Exploratory versus Predictive Approach for Proactive Decision-making in Water Resource Management

A

Dissertation

Presented to

the faculty of the School of Engineering and Applied Science

University of Virginia

in partial fulfillment

of the requirements for the degree

Doctor of Philosophy

by

Neda Nazemi

May 2023

APPROVAL SHEET

This

Dissertation

is submitted in partial fulfillment of the requirements
for the degree of

Doctor of Philosophy

Author: Nedanazemi

This Dissertation has been read and approved by the examing committee:

Advisor: Dr. Garrick Louis

Advisor:

Committee Member: Dr. James H. Lambert

Committee Member: Dr. Rider W. Foley

Committee Member: Dr. Michael L. Pace

Committee Member: Dr. Michael D. Porter

Committee Member:

Committee Member:

Accepted for the School of Engineering and Applied Science:

Jennifer L. West, School of Engineering and Applied Science

May 2023

by

Neda Nazemi

Submitted to the
Engineering Systems and Environment Department
Ph.D. Program in Systems Engineering
in partial fulfillment of the requirements for the
Doctor of Philosophy Degree
at the UNIVERSITY OF VIRGINIA

Abstract

Water resource management (WRM) is a complex and challenging task, as it frequently involves making critical trade-offs under conditions of high uncertainty, complexity, and knowledge constraints. These challenges arise from the numerous interconnected and interdependent factors that influence water resources, the diversity of stakeholders with conflicting interests and values, and the incomplete, uncertain, and often contradictory understanding of the system. In such a context, forward-thinking and adaptive decision-making are essential for effective WRM. The overarching aim of this research is to compare a range of exploratory and predictive foresight methods to assess their potential applicability in addressing various WRM problems.

This research specifically investigates agricultural water management (**AgWM**) and hazardous algal bloom (**HAB**) management as two critical and challenging WRM problems that have significant environmental, social, and economic implications. To tackle these issues, the research is divided into two main parts.

In the first part, a formative scenario planning method is employed to explore the adaptation strategies for AgWM in arid and semi-arid regions. This process involves constructing a small set of coherent and distinctive governance scenarios that consider various factors, such as climate change, technological advancements, and social and political developments. These scenarios provide a robust framework for decision-makers to develop proactive and flexible strategies that can effectively respond to the evolving challenges in AgWM.

In the second part of this research, a set of data-driven predictive models is developed to provide near-term forecasts of HABs, which can support the prevention, control, and mitigation of these harmful events. These models leverage advanced machine learning techniques and a variety of data sources to generate accurate and timely predictions of algal bloom occurrences. By providing reliable and actionable information, these predictive models can inform WRM stakeholders and support evidence-based decision-making to minimize the negative impacts of HABs on water quality, public health, and the environment.

In conclusion, this research contributes to the field of WRM by comparing and evaluating a range of foresight methods that can address the complex challenges associated with AgWM and HAB management. The findings of this study can provide valuable insights for policymakers, practitioners, and researchers in WRM, and help inform the development of more effective, adaptive, and sustainable strategies for managing water resources in the face of uncertainty and change.

To:

"Women, Life, Freedom"

Acknowledgment

I would like to express my deepest gratitude to my advisor, Dr. Garrick Louis, for his unwavering support, guidance, and encouragement throughout the course of my dissertation journey. I am truly grateful for the opportunity to learn and grow under his exceptional mentorship. I would also like to extend my heartfelt appreciation to my co-advisors, Dr. Rider Foley and Dr. Michael Pace, for their invaluable insights and advice that greatly contributed to the success of my research.

My sincere thanks go to my committee members, Dr. James Lambert and Dr. Mike Porter, who have generously offered their time and expertise to review and provide feedback on my work. Their thoughtful comments and suggestions have significantly enhanced the quality of my research.

I am incredibly grateful for the unwavering love and support of my husband, Dr. Faraz Dadgostari. His endless patience, understanding, and encouragement have been my source of strength and motivation throughout this journey. I am also immensely thankful to my parents for their unconditional love who have always believed in me and encouraged me to pursue my dreams.

Lastly, I would like to express my gratitude to my dear friends Dr. Erfaneh Gharavi, Dr. Sadegh Eghdami, and Dr. Mohammad Khosravi. Their camaraderie, advice, and encouragement have been invaluable, and I am truly fortunate to have them in my life.

In conclusion, I would like to acknowledge the countless individuals who have contributed to my research, both directly and indirectly. I am deeply grateful for all the support, encouragement, and inspiration I have received throughout this journey, and I am honored to share the results of my work with all those who have played a part in its realization.

Table of Contents

List of Figures

List of Tables

Chapter 1
Introduction

This chapter serves as an introduction to the research agenda for this dissertation. It begins by discussing the global challenges related to water resource management (WRM) and the decision-making complexities associated with these issues. Subsequently, it provides an overview of various foresight methods that facilitate uncertainty-informed decision-making in the context of WRM. The motivation for this research, the goals, research questions, and the methodologies employed to achieve the objectives, are then presented.

Finally, this chapter offers an outline of the subsequent chapters, delineating the connections between them and the research goals and questions.

1.1. Motivation and Background

Viewed from outer space, our seemingly vibrant blue planet might suggest an abundance of fresh water resources, yet access to safe, clean water remains one of humanity's most enduring challenges. Renewable, non-frozen fresh water constitutes a mere 0.005% of Earth's total water, which, if equally distributed, would suffice for the current global population. For example, the Middle East and North Africa (MENA) region possesses only about 1% of the world's fresh water resources, while accommodating 6% of the global population. Furthermore, the availability of water resources within the MENA region varies significantly.

Climate change has introduced additional uncertainty to the spatial and temporal distribution of precipitation, exacerbating the frequency and severity of flood and drought events. The UN Office for Disaster Risk Reduction (UNDRR) reported that between 2000 and 2019, four billion people were affected by natural disasters, with 79% of these incidents related to floods and droughts (UNDRR, 2019). Moreover, surging water demand, driven by rapid population growth and urbanization, places immense stress on this finite and vulnerable resource (Cosgrove and Loucks, 2015).

In addition to water quantity concerns, water quality has also been negatively impacted by factors such as extensive agricultural activities, over-fertilization near water bodies, and inadequate waste management. Agricultural runoff contaminates both surface and groundwater resources, disrupting natural ecological systems and leading to the increased occurrence of phenomena such as Harmful Algal Blooms (HABs) in water sources. (Palaniappan *et al.*, 2010).

These challenges disproportionately affect the most economically vulnerable social groups. For instance, Keshavarz et al. (2013) outline numerous socio-economic difficulties faced by rural communities in the MENA region as a result of the ongoing water crisis. These issues encompass decreased income and limited alternative income sources, heightened water disputes, food insecurity, health impacts coupled with reduced access to healthcare services, diminished access to education, forced displacement, impoverishment, and a decline in overall quality of life. The water crisis can also lead to psychological and emotional distress, including depression and frustration, alterations in family plans such as postponing marriage, as well as family and community disharmony and disintegration. (Keshavarz, Karami and Vanclay, 2013).

Water resource management is acknowledged as a wicked problem due to its numerous interconnected and interdependent factors, the presence of multiple stakeholders with conflicting interests and values, and the incomplete, uncertain, and contradictory understanding of the system (Grafton, 2017). Notably, in arid and semi-arid regions such as the Middle East and North Africa (MENA), water resource management is further complicated by the scarcity of water resources. This challenge is exacerbated by the uncertainties associated with climate change. As a result, the trade-off between food and water security becomes a critical issue in these regions, frequently leading to social fragmentation and conflicts among stakeholders.

Considering this context, attempting to address this wicked problem by simplifying it into a single-objective issue has led, and will continue to lead, to simplistic solutions that may provide short-term success but could create more severe problems in the long run. Furthermore, efforts to maximize the benefits for a single dominant stakeholder typically result in the neglect or marginalization of the preferences and needs of less influential stakeholders (Hearnshaw, Tompkins and Cullen, 2011).

An additional challenge in WRM decision-making is that it often involves substantial investments in policies or infrastructure that impact numerous stakeholders at once. As a result, not only is the implementation of these decisions highly expensive, but the repercussions of mistakes can be far-reaching and potentially irreversible.

Under circumstances where decision-making entails crucial trade-offs amid high uncertainty, complexity, and limited knowledge, forward-thinking becomes essential. This approach allows for the exploration of uncertain futures, the anticipation of potential pitfalls, and the development of adaptive responses and plans for decision-makers.

Numerous methodologies and tools have been developed to facilitate forward-thinking, in efforts to shine a ray of light into the various pathways that may evolve from the present to the future. The *cone of plausibility* introduced by Hancock and Bezold, illustrates diverse pathways (scenarios) that can lead to the future. Some pathways lead to the most *probable* future, and some pathways are our most *preferred* future or the *normative* scenarios. However, many more pathways are *plausible*, and even more, are *possible* (Hancock and Bezold, 1994).

Most studies in WRM and decision-making concentrate on *predicting* the most probable futures. Nonetheless, *predictive* methods prove to be more effective and insightful for near-term decision-making, such as operational water system management issues (Dietze et al. 2018).

Advancements in technology for collecting high-frequency data, such as satellite imagery, automated sensing devices, and wireless communication technologies, coupled with data processing techniques like machine learning algorithms, have revolutionized prediction methods within the field of water resource management. This revolution in data collection and processing has allowed for more accurate and timely predictions, leading to better decision-making and improved outcomes in managing water resources, especially in addressing complex and uncertain challenges (Mehmood *et al.*, 2020). In particular, the growing impacts of climate change on water quality and quantity have made it increasingly important to improve forecasting methods, as they can play a crucial role in enhancing the resilience and efficiency of water management operations. These operations encompass various aspects of water resources, such as water supply, distribution, and storage, as well as wastewater collection and treatment systems. By utilizing cutting-edge forecasting techniques, decision-makers can better anticipate potential changes and disruptions in water resources and develop proactive strategies to adapt and mitigate the effects of climate change. This, in turn, enables more sustainable and effective management of water resources, ensuring that communities can continue to rely on a safe and reliable water supply while minimizing the environmental impacts on water quality and ecosystems.

In situations where numerous interconnected factors influence water governance, it is crucial to assess the long-term impacts of decisions and policies. This necessitates defining the boundaries of plausible and possible outcomes, which tend to expand as time progresses. However, as these boundaries widen, so does the associated uncertainty in any estimations or predictions, ultimately undermining the value of future forecasting. Consequently, while the predictive approach offers notable benefits in the short term, its efficacy diminishes due to the inherent complexity of modeling human and organizational behavior. As a result, a paradigm shift from predicting the most probable future to examining all plausible futures is essential for enhancing anticipatory capacity in the governance aspect of water resource management. This shift enables decision-makers to consider a broader range of possibilities and adopt more adaptive and robust strategies for addressing the complex challenges of water governance (Haasnoot and Middelkoop, 2012).

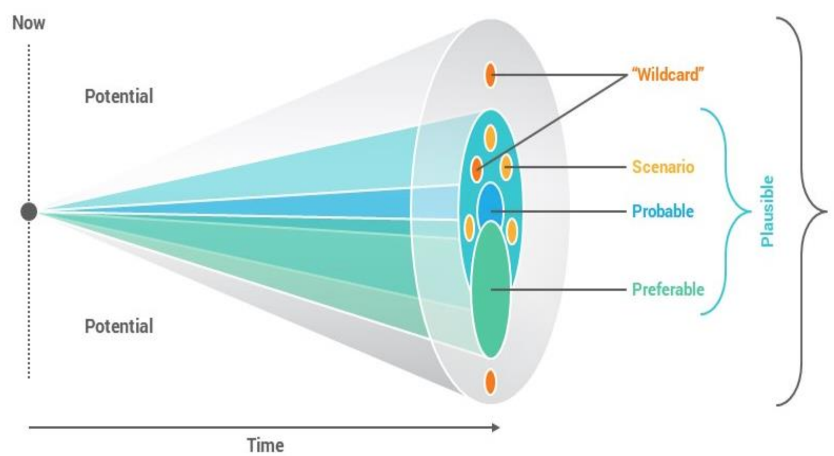

Figure 1-1- Cone of Plausibility

Strategic foresight methodologies, including scenario planning, visioning, and back-casting, play a critical role in fostering improved anticipation in decision-making processes. By facilitating the exploration of alternative futures, these methods enable policymakers to better prepare for and adapt to potential opportunities and challenges that may arise in the future. In doing so, they encourage proactive and informed decision-making, allowing stakeholders to account for a broader range of possibilities, minimize risks, and maximize the potential benefits of their choices. Ultimately, the incorporation of strategic foresight methods into water resource management helps build more resilient and adaptable systems, capable of navigating the complexities and uncertainties inherent in this field (OECD, 2019). In essence, foresight methods provide a valuable tool that enables us to virtually investigate various alternative futures and evaluate potential courses of action before implementing them (Fuerth, 2009).

Strategic foresight methods play a crucial role in building the confidence of decision-makers and other stakeholders in water resource management by facilitating a deeper understanding of potential opportunities and risks. By focusing on medium to long-term strategies, these methods enable the effective management of complex systems. Rather than attempting to predict the future, strategic foresight methods emphasize the evaluation of possible future outcomes that result from current decisions and intermediate events. This approach empowers decision-makers to anticipate and prepare for a wide array of possible future states, fostering adaptive and resilient planning in the face of uncertainty and change.

Although there has been a growing interest in future studies within the context of WRM, a holistic framework to categorize various methods and techniques is missing., as well as the advantages various methods provide for resilient, adaptive decision-making in WRM. This research seeks to address some of these gaps by exploring and comparing the applications of exploratory and predictive perspectives for two distinct WRM issues, one at the governance level and the other at the operational level.

1.2. Overall goals and objectives

The primary objective of this research is to examine and compare the implementation of exploratory and predictive foresight methods, along with their influence on decision-making processes within the context of WRM. This dissertation asks the question, "In what ways can foresight methods enhance decision-making and lead to more adaptive water resources management?" To investigate this question, the study is divided into two parts, each focusing on the exploratory and predictive approaches, respectively.

The research commences by addressing the water supply challenge. The first part of this study delves into the WRM problem from a water governance perspective, employing an explanatory approach. The objective is to present an extensive framework that enables the exploration of diverse water governance scenarios. Part 1 concentrates on a case study of agricultural water demand management within the Zayandehrud watershed in Iran. The primary objectives of this part are to:

1.1 Engage stakeholders in the identification of crucial adaptation strategies and policy interventions for AgWM.

1.2 Evaluate the interactions and interdependencies among these strategies.

1.3 Employ formative scenario planning to develop a limited set of plausible, distinct regional agricultural water governance alternative scenarios.

1.4 Assess the effects of these scenarios on the sustainability and adaptability of the watershed.

In the second part of this research, the focus transitions from the governance level to the operational level and from an exploratory lens to a predictive one. This portion of the study investigates the utilization of cutting-edge forecasting techniques in decision-making concerning operational WRM challenges.

This section concentrates on the topic of water quality through an examination of Harmful Algal Blooms (HABs) in freshwater resources. The primary objectives of this part include:

2.1 Developing a comprehensive framework for evaluating the performance of near-term forecasting models.

2.2 Improving existing algal bloom predictions by utilizing high-frequency data and advanced deep learning techniques.

1.3. Investigation Approach and Dissertation Outline

Table 1-1 summarizes the WRM problem, case study, and methods employed to achieve the research objectives of each chapter. Every chapter in this dissertation has its own scope, contributions, and methodology. Based on published journal articles or conference papers, or working papers they together form a research framework for applying foresight methods to facilitate adaptive decision-making in WRM problems.

Chapters 2 and 3 demonstrate the application of the exploratory framework to water supply issues in the context of the agricultural water demand problem in the Zayandehrud watershed. In Chapter 2, we employ a formative scenario planning approach to identify key variables that may influence agricultural water demand in the watershed and analyze alternative policies and infrastructures with the potential to effectively address the problem or that are already in use elsewhere. Based on these findings, we develop a concise set of governance-oriented scenarios to inform ongoing planning. Additionally, we assess the impacts of each scenario on the socio-economic and ecological sustainability of the watershed.

In Chapter 3, we delve deeper into one of the five scenarios created in Chapter 2, seeking to answer the question: How will water markets impact irrigation water demand and overall utility in a watershed under a free trade regulation scenario? To address this question, we develop a partial equilibrium model.

Chapters 4 and 5 shift the focus from exploratory to predictive approaches, exploring these methods in relation to water quality issues, specifically the challenge of algal blooms in freshwater resources. In both chapters, historical data from Peter Lake, an experimental lake in the Notre Dame Environmental Research Center, is used as the case study.

In Chapter 4, we establish a comprehensive framework for assessing the performance of near-term forecasting models. Additionally, we develop univariate algal bloom forecasts using historical chlorophyll-a data and deep learning techniques.

Chapter 5 expands upon the scope of Chapter 4 by incorporating water quality and environmental variables to improve the performance of univariate models. We compare the performance of multivariate and univariate models using the evaluation criteria established in Chapter 4.

In Chapter 6, I conclude by summarizing the motivation behind my research, the research goals and objectives, the results obtained, their contributions to the field, and my recommendations for future work.

Table 1-1 Research goals, questions, methods, and associated chapters

Ch	WRM problem	Chapter Description	Research Objective	Methods	Case Study
1	General WRM	Introduction	-	-	-
2	AgWM	Divergent agricultural water governance scenarios: the case of Zayandehrud basin, Iran	• To identify the adaptation policies • To construct a small set of plausible, distinct regional agricultural water governance alternative scenarios	• Formative scenario planning	Zayandehrud Watershed, Iran
3		Modeling water market and food free-trade as instruments for the governance of agricultural water demand in arid and semi-arid regions	• To assess the impact of water markets on irrigation water demand and overall utility in a watershed under a free trade regulation scenario	• Mathematical modeling (partial equilibrium)	
4	HAB	Univariate Deep Learning for Short-Term Algal Bloom Prediction: A Comparative Analysis of MLP, 1D-CNN, and LSTM Models	• To develop a framework for assessing the performance of near-term forecasting models • To develop univariate algal bloom forecasts using chlorophyll-a historic data and deep learning techniques.	• Univariate deep learning models (MLP, LSTM, CNN)	Experimental Lakes, MI
5		Comparative Assessment of Multivariate and Univariate Deep Neural Networks for Near-Term Algal Bloom Forecasting: 1D-CNN and LSTM Approaches	• To develop multivariate deep learning models using experimental data • Compare their performance with Univariate models	• Multivaiate deep learning (LSTM, CNN)	
6	General WRM	Conclusion	-	-	-

Chapter 2

Divergent agricultural water governance scenarios: The case of Zayanderud basin, Iran

Published in Agricultural Water Management https://doi.org/10.1016/j.agwat.2019.105921

Neda Nazemi[a] , Rider W. Foley[b], Garrick Louis[a], Lauren Withycombe Keeler[c]

[a] Engineering Systems and Environment, University of Virginia, VA, US

[b] Engineering and Society, University of Virginia, VA, US

[c] School for the Future of Innovation in Society, Arizona State University, AZ, US

Declarations of interest: None

CHAPTER 2: DIVERGENT AGRICULTURAL WATER GOVERNANCE SCENARIOS: THE CASE OF ZAYANDERUD BASIN, IRAN

Abstract

There is an urgent need to consider adaptation strategies for agricultural water resources in response to the ever-growing demand for freshwater around the world. This is especially poignant in arid and semi-arid regions, like the Middle East and North Africa (MENA) where water resources have been extremely limited historically. Today, water resources are declining due to a variety of factors, including climate change, population growth and changing food preferences. Research on this topic typically seeks to assess the impact of discreet alternative interventions in isolation. However, it is necessary to analyze the broader factors affecting agricultural water management as interconnected components of a complex water governance system within a specific geographic context. This research uses an exploratory, formative scenario planning approach to a) identify important adaptation strategies, b) use those adaptation strategies to construct a small set of coherent, plausible and diverse regional agricultural water governance scenarios, and c) analyze future scenarios of the Zayandehroud watershed in Iran in the year 2040. The research shares five scenarios that exemplify divergent adaptation and mitigation approaches to agriculture water demand in Zayandehroud watershed, including adhering to the status quo. Each scenario embodies different economic and political priorities to reveal how those priorities impact the ecological, social, and economic sustainability of this watershed. These scenarios provide insights into the long-term implications of near-term decisions about water and food security, resilience of local communities and the ecological integrity of the regional watershed. This research explores the conceptual relationships between components of the water governance system and demonstrates an approach to analyzing alternative constellations of factors that will impact agricultural water management. Policymakers can make more effective policies if they consider how to transform the broader system of regional water governance, rather than only evaluating discrete agricultural water management projects on a project-by-project basis.

Keywords

Adaptive Governance, Scenario Planning, Water Market, Rural Development, Local Governance, Land Use Planning

2.1. Introduction

Climate change and population growth are often the most discussed causes for global water scarcity in terms of supply uncertainty and increasing demand, respectively. Yet, water crises can also be attributed to governance—including a broad range of political, social, economic and administrative systems that are in place to develop and manage water resources. This is especially the case in developing countries where rigid and hierarchical governance systems, which exercise monopolies via governmental control, corporate contractors, water-market manipulation through trade policies, incentives and water credits inhibit rational, objective water policies (Rogers and Hall, 2003).

In arid and semi-arid regions—characterized by low precipitation, high evaporation and uneven temporal and spatial distribution of water resources —agricultural water governance is of utmost importance, since the decisions impact the dual goals of food security and water security. For instance, in the Middle East and North Africa (MENA) region, over 85% of available fresh water is being consumed by the agricultural sector to guarantee food security, yet water demand far outstrips water availability (Shetty, 2006; Bucknall, 2007). Classic approaches to agricultural water management in these regions rely mostly on technologies (and connected infrastructure) to augment the irrigation water supply and to enhance the productivity and efficiency of irrigation.

The appeal of technological solutions can lead decisionmakers to overlook the potential of alternative solutions like market policies, institutional reforms and social changes (Madani, 2014). In fact, adaptation processes can be constrained by a lack of political will and consensus, oppositional cultural factors, and the lack of stakeholder engagement (Ricart et al., 2019b; 2019a). As an example, intra-basin competition over water resources can arise when public officials seek to implement short-term, visible outcomes for the landowning farmers that elected them, thereby contributing to the persistence of technocratic approaches (Dietz, Ostrom and Stern, 2003). In developing regions around the world, international donors and other financial organizations historically have been strong external drivers of policy. They can incentivize technology-oriented solutions and centralized governance structures in order to control and protect their investments.

Iglesias and Garroteb (2015) performed a comprehensive study to identify agricultural water management adaptation strategies and evaluate their feasibility and effectiveness in Europe (Iglesias and Garrote, 2015). The adaptation strategies they cataloged cannot be considered a comprehensive set of neutral and independent tools that can be implemented globally to mitigate the water management crisis. Boelens and Vos (2012) explored the effects of discrete interventions that would affect water efficiency and enhance productivity, yet they concluded that while those interventions represent important alternative decisions they need to be understood within complex social and power relationships in the specific geographic contexts where they are being implemented (Boelens and Vos, 2012). Given the increasing vulnerability of water resources, climate uncertainty, and complex governance, effective water management policies must account systematically for a wider range of adaptation strategies that embrace aspects of the built environment, social institutions, and socio-ecological systems as well as different water activity domains including supply, delivery, use and outflow (Larson, Wiek and Keeler, 2013; Field, 2014; White et al., 2015).

Despite this need, there is a dearth of studies that attend to the interplay between adaptation choices (discrete interventions) and geo-political context and social relationships, which are often neglected in these studies. This means that the effectiveness and plausibility of a particular adaptation strategy is not considered in relation to other interventions, despite Boelens & Vos (2012) arguments to the contrary. To this point, Knieper and colleagues (2010) argue that there is a need for policy makers to explore alternative governance scenarios that attend to the technological and societal forces at work in their decisions (Knieper et al., 2010; Foley and Wiek, 2014).

Scenario planning offers a powerful tool to study the future-states of a system by exploring alternative, yet plausible and consistent futures that could evolve out of present conditions (Stewart et al., 2007; Mahmoud et al., 2009; Funke, Claassen and Nienaber, 2013). Scenarios can help decision-makers (broadly defined) to understand and analyze the key connections, explore the uncertainties of a specific system to take a more holistic perspective, and to assess coordinated actions in a highly uncertain environment (Henriques et al., 2015). Scenarios can be qualitative or quantitative, based upon the nature of the data. Qualitative scenarios are more suitable for the analysis of complex systems with high degrees of uncertainty and when most of information cannot be readily quantified due to data uncertainties (Van Notten et al., 2003). On the other hand, scenarios can be categorized as predictive, explorative or normative based on the research question that the researcher aims to address. While predictive scenarios seek to identify the most probable futures by answering questions related to what will happen, explorative scenarios develop knowledge about what are the most plausible futures, i.e. what can happen? Finally, normative scenarios explore questions about the most preferable futures (Bishop, Hines and Collins, 2007). This typology of scenario analysis is important to consider and will help the reader position our work within the field of scenario methodologies. It also should be noted that the nature of scenarios as a type of foresight knowledge is non-verifiable since it is not able to provide an exact representation of an observed reality. So for qualitative scenarios, quality criteria include: logical coherence, plausibility, divergence, and relevance to decision making rather than the accuracy of the prediction (Guimaraes Pereira, Von Schomberg and Funtowicz, 2006). For example, the National Parks Service uses scenarios to “anticipate plausible but unprecedented conditions, and expect surprises” with respect to the effects of climate change on the national parks (National Park services, 2013)

This study offers a conceptual framework that attends to the interplay among multiple social, political, and technological factors and employs an explorative scenario development approach to study different constellations of those factors qualitatively. The arrangement of those factors will inform distinct water governance scenarios, some of which may contribute to key aspects of sustainability and less so for others. The scenarios are not a blue-print for sustainable water governance, rather this study demonstrates conceptual relationships and explores the interplay of alternative strategy elements. Our research explores an important, yet modest goal by addressing the question: What adaptation policies, technical and infrastructure investments can alleviate future water scarcity of this watershed? How does each mitigation strategy promote or obstruct other choices? How will understanding about these interplays guide us to delineate alternative water governance scenarios? Finally, how will these alternative scenarios affect the ecosystems, agricultural sector, and rural communities?

This paper offers a small set of alternative scenarios, which depict plausible, comprehensive governance regimes that address agricultural water demand. At its core is an exploration of the societal and technological transformations that may arise in parallel and ameliorate the conditions that are promulgating “water wars” across the globe Left unchecked, the current rates of water overexploitation will lead to the

"Tragedy of the Commons" (Hardin, 1968; Ostrom, 2009) with dire consequences for millions of people. Rather than focusing on "silver bullet" solutions to water crises, this research treats water governance as a "wicked problem" that demands more holistic, adaptive management strategies.

This study explores sustainable water governance by considering how alternative adaptation choices could function consistently without major obstructions. To bring the people and places into focus, next we introduce the Zayandehrud Basin in Iran as a means of highlighting the key geopolitical factors unique to that watershed. This case study will serve to illustrate the use of scenarios to explore potential approaches to the broader issues of water governance in arid and semi-arid regions generally, and the MENA region specifically.

2.2. Case Study Context: Zayandehrud Watershed

The Zayandehrud river originates from the Zagros mountains in the Northwest of Iran and flows 250 miles through the arid and semi-arid central plains before emptying into the Gavkhooni swamp (Fig.1). The total basin area of 16,000 mi^2 extends into the provinces of Isfahan and Chahar Mahal. Charmahal province is located upstream of the river and its share of the river basin is just 7% of the land and 1.8% of the population (Mohajeri *et al.*, 2016a). Beside Isfahan and Charmahal provinces, Zayandehrud also provides residential water to residents of two arid neighbor cities of Yazd and Kashan. Currently, more than one million (about 20%) residents of the basin depend on farming income and subsistence food supplies over an area of nearly 200,000 hectares of cultivated land, which is more than 90% irrigated. Food security concerns arose in the 1980's during an eight-year war between Iraq and Iran. This event made food self-sufficiency one of the highest national priorities regardless of severe water crises in most parts of the country [*self-sufficiency*][1]. Policies for food self-sufficiency include high tariffs on imported foods and incentives, such as; subsidized water, energy, fertilizer and equipment to support domestic food production [*food trade regulation, water pricing and subsidies*].

Subsequently, the agriculture sector is expanding in this watershed even though it is a closed basin [*irrigated land area*] (Molle and Mamanpoush, 2012). The food self-sufficiency incentives are not keyed to knowledge of the available water resources or their conservation. Therefore, they prevent the agriculture sector from shifting toward more efficient and productive practices [*agricultural practices*]. As a result, despite the existence of severe water scarcity in the basin, about 90% of its cultivated area is still supplied with water by flood irrigation [*irrigation system*] (Nikouei and Ward, 2013; Shahdany *et al.*, 2018). The irrigation water storage and distribution networks are mostly open and uncovered canals and there is no infrastructure to gather, treat and redistribute marginal quality water in farms [*storage and distribution system*]. Farms in close vicinity to the river rely on surface water (30%), while other farms use spring water (6%) and groundwater from wells (58%) and qanats (6%) for irrigating their farms (Felmeden, 2014).

A key historical and cultural feature of the agricultural water systems in Iran are qanats, which are underground horizontal tunnels excavated to convey groundwater from mountainous areas where the water table is closest to the surface, to arid regions. Qanats minimize water contamination and evaporation. Unlike the pumping system, qanats only extract renewable water (Yazdanpanah, Hayati, *et al.*, 2013).

[1] The terms in bracket refer to adaptation strategies and are identified as key variables, listed in Table 1.

Overdevelopment of upstream irrigated areas, in addition to unauthorized groundwater extraction, have disturbed the traditional qanat water allocation system substantially. Downstream farmers along the river as well as qanat water right holders no longer receive their full water rights [*water allocation*]. This problem has led to widespread dissatisfaction and continuous protests. Protesters believe that the current water allocation system is unfair and water managers must stop pumping water to neighboring cities like Yazd and Kashan. In fact, angry farmers have frequently damaged the exporting water pipeline to those cities. For instance, as recently as October 2018, the water pipeline to the city of Yazd was vandalized and ruptured by protesters 22 times according to the governor of Yazd province.(BBC, 2018).

To satisfy increasing demand, almost all river runoff is stored behind the Chadegan dam. Three tunnels divert water from the neighboring watershed, Karoon, while several new tunnels are under construction to increase the supply [*water transfer projects*], shown in Fig.1. Despite these efforts, the Gavkhooni wetland, which Iran committed to preserve under the Ramsar Convention, has not been receiving its minimum water requirements to preserve ecological integrity since 1995 [*wetland water right*].

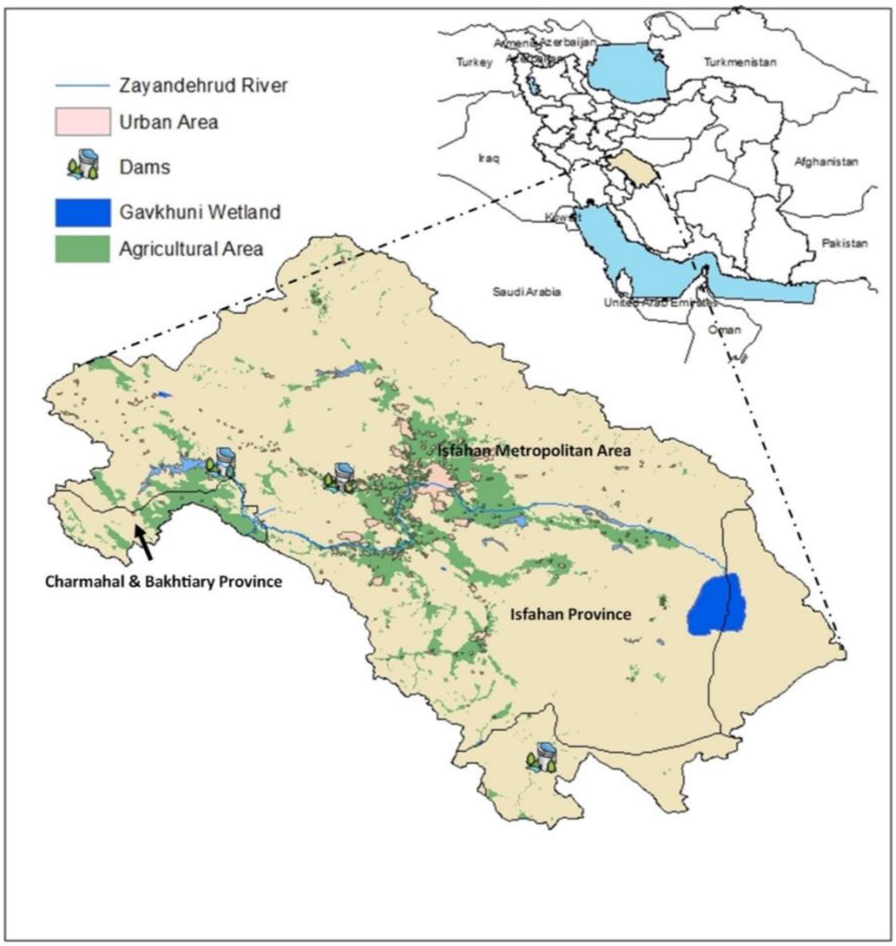

Figure 2-1 Zayandehrud watershed. Iran is in the inset map and is delineated by provinces. The Zayandehrud basis in called out and is divided among four provinces with Charmahal & Bakhtiary Province and Isfahan Province as the primary political stakeholder. The economic and populous center in the City of Isfahan.

The Zayandehroud river passes through the city of Isfahan, the third most populous city in Iran. Zayandehrud is a key feature of Isfahan City, a hub of tourism in Iran. Many outstanding features of this ancient city, such as bridges and palaces, rely on the glory of this "life-giving" river[2] (Schramm and Sattary, 2014). The Zayandehrud watershed was chosen as an illustrative case study due to its socioeconomic and ecological importance and as a complex case of agricultural water demand management. A few scenario planning studies have been conducted on different aspects of the Zayandehrud watershed. Gohari et al. (2013) developed a system dynamics model to evaluate new water augmentation projects on supply-demand dynamics in the Zayandehrud watershed (Gohari *et al.*, 2013). Safavi et al. (2016) also developed an Adaptive Network-based Fussy Inference System (ANFIS) model to evaluate the impact of climate change and supply augmentation projects on the near future condition (2015-2019) of this watershed. Felmeden (2014) developed three scenarios with special focus on integrated water management, though that study offered very narrow recommendations. This broad range of studies and the complex characteristics of the Zayandehrud watershed make it an ideal case study to explore alternative governance arrangements through scenarios, and thus offer findings for other watersheds in the MENA region.

2.3. Research Design and Methods

2.3.1. Theoretical framing

This study draws upon Elinor Ostrom's (2009) scholarship on the governance of the commons and integrates aspects of the built environment, socio-economic, and ecological environment into an analytical framework (Ostrom, 2009). The built environment mostly embraces physical variables like technologies and infrastructures, while socio-economic conditions covers factors such as policies and regulations. Finally, the ecological interface includes environmental conditions and systems. Those three categories were complemented by the work of Keeler and colleagues (2015), which added phases of water governance; including the five domains of supply, delivery, use, outflow and cross-cutting activities (Larson, Wiek and Keeler, 2013; White *et al.*, 2015). These two frameworks, together, inform the theoretical framework for this paper's governance of agricultural water demand and demonstrate the conceptual alignment of the governance factors identified by Ostrom with the five phases offered by Keeler, see Figure 2. Such an alignment allows this research to interrogate the interdependencies between and among the system elements and sustainability principles, such as social institutions and water delivery or the built environment and socio-ecological integrity.

[2] The meaning of Zayandehrud in Farsi is the "life-giving river".

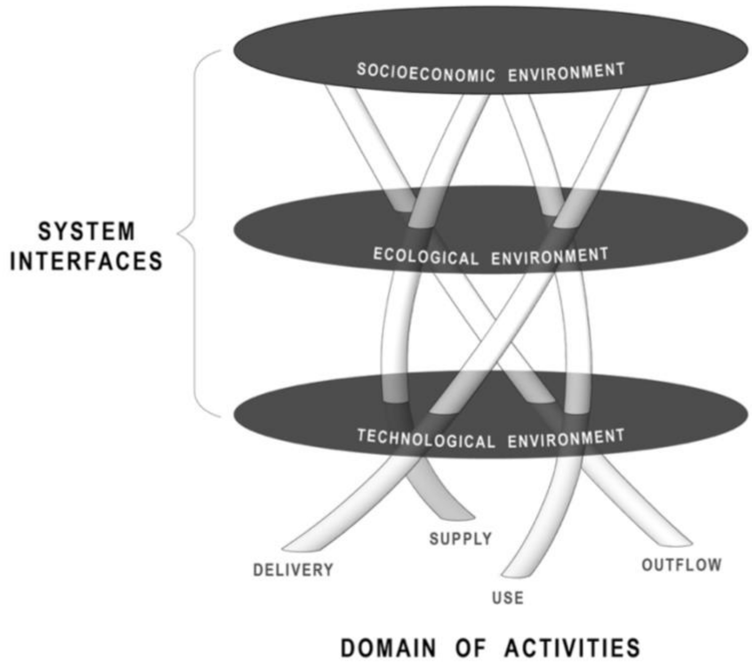

Figure 2-2 Conceptual framework. The three system interfaces are cross-cut by four domains of activities. This framework supporting the identification of adaptation choices, which were selected as variables via the scenario construction process.

2.3.2. Scenario Construction Methodology

Scenario development is usually a step-wise process in which all tasks can be categorized into three standard groups; idea generation, integration, and consistency checking (Bishop, Hines and Collins, 2007). There are several available techniques that are used in each group, and these can be adapted individually or in hybrid format based on the context, nature of study and available resources. Generating techniques include collecting information from experts and/or stakeholders. Integrating techniques are used to combine parts into wholes. Consistency techniques are utilized to secure the consistency between or within scenarios (Börjeson *et al.*, 2005). This research generated data from qualitative sources, including individual interviews, group discussions, and desk research. This research adapted a step-wise formative scenario analysis methodology developed by Scholz and Tietje (Scholz and Tietje, 2002; Tietje, 2005) to integrate the information into a discrete set of governance-oriented scenarios for the Zayandehrud basin through 2040. The method was also used to secure consistency and diversity across the scenarios. This exploratory approach helps to link the “formative” scenarios with expert and stakeholder knowledge to create a subset of signature scenarios which are normative, comprehensible and informative for decision-makers (Foley and Wiek, 2014; Keeler *et al.*, 2015). The process that the research team followed to construct the formative scenarios is described next.

<u>Step 1- Variable Identification</u>

Proposed adaptation measures, policy interventions and investments which may contribute "independently" to agricultural water demand (AgWD) management were identified and cataloged in order to construct consistent and distinct water governance scenarios. The semi-participatory approach involved 15 individual interviews, eight online discussion forums with about 8000 participants, secondary sources from media-based interviews, government reports and documents, and previous studies. The individual interviews were recorded in person, during January 2015. The interviewees were selected from a diverse range of water managers, environmental activists and decision-makers in Iran. The online discussions occurred through the "Telegram" application, which is the most popular phone-based communication application among Iranian citizens. It provides a flexible, affordable, free and secure medium for stakeholders to express their ideas freely to persons outside of Iran. Some forums involved official think tank and government advisors and others were unofficial discussion groups, which support different stakeholder groups and their interests and values. Due to the nature of this research, the individuals and organizations involved must remain anonymous.

This approach gathered data that fit the theoretical framework and provided a broad range of strategies for the different interfaces and domain activities. The data gathered encompasses the three interfaces of socio-economic (formal and informal institutions), built environment (technological systems), and environment (ecological) and five domains of supply, delivery, use, outflow and cross-cutting activities. Further, the research team condensed the list of variables to include only 20 independent variables in the final set of variables based upon the following criteria:

1- <u>Sustainability importance</u> of the independent variable on AgWD.

2- <u>Systemic importance</u>, including the potential uncertainty and complexity that any single variable adds to the whole system. For example, projections for population growth have a high confidence or low degree of uncertainty. Therefore, this variable, and others like it were removed because they do not contribute significant uncertainty to the model.

3- <u>Minimum redundancy</u> for any variable that is already represented by other variables or if it is possible to combine two or more variables into a single variable. For example, variables like land consolidation, irrigation scheduling, and crop rotation programming were combined into a single variable called *agricultural practice*.

4- <u>Maximum diversity</u> across different interfaces (socio-economic, technological, ecological) and activity domains (supply, delivery, use, outflow) was evaluated iteratively by the researchers to have the most comprehensive set of variables.

Two to three future projections that were drawn from the generated data were used to explore how the independent variables could change in the long-term future, and thus how the governance arrangement could change. Table 1 presents the variables selected and the future projections explored.

Table 2-1 List of final selected variables. The first column lists the variables that were selected from the adaptation strategies. The second column shows the alignment with the conceptual framework. While the right-side column offers two to three diverse future projections for each variable.

Variable	Environment /Domain	Future Projections
1- Food Trade Regulation	Socio-econ/Supply	1-Trade is regulation-free and based on economic probability (free market) 2-Trade is regulated based on their water productivity (Virtual water trading) 3-Trade is regulated based on food security concern (self-sufficiency approach)
2- Water Market	Socio-econ/Supply	1-Established water markets/banks facilitate water trade 2-There are only informal, small scale and direct bartering of water rights among farmers.
3- Water Pricing	Socio-econ/Delivery	1-Volumetric irrigation water consumption is being priced based on supply-demand and charged 2-Irrigation water is almost unpriced and ineffective
4- Water Allocation	Socio-econ/Delivery	1-Water is distributed based on government discretion and priorities, in an unfair way 2-Traditional water rights are followed as the central criteria for water allocation 3-Traditional water allocation system is modified and followed
5- Irrigated Land Area	Socio-econ/Use	1- A restrictive cap on total irrigated land is set and enforced 2- There is no regulation to control irrigated area
6- Cultivation Plan (Crop choice)	Socio-econ/Use	1- Farmers follow a comprehensive cultivation plan based on water availability 2- Farmers plan cultivation collectively considering available water and socio-economic concerns 3-Farmers individually decide about their cultivation plan based on their experience and discretion
7- Agricultural Practice	Socio-econ/Use	1- Industrial Farms are dominant 2-Small and improved traditional agricultural practices are the dominant practice 3-Farms are mostly small, traditional and un-mechanized
8- Runoff and Drainage Recycling	Socio-econ/Outflow	1-Most of agricultural runoff is recycled and reused 2- Most of agricultural runoff is disposed without treatment and recycling
9- Water Transfer Projects	Built/Supply	1-New water transfer projects (i.e. Behesht Abad tunnel) are pursed 2-No new water transfer projects are pursed
10- Storage & Distribution System	Built/Delivery	1- Distribution system is lined and covered to minimize percolation and evaporation 2- Open and unlined distribution system is dominant
11- Efficient Irrigation Technologies	Built/Use	1- Efficient irrigation technologies (like drip irrigation) are used in most farms 2-Traditional irrigation system (like float irrigation) is still dominant among farmers

12- Groundwater Safe Yield	Ecological/Supply	1- Effective groundwater safe yield regulation exists and is enforced at any condition 2- Safe yield regulations are not effective enough or is not pursued at water deficient condition.
13- Gavkhouni Water Right	Ecological/Delivery	1-Gavkhouni receives its water right continuously. 2-Gavkhouni does not receive its water need.
14- Unauthorized Extraction	Ecological/Use	1-Unauthrized extraction regulation is enforced effectively and fairly administered. 2-Unauthorized extraction is not regulated and/or unenforced properly.
15- Subsidies	Cross-cutting	1- Both direct and indirect subsidies used to support food production 2- Subsidies are used purposefully to motivate sustainable farming and conservative water consumption 3- All kind of subsidies are totally removed
16- Knowledge Sharing System	Cross-cutting	1- Collaborative Knowledge System: Knowledge is generated and shared equally between farmers, bureaucrats, scientists, agricultural-product businesses, and consumers 2- Knowledge Push: Farmers are trained through education packages provided by government 3- Traditional Knowledge Sharing: Farmers are trained by their elders
17- Rural Development Plan	Cross-cutting	1- Local non-farming entrepreneurships are highly encouraged and incentivized 2- Access to basic services are provided and subsidized 3-There is no supportive plan for rural development
18- Governance Integrity	Cross-cutting	1- There is a high level of institutional integrity among all parties over objectives, approach and decisions 2- The system is fragmented in which actors follow different and conflicting objectives and approach.
19- Governance Hierarchical System	Cross-cutting	1-Top-Down (Centralized) 2-Local water governance (Decentralized) 3-Collaborative governance
20- Food Self- Sufficiency	Cross-cutting	1-Food Self-sufficiency is the principle guideline for decision/policy making 2-Food Self-sufficiency is not the central principal in water governance system

Step 2- System Analysis

The selected variables were scored for their cross-influence on a scale from 0 (no impact), 1 (indirect impact) to 2 (Direct impact). The scoring system is two-ways, because the impact of variable A on Variable B might be different from the impact of variable B on variable A. Subsequently, this will yield a non-symmetric impact matrix, which includes impact relationships among all pairs of variables, see Appendix 2-1 for the completed impact matrix uploaded as Research Data. This analyzes the key interconnections of the system and illustrates the level of activity (influence) or passivity (sensitivity) of each variable (Kuzdas and Wiek, 2014; Michel *et al.*, 2018). It should be noted the cross-impact and consistency scoring (the next step) were performed through an iterative process among the research team. Consequently, the process involves a level of subjectivity, where team members utilized their case-specific knowledge about the variables to perform these tasks. (Scholz and Tietje, 2002).

Step 3- Consistency Analysis

The consistency of each scenario, and logical coherence (Godet, 2000; Carpenter and Rissman, 2012) of paired variable-projections were scored from -2 (prevents the occurrence) to 2 (required to occur) following Tietje (2005). Unlike previous analysis, consistency scoring is a one-way analysis, because for each projection pair, the plausibility of their occurrence at a same time was scored. For example, the consistency score for having effective water markets without changing subsidies was -1 which means the levels hinder each other, but it's not impossible that they

occur at the same time. The result is a triangular matrix (see Appendix 2-2 uploaded as Research Data). This matrix was used to calculate additive and multiplicative consistency scores and number of inconsistencies for each scenario. The different indices complement each other and support the selection of the most consistent scenarios, which are neither too excluding nor on the other hand, compromising the major inconsistencies. For instance, the additive consistency index could compromise a major inconsistency between two future projections if the total consistency value is high enough. For example, for a given scenario if there are two -2 (absolutely inconsistent) scores but all other 18 scores are 2 (totally consistent), the additive consistency will be higher than many scenarios without major inconsistencies. In contrast, Multiplicative consistency could be too excluding, since even one major inconsistency leads to total score of zero (Tietje, 2005). A computational model using Python programming language expedited the calculations. The filtering criterion combined additive consistency (> 3**0**) and the number of inconsistencies (< 2) to narrow the number of scenarios down from about 26.8 million initial scenarios to a smaller set of consistent scenarios (one million) which can be used in step 4, diversity analysis. It means all scenario with additive consistency above 30 were selected condition to have no more than one major inconsistency.

Step 4- Diversity Analysis

While 96% of the scenarios were excluded based upon the consistency analysis, the remaining consistent ones needed to be narrowed to a small set of plausible, and distinctive scenarios. For this purpose, the *distance-to-selected* (dts) methodology was adapted and combined with a set of exclusive criteria to select the final scenarios (Tietje, 2005). The most consistent scenario, which is close to the status quo scenario, was used as an "anchor" to find the second scenario. To choose the second scenario a tradeoff needs to be considered between the consistency values and distance value (harmonic mean distance from other selected scenarios). Since the intent of the study was to inform sustainable water governance, we elected to focus on scenarios that exhibit strong coherence (highly consistent) while also adhering, to the extent possible, to sustainability principles (Foley and Wiek, 2014; White *et al.*, 2015). To do so, in each round, we chose scenarios that have the highest distance value from the most consistent scenarios while holding promise for a sustainable future. This process was iterated until there was no scenario with harmonic mean distance greater than 50%, while no unsustainable (i.e. societal collapse) scenarios were included. It means that 50% similarity was set as the maximum permitted similarity between the signature scenarios.

Step 5- Scenario Interpretation

As Scholz and Tietje (2002) claim, the most natural way to interpret the scenarios is through deep discussions about future states of the system. This method is consistent with our approach to transform the scenarios from "operations on numbers to operation on concepts" (Scholz and Tietje, 2002). This method also helps to communicate and validate the scenarios with targeted audiences more effectively. Accordingly, key systemic features of our scenarios were shared with participants who deliberated on them and explained their vision of the Zayandehrud basin in 2040 under each future scenario of the governance regime. The time frame was chosen to be long enough that each scenario gets fully established and short enough that could be imaginable without clashing with fundamental technological changes.

Those discussions were used to evaluate each scenario with the following sustainability concerns:

- Agricultural water demand
- Ecological sustainability
- Agriculture sector development
- Welfare of rural communities
- Food security
- Conflict level

The deliberations produced a storyline for each scenario and those narratives, along with some visualizations, were used to refine participant perceptions of the scenarios.

2.4. Results: Scenario Construction and Selection

The water governance system of Zayandehrud watershed was explored thoroughly using the scenario planning methodology described above. The major irrigation water demand management strategies were identified (Table 1 above) and their dyads were studied to find their key interactions and to analyze this system of systems thoroughly. Furthermore, five plausible and distinct scenarios were constructed and interpreted to address different approaches to irrigation water demand management in the Zayandehrud watershed, 2040.

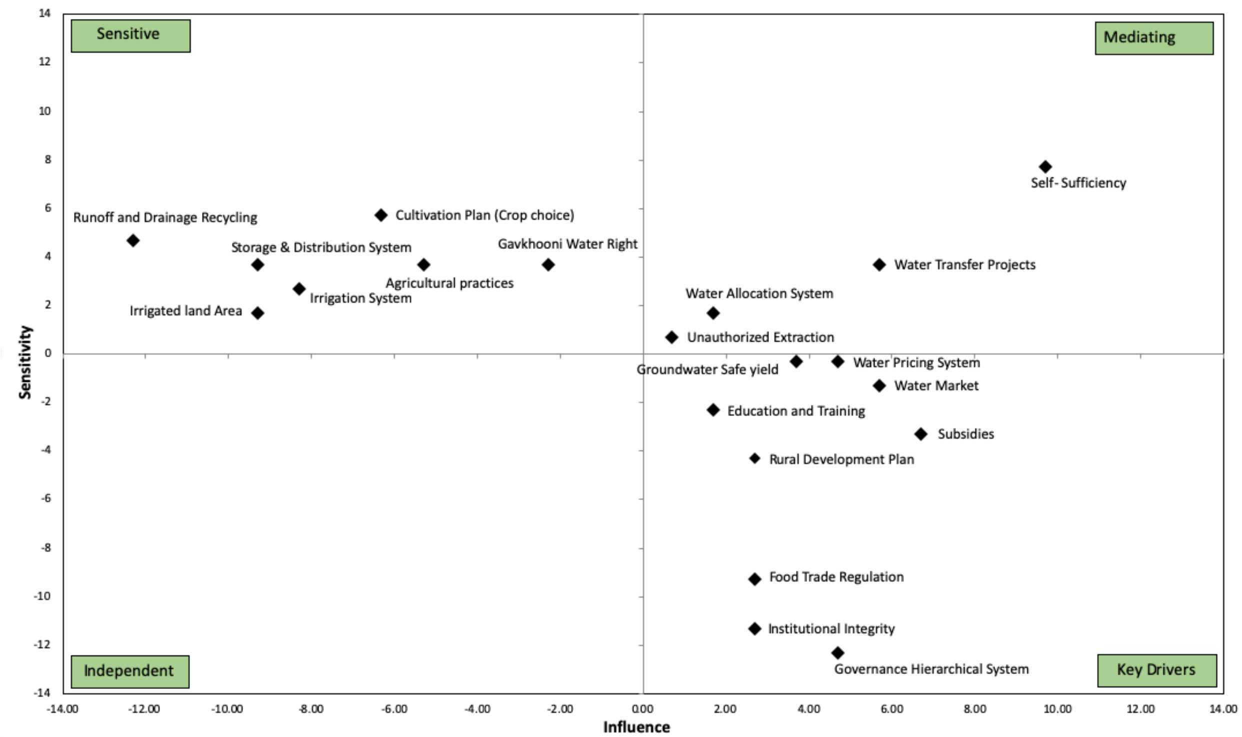

Figure 2-3 Impact analysis. This plot shows the results of the systems analysis with the aggregate level of bi-directional influence resulted from scoring the interaction effects between the variables.

The impact analysis identified institutional reforms and the general approach to trade policy as key drivers of the system since they have high activity and low passivity scores. Therefore, it is expected that any change in governance, its hierarchy and integrity level, and general food trade regulations, would trigger substantial movement in other variables. For instance, the central food trade regulation approach is a key driver for other market variables like subsidies, water markets and the water pricing system, which can also stimulate change in agricultural and ecological variables. As is illustrated in Fig. 3 many market variables are assigned a mediating role, since they can highly influence other variables and be influenced by other variables at same time.

This analysis also shows that the food self-sufficiency approach has the highest activity and passivity score in this system, which implies its critical mediating role. While the food self-sufficiency approach can greatly affect the other water policies, such as market regulation and agriculture practices, it can also get influenced by any change in these policies. On the other hand, the adaptation strategies related to agricultural and efficiency and productivity fall in the third category, sensitive policies, including passive variables which are highly influenced by first and second groups. However, these have the least power to influence other variables. The last category includes buffer variables, which are neither drivers nor influence absorbers, but exert an indirect impact on system outcome variables. The results recognize no buffer variables. This implies a high level of system complexity, which means that none of these mitigatory actions happens in the vacuum without influencing or being influenced by other variables.

Table 2-2 Variable-Future Projection Alignment. The configuration of future projections for each variable across the five scenarios. The selected variables are referred in section 2 (case study context) in italic font.

Variables	S1: Status Quo	S2: Free market	S3: Reformed Top-Down	S4: Local Power	S5: Rural Development
Food Trade Regulation	Highly regulated in favor of domestic production	Regulation-free	Highly regulated in favor of domestic production	Regulation-Free	Regulated based on Water Productivity
Water Market	Not Available	Available	Not Available	Not Available	Available
Water Pricing	Unmodified	Modified	Unmodified	Unmodified	Modified
Subsidies	Highly Subsidized	No Subsidy	Subsidized purposefully	No subsidy	Subsidized purposefully
Water Allocation	Government discretion	Traditional Water Rights	Government discretion	Traditional water rights	Modified
Unauthorized Extraction	Not enforced	Not Enforced	Highly regulated and enforced	Not enforced	Highly regulated and enforced
Irrigated Land Area	Unrestricted	Unrestricted	Restricted	Unrestricted	Restricted
Cultivation Plan	Individual choice	Individual Choice	Comprehensive Plan	Locally Collective	Comprehensive Plan
Runoff and Drainage Recycling	No reuse	Recycled	Recycled	No Reuse	No Reuse
Water Transfer Projects	Pursued	Unpursued	Pursued	Unpursued	Unpursued
Storage & Distribution System	Unchanged	Upgraded	Upgraded	Unchanged	Unchanged
Irrigation System	Inefficient	Efficient	Efficient	Inefficient	Inefficient
Groundwater Safe Yield	Unpursued	Unpursued	Pursued	Pursued	Pursued
Agricultural Practice	Traditional	Industrialized	Industrialized	Traditional	Improved Traditional
Gavkhooni Water Right	Not Allocated	Allocated	Not Allocated	Not Allocated	Allocated
Education and Training	Knowledge Push	Traditional Knowledge	Knowledge Push	Traditional Knowledge	collaborative
Rural Development Plan	Basic Needs	No plan	Basic Needs	No Plan	Alternative Income
Institutional Integrity	Fragmented	Fragmented	Integrated	Fragmented	Integrated
Governance Hierarchical System	Top-down	Top-down	Top-down	Local	Collaborative
Food Self- Sufficiency	Principle Guideline	Not Pursued	Principle Guideline	Not Pursued	Not Pursued

2.4.1. Selected Scenarios

Five consistent, systematically different scenarios were selected out of approximately 27 million scenarios (algorithm generated) by following the five-step filtering procedure explained in section 3. A summary of the selected scenarios' configuration of future projections is offered in Table 2, below. The consistency and diversity scores for each selected scenario (shown in Table 3) show no obstructive relations (no -2 score), additive scores above 45, and multiplicative consistencies greater than 1.5^{E+13}. This provides confidence about the plausibility of the scenarios. The high Distance-to-Selected (dts) values (≥60) and their low deviation (<6) scores satisfy a high diversity level between the final scenarios (Kuzdas and Wiek, 2014).

Table 2-3 Consistency and diversity analyses. Statistical results are reported for each scenario with four different tests for consistency and diversity, as measured by distance-to-selected. Note: Major inconsistencies (scores of -2) were filtered out during the scenario construction process, thus all remaining scenarios have zero major inconsistencies

	SCENARIO #1 STATUS QUO	SCENARIO #2 FREE MARKET	SCENARIO #3 REFORMED TOP- DOWN	SCENARIO #4 LOCAL POWER	SCENARIO #5 RURAL DEVELOPMENT
ADDITIVE CONSISTENCY	76	53	66	48	67
MULTIPLICATIVE CONSISTENCY	3.2E+21	9.0E+16	1.7E+18	1.6E+13	8.3E+18
NUMBER OF MAJOR INCONSISTENCIES	0	0	0	0	0
DISTANCE-TO-SELECTED (%)	61	66	67	60	75

2.4.2. Scenario Interpretation

The key systemic features of each scenario are depicted in Fig. 4a – Fig. 4e. These diagrams along with deliberation and participatory research methods informed the following interpretations and insights about each scenario and the alternative approaches to ameliorating the ongoing water crisis in Zayandehrud watershed.

Scenario #1- Status quo continues.

This scenario carries forward the dominant governance system since the 1970s into the year 2040 (Fig. 4a). The central objective for Iranian agricultural water management in this scenario is to safeguard food security by achieving self-sufficiency and decreasing the nation's dependence on imported foods, specifically staple crops. The key challenge to overcome is water shortage, and that is addressed through supply augmentation via large-scale technical developments with a focus on building new infrastructure, such as dams and water transfer tunnels. This scenario is characterized by a top-down governance system where agricultural water policies are made at the national level, while regional and local water managers, who mediate interactions between the farmers and policymakers, have limited decision-making authority.

Farmers and other residents have minimum participation in national policy decisions, which makes them highly dependent on government decisions and affords them little recourse.

This top-down approach does not yield coordinated decision-making across different levels of governance to support comprehensive mitigation strategies. For instance, the water management authority remains fragmented based on provincial political borders, rather than watershed borders. This exacerbates competition over limited resources among different stakeholders. There are legally documented water rights, which have been followed for several centuries, that guide the distribution of water among farmers in Zayandehrud watershed. Currently, decisions about which farmers get water are made in an unclear and unfair process in which residential and industry water users have the highest priority, while the remaining water is allocated to the agricultural sector based on government discretion. In other words, the current water allocation system doesn't comply with the traditional documented water sharing system which specifies the water apportioned each month to each of the 33 districts (boluks) along the river based on their water rights (Molle and Mamanpoush, 2012). As a result, many downstream rightsholders receive almost no water. Moreover, the Gavkhooni wetland water rights are de-prioritized in this scenario. Water shortages are addressed (where possible) through overexploitation of nonrenewable groundwater resources (Mahdavinia and Mokhtar, 2018). Safe yield for the watershed in terms of meeting social and ecological water demand is not achieved.

To achieve food self-sufficiency, market manipulation tools are extensively used to facilitate domestic production and national security. For instance, trading of food products, especially staple crops, is highly regulated and strictly controlled by the central government. Therefore, only the deficit (gap between demand and domestic production) is imported, which is done directly by government- or semi-public companies. The water pricing system is unchanged and calculates the surface water price as 1-3% of total production value, while groundwater is free of charge, with farmers only paying for the capital to drill wells and operate pumps. Market interventions that affect the final sale price of domestic products are not competitive with global prices. So, to support domestic production and control food price inflation, the government compensates part of the production costs in the form of direct and indirect subsidies to farmers and customers. Restrictions on unauthorized water extraction are not prohibitive enough to dissuade farmers, and the administration process is ineffective and often corrupted, meaning that farmers create illegal wells.

Figure 4a. Scenario #1- Status quo continues

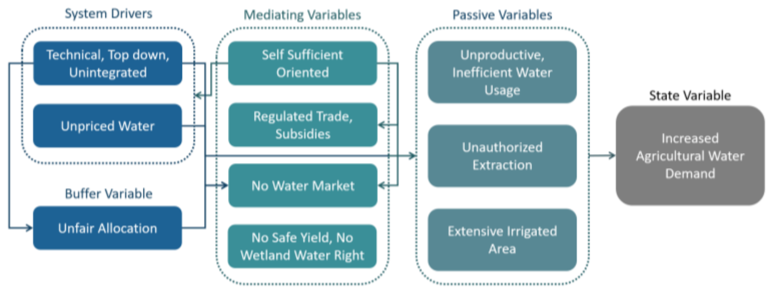

Figure 4b. Scenario #2- Iranian capitalism reins

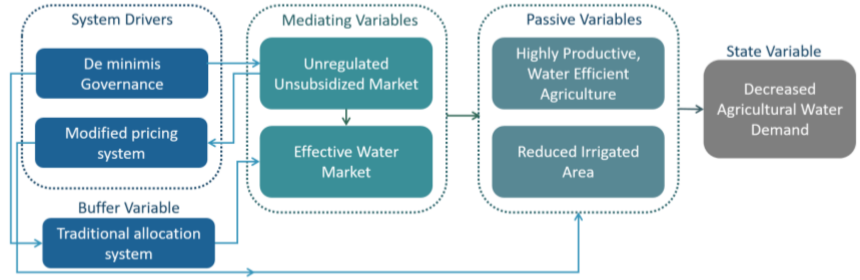

Figure 4c. Scenario #3- Planned agricultural economy

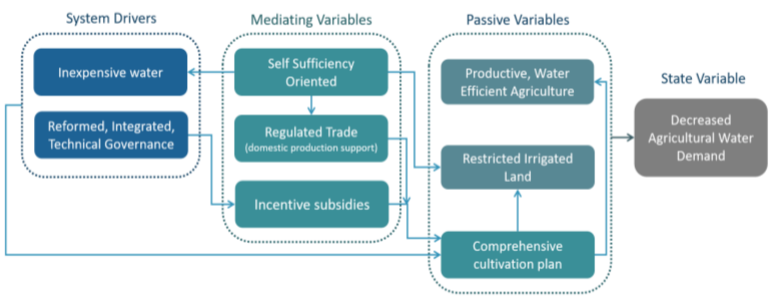

Figure 4d. Scenario#4- Interpreting traditions to shape the future

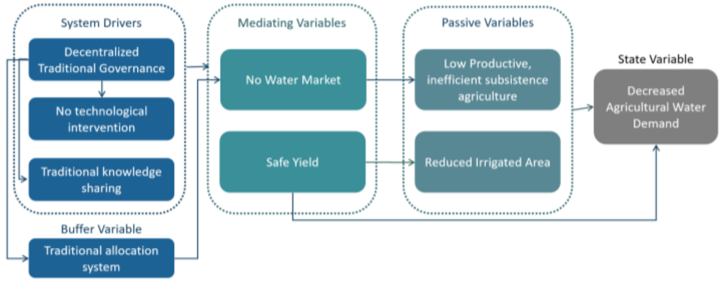

Figure 4e. Scenario #5- Collaborative rural development

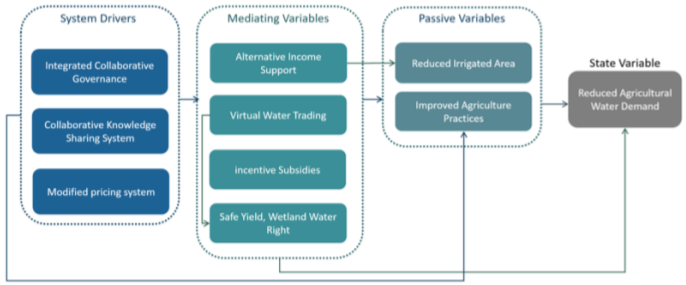

Figure 2-4 a - e. System diagrams for each scenario (1 to 5). This series of figures show the interactions between the future projections of each variable based upon the impact analysis for drivers, mediating, passive and state variables for every scenario.

Scenario #2- Iranian capitalism reigns

This scenario carries forward many economists' notions of free-market governance (Fig. 4b). The extensive market manipulation during the last decades is dissolved and deregulated markets correct for the value of limited resources like water (Chong and Sunding, 2006; Rosegrant, Ringler and Zhu, 2009; Madani, 2014). The core concept is that both the water and agricultural sector exist within deregulated conditions in which market equilibrium redefines the water governance system. The water markets yielded positive outcomes in both ecological and socio-economic systems. The primary objective of this scenario is to provide a *de minimis* regulatory framework in which water creates the greatest economic value (Debaere, 2014). This scenario is not plausible without effective foreign diplomacy efforts that provide stable and constructive economic relationships between Iran and the vast majority of foreign nations.

Water governance is still top-down, but with the central government's role and responsibilities curtailed to mediating market conditions, monitoring, and facilitating trade processes. Subsequently, the central government works to remove regulations that hinder international and inter-watershed food trading to create open markets where individuals and firms seek maximum economic profits. Government regulations have no impact on farm-level decisions like crop choice, irrigation methods, total cultivated area and education.

All available water rights (that were traditionally allocated) are traded among farmers, industries and even government entities throughout the watershed. This water allocation system does not afford water rights to critical ecosystems like the Gavkhooni wetland. The volumetric value of allocated water is calculated and priced by water markets with high accuracy. The water price covers all human-related costs such as supply, distribution and maintenance. Yet, all forms of direct subsidies, including energy, agricultural equipment and other supplies like seed and fertilizer as well as indirect subsidies like specific food subsidies are totally removed.

Scenario #3- Planned agricultural economy

This scenario resonated with many participants and entailed reformed and integrated national planning efforts (Fig. 4c). Water efficiency and agricultural and economic productivity are increased through integrated planning and strategic policies. Such a national integrated plan does not "solve" the ongoing water crisis, but rather assures food self-sufficiency and economic growth in the agricultural sector. This scenario responds to the current lack of integration and shared objectives, which do not encourage adaptive agricultural water management strategies.

This scenario focuses on achieving food self-sufficiency and safeguarding people (especially farmers) from water scarcity through an integrated approach and comprehensive plan (at the national level). The planning efforts aim to develop a productive and water-efficient agricultural sector. To fulfill this goal, a comprehensive cultivation plan is prepared dynamically, based on soil properties, available water, and food demands. To execute this plan, incentive-based policies like directed subsidies are used for energy, equipment, seeds and fertilizer. Water allocation is based on this comprehensive plan rather than traditional water rights. Similarly, incentives are used to encourage the use of efficient irrigation technologies and improved practices. In addition to a traditional education system, the governing system uses a "knowledge push" approach to inform farmers about adaptive strategies.

Development of large infrastructure is still followed intensively, including new tunnel projects, lining and covering channels and reservoirs to prevent extra evaporation, and recycling the marginal quality effluent to be used as irrigation water. On the other hand, the extent of cultivated land is controlled and water resources are allocated to ensure safe yield of groundwater. However, wetland water rights are not a priority in this allocation system.

Scenario#4- Interpreting traditions to shape the future

The periodic cycles of drought in Iran no longer create a crisis among farmers, rather water management is understood as part of daily life by rural farmers. Darius the Great's famous prayer from 500 BC, that wished for the Persian Empire to be preserved from enemies, drought and lies offers inspiration and a backdrop for the cultural significance of water. People rediscover the important role of water in human flourishing in this region by returning to those origin stories. This water governance system includes every citizen from 'kings to kids' and employs all traditional sociocultural tools to establish a fair, legitimate, productive and, most importantly, sustainable governance system. This unique water governance system that gave rise to the great civilization of Persia and survived for thousands of years was abandoned by technocrats during the 19th and early 20th century. This scenario expresses an idea for how a decentralized, pluralistic governance system with minimum top-down intervention might positively affect agricultural water management (Fig. 4d). The scenario revives a traditional water governance framework by acknowledging water resource ownerships and allowing the owners to govern the waterways that preserves their long-term profits and celebrates farming as a way of life.

Subsequently, all kinds of subsidies and regulations are rescinded, trade restrictions are removed, and water is allocated per traditional water rights, while the water pricing system remains intact. New water transfer tunnel projects are canceled, and once again qanats (traditional underground tunnels) become the dominant groundwater distribution system. The governing structure is held by the collective local villagers, farmers, and water right holders. There is no official mediating or watershed governing system at the federal level, rather there is an extensive network of local research projects that are designed to share best practices and offer demonstration sites for farmers in other regions. Accordingly, the education system that was once limited to intra- family/clan knowledge transfer is expanded to knowledge sharing between local communities.

Scenario #5- Collaborative rural development

The final scenario supports some interviewees' idea that the most effective and least harmful strategy to manage agricultural water demand in this watershed is to downsize the agriculture sector by supporting alternative, less water-intensive businesses in rural communities (Fig. 4e). Given the highly variable rainfall amounts related to climate change and resulting water crisis, continued investments in the agricultural sector are neither economically nor environmentally defensible. Participants suggested downsizing agriculture from 20% of the labor force and 11% of GDP. However, this is not possible without a strategy to transition towards less water-intensive employment. Otherwise, higher unemployment rates (than the current 12% unemployment rates) will cause more social distress in the region. The key goal in this scenario is to have flourishing and resilient rural communities with less reliance on income from agriculture.

This goal cannot be fulfilled without a close collaboration between all parties, including the local population, policy and lawmakers as well as academia and NGOs. This scenario requires an integrated effort to foster new economic opportunities by federal and state policy-makers, and NGOs to support the robust local governing system. The guiding vision for the collaboration and new industries would be to achieve sustainable development without compromising water and food security. Yet, it must be noted that national food self-sufficiency is not a central tenet of this plan.

Traditional water allocation is modified to disincentivize the cultivation of marginal lands and greater value is placed on cultural uses for water, as well as ecological water demand. Irrigation water is measured and priced properly to cover all supply and maintenance fees. The "life giving" force of the river is reframed as a cultural attraction with daytime river cruises and restaurants competing for "river front" property in the heart of Isfahan. Wetland water rights are secured by an allocation system and appreciation for the sightseeing tours to see exotic birds that provide new jobs. Water markets are effective and trade regulations support more positive virtual water import. The subsidy option is also available to incentivize this transition from farming to rural industries.

Despite the regulations and policies at the local level, there is a democratic, inclusive and legitimate water governing system, which is run by farmers' representatives and in coordination with businesses that benefit directly and indirectly from the river. An elected board of representatives facilitates a collective decision-making process, as well as administers the rules and regulations. This elected board cooperates closely with the court system to handle potential disputes. Elected boards across the regional engage in semi-annual conferences to facilitate knowledge sharing and develop collaborative projects that span state boundaries.

2.5. Discussion

Scenarios presented here are intended to move decision-makers beyond a binary selection of good or bad futures, many water-centric scenarios have fallen victim to this duality, presenting two (or maybe three) options, e.g. build the dam or not. In contrast, the future, like the present, is rarely so simple. This study aims to "open up" those constrained decisions and place them within a broader decision-making governance context that systematically connects the dots between economic, technological, societal and ecological forces. To isolate any single adaptation choice and hold the rest of the system constant ignores the interrelations within socio-eco-techno systems (SETS). To be clear, there are quite a few alternative pathways (and outcomes) for Iran and many other nations facing serious water resource management challenges. By exploring several alternatives to water governance, this research shows that there are far more choices than simply building a tunnel or not, and such a narrow framing of alternatives has implications far beyond the mere presence or absence of a piece of infrastructure. Rather, there are entirely different governance arrangements that can support socio-technological changes, and that combination has significant implications for the economic and ecological well-being of the region.

Our research shows that scenario 1 (*Status quo continues*) is the most consistent failure scenario for Zayandehrud watershed. Food self-sufficiency is politicized and buttressed as a necessity of independence and geopolitical stability (Madani, 2014). Such stability will be supported by policies and regulations like protectionism that will decrease food trading, development of canals for water distribution and expanding irrigated land area, underpriced irrigation water and indiscriminative subsidies (Molle and Mamanpoush, 2012). By 2040, it is plausible that socio-economic sustainability of the Zayandehrud watershed will be degraded, while neither food security nor water security will be achieved (Heslot, 2018).

If food self-sufficiency remains the central guiding policy in Iran, then *Planned Agriculture* (Scenario #3) would offer a means to secure production of essential crops without compromising the water security of the watershed. However, absolute food self-sufficiency is not a plausible plan given current and future projections of water availability (Heslot, 2018; Mesgaran and Azadi, 2018). To achieve this goal, *Planned Agriculture* pursues new heavy infrastructure projects to augment the irrigation water supply. Yet, irrigation efficiency and water productivity are improved in the *Planned Agriculture* scenario through an integrated and dynamic national planning effort. This comprehensive plan dictates who gets water and how much; and, what should be cultivated and how much. This plan will be supported by incentive policies like subsidies and pre-purchase plans. The *Planned Agriculture* scenario portrays an extensive and costly governance scheme which is greatly dependent on supportive monetary policies.

In contrast to this extensive top-down governance system, scenario 2 (*Capitalism Reigns*) offers a minimalistic governance system, in which water markets will determine the distribution of irrigation water. Food self-sufficiency is no longer a central principle in the *Capitalism Reigns* scenario, and a free trade environment facilitates the shift of water rights from small traditional farms to consolidated highly productive ones. This means water will go where it yields the greatest value (Bekchanov, Bhaduri and Ringler, 2015). Debaere et.al (2014) empirically demonstrated the positive impact of a cap and trade approach that was facilitated by a water market in seven different watersheds. For instance, total well pumping from the Edwards aquifer in Texas has generally decreased since 1990, while the population of the region increased by nearly 50% (Debaere *et al.*, 2014). Subsequently, it is expected that relatively lower world prices for certain commodity crops and small or even negative marginal profit will discourage new entrants to farming, and existing small farmers may shift their investments from farming to other businesses (Nazemi *et al.*, 2018). Therefore, the demand for irrigation water will be slightly reduced and is replaced by industrial and/or residential demand. Since traditional water rights are acknowledged in the *Capitalism Reigns* scenario, it is expected that the Gavkhooni wetland ecological water right will be recognized again.

The *Status Quo* stands in stark contrast to the traditional water allocation system in which a fair distribution of water was guaranteed (scenario 4). *Interpreting Traditions* scenario offers a return to traditional cultural practices of community-based traditions that celebrate and place great value on water (Yazdanpanah, Thompson, *et al.*, 2013). In this scenario, as in the *Capitalism Reins* scenario, ecological water rights (Gavkhooni water rights) have been incorporated into the water allocation system. The dominance of traditional water distribution networks (qanats) guarantees safe yield[3] for groundwater extraction (Molle and Mamanpoush, 2012). This is compatible with traditional, family-based subsistence farming practices. Therefore, it is expected that domestic food production would decrease because it cannot compete with global prices, which means the farmer income would also decline. However, the collective and fair governance system, which is based on great respect for a community's values and traditions (i.e. the respect for nature and contentment with simple country life), can provide a high degree of stability and ecological and socio-economic sustainability (Yazdanpanah, Hayati, *et al.*, 2013).

[3]The maximum amount of water that can be withdrawn, yet still the supply is maintained and unimpaired.

Collaborative Rural Development (scenario#5) supports the idea of reducing the agricultural activities in Zayandehrud watershed through a collaborative rural development plan to support farmers' career shift from farming to less water-intensive businesses, which is an approach advocated by Heslot (2018). Such a scenario plausibly will allow rural communities to flourish and foster resilience against changing climatic and economic conditions through building local capacity for development (Louis, Nazemi and Remer Technology, 2017). Rug weaving is an ancient art and important industry in this watershed, especially in rural areas, and it might well be expected that by 2040, rug weaving workshops and other local crafts could be thriving. Reducing irrigation water consumption, will increase the level of water in the river, which is essential for absorbing eco-tourism to this region (Abyareh, 2009).

With respect to ecological sustainability, *Collaborative Rural Development* is the only scenario which acknowledges the Gavkhooni wetland water rights in the allocation system. The *Capitalism Reigns* scenario may meet the wetland water rights intermittently because of shrinking of the agricultural sector, although this is not guaranteed. Nikoui et al. (2012), argue that incentivizing farmers to adopt water efficiency measures would help to save water to preserve the Gavkhouni wetland, although scenario 3 of this research proves that increasing the water efficiency and productivity does not necessarily secure the sustainability of wetlands, since the water demand in this watershed is always greater than the supply. Furthermore, increasing productivity and efficiency will incentivize farmers to put more land under cultivation (Nikouei, Zibaei and Ward, 2012). Safe yield, in which annual groundwater withdrawals do not exceed the natural recharge rate, is also considered a central governance principle in scenarios 3,4, and 5. This relieves stress on the aquifers, but does not fully resolve the tension between agricultural water use and the ecological requirements of healthy wetlands.

Even though each selected scenario represents a systematically different governance system, four of them (all except the *status quo* scenario) contributes positively to managing agriculture water demand. However, the watershed experiences different socio-economic conditions under each governance scenario. For example, it is expected that in the absence of supportive plans and limited capacity for job creation, the *Capitalism Reigns* scenario, which is grounded on free market principles, will cause the most intensive transition for farmers who will lose their jobs (Mesgaran and Azadi, 2018). It may cause a long lag phase before efficient and productive farms can emerge. This also can worsen water disputes and public dissatisfaction, which are already a big issue in the watershed (Kuzdas *et al.*, 2016).

The scenario, *Collaborative rural development* shares similar trade regulations with the *Capitalism Reigns* scenario; the difference is that inexpensive water, in addition to robust local governance, facilitates the adaptation process and dampens the shock of market change. When compared to the *Capitalism Reigns* scenario, *Collaborative rural development*, causes a smoother transition and ends in more resilient rural communities (Yazdanpanah, Thompson, *et al.*, 2013). Ricart et. al (2019) studies ten successful cases, which use different tools to promote stakeholder engagement. They conclude that engagement of stakeholders in irrigation water governance will reduce tension between stakeholders and help with easier conflict resolution in these communities (Ricart *et al.*, 2019). The *Planned Agriculture* scenario, causes the least shock to the agricultural sector. It is anticipated that AWD reduction is less noticeable than the other three scenarios while domestic food production is higher than the others. Although this scenario includes many supportive plans for farmers, it is projected that it will not reduce water disputes, since it does not recognize traditional water rights (Molle, Hoogesteger and Mamanpoush, 2008). Moreover, dictating the national cultivation plan makes the governance system responsible for most risks and may generate greater protests if farmers are not satisfied with the outcome. More accurate evaluation of the transition phase and its impact on different stakeholders requires a comprehensive study, which was beyond the scope of this paper.

To deal with the challenging trade-off between the comprehensiveness (to include all important variables and their interconnections) and coherence of governance scenarios (to avoid too much complexity), the scope of the current study focused on irrigation water demand and rural communities. Thus, the impacts of selected scenarios on industry or residential water security was not assessed. Future studies can focus on urban water demand and/or industrial water demand governance scenarios and a holistic study to develop signature scenarios which support the overall watershed sustainability. Moreover, this study's model was kept as qualitative and conceptual as possible, which helped to include many governance features that cannot be integrated to computational models. Future researches can acquire relevant data on water resource availability, distribution and use by sector, and develop a computational model to reassess the findings of this study in a quantitative framework.

2.6. Conclusion

Formative scenarios offer a means to explore the interplay between socio-economic, technical and ecological forces. This approach moves away from assessing discrete interventions and engages with the complex geo-political and societal context of regional water resources management. This study walked through a methodical approach for constructing scenarios in a systematic process and then evaluated a set of distinct, consistent and normative governance alternatives for agricultural water governance. Such a technique can help decision-makers consider a greater range of choices and allow them to take into account more alternatives without applying strict boundaries to the analysis. Indeed, the flexible participatory approach of this study also helped to develop scenarios that represent the watershed's diverse stakeholders and their different and conflicting interests and values. It also provided these stakeholders with a great opportunity to communicate their concerns with each other, which can induce and facilitate collective informed decision-making in the Zayandehrud watershed and other regions in search of approaches to sustainable water resources management. Each scenario also reflects a combination of mitigation policies and actions from the domains of supply, delivery, uses, outflow and cross-cutting aspects to fully account for the system's features. The scenarios portrayed above are not the blue-print for sustainable water resource management. Rather they offer critical reflection upon a diversity of alternatives. It remains to be seen if key decision-makers in Iran and other water constrained regions move toward sustainable water resource management. This research does not portend to know what will happen in the future, rather our intention was to embrace uncertainty and complexity and explore alternative pathways and outcomes.

Acknowledgement

The authors want to thank the participants, who through they will remain anonymous, were instrumental in the completion of this research.

Appendices

Appendix 2-1- Impact Matrix

	Food Trade Regulation	Water Market	Water Pricing System	Subsidies	Water Allocation System	Unauthorized Extraction	Irrigated land Area	Cultivation Plan (Crop choice)	Runoff and Drainage Recycling	Water Transfer Projects	Storage & Distribution System	Irrigation System	Groundwater Safe yield	Agricultural practices	Gavkhooni Water Right	Education and Training	Rural Development Plan	Institutional Integrity	Governance Hierarchical System	Self- Sufficiency	Activity	Normalized Activity
Food Trade Regulation	0	1	2	2	1	1	2	1	1	2	1	1	1	1	1	1	1	0	0	2	**22**	**3**
Water Market	1	0	2	1	2	2	1	2	2	2	2	1	1	2	1	1	0	1	0	1	**25**	**6**
Water Pricing System	0	2	0	1	1	2	2	2	2	1	2	2	1	2	1	1	0	0	0	2	**24**	**5**
Subsidies	0	2	2	0	1	2	2	2	2	1	2	2	1	2	1	1	2	0	0	1	**26**	**7**
Water Allocation System	0	2	2	0	0	2	2	1	1	1	1	1	1	1	2	0	1	1	1	1	**21**	**2**
Unauthorized Extraction	0	2	1	0	2	0	2	1	2	1	1	2	2	1	2	1	0	0	0	0	**20**	**1**
Irrigated land Area	1	0	0	0	0	0	0	1	0	1	1	0	1	1	2	0	1	0	0	2	**11**	**-8**
Cultivation Plan (Crop choice)	0	0	0	0	0	1	2	0	0	0	0	0	1	2	1	2	0	0	2	2	**13**	**-6**
Runoff and Drainage Recycling	0	0	0	0	0	1	0	0	0	1	2	1	0	1	0	0	0	0	0	1	**7**	**-12**
Water Transfer Projects	0	0	1	2	2	2	2	2	2	0	1	1	1	1	2	1	1	2	0	2	**25**	**6**
Storage & Distribution System	0	1	0	0	1	1	0	0	2	1	0	1	1	1	0	0	0	0	0	1	**10**	**-9**
Irrigation System	0	0	0	0	0	0	1	1	1	1	1	0	0	1	0	1	1	0	0	2	**10**	**-9**
Groundwater Safe yield	1	1	1	1	2	2	1	1	1	1	1	1	0	1	2	2	1	1	0	2	**23**	**4**
Agricultural practices	0	1	1	0	0	0	0	2	2	1	2	2	1	0	0	0	0	0	0	2	**14**	**-5**
Gavkhooni Water Right	1	1	1	0	2	1	1	1	1	1	1	1	1	1	0	0	1	0	0	2	**17**	**-2**
Education and Training	0	1	0	1	0	2	1	2	2	1	2	2	1	2	1	0	1	0	1	1	**21**	**2**
Rural Development Plan	1	1	1	2	1	2	0	1	1	2	1	1	1	2	1	2	0	0	1	1	**22**	**3**
Institutional Integrity	2	1	2	2	2	2	1	1	1	1	0	1	1	0	2	1	2	0	0	0	**22**	**3**
Governance Hierarchical System	1	1	1	2	2	1	0	2	0	2	1	0	1	0	2	2	2	2	0	2	**24**	**5**
Self- Sufficiency	2	1	2	2	2	1	2	2	1	2	1	1	2	1	2	1	1	1	2	0	**29**	**10**
Passivity	**10**	**18**	**19**	**16**	**21**	**25**	**22**	**25**	**24**	**23**	**23**	**21**	**19**	**23**	**23**	**17**	**15**	**8**	**7**	**27**		
Normalized Passivity	**-9**	**-1**	**0**	**-3**	**2**	**6**	**3**	**6**	**5**	**4**	**4**	**2**	**0**	**4**	**4**	**-2**	**-4**	**-11**	**-12**	**8**		

Appendix 2-2- Consistency Matrix

			1 Trading regulation			2 Water market		3 Water Pricing System		4 Subsidies			5 Water Allocation System			6 Unauthorized extraction		7 Irrigated land area regulation		8 Land use planning (crop choice)			9 Runoff and drainage recycling		10 Water Transfer projects	
			No regulation	Virtual water	Domestic production	Effective	Not effective	Modified	Unmodified	Subsidized	Purposeful	Not subsidized	Government discretion	Traditional water rights	Modified water rights	Regulated and enforced	Unregulated	Restricted	Not restricted	comprehensive	collective	Individual	Pursued	Unpursued	Pursued	Unpursued
2	Water market	Effective	1	1	0																					
		Not effective	0	0	1																					
3	Water Pricing System	Modified	0	2	0	2	-2																			
		Unmodified	0	0	1	-2	2																			
4	Subsidies	Subsidized	0	-2	2	-1	1	-1	1																	
		Purposeful	1	1	1	1	0	1	-1																	
		Not subsidized	2	2	-2	1	0	1	-1																	
5	Water Allocation System	Government discretion	0	0	1	-2	2	-2	0	0	0	0														
		Traditional water rights	0	0	0	1	-1	2	0	0	0	0														
		Modified water rights	0	0	0	1	-1	2	0	0	0	0														
6	Unauthorized extraction	Regulated and enforced	0	1	0	0	0	0	0	0	0	0	0	0	0											
		Unregulated	0	-1	0	-1	1	0	0	0	0	0	0	0	0											
7	Irrigated land area regulation	Restricted	1	0	0	1	0	0	0	0	1	0	1	0	0	2	-1									
		Not restricted	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0									
8	Land use planning (crop choice)	comprehensive	-2	1	2	0	0	0	0	0	1	0	1	0	0	0	0	1	-1							
		collective	1	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0							
		Individual	0	-1	-1	0	0	0	0	0	0	0	0	1	1	0	0	0	0							
9	Runoff and drainage recycling	Pursued	1	0	0	1	0	1	0	-2	1	2	0	0	0	1	-1	0	0	0	0	0				
		Unpursued	-1	0	0	0	1	0	1	1	0	-1	0	0	0	0	0	0	0	0	0	0				
10	Water Transfer projects	Pursued	-1	-2	1	0	1	0	0	0	0	0	0	0	0	0	0	-1	1	0	0	0	-1	1		
		Unpursued	1	2	-1	0	0	0	0	0	0	0	0	0	0	0	0	-1	1	0	0	0	-1	-1		
11	Storage & distribution system	Modified	0	0	0	1	0	1	-1	0	1	1	0	0	0	1	-1	0	0	0	0	0	-1	-1	0	1
		Unchanged	0	0	0	0	1	-1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-1	1	1	0

11 Storage & distribution system		12 Efficient Irrigation Technologies		13 Groundwater Safe yield		14 Agricultural practices			15 Gavkhooni Wetland water right		16 Education and Training			17 Rural Development Plan			18 Institutional integrity		19 Governance hierarchical system			20 Food security	
Modified	Unchanged	Efficient	inefficient	Principle	not a principle	Industrialized	Modified traditional	Traditional	Allocated	Unallocated	Collaborative	Knowledge push	Traditional	Alternative income	only basic need	No support	Integrated	Unintegrated	Top-down	Collaborative	Local	Self-sufficiency	No concern

12	Efficient Irrigation Technologies	Efficient	0	1	0	1	0	1	-1	-1	2	1	0	0	0	1	-1	1	-1	0	0	0	0	0	-1	1	1	0																				
		inefficient	0	-1	0	0	1	-1	1	2	0	-1	0	0	0	0	0	-1	1	0	0	0	0	0	1	-1	0	1																				
13	Groundwater Safe yield	Principle	1	1	-1	0	0	1	0	0	0	0	0	0	0	1	-1	0	0	1	1	0	1	0	-1	1	0	0	0	0																		
		not a principle	-1	-1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	-1	0	0	0	0																		
14	Agricultural practices	Industrialized	0	1	0	1	0	1	0	0	0	0	0	0	0	1	-1	1	0	1	0	0	1	0	-1	1	1	-1	1	-1	1	0																
		Modified traditional	0	1	0	0	0	0	0	0	0	0	0	0	0	1	-1	0	0	0	1	0	1	0	-1	1	1	-1	1	0	1	-1																
		Traditional	0	-1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	1	-1	-1	1	-1	1	0	1																
15	Gavkhooni Wetland water right	Allocated	1	1	-1	0	0	0	0	0	0	0	0	-1	1	1	-1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0													
		Unallocated	-1	-1	1	0	0	0	0	0	0	0	0	1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0													
16	Education and Training	Collaborative	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	1	0	1	0	1	0	1	1	0	0	0											
		Knowledge push	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	1	0	1	0	1	0	1	0	0	0	0											
		Traditional	0	-1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	-1	-1	1	0	0											
17	Rural Development Plan	Alternative income	1	1	-2	0	0	1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								
		only basic need	-1	0	1	0	1	-1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								
		No support	1	0	0	0	1	1	-1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								
18	Institutional integrity	Integrated	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0					
		Unintegrated	0	-1	0	0	1	0	0	0	-1	0	0	0	0	0	0	0	1	-1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	-1	0	0					
19	Governance hierarchical system	Top-down	0	1	1	1	0	0	0	2	0	0	1	-1	1	-1	1	2	0	2	-1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	-1			
		Collaborative	0	0	0	1	0	1	-1	-1	2	-1	-1	1	1	1	-1	1	-1	1	1	-1	0	0	0	0	0	0	0	0	1	-1	1	1	-1	1	-1	2	1	-2	1	0	-1	1	-1			
		Local	2	-1	-2	-1	1	-1	1	-2	-2	2	-2	2	1	0	1	-1	1	-2	2	1	-1	1	-1	1	-1	1	-1	1	1	-1	-1	1	2	-1	1	-1	-1	1	-2	-2	2	-1	1			
20	Food security	Self-sufficiency	-2	-2	2	0	0	-1	1	2	1	-1	2	-2	-1	-1	1	-1	1	1	1	0	0	0	2	-2	0	0	0	0	-1	1	2	1	-1	-2	2	0	0	0	-2	1	-2	0	0	2	-1	-2
		No concern	2	2	-2	0	0	1	-1	-2	-1	1	0	1	1	1	-1	1	-1	-1	-1	1	0	0	-2	2	0	0	0	0	0	0	-1	0	1	2	-1	0	0	0	1	-1	1	0	0	0	1	2

Chapter 3

Modeling Water Market and Food Free-Trade as Instruments for Governance of Agricultural Water Demand in Arid and Semi-Arid Regions

Published in Proceedings of the American Society for Engineering Management 2018 International Annual Conference

Neda Nazemi[a] , Sadegh Eghdami[a], Rider W. Foley[b], Garrick Louis[a]

[a] Engineering Systems and Environment, University of Virginia, VA, US

[b] Engineering and Society, University of Virginia, VA, US

Declarations of interest: None

Abstract

In water-scarce regions, such as the Middle East and North Africa (MENA), the agricultural sector consumes most of the freshwater resources. It makes irrigation water demand management an issue of critical concern, especially since it involves trade-offs between water security and food security. Market features like water markets, trade policies, and land-use subsidies are common tools that policymakers use to manage water demand. Nevertheless, these instruments can lead to water market failures and unsustainable outcomes. Current research tends to study the impact of water markets under different agricultural trade regimes, including protectionism and free trade policies, especially in resource-constrained regions where the trade-offs are stark. This study offers a partial equilibrium economic model to explain the influence of the water market and food trade policies on the agricultural sector and the effects on farmers' welfare and ecological sustainability. The Zayandehrud, a critical watershed in central Iran, was chosen as a case study to test this model. The results portray that an intra-national water market in a closed economy can yield increased utility, though it may not lead to less irrigation water demand. In contrast, free trade conditions coupled with water markets can decrease pressure on water resources, offer more consumer utility, and better conditions in terms of unauthorized extraction. This research could be instructive for sustainable economic development, strategic planning, and optimal resource allocation in semi-arid regions. Future research will explore the framework via a dynamic stochastic general equilibrium (DSGE) model to get clearer and more accurate forecasts.

Keywords

Food Trade Regulation, Partial Equilibrium Models, Middle East, and North Africa (MENA), Zayandehrud Watershed, Agricultural Productivity, Irrigation Efficiency, Water Resource Management

3.1. Introduction

Due to the complexities at the intersection of food security and water security, agricultural water demand management is a major global challenge. It is especially the case for arid and semi-arid regions, like the countries of the Middle East and North Africa (MENA), where water resources are extremely limited and in decline due to factors like climate change and rapid population growth. Currently, over 85% of available fresh water in this region is being used for crop irrigation, yet many nations cannot entirely satisfy the food requirements of their population (Bucknall, 2007). This condition puts extra pressure on both renewable and non-renewable water resources, i.e., surface and deep groundwater, which results in the overexploitation of water resources in most MENA countries. Moreover, declining water tables have led to high concentrations of contaminants such as heavy metals, nitrates, and phosphates in aquifers. Overexploitation of groundwater is also causing land subsidence and soil degradation, negatively affecting farming yield (Madani, 2014). There are many cases where this has caused irreversible damage to ecological and socio-economic sustainability.

The village of Ashan is quite emblematic of many arid regions in Persia and the MENA region, more broadly. The dire consequences of groundwater overexploitation are obviously observable in the dry and empty *qanats,* ancient hand-dug underground tunnels that distribute water. For centuries qanats conveyed groundwater from mountainous to low-lying arid regions like Ashan. For hundreds of years, a single qanat network was used to provide water to this small village's residents, farms, and orchards. However, contemporary diesel-electric pumps allowed farmers to extract groundwater which led them to convert arid lands to agriculture in upstream areas, which drained the water supply that fed the qanats. That created the pressure that led to many farmers digging unauthorized deeper wells to extract groundwater (Yazdanpanah, Thompson, *et al.*, 2013). Consequently, not only the Ashan qanat network is now totally dried out, but even as the farmers dig deep wells, they barely yield enough water. Consequently, all the farms and livestock are dying, younger residents are leaving for the cities, and those who remain behind mostly rely on small governmental monetary aid (~$10 per month).

It is crucial to investigate alternative water management practices to avoid overexploitation problems. Since irrigation water accounts for the majority of freshwater use in many parts of the world, agricultural demand management is one of the critical intervention points in the system. One promising intervention is the concept of the *water market*. *Water markets* are institutions that facilitate trading water rights in the form of permanent sales or temporary leases, which might motivate water rights holders (primarily farmers) to transfer water rights to economic activities that yield a higher value (Bjornlund, 2003). Water markets could be employed to stimulate food-water trade-offs in compliance with the guiding principles of policymakers.

Debaere et al (2014) empirically demonstrated the positive impact of a cap and trade approach facilitated by a water market in seven different watersheds, four inside the US and three in Australia, Chile, and Mexico. The water markets yielded positive outcomes in both ecological and socio-economic systems (Debaere, 2014). However, previous studies reveal that establishing a successful water market requires various essential prerequisites like geographic connection, proper water allocation, water rights systems, suitable water pricing systems, well-indicated and enforced caps as well as enough social awareness and cultural compatibility (Livingston, 1995; Debaere, 2014; Beruvides Mario, 2015; Nazari, 2016). Therefore, without a deeper understanding of these settings, water markets can add to the complexity, fail or backfire, and worsen the problem.

A second promising intervention is trade policies, which indicate how closed or open economies are to trade water. Food trade policies and regulations are other essential tools utilized extensively by governments to support domestic production and resource management. Two major approaches to food trade regulation include protectionism (closed market) and free-market (minimal regulation). Protectionism tends to restrict food trade to stimulate domestic production toward the ultimate goal of food self-sufficiency and security (Clapp, 2017). Regulating the food trade increases the transaction cost, disturbing supply-demand market dynamics, and pricing adjustments. This school of thought believes that the market's supply-demand relationship will change based on water resource availability (Walton and Seddon, 2008). The food trade regulation systems can significantly affect the performance of a water market. Nazemi, et al. (2018) developed governance scenarios for the Zayandehrud watershed in Iran, one of which incorporated water markets. They perform a wholistic consistency analysis through a participatory approach to ensure the consistency and plausibility of water markets. In such a scenario, establishing a water market along with free trade regulations is projected to decrease irrigation water demand (Nazemi *et al.*, 2020). However, there is a paucity of empirical evidence, nor are there sufficient case studies that involve water markets to validate this theory and, thus, evaluate the impacts on the ecological and socio-economic sustainability in a given watershed.

This gap leads to the question: How will water markets affect the irrigation water demand and overall utility in a watershed under a free trade regulation scenario? Given the state of affairs in the MENA region, trade policies are in flux, and water resources are scarce. This question is of grave importance to the people in the region and for global security and stability. This research explores this question and considers different possible outcomes when trade policy changes between closed markets or a free trade approach. Further, this research paper aims to evaluate outcomes regarding safe water yield, consumer utility, and rule enforcement to maximize the efficacy of water markets.

3.2. Case Study Context

Zayandehrud is a seasonal river located in an arid and semi-arid part of Iran. It extends from the northwest to central Iran and includes a 16000 square miles catchment area called by the same name (Figure 3-1). It provides residential water to 4.5 million citizens in this catchment, in addition to the neighboring cities of Yazd and Kashan. The Zayandehrud also provides irrigation water for over one million farmers (Mohajeri *et al.*, 2016b). Moreover, this watershed is vital to many heavy industries like cement, steel, oil, and petrochemical plants along this river, making this area one of Iran's major industrial hubs. Furthermore, the river passes through Isfahan City, an important tourism hub, and ends in the Gavkhouni, a wetland preserved under the 1971 Ramsar convention. During the past three decades, rapid population growth and frequent and long-lasting drought have endangered this critical river's viability and the Gavkhouni wetland.

Despite severe water scarcity in this region, the agricultural sector still uses over 92% of available water for irrigation for 180,000 ha, which mainly includes small farms with flood irrigation (approximately 90%). The major agricultural products in this area are water-intensive commodities such as wheat, barley, rice, and alfalfa. The water productivity of these products is much less than the global average due to high evaporation rates and inefficient irrigation (Felmeden, 2014). Unauthorized water extraction is prevalent as about half of the wells in this watershed are illegal. Following the government measures to increase

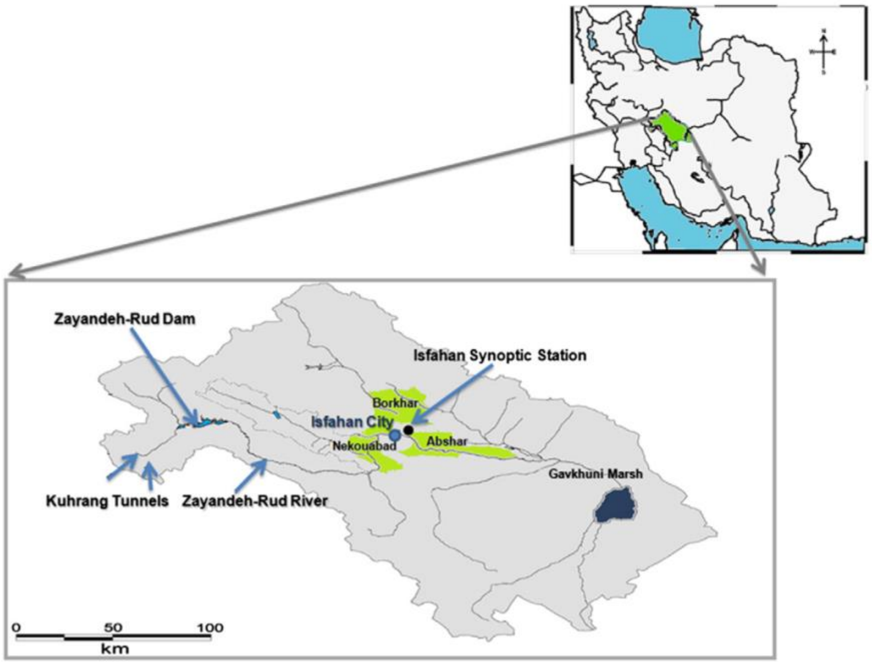

Figure 3-1 Zayandehrud basin location (Gohari *et al.*, 2013)

domestic agricultural production to gain food self-sufficiency, the practice of food trade became highly restricted, especially for staple crops like wheat and barley.

Moreover, there is no volumetric measurement for irrigation water consumption, and it is not priced appropriately. Subsequently, surface water prices are insignificant compared to other production costs, and groundwater price is zero. Moreover, farmers benefit from subsidized energy, fertilizer, pesticides, and seeds to support domestic agricultural production (NationalResearchCouncil, 2005). The government lacks law enforcement capacity in this watershed. This has led to frequent and violent farmer-farmer and farmers-government disputes and protests. The complexity of the Zayandehrud watershed makes it an ideal case study to explore alternative governance settings and market arrangements and thus offer findings for other watersheds in Iran and throughout the MENA region.

3.3. Model Development

Here we present a partial equilibrium economic model which builds upon supply-demand mechanisms to formulate the status quo and water markets under different regimes of food trade regulations Table 3-1 Evaluated scenarios and their settings . The model considers only one representative agricultural commodity produced and consumed in this economy as a proxy for all agricultural production. The heterogeneous supply side comprises two firms (called "farms"). Farm A has high productivity, and farm B has low productivity, which are representatives of diverse farms in the economy. Indeed, these are considered price-taking farms, which avoids any claims or notions that the farms are oligopolistic, which is an unnecessary complication to pricing.

On the demand side, we assume a simplistic, log-linear function depicting the decreasing demand trend regarding price. Equilibrium in the model occurs at the supply intersect, as the aggregated behavior of the firms and the demand function shows that consumption achieves equilibrium. Interpreting the results of the model, we take advantage of assumptions from economics regarding higher consumption as equivalent to higher public welfare for society.

Table 3-1 Evaluated scenarios and their settings

No.	**Scenario Description**
1	Status quo (No water market, closed economy)
2	Water market in closed economy
3	Water market under free trade economy

Scenario 1: Status quo

As discussed previously, currently, there is no free trade nor water market in Iran, generally, or in the Zayandehrud, specifically. Water is allocated to each farm (shown as "s") and incurs no additional cost for the farmers per additional unit demanded. The production function takes a Cobb-Douglass formulation (Cobb and Douglas, 1928), which is widely used in economics to demonstrate the relationship between production inputs and outputs, with one input, water (shown as "X"). Firm A has higher productivity (A_1) while firm B yields lower productivity (A_2). There is a fixed cost of production, which is equal for both farms. The fixed cost is assumed at a level that makes it possible for both farms to produce and exist in the economy. Equations (3-1) and (3-2) portray the profit functions of both farms. The product's price (P^*) is the market price, which is determined by equalizing supply and demand. The model assumes that subsidy (shown as "sb") is allocated to each production unit, which takes the form of a price multiplier.

It is necessary to highlight two points here. First, since the water is provided for free, it is not considered as a cost. Second, regarding water as the only production factor does not mean that no other factors contribute to the production. However, this means that we are focusing on water for modeling. Equation (3-3) depicts the demand function, which is technically the consumption side of the economy. It is a log-linear function that is negatively affected by the price of the product in the market, price elasticity of demand (b) having a negative value. Demand function parameters (a) and (b) are estimated in the later sections of this paper.

$$\pi_1 = P^*(1+sb) * \ y_1 - Cost = A_1 * {w_1}^{\alpha} - F \text{ , } 0 < \alpha \leq 1 \tag{3-1}$$

$$\pi_2 = P^*(1+sb) * y_2 - Cost = A_2 * {w_2}^{\alpha} - F, 0 < \alpha \leq 1 \tag{3-2}$$

$$\ln(Demand) = a - b * \ln(P) \text{ or } Demand = e^{a} * P^{-b} \tag{3-3}$$

Scenario 2: Water market in a closed economy

In this scenario, we add the "water market" to the model. Within the water market framework, each farm can sell (or buy) part of its water rights in the market. It happens through one farm selling part of their water rights (x) to the other one. The transaction cost is assumed to be zero, and the price of the transacted water (pw) would be determined in the market (discussed in the next section). The rule of supply and demand would also realize the product's price in this setting (P^{wm}). Equations (3-4) and (3-5) represent profit functions for farms A and B, respectively. The demand side of the market remains the same as the status quo scenario.

$$\pi_1 = P^{wm} * [A_1 * (s + x)^{\alpha}] - pw * x - F \tag{3-4}$$

$$\pi_2 = P^{wm} * [A_2 * (s - x)^{\alpha}] + pw * x - F \tag{3-5}$$

Scenario 3: Water market in an open economy

Free trade is the new element within this scenario. Free trade requires products to enter the domestic market without any restrictions. It implies that the price in the domestic market would equal the international price for all farm products (p^{int}). It is assumed that the international price is lower than the domestic prices established in the previous scenario (closed economy) mainly because domestic farms' productivity is lower than the international average (National Research Council, 2005). Consequently, domestic producers would remain in the local market. Indeed, the lower productivity will be the main impediment for them to bear the cost and risk of entering the international market and having exports. Equations (3-6) and (3-7) show the profit function of the farms. Demand is assumed to be the same as in the previous scenario.

$$\pi_1 = P^{int} * [A_1 * (s + x)^{\alpha}] - pw * x - F \tag{3-6}$$

$$\pi_2 = P^{int} * [A_2 * (s - x)^{\alpha}] + pw * x - F \tag{3-7}$$

3.4. Results

The results demonstrate that a water market within a closed economy yields positive outcomes for the Zayandehrud watershed in terms of increased public welfare increase that takes the form of increased consumption. Other positive outcomes include increased productivity and water consumption decreases as illegal water extraction is curtailed. The combination of water markets and free trade achieves further public welfare increase; while it does change the water allocation among the productive and unproductive farms, the overall water consumption would decrease further as illegal water extraction is controlled.

The model achieved market equilibrium within each scenario as each agent (farm) optimized its decisions to gain the highest profits. It occurred by deriving the first-order conditions of each firm and intersecting two sides of supply and demand in the market. Each scenario yields different outcomes regarding the production and consumption of the representative agricultural commodity (wheat), and changes occur in its price, water consumption, and public welfare. The modeling outputs from each scenario suggest how the interaction of different forces in an equilibrium sense would pave the way for scenario analysis. There is no dynamic analysis in the model in the sense of capital accumulation or technology investments, as the model is static and tries to explain events by comparative statics.

Scenario 1: Status quo

Since water is free of charge and there is no mechanism (or price incentive) for water transactions, each farm would consume all their water right (s) and yield products that generate an equilibrium between supply and demand. Thus, as portrayed in equations (3-8) and (3-9), the price equilibrium of the market can be found by assuming there are n_1 and n_2 farms like A and B in the market.

$$y_1 = A_1 * s^{\alpha} , y_2 = A_2 * s^{\alpha} \tag{3-8}$$

$$\ln (P^*) = \frac{a - \ln [s^{\alpha} * (n_1 * A_1 + n_2 * A_2)]}{b} \tag{3-9}$$

As an economic assumption, if there is free entry and exit in a market, the model predicts an observation of zero profit on the firm side, which is the definition of subsistent farming. However, there is no free entry to new water rights, limiting the entrance by allocating all renewable water to water right (s) for the farmers ($water\ supply = (n_1 + n_2) * s$). Thus, farms would have positive profit due to the constraints maintained by the water rights. This theoretical analysis ignores the lack of rule enforcement for water rights, which encourages new farmers to extract water illegally and enter the market. It implies that water consumption is higher than the sustainable, safe yield, which puts groundwater and surface water resources at risk. The sustainable, safe yield is defined as the level of extraction that can be replaced annually through precipitation. It is compatible with the observations that this watershed has a large and unknown number of unauthorized operational wells (Molle, Hoogesteger, & Mamanpoush, 2008). Thus, the model describes the phenomenon of unauthorized extraction in the market's current situation in the given context. This model successfully identifies that illegitimate extraction happens as incentives are given to new entrants to take advantage of the not-zero profit conditions on the supply side of agricultural commodities.

Moreover, subsidies for agricultural production do not show up on the model's outputs. We can see it is not affecting the equilibrium price in the equation (3-9). It, indeed, positively affects the profitability of the representative farms resulting in higher incentives for new entrants and putting extra pressure on water resources. Subsidies partly describe the unauthorized water extraction in the existing conditions of the market. Subsidies for wheat, for instance, are about 47 percent of current international wheat prices, which are about 180 euros per 1000 kg, while the guaranteed purchase price offered by the Iranian government is about 264 euros per 1000 kg. As shown in equation (3-10), if we consider the productivity of wheat-producing firms as a continuum $[0\ to\ A^{max}]$,, this subsidy explains how inefficient wheat farms, with productivity 32 percent lower than the minimum viable threshold in a no-subsidy situation ($a_i^{*(no-sb)}$) have the opportunity to continue producing under the subsidy regime present in the status quo.

$$A_i = a_i * A^{max}, \qquad a_i \in [0,1]$$

$$\frac{{a_i}^{*(no-sb)} - {a_i}^{*(sb)}}{{a_i}^{*(no-sb)}} = \frac{\frac{F}{A^{max} * s^{\alpha}} - \frac{F}{A^{max} * s^{\alpha} * (1+sb)}}{\frac{F}{A^{max} * s^{\alpha}}} = \frac{sb}{1+sb} \approx 0.32 \tag{3-10}$$

Scenario 2: Water market in a closed economy

This scenario illustrates that farms need to optimize their behavior in terms of selling (and buying) water. Doing so for each farm and making the price of water equal in the equilibrium, we reach equation (3-11). Solving this would bring us to the equilibrium price and quantity of transacted water between the two farms (equations (3-12) and (3-13)). It would increase the production and water consumption of the more productive firm (A) while the opposite affects the less productive farm. Thus, the water market changes the water allocation between the farms, encouraging the farms with higher productivity to produce more. It implies that as there is a gap in productivity of two farms, in a water market setting, the low productivity farm would sell a large portion of their water rights (46 percent) to the productive one, which would bring about lower production (exit) of low productivity farms (farm B) with a replacement of higher productivity ones (farm A). Overall, the production (y_1+y_2) will be higher compared to the previous scenario in which no water market existed.

Wheat is the main cultivated crop which covers about half of the irrigated land area in the Zayandehrud watershed and at the national scale (Felmeden, 2014). We estimate alpha as the share of value added by water in the value of the wheat product, based on the data provided by Khoshakhlagh (2007). Averaging and rounding the value over the available years of data would lead us to 0.3 as share of value added by water. Given the assumption that the productive firm creates twice the value as the unproductive one, our estimates show that production of the commodity would be 2.4 percent higher in the water market regime, bringing about an 18 percent drop in market prices for wheat. It is an exciting finding as it is often assumed that water markets would make farms pay for the water they use, which would boost the price through the higher cost of production.

$$P^{wm} * \alpha * A_1 (s+x)^{\alpha-1} = P^{wm} * \alpha * A_2 (s-x)^{\alpha-1} \tag{3-11}$$

$$x = \frac{\theta-1}{\theta+1} * s = 0.46 * s\ , \ \theta = \left(\frac{A_1}{A_2}\right)^{\frac{1}{1-\alpha}} = 2.7 \tag{3-12}$$

$$pw = \alpha * A_1 * s^{\alpha-1} * \left(\frac{2*\theta}{\theta+1}\right)^{\alpha-1} \tag{3-13}$$

$$\ln(P^{wm}) = \frac{a - \ln\left[s^{\alpha} * \left(n_1 * A_1 * \left(\frac{2\theta}{\theta+1}\right)^{\alpha} + n_2 * A_2 * \left(\frac{2}{\theta+1}\right)^{\alpha}\right)\right]}{b} \tag{3-14}$$

As production of agricultural commodities are higher in the closed economy, commodity prices fall compared to the status quo. The price elasticity of demand is -0.12, according to (Najafi Alamdarlo, Riyahi and Vakilpour, 2017) and this means that the price of the commodity would fall 18 percent as compared to the no water market scenario. Thus, the water market not only reallocates water toward higher productivity but encourages higher production levels in the economy resulting in lower prices, higher consumption and greater consumers welfare, see equation (3-14).

It is worth mentioning that the estimated values for price and production are a minimum change level in a water market regime in that we assume the higher productivity farm has twice the production level. The higher difference of productivity would result in higher increase of consumption across the economy. Thus, due to an abundance of low productivity farms, which are being managed traditionally based on outdated technologies, this level of increase acts as a lower bound for our expectation of welfare improvement by establishing a water market. Of course, finding the exact number for welfare and price improvements requires in depth knowledge about the distribution of productivity among the farms in our target area which is beyond the scope of this work.

In terms of water consumption, the model reveals only reallocation of water and not decreasing water consumption level. However, according to the argument in the previous scenario, profit levels fall for both farms in comparison to no-market setting as a consequence of lower market price of the commodity – about 8 and 32 percent for the productive and non-productive farms, respectively. This would significantly discourage illegitimate extraction of water and would bring down water use within this scenario. This effect would be intensified as establishing a water market requires high levels of law enforcement during the implementation of water caps for each water right holder. An exact number for this water consumption decrease has not been achieved here due to lack of data regarding distribution of farm productivity in this case study.

Scenario 3: Water market in an open economy

Introducing free trade into the model does not change the allocation of water among the two farms in comparison with the second scenario. Both farms are price takers, and while the price is lower in this scenario, it does not affect their decision to buy (or sell) water rights. On the other hand, free trade results in a lower market price for the commodity and means higher consumption and public welfare for consumers. The level of consumption depends on price differences in the closed economy and the international price, and also the price elasticity of demand. The higher price difference or price elasticity of demand, the more improvement in welfare. Regarding the equilibrium price of wheat, this scenario yields a 17 percent drop in the price of the commodity and implies a 2.3 percent increase in consumption. The gap between domestic production and consumption would be filled with commodity imports. In terms of water use, this scenario discourages unauthorized water consumption even more than the closed economy scenario. This is due to lower prices that yield a 17 percent decrease in profit for both farms in comparison to scenario 2. This would disincentivize illegal water extraction and trade openness would further lead to greater markets efficiency in agriculture. The new settings would tremendously discourage illegal water consumption, as it is playing an important role in water consumption in Zayandehrud watershed, and in Iran more generally. The combination of the water market and free trade would improve wheat consumption by about 4.7 percent.

3.5. Discussion

The different scenarios provide several insights on the effectuality of market manipulation tools, including the water markets and trade policies and their synergic influence on ecological and socio-economic sustainability for arid and semi-arid watersheds like Zayandehrud in Iran. Table 3-2Figure 3-2 summarizes each scenario's impact on farm water productivity, economic growth, food self-sufficiency, irrigation water demand, and unauthorized water consumption. The water market will increase the farms' average water productivity in scenarios 2 and 3 by facilitating the water rights transactions between farmers and water rights holders.

The results show that these transactions will ultimately transfer water rights from unproductive to productive farmers. While the current global average productivity for wheat is 0.7 kg per m^3 of water (National Research Council, 2005), 1 kg per m^3 is an estimated expected outcome in scenarios 2 and 3. It means that a productivity increase of at least 50% could be achieved, and Iran could reach the average world productivity of wheat per unit of water. The resultant model also depicts that the overall production will increase by 2.4% in these two scenarios. Thus, launching a water market will escalate the contribution of agriculture to the gross domestic production through increasing production. Further, it will lead to more consumption of agricultural commodities, which can be interpreted as improving consumers' welfare. However, this model cannot explain the transient period in scenarios 2 and 3, before the water market is mature and trade policies are fully established, and trades are negotiated.

Table 3-2 The impact analysis results for evaluated scenarios. Note: Green cells indicate greater sustainability, gray indicates no change and red indicates a negative outcome in terms of sustainability.

Output Variable/ Scenario	**Status Quo**	**Water Market in closed Economy**	**Water Market in Open Economy**
Water Productivity	No change	Increase	Increase
Utility/Economic Growth	No change	Increase	Increase
Food Self-sufficiency	Slightly increase	Slightly increase	No change
Irrigation Water Demand	Increase	No change	Slightly Decrease
Unauthorized Extraction	Increase	Decrease	Decrease

Food self-sufficiency is a guiding policy in Iran due to national security concerns and the desire for greater autonomy. Iranian leaders have executed this strategy through capital investments in the agricultural sector instead of relying on international trade. This investment covers a wide range of infrastructures and policies such as expensive dams, expansive irrigation canals, high tariffs on imported foods especially staple crops like wheat, and extensive subsidies on energy and farming necessities (Bucknall, 2007; Clapp, 2017; Madani, 2014; Wichelns, 2005).

Iranian policymakers believe that creating a water market and liberalizing the economy will lead to less domestic production and consider it a win-lose trade-off between ecological and economic outcomes. In direct contrast to those sentiments, this study reveals that the water market and open trade policy will increase the water productivity of farms and cause an improvement of 2.4% in agricultural production, even without current protections and subsidies. It may also decrease governmental budgets and free up capital for other long-term projects like renewable energy, and solar desalination plants.

Furthermore, agricultural water demand, which consumes over 90% of water in this watershed, will decline by establishing a water market and trade policy reforms toward a more open economy (scenario 3). If that occurs, the production of agricultural goods will be on par with world market prices (Debaere, 2014). Subsequently, it is expected that lower world prices and small or even negative marginal profit will discourage new entrants to farming, and existing farmers may trade their water rights and shift their investments to other businesses.

Unauthorized water extraction will also decrease in the second and third scenarios due to the lack of a marginal profit in farming, though this effect would be more severe in scenario 3. Despite a projected decline in irrigation water demand and a decrease in the unauthorized extraction of water in this scenario, it is not enough to secure the ecological sustainability of the watershed. As shown by Sarhadi & Soltani (2013), the ecological water rights will be insufficient for the Gavkhouni wetland in terms of water requirements. To address this problem, the water requirements for Gavkhouni should be calculated and considered as an equal holder of water rights. The groundwater safe yield (cap) should be indicated and enforced strictly to ensure that the water market can contribute to ecological sustainability (Debaere et al., 2014).

Finally, the results show that linking the water market and free trade policies contributes positively to sustainability in this watershed. This mathematical approach supports the plausibility of the "Free market" water governance scenario generated during a participatory study in this watershed (Nazemi et al., 2018). Exhibit 4 illustrates a systemic diagram for the third scenario and shows how its governance settings, like modified pricing and water allocation system, and its legitimacy and the rule of law are prerequisites for market settings. It also shows that linking these two market features can positively affect the irrigation water demand, farm productivity, unauthorized extraction, and consumers' welfare.

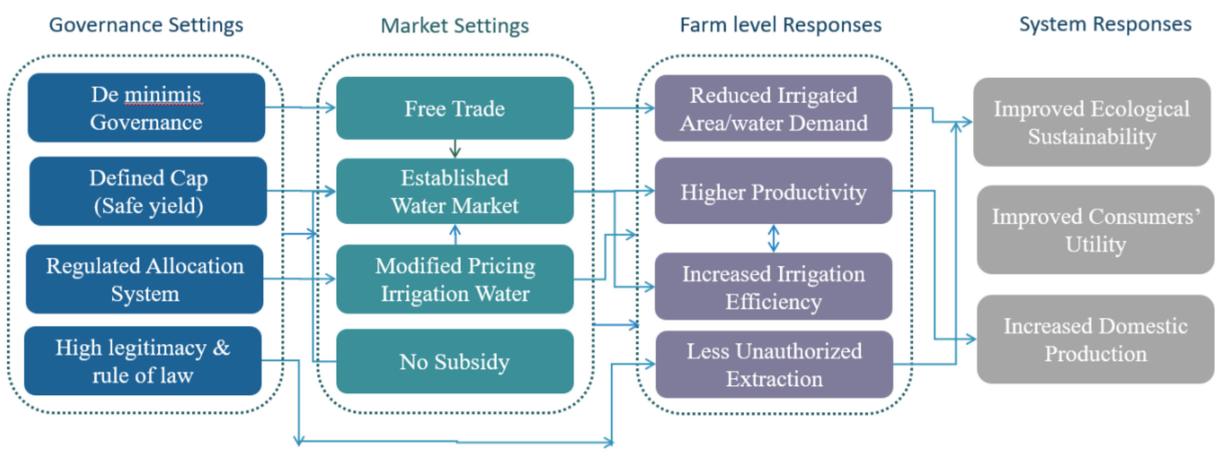

Figure 3-2 Scenario 3(Water Market in Open Economy) systemic block diagram

3.6. Conclusion and Recommendations

This study offers a partial equilibrium model to investigate the impact of the water market on the ecological and socio-economic sustainability of the Zayandehrud watershed in central Iran. The results demonstrate that launching water markets in the Zayandehrud watershed can positively affect agricultural productivity by shifting water rights from unproductive to productive farmers. It will also contribute to water demand management by curbing unauthorized water extraction. In a free trade environment, this model projects that a water market can lead to productive farms, less overall irrigation water demand, and unauthorized extraction.

In response to an ever-growing demand for fresh water in the agricultural sector, while most available water resources are already exhausted, irrigation demand management strategies are now more essential than ever in arid and semi-arid regions like MENA. The water market is one approach that can be used as a tool to guide farms toward less wasteful consumption of available freshwater by facilitating the water rights transactions between water rights holders and water users. It should be noted that many interactions between variables significantly affect outputs in a high complexity system like water governance systems. Other governance conditions should also be adjusted to achieve expected outcomes in the open market scenario, e.g., irrigation water measurement and pricing system, water allocation, and law enforcement capacity. Despite their importance, such governance conditions are not included in the scope of this paper. An essential prerequisite for this scenario to succeed is a well-defined and enforced cap based on the safe yield of the watershed.

There are several paths to advance this research. The First would be introducing a dynamic stochastic general equilibrium model, which can include more factors in the scenarios and thus make the results more accurate and elaborate. Moreover, clear measures should be defined for sustainability to assess each scenario and offer specific recommendations to high-level policymakers. Each possible scenario would bring about some changes, and there would be winners and losers. Outcomes are not distributed equally according to an optimal economic model; rather, the outcomes arise through interactions among different stakeholders who are influencing the political processes. It opens up another exciting avenue to include an analysis of political economy to consider the feasibility of the recommendations

Chapter 4

Univariate Deep Learning for Short-Term Algal Bloom Prediction: A Comparative Analysis of MLP, 1D-CNN, and LSTM Models

Neda Nazemi[1], Cal Buelo[3], Michael Pace[3], Garrick Louis[1]

[1]Engineering Systems and Environment, University of Virginia, Charlottesville, VA
[2] Gianforte School of Computing, Montana State University, Bozeman, MT

[3] Environmental Sciences, University of Virginia, Charlottesville, VA

Abstract

Algal blooms in freshwater sources pose a significant environmental challenge, disrupting the ecological balance of water bodies, threatening community water supplies, and causing economic losses in industries such as aquaculture. Forecasting near-term Chlorophyll-a (Chl-a) concentrations, a proxy for algal biomass, can help make informed decisions and proactively manage algal blooms. While conventional algal bloom forecasting models require various water quality and climate data inputs, univariate deep neural networks can predict algal biomass using only the temporal nature of Chl-a time series. In this study, we employed past Chl-a observations (2008-2019) from Peter Lake to develop three univariate deep neural networks: multilayer perceptron (MLP), one-dimensional convolutional neural network (1-D CNN), and Long short-term memory network (LSTM) for predicting Chl-a concentrations one to seven days in advance. A persistence forecast served as the benchmark to assess each model's accuracy. The results demonstrated that all three models outperformed the persistence forecast at forecast horizons of three days or longer. The performance of the CNN, MLP, and persistence forecasts declined rapidly with increasing forecast horizons, whereas the LSTM model exhibited marginally more accurate forecasts at longer forecast lengths, which are crucial for decision-makers and stakeholders. These findings can enhance algal bloom prevention by eliminating the need for collecting and processing multiple variables over an extended period. Furthermore, this study's results can provide a reference for evaluating the performance of multivariate models.

Keywords

Ecological Forecasting, Time Series Analysis, Recurrent Networks, One-Dimensional Convolutional Neural Network (1-D CNN), Algal Bloom Management, Long Short-term Memory (LSTM), Proactive Water Resource Management

4.1. Introduction

Algae are simple photosynthetic organisms that proliferate in seawater and freshwater. When their growth becomes excessive, it results in an "Algal Bloom". In some cases, this can lead to negative outcomes, which is referred to as a "Harmful Algal Bloom (HAB)" (Finlayson *et al.*, 2005).

HABs may affect the health of people and marine ecosystems. They cause dissolved oxygen depletion in water resources and release biotoxins that harm fish and their consumers (Buelo, Carpenter and Pace, 2018). Drinking HAB-contaminated water directly or consuming sea foods harvested from these resources, especially shellfish, may cause illness or even death in humans (Jeppesen *et al.*, 2005). HABs that occur in water reservoirs, put pressure on water supply systems to treat and remove the algal byproducts or seek other water sources to service their customers. HABs also may damage local and regional economies like aquaculture, fisheries, recreational beaches, and local real estate businesses.

The most sustainable solution to HABs is to prevent them by addressing the root cause of the problem, which is usually reducing and controlling the nutrient discharge to water bodies. However, in many cases, decades of nutrient input have made entirely avoiding blooms difficult or impossible.

Given this context, forecasting the timing and intensity of HABs would be highly useful for water managers, the aquaculture industry, and public health managers. With sufficient warning, actions could be taken to avoid or at least minimize the impacts of blooms, such as shifting water treatment plants to alternative sources or closing recreational beaches (Davidson *et al.*, 2016). Such proactive strategies could minimize the treatment costs and economic losses and prevent ecological disturbance and potential health issues caused by algal blooms (Carmichael *et al.*, 2001).

Excess nutrients are often the most critical driver of HABs. However, several other factors can contribute to bloom timing and severity, including weather conditions (i.e., water temperature, the amount of sunlight, and wind condition), in addition to variability in algae species and their different biological characteristics. Other components of the food web, such as which zooplankton and fish species are present and their prevalence, can promote or suppress a bloom. However, these variables are hard to measure and can change quickly. These interacting variables make the prediction of HABs difficult (Oliver *et al.*, 2012).

Several different modeling approaches have been employed to capture the dynamics of blooms to predict them eventually. These methods comprise processed-based, statistical, and recent advanced machine learning models. Mechanistic models, such as PROTECH (Reynolds, Oliver and Walsby, 1987), DYRESM-CAEDYM (Hamilton and Schladow, 1997), CLAMM (Easthope and Howard, 1999), MyLake (Soranno, 1997), PCLake (Janse and van Liere, 1995), SALMO (Benndorf and Recknagel, 1982), seek to capture explicitly the physical and biological processes that lead to algal proliferation. These models usually rely on prior assumptions about the interactions and mechanisms that regulate phytoplankton . Due to the complex and non-linear nature of these mechanisms, process-based models have difficulties in accurately predicting the future biomass of algae (Shimoda and Arhonditsis, 2016).

Statistical forecasting methods, on the other hand, are effective when the physical relationships are not fully known (Muttil and Chau, 2006) and do not require the a-priori assumptions used by the process-based models (Derot, Yajima and Jacquet, 2020). These models utilize past data to identify patterns between phytoplankton biomass and potentially causative environmental variables, then use those patterns to predict what the future will look like (Davidson *et al.*, 2016).

Autoregressive Models, a traditional class of statistical methods for time-series forecasting, like ARIMA and VAR, offer more flexibility and simplicity. However, they neither model the non-linearity of the ecological system nor can they forecast algal biomass except at short time scales. Moreover, they focus on complete series, so missing data is generally not supported by autoregression models (Chen *et al.*, 2015; Qin, Li and Du, 2017).

4.1.1. Deep Learning Models

Recent advancement in collecting high-frequency data provides the opportunity to use machine learning methods to advance bloom prediction. Specifically, state-of-the-art deep learning networks (DNN) can automatically learn the temporal dependence structures for challenging time series problems. Although the complex structure of deep neural networks is not as interpretable and provides less insight into the system's physical and biological processes compared to mechanistic models, they often result in more accurate predictions because such models can explain dynamic, non-linear, and noisy data. Therefore, deep learning might be a desirable methodology when the objective is to provide more reliable and accurate bloom forecasts (Cruz *et al.*, 2021).

DNNs can be used to develop both univariate and multivariate forecasting models. Univariate deep networks project the behavior of a time series solely based on its past trend but not on any other variable. In contrast, multivariate models feed all possible causative variables into the model to predict future algal biomass.

Univariate models are simple, easy to develop, and computationally inexpensive. They can also be used as a baseline to assess multivariate DNN models. In this study, we focused on developing and comparing three different univariate DNNs and evaluating their performance and skillfulness through a comprehensive framework. We used three major categories of neural network architectures (or their hybrid format).

Multilayer Perceptron (MLP)

The first and oldest category is the MLP or feed-forward neural networks. This architecture usually comprises a single input layer that receives inputs variables, one output layer, which returns the network's response, and one or more intermediate hidden layers that approximates a mapping function from input variables to output variables (Brownlee, 2018). The MLP models are simple and easy to develop. As a result, this is the most explored type of ANN models to forecast algal blooms (Recknagel *et al.*, 1997; Maier, Dandy and Burch, 1998; Lee *et al.*, 2003; Shamshirband *et al.*, 2019).

One-dimensional Convolutional Neural Networks (1-D CNNs)

Convolutional Neural Networks or CNNs are a type of neural network initially designed to process three-dimensional data (i.e., image data). In this approach, the model learns how to automatically extract the features from the raw data that are directly useful in solving the problem. This capability can be applied to time series forecasting problems by treating a sequence of observations like a one-dimensional image that a CNN model can read and distill into the most salient elements (Brownlee, 2018). The current study applied 1-D CNN architecture for algal bloom forecasting for the first time.

Long Short-Term Memory network (LSTM)

Recurrent neural networks like the Long Short-Term Memory network (LSTM) are another type of neural network that designed to handle sequential data types such as time series, speech, and text. This capability of LSTMs has been used to great effect in complex natural language processing problems such as neural machine translation, where the model must learn the complex inter-relationships between words within a given language and across languages in translating from one language to another. This capability can be leveraged in time series forecasting since the method can automatically learn the temporal dependence from the data. The model both learns a mapping from inputs to outputs and learns what context from the input sequence is beneficial for the mapping and can dynamically change this context as needed (Brownlee, 2018).

Algal bloom forecasting studies suffer from lack of a standard model evaluation framework, making it difficult to compare the performance of different modeling techniques (Rousso *et al.*, 2020). In this study, we developed a comprehensive performance evaluation to assess the skillfulness of each model overall and for different forecast horizons. We then developed and compared three univariate DNN models; MLP, 1D-CNN, and LSTM, to assess their capability in forecasting algal biomass from one day to seven days in advance. This research introduces the application of novel 1D-CNN architecture for algal bloom forecasting.

4.2. Method of Study

4.2.1. Proposed Approach

The objective of this investigation is to develop univariate models to predict algal blooms for proactive management of harmful algal blooms (HAB). While various methods exist for measuring algal biomass, chlorophyll-a (Chl-a) is commonly used as an indicator for the total phytoplankton biomass (Kim *et al.*, 2021). Therefore, the main aim of this study is to forecast Chl-a concentration as a proxy for algal biomass. Figure 4-1 outlines the proposed approach, which employs deep neural networks to predict Chl-a concentration for the following seven days based on the time-series data of daily Chl-a concentration. The temporal correlation of the dependent variable, Chl-a, is leveraged to construct accurate forecasting models.

To enable the use of sequential models, the daily time-series data for Chl-a were converted into a supervised dataset that comprised of overlapping moving windows of size M (the input sequence size) and output windows of size N (the forecast window size). Validation of time series models cannot be done using random split methods due to the presence of temporal correlation and lag effects. It is crucial to select a testing set that occurs after the training set to ensure that the test set remains entirely unseen during model fitting. Accordingly, the last year of the time-series data were utilized as the testing set, consisting of completely unseen data. Using this configuration, each deep learning model acquires knowledge and constructs a function that maps the input sequence of M past observations to an output sequence of N predictions. The evaluation of model performance was carried out using the 2019 testing set.

In summary, we developed MLP, LSTM, and 1-D CNN models, optimized the settings of these models (referred to as “hyperparameters”), and compared their performance against a baseline naïve (persistence) model. The selected model would be updated regularly with new observations to generate subsequent forecasts in real-time applications. Below, we detail the model development, selection, and final performance evaluation procedures.

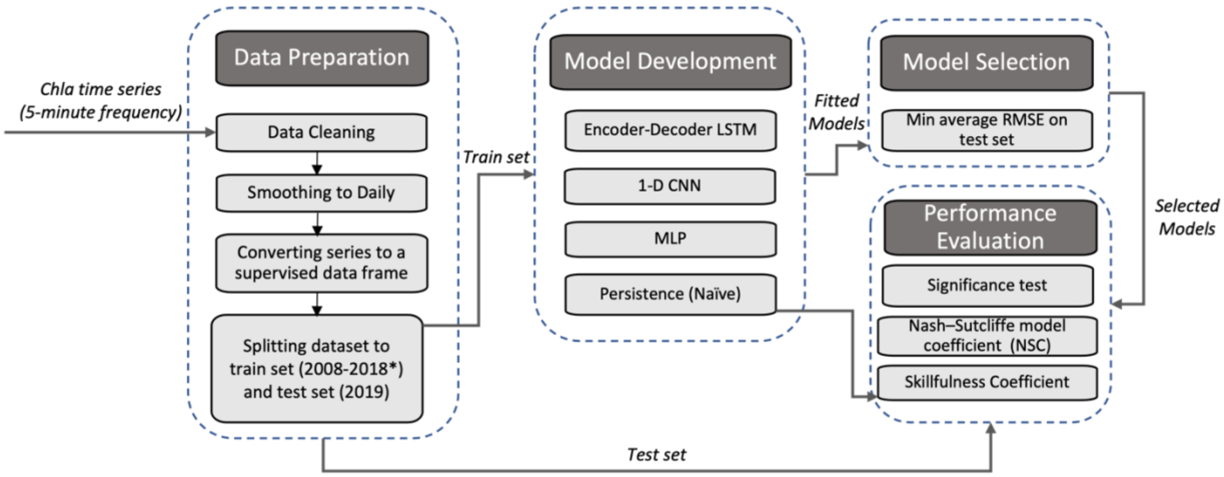

*Figure 4-1 Overview of Proposed Method- *No data was available for 2012, 2016 and 2017*

4.2.2. Model Development

To facilitate the application of supervised learning models, it is necessary to first transform the time series data into a supervised data frame through a sliding window or lag method, which involves selecting a lag size (M input) and a number of forecast steps (N output). This transformation enables the time series to be represented as independent observations, which can be used to train a model. Each lag input is treated as a distinct feature, while each forecast step is considered an independent output. In the present study, we aimed to forecast Chl-a levels for the subsequent 7-day period; thus the N output value was set to 7. The optimal number of inputs (M input) was determined through a validation process, in which the model was tuned to achieve optimal performance. For additional information on model development, please refer to Appendix 4-1.

Persistence Model (Naïve model)

To provide a basis for evaluating the performance of developed models, it is essential to establish a naïve unskilled model as a baseline. This enables the learning capabilities of each model to be quantified in comparison to the baseline. In the present study, we employed a persistence model as the naïve baseline. This model operates under the assumption that Chl-a concentrations will remain constant for the next seven days. Specifically, the model predicts the Chl-a concentration for the next seven days as the average concentration on the current day. Any model that surpasses the performance of the persistence model is considered to be skillful. This approach provides a reliable means for assessing the predictive skill of the developed models.

MLP model

As illustrated in Figure 4-2 the developed Multilayer Perceptron (MLP) model in this research comprises a single hidden layer of nodes, followed by an output layer responsible for generating predictions. The Rectified Linear Unit (ReLU) function serves as the activation function, while the model fitting relies on the efficient Adam variant of stochastic gradient descent. The optimization process employs the mean squared error (MSE) loss function. A comprehensive grid search was conducted to determine the optimal number of hidden layer nodes, input window length, epochs, and batch size.

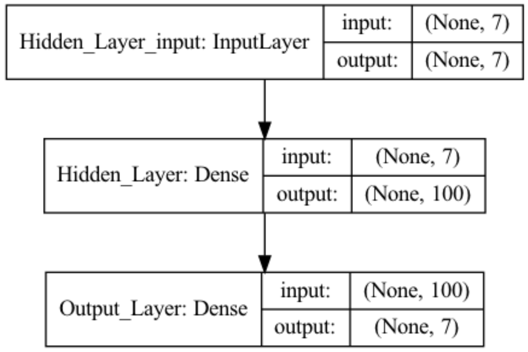

Figure 4-2 Architecture of the MLP model featuring a single hidden layer. The number of nodes within the hidden layer was optimized as a hyperparameter.

1-D CNN model

In the one-dimensional CNN model (Figure 4-3), a convolutional hidden layer operates over a 1D sequence, followed by an additional convolutional layer and a subsequent pooling layer responsible for extracting the most significant features from the convolutional layer output. The convolutional and pooling layers precede a densely connected layer that interprets the features acquired by the convolutional components of the model. To reduce the feature maps to a single one-dimensional vector, a flattening layer is incorporated between the convolutional layers and the dense layer.

The model fitting employs the efficient Adam variant of stochastic gradient descent, with optimization based on the mean squared error loss function. A grid search was conducted to optimize parameters such as input window size, number of filters, kernel size, epochs, and batch sizes.

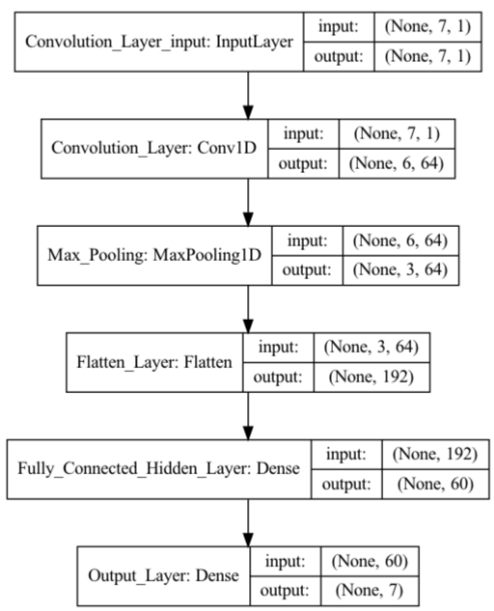

Figure 4-3- Schematic representation of the 1D-CNN model, comprising a solitary convolutional layer succeeded by a fully connected hidden layer. The number of convolutional filters was fine-tuned as a hyperparameter.

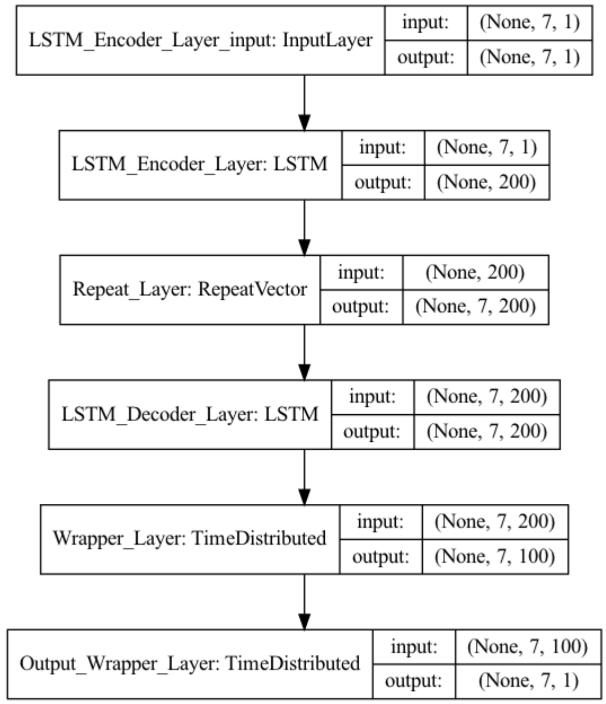

Figure 4-4 Schematic representation of the Encoder-Decoder LSTM model, comprising a single encoder layer and a single decoder layer, succeeded by a densely connected hidden layer. The number of memory units was optimized in hyperparameter tuning process.

Encoder-Decoder LSTM model

The Encoder-Decoder LSTM architecture (Figure 4-4) consists of two primary components: an encoder responsible for processing the input sequence and converting it into a fixed-length vector, and a decoder that interprets the fixed-length vector to generate the predicted output sequence. This architecture has demonstrated its effectiveness in various sequence-to-sequence forecasting tasks (Brownlee, 2017).

The encoder model was implemented using a single LSTM layer, which outputs a fixed-size vector representing the input sequence's internal representation. The decoder's role is to transform the learned internal representation of the input sequence into the correct output sequence. To achieve this, another LSTM layer was utilized to construct the decoder model, which reads the fixed-sized output generated by the encoder model. As with any deep neural network (DNN), a Dense layer was employed as the network's output layer. By wrapping the Dense layer in a TimeDistributed wrapper, the same weights were used to generate each time step within the output sequence. Additionally, a RepeatVector layer was employed to bridge the encoder and decoder components of the model.

The output layer leverages the mean squared error (MSE) loss function and the efficient Adam implementation of gradient descent for weight optimization. During the model selection step, hyperparameters such as the number of memory cells in the encoder and decoder LSTM layers, batch size, and epoch count were tuned.

4.2.3. Model Selection and Evaluation

In order to optimize the hyperparameters of the model, a grid search was conducted with the objective of identifying the model configuration that yields the lowest root mean squared error (RMSE) and, consequently, the highest prediction accuracy for each deep neural network category. Given the stochastic nature of DNNs, which results in varying estimated weights even when trained with identical configurations, the training process was repeated 50 times for each configuration setting. The average across all iterations was then used as the basis for comparison.

Apart from RMSE, we employed additional evaluation metrics, including the Nash-Sutcliffe Model Efficiency Coefficient (NSC) and the Model Skillfulness Coefficient, a novel metric introduced to assess the learning capabilities of each DNN model. Furthermore, a t-test was performed to confirm the statistical significance of the results in comparison to a naïve model, as detailed in the subsequent sections.

Root Mean Square Error (RMSE)

To comparatively assess the accuracy of predictions between the models, we examined the root mean squared error (RMSE) values, which are commonly employed to gauge model performance. For each forecast window, the RMSE was calculated separately, indicating the dispersion of residuals. The RMSE for an i-day forecast can be expressed using Equation 4-1:

$$RMSE_i = \sqrt{\textstyle\sum_j^n (y_j - \hat{y}_j)^2} / N \qquad \text{(Eq. 4-1)}$$

$RMSE_i$: Root Mean Square Error of i-day forecasts

i: Forecast length (day)

y_j : Actual Chl-a observation in day j

$\hat{y}_j$: Forecasted Chl-a concentration in day j

N: number of observations

The overall forecast error is determined by computing the average across various forecast horizons, ranging from 1 to 7 days (equation 4-2):

$$RMSE = \textstyle\sum_i^7 RMSE_i / 7 \qquad \text{(Eq. 4-2)}$$

$RMSE$: Overall Root Mean Square Error

Nash–Sutcliffe model efficiency coefficient (NSC)

The Nash-Sutcliffe model efficiency coefficient (NSE) is employed to evaluate the predictive capabilities of forecasting models (Nash and Sutcliffe, 1970) . We computed the NSE for each forecasting step (1 to 7 days). The NSE is defined by Equation 4-3:

$$NSE_i = 1 - \textstyle\sum_j^n (y_j - \hat{y}_j)^2 / \sum_j^n (y_j - \overline{y})^2 \qquad \text{(Eq. 4-3)}$$

$\overline{y}$: Mean value of Chl-a observations

Indeed, the NSE normalizes the sum of squared residuals by the total variance. A coefficient of 1 signifies a perfect match between the model and the observed data, as it accounts for the entire bias of the test data.

An NSE coefficient of 0 indicates that the model's skillfulness is equivalent to the mean of the observed data. NSE values less than zero suggest that the observed mean outperforms the forecasting model.

A limitation of this metric is that it does not adequately represent the variation in predictive power across different forecasting horizons. This is because the denominator of the equation remains constant for all forecasting steps.

Model Skillfulness Coefficient (MSC)

To address the limitations of the NSE, this study introduces an innovative metric capable of more effectively differentiating the predictive power of each model at individual forecast horizons. This new measure normalizes the model residuals by the residuals of persistence forecasts within the same forecast horizon. (Eq. 4-4).

$$MSC_i = 1 - \sum_j^n (y_j - \hat{y}_j)^2 / \sum_j^n (y_j - \hat{Y}_j)^2 \qquad \text{(Eq. 4-4)}$$

$\hat{Y}_j$: Persistent Chl-a forecast in day j

The difference between NSC and MSC is that NSC considers the average value of observed data as the naïve model, which is stationary for any forecast length. However, the persistence forecasts are different for each forecast horizon. It also sets a more rigorous baseline to measure the skillfulness of the model. For example, the one-day persistence model may outperform any sophisticated model because considering tomorrow's Chl-a concentration equal to today’s average value would probably be a close approximation of reality. A value of 1 represents a perfect model with sum square residuals of zero. A value of zero shows that model is not skillful enough to outperform the persistence model. A more positive value means the model has higher predictive power than the persistent forecast. In contrast, the negative value shows that the model is unskilled, and the persistence model is a better forecaster.

Significance Analysis

To assess the performance of the deep neural network (DNN) models, a single-sample t-test was conducted to determine if the average root mean square error (RMSE) values of each DNN model were significantly lower than the RMSE value of the naïve model. The null and alternative hypotheses were established as follows:

H^0: The average RMSE value of each DNN model is equal to or less than the RMSE value of the naïve model.

H^1: The average RMSE value of each DNN model is greater than the RMSE value of the naïve model.

This statistical test enables a comparison of the DNN models' performances with the benchmark naïve model, facilitating the identification of any significant improvements in prediction accuracy.

4.2.4. Data Collection and Pre-Processing

This work utilizes collected data from Peter Lake an experimental lake situated at the University of Notre Dame Environmental Research Center in the Upper Peninsula of Michigan, United States. In this lake, algal blooms do not occur naturally without experimental fertilization due to the unique characteristics of the lake (Carpenter and Pace, 2018). Chlorophyll-a was measured daily using a surface water sample that were filtered. Filters were frozen and extracted in methanol with pigment concentration determined fluorometrically (Buelo *et al.*, 2022) . The time series encompasses Chl-a data from 2008 to 2019, although data were not collected in 2012, 2016, and 2017.

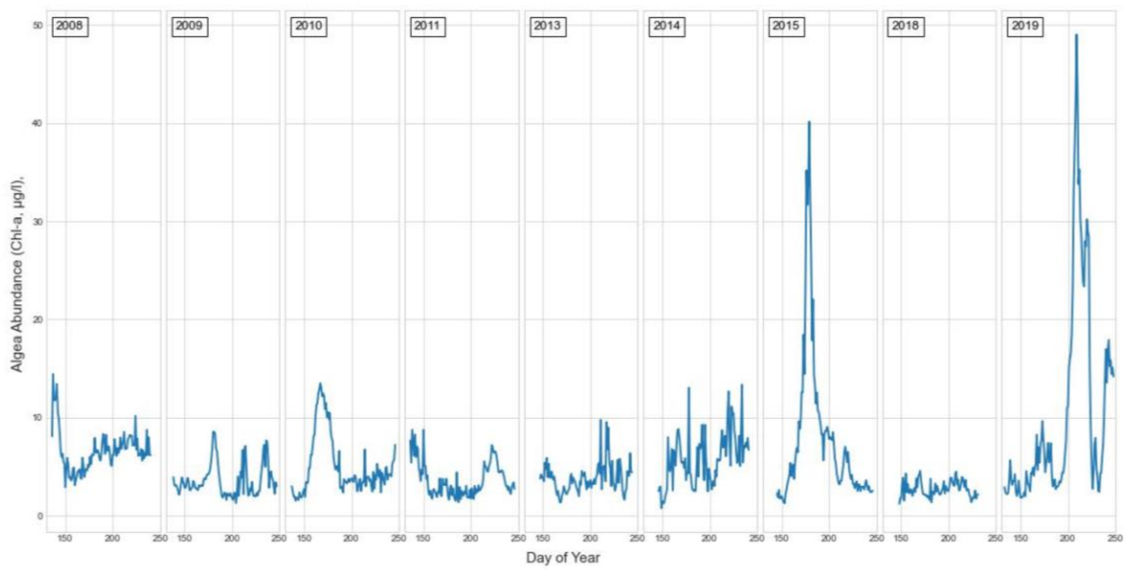

Figure 4-5- Chlorophyll-a Concentration Time series- Peter Lake
**No data was collected in 2012, 2016 and 2017*

The entire series consists of nine lake years, with fertilization occurring in 2013, 2014, 2015, and 2019. Figure 6 depicts the Chl-a time series for these nine years. Notably, the majority of data were collected during spring and summer, when algal blooms are most likely to transpire. This series features two major bloom events in 2015 and 2019, the later serving as unseen dataset to evaluate the performance of the selected models.

4.3. Results

Three different categories of neural networks, namely MLP, 1-D CNN, and LSTM, were investigated for short-term prediction of Chl-a concentration. Each model was fitted to the training set and evaluated against the test set. The hyperparameters of each model were tuned and selected using a grid search approach, with 50 iterations performed for each configuration setting. The complete configuration list for each model can be found in Appendix 4-2. The distribution of average RMSE for each configuration can be found in Appendix 4-3. Ultimately, the model with the lowest root mean square error in each group was chosen. Table 4-1 summarizes the configuration of the selected model for each category and their average and 7-day RMSE values on validation and test sets.

The summary of the results indicates that the input window size of seven yields the best accuracy for the MLP model, while for CNN and LSTM models, the optimal window sizes are 7 and 5, respectively.

In addition, comparing the test errors reveals that, on average (mean of one to seven days forecast error), all three models outperform the naïve model. This observation remains valid for 7-day forecasts, which is crucial for decision-making purposes. The performances of the MLP and 1-D CNN models are found to be similar, while the LSTM model exhibits a slight advantage over the other two models.

Upon examining the p-values, which are close to zero for all three models, it is confirmed that the average RMSE of each of the three models is significantly lower than the average RMSE of the naïve model.

Table 4-1- Selected models'' configuration and their accuracy and significance

	Model Configuration					Performance		Significance	
	Inputs Size	**Nodes/ Units**	**Filters**	**Epoch No.**	**Bath No.**	**Overall RMSE**	**7-days RMSE**	**t-statistic**	**P-value**
NAÏVE	-	-	-	-	-	7.25	10.30	-	-
MLP	3	128	-	40	10	6.83	9.46	-14.93	≅0
1-D CNN	7	100	64	20	1	6.70	9.01	-6.62	1.27e-08
LSTM	5	200/100	-	20	16	6.48	8.58	-4.22	5.18e-5

Figure 4-6 zooms into the selected models and shows how RMSE scores of the 50 iterations for each model are distributed across each forecast horizon. It reveals that the LSTM model has a significantly wider distribution, while the other two models demonstrate more robust results. As expected intuitively, the accuracy of forecasts for all models consistently declines as the forecast horizon expands. However, for the LSTM model, the accuracy declines more slowly than for the MLP and CNN models. It is also observed that for shorter forecasts, such as one-day and two-day predictions, the MLP and CNN models outperform Figure 4-7 the LSTM model. However, as the forecast horizon expands, the median RMSE score of the LSTM model consistently remains lower than the other two models, proving that the LSTM model returns more accurate forecasts at longer forecast horizons.

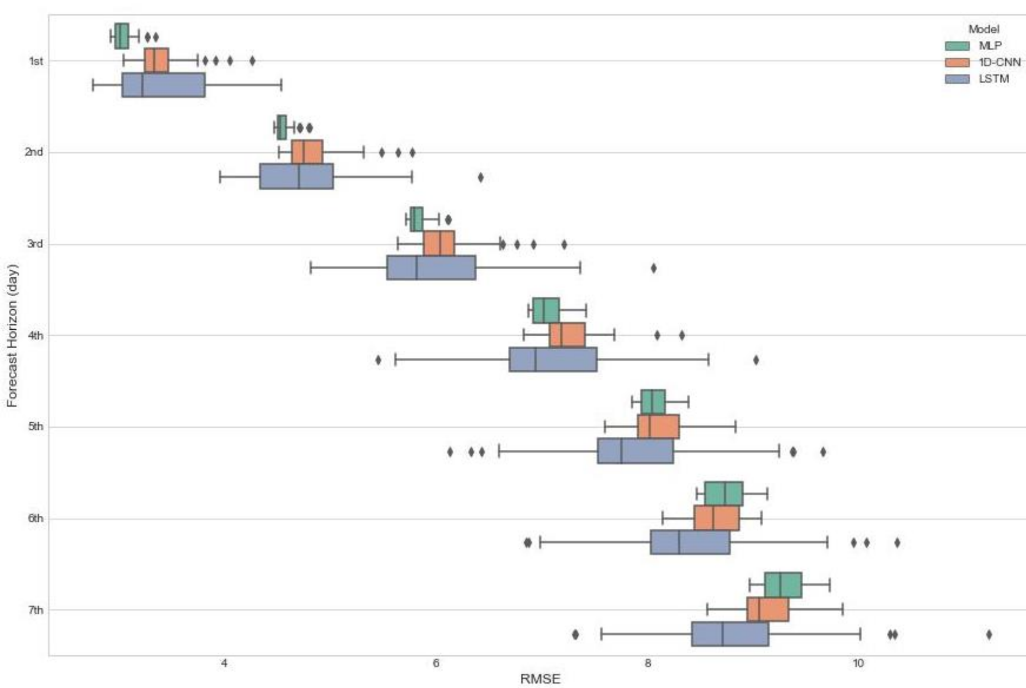

Figure 4-6- Selected models distribution of RMSE scores for each forecast horizon

Figure 4-7 compares the performance of these four models using the Nash Coefficient metric on the test set for forecast windows of one day to seven days. The results show that while nearly all of these models do not outperform the naïve model at short forecast horizons (one and two days), they demonstrate significant improvement over the naïve forecast at longer forecast lengths, especially at 7-day forecasting. The figure also illustrates that the performance of the LSTM model declines less with increasing forecast steps. Ranking the models based on their Nash coefficient, it can be concluded that the LSTM performs best, followed by the 1D-CNN and MLP models, while the persistence model performs worst, particularly at longer forecast lengths.

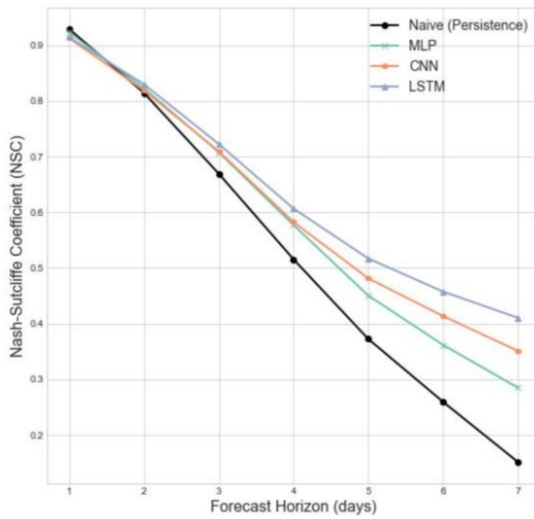

Figure 4-7- Nash-Sutcliff coefficient on the test set for different models and forecast horizons.

Figure 4-8 illustrates the skillfulness coefficient (MSC) for each model across various forecast horizons. Skillfulness is defined as a relative measure that demonstrates a model's predictive power compared to Naïve (persistent) forecasts. The results confirm that in shorter forecast windows, all three models perform worse than the persistent model (naïve); however, as the forecast length increases, deep learning models gradually exhibit greater skill than the naïve model. This is particularly evident for the LSTM model: while its skillfulness coefficient is strongly negative (around -0.2) for the one-day forecast, its comparative skillfulness improves for longer forecast horizons. Consequently, the LSTM model's MSC consistently increases as the forecast horizon expands. The same increasing trend is visible for the CNN model, while the MLP model's relative performance remains constant after three forecast steps.

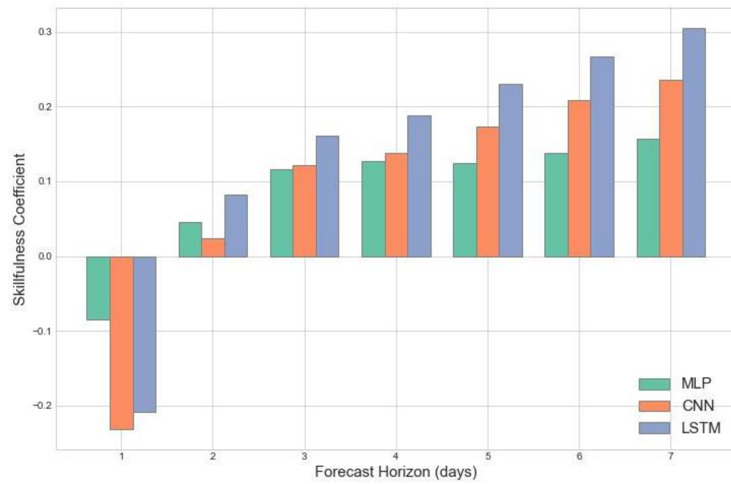

Figure 4-8- Skillfulness Coefficient for each of the three deep learning models versus seven-day forecasts; negative values indicate the inability of a model to outperform the naïve model for that specific forecast horizon.

4.3.1. 1-day forecasts

Figure 4-9 displays the Chl-a predictions for the next day generated by each deep learning model using the test set, alongside the actual observations. The shaded area represents the 95% confidence interval, and the solid lines indicate the average forecast. Although all three models are capable of accurately predicting the next day's Chl-a concentration, the figure reveals a one-day delay in the timing of the forecasts for the CNN and MLP models. This suggests that these two models perform comparably to the one-day persistent model. In contrast, the LSTM model exhibits an even greater delay, leading to inferior outcomes compared to the naïve model. Figure 4-10 further supports this observation, revealing a strong agreement between the forecasts and actual observations for the MLP and CNN models. Conversely, the LSTM model appears to perform less effectively, particularly at higher Chl-a values.

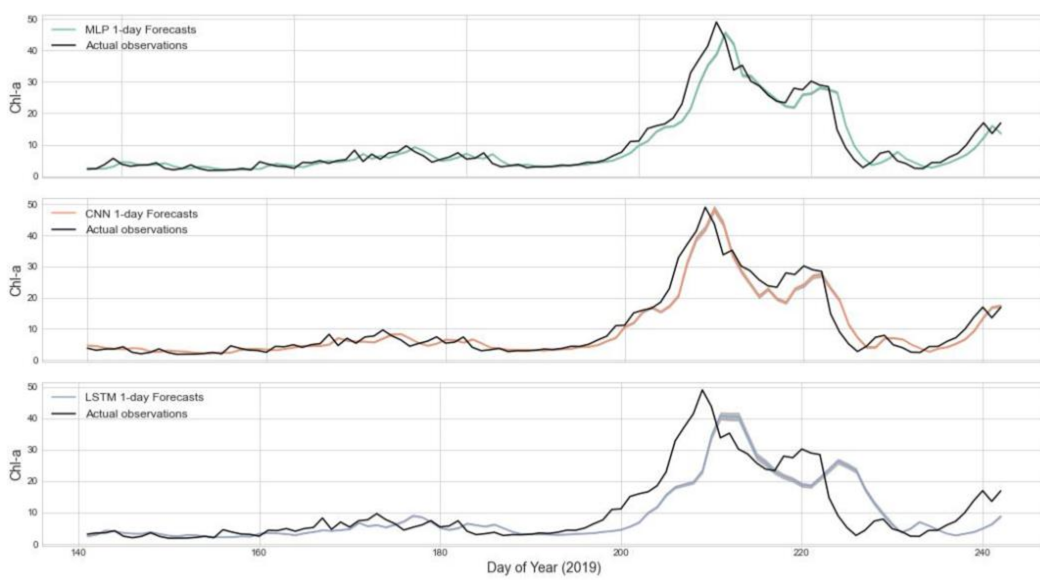

Figure 4-9- Comparison of one-day forecasts on the test set (2019)

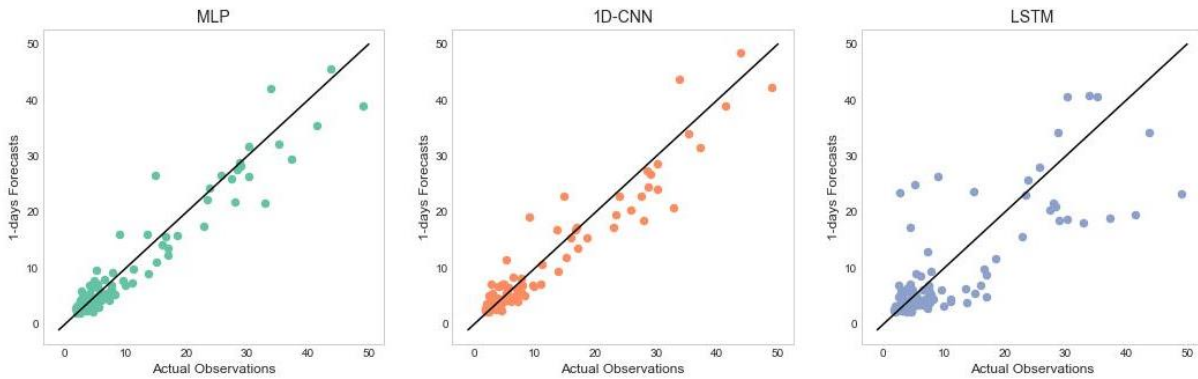

Figure 4-10-1-day forecasts and actual observation agreement

4.3.2. 3-day forecasts

Figure 4-11 presents a comparison between the three-day-ahead forecasts and the actual observations, demonstrating that the CNN model performs better at predicting the intensity of major blooms. However, both the MLP and LSTM models tend to under-predict the intensity of these blooms. All three models exhibit a delay in forecasting bloom events.

Figure 4-12 indicates that the agreement between forecasts and actual observations is weaker for all three models in the three-day-ahead forecasts compared to one-day forecasts. The LSTM model exhibits a tendency to under-forecast the actual values, as most of the points fall below the perfect agreement line, especially at higher Chl-a values.

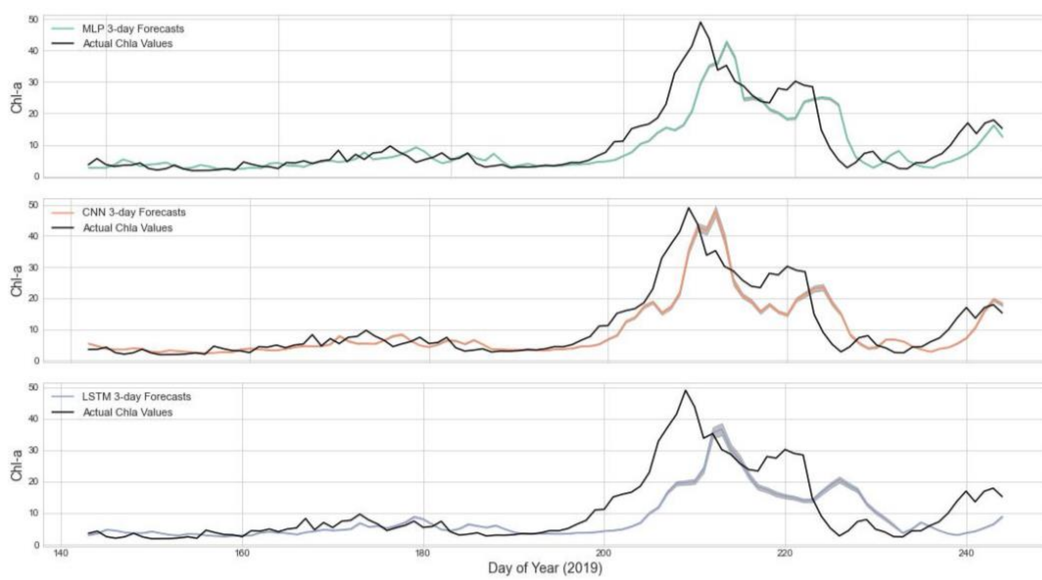

Figure 4-11- Comparison of three-day forecasts on the test set (2019)

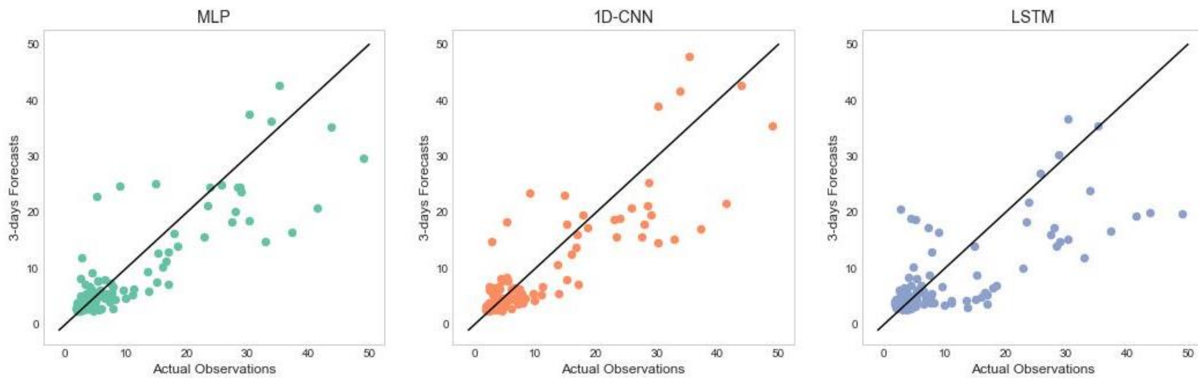

Figure 4-12-Three-day forecasts and actual observation agreement

4.3.3. 7-day forecasts

Figure 5-13 displays the 7-day forecasts of the models compared to the actual observations. The LSTM model demonstrates a reasonable ability to predict the timing of major bloom event but under-predicts its intensity. In contrast, both MLP and CNN models exhibit significant delays and less accurate forecasts of bloom intensity.

Figure 5-14 supports these findings, revealing that all three models tend to under-predict Chl-a values, particularly at higher Chl-a concentrations.

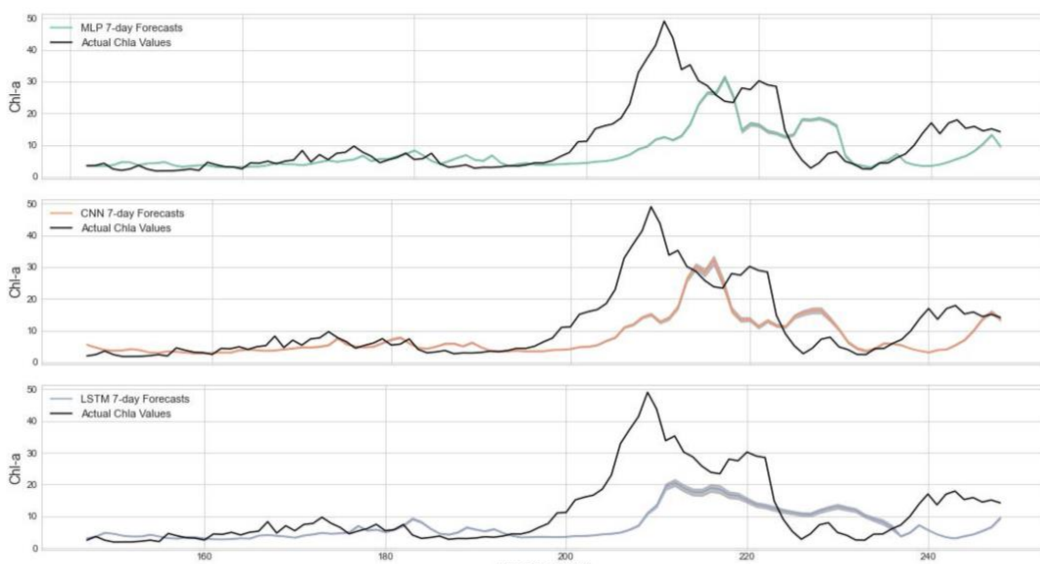

Figure 4-13-Comparison of 7-day forecasts on the test set (2019)

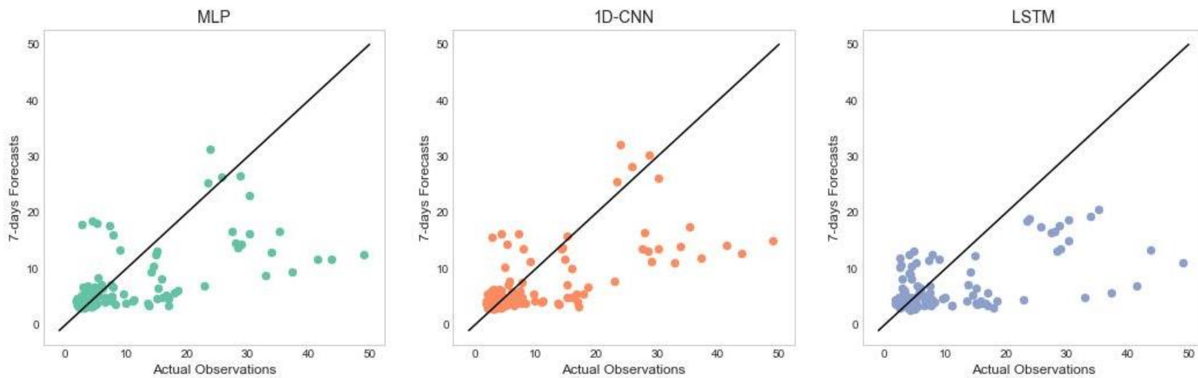

Figure 4-14- 7-day forecasts and actual observation agreement

4.4. Discussion

Deep artificial neural networks have become more prevalent in the realm of short-term, multi-step ecological forecasting as a result of their aptitude for managing complex and non-linear systems (Borowiec *et al.*, 2022; Perry *et al.*, 2022) . These networks also possess the ability to efficiently process and analyze disordered data, which is often a challenge associated with high-frequency time series data. As such, the adoption of these advanced computational techniques is enhancing the accuracy and reliability of ecological predictions.

However, The absence of a standardized performance evaluation framework makes it difficult to directly compare various artificial neural network (ANN) models or contrast them with mechanistic and statistical models.(Rousso *et al.*, 2020). Rousso et al. 2020 report that approximately 50% of algal bloom forecasting studies rely on determination coefficients (R^2) or Pearson correlation coefficients (R) as performance indicators. However, a high R^2 value doesn't necessarily guarantee accurate forecasting. This is because some models can be overfitted to the training datasets, leading to excellent performance on the training data but poor performance when applied to new, unseen data (Cawley and Talbot, 2010). In the present study, it is proposed to employ the Nash-Sutcliffe efficiency coefficient and the Root Mean Square Error (RMSE) as evaluation metrics to ascertain the accuracy of forecast models. These measures serve as valuable alternatives to the determination coefficient (R^2) or Pearson correlation coefficient (R), which have been previously discussed as potentially inadequate in certain situations.

Moreover, a notable limitation of the extant literature is the absence of an efficacious metric for appraising the skillfulness of the models under investigation. To address this shortcoming, the current paper introduces the Skillfulness coefficient. This novel metric juxtaposes the forecast at each step with a persistent (unskillful) prediction that possesses an identical forecast horizon. By contrasting the model's prognostications with a rudimentary unskillful prediction, the Skillfulness coefficient can effectively gauge the degree to which the model's predictions surpass the utilization of the most recent observed value as the forecast.

This study demonstrates that the predictive capabilities of all three deep neural network (DNN) models exhibit an improvement as the forecast horizon (steps) expands compared to the naïve model. This phenomenon can be elucidated by considering a hypothetical unskillful weather forecaster who predicts tomorrow's temperature by assuming it will be identical to today's temperature (persistent forecast). While this approach might yield reasonable short-term forecasts, its efficacy would diminish for longer-term predictions, such as forecasting the temperature for the following week. This is where a skillful weather forecasting model could distinguish itself. This analogy clarifies why the skillfulness metric is negative for all three models in the case of one-day forecasts, while it becomes positive after day two.

The skillfulness of the one-dimensional convolutional neural network (1D-CNN) and Long Short-Term Memory (LSTM) models both exhibit a marked increase after day three in comparison to the Multi-Layer Perceptron (MLP) model. For seven-day forecasts, their average skillfulness coefficients are 0.24 and 0.32, respectively. This highlights the enhanced predictive capabilities of the 1D-CNN and LSTM models, particularly for longer-term forecasts, in contrast to the MLP model.

In this study, a one-dimensional convolutional neural network (1D-CNN) was applied for the first time to forecast algal blooms, demonstrating its potential to significantly enhance the performance of conventional artificial neural networks, such as the Multi-Layer Perceptron (MLP), particularly at longer forecast horizons. The average Nash coefficients for seven-day forecasts using the 1D-CNN and MLP models were found to be 0.35 and 0.28, respectively, indicating the superior performance of the 1D-CNN approach.

4.5. Conclusions and Recommendations for Future Research

This study applied and compared three categories of deep learning neural networks - multilayer perceptron (MLP), one-dimensional convolutional neural network (1-D CNN), and long short-term memory (LSTM) as a subcategory of recurrent neural networks (RNNs) - to predict chlorophyll-a concentrations as a proxy for algal biomass in Peter Lake. All three models were univariate, utilizing only past Chl-a concentration sequences to forecast future values. This approach eliminates the need for and cost of collecting and processing multiple climate and water quality variables over extended periods. Furthermore, it significantly reduces computational costs as it operates with a single variable instead of multiple variables.

The architecture and hyperparameters of the models were tuned, and their performance was evaluated using a test set. Each model provided Chl-a forecasts for 1 to 7 days in advance. The results revealed that all three models outperformed the naïve model at forecast horizons longer than three days.

This study presented a comprehensive evaluation criterion for algal bloom forecasting models, which can be employed in future forecasting studies to better compare different modeling approaches. Additionally, this research marks the first application of the one-dimensional convolutional neural network (1D-CNN) model for algal bloom forecasting. Since both the 1D-CNN and LSTM models outperformed the MLP model, it suggests that developing hybrid CNN-LSTM models might help achieve better forecasting capacity.

The study of univariate deep learning models can also serve as a baseline to assess the performance of multivariate models. Therefore, it is recommended to examine the impact of water quality and climate variables, such as water temperature profiles, dissolved oxygen, and nutrient loading rates, on the performance of deep learning models. It would also be worthwhile to compare univariate deep learning models with traditional statistical models like ARIMA and mechanistic process-based models like GLM to better understand each category's forecasting power.

Finally, we recommend exploring regularization methods at the model selection step to investigate the potential for reducing overfitting and achieving more robust models.

Acknowledgment

This work was financially supported by the University of Virginia School of Data Science under the Presidential Data Science Fellowship program.

Appendices

Appendix 4-1 More details on model development

The data wrangling, model development, and result analysis for this project were all carried out using Python 3. The deep neural networks were implemented in the Keras environment, which is an open-source high-level neural network library that prioritizes user-friendliness, modularity, and flexibility. Keras supports a wide range of neural network architectures, including multi-layer perceptron, convolutional, and recurrent neural networks, as well as combinations of these. The library includes pre-built layers for different types of neural networks, such as fully connected, convolutional, and pooling layers. Keras is built on top of TensorFlow and Theano, which provide efficient computation of mathematical operations on CPUs and GPUs. With Keras, users can quickly prototype and experiment with deep learning models by defining models, compiling them with different optimization options, and training them on various datasets using an easy-to-use API. If you would like to access the dataset and the full Python scripts for each model, please refer to our GitHub repository.

Appendix 4-2- Configuration list tested for different models

Table 4-2- Configuration list tested for MLP model

Iteration Index	Input Window Size	Hidden Layer Nodes No.	Epoch No.	Batch No.
0	3	128	20	10
1	3	128	20	50
2	3	128	40	10
3	3	128	40	50
4	3	256	20	10
5	3	256	20	50
6	3	256	40	10
7	3	256	40	50
8	5	128	20	10
9	5	128	20	50
10	5	128	40	10
11	5	128	40	50
12	5	256	20	10
13	5	256	20	50
14	5	256	40	10
15	5	256	40	50
16	7	128	20	10
17	7	128	20	50
18	7	128	40	10
19	7	128	40	50
20	7	256	20	10
21	7	256	20	50
22	7	256	40	10
23	7	256	40	50

Table 4-3- Configuration list tested for CNN model

Iteration Index	Input Window Size	Convolution Layer Filter No.	Epoch No.	Batch No.
0	5	32	10	1
1	5	32	10	10
2	5	32	20	1
3	5	32	20	10
4	5	64	10	1
5	5	64	10	10
6	5	64	20	1
7	5	64	20	10
8	5	128	10	1
9	5	128	10	10
10	5	128	20	1
11	5	128	20	10
12	5	256	10	1
13	5	256	10	10
14	5	256	20	1
15	5	256	20	10
16	7	32	10	1
17	7	32	10	10
18	7	32	20	1
19	7	32	20	10
20	7	64	10	1
21	7	64	10	10
22	7	64	20	1
23	7	64	20	10
24	7	128	10	1
25	7	128	10	10
26	7	128	20	1
27	7	128	20	10
28	7	256	10	1
29	7	256	10	10
30	7	256	20	1
31	7	256	20	10
32	14	32	10	1
33	14	32	10	10
34	14	32	20	1
35	14	32	20	10
36	14	64	10	1
37	14	64	10	10
38	14	64	20	1
39	14	64	20	10
40	14	128	10	1
41	14	128	10	10
42	14	128	20	1
43	14	128	20	10
44	14	256	10	1
45	14	256	10	10
46	14	256	20	1
47	14	256	20	10

Table 4-4- Configuration list tested for LSTM model

Iteration Index	Input Window Size	LSTM layer memory units	Epoch No.	Batch No.
0	5	200	10	1
1	5	200	10	16
2	5	200	20	1
3	5	200	20	16
4	7	200	10	1
5	7	200	10	16
6	7	200	20	1
7	7	200	20	16

Appendix 4-3- The distribution of average RMSE values for the deep learning models across 50 iterations for each configuration set

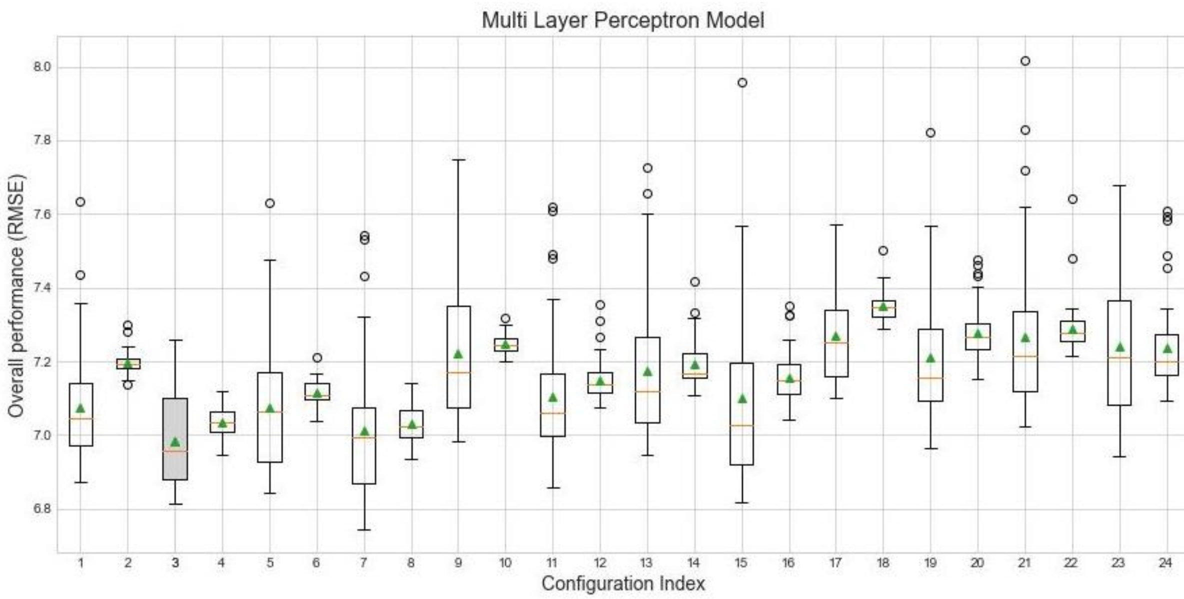

Figure 4-15- The distribution of average RMSE values for the MLP model across 50 iterations for each configuration set

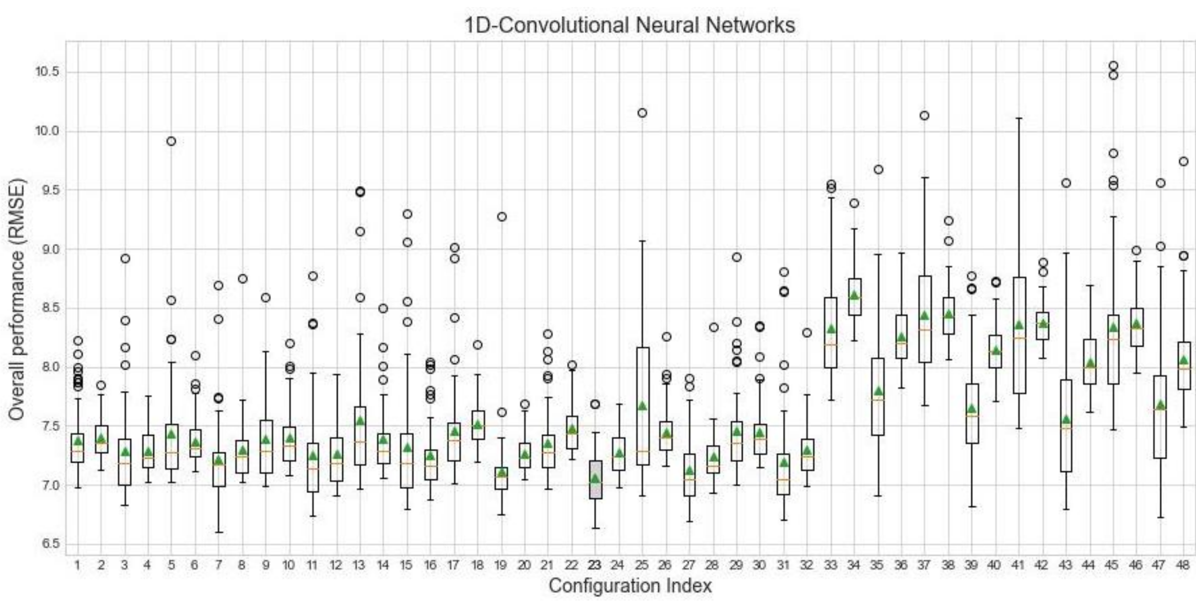

Figure 4-16- The distribution of average RMSE values for the 1D-CNN model across 50 iterations for each configuration setting.

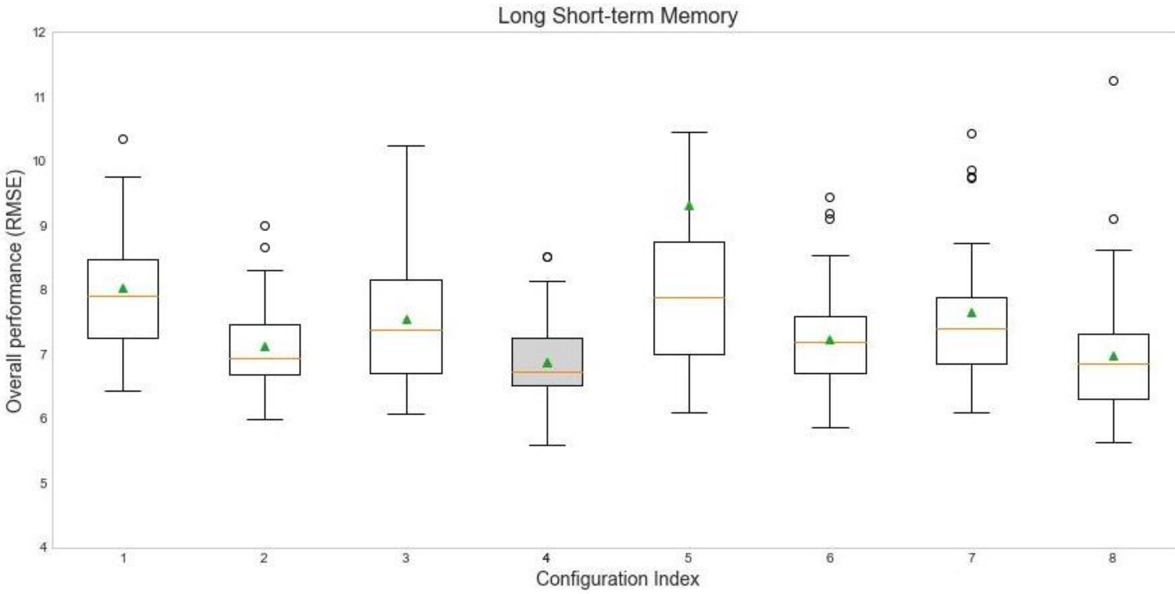

Figure 4-17- The distribution of average RMSE values for the LSTM model across 50 iterations for each configuration setting.

Chapter 5

Comparative Assessment of Multivariate and Univariate Deep Neural Networks for Near-Term Algal Bloom Forecasting: 1D-CNN and LSTM Approaches

Neda Nazemi[1], Cal Buelo[3], Michael Pace[3], Garrick Louis[1]

[1]Engineering Systems and Environment, University of Virginia, Charlottesville, VA
[2] Gianforte School of Computing, Montana State University, Bozeman, MT

[3] Environmental Sciences, University of Virginia, Charlottesville, VA

Abstract

Algal blooms present a substantial threat to aquatic ecosystems and aquaculture economies, underscoring the need for accurate forecasting models for these events. This study employed deep neural networks, known for their ability to identify complex patterns in multivariate time series data, to develop predictive models for algal blooms. Utilizing a multivariate time series from Peter Lake between 2008 and 2019, we created two multivariate, multi-step deep neural networks: a one-dimensional convolutional neural network (1D-CNN) and a long short-term memory network (LSTM) to forecast Chlorophyll-a (Chl-a) concentrations from one to seven days in advance. The mixed layer depth, mixed layer temperature, and color-normalized cumulative phosphorus loading rate emerged as the three important variables for multivariate models. Both 1D-CNN and LSTM multivariate models were evaluated, revealing that they significantly outperformed persistence (naïve) models in terms of forecast accuracy from day 2 to day 7 of the forecast window. Furthermore, the multivariate models considerably enhanced the performance of their univariate counterparts. Although both multivariate models exhibited similar performance, the 1D-CNN model demonstrated superior capabilities in predicting the intensity of blooms, particularly over longer forecast horizons. These findings hold significant implications for algal bloom forecasting and can potentially contribute to improved environmental management efforts.

Keywords

Ecological Forecasting, Multivariate Time Series Forecasting, Recurrent Networks, One-Dimensional Convolutional Neural Network (1-D CNN), Algal Bloom Management, Long Short-term Memory (LSTM), Proactive Water Resource Management

5.1. Introduction

Algal blooms are a natural phenomenon that can lead to severe ecological and economic damage. With the increasing occurrence and severity of harmful algal blooms, accurate forecasting models are necessary to prevent or mitigate their adverse effects. Forecasting models can provide early warning systems, enabling policymakers and stakeholders to take proactive measures to manage blooms (Cruz *et al.*, 2021).

When the priority is on achieving more accurate forecasts at longer forecasting windows, advanced machine learning techniques like deep neural networks are generally favored over other methods, although they sacrifice some interpretability (Borowiec *et al.*, 2022; Perry *et al.*, 2022). These techniques are better suited for dealing with complex, nonlinear, and noisy datasets, particularly when the underlying physical relationships are not fully understood. Unlike process-based models, which require prior assumptions about interactions and mechanisms of phytoplankton dynamics, machine learning (ML) models do not need such a priori assumptions (Shimoda and Arhonditsis, 2016). By leveraging the powerful ability of deep neural networks to analyze large amounts of data and identify intricate patterns, more robust and accurate forecasting models can be developed (Muttil and Chau, 2006; Derot, Yajima and Jacquet, 2020).

There are two types of time series forecasting methods: univariate and multivariate. Univariate methods solely rely on the current and past values of a single series being forecasted. On the other hand, multivariate methods incorporate the values of one or more additional time-series variables, referred to as predictor or explanatory variables, to forecast the given variable.

Univariate time series forecasting models offer simplicity and ease of implementation as they require data from a single variable. Moreover, the interpretability and transparency of univariate models are higher than multivariate models, as they solely focus on the dynamics of the target variable without accounting for the complexities of interdependence with other variables. Additionally, utilizing an increased number of features in multivariate models can raise the risk of overfitting, which is a concern for forecasting models that could affect their generalizability and performance on new data (Chapter 4).

Despite the advantages of univariate models, multivariate forecasting models offer several advantages as well. The use of multivariate models allows for the incorporation of additional information from other relevant variables, which can improve the accuracy of the forecasts. Multivariate models can also capture complex relationships between variables and identify patterns that might not be apparent in a univariate analysis. Additionally, the inclusion of explanatory variables can provide insights into the underlying mechanisms driving the observed patterns, which can be valuable for decision-making and policy development. Finally, multivariate models can handle situations where the target variable is influenced by multiple predictors, which can be useful in many real-world applications (Lai *et al.*, 2018; Shih, Sun and Lee, 2019).

In Chapter 4 of this dissertation, the performance of three categories of univariate deep neural networks, namely, multilayer perceptron (MLP), one-dimensional convolutional neural network (1-D CNN), and long short-term memory network (LSTM), was investigated to predict Chl-a concentrations one to seven days in advance. The results demonstrated that all three models outperformed the persistence forecast at forecast horizons of three days or longer. In this chapter, the aim is to harness the power of deep neural networks to capture the intricate and complex patterns in multivariate data, thereby enhancing the forecasting capability of the developed models. Due to the higher complexity of multivariate models and the computational cost of running multiple iterations, two types of more complex models, 1D-CNN and LSTM models were selected for this investigation.

Overall, the objective of this study was to enhance the accuracy of forecasting models for proactive measures toward preventing or mitigating harmful algal blooms. The approach included the selection and manipulation of independent variables, known to impact the occurrence of algal blooms, followed by a comparative evaluation of the performance of multivariate 1D-CNN and LSTM deep learning models.

5.2. Method of Study

The aim of this study was to harness the potential of deep neural networks for developing multivariate, multi-step forecasting models for algal blooms. As indicated by the results in Chapter 4, two types of neural networks demonstrated superior forecasting capabilities: one-dimensional convolutional neural networks (1D-CNNs) and Long Short-Term Memory networks (LSTMs). In this chapter, we investigate their performance when provided with multiple variables as input, as opposed to a single variable.

5.2.1. Data Collection and Pre-Processing

The data used in this study was gathered from Peter Lake, which is an experimental lake situated at the University of Notre Dame Environmental Research Center in the Upper Peninsula of Michigan, USA. Algal blooms are artificially induced in this lake through the additions of inorganic nitrogen and phosphorus (Carpenter and Pace, 2018). The time series data spans from 2008 to 2019, excluding data for 2012, 2016, and 2017 where high frequency observations of phytoplankton were not made. Lake fertilization occurred in 2013, 2014, 2015, and 2019, and it's worth noting that data collection was mainly carried out during the spring and summer seasons, which are prime bloom periods. Water samples for chlorophyll-a (chl-a) were collected daily at the center of the lake at a depth of 0.5m. Additionally, water quality parameters (phycocyanin, dissolved oxygen, pH) and temperature were measured in-situ at 0.75m every 5 minutes using automated sensors. Water temperature was also recorded every 5 minutes with a string of thermistors at intervals of 0.5m from 0.5 to 5 meters below the surface. Meteorological conditions (air temperature, wind speed, photosynthetically active radiation [PAR]) were measured every 5 minutes from a raft on Peter Lake. Other potential bloom drivers and limnological variables, such as light extinction profiles, water color (g440), nutrient concentrations (TN and TP), dissolved oxygen profiles, and zooplankton biomass, were measured on a weekly basis. (Buelo, 2021; Buelo *et al.*, 2022).

Finally, the available data was first cleaned by filling any missing values and removing outliers. The moving average method was then used to smoothen the data to daily values. Table 5-1 lists the parameters included in the pre-processed dataset.

Table 5-1- Raw Data Summary

Variable	**Units**
Year	-
Day of Year (doy)	-
Chlorophyll-a	$\mu g/l$
Water Temperature profile (every 30 cm)	^0C
PH	-
Saturated Dissolved Oxygen Concentration	%
Dissolved Oxygen Concentration	mg/l
Photosynthetically Active Radiation (PAR)	$\mu E/\,m^2.s$
Air Temperature	^0C
Wind Speed	mph
Wind Gust	mph
Wind Direction	$degree$
Phosphorus loading	$mgP/m^2/day$
Color	$Light\ Absorbance\ at\ 440\ nm\ (m^{-1})$

5.2.2. Feature Selection

Deep neural networks have a substantial number of parameters, necessitating a considerable volume of training data for effective learning. Feature selection can assist in reducing the input data's dimensionality, thereby decreasing the amount of data needed for training and allowing the model to learn more complex relationships and improve its predictive accuracy. Furthermore, feature selection aids in preventing overfitting by providing the model with more relevant and informative features. It is also worth noting that recurrent neural networks, such as LSTMs, can be computationally intensive to train, especially when dealing with large datasets. In light of these factors, feature selection becomes an essential pre-processing step before training the model.

To reduce the dimensionality of raw data, two approaches are commonly employed. The first approach involves generic transformation methods, such as Principal Component Analysis (PCA), which generates new features that are linear combinations of the original features while preserving most of the data variability. The second approach, known as feature engineering, leverages domain expertise to create new features or transform existing ones, making them more relevant and informative for the specific problem at hand (Zaki and Meira, 2014).

This study opted for the second approach, feature engineering, with the goal of creating meaningful and interpretable features based on domain knowledge. After an extensive analysis, we identified two features that could significantly reduce the data dimensionality without sacrificing the interpretability of the results. These two features are described as follows:

Mixed layer depth (Z_{mix}) and the average temperature at Z_{mix}

The mixed layer depth of a lake refers to the uppermost stratum in which water temperature, dissolved gases, and other properties exhibit relative uniformity due to mixing processes. Fluctuations in $\mathbf{Z_{mix}}$ may occur due to factors such as seasonal changes, weather conditions, and lake morphology. The depth of the mixed layer (Z_{mix}) can impact phytoplankton distribution and growth, and consequently, chlorophyll-a (chl-a) concentrations, by altering light availability, nutrient accessibility, and water temperature. In this study, Z_{mix} depth and the average temperature of the Z_{mix} layer were incorporated as input variables for the multivariate deep neural networks (Pace, Buelo and Carpenter, 2021). Figure 5-1 illustrates the variations in chl-a concentration and Z_{mix} temperature for each lake year.

Cumulative Nutrient Loading Normalized by Color (CNCP)

The phosphorus loading was converted into annual cumulative values and then normalized by the lake's color represented as g440, which is the absorbance at 440 nm with units in m^{-1}. This particular feature was chosen as it exhibited a threshold-like behavior, suggesting that blooms occur once the loading threshold is reached (Buelo, 2021; Buelo *et al.*, 2022).

5.2.3. Model Development

To prepare multivariate time series data for input into sequential models, the data must be transformed into a supervised learning problem by generating input-output sequences comprising M past observations as the input sequence and the subsequent N observations as the output sequence. In this context, M represents the number of lag observations, while N denotes the number of time steps targeted for forecasting. This study aims to forecast chlorophyll-a concentration up to seven days in advance, setting N to seven, while the input sequence size will be determined and optimized during the model selection process.

Subsequently, the supervised dataset should be divided into a training set and a test set, maintaining the temporal order of the data during the split to prevent data leakage. As such, the final year of data, 2019, was designated as the test dataset.

Additionally, it is necessary to reshape the input data into a 3D array with dimensions (samples, time steps, features), as this format is required by both LSTM and 1D-CNN sequential models. The architectures of each deep neural network model are detailed in the following sections.

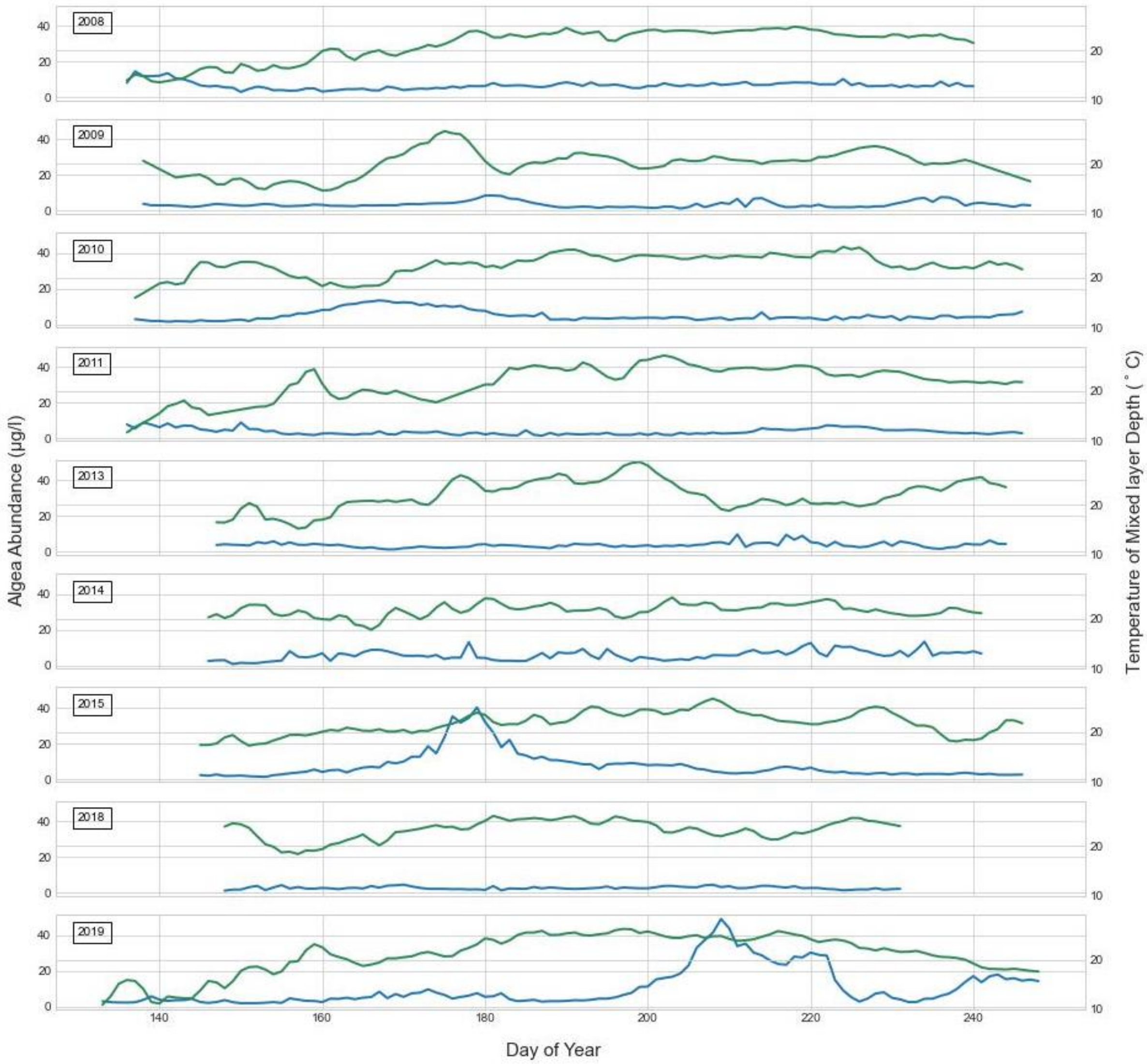

Figure 5-1- Chlorophyll-a (Chl-a) concentration (blue line, left y-axis) and Mixed Layer Depth (Z_{mix}) Temperature (green line, right y-axis) time series

DNN structure (multi-channel)

As depicted in Figure 5-2 the one-dimensional CNN model consists of two convolutional hidden layers, with each followed by a max pooling layer responsible for downsampling the feature maps while retaining the most salient information. The convolutional and pooling layers precede a densely connected layer that interprets the features extracted by the convolutional components of the model. To reduce the feature maps to a single one-dimensional vector, a flattening layer is incorporated between the convolutional layers and the dense layer.

Model fitting employs the efficient Adam variant of stochastic gradient descent, optimizing based on the mean squared error loss function. A grid search was conducted to optimize parameters such as input window size, number of filters, kernel size, epochs, and batch sizes.

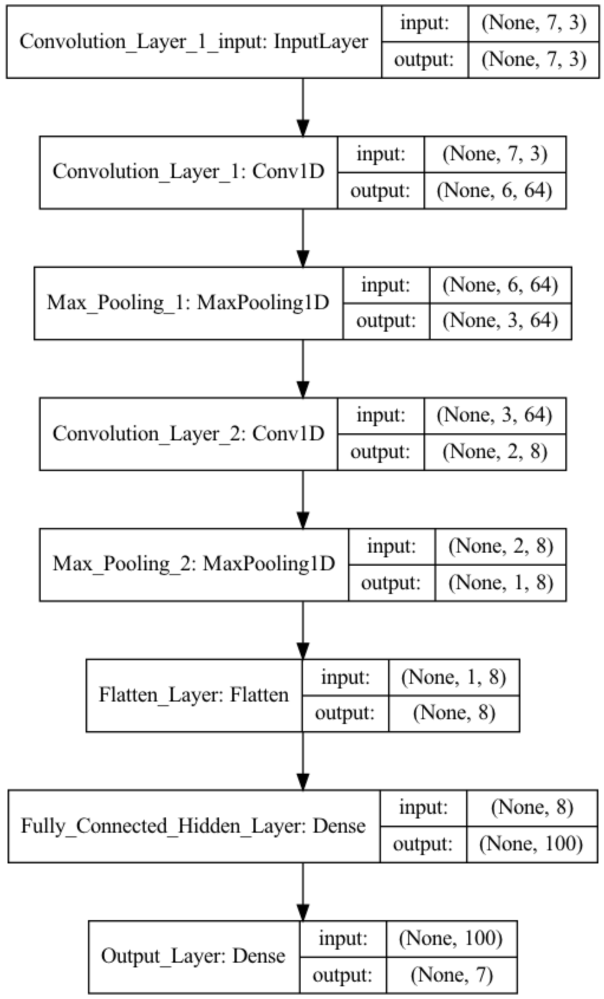

Figure 5-2- The structure of Multichannel One-Dimensional Convolutional Neural Network (1D-CNN)

LSTM structure (encoder-decoder)

The Encoder-Decoder LSTM architecture as shown in Figure 5-3 consists of two primary components: an encoder and a decoder.

The encoder model was implemented using a single LSTM layer, which outputs a fixed-size vector representing the input sequence's internal representation. The decoder's role is to transform the learned internal representation of the input sequence into the correct output sequence. To achieve this, another LSTM layer was utilized to construct the decoder model, which reads the fixed-sized output generated by the encoder model. As with any deep neural network (DNN), a Dense layer was employed as the network's output layer. By wrapping the Dense layer in a TimeDistributed wrapper, the same weights were used to generate each time step within the output sequence. Additionally, a RepeatVector layer was employed to bridge the encoder and decoder components of the model.

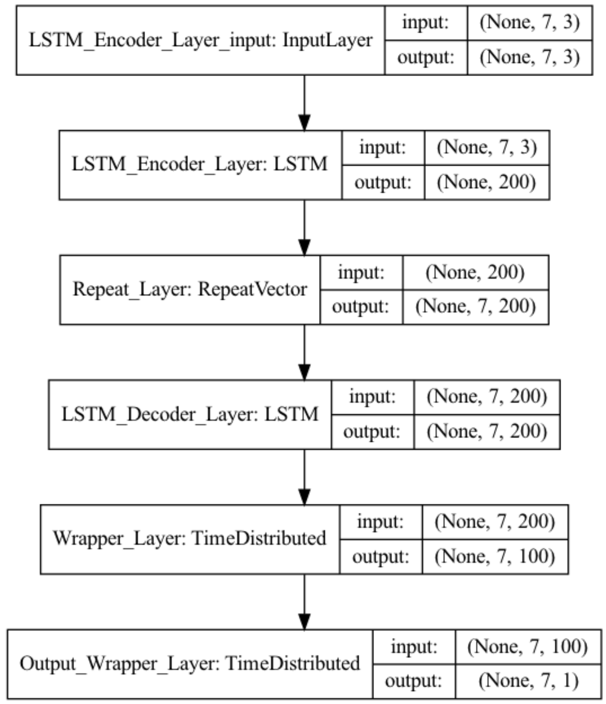

Figure 5-3- Graphical illustration of the multivariate time series forecasting framework via a sequence-to-sequence encoder-decoder model

The output layer leverages the mean squared error (MSE) loss function and the efficient Adam implementation of gradient descent for weight optimization. During the model selection step, hyperparameters such as the number of memory cells in the encoder and decoder LSTM layers, batch size, and epoch count were tuned.

5.2.4. Model Selection and Evaluation

The hyperparameter tuning process was conducted for each model using the grid search technique, with 50 iterations performed for each configuration setting to ensure robust forecasts. The Root Mean Square Error (RMSE) served as the accuracy measure for the model selection process. RMSE was computed for each forecast horizon (1-7 days), and the overall model accuracy was determined by averaging the accuracy scores for all seven forecasting steps. The model with the highest overall accuracy (lowest average RMSE) was chosen from each Deep Neural Network (DNN) category.

In addition to RMSE, the Nash-Sutcliffe model efficiency coefficient (NSC) was calculated to further illustrate the predictive power of each model at each forecast horizon. Moreover, the Model Skillfulness Coefficient (MSC), introduced in Chapter 4, was computed for each model and each forecast step. This coefficient compares the performance of each developed model to the persistence model at each forecast step. Positive MSC values indicate the model's superiority over the persistence forecasts, while negative values confirm that the selected model does not outperform the naïve model.

Finally, a t-test was conducted to evaluate the significance of the results in comparison to naïve forecasts. For more information on each evaluation approach, please refer to Chapter 4.

5.3. Results and Discussion

This study examined two categories of neural networks, namely 1-D CNN and LSTM, for the purpose of multivariate multi-step short-term algae bloom forecasting. Each model was trained on the training set spanning from 2008 to 2018 and then evaluated on the test set from 2019. A grid search approach was used to tune and select the hyperparameters of each model, with 50 iterations performed for each configuration setting. The complete configuration list for each model can be found in Appendices 1 and 2. The model with the lowest average test error in each group was selected as the optimal model.

As shown in Figure 5-4the average root mean squared error (RMSE) over all seven forecasting steps was calculated for the LSTM model. The results indicate that configuration 10 achieved the least average error. Furthermore, this configuration produced more consistent results when compared to configurations like 13 and 22, which showed a wide distribution of results.

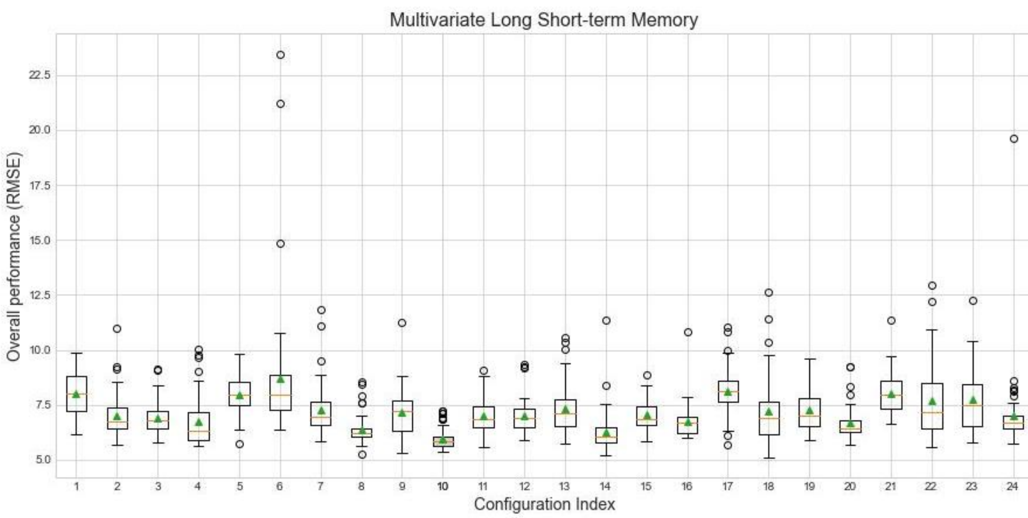

Figure 5-4- The distribution of average RMSE values for the LSTM model across 50 iterations for each configuration setting.

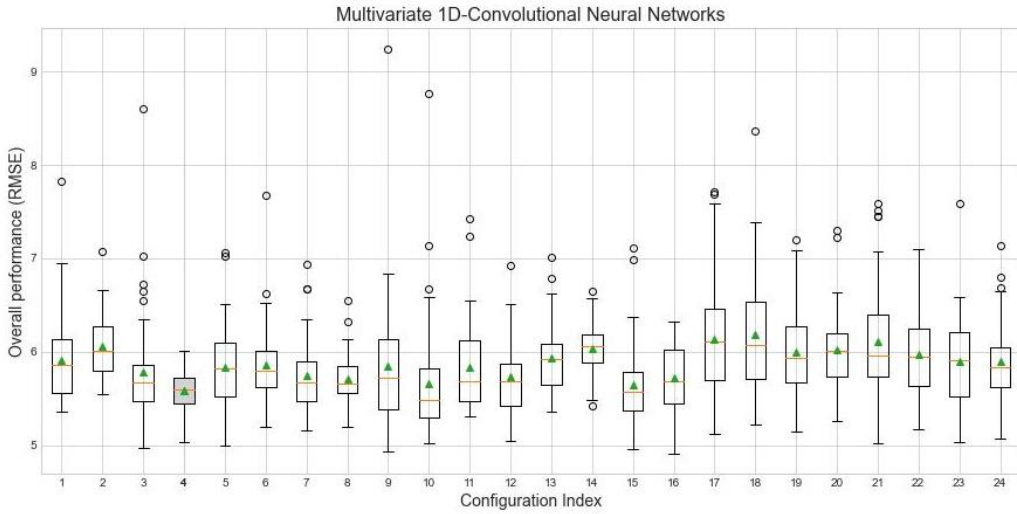

Figure 5-5- The distribution of average RMSE values for the 1-D CNN model across 50 iterations for each configuration setting.

Likewise, Figure 5-5 presents the distribution of average RMSE values for the 1D-CNN model for each configuration setting based on 50 iterations. The findings reveal that the configuration number 4 produced the lowest average error and resulted in more consistent forecasts. The selected configuration is provided in Table 5-2 which presents a summary of the selected models, including their overall performance in comparison to the naive (persistence) model.

Table 5-2- Configuration and Summary of Selected Models: This table summarizes the configuration of the selected models, along with their performance evaluation based on the average RMSE over all seven forecasting steps and the RMSE of 7-day forecasts.

	Model Configuration					Performance		Significance	
	Inputs Size	Nodes/ Units	Filters	Epoch No.	Batch No.	Overall RMSE	7-days RMSE	t-statistic	P-value
NAÏVE	-	-		-	-	7.25	10.30	-	-
1-D CNN	5	100	64	70	10	5.26	6.69	-55.00	≅0
LSTM	5	200/100	-	20	16	5.50	6.75	-21.22	≅0

The findings indicate that both models demonstrated superior performance when the input sequence consisted of the previous five days of observations. Specifically, the 1D-CNN model was trained with 64 convolution filters, 70 epochs, and 10 batches, while the selected LSTM model was trained on 20 epochs, 16 batches, and 200 and 100 memory units for its encoder and decoder layer respectively. The LSTM and 1D-CNN models outperformed the Naive model significantly, with overall RMSE values of 5.5 and 5.26, respectively, compared to the Naive model's overall RMSE value of 7.25. Furthermore, both models

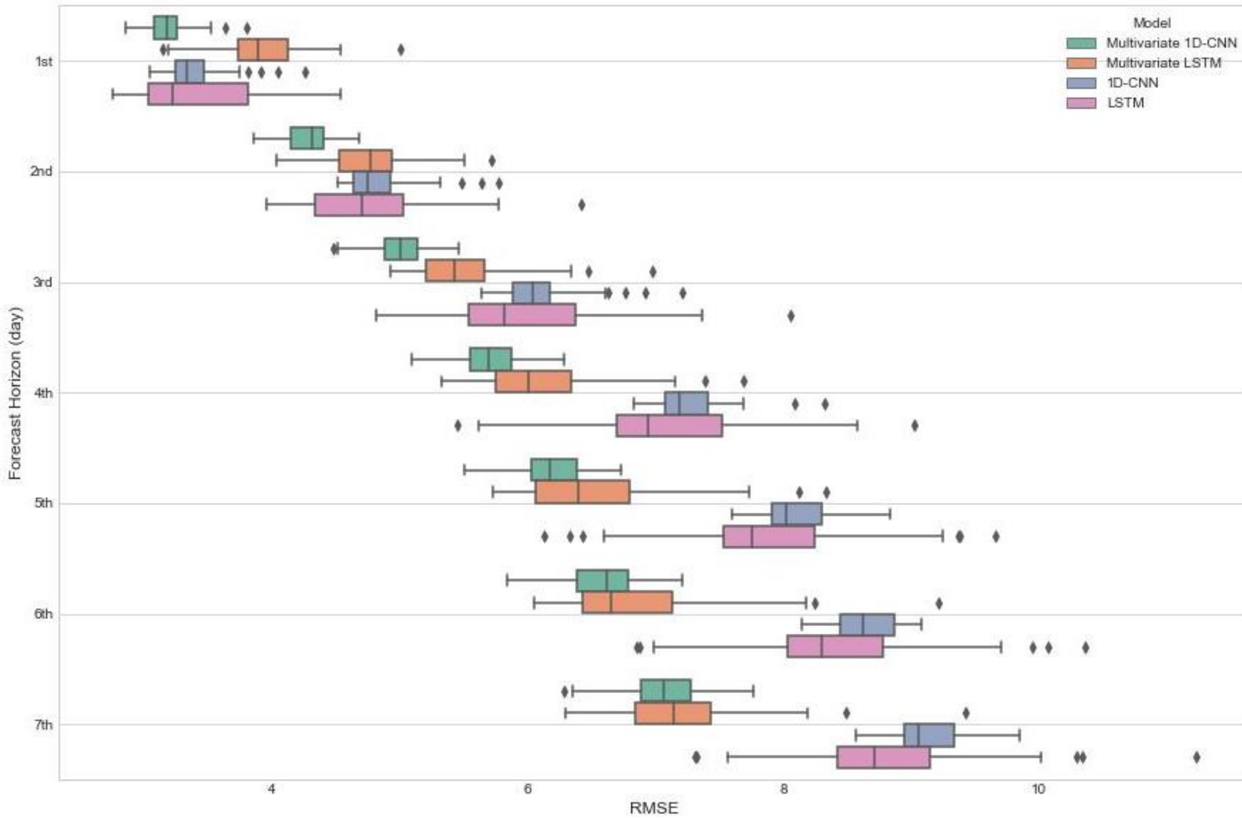

Figure 5-6- Selected models RMSE distribution of 50 iterations for each model

demonstrated more noteworthy outcomes when challenged with a seven-day forecast, which is the most demanding forecasting task for all models in this study, with 7-day RMSE values of 6.75 and 6.69, respectively, in contrast to the Naive model's 10.30 RMSE value.

Figure 5-6 illustrates that the RMSE scores of both multivariate and compare it with their corresponding univariate models. All four models consistently lose their forecasting power as the forecast horizon advances further into the future. Notably, the distribution of the LSTM models for all forecast steps exhibited greater variability than that of the 1D-CNN models; however, this variability is more significant in univariate models compared to the multivariate model. These results suggest that the 1D-CNN model is more robust than the LSTM model. Furthermore, the average error of the multivariate 1D-CNN model was smaller than that of the multivariate LSTM model for all forecast horizons. It is also evident that as of the third day both multivariate models outperformed the univariate models, and the gap becomes more apparent at longer forecast horizons. This conclusion is more visible when their Nash-Sutcliff coefficients are compared (Figure 5-7) All four selected models outperformed the naive model significantly, with the difference being more pronounced in longer forecast horizons. The difference between multivariate at longer forecast lengths is less significant; however, both multivariate models outperformed the univariate ones, which leads us to the conclusion that multivariate models enhance the algal bloom forecasting.

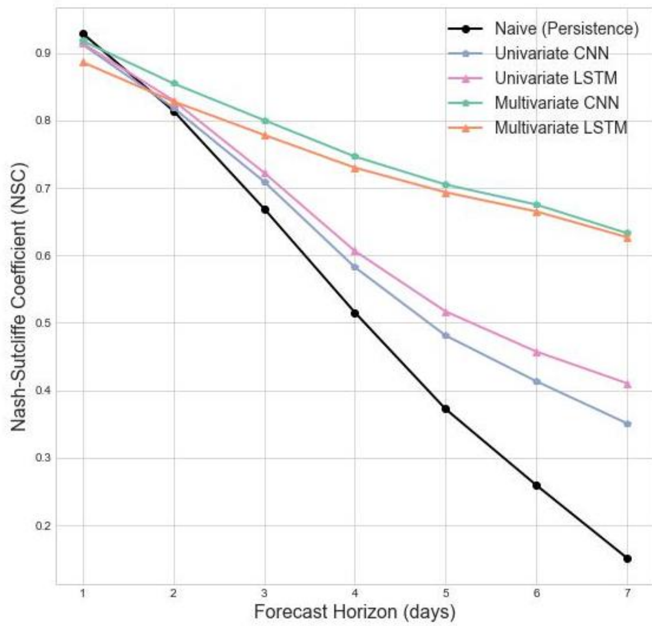

Figure 5-7- Nash-Sutcliff coefficient on the test set for different models and forecast horizons

The skillfulness measure (Figure 5-8) validates the above assertion. It shows that neither of the DNN models could forecast the algal bloom of the next day (1-day horizon) better than the persistence model. As a result, both models exhibited negative skillfulness values, indicating their inferiority when compared to the persistence model. However, for forecast horizons ranging from day 2 to day 7, the skillfulness measure consistently increases for both models. The DNN models are more accurate predictions as the forecast horizon expands.

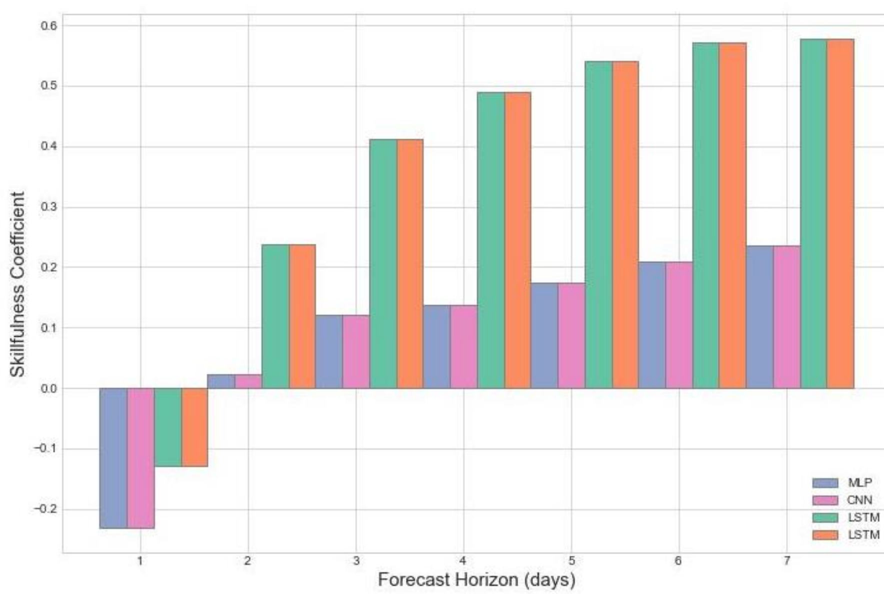

Figure 5-8- Skillfulness Coefficient for each of the two deep learning models versus seven days forecasts; negative values show their failure to outperform the naïve model for that forecast horizon

5.3.1. 1-day forecast

Figure 5-9- Comparison of one-day forecasts on the test set (2019)Figure 5-9 presents the Chl-a predictions of each deep learning model for the next day, as well as the actual observations based on the test set. Qualitatively, it indicates that both DNN models were able to accurately predict the Chl-a concentration for the following day. These findings are further supported Figure 5-10, which depicts a strong agreement between the forecasts and the actual observations. However, the LSTM model appeared to perform slightly weaker than the CNN models.

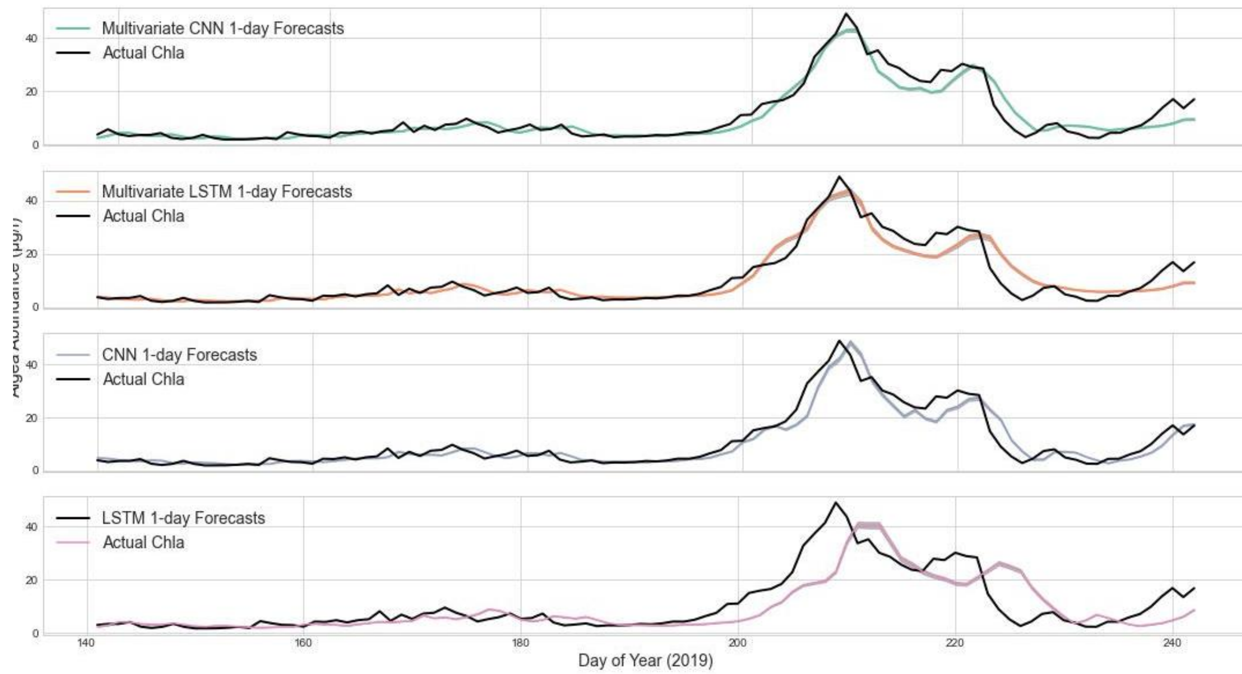

Figure 5-9- Comparison of one-day forecasts on the test set (2019)

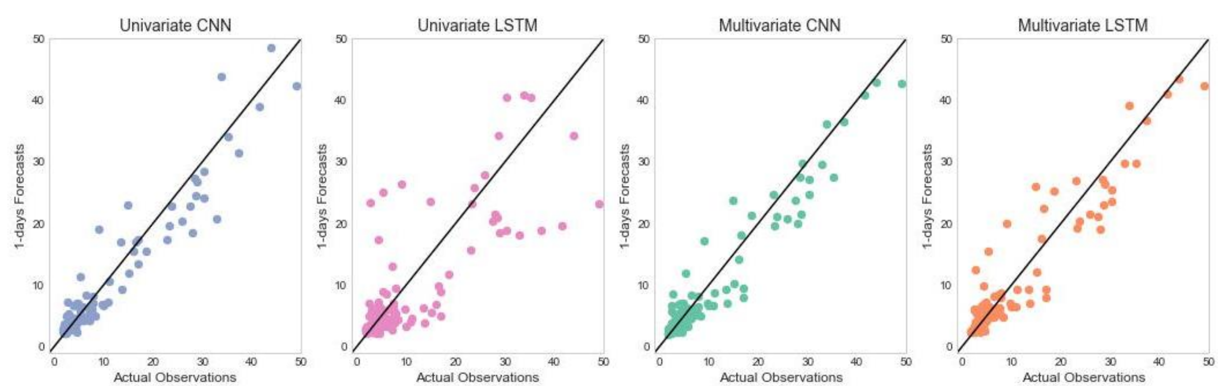

Figure 5-10- 1-day forecasts and actual observation agreement

5.3.2. 3-day forecast

A comparison between the three-day forecasts and actual observations was also conducted, as illustrated in Figure 5-11. The results demonstrate a strong agreement between the projections and actual values. Nevertheless, the 1D-CNN model performs slightly better than the other models at predicting the timing of major blooms.

Moreover, Figure 5-12 indicates that residuals are higher in three-day forecasts, particularly at higher Chl-a values. Nonetheless, the 1D-CNN forecasts exhibit better agreement with actual observations, as the points are less scattered.

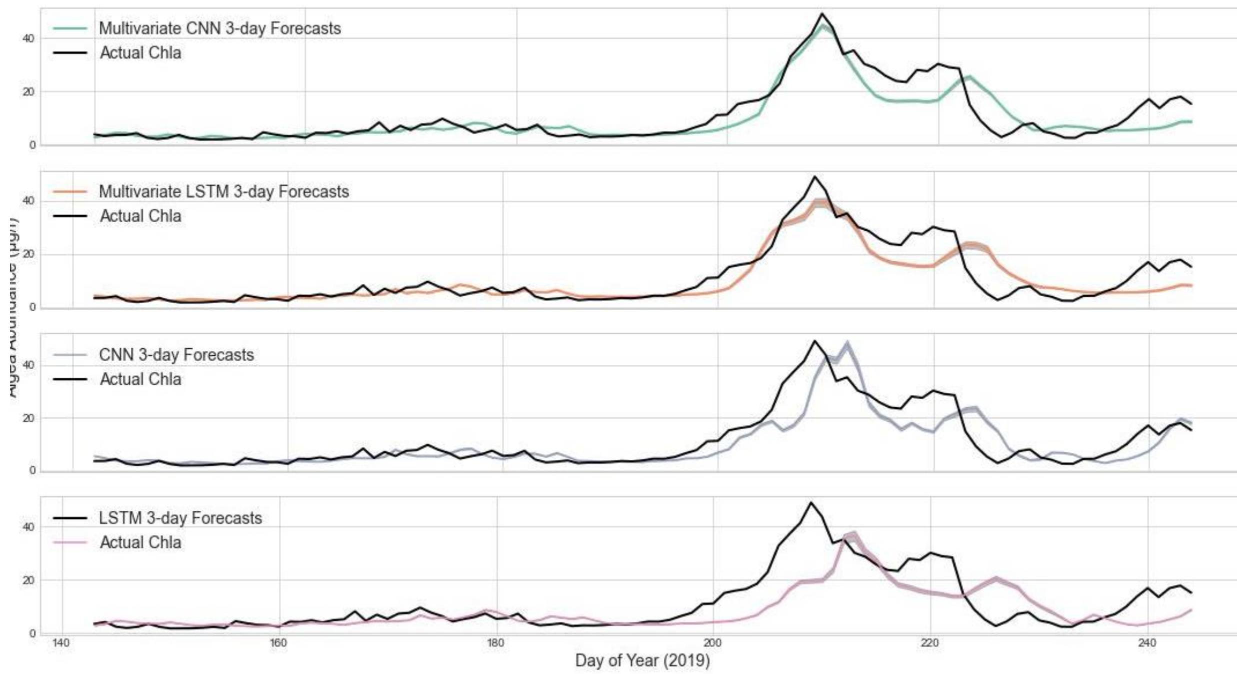

Figure 5-11- Comparison of 3-day forecasts on the test set (2019)

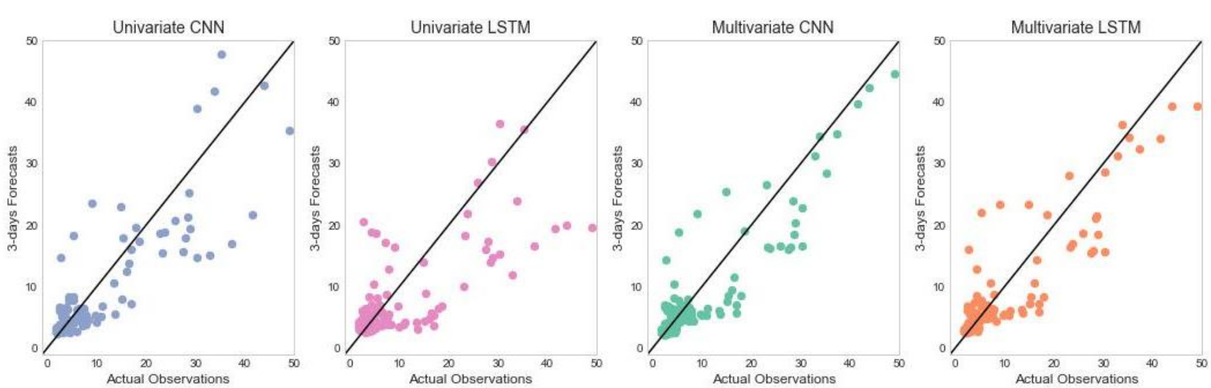

Figure 5-12- 3-day forecasts and actual observation agreement

5.3.3. 7-day forecast

The results indicate that both models performed reasonably well in predicting the timing of major bloom event. However, the 1D-CNN models showed more accurate forecasts of the intensity of the event. Furthermore, Figure 15 demonstrates that both models under-predicted the Chl-a values, as most of the points fell below the perfect agreement line.

In summary, these findings suggest that both models are effective in predicting the timing of major bloom event, but the 1D-CNN models may offer better accuracy in forecasting its intensity. Nonetheless, there is room for further improvement to enhance the forecasting accuracy of both models for Chl-a concentrations in Peter Lake.

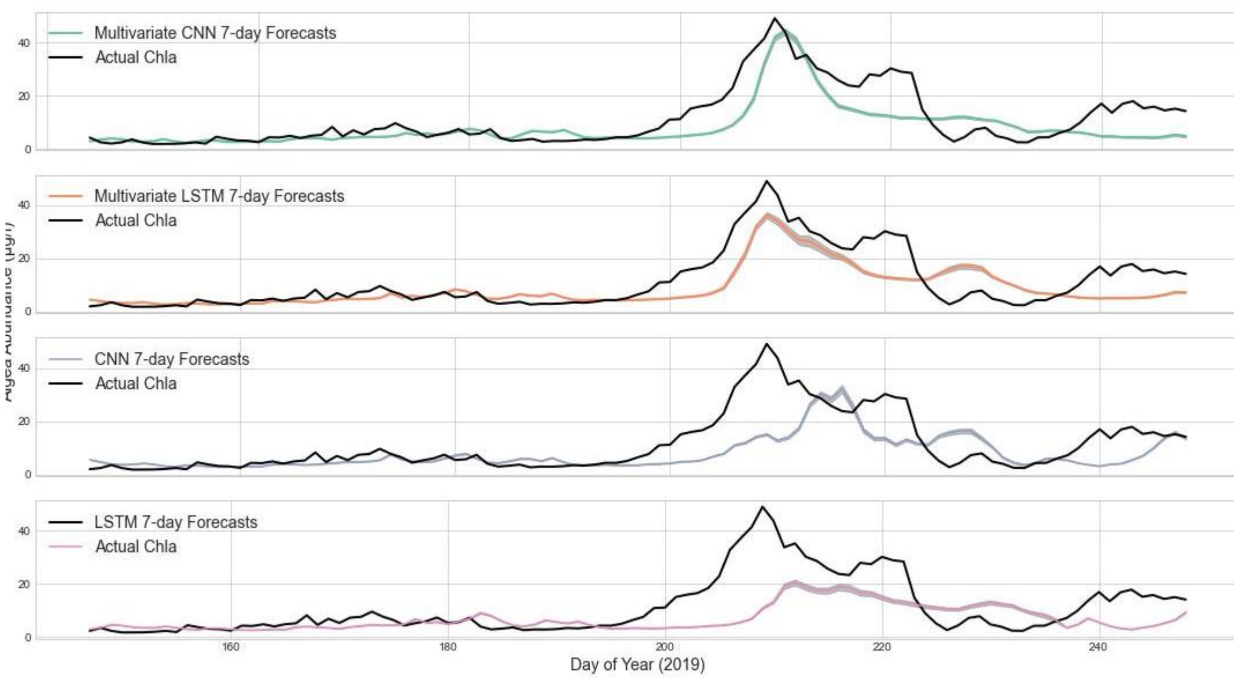

Figure 5-13- Comparison of seven-day forecasts on the test set (2019)

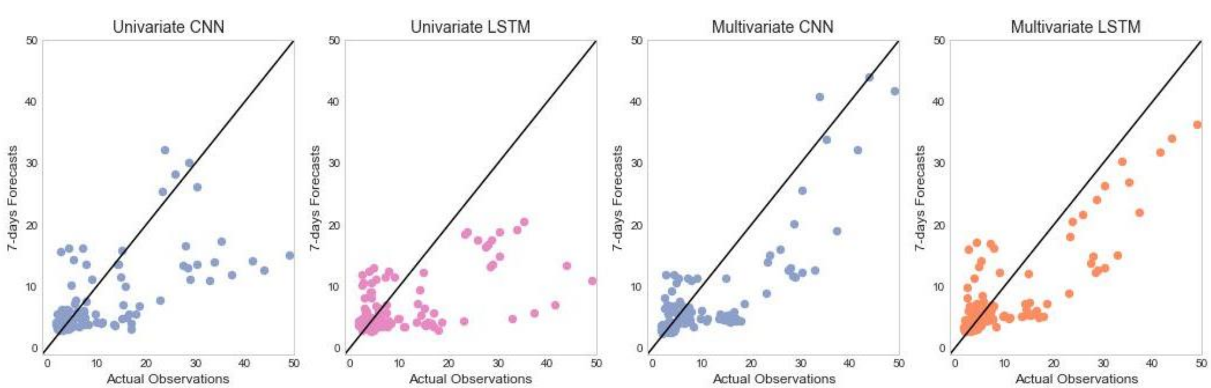

Figure 5-14- 7-days forecasts and actual observation agreement

5.4. Conclusions and Recommendations for Future Research

In this study, we investigated two multivariate deep neural network models, a one-dimensional Convolutional Neural Network (1-D CNN) and a Long Short-term Memory (LSTM), for near-term algal bloom forecasting in Peter Lake. The multivariate models are more complex than univariate models, which solely utilize the past observation of the target variable to predict its future values. To minimize the risk of overfitting and maintain reasonable computational costs, we only added three extra predictors to univariate models, including mixed layer depth and temperature and cumulative phosphorus loading rate normalized by watercolor. We employed the persistence model and univariate CNN and LSTM models as baselines to evaluate the performance of multivariate models.

The models were trained to provide Chl-a forecasts up to 7 days in advance. The results demonstrated that both LSTM and 1D-CNN models significantly outperformed the naïve model and their univariate counterparts, especially at forecast horizons longer than two days. While the performance of the persistence and univariate models declined with increasing forecast steps, the multivariate models displayed more robust forecasts across all forecast horizons.

Overall, our comparative investigation revealed that despite the increased complexity introduced by additional variables in deep neural network models, their inclusion helped enhance the forecasting accuracy of these models. Since both the LSTM and 1D-CNN models were able to improve significantly upon the univariate models, developing hybrid CNN-LSTM models might lead to achieving even better forecasting accuracy.

As a further step, we recommend applying the trained models to predict Chl-a concentration in other lakes to gain a better understanding of their generalization capabilities. This will help determine if the models can maintain their forecasting accuracy across different ecosystems, providing valuable insight into the broader applicability of the developed models for algal bloom forecasting and management.

Acknowledgment

This work was financially supported by the University of Virginia School of Data Science under the Presidential Data Science Fellowship program.

Appendices

Appendix 5-1- Configuration list tested for each model.

Table 5-3- Configuration list tested for CNN model

Iteration Index	Input Window Size	Convolution Layer Filter No.	Epoch No.	Batch No.
0	7	64	20	4
1	7	64	20	10
2	7	64	70	4
3	7	64	70	10
4	7	128	20	4
5	7	128	20	10
6	7	128	70	4
7	7	128	70	10
8	7	256	20	4
9	7	256	20	10
10	7	256	70	4
11	7	256	70	10
12	5	64	20	4
13	5	64	20	10
14	5	64	70	4
15	5	64	70	10
16	5	128	20	4
17	5	128	20	10
18	5	128	70	4
19	5	128	70	10
20	5	256	20	4
21	5	256	20	10
22	5	256	70	4
23	5	256	70	10

Table 5-4- Configuration list tested for LSTM model

Iteration Index	Input Window Size	LSTM layer memory units	Epoch No.	Batch No.
0	5	200	20	4
1	5	200	20	16
2	5	200	50	4
3	5	200	50	16
4	5	400	20	4
5	5	400	20	16
6	5	400	50	4
7	5	400	50	16
8	7	200	20	4
9	7	200	20	16
10	7	200	50	4
11	7	200	50	16
12	7	400	20	4
13	7	400	20	16
14	7	400	50	4
15	7	400	50	16
16	9	200	20	4
17	9	200	20	16
18	9	200	50	4
19	9	200	50	16
20	9	400	20	4
21	9	400	20	16
22	9	400	50	4
23	9	400	50	16

Chapter 6
Conclusion

In this chapter, the key insights and significant contributions of the present dissertation are thoroughly synthesized, offering a comprehensive overview of the work. Additionally, it identifies potential directions for further research in the field, exploring new opportunities for advancing knowledge. Lastly, the chapter outlines the author's professional journey post-graduation, highlighting the impact of their academic achievements on career development.

6.1. Overview of Findings and Contributions

In this dissertation, we conducted a thorough investigation of two distinct foresight perspectives, namely exploratory and predictive, as they relate to adaptive water resource management (WRM). Our research is divided into two main parts, each focusing on a specific approach.

In the first part, encompassing chapters 2 and 3, we delved into an exploratory approach to water governance, particularly in arid and semi-arid regions, where managing water supply represents a formidable challenge. The focus of Part 1 is a case study that examines agricultural water demand management within the Zayandehrud watershed in Iran.

Chapter 2 employed an exploratory, formative scenario planning method to pinpoint crucial adaptation strategies and create a coherent, plausible, and diverse set of regional agricultural water governance scenarios for the Zayandehroud watershed in Iran by 2040. This led to five scenarios illustrating varied adaptation and mitigation approaches to agricultural water demand, including maintaining the status quo. Each scenario represents distinct economic and political priorities, showcasing their effects on the ecological, social, and economic sustainability of the watershed.

Building on the findings from Chapter 2, Chapter 3 developed a partial equilibrium economic model to examine the long-term impact of water markets and various food trade policies on the agricultural sector, as well as their effects on farmers' welfare and ecological sustainability within the Zayandehrud watershed. The results confirmed that an intra-national water market in a closed economy can lead to increased utility, although it might not necessarily reduce irrigation water demand. Conversely, free trade conditions combined with water markets can alleviate pressure on water resources, provide greater consumer utility, and improve conditions concerning unauthorized extraction. The primary contributions of this section of the research can be summarized as:

- Actively involving stakeholders in the identification of key adaptation strategies and policy interventions for agricultural water management (AgWM), ensuring diverse perspectives.
- Presenting a comprehensive framework for exploring a range of normative water governance scenarios
- Utilizing the formative scenario planning approach to develop a select set of plausible, distinct regional agricultural water governance alternative scenarios.
- Evaluating the potential impacts of these scenarios on the overall sustainability and adaptability of the watershed to identify effective strategies for long-term water resource management.

The results of this part can inform policy development and decision-making processes in this watershed. Ultimately, this in-depth examination of the Zayandehrud watershed case study serves as a foundation for further research on exploratory foresight methods in similar contexts around the world.

In the subsequent segment of this investigation, the emphasis transitioned from the governance aspect of water resource management to the operational dimension, and from an exploratory perspective to a predictive approach. Consequently, rather than examining the spectrum of plausible futures, our concentration was directed towards the projection of the most likely outcome, which can facilitate proactive water resource management at the operational level. This section of the research delved into the utilization of deep neural networks as a cutting-edge short-term forecasting methodology in the decision-making process for operational water resource management.

This section's focus was centered on water quality, specifically scrutinizing Harmful Algal Blooms (HABs) in freshwater resources. In particular, Chapter 4 utilized historical Chl-a observations (2008-2019) from Peter Lake to develop three univariate deep neural networks: multilayer perceptron (MLP), one-dimensional convolutional neural network (1-D CNN), and Long short-term memory network (LSTM) for predicting Chl-a concentrations with a one to seven-day lead time. A persistence forecast functioned as the benchmark to evaluate each model's precision. The outcomes indicated that all three models surpassed the persistence forecast for prediction horizons of three days or longer. Chapter 5 broadened the scope of Chapter 4 by integrating water quality and environmental variables to augment the performance of univariate models. Both 1D-CNN and LSTM multivariate models were assessed, demonstrating that they significantly outperformed persistence (naïve) models concerning forecast accuracy from day 2 to day 7 of the forecast window. Moreover, the multivariate models substantially improved the performance of their univariate counterparts.

The principal contributions of this segment of the investigation can be encapsulated as follows:

- Establishing a holistic framework for appraising the performance of short-term forecasting models, which empowers stakeholders to effectively assess and compare diverse predictive instruments.
- Ameliorating existing algal bloom predictions by employing high-frequency data and sophisticated deep learning methodologies, culminating in more precise and timely forecasts that can more adequately inform water management decisions.

Focusing on water quality and HABs, this segment of the research underscored the significance of incorporating predictive methodologies in operational water resource management. The creation of a robust evaluation framework for forecasting models and the employment of state-of-the-art deep learning techniques facilitates enhanced prediction of algal blooms, thereby enabling informed decision-making and proactive management of algal blooms, ultimately contributing to water quality management. These advancements provide valuable insights applicable to diverse operational water resource management challenges, accentuating the potential of predictive approaches in devising effective water resource management strategies. Moreover, the findings of this study extend beyond the realm of water resource management, demonstrating applicability in other domains of knowledge as the methodologies and frameworks developed can be applied to a variety of fields that require short-term forecasting and decision-making. For example, the comprehensive framework for evaluating near-term forecasting models and the use of advanced deep learning techniques can be applied to predict energy demand or renewable energy generation, such as solar and wind power. Accurate and timely forecasts in this domain can inform grid operators, enabling them to manage power distribution more efficiently and optimize the integration of renewable energy sources. This, in turn, can contribute to enhanced energy reliability, reduced costs, and decreased greenhouse gas emissions. As another example, the enhanced predictive capabilities derived from high-frequency data and deep learning methodologies can be utilized for forecasting the spread of infectious diseases or predicting the occurrence of disease outbreaks. Accurate and timely predictions in public health can inform policymakers and healthcare professionals, allowing them to allocate resources efficiently, develop targeted interventions, and implement preventive measures.

In its entirety, this dissertation aimed to provide exploratory and predictive foresight methodologies and their application to the pressing issue of water resource management. The research sought to delineate the suitability of these two distinct approaches, elucidating how and when each perspective can contribute to adaptive policy-making and proactive water resource management.

The exploratory approach was used to examine a wide range of plausible futures, identifying critical adaptation strategies and formulating diverse regional agricultural water governance scenarios. Through this method, the research emphasized the importance of considering all plausible futures rather than just the most likely ones. This process allowed for the development of well-rounded, adaptable strategies that can accommodate future uncertainties and shifts in regional dynamics.

In contrast, the predictive foresight methodology concentrated on generating short-term, data-driven forecasts for specific water resource management challenges, such as water quality and harmful algal blooms. This part focused on predicting the most probable short-term future.

Throughout the dissertation, the interplay between these two foresight approaches was highlighted, demonstrating that a combination of both perspectives can offer comprehensive, well-rounded solutions for water resource management. By employing exploratory methods to develop adaptable strategies and using predictive techniques for operational decision-making, policymakers and water resource managers can better navigate the complexities and uncertainties surrounding water resource management.

6.2. Suggestions for Future Research

Based on the analyses performed and reported in this dissertation, the following future work is

recommended to further improve the water resource management:

1. Expanding the application of exploratory and predictive foresight approaches to other water resource management challenges, such as flood management, drought resilience, and ecosystem conservation. Investigating these areas could help identify new adaptation strategies and advance decision-making processes across various aspects of water resource management.
2. Exploring the integration of additional data sources and novel deep learning techniques to enhance the accuracy and timeliness of short-term forecasts. This could involve examining the potential of incorporating remote sensing data, real-time monitoring systems, or other emerging technologies to augment the existing models and improve their performance.
3. Investigating the effectiveness of the developed methodologies and frameworks in different geographical contexts and diverse socio-economic settings. Comparing the outcomes of various case studies can offer valuable insights into the transferability and generalizability of the exploratory and predictive foresight approaches, thus enriching the knowledge base for adaptive policy-making and proactive management in water resource management worldwide.

4. Assessing the long-term effectiveness and adaptability of the developed strategies and policies in real-world scenarios, including their ability to respond to changing climatic conditions, socio-economic transformations, and technological advancements. This could involve periodic evaluations and updates to ensure their continued relevance and effectiveness.
5. Investigating the potential for cross-sectoral applications of the developed methodologies and frameworks, particularly in sectors such as energy, public health, and environmental conservation, where short-term forecasting and decision-making are critical. The versatility of exploratory and predictive foresight approaches may offer innovative solutions to complex problems in these domains, further enhancing their value and applicability.

6.3. Career Forward

I began my career as an Assistant General Faculty member at the Gianforte School of Computing at Montana State University, Bozeman. My educational and research experience in the Ph.D. program in Systems Engineering equipped me with a diverse skillset, enabling me to promote interdisciplinary research and tackle pressing real-world challenges. I am currently working on establishing a new lab called "AI for Sustainability, Resilience, and Security," leveraging my multidisciplinary research background and technical expertise to advance knowledge in this field.

6.4. Publications

This research has resulted in the following publications:

1. *Nazemi, N.*, Foley, R.W, Louis, G., Keeler, L.W. (2020) 'Divergent agricultural water governance scenarios: The case of Zayanderud basin, Iran', *Agricultural Water Management*, 229. doi: 10.1016/j.agwat.2019.105921.

2. *Nazemi, N.*, Eghdami, S. and Foley, R. W., Louis, G. (2018) 'Modeling water market and food free-trade policies as instruments for governance of agricultural water demand in arid and semi-arid regions', in *proceeding of 39th International Annual Conference of the American Society for Engineering Management, ASEM 2018: Bridging the Gap Between Engineering and Business*.

3. *Nazemi N*, Buelo C.D., Pace M.L., Louis G.E. 'Univariate Deep Learning for Short-Term Algal Bloom Prediction: A Comparative Analysis of MLP, 1D-CNN, and LSTM Models' (To be submitted)

4. *Nazemi N*, Buelo C.D., Pace M.L., Louis G.E. Comparative Assessment of Multivariate and Univariate Deep Neural Networks for Near-Term Algal Bloom Forecasting: 1D-CNN and LSTM Approaches (To be submitted)

References

Abyareh, R. (2009) *Tourism Attractions and their Influence on Handicraft Employment in Isfahan*. Lulea University of Technology.

BBC (2018) ‘استاندار یزد از ۲۲ بار خرابکاری در خط لوله انتقال آب به یزد انتقاد کرد’, *BBC News*, 21 October. Available at: https://www.bbc.com/persian/iran-45931358 (Accessed: 26 October 2019).

Bekchanov, M., Bhaduri, A. and Ringler, C. %J A. water management (2015) ‘Potential gains from water rights trading in the Aral Sea Basin’, *Agricultural Water Management*, 152, pp. 41–56.

Benndorf, J. and Recknagel, F. (1982) ‘Problems of application of the ecological model SALMO to lakes and reservoirs having various trophic states’, *Ecological Modelling*. Elsevier, 17(2), pp. 129–145.

Beruvides Mario (2015) ‘Financial and Groundwater Credit in Contractionary Environments: Implications for Sustainable Groundwater Management and the Groundwater Credit Crunch’, *Proceedings of the International Annual Conference of the American Society for Engineering Management.* American Society for Engineering Management (ASEM), p. 1.

Bishop, P., Hines, A. and Collins, T. (2007) ‘The current state of scenario development: an overview of techniques’, *foresight*. Emerald Group Publishing Limited, 9(1), pp. 5–25.

Bjornlund, H. (2003) ‘Efficient water market mechanisms to cope with water scarcity’, *Water Resources Development*, 19(4), pp. 553–567.

Boelens, R. and Vos, J. (2012) ‘The danger of naturalizing water policy concepts: Water productivity and efficiency discourses from field irrigation to virtual water trade’, *Agricultural Water Management*. Elsevier, 108, pp. 16–26.

Börjeson, L. *et al.* (2005) ‘Towards a user’s guide to scenarios-a report on scenario types and scenario techniques’, *Royal Institute of Technology, Stockholm*.

Borowiec, M. L. *et al.* (2022) ‘Deep learning as a tool for ecology and evolution’, *Methods in Ecology and Evolution*. Wiley Online Library, 13(8), pp. 1640–1660.

Brownlee, J. (2017) *Long short-term memory networks with python: develop sequence prediction models with deep learning*. Machine Learning Mastery.

Brownlee, J. (2018) *Deep learning for time series forecasting: predict the future with MLPs, CNNs and LSTMs in Python*. Machine Learning Mastery.

Bucknall, J. (2007) *Making the most of scarcity: accountability for better water management results in the Middle East and North Africa*. World Bank Publications.

Buelo, C. D. (2021) *Change in aquatic ecosystems: advancing resilience concepts towards practical applications*. Univesity of Virginia.

Buelo, C. D. *et al.* (2022) ‘Evaluating the performance of temporal and spatial early warning statistics of algal blooms’, *Ecological Applications*. Wiley Online Library, 32(5), p. e2616.

REFRENCES

Buelo, C. D., Carpenter, S. R. and Pace, M. L. (2018) 'A modeling analysis of spatial statistical indicators of thresholds for algal blooms', *Limnology and Oceanography Letters*. Wiley Online Library, 3(5), pp. 384–392.

Carmichael, W. W. *et al.* (2001) 'Human fatalities from cyanobacteria: chemical and biological evidence for cyanotoxins.', *Environmental health perspectives*, 109(7), pp. 663–668.

Carpenter, S. R. and Pace, M. L. (2018) 'Synthesis of a 33-yr series of whole-lake experiments: Effects of nutrients, grazers, and precipitation-driven water color on chlorophyll', *Limnology and Oceanography Letters*. Wiley Online Library, 3(6), pp. 419–427.

Carpenter, S. R. and Rissman, A. R. (2012) 'Scenarios and decisionmaking for complex environmental systems'.

Cawley, G. C. and Talbot, N. L. C. (2010) 'On over-fitting in model selection and subsequent selection bias in performance evaluation', *The Journal of Machine Learning Research*. JMLR. org, 11, pp. 2079–2107.

Chen, Q. *et al.* (2015) 'Online forecasting chlorophyll a concentrations by an auto-regressive integrated moving average model: Feasibilities and potentials', *Harmful Algae*. Elsevier, 43, pp. 58–65.

Chong, H. and Sunding, D. (2006) 'Water markets and trading', *Annu. Rev. Environ. Resour.*, 31, pp. 239–264.

Clapp, J. (2017) 'Food self-sufficiency: Making sense of it, and when it makes sense', *Food policy*, 66, pp. 88–96.

Cobb, C. W. and Douglas, P. H. (1928) 'A theory of production', *The American Economic Review*, 18(1), pp. 139–165.

Cosgrove, W. J. and Loucks, D. P. (2015) 'Water management: Current and future challenges and research directions', *Water Resources Research*. Wiley Online Library, 51(6), pp. 4823–4839.

Cruz, R. C. *et al.* (2021) 'A Review of recent machine learning advances for forecasting harmful algal blooms and shellfish contamination', *Journal of Marine Science and Engineering*. MDPI, 9(3), p. 283.

Davidson, K. *et al.* (2016) 'Forecasting the risk of harmful algal blooms'. Elsevier.

Debaere, P. (2014) 'The global economics of water: is water a source of comparative advantage?', *American Economic Journal: Applied Economics*, 6(2), pp. 32–48.

Debaere, P. *et al.* (2014) 'Water markets as a response to scarcity', *Water Policy*, 16(4), pp. 625–649.

Derot, J., Yajima, H. and Jacquet, S. (2020) 'Advances in forecasting harmful algal blooms using machine learning models: A case study with Planktothrix rubescens in Lake Geneva', *Harmful Algae*. Elsevier, 99, p. 101906.

Dietz, T., Ostrom, E. and Stern, P. C. (2003) 'The struggle to govern the commons', *science*, 302(5652), pp. 1907–1912.

Easthope, M. P. and Howard, A. (1999) 'Simulating cyanobacterial growth in a lowland reservoir', *Science of the total environment*. Elsevier, 241(1–3), pp. 17–25.

REFRENCES

Felmeden, J. (2014) *Agriculture in the Zayandeh Rud Catchment*. Institut für sozial-ökologische Forschung ISOE GmbH.

Field, C. B. (2014) *Climate change 2014–Impacts, adaptation and vulnerability: Regional aspects*. Cambridge University Press.

Finlayson, M. *et al.* (2005) *Millennium Ecosystem Assessment: Ecosystems and human well-being: wetlands and water synthesis*. Island Press.

Foley, R. W. and Wiek, A. (2014) 'Scenarios of nanotechnology innovation vis-à-vis sustainability challenges', *Futures*, 64, pp. 1–14.

Fuerth, L. S. (2009) 'Foresight and anticipatory governance', *Foresight-The journal of future studies, strategic thinking and policy*. Emerald Group Publishing Limited, 11(4), pp. 14–32.

Funke, N., Claassen, M. and Nienaber, S. (2013) 'Development and Uptake of Scenarios to Support Water Resources Planning, Development and Management–Examples from South Africa', in *Water Resources Planning, Development and Management*. Intech.

Godet, M. (2000) 'The art of scenarios and strategic planning: tools and pitfalls', *Technological forecasting and social change*. Elsevier, 65(1), pp. 3–22.

Gohari, A. *et al.* (2013) 'Climate change impacts on crop production in Iran's Zayandeh-Rud River Basin', *Science of the Total Environment*, 442, pp. 405–419.

Grafton, R. Q. (2017) 'Responding to the 'wicked problem'of water insecurity', *Water Resources Management*. Springer, 31(10), pp. 3023–3041.

Guimaraes Pereira, A., Von Schomberg, R. and Funtowicz, S. (2006) 'Foresight knowledge assessment', *International Journal of Foresight and Innovation Policy*. Inderscience Publishers, 3(1), pp. 53–75.

Haasnoot, M. and Middelkoop, H. (2012) 'A history of futures: a review of scenario use in water policy studies in the Netherlands', *Environmental science & policy*. Elsevier, 19, pp. 108–120.

Hamilton, D. P. and Schladow, S. G. (1997) 'Prediction of water quality in lakes and reservoirs. Part I—Model description', *Ecological modelling*. Elsevier, 96(1–3), pp. 91–110.

Hancock, T. and Bezold, C. (1994) 'Possible futures, preferable futures.', in *The Healthcare Forum Journal*, pp. 23–29.

Hardin, G. (1968) 'The tragedy of the commons', *science*. American Association for the Advancement of Science, 162(3859), pp. 1243–1248.

Hearnshaw, E. J. S., Tompkins, J.-M. and Cullen, R. (2011) 'Addressing the wicked problem of water resource management: An ecosystem services approach'. Australian Agricultural & Resource Economics Society.

Henriques, C. *et al.* (2015) 'The future water environment—Using scenarios to explore the significant water management challenges in England and Wales to 2050', *Science of the Total Environment*, 512, pp. 381–396.

Heslot, S. (2018) 'Iran's food security'.

REFRENCES

Iglesias, A. and Garrote, L. (2015) ‘Adaptation strategies for agricultural water management under climate change in Europe’, *Agricultural water management*, 155, pp. 113–124.

Janse, J. H. and van Liere, L. (1995) ‘PCLake: a modelling tool for the evaluation of lake restoration scenarios’, *Water Science and Technology*. Elsevier, 31(8), pp. 371–374.

Jeppesen, E. *et al.* (2005) ‘Lake responses to reduced nutrient loading–an analysis of contemporary long-term data from 35 case studies’, *Freshwater Biology*. Wiley Online Library, 50(10), pp. 1747–1771.

Keeler, L. W. *et al.* (2015) ‘Linking stakeholder survey, scenario analysis, and simulation modeling to explore the long-term impacts of regional water governance regimes’, *Environmental Science & Policy*, 48, pp. 237–249.

Keshavarz, M., Karami, E. and Vanclay, F. (2013) ‘The social experience of drought in rural Iran’, *Land use policy*. Elsevier, 30(1), pp. 120–129.

Kim, Seungbeom *et al.* (2021) ‘Probabilistic forecasting of cyanobacterial concentration in riverine systems using environmental drivers’, *Journal of Hydrology*. Elsevier, 593, p. 125626.

Knieper, C. *et al.* (2010) ‘Analysing water governance in heterogeneous case studies—experiences with a database approach’, *environmental science & policy*. Elsevier, 13(7), pp. 592–603.

Kuzdas, C. *et al.* (2016) ‘Identifying the potential of governance regimes to aggravate or mitigate local water conflicts in regions threatened by climate change’, *Local Environment*, 21(11), pp. 1387–1408.

Kuzdas, C. and Wiek, A. (2014) ‘Governance scenarios for addressing water conflicts and climate change impacts’, *Environmental Science & Policy*, 42, pp. 181–196.

Lai, G. *et al.* (2018) ‘Modeling long-and short-term temporal patterns with deep neural networks’, in *The 41st international ACM SIGIR conference on research & development in information retrieval*, pp. 95–104.

Larson, K. L., Wiek, A. and Keeler, L. W. (2013) ‘A comprehensive sustainability appraisal of water governance in Phoenix, AZ’, *Journal of environmental management*, 116, pp. 58–71.

Lee, J. H. W. *et al.* (2003) ‘Neural network modelling of coastal algal blooms’, *Ecological Modelling*. Elsevier, 159(2–3), pp. 179–201.

Livingston, M. L. (1995) ‘Designing water institutions: market failures and institutional response’, *Water Resources Management*, 9(3), pp. 203–220.

Louis, G. E., Nazemi, N. and Remer Technology, S. (2017) ‘Innovation for Development: Africa’, in *What Do Science, Technology, and Innovation Mean from Africa?*, p. 151.

Madani, K. (2014) ‘Water management in Iran: what is causing the looming crisis?’, *Journal of environmental studies and sciences*, 4(4), pp. 315–328.

Mahdavinia, R. and Mokhtar, A. (2018) ‘Dealing with sustainability in groundwater management using system dynamics approach, a case study in Iran’, *Sustainable Water Resources Management*. Springer, pp. 1–13.

Mahmoud, M. *et al.* (2009) ‘A formal framework for scenario development in support of environmental decision-making', *Environmental Modelling & Software*, 24(7), pp. 798–808.

Maier, H. R., Dandy, G. C. and Burch, M. D. (1998) 'Use of artificial neural networks for modelling cyanobacteria Anabaena spp. in the River Murray, South Australia', *Ecological Modelling*. Elsevier, 105(2–3), pp. 257–272.

Mehmood, H. *et al.* (2020) 'Strategic Foresight to Applications of Artificial Intelligence to Achieve Water-related Sustainable Development Goals'. United Nations University, Institute for Water, Environment and Health.

Mesgaran, B. and Azadi, P. (2018) *A national adaptation plan for water scarcity in Iran*. working paper 6, Stanford Iran 2040 project, Stanford University.

Michel, V. *et al.* (2018) 'Identifying vulnerable stakeholders from dependent relationships in California's water system', in *39th International Annual Conference of the American Society for Engineering Management, ASEM 2018: Bridging the Gap Between Engineering and Business*.

Mohajeri, S. *et al.* (2016a) 'Integrated water resource management in Isfahan: the Zayandeh Rud catchment', *Integrated Water Resources Management: Concepts, Research and Implementation. Springer, Heidelberg*.

Mohajeri, S. *et al.* (2016b) 'Integrated water resource management in Isfahan: the Zayandeh Rud catchment', *Integrated Water Resources Management: Concepts, Research and Implementation. Springer, Heidelberg*, pp. 603–627.

Molle, F., Hoogesteger, J. and Mamanpoush, A. (2008) 'Macro-and micro-level impacts of droughts: the case of the Zayandeh Rud river basin, Iran', *Irrigation and Drainage*, 57(2), pp. 219–227.

Molle, F. and Mamanpoush, A. (2012) 'Scale, governance and the management of river basins: A case study from Central Iran', *Geoforum*, 43(2), pp. 285–294.

Muttil, N. and Chau, K. (2006) 'Neural network and genetic programming for modelling coastal algal blooms', *International Journal of Environment and Pollution*. Interscience Enterprises; 1997, 28(3/4), p. 223.

Najafi Alamdarlo, H., Riyahi, F. and Vakilpour, M. H. (2017) 'Wheat self-sufficiency effects on the flow of virtual water trade in Iran', *Iran Applied Economy Studies*, 5(20), pp. 63–79.

Nash, J. E. and Sutcliffe, J. V (1970) 'River flow forecasting through conceptual models part I—A discussion of principles', *Journal of hydrology*. Elsevier, 10(3), pp. 282–290.

National Park services (2013) 'Using scenarios to explore climate change: a handbook for practitioners'. National Park Service Climate Change Response Program Fort Collins, Colorado ….

NationalResearchCouncil (2005) *Water Conservation, Reuse, and Recycling: Proceedings of an Iranian-American Workshop*. National Academies Press.

Nazari, M. R. (2016) 'Water Market in Theory and Practice: Market Failure and Public Policy', *Journal of Water and Sustainable Development*, 3(1), pp. 103–114.

Nazemi, N. *et al.* (2018) 'Modeling a water market and food free-trade as instruments for governance of agricultural water demand in arid and semi-arid regions', in *39th International Annual Conference of the American Society for Engineering Management, ASEM 2018: Bridging the Gap Between Engineering and Business*.

Nazemi, N. *et al.* (2020) 'Divergent agricultural water governance scenarios: The case of Zayanderud basin, Iran', *Agricultural Water Management*, 229. doi: 10.1016/j.agwat.2019.105921.

Nikouei, A. and Ward, F. A. (2013) 'Pricing irrigation water for drought adaptation in Iran', *Journal of hydrology*, 503, pp. 29–46.

Nikouei, A., Zibaei, M. and Ward, F. A. (2012) 'Incentives to adopt irrigation water saving measures for wetlands preservation: an integrated basin scale analysis', *Journal of hydrology*, 464, pp. 216–232.

Van Notten, P. W. F. *et al.* (2003) 'An updated scenario typology', *Futures*. Elsevier, 35(5), pp. 423–443.

OECD (2019) *Strategic Foresight for Better Policies*. Available at: https://www.oecd.org/strategic-foresight/ourwork/Strategic Foresight for Better Policies.pdf.

Oliver, R. L. *et al.* (2012) 'Physiology, blooms and prediction of planktonic cyanobacteria', in *Ecology of cyanobacteria II*. Springer, pp. 155–194.

Ostrom, E. (2009) 'A general framework for analyzing sustainability of social-ecological systems', *Science*. American Association for the Advancement of Science, 325(5939), pp. 419–422.

Pace, M. L., Buelo, C. D. and Carpenter, S. R. (2021) 'Phytoplankton biomass, dissolved organic matter, and temperature drive respiration in whole lake nutrient additions', *Limnology and Oceanography*. Wiley Online Library, 66(6), pp. 2174–2186.

Palaniappan, M. *et al.* (2010) *Clearing the waters: a focus on water quality solutions*.

Perry, G. L. W. *et al.* (2022) 'An outlook for deep learning in ecosystem science', *Ecosystems*. Springer, 25(8), pp. 1700–1718.

Qin, M., Li, Z. and Du, Z. (2017) 'Red tide time series forecasting by combining ARIMA and deep belief network', *Knowledge-Based Systems*. Elsevier, 125, pp. 39–52.

Recknagel, F. *et al.* (1997) 'Artificial neural network approach for modelling and prediction of algal blooms', *Ecological Modelling*. Elsevier, 96(1–3), pp. 11–28.

Reynolds, C. S., Oliver, R. L. and Walsby, A. E. (1987) 'Cyanobacterial dominance: the role of buoyancy regulation in dynamic lake environments', *New Zealand journal of marine and freshwater research*. Taylor & Francis, 21(3), pp. 379–390.

Ricart, S. *et al.* (2019) 'How to improve water governance in multifunctional irrigation systems? Balancing stakeholder engagement in hydrosocial territories', *International Journal of Water Resources Development*. Taylor & Francis, 35(3), pp. 491–524.

Ricart, S., Olcina, J. and Rico, A. M. (2019) 'Evaluating public attitudes and farmers' beliefs towards climate change adaptation: Awareness, perception, and populism at European level', *Land*. Multidisciplinary Digital Publishing Institute, 8(1), p. 4.

REFRENCES

Rogers, P. and Hall, A. W. (2003) *Effective Water Governance, Vol. 7. Stockholm: Global water partnership*. Available at: www.gwpforum.org (Accessed: 7 October 2019).

Rosegrant, M. W., Ringler, C. and Zhu, T. (2009) ‘Water for agriculture: maintaining food security under growing scarcity’, *Annual review of Environment and resources*, 34, pp. 205–222.

Rousso, B. Z. *et al.* (2020) ‘A systematic literature review of forecasting and predictive models for cyanobacteria blooms in freshwater lakes’, *Water Research*. Elsevier, 182, p. 115959.

Safavi, H. R., Golmohammadi, M. H. and Sandoval-Solis, S. (2016) ‘Scenario analysis for integrated water resources planning and management under uncertainty in the Zayandehrud river basin’, *Journal of hydrology*, 539, pp. 625–639.

Scholz, R. W. and Tietje, O. (2002) *Embedded case study methods: Integrating quantitative and qualitative knowledge*. Sage.

Schramm, E. and Sattary, E. (2014) *Scenarios for Closed Basin Water Management in the Zayandeh Rud Catchment Area*. Frankfurt am Main: ISOE - Institut für sozial-ökologische Forschung.

Shahdany, S. M. H. *et al.* (2018) ‘Operational performance improvements in irrigation canals to overcome groundwater overexploitation’, *Agricultural Water Management*. Elsevier, 204, pp. 234–246.

Shamshirband, S. *et al.* (2019) ‘Ensemble models with uncertainty analysis for multi-day ahead forecasting of chlorophyll a concentration in coastal waters’, *Engineering Applications of Computational Fluid Mechanics*. Taylor & Francis, 13(1), pp. 91–101.

Shetty, S. (2006) *Water, food security and agricultural policy in the Middle East and North Africa region*. World Bank.

Shih, S.-Y., Sun, F.-K. and Lee, H. (2019) ‘Temporal pattern attention for multivariate time series forecasting’, *Machine Learning*. Springer, 108, pp. 1421–1441.

Shimoda, Y. and Arhonditsis, G. B. (2016) ‘Phytoplankton functional type modelling: Running before we can walk? A critical evaluation of the current state of knowledge’, *Ecological Modelling*. Elsevier, 320, pp. 29–43.

Soranno, P. A. (1997) ‘Factors affecting the timing of surface scums and epilimnetic blooms of blue-green algae in a eutrophic lake’, *Canadian Journal of Fisheries and Aquatic Sciences*. NRC Research Press Ottawa, Canada, 54(9), pp. 1965–1975.

Stewart, S. *et al.* (2007) ‘Scenario development for water resources planning and management’, *IAHS Publications-Series of Proceedings and Reports*, 315, pp. 192–198.

Tietje, O. (2005) ‘Identification of a small reliable and efficient set of consistent scenarios’, *European Journal of Operational Research*, 162(2), pp. 418–432.

UNDRR (2019) *UNDRR 2019 Annual Report*.

Walton, J. K. and Seddon, D. (2008) *Free markets and food riots: The politics of global adjustment*. John Wiley & Sons.

White, D. D. *et al.* (2015) ‘Envisioning the future of water governance: A survey of central Arizona water decision makers', *Environmental Practice*, 17(1), pp. 25–35.

Yazdanpanah, M., Thompson, M., *et al.* (2013) 'A new enemy at the gate: Tackling Iran's water super-crisis by way of a transition from government to governance', *Progress in Development Studies*, 13(3), pp. 177–194.

Yazdanpanah, M., Hayati, D., *et al.* (2013) 'Water management from tradition to second modernity: an analysis of the water crisis in Iran', *Environment, development and sustainability*, 15(6), pp. 1605–1621.

Zaki, M. J. and Meira, W. (2014) *Data mining and analysis: fundamental concepts and algorithms*. Cambridge University Press.