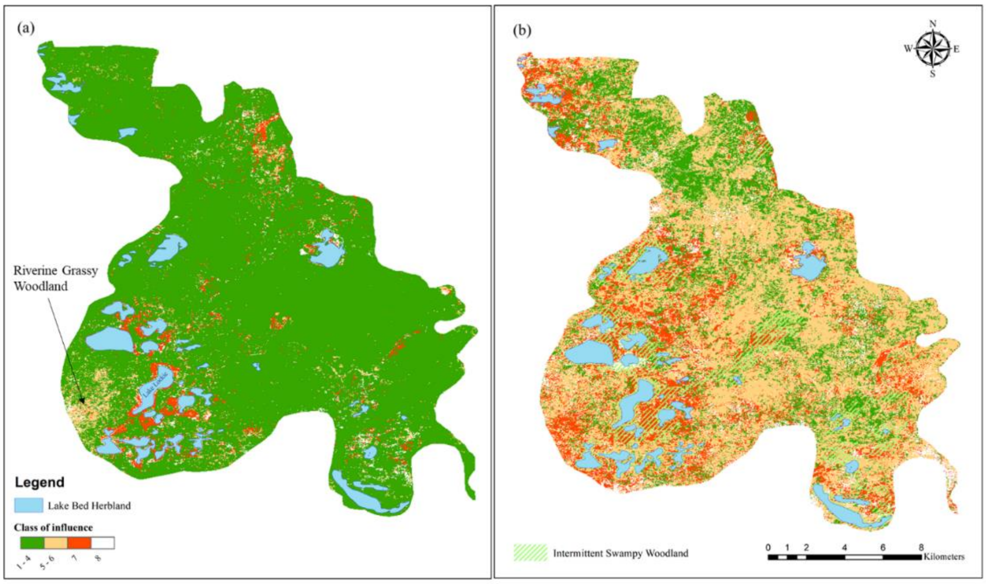


Figure 3.4 Pattern of vegetation response to (a) Natural floods (b) Environmental water with different lag time.

3.4.3 Other Explanatory Variables and Model Evaluation

3.4.3.1 Influence of climate factors and other variables

Coefficients from the models were used to represent the influences of 16-day accumulated precipitation and maximum temperature on vegetation (Figure 3.5). The influences are spatially distributed and there are differences among EVCs.

Most areas in Hattah Lakes negatively respond to increasing temperature, while a small proportion of semi-arid woodland shows a positive response to temperature. Vegetation along Chalka creek, which is grassy riverine forest, and in riverine grassy woodland, are more strongly influenced by temperature compared to other vegetation types (Figure 3.5a).

NDVI increases when there is more rainfall in most part of Hattah Lakes, but a major portion of semi-arid woodland responds negatively to precipitation (blue area in Figure 3.5b). The yellow area with larger precipitation coefficients in the model is covered by riverine chenopod woodland and shows a stronger positive response to precipitation.

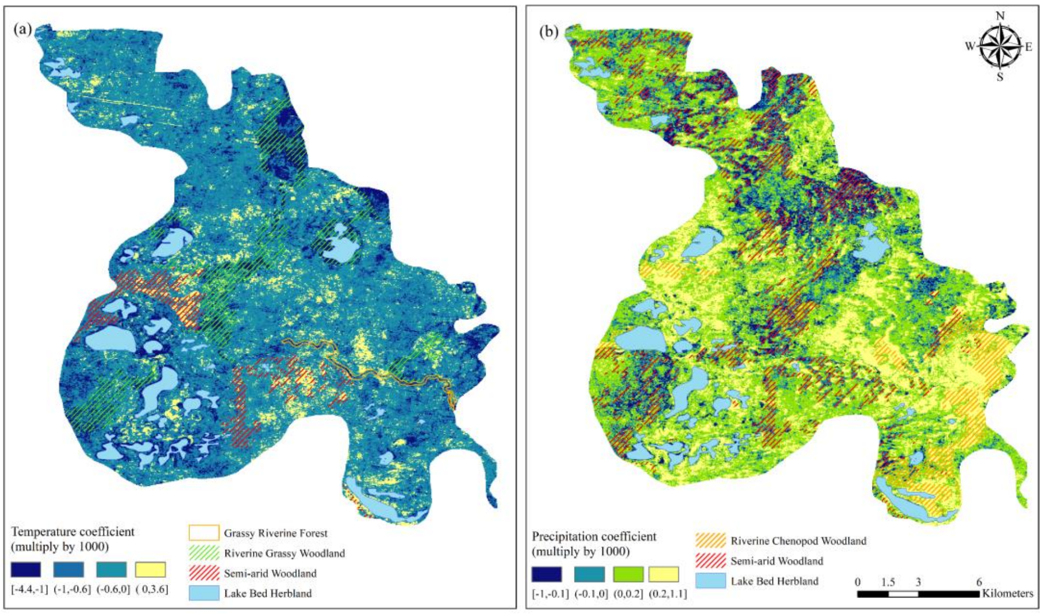


Figure 3.5 Influence of (a) temperature and (b) precipitation on vegetation.

The results of the variable 'day of year' indicate that the GAMM model captures vegetation phenology in Hattah lakes successfully. In most pixels, the peak of season is between the 175th and 212th day of the year. Multiple pixels are selected to show the influence curves of distance to water generated by GAMM, and it shows that distance to water has a slightly negative influence on NDVI value.

3.4.3.2 Model evaluation

The four maps in Figure 3.6 illustrate that autocorrelation was largely removed for temporal lags 1 to 4. Autocorrelation was almost completely removed for lag 1 and 2, while there is a small number of pixels that have substantial serial autocorrelation for lag 3 and 4 (blue area in Figure 3.6(c) and (d)). This shows that the ARMA error function performed as hoped.

The mean adjusted R square for all models is 0.52. Models in the drier areas of the landscape, and in particular semi-arid woodlands, have higher R square values (Figure 3.7). Models in the fringing area of the lakes themselves have the lowest adjusted R square values. This is mainly because they are periodically inundated, which influences NDVI value substantially.

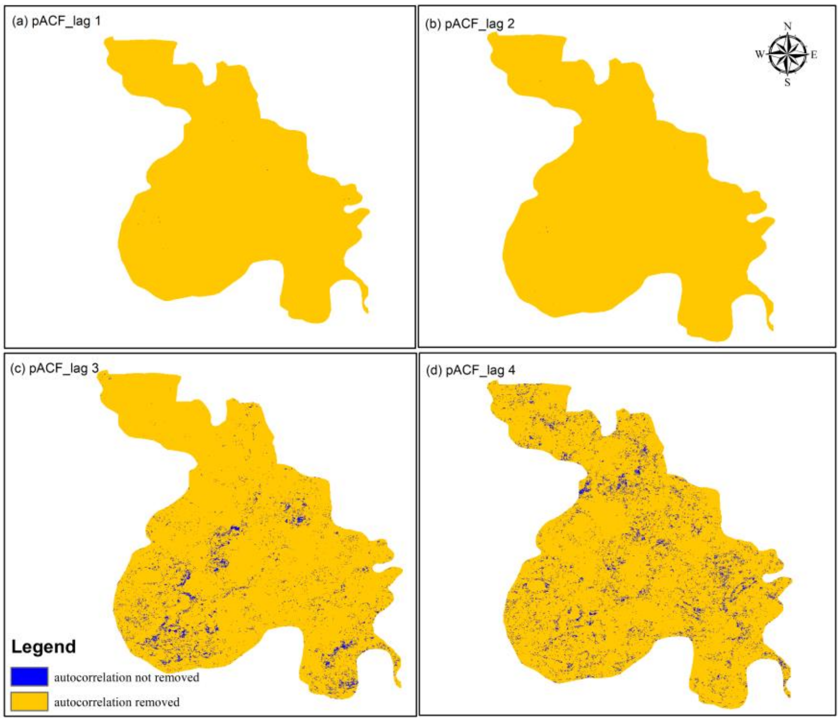


Figure 3.6 Result of PACF (If the value of Partial autocorrelation is within the 95% interval, the pixel is recognized as autocorrelation removed and vice versa).

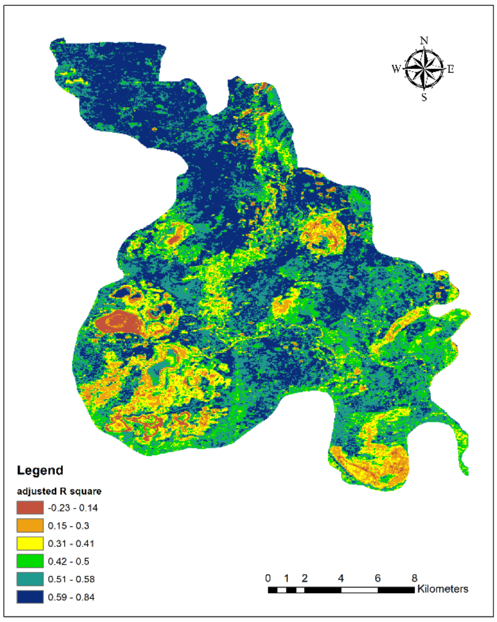


Figure 3.7 Adjusted R square.

3.5 Discussion

The results provide new insight to support environmental water management to maintain vegetation health. It is generally assumed that environmental water can be used to provide equivalent outcomes as overbank flows in supporting floodplain vegetation. However, this study found that vegetation responses to environmental water and natural floods were found to be very different in terms of lag time and spatial distribution.

3.5.1 Different Effects of Environmental Water and Natural Floods on Floodplain Vegetation

Our results show that although both environmental water and natural floods have benefits for floodplain vegetation, those benefits are very different in terms of the spatial extent of the effect and to a lesser extent the temporal extent. In general, environmental water takes a longer time (1 to 3 months) to display a positive effect than natural floods, which produce effects within 1 month of inundation.

Despite this important difference, vegetation in the Hattah Lakes floodplain responds positively to both environmental water and natural floods events occurring over the previous year. These results are coherent with previous findings. Both precipitation and flooding are important drivers of vegetation variation in the floodplain (Broich et al, 2018; Parsons & Thoms, 2013). In drought conditions, many eucalypts exhibit a survival strategy by shedding their leaves to reduce water loss. This shedding results in a decrease in foliar cover, which can be observed as lower NDVI. Conversely, following wetting events, eucalypts tend to retain their leaves as they capitalize on the improved water availability. This change in leaf retention and growth can lead to higher NDVI values, reflecting the increased vegetation vigor. In the Narran Lakes floodplains in northern New South Wales, Australia, response patterns are complex and vary among different vegetation communities, but flow remains the main influence on vegetation productivity (Thapa et al, 2016a). NDVI has previously been found to increase up to 19% above non-flood levels and for a period of 13 months following recession of a flood that inundated more than 50% of the Paroo River Wetlands in 2008 (Sims & Colloff, 2012). Vegetation recruitment has been shown to respond to a combination of environmental flows and riparian vegetation enhancement (Schlatter et al, 2017). In Hattah Lakes, environmental water has previously been shown to promote short-term positive responses in native vegetation based on data collected in the field (Moxham et al, 2019).

3.5.2 Why Are There the Differences in the Influence of Environmental Water and Natural Floods?

The most obvious potential reason for the difference in the effects of environmental water and natural floods is that delivery mechanisms vary between the two sources of water. The floodplain will be inundated if natural floods occur, but environmental water is directed along individual channels. This restricts the inundated area for environmental water. The time of occurrence, flooding duration and volume may also differ between natural floods and environmental water. For example, volume of natural floods is larger than environmental water, so that overbank flows occur. These factors influence watering extent and in turn the reproductive processes of vegetation.

There are some spatial differences among the different EVCs. *Riverine grassy woodland* in the western part of the Hattah Lakes floodplain responds to natural floods 1 to 3 months after the overbank event. That area is the greatest distance from the river in the floodplain and in a slightly elevated position where floods are rare (DELWP, 2005). This means that water from natural floods does not reach the areas immediately. Vegetation in the fringing areas, especially around Lake Lockie, is improved 4 to 12 months after natural flooding. Because of the large volume of natural floods, the area around the lakes is flooded and will remain inundated for some time. Standing water will reduce the NDVI value, and at the same time, we will not see an increase in vegetation condition in those pixels around the lakes until after the water recedes. This phenomenon is more apparent in response to environmental water. In most areas of intermittent swampy woodland, which includes fringing area of lakes, environmental water improves vegetation condition 4 to 12 months after delivery. This EVC is mainly *Eucalypt* woodland up to 15 meters tall and is close to the path of environmental water. Therefore, it will be inundated and influenced directly when environmental water is delivered.

3.5.3 Implications for Environmental Water Management

This research provides a counterpoint to assumptions implicit in environmental water management in Australia, and in particular the management of sustainable diversion limits (SDL) in the Murray-Darling Basin Plan. In calculating SDLs, and in particular the 'Adjustment mechanism' to increase the amount of water retained for agricultural consumption (Hart, 2015), environmental water is used to replace natural floods. It is assumed that environmental works such as regulators provide 'equivalent environmental outcomes' as do overbank flows, but with greater watering efficiency (Foundation, 2014; MDBA, 2015b). However, our results clearly show that pumping environmental water using regulators does not achieve the same benefits as natural floods. Many projects have been designed to reinstate the natural flooding regime by delivering environmental water (MDBA, 2017), and many propose to do so by constructing pumping stations and other regulators. With regards to such projects, we suggest continuing with environmental watering to help vegetation health in the changing climate. However, managers need to be aware that the beneficial effects of such flows will be much more spatially constrained than those of natural floods, and that the time scale of effect may be different to that of natural floods.

Long-term vegetation condition has been modelled in this paper, supporting adaptive management of environmental flows in term of vegetation monitoring and evaluation (Webb et al, 2017). In Hattah Lakes, the release of environmental water will continue to play an important role in maintaining and improving vegetation growth under climate change, as was demonstrated throughout the Millennium drought period. Based on the results from this study, the implementation of new infrastructures needs to be planned carefully. Environmental water benefits accrue more slowly for floodplain vegetation than those from natural floods. If a decreasing trend of precipitation and lack of natural floods are predicted, it is worth considering pumping environmental water into floodplain system in advance of any full-blown drought. According to the distribution of results among EVCs observed here, *intermittent swampy woodland* should be a focus because it shows a longer lag response to environmental water. Monitoring of this area can be more frequency and more research are needed on this EVC.

3.5.4 Benefit of the Methods and Future Opportunities

This is the first application of GAMM to analysis of environmental water effects of which we are aware. There were several advantages of GAMM for our study. First, it is suitable for qualitative factors, where the watering events were categorized into 3 classes for each date. Data temporal autocorrelation problems were also solved. Most importantly, we have shown that GAMM can separate the influence of environmental water on vegetation from that of natural floods and is suitable for applications in lake-connected floodplains. The work illustrates the complexity of the spatial distribution of vegetation response to environmental water. It is also based on a 30-year satellite data set, thus making full use of historical data and giving greater confidence in the long-term results. The different lag times and spatial influences will be the foundation of further analysis, such as the effects of specific environmental water regimes.

Vegetation condition was represented by NDVI based on the 30-year Landsat dataset, which solved the problem of discontinuous and incomplete field data. Some errors existed due to image quality, including gap pixels and missing images. Moreover, the condition of trees and understory vegetation have not been separated in this research. A more specific vegetation response, such as River Red Gum condition, would be needed to model individual priority species in the floodplain.

A lag time on the influence of climatic factors could be added to the model to increase biophysical accuracy. In semi-arid areas, vegetation shows a time-lagged response to rainfall pulses (Broich et al, 2018). Therefore, in future modelling, different lag times of climate factors could help improve model fit.

In future research, we would like to consider the influence of groundwater and human activities. Increasing groundwater extraction has been shown to lead to decrease in floodplain productivity, including in the EVC *semi-arid floodplain woodland* (Horner et al, 2009; Thapa et al, 2019). Although distance to water was used in the model, the relative influences of surface water and groundwater need to be further explored. Our model tests the effect of environmental water and natural floods regardless how far that pixel is from surface water. To further explore how environmental water aids vegetation health, it would be worth including a physical model considering flow path, flow volume and release timing. Improved understanding from such an approach may offer an opportunity to improve the efficiency of environmental water use, making full use of precious water resources.

3.6 Conclusions

In this paper, we modelled vegetation response to environmental water using GAMM based on 30-year Landsat data, combining with climate factors and natural floods. We found that the influences of environmental water and natural floods are different in lag time and spatial distribution. In most area of Hattah Lakes, environmental water can help vegetation growth in 1 to 3 months and different patterns between EVCs have been found. To better support environmental water delivery strategy and management, further studies such as combining with water balance model are needed. Overall, this work can help management better understand and manage environmental water to restore and maintain vegetation health under climate change.

Chapter 4 . Assessment of environmental water strategies for improving fringing vegetation health by modelling vegetation condition in a lakes-connected floodplain

This Chapter has been published in *Ecohydrology* in March 2024:

Wu, C., Webb, J.A. and Stewardson, M.J., Assessment of environmental water strategies for improving fringing vegetation health by modelling vegetation condition in a lakes-connected floodplain. *Ecohydrology*, p.e2644.

4.1 Abstract

Across the globe, environmental water has been allocated with the purpose of preserving the health and vitality of floodplain vegetation. However, the influence of environmental water volume and current environmental water delivery strategies have not been studied widely because of a lack of on-ground monitoring data. Remotely sensed data can bridge this gap by providing long-term and continuous information; Landsat imagery from 1988 to 2020 was used in this research. We used the Normalized Difference Vegetation Index (NDVI) as an indicator of long-term condition of vegetation on the Hattah Lakes floodplain, south-east Australia. We employed the Random Forest (RF) regression method to model the relationship between NDVI and various climate and hydrological factors, such as the volume of water delivered to the floodplain system as environmental water allocations or natural floods. The RF models performed well overall, with a mean R^2 value of 0.73. The analysis identified the monthly total of environmental water three months prior to the Landsat image date as a more crucial factor than natural floods for driving vegetation condition. The volume of environmental water from three months previously exerts a positive

influence on NDVI until the volume reaches a specific threshold. We have observed significant improvements in floodplain vegetation through the current environmental water strategy, particularly since the construction of pumping infrastructure in 2013. We suggest that managers aim to inundate the lake fringing area every three years, specifically from August to September, by delivering environmental water up to the modelled volume threshold. Finally, the use of infrastructure has proven to be an effective and efficient method for irrigating floodplain wetlands, leading to improvements in vegetation condition while conserving water resources.

4.2 Introduction

Known as Earth's kidneys, wetlands are one of the world's most significant ecosystems. They provide ecosystem services in the form of flood control, water purification and habitat (Wu & Chen, 2020; Wu et al, 2022; Xi et al, 2020). However, they have suffered extensive damage over recent decades because of climate change and human activities (Steinfeld & Kingsford, 2013).

In the context of disruption by dams and river regulation, there is growing recognition of the importance of conserving floodplains and particularly river-floodplain connections for wetland ecosystems (Steinfeld & Kingsford, 2013). Rivers across the globe have undergone regulation for diverse purposes such as public water supply, irrigation, electricity generation and flood mitigation (Kuiper et al, 2014). More than 60% of river systems worldwide have experienced changes in stream flows (Kuiper et al, 2014). River regulation influences various hydro-geomorphic processes, resulting in a significant reduction in the occurrences of small and moderate floods (Netsvetov et al, 2019; Peake et al, 2011; Souter et al, 2014). As a result, river regulation has detrimental effects on the growth of floodplain trees, the density of forest stands and the overall structure of floodplain ecosystems (Netsvetov et al, 2019). Deaths of floodplain forests and woodlands are occurring globally (Zhang et al, 2021). Therefore, appropriate measures and policies to address competing water demands for human and environmental uses are urgently needed to maintain floodplain ecosystems (Doody et al, 2015; Steinfeld & Kingsford, 2013). In response, many countries have implemented environmental water delivery programs to provide water to floodplain ecosystems (Galat, Fredrickson et al.

1998, Doody, Colloff et al. 2015, Stewardson and Guarino 2018, Wu, Webb et al. 2022).

Restoring and maintaining floodplain vegetation communities are often the primary objectives when supplying environmental water into floodplain wetland systems. The vegetation of floodplain wetlands in regulated rivers often undergo changes as a direct consequence of altered timing and reduced magnitude and duration of floods (Reid & Brooks, 2000). This has occurred in many regulated rivers around the world (Catelotti et al, 2015). These communities are highly sensitive to climate change and river regulation, especially in semi-arid and arid regions. This situation is more pronounced in dominant perennial species of floodplain vegetation communities of south-east Australia, particularly black box (*E. largiflorens*) and river red gum (*Eucalyptus camaldulensis*) (Jensen & Walker, 2017).

Many studies have been conducted to determine floodplain vegetation water requirements and environmental water effects on vegetation. In Australia, river red gum communities have often been monitored using field-based methods during environmental water delivery. Such studies show a consistent pattern of benefiting from watering in summer, with increased growth and condition (Jensen and Walker 2017). However, field-based monitoring data are sparse and can only ever cover a fraction of a floodplain's area. To compensate for the shortcoming of field-based methods, remote sensing imagery has recently been used to study long-term vegetation condition (Broich et al, 2018). As a convenient method, remote sensing techniques have gained recognition for acquisition of continuous data across various spatial resolutions (Norman et al, 2014). These data have been increasingly employed in the study of fluvial environments and demonstrate excellent results (Pace et al, 2021; Sims & Colloff, 2012).

Separately, vegetation response to environmental watering has been modelled by multiple modelling methods. These modelling methods includes generalized additive mixed models, Bayesian hierarchical models and System dynamics models (Morrison & Stone, 2015; Moxham et al, 2019; Wu et al, 2022).

Different vegetation types have varying responses to environmental water in terms of lag time. This is especially the case in the fringing area of lakes surrounded by stands of River Red Gum and Black Box (Wu et al, 2022). However, studies related to the influence of environmental water volume and timing in floodplain vegetation remain scarce due to limited monitoring data and computational difficulties (Canham et al, 2021; Jensen et al, 2007; Wu et al, 2022).

To improve vegetation outcomes and achieve the objective of maintaining vegetation health through environmental water allocation, it is essential to understand the collective effects of environmental water and other factors on riparian vegetation condition (Capon et al, 2017). An environmental water strategy evaluation model is urgently needed to examine the efficiency of past and ongoing environmental watering strategies. In this study, Random Forest regression models and machine learning explanation methods have been applied to a 30-year Landsat dataset to model response to environmental water volume and climate factors in a lakes-connected floodplain.

4.3 Methods

4.3.1 Study Area

Lying in north-western Victoria, south-eastern Australia, on the banks of the River Murray, the Hattah Lakes floodplain system is comprised of more than 20 permanent and semi-permanent freshwater lakes with associated floodplains and waterways (Figure 4.1). Twelve of these wetlands are listed as Ramsar wetlands. As a semi-arid environment with hot dry summers and cooler winters, the floodplain has higher rainfall in the winter (Butcher & Hale, 2011). However, rainfall occurs all year with an average annual rainfall of about 250 mm (Wu et al, 2022).

The Hattah lakes floodplain provides high biodiversity and habitat values, including vegetation communities such as black box and river red gum woodlands. These vegetation communities provide habitat for more than 47 waterbird species and other fauna (MDBA, 2012b). As a national park, the Hattah Lakes floodplain is important for social and cultural activities. Therefore, based on its many values, the Hattah lakes floodplain was designated as an 'icon site' in The Living Murray program – Australia's first major river restoration program

(Wood et al, 2016). Fringing river red gum woodland is one of the environmental objectives of the environmental water program (MDBA, 2012b). So the study area of this research is focused on the fringing vegetation area of 9 selected Ramsar-listed wetlands (Table 4.1).

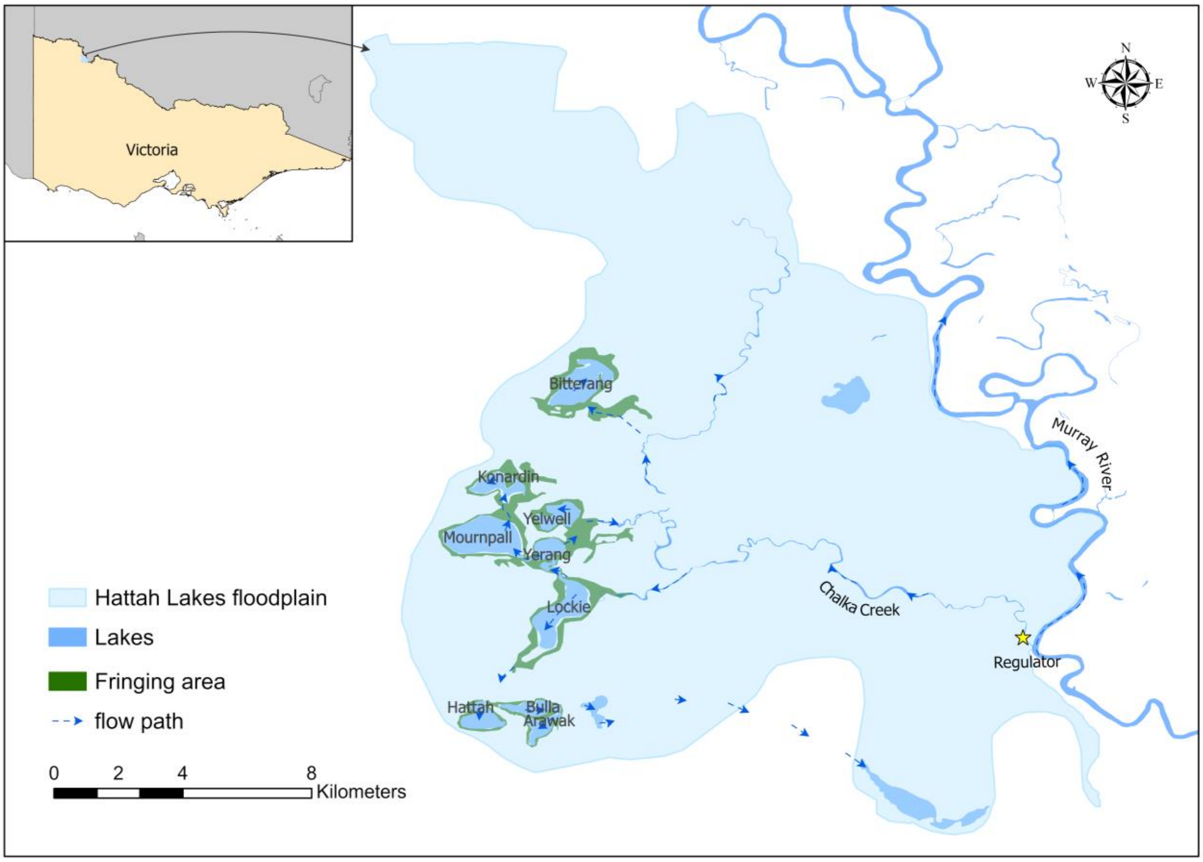


Figure 4.1 Location and lake distribution of study area: the Hattah lakes.

Due to the River Murray and its floodplains being highly regulated, the Hattah Lakes ecosystem has been damaged by the loss of natural connectivity to the river over many decades (Cunningham, 2009). Wetland vegetation requires periodic flooding to maintain ecological condition. To partly restore the floodplain system, the flooding regime of the Hattah Lakes has been managed with environmental water since 2005 (MDBA, 2012b). Environmental water is pumped into the floodplain through Chalka Creek and fills the lakes one by one (Figure 4.2). Lake Lockie is the first one to be filled when environmental water is delivered in this way, and then water flows toward Lake Hattah and on to a sequence of lakes in the south (starting with Lake Bulla and ending with Lake Nip Nip). Meanwhile, water moves from Lake Lockie to Lake Yerang and feeds the northern lakes. The use of pumping allows lakes to be filled with environmental water at flows that are feasible to deliver along the Murray River. Elevating Murray River flows to thresholds for natural filling (Table 4.1) using environmental water is not possible because of i) limits on the total amount of environmental water available, ii) limited release capabilities from upstream dams and iii) operational constraints on the river designed to avoid flood impacts on riparian landholders and infrastructure.

Table 4.1 Description of 9 lakes selected

Lake name	Lake area (ha)	Flows at Euston Weir (~70 km upstream of Hattah Lakes) for lake to fill naturally (ML/day)
Lake Lockie	123	40000
Lake Hattah	52	40000
Lake Bulla	32	55000
Lake Mournpall	181	40000
Lake Yerang	43	40000
Lake Arawak	37	55000
Lake Yelwell	55	55000
Lake Konardin	57	70000
Lake Bitterang	109	70000

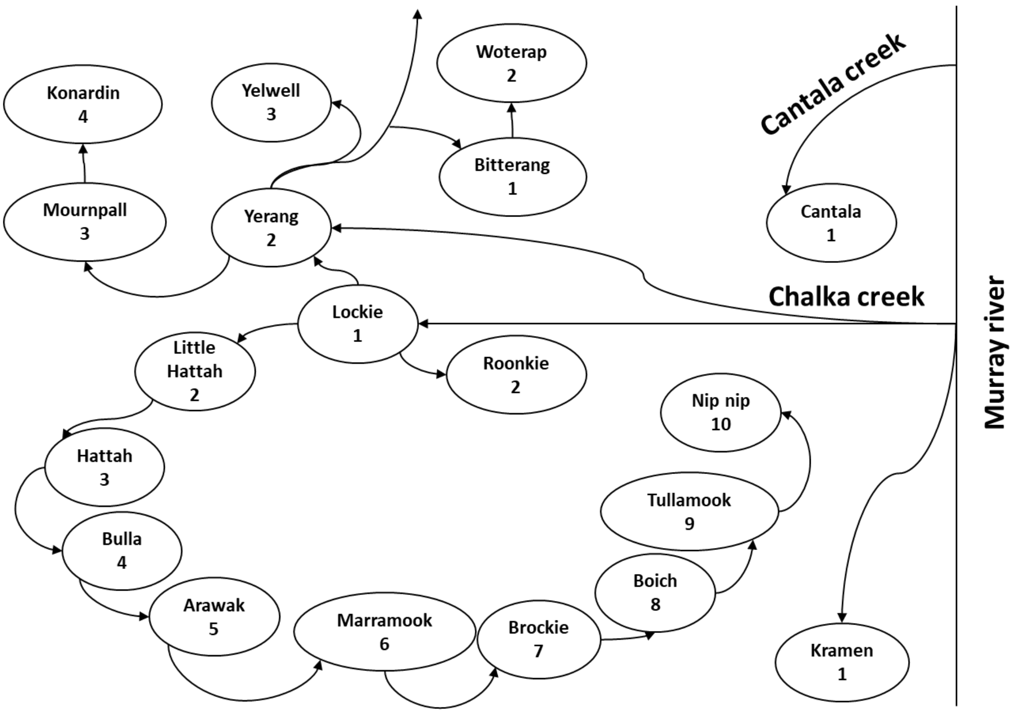


Figure 4.2 Environmental water flow path diagram and filling pattern of the Hattah Lakes system redrawn from (Wijesuriya, 2022)

4.3.2 Datasets and pre-processing

In this study, multiple kinds of data have been used, including Landsat images with 16-day intervals and 30 meters resolution, historical climate data and hydrological records.

4.3.2.1 Remote sensing images

Landsat 5, 7 and 8 collection 1 datasets from 1988 to 2020 were used in this study, with the data being processed in Google Earth Engine (GEE). Clouds and cloud shadows were removed and filled by the mean of the values of images 1.5 months before and after the image with missing values. Poor-quality images were identified by counting the gap pixels and removed from the data set. Landsat 7 Scan Line Corrector (SLC)-off gap was repaired by applying the morphological mean filter in GEE. To deal with the differences between the spectral characteristics of Landsat OLI and TM/ETM+ (Roy et al, 2016), the Landsat TM/ETM+ to OLI Harmonization function developed by GEE was applied to the imagery.

Recent research has shown that the Normalized Difference Vegetation Index (NDVI) can represent vegetation condition better than other vegetation indices in Hattah Lakes (Wu et al, 2022). NDVI is calculated by the following formula:

$$NDVI = \frac{\rho NIR - \rho RED}{\rho NIR + \rho RED}, \text{Equation 4.1}$$

where ρNIR is the reflectance value of the near infrared band, and ρRED is the reflectance value of red band. Higher values of NDVI are indicative of better vegetation condition.

4.3.2.2 Climate data

Climate data, including daily precipitation, maximum temperature, and vapor pressure were extracted from the Australian Water Availability Project (AWAP), which is a high-quality dataset of historical and ongoing climate analyses for Australia with a spatial resolution of 5km (Jones et al, 2009). To match the Landsat data acquisition date, we calculated monthly accumulated precipitation, mean maximum temperature and mean vapor pressure with different lag periods (see below).

4.3.2.3 Hydrological data

Between 2005 and 2010, environmental water was delivered to the Hattah Lakes from the River Murray through transportable pumps (Wood et al, 2018). In October 2013, a permanent pumping station – the Chalka Creek regulator – was built on the Hattah Lakes floodplain (Butcher & Hale, 2011), and environmental water has been delivered by that regulator since then.

Natural floods occur, and flow through Chalka Creek into Hattah Lakes when discharges at Euston Weir (~70 km upstream of Hattah Lakes) exceed the Commence to flow (CTF) threshold (36,700 ML/day prior to October 2013 and 25,000 ML/day thereafter). To quantitatively calculate natural floods volume flowing into Hattah Lakes, we constructed a linear function between discharge at the Chalka Creek regulator and discharge at Euston Weir in excess of the CTF threshold during natural flooding period between August 2016 and December 2016 (Figure 4.3). The relationship and linear function were applied to long-term discharge records at Euston Weir.

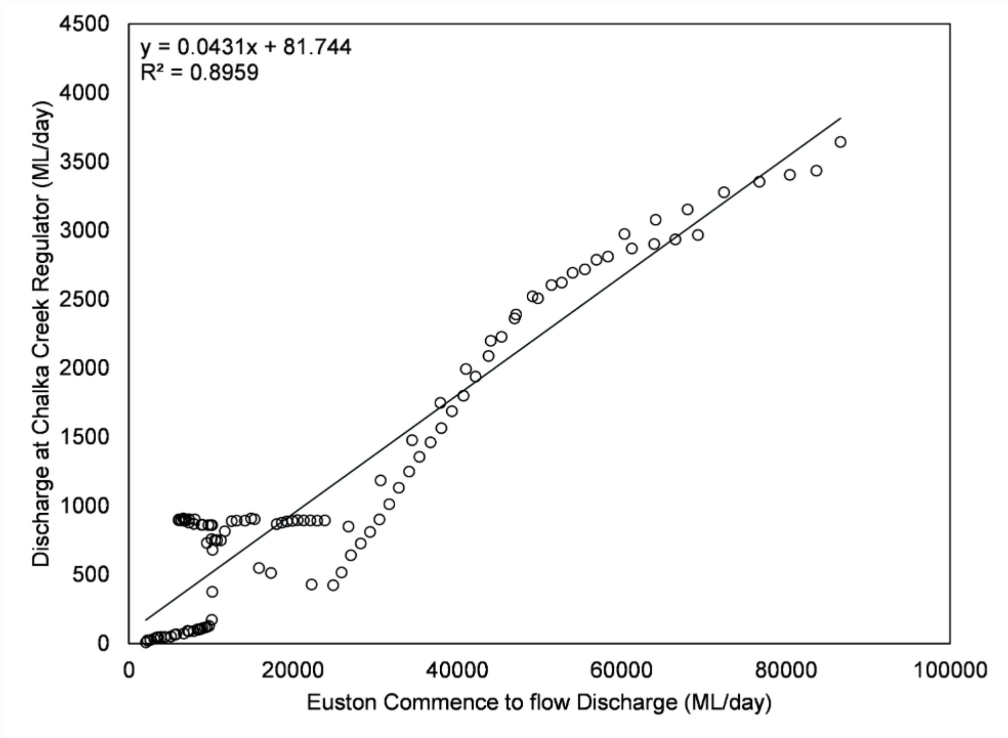


Figure 4.3 Relationship between discharge at the Chalka creek regulator and difference between the discharge at Euston Weir and CTF threshold (25000ML/day)

4.3.3 Random Forest regression

4.3.3.1 Explanatory variables

Explanatory variables for our models of vegetation condition are listed in Table 4.2. Our previous work found that a positive influence on floodplain vegetation can be detected 1 to 3 months after inundation with environmental water (Wu et al, 2022). With this in mind, we selected accumulated environmental water volume with 1-month, 2-month and 3-month lags as independent variables. We also tested whether precipitation within 3 months and natural floods within 3 months affect vegetation growth.

Table 4.2 Description of features (explanatory variables)

Abbreviation	Feature	Unit	Rationale
tempmax_1m	Monthly mean max temperature	deg. Celsius	Temperature and precipitation are prerequisite climatic factor for vegetation growth (Ren et al, 2022). Atmospheric water demand for plants is strongly influenced by Vapor Pressure Deficit (VPD) (Yuan et al, 2019).
vapourpre_1m	Monthly mean vapor pressure	hPa	
prec_1m	Accumulated precipitation one month prior	mm	
prec_2m	Accumulated precipitation two month prior	mm	
prec_3m	Accumulated precipitation three month prior	mm	
envwater_1m	Accumulated Environmental water one month prior	ML	Vegetation exhibits favorable responses to environmental water typically within a period of 1 to 3 months following inundation (Wu et al, 2022).
envwater_2m	Accumulated Environmental water two month prior	ML	
envwater_3m	Accumulated Environmental water three month prior	ML	

Abbreviation	Feature	Unit	Rationale
natflood_1m	Accumulated natural floods one month prior	ML	
natflood_2m	Accumulated natural floods two month prior	ML	The dynamics of floodplain vegetation are impacted by flooding, which serves as a crucial driving factor (Broich et al, 2018).
natflood_3m	Accumulated natural floods three month prior	ML	
season	Season of current date	NA	We assume that coupled with season variable, influence of variables above shows different patterns.

4.3.3.2 Model description

Random forests (RF) modelling is a machine-learning approach for identifying complex and non-linear relationships between a dependent variable and potential explanatory variables (Breiman, 2001). RF is a regression and classification method (Singh et al, 2017), but this study used RF regression. This non-parametric machine learning method is comprised of an ensemble of decision trees that predict the outcome measure. In the Random Forest (RF) algorithm, a decision tree is constructed using a bootstrapped dataset and this process is repeated multiple times to create a forest of trees. The final prediction is calculated by taking the average of the predictions made by all the trees in the forest. The result of this process is a comprehensive model that illustrates the relationship between Landsat NDVI levels and the key driving variables influencing vegetation growth in the Hattah Lakes ecosystem. This model enables users to explore the relative importance of these driving variables on NDVI levels, providing insights into how changes in specific factors could impact vegetation dynamics. By simulating adjustments to these driving variables, the model can predict corresponding changes in NDVI outcomes, offering a valuable tool for understanding and managing ecosystem health.

Random forests have been applied in many fields, including vegetation forecasting, land use classification, crop yield prediction and environmental impact analysis (Ferchichi et al, 2022). We had previously compared RFs with support vector machine and long-short term memory network models and found that RFs have the best predictive performance for data in the Hattah Lakes system (C. Wu, unpubl. data).

The model was implemented using *sklearn*'s Random Forest Regressor function (Pedregosa et al, 2011) in Python. The dataset was divided into training (90%) and outer testing (10%) sets (the outer test means the test dataset have never been used in model training process). The training set was used in model fitting and the model was tuned by Grid Search with 5-fold cross-validation to find the optimal set of hyperparameters. The *bootstrap sample* function was used when building the trees to randomly split the dataset into homogeneous subsets. The training set was shuffled during cross validation, which makes each split comparable with our dataset. The model was evaluated by the coefficient of determination (R^2).

4.3.4 Model explanation methods

As a 'Black Box' Model, the RF regression model cannot be understood by looking at its parameters (Molnar, 2019). In this study, we use model explanation methods to extract relationships between NDVI and the explanatory variables.

Feature importance, as the name suggests, compares the importance of different explanatory variables for explaining the dependent variable (Breiman, 2001). It calculates a score for each feature of each tree in the random forest, then takes an average across trees to assess the feature's contribution. Feature importance is implemented in Python using the *scikit-learn* Random Forest regression function.

Individual Conditional Expectation (ICE) plots illustrate the prediction changes by displaying a distinct line for every instance, showcasing the impact of feature variations on the predictions (one line per instance) (Molnar, 2019). In contrast, the Partial Dependence plot (PDP) displays the average relationship between the feature and the prediction, shown as a single line across all instances. The PDP shows the marginal effect of one or two independent variables in the RF model on the predicted outcome of the fitted model (Jiang et al, 2022). Usually, there are one or two features considered in a PDP. In this study, we used the 2D PDP to see the interaction between features.

To avoid the issues with extrapolation when features are highly correlated, we used the Accumulated Local Effect (ALE) plot to describe how different variables affect the prediction (Apley & Zhu, 2020). The features are initially divided into intervals, and the prediction difference is computed by replacing the feature with the upper and lower limits of each interval. These differences are subsequently aggregated and centered, ultimately yielding the ALE curve (Molnar, 2019). For this study, ALE plots of 1D and 2D were implemented using Python package *PyALE*.

In this study, the PDPs give an overall idea of the impact of each feature, while the ALE plots were used to examine if the slopes seen in the PDPs could be an artefact caused by extrapolation problems.

4.4 Results

4.4.1 Model performance

The RF regression model shows good overall performance for modelling NDVI. The model showed different performance among the nine lakes (Figure 4.4). The R^2 of outer test for Lake Kondardin is the highest with a value of 0.82, while the mean R^2 of outer test for nine lakes is 0.73.

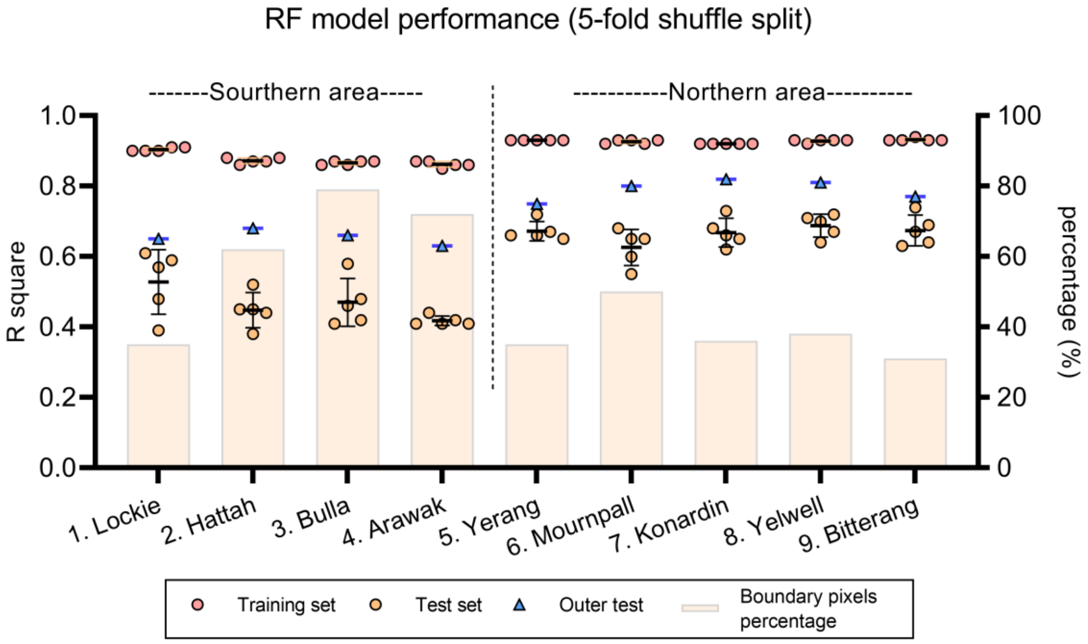


Figure 4.4 Random Forest model performance (the bar plot shows percentage of boundary pixels for each lake pixels. Boundary pixels refer to pixel with mixed land use type). Variability in performance for the training and test sets is summarized by error bar of 1SD.

Model performances for lakes in the northern area are better than those of lakes in the southern area (Figure 4.4). At the same time, lakes with higher percentages of boundary pixels have lower R^2 values than others (Figure 4.4).

4.4.2 Feature importance

The most important features for predicting NDVI are very similar among lakes (Figure 4.5). *Tempmax_1m* is the most important feature for NDVI modelling for all lakes, followed by *prec_3m* for most of the lakes and then *envwater_3m* for the four southern lakes.

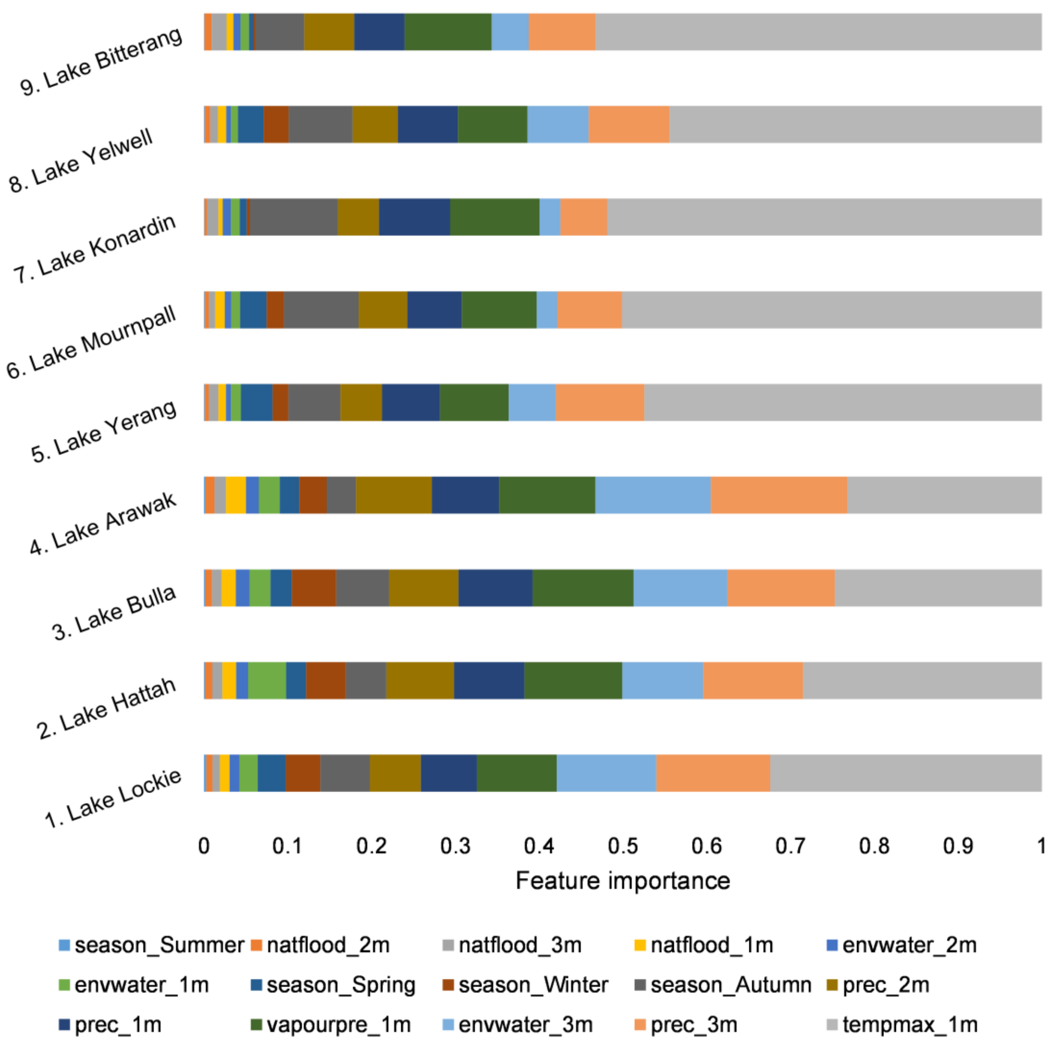


Figure 4.5 Stacked bar plot of feature importance for each lake

There are some order differences in variable importance among lakes. Focusing on *envwater_3m*, it is more important for vegetation around Lake Lockie, Lake Hattah, Lake Bulla, and Lake Arawak than the other 5 lakes (Figure 4.5). Conversely, temperature accounts for almost 50 percent of the variation for the 5 lakes in northern area, while environmental water has a lower value of importance.

4.4.3 Influence of environmental water on NDVI and environmental water delivery strategies evaluation

Envwater_3m is more important to NDVI response than *envwater_1m* and *envwater_2m* (Figure 4.5). Lake Lockie, Lake Hattah, Lake Bulla, and Lake Arawak show similar influence curves, with partial dependence of NDVI increasing almost 0.1 when environmental water volume reaches 7000 ML before levelling off (Figure 4.6a-d). For the other 5 lakes, the effect of environmental water is small, but also levels off when environmental water 3 months prior reaches a high volume.

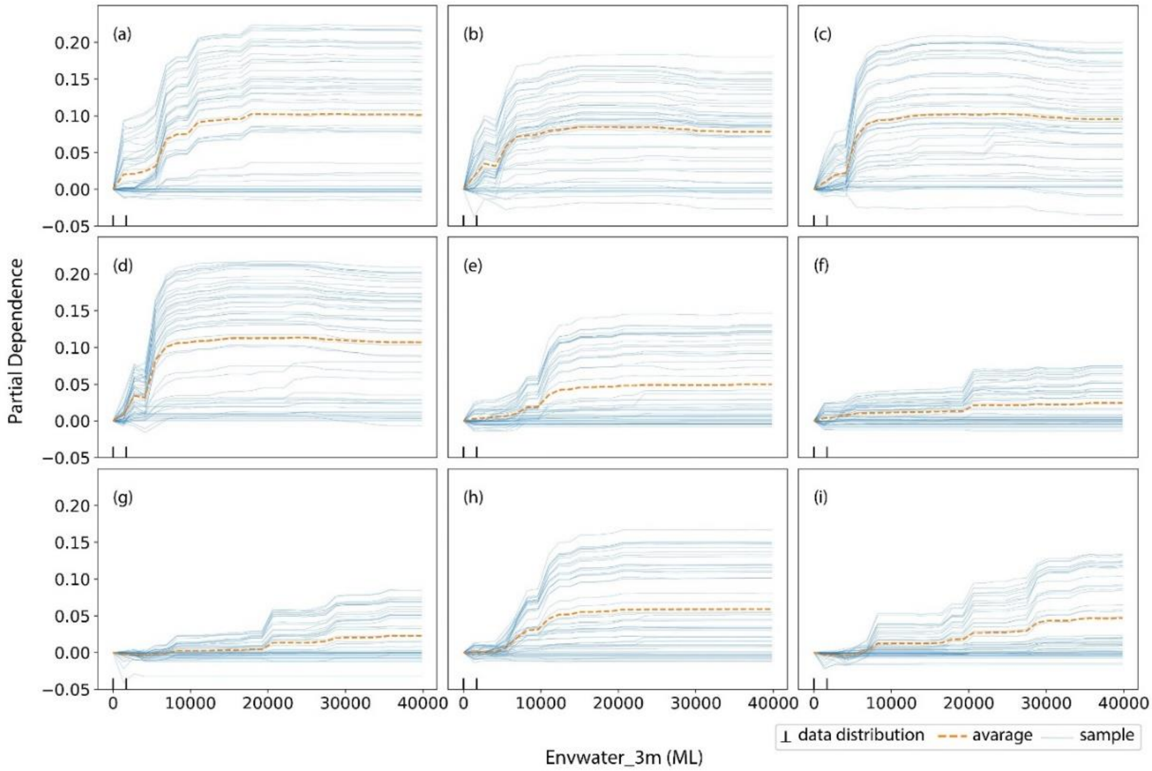


Figure 4.6 ICE plot of environmental water 3 months prior among nine lakes ((a) Lake Lockie (the first connected lake); (b) Lake Hattah; (c) Lake Bulla; (d) Lake Arawak; (e) Lake Yerang; (f) Lake Mournpall; (g) Lake Konardin; (h) Lake Yelwell; (i) Lake Bitterang). The orange dotted line represents the average PDP line, while the blue lines depict the individual ICE lines for each instance.

To evaluate the current environmental watering strategy, differences between modelled NDVI both with and without environmental water delivery were calculated (Figure 4.7) for fringing area of Lake Lockie and Lake Bitterang. For both lakes, modelled NDVI with environmental water is higher than modelled NDVI without environmental water delivery (especially for environmental water delivery after 2010).

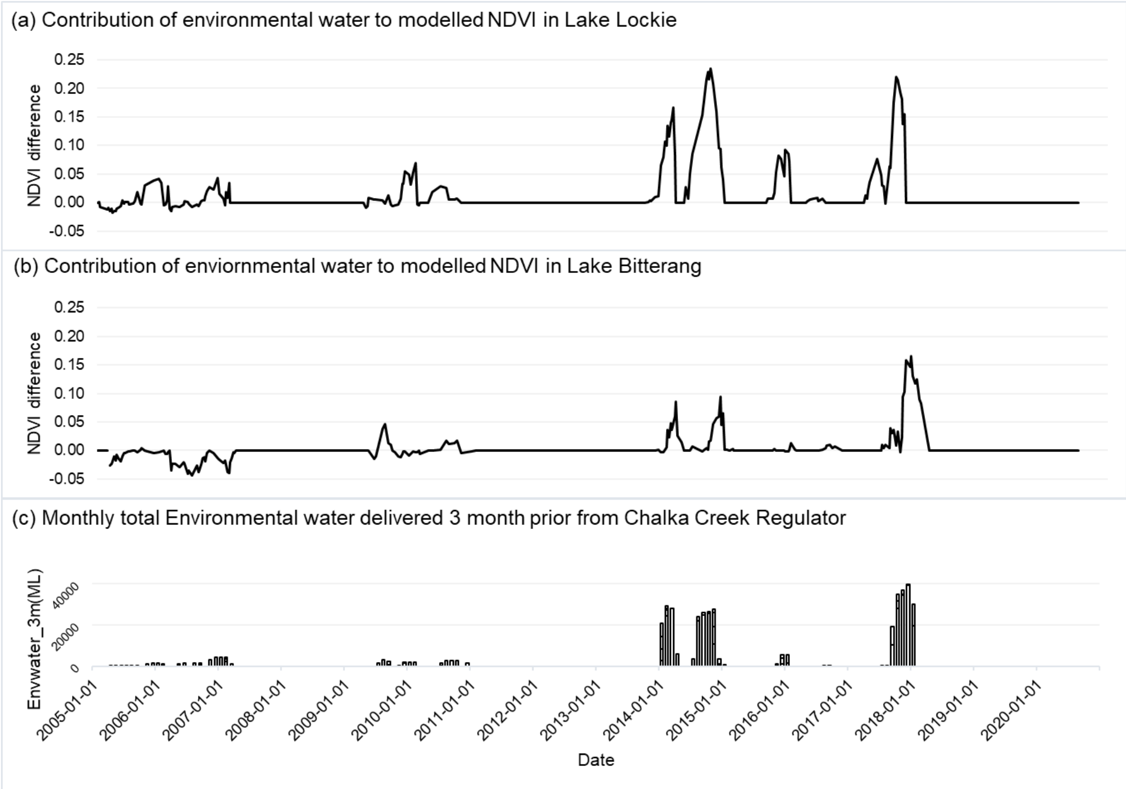


Figure 4.7 Modelled NDVI difference in situation of with and without environmental water for Lake Lockie (a) and Lake Bitterang (b). Panel (c) shows the amount of environmental water delivered over time

4.4.4 Interacting influences of environmental water and precipitation on vegetation

The combined influence of *envwater_3m* and *prec_1m* on modelled NDVI values is shown in Figure 4.8. For Lake Lockie (Figure 4.8(a)), environmental water has a strong impact on NDVI when environmental water 3 months prior volume is less than 10000 ML. For Lake Hattah (Figure 4.8(b)), Lake Bulla (Figure 4.8(c)), and Lake Arawak (Figure 4.8(d)) this number is about 7000 ML. For Lake Mournpall, Lake Konardin and Lake Bitterang, both, precipitation, and environmental water have an impact on NDVI when precipitation is less than 80mm (Figure 4.8 (f), (g) and (i)). Focusing on the area for which precipitation is less than 20 mm, environmental water improves NDVI of fringing area of these three lakes.

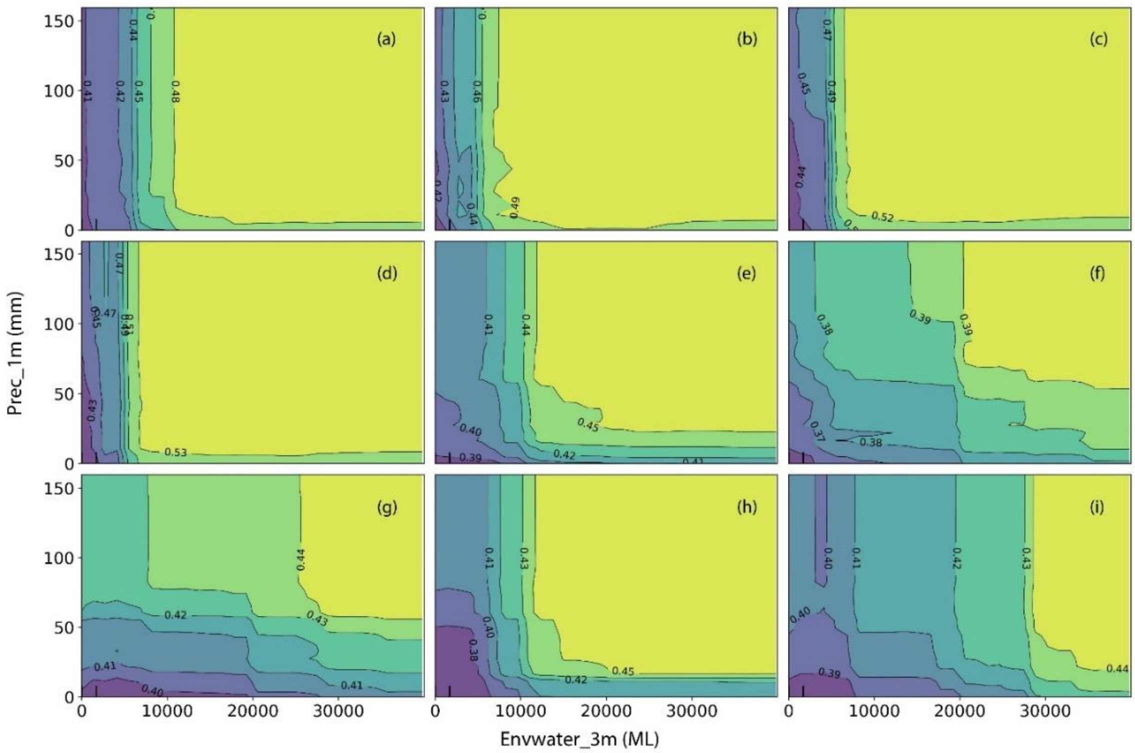


Figure 4.8 2D-PDP plot of *envwater_3m* and *prec_1m* ((a) Lake Lockie (the first connected lake); (b) Lake Hattah; (c) Lake Bulla; (d) Lake Arawak; (e) Lake Yerang; (f) Lake Mournpall; (g) Lake Konardin; (h) Lake Yelwell; (i) Lake Bitterang); The values along the contour lines represent the partial dependence of joint influence, while the colour gradient from purple to yellow indicates the corresponding dependence values, ranging from low to high.

4.4.5 Influence of climate factors on vegetation

Partial dependence in Figure 4.9 shows NDVI's response to the driving variables. *Prec_3m* has a nonlinear relationship with NDVI (Figure 4.9). When *prec_3m* is less than 50 mm, the mean dependence of NDVI slightly decreases for Lake Lockie, Lake Hattah, Lake Bulla and Lake Arawak, while it slightly increases for the other five lakes. For all lakes, the dependence of NDVI increases suddenly when *prec_3m* increases from 50 mm to 80 mm.

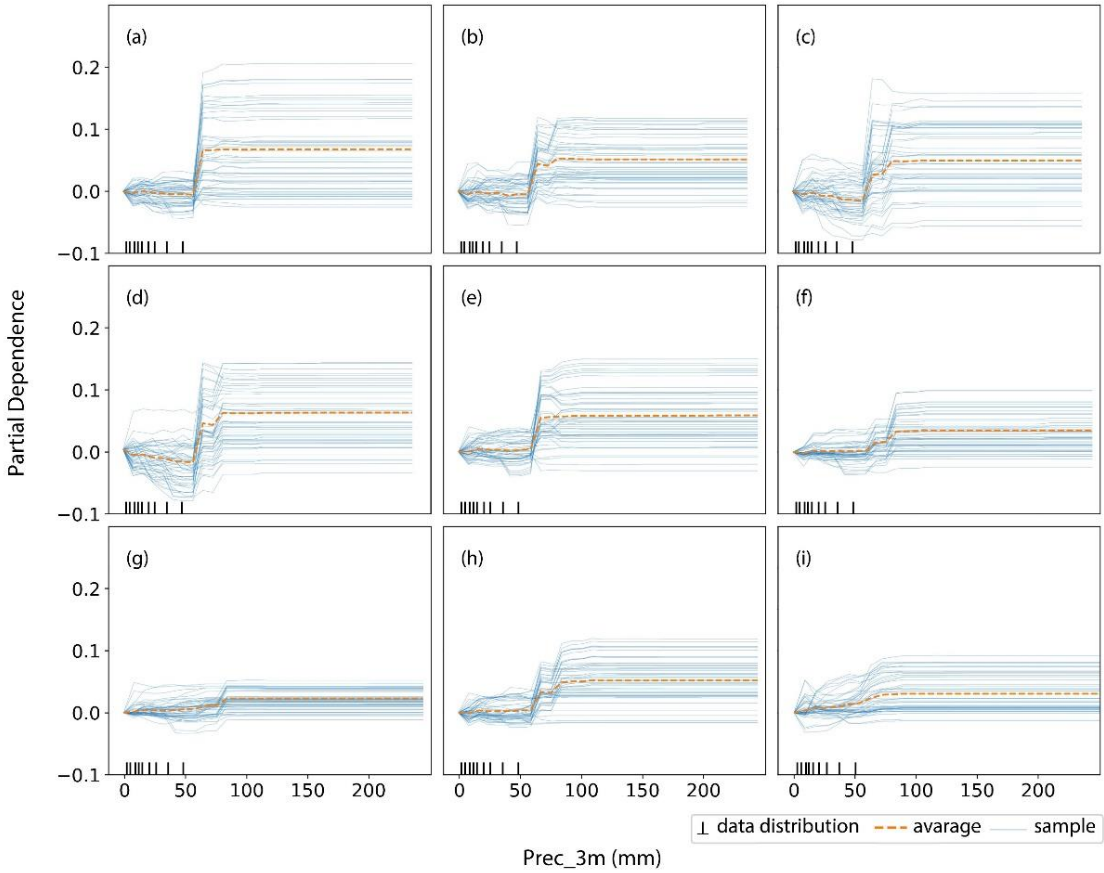


Figure 4.9 ICE plot of precipitation 3 months prior ((a) Lake Lockie (the first connected lake); (b) Lake Hattah; (c)Lake Bulla; (d)Lake Arawak; (e)Lake Yerang; (f)Lake Mournpall; (g)Lake Konardin; (h)Lake Yelwell; (i)Lake Bitterang)). The orange dotted line represents the average PDP line, while the blue lines depict the individual ICE lines for each instance.

Tempmax_1m has a negative influence on NDVI. From the ICE plot (Figure S2 in Appendix 2), the partial dependence of NDVI decreases when max temperature increases from 18 to 25 °C. The influence of temperature on fringing vegetation is similar for all the lakes.

Vapourpre_1m has a positive relationship with NDVI according to the ICE plot (Figure S3 in Appendix 2). NDVI responds positively to vapor pressure levels greater than 8hPa.

4.5 Discussion

Our results indicate that environmental water is more important for fringing vegetation condition than natural floods, especially with a lag time of 3 months. This is major finding and speaks to the value of managed inundation events delivered to regulated floodplains. Additionally, these results suggest that the current environmental water strategy is beneficial for enhancing floodplain vegetation. Together, these results emphasize the significance of environmental water as a critical factor in floodplain management to support vegetation health and sustainable water resource use. The findings can provide valuable insights for decision-makers regarding the effective utilization of environmental water to enhance the fringing areas of lakes.

4.5.1 NDVI response to environmental water volume and its spatial pattern

Our finding of the importance of environmental water 3 months prior aligns with previous findings, suggesting its greater significance compared to water from 1 or 2 months prior to data collection (Wu et al, 2022). Also, as noted above, environmental water has a greater impact on vegetation health than natural floods, a finding of major significance.

The PDP plots showed increases in NDVI with environmental water volume 3 months prior, but this relation had an upper limit above which NDVI remained stable. This breakpoint can serve as a useful guideline for floodplain managers when determining the appropriate volume of environmental water, thereby enhancing water use efficiency. However, the partial dependence estimates are less reliable at these higher volumes because of the smaller number of data points (Molnar, 2019). Further monitoring that takes in periods with larger volumes of environmental water would provide more data points and increase the accuracy of the model at these higher levels.

The variable results among lakes demonstrate spatial heterogeneity in terms of model performance, feature importance and partial dependence degree. In addition, the mix of vegetation type in the boundary pixels influences model performance. Therefore, in future study, selection of pixels for fringing area by clustering methods (Wang et al, 2022) to classify the mixed-vegetation pixels, or to simply exclude boundary pixels, could be used to improve the model performance.

The feature importance and partial dependences plots highlight substantial differences between the four southern lakes and the five northern lakes. In the southern lake the feature *environmental water 3 months prior* is more important and partial dependence degree of that feature is higher. One of the key factors explaining these findings is the variation in hydrological conditions. Lake Lockie, being the first lake in the filling sequence in the southern area, receives environmental water earlier (McCarthy, 2009). Moreover, Lake Hattah and Lake Arawak experienced inundation by environmental water prior to 2010 for longer periods compared to northern lakes (Palmer et al, 2021). These conditions make environmental water more impactful on the fringing vegetation of the southern lakes. The size of the lake may also be an explanation for these discrepancies. For instance, Lake Mournpall, located in the northern region, is six times larger than lakes Bulla and Arawak in the south. This means that it requires much more water to be delivered through Chalka Creek to reach the fringing trees. Conversely, Lake Bulla in southern area is the smallest among the lakes, and therefore, with same volume of environmental water flowing through Chalka Creek, the fringing vegetation can benefit more because of its proximity to the adjacent lakes.

4.5.2 Environmental water strategies and management implications

Bearing in mind the spatial distribution of the results, we suggest that floodplain managers could consider different strategies for the improvement of different regions in Hattah Lakes.

The health of vegetation in the fringing areas of lakes can be enhanced by maintaining current environmental water strategies and utilizing existing or newly constructed infrastructure. The modelled results show that the current environmental water strategy helps to improve vegetation in the fringing areas of Hattah Lakes, especially after 2013 when the Chalka Creek pumping station (MDBA, 2018) was built to increase the capacity to deliver larger amounts of environmental water into the Hattah Lakes system. This is consistent with in-situ monitoring of Hattah Lakes, which showed tree canopy cover of River Red Gum increasing after watering from 2014 to 2020 (Moxham et al, 2020). In other systems, using existing irrigation supply infrastructure has proven to be an effective and water-saving option for watering floodplain wetlands to help improve vegetation condition, requiring considerably less water than what is needed to induce an overbank flood (Stewardson & Guarino, 2018).

This research has the potential to inform decision-making for environmental water use to enhance the fringing area of lakes, especially for river red gum trees. River red gums demonstrate adaptation to both episodic flood and drought, but rainfall alone cannot fulfill its water requirements (Doody et al, 2015). While this study found that NDVI experiences the greatest increase when environmental water reaches a threshold, further studies on the optimal frequency of environmental watering are needed to support the design of efficient and effective environmental water management strategies. It is crucial to prioritize the maintenance of flow variability rather than stable flows for regulated ecosystems, as the rivers and adjacent floodplains rely on annual and interannual fluctuations (Naiman et al, 2008). Previous investigations have determined that a flooding frequency of every three years optimally supports the life cycles of the river red gum (Catelotti et al, 2015). Increasing flows in early August to ensure water availability for the trees in late September will take advantage of the amplified evaporative demand (through increasing temperatures) and solar radiation characteristic of the spring season (Doody et al, 2014). Therefore, based on current knowledge, we suggest that environmental water management should aim to inundate lake fringing areas every three years from August to September by allocating environmental water at the modelled volume threshold identified in this research to maintain river red gum health. More studies on environmental water frequency would be useful to help improve outcomes through adaptive management.

4.5.3 Recommendations for future works

The long-term Landsat dataset provides continuous monitoring of floodplain vegetation condition, overcoming the limitation of the irregular and point-based field data. This enables us to model long-term vegetation condition using daily hydrological and climate records, which is not achievable using field-based monitoring. In the future, remote sensing datasets can be updated to higher-resolution satellite imagery, such as Sentinel-2 imagery with a 10-meter resolution, to capture more detailed vegetation conditions. By employing per-pixel modelling (training models for each pixel), we can explore potential spatial differences in the floodplain, gaining deeper insights into the distribution and variation of vegetation responses across the area.

In this work, Random Forest regression, in combination with "Black Box" explanation methods, has been demonstrated to effectively extract the quantitative relationship between NDVI and hydrological and climate factors. This type of relationship has proved difficult to describe using classical statistical regression methods, such as generalized additive mixed modelling (GAMM) (Wu et al, 2022).

We found that climate factors play an important role in vegetation growth. Hotter and drier climates in the future will have a negative impact on floodplain vegetation. Modelling vegetation condition under various climate predictions and environmental water scenarios would be a good approach to developing management plans for effective vegetation protection under climate change. However, it is important to acknowledge that Random Forest regression has its limitations; for instance, it is not suitable for data extrapolation (Breiman, 2001). Thus, it becomes necessary to consider alternative modelling methods, such as neural networks (Wang et al, 2022), to achieve accurate modelling results for future NDVI predictions.

Chapter 5 . Assessing the Potential of Environmental Water to Mitigate Effects of Future Climate Change on Riparian Vegetation

This Chapter has been completed to journal-submission standard and will be submitted to the *Remote Sensing*:

Wu, C., Webb, J.A. Assessing the Potential of Environmental Water to Mitigate Effects of Future Climate Change on Floodplain Vegetation. *Remote Sensing* (to be submitted)

5.1 Abstract

Vegetation provides crucial ecosystem services in floodplain ecosystems, helping to buffer these systems against the challenges posed by climate change and river regulation. The allocation and delivery of environmental water aims to enhance floodplain vegetation, but future climate uncertainties present a formidable challenge for its management. Therefore, an important question is whether environmental water can offset the influence of future climate on floodplain vegetation condition. We used a Long Short-Term Memory network model to predict Normalized Difference Vegetation Index (NDVI) as a representation of vegetation condition for the Hattah Lakes floodplain in north-west Victoria, Australia. We predict NDVI under 16 future climate scenarios and 3 environmental water scenarios. Modelled NDVI is greater for all environmental water scenarios than without under all future climates assessed. Additionally, our analysis indicates that all three environmental water allocation scenarios have the capacity to effectively mitigate the impacts of climate change over the period of prediction (through to 2045). For future management, we suggest that delivering environmental water to the Hattah Lakes floodplain yearly from October to December is the most effective strategy for mitigating the effects of future climate conditions. Different outcomes across the Hattah Lakes floodplain

suggest that it is also worth considering the construction of new infrastructure to aid the direct delivery of environmental water to the northern floodplain. Amidst a shifting climate, environmental water is predicted to be an effective measure to boost vegetation growth, offering valuable support to environmental managers in their preparations for future climate challenges.

5.2 Introduction

River floodplains, characterized by high biodiversity and seasonal inundation due to river overbank flows, foster unique community structures through biotic adaptations to changing water levels (Petsch et al, 2022). They offer numerous environmental benefits, including flood mitigation, groundwater storage, sediment regulation, and habitat provision (Morrison et al, 2023; Wallace et al, 2020). Additionally, floodplains serve as vital providers of other ecosystem services, such as supplying groundwater for consumption and agriculture, holding cultural significance, supporting fisheries, and offering recreational opportunities (Wu & Chen, 2020). However, the functioning of these ecosystems has been seriously damaged due to damming and river regulation, especially for semi-arid and arid ecosystems where water is scarce (Fu & Burgher, 2015). These impacts include decreased water volumes supplied to wetland systems, compromised water quality, deterioration of vegetation health, and declines in breeding populations of faunal species (Paquier et al, 2018).

Beyond the influence of other human activities, climate change is a key factor affecting floodplain ecosystems, especially floodplain vegetation. Extensive research has explored the influence of climate change on the dynamics of vegetation across diverse ecosystems (Gong et al, 2021). Rainfall serves as a critical determinant affecting year-to-year fluctuations in average vegetation cover (Xu et al, 2018), and increased rainfall has been shown to improve vegetation growth in semi-arid and arid regions (Ren et al, 2019). Furthermore, seasonal changes in vegetation are primarily driven by fluctuations in temperature (Gong et al, 2021). In instances of drought, because of elevated temperatures and reduced precipitation, vegetation loses condition and can disappear altogether in the harshest conditions (Gong et al, 2021; Xu et al, 2018).

To help restore and protect floodplains, environmental water programs have been proposed (and sometimes implemented) all over the world (Wu et al, 2022). Environmental water is water allocated for ecological purposes, partially restoring flow regimes to safeguard riverine and riparian ecosystems (Horne et al, 2017a). Maintaining vegetation health is a common objective of environmental watering programs, and the monitoring and analysis of vegetation responses to environmental water is becoming increasingly common in environmental water management research (Capon et al, 2017; Gawne et al, 2019). Within these studies, the vigour of vegetative response to inundation is often used as an indicator of the success of environmental watering (Whitaker et al, 2015).

While numerous contemporary studies have examined vegetation response to environmental water or watering events (Broich et al, 2018; Colloff et al, 2010; Doody et al, 2014; Doody et al, 2015; Wu et al, 2022), there remains a significant gap in understanding the importance of environmental water allocation in the context of future climate projections. The profound uncertainty surrounding future climate conditions raises substantial questions regarding the future performance of environmental water projects (Poff et al, 2015). Failing to address the threat of climate change to ecosystems through adaptation measures could lead to widespread environmental and social consequences (John et al, 2020b; Ripple et al, 2020). Therefore, quantifying the mitigating effects of environmental water on vegetation under future climates will help to inform management to protect future vegetation health.

Novel modelling and decision-making methods are necessary for understanding complex environmental responses, especially under non-stationary climates (John et al, 2020a). Currently, statistical modelling and machine learning methods are the main methods used to model vegetation condition based on climate factors and watering events (Canham et al, 2021; Horne et al, 2018; Jensen & Walker, 2017; Lyons et al, 2022; M.C. Thoms & Sheldon, 2002). Most of these analyses rely on ground-based monitoring records to represent vegetation condition, with only a limited number using long-term remote sensing imagery for consistent and continuous monitoring of vegetation health. However, remotely-sensed data have far greater spatial and temporal coverage than ground-based data, potentially increasing the strength of inference possible from analyses (Lawley et al, 2016). Furthermore, when incorporating future climate projections into the model, it is essential to consider the issue of data extrapolation when selecting appropriate methods, as certain future combinations of climate factors may not have occurred in the historical record.

In this study, we employed a Long Short-Term Memory (LSTM) network to model future vegetation condition under various future climate scenarios and environmental water allocation scenarios. Modelled vegetation condition was compared to assess whether environmental water allocation has the potential to offset the effects of changing climates on vegetation condition. These findings provide robust support for environmental water management under the future climate uncertainties and offer insights into future vegetation dynamics with and without environmental water.

5.3 Methods

5.3.1 Study Area

Situated in north-western Victoria, Australia, Hattah Lakes is a semi-arid floodplain lake system on the Murray River (Figure 5.1), with an annual average precipitation of 250mm. With an area of 955ha, Hattah-Kulkyne Lakes is one of the 67 Wetlands of International Importance (Ramsar wetlands) in Australia, highlighting their ecological significance and unique biodiversity. The Hattah Lakes system comprises more than 20 semi-permanent freshwater lakes, interconnected by a network of floodplain channels. These lakes are periodically filled by the Murray River when the river has high flows.

River regulation has had a significant impact on Hattah Lakes in terms of ecological value. Under regulation, the discharge of the Murray River in this region has been reduced to approximately half of its natural levels, and the frequency, duration and volume of flooding in Hattah Lakes have been greatly reduced (MDBA, 2012a). Periodically, drought also influences ecosystem condition of Hattah Lakes, causing a further decline in the health of flood-dependent floodplain vegetation (MDBA, 2012b).

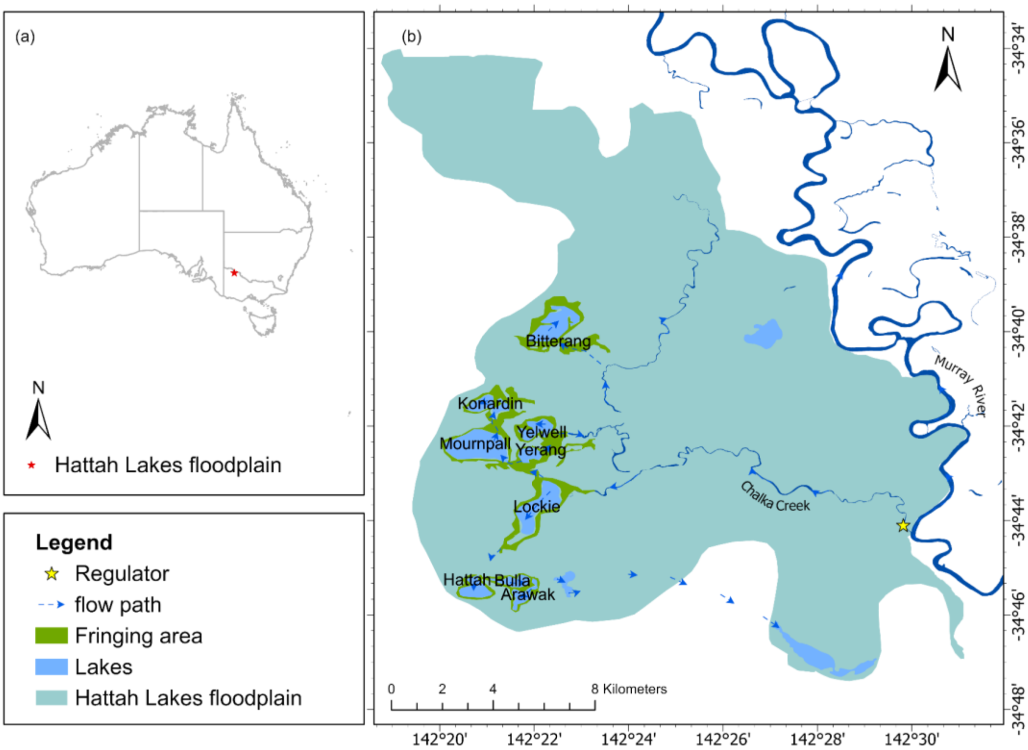


Figure 5.1 Location of study area (including the regulator location and flow path through the selected nine lakes)

To counter the adverse impacts resulting from reduced natural flooding, environmental water is delivered to the Hattah Lakes floodplain. This intervention aims to improve ecosystem health by simulating a more natural flooding pattern and therefore restoring the ecological balance of the area (McCarthy, 2009). Environmental water was first delivered to Hattah Lakes in 2005 using portable pumps, while water has been transferred into the system through the permanent Chalka Creek Regulator since 2013.

We assessed the effect of environmental water and climate change on the fringing vegetated area of 9 selected lakes. These comprised Lake Lockie, which is the first water-connected lake; Lake Hattah, Lake Bulla, and Lake Arawak in the southern system; and Lake Yerang, Lake Mournpall, Lake Konardin, Lake Yelwell and Lake Bitterang in the north (Figure 5.1). Lake fringing areas are covered by Eucalypt woodland including River Red Gum (*Eucalyptus camaldulensis*) and Black Box (*E. largiflorens*).

5.3.2 Datasets and preprocessing

5.3.2.1 Environmental water and its scenarios construction

We used the daily environmental water volume supplied to the Hattah Lakes system. The dataset before 2013 consists of pumping records from the Mallee Catchment Management Authority. Data after 2013 were obtained from discharge information at the Chalka Creek Regulator (site id: 414230) from the Victorian government's water data warehouse (https://data.water.vic.gov.au/).

Table 5.1 Description of environmental water scenarios

Environmental water	Frequency	Month	Rationale
Scenario 1	Every second year	Sep - Nov	This scenario is designed based on current environmental water management strategy (Wood et al, 2018).
Scenario 2	Every year	Dec - Feb	During these three months, trees are at flowering/bud set for both RRG and BB, and RRG is at peak seed rain (Jensen et al, 2007).
Scenario 3	Every year	Oct - Dec	The months from October to December are 1-2 months after spring rain, to support seedlings (Jensen et al, 2007).

Three environmental water scenarios were designated based on current management strategy and the phenology of River Red Gum. Each scenario has 3 months of environmental water, delivered at the same volume as the records through the Chalka Creek Regulator from July to September in 2014 (mean discharge of 880 ML/day). The difference in scenarios lie in their timing and whether water is delivered every year or every second year (Table 5.1).

5.3.2.2 Future climate models

The future climate datasets were obtained from the application-ready data from the Climate Change in Australia website (CCIA., 2015). In these datasets, 40 climate models have been assessed and 8 climate models suitable for the Australian region selected by the CCIA website (Table 5.2).

Table 5.2 Descriptions of 8 climate models (CSIRO & BOM, 2015)

Selected climate models	Institute	Projected future climate
ACCESS1.0	CSIRO-BOM, Australia	Maximum consensus for many regions
CESM1-CAM5	NSF-DOE-NCAR, USA	Hotter and wetter climate
CNRM-CM5	CNRM-CERFACS, France	Hot/wet end of range in Southern Australia
GFDL-ESM2M	NOAA, GFDL, USA	Hotter and drier climate
HadGEM2-CC	MOHC, UK	Maximum consensus for many regions
CanESM2	CCCMA, Canada	Hot/wet tropical sea surface temperature (SST) mode
MIROC5	JAMSTEC, Japan	Model with low warming wetter future
NorESM1-M	NCC, Norway	Model with low warming wettest representative

The climate models are based on the Coupled Model Intercomparison Project phase 5 (CMIP5) design. Each climate scenario is projected under 2 Representative Concentration Pathways (RCPs). RCP 4.5 and RCP 8.5 are often selected because they represent a mid-range and a high-end scenario. RCP 4.5 predicts a near-term increase in greenhouse gas emissions and then a gradual decrease over time (CO2 concentration increasing to approximately 540 ppm by 2100), and RCP8.5 assumes continual increase of emissions (CO2 concentration of around 940 ppm by 2100) (CSIRO & BOM, 2015).

5.3.2.3 Past climate data

Climate data from 1988 to 2020, encompassing daily precipitation, maximum temperature, and vapor pressure, were extracted from the Australian Water Availability Project (AWAP). This dataset provides high-quality historical and continuous climate data for Australia, with a spatial resolution of 5km2 (Jones et al, 2009). To synchronize with the remote sensing (see below Section 2.2.4), we computed monthly accumulated precipitation, mean maximum temperature, and mean vapor pressure, incorporating various lag periods as specified below (Section 2.3).

5.3.2.4 Remote sensing dataset and vegetation index

In this study, Landsat 5, 7, and 8 collection 1 datasets spanning the period from 1988 to 2020 were employed. This provides an image every 16 days. The data processing was conducted using Google Earth Engine (GEE). To ensure data quality, clouds and cloud shadows were removed and filled by averaging the values from images captured 1.5 months before and after the image containing missing data. Poor-quality images were identified based on gap pixel counts and were subsequently excluded from the dataset. To address the spectral differences between Landsat OLI and TM/ETM+ sensors, the Landsat TM/ETM+ to OLI Harmonization function (Roy et al, 2016) was employed to harmonize the imagery.

Normalized Difference Vegetation Index (NDVI) of the study area was calculated to represent vegetation condition. NDVI can better represent vegetation condition than other vegetation indices in semi-arid region (Wu et al, 2022). The formula of NDVI is as follows.

$$NDVI = \frac{\rho NIR - \rho RED}{\rho NIR + \rho RED}, \text{Equation 5.1}$$

where ρNIR represents the reflectance value of the near infrared band, while ρRED represents the reflectance value of the red band.

Increased NDVI values are a reliable indicator of improved vegetation condition (Maselli, 2004; Reddy & Prasad, 2018). The mean NDVI value for each lake fringing area was calculated for each Landsat image and the time series were smoothed by Savitzky-Golay Filters (SG filter) for non-uniform data (Cao et al, 2018; Chen et al, 2004; Chen et al, 2021a) with a window of 5 and the order of polynomial of 2. I tried several parameters composition and determined these parameters to capture the desired trend and avoid excessive smoothing.

5.3.3 Long Short-Term Memory (LSTM) model with fully connected layers

The Long Short-Term Memory (LSTM) model is an advanced recurrent neural network (RNN) architecture designed to capture long-term dependencies and handle vanishing or exploding gradients in sequential data (Hochreiter & Schmidhuber, 1997). The basic structure of an LSTM unit consists of three interacting gates (input gate, forget gate, and output gate) and a memory cell. Each gate is responsible for controlling the flow of information into and out of the cell, allowing the LSTM to selectively update and retain relevant information over long sequences (Kheyruri et al, 2023).

In this study's model implementation, the sequence input layer, LSTM layer, fully connected layer, regression layer, and output layer are integrated to model the NDVI based on 12 input features. (Figure 5.2). The architecture of the model is as follows.

Sequence Input Layer: This is the input layer that handles time series data, and refers to the independent variables in this study (Table 5.3).

LSTM Layer: The LSTM layer is the main recurrent layer responsible for retaining important information (Xue et al, 2022) and extracting the nonlinear relations between the predictor variables and NDVI.

Fully Connected Layer: After the LSTM layer, one fully connected layer (also known as a Dense Layer) is added. These fully connected layers help in learning more complex patterns and relationships from the output of the LSTM layer.

Regression Layer: this layer refers to the output layer of the LSTM network that is applied on regression tasks. It typically contains one or more neurons that produce continuous numerical values as the model's predictions (NDVI time series in this study).

Table 5.3 Description of input variables

	Features with lag time (abbreviation)	Description
Day of year	'doy'	
Climate factors: Precipitation	'prec_1m', 'prec_2m', 'prec_3m'	Precipitation with lag time of 1, 2, 3 months
Climate factors: Max Temperature	'tempmax_1m'	Monthly mean max temperature
Climate factors: Vapor pressure	'vapourpre_1m'	Monthly mean vapor pressure
Environmental water	'envwater_1m', 'envwater_2m', 'envwater_3m', 'envwater_4m','envwater_5m','envwater_6m'	Environmental water with lag time of 1 to 6 months

The model was implemented using the Deep Learning Toolbox in MATLAB R2023. The datasets were divided into training (80%), validation (10%) and testing (10%) datasets.

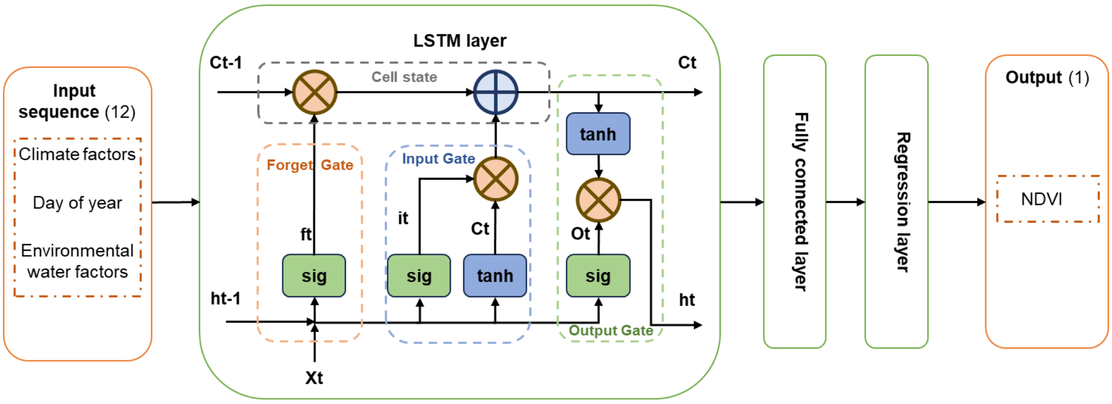


Figure 5.2 Architecture of the model (including input layer that inputs sequence data, LSTM layer that is the main layer of the model, fully connected layer helping in learning complex patterns and regression layer showing this is the regression task)

5.3.4 trend analysis

To compare NDVI time series trends and overall patterns from 2016 to 2045, we applied the time series decomposition method, Singular Spectrum Analysis (SSA;(Golyandina et al, 2001)). The main idea behind SSA is to transform the time series into a set of univariate time series called eigentime series. The components represent the basic patterns in NDVI time series, including trends, seasonality and residuals, smoothing the time series considerably. By applying this decomposition methods, the seasonality and other regular patterns in the time series are removed, making the results more comparable.

5.3.5 Evaluation metrics

Model performance was quantified via four evaluation metrics including Coefficient of Determination (R2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Bias Error (MBE). Those metrics were calculated for training, validation and testing datasets. The model shows a good predictive performance and good fitting effect when RMSE and MAE are small, MBE is close to zero, and R^2 is close to 1.

5.4 Results

5.4.1 Model performance evaluation

Predictions of NDVI from environmental variables were highly accurate across all lakes using the LSTM model (Table 5.4), with a mean training R2 of 0.62. The model performs best in Lake Mournpall, Lake Konardin, Lake Yelwell and Lake Bitterang.

Table 5.4 Performance of LSTM model (reported to two significant figures)

Lake name	Validation RMSE	training R2	testing R2	training MAE	testing MAE	training MBE	testing MBE	training RMSE	testing RMSE
1. Lake Lockie	0.11	0.71	0.6	0.036	0.038	-0.0020	-0.012	0.046	0.048
2. Lake Hattah	0.12	0.59	0.55	0.052	0.050	0.0046	0.0076	0.064	0.060
3. Lake Bulla	0.12	0.61	0.54	0.050	0.049	-0.0017	0.0012	0.062	0.063
4. Lake Arawak	0.12	0.61	0.61	0.049	0.049	0.00094	0.0058	0.062	0.061
5. Lake Yerang	0.10	0.73	0.62	0.033	0.042	0.0041	-0.0052	0.042	0.049
6. Lake Mournpall	0.12	0.67	0.66	0.038	0.032	0.0031	0.0037	0.048	0.042
7. Lake Konardin	0.13	0.68	0.66	0.036	0.035	0.0014	-0.00025	0.046	0.043
8. Lake Yelwell	0.14	0.73	0.67	0.033	0.038	0.00075	-0.0046	0.043	0.049
9. Lake Bitterang	0.12	0.73	0.69	0.036	0.035	-0.0012	0.0015	0.045	0.044

Scatter plots of observed and modelled NDVI (Figure 5.3) indicate that for predicted NDVI less than 0.4, there are more points above the diagonal line, indicating that the predictions are higher than the observed values (overestimation). The reverse is true for predicted NDVI of greater than 0.4.

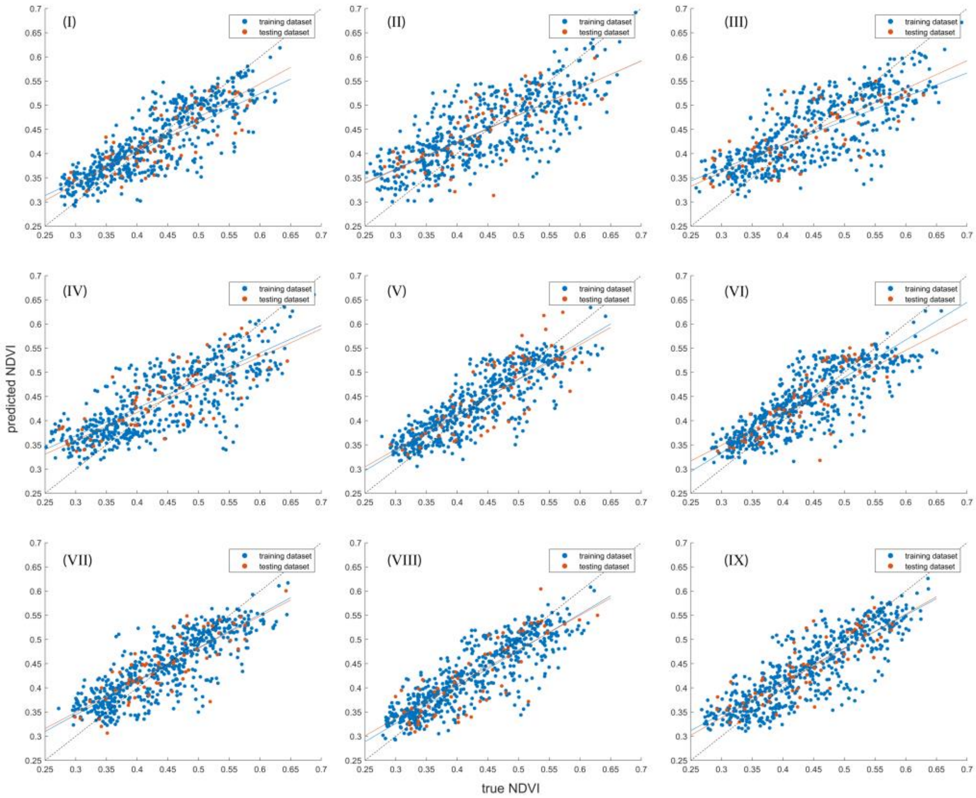


Figure 5.3 Scatter plot of predicted and observed NDVI for training and testing dataset among (I) Lake Lockie (the first connected lake); (II) Lake Hattah; (III) Lake Bulla; (IV) Lake Arawak (southern lakes); (V) Lake Yerang; (VI) Lake Mournpall; (VII) Lake Konardin; (VIII) Lake Yelwell; (IX) Lake Bitterang (northern lakes)

5.4.2 NDVI trends under future climate without environmental water allocation

NDVI SSA time series from 2016 to 2045, run for flow series from which environmental water has been removed, show different patterns among nine lakes. These can be classified into two types based on patterns of NDVI SSA time series: type one is for Lake Bitterang, Lake Lockie, Yerang, Yelwell and Konardin (Figure S4 (a) – (e)), while the other type is for Lake Bulla, Lake Mournpall, Hattah, and Arawak (Figure S4 (f) – (i)). These groups separate mostly, but not completely, by the north-south division of the lakes.

Taking the result of Lake Bitterang as an example for type one (Figure 5.4), overall, the NDVI shows an initial increase from 2016 to 2024 and then decreases until 2044. Modelled NDVI time series exhibit slight variations under different climate models and RCPs. NDVI is projected to remain lowest under climate model GFDL-ESM2M, known for its hotter and drier conditions (CSIRO & BOM, 2015). Although each climate model presents slightly varying absolute predictions of NDVI under RCPs, it is noteworthy that the choice of RCP does not appear to exert a significant influence on projected NDVI trends from 2016 to 2045. While some fluctuations are discernible among distinct climate models within each RCP scenario, these variations remain relatively modest.

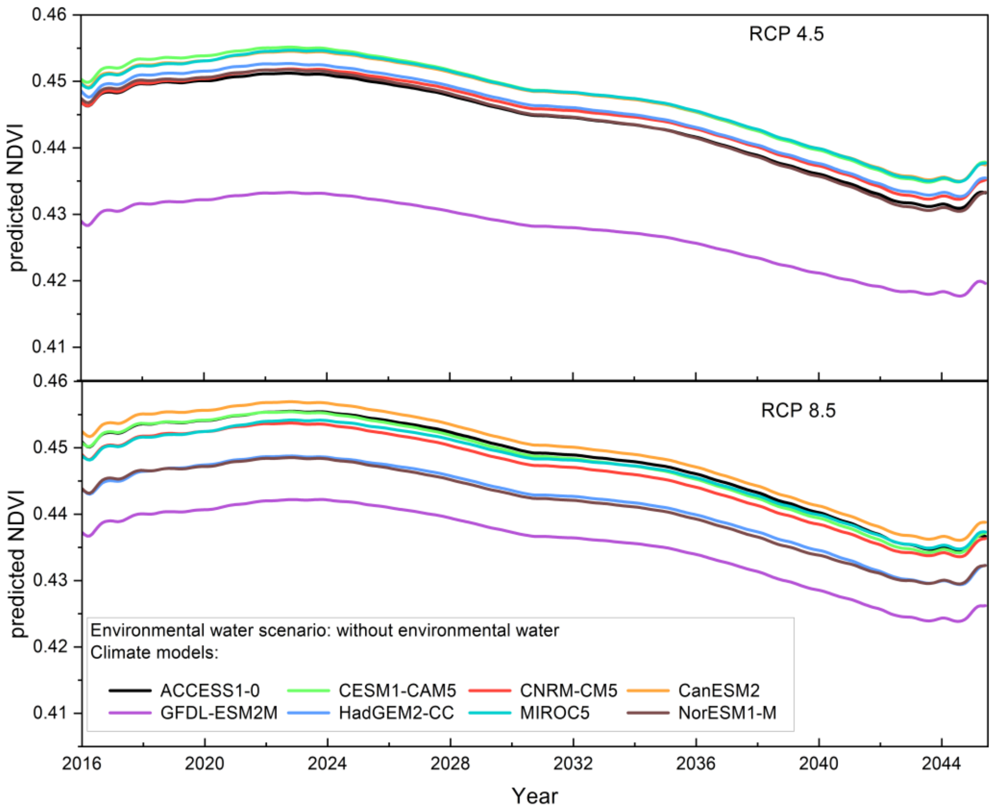


Figure 5.4 Predicted NDVI SSA time series from 2016 to 2045 without environmental water delivery under 8 climate models and 2 RCPs for lake Bitterang, also representing lakes Lockie, Yerang, Yelwell and Konardin

Taking Lake Bulla as an example of pattern type 2 (Figure 5.5), the NDVI remains quite stable over the 30-year period among the 8 climate models and RCPs. The magnitude of difference for the more severe GFDL-ESM2M model is smaller than that of pattern type 1.

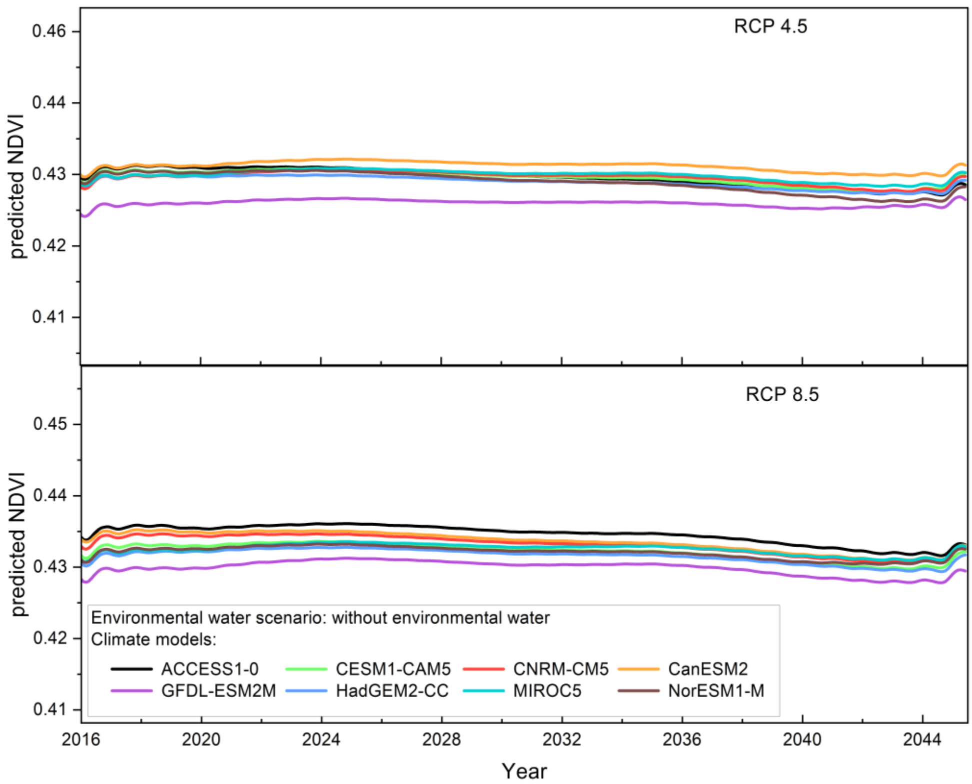


Figure 5.5 Predicted NDVI SSA time series from 2016 to 2045 without environmental water delivery under 8 climate models and 2 RCPs for Lake Bulla, also representing lakes Mournpall, Hattah, and Arawak

5.4.3 Future NDVI changes under different environmental water scenarios

The average NDVI differs between environmental water scenarios 1, 2 and 3 and without environmental water (Figure 5.6). In Scenario 1, water is delivered every second year from September to November. Scenario 2 involves annual water delivery from December to February. Scenario 3 schedules water delivery every year from October to December. It is evident that all environmental water scenarios contribute to improving vegetation condition under future climate. Among the scenarios, environmental water scenario 3 exhibits the largest increase in NDVI, followed by environmental water scenario 2.

Regarding spatial variation, the magnitude of environmental water benefit for NDVI is greater for Lake Lockie, Lake Hattah, Lake Bulla, and Lake Arawak (approximately 0.1) than that of the other five lakes (approximately 0.05). This pattern again shows a difference between southern and northern lakes.

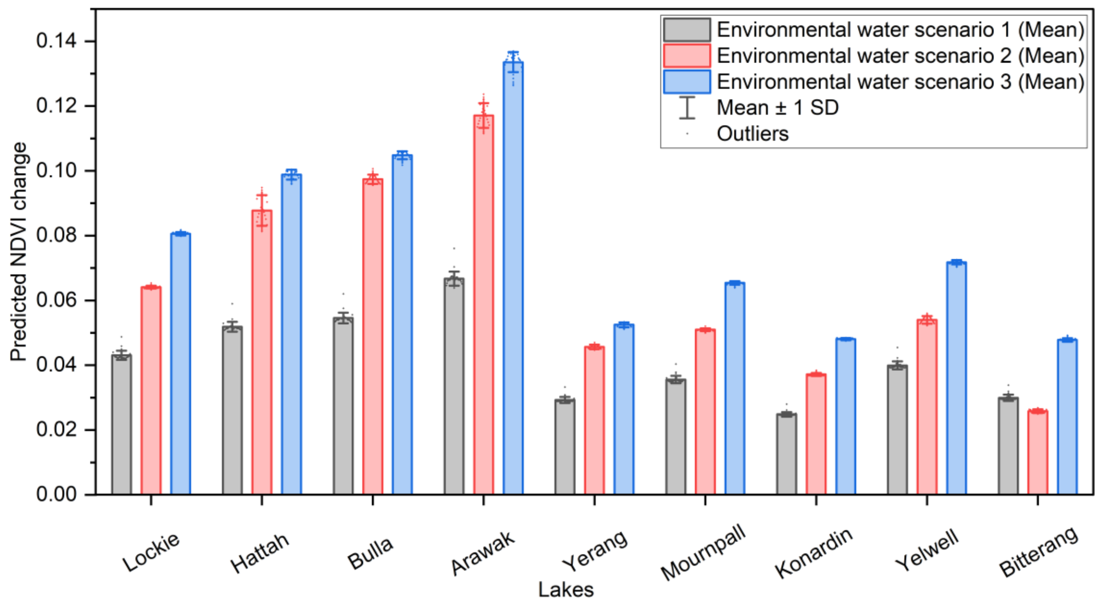


Figure 5.6 Predicted NDVI change under mean future climate from 8 climate models under 3 environmental water scenarios (each bar represents yearly mean NDVI change from 2016 to 2045)

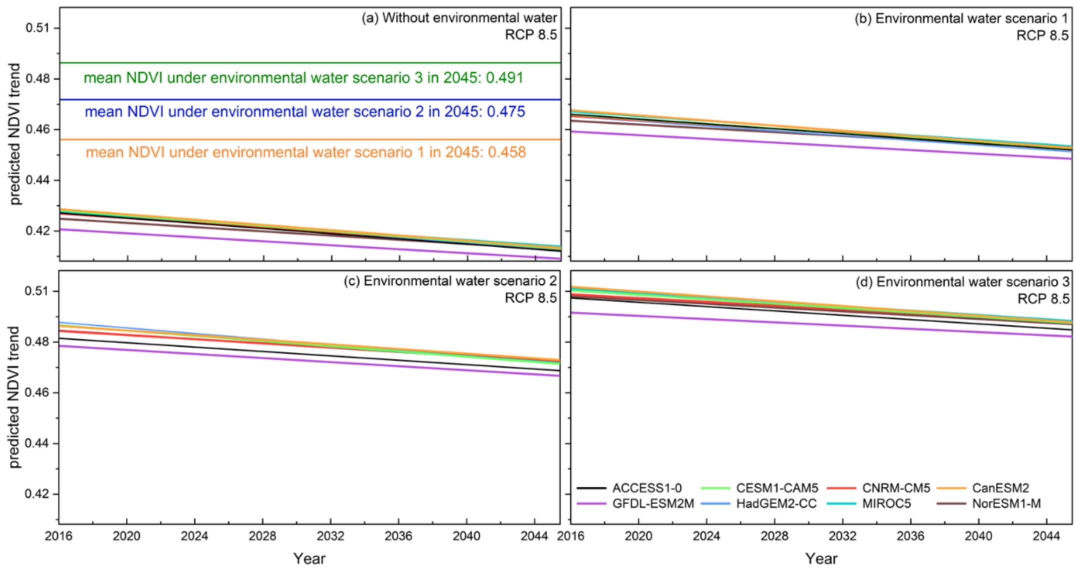


Figure 5.7 Predicted NDVI trends (linear fitting) from 2016 to 2045 of lake Lockie under a) no environmental water; b) environmental water scenario 1; c) environmental water scenario 2; d) environmental water scenario 3.

While the environmental water scenarios substantially enhance the overall NDVI condition under future climate, future trends of NDVI with environmental water are consistent with those without environmental water (Figure 5.7). For all NDVI trends across lakes and different environmental water scenarios, the slope is negative, and the magnitude of difference in slope is very small (Figure 5.7). The mean NDVI values under environmental water scenarios 1, 2 and 3 in 2045 are 0.458, 0.475 and 0.491 respectively, and all of them are greater than the NDVI value without environmental water in 2016 (0.425). This shows that any of the environmental water scenarios will offset the effect of climate change over the thirty-year window, but that Scenario 3 will be the best by far.

5.5 Discussion

5.5.1 Can environmental water offset the influence of future climate?

This study demonstrated that environmental water may be able to offset the impact of future climate change on floodplain vegetation. This assertion is based on our findings that, across 16 future climate models, vegetation conditions are consistently projected to be better when environmental water is allocated under each of the three distinct scenarios, as compared to scenarios where no environmental water delivery is delivered.

To explain this capacity of environmental water to mitigate the effects of climate change, it is necessary to consider the underlying mechanisms through which future climate impacts vegetation. Our modelling results reveal that NDVI in the Hattah Lakes floodplain exhibits lower values compared to current conditions under projected future climate scenarios, particularly under a hotter and drier condition. This observed decline can be attributed to the anticipated warming of the future climate (IPCC, 2014a), which will cause changes in precipitation patterns and evapotranspiration rates. These changes, in turn, have consequential effects on river flows and groundwater levels (Thompson et al, 2017a), indirectly impacting riparian ecosystems and the vegetation they support (Perry et al, 2015). More water is required during the warmer months to maintain comparable mean NDVI values under future climate conditions (Fu & Burgher, 2015). Consequently, in semi-arid and arid regions like the Hattah Lakes floodplain, environmental water to support floodplain vegetation facing warming climate becomes of paramount importance.

5.5.2 Influence of different environmental water delivery strategies on NDVI prediction

While all the tested environmental water delivery strategies improve vegetation condition, the different timings and frequencies of environmental water achieve different degrees of NDVI improvement in the model. Vegetation demonstrated more pronounced improvements when the frequencies of environmental water delivery was increased, with each environmental watering event characterized by uniform total volumes. Therefore, the increased frequency means a greater allocation of environmental water volume into the system over the course of 30 years. This finding is consistent with earlier research in this system indicating that increased environmental water allocations lead to higher NDVI values, and that NDVI tends to stabilize when a specific environmental water volume threshold is reached (Wu et al., under review). Therefore, within the confines of an economically sustainable environmental water volume, vegetation demonstrates more significant improvement when environmental water is allocated on an annual basis.

Beyond this, the delivery of environmental water from October to December yields more substantial modelled improvements in NDVI compared to the period from December to February. We have assumed that environmental water allocations with lag times ranging from 1 to 6 months exert influence on floodplain vegetation. As a result, the potential period of influence of environmental water in Scenario 3 spans from October to May. This implies that under Scenario 3, both germination (Oct to Dec) and flowering (Dec to Feb) processes can be supported by environmental water (Jensen et al, 2007). This would be an improvement on a December to February delivery, where only flowering would be supported.

We observed spatial variation in the degree of influence exerted by environmental water between northern and southern lakes. The improvement in NDVI observed in the southern lakes (Lake Lockie, Lake Hattah, Lake Bulla and Lake Arawak) was around twice that observed in the northern lakes (Lake Yerang, Lake Mournpall, Lake Konardin, Lake Yelwell and Lake Bitterang). This difference was consistent among all three environmental water scenarios under climate change. The observation may be explained by the different flow paths of environmental water to the northern and southern lakes. Initially, environmental water flows through Chalka Creek from the pumping station on the banks of the Murray River and enters Lake Lockie. From here, water spills to fill the southern lakes first. Once water levels in Lake Lockie are high enough to have mostly flooded the southern lakes, water moves from Lake Lockie to Lake Yerang and fills the northern lakes (MDBA, 2016). In this study, the allocation volume of each environmental water event was restricted (averaging 880ML/day), resulting in varying volumes reaching each lake and varying times that lakes fill. With the northern lakes filling later and potentially receiving a smaller fraction of the overall environmental watering event, this provides a potential explanation for the observed spatial heterogeneity in vegetation response to environmental water.

5.5.3 Research significance and Future Recommendations

This work has demonstrated the Long Short-Term Memory (LSTM) model as an effective tool for forecasting future NDVI values across various combinations of climate and environmental water scenarios. Its intrinsic capabilities for managing time series data, along with its capacity to make reasonable predictions for combinations of driving variables not experienced within the historic record, render it highly adept at realising value from long-term remote sensing datasets.

Previous studies have established statistical relationships between climate or hydrological variables and vegetation response (Broich et al, 2018; Cunningham et al, 2007; Fu & Burgher, 2015; John et al, 2020b; Wu et al, 2022; Xu et al, 2012). However, none of the approaches used are directly applicable to predicting outcomes under potential future climate change (Poff, 2018). Our study addresses this gap by introducing an effective method for evaluation of the effectiveness of various environmental water scenarios in predicting future NDVI within the context of evolving climate conditions. This novel approach overcomes the limitations associated with relying solely on historical relationships to model ecological responses, recognizing that these relationships may remain valid under the novel conditions imposed by climate change. As a result, our research provides a foundational framework, assisting environmental water managers to manage vegetation while adapting to a changing climate.

This study serves as a first step in advancing research on the impact of environmental water on vegetation under future climate scenarios. Future research could incorporate several obvious improvements to provide better support for environmental water management. Firstly, the integration of natural flood forecasting within the model, achieved through an amalgamation of a hydrological model within the LSTM model, could potentially improve the accuracy of NDVI predictions. However, we must be mindful of the potential increase in model complexity and associated trade-offs in prediction performance. Therefore, we recommend exploring streamlined natural flood forecasting methods (e.g., MIKE21(Warren & Bach, 1992)). Secondly, this method should be applied to other floodplain regions that receive environmental water allocations. To facilitate broader adoption, we intend to apply this approach to diverse floodplains to ascertain the generality of its findings, thereby extending valuable management support to more environments. Finally, testing with more environmental water scenarios, and with different total volumes, could be used to identify the best scenarios to offset influence of future climate. The examination of diverse total water volumes is essential for the exploration of economically sustainable strategies that can achieve equivalent improvements in vegetation with reduced water application volumes.

5.5.4 Implications for environmental water management and riparian vegetation protection

Our results indicate that environmental flows can mitigate many of the predicted negative impacts of climate change over a 30-year period. Consequently, we recommend that management authorities consider periodic updates to their modelling efforts, incorporating newly available datasets to improve forecasts and modelled outcomes into the future. This approach will facilitate ongoing and sustainable environmental water allocation and management practices, thereby enhancing the effectiveness of vegetation preservation efforts under future climatic conditions.

We propose the delivery of environmental water to the Hattah Lake floodplain from October to December every year as a strategy for promoting the growth of fringing River Red Gum (RRG) trees within the vicinity of the lakes. This timeframe aligns with the period of one to two months following spring rains and can effectively support both the seedling and flowering stages of the trees. It is important to distinguish between the needs of the northern and southern lakes. Should a decline in vegetation condition in the fringing areas of the northern lakes become apparent in future, it may be worth considering the construction of new infrastructure (Poff et al, 2015) for the direct delivery of environmental water to the northern region. Regulators at Hattah Lakes and a pumping station on the Murray River could be constructed in the future. This infrastructure would enable managers to achieve and control the inundation of RRG fringing northern area of the Hattah Lakes in terms of timing and duration of flooding events.

Our methodology lends itself readily to adaptation for application in other floodplains within Australia, and could be extended globally. The use of advanced modelling techniques and novel datasets, such as the remote sensing imagery in this study, contributes to a more comprehensive understanding of the advantages of environmental water for vegetation. This, in turn, offers valuable technological support for environmental managers and promotes the efficient use of limited water resources.

Chapter 6 . Discussion and conclusion

In this final chapter of the thesis, I began by offering a comprehensive summary of the research findings (Section 6.1), providing readers with a recapitulation of the key results. In Section 6.2, I provide a general discussion that combines insights from all three research questions, fostering a holistic and broader understanding of the study. Section 6.3 delves into implications of this work for environmental water management, emphasizing the practical relevance of the research findings in guiding management strategies. Finally, in Section 6.4, I highlight the main contributions of this research, underscoring its significance and potential impact on the field of environmental water management.

6.1 Summary of outcomes

The first research question investigated the effects of environmental water on vegetation health across the entire Hattah Lakes floodplain and whether the benefits of environmental water match those of natural floods. The results indicate that the benefits in apparent plant health (NDVI) from environmental watering appear to occur more slowly than from natural flooding. This might occur if, for example, the landscape is drier before an environmental flow is released, compared to natural flooding which may occur during periods of high rainfall, when soil moisture is likely to be higher. Even though they act differently, both natural floods and environmental water yield beneficial effects on floodplain vegetation within one year of their occurrence.

The second research question refined the study's focus to the fringing area around individual lakes, where vegetation is dominated by River Red Gum and Black Box trees. It aimed to analyze the correlation between changes in vegetation condition and environmental water volume and timing. The results show that environmental water for fringing vegetation condition is more important than natural floods, particularly when there is a 3-month lag between inundation and vegetation sampling. Vegetation condition increases when there is an increase in environmental water volume three months prior to sampling, but this relationship has an upper limit, beyond which vegetation condition is not improved further by additional environmental water. We can conclude that the current environmental water strategy will be effective in promoting the health of floodplain vegetation.

The third research question explored potential vegetation outcomes from environmental water under climate projections from 2016 to 2045. The findings confirmed that all the tested environmental water scenarios can effectively mitigate the impacts of climate change over this thirty-year period. Furthermore, the study suggests that delivering environmental water between October and December yearly leads to the most substantial increase in vegetation condition.

Thus, my thesis demonstrates the significant influence of environmental water on floodplain vegetation condition through multiple dimensions. Both qualitative and quantitative analyses offer valuable technical insights to assist managers in the efficient allocation of environmental water resources. The existing delivery strategies have been shown to lead to positive outcomes in vegetation condition based on long-term, remotely sensed vegetation monitoring data. Furthermore, environmental water can play a crucial role in maintaining future vegetation condition under the influence of climate change. As a result, this research collectively provides valuable support for decision-making in effective environmental water management and the protection of future vegetation.

6.2 General Discussion

In this thesis, I modelled vegetation condition by considering factors related to watering events and climatic conditions, considering past observations and analysis, the evaluation of current strategies, and future adaptations under various watering scenarios. The three main research components exhibit mutually reinforcing progressive relationships. Research Question 1 focuses on qualitative relationships between vegetation condition and watering events. Research Question 2 builds on this by extracting quantitative relationships regarding vegetation responses to environmental water volume and timing, while Research Question 3 goes further again by predicting future vegetation conditions under multiple future climate projections and environmental water scenarios. The findings of RQ1 aid in selecting variables for RQ2 and RQ3, while the results of RQ2 provide support for the conclusions drawn in RQ3. Together, these individual pieces of work confirm the significant influence of environmental water on floodplain vegetation, and whether existing environmental water strategies can potentially offset effects of future climate conditions. In the following subsections, I provide a comprehensive discussion that synthesizes the findings of all three research studies.

6.2.1 Influence of Environmental water and natural floods on floodplain vegetation

In RQ1, utilizing the GAMM model, environmental water and natural floods were both treated as categorical variables, categorized as either present or absent, with lag times encompassing events within one month, 1 to 3 months, and 4 to 12 months prior to vegetation sampling. Conversely, in RQ2, employing the RF model, I incorporated the cumulative volume of environmental water with 1 month, 2 months and 3-month lags as input factors. What was the reason for this difference in lag time characterization? Our initial research (RQ1) led to the observation that environmental water with a lag of 1 to 3 months had a predominantly positive impact on most areas of the Hattah Lakes floodplain. More specifically, in the fringing area of Hattah Lakes, which is the focal area of RQ2, some pixels began to exhibit a positive influence on vegetation with a lag of 4 to 12 months. These two insights guided my selection of input variables for the subsequent research. However, my analysis revealed that the model performed best when considering environmental water volumes from 1, 2, and 3 months prior, as opposed to those with a lag of 4, 5, and 6 months (this detail is not provided in Chapter 4). Therefore, in the selection of variables for the RF model for RQ2, a lag time of 1 to 3 months was used.

By comparing results from RQ1 and RQ2, it is evident that within the lag periods of 1 to 3 months, the environmental water volume over the 3 months prior to vegetation sampling emerges as the most influential factor impacting vegetation condition. This finding aligns with prior research suggesting that enduring vegetation exhibits delayed responses to environmental flow events (Hughes & Rood, 2003; Thompson et al, 2017b). It is worth noting that the length of these lag periods is not fixed but appears to depend on the prevailing ecological conditions (Thompson et al, 2017b). There are multiple reasons for the lag time of vegetation response. Firstly, a lag can stem from hydrological processes, wherein environmental flows must initially recharge shallow groundwater systems before surface water can provide ecological benefits (Wilby et al, 2011). This observation is supported by the spatial heterogeneity of environmental water effect observed in RQ1. Additionally, delays in responses can be attributed to fundamental biochemical processes such as litter dynamics (Baldwin & Mitchell, 2000; Hamilton, 2012; Thompson et al, 2017b).

Both RQ1 and RQ2 sought to investigate the impact of natural floods and their different effects compared to environmental water. My results found that environmental water takes a longer time to have positive effects on floodplain vegetation than natural floods, but overall has greater significance for vegetation dynamics than natural floods. A fundamental distinction between these two hydrological events lies in their nature; natural floods are uncontrolled and characterized by high variability (Džubáková et al, 2015), while environmental water is tightly managed to balance ecological and human requirements while using a relatively small amount of water (Duong et al, 2019). It is noteworthy that the frequency of natural floods in the Hattah Lakes region under regulated conditions is considerably lower than that of environmental water delivered since 2005 (Vilizzi et al, 2013). However, observation alone does not explain the conclusion regarding the relative importance of environmental water versus natural floods. The conclusion, as derived from the RF model, is primarily applicable to the broader assessment of overall vegetation condition. Both major and minor floods are important, as they have been demonstrated to promote the occurrence of certain target species (RenöFält et al, 2006; Stammel et al, 2021), and remove exotic plants (Caruso et al, 2013).

Regarding the impact of environmental water on vegetation condition, the RF model employed in RQ2 demonstrates a superior R square value compared to the GAMM model from RQ1. Notably, the RF approach allows the identification of vegetation responses to environmental water without requiring assumptions about the form of relationships. In contrast, the GAMM requires the selection of either a linear or non-linear function for each variable prior to model training (Baayen et al, 2017). Therefore, for a more comprehensive and in-depth understanding of the influence of environmental water on vegetation, we recommend the use of the RF regression model over GAMM. Additionally, an exploration of a combination of these two models may provide valuable insights (Cheung et al, 2021).

6.2.2 Influence of environmental water and climatic factors on floodplain vegetation

The interacting influence of environmental water and climatic factors, including precipitation and temperature, on the variation in vegetation condition was explored through the utilization of 2D-PDP in RQ2. These plots capture the interactions between these variables. I observed that, particularly under conditions of a maximum temperature exceeding 25 °C and precipitation levels below 20 mm (Appendix A2), environmental water emerges as the predominant factor for maintaining vegetation condition.

The collective evidence from both RQ1 and RQ2 unequivocally demonstrates that diminishing precipitation and escalating temperatures will exert an adverse influence on floodplain vegetation. These findings are corroborated by many prior studies (Tang et al, 2016; Thoma et al, 2016; Xu et al, 2012).

These two conclusions collectively bolster the findings presented in RQ3, underscoring the mitigating role of environmental water for vegetation condition under future climates. Climate-related factors significantly affect water availability in floodplains (Xu et al, 2012), and environmental water can contribute to addressing this issue.

6.2.3 Spatial heterogeneity in the influence of environmental water on fringing vegetation

Working within the same study area, comprising the fringing vegetation of nine lakes, both RQ2 and RQ3 revealed notable spatial variation between the southern and northern regions within the Hattah Lakes floodplain. This spatial variation persists despite the utilization of distinct models and the pursuit of different research objectives. In RQ2, different relationships were found between environmental water volume and vegetation condition between the southern and northern lakes. In the four southern lakes, there was a substantial increase in NDVI (approximately 0.1) when the environmental water volume reached 7000

ML. In the five northern lakes, the increase was only approximately 0.05. In RQ3, the average difference in NDVI over the period 2016-2045, as predicted by the model under the designated environmental water scenarios compared to scenarios without environmental water, was again roughly 0.1 in the southern region and about 0.05 in the northern region. Not only do these findings reaffirm the consistency of the spatial disparities observed, they also show a remarkable similarity in the degree of NDVI change modeled by both studies. This serves to further affirm the robustness of the two modelling approaches.

The design of the models provides a high-level explanation for the similarity in results. In both RQ2 and RQ3, using the volume of environmental water at Chalka Creek as the quantification of environmental water for each lake, rather than accounting for the separate volumes reaching each lake through hydrological models, partly obscures the actual flow of environmental water within the model results. By relying on the volume of environmental water at Chalka Creek as a proxy for environmental water across all lakes, the models may not fully capture the specific dynamics and variations in water distribution within the floodplain. This simplification can result in a spatial bias, as it does not account for the unique hydrological characteristics and pathways that may affect the availability and distribution of environmental water to individual lakes. Consequently, the observed spatial heterogeneity in both research studies may be influenced by this simplification in the representation of environmental water inputs.

However, the underlying environmental flow paths provide the most likely explanation for the spatial heterogeneity observed above. In the Hattah Lakes system, the flow of water through each lake follows a consistent order both under managed and unmanaged water conditions. This flow sequence begins with Lake Lockie as the first to be filled, after which water proceeds through southern Chalka Creek, subsequently inundating the southern lakes. Only once the water levels in Lake Lockie reach a sufficient height to flood the southern lakes, does a diversion occur, redirecting water towards the northern lakes through Chalka Creek north (MDBA, 2012a; 2016). Thus, the northern lakes receive water later, and at reduced volumes compared to the southern lakes, which affects the outcomes for fringing vegetation (Vilizzi et al, 2013). Therefore, an equal volume of environmental water at Chalka Creek produces different impacts on the fringing areas of the southern and northern lakes.

To enhance the accuracy of future studies, it may be beneficial to consider more detailed hydrological models (Wang et al, 2022) that account for the distinct flow paths and mechanisms influencing environmental water distribution to each lake within the study area. This approach could help provide a more precise understanding of the spatial variations in vegetation response to environmental water inputs.

6.2.4 Evaluating different modelling methods for environmental water

Within this thesis, three distinct modelling methods were employed to predict vegetation condition (as NDVI) by incorporating climatic factors and watering events. Each of these methods sought to evaluate the influence of environmental water on vegetation condition, albeit with differing research objectives.

The GAMM treated environmental water as a categorical variable and was applied to the entire floodplain. In the practical implementation phase, this model demonstrated shorter processing times compared to the other two models. However, it's important to note that the GAMM model requires prior knowledge (Wood, 2017) to determine whether the relationship between NDVI and input factors should be represented as linear or nonlinear influence curves. This model is most suited to quickly understanding the qualitative and initial effects of environmental water and its difference from other factors.

The RF regression model and LSTM model are both machine learning techniques known for their ability to handle issues related to collinearity of predictor variables and the avoidance of model selection complexities (Baayen et al, 2017). Both exhibit strong performance in predicting NDVI. Comparatively, the RF regression model slightly outperforms LSTM in this specific context, making it the preferred choice for extracting quantitative relationships between NDVI and environmental water volume.

However, it's worth highlighting that the LSTM possesses the capability to predict from inputs it has not encountered previously (Pershin et al, 2021), a feature not shared by the RF model (Takoutsing & Heuvelink, 2022). Considering the research's third objective, predicting NDVI under potential future climate conditions, the LSTM model emerges as the superior option compared to the RF model. The regression-enhanced random forest model, which incorporates linear regression initially and then models the residuals using the RF model (Zhang et al, 2019) to try to solve the data extrapolation limitations of the RF model, was investigated before applying LSTM. However, the outcomes of this approach did not align with real-world observations because linear regression cannot capture the relationship between NDVI and environmental water factors.

In this study, each modelling approach was selected based on the particular research objectives and each of the three models has its own advantages and disadvantages. These findings underscore the complexity of model selection and the importance of choosing the most appropriate modelling technique to effectively address specific research objectives and datasets.

6.2.5 Research Limitations

This research is limited in that it concentrates solely on the Hattah Lakes, without testing the generalizability of the methods to other areas. Numerous floodplains across the Murray-Darling Basin of Australia receive environmental water allocations (MDBA, 2015a). Consequently, it would be valuable to extend this research to assess how vegetation responds to environmental water programs in other floodplains. Furthermore, RQ2 and RQ3 concentrate on the fringing trees surrounding the lakes. This was a deliberate choice to focus the research more precisely. However, vegetation in other parts of the floodplain also warrant exploration and investigation to comprehensively understand the broader impact of environmental water management. Expanding the research to encompass a broader range of floodplains and vegetation types could provide valuable insights into the effectiveness of environmental water allocations in multiple ecosystems.

Due to limitations in the available datasets, a water balance model was not used in the research. Incorporating a comprehensive water balance model that considers changes in both groundwater and surface water could be an effective method for delving into the intricate mechanisms of environmental water influence (Hamilton et al, 2019; Zeabraha et al, 2020). The limitation stems from the scarcity of hydrological observations and the relatively small spatial scale of the study area, both of which hinder the attainment of precise and accurate results from hydrological models. I made several attempts during the PhD project to integrate such models, but they had quite poor performance, underscoring the complexities involved in modelling hydrological processes.

The absence of ground-based data for connecting real vegetation condition and growth with NDVI is acknowledged as a limitation in the research. While NDVI is a valuable indicator of vegetation condition, incorporating field verification data could have provided a more comprehensive and nuanced understanding of the results obtained from each model. Unfortunately, the COVID-19 pandemic disrupted the planned field trips to Hattah Lakes, ultimately leading to their cancellation. This unforeseen circumstance constitutes an unavoidable limitation in the research, as it prevented the collection of field data that could have enriched the analysis and interpretation of NDVI trends and their underlying ecological mechanisms.

Finally, a natural flood forecasting model was not integrated into the prediction of future NDVI in this study. While natural floods may not be the most important variable for future NDVI prediction, it is crucial to recognize their potential to have a sudden and substantial influence when large natural floods occur throughout the entire floodplain (see RQ1). With this in mind, incorporating a simplified natural flood forecasting component into future climate scenario modelling done in RQ3, would be a valuable addition.

6.2.6 Future research directions

Based on the limitations identified above, there are several areas of potential improvement for future research. These can be classified as improvements in: datasets, model structure, evaluating new models, and testing more environmental water allocation scenarios.

Firstly, in the context of enhanced vegetation monitoring, the utilization of high-resolution remote sensing datasets, such as Sentinel-2, emerges as a promising avenue. High-resolution images offer a wealth of detailed information pertaining to vegetation conditions. Furthermore, it is worth noting the availability of combined datasets that integrate Landsat 8 and Sentinel 2, offering an augmented temporal resolution, with updates every 2 to 3 days, and superior spatial resolution compared to Landsat 8 data (Broich et al, 2018; Claverie et al, 2017). These improvements in temporal and spatial resolution afforded by alternative remote sensing imagery enable a more granular analysis of vegetation changes and an enhanced characterization of vegetation properties (Pace et al, 2021).

As identified above, fieldwork to acquire ground-truth data could serve as a crucial validation source for the remotely sensed findings. The integration of field experimental or survey data with the time series results of NDVI would lend a heightened degree of credibility to the outcomes, and could mitigate potential sources of error attributable to factors such as cloud shadows and other data acquisition challenges in remote sensing imagery (Telesca et al, 2023; Zhu et al, 2019). It would also be highly beneficial to individually record the water levels in each lake. Such data would not only facilitate the tracking of environmental water flow across individual lakes but also aid the inclusion of more comprehensive environmental water data within the models.

An integrated framework that harmonizes machine learning techniques with hydrological models would be a major advance to help assess spatial variation of the influence of environmental water volume on floodplain vegetation. Central to this approach is the incorporation of environmental water flow pathways. By doing so, the precision of spatial assessments across the entire floodplain will be enhanced. Additionally, we could incorporate elevation, latitude, and longitude data into the model to describe the relationship between spatial location and vegetation response. This would further refine our ability to analyze and understand the geographic variations in environmental water responses within the study area.

There are multiple emerging deep learning methods for time series modelling (Kheyruri et al, 2023; Xue et al, 2022; Yan & Roy, 2020). For future research, it would be advisable to explore more models in order to enhance modelling performance for assessing vegetation condition. And it would be desirable to train more types of models to identify the best options to combine with hydrological data and models (Wang et al, 2022).

To solve the limitation that this research only focused on one study site (Section 6.2.5) and enhance the practicality of the findings regarding the relationships between environmental water allocation and vegetation condition, it would be advisable to extend the entire methodology to other floodplain ecosystems. The six icon sites within the Living Murray project (MDBA, 2018) located in the Murray-Darling Basin represent a promising starting point for such an expansion. By conducting similar assessments at these sites, researchers could investigate whether consistent trends and outcomes emerge across different ecosystems. Any consistent results could serve as invaluable reference points for ecosystem managers, streamlining their decision-making processes and reducing the need for them to independently model these relationships at yet more sites.

In RQ3, only three environmental water allocation strategies were investigated. Future research could expand the scope by generating and rigorously testing a more extensive array of strategies. Input and insights from environmental water experts and managers would enrich the diversity of these strategies. Furthermore, it is worth acknowledging that while the analysis period of 30 years (2016 to 2045) revealed valuable insights, it is relatively temporally limited. Future research could extend this temporal scope to a century or more. An extended timeframe would enable us to assess the influence of RCPs more comprehensively and, in turn, provide more targeted and informed recommendations for the effective utilization of environmental water resources for mitigating the effects of climate change.

In summary, while the research presented in this thesis has made important contributions to understanding the effects of environmental water on floodplain vegetation, it is clear that there remains a substantial journey ahead in our efforts to enhance environmental water management for the preservation and enhancement of floodplain vegetation health. The development of a comprehensive, long-term, field-based monitoring plan, coupled with the effective utilization of existing remote sensing technologies and the integration of advanced modelling methods, represents a potential approach to enhancing model performance and generating more meaningful and actionable results.

6.3 Implications for management

In this section, I provide several recommendations for environmental water management by synthesizing the results from all three research questions. It is worth noting that specific management implications are also presented within the individual research chapters.

Remote sensing imagery has proven to be a highly effective resource for the ongoing monitoring of long-term vegetation conditions (Fu & Burgher, 2015). These images can be integrated into modelling processes to identify the principles of vegetation responses to various environmental factors (Colloff et al, 2010). Consequently, leveraging emerging technologies, such as higher-resolution remote sensing monitoring of floodplain vegetation and water inundation stands as the strongest recommendation for management. This application extends beyond academic research; it serves as a vital tool for environmental water management, providing valuable insights into the state of vegetation and inundation.

Long-term monitoring programs focusing on vegetation conditions and hydrological indicators remain imperative for effective environmental management. This research has highlighted the constraint posed by the scarcity of water level datasets for the individual lakes, underscoring the need for such data to facilitate a more comprehensive understanding of the influence of environmental water. Moreover, while this research has employed satellite imagery, managers should consider the adoption of unmanned aerial vehicles (UAVs) for acquiring higher-resolution imagery to monitor vegetation conditions (Xue & Su, 2017). Such imagery not only provides a clearer depiction of ground conditions but also serves as valuable verification data. It is recommended that these monitoring datasets be meticulously managed (Colloff et al, 2010), so that they may not only support academic research but also contribute to establishing a robust baseline for effective environmental water management.

Another recommendation for environmental water management is the establishment of priorities for vegetation protection within the floodplain. This recommendation arises from the spatial heterogeneity and complexity revealed by this research in the impacts of environmental water on floodplain vegetation. It is important to recognize that not all vegetation types can be simultaneously safeguarded and enhanced through uniform environmental water allocations across the entire floodplain. Hence, managers need to identify specific protection targets based on their ecological goals and objectives (Meitzen et al, 2013). Environmental water strategies can then be devised to support these priorities. This measure allows for a more tailored and effective approach to environmental water management, ensuring the preservation and enhancement of critical vegetation types within the floodplain.

The construction of new infrastructure to support environmental water delivery emerges as an important suggestion arising from the synthesis of findings across the three research questions. One significant result, derived from RQ2, demonstrates that the establishment of a permanent pumping station in 2013 has led to notable improvements in vegetation condition. Furthermore, past data and future predictions consistently reveals smaller increases in NDVI in the northern area of Hattah Lakes compared to the southern area (RQ2, RQ3), with the northern area receiving less environmental water than the southern area. Considering these findings, it is advisable for managers to consider the possibility of establishing new pumping stations or channels to facilitate the direct delivery of environmental water to the northern lakes. This strategic recommendation offers the potential to improve vegetation condition in these specific regions and enhance overall floodplain ecosystem health without the need for additional environmental water.

For future environmental water management, I recommend the implementation of a strategy involving the yearly delivery of environmental water to the Hattah Lakes floodplain during the period from October to December. This strategy was identified as the most effective among the three testing scenarios for adapting to anticipated future climate conditions (RQ3).

I also recommend that environmental management agency staff consider collaborating with academic researchers to facilitate the implementation of these modelling frameworks. Such partnerships can harness the strengths of both parties, ensuring that these valuable tools are effectively employed to enhance floodplain management practices. Furthermore, it is recommended that managers maintain detailed records of daily environmental water allocations to the floodplain if they are not already doing so.. These data are often unique to each floodplain but are essential for accurate modelling. Sufficient monitoring datasets and collaborative engagement with professionals are both important in facilitating informed decision-making in support of effective environmental water management.

6.4 Main Contributions

This PhD thesis comprehensively analyzes vegetation response to environmental water and offers adaptive strategies for safeguarding vegetation under a changing climate. While acknowledging the presence of certain limitations, this research presents several significant contributions to the fields of environmental water management and vegetation enhancement, as outlined below.

- This research was the first to employ a GAMM to evaluate the capacity of environmental water to mimic the impacts of environmental water and natural floods on floodplain vegetation (RQ1). The study establishes that environmental water being delivered 1 to 3 months before vegetation sampling has a demonstrably positive influence on vegetation condition across most of the Hattah Lakes region. It is noteworthy that the detail of improvement in vegetation condition diverges from that of natural floods, which typically enhance vegetation within one month of the flood event.
- A quantitative relationship depicting the impact of environmental water volume on floodplain fringing vegetation was developed (RQ2). This curve serves as a fundamental foundation for informed decision-making regarding the requisite volume of environmental water necessary for effective vegetation condition management. It is worth noting that the feature importance and partial dependences plots highlight substantial differences between the four southern lakes and the five northern lakes in the Hattah Lakes system (section 4.5.1).
- The assessment of the current environmental water strategy was conducted through a comprehensive analysis of long-term vegetation data spanning a period of 30 years (RQ2). This evaluation clearly demonstrates the efficacy of the current strategy in enhancing the vegetation within Hattah Lakes. Such a long-term perspective offers a more compelling and robust assessment compared to evaluations based on shorter-term field-based monitoring.
- The LSTM model surpasses the RF model in its ability to predict future vegetation conditions (RQ3). While the RF model excels in extracting relationships from existing observations, the LSTM model exhibits superior predictive capabilities specifically tailored for forecasting

outcomes in the future that may be driven by combinations of drivers not seen in the past.

- Specific environmental water allocation scenarios, derived from the phenology of RRG trees and informed by prior experience, were rigorously assessed under the influence of future climate changes (RQ3). The modelling study identified the most optimal scenario for enhancing vegetation condition over the next 30 years. We propose the delivery of environmental water to the Hattah Lake floodplain from October to December every year as a strategy for promoting the growth of fringing River Red Gum trees within the vicinity of the lakes (section 5.5.4). This methodology can be readily applied to discern and evaluate the most effective environmental water allocation strategies for future management initiatives.
- The cumulative results from addressing three key research questions collectively affirm the significant role of environmental water in enhancing vegetation within this semi-arid floodplain. Furthermore, the spatial variation in these findings suggest that the implementation of new infrastructure could contribute to the overall health of vegetation across the entire floodplain. Additionally, the methodology employed in this study has the potential to be extended to other floodplain ecosystems, offering valuable insights to facilitate informed decision-making regarding environmental water allocation for the enhancement of vegetation health.

In conclusion, through the utilization of multiple modelling methods, and drawing upon extensive datasets derived from long-term monitoring efforts, this study has begun to explore the intricate relationship between environmental water allocation, changing climates, and vegetation condition. As a result, this research not only equips government agencies involved in environmental water management with a valuable tool to guide decision making, but also imparts fundamental knowledge regarding the processes driving floodplain vegetation condition. Collectively, these advances can facilitate the preservation and enhancement of vegetation health in these critical ecosystems.

Appendices

A1. Supplementary Materials for Chapter 3

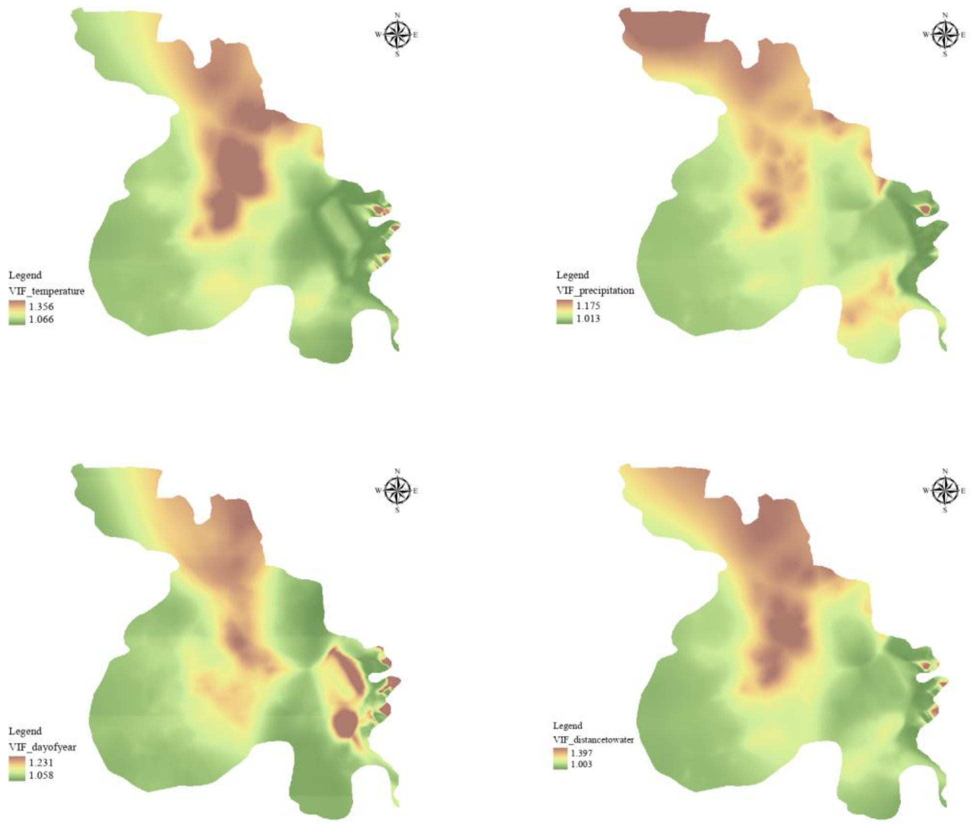


Figure S1. VIF results for predictor variables

A2. Supplementary Materials for Chapter 4

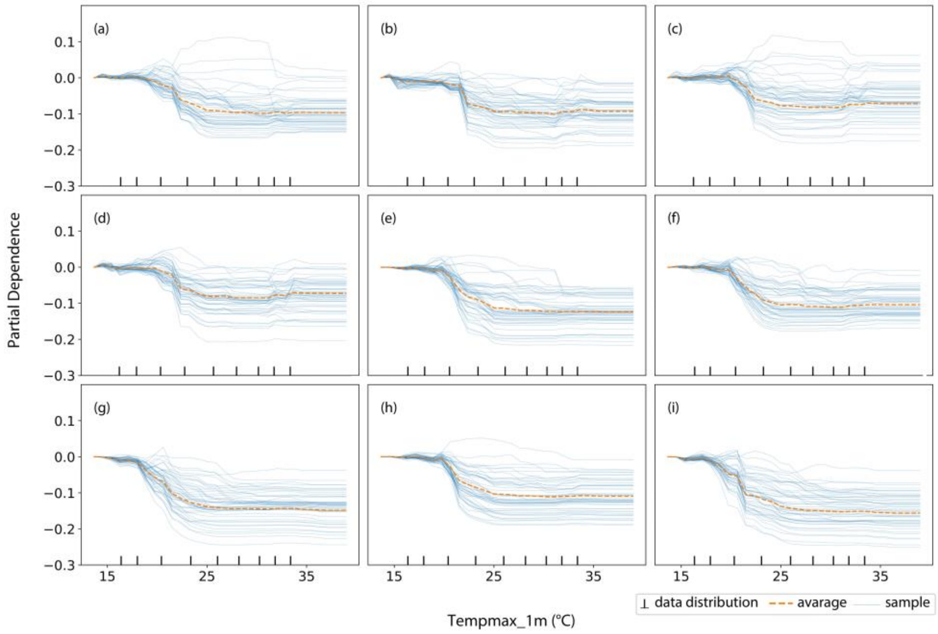


Figure S2. ICE plot of monthly mean max temperature among nine lakes showing a negative influence on NDVI ((a) Lake Lockie (the first connected lake); (b) Lake Hattah; (c)Lake Bulla; (d)Lake Arawak; (e)Lake Yerang; (f)Lake Mournpall; (g)Lake Konardin; (h)Lake Yelwell; (i)Lake Bitterang

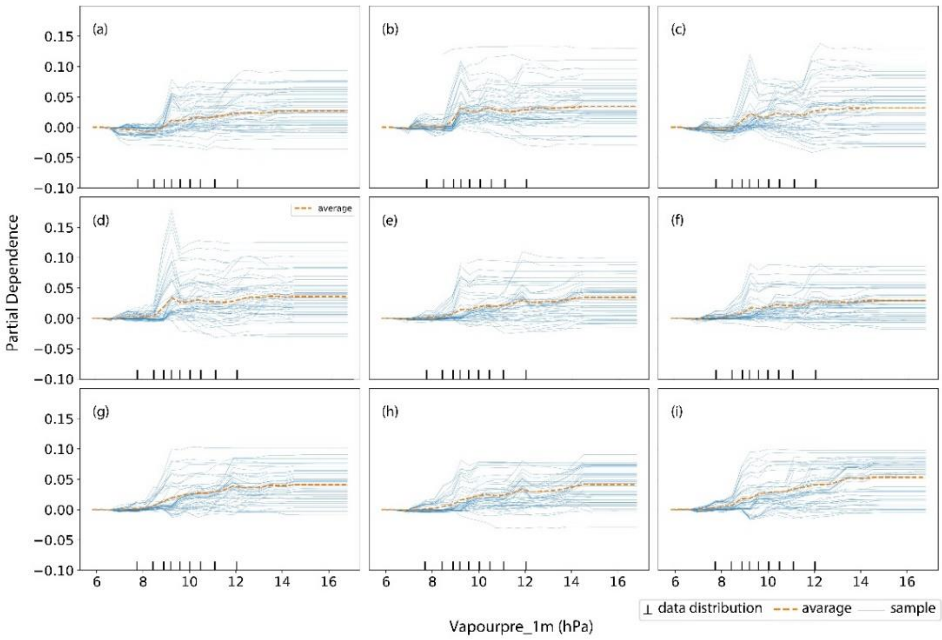
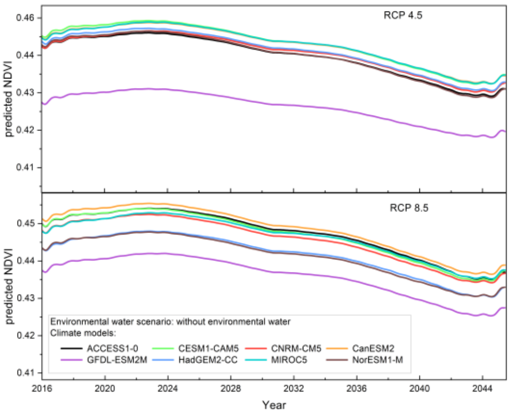


Figure S3. ICE plot of vapor pressure among nine lakes ((a) Lake Lockie (the first connected lake); (b) Lake Hattah; (c)Lake Bulla; (d)Lake Arawak; (e)Lake Yerang; (f)Lake Mournpall; (g)Lake Konardin; (h)Lake Yelwell; (i)Lake Bitterang)

A3. Supplementary Materials for Chapter 5



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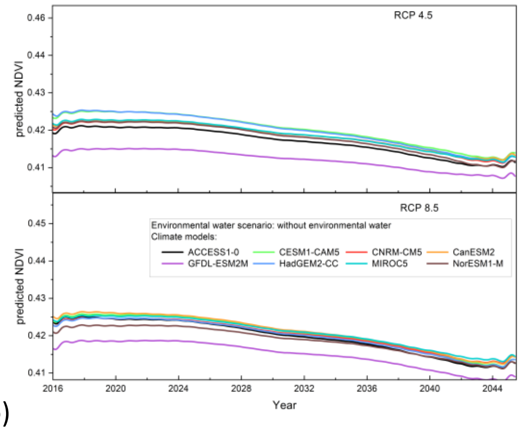

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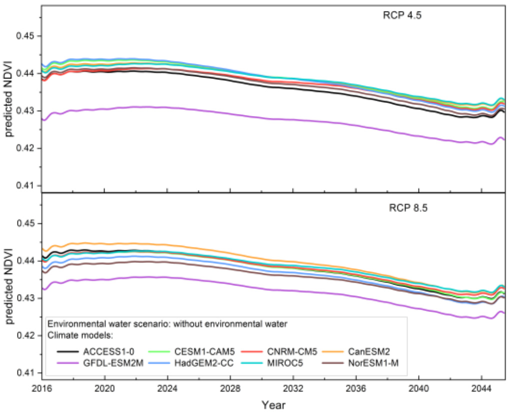

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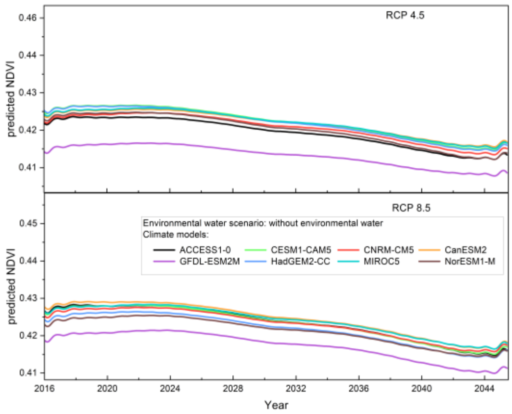

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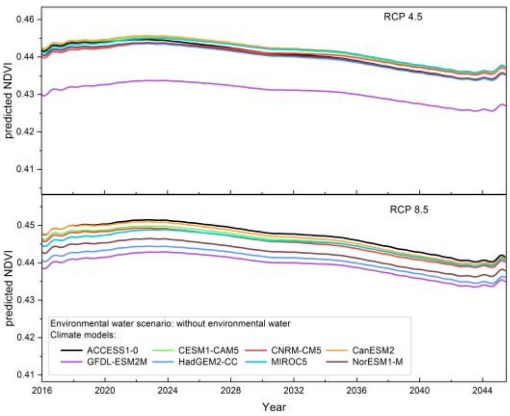

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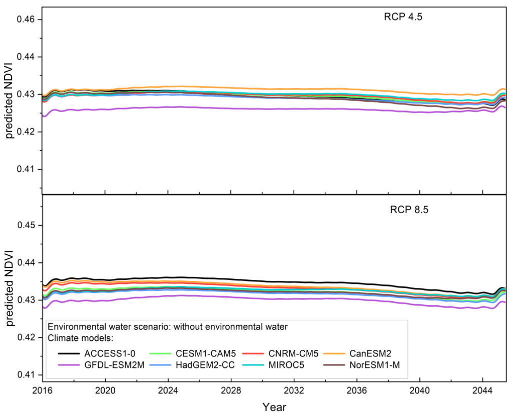

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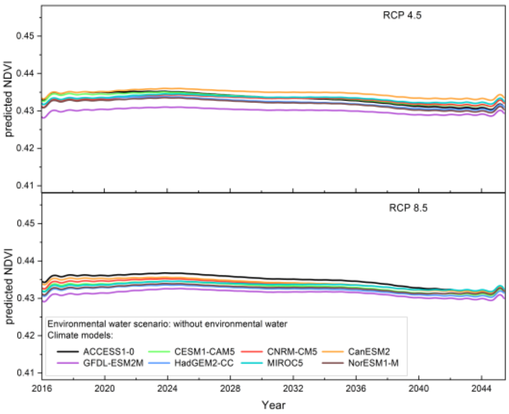

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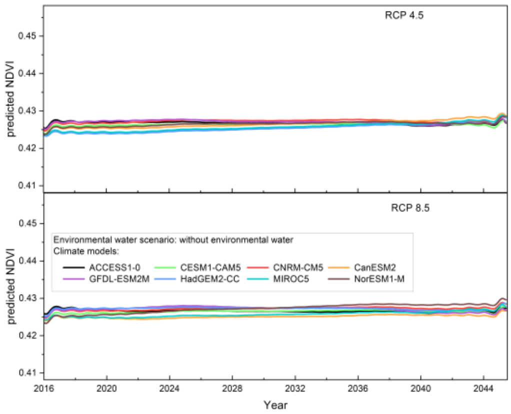

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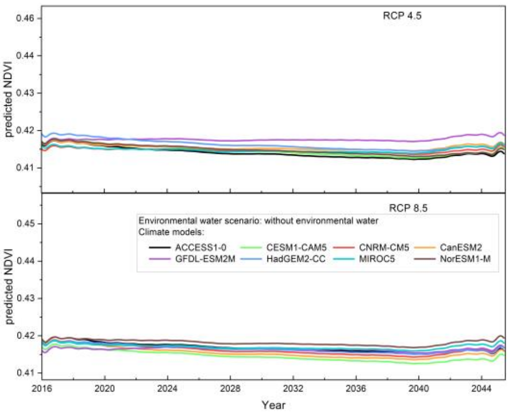

(i)

Figure S4 : Predicted NDVI SSA time series from 2016 to 2045 without environmental water delivery under 8 climate models and 2 RCPs for (a) Lake Bitterang, (b) Lake Lockie, (c) Lake Yerang, (d) Lake Yelwell, (e) Lake Konardin, (f) Lake Bulla, (g) Lake Mournpall, (h) Lake Hattah, and (i) Lake Arawak

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