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Modelling Hydrological, Economic and Governance Aspects of Water Allocation in the Lake Naivasha Basin Kenya

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Kurzfassung

Süßwasserknappheit stellt in vielen Teilen der Welt eine große Herausforderung dar, insbesondere in ariden und semi-ariden Gebieten, in denen die Niederschläge und die Wasserversorgung stark schwanken. Die wachsende Bevölkerung und der Klimawandel verschärfen diese Knappheit noch. Die für die Wasserbewirtschaftung zuständigen Behörden oder Staaten können mit Regeln für die Wasserzuteilung reagieren. In einem wasserarmen nationalen oder grenzüberschreitenden Flusseinzugsgebiet, das durch eine Vielzahl von Wechselwirkungen gekennzeichnet ist, hängt die Wirksamkeit einer regelbasierten Wasserzuteilung jedoch stark von geeigneten Institutionen und Systemkenntnissen zur Koordinierung der Wassernutzung ab. Die meisten Flusseinzugsgebiete, vor allem in Entwicklungsländern, sind durch schwache Institutionen, Marktversagen und mangelndes Wissen über das hydrologische System gekennzeichnet. Dies führt zu einer nicht-kooperativen Wassernutzung, bei der mehrere, institutionell unabhängige, physisch miteinander verbundene Nutzer ihre Wassernutzungsentscheidungen auf der Grundlage individueller Rationalität treffen und räumliche Externalitäten ignorieren.

Herkömmliche Modelle für Flusseinzugsgebiete zur Bewertung alternativer Wasserzuteilungsstrategien haben meist zielorientiert gestaltete Wassernutzungssysteme abgebildet, bei denen eine zentralisierte Verwaltung und eine regelbasierte Zusammenarbeit der Akteure vorausgesetzt werden. Dies ist eine starke und oft unrealistische Annahme angesichts der nicht-kooperativen Wassernutzung. Obwohl alternative Modellierungswerkzeuge auf dem Vormarsch sind, gibt es nur ein begrenztes Verständnis der Funktionsweise dieser Werkzeuge und nur wenige empirische Anwendungen. Die vorliegende Arbeit soll dazu beitragen, diese Lücke zu schließen, indem sie das Naivasha-Becken (LNB) in Kenia als Fallstudie verwendet. Jedes der drei Hauptkapitel der Arbeit befasst sich mit wichtigen Fragen für eine realistische Modellierung effektiver alternativer Wasserzuteilungsstrategien.

Das Fehlen verlässlicher Wasserflussdaten und damit verbunden Daten zur lokalen Wasserverfügbarkeit, volatile Niederschlag, und stark variierende Seespiegel erschweren hochwertige Vorhersagen und effektive Wasserzuteilungspolitiken im LNB. In Kapitel zwei nutzen wir relative verlässliche Seespiegeldaten und ein invertiertes Wasserbilanzmodell zur Rekonstruktion von Wasserflüssen und Wasserverfügbarkeit. Dieses Kapitel liefert einen methodischen Beitrag zur Literatur der Vorhersage von Wasserflüssen in Flusseinzugsgebieten ohne Pegel- und Durchflussmessung.

Kapitel drei enthält eine systematische Übersicht über neue Instrumente zur Modellierung der nicht-kooperativen Wassernutzung in Flusseinzugsgebieten. Die neuen Instrumente machen Fortschritte bei der Abbildung individueller Entscheidungsfindung und allgemeiner strategischer Interaktionen, doch fehlt es oft an einer ausreichenden Darstellung der relevanten hydrologischen und wirtschaftlichen Verbindungen zwischen den Wassernutzern. Obwohl die Entscheidungen der einzelnen Wassernutzer bei der nicht-kooperativen Wassernutzung mit dezentralen Modellierungsansatz modelliert werden, gehen die meisten Studien immer noch von einer koordinierenden Stelle oder einem funktionierenden Marktmechanis aus.

In Kapitel vier schließlich simulieren wir die möglichen hydrologischen und wirtschaftlichen Auswirkungen des Handels mit Wasserrechten im LNB. Im Gegensatz zu früheren Studien definieren wir eine Referenzsituation mit ungeregelter Wassernutzung, die die tatsächliche Wasserbewirtschaftung des Einzugsgebiets genauer abbildet und anhand derer wir alternative Szenarien bewerten. Zu diesem Zweck wurden individuelle Optimierungsmodelle verwendet. Die wichtigsten Ergebnisse offenbaren einige Muster mit relevanten Implikationen für die Regulierung der Wasserzuteilung. Wir zeigen, dass eine unregulierte Wassernutzung den höchsten wirtschaftlichen Gewinn bringt, was jedoch auf Kosten eines erheblichen Rückgangs des Seespiegels geht, was ein nicht nachhaltiges und unerwünschtes Ergebnis ist. Bei Wasserknappheit können Käufer gezwungen sein, mehr Wasserrechte zu kaufen, als sie zu nutzen beabsichtigen, um den Wasserfluss sicherzustellen.

Abstract

Freshwater scarcity poses a significant challenge in many parts of the world, particularly in arid and semi-arid areas prone to volatile rainfall and water supply. The growing population and climate change exacerbate this scarcity. Governing agencies or states responsible for water management may respond using some water allocation rules. However, in a water-scarce national or transboundary river basin characterized by a multiplicity of interactions, the effectiveness of rule-based water allocation heavily relies on adequate institutions and system knowledge to coordinate water use. Most river basins, especially in developing countries, are characterized by weak institutions, market failure, and poor understanding of the hydrological system. This results in non-cooperative water use whereby multiple, institutionally independent, physically interconnected users base their water use decisions on individual rationality ignoring spatial externalities.

Conventional river basin models for evaluating alternative water allocation policies have mostly emulated purposefully designed water use systems where centralized governance and rule-based cooperation of agents are assumed. This is a strong and often unrealistic assumption in the face of non-cooperative water use. Although alternative modelling tools are emerging, there is a limited understanding of how these tools work and few empirical applications. This thesis aims to contribute to filling this gap using the Lake Naivasha Basin (LNB) in Kenya as a case study. Each of the three main chapters of the thesis addresses vital issues for realistically modeling effective alternative water allocation policies.

Lack of reliable streamflow data, thus water availability, volatile rainfall, and highly variable lake levels, hinder proper predictions and effective water allocation policies in the LNB. In Chapter two, we use relatively reliable lake-level data and an inverted water balance model to reconstruct streamflow and estimate water availability. By doing so, we contribute methodologically to the literature on predicting streamflow in ungauged basins.

Chapter three presents a systematic review of emerging tools for modelling non-cooperative water use in river basins. The new tools make progress in depicting individual decision making and general strategic interactions but often lack a sufficient representation of the relevant hydrological and economic connections between the water users. Although individual water users' decisions in non-cooperative water use are modelled using a decentralized modelling approach, most studies still assume a coordinating agency or functioning market mechanism.

Finally, in chapter four, we simulate the potential hydrological and economic impacts of water rights trade in the LNB. In contrast to previous studies, we define a reference situation of unregulated water use that more accurately depicts the basin's actual water governance against which we evaluate alternative scenarios. We applied an individual optimization technique for this purpose. The key findings reveal some patterns with relevant policy implications for water allocation. We show that unregulated water use provides the highest economic gain, but that comes at the expense of a significant drop in lake level, which is an unstainable and undesirable outcome. In water scarce situation, buyers may be forced to purchase more water rights than they intend to use to ensure water flow.

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Abbreviations

ACRONYM	Definition
ABM	Agent-Based Model
CHNS	Coupled Human Natural System
CPR	Common Pool Resource
DEM	Digital Elevation Model
DNLP	Discontinuous Non-Linear Programming
DWR	Dynamic Water Right
EMP	Extended Mathematical Programming
FAO	Food and Agricultural Organization
FOC	First Order Condition
FWWCC	Food and Water Watch and the Council of Canadians
GA	Genetic Algorithm
GAMS	General Algebraic Modelling System
GLM	Gauss-Marquard-Levenbeger
GTM	Game Theoretic Model
HEBAMO	Hydro Economic Basin Modelling
HEM	Hydro Economic Model
HERBM	Hydro Economic River Basin Modelling
IAHS	International Association of Hydrological Sciences
IWMI	International Water Management Institute
IWRAP	Integrated Water Resources Action Plan
IWRM	Integrated Water Resources Management
KFC	Kenyan Flower Council
KGE	Kling-Gupta Efficiency
KNBS	Kenyan National Bureau of Statistics
LANAWRUA	Lake Naivasha Water Resources User Association
LNB	Lake Naivasha Basin
LNGG	Lake Naivasha Growers Group
LNRA	Lake Naivasha Riparian Association
MAS	Multi Agent System
MCP	Mixed Complementarity Programming
MOPEC	Multiple Optimization Problem with Equilbrium Constraint
MP-MAS	Mathematical Programming Based Multi Agent System
MPC	Model Predictive Control

NEMA	National Environment Management
NSE	Nash Sutcliffe Efficiency
NWLAKE	North West Lake
PDG	Prisoner's Dilemma Game
PMP	Positive Mathematical Programming
SELAKE	South East Lake
STRM	Shuttle Radar Topography Mission
SWR	Static Non-tradbale Water Rights
TDWR	Tradable Dynamic Water Rights
TSWR	Tradable Static Water Rights
UN	United Nations
UWU	Unregulated Water Use
WAP	Water Allocation Plan
WRA	Water Resource Authority
WRMA	Water Resources Management Authority
WRUA	Water Resource Users Authority
WWF	World Wide Fund for Nature

Chapter 1
Introduction

1.1 Motivation

Freshwater scarcity[1] poses a significant challenge in many parts of the world, particularly in arid and semi-arid areas prone to droughts. The growing population and volatile weather conditions exacerbate this scarcity. It is a major threat to sustainable food production, livelihoods, and the environment (Rosegrant et al., 2009; Rosengrant & Cai, 2001; Wang et al., 2017). This calls for better management of scarce water resources and efficient allocation, which depend on evidence-based policy design, management reform, and feasible institutional arrangements suited to specific country and basin contexts.

Hydroeconomic river basin modelling tools have been used to holistically assess water management and the efficiency of water allocation institutions and to inform policy at the river basin scale. These modelling tools are based on the economic concepts of scarcity, where water allocation is assumed to be driven by the economic value that water generates in different uses and the water availability.

Early use of hydroeconomic models can be traced back to the 1960s and 1970s. However, application to large-scale integrated water management

[1] Defined as over-exploitation of freshwater resources when there is greater demand than the supply (Van Loon & Van Lanen, 2013). Scarcity can be caused by natural processes or human activities. The scarcity caused by arid climates and droughts may worsen due to human factors such as poor water management, rising demand, pollution, and contamination.

was developed only over the last three decades (Harou et al., 2009). They have been widely utilized as economic evaluation tools to support integrated water resources management (IWRM) at the river basin scale and assess the economic and hydrological impacts of alternative water allocation options (Cai et al., 2006; Heidecke & Heckelei, 2010; Ringler, 2001). These models are based on the assumption of system-wide optimization, which seeks to maximize aggregate economic welfare using linear or nonlinear mathematical programming techniques. In other words, water is reallocated among users such that joint aggregate welfare is maximized. Recently, this basin-wide optimization approach has been challenged, and its applicability to real-world situations characterized by weak institutions and market imperfections, resulting in non-cooperative water use, has been questioned (Britz et al., 2013; Harou, 2014; Kuhn A. & Britz W., 2012). According to Britz et al. (2013), the basin-wide optimization approach implicitly assumes that essential institutions for perfect cooperation between water users have already been established and are functional. In other words, it assumes centralized planning for allocating water and other related resources or that a perfect market exists. This is a strong and often unrealistic assumption, given that most river basins worldwide, especially in developing countries, lack strong regulatory agency for managing water allocation and experience market failures due to high transaction costs in water rights trade. In such cases, aggregate optimization-based hydroeconomic models would not be useful for assessing various institutional frameworks governing access to water.

There is an emerging body of literature concerned with this limitation, and alternative modelling tools have been proposed. Nevertheless, there are few empirical applications of these tools in simulating non-cooperative water use in river basins. Furthermore, for improvements and wider application of these tools, it is essential to understand and explain their strengths and gaps. The general objective of this dissertation is to contribute to this growing body of empirical literature by examining the state-of-the-art modelling of non-cooperative water use.

The rest of this introductory chapter presents contextual information regarding the case study area – The Lake Naivasha Basin, followed by the key research questions addressed along with contributions and key findings. Finally, limitations and prospects for future research are discussed.

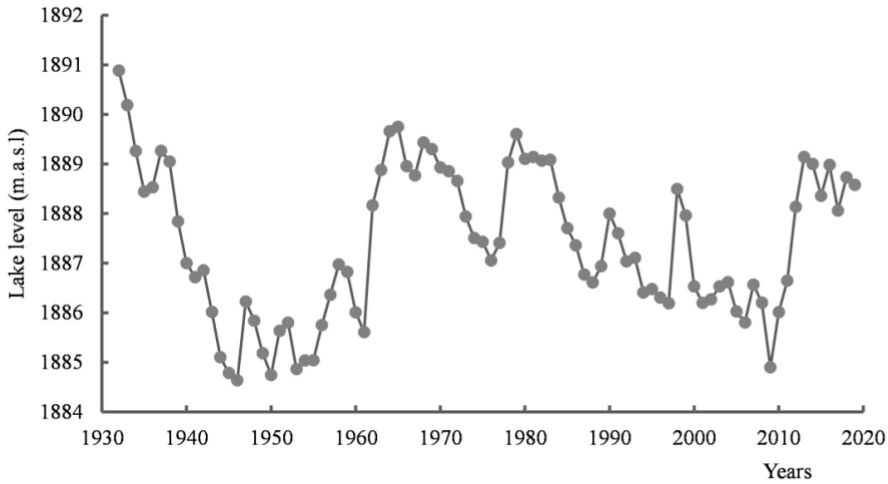
1.2 Why Lake Naivasha Basin?

Two chapters of the thesis deal with water allocation in the Lake Naivasha Basin, emphasizing the hydrological subsystem and water rights market. In this section, we provide contextual background on the basin's biophysical and socioeconomic aspects pertinent to water allocation.

Lake Naivasha is the second largest freshwater in Kenya, and the lake and wetlands are designated as a Ramsar site (Ramsar, 2012). The lake levels are highly variable due to volatile weather conditions and inflows in the basin. Between 2009 and 2010, the level of Lake Naivasha receded to its lowest level since the late 1940s (Figure 1.1). This attracted media and environmental activists' attention, complaining that the lake could die due to excessive water extraction for irrigation (FWWCC, 2009; ILEC, 2005; Mekonnen et al., 2012). This claim, however, has been strongly contested and intensively debated.

The debates and disputes have several reasons. First, the levels of Lake Naivasha were historically subject to significant natural fluctuation due to rainfall, inflows, and evapotranspiration in the basin that varies markedly both temporally and spatially with altitude. As shown in Figure 1.2, high-altitude areas such as the Mau Escarpment (3048 m.a.s.l) and Kinangop plateau (2591 m.a.s.l) receive relatively higher annual precipitation and potential evapotranspiration is lower. In contrast, more downstream, towards Lake Naivasha (1890 m.a.s.l.), there is insufficient rain, and the evaporation is too high to sustain rainfed agriculture (Becht & Harper, 2002). So in the Lake Naivasha sub-catchment, the farmers rely on irrigation from either groundwater or surface water.

Figure 1.1 Lake levels of Lake Naivasha over the last nine decades (1930-2020)

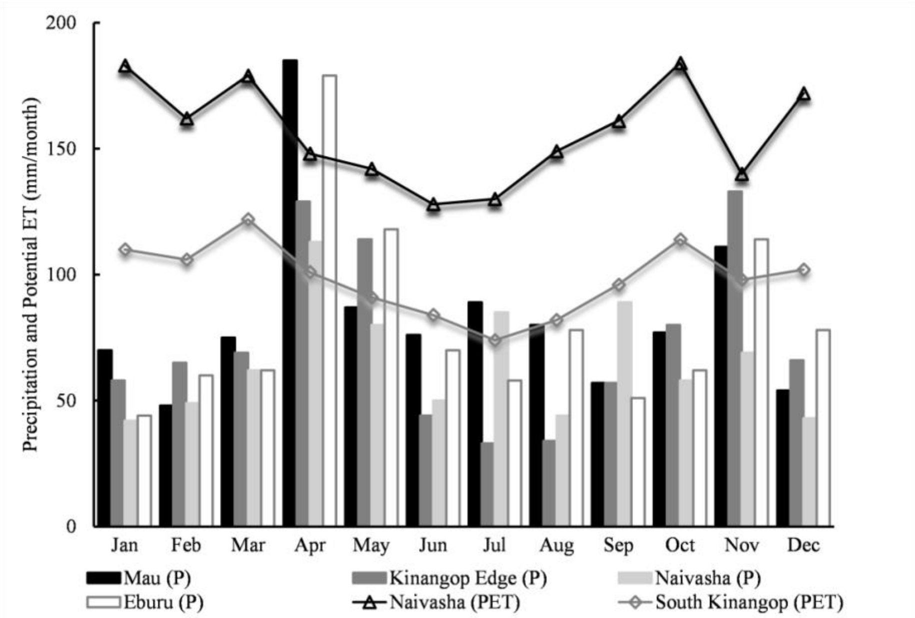


Source: Own illustration based on data from the University of Twente, ITC and Lake Naivasha Riparian Association (LNRA)

Regarding temporal variability, Verschuren et al. (2000) identified four periods in the last 1100 years where the lake dried up and periods with higher water levels than at present. Richardson and Richardson (1972) also indicated that the lake was nearly twice as large in the 1920s as in 1960-1961. They attribute the decrease in the lake's water between the 1920s and 1960s to a slight trend of decreasing rainfall, averaging 5 mm year-1 over the basin between 1920 and 1949 (Richardson & Richardson, 1972).

Second, although (over)abstraction of water for irrigation could exacerbate the lake level fluctuations from natural dynamics, especially during a drought spell, there is no clear evidence to what extent this practice contributed to the variability. Few studies documented the association between water use for irrigation, lake level variability, and water scarcity in the basin. Darling (1990) implicated the continued lake level decline in the 1980s could be due to water use for irrigation activity around the lake apart from the weather variability. Becht and Harper (2002) using a water balance model, indicated that during 1982-1999, the lake level was 3-4 m lower than without commercial irrigation water use. This period coincides with the onset of irrigated horticulture in the catchment. A water footprint study by Mekonnen et al. (2012) showed that the total virtual water exported with cut flowers from the Lake Naivasha Basin was 16 Mm^3 $year^{-1}$ between 1996 and 2005. Another study by Odongo et al.(2014) showed that water abstraction from the lake and its conjunctive aquifer had a negative effect on lake storage. However, since these studies are based on time series analysis, none of them convinciengly document the direct connection between water use for irrigation and the lake levels as other confounding factors can influence it. Furthermore, reliable data and knowledge on hydrology (streamflow and water availability) and water abstraction are missing in the basin (Kuhn et al., 2016; van Oel et al., 2014). The lack of reliable data and evidence may imply the actor's perception, power, and response to water scarcity.

Figure 1.2 Precipitation (P) and potential evapotranspiration (PET) at different locations in the Lake Naivasha Basin



Source: Own illustration based on data from Meins, 2013

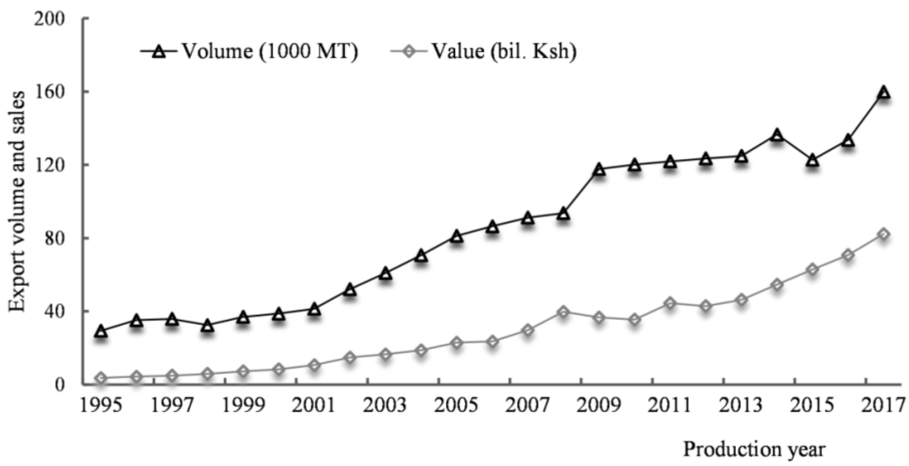
There is a large number of stakeholders and actors in the Basin, including commercial and smallholder farmers, pastoralists, the regional Water Resource Authority (WRA-Naivasha), the National Environment Management Authority (NEMA), Lake Naivasha Growers Group (LNGG), Water Resource Users Associations (WRUA), Lake Naivasha WRUA (LanaWRUA), Lake Naivasha Riparian Association (LNRA), NGOs and Universities, and government officials. These actors have different and sometimes competing interests, as well as varying perceptions and responses to water scarcity.

Commercial farmers play a pivotal role in the economic position of Naivasha and Kenya. The cut flower industry in the LNB accounts for 70% of Kenya's floriculture industry, generating 9% of the Kenyan total foreign exchange earnings and 2-3% of the country's GDP (WWF, 2011). The industry employs an estimated 40,000 people directly and indirectly through affiliated services (Kuiper & Gemählich, 2017). Flower production has experienced remarkable growth, maintaining an average growth rate of 20% per year over the last decades. Export volumes of flowers rose fivefold, with expanding sales (Figure 1.3). Due to their strong economic position, flower growers have the support of the national government and thereby gain much power. Verstoep (2015) even claims they use their power and connection to get away with violating water allocation rules (Verstoep, 2015). This would be consistent with Acemoglu's (2006) argument that an ineffective economic institution may persist due to the private interests of national or regional elites. Verstoep (2015) conducted structured and unstructured intrviews[2] with 20 commercial flower farmers around Lake Naivasha on water use and water management issues. According to their findings, commercial farmers do not care much about compliance with water allocation rules, especially during the wet season. However, during the dry spell, when the water becomes scarce, commercial farmers take the risk of fines or use their connections and ensure the flow of water (Verstoep, 2015). This appears to be consistent with the concept of rational crime (Cooter & Ulen, 2000; Filho et al., 2008) and Bardhan's (1993) point that when water is extremely scarce, cooperation is undermined by highly profitable cheating, while there is also no need to cooperate when water is plenty.

[2] Sampling was not based on statistical procíple but willingness of the respondents. So, responses of the 20 farmers maynot be represent the opionion of the remaining 30 or more commercial flower farmers in the lake Naivasha.

The role of smallholder farmers is quite different. They are highly interested in water availability as they need it for subsistence food production, but they have limited power. Commercial farmers and environmental activists blame them for polluting the lake. However, they are strategically located in the upstream catchment and have first access to water, their action is hardly regulated, and illegal water abstraction from ground and surface water is very common (De Jong, 2011; Kuhn et al., 2016).

Figure 1.3 Kenya's flower export volume and sales value (Bil. Ksh) (1995-2017)



Source: Own illustration based on data from Kenyan Flower Council (KFC)

In Kenya, the central government is in charge of water resources management. The government uses different demand management strategies to respond to water scarcity, including the reallocation of water using non-tradable water permits and volumetric water charges. These regulations are laid down in the Water Act 2002, which established the Water Resource Management Authority (WRMA). WRMA is a government agency that issues water permits and regulates water use with local stakeholders (GoK, 2002). WRMA-Naivasha is a sub-regional official authority in charge of water management in the LNB. Although it has authority as an enforcing and regulating organization, WRMA-Naivasha has limited power due to a lack of capacity, data, and knowledge, and undermind through farmers connection with elites in the state (Verstoep, 2015). A good example is the challenge to enforce the Water Allocation Plan (WAP), a bottom-up initiative that emerged in response to the 2009 drought and suggests temporary cuts of water permits during low water availability in the lake and groundwater. It was initiated by a group of commercial farmers in the Lake Naivasha (LNGG) and Lake Naivasha Water Resource Users Association (LANAWRUA) and implemented by WRMA since 2010 (Verstoep, 2015). However, some commercial farmers around the lake and part of the initiative criticize WAP and question its applicability (Verstoep, 2015).

In summary, LNB is a good example of a national river basin with a non-cooperative water use system characterized by multiple agents with individual and competing objectives and weak institutions. In such cases, it is reasonable to simulate a non-cooperative baseline scenario against which outcomes of alternative policies can be assessed. Furthermore, although Lake Naivasha and its basin have received much academic attention during recent decades, the knowledge gaps are still overwhelming (Pieter Richard van Oel et al., 2014). Specifically, previous studies focused on the hydrological subsystem and research on the potential impacts of alternative water allocation options are scant. This dissertation aims to contribute to filling this gap and generating knowledge for informed decision-making.

1.3 Contributions and key findings

In this section, the dessetation's three main chapters summarized. It highlights the key gaps in the literature each chapter addresses and the key findings. The order follows the structure of the thesis.

1.3.1 *Learning from lakes in data-limited basins: An inverted water-balance approach for reconstructing streamflow using lake-level observation*

Water resource management and allocation heavily rely on long-term records of hydrometeorological observations. There is a notable lack of reliable meteorological and hydrological data, particularly in tropical African basins, at detailed spatial and temporal scales required for assessing water availability.

For endorheic basins[3] where streamflow feeds downstream lakes, lake levels are relatively easy to monitor and are more reliable than streamflow observations. Therefore lake-level data offer a valuable source of information. Although predicting streamflow in ungauged basins using various techniques is far from a new approach, lake-level data have not been used to calibrate streamflow data. In chapter two, we contribute to the literature by addressing a crucial research question: Could streamflow in ungauged river basins be effectively reconstructed using lake-level and rainfall series data when the availability of dischargem measurements is insufficient?

Our modelling approach, which we termed Lake Streamflow Reconstruction Algorithm (LakeStReAM), uses an objective function that maximizes log-transformed Nash Sutcliffe Efficiency (NSE) of the observed and simulated lake volumes for calibration. It is based on an inverted water balance model and simplified rainfall-runoff relationships that specify monthly runoff as a share of precipitation from three representative rainfall stations in the Lake Naivasha Basin. The model simulates the long-term interannual variations in lake volume and the resulting overall water balance of Lake Naivasha before and after the onset of large-scale irrigation in the basin. Using different goodness of fit measures to assess the model's validity, the performance scores show strong agreement between the simulated and observed lake volumes for the period before the onset of large-scale irrigation. In general, the reconstructed stream flow produced excellent correspondence between the observed and simulated lake levels.

Furthermore, correlation coefficients and Kling–Gupta Efficiency (KGE) values demonstrate that the reconstructed streamflow replicate the observed streamflow quite well. It is interesting to note that for the irrigation period, the agreement between the reconstructed and observed streamflow improved. This might be attributed to better data coverage and availability in later years. For instance, the coverage of daily readings for the Malewa River, a significant contributor to Lake Naivasha, was 33% for the period

[3] Endorheic basin is drainage basin with no outflows to external water bodies, which is land locked (e.g., the Arial Sea bain in Centeral Asia) (Wang et al., 2018).

1965-1979 and increased to 99% for 1999 – 2010 (van Oel et al., 2013). Similarly, the data coverage for the Gilgil River, the second-largest contributor, increased from 89% to 92% in the same period. Our model could benefit from this and produced a better agreement between the reconstructed and observed streamflow into the lake for the Irrigation period (1984 - 2010). Under limited data availability, the modelling approach is deemed useful in reproducing plausible estimates of streamflow and, thus, water availability in the vicinity of Lake Naivasha.

1.3.2 *Modelling non-cooperative water use in river basins*

Limitations of traditional hydroeconomic river basin modelling for evaluating water allocation policies in the face of non-cooperative water use have been acknowledged and alternative modelling tools are emerging. These models include decentralized Hydro-economic Models (HEMs) based on individual optimization, Agent-Based Models (ABM), and Game-theoretic models (GTM). There is little systematic discussion in the literature on the advantages and drawbacks of these modelling approaches compared to classical hydroeconomic river basin modelling. More specifically, the extent to which these models realistically simulate non-cooperative water use without compromising on the classical hydroeconomic river basin models' (HERBM) capacity to simulate the specific features of the hydrological and economic processes remains to be investigated. In chapter three, we review existing modelling tools proposed to address the limitations of the classical hydroeconomic model in simulating water allocation in non-cooperative water use systems asking two key research questions: What are the benefits and disadvantages of these emerging modelling tools for simulating non-cooperative water use when water institutions are weak or non-existent? Can these cutting-edge models maintain the extensive ability of the traditional HERBMs to mimic the precise aspects of hydrological and economic processes? By doing so, we add to the broader river basin modelling literature, focusing on the representation of non-cooperative water use systems characterized by weak institutions and market failures.

To achieve this objective, the chapter discusses a small but diverse pool of modelling tools published between 2000 and 2020. The key findings of the systematic review can be summarised as follows: 1) While there has been some progress in modelling water allocation problems using decentralized approaches, only a few studies have demonstrated the ability to retain the classical HERBM's capacity to represent economic and biophysical processes in detail without sacrificing computational efficiency. 2) Most agent-based and game-theoretic models employ a sequential solution approach, which means that economic decisions are evaluated separately for each step using pre-defined conditions and heuristics. We contend that inter-locational and inter-agent trade-offs and synergies in allocating scarce resources cannot be sufficiently captured by the resulting isolated evaluation of economic decisions made by agents. 3) Although individual water users' decisions in non-cooperative water use are modelled using a decentralized modelling approach, most studies still included a coordinating agency or market mechanism in the models. This may not be a realistic assumption for most river basins, which future studies should consider. Finally, more emphasis is needed to capture the inter-temporal dynamics and uncertainties in water supply due to weather variability for a reliable impact evaluation of alternative water policies.

1.3.3 *Simulating potential hydroeconomic impacts of water rights trade in the Lake Naivasha Basin using a MOPEC modelling framework*

The Lake Naivasha Basin in Kenya faces recurring drought and water scarcity. Challenges include non-compliance with administrative permits and free-riding. A water rights market could offer a viable solution for improved water allocation amid growing scarcity.

While a rich body of literature evaluates the potential economic and environmental impacts of water rights markets, the studies largely use fully regulated water use as a reference in evaluating alternative water allocation options, including water rights trade. This might be acceptable if there is a strong regulatory body that can effectively enforce the existing distribution of water use rights, or if perfectly functioning water markets have emerged. But given that the water use system is characterized by decentralized multi-actor decision processes and that suitable institutions for coordinating the decision or enforcing the rules have yet to be established (as for instance the LNB), this is not a viable starting point. In chapter four, we define a reference situation of unregulated water use that more accurately depicts the basin’s actual water governance and contributes to the body of literature on water allocation, answering two broad questions. First, what would be the potential benefits, in terms of economic gains and hydrologic performance, of introducing tradable water rights compared to unregulated water use and the existing nontradable water rights if fully enforced? Second, how would the actor's behavior and the performance of the entire water use system change in the face of a volatile water supply and rising water scarcity?

The main contribution of this chapter is that we define a reference situation of unregulated water use that better reflects the current water governance in the Lake Naivasha Basin using the multiple optimization problems with equilibrium constraints (MOPEC) modelling framework. This framework enabled us to integrate each user’s decision-making calculus separately within a partial equilibrium model. We evaluated five alternative scenarios for managing agricultural water resources. These alternatives are unregulated water use (current), static water rights (SWR), tradable static water rights (TSWR), dynamic water rights (adjustable to changing hydrologic conditions) (DWR), and tradable dynamic water rights (TDWR).

The key findings reveal some compelling patterns with significant policy implications for water allocation. Regarding economic impacts, the unregulated flow option provides the highest benefit among all water allocation scenarios. The gain, however, comes at the expense of a significant drop in the lake level, which is an undesirable and unsustainable long-term outcome that policy design must take into account. Introducing trade in water rights among irrigators transfers water from less productive uses and users to more productive and high-value uses by compensating the former for income loss. For example, farmers reduce the area planted with irrigated maize over the years because it has relatively low returns to water use, and sell their use rights to floricultural producers. Allowing water rights trade among users improves water use efficiency at the basin scale.

However, this finding should be interpreted cautiously because smallholder farmers may have goals other than profit maximization, such as food self-sufficiency, which our model did not account for.

In water rights trading scenarios, an interesting result emerges when we compare changes in water use and volumes of water traded. In a water scarcity situation where potential sellers' amount of water rights exceeds the water actually available to them, buyers are compelled to purchase more water rights than they intend to use. This is to prevent the sellers from restricting water use downstream by utilizing the scarce water within their remaining water rights. This finding agrees with Britz et al. (2013). This overbuying behavior increases average water shadow prices, especially in the TDWR scenario, where only the water rights of the buyers (LanaWRUAs) have been reduced and not those of the sellers in the upper catchment. The effect has far-reaching implications for the design of regional water use and trading policies. This can only be simulated in a simultaneous optimization model with independently acting agents, as used in this study.

Finally, our result shows that maximum benefits could be realized by adjusting tradable water rights based on water availability, although its practicality can be challenging. Nonetheless, fully implementing the Water Allocation Plan, extending it to the upstream users, and allowing trade in these entitlements would benefit the efficient and sustainable use of water resources in the Lake Naivasha Basin.

1.4 Limitations and outlooks

We end this chapter by pointing out some limitations that could be taken up in future research. Our streamflow reconstruction model assumed that the runoff parameters are uniform across the entire basin. As the terrain varies across sub-catchments, this uniformity is likely to be an over-simplification. The insufficient reliability of the rainfall data for each sub-catchment, as claimed by Meins (2013), prevents the estimation of locally differentiated runoff coefficients. The model parameters are also static and do not vary over time. This may not be correct, as land-use changes such as deforestation are likely to increase the share of runoff from rainfall, particularly at the peak of the rainy season when the vegetation cover that fosters infiltration into deeper soil layers becomes thinner or absent at times. However, sample estimations of sub-periods do not reveal noticeable shifts in runoff coefficients over time.

Furthermore, insufficient knowledge about groundwater bodies and flows in the upper Naivasha catchment makes it uncertain whether there are neglected underground water flows into the lake. Across the different estimation approaches and periods, the average reconstructed streamflow per month is around 15% higher than observed levels, suggesting that underground flows could be minor but still play a significant role as a water source for the lake. Future research needs to account for groundwater interaction with surface water explicitly.

Our systematic review of the emerging modelling tools for non-cooperative water use identified key gaps and pointed out the directions for future research. First, while the new tools, particularly the ABM, make progress in depicting individual decision making and general strategic interactions, they lack a sufficient representation of the relevant hydrological and economic connections between the water users. Second, agent-based and game-theoretic models could use the simultaneous solution approach employed in equilibrium models in evaluating the economic decisions made by agents. Third, although individual water users' decisions in non-cooperative water use are modelled using a decentralized modelling approach, most studies still assume a coordinating agency which future research can relax.

The economic component of multiple objective functions in our water rights trade analyses is represented by profit maximization from agricultural water use and water rights trade. This, however, may not fully capture the goal of some water users in the system, specifically when the system is represented by heterogeneous agents with varying priorities and objectives, like in the LNB. For example, the objective of commercial flower farmers downstream can be well represented by profit maximization. In contrast, the smallholder farmers in the upstream catchment might have other objectives in addition, like achieving food self-sufficiency. Future research needs to account for such diverse objectives to assess the impacts of the water rights market more accurately.

In chapter four, we focused on agricultural water use because this sector uses substantial amounts of water accounting for 94% of all consumptive uses, and it has been growing over the last decades and is expected to grow further. With urbanization, the share of industrial water use may rise; however, due to a lack of data to parametrize the model, this is not accounted for. We included only municipal water use as a constant parameter in addition to agricultural water use. Future research must consider the potential entry of new non-agricultural water users, such as industry and energy production.

Finally, the potential benefits from water rights trading largely depend on their transaction costs, particularly in developing countries like Kenya. Additional calculations indicating the impact of the water allocation institution's transaction costs would be useful for policy implications. In our study, we use only a small amount (0.01 Ksh/M^3) mainly to facilitate model solutions rather than to allow for policy conclusions. Future research can look into the effects of transaction costs and their policy implications, especially in the context of the water right markets in developing countries.

1.5 **References**

Acemoglu, D. (2006). A Simple Model of Inefficient Institutions. *The Scandinavian Journal of Economics*, *108*(4), 515–546. https://doi.org/10.1111/j.1467-9442.2006.00460.x

Bardhan, P. (1993). Analytics of the institutions of informal cooperation in rural development. *World Development*, *21*(4), 633–639. https://doi.org/10.1016/0305-750X(93)90115-P

Becht, R., & Harper, D. M. (2002). Towards an understanding of human impact upon the hydrology of Lake Naivasha. *Hydrobiologia*, *488*(1–3), 1–11.

Britz, W., Ferris, M., & Kuhn, A. (2013). Modeling water allocating institutions based on Multiple Optimization Problems with Equilibrium

Constraints. *Environmental Modelling & Software*, *46*, 196–207. https://doi.org/10.1016/j.envsoft.2013.03.010

Cai, X., Claudia Ringler, & Mark W. Rosegrant. (2006). *Modeling Water Resources Management at the Basin Level Basin*. International Food Policy Research Institute. http://www.ifpri.org/pubs/abstract/149/rr149.pdf

Cooter, R., & Ulen, T. (2000). *Law and Economics, 6th edition* (3rd ed.). AddisonWesley Longman, Boston, Mass.

Darling, W. G., Allen, D. J., & Armannsson, H. (1990). Indirect detection of subsurface outflow from a rift valley lake. *Journal of Hydrology*, *113*(1–4), 297–306. https://doi.org/10.1016/0022-1694(90)90180-6

De Jong, T. (2011). *Water abstraction survey in Lake Naivasha basin, Kenya* [BSc Internship thesis, Wageningen University]. ftp://ftp.itc.nl/pub/naivasha/DeJong2011.pdf

Filho, F. A. S., Lall, U., & Porto, R. L. L. (2008). Role of price and enforcement in water allocation: Insights from Game Theory. *Water Resources Research*, *44*(12). https://doi.org/10.1029/2007WR006163

FWWCC. (2009). Lake Naivasha withering under the assault of international flower vendors. *Food & Water Watch and the Council of Canadians*. http://www.foodandwatereurope.org/wp-content/uploads/2009/11/FoodandWaterEuropeLakeNavaisha.pdf

GoK. (2002). *National government of Kenya, National Council for Law Reporting (KLR) Water Act, Act No.8 of 2002*. http://www.kenyalaw.org/kl/fileadmin/pdfdownloads/Acts/WaterActNo8of2002.pdf

Harou, J. J. (2014). *Should hydro-economic models be agent-based? Should they include non-economic behaviors and metrics?* http://scholarsarchive.byu.edu/iemssconference/2014/Stream-H/32/

Harou, J. J., Pulido-Velazquez, M., Rosenberg, D. E., Medellín-Azuara, J., Lund, J. R., & Howitt, R. E. (2009). Hydro-economic models: Concepts, design, applications, and future prospects. *Journal of Hydrology*, *375*(3–4), 627–643. https://doi.org/10.1016/j.jhydrol.2009.06.037

Heidecke, C., & Heckelei, T. (2010). Impacts of changing water inflow distributions on irrigation and farm income along the Drâa River in Morocco. *Agricultural Economics*, *41*(2), 135–149. https://doi.org/10.1111/j.1574-0862.2009.00431.x

ILEC. (2005). *Managing lakes and their Basins for Sustainable Use: A Report for Lake managers and Stakeholders.* International Lake Environment Committee Foundation.

Kuhn A. & Britz W. (2012). Can hydro-economic river basin models simulate water shadow prices under asymmetric access? *Water Science & Technology*, *66*(4), 879–886. https://doi.org/10.2166/wst.2012.251

Kuhn, A., Britz, W., Willy, D. K., & van Oel, P. (2016). Simulating the viability of water institutions under volatile rainfall conditions – The case of the Lake Naivasha Basin. *Environmental Modelling & Software*, *75*, 373–387. https://doi.org/10.1016/j.envsoft.2014.08.021

Kuiper, G., & Gemählich, A. (2017). Sustainability and Depoliticisation: Certifications in the Cut-Flower Industry at Lake Naivasha, Kenya. *Africa Spectrum*, *52*(3), 31–53. https://doi.org/10.1177/000203971705200302

Mekonnen, M. M., Hoekstra, A. Y., & Becht, R. (2012). Mitigating the water footprint of export cut flowers from the Lake Naivasha Basin, Kenya. *Water Resources Management*, *26*(13), 3725–3742.

Odongo, V. O., Mulatu, D. W., Muthoni, F. K., van Oel, P. R., Meins, F. M., van der Tol, C., Skidmore, A. K., Groen, T. A., Becht, R., Onyando, J. O., & van der Veen, A. (2014). Coupling socio-economic factors and eco-hydrological processes using a cascade-modeling approach. *Journal of Hydrology*, *518*, 49–59. https://doi.org/10.1016/j.jhydrol.2014.01.012

Ramsar. (2012). *Ramsar report for Lake Naivasha, Site No. 724, Wetlands International Site Reference , Designation Date: 10-04-1995*.

Richardson, J. L., & Richardson, A. E. (1972). History of an African Rift Lake and Its Climatic Implications. *Ecological Monographs*, *42*(4), 499–534. https://doi.org/10.2307/1942169

Ringler, C. (2001). *Zentrum für Entwicklungsforschung Center for Development Research*. 55.

Rosegrant, M. W., Ringler, C., & Zhu, T. (2009). Water for Agriculture: Maintaining Food Security under Growing Scarcity. *Annual Review of Environment and Resources*, *34*(1), 205–222. https://doi.org/10.1146/annurev.environ.030308.090351

Rosengrant, M. W., & Cai, X. (2001). Water scarcity and food security: Alternative futures for the 21st century. *Water Science and Technology*, *43*(4), 61–70. https://doi.org/10.2166/wst.2001.0179

Van Loon, A. F., & Van Lanen, H. A. J. (2013). Making the distinction between water scarcity and drought using an observation-modeling framework: DISTINGUISHING BETWEEN WATER SCARCITY AND DROUGHT. *Water Resources Research*, *49*(3), 1483–1502. https://doi.org/10.1002/wrcr.20147

van Oel, P. R., Mulatu, D. W., Odongo, V. O., Meins, F. M., Hogeboom, R. J., Becht, R., Stein, A., Onyando, J. O., & van der Veen, A. (2013). The Effects of Groundwater and Surface Water Use on Total Water Availability and Implications for Water Management: The Case of Lake Naivasha, Kenya. *Water Resources Management*, *27*(9), 3477–3492. https://doi.org/10.1007/s11269-013-0359-3

van Oel, P. R., Odongo, V. O., Mulatu, D. W., Muthoni, F. K., Ndungu, J. N., Ogada, J. O., & van der Veen, A. (2014a). Supporting IWRM through spatial integrated assessment in the Lake Naivasha basin, Kenya. *International Journal of Water Resources Development*, *30*(3), 605–618. https://doi.org/10.1080/07900627.2014.920248

van Oel, P. R., Odongo, V. O., Mulatu, D. W., Muthoni, F. K., Ndungu, J. N., Ogada, J. O., & van der Veen, A. (2014b). Supporting IWRM through spatial integrated assessment in the Lake Naivasha basin, Kenya. *International Journal of Water Resources Development*, *30*(3), 605–618. https://doi.org/10.1080/07900627.2014.920248

Verschuren, D., Laird, K. R., & Cumming, B. F. (2000). Rainfall and drought in equatorial east Africa during the past 1,100 years. *Nature*, *403*(6768), 410–414.

Verstoep, J. (2015). *Challenges in water management in the Lake Naivasha Basin: Analysis on the effects and performance of IWRAP for different irrigation water user groups in the Lake Naivasha Basin, Kenya* [MSc Thesis]. Wageningen University.

Wang, J., Li, Y., Huang, J., Yan, T., & Sun, T. (2017). Growing water scarcity, food security and government responses in China. *Global Food Security*, *14*, 9–17. https://doi.org/10.1016/j.gfs.2017.01.003

Wang, J., Song, C., Reager, J. T., Yao, F., Famiglietti, J. S., Sheng, Y., MacDonald, G. M., Brun, F., Schmied, H. M., Marston, R. A., & Wada, Y. (2018). Recent global decline in endorheic basin water storages. Nature Geoscience, 11(12), 926–932. https://doi.org/10.1038/s41561-018-0265-7

WWF. (2011). *Seeking a sustainable future for Lake Naivasha* [WWF Report 2011]. PegaSys Strategy and Development. ftp://ftp.itc.nl/pub/naivasha/PolicyNGO/WWF2011.pdf

Chapter 2
Learning from lakes in data-limited basins: An inverted water-balance approach for reconstructing streamflow using lake-level observation

Abstract.

Water management in Sub-Saharan Africa faces huge challenges in understanding hydrological processes under evolving human and climate impacts. Availability and quality of streamflow data in most Sub-Saharan Africa are hampered by a lack of (dense) observation networks and poor monitoring practices. The consequent poor data availability leads to high uncertainty in water-balance estimates. For endorheic basins where streamflow feeds downstream lakes, lake levels are relatively easy to monitor and are more reliable than streamflow observations, particularly for hydrological extremes. Therefore lake-level data offer a valuable source of information that is currently barely used for understanding basin hydrology. This paper presents the **Lake St**reamflow **Re**construction **A**lgorith**m** (LakeStReAM) approach that uses an objective function that maximizes log-transformed Nash Sutcliffe Efficiency (NSE) of the observed and simulated lake volumes for calibration. Using this approach, we demonstrate how to reconstruct proxy streamflow estimates that match observed values for the Lake Naivasha basin, Kenya. We used the Nash Sutcliffe Efficiency (NSE) and Kling-Gupta Efficiency (KGE) indexes to assess the model's performance in simulating monthly lake volume and streamflow. The model performed well in simulating lake volume prior to large-scale water abstractions for irrigation, with some discrepancies in the later years. The reconstructed streamflow also showed close agreement with observations, especially for the latter years where a good coverage of observed streamflow series is available. The result indicates the inverted water-balance approach provides a useful tool for predicting streamflow for ungauged endorheic basins based on lake-level observations only. This innovative approach adds to streamflow reconstruction and prediction knowledge such as tree-ring observations, statistical, hydrological, stochastic modelling, and regionalization approaches.

Keywords: streamflow reconstrcution, watershade modelling, water resources managment, Lake Naivasha, Kenya

2.1 Introduction

Long-term instrumental records of hydrometeorological observations are vital in water resources management and water allocation (Ferrero et al., 2015). However, quality meteorological and hydrological data at sufficient time and location-scale to estimate water availability are too scarce, especially in tropical Africa basins. Data for estimating lake inflow are usually sparsely distributed and error-prone such that modelled estimates are highly uncertain in assessing the lake water balance (Kizza et al., 2011). Therefore, most of these river basins are considered ungauged basins. Predicting streamflow in ungauged basins has been recognized by the international scientific community, resulting in the International Association of Hydrological Sciences (IAHS) the "Decade (2003-2012) on Prediction in Ungauged Basins (PUB)" (Loukas & Vasiliades, 2014). This decade led to science and technological advancements that provided hydrometeorological data where in situ observations were needed but were lacking (Hrachowitz et al., 2013). These techniques usually do not require the availability of long time series of measurements. Instead, parameters obtained from models of gauged catchments with similar physiographic characteristics are transferred and linked, and applied to estimate flows in ungauged catchments. These methods of predicting flows can be classified into statistical, hydrological, and stochastic modelling methods (Hrachowitz et al., 2013; Loukas & Vasiliades, 2014). The use of tree rings to predict flows as well as lake levels has also been explored (Barria et al., 2018; Chen et al., 2017; DeRose et al., 2014; Ferrero et al., 2015; Gallant & Gergis, 2011; Urrutia et al., 2011; Verschuren et al., 2000; Wise, 2010). However, most of these studies are based on the annual-decadal scale and long-term (>100 years) analysis of past climatic variability. In tropical Africa, this approach is limited due to the lack of standard high-resolution proxy records such as tree rings and ice cores (Verschuren et al., 2000). Paleolimnological proxies such as sediment stratigraphy and species composition of fossil diatoms of Lake Naivasha in Kenya have also been used to study the decadal-scale rainfall and drought variability in Eastern Africa (Verschuren et al., 2000).

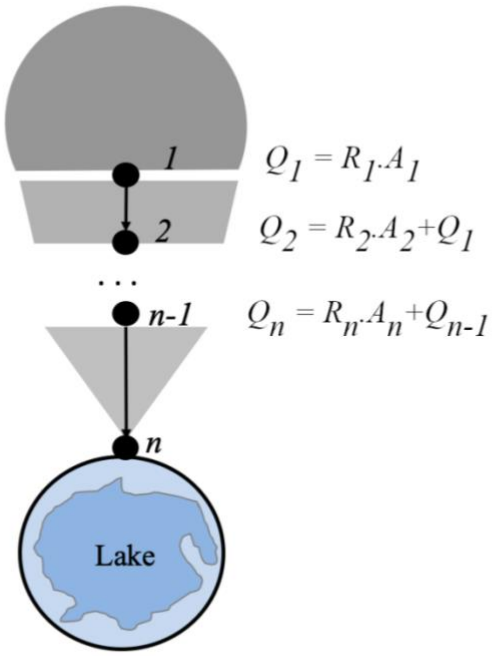
The use of lake-sediment cores does provide evidence of climatic and environmental changes over a geological time scale of centuries (Nicholson et al., 2000). This is because lakes integrate conditions of their draining catchment areas, which may also be manifested regionally. Other than the use of sediment cores, fluctuations of lake levels have been known to correspond to rainfall variability in tropical Africa. Therefore, attempts have been made to estimate rainfall from lake levels by inverting the water balance equation (e.g., Nicholson et al., 2000). However, such an undertaking would require an understanding of the relative magnitude of the water balance components of individual lakes. For example, for larger lakes like Lake Victoria, emphasis is usually placed on the accurate estimation of rainfall and evaporation because these are the largest components of the lake water balance (Kizza et al., 2011; Nicholson et al., 2000; Tate et al., 2004; Yin & Nicholson, 1998). Similarly, an inversion of the water balance equation can be used to estimate streamflows from lake-level records where the streamflow component is a major contributor to the variability of the lake fluctuations. This is a significant undertaking, especially in tropical basins with internal drainage systems where inflows dominate the water cycle component that determines lake fluctuations, such as Lake Naivasha.

Hydrological data for the Lake Naivasha basin are generally sparse and disparate, and simplified assumptions have been used to quantify the water budget in several previous studies (e.g., Åse et al. 1986, Gaudet and Melack 1981, McCann 1974, van Oel et al. 2013). The reason for these simplifications has been a lack of data availability and analysis to support management solutions by the local Water Resources Authority (WRA). This also applies to streamflow data (Becht and Harper 2002, Becht et al. 2005, van Oel et al. 2013, van Oel et al. 2014). Consequently, catchment flows and water balance estimates vary considerably (e.g., Åse et al. 1986, Gaudet and Melack 1981, McCann 1974, van Oel et al. 2013). This lack of data impedes the development and enforcement of rules and regulations (WRMA 2010, van Oel et al. 2014). Recently, however, there have been efforts to improve the data collection through improved fundings and resource allocation (IWRAP 2013). Despite the sparseness of streamflow data at most river gauging outlets, the lake levels have been monitored and recorded since 1898 (Odongo et al., 2015). These recordings were intermittent at the beginning of the last century, but consistent monthly recordings commenced in 1952 until 1997, when daily recordings have been maintained reliably to present. Unlike larger water bodies such as Lake Victoria that receive over 80% of its water through precipitation (Awange et al., 2008; Yin & Nicholson, 1998), Lake Naivasha receive at least 90% of its water through three major stream inflow from its headwater catchments (Aloo et al., 1996; Becht & Harper, 2002; Gaudet & Melack, 1981). This makes streamflow an important input component that defines the variability of the net basin supply of Lake Naivasha. However, only a tiny proportion of gauging stations have maintained gaps of less than 10 % in streamflow records in the basin covering the period between 1960 and 2010 (Odongo et al., 2015). Therefore, the objective of this study was to introduce a new approach of simulating streamflow into Lake Naivasha using an inverted mass balance model constrained by lake volume changes. The method, which we call **Lake St**reamflow **Re**construction **A**lgorith**m** (LakeStReAM), modifies the water balance model such that it can be used in the absence of discharge data and assess the feasibility of using it to interpret the historical and future-fluctuations of Lake Naivasha in terms of changes in streamflow.

2.2 **The LakeStReam Model**

The LakeStreaM model builds on water balance model by Becht and Harper (2002) for Lake Naivasha and modified it by endogenously reconstructing streamflow into the lake based on information entrenched in the long term lake level changes. Becht and Harper's water balance model used instrumental records of streamflows from Malewa, Gilgil and Karati rivers with missing data infilled with the nearest station. In our model the water balance is estimated independent of the availability of streamflow data.

Figure 2.1 Graphical representation of the semi-distributed surface hydrological model for Lake Naivasha Basin



Source: own illustration

The model is based on a node-link network for water mass balance in the rivers, lakes, and groundwater, where the node represents demand locations (irrigation and household use) at sub-catchment outlets and the link representing river reaches in the basin. The mass balance is constructed assuming discharge in the catchment Q is generated by runoff from rainfall

P over the sub-catchment areas A feeding local streams that eventually drain into the lake, as shown in Figure 2.1.

The generated runoff R is endogenously estimated using semi-distributed rainfall-runoff relationships. Four simple non-linear rainfall-runoff models for the runoff generation process are specified as

$$R_{sc,t} = \alpha(P_{sc,t} + P_{sc,t-1})^{\beta} + \gamma(P_{sc,t-2}) \tag{1}$$

$$R_{sc,t} = \alpha(P_{sc,t})^{\beta} + \gamma(P_{sc,t-1} + P_{sc,t-2}) \tag{2}$$

$$R_{sc,t} = \alpha(P_{sc,t} + P_{sc,t-1} + P_{sc,t-2})^{\beta} \tag{3}$$

$$R_{sc,t} = \alpha(P_{sc,t} + P_{sc,t-1})^{\beta} + \gamma(P_{sc,t-1} + P_{sc,t-2}) \tag{4}$$

where $R_{sc,t}$ and $P_{sc,t}$ are runoff (mm) and precipitation (mm) for the month t in a given sub-catchment area sc, $P_{sc,t-1}$ and $P_{sc,t-2}$ are precipitations at the preceding month $t-1$ and $t-2$, respectively. The coefficients α and γ are slope parameters whereas β is a nonlinear shape parameter of the rainfall-runoff functions.

These equations express the runoff as a function of the temporal and spatial rainfall. The parameters represent the runoff generation process in a simplified way. We assume that the rainfall-runoff relationship contains both linear and nonlinear precipitation components at the time t and lags $t-1$ and $t-2$. These slope and shape parameters in the rainfall-runoff functions are optimized based on the automatic calibration of the model.

Different local and global search algorithms such as gradient-based Gauss-Marquardt-Levenbeger (GLM) and global search algorithms such as Shuffled Complex Evolution Algorithms (SCE) (Duan et al. 1994) are used in the automatic calibration of hydrologic models. In our case, we have used Conopt solver, a gradient-based local search process suited to solve highly non-linear optimization problems (Drud, 1994). The algorithm seeks to maximize the Nash-Sutcliffe Efficiency (NSE) (Nash & Sutcliffe, 1970) for the observed and simulated lake volumes.

The total runoff in each sub-catchment is the product of estimated runoff shares and surface area of that sub-catchment

$$Q_{sc,t} = R_{sc,t} * A_{sc} \tag{5}$$

This total runoff is assumed to reach local stream channels, either by overland flows or flows through saturated soil. Even though our specification simplifies complex real-world hydrological processes, it can reasonably approximate the amount of runoff generated from rainfall in a data-scarce situation.

We specify the four rainfall-runoff relationships drawing on different assumptions on how rainfall events are partitioned into the runoff. The non-linear component β captures a percentage of runoff from rainstorms which is highly variable depending on catchment-specific factors. This might apply only to the month t, the most recent $t-1$, or the preceding months up to $t-2$. The sometimes-sudden increases of lake levels observed after months with high precipitation suggest that runoff may indeed be non-linear to a considerable degree. The monthly time lags are important to capture the natural catchment response for the time taken to soil moisture deficit after the dry season (Becht & Harper, 2002).

The proposed runoff model calibrates basin-wide parameters using in-situ rainfall measurements representative of the various regions in the catchment. The model parameters are optimized such that the simulated streamflow consistently explains the monthly lake volume changes such that simulated lake volume nicely reproduces the observed lake volume. The simulated streamflow enters the water balance in the river nodes and the lake as

$$\frac{\Delta V_n}{\Delta t} = \sum_{n\_up} Q_{n\_up,t} + Q_{sc,t} - \sum_{n\_down} Q_{n\_down,t} - \sum_{n\_lake} Q_{n\_lake,t} \tag{6}$$

where $\Delta V_n / \Delta t$ is the monthly change in water balance at the node n, $Q_{sc,t}$ is local runoff from the sub-catchment area sc (for $\forall sc \in n$), $Q_{n\_up,t}$ is water inflow from upstream nodes, $Q_{n\_down,t}$ and $Q_{n\_lake,t}$ are water outflows to downstream nodes and the Lake, respectively. Then, following Becht and

Harper (2002) and van Oel et al. (2013), the lake water balance is specified as:

$$V_t = V_{t-1} + P_t - E_t + \sum_{n\_lake} Q_{n\_lake,t} - Q_{aq,t} - Q_{abst,t} \tag{7}$$

where V_t and V_{t-1} are lake volumes at month t and $t-1$, P_t is precipitation over the lake, and E_t evapotranspiration from the lake surface, $Q_{n\_lake,t}$ are inflows into the lake, $Q_{aq,t}$ is an outflow to the groundwater aquifer connected to the lake, and $Q_{abst,t}$ is the total amount of water used for irrigation.

We specify Lake level-area-volume relationship following Åse et al.(1986) and van Oel et al. (2013) and converted the monthly lake levels (m.a.s.l.) to the corresponding lake volume. Based on this relationship, monthly rainfall over the lake and the evaporation components of the lake balance are calculated. Previous studies indicated the existence of a spatially and temporally variable interaction between the lake and the surrounding aquifer (Hogeboom et al., 2015; Reta, 2011; Yihdego et al., 2016; Yihdego & Becht, 2013). Yihdego et al. (2016) estimated long-term lake seepage in and out to be 1.14 and 5.56 million m^3 per month for the period 1932-2010. In our model, this water exchange between the lake and aquifer $Q_{aq,t}$ is calculated as:

$$Q_{aq,t} = \bar{C}\left(H_{lake,t} - H_{aq,t}\right) \tag{8}$$

Where $\bar{C}$ is the hydraulic conductance of the aquifer (m^2 month^{-1}), $H_{lake,t}$ and $H_{aq,t}$ are the lake and groundwater levels per month (m), respectively. Then, the groundwater level is updated based on the inflow and outflow calculated for the previous month as follows

$$H_{aq,t} = H_{aq,t-1} + \frac{\left(Q_{aq,t} - \bar{Q}_{outflow}\right)}{\bar{a} * \bar{S}_y} \tag{9}$$

where $\bar{Q}_{outflow}$ is a constant for net water loss from the lake to the external area by the process other than evaporation and outflow to the aquifer, $\bar{a}$ is a constant for the surface area of the aquifer, and $\overline{S_y}$ is a constant for a specific yield of the aquifer.

As mentioned above, the model maximizes an objective function represented by the Nash-Sutcliffe Efficiency (NSE) measure applied to the log-transformations of observed and simulated lake volumes, as shown in the equation (10). The NSE measure, which ranges from minus infinity to 1.0, is commonly used to evaluate the performance of hydrologic models (cf. Legates & McCabe, 1999). We use log-transformation of observed and simulated lake volumes because initial runs using untransformed volumes showed that the resulting hydrographs, especially the reconstructed streamflow greatly influenced by high lake volumes, with the fit between the observed and reconstructed streamflow being poor. A similar transformation approach of the raw data was used to achieve better agreement between the observed and simulated flows in Kizza et al.(2011).

$$Max\ NS(\Theta) = 1 - \frac{\sum_{t=1}^{N}[\log(O_t) - \log(S_t(\Theta))]^2}{\sum_{t=1}^{N}[\log(O_t) - \overline{\log(O_t)}]^2} \tag{10}$$

The objective function was maximized to find the optimal solution to the rainfall-runoff function parameters. The model was coded in GAMS (General Algebraic Modelling System) (Brook et al., 1988) and solved using a Conopt solver.

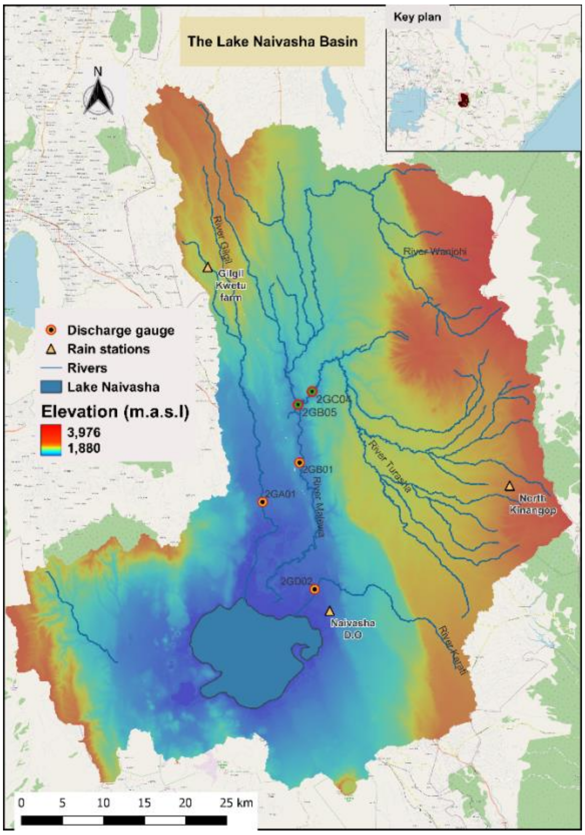
2.3 Data sets

Daily rainfall readings from 1960 to 2010 are available for 65 gauging stations in the basin and obtained from the archive of the University of Twente (ITC), the Netherlands. Out of the 65 rain stations, only a few have reliable data with minimal gaps in the dataset. We chose three stations: Naivasha District Office (Naivasha D.O) at an elevation of 1923 m (0.02 % missing data), Gilgil Kwetu Farm at 2391m (no missing data), and North Kinangop Forest Station at 2617m (0.10% missing data). The three stations are chosen for two reasons: first, the number of gaps in readings is lower for all daily measurements, and second, they nicely represent the range of elevation above sea level, which characterizes the basin. Given the positive correlation of elevation and rainfall generally observed in the basin (e.g. Meins, 2013), rainfall at the chosen locations is assumed to represent various sub-catchments of the basin within an elevation class. The entire basin is divided into twelve sub-catchments corresponding to Water Resources User Associations (WRUAs). Accordingly, rainfall from the chosen stations is attributed to these sub-catchments based on elevation classes. Figure 2.2 shows the map of Lake Naivasha Basin with the location of rainfall and river gauging stations used in the model.

Monthly lake level recordings have been made since 1952, and consistent daily lake level monitoring is available since 1997 (Odongo et al., 2015). In a second step, an average across the different series was calculated which also served to fill gaps in individual series. Finally, a few obvious outliers or other singular errors were corrected by replacing dubious values with the arithmetic mean of the two neighboring readings. Based on the consolidated and corrected lake levels, corresponding lake water volumes were estimated.

Values for the following hydrological coefficients are taken from Van Oel et al. (2013): the constant groundwater outflow ($\overline{Q_{outflow}}$) is 2833 m^3 $month^{-1}$. The hydraulic conductance ($\overline{C}$) is 2833 m^2 $month^{-1}$, the specific yield of the aquifer ($\overline{S}_y$) is 0.2, and the area of the aquifer ($\bar{a}$) is 100 sq.km.

Figure 2.2 Location map of the Lake Naivasha Basin showing hydrological and topographical features, and the rainfall and discharge gauging stations



Source: own illustration based on shapefiles from University of Twente/ITC database for Naivasha

A correct lake bathymetry is critical to determine lake area and volume changes. We use bathymetry data which was collected in October 2011 (Ndungu et al., 2015). The data consisted of depth measurements in meters that we later converted to meters above sea level by adding the datum (1885.26 m) defined by Ase et al. (1986). The data were then interpolated over the lake surface. Contours were generated at 0.5 m depth intervals. The 30 minutes resolution STRM (Shuttle Radar Topography Mission) digital elevation model was used to create the contours in the area that did not contain water at the time of sampling.

The lake mainly loses water through evaporation, for which no reliable time series exist. Instead, an inter-month variation taken from a stylized annual evaporation cycle (mm per month) for the region suggested by Stein (2009) was applied to match the average annual evaporation from the lake surface from previous studies.

Water outflow from the groundwater aquifer surrounding the lake to neighboring basins within the Rift Valley is another outlet water balance component. It is difficult to measure this value, and it is introduced as a constant residual in the groundwater balance equation (9) .

Another water balance component for which time series data do not exist is human water use. This is less of a problem as it can be assumed to be mainly neutral to the overall water balance of the region because most of the abstracted water will return to the regional cycle and thus still end up in Lake, albeit in lower quality. A large share of water abstractions for irrigation leaves the regional cycle as evapotranspiration. According to van Oel et al. (2013), the estimated irrigation water abstraction for 1999-2010 accounts for 94% of total water abstraction. We use estimated irrigation abstraction for 1983 - 2010, drawing on the analysis of satellite images for irrigated areas and water consumption (van Oel et al., 2013).

Finally, we evaluate the performance of our model by comparing the reconstructed streamflow into the lake with the observed total river discharges. We use discharge data from the three most downstream gauging stations with relatively appreciable continuous observations. These stations represent the outlet from the three main rivers that fed the lake – Gilgil, Malewa, and Karati Rivers. River discharge data is available from 1960 onwards. The discharge data we use in this study was interpolated by Meins (2013) with original data having more than 75% gaps.

We split the time series dataset into pre irrigation (1960-1983) and irrigation (1984-2010). We use 70% of the pre irrigation for calibration (1960-1976) and 30 % for validation (1977-1983). Similarly, We use 75 % of the post-calibration data for calibration (1984-2003) and the rest for validation (2004-2010).

2.4 **Model assessment**

Different statistical scores can be used to evaluate the performance of hydrological models based on how well the simulated data fits the observed. Here we use correlation coefficients (CC), the Nash Sutcliffe Efficiency (NSE) (Nash & Sutcliffe, 1970), and (KGE)(Gupta et al., 2009) to measure the model performance. These model performance measures are presented in equations (11)-(13) as.

$$CC = \frac{\sum_{t=1}^{N}\left(O_t - \overline{O_t}\right)\left(S_t - \overline{S_t}\right)}{\sqrt{\sum_{t=1}^{N}\left(O_t - \overline{O_t}\right)^2} \cdot \sqrt{\sum_{t=1}^{N}\left(S_t - \overline{S_t}\right)^2}} \tag{11}$$

$$NSE = 1 - \frac{\sum_{t=1}^{N}(O_t - S_t)^2}{\sum_{t=1}^{N}(O_t - \overline{O_t})^2} \tag{12}$$

$$KGE = 1 - \sqrt{(r-1)^2 + (\theta - 1)^2 + (\psi - 1)^2} \tag{13}$$

where S and O represent the simulated and observed values $\overline{S}$ and $\overline{O}$ are the corresponding average values. The index t denotes the hydrological period on a monthly scale from 1960 to 2010.

The CC measures the degree of linear correlation between the model simulation and observation for the streamflow and lake volume. The NSE is a measure of the ratio of mean square error and the variance of the observed data subtracted from unity. The value of NSE ranges from minus infinity to one where one indicates perfect correspondence, whereas values less than zero indicate the mean of observed data is a better predictor than the model simulation (Legates & McCabe, 1999).

The KGE is an alternative measure developed to address several limitations in NSE and is increasingly used for the performance evaluation of hydrological models (Camici et al., 2020). It decomposes NSE into three model errors representing the correlation, the bias, and relative variability in the simulated and observed values (Gupta et al., 2009). In equation (13) r

represents the correlation, α is the variability component, and β is the bias between the simulated and observations. Like NSE, the KGE value equal to one indicates a perfect correspondence between the model simulation and observation. The corresponding NSE zero (mean of observation as a benchmark) is – 0.41 for KGE (Knoben et al., 2019).

2.5 Results and discussion

2.5.1 *Calibrated parameters*

The optimized model parameters for rainfall-runoff specifications for the period before and after the onset of commercial irrigation are presented in Table 2.1. The linear parameters α and γ are relatively stable and show slight variation across the model specifications and simulation periods. The nonlinear parameter, however, shows considerable variation.

Table 2.1 optimized model parameters, pre and irrigation periods

Model parameters	**Pre irrigation period (1960-1976)**				**Irrigation period (1984-2003)**			
	I	II	III	IV	I	II	III	IV
α	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.01
β	5.02	3.93	2.28	4.90	2.98	1.98	2.36	2.94
γ	0.08	0.07	-	0.04	0.03	0.02	-	0.01

Source: own calculation

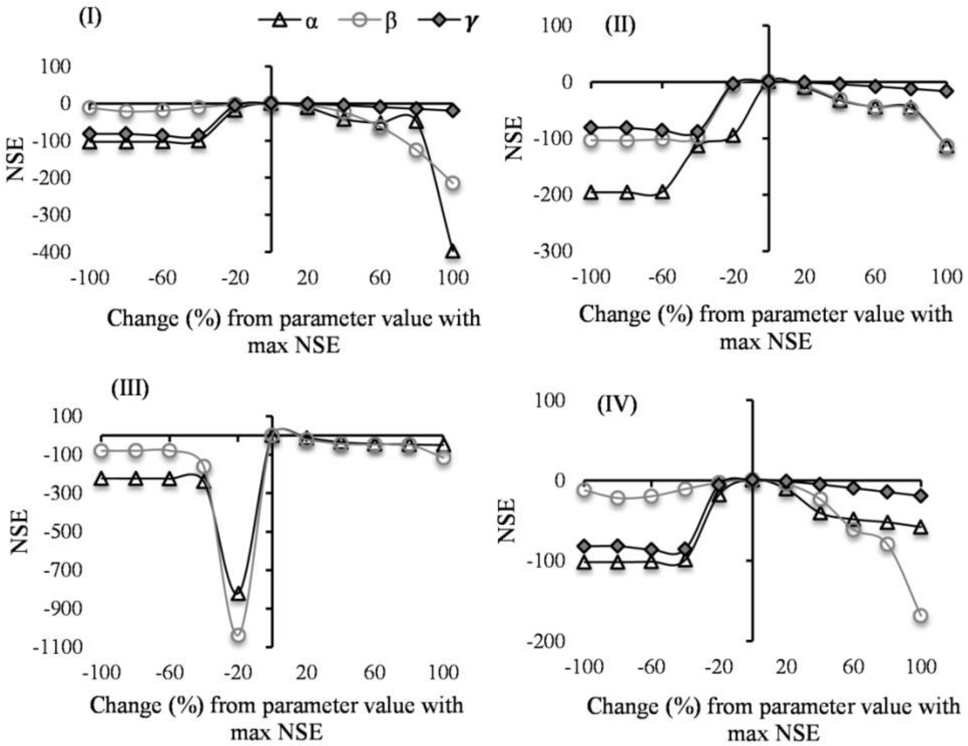
From equations (1) and (4), we can notice that there are only slight specification differences in the rainfall-runoff relationships. The precipitation of one month lag is part of the equation's linear and nonlinear terms in (4) while it is only part of the nonlinear component in (1). From a hydrological perspective, both specifications assume that runoff as a percentage of rainfall is nonlinear in the short-run (in the extreme case, a tropical downpour creates almost 100 percent of runoff) but relatively constant for periods further in the past. However, such a slight specification difference resulted in significant variations in the optimum parameter values, especially in the nonlinear (β) and the slope (γ) parameters.

2.5.2 *Sensitivity analysis*

We conduct sensitivity analysis on the parameter values to gain insight into the impact of each parameter on the model simulation. The local sensitivity analysis was done by sequentially varying each parameter value by a certain percentage and fixing all other parameters at their optimal. The NSE is used as the objective function for the sensitivity analysis.

The results are presented in Figure 2.3 and Figure 2.4 for the period pre and irrigation across the four model specifications. The figures demonstrate how the model performance, reflected by the values of NSE, depreciates from the maximum NSE values with a slight increase or decrease in the value of a given parameter at a time. The result shows that the parameter γ is the least sensitive. The model output is relatively sensitive to a percentage decrease in γ from its optimal values than the percentage increase. The model output is highly sensitive to percentage changes in the other two slope parameters, and it is more sensitive to percentage changes in α than β.

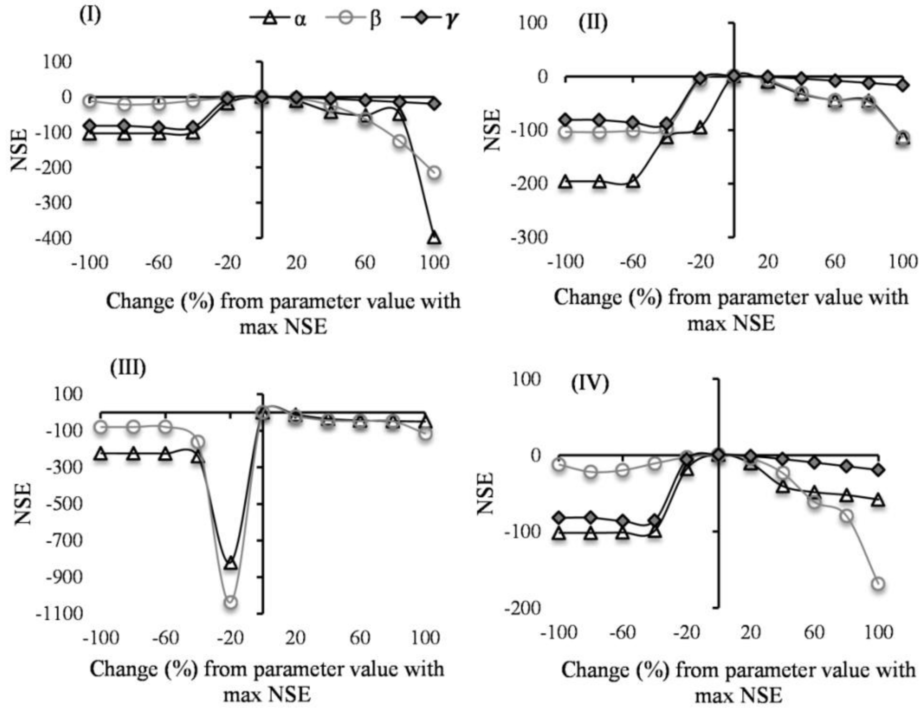
Figure 2.3 Model parameters sensitivity for the pre irrigation period: the x-axis shows the relative deviation of parameter values from their optimal values and the y-axis shows the NSE criterion for model specifications I to IV



Source: own illustration based on LakeStReAM estimation result

Comparing sensitivity results across the model specifications shows a mixed picture, which is hard to distinguish. Nevertheless, a closer look at the figures reveals that the model output seems less sensitive to percentage changes in parameter values for specification IV (Figure 2.3 (IV)) for the pre irrigation period. For the irrigation period, model output is equally sensitive to changes in parameter values for specifications I and IV (Figure 2.4).

Figure 2.4 Model parameters sensitivity for the irrigation period: the x-axis shows the relative deviation of parameter values from their optimal values, and the y-axis shows the NSE criterion for model specifications I to IV



Source: own illustration based on LakeStReAM result

Table 2.2-Table 2.5 presents statistical measures for model performance assessments comparing monthly observed and simulated lake volume and streamflow into the lake. The performance scores show strong agreement between the simulated and observed volumes for the pre irrigation period calibration phase (Table 2.2). In general, simulations from all the model specifications show excellent correspondence with the observed data. The values of NSE and KGE being closer to 1 and high correlation coefficient (r=0.97) indicate the model's high predictive capacity.

Table 2.2 Means and standard deviations of observed and simulated lake volume and the model performance scores for the pre irrigation period across model specifications I to IV

		Pre irrigation calibration phase (1960-1976)			
Statistic	**Observed**	I	II	III	IV
Mean (μ)	1039.33	1037.75	1035.38	1033.57	1038.54
Standard deviation (σ)	202.66	200.60	201.55	206.17	198.76
r		0.98	0.97	0.98	0.98
NSE		0.96	0.95	0.95	0.96
KGE		0.98	0.97	0.97	0.97
Statistic	**Observed**	**Pre irrigation validation phase (2004-2010)**			
Mean (μ)	1151.61	1199.74	1176.13	1112.30	1197.66
Standard deviation (σ)	139.73	152.30	163.43	127.67	150.82
r		0.89	0.81	0.96	0.90
NSE		0.64	0.48	0.84	0.70
KGE		0.86	0.73	0.90	0.88

Source: own estimation

Table 2.3 Means and standard deviations of observed and simulated lake volume and the model performance scores for the irrigation periods and model specifications I to IV

		Irrigation period calibration phase (1984-2003)			
Statistic	**Observed**	**I**	**II**	**III**	**IV**
Mean (μ)	853.41	513.28	870.72	857.00	862.40
Standard deviation (σ)	126.86	288.69	109.17	122.32	121.17
r		0.88	0.81	0.88	0.88
NSE		0.76	0.64	0.77	0.76
KGE		0.87	0.76	0.87	0.87
Statistic	**Observed**	**Irrigation period validation phase (2004-2010)**			
Mean (μ)	676.57	575.98	671.19	604.64	626.53
Standard deviation (σ)	90.57	97.02	63.10	90.63	85.92
r		0.89	0.89	0.88	0.89
NSE		0.43	0.74	0.23	0.46
KGE		0.85	0.65	0.85	0.85

Source: own estimation

As shown in Table 2.2, the values of statistical measures are depreciated in the validation phase compared to the calibration. Nevertheless, the model still nicely reproduces the observed data for all the model specifications, showing minimal discrepancies between calibration and validation phases. The rainfall-runoff relation specified in III performed best in the validation phase, relative to other specifications, with NSE and KGE values of 0.84

and 0.90, respectively, followed by specification IV. It also has the smallest standard deviation.

In the irrigation period (Table 2.3), the model is much less successful in reproducing the observed lake volume than the pre irrigation period. The correspondence between the simulated and observed lake volumes was significantly reduced across all specifications. There are also some inconsistencies between the calibration and validation of specification II with a higher value of NSE in the validation phase compared to the calibration. This specification also performed the least compared to others in the calibration and validation phase when looking at the KGE index.

Table 2.4 Means and standard deviations of observed and reconstructed streamflow and model performance scores – for the pre irrigation period and model specifications I to IV

		Pre irrigation calibration phase (1960-1976) [a]			
Statistic	**Observed**	I	II	III	IV
Mean (μ)	20.24	23.60	23.53	23.69	23.59
Standard deviation (σ)	18.87	22.05	21.54	22.44	23.04
r		0.40	0.60	0.47	0.43
NSE		-0.25	0.04	-0.31	-0.24
KGE		0.39	0.55	0.42	0.41
Statistic	Observed	Pre irrigation validation phase (1977-1983)[a]			
Mean (μ)	24.49	30.98	31.33	29.05	30.94
Standard deviation (σ)	20.63	42.05	43.34	27.57	44.31
r		0.61	0.64	0.57	0.63
NSE		-0.22	-0.34	-0.28	-0.09
KGE		0.45	0.37	0.44	0.50

Source: own estimation

Rainfall-runoff specifications I, III, and IV performed better in the calibration and validation phases. However, specification IV outperformed all in the validation phase with a relatively higher value of NSE (0.46). Although the NSE values for the three specifications are less than 0.5, the larger values of KGE indicate that the model is still a better predictor of the lake volume change than the observed mean.

Table 2.5 Means and standard deviations of observed and reconstructed streamflow into the lake and model performance measures – for the irrigation period and I – IV model specifications

		Irrigation period calibration phase (1984-2003)[a]			
Statistic	**Observed**	I	II	III	IV
Mean (μ)	20.27	17.26	20.38	20.27	20.92
Standard deviation (σ)	22.10	11.71	18.35	20.84	22.71
r		0.65	0.81	0.53	0.63
NSE		0.38	0.66	0.22	0.33
KGE		0.62	0.68	0.48	0.62
Statistic	**Observed**	**Irrigation period validation phase (2004-2010)[a]**			
Mean (μ)	17.93	15.81	19.39	18.33	18.96
Standard deviation (σ)	17.18	11.42	16.49	19.13	21.05
r		0.77	0.74	0.65	0.76
NSE		0.59	0.50	0.42	0.58
KGE		0.63	0.45	0.49	0.65

Source: own estimation

Note: [a] The calibration and validation periods are for the lake volume calibration and validation since the reconstructed streamflow was not calibrated.

We examine how the reconstructed streamflow matches the observed monthly streamflow into the lake. As shown in Table 2.4, both the correlation coefficient and measure of efficiencies indicate lower agreements between the reconstructed and observed streamflows. The NSE values are below zero for pre irrigation periods for both the calibration and validation phase and across all specifications, except for II (NSE=0.04). The Pearson's product-moment correlation coefficients were also below 0.5 (except specification II) for the calibration phase. This indicates the mean of the observations (20.24 x 10^6 m^3 for calibration and 24.5 x 10^6 m^3 for validation) is a better predictor than the reconstructed values. However, the Kling–Gupta Efficiencies (KGE) being larger than the minimum threshold values of -0.41 contradicts this conclusion. The correlation coefficients and KGE values showed better agreement between the reconstructed and observed streamflow in the validation phase.

The match between reconstructed and observed streamflow into the lake improved for the irrigation period (Table 2.5). All rainfall-runoff relationship specifications have produced positive NSE and KGE values and correlation coefficients above 0.5 for both the calibration and validation phases.

The discrepancies between reconstructed and observed streamflow could be due to the uncertainties in the observed data. We used three river gauging stations with reasonable data coverage, and the gaps were filled using interpolation (Meins, 2013). However, interpolation always introduces uncertainties that are expected to contribute to the observed disagreements. On the contrary, the improved agreements between the reconstructed and observed streamflow for the irrigation period could be attributed to better data coverage in recent years. For instance, the coverage of daily readings for the Malewa River, a significant contributor to Lake Naivasha, was 33% for the period 1965-1979 and increased to 99% for 1999 – 2010 (van Oel et al., 2013). Similarly, the data coverage for the Gilgil River in the same period increased from 89% to 92%. Our result agrees with this better data coverage in the later years, where the irrigation period (1984 - 2010) produced a better agreement between the reconstructed and observed streamflow into the lake.

2.5.3 *Residual analysis*

We compute the residuals as the difference between log-transformed observed and the reconstructed streamflow and performed residual analysis. The results for pre irrigation period are presented in Figures Figure 2.5 and Figure 2.6. A Scatter plot for the residual and reconstructed streamflow shows that the residuals have constant variance (Figure 2.6). The residuals also followed a normal distribution (Figure 2.5), demonstrating the model nicely capturing the information in the data. The residuals for the irrigation period showed similar patterns with constant variance and a normal distribution.

Figure 2.5 Pre irrigation period residuals cumulative distribution for the reconstructed and observed streamflow

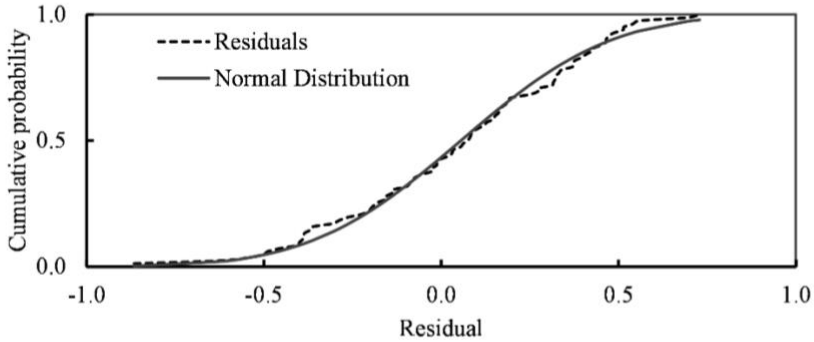
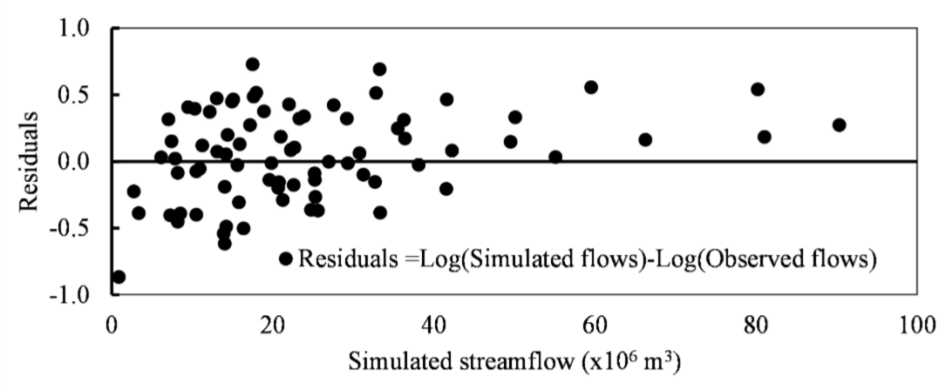


Figure 2.6 Scatter plot of residuals and reconstructed streamflow for the pre irrigation period.



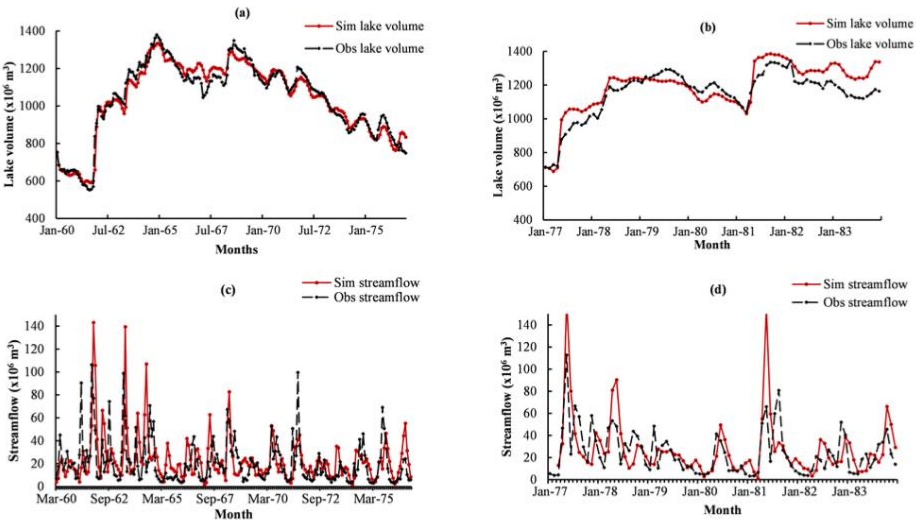
Source: own estimation

Analysis of the hydrographs provides more insights into the model performance. Figures Figure 2.7 and Figure 2.8 show observed and simulated lake volume and streamflow for the pre and irrigation periods using specification IV. We chose specification IV simply for demonstration purposes, not because of its performance since this is not revealed from the performance analysis.

As shown in Figure 2.7, the simulated lake volume corresponds well with the observed time series with a slight divergence between simulated and observed lake volume in the validation phase for the pre irrigation period. The reconstructed streamflow also produced values close to the observed streamflow for the most part of the calibration and validation phases. However, both in the calibration and validation phase, there are some outliers in which peak flows in the reconstructed streamflow overestimate the observations. The depreciated values for the performance scores can be attributed to this lack of convergence.

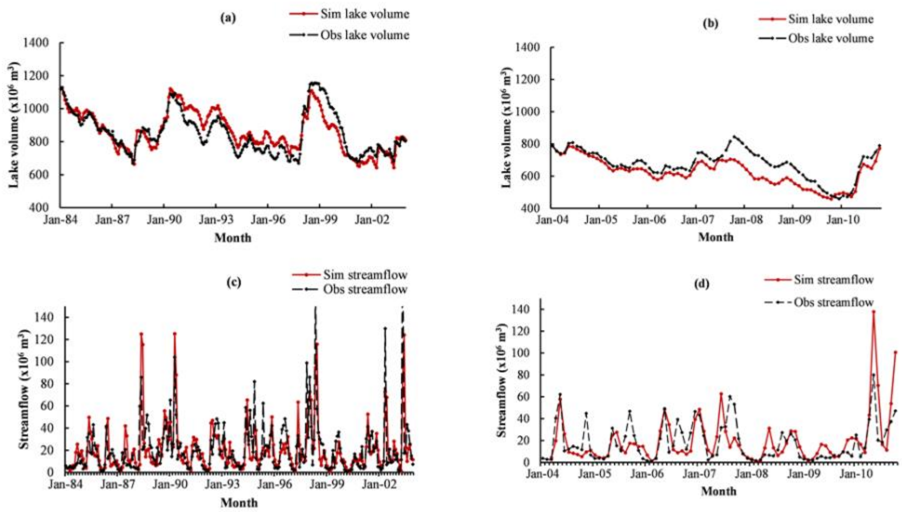
For the irrigation period, the simulation consistently overestimated observed lake volumes from the late 1980s to the late1990s and then starting from the early 2000s, it underestimated the observations for most of the remaining periods, including the validation years (Figure 2.8). As discussed above, the reconstructed streamflow into the lake nicely reproduced the observed inflows with slight variations in the validation phase.

Figure 2.7 Hydrographs for the pre irrigation period: Simulated and observed lake volumes for the calibration (a) and validation (b) phases; reconstructed and observed streamflow for the calibration (a) and validation (d) phases.



Source: own illustration based on the estimation result

Figure 2.8 Irrigation: Simulated and observed lake volumes for the calibration (a) and validation phase (b), reconstructed and observed streamflow for the calibration (c) and validation phase (d)



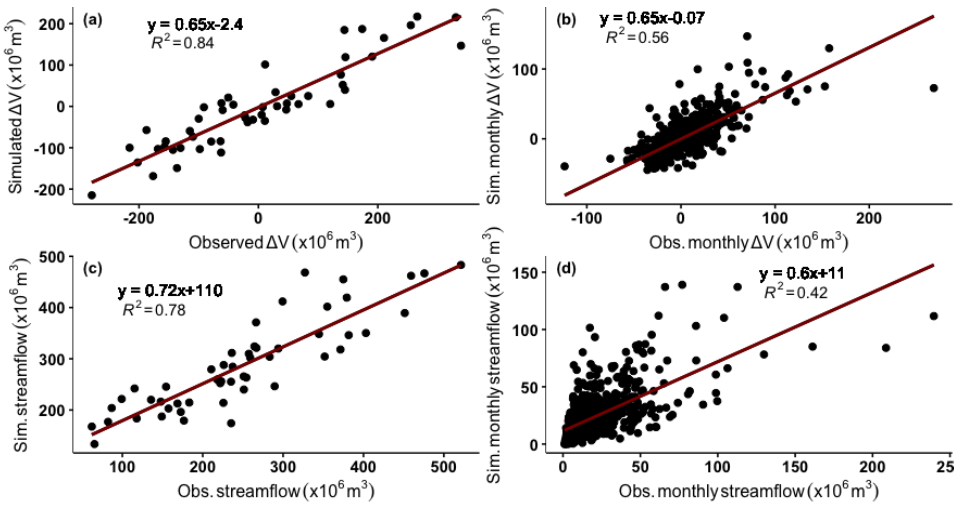
Source: *own illustration based on the estimation result*

We would not expect the model to exactly reproduce the actual data due to a host of other factors not accounted for and inaccuracies in the input data. Therefore inaccuracies of this much are not surprising. Becht and Harper (2002) simulated lake volumes higher than the observations from the 1980s to 1990s using measured inflows from Turasha and Malewa sub-catchments. Odongo et al. (2015) also simulated greeater variability of the difference between simulated and observed lake volumes, measured as residual for the period between 1987 and 1998 and in the 2000s. However, it is important to highlight the possible underlying factors for the model performance variation for the pre and irrigation periods for the two variables. The source of deviation between simulated and observed lake volume for the late 1980s and 1990s could be related to the estimated water abstraction series. The estimated water abstraction assumes constant average actual evapotranspiration for crop water requirements for different crop patterns during the irrigation period, irrespective of the irrigation techniques used and water use efficiency. The fact that our simulated lake volume overestimates observed lake volumes for the period between the late 1980s and late 1990s and underestimate the later years indicate that the amount of irrigation water use in the 1980s and 1990s was higher per ha than the most recent past due to less water-saving irrigation techniques in the earlier years. This variation was not captured in estimating irrigation water use.

2.5.4 *Lake volume change and water balance*

Using parameter estimates for specification IV, we show the variation in annual and monthly lake volume changes and streamflow explained by our reconstruction model. As shown in the scatter plots (Figure 2.9), the variation in long-term inter-annual and inter-monthly simulated lake volume changes are well explained with R^2 0.84 ($p < 0.000$) and 0.56 ($p < 0.000$), respectively. For the streamflow, the reconstructed annual and monthly values fit the observation well with R^2 equal to 0.78 ($p < 0.000$) and 0.46 ($p < 0.000$), respectively. The result shows that the long-term inter-annual volume changes and streamflow shows good agreement with the data than the monthly time scale. The difference is likely due to the monthly time-step that the model applies, where the model performance is influenced by inaccuracies caused by the temporal resolution of the input data series used.

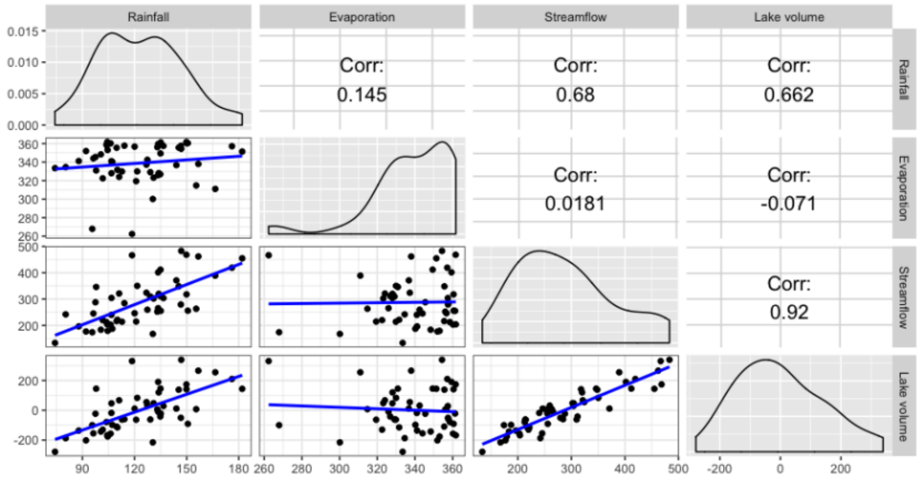
Figure 2.9 Scatter plot of (a) simulated and observed annual lake volume change, (b) simulated and observed monthly lake volume change, (c) annual streamflow and (d) monthly streamflow for the period 1960-2010



Source: own illustration based on the estimation result

Among the major water balance components, the annual changes in lake volume is highly correlated to the reconstructed streamflow ($R^2 = 0.85$, $p < 0.000$) and precipitation over the lake ($R^2 = 0.44$, $p < 0.000$) but poorly correlated with evapotranspiration ($R^2 = 0.005$, $p > 0.6$). The result agrees with Odongo et al. (2015) for Lake Naivasha.

Figure 2.10 A matrix of scatter plots (the lower triangular portion), density plots (diagonal) and the correlation coefficients (the upper triangular portion) for the lake balance components - rainfall (x10^6 m^3), lake evaporation (x10^6 m^3), reconstructed streamflow.



Source: own illustration based on the estimation results

The cross-correlation matrix with scatter plots in Figure 2.10 shows relationships between changes in annual lake volume and major water balance components. The reconstructed streamflow, which is an inflow into the lake, was strongly correlated (r = 0.92) to changes in lake volume followed by precipitation over the lake (r = 0.66). The evaporation from the lake is poorly correlated to lake volume changes (r = -0.07). The strong correlation of the streamflow and changes in lake volumes shows the importance of this variable in explaining variation in lake volumes.

The diagonal of the matrix shows density plots for the water balance components. The density plot for rainfall on the lake indicates that rainfall in the basin is bimodal. For the reconstructed streamflow, it is right-skewed, showing the peak flows. Similarly, the density plot for evaporation from the lake surface is bimodal and left-skewed.

2.6 **Conclusion**

This study demonstrates how to reconstruct streamflow and estimate water availability when reliable data on discharge measurements are not sufficiently available. We used precipitation data from three representative rainfall stations in the Basin at a monthly scale, relatively reliable lake-level data, and plausible estimates of net water withdrawal. The model simulates the long-term inter-annual changes in lake volume and relationships to major water balance in the lake using an inverted water balance model and simplified rainfall-runoff relationships. The calibrated model is subjected to different goodness of fit measurements to evaluate its performance.

Given the limited data availability, the statistical fit of the approach used in this study suggests that it is possible to adequately reproduce a time series of lake volume based on reconstructed streamflow into the lake. We showed that the methodology used in this study is deemed useful to produce plausible estimates of streamflow and, thus, water availability in the vicinity of Lake Naivasha. It can serve as an example for similar hydrological studies where partial data uncertainty prevents direct estimation of streamflow in ungauged basins.

2.7 **References**

Aloo, P. A., Okelo, R. O., & Ntiba, M. J. (1996). Helminth Fauna of *Oreochromis leucostictus* (Pisces: CICHLIDAE) from a tropical lake, Lake Naivasha, Kenya. *African Journal of Tropical Hydrobiology and Fisheries*, *7*(1), 7–16. https://doi.org/10.4314/ajthf.v7i1.1377

Åse, L.-E., SERNBO, K., & SYREN, P. (1986). *A study of Lake naviasha basin and it's drainage*. Naturgeografiska Institutionen. ftp://ftp.itc.nl/pub/naivasha/Ase1986.pdf

Awange, J. L., Sharifi, M. A., Ogonda, G., Wickert, J., Grafarend, E. W., & Omulo, M. A. (2008). The Falling Lake Victoria Water Level: GRACE, TRIMM and CHAMP Satellite Analysis of the Lake Basin. *Water Resources Management*, *22*(7), 775–796. https://doi.org/10.1007/s11269-007-9191-y

Barria, P., Peel, M. C., Walsh, K. J. E., & Muñoz, A. (2018). The first 300-year streamflow reconstruction of a high-elevation river in Chile using tree rings. *International Journal of Climatology*, *38*(1), 436–451. https://doi.org/10.1002/joc.5186

Becht, R., & Harper, D. M. (2002). Towards an understanding of human impact upon the hydrology of Lake Naivasha. *Hydrobiologia*, *488*(1–3), 1–11.

Brook, A., Kendrick, D., & Meeraus, A. (1988). GAMS, a User's Guide. *SIGNUM Newsl.*, *23*(3–4), 10–11. https://doi.org/10.1145/58859.58863

Chen, F., He, Q., Bakytbek, E., Yu, S., & Zhang, R. (2017). Reconstruction of a long streamflow record using tree rings in the upper Kurshab River (Pamir-Alai Mountains) and its application to water resources management. *International Journal of Water Resources Development*, *33*(6), 976–986. https://doi.org/10.1080/07900627.2016.1238347

DeRose, R. J., Wang, S.-Y., Buckley, B. M., & Bekker, M. F. (2014). Tree-ring reconstruction of the level of Great Salt Lake, USA. *The Holocene*, *24*(7), 805–813. https://doi.org/10.1177/0959683614530441

Duan, Q., Sorooshian, S., & Gupta, V. K. (1994). Optimal use of the SCE-UA global optimization method for calibrating watershed models. *Journal of Hydrology*, *158*(3), 265–284. https://doi.org/10.1016/0022-1694(94)90057-4

Ferrero, M. E., Villalba, R., De Membiela, M., Ferri Hidalgo, L., & Luckman, B. H. (2015). Tree-ring based reconstruction of Río Bermejo streamflow in subtropical South America. *Journal of Hydrology*, *525*, 572–584. https://doi.org/10.1016/j.jhydrol.2015.04.004

Gallant, A. J. E., & Gergis, J. (2011). An experimental streamflow reconstruction for the River Murray, Australia, 1783–1988. *Water Resources Research*, *47*(12). https://doi.org/10.1029/2010WR009832

Gaudet, J. J., & Melack, J. M. (1981). Major ion chemistry in a tropical African lake basin. *Freshwater Biology*, *11*(4), 309–333.

Gupta, H. V., Kling, H., Yilmaz, K. K., & Martinez, G. F. (2009). Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology*, *377*(1–2), 80–91. https://doi.org/10.1016/j.jhydrol.2009.08.003

Hogeboom, R. H. J., van Oel, P. R., Krol, M. S., & Booij, M. J. (2015). Modelling the Influence of Groundwater Abstractions on the Water Level of Lake Naivasha, Kenya Under Data-Scarce Conditions. *Water Resources Management*, *29*(12), 4447–4463. https://doi.org/10.1007/s11269-015-1069-9

Hrachowitz, M., Savenije, H. H. G., Blöschl, G., McDonnell, J. J., Sivapalan, M., Pomeroy, J. W., Arheimer, B., Blume, T., Clark, M. P., Ehret, U., Fenicia, F., Freer, J. E., Gelfan, A., Gupta, H. V., Hughes, D. A., Hut, R. W., Montanari, A., Pande, S., Tetzlaff, D., … Cudennec, C. (2013). A decade of Predictions in Ungauged Basins (PUB)—A review. *Hydrological Sciences Journal*, *58*(6), 1198–1255. https://doi.org/10.1080/02626667.2013.803183

Kizza, M., Rodhe, A., Xu, C.-Y., & Ntale, H. K. (2011). Modelling catchment inflows into Lake Victoria: Uncertainties in rainfall–runoff modelling for the Nzoia River. *Hydrological Sciences Journal*, *56*(7), 1210–1226. https://doi.org/10.1080/02626667.2011.610323

Knoben, W. J. M., Freer, J. E., & Woods, R. A. (2019). Technical note: Inherent benchmark or not? Comparing Nash-Sutcliffe and Kling-Gupta efficiency scores. *Hydrology and Earth System Sciences Discussions*, 1–7. https://doi.org/10.5194/hess-2019-327

Legates, D. R., & McCabe, G. J. (1999). Evaluating the use of "goodness-of-fit" Measures in hydrologic and hydroclimatic model validation. *Water Resources Research*, *35*(1), 233–241. https://doi.org/10.1029/1998WR900018

Loukas, A., & Vasiliades, L. (2014). Streamflow simulation methods for ungauged and poorly gauged watersheds. *Natural Hazards and Earth*

System Sciences, *14*(7), 1641–1661. https://doi.org/10.5194/nhess-14-1641-2014

Meins, F. M. (2013). *Evaluation of spatial scale alternatives for hydrological modelling of the Lake Naivasha basin, Kenya*. http://essay.utwente.nl/63061/

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I — A discussion of principles. *Journal of Hydrology*, *10*(3), 282–290. https://doi.org/10.1016/0022-1694(70)90255-6

Nicholson, S. E., Yin, X., & Ba, M. B. (2000). On the feasibility of using a lake water balance model to infer rainfall: An example from Lake Victoria. *Hydrological Sciences Journal*, *45*(1), 75–95. https://doi.org/10.1080/02626660009492307

Odongo, V. O., van der Tol, C., van Oel, P. R., Meins, F. M., Becht, R., Onyando, J., & Su, Z. (2015). Characterisation of hydroclimatological trends and variability in the Lake Naivasha basin, Kenya: HYDROCLIMATOLOGICAL TRENDS AND VARIABILITY OF LAKE NAIVASHA. *Hydrological Processes*, *29*(15), 3276–3293. https://doi.org/10.1002/hyp.10443

Reta, L. (2011). *Groundwater and lake water balance of lake Naivasha using 3—D transient groundwater model* [University of Twente Faculty of Geo-Information and Earth Observation ITC]. ftp://ftp.itc.nl/pub/naivasha/ITC/LegeseReta2011.pdf

Stein, C. (2009). *Räumliche und klimatische Einordnung von Naivasha in Kenia. Diercke 360° 1/2009*. http://www.diercke.de/bilder/omeda/Copy_Naivasha.pdf

Tate, E., Sutcliffe, J., Conway, D., & Farquharson, F. (2004). Water balance of Lake Victoria: Update to 2000 and climate change modelling to 2100 / Bilan hydrologique du Lac Victoria: mise à jour jusqu’en 2000 et modélisation des impacts du changement climatique jusqu’en 2100. *Hydrological Sciences Journal*, *49*(4), null-574. https://doi.org/10.1623/hysj.49.4.563.54422

Urrutia, R. B., Lara, A., Villalba, R., Christie, D. A., Le Quesne, C., & Cuq, A. (2011). Multicentury tree ring reconstruction of annual streamflow for the Maule River watershed in south central Chile. *Water Resources Research*, *47*(6). https://doi.org/10.1029/2010WR009562

van Oel, P. R., Mulatu, D. W., Odongo, V. O., Meins, F. M., Hogeboom, R. J., Becht, R., Stein, A., Onyando, J. O., & van der Veen, A. (2013). The Effects of Groundwater and Surface Water Use on Total Water Availability and Implications for Water Management: The Case of Lake Naivasha, Kenya. *Water Resources Management*, *27*(9), 3477–3492. https://doi.org/10.1007/s11269-013-0359-3

Verschuren, D., Laird, K. R., & Cumming, B. F. (2000). Rainfall and drought in equatorial east Africa during the past 1,100 years. *Nature*, *403*(6768), 410–414. https://doi.org/10.1038/35000179

Wise, E. K. (2010). Tree ring record of streamflow and drought in the upper Snake River. *Water Resources Research*, *46*(11). https://doi.org/10.1029/2010WR009282

Yihdego, Y., & Becht, R. (2013). Simulation of lake–aquifer interaction at Lake Naivasha, Kenya using a three-dimensional flow model with the high conductivity technique and a DEM with bathymetry. *Journal of Hydrology*, *503*, 111–122. https://doi.org/10.1016/j.jhydrol.2013.08.034

Yihdego, Y., Reta, G., & Becht, R. (2016). Hydrological analysis as a technical tool to support strategic and economic development: A case study of Lake Navaisha, Kenya: Water Resources Assessment Project. *Water and Environment Journal*. https://doi.org/10.1111/wej.12162

Yin, X., & Nicholson, S. E. (1998). The water balance of Lake Victoria. *Hydrological Sciences Journal*, *43*(5), 789–811. https://doi.org/10.1080/02626669809492173

Chapter 3
Modelling non-cooperative water use in river basins[1]

Abstract

Conventional water use and management models have mostly emulated purposefully designed water use systems where centralized governance and rule-based cooperation of agents are assumed. However, whether actively governed or not, water use systems involve multiple, independent decision makers with diverse and often conflicting interests. In the absence of adequate water management institutions to effectively coordinate decision processes on water use, water users' behaviors are rather likely to be non-cooperative, meaning that actions by individual users generate externalities and lead to sub-optimal water use efficiency. The objective of this review is to evaluate the advantages and disadvantages of recently proposed modelling systems dealing with non-cooperative water use regarding their ability to realistically represent the features of complex hydrological and socioeconomic processes and their tractability in terms of modelling tools and computational efficiency. For that purpose, we conducted a systematic review of 47 studies that address non-cooperative water use in decentralized modelling approaches. Even though such a decentralized approach should aim to model decisions by individual water users in non-cooperative water use, we find that most studies assumed the presence of a coordinating agency or market in their model. It also turns out that most of these models

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[1] This chapter is the basis for a paper published in sustainability entitled: Woldeyohanes, T.; Kuhn, A.; Heckelei, T.; Duguma, L. Modelling Non-Cooperative Water Use in River Basins. Sustainability 2021, 13, 8269. https://doi.org/ 10.3390/su13158269

employed a solution procedure that sequentially solved independent economic decisions based on pre-defined conditions and heuristics, while only a few modelling approaches offered simultaneous solution algorithms. We argue that this approach cannot adequately capture economic trade-offs in resource allocation, in contrast to models with simultaneous solution procedures.

Keywords: Water allocation, non-cooperative, river basin, decentralized decisions, sustainability

3.1 Introduction

The complexities of biophysical and socio-economic processes in water allocation and use presents a considerable challenge to manage water resources efficiently and sustainably. The challenge is more evident in regions where adequate institutional arrangements for large-scale water use governance have yet to emerge and non-cooperative water use is dominant (Filho et al., 2008). There has been a growing awareness that appropriate policy instruments and institutional arrangements are needed to promote efficient and sustainable water use. Identifying policy options that fit the complex water management situation in the coupled human-natural system requires addressing a number of questions: What are the potential efficiency gains from implementing market-based water allocation compared to control and command or completely uncoordinated water use? Can gains from such policies offset any increased administrative or monitoring costs? What is the distributional impact or externalities of implementing such policies, and do they give rise to or instead reduce externalities? How do these conclusions depend on spatially and temporally dynamic hydro-economic conditions and their interactions in the coupled system?

Answers to these questions demand appropriate decision support tools for the ex-ante impact evaluation of proposed water policies and institutional arrangements. Water policies cannot be meaningfully evaluated if the models used do not realistically simulate the interaction of hydrological conditions and water users' behavior (Lei et al., 2019). Integrated hydrologic and economic optimization or simulation models have been used for the economic impact assessment of water management institutions at the river basin scale (Harou et al., 2009). Wang et al. (2008) described these models as hydrologic-economic river basin model (HERBM), a terminology adopted by Kuhn and Britz (2012) and Britz et al.(2013). These models account for the complex biophysical and socio-economic processes of water use and management problems. The main advantage of this modelling approach is the integration of spatially distributed hydrologic, engineering, ecologic, social, and economic components of the water resource system in a consistent framework for a comprehensive assessment of the tradeoffs between water policy choices (Cai et al., 2006; McKinney, 1999). The integration is based on a node-link network, where the nodes represent physical entities producing or using water and links represent the water flows between these entities. Water use by agents represented by the nodes causes costs and generates value, both of which can be expressed in monetary terms. In this way, a multiple-objective use and management problem simplifies into a single-objective optimization problem by summarizing the interests of all agents into a single financial metric.

Most HERBMs are constrained numerical optimization problems that are based on mathematical programming where the basin-wide aggregate social welfare criterion is maximized subject to a set of biophysical and institutional constraints. An early example such model by Young et al. (1986) was used to evaluate alternative institutional arrangements for managing water resources for the South Platte River Basin in Colorado. Over the last four decades, HERBMs evolved in theory and methods and applied to water allocation and management issues worldwide. Comprehensive reviews of HERBMs and their application to river basin water management and allocation problems are given by Harou et al. (2009) and Bekchanov et al. (2015).

Despite the significant advancement in HERBMs modelling since the early 1980s, several limitations remain (cf. Harou et al., 2009), one of them being the simplified representation of individual water users' behavior and interaction with one another and the hydrological conditions. Commonly designed as optimization problems based on aggregate welfare maximization, HERBMs assume the presence of (1) a centralized social planner and (2) water users willing to cooperatively reallocate water among each other such that their joint aggregate welfare is maximized. This is equivalent to reallocating water until marginal net benefits (shadow prices) of one additional unit of water are equal among all uses, users, and time in point. According to this hypothesis, some agents (e.g., upstream water users) are willing to decrease their local benefit to improve the benefit of other agents (e.g., downstream users). This assumption is hardly plausible in most real-world institutional contexts, as Kuhn and Britz (2012) pointed out.

Generally, water use modelling that leads to optimal solutions based on aggregate optimization may not well fit many real-world situations characterized by weak institutions and market failures. Non-cooperative behavior in water use may be much more common when multiple, institutionally independent, but physically interconnected decision-makers base their water use decisions on individual rationality, ignoring the spatial externalities (Madani & Dinar, 2012). For instance, excessive water use by upstream users may reduce the aggregate basin-wide welfare by reducing water availability for economically more efficient downstream users (Barbier, 2003). Transnational river basins are a good example in that water flow creates hydrological interdependences, whereas each riparian country is institutionally independent to manage and allocate water within its national boundary (Giuliani & Castelletti, 2013). In such a scenario, non-cooperative water use is likely to dominate, degenerating the common water resource into an open access system marked by free-rider behavior and sub-optimal system performance. Various factors, including lack of financial and administrative capacity and political will, may cause weak water allocation and management institutions. For example, Acemoglu (2006) showed that an ineffective economic institution, in general, may persist due to the private interests of national or regional elites.

Even though this limitation of HERBM has been recognized in the literature much earlier (Barbier, 2003; Young, 1996; Young et al., 1986), it is only recently that explicit alternative model designs have been suggested to address this problem. The suggested modelling approaches include decentralized hydro-economic models (HEM) based on individual optimization (Britz et al., 2013; Kuhn and Britz, 2012) and Agent-Based Models (ABM) (Barreteau et al., 2003; Giuliani & Castelletti, 2013; Schlueter & Pahl-Wostl, 2007; Yang et al., 2009). Game-theoretic models (GTM) have also been used to simulate water allocation problems based on both cooperative and non-cooperative game theory (Madani, 2010; Madani and Dinar, 2012).

The objective of this review is to evaluate the advantages and disadvantages of these alternative modelling approaches with respect to several aspects. The first is the capability of the suggested models to realistically simulate non-cooperative water use under absent or weak water institutions. We will also ascertain whether these novel models retain the classical HERBMs' extensive capacity to simulate the specific features of the hydrological and economic processes. Finally, we will discuss implications of the alternative modelling approaches for the design of sustainable water management systems.

The remainder of the chapter is organized as follows. In the next section, we present a brief overview of the unique features of water resource and use systems and implications for institutional design. This is followed by a description of the methods we used to select the relevant literature. In Section 3.4, we present the main results of the review. Section 3.5 discusses the results before we conclude in Section 3.6.

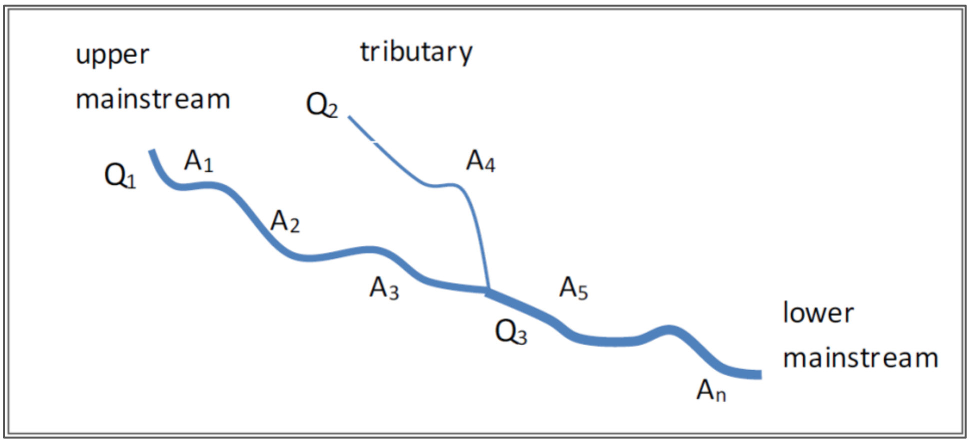
3.2 **Spatio-temporal dynamics of hydrological conditions, users interaction and implication for institutional design**

In this section, we layout hydrological conditions and water use systems to define some analytical framework to guide the assessment of models suggested in studies we reviewed in this paper. The peculiar characteristics of water resources pose a special challenge in designing an efficient institution for water allocation and regulation (Livingston, 1995; Meinzen-Dick, 2007). Water resources have a number of unique features such as mobility and supply uncertainty that distinguish it from most other resources and commodities (Young, 1996 p.35). Like any other natural resource, water supply and demand are characterized by spatial and temporal dynamics (Liu et al., 2007) and pervasive interdependence among heterogeneous users (Young, 1996).

The mobile nature of water combined with often uncertain availability creates unique interrelationships between heterogenous water users. Water flows downstream in river basins, and actions by upstream users generate unidirectional externalities that affect downstream users. In an unregulated setting, an upstream user has a locational advantage to use all or part of the water within his or her boundary and has no incentive to consider externalities such as reduced water availability or quality for downstream users. This would result in a reduced total net benefit and suboptimal outcome, especially if the downstream users are economically more efficient, as described by Hirsch (Hirsch, 1961)in general and Nepal et al. (Nepal et al., 2014) for the Himalayan region. Actions of downstream users, however, are rarely able to influence the behavior of upstream users. This locational disadvantage of downstream users may be compensated to some degree by the hierarchical structure of most basins in which the main river channel is fed by an increasing number of tributaries that collect runoff from the watershed as it flows along, increasing potential water availability for downstream users as compared to users farther upstream.

These locational (dis) advantages of users in a river basin have a significant implication for socio-economic and hydrologic interactions and the design of appropriate institutional arrangements (Izquierdo et al., 2003; Livingston, 1995). Consider a hypothetical river system consisting of a finite number of n users (A_1, A_2, A_3, …A_n) sequentially along the river, as shown in figure 4.1. It has three channels or river sections – the upper mainstream is represented by Q_1 water flow and joined by a smaller tributary represented by Q_2 water flow to form a bigger river channel in the lower mainstream with Q_3 water flow. The subscripts denote the geographical location of the users.

Figure 3.1 Spatial distribution of water resource and users in a river basin system (Q_i and A_i represent water flows and water users along the river, respectively)



Source: Own illustration

In this case, enforcement of water rights without an adequate regulatory system would be problematic. The two upstream agents and A_1 and A_2 may divert more water than their allocated quota as long as the marginal benefit from water use is larger than the punishment for the illegal abstraction if detected (Filho et al., 2008; Zhao et al., 2013). As pointed out by Livingston (1995), the nature of water as a mobile and high-exclusion cost resource could also impede the establishment and functioning of a market for water use rights. For instance, it could be difficult for A_1 and A_3 to reach a water rights trade agreement if the middle agent A_2 is not willing to take part but decides to free-ride such that water sold by may not be fully transferred to A_3. Moreover, consider the trade of water rights between agents, such as A_5, located at a river section with relatively abundant water, and the upstream agents, such as A_4, situated in a river section where flow is small. It would be impossible to transfer water upstream without extra investment in infrastructure, i.e., efficiency gains are only achieved if the benefit of reallocation exceeds against-gravity transfer costs.

In addition to the physical nature, spatial and temporal dynamics due to climatic variability such as precipitation and temperature determine water supply distribution over space and time, especially in arid regions (Peters & Meybeck, 2000; Tagliapietra et al., 2020). This has important impacts on the economic viability of water management institutions: As long as the water is abundant, externalities generated by upstream users may hardly be noticeable. During water shortages, however, users may react, for example, by overexploiting available water, and free-riding may become difficult to manage (Dinar et al., 1997). The often volatile nature of water supply makes the establishment and maintenance of effective institutional arrangements difficult due to high transactions costs (Bardhan, 1993; Kuhn et al., 2016). As Bardhan (1993) points out, when water is extremely scarce, cooperation is challenged by highly profitable cheating, whereas when water is abundant, there is no need to cooperate.

In conclusion, the following key points will guide the assessment of alternative modelling approaches suggested in the studies we reviewed in this paper: For effective evaluation of alternative water policies in a river basin, models should explicitly address externalities due to spatial and temporal heterogeneity and variability in an integrated modelling framework. The models also need to consider the sociopolitical realities, specifically the existence of adequate water institutions and administrative capacities for effective monitoring and enforcement in water governance. Under absent or weak institutions, a model should be able to simulate non-cooperative water use baseline scenarios against which outcomes of alternative policies can be compared.

3.3 Methods

To understand the current state of the art of water policy evaluation models, we carried out a systematic review of relevant studies between 2000 and 2020. In this section, we describe the process we followed to carry out the systematic review, including the selection criteria and search method.

3.3.1 *Search method and selection criteria*

We performed a systematic search of the academic literature to identify relevant studies for our review using Web of Science and Google Scholar to compile post-2000 relevant studies. We used the topic search in Web of Science's core collection database and Advanced Search in Google Scholar. We used search keywords that covered five aspects of the focus of this study—modelling, water use and management, non-cooperative, river basin, and water policy and institutions.

To keep the search broad and minimize the chance of missing any modelling approach in the literature, we used a combination of eight search terms: "agent-based model*", "game-theor* model*", "non-cooperat*", "individual optimization", "multiple optimizations", "bi-level program*", "decentralized approach", "hydro-economic model*". To identify studies that deal with water use and management, water policies, and institutions in a river basin setting, we used another combination of eight search terms: "water use", "water allocation", "irrigation", "river basin", "spatial external*", "watershed"," policy", "institutional arrangements" and "asymmetric access". Each of these search terms were joined with a Boolean "OR", and the two sets of combinations of search terms for modelling and topic were combined using a Boolean "AND". We carried out the initial literature search on 5 July 2019 and updated 12 March 2021, extending the search period to 2020.

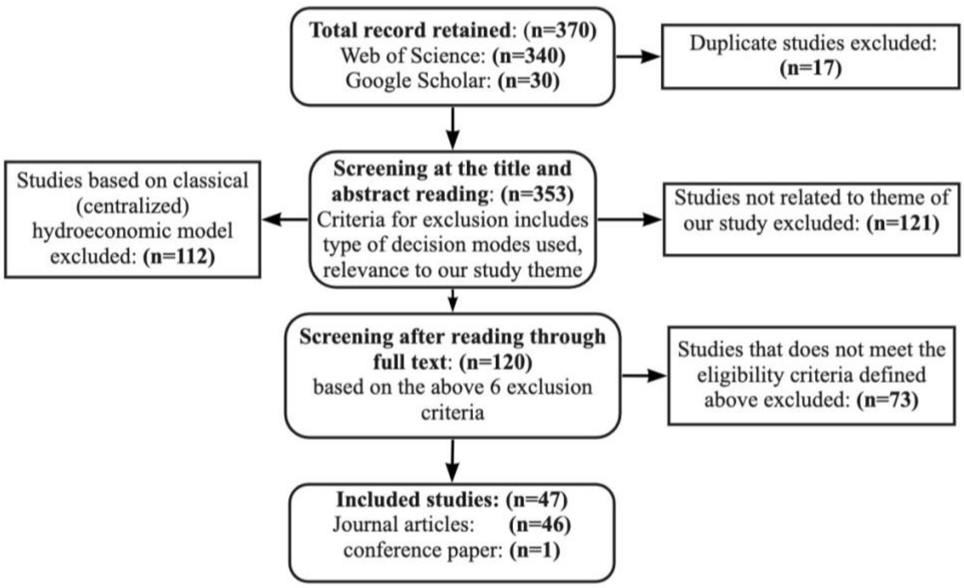
From our search result, we retained studies that met the following eligibility criteria:

1. Study used a decentralized rather than centralized approach to model water users' decision-making behavior.
2. Study was at river basin scale with upstream and downstream set up.
3. Study that dealt with surface water or groundwater use and management or both. Study that deals with groundwater pumping but not connected streamflow at basin scale is excluded.
4. Study that discussed a theoretical model with hypothetical example or an empirical application.

5. Study was relevant to the theme of our study—modelling, water use and management in river basin, non-cooperative behavior, and water policies and institutions.
6. Only one of substantively similar versions of the same study, e.g., only published papers and not their associated working papers were included in the review.

A total of 370 items in the Web of Science and Google scholar matched the search criteria. After we remove duplicates, screening at title and abstract and reading the full text, a total of 47 studies are selected for the review (Figure 3.2).

Figure 3.2 Screening process and number of studies excluded at each stage



Source: own illustration

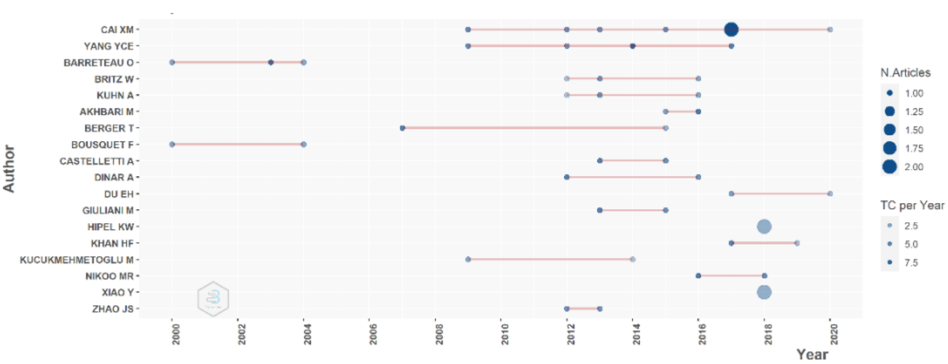
Of the 47 studies, 12 relied on hypothetical data to demonstrate the performance of newly developed or extended modelling frameworks. Most of the studies with empirical data were applied to river basins located in different parts of Asian countries, followed by North America.

3.4 **Results**

3.4.1 *Description of selected studies*

In this section, we present a brief scientometric analysis of the selected 47 studies to understand the research and publication patterns on the topic of this study. Annual scientific production on the modelling of non-cooperative water use steadily increased from 2010 to 2018. About 66% of the selected studies were published during this period. However, there was a declining trend over the recent years. This may not necessarily imply a decreasing interest in the field. To better understand this, we looked at scientific production by top authors in the field. Figure 3.3 shows that, as much as new authors are joining, the leading authors active in the field for a longer period continued producing scientific publications with up to two articles per year and these publications also received big total citation numbers per year. This demonstrates that the field of modelling non-cooperative water use is still an active research agenda.

Figure 3.3 Scientific production by top author per year. The *y*-axis represents the list of authors; the *x*-axis represents number of articles per author per year (N. Articles) and total citation per article per year (TC per Year).



Source: own illustration of reviewed studies using bibiliometrix (Aria & Cuccurullo, 2017)

3.4.2 *An overview of decision models used in the studies*

The results showed most of the studies used Agent-Based Models (ABMs), 23 studies, to characterize a water user's decision process. This was followed by decentralized Hydro-economic Models (HEMs) and Game-theoretic Models (GTMs), 12 studies each. We will present a detailed description of the model types in this section.

As mentioned above, we classified the decision models used in the studies into ABMs, HEMs, and GTMs based on how they characterize the decision behavior of water users interacting with each other and the physically connected hydrological systems. However, classifying them into these three categories was not straightforward. Authors may denominate their model as 'game-theoretic,' which can also fit well into the ABMs' category or vice versa. For example, Filho et al. (Filho et al., 2008) claimed they modeled users' behavior with a game-theoretic approach. Nevertheless, their analytical model simulates the role of price and enforcement in water allocation where water users' interaction, decision behavior, and possible system-level emergences were characterized following an ABM framework. Zhao et al. (2019) cited this work as an example of an early application of an ABM model in water economics. We encountered similar issues when trying to classify models as HEMs or GTMs. It may not be surprising to observe similar features among these models since game theory lends an overarching theoretical framework for both HEMs and ABMs. Nevertheless, we classified the reviewed publications into the three categories based on certain distinct features, for example, how an agent's decision rules were defined and system equilibrium emerged, in addition to what was claimed of the model type in the study.

Agents in the reviewed studies were usually not real or stylized individuals, but rather 'representative agents' that signified locally or regionally aggregated groups of water users. They were represented by different economic, social, and ecosystem agents interacting with one another and the hydrological environment to achieve certain defined goals. In HEM- and GTM-based studies, individual water users were typically aggregated to representative agents at sub-basin or regional (Bauman et al., 2015; Dozier et al., 2017; Han et al., 2018; Kahil et al., 2016; Kuhn et al., 2016; Mahjouri & Ardestani, 2011; Pande et al., 2011; Safari et al., 2014; Sedghamiz et al., 2018; Tu et al., 2015) or national(Bhaduri & Barbier, 2008; Digna et al., 2018; Kucukmehmetoglu, 2009; Teasley & McKinney, 2011) levels within a river basin. Jeuland et al. (2014) used hydropower facilities in the Nam Ngum Basin as individual agents deciding the timing and quantity of water releases for hydroelectric generation and agricultural production. Britz et al. (2013) used hypothetical firms as respective agents that make water and factor use decisions to maximize individual profit. Hypothetical riparian countries sharing river water were also represented as single agents in game-theoretic models (Ambec & Ehlers, 2008; Ambec & Sprumont, 2002; Ansink & Ruijs, 2008; Ng et al., 2013). Hydro-economic and Game-theoretic models tend to work with fewer agents on the aggregated level, whereas this is less uniform in ABMs.

Studies based on Hydro-economic Models (HEM)

Table 3.1 summarizes selected studies that used HEM simulation. The HEMs are decentralized partial equilibrium models that integrate economic, hydrologic, biophysical, and policy and institutional aspects of water resources management. They are driven by a decentralized optimization framework based on an individual decision-making process to realistically represent water users' behavior at the micro-level. Under non-cooperative water use, HEM characterizes individual water users as independent decision-maker that uses the water available at one's location to maximize their utility. In doing so upstream, users ignore the externalities generated to downstream users. In this approach, the water that outflow, after satisfying upstream user's demand, is used as exogenous input to solve the downstream agent's water use problem.

In HEM, the agent's decision mechanism are represented by constrained optimization, which is solved simultaneously or sequentially using a conventional calculus-based optimization algorithm or Genetic Algorithm (Table 3.1). A Genetic Algorithm is an evolutionary optimization approach used to solve complex non-linear models not well suited for standard optimization algorithms (Goldberg, 1989). Eight out of the 12 HEMs were coded in General Algebraic Modelling System (GAMS), while 1 used MATLAB, and no information was provided for the remaining two. The tractability and computational efficiency of the model used were not commonly reported in the reviewed studies.

Table 3.1 Summary of studies based on hydro-economic models (HEMs).

Document	Water resources and their location	Purpose of the study (broadly defined)	Decision-making mechanism	Solution algorithm	Modelling tools and computational efficiency
Bauman et al. (2015)[1]	South Platte River Basin in Colorado, USA.	Explore welfare impact of imperfectly competitive conditions for water market with transaction cost	Constrained Optimizatio n	Simultaneo us	Coded in GAMS and solved using MOPEC approach
Britz et al. (2013)	Hypothetical	Demonstrate alternative decentralized modelling approach of water allocation problems using MOPEC framework	Constrained optimizatio n	Simultaneo us	Used EMP in GAMS to automatically generate MOPEC and solved using the path solver.
Digna et al. (2018)	Eastern Nile Basin	Simulate the benefits of cooperative and non-cooperative management of hydraulic infrastructures	Bi-objective constrained optimizatio n	Sequential	Coded in MATLAB and solved using a Genetic algorithm (GA).
Dinar and Nigatu (2013)	Eastern Nile Basin	Conduct a comparative analysis of water allocation under social planner and different coalitional arrangements with water trade and soil erosion externality.	Constrained optimizatio n	Sequential	Coded in GAMS and solved using NLP solver
Dozier et al. (2017)	South Platte River Basin, Colorado, USA	Analyze the impacts of alternative institutional and policy scenarios for water rights administration and urban conservations	Constrained optimizatio n	Simultaneo us	Used GAMS to solve the MOPEC problem and Python to run the entire workflow

[1] This is a conference proceeding

Jeuland et al. (2014)	Nam Ngum sub-catchment in Mekong Basin	Compare benefit from full cooperation with non-coordinated infrastructural development	Constrained optimization	Sequential	The nonlinear model was coded in GAMS
Kuhn and Britz (2012)	Hypothetical	Develop a decentralized water allocation approach using mixed complementarity programming (MCP)	Constrained optimization	Simultaneous	NLP was converted into MCP using manually tied FOC equations and decision variables in GAMS.
Kuhn et al. (2016)	Lake Naivasha basin, Kenya	Simulate economic viability of water institutions under climate variability	Constrained optimization	Simultaneous	Used GAMS to solve the MOPEC problem
Mahjouri and Ardestan (2011)	Irrigation schemes in Khuzestan Province, Southern Iran	Compare benefit of cooperative and non-cooperative water allocation	Constrained optimization	Sequential	No information
Pande et al. (2011)	River Basin in Gujarat and Rajasthan, India	Simulate decentralized water allocation dealing with the externalities from upstream-downstream linkages	Constrained Optimization	Sequential	Coded in GAMS and solved with MINOS5 DNLP solver
Teasley and McKinney (2011)	Syr Darya Basin, Central Asia (CA)	Apply HEM and game theory concepts to analyze various cooperation and benefit-sharing arrangements	Constrained Optimization	Sequential	The nonlinear model was coded in GAMS
Tu et al. (2015)	Irrigation district of Gan-Fu plain in Jiangxi Province, central China	Administrative and market-based optimization method to solve the regional water allocation problems	Bi-level constrained optimization	Simultaneous	The model was solved using a GA, but no information about modelling tools

Six of the 12 HEM-based studies used the model to analyze large-scale water allocation problems at the river basin scale (Bauman et al., 2015; Dozier et al., 2017; Kuhn et al., 2016a; Mahjouri and Ardestani, 2011; Pande et al., 2011; Tu et al., 2015), focusing on the policy and institutional aspects of water allocation problems. Moreover, three studies used HEM to analyze the benefits of cooperative water use in transboundary rivers shared by two or more riparian countries and compared the outcome to non-cooperative use (Digna et al., 2018; Jeuland et al., 2014; Teasley and McKinney, 2011). The non-cooperative scenario was also used for the benefit sharing and stability analysis. Two studies, Britz et al. (2013) and Kuhn and Britz (2012) used a conceptual model with hypothetical examples to demonstrate how HEM can be used to simulate water allocation problems based on decentralized decision-making under non-cooperative water use. Kuhn and Britz (2012) specifically designed a decentralized modelling framework to address the limitation of HERBM based on the centralized approach. The model was further developed by Britz et al. (2013) using Multiple Optimization Problem with Equilibrium Constraints (MOPEC) framework (Ferris, 2013) in mathematical programming. The MOPEC framework allowed simultaneous solutions to the problem by defining equilibrium constraints.

Apart from individual optimization, HEMs based on a bi-level programming approach were also used in some of the studies. Bi-level programming allows the maximization of system-wide social welfare while considering individual-level decision-making in resource allocation. In this case, individual water users react to a chosen policy instrument through their decision on water use. Tu et al. (2015) used this approach to model joint administrative and market-based regional water allocation problems. The regional authority is top decision-maker at the administrative level, and sub-regions are the decision-makers of the market level. However, this modelling approach makes an institutional assumption that the central agency provided full or partial coordination and enforcement of water allocation policies.

Studies based on Agent-Based Models (ABM)

Agent-Based Models emerged as promising decision support tools in the area of environmental and natural resource management (Page et al., 2013). In the field of water resource management, early ABMs have been used to simulate the management of irrigated ecosystems, evaluate scenarios based on policy options and represent the interaction between stakeholders by formalizing their views as decision-makers (Barreteau et al., 2004, 2003; Barreteau and Bousquet, 2000; Becu et al., 2003; Berger et al., 2007).

The 23 ABM-based studies used different nomenclature such as "agent-based modelling" and "multi-agent simulation systems" to identify their model. Here we refer to all as agent-based models (ABMs) to avoid confusion. The studies dealt with different issues of water management and allocation problems using ABMs either as a methodological framework to demonstrate its suitability or empirical application to a specific problem. Of the 23 ABM-based publications, seven did not explicitly model externalities and agents' spatial interaction in non-cooperative water use. For example, Barreteau and Bousquet (2000) developed an ABM model called SHADOC to study the effect of social networks on the viability of irrigation systems and applied it to the Senegal River Valley irrigation system (Barreteau et al., 2004). Their heuristic-based model was limited to a single irrigation scheme focusing on the role that collective action plays in the evolution of irrigation systems. Even though the authors recognized asymmetric access of users to water due to their geographic location, they did not explicitly modeled this. Berger et al. (2007) introduced a mathematical programming-based ABM called MP-MAS and demonstrated its suitability to simulate policy options in complex water use systems in the Maule River Basin in Central Chile. Their model was used to study the economic importance of irrigation water reuse in the watershed of Loncomilla River in Central Chile (Arnold et al., 2015). Similarly, their primary focus was not spatial interaction between water users and the resulting externalities under non-cooperative water use. Other ABMs were used as decision support tools for managing conflicts in water use (Akhbari and Grigg, 2013) or to understand the role of individual groundwater users in coupled human-natural systems (Farhadi et al., 2016; Noel and Cai, 2017) with less emphasis on the spatial interaction between water users in a river basin. Table 3.3 summarizes shortlisted ABM-based studies that explicitly modeled water user's interaction in upstream and downstream set up under non-cooperative water use. We will focus on these models in our discussion.

Table 3.2 Summary of studies based on Agent-Based models (ABMs)

Document	Water resources and their location	Purpose of the study (broadly defined)	Decision-making mechanism	Remarks on modelling tools, computational efficiency, and assumptions
Becu et al., (2003)	Mae Uam small catchment, Northern Thailand	Simulate the impact of upstream water management on the downstream farming viability under different irrigation management options.	Constrained optimization: combined with heuristics solved sequentially	Developed with CORMAS platform under VISUALWORKS environment using object-oriented programming language called SmallTalk.
Du et al., (2020)	Heihe River Basin, China	simulate the impact of water policies on farmers conjunctive water use and on hydrological processes under spatial heterogeneity and temporal dynamics	Heuristic optimization	No information is provided about the modelling tools used and computational efficiency. Yet, as their model integrates different models, more than one modelling tools might have been used
Ding et al. (2016)	Nile River Basin	Simulation of fair distribution of benefits from efficient water allocation with an empirical example from Nile Basin	Constrained optimization solved simultaneously.	Coded in MATLAB and solved using GA.
Giuliani et al. (2015a)	Theoretical	A modelling framework for regulatory design in water management	Distributed constrained optimization solved sequentially	The authors indicated computational efficiency could reduce as the model becomes larger
Giuliani and Castelletti (2013)	Zambezi River Basin	Assess the value of cooperation and information exchange using MAS framework	Constrained dynamic optimization solved sequentially	The model predictive control (a variant of stochastic dynamic programming) was coded in C++

Document	Water resources and their location	Purpose of the study (broadly defined)	Decision-making mechanism	Remarks on modelling tools, computational efficiency, and assumptions
Khan et al., (2017)	Niger and Mekong River Basins	Simulate the impacts of water management decisions that affect food-water- energy-environment (FWEE) nexus at a river basin	Heuristic optimization: Agents interact through a willingness to cooperate by changing their water management actions.	Coded in R, the socio-economic decision mechanism is highly simplified.
Khan and Brown (2019)	Frenchman River Basin, USA	Simulate the impact of water permit and climatic variability on the performance of groundwater market	Constrained optimization	Coded in R and solved using Active set solver
Mulligan et al. (2014)	Republican River Basin, USA	Assess groundwater policy with coupled economic-hydrologic model	Constrained optimization: unregulated water use problem is sequentially solved	ABM is coded in MATLAB and solved with Active set
Schlüter and Pahl-Wostl(2007)	Amu Drya River Basin Delta, Central Asia	Application of ABM to study system characteristics and mechanism of resilience in complex water management	Heuristic optimization:	No information is provided about the modelling tools and model efficiency.
Xiao et al. (2018a)	South Saskatchewan river basin, Alberta, Canada.	Simulate impact of water demand management using	Constrained optimization:	Coded in GAMS and solved using MINOS. Unlike Britz et al. (2013) agents interact indirectly through the central processor, no direct interaction between agents.

Document	Water resources and their location	Purpose of the study (broadly defined)	Decision-making mechanism	Remarks on modelling tools, computational efficiency, and assumptions
Xiao et al. (2018b)	South Saskatchewan River basin, Alberta, Canada	Compare centralized and decentralized approaches to water demand management	Constrained optimization:	Same as Xiao et al. 2018a
Yang et al. (2009a)	Theoretical	Developed a decentralized optimization approach for Multi-agent-based watershed management	Distributed constrained optimization solved simultaneously	Coded in MATALB and solved using a solution algorithm for the distributed constraint optimization problem.
Yang et al. (2012)	Yellow River Basin, China	A decentralized approach for water allocation management (empirical application of Yang et al., 2009)	Distributed constrained optimization: sequentially solved for unregulated water use	Same as Yang et al. (2009a).
Zhao et al. (2013)	Theoretical	Developed ABM and conducted a comparative analysis of administrative and market-based water allocation	Constrained optimization solved simultaneously	It is only an analytical solution without numerical simulation.
Izquierdo et al. (2003)	Theoretical	Extended an already existing land use ABM model to FEARLUS-W that deals with water allocation and pollution control problems	Heuristic optimization	Analytical model with no numerical example

Studies based on Game-theoretic Models (GTM)

Game-Theoretic Model has been applied extensively to common-pool resource management problems, including water, following Ostrom's (1990) seminal work. The model is based on the game-theoretic principle that multiple economic and social agents frequently interact in a strategic and competitive setting. As discussed above, the spatial location can affect this strategic interaction between water users in a river basin. In the game-theoretic approach the assumption of perfect cooperation among the decision-makers is relaxed, and each decision-maker acts to optimize one's objective, knowing that other players' decisions affect one's payoffs (Madani, 2010). However, the game-theoretic approach is often used to simulate water allocation problems that involve only a few players (actors), and cooperative game theory applications are more common than non-cooperative ones (Madani, 2010). Moreover, it is difficult to interpret the restrictive upstream-downstream setup where actions of the downstream users have little influence on the outcome of upstream users as a game.

Table 3.3 summarizes studies that used GTMs to simulate non-cooperative water use problems. Whether they are theoretical or empirical applications, studies based on GTM focused mainly on efficient allocation through different coalitional agreements among water users and fair distribution of additional benefits from the cooperation (Ambec and Ehlers, 2008; Ambec and Sprumont, 2002; Ansink and Ruijs, 2008; Kahil et al., 2016; Kucukmehmetoglu, 2009).

The simulation often follows two steps. First, the constrained optimization problem is solved using conventional mathematical programming or a Genetic Algorithm to simulate optimal water allocation by maximizing the aggregate utility of different parties in coalitional arrangements. Then, game theory concepts are applied to calculate the fair allocation of the additional benefit to the parties in agreement. Finally, benefit from different coalitional agreements compared with the non-cooperative outcome where each user sequentially and unilaterally maximizes one's economic benefit given the water release decisions from upstream users, following a similar approach with HEM.

Table 3.3 Summary of studies based on Game-theoretic models (GTMs)

Document	Water resources and their location	Purpose of the study (broadly defined)	Decision-making mechanism	Remarks on modelling tools, computational efficiency, and special assumptions
Ambec and Ehlers (2008)	Theoretical	Fair river sharing problem	Constrained optimization	A theoretical model with analytical solutions, agents, maximize satiable water benefit function
Ambec and Sprumont (2002)	Theoretical	Fair river sharing problem	Constrained optimization	A theoretical model with analytical solutions, agents, maximize non-satiable water benefit function
Ansink and Ruijs (2008)	Hypothetical River	Climate change and stability of water-sharing agreements	Constrained optimization solved sequentially	Analytical solutions and hypothetical numerical simulations with increasing and concave objective functions
Bhaduri and Barbier(2008)	Ganges River Basin	Water transfer in international river basin context	Constrained optimization	Analytical solutions
Han et al. (2018)	Hanjiang River Basin	Optimal water allocation and benefit-sharing	Bi-level constrained optimization solved sequentially	Highly simplified regarding the biophysical aspect with five water users
Kahil et al. (2016)	Jucar River Basin, Spain	Optimal water allocation and benefit-sharing	Constrained optimization solved sequentially	Coded in GAMS. Non-cooperation is equivalent to fixed water right
Kucukmehmet oglu (2009)	Euphrates and Tigris	Impact of infrastructural development on water allocation and benefit-sharing	Constrained optimization solved sequentially	Linear programming model coded in GAMS
Kucukmehmet oglu and Geymen(2014)	Euphrates and Tigris	Simulate the impact of price variability for energy, water and transport on inter-basin water allocation	Constrained optimization solved sequentially	Mixed integer programming coded in GAMS

Document	Water resources and their location	Purpose of the study (broadly defined)	Decision-making mechanism	Remarks on modelling tools, computational efficiency, and special assumptions
Madani and Dinar (2012)	Hypothetical groundwater aquifer	Proposed non-cooperative management of Common Pool Resources (CPR)	Constrained optimization solved sequentially	Numerical simulations using three hypothetical aquifers. Cooperative and non-cooperative water use is represented by whether the agent internalize externalities or not
Ng et al. (2013)	Hypothetical River Basin	Joint effect of physical and social mechanism on cooperation in water sharing	Constrained optimization solved simultaneously	Analytical and numerical simulation in MATLAB. They argue the action of downstream users could affect the outcome of upstream users
Safari et al. (2014)	Zarrinehrud River basin, Iran	Leader-follower game-theoretic for water allocation problem	Bi-level constrained optimization solved simultaneously	Assumed followers have equal bargaining power which violates the asymmetric access to water. Also assumes established a functioning market for water
Sedghamiz et al.(2018)	Irrigation scheme in Golestan province in Iran	Leader-follower game-theoretic for water allocation problem	Bi-level constrained optimization solved simultaneously using non-dominant sorting genetic algorithm	Recognizes unequal bargaining power but the source of power heterogeneity is not spatial asymmetry, population size

Bi-level programming is also used in GTMs. In that case, the strategic interaction is not only between the user agents but also between the user and enforcing agents at the top level. A leader-follower game often consists of one leader, the government agency, and multiple followers representing different water use agents (Han et al., 2018; Safari et al., 2014; Sedghamiz et al., 2018). The only difference between bi-level approach in HEM and GTM is that the former allows representation of a relatively large number of follower agents

3.5 Discussion

In this section, we present and discuss how these models simulate non-cooperative water use focusing on the decision rules and solution algorithms employed and implications for water policy assessment and sustainable water management. Then, we analyze the models' ability to retain the ability of classical HERBMs to represent complex hydrological and socioeconomic processes without greatly compromising on computational efficiency. We do so by exploring the representation of the biophysical and economic processes in the model, their linkages, the heterogeneity of agents, and their mutual interactions. We will also analyze if the stochastic nature of water supply can be captured in the model realistically. Finally, we discuss the implications for informing water policies and the design of sustainable water resources management. The discussion will follow the model-type sequence from above but will make comparisons between modelling approaches when necessary.

3.5.1 *Decision rules and solution algorithms*

Individual-based modelling allows representation of the decision-making behavior of multiple agents(Ferris & Wets, 2013; Yang et al., 2012). In our context, the decision-makers include regulatory agencies or markets and agents demanding water for off-stream (agriculture, municipal, and industry) or in-stream use (hydropower and ecosystem services) (Akhbari &

Grigg, 2013). These heterogenous users act and interact based on different water-related value systems and objectives (Schlueter & Pahl-Wostl, 2007).

In HEMs, agents' decisions are simulated by individual optimization, formulated as mathematical programs (e.g., NLP, MCP, MOPEC, etc.), and solved using calculus-based conventional optimization or genetic algorithms (Table 3.1). The problems are formulated as maximization (or minimization) of single or multiple objective functions subject to biophysical and institutional constraints. The problem is solved either simultaneously or sequentially. When the sequential solution approach is used for non-cooperative water use, each user's problem is solved independently and sequentially starting with the uppermost user (Ambec & Ehlers, 2008; Jeuland et al., 2014; Kucukmehmetoglu, 2009). Then, water outflow from the optimal state of the upstream user represents a regulated inflow used by the program to optimize the downstream user's individual objective function. By contrast, a simultaneous solution, as proposed, e.g., by Kuhn and Britz (2012) and Britz et al. (2013), allows independent optimization problems across all individuals to be solved in a single step and, thereby, the solution for market equilibria of relevant factors and products other than water. This approach is equivalent to solving Nash Equilibria of non-cooperative games and is implemented using the mathematical programming format MOPEC (Multiple Optimization Problem with Equilibrium Constraints). MOPEC offers considerable flexibility compared to other decentralized hydro-economic models by allowing the definition of multiple objective functions per individual agent that can be solved simultaneously. The MOPEC approach was employed empirically to simulate water allocation problems in the Platte River Basin in Colorado focusing on water rights markets and transaction costs(Bauman et al., 2015; Dozier et al., 2017), but a non-cooperative water allocation scenario was not simulated. Kuhn et al. (2016) applied MOPEC to simulate the viability of water institutions including unregulated (non-cooperative) water use for the Lake Naivasha Basin in Kenya.

In ABMs, the decisions of agents are guided by optimization or heuristics (prior defined rules) (Schreinemachers and Berger, 2006). Our review showed that the use of optimization-based ABMs in water resource management is on the rise. Of the 16 ABMs based studies that simulated non-cooperative water use, ten are based on optimizing agents (Ding et al., 2016; Giuliani et al., 2015a; Giuliani and Castelletti, 2013b; Khan and Brown, 2019; Mulligan et al., 2014; Xiao et al., 2018b, 2018a; Yang et al., 2012, 2009b; Zhao et al., 2013). Three ABM studies, Schlueter and Pahl-Wostl (2007), Khan et al., (2017) and Du et al., (Du et al. (2020), used heuristics, while Becu et al. (2003) combined optimization with heuristics for decisions on rice planting and off-farm labor participation. The optimization approaches are theoretically strong but accused of seeing the human decision-makers as rational optimizers with perfect foresight based on classical microeconomic theory. Even though the heuristic approach, in general, is intuitive and based on simple decision rules, identifying the most important decisions, their correct sequence and appropriate conditions might not be easy.

In ABM-based studies, both uncoordinated (non-cooperative) and partially coordinated scenarios are simulated. The coordinated optimization problem assumes the presence of third party to coordinate the agents' distributed decision based on administrative rules (Giuliani et al., 2015b), market mechanism(Han et al., 2018; Xiao et al., 2018b) or the combination of both (Yang et al., 2012; Zhao et al., 2013). This modelling framework is based on the concept of rational crime where agents can violate imposed constraints (normative policy) as long as the potential benefit of the violation exceeds the penality (Cooter and Ulen, 2000; Filho et al., 2008). Although both sequential (Giuliani et al., 2015a; Giuliani and Castelletti, 2013b; Mulligan et al., 2014) and simultaneous (Xiao et al., 2018a, 2018b; Yang et al., 2009a; Zhao et al., 2013) solution algorithms were used to solve the coordinated optimization problems, all the ABMs represent the non-cooperative scenarios as a sequence of optimization problems where each agent is considering only one's local objective function from the upstream to downstream. The total inflow to the agents' subsystem is modeled as deterministic (Giuliani et al., 2015a; Xiao et al., 2018b, 2018a; Yang et al., 2012) and stochastic (Giuliani and Castelletti, 2013b) input. In Ding et al.

(2016) two problems were solved simultaneously for each agent using a parallel search algorithm. The first problem described a coalitional group of water users in the basin maximizing their aggregate benefit. The second problem represented an agent that left the group and maximized one's own benefit in singleton and competed for water with the coalitional group. The model was applied to solve the water sharing problem of countries in the Nile River Basin and to simulate fair revenue distribution from an efficient central planner (CP) solution after identifying the contribution of each nation to the CP solution.

Varying solution algorithms were employed to solve the ABMs optimization problems based on the nature and scale of the problem. These include the conventional calculus-based optimization algorithms in mathematical programming (Becu et al., 2003; Mulligan et al., 2014; Xiao et al., 2018b, 2018a; Yang et al., 2012, 2009a; Zhao et al., 2013), model predictive control (MPC)(Giuliani and Castelletti, 2013b), Adopt (Asynchronous Distributed OPTimization) algorithm (Giuliani et al., 2015a) and genetic algorithm (Ding et al., 2016).

In GTMs, the scenarios were formulated as an optimization problem. Of the 11 GTMs, only three were solved simultaneously (Ng et al., 2013; Safari et al., 2014; Sedghamiz et al., 2018); the rest used a sequential solution approach. Ng et al. (2013) used an evolutionary-based game-theoretic approach to show how physical mechanisms (asymmetric payoffs) and social mechanisms (reciprocity) jointly affect water-sharing cooperation in a river system. Heterogeneous water users located sequentially along the river system simultaneously play an iterative N-person Prisoner's Dilemma Game (PDG), which enabled the direct reciprocity mechanism under which peer punishment could be enforced in future encounters between any two actors. They assumed that downstream users' behaviors could affect the upstream user to consider the interaction between actors located serially along the river as a game. As discussed in the introduction, this may not hold. Safari et al. (2014) and Sedghamiz et al. (2018) used a bi-level programming model, assuming that a water resource manager as a leader in a game sets the water price, and multiple water users as followers compete among themselves by maximizing a Nash bargaining solution. A simultaneous solution approach was used to solve the model.

In conclusion, the reviewed studies used both sequential and simultaneous solution approaches for solving non-cooperative water use problems in a river basin. The ABM-based studies try to overcome the limitations of the fully centralized decision-making approach by creating agents that made a completely independent economic decision that was solved sequentially, both in time and space. Water users' problems were sequentially and independently evaluated using either heuristic or optimizing agents at the cost of dropping the simultaneous solution approach. However, as Schreinemakers and Berger (2006) pointed out, an isolated evaluation of economic decisions by agents may not completely capture the economic trade-offs of alternative allocations of scarce resources. Water users may exchange commodities or factors of production other than water that could also affect water allocation decisions. Trade in energy and agricultural products between countries in the Syr and Amu Darya Basins of Central Asia (Teasley & McKinney, 2011) could be cited as an example. In general, countries and regions can interact in product and factor markets other than water according to their comparative advantage, which needs to be jointly evaluated in a simultaneous setting. The simultaneous solution approach proposed by Kuhn and Britz (2012) and Britz et al.(2013) allows the joint evaluation of problems involving numerous water users that are solved across all individuals in one step.

3.5.2 *Agents' behaviors, interactions, uncertainties and spatio-temporal dynamics*

In studies based on ABMs, agents represent water users and administrative controllers or market coordinators. The water user agents include farmer agents—representing individual farm units (Becu et al., 2003; Schlueter & Pahl-Wostl, 2007), spatial grids(Berger et al., 2007; Ding et al., 2016; Izquierdo et al., 2003), or aggregate pumping wells (Khan & Brown, 2019; Mulligan et al., 2014); sectoral water users such as agriculture, domestic, industrial, and ecosystem(Giuliani et al., 2015; Giuliani & Castelletti, 2013;

Xiao et al., 2018a, 2018b; Yang et al., 2012, 2009); politically or hydrologically similar sub-regions consisting of the agricultural sector, hydropower plants, and ecosystem (Khan et al., 2017); or riparian countries (Ding et al., 2016). Ecosystem agents are represented by fish habitats, preserved areas, wetlands, or river delta (Giuliani & Castelletti, 2013; Khan et al., 2017; Yang et al., 2012). The ecosystem agents are defined as passive agents who do not make decisions but react to decisions made by active agents. Accordingly, the water demand for ecosystem agents is typically implemented as a minimum flow requirement.

The relative spatial location of the water users in the river basin is a primary source of heterogeneity, as already discussed above. Moreover, the intensity of water-related economic activities, which determine water demand, such as cropping patterns or hydropower generation, and population and local climatic conditions, are other sources of heterogeneity among decision-makers. In addition to this, heterogeneity among water users emerges from their priorities and objectives regarding water use. For example, Dozier et al. (2017), in their decentralized HEMs, represented the objective of municipalities as cost minimization and of agricultural producers as profit maximization.

Representing economic and biophysical processes at appropriate levels of detail and their integration in a coherent manner is essential to understand the spatio-temporal characteristics of human–hydrological interactions. The classical HERBMs made significant progress in this direction where hydrologic, agronomic, engineering, and economic processes are tightly coupled using the node-link network framework (2009). Yet, rainfall-runoff processes are mostly not explicitly modeled, and water supply is exogenously derived from historical streamflow data. Our results showed that most of the reviewed studies focused on developing a decentralized modelling framework with a simplified representation of the biophysical and economic processes. Of the 26 studies with empirical applications, only 11 (five HEMs, one GTM, and five ABMs) explicitly represented the hydrological and economic processes in relatively rich detail. Overall, the

ABM-based studies focus more on the biophysical processes where physically-based distributed hydrological models are linked to simplified economic components. The agents in ABM studies are often defined as rule-based agents, meaning that water-related economic decisions draw on predefined heuristics (Du et al., 2020; Khan et al., 2017). This is mainly due to model tractability and computation time, especially with large agents represented in the model.

Only a few studies accounted for inter-temporal dynamics and uncertainties in the water supply. Kuhn et al. (2016) conducted a stochastic simulation to account for variability in water supply based on randomly drawn rainfall from monthly average time series data. Giuliani and Castelletti (2013), in their ABM model for Zambezi Basin, modeled the temporal dynamics by stochastic inflow to the reservoir, which is updated as each time step based on predicted value. In Becu et al. (2003) and Schlüter and Pahl-Wostl (2007), farmers' expectation of water supply was continuously updated according to past experience, which also varied with farmers' recollections of the past (Schlueter & Pahl-Wostl, 2007). Farmers' crop choice and yield was updated accordingly. Khan and Brown (2019) analyzed the impact of water supply uncertainty based on the range of variability for climatic input. Accordingly, crop irrigation requirements were varied in each growing season.

The reviewed studies modeled interactions between heterogeneous water users and between water users and the hydrological systems differently depending on the type of models they used, seemingly as a result of a trade-off between representing biophysical and behavioral detail. In HEMs and GTMs, in the absence of water institutions (administrative or market), the interaction between water users is implemented using inter-spatial water balances. The water balance representing the hydrological process is often simplified by relying on exogenous hydrological and weather inputs. Thus, the economic and hydrological models are typically integrated loosely, exchanging input and output data externally. As indicated above, the interaction between water users, in this case, was only unidirectional, where water outflow from the optimal state of the upstream user was used as a regulated inflow to optimize the downstream user's problem. In ABMs, especially those basing behavior on heuristics, spatially explicit and fully calibrated hydrological simulation models are coupled with the ABM model to endogenously simulate the stock and flow of environmental variables linked to the ABM models. However, this is achieved at the cost of simplifying the socio-economic decision process due to computational efficiency.

In summary, even if a number of interesting modelling frameworks have been put forward to overcome the deficiencies of existing tools in dealing with non-cooperative water use problems, there are still limitations that need to be addressed. First, the sequential solution approach mostly used in ABM models may not be appropriate as it fails to capture the full economic trade-offs of alternative allocation of scarce resources. Second, due to computational efficiency and tractability, the biophysical and economic processes are overly simplified and less realistic to capture many real-world problems. Third, only a few studies accounted for inter-temporal dynamics and uncertainties in dealing with decentralized water allocation problems.

3.5.3 *Insights for sustainable water management*

The demand for fresh water is projected to increase as the population and economy expand (Boretti and Rosa, 2019). As demand rises, developing management institutions that ensure the sustainable use of water resources is essential. In addition to designing water institutions, clear regulation and enforcement mechanisms are equally important to achieve the required outcome.

An evaluation of alternative water policies and institutions needs to consider the expected levels of enforcement of and compliance to water use rules. In the studies we reviewed, explicit modelling of weak enforcement or lack of compliance to any proposed water policies (water use rights, maximum exploitation limits, taxes, and penalties) was less emphasized. There were a few exceptions, though. Based on the theory of rational violation, Filho et al. (2008) developed an analytical ABM model to simulate strategic interaction between user agents and enforcing agents considering social and climatic risk. Their model accounted for regulatory effectiveness using the probability of detecting transgressors conditional on the institution's capacity, proxied by budget allocated to it.

In CPR management settings where all actors hold the same strategic position, such as small-scale irrigation from the same groundwater body, water users may base their water use decision on group rationality and cooperation (Madani, 2010) to minimize externalities and, thus, ultimately contribute to its sustainability. In this situation, reciprocity mechanisms or punishment could be enforced to discourage the deviation of an individual user from the cooperative agreement. Even under non-cooperative water use, individual water users, based on learning from experience, may develop a heuristic CPR management plan considering future outcomes and externalities (Madani & Dinar, 2012; Ostrom, 1990).

However, in the context of a river basin or large-scale irrigation system, the mobile nature of water results in a fixed order of priority in which water users act. As indicated above, in this situation, upstream users act before the downstream counterparts and very often, the action of downstream users has no influence on the outcomes for upstream users, resulting in unidirectional externalities. Consequently, such a water resource resembles a sequential chain of private goods (Izquierdo et al., 2003) instead of a CPR because a system of mutual restraint cannot emerge. Under such conditions, a lack of institutional structures that enforce sustainable water use and management leads to the growing problem of a variety of the free rider’s problem, in which some members exploit the resource with no restriction while investing little or none for the management of the resource (Panchanathan & Boyd, 2004; Shinada & Yamagishi, 2007). Therefore, regulation and enforcement of water rules and policies in such a context becomes increasingly challenging, which needs to be adequately considered in evaluating alternative water policies to provide reliable evidence for policymakers.

3.6 **Conclusion**

In this paper, we reviewed water management models that simulate water allocation problems as a decentralized decision process. The primary focus was on how a non-cooperative water use scenario is realistically simulated in complex water use and management systems.

From our review result, the following important conclusions can be made. First, even though there has been some progress in modelling water allocation problems using decentralized approaches, only a few studies demonstrated the ability to retain the ability of classical HERBMs to represent the economic and biophysical processes in detail without compromising on computational effort. Second, most agent-based and game-theoretic models employ a sequential solution approach where economic decisions are separately evaluated using pre-defined conditions and heuristics. However, independent evaluation of the economic decisions by agents cannot adequately capture trade-offs and synergies in allocation of scarce resources. Third, even though the decentralized modelling approach is pursued to model decisions by individual water users in non-cooperative water use, most studies assumed the presence of a coordinating agency or market in their model. This may not be a realistic assumption for most river basins, which future studies should consider. Finally, more emphasis is needed to capture the inter-temporal dynamics and uncertainties in water supply due to climatic variabilities in modelling alternative water policies for reliable impact evaluation.

3.7 References

Acemoglu, D. (2006). A Simple Model of Inefficient Institutions. The Scandinavian Journal of Economics, 108(4), 515–546. https://doi.org/10.1111/j.1467-9442.2006.00460.x

Akhbari, M., & Grigg, N. S. (2013). A Framework for an Agent-Based Model to Manage Water Resources Conflicts. Water Resources Management, 27(11), 4039–4052. https://doi.org/10.1007/s11269-013-0394-0

Ambec, S., & Ehlers, L. (2008). Sharing a river among satiable agents. Games and Economic Behavior, 64(1), 35–50. https://doi.org/10.1016/j.geb.2007.09.005

Ambec, S., & Sprumont, Y. (2002). Sharing a River. Journal of Economic Theory, 107(2), 453–462. https://doi.org/10.1006/jeth.2001.2949

Ansink, E., & Ruijs, A. (2008). Climate change and the stability of water allocation agreements. Environmental & Resource Economics, 41(2), 249–266. https://doi.org/10.1007/s10640-008-9190-3

Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. Journal of Informetrics, 11(4), 959–975. https://doi.org/10.1016/j.joi.2017.08.007

Arnold, R. T., Troost, C., & Berger, T. (2015). Quantifying the economic importance of irrigation water reuse in a Chilean watershed using an integrated agent-based model. Water Resources Research, 51(1), 648–668. https://doi.org/10.1002/2014WR015382

Barbier, E. B. (2003a). Upstream dams and downstream water allocation: The case of the Hadejia-Jama'are floodplain, northern Nigeria: UPSTREAM DAMS AND DOWNSTREAM LOSSES, NIGERIA. Water Resources Research, 39(11). https://doi.org/10.1029/2003WR002249

Barbier, E. B. (2003b). Upstream dams and downstream water allocation: The case of the Hadejia-Jama'are floodplain, northern Nigeria: UPSTREAM DAMS AND DOWNSTREAM LOSSES, NIGERIA. Water Resources Research, 39(11). https://doi.org/10.1029/2003WR002249

Bardhan, P. (1993). Analytics of the institutions of informal cooperation in rural development. World Development, 21(4), 633–639. https://doi.org/10.1016/0305-750X(93)90115-P

Barreteau, O., & Bousquet, F. (2000). SHADOC: a multi-agent model to tackle viability of irrigated systems. 24.

Barreteau, O., Bousquet, F., Millier, C., & Weber, J. (2004). Suitability of Multi-Agent Simulations to study irrigated system viability: Application to case studies in the Senegal River Valley. Agricultural Systems, 80(3), 255–275. https://doi.org/10.1016/j.agsy.2003.07.005

Barreteau, O., Garin, P., Dumontier, A., Abrami, G., & Cernesson, F. (2003). Agent-based facilitation of water allocation: Case study in the Drome River Valley. Group Decision and Negotiation, 12(5), 441–461. https://doi.org/10.1023/B:GRUP.0000003743.65698.78

Bauman, A., Goemans, C., Pritchett, J., Thilmany McFadden, D., & others. (2015). Modeling Imperfectly Competitive Water Markets in the Western US. 2015 AAEA & WAEA Joint Annual Meeting, July 26-28, San Francisco, California. http://ageconsearch.umn.edu/bitstream/201448/2/Bauman-AAEA%202015.pdf

Becu, N., Perez, P., Walker, A., Barreteau, O., & Page, C. L. (2003). Agent based simulation of a small catchment water management in northern Thailand: Description of the CATCHSCAPE model. Ecological Modelling, 170(2), 319–331. https://doi.org/10.1016/S0304-3800(03)00236-9

Bekchanov, M., Sood, A., & Jeuland, M. (2015). Review of hydro-economic models to address river basin management problems: Structure, applications and research gaps. International Water Management Institute (IWMI). https://doi.org/10.5337/2015.218

Berger, T., Birner, R., Díaz, J., McCarthy, N., & Wittmer, H. (2007). Capturing the complexity of water uses and water users within a multi-agent framework. In E. Craswell, M. Bonnell, D. Bossio, S. Demuth, & N. Van De Giesen (Eds.), Integrated Assessment of Water Resources and Global Change: A North-South Analysis (pp. 129–148). Springer Netherlands. https://doi.org/10.1007/978-1-4020-5591-1_9

Bhaduri, A., & Barbier, E. B. (2008). International water transfer and sharing: The case of the Ganges River. Environment and Development Economics, 13(1), 29–51. https://doi.org/10.1017/S1355770X07004056

Britz, W., Ferris, M., & Kuhn, A. (2013). Modeling water allocating institutions based on Multiple Optimization Problems with Equilibrium Constraints. Environmental Modelling & Software, 46, 196–207. https://doi.org/10.1016/j.envsoft.2013.03.010

Cai, X., Claudia Ringler, & Mark W. Rosegrant. (2006). Modeling Water Resources Management at the Basin Level Basin. International Food Policy Research Institute. http://www.ifpri.org/pubs/abstract/149/rr149.pdf

Digna, R. F., Castro-Gama, M. E., van der Zaag, P., Mohamed, Y. A., Corzo, G., & Uhlenbrook, S. (2018). Optimal Operation of the Eastern Nile System Using Genetic Algorithm, and Benefits Distribution of Water Resources Development. Water, 10(7), 22. https://doi.org/10.3390/w10070921

Dinar, A., & Nigatu, G. S. (2013). Distributional considerations of international water resources under externality: The case of Ethiopia, Sudan and Egypt on the Blue Nile. Water Resources and Economics, 2–3, 1–16. https://doi.org/10.1016/j.wre.2013.07.001

Dinar, A., Rosegrant, M. W., & Meinzen-Dick, R. S. (1997). Water allocation mechanisms: Principles and examples. World Bank Publications.

Ding, N., Erfani, R., Mokhtar, H., & Erfani, T. (2016). Agent Based Modelling for Water Resource Allocation in the Transboundary Nile River. Water, 8(4), 139. https://doi.org/10.3390/w8040139

Dozier, A. Q., Arabi, M., Wostoupal, B. C., Goemans, C. G., Zhang, Y., & Paustian, K. (2017). Declining agricultural production in rapidly urbanizing semi-arid regions: Policy tradeoffs and sustainability indicators. Environmental Research Letters, 12(8), 085005. https://doi.org/10.1088/1748-9326/aa7287

Du, E., Tian, Y., Cai, X., Zheng, Y., Li, X., & Zheng, C. (2020). Exploring spatial heterogeneity and temporal dynamics of human-hydrological interactions in large river basins with intensive agriculture: A tightly coupled, fully integrated modeling approach. Journal of Hydrology, 591, 125313. https://doi.org/10.1016/j.jhydrol.2020.125313

Farhadi, S., Nikoo, M. R., Rakhshandehroo, G. R., Akhbari, M., & Alizadeh, M. R. (2016). An agent-based-nash modeling framework for sustainable groundwater management: A case study. Agricultural Water Management, 177, 348–358. https://doi.org/10.1016/j.agwat.2016.08.018

Ferris, M. C. (2013). MOPEC: Multiple Optimization Problems with Equilibrium Constraints.

Filho, F. A. S., Lall, U., & Porto, R. L. L. (2008). Role of price and enforcement in water allocation: Insights from Game Theory. Water Resources Research, 44(12). https://doi.org/10.1029/2007WR006163

Giuliani, M., & Castelletti, A. (2013). Assessing the value of cooperation and information exchange in large water resources systems by agent-based optimization: MAS Framework for Large Water Resources Systems. Water Resources Research, 49(7), 3912–3926. https://doi.org/10.1002/wrcr.20287

Giuliani, M., Castelletti, A., Amigoni, F., & Cai, X. (2015). Multiagent Systems and Distributed Constraint Reasoning for Regulatory Mechanism Design in Water Management. Journal of Water Resources Planning and Management, 141(4), 04014068. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000463

Goldberg, D. E. (1989). Genetic Algorithms in Search, Optimization AND Machine Learning. AddisonWesley Reading, Mass.

Han, Q., Tan, G., Fu, X., Mei, Y., & Yang, Z. (2018). Water Resource Optimal Allocation Based on Multi-Agent Game Theory of HanJiang River Basin. Water, 10(9), 1184. https://doi.org/10.3390/w10091184

Harou, J. J., Pulido-Velazquez, M., Rosenberg, D. E., Medellín-Azuara, J., Lund, J. R., & Howitt, R. E. (2009). Hydro-economic models: Concepts, design, applications, and future prospects. Journal of Hydrology, 375(3–4), 627–643. https://doi.org/10.1016/j.jhydrol.2009.06.037

Hirsch, A. M. (1961). Some Aspects of River Utilization in Arid Areas: The Hydro-economics of Inadequate Supply. American Journal of Economics and Sociology, 20(3), 271–271. https://doi.org/10.1111/j.1536-7150.1961.tb00582.x

Izquierdo, L. R., Gotts, N. M., & Polhill, J. G. (2003). FEARLUS-W: An Agent-Based Model of River Basin Land Use and Water Management. 22.

Jeuland, M., Baker, J., Bartlett, R., & Lacombe, G. (2014). The costs of uncoordinated infrastructure management in multi-reservoir river basins. Environmental Research Letters, 9(10), 105006. https://doi.org/10.1088/1748-9326/9/10/105006

Kahil, M. T., Dinar, A., & Albiac, J. (2016). Cooperative water management and ecosystem protection under scarcity and drought in arid and semiarid regions. Water Resources and Economics, 13, 60–74. https://doi.org/10.1016/j.wre.2015.10.001

Khan, H. F., & Brown, C. M. (2019). Effect of Hydrogeologic and Climatic Variability on Performance of a Groundwater Market. Water Resources Research, 55(5), 4304–4321. https://doi.org/10.1029/2018WR024180

Khan, H. F., Yang, Y. C. E., Xie, H., & Ringler, C. (2017). A coupled modeling framework for sustainable watershed management in transboundary river basins. Hydrology and Earth System Sciences, 21(12), 6275–6288. https://doi.org/10.5194/hess-21-6275-2017

Kucukmehmetoglu, M. (2009). A Game Theoretic Approach to Assess the Impacts of Major Investments on Transboundary Water Resources: The Case of the Euphrates and Tigris. Water Resources Management, 23(15), 3069–3099. https://doi.org/10.1007/s11269-009-9424-3

Kucukmehmetoglu, M., & Geymen, A. (2014). The significance and impacts of large investments over the determination of irrigated agricultural land use: The case of the Euphrates & Tigris River Basin. Land Use Policy, 41, 514–525. https://doi.org/10.1016/j.landusepol.2014.04.006

Kuhn A. & Britz W. (2012). Can hydro-economic river basin models simulate water shadow prices under asymmetric access? Water Science & Technology, 66(4), 879–886. https://doi.org/10.2166/wst.2012.251

Kuhn, A., & Britz, W. (2012). Can hydro-economic river basin models simulate water shadow prices under asymmetric access? Water Science and Technology, 66(4), 879–886. https://doi.org/10.2166/wst.2012.251

Kuhn, A., Britz, W., Willy, D. K., & van Oel, P. (2016). Simulating the viability of water institutions under volatile rainfall conditions – The case of the Lake Naivasha Basin. Environmental Modelling & Software, 75, 373–387. https://doi.org/10.1016/j.envsoft.2014.08.021

Lei, X., Zhao, J., Yang, Y.-C. E., & Wang, Z. (2019). Comparing the Economic and Environmental Effects of Different Water Management Schemes Using a Coupled Agent–Hydrologic Model. Journal of Water Resources Planning and Management, 145(6), 05019010. https://doi.org/10.1061/(ASCE)WR.1943-5452.0001074

Liu, J., Dietz, T., Carpenter, S. R., Alberti, M., Folke, C., Moran, E., Pell, A. N., Deadman, P., Kratz, T., Lubchenco, J., Ostrom, E., Ouyang, Z., Provencher, W., Redman, C. L., Schneider, S. H., & Taylor, W. W. (2007). Complexity of Coupled Human and Natural Systems. Science, 317(5844), 1513–1516. https://doi.org/10.1126/science.1144004

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

Madani, K. (2010). Game theory and water resources. Journal of Hydrology, 381(3), 225–238. https://doi.org/10.1016/j.jhydrol.2009.11.045

Madani, K., & Dinar, A. (2012). Non-cooperative institutions for sustainable common pool resource management: Application to groundwater. Ecological Economics, 74, 34–45. https://doi.org/10.1016/j.ecolecon.2011.12.006

Mahjouri, N., & Ardestani, M. (2011). Application of cooperative and non-cooperative games in large-scale water quantity and quality management:

A case study. Environmental Monitoring and Assessment, 172(1–4), 157–169. https://doi.org/10.1007/s10661-010-1324-8

McKinney, D. C. (Ed.). (1999). Modeling water resources management at the basin level: Review and future directions. International Water Management Institute.

Meinzen-Dick, R. (2007). Beyond panaceas in water institutions. Proceedings of the National Academy of Sciences, 104(39), 15200–15205. https://doi.org/10.1073/pnas.0702296104

Mulligan, K. B., Brown, C., Yang, Y.-C. E., & Ahlfeld, D. P. (2014). Assessing groundwater policy with coupled economic- groundwater hydrologic modeling. Water Resources Research, 50(3), 2257–2275. https://doi.org/10.1002/2013WR013666

Nepal, S., Flügel, W.-A., & Shrestha, A. B. (2014). Upstream-downstream linkages of hydrological processes in the Himalayan region. Ecological Processes, 3(1), 19. https://doi.org/10.1186/s13717-014-0019-4

Ng, C. N., Wang, R. Y., & Zhao, T. (2013). Joint Effects of Asymmetric Payoff and Reciprocity Mechanisms on Collective Cooperation in Water Sharing Interactions: A Game Theoretic Perspective. PLOS ONE, 8(8), e73793. https://doi.org/10.1371/journal.pone.0073793

Noel, P. H., & Cai, X. (2017). On the role of individuals in models of coupled human and natural systems: Lessons from a case study in the Republican River Basin. Environmental Modelling & Software, 92, 1–16. https://doi.org/10.1016/j.envsoft.2017.02.010

Ostrom, E. (1990). Governing the commons: The evolution of institutions for collective action. Cambridge University Press.

Page, C. L., Bazile, D., Becu, N., Bommel, P., Bousquet, F., Etienne, M., Mathevet, R., Souchère, V., Trébuil, G., & Weber, J. (2013). Agent-Based Modelling and Simulation Applied to Environmental Management. In B. Edmonds & R. Meyer (Eds.), Simulating Social Complexity (pp. 499–540). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-93813-2_19

Panchanathan, K., & Boyd, R. (2004). Indirect reciprocity can stabilize cooperation without the second-order free rider problem. Nature, 432(7016), 499–502. https://doi.org/10.1038/nature02978

Pande, S., van den Boom, B., Savenije, H. H. G., & Gosain, A. K. (2011). Water valuation at basin scale with application to western India. Ecological Economics, 70(12), 2416–2428. https://doi.org/10.1016/j.ecolecon.2011.07.025

Peters, N. E., & Meybeck, M. (2000). Water Quality Degradation Effects on Freshwater Availability: Impacts of Human Activities. Water International, 25(2), 185–193. https://doi.org/10.1080/02508060008686817

Safari, N., Zarghami, M., & Szidarovszky, F. (2014). Nash bargaining and leader–follower models in water allocation: Application to the Zarrinehrud River basin, Iran. Applied Mathematical Modelling, 38(7), 1959–1968. https://doi.org/10.1016/j.apm.2013.10.018

Schlueter, M., & Pahl-Wostl, C. (2007). Mechanisms of resilience in common-pool resource management systems: An agent-based model of water use in a river basin. Ecology and Society, 12(2), 4.

Schreinemachers, P., & Berger, T. (2006). Land use decisions in developing countries and their representation in multi-agent systems. Journal of Land Use Science, 1(1), 29–44. https://doi.org/10.1080/17474230600605202

Sedghamiz, A., Nikoo, M. R., Heidarpour, M., & Sadegh, M. (2018). Developing a non-cooperative optimization model for water and crop area allocation based on leader-follower game. Journal of Hydrology, 567, 51–59. https://doi.org/10.1016/j.jhydrol.2018.09.035

Shinada, M., & Yamagishi, T. (2007). Punishing free riders: Direct and indirect promotion of cooperation. Evolution and Human Behavior, 28(5), 330–339. https://doi.org/10.1016/j.evolhumbehav.2007.04.001

Tagliapietra, D., Povilanskas, R., Razinkovas-Baziukas, A., & Taminskas, J. (2020). Emerald Growth: A New Framework Concept for Managing

Ecological Quality and Ecosystem Services of Transitional Waters. Water, 12(3), 894. https://doi.org/10.3390/w12030894

Teasley, R. L., & McKinney, D. C. (2011). Calculating the Benefits of Transboundary River Basin Cooperation: Syr Darya Basin. Journal of Water Resources Planning and Management-Asce, 137(6), 481–490. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000141

Tu, Y., Zhou, X., Gang, J., Liechty, M., Xu, J., & Lev, B. (2015). Administrative and market-based allocation mechanism for regional water resources planning. Resources Conservation and Recycling, 95, 156–173. https://doi.org/10.1016/j.resconrec.2014.12.011

Wang, L., Fang, L., & Hipel, K. W. (2008). Basin-wide cooperative water resources allocation. European Journal of Operational Research, 190(3), 798–817. https://doi.org/10.1016/j.ejor.2007.06.045

Xiao, Y., Fang, L., & Hipel, K. W. (2018a). Agent-Based Modeling Approach to Investigating the Impact of Water Demand Management. Journal of Water Resources Planning and Management, 144(3), 04018006. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000907

Xiao, Y., Fang, L., & Hipel, K. W. (2018b). Centralized and Decentralized Approaches to Water Demand Management. Sustainability, 10(10), 3466. https://doi.org/10.3390/su10103466

Yang, Y.-C. E., Cai, X., & Stipanović, D. M. (2009). A Decentralized Optimization Algorithm for Multi-Agent System Based Watershed Management. 1–8. https://doi.org/10.1061/41036(342)463

Yang, Y.-C. E., Zhao, J., & Cai, X. (2012). Decentralized Optimization Method for Water Allocation Management in the Yellow River Basin. Journal of Water Resources Planning and Management, 138(4), 313–325. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000199

Young, R. A. (1996). Water Economics. In L. W. Mays (Ed.), Water resources handbook (p. 3.1-3.57). McGraw-Hill.

Young, R. A., Daubert, J. T., & Morel-Seytoux, H. J. (1986). Evaluating Institutional Alternatives for Managing an Interrelated Stream-Aquifer System. American Journal of Agricultural Economics, 68(4), 787–797.

Zhao, J., Cai, X., & Wang, Z. (2013). Comparing administered and market-based water allocation systems through a consistent agent-based modeling framework. Journal of Environmental Management, 123, 120–130. https://doi.org/10.1016/j.jenvman.2013.03.005

Chapter 4
Simulating potential hydroeconomic impacts of water rights trade in the Lake Naivasha Basin using a MOPEC modelling framework

Abstract

The Lake Naivasha Basin in Kenya (LNB) suffers from recurrent drought and water scarcity problems. Poor compliance with the current administrative-based permit system and free-riding are major challenges to the basin's water management. Establishing a market in water use rights might be suitable policy instrument for more efficient water allocation amidst increasing water scarcity. This paper aims to simulate the potential economic and hydrological impacts of water rights trade among agricultural water users in the LNB using a modified version of the Lake Naivasha Hydro-economic Basin Model (LANA-HEBAMO). A key contribution of this paper is to define unregulated water use as a reference situation which is facilitated by the use of an individual optimization (IO) approach. Four alternative water management scenarios under randomly generated rainfall are compared to an unregulated water use reference situation. Our results show that allowing tradable water rights improves water use efficiency in the basin as compared to the unregulated water use and the existing nontradable water rights regimes. However, trading water rights during drought situations might compel buyers to buy water rights from sellers

excessively if the total volume of water rights is much higher than physically available water. The simulation of this effect requires the use of the IO problem format as employed by this study. Nevertheless, allowing water rights trade, particularly in combination with water rights that are reduced in situations of acute water scarcity, would increase net agricultural revenues while making severe lake level decline less likely.

Keywords: Hydroeconomic model, MOPEC, individual optimization, water rights market, irrigation, dynamic water rights

4.1 Introduction

Water scarcity is becoming a big concern in many parts of the world, especially where policies and institutions fail to effectively regulate water use (Barbier, 2019; Easter et al., 1999; Livingston, 1995). Establishing water markets in water-scarce regions has been considered a promising policy instrument for efficient allocation of water among users and address water scarcity problem (Easter et al., 1999; Eheart & Lyon, 1983; Rosegrant & Binswanger, 1994). Various studies argued that privatization of water rights and making it tradable improves economic efficiency by placing water in its most valued uses (Griffin & Hsu, 1993; Rosegrant et al., 2000; Rosegrant & Binswanger, 1994). Other studies stressed water market needs to be adequately regulated to safeguard other social and ecological objectives in addition to economic efficiency (Bauer, 2004; Debaere et al., 2014; Dinar et al., 1997). Rosegrant and Binswanger (1994) indicated transaction costs, including the cost of infrastructure for transferring traded water, establishing an institutional framework, and regulating third-party externalities, are the primary limiting factors to market-based water allocation. This may be part of the reason why water markets are mainly used in wealthier countries such as the USA, Australia, Chile, Spain, and the UK (Bjornlund & McKay, 2002; Calatrava & Martínez-Granados, 2017; Debaere et al., 2014; Erfani et al., 2014; Hearne & Easter, 1997), while only being at an infant stage in a limited number of developing countries (Grafton et al., 2011).

This paper explores the potential benefits of introducing water rights trade compared to unregulated water use and the existing administrative-based allocation in terms of economic gains and hydrological performance under volatile water supply in the LNB. The basin suffers from recurrent droughts and ensuing water scarcity. Water users' poor compliance with water rules and free-riding behavior is prevalent in the basin due to a lack of resources and political will for effective monitoring and enforcement by the regulating agency (Harper et al., 2011; WRMA, 2010). Free-riding is a severe problem during the dry season when there is a water shortage (WRMA, 2010). Previous work by Kuhn et al. (2016a) showed that the water permit system is insufficient to effectively prevent over-exploitation of water and severe lake level decline during the dry season. The LNB is a hotspot of Kenya's horticultural industry, contributing 70% of national flower export (Mekonnen et al., 2012). Because of the high marginal profitability of water use in the horticultural sector, moderate fines would not ensure compliance with water rights (Kuhn et al., 2016a). This calls for the investigation of alternative policy options that might be suitable to effectively deal with current and future challenges of water scarcity and allocation problems in the basin. Thus, we aim to illustrate the potential benefits of introducing water rights trade among agricultural water users, the water resource users associations (WRUAs) of the LNB in Kenya.

Several previous studies on water markets enumerated potential economic gains using analytical or numerical simulation models (Bekchanov et al., 2015a; Dozier et al., 2017; Easter et al., 1998; Erfani et al., 2014; Hearne & Easter, 1997; Rosegrant et al., 2000; Zhu et al., 2015). But the economic gains crucially depend on choosing an appropriate reference situation or scenario. The previous studies have used reference scenarios that implicitly assumed the adherence of water users to a given water rights rule (Bekchanov et al., 2015b; Rosegrant et al., 2000; Zhu et al., 2015). The inherent reason for this implicit misspecification was that unregulated water use by multiple water users could not be reproduced by common aggregate optimization frameworks (Britz et al., 2013). The resulting reference scenarios might be appropriate in a situation where a strong regulatory agency can effectively enforce an existing distribution of water use rights. But this is not a realistic starting point when the current water use system is characterized by a decentralized multi-actor decision process where adequate institutions for coordinating the decisions or enforcing the rules have yet to emerge, such as the in the LNB. Thus, a particular novelty of our approach is that we define a reference situation of unregulated water use that better reflects the current water governance in the basin. We are able to represent such a reference scenario using an individual optimization approach, benefiting from the recent advancement in mathematical programming (Woldeyohanes et al., 2021). Specifically, we use the Multiple Optimization Problem with Equilibrium Constraint (MOPEC) approach by Britz et al. (2013). In MOPEC, each economically independent but hydrologically linked water user makes a rational economic decision to use water and maximize their profit. Under the water rights trade scenario, the model integrates each water user's decision-making within a partial equilibrium model formulated as MOPEC problem.

Water supply in arid and semi-arid regions is frequently marked by extreme variability in precipitation and streamflow. The interannual fluctuation of Lake Naivasha's surface elevation is driven by rainfall anomalies linked to EL Nino or Southern Oscillation (ENSO) events in the region (Verschuren et al., 2000). To reproduce these patterns of variability, the distribution of local water supply in the LNB is determined by stochastic monthly precipitation, randomly drawn from historical (1960-2010) rainfall time series. This enables us to perform a stochastic simulation of the effects of the empirical regional rainfall distribution and define variable water rights that are reduced in times of acute water scarcity.

In summary, our paper contributes to the existing literature on water allocation problems, answering two broad questions. First, what would be the potential benefits, in terms of economic gains and hydrologic performance, of introducing tradable water rights compared to unregulated water use and the existing nontradable water rights if fully enforced? Second, how would the actor's behavior and the performance of the entire water use system change in the face of volatile water supply and rising water scarcity?

The remainder of the article is structured as follows: the following section describes the study area. Section 4.3 introduces the model and explains the scenario design and the data used. Results and discussion are offered in Section 4.4 before concluding in Section 0.

4.2 Study area – The Lake Naivasha Basin

4.2.1 *Geographic and economic features*

The Lake Naivasha Basin (Figure 4.1) is located in the Kenyan Rift Valley. It covers a total catchment area of about 3500 km2, with the Lake covering an area ranging between 100-200 km2 (Harper et al., 2011). The runoff generated in the basin feeds the lake ecosystem and connected shallow aquifer through its three major tributaries, the Malewa and Gilgil rivers and Karati, the ephemeral streamflow.

Lake Naivasha Basin is Kenya's economic hotspot, the most significant cut-flower-producing region globally and prominently contributing to the regional and national economy (Kuiper & Gemählich, 2017; Mekonnen et al., 2012). Demand for water, particularly by the agricultural sector, has been rising with the expansion of irrigated agriculture and population growth. Irrigation uses significant amounts of water, accounting for 94% of all consumptive uses (van Oel et al., 2013). Commercial irrigated horticultural farms, mainly roses, are located in the downstream section of the Lake's basin, whereas smallholder farmers dominate the upper catchment (Figure 1).

Water supply, in contrast, is highly volatile with recurrent and prolonged droughts. A prolonged drought in Kenya between 2009 and 2010 caused the Lake to decline to its lowest level since the late 1940s and resulted in severe ecological degradation (Harper et al., 2011). Such fluctuations are continued, with lake level declining again beginning in 2017 and rising back following a relatively abundant rainfall period in recent years (Wanjala et al., 2017). Unsustainable land-use practices in the upper catchment and substantial water abstraction in the downstream catchment coupled with recurrent droughts put the basin and socio-ecological system under pressure and its sustainability at stake (Harper et al., 2011; Wanjala et al., 2017).

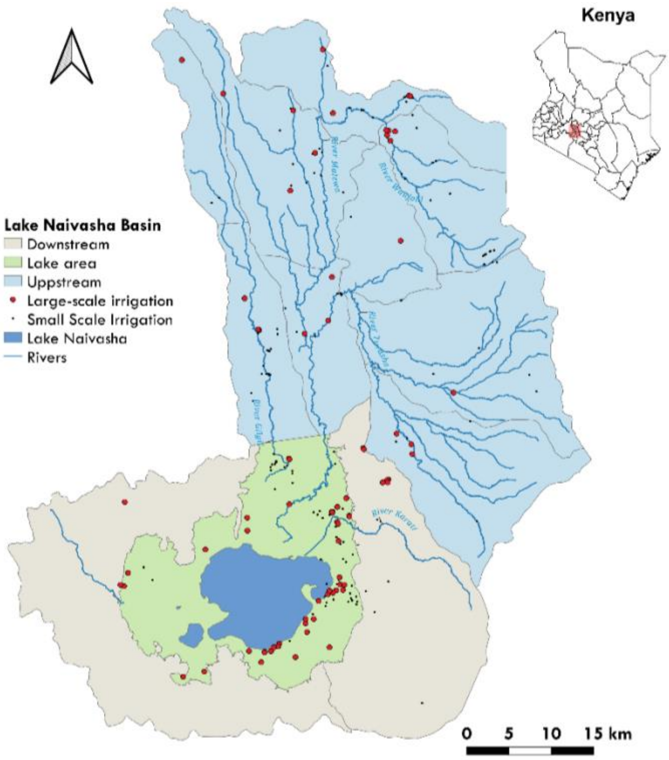
Thus, reforms to the existing water management strategy have become a pressing policy issue (WRMA, 2010).

4.2.2 *Water permit system in the Lake Naivasha Basin*

The government and local and international stakeholders have responded with various policy proposals to manage the water scarcity crisis in the basin. The current administrative-based water management scheme includes a water permit system and volumetric water charges based on the volume of water use. The Kenyan Water Act 2002 authorized the Water Management Authority (WRMA), a national agency, to manage and regulate water resources. WRMA has different regional offices in the major basins of the country and is mandated to establish local Water Resource User Associations (WRUAs). Twelve WRUAs in the LNB provide services to their members regarding water permits and support WRMA in regulating water use.

In consultation with the WRUAs, WRMA grants nontransferable water permits that allow a legitimate member of each WRUA the right to abstract water for a specified use. The permit specifies the quantity of water allowed per day, water sources, intended use, and method of abstraction and should be renewed every five years to continue using water. The permit holder is obliged to pay a monthly fee depending on the total volume of water abstracted within a month. The water charge ranges from 0.5 to 0.75 Kenyan shillings (KSh) per M^3 for abstraction up to 300 and over 300 M^3 day-1, respectively (De Jong, 2011).

Figure 4.1 Map of Lake Naivasha Basin showing the approximate location of agricultural water abstraction points for commercial and small-scale irrigation in the upper and downstream catchments, the main rives, and the Lake.



Source: GPS data for Small-scale irrigated farms are based on a water allocation survey (De Jong, 2011). Shapefiles for the Lake Naivasha basin, the main rivers, and tributaries are obtained from the University of Twente (ITC). For commercial irrigation, data from 2015 and 2016 field surveys are used.

In addition, the Water Allocation Plan (WAP), specific to the Lake Naivasha basin, was introduced. It was initiated by local stakeholders, particularly the riparian Lake Naivasha WRUA (LaNaWRUA) and commercial farmers in the lake area in response to drought and water shortage in the basin (Harper et al., 2011). The plan defines minimum environmental flows for the rivers and levels in the lake and groundwater bodies. It restricts the abstraction of water by water users to a fraction of the water permits they own when water is below that threshold in the case of severe water shortages. WRMA legalized and implemented the WAP in 2010 (Verstoep, 2015).

4.3 The hydroeconomic river basin model

4.3.1 *Basic model features*

The river basin model we use, Lake Naivasha Hydroeconomic Basin Model (LANA-HEBAMO), initially developed by Kuhn et al. (2014) for water allocation simulation. The model is based on a node-link network representing source nodes, demand nodes, and the links that connect these entities (Figure 4.2). We extend Kuhn et al. (2014) model by adjusting the agronomic and hydrological components and introducing water rights trade options. The original model description can be found in (Kuhn et al., 2014).

LANA-HEBAMO consists of hydrologic, agronomic, and economic components of the spatially distributed water use system. The hydrological relations and processes include water flows and balances in the rivers, reservoirs, groundwater aquifer, and crop fields, and flows to the agricultural and household demand sites. It also includes the interaction between the lake and groundwater aquifer system, lake-area-volume relations, evaporation from the Lake, and rainfall on the lake surface. The inflows to the node include water flows from the headwater of the river basin and runoff from precipitation on the area attributed to the respective node. The demand nodes connected to the networks are agricultural demand sites and household water users.

The economic component is represented as maximization of benefits from water use in agriculture. The agricultural demand sites represent 13 WRUAs (We divide LaNaWRUA into North-West and South-East Lake). Each demand site independently maximizes its benefit, not considering basin-wide wellbeing[1], by diverting water from a river, groundwater aquifer, or the Lake and allocating to different crops according to their agronomic requirement and economic profitability. The model represents

[1] Social planner based basin-wide aggregate optimisation has been the common feature in hydroeconomic river basin model that this study aims to overcome.

five categories of irrigated crops: indoor flowers (mainly roses grown in greenhouses), outdoor flowers, vegetables, maize, and fodder grown primarily in the area.

Table 4.1 Shows the estimated gross margin per hectare of major irrigated crops and observed area per demand region. Both crop area and yields are determined endogenously in the model except for indoor flowers. The yield is fixed at the maximum observed level for indoor flowers due to a lack of data on the yield response coefficient ky. Actual yield Y^a is derived from crop yield-water stress relationships following the FAO approach (Doorenbos and Kassam, 1979; Ringler et al., 2004). The maximum yield, Y^m is reduced by a factor accounting for seasonal water deficit. The function for each crop c and demand site dma is specified as

$$Y^a_{c,dma} = Y^m_c . \left[1 - \left(ky_c . \left(1 - ET^a_{c,dma} / ET^m_{c,dma}\right)\right)\right] \tag{14}$$

where Y^a is actual yield (t/ha); Y^m is maximum yield (t/ha); ET^a is actual seasonal evapotranspiration (mm); ET^m is potential seasonal evapotranspiration (mm), and ky is the seasonal crop yield response coefficient. The hydrological effects of rainfed crops are not captured in the model as replacing natural bushland vegetation with rainfed crops is unlikely to significantly impact the water cycle in the basin, which is different for irrigated crops.

The income from irrigation agriculture depends on crop area and yield, which depends on the quantity of available water for irrigation and thus rainfall. Crop and location-specific evapotranspiration (ET_c) and effective rainfall (zero in case of indoor flowers) are used to calculate total crop water requirements during the cropping season. As shown in equation (14), crop yield is reduced when actual seasonal evapotranspiration (ET_c) is inferior to the potential seasonal evapotranspiration (ET^a), which happens if effective rainfall plus irrigation do not provide enough water to the crop.

We introduce an additional objective function for the Lake management representing the ecological interests in the system. This is implemented as minimization of the sum of square deviations between lake fill level and a predefined desired fill rate, which is defined as 50 % of maximum Lake storage capacity subject to the mass balance and other physical constraints. The aim is to keep the lake volume close to the predefined threshold.

The model is calibrated to the baseline crop area using positive mathematical programming (PMP) (Howitt, 1995), with crop supply elasticities introduced as prior information (Heckelei, 2002; Heckelei & Wolff, 2003). Supply elasticities for perennial crops such as indoor and outdoor flowers are low compared to other crops due to the high share of quasi-fixed costs like capital invested in irrigation infrastructure and greenhouses. The objective function, net agricultural profit for each demand site (WRUAs), dma is specified as

$$MaxPA_{dma} = \sum_{c}\left[A_{dma,c}\cdot\left(P_c.Y^a_{dma,c} - \sum_{j}\left(I_{dma,c,j}.IP_{c,j}\right) - \left(\alpha_{dma,c} + 0.5\gamma_{dma,c}A_{dma,c}\right)\right)\right]$$
$$-\sum_{ws}\sum_{pd}W_{dma,ws,pd}\cdot pw_{dma,ws} - pdft_{dma} \qquad (15)$$

where PA is net agricultural profit; P is the exogenous product price (000 KSh/ton);Y^a is crop yield (ton/ha) and A is cultivated land (ha). Non-water related intermediates such as agrochemicals, energy, and labor are crop-specific and constant per ha. It is represented by I , and its exogenous price is IP (000Ksh/ha) for each variable input j . The quadratic term is the nonlinear cost function used to calibrate the model to the baseline crop areas and represents the costs for deviating cropping patterns from the baseline observation. The parameters α and γ are the intercept and slope parameters of the PMP quadratic cost function, respectively, and are derived from crop area elasticities (Kuhn et al., 2016) as previously discussed. Total water abstraction costs during the growth period pd are a product of administrative price per unit of water use pw (KSh/M^3) and the amount of water withdrawn W (1000 M^3) from the water sources ws. A penalty term for yield deficit $pdft$ is introduced in the profit function to achieve consistency between the seasonal yield function, equation (16), and monthly water balance in the hydrologic system (Ringler et al., 2004; Rosegrant et al., 2000). It minimizes the difference between the maximum and average crop stage deficit due to water for a given crop and demand site and formulated as

$$pdf_{dma} = \sum_{c} Y^{m}.A_{dma,c}.P_{c}\left(mdft_{dma,c} - adft_{dma,c}\right) \tag{16}$$

where $mdft$ is the maximum stage deficit; and $adft$ is the average stage deficit within a crop growth season due to water stress, with

$$dft_{dma,c} = kym_{c}.\left(1 - ET^{a}_{dma,c} / ET^{m}_{dma,c}\right) \tag{17}$$

calculating the monthly stage deficit by crop and demand site, and kym is a monthly crop yield response coefficient (Doorenbos and Kassam, 1979).

Monthly water needs for domestic purpose is exogenous and calculated based on estimated daily per capita water use of 37 liters (De Jong, 2011) and population census of 2009 for each WRUA (KNBS, 2009). Eleven synthetic municipalities, the populations of all inhabitants of the WRUAs, are created. Their monthly consumption demand is met by water abstraction from rivers. Additionally, since 1992, 18,000 M^3 of water per day has been transferred from Turasha Dam in the river Malewa basin to Nakuru town (Figure 4.2) outside the basin (Otiang'a-Owiti & Oswe, 2007). Naivasha town gets its domestic water needs from groundwater. Each demand region independently maximizes its objective function shown in (15), subject to a set of institutional and biophysical constraints.

Agricultural demand regions (WRUAs) receive water for irrigation from three different sources depending on their spatial location in the basin (Figure 4.2). Upstream users withdraw water from rivers and streams; North West Lake from the groundwater aquifer surrounding the Lake, and South East Lake from the Lake itself. Water availability in the basin is driven by monthly rainfall. The monthly rainfall generates water supply for agriculture in two ways. First, rainfall directly enters the field balance for supplementarily irrigated crops as effective rainfall. Second, rainfall generates surface runoff that feeds the river system, aquifers, and the lake, where irrigation water is abstracted. A location-specific rainfall dataset for 1960-2010 is used to generate the runoff flows for each of the 13 sub-basin areas using an externally calibrated rainfall-runoff simulation model (Kuhn et al., 2014). The rainfall-runoff simulation model in Kuhn et al. (2014) is modified to account for a share of two rainfall lags that contribute to the current runoff flow formation as

$$K_{dma,pd} = \alpha.\left(\Phi_{dma,pd} + \Phi_{dma,pd-1}\right)^{\beta} + \gamma.\left(\Phi_{dma,pd} - 1 + \Phi_{dma,pd-2}\right) \tag{18}$$

where K is the runoff coefficient (mm); Φ is amounts rainfall (mm) and its lag during a period month pd and sub-basin area dma. The parameters, α , β and γ are externally estimated using the rainfall-runoff simulation model as shown in chapter 2 and used as a constant input in the LANA-HEBAMO. Finally, the total runoff flow Γ (1000 M^3) available in stream channels n, through either surface or sub-surface flows through saturated soil is a function of the drainage area of the demand site A (ha) and runoff coefficients K which is calculated as

$$\Gamma_{n,pd} = \sum_{n \in dma} 10^{-2}.K_{dma,pd}.A_{dma} \tag{19}$$

A stochastic rainfall generator initially drives water availability to account for uncertainty in the water supply. Monthly rainfall is randomly drawn from a historical dataset of monthly rainfall (1960-2010). The model uses a stochastic sequence of past years while maintaining the observed monthly and regional rainfall pattern for each chosen year. Then, this input is used to drive the water inflows into the river system according to equations (18) and (19), and the mass balances in the river, reservoir, and groundwater are updated on a monthly time scale.

4.3.2 *Scenario analysis of alternative water allocation institutions*

This study aims to assess the potential benefits of water rights trade among water users in terms of economic gains and hydrologic performance compared to the current mostly unregulated water use and the nontradable water rights. The nontradable water rights scenarios are based on the assumption that WRMA legalizes the current water use patterns per WRUA by granting nontransferable monthly water permits that are uniform across the year, as indicated in the policy guideline (WRMA, 2009). The monthly allocation of permit is based on the 'use it or lose it' principle, which prevents farmers from smoothing monthly scarcities by shifting part of their permits to other periods of the year.

We also assume that technical progress in agriculture reduces the marginal production cost over time. Population growth incentivizes expanding irrigated areas and gradually increases agricultural water demand. As a result, a 1% growth of irrigated area per year is part of any scenario. The alternative scenarios of water management institutions are simulated using a randomized rainfall ensemble consisting of 100 draws over a 20 year-period such that each scenario delivers 2000 yearly results for the hydrological and other variables of our interest, most of them with a monthly resolution. The starting level of Lake Naivasha in the first year of each scenario and draw is 1887.65 m above sea level.

Because domestic water use is a priority in water allocation (WRMA, 2010) and accounts for a relatively low share of total water consumption (van Oel et al., 2013), water rights trade is simulated only for agricultural water use. Based on these assumptions, five water management scenarios are developed and analyzed. Next, we describe these scenarios in detail.

a. Unregulated water use – UWU (Reference scenario)

This scenario simulates a situation of no institutional restrictions to water access such that farmers can use the water available at their demand node at liberty. It is close to the current water use situation in the basin, where permits are only weakly enforced, and illegal water abstraction is common, particularly in the upstream catchment (De Jong, 2011; Mekonnen et al., 2012). Therefore, we use the UWU as our reference scenario to evaluate the performance of counterfactual management scenarios. It is modeled as a decentralized decision-making process using individual optimization (IO) (Britz et al., 2013) in which economically independent but hydrologically interconnected individual users maximize their local objective function as shown in (2) subject to water availability. Since water is used as far as the marginal benefit (shadow price) is greater than zero, some farmers may excessively use water using their positional advantage in the basin and generate a unidirectional externality. That can mean that the action of the upstream user affects water availability to the downstream users, or other environmental externalities like a drawdown of lake levels. The advantage of using the IO format is that it can flexibly show such externalities by solving each problem independently according to the inter-spatial water balance without imposing an equalization of shadow prices across locations (Britz et al., 2013; Kuhn A. & Britz W., 2012).

b. Static non-tradable water rights (SWR)

Under this scenario, water use by a specific region is limited by the nontradable monthly water permits it owns. It is static because the permitted quantity for abstraction does not vary based on water availability. This scenario would mimic the current water abstraction permit policy if fully enforced. Therefore, the difference between the reference scenario and static nontradable water rights can be used to measure the effect of compliance with water rights. If fully enforced, a nontradable water right may help to prevent the overexploitation of water resources and related ecological degradation. On the other hand, it could also reduce water use efficiency and benefits from water use by locking resources into relatively low valued use during shortages (Rosegrant & Binswanger, 1994).

A basin-wide survey on water abstraction was conducted in 2010 (De Jong, 2011). However, since water permits have not been imposed on smallholder irrigators in the upstream catchment, and their water use has not been regularly monitored, water rights distribution based on the abstraction survey may not be complete. Thus, actual water use by each demand region from a deterministic model solution in combination with survey data is used to define the water rights. Monthly water use permits $\overline{wpr}$ for each of the WRUAs is defined as the maximum of either a) a permit observed from the survey data, $\overline{pr}_{dma,pd}$, or b) monthly water withdrawal at the observed crop cultivation program $W^{o}_{dma,pd}$.

$$\overline{wpr}_{dma,pd} = \max\left(\overline{pr}_{dma,pd}, W^{o}_{dma,pd}\right) \tag{20}$$

Then, the water right constraint is defined such that monthly water intake at the irrigation demand sites $W_{dma,pd}$ should not be higher than the water permit $\overline{wpr}_{dma,pd}$

$$W_{dma,pd} \leq \overline{wpr}_{dma,pd} \tag{21}$$

c. Dynamic non-tradable water rights (DWR)

This scenario combines the nontradable SWR scenario described above, which applies to upstream users, and scalable water rights that vary conditional on water availability for the downstream users (North Lake and South Lake WRUAs). The purpose of this scenario is to simulate the Water Allocation Plan (WAP), the idea of which is to restrict water use by irrigators in the lake area during possible water shortages when lake and groundwater levels fall below critical thresholds. Under this scenario, water rights of the lake area irrigators are reduced for simulation years when lake levels in the previous simulation year have fallen below the thresholds defined in WAP. These threshold levels (m.a.s.l) for the Lake are the water stress (1885.3), water scarcity (1884.6), and the alarm or reserve level (1882.5). The corresponding cut in water permits is 25%, 50%, and 100%, respectively. Compared to the static nontradable water rights scenario, this scenario which is also nontradable, will put further restrictions on water use by Lake riparian irrigators, and their agricultural income will decrease. However, it may help prevent rapid lake level decline and severe water scarcity. This scenario enables us to assess the effectiveness of the WAP regarding sustainable water use in the basin.

d. Tradable static water rights (TSWR)

This scenario simulates the potential economic gains from introducing water rights trade and its impact on the hydrological system performance. The static water right defined in *b* is now tradable among users and implemented as an equilibrium constraint using the MOPEC framework. Thus, the objective function in the equation (15) is modified, as in the equation (22). Each agricultural demand region maximizes its new objective function PA_WT_{dma}, an aggregation of net profit from water use in agriculture and net income from water rights trade, were wps and wpb are water rights sold and bought by each demand site during the period pd, respectively. The equilibrium water rights price wtp is an outcome of market interaction, which is determined by solving the model simultaneously

$$\max PA\_WT_{dma} = PA_{dma} + \sum_{pd} wtp_{pd}(wps_{dma,pd} - wpb_{dma,pd}) \tag{22}$$

With water rights trade, water intake at the irrigation demand sites $W_{dma,pd}$ should be no higher than owned water permit $\overline{wpr}_{dma,pd}$ plus any amount of additional water permit bought $wpb_{dma,pd}$ minus the amount of water permit sold $wps_{dma,pd}$ if the user sells all or part of his water use permit. So, the water rights constraint in (20) can be written as

$$W_{dma,pd} \leq \overline{wpr}_{dma,pd} + wpb_{dma,pd} - wps_{dma,pd} \tag{23}$$

The equilibrium constraint for water trading implies that aggregate monthly rights sold $wps_{dma,pd}$ must be equal to or higher than aggregate rights bought $wpb_{dma,pd}$ (23). This constraint connects water users via shared variables and is in a complementarity relation, denoted by $\perp$, the water trading price under the MOPEC solution format (Britz et al., 2013). The interaction between water users in the water rights market determines the equilibrium price for water. Trade among irrigators in the entire basin is allowed on a monthly basis. To avoid excessive trading volumes, both buyers and sellers incur small transaction costs (0.01 KSh/M^3). This amount may not be sufficient for farmers' search, legal procedure, and enforcement-related transaction costs. So, we do not claim to capture the policy impact of transaction cost, and the transaction cost here is only to facilitate the model solution and avoid excessive trading volume.

$$\sum_{dma} wps_{dma,pd} - \sum_{dma} wpb_{dma,pd} \geq 0 \perp wtp_{pd} \geq 0 \tag{24}$$

Moreover, an additional constraint related to water rights trading is that the total volume of permits he/she owns limits the amount of water the user can sell:

$$\overline{wpr}_{dma,pd} \geq wps_{dma,pd} \tag{25}$$

e. Tradable dynamic water rights (TDWR)

Finally, this scenario simulates the impact of trade with dynamic water rights, as defined above in the third scenario. The difference between this and the preceding scenario of tradable static rights is that under the latter scenario, the water right owned by the lake riparian users is subject to cuts during water scarcity. However, unlike the nontradable scenario, these users can now buy water from users with less restricted water availability. Theoretically, water rights trading improves water use efficiency compared to the nontradable rights moving water from low-valued to high-valued uses.

4.3.3 *Data*

Because data on economic activities is collected and monitored centrally, it is challenging to obtain regularly monitored regional-level data. Therefore, we use data from previous studies and are updated with field surveys conducted in the basin. Observed crop areas for commercial horticultural crops in the Lake's riparian are adopted from previous studies (Becht, 2007; Mekonnen et al., 2012). The spatial location of each agricultural demand region (WRUAs) in the basin and water supply sources are shown in Figure 4.2.

Table 4.1 Irrigated area, the share of flowers and the average gross margin per demand regions (WRUAs)

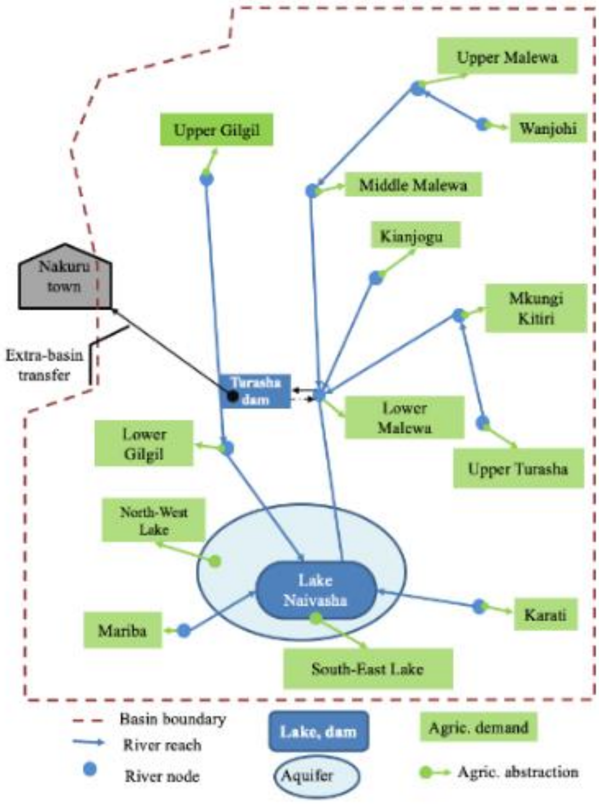
Demand regions (WRUAs)	**Total Irrigated area (ha)**	**Share of flowers (%)**	**Average gross margin (1000 KSh/ha)**
Wanjohi	128.50	33.46	1127.07
Upper Malewa	130.70	22.95	823.09
Middle Malewa	312.60	18.55	666.29
Kianjogu	104.50	0.00	158.71
Upper Turasha	256.00	18.36	621.59
Mkungi	197.60	0.00	158.77
Lower Malewa	88.60	5.64	320.71
Upper Gilgil	86.70	5.77	325.02
Lower Gilgil	123.90	21.79	707.09
Karati	367.40	40.01	1231.24
North West Lake	3435.00	25.33	799.55
Mariba	165.30	0.00	158.54
South East Lake	2507.00	74.39	2165.91

Sources :Becht (2007) and Mekonnen et al. (2012)

We have collected additional data on irrigated areas through field surveys conducted in 2015 and 2016. This includes several newly established commercial farms in the upstream catchment, mainly cut flowers and vegetables (See Figure 4.1). Information from this survey was used to update and supplement the data from the previous study. Maximum potential crop yield and prices are exogenous and obtained from previous studies (Kuhn et al., 2016). Factor costs such as agrochemicals, labor, energy, and transport are based on data collected in 2015 for the commercial farmers around Lake Naivasha. An earlier survey in 2012 was used for the upstream catchment smallholder farmers (Willy, 2013)[2].

[2] All the monetray values are in KES at 2012 constant prices; at the time of submitting (August 2023), on average, 1 EURO = 158 KSh; https://www.centralbank.go.ke/rates/forex-exchange-rates/

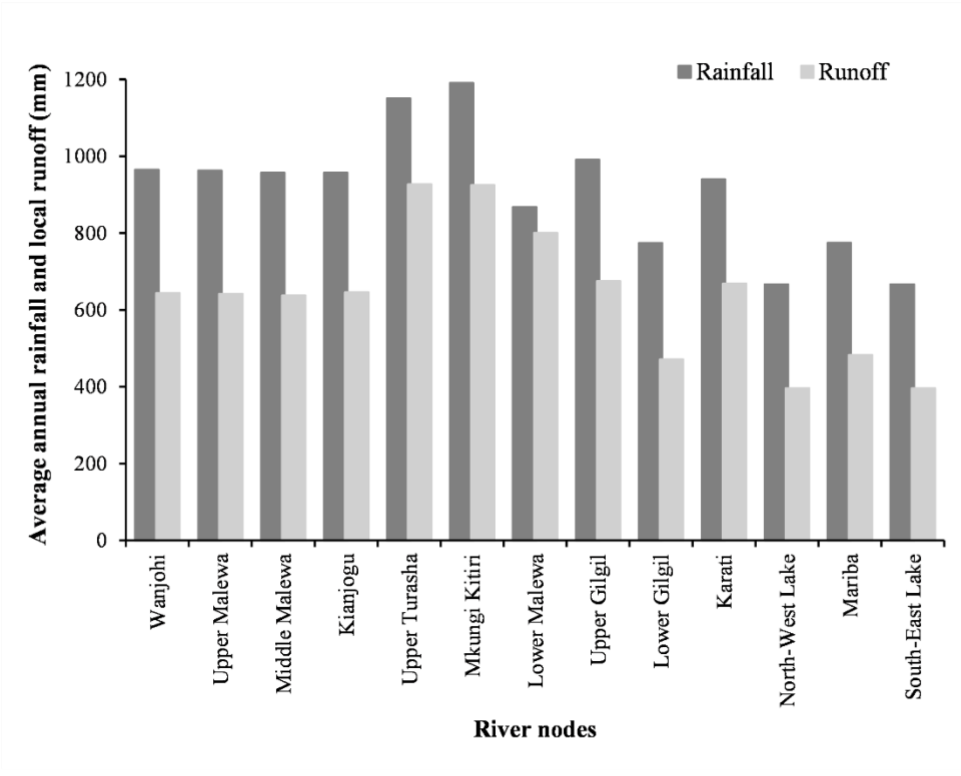
Figure 4.2 Node-link-network showing the river reaches, river nodes and spatial location of each agricultural demand regions (WRUAs) in the basin.



Source: Adapted from Kuhn et al. 2016

Hydrological data such as rainfall, lake levels, and evaporation are obtained from the University of Twente in the Netherlands (ITC), which has established a hydrological database through its long-term research activities in the Lake Naivasha Basin. Figure 4.3 shows annual rainfall (mm) and estimated local runoff (mm) for each sub-catchment area linked to the river nodes. Crop water requirement is calculated based on location-specific grid-based average monthly evapotranspiration (ET_0) at 0.5 arc minute resolution obtained from WorldClim (Trabucco and Zomer, 2010) and crop and stage-specific Kc values (Allen et al., 1998).

Figure 4.3 Average annual rainfall (mm) and estimated local runoff (mm) for each sub-catchment areas linked to the river nodes



Source: own calculation based on WorldClim data (Trabucco & Zomer, 2010))

4.3.4 *Model solution*

We encoded the model in GAMS (Brook et al., 1988) and used the Extended Mathematical Programming (EMP) framework of GAMS (Ferris et al., 2009) to reformulate the MOPEC problem into a mixed complementarity problem (MCP) which is then solved using the GAMS Path solver (Ferris & Munson, 2000). We used GAMS GUI based on GGIG (GAMS Graphical Interface Generator) (Britz, 2021) to steer the simulation and exploit results.

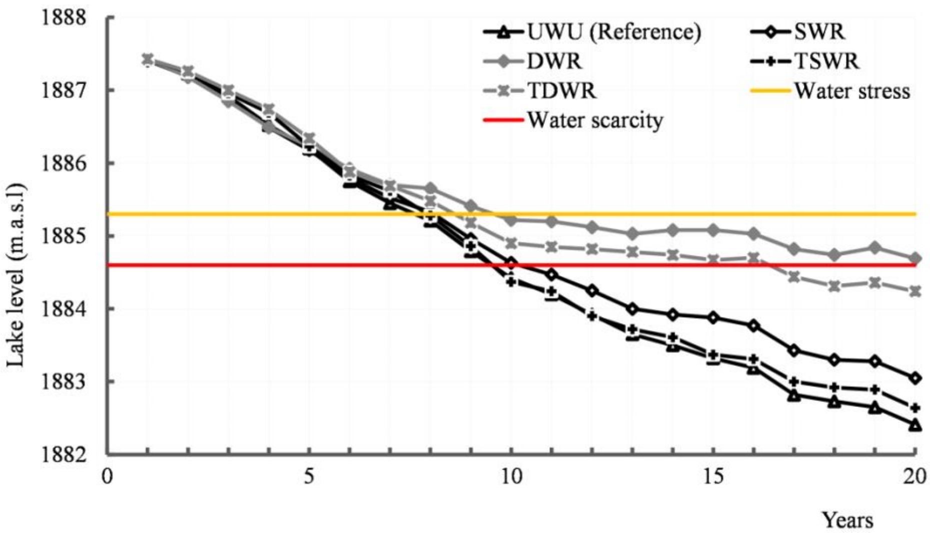
4.4 Results and discussion

4.4.1 *An overview of alternative institutions on the performance of the hydrological system*

The natural rainfall variability in the basin and associated variable river inflow causes interannual fluctuation in Lake Naivasha's surface elevation. Verschuren (2000) identified four aridity periods, more than any recorded droughts of the twentieth century, in the last 1100 years (900-1993), and Lake Naivasha has fallen dry during these periods. Odongo et al. (2015) found no evidence of rainfall and inflow changes contributing to the gradual decline in lake level in the past 50 years. That means the natural long-term climatic variability provided sufficient rainfall that kept the lake balance around the long-term equilibrium, albeit considerable variability (Becht and Harper, 2002). Given that assumption, what difference irrigation water abstraction from the Lake and the whole Naivasha catchment can make to this equilibrium. We generally expect water abstraction for irrigation to reduce the equilibrium lake level over the 20 simulation periods considered in this study. Still, there will be differences between the proposed scenarios.

Three indicators – lake level, inflows into the lake, and annual lake balance are used to analyze the hydrological sub-system performance, as shown in Figures 3.4 – 3.7. All the water management scenarios considered in this study result in a declining trend in the levels of Lake Naivasha (Figure 4.4). The reference scenario of UWU would, on average, lead to a significant decline in lake level ending up below the red scarcity level of 1884.6 meters above sea level (m.a.s.l), as defined in the WAP. Full enforcement of the nontradable static water right (SWR) yields a slightly better result, yet the scarcity threshold would be violated after the 10th simulation year. If water users were allowed to trade with the static water right (TSWR), it would lead to a further decline in lake level compared to the SWR, with a slight improvement in the rate of decline towards the end of the simulation period as compared to the reference scenario. The reason is that when rights become tradable, farmers whose water use was constrained by water rights would now buy the right and use more water.

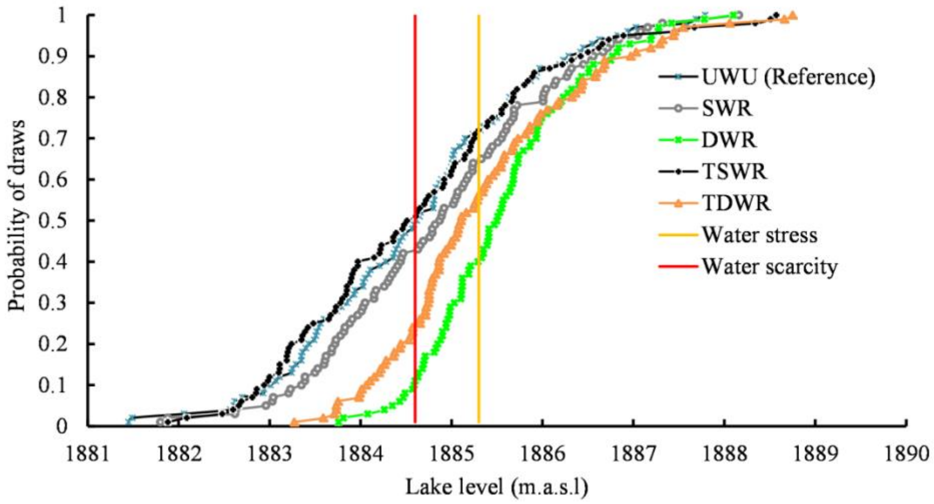
Figure 4.4 Trends in the levels of Lake Naivasha over 20 years of the simulation period. The horizontal lines show the 1884.6 and 1885.3 m.a.s.l water scarcity and water stress level, respectively.



Source: own illustration based on the simulation result

The best result in lake level preservation would be attained when the dynamic water right (DWR) is fully implemented, and trade in this right (TDWR) is allowed among irrigators. Under these two regimes, the water stress threshold level of 1885.3 m.a.s.l (yellow horizontal line) would be violated earlier, after the 10th simulation year. However, the water scarcity level would not be violated during simulation, especially with the DWR. This is because the dynamic water right constraint is applied to irrigators in the lake region growing flowers and vegetables with substantial water use. The dynamic water rights, if fully implemented, would significantly constrain their activity, which would be relaxed if the right becomes tradable.

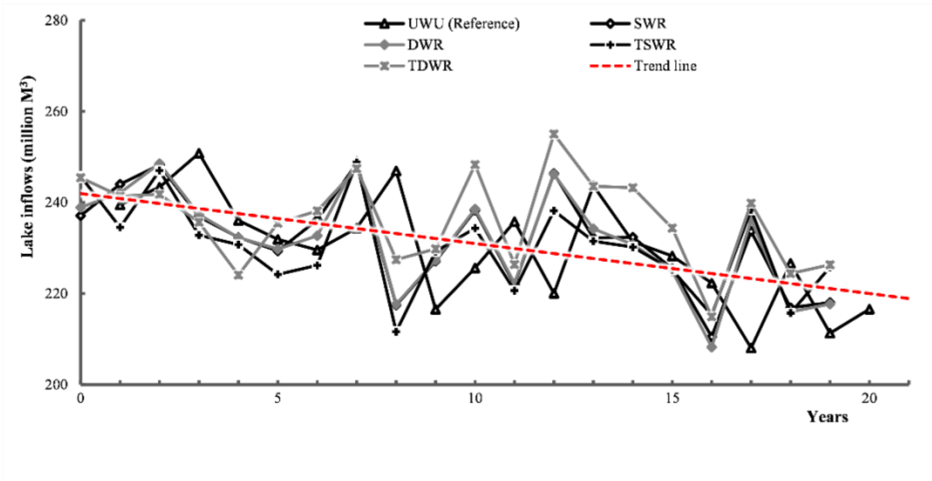
Figure 4.5 Cumulative distribution of the levels of Lake Naivasha (average of 100 stochastic draws over 20 simulation years).



Source: own illustration based on the simulation result

Figure 4.5 compares the cumulative (from 100 stochastic draws) of average lake levels throughout the 20 years. Based on fifty years rainfall variability in the basin and an extrapolation of the current water use trend with no policy constraint, the probability of lake levels to fall below the severe scarcity level in a random draw is about 50% on average across all simulation years and down to below 42.5% if the SWR would be fully enforced. The probability of ending up in severe water scarcity would still be about 50% under TSWR due to increasing water use with trade. However, strict enforcement of the DWR would result in a low probability of violating the scarcity threshold (10%), which increases to less than 25% if trade in this right is allowed. Kuhn et al. (2016) showed a similar effect of human water use. Still, they simulated a low probability of violating the scarcity level, mainly if the static water right would be fully enforced. The difference could be due to the recent irrigation expansion into the upper catchment, which was not considered in their model.

Figure 4.6 Inflows into the Lake in million M^3 per year over the 20 simulation years

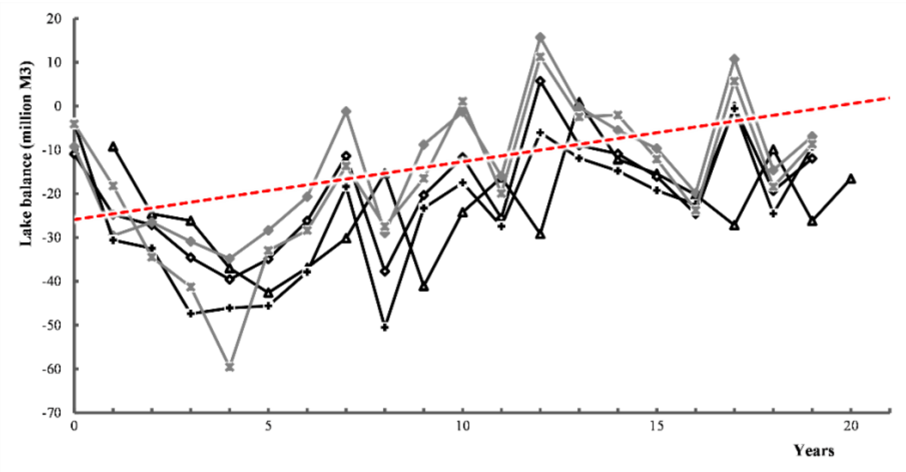


Source: Own illustration based on the simulation result

Inflows into the Lake show a declining trend over the simulation period (Figure 4.6). Compared to other management alternatives, trade with dynamic water rights would induce higher inflows into the Lake. Similarly, the annual lake balance (net gain or loss) would be higher under DWR and TDWR than the reference and other management alternatives (Figure 4.7). The yearly lake balance shows an increasing trend over the simulation years which could be due to the evaporation loss that will decrease proportionally with a shrinking lake surface.

The results presented so far imply two things. First, under the climatic conditions of 1960 to 2010, the continuation of current water use trends in agriculture could lead to more frequent water scarcity situations in the LNB and draw lake levels down from the long-term equilibrium. A new equilibrium at some lower lake level is not achieved across the average of the simulation periods, showing the system needs considerable time to become stable. Second, enforcement of the current static water rights permit or allowing trade with these rights would not be sufficient to address the severe water scarcity or drawdown in the lake levels, but variable water rights and making this right tradeable could be helpful.

Figure 4.7 Annual lake balance (net input-output) in million M^3 over the 20 simulation years



Source: Own illustration based on the simulation result

4.4.2 *Impacts of water rights trade at the basin scale*

This section compares simulation results of aggregate basin water use, irrigated area and cropping patterns, and its impact on agricultural profit under the alternative management scenarios. We will also present and discuss the total water trade activities over the simulation period. Under the baseline scenario, the 1% growth of irrigated area per year, due to technical progress and population growth, will lead to an expansion of irrigated area and linked water use by about 14% and 16%, respectively, as shown in Figure 4.8 and Figure 4.9. Irrigated area expansion and associated water use would be constrained to around 1% and 3%, respectively if the static water right would be fully enforced. The increase in water use and irrigated areas under SWR drops because water use is now limited to monthly water rights, as trading is not allowed. Previous studies report similar impacts of fully implemented fixed water rights, such as Kuhn et al. (2016) for the Lake Naivasha Basin and Rosegrant et al. (2000) for the Maipo river basin in Chile. If trade in the static water right is permitted, irrigated area and water use will expand by 7% and 10%, respectively, showing the water right trade would somewhat relax the water use constraint and improve water use efficiency.

Figure 4.8 Trends in the total irrigation water use in million M^3 over the 20 simulation years

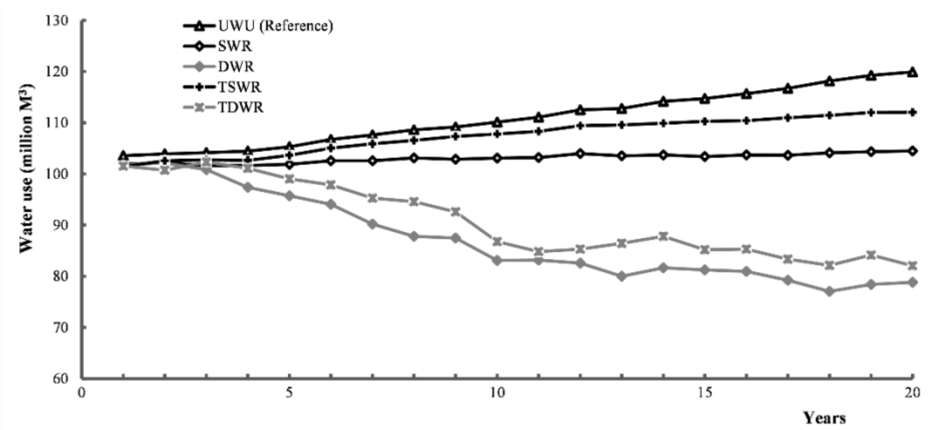
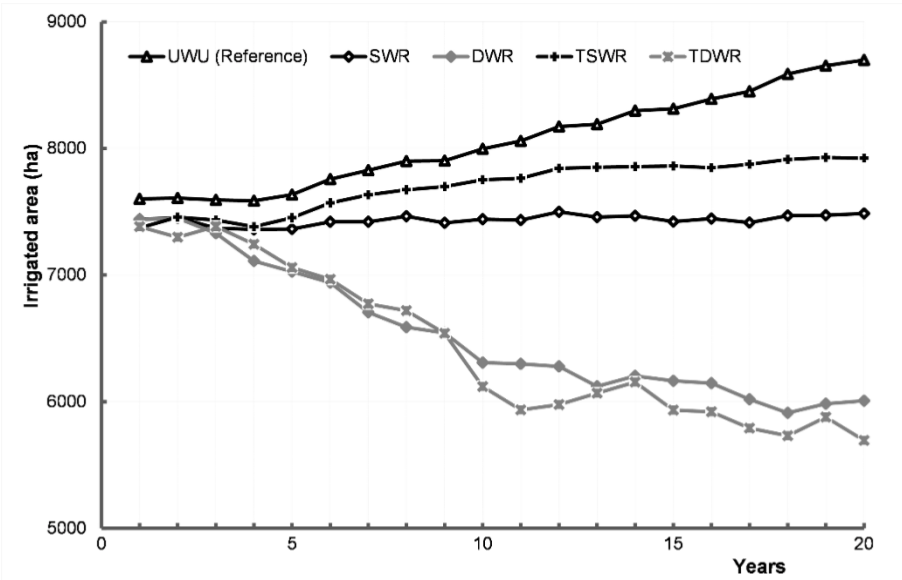


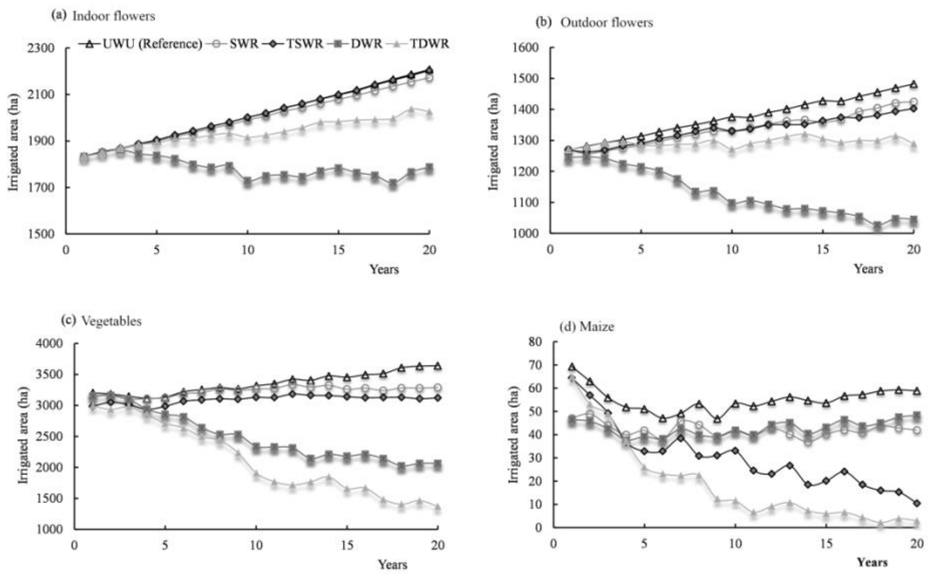
Figure 4.9 Trends in the total irrigated area over the 20 simulation years (ha)



Source: Own illustration based on the simulation result

A significant decrease in water withdrawal and irrigated area is obtained under the dynamic water rights as per WAP. It would decrease the basin water withdrawal by 23% and irrigated area by about 19%. We would expect this since the WAP is implemented in the LaNaWRUA region, where large commercial farms with substantial irrigation water demands are located. Under DWR, their water need is limited to a fraction of their monthly water rights permit depending on the lake level from the end month of the previous simulation year. Allowing water rights trade among irrigators with the dynamic water right (TDWR) would further decline the basin irrigated area by about 23%. The total agricultural water use would decrease by about 19%, which means a 4% growth compared to the non-tradable DWR. Basin irrigated area declines further under TDWR because some WRUAs in the upper catchment can now sell part of their water right to more productive downstream users, thereby reducing their cultivated area and water use.

Figure 4.10 Trends in irrigated area and changes in cropping patterns of major irrigated crops over the 20 simulation years



Source: Own illustration based on the simulation result

As shown in Figure 3.10, this change in water allocation with water rights trade is also reflected in the cropping pattern in the basin. The area allocated to crops with high economic benefits such as indoor and outdoor flowers would not react much to implementing non-tradable and tradable static water rights. In contrast, the vegetable area would decline remarkably, particularly with the water rights trade. Dynamic water rights would induce a substantial decline in the area allocated even to high-value crops. Permitting water rights trade with the dynamic water rights would increase the area allocated to high-value crops such as indoor and outdoor flowers but further decline for vegetables compared to the non-tradable dynamic water right.

Looking at the trends of the area allocated to maize, which is grown mainly by smallholder farmers in the upstream catchment using small-scale irrigation technologies, reveals another interesting pattern. Under UWU, the area under irrigated maize would slightly decline. When non-tradable static and dynamic water rights are implemented, the total area allocated to maize shows a strong decrease in the initial simulation years and becomes steady afterward. However, if the water rights trade is allowed, the opportunity cost of water used to grow this crop would increase because the farmers can sell their water rights to other farmers with higher returns to irrigation farming. As a result, farmers reduce the area planted to maize over the years and ultimately cease production because it has relatively low returns to water use. Similar findings of impacts of water rights markets on cropping patterns were reported for the Maipo River Basin in Chile (Rosegrant et al., 2000). However, this finding should be interpreted cautiously because smallholder farmers may have goals other than profit maximization, such as food self-sufficiency, which our model does not account for.

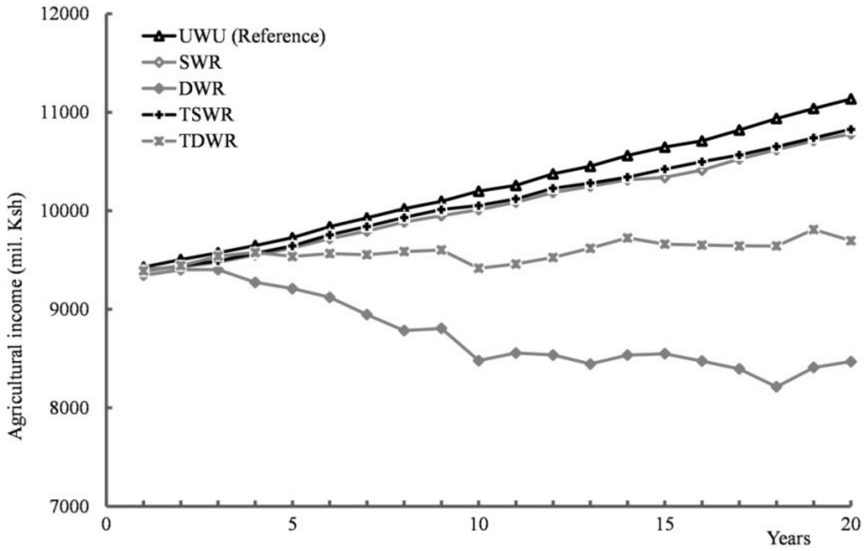
Understanding the impact of changes in water use on economic benefits has important policy implications. Figure 4.10 shows that the basin-wide agricultural profit would increase, on average, by 19% without institutional restrictions. The non-tradable (SWR) and tradable (TSWR) static water rights regime would slightly reduce the growth of agricultural profit compared to the unregulated use, and the profit would increase by about 15% under the two regimes. This may appear to imply that unregulated flow is preferable to regulated water allocation and trading of water rights. However, it is critical to notice the trade-offs. As seen in the previous section, the economic benefit of unregulated water use comes at the expense of a significant decline in the lake level and, thus, unsustainable long-term water use in the basin.

The difference in agricultural profit is very limited under the static and trading of water rights, despite noticeable increases in water use and irrigated areas when the static water right is tradable. As mentioned earlier, this might be because of the existing permit distribution under SWR, which is large enough for some regions, and imposing a water abstraction limit may not severely constrain water demand. Therefore, the demand for water rights and the price for traded water would be lower. This is the case, particularly for LaNaWRUA, where irrigation activities with mainly high-valued crops occur. LaNaWRUA's share of irrigated agricultural income is about 70% within the LNB. As shown in Figure 4.12, water trade activity and total basin water traded under the SWR distributions would be limited compared to the dynamic water right. North-West Lake and South-East Lake WRUAs would buy a substantial share of the traded water in the basin.

As expected, implementing the non-tradable dynamic water right (DWR) would reduce the total growth in agricultural profit by about 9% compared to the reference situation. If the trade of this right (TDWR) is allowed among the irrigators, it will increase the total agricultural profit by about 3%.

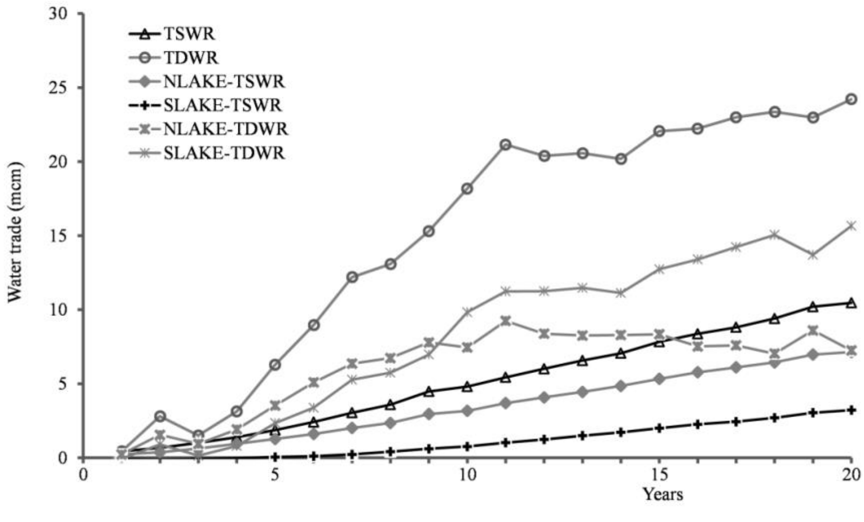
Non-tradable water rights do not allow water transfer to more productive uses. So, as we have seen from the changes in cropping patterns, water use benefits are reduced by locking the resource into relatively low-value uses during a water shortage. By allowing water rights trade among irrigators, water is transferred from less productive agricultural uses and users to more productive and high-value uses by compensating for income loss. This shows that allowing water rights trade among users improves water use efficiency at the basin scale.

Figure 4.11 Trends in total agricultural income over the 20 years



Source: Own illustration based on the simulation result

Figure 4.12 Trends of total water traded in the basin under the two scenarios (TSWR and TDWR) and net water rights bought per year by SELAKE and NWLAKE WRUAs - the two major water users in the lake region over the 20 year



Source: Own illustration based on the simulation result

4.4.3 *Impacts of water rights trade at the WRUA scale*

This section presents and analyzes results on the sub-basin level, focusing on changes in water use, water trade, and its impact on agricultural income. Results presented so far are mainly aggregated for the entire basin and do not reflect potential gains and losses from the water rights trade for sub-catchments or individual WRUAs. An important aspect of results at the sub-basin level is the relative position of the sub-catchment (Figure 4.2), as this may entail both advantages and disadvantages with respect to water availability. Users located upstream have privileged access to river water, as no other user can interfere with their water supply. Still, their relevant sub-catchments are smaller and thus are likely to generate less runoff.

Moreover, even though upstream users might buy water use rights from downstream users, the model does not enable water to be transported upstream, so upstream users would rarely consider buying water rights from downstream users. We thus attribute the 12 WRUAs to three distinct groups of water users: the semi-humid Malewa sub-catchment, 'other sub-catchments encompassing the Gilgil, Mariba and Karati sub-catchments which are semi-arid, and the Lake area (LaNaWRUA), the latter which, in contrast to the two previous groups, offers irrigators access to natural water storage in the form of ground- and lake water. Results are shown in Table 4.2. As for water withdrawal, the horticultural farms of the Lake area would further dominate irrigation water use in the basin. The enforcement of static water rights (SWR) would primarily affect the water use in the catchment and less so in the Lake area. An enforcement of the Water Allocation Plan (DWR) would further reduce water use in the Lake area by 24%. Tradability of both static (TSWR) and dynamic water rights (TDWR) would generally initiate a substantial selling of water rights from the first to groups of subcatchments to the Lake area, most pronounced when the Lake area starts to buy water rights upstream to compensate for the curtailing of initial water use rights under DWR.

Table 4.2 Results for water use, agricultural net revenues, water rights shadow prices, and net water rights trade for distinct groups of sub-catchments for all scenarios [annual averages across 100 draws and 20 simulation years

	Scenarios	**Malewa Sub-catchment (semi-humid)**	**Other Sub-catchments (semi-arid)**	**Lake area (lake or ground-water access)**
Water withdrawal (Mil. M^3) change to UWU in %	UWU	10.7	7.4	92.8
	SWR	-9.2	-8.9	-6.6
	TSWR	-15.6	-14.1	-0.5
	DWR	-8.8	-9.2	-23.9
	TDWR	-44.5	-39.2	-13.3
Agricultural net revenues (Mil. KSh) change to UWU in %	UWU	702.0	617.0	8921.0
	SWR	-4.5	-4.2	-1.5
	TSWR	-1.5	-2.6	-0.5
	DWR	-6.3	-5.6	-15.7
	TDWR	4.2	3.1	-2.9
Water shadow prices (KSh per M^3)	UWU	1.06	1.14	0.96
	SWR	1.21	1.27	2.35
	TSWR	1.09	1.19	1.08
	DWR	1.20	1.25	8.43
	TDWR	3.59	3.69	4.09
Water rights net trade (Mil. M^3)	TSWR	3.62	1.16	-4.77
	TDWR	10.29	4.35	-14.63

Emerging differences in water shadow prices drive water trade. Under UWU, differences between regions located upstream and downstream are not pronounced. The reason is that being located upstream offers privileged access to water but at the same time entails access to a much smaller area collecting runoff from rainfall. Introducing the different water use rights regimes changes this: under SWR, for instance, the marginal value of water in the Lake area becomes twice as high as in the other two groups. The introduction of the water rights trade (TSWR) then largely (re-) equalizes water shadow price levels. Enforcement of the Water Allocation Plan

(DWR) would curtail water use in the Lake area, albeit temporarily and massively increasing water scarcity and shadow prices. Then allowing WRUAs to trade water rights would largely equalize water shadow price levels again, but on a much higher level, driven by the 'administrative' water scarcity in the Lake area. The changes in average net revenues are plausible across the scenarios. While the introduction of water rights lets revenues drop for all regions, the introduction of the trade then improves the situation for all participants (SWR vs. TSWR and DWR vs. TDWR).

In the water rights trading scenarios, an interesting result emerges when we compare changes in water use and volumes of water traded. As Britz et al. (2013) indicated, in a water scarcity situation where potential sellers have more water rights than actual water available, the buyers are compelled to purchase more water rights than they intend to use. This is to prevent the sellers from restricting water use downstream by utilizing the scarce water within their remaining water rights. Simply put, buyers must over-buy to ensure that enough water arrives at their location, even if it is only a fraction of the obtained water rights. This behavior increases average water shadow prices, especially in the TDWR scenario, where only the water rights of the buyers (Lake region WRUAs) have been reduced and not those of the sellers in the upper catchment. In this case, the lake area purchases 14.6 million M^3 but uses only an additional 9.8 million M3 compared to DWR (same rights regulation, but without trade). That means roughly 33% overbuying was required on average years and draws. Accordingly, the water rights sellers could sell 14.6 million M^3 while reducing their remaining water use by 6.0 million M^3. This effect has far-reaching implications for the design of regional water use and trading policies. This can only be simulated in a simultaneous optimization model with independently acting agents, as used in this study.

4.5 Conclusion

Using a hydro-economic river basin model for the Lake Naivasha Basin (LANA-HEBAMO), we simulate water allocation decisions under different institutional arrangements and stochastic rainfall. We analyze the potential benefit of introducing tradable water rights in the Lake Naivasha Basin as an alternative water management option to the existing permit system. We chose unregulated water use as the most realistic reference situation. The simulation model is set up as an individual optimization problem, benefiting from recent developments in mathematical programming that allow the solution of Multiple Optimization Problems with Equilibrium Constraints (MOPEC). This framework enabled us to integrate each user's decision-making calculus separately within a partial equilibrium model.

Our simulation reveal some patterns with relevant policy implications for water allocation. In terms of economic impacts, the unregulated flow option provides the highest benefit among all water allocation scenarios. The gain, however, comes at the expense of a significant drop in the lake level, which is an undesirable and unsustainable long-term outcome. As a result, water allocation policy design must account for such trade-offs in economic and hydrological impacts.

Compared to the existing fixed water rights, allowing trade in water rights would increase the basin-wide benefit of water use by shifting water into higher-valued agricultural uses. Agricultural profit, for most demand regions, increased under tradable water rights compared to the non-tradable static and dynamic water rights. Dynamic water rights, which restrict water use during meteorological water scarcity situations, further reduce water use and agricultural income compared to static water rights. However, allowing trade in this dynamic water right among water users would reduce the decline in agricultural profit, highlighting an improvement in water use efficiency. Moreover, according to the WAP, water allocation would prevent a severe lake level decline and increase inflows into the lake, albeit at the cost of decreased water availability for irrigation. Again, this clearly shows the trade-offs between protecting the ecosystem and foregone production and income opportunities resulting from this regime. However, allowing water rights trade among irrigators would result in much better results by reducing the tradeoffs and maximizing synergies from water allocation to agriculture and the environment. That does not mean that water trade would not allow economic leakage effects. The necessary over-buying of water rights in water scarcity situations creates rents on sellers that might be considered undesirable. Maximum benefits could be achieved by adjusting tradable water rights based on current water availability; however, this policy may be more challenging to implement, monitor, and enforce. Nonetheless, fully implementing the Water Allocation Plan, extending it to the upstream users, and allowing trade in this right, would benefit the Lake Naivasha Basin's efficient and sustainable use of water resources.

4.6 **References**

Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop evapotranspiration - Guidelines for computing crop water requirements - FAO Irrigation and drainage paper 56.

Barbier, E., 2019. The Water Paradox: Overcoming the Global Crisis in Water Management. Yale University Press.

Bauer, C.J., 2004. Results of Chilean water markets: Empirical research since 1990: RESULTS OF CHILEAN WATER MARKETS. Water Resour. Res. 40. https://doi.org/10.1029/2003WR002838

Becht, R., 2007. Environmental Effects of the Floricultural Industry on the Lake Naivasha Basin.

Becht, R., Harper, D.M., 2002. Towards an understanding of human impact upon the hydrology of Lake Naivasha. Hydrobiologia 488, 1–11.

Bekchanov, M., Bhaduri, A., Ringler, C., 2015a. Potential gains from water rights trading in the Aral Sea Basin. Agric. Water Manag. 152, 41–56. https://doi.org/10.1016/j.agwat.2014.12.011

Bekchanov, M., Bhaduri, A., Ringler, C., 2015b. Potential gains from water rights trading in the Aral Sea Basin. Agric. Water Manag. 152, 41–56. https://doi.org/10.1016/j.agwat.2014.12.011

Bjornlund, H., McKay, J., 2002. Aspects of water markets for developing countries: experiences from Australia, Chile, and the US. Environ. Dev.

Econ. 7, 769–795. https://doi.org/10.1017/S1355770X02000463

Britz, W., Ferris, M., Kuhn, A., 2013. Modelling water allocating institutions based on Multiple Optimization Problems with Equilibrium Constraints. Environ. Model. Softw. 46, 196–207. https://doi.org/10.1016/j.envsoft.2013.03.010

Brook, A., Kendrick, D., Meeraus, A., 1988. GAMS, a User's Guide. SIGNUM Newsl 23, 10–11. https://doi.org/10.1145/58859.58863

Calatrava, J., Martínez-Granados, D., 2017. The limited success of formal water markets in the Segura River basin, Spain. Int. J. Water Resour. Dev. 1–21. https://doi.org/10.1080/07900627.2017.1378628

De Jong, T., 2011. Water abstraction survey in Lake Naivasha basin, Kenya (BSc Internship thesis). Wageningen University, Wageningen.

Debaere, P., Richter, B.D., Davis, K.F., Duvall, M.S., Gephart, J.A., O'Bannon, C.E., Pelnik, C., Powell, E.M., Smith, T.W., 2014. Water markets as a response to scarcity. Water Policy 16, 625–649. https://doi.org/10.2166/wp.2014.165

Dinar, A., Rosegrant, M.W., Meinzen-Dick, R.S., 1997. Water allocation mechanisms: principles and examples. World Bank Publications.

Doorenbos, J., Kassam, A.H., 1979. Yield response to water. Yield Response Water.

Dozier, A.Q., Arabi, M., Wostoupal, B.C., Goemans, C.G., Zhang, Y., Paustian, K., 2017. Declining agricultural production in rapidly urbanizing semi-arid regions: policy tradeoffs and sustainability indicators. Environ. Res. Lett. 12, 085005. https://doi.org/10.1088/1748-9326/aa7287

Easter, K.W., Rosegrant, M.W., Dinar, A., 1999. Formal and informal markets for water: institutions, performance, and constraints. World Bank Res. Obs. 14, 99–116.

Easter, K.W., Rosegrant, M.W., Dinar, A., 1998. Markets for water: Potential and performance. Springer Science & Business Media.

Eheart, J.W., Lyon, R.M., 1983. Alternative structures for water rights markets. Water Resour. Res. 19, 887–894. https://doi.org/10.1029/WR019i004p00887

Erfani, T., Binions, O., Harou, J.J., 2014. Simulating water markets with transaction costs. Water Resour. Res. 50, 4726–4745. https://doi.org/10.1002/2013WR014493

Ferris, M.C., Dirkse, S.P., Jagla, J.-H., Meeraus, A., 2009. An extended mathematical programming framework. Comput. Chem. Eng. 33, 1973–1982. https://doi.org/10.1016/j.compchemeng.2009.06.013

Ferris, M.C., Munson, T.S., 2000. Complementarity problems in GAMS and the PATH solver 24.

Grafton, R.Q., Libecap, G., McGlennon, S., Landry, C., O'Brien, B., 2011. An Integrated Assessment of Water Markets: A Cross-Country Comparison. Rev. Environ. Econ. Policy 5, 219–239. https://doi.org/10.1093/reep/rer002

Griffin, R.C., Hsu, S.-H., 1993. The Potential for Water Market Efficiency When Instream Flows Have Value. Am. J. Agric. Econ. 75, 292. https://doi.org/10.2307/1242913

Harper, D.M., Morrison, E.H.J., Macharia, M.M., Mavuti, K.M., Upton, C., 2011. Lake Naivasha, Kenya: Ecology, Society and Future. Freshw. Rev. 4, 89–114. https://doi.org/10.1608/FRJ-4.2.149

Hearne, R.R., Easter, K.W., 1997. The economic and financial gains from water markets in Chile. Agric. Econ. 15, 187–199.

Heckelei, T., 2002. Calibration and estimation of programming models for agricultural supply analysis (Habilitation Thesis). University of Bonn, Germany.

Heckelei, T., Wolff, H., 2003. Estimation of constrained optimisation models for agricultural supply analysis based on generalised maximum entropy. Eur. Rev. Agric. Econ. 30, 27–50. https://doi.org/10.1093/erae/30.1.27

Howitt, R.E., 1995. Positive Mathematical Programming. Am. J. Agric. Econ. 77, 329. https://doi.org/10.2307/1243543

KNBS, 2009. Population and Housing Census.

Kuhn A., Britz W., 2012. Can hydro-economic river basin models simulate water shadow prices under asymmetric access? Water Sci. Technol. 66, 879–886. https://doi.org/10.2166/wst.2012.251

Kuhn, A., Britz, W., Van Oel, P.R., Meins, F.M., 2014. The Lake Naivasha Hydro-economic Basin Model (LANA-HEBAMO) - a Technical Documentation, Version 04/2014. DFG Research Unit 1501, Sub-Project B2, (No. Technical Paper 10).

Kuhn, Arnim, Britz, W., Willy, D.K., van Oel, P., 2016b. Simulating the viability of water institutions under volatile rainfall conditions – The case of the Lake Naivasha Basin. Environ. Model. Softw. 75, 373–387. https://doi.org/10.1016/j.envsoft.2014.08.021

Livingston, M.L., 1995. Designing water institutions: Market failures and institutional response. Water Resour. Manag. 9, 203–220. https://doi.org/10.1007/BF00872129

Mekonnen, M.M., Hoekstra, A.Y., Becht, R., 2012. Mitigating the Water Footprint of Export Cut Flowers from the Lake Naivasha Basin, Kenya. Water Resour. Manag. 26, 3725–3742. https://doi.org/10.1007/s11269-012-0099-9

Odongo, V.O., van der Tol, C., van Oel, P.R., Meins, F.M., Becht, R., Onyando, J., Su, Z., 2015. Characterisation of hydroclimatological trends and variability in the Lake Naivasha basin, Kenya. Hydrol. Process. 29, 3276–3293. https://doi.org/10.1002/hyp.10443

Otiang’a-Owiti, G.E., Oswe, I.A., 2007. Human impact on lake ecosystems: the case of Lake Naivasha, Kenya. Afr. J. Aquat. Sci. 32, 79–88. https://doi.org/10.2989/AJAS.2007.32.1.11.148

Ringler, C., von Braun, J., Rosegrant, M.W., 2004. Water Policy Analysis for the Mekong River Basin. Water Int. 29, 30–42. https://doi.org/10.1080/02508060408691746

Rosegrant, M.W., Binswanger, H.P., 1994. Markets in tradable water rights: Potential for efficiency gains in developing country water resource allocation. World Dev. 22, 1613–1625. https://doi.org/10.1016/0305-750X(94)00075-1

Rosegrant, M.W., Ringler, C., McKinney, D.C., Cai, X., Keller, A., Donoso, G., 2000. Integrated economic-hydrologic water modelling at the basin scale: The Maipo River basin. Agric. Econ. 24, 33–46.

Trabucco, A., Zomer, R.J., 2010. Global High-Resolution Soil-Water Balance Geospatial Database.

van Oel, P.R., Mulatu, D.W., Odongo, V.O., Meins, F.M., Hogeboom, R.J., Becht, R., Stein, A., Onyando, J.O., van der Veen, A., 2013. The Effects of Groundwater and Surface Water Use on Total Water Availability and Implications for Water Management: The Case of Lake Naivasha, Kenya. Water Resour. Manag. 27, 3477–3492. https://doi.org/10.1007/s11269-013-0359-3

Verschuren, D., Laird, K.R., Cumming, B.F., 2000. Rainfall and drought in equatorial east Africa during the past 1,100 years. Nature 403, 410–414.

Verstoep, J., 2015. Challenges in water management in the Lake Naivasha Basin : Analysis on the effects and performance of IWRAP for different irrigation water user groups in the Lake Naivasha Basin, Kenya (MSc Thesis). Wageningen University.

Wanjala, S., Mwinami, T., Harper, D.M., Morrison, E.H.J., Pacini, N., 2017. Ecohydrological tools for the preservation and enhancement of ecosystem services in the Naivasha Basin, Kenya. Ecohydrol. Hydrobiol.

Willy, D.K., 2013. Institutional Analysis of Agri-Environmental Externalities - Issues on Collective Action and Technology Diffusion in the Lake Naivasha Basin, Kenya 210.

WRMA, 2010. Water Allocation Plan - Naivasha basin 2010 - 2012. Naivasha, Kenya.

WRMA, 2009. Water Allocation Guidline. Naivasha, kenya