

ADDIS ABABA UNIVERSITY INSTITUTE OF TECHNOLOGY
SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

OPTIMIZATION OF WATER RESOURCE SYSTEM FOR PRODUCTIVITY: RESOURCE AND DEMAND ASSESSMENT, PERFORMANCE EVALUATION, AND ALLOCATION IN RIFT VALLEY BASIN, ETHIOPIA.

Dissertation research for the partial fulfilment of PhD degree in Hydraulic Engineering

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OPTIMIZATION OF WATER RESOURCE SYSTEM FOR PRODUCTIVITY: ASSESSMENT, EVALUATION, AND ALLOCATION IN RIFT VALLEY BASIN, ETHIOPIA.

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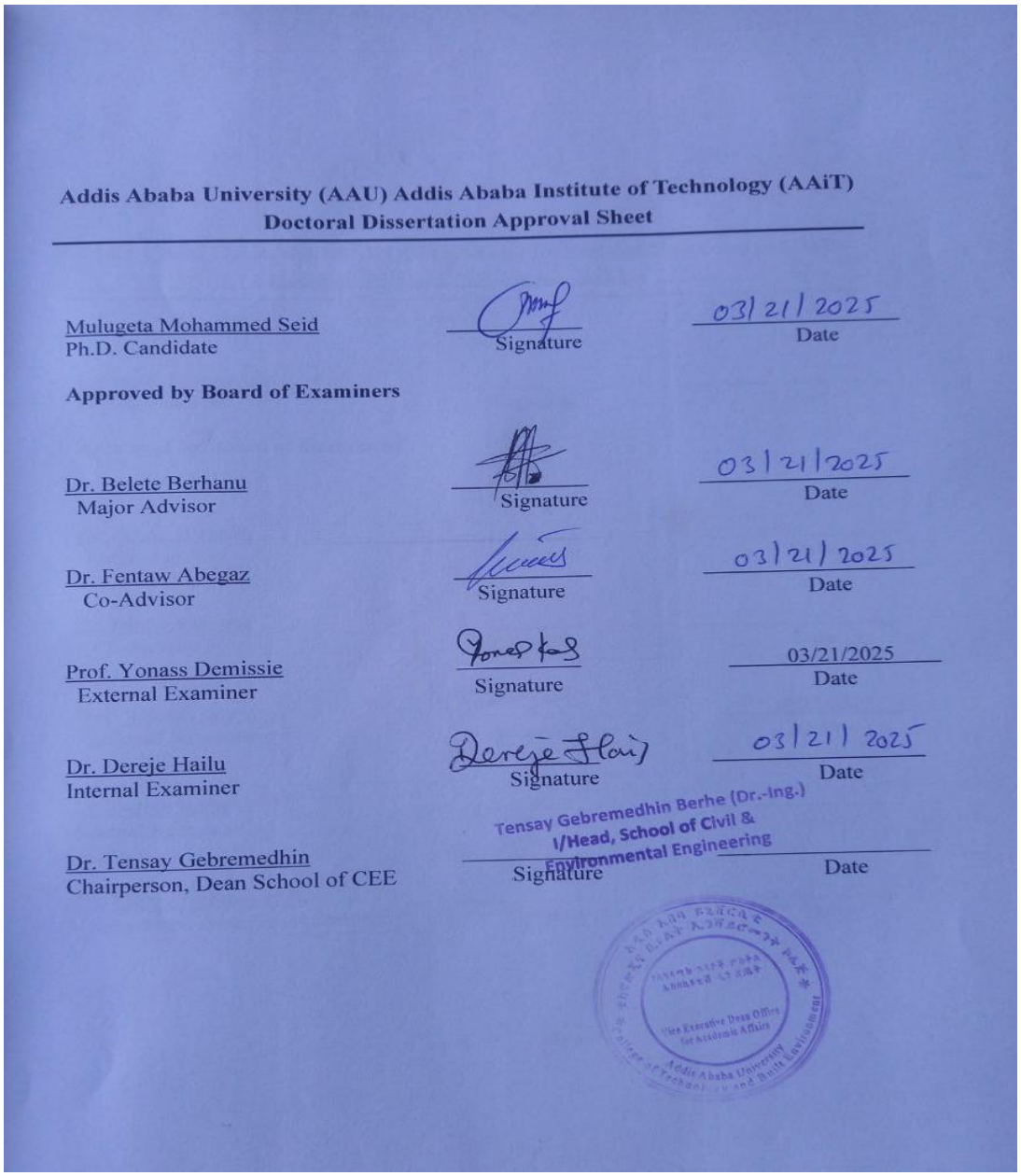
Dedication

This dissertation is dedicated to the loving memory of my beloved younger brother, **Fikadu Gebre**, who left this world too soon at 30. A brilliant Electrical Engineer and a dedicated lecturer at Dire Dawa University, his passion for knowledge, commitment to education, and unwavering support have guided my academic journey.

Though his time with us was short, his impact was profound. His wisdom, kindness, and dreams continue to inspire me every day. His spirit lives on in my heart and in the work I have accomplished. May this achievement serve as a tribute to his life, his contributions, and the legacy he left behind.

Rest in peace, dear brother.

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SUMMARY

Developing an optimized water allocation model that includes a comprehensive assessment of water demand and resources, as well as system performance evaluation, to enhance water productivity and sustainability in the basin is the main objective of this study. Because it addresses the challenges of inconsistent water availability data, evaluates the water resource system's performance, and proposes solutions for optimized economic efficiency and environmental sustainability.

This study examines the optimization of water resource systems in the Rift Valley Lakes Basin (RVLB) of Ethiopia, with a focus on enhancing water productivity, economic efficiency, and environmental sustainability. The research addresses critical challenges such as water scarcity, inefficient resource use, climate variability, and environmental degradation, which collectively threaten the socio-economic development and ecological health of the basin.

The study also employs advanced tools such as the Water Evaluation and Planning (WEAP) model and multispectral remote sensing to assess the basin's water resources and demand. A comprehensive hydrological analysis reveals that while the RVLB receives substantial rainfall annually, the majority is lost through evaporation, leaving limited surface and groundwater resources for abstraction. Irrigated agriculture, which consumes the largest share of water, is characterized by inefficiencies due to traditional irrigation practices and inadequate infrastructure.

A detailed mapping of irrigated areas using Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) techniques highlights discrepancies in reported data and demonstrates the value of remote sensing for accurate resource management. The water demand analysis projects a significant increase in demand by 2050 due to population growth and expanded irrigation, underscoring the urgent need for strategic interventions.

The research evaluates the water resource system's performance through indicators such as reliability, resilience, and vulnerability, revealing gaps in the current system. To address these challenges, a multi-objective optimization model based on the NSGA-II approach is developed. This model balances competing objectives such as economic returns, equity, and sustainability, providing decision-makers with actionable insights into efficient water allocation strategies.

Key recommendations include the development of integrated water resource management (IWRM) policies, investments in modern irrigation and storage infrastructure, and the enhancement of data collection and monitoring systems using GIS and remote sensing technologies. Additionally, stakeholder engagement, climate-resilient planning, and environmental protection measures are emphasized. Strategic interventions must align with projected demands while ensuring equitable and sustainable resource use.

This study contributes significantly to water resource management by providing a holistic framework for optimizing allocation and enhancing productivity. Its findings and recommendations serve as a roadmap for policymakers, stakeholders, and researchers, offering solutions to safeguard the RVLB's water resources and promote sustainable development. The major findings are:

- The current irrigated area of the RVLB is 108,000 ha, estimated using multispectral satellite imagery and ground truth verification and the potential irrigable area is 230,400 ha.
- The basin receives 50.03 BCM of mean annual precipitation, with 83% (41.32 BCM) lost to evaporation. And the available surface water for abstraction includes 358 MCM from lakes and 6,534 MCM from streamflow, totalling 6,892 MCM.
- The total current water demand is 1,796.34 MCM, with irrigation taking the largest share (58%), followed by livestock (13%). Agricultural water demand accounts for 71% of total demand. Seasonal water deficits occur, especially in January (329 MCM demand vs. 216 MCM supply) and December (304 MCM demand vs. 250 MCM supply). The projected demand for 2035 ranges from 1,628.23 MCM to 3,146.89 MCM, depending on different scenarios.
- Water productivity varies from 0.7 kg/m³ to 1.58 kg/m³, with an average of 1.13 kg/m³.
- A multi-objective optimization model (NSGA-II) was developed to balance economic efficiency, equity, and environmental sustainability. Pareto front solutions: If the goal is to minimize f_1 (maximizing economic return), solution S_1 can be chosen, as it is preference degree for f1 is 0.995, while for f_2 (maximizing equity) it is only 0.005. Similarly, if the aim is to maximize f_2, S_{20} is ideal, with a preference degree of 0.992 for f_2 and just 0.008 for f_1. For decision-makers who value both objectives equally, S10 is recommended, as it is preference degree for f_1 (0.566) is closest to that for f_2 (0.434) among all non-inferior solutions.

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LIST OF SYMBOLS

Dw	Deepwater capacity
f	preferred flow direction
Kc	Crop coefficient
Kd	Deep Conductivity
Ks	Root zone conductivity
R2	coefficient of determination
Sw	Soil Water Capacity
α	Reliability
γ	Resilience
δ	Sensitivity ratio
ε	Dimensionless sensitivity ratio
ύ	Vulnerability
ω	Bias degree

LIST OF ACRONYMS

AIT	Advanced Irrigation Technology
BCM	Billion Cubic Meter
CC	Climate Change
CD	Crawling Distance
CHRIPS	Climate Hazard Group Infrared with Station
CLD	Causal Loop Diagram
CSA	Central Statistics Agency
CWR	Crop Water Requirement
EFR	The Environmental Flow Requirement
EIAR	Ethiopian Institute Of Agricultural Research
ETc	Crop Evapotranspiration
ETo	Reference Evapotranspiration
EVI	Enhanced Vegetation Index
FAO	Food And Agriculture Organization
GDP	Gross Domestic Product
GTP-II	Growth And Transformation Plan
GIRDC	Generation Integrated Rural Development Consultant
IA	Index of Agreement
IAE	Irrigated Area Expansion
IHA	Indicators of Hydrologic Alteration
IWRM	Integrated Water Resource Management
JICA	Japan International Corporation Agency
LAI	Leaf Area Index
LGP	Length of Growth Period
LULC	Land Use Land Cover
MCM	Million Cubic Meter
MoA	Ministry of Agriculture
MODIS	Moderate Resolution Imaging Spectroradiometer
MOP	Multi-Objective Programming
MoWE	Ministry Of Water and Energy
MoWIE	Ministry Of Water Irrigation and Electric
NDVI	Normalized Difference of Vegetation Index
NMA	National Meteorology Agency
NSE	Nash-Sutcliffe Efficiency
NSGA	Non-Sorting Genetic Algorithm
OIDA	Oromia Irrigation Development Authority
RGB	Red, Green, Blue
RMSE	Root Mean Square Error
RRF	Runoff Resistance Factor
RSR	Standard Deviation Ratio
RVLB	Rift Valley Lakes Basin
SD	System Dynamics
SEI	Sweis Environment Institute
SFD	Stock Flow Diagram
SWAT	Soil and Water Assessment Tool
TLU	Tropical Livestock Unit
WaPOR	Water Productivity
WHO	World Health Organization
WLRC	Water And Land Resource Center
WP	Water Productivity
WEAP	Water Evaluation and Planning

CHAPTER 1: INTRODUCTION

1.1. BACKGROUND

Ethiopia, often referred to as the "Water Tower of Africa," is endowed with abundant water resources due to its unique topography, climatic diversity, and extensive river systems. Ethiopia's water resources are critical for sustaining its ecosystems, agriculture, energy production, and socio-economic development, the water sources are characterized by significant spatial and temporal variability, influenced by diverse environmental and climatological factors. The Rift Valley Lakes Basin (RVLB) is one of twelve major river basins in Ethiopia. The basin is considered a high priority because it is an area of significant ecological and environmental interest, with a system of lakes and wildlife parks and reserves, has substantial areas of productive rainfed agricultural land and good rangelands. Based on the masterplan study report (Halcraw and GIRDC, 2009) the RVLB has an estimated annual per capita water availability of 420m3, already in a water scarcity situation. This will continue to decline as the population grows. And not more than 30% of the basin is under cultivation and food security is a problem in the basin. The RVLB is not considered an area of high potential for hydropower development because it lacks the physical attributes necessary for production. However, there is some potential for developing hydropower, especially if it is combined with other objectives, such as irrigation (Halcraw and GIRDC, 2009).

The climate within the RVLB varies broadly categorized into two main zones. The semi-arid climate is predominant in the lowland areas surrounding the lakes, characterized by lower rainfall and higher temperatures while tropical humid to dry sub-humid climate is found in the highland regions, with relatively higher rainfall and moderate temperatures. The Basin experiences a bimodal rainfall pattern a long rainy season from June to September and a shorter rainy season from March to May, interspersed with dry periods. This variability in climate influences water availability and has implications for agricultural productivity and water resource management (Mersha et al., 2023). The RVLB is a hub of socio-economic activities, with communities relying heavily on its water resources for agriculture, fishing, and livestock rearing. Rapid socio-economic development in the region has increased pressure on water resources, leading to challenges such as over-extraction, pollution, and conflicts among different water users. Effective water resource management is essential to balance the competing demands and ensure sustainable utilization of the basin's water resources(Ayalew et al., 2023).

Industry may be built on a wide range of natural resources, such as lakes, fisheries, forestry, mining, and agriculture. The basin's industry is focused on agricultural products, and efforts to utilize its other natural resources some mineral resources and some tourism have only been sporadically made thus far. There is a good chance that the Rift Valley Lakes Basin (RVLB) will see an increase in tourism. The living culture, animals (including mammals, birds, and reptiles), geography and breathtaking beauty, boating, swimming, fishing, hot springs, waterfalls, canyons, and different arts and crafts are all popular tourist destinations. The RVLB is also home to a variety of natural ecosystems, including marshes, woods, and grasslands (Halcraw and GIRDC, 2009).

The RVLB is primarily an agricultural basin and agriculture will continue to be an important part of the economy. Related sectors of livestock and industry based on the processing of agricultural and livestock products will also be of importance. Most of the agriculture in the RVLB is subsistence farming. Subsistence agriculture is not a basis for economic growth and social development. It is well known to perpetuate poverty simply because farmers cannot create a buffer to protect themselves from the impact of poor crop years. So, while agriculture will remain important there will need to be a move away from subsistence agriculture and toward more commercial, market-oriented agriculture. The main characteristic of agriculture in the basin is low productivity. Partly this is due to the fact that most are rainfed. There is a strong correlation between GDP and annual rainfall in Ethiopia and this will continue unless changes are made in the approach to agriculture. Rainfed agriculture, which predominates in the basin, is not a bad thing in itself, except that land pressure has moved new farms to marginal areas where rainfall may be insufficient or unreliable. There is some potential to increase the area under irrigation, but all new irrigation must be developed with caution as all water abstractions will impact the sensitive lakes of the RVLB and may not be sustainable. Agriculture in the basin will remain predominantly rainfed, enhanced where possible with rainwater harvesting and other small-scale interventions (MoWR, 2010).

In relation to the ideas raised in the above paragraphs, sustainable utilization of the available water resources in Ethiopia at large and in Rift Valley Lakes Basin especially is crucial in addressing the concerns. Among the computing sectors for water, agriculture takes a significant share, while other sectors such as industry, urban water supply, hydropower, tourism and environment have also increased their shares with the increase of population, urbanization, and expansion of industrialization. Considering the climate change and variability, and existing and future demand for water in the sectors, developing an optimized water resource development system and improving the water resource system performance is a must.

The information regarding the water availability of the water resources in the basin lacks consistency, efforts made to come up with reliable data on the water resource potential of the basin have limitations such as discrepancies, for example (Halcraw and GIRDC, 2009) reported the basin has a water resource potential of 5.3BCM, while the (JICA, 2012) report stated the river basin has a water resource potential of 3.5BCM and (Ermias Mekonin, 2019) reported the basin's water resource potential is about 6.12BCM, other efforts made to estimate the water resource potential of the basin were scattered and based on fragmented catchments and most of the results negate the findings of the masterplan study report. Hence, it was necessary to make a comprehensive assessment of the existing water resource potential and the water demand of the major computing sectors in the basin with the spatial and temporal distribution. The river basin water resource system has to be evaluated for its performance, and studies regarding the water resource system performance are not available, this study conducted a performance evaluation with water productivity, resilience, reliability and vulnerability of the basin. The available water resource of the basin should be allocated to the sectors bearing in mind the improvement of water productivity optimized economic efficiency and environmental sustainability.

1.2. STATEMENT OF THE PROBLEM

The master plan study for the Rift Valley Lakes basin was conducted by (Halcraw and GIRDC 2009). According to the study the basin area covers about 53,000 km2, during the masterplan study time, the total population was estimated at 8.9 million and is expected to reach 19 million by 2025. The study further stated that, unlike other river basins, the Rift Valley basin has limited water resources for development. The basin has been threatened by land degradation due to soil erosion and deforestation. Moreover, the master plan study raised climate change, drought risk, population growth, low agricultural productivity, land tenure, low productivity and overpopulation of livestock, limited water resources and management, overgrazing and declining biomass, soil erosion and land degradation, water quality, and public health, depletion of fish stocks, loss of wildlife biodiversity, poor economic infrastructure, inadequate education services, inadequate health services, and limited institutional capacity were the major issues should be addressed in the basin. The masterplan study from fifteen years ago laid the groundwork for understanding water resource management in the basin. Nonetheless, it revealed several limitations. The emergence of advanced data collection and analysis techniques now enables more precise and comprehensive water resource estimation, underscoring the need for a new and updated assessment. Additionally, the master plan study lacked a strategic approach to water allocation and did not include demand estimation, leading to suboptimal management practices. Present technological advancements make it possible

to devise more effective allocation strategies and accurately estimate water demand, thereby addressing the deficiencies of earlier methodologies.

Other studies showed that the water resources system of the basin is characterized by overexploitation of water resources, poor water quality, sensitivity to the climatic situation, high livelihood dependency on water resources, and environmental degradation (Abera Hirpo, 2016; Graichen, 2014.; JICA, 2012; Mulugeta Dadi, 2015; Pascual-Ferrer et al., 2014). The studies focused more on the water management aspect and evaluated the water management system of the basin's lack of organized planning, regulated, and monitoring systems. Uncontrolled and over-abstraction of water from the lakes is also another big challenge for the lakes in the Rift Valley and over 9,000 small pumps are reported to abstract water from a single lake Ziway on the inventory conducted (GIRDC, 2020). The above problems of water level reduction and pollution of the aquatic ecosystem are closely related to the land use land cover (LULC) of the surrounding terrestrial environment (Desta et al. 2020; Elias et al. 2019). Climate change is also another threat to the Rift Valley Lakes basin (Abraham et al. 2021). It is largely agreed that the major cause for the accelerated water quality degradation of the lakes in the basin is human intervention and land use changes removal of vegetation cover, irrigation, diversion of inflows, and industrial use of the water are the causes for decline in water quality that would have various implications on the biodiversity of the lake. The application of agrochemicals and fertilizers due to the intensification of irrigation practices around the lakes has also increased and affected the water chemistry of the lake (Desta and Lemma, 2017; Getu, 2009; Girma, 2015; Haile and Mohammed, 2019; Hengsdijk et al., 2009; Mekuyie, 2014; Zigde and Tsegaye, 2019). Most of the studies were fragmented and tried to address more specific issues. They used the RVLB master plan as the base information source and their findings area against the masterplan expectations.

Most irrigation in the RVLB is done using surface irrigation methods, which have low water use efficiency due to evaporation and conveyance losses in unlined canals. Poor irrigation scheduling and lack of knowledge about crop water requirements also contribute to inefficient water use, leading to water wastage (Amede et al., 2019). Farmers in the basin often lack access to improved seeds, fertilizers, and water-efficient technologies. Without these inputs, achieving high water productivity is difficult. High costs and limited availability of these resources prevent farmers from adopting better practices (Deressa et al., 2011). WUAs and local agricultural extension services cannot often manage water resources efficiently or provide farmers with adequate support. This gap contributes to poor resource management and restricts productivity improvements.

Studies have found that only about 30-40% of the irrigation water is effectively used for crop production in the RVLB, leading to inefficiencies and water scarcity (Awulachew and Ayana, 2011). Water and land productivity in the Basin remain low due to poor irrigation practices, soil degradation, and limited access to improved technologies. Traditional flood irrigation, which dominates, results in inefficient water usage and low productivity levels. Crop yields are inconsistent and threatened by soil erosion and nutrient loss, aggravated by inadequate water management and unsustainable farming methods (FAO, 2022).

There is a pressing need for a comprehensive assessment of both water demand and available resources to address these challenges. Additionally, evaluating the performance of the existing water resource systems is crucial to identify gaps and inefficiencies. Optimizing water allocation strategies is also necessary to ensure sustainable water use that meets the diverse needs of the population, agriculture, and the environment. This research aims to provide a thorough analysis and propose solutions for improving water productivity and resource management in the Rift Valley Lakes Basin, contributing to the basin's socio-economic development and environmental sustainability.

1.3. GENERAL OBJECTIVES

To develop an optimized water allocation system that integrates hydrological, economic, and environmental sustainability principles, leveraging multi-objective optimization techniques to enhance water productivity and improve the resilience of the Rift Valley Lakes Basin's water resource system. Provide insights by assessing system performance under various future scenarios and introducing a decision-support tool that enables policymakers to balance trade-offs between economic efficiency, equity, and environmental sustainability in water resource management.

1.3.1. Specific objectives

- To conduct a comprehensive analysis of the basin's hydrological dynamics to enhance the understanding of water resource availability and variability, providing insights into the basin's response to hydrological and climatic factors.
- To estimate the irrigated area and sectoral water demand using advanced modelling approaches, contributing to improved precision in water allocation assessments and future planning.

- To evaluate the performance of the basin's water resource system in terms of reliability, resiliency, vulnerability, and water productivity.
- To develop an optimized water allocation model that integrates hydrological, economic, and environmental considerations, serving as a decision-support tool to enhance water productivity, economic efficiency, and sustainability in the basin.

1.4. RESEARCH QUESTIONS

1. How much is the water resource potential of the basin?
2. How much is the current irrigated area of the basin?
3. How much is the water use demand of the basin?
4. How does the water resource system perform in terms of resiliency, reliability, vulnerability and water productivity?
5. How can an optimization water allocation model be developed for improved water productivity, efficient and sustainable utilization of water resources in the basin?

1.5. SCOPE AND LIMITATIONS

The scope of the study is to have a compressive assessment of the basin water resources and demands that help for an effective water allocation system. It also envisages using of different methodologies and models, to evaluate the water resource system performance and develop an optimizing water allocation model that can improve water productivity, economic efficiency and environmentally sustainable use.

1.6. DISSERTATION STRUCTURE

The dissertation is structured as nine chapters, with chapter one as an introduction that incorporates the statement of the problem, objectives, research questions, and scope, the second chapter has a literature review, the third chapter discusses the description of the study area, the fourth chapter is about the hydrological dynamics and water resource availability, the fifth chapter discusses the current irrigated area mapping of the basin using multispectral image analysis, chapter six is about the water demand of the river basin, the seventh chapter discusses the water resource system performance for water productivity the eighth chapter is about the optimized water allocation model and the final chapter is conclusion and recommendation of the dissertation. The dissertation has additional sections such as references, annexes, acknowledgements and about the author.

CHAPTER 2: LITERATURE REVIEW

2.1. WATER RESOURCE SYSTEM ANALYSIS

Enda O'Connell (2017) stated that water resource systems have benefited people and their economies for centuries. The services provided by such systems are multiple. Yet in many regions, water resource systems can neither meet the demands or even the basic needs, for clean freshwater, nor can they support and maintain resilient biodiverse ecosystems. Typical causes of such failures include degraded infrastructures, excessive withdrawals of river flows, pollution from industrial and agricultural activities, eutrophication from excessive nutrient loads, salinization from irrigation return flows, infestations of exotic plants and animals, excessive fish harvesting, floodplain and habitat alteration from development activities, and changes in water and sediment flow regimes. Inadequate water resource systems reflect failures in planning, management and decision-making – and at levels broader than water. Planning, developing and managing water resource systems to ensure adequate, inexpensive and sustainable supplies and qualities of water for both humans and natural ecosystems can only be successful if such activities address the causal socio-economic factors, such as inadequate education, population pressures, and poverty.

2.2. OVERVIEW OF HYDROLOGICAL DYNAMICS AND CLIMATE CHANGE

According to the recent study report by MWIE, (2018), Ethiopia has a huge renewable amount of water resources within the 12 major basins, which are categorized into three types, river basins include eight of them; lake basins have one basin, and the remaining three dry basins. Since all river basins originate from the highlands and high rainfall areas, they have extensive amounts of surface water running in the river basin systems. The surface water of the country accounted for its two basic parts streamflow and open water system. Most of the rivers in the basins are seasonal and about 70 percent of the total runoff takes place during June-September. Therefore, the basins in the country experienced two extreme challenges, flood in the rainy season and water stress in the dry season. In addition, following the transboundary nature of most of the rivers (seven) in Ethiopia, a significant amount of the runoff generated in Ethiopia flows to surrounding countries, making Ethiopia the "Water Tower of East Africa. This, however, has become a challenge for the country to develop its water resources.

According to JICA (2012), the number of water resources in the Rift Valley Lakes basin was found to be 3,246.5 MCM and the total groundwater recharge of Lakes in the Rift Valley is 1965.7M. Hayal Desta and Brook Lemma (2017) reported a decrease in surface

and base flow and an increase of ET is observed in Lake Ziway sub-watersheds including the lake itself. This will lead in the long-term to the undesired effects on the lake. The increased irrigation development works in the watershed are one of the major drivers in reducing the flow of the Katar and Meki Rivers. This can, in turn, affect the hydrology of Lake Ziway by making it shallower and increasing ET as has been observed in this study, along with increasing air temperature in these times of climate change. Consequently, a more detailed study should be conducted to assess the influences of human pressures and climate changes on land and water resources in the Lake Ziway watershed. Nonetheless, all concerned public institutions, private companies, and local communities in the watershed should be warned about the consequences that may follow in future generations because of the actions people take today without committing themselves to protect the watershed from further degradation. Otherwise, Lake Ziway will face severe problems in the future and might become the second to go next to Lake Haramaya (Alemaya). Ermias Mekonnen (2019) reported that the Rift Valley Lakes basin is endowed with several rivers and lakes of all sizes. Although the basin possesses a significant amount of water resources, little has been developed for drinking water supply, hydropower, agriculture and other purposes. The Rift Valley Lakes basin has an annual runoff volume of 5.6 billion m3 of water and an estimated 0.10 billion m3 of groundwater potential. Conversely, due to a lack of water storage infrastructure and large spatial and temporal variations in rainfall, and a poor water governance system, there is insufficient water for agriculture, water supply, hydropower and other intended uses. As a result, attention must be given to interventions that moderate hydrological variability, mitigate the physical impacts of hydrologic shocks on the environment and watersheds, and arrest land degradation. Therefore, this review paper attempts to explore interventions like infrastructure investments to provide storage and regulate river flows and runoff, and land and soil management practices to enhance the natural capacity of watersheds to moderate hydrology.

Mulugeta et al, (2015) reported that the hydrological stability of most of the Ethiopian Rift Valley lakes is sensitive to climate variability. In terms of monotonic trends, Lake Ziway, Hawassa, Abaya and Beseka experienced a significant increasing trend, while Ziway, Langano and Chamo did not. In addition, the homogeneity test revealed that Lake Hawassa and Abaya showed a significant upward shift around 1991/1992, which was likely caused by climate anomalies such as the El Niño / Southern Oscillation (ENSO) phenomena. Lake Abiyata is depicted by its significant decreasing monotonic trend and downward regime shift around 1984/1985, which is likely related to the extended water abstraction for industrial consumption. For long-term trends in the water level rise of the closed lakes, one has to differentiate between climate variability, climate change as well

as land use change effects. While the first aspects have been analyzed in this study, land use change impacts, on the one hand, total discharge, which usually increases in discharge with increasing agricultural use, and on the other hand, soil erosion and therefore storage capacity of the lakes. In terms of the research gap, it was found that there existed nearly no attempt to estimate the impact of sedimentation on the storage capacity of the lakes. The explicit attempt to study the relationship between lake level dynamics and climate anomalies impacting hydrological and erosion processes is also absent and deserves future investigation. Lake management requires a thorough understanding of the causes of lake-level dynamics to be prepared for extreme events but also for managing long-term water abstraction.

GIRDIC, (2020) reported that 1,065MCM surface water and 953 MCM of groundwater are available for any abstraction use in Ziway-Shalla sub-Basin. According to the masterplan study by Halcrow, (2009), the total surface water resource of the RVLB is estimated at just over 5,300 MCM, calculated from total annual average river flow into the lake systems under 'natural' conditions - without human abstractions. This analysis shows that of the 153,000 ha of irrigation currently planned, only about 18,350 ha of new irrigation development is allowable from a water resources perspective. It must be cautioned that this is based on an assumed acceptable threshold of lake level decline of 10% of LTA levels. The estimate of direct groundwater recharge of 1,080 Mm^3/year represents about 20% of the surface water resource). The water balance modeling shows that climate change reduces the total available surface water resources of the RVLB to approximately 3,939 Mm3/year, a decrease of 1,244 Mm3/year (Halcrow, 2009). The response of the RVLB lakes to climate change shows a continual decline in lake levels over the study period. The study also indicated that the total existing irrigation during the study time was about 29,672 ha. Ziway-Abiyata-Langano-Shalla sub-basin comprises 7,156 ha or 24.1%, Hawassa sub-basin 1900 ha or 6.4%, Abaya-Chamo 13,591 ha or 45.8% and Segen Weito sub-basin comprise about 7025 ha or 23.7%. Based on the soil type and land slope analysis about 29,000 ha was identified as suitable, 140,000 ha moderately suitable for irrigation development. According to the Rift Valley Integrated Resource Master Plan, the water resource of RVLB was estimated at 5.3 BCM. According to the WLRC, (2023) report, the primary water resource management challenges of the Rift Valley Lakes Basin are its extreme hydrological variability and seasonality. The ever-increasing abstraction of water resources is a significant issue. The expanding water hyacinth invasion, particularly on the western side of Lake Ziway, is a major environmental concern. The siltation and sedimentation of the lakes' floor are causing problems. Changes in the hydro-ecosystem and pollution are the main problems of the lake environment. There is an encroached farm area by the expanding lake surface area.

2.3. HYDROLOGICAL MODELLING

Surface water input data were compiled and analyzed in the basin. An initial review and assessment of the existing lake level were undertaken. Monthly river flow, lake levels, and climatic data were obtained from MOWIE and NMA, respectively, based on the locations of gauging stations and lake levels. To assist in the verification of the datasets, daily river flow, lake level data, stage-discharge rating curves, and spot flow measurements were also obtained. Relevant statistical methods were used to fill in missing data. The responses of each lake in the basin to water abstraction, climate change, irrigation expansion, industrial expansion, urbanization, and population increase were assessed.

Hydrological water balance models such as WEAP, SWAT, MIKE HYDRO Basin, and WatBal are commonly used to study integrated water resource management and planning analysis. In this study, the Water Evaluation and Planning" (WEAP) model was applied to estimate the values of hydrological water balance elements. The soil moisture hydrological method in WEAP is one of the best soil moisture accounting hydrological methods that helps easily separate the surface runoff, interflow, and base flow parts of the stream flow analysis (Romilly 2011), and the volume and water levels of the lakes. It is a tool for integrated water resource planning that attempts to assist planners and decision-making processes in providing a comprehensive, flexible, and user-friendly framework for planning and policy analysis. It also provides catchment scale and stream scale water balance, which helps to separate the causes of changes, as natural and manmade, on the quantity and quality of water in the basin. The model was chosen for its ease of use in integrated water resource planning systems (water supplies, demands, and forecasting), including built-in models for rainfall runoff and infiltration, evapotranspiration, crop requirements and yields, surface water/groundwater interaction, and in-stream water quality. Using different scenarios and/or DSS modules, water resource management simulation, and optimization, a powerful reporting system with graphs, tables, and maps is provided by the GIS-based graphical interface.

2.4. Irrigated Area and Irrigation Potential

Studies results have refined the potentially irrigable land of Ethiopia as 5.4 million ha (IWMI, 2010) and 11.1 million ha (MoA, 2016). Habtamu Girma, (2015) reported on Lake Ziway, that the whole existing and potential irrigation development area crop water requirements are 197,84MCM. This much irrigation water abstraction holds 9.31% of the initial volume of Lake Ziway and it reduces 0.4m water level of the lake annually. This rate of lake level reduction (0.4m/year) may lead to the disappearance of the lake after

27.5 years and may also cause the downstream flow to cease after 6.25 years. Moreover, the results showed that regardless of irrigation water abstraction only 7.74% of the initial volume of the lake was reduced, but when irrigation water abstraction was considered, it was 17.05% of the initial volume of the lake was reduced and this showed that irrigation water abstraction merely reduced 9.31% of the initial volume of the lake which indicated greater reduction due to irrigation water abstraction relative to reduction with no irrigation water use condition (7.74%).

HU_RGE, (2020) reported that four large-scale irrigation schemes have been planned by MoWR in RVLB. The first is the development on the Gelana River which flows into Lake Abaya where there are plans for a net irrigation command area of 5,356 ha. The Gidabo dam project is also developing an area of 9,215 ha. A dam is being considered at Dendo on the Bilate River to be used to provide water for a rehabilitated state farm in the lower Bilate to irrigate a net area of 7,715 ha. Furthermore, the master plan study stated that a pre-feasibility study has been carried out for plans to expand the existing irrigation area at Sego from 500 ha to 4,000 ha, with a dam on the River Sego. River Sego flows into Lake Chamo. Another pre-feasibility study has been carried out for a dam located on the Lower Segen River to provide water for a command area of 7,000 ha some 15 km downstream. Since all of this information was collected 15 years ago, new up-to-date information and new studies are required for better planning and management of water resources in the future.

OIDA, (2018) studied the Oromia region part of the RVLB and reported, the total identified and delineated area among the available potential was found to be for the irrigable land with modern and traditional is 34,634.03 ha. In the areas identified for suitable land, the mean available water resource was found to be 441,700 ha and 2,430.6ha by surface and groundwater respectively without considering catchment transfer technology, out of estimated agricultural suitable land of 826,063 ha. From this irrigation potential land by constructing 23 diversions and 15 dam sites the area that is proposed to be developed will be 26404ha This will increase the development of irrigation in the basin from 5.45 to 11.4%. To develop the remaining irrigation potential land (393,489.07ha) additional strategic plan has to be considered like water harvesting at the micro level, groundwater pump at the household level, etc, but to develop the remaining suitable agricultural land catchment transfer technology has to be adopted. GIRDIC, (2020) reported only on the Ziway-Shalla sub-basin, the total irrigated area based on the NDVI analysis is 31,113.37 ha while based on the data collected from Woreda offices during the field survey the total irrigated area is 42,119.66 ha, and accordingly the monthly distributed annual water demand is found to be 451.05MCM

The irrigation water demand reaches its peak in January (87.10MCM) and December (86.46MCM) while the lowest demand is in June (3.15MCM).

2.5. Water Resource System Performance

According to Vedula and Mujumdar (2016), the basic concept of a system is that it relates to two or more things. Out of the several definitions of a system, the simplest one states that it is a device that accepts one or more inputs and generates one or more outputs. Systems analysis may be said to be a formalization of the operation of the total system with all of its subsystems together. Systems analysis is usually understood as a set of mathematical planning and design techniques, which includes some formal optimization procedures. When scarce resources must be used effectively, systems analysis techniques stand particularly promising (for example, in optimal crop water allocation to several competing crops, under conditions of limited water supply). It must be clearly understood that systems analysis is not merely an exercise in mathematical modeling but spans much farther into processes such as design and decision. The techniques may use both descriptive as well as prescriptive models. The descriptive models deal with the way the system works, whereas the prescriptive ones are aimed at deciding how the system should be operated to best achieve the specified objectives. Ibrahim El-Baroudy, (2004) stated that water resource systems are vulnerable to a wide variety of hazards that could potentially limit their ability to perform satisfactorily. The diversity of uncertainty sources presents a great challenge to water resource systems design, planning and management. The probabilistic approach usually fails to address the problems of human error, subjectivity, and the lack of system performance history and records. The fuzzy set approach addresses those issues. A fuzzy system reliability analysis is ideally based on the comparison between the fuzzy sets representing both the system's state of safety and the potential for system failure.

2.6. Water Productivity

Cai et al. (2011) discussed water productivity (WP) defined as the ratio of net (economic) benefits from water use (agriculture, industry, energy or other mixed systems) and the amount of water utilized in its production, which appears to be a more relevant metric that measures how the system converts water and other resources to goods and services. It is a performance metric relating to two state variables (economic output and resource utilization) and assesses existing conditions that could be tracked over time to determine relative changes and improvements. Cai et al. (2011) assessed WP across 10 major river basins, in several continents, at different stages of development and in various hydro-climatic zones with varying proportions of irrigated land from a high (78 %) to low (1

%). Crop yields were highest in the river basins with the highest proportion of irrigation and lowest in rain-fed systems. The authors ultimately concluded that there was too much variability in the river basins and factors other than water availability were at least as important in WP, especially the availability of markets and highly variable prices for commodities. Kemp-Benedict et al. (2011) studying the same 10 river basins from a different perspective arrived at a similar conclusion. They tried to link water availability and poverty. Arnell, (2010); Schewe et al. (2013) have raised the issue of WP in another aspect, The Water Performance index appears to be a step in the right direction, but it still misses the essence of acknowledging the differences in the value of water. Water-rich countries like Canada or Japan will rank poorly in terms of return on each ‘‘drop of water’’ since their agriculture tends to produce water-intensive crops. In contrast, countries with limited water resources such as Israel are likely to invest in high-value crops (e.g., fruits, vegetables) providing a high return on investment in water infrastructure rarely take into account the inherent temporal variability of the underlying natural, human-induced and socioeconomic processes, although a considerable number of studies were carried out to assess how certain indicators would change under future climate conditions.

According to Molden et al., (2010), crop water productivity (CWP) is defined as the ratio of crop yield (Y) to the amount of water required to produce that yield. Increasing WP is necessary to meet decreasing water availability and is a key element in improving agricultural water productivity, which is central to both economic and social development. Nhamo, et al. (2016) study report revealed that, evaluated crop evapotranspiration, crop production and agricultural gross domestic product contribution to assess the crop water productivity of Malawi from 2000 to 2013. They found an overall increase of 33% of crop water productivity. Molden et al., (2010) also stated that WP can be defined as the ratio of food output to the amount of water consumed. It is essentially an efficiency problem that falls within the capability of fractional programming. In recent years, some researchers attempted to optimize WP using linear fractional programming (Guo et al., 2014; Li et al., 2015; Zhou et al., 2016) with the numerator part expressing total crop yield and the denominator part expressing total water consumption or use.

Jiang et al., 2015; Li et al., (2017) reported that, from the perspective of crops, WP is related to factors such as crop types, crop yields, and irrigation quota. With respect of management, WP is related to factors such as irrigation methods, irrigation costs, economic benefits and social values of crop planting. For example, higher crop yields will lead to a higher WP under the same water consumption. Water-saving measures such as trickle irrigation, sprinkling irrigation, and tube-well irrigation will also increase WP through saving water and increasing water utilization efficiency. The changes in any of

these influence factors can result in different crop production and water allocation plans, leading to variations in WP. The problem becomes more complex when considering the combined effects of these varying factors. However, few studies that focused on the optimization of WP using fractional programming considered the coordination of multiple factors. WP can potentially be improved by decreasing the water use amount. However, the decrease in irrigation water amount will also lead to a drop in crop production, threatening food security and economic development. With the widely perceived theory of sustainable development, water resources management should be directed towards the coordinated development of the economy, society, and environment. Moreover, the multi-dimensional attributes of water resources require managing water resources through equally weighing social, economic, ecological and environmental aspects. Therefore, how to quantitatively evaluate the efficiency of water resources management, and how to analyze the impacts of water allocation schemes on the socioeconomic and ecological environment are issues that deserve research. According to Mihret and Ermias (2014), the production gain from irrigated agriculture in the Rift Valley Lakes Basin is below the expected value due to the inefficient scheme of water management. Generally, water supply unreliability (68% of all scheme users' observation), unfair distribution of water (79.1% of all scheme users' opinion) and timeliness of water distribution (66 % of all scheme users' remark) are major problems in all investigated schemes. All the schemes witnessed a weak organization (50 % of all scheme users noted poor organization) of irrigation scheme administration.

2.7. Reliable and Resilient Water Management

Resilient water management is based on several key elements, including flexibility, redundancy, diversity, connectedness, and adaptive capacity. These guidelines highlight the need for diverse approaches that can sustain the health of ecological and human systems while withstanding shocks and stressors and remaining effective in the face of changing circumstances. In an era of climate change and growing water scarcity, a resilient approach to water management is crucial. This involves moving beyond traditional methods and embracing strategies that anticipate and adapt to changing circumstances. One such strategy is integrated water resource management (IWRM), which considers the interconnectedness of all water users and ecosystems within a river basin (Meran et al., 2021). IWRM emphasizes collaborative decision-making, stakeholder engagement, and investment in innovative technologies and infrastructure. Climate-resilient water management is a comprehensive approach that aims to address the long-term security of water and wastewater utilities planning to limit consequences from natural hazards. This approach is crucial in the face of climate change, as water is the primary medium through which we feel its impacts. It plays an important role in

climate change adaptation and resilience, with more than 90 percent of disasters being water-related (SIWI, 2019).

Sustainable development, as stated in the Bruntland (1987), Report, is development that "meets the needs of the present without compromising the ability of future generations to meet their own needs." To counter the likelihood of future water shortages, the World Summit on Sustainable Development, held in Johannesburg, South Africa, in September 2002, committed (WSSD, 2002) to "halving the proportion of people without access to safe drinking water by 2015." The commitments made and the implementation activities recommended at the Johannesburg Summit are now being acted upon by the US engineering community (ASCE, 2004) to move "beyond Johannesburg." Though significant efforts have been made, much more needs to be done to realize this grand goal. Water resource systems may be regarded as social-ecological systems (Berkes et al 2003). Berkes et al. saw sustainable development of water resource systems as a concept integrating humans in nature and viewing the delineation between social and natural systems as artificial and arbitrary; a key property to consider if sustainable development is to be achieved is their resilience (Berkes et al. 2003; Carpenter et al. 2005; Walker and Salt 2006). The essential aspect of a resilient system is that it has an adequate capability to avert adverse consequences under disturbances, and a capacity of self-organization and adaptation, and thus displays a greater capacity to provide wanted services that support our, and the environment's, quality of life.

Since the 1960s there have been several studies on developing the quantitative resilience of water resource systems. The most widely used and cited definition may be the one by Hashimoto et al. (1982), though a similar concept has been applied earlier to show the sensitivity of a water supply system to drought (Fiering 1969), and water resources system resilience for data collection programs (Matalas and Fiering 1977). Hashimoto et al. (1982) defined resilience as the average probability of recovery at time step $t+1$ from a failure state at time step t. By this definition, the higher the probability of recovery, the higher the resilience; therefore, in this sense, it represents the rapidity of the system returning to a satisfactory state after an occurrence of failure (i.e. resilience for system recovery). Moy et al. (1986) used the maximum time duration of failure as a measure of resilience; the longer the duration, the less resilient the system. Moy's definition of resilience is monotonic to the duration of records; i.e. it guarantees a longer period of records will have a resilience measure less than or equal to that given by a shorter period of records. According to Gunderson et al, (2002), an ecological system is inherently a complex adaptive system governed by four key properties: resilience, complexity, self-organization, and emergence Resilience, as stated previously, is the ability of a system to

withstand disturbances without shifting into another system state. Complexity results from the variety of elements and components, and their interdependent behaviors, that compose the system. Self-organization is the ability due to the interaction of constituent elements that mutually reinforce or hamper each other, an ability that enables the system to re-establish order from disorder after a perturbation.

2.8. SUSTAINABLE USE OF WATER RESOURCE

Sustainable use of water resources in a river basin involves a comprehensive approach that considers various aspects of water use, from its economic value to its role in supporting ecosystems and human well-being (Li et al., 2022a). Implementing water-saving technologies and practices can significantly reduce water use, this includes efficient irrigation methods in agriculture, water-saving appliances in homes, and water-efficient processes in industries. Protecting water quality is crucial to preventing pollution from industrial, agricultural, and domestic sources, and implementing measures to clean polluted water. The other option for sustainable and optimized use of water resources is using the IWRM tool, it is a process that promotes the coordinated development and management of water, land, and related resources to maximize economic and social welfare without compromising the sustainability of ecosystems. Involving all stakeholders in water management decisions can help ensure that the interests of all parties are considered and conflicts are minimized. Establishing strong legal and institutional frameworks can help regulate water use, protect water rights, and ensure compliance with water management policies (Hatamkhani et al., 2022). As climate change can significantly impact water availability and demand, it's important to incorporate climate change adaptation strategies into water management plans. Ongoing research and innovation can lead to new technologies and strategies for sustainable water use (Wang et al., 2022).

Efficient and optimized use of water resources in a river basin can be achieved through several strategies including IWRM which is a systematic process for sustainable development, allocation, and monitoring of water resources used for social, economic, and environmental purposes (Hatamkhani et al., 2022). Optimization models to optimize water resource allocation among the stakeholders. The objective functions could include maximizing the economic profits of all stakeholders and minimizing the Gini coefficient (a socioeconomic indicator) to achieve equity in water resource allocation (Derepasko et al., 2023). It also involves water conservation through increasing the fraction of water beneficially used over water applied. Economic efficiency enhancement seeks the highest economic value of water use through both physical and managerial measures. Sustainable development planning using a reliability-based simulation optimization approach,

development planning in the basin with objectives like total area under cultivation of agricultural development sectors and supply reliability of the environmental flow requirement can be investigated. Adaptive water management by designing an optimization model for river flow diversion and ecosystem services supply capacity at the basin scale under climate and land use change scenarios. the specific strategies and their implementation can vary depending on the characteristics of the river basin, the needs of the stakeholders, and the local climatic, economic, and political conditions. It's always best to involve all stakeholders in the planning and decision-making process to ensure the most equitable and sustainable use of water resources.(Cai et al., 2003; Degefu et al., 2016; Kazemi et al., 2022; Li et al., 2022a; Wang et al., 2022)

The world faces an increasingly complex water landscape, marked by a myriad of challenges and issues. Water scarcity, driven by population growth, climate change, and unsustainable consumption patterns, poses a significant threat to global water security (Mishra et al., 2021). Unequal access to clean water, particularly in developing nations, exacerbates existing inequalities and hinders socio-economic development (Gomez et al., 2019). Furthermore, deteriorating water quality due to pollution from agricultural runoff, industrial waste, and inadequate sanitation infrastructure poses a significant threat to human health and ecosystems (FAO, 2017). Additionally, climate extremes, like floods and droughts, further strain water resources and infrastructure, leading to losses and vulnerabilities (Handmer et al., 2012). These interconnected challenges necessitate a comprehensive and collaborative approach to water resource management, prioritizing both sustainability and equity.

2.9. Basin Water Allocation Planning

Degefu et al, (2016) discussed that water allocation in a river basin is a complex process that aims to balance competing demands with the overall health of the aquatic ecosystem. Stakeholders such as farmers, cities, and industries all require water, and determining fair and sustainable distribution is crucial. It also involves various socio-economic and environmental factors such as Water scarcity in transboundary river basins which can lead to overexploitation of water resources. Optimization models can be used to allocate water resources among stakeholders to maximize economic benefits while minimizing socio-economic disparities. Water allocation policies can create cooperation or tension among different stakeholders, thus hydro-political considerations are crucial in water resources management. Developing a water allocation plan necessitates a meticulous assessment of both water availability and demand. Rainfall patterns, river flow rates, and groundwater levels are all vital factors to be considered. Additionally, water needs for agriculture, domestic use, and industrial processes must be carefully evaluated.

Speed et al, (2013) explained modern basin water allocation planning typically takes place in the context of 'closed' basins, with limited or no extra water availability. This implies that the focus of basin water allocation planning has shifted substantially, with a greater focus on demand management and on optimizing the use of existing supplies. This is coupled with a shift away from the more traditional emphasis on the construction of new infrastructure to meet rising demand. This new approach to water allocation is fundamentally different and involves significant economic, social and environmental analyses and the assessment of trade between competing users. At its core, therefore, modern basin water allocation planning is as much a socio-economic exercise as one based on hydrology and engineering. This requires both new planning techniques and new sets of skills amongst those conducting the basin planning exercise. As water has become a limiting factor to social and economic development in many regions, and as options to increase water availability become more limited, choices and trade-offs increasingly need to be made between competing uses of water. This has driven a greater understanding and deeper analyses of the value of water. In modern allocation planning, greater consideration is now given to basin and national development objectives, more detailed socio-economic assessments are used to inform allocation decisions, there is greater consideration of the efficiency of use in determining water requirements for different sectors and users, and environmental flow assessments are now a central component of the water allocation process. Rapid economic and social changes in the context of stressed basins increase the need for changes in the way water is allocated over time. Climate change is only likely to exacerbate this need. Adjustments to water entitlements – including the total volume of entitlements, as well as by whom they are held – can be achieved through either regulatory measures (such as revision of an existing basin plan), or market-based reallocation mechanisms. Regional shares and individual water rights need to be structured in a way that enables this flexibility.

Tewodros et al, (2019) reported a growing number of water specialists and environmentalists are finding WEAP to be an important addition to their toolbox of models, databases, spreadsheets, and other software. Many countries are facing challenges in the management and development of water resources. The allocation of limited water resources, water quality, catchment water protection, and appropriate policies for sustainable water use and management are the current issues concerning policymakers. The WEAP model has an integrated approach to simulate both natural and engineering components such as reservoirs, groundwater discharge, and water demand and supply. WEAP can give water planners a more comprehensive view of the broad range of factors that must be considered in managing water resources for present and future uses (CSO, 2010). Operating on the basic principle of a water balance, WEAP

applies to municipal and agricultural systems, single catchments, or complex transboundary river systems. Furthermore, WEAP can also address a wide range of issues, e.g., sectoral demand analyses, water conservation, water rights and allocation priorities, groundwater and streamflow simulations, reservoir operations, hydropower generation, pollution tracking, ecosystem requirements, vulnerability assessments, and project benefit-cost analyses (Tena et.al, 2019). WEAP aims to incorporate these values into a practical tool for water resources planning. WEAP is distinguished by its combined approach to simulating water systems and by its policy orientation. Data linked to land use; slope, soils, and vegetation are needed to simulate these hydrological processes. WEAP sets the demand and supply side of the equation in an organized way. Water use patterns, efficiencies, reuse, and allocation are placed on the demand side, while the supply side includes streamflow, groundwater, and water transfers. WEAP is a laboratory for examining alternative water development and management strategies (Tena et.al, 2019). The quantitative estimations of water availability, water demand, and water consumption both on a temporal and a spatial scale can be supported by modelling tools, capable of simulating the hydrological processes and the water management practices at the catchment level for the current status, as well as for various alternative scenarios (Wagner et al, 2013). Unlike other models, WEAP offers scenario analyses in a friendly approach giving a wide range of model results in a simplified manner. The model is also a scalable tool, and it can be updated at any time. This allows for future improvement of the model results. Furthermore, WEAP is the most commonly used tool for integrated water resource management (IWRM) worldwide (Tena et.al, 2019).

2.10. OPTIMIZATION TECHNIQUES

Deng et al (2022), uses a comprehensive approach to optimizing water resource allocation in the Han River Basin, China, by integrating the principles of efficiency, equity, and sustainability. Using a multi-objective optimization model driven by the Non-dominated Sorting Genetic Algorithm II (NSGA-II), the research explores trade-offs between economic benefits and equitable distribution of water resources. The findings reveal a conflicting relationship between efficiency and equity, where increased economic output often comes at the expense of fairness in resource allocation. The model's Pareto front analysis provides policymakers with decision-making tools to balance these competing objectives, while sustainability constraints ensure ecological water flows are maintained. The study highlights the importance of incorporating regional variability, dynamic demands, and adaptive decision-making into water resource management, offering a scalable framework for addressing global water allocation challenges.

Tian eta al (2019), explores an innovative method for resolving conflicts in water resource allocation amidst competing demands and environmental considerations. Employing a multi-objective optimization model coupled with Sperner's Lemma, the research aims to balance economic interests and environmental protection while achieving fair distribution. Through case studies in China's Hanjiang River Basin, the model generates Pareto-optimal solutions and negotiates water allocation using game theory principles to ensure envy-free results. The findings emphasize the utility of fair allocation methods in addressing trade-offs, enhancing decision-making efficiency, and maintaining ecological sustainability. This approach demonstrates strong applicability in diverse water management scenarios.

CHAPTER 3: STUDY AREA DESCRIPTION

3.1. RIFT VALLEY LAKES BASIN

The Rift Valley Lakes Basin (RVLB) is one of the twelve major river basins in Ethiopia with a total area of about 53,000 km^2. The basin is characterized by a chain of lakes varying in size as well as in hydrological and hydrogeological settings. It constitutes eight lakes, Lake Ziway, Lake Langano, Lake Abijata, Lake Shalla, Lake Hawassa, Lake Abaya, Lake Chamo, and Lake Chew Bahir (Figure 1), and all are located south and southwest of the Ethiopian capital, Addis Ababa. The RVLB is shared administratively between four Regional States, Oromia, Sidama, Central Ethiopia and South Ethiopia. It comprises four primary sub-basins defined by their main lake systems, the first comprising Lakes Ziway, Abijata, Shala and Langano, the second Lake Hawassa, the third Lakes Abaya, Chamo and the fourth sub-basin is Lake Chew Bahir. The northern and central parts of the valley from Hawassa northwards and across to Sodo in the west have reasonably good access to the capital Addis Ababa, which is important for many reasons, not least the access to markets. The south and south-west are remote with no nearby major centers and poor (though improving) transportation networks making travel difficult and many areas largely inaccessible during the rainy season.

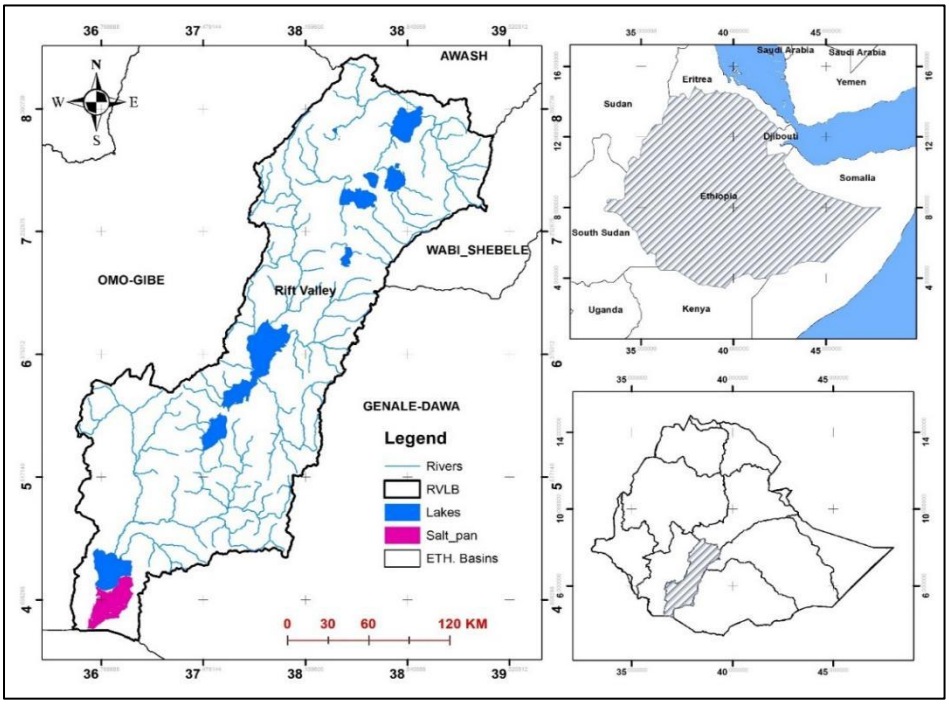


Figure 1: Geographic location of the study area

3.2. CLIMATE AND HYDROLOGY

The principal feature of the RVLB is that it is a graben, a block fault geological structure in which the floor of the valley has become vertically displaced with respect to the valley sides. As in all areas, the temperature and rainfall of the RVLB tend to vary as a function of elevation and, in consequence, so do relative humidity and potential evapotranspiration. The top of the Rift Valley on the east and west sides is, therefore, cooler, wetter and with lower evapotranspiration rates, and hotter, drier and with higher evapotranspiration in the central lowlands. On the valley bottom, average annual rainfall varies from approximately 400mm at Chew Bahir in the extreme south of the basin, to approximately 700mm near the northern lakes. In contrast, average annual rainfall approaches 2,000mm near Gerese, west of Lake Chamo, and also at Yirga-Chefe, east of Lake Abaya, both on the higher edges of the basin.

Two principal patterns of rainfall season are apparent in the RVLB. North of Lake Abaya, the main rains occur July through September, with a secondary peak in March or April. South of Lake Abaya, the main rains occur earlier in the year, between March and May. Annual average potential evapotranspiration varies from approximately 1,200mm in the northeast of the basin to approximately 1,900mm at Chew Bahir. Throughout the Rift Valley floor, from Lake Ziway to Lake Chamo, the average values are typically on the order of 1,550mm. Annual average temperatures vary from approximately 27ºC on the valley floor near Chew Bahir to a low of approximately 13ºC at higher elevations, particularly in the northeast of the basin. The hydrology of the RVLB is generally considered to be centered on four interdependent hydrological basins, The Ziway-Shala basin (14,477 km^2), The Hawassa basin (1,403 km^2), The Abaya-Chamo basin (18,118 km^2) and Chew Bahir basin (19,029 km^2).

The major rivers tend to rise on the elevated east and west sides of the Rift Valley and flow in a southerly direction into the terminal lakes. The RVLB is a hydrologically closed system, with no surface flow from the terminal lakes. There may be groundwater outflows but there is no real evidence for this at this time and little data to support hypotheses either way. The total annual average river flows into the lake system have been estimated at approximately 4,000MCM/year. Significant inflows in the north of the basin include the Meki (180MCM/year) and Katar (300MCM/year) Rivers; the Pilate, Gidabo and Gelana Rivers produce estimated inflows of 830MCM/year, 550MCM/year, and 280 MCM/year respectively into Lake Abaya. The Weito and Segen Rivers produce a combined total flow of approximately 700MCM/year, although much of this flows into the wetland area upstream of Chew Bahir.

3.3. PHYSICAL CHARACTERISTICS

3.3.1. Major catchments

Based on the hydrological units, major water resource development, and hydrological gauging stations, the basin was classified into 23 major watersheds. This watershed classification helps address the spatial variability of the input dataset as well as the calibrated parameters of the model (Figure 2). Accordingly, all the remaining input datasets of the model were organized based on these watersheds.

3.3.2. Land use

After the acquisition of high-resolution images from the Sentinel-2 satellite, the images were processed to remove noises and artifacts using filtering, feature extraction was the next step to use for classification and then with semi-supervised classification the land use map was developed using GIS and finally, outputs were evaluated to verify the accuracy. The land use map is developed as part of this study. (Figure 2). Further rearrangement of the land cover was done to facilitate the model to account for the irrigation and rainfed cultivation water use differently. The information for irrigated area mapping, which is conducted as part of this study using NDVI imagery analysis, Google Earth survey, and ground truthing techniques was superimposed to the land use map and the share of the cropland divided into two as rainfed and irrigated cultivation.

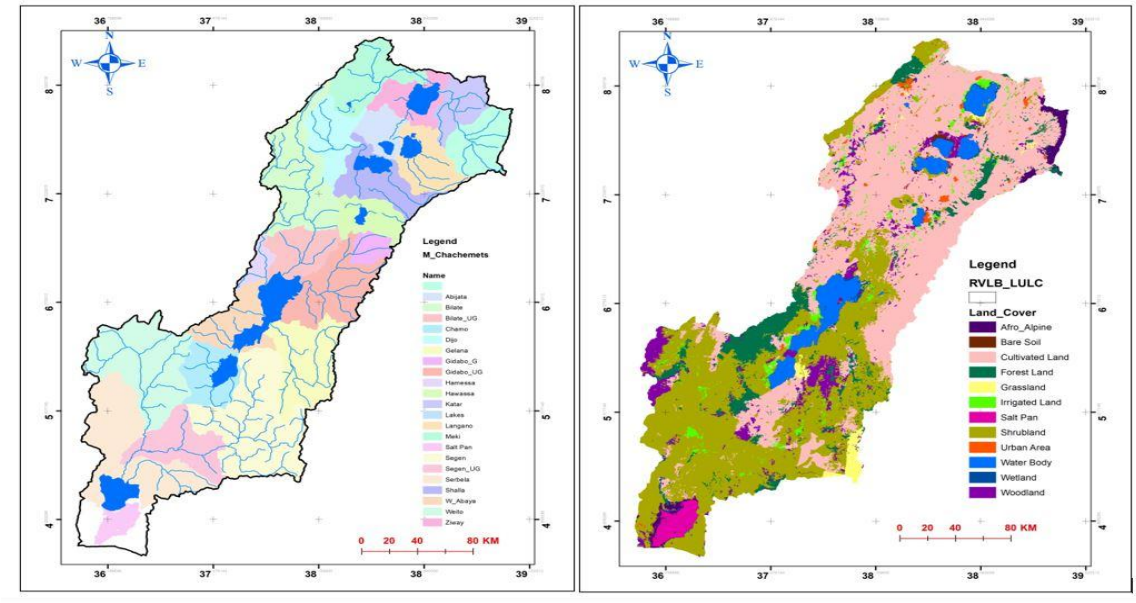


Figure 2: Major Catchments and Land Use Classification of RVLB

When calculating evapotranspiration using the soil moisture balance method, the impacts of land use and cover were represented by the Kc value. The Kc value for the dominant crop type was considered in the model according to the crop calendar for each major catchment. The Kc values for each land-use type were adopted from the FAO/EIAR reports and used as monthly data. Both the cropping calendar and Kc values differed between rainfed and irrigated areas.

3.3.3. Slope/Topography

The physiography of the basin is characterized by the altitude and slope of the basin using a reconditioned digital elevation model of Ethiopia at 12.5m resolution. The altitude of the basin ranges from 1507–4201masl, which indicates that significant parts of the basin fall in the midlands. The slope classification is also characterized according to which most of the area has a gentle (mild) slope in the range of 0-8% (Figure 3) Moreover, the basin is characterized by seven major lakes, namely: Ziway, Langano, Abijata, Shalla, Hawassa, Abaya and Chamo three small lakes namely: Tinishu Abaya, Chitu, and Hara Hidi; perennial rivers such as; Meki, Ketar, Bilate, Gidabo, Gelana, Segen and Weito. Lake Abijata is interconnected to both Ziway and Langano lakes through the Bulbula and Horakalo rivers, respectively.

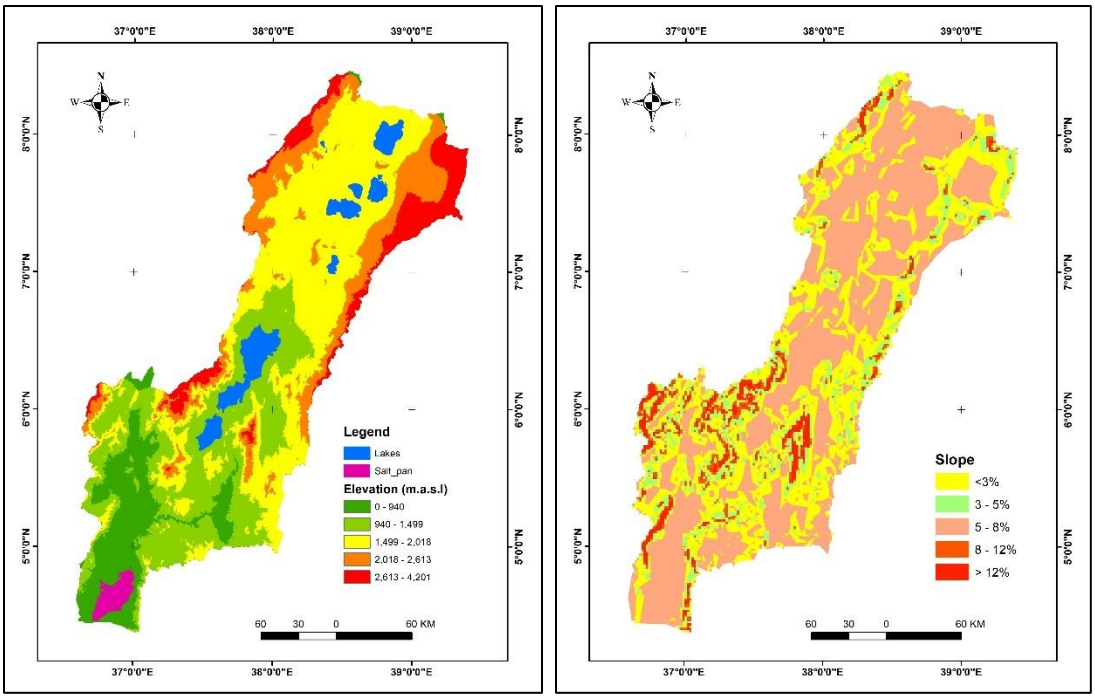


Figure 3: Slope and topographic map of the RVLB

3.3.4. Soil

The soil type of the basin has been characterized using the soil data set compiled by the water and land resources center (WLRC, 2017). Accordingly, the basin is classified into 16 soil types, excluding the water body (Figure 4). Although the classification shows 17 soil types, the primary area of the sub-basin (80.4%) is characterized by three soil classes, Rhodic Nitisols, Vitric Andosols, and Haplic Solonetz with 56.7%, 15.3%, and 8.4% share respectively. Out of the total area of the basin, 8.3% is covered with water bodies and the remaining 14 soil classes' share 11.3% of the basin area.

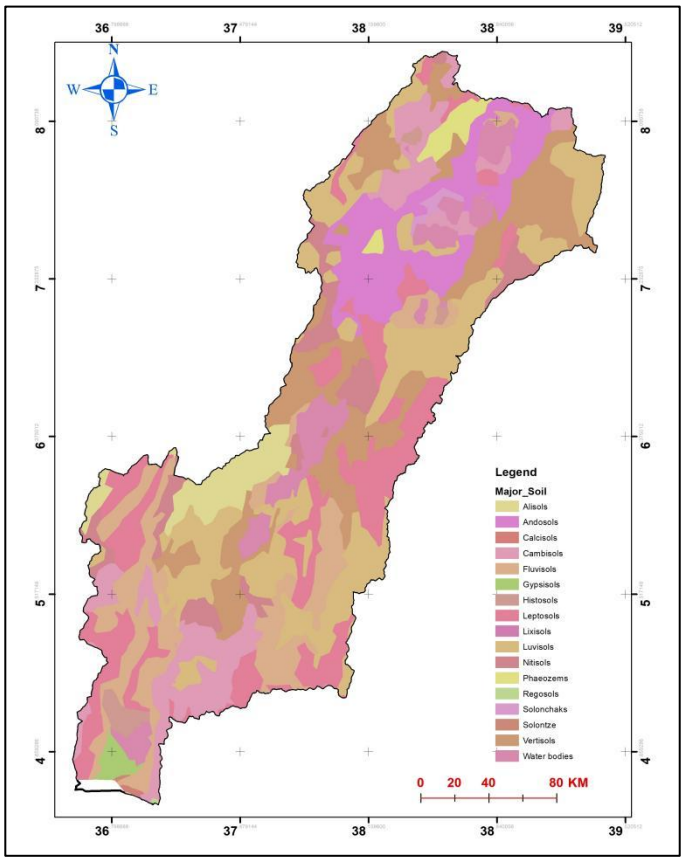


Figure 4: Soil map of the RVLB

3.4. SOCIOECONOMIC SETTING AND ENVIRONMENT

3.4.1. Socioeconomic setting

The socioeconomic setting of the Rift Valley Lakes Basin is shaped by a combination of rapidly growing population, agriculture, urbanization, and increasing pressure on natural resources. The basin's economy has traditionally relied on small-scale, rainfed

agriculture, with farming systems predominantly based on cereal monoculture. However, this approach has faced challenges in meeting the growing food demand of the population, especially since the 1980s, when significant population growth led to intensified land use pressure. The basin's agricultural practices are complemented by emerging industries, particularly in floriculture and horticulture, as the region becomes an increasingly important center for these sectors. These developments, along with the rise of urban centers, have driven land use changes, including deforestation, which have altered hydrological processes in the basin. In addition to this, the effects of climate change, such as increased temperature and variable rainfall, have compounded the challenges in water management

The Rift Valley Lakes Basin is also experiencing increasing investments in irrigation and water resources development to support agricultural and industrial growth. However, this is causing significant stress on water resources, as the demand for water for both irrigation and urban use continues to rise. The socio-economic dynamics of the region thus present a complex interplay between environmental sustainability, agricultural development, and urban growth, necessitating careful management to address both water scarcity and socio-economic challenges.

3.4.2. Environmental issues

The Rift Valley Lakes Basin is a region of immense ecological and socio-economic importance. However, this basin faces numerous environmental challenges, which threaten its sustainability and biodiversity. Industrial discharge, agricultural runoff, and urban wastewater contribute significantly to water pollution in the Rift Valley lakes. The use of chemical fertilizers and pesticides in farming introduces harmful substances like nitrates and phosphates into the water, leading to eutrophication. This promotes the growth of algae and depletes oxygen levels, adversely affecting aquatic life. Increased water demand for irrigation, industrial use, and domestic consumption has led to the over-extraction of water from lakes, rivers, and groundwater sources. This unsustainable practice reduces water availability for ecosystems and communities, particularly during drought periods, exacerbating the impacts of climate change.

Deforestation for agriculture, fuelwood, and settlement expansion has degraded the surrounding landscapes. The loss of vegetation contributes to soil erosion and reduced water infiltration, leading to sedimentation in the lakes and wetlands. This sedimentation disrupts aquatic ecosystems and reduces water storage capacity. The Rift Valley Lakes Basin hosts unique flora and fauna, some of which are endemic to the region. Habitat destruction due to urbanization, agriculture, and industrial development threatens the

survival of these species. Overfishing and the introduction of invasive species further compound biodiversity loss. The basin is highly vulnerable to the impacts of climate change, including erratic rainfall patterns, rising temperatures, and prolonged droughts. These changes disrupt the hydrological cycle, reduce water levels in the lakes, and affect the livelihoods of communities dependent on natural resources. Rapid population growth in the region has led to increased demand for resources, unplanned urbanization, and expansion of agricultural lands. This pressure strains the natural environment, leading to unsustainable exploitation of land and water resources. Some of the Rift Valley lakes, such as Lake Abijatta, face rising salinity levels due to reduced inflows, evaporation, and human activities. High salinity negatively affects freshwater ecosystems and agricultural practices in surrounding areas.

CHAPTER 4: HYDROLOGICAL ANALYSIS AND WATER RESOURCE ASSESSMENT OF THE RIFT VALLEY LAKES BASIN

4.1. INTRODUCTION

The Rift Valley Lakes Basin is endowed with several rivers and lakes of all sizes. Although the basin possesses a significant amount of water resources, little has been developed for drinking water supply, hydropower, agriculture and other purposes, (Ermias, 2019). Over 80% of Ethiopia's sizable freshwater lakes are found in the Rift Valley Lake Basin, and for more than 15 million people, this basin provides a versatile source of water (Abraham et al., 2021). The hydrological stability of most of the Ethiopian Rift Valley lakes is sensitive to climate variability (Mulugeta Dadi, 2015).

The Rift Valley Lakes Basin has a 5.3 BCM – 7.83 BCM water resource potential (Halcraw and GIRDC 2009; MoWIE 2018; Ermias, 2019; JICA 2012). All the inconsistent reports generated regarding the actual current water resource potential of the RVLB are mainly due to the input data, selected hydrological models and methodology used. This will have an impact on the sustainable and efficient utilization and planning of water resources. Besides the discrepancies of the reports, the establishment of effective water resource management plans is hampered by the fact that the majority of the catchments that replenish these lakes are ungauged and have poorly measured water balances (Abraham et al., 2021).

Assessing water resources at a river basin scale is important for understanding the availability and use of water in a basin, the health of waterways and the impact of human activities on these ecosystems and efficient water resources management, the potential impact of climate change on freshwater resources, it also provide regulators with the confidence they need to make sound water allocation decisions which leads to more efficient use of water resources and prevent conflicts over water use.(ACIL, 2014; VSG, 2020; Zy Harifidy et al., 2022).

Considering the climate change and variability, and existing and future demand for water in the sectors; developing an optimized water resource development system and improving the water resource system performance is also a must. Hence, determining the hydrological dynamics and water resource potential of the basin helps to water resource planning, sustainable and efficient utilization of water and land resources and optimize

water allocation. This study assesses the hydrological dynamics and water resource potential of the basin using the Water Evaluation and Planning (WEAP) model with the soil moisture balance method approach, and optimized water allocation is conducted to the competitive sectors based on their demand, efficiency, equity and environmental sustainability (discussed in chapter eight). The outcomes of this study are useful for the Rift Valley Lakes Basin Authority; in managing the water resource and understanding its temporal and spatial distribution, it is useful for the policymakers and stakeholders in the basin to attempt efficient and sustainable utilization of the available water resource in the basin.

The model utilized enhanced input data, including longer time series, high-resolution climatic data, and updated land use information. Additionally, the RVLB was divided into 23 major watersheds to capture detailed spatial variability, offering localized insights into water balance components compared to the broader aggregations in earlier studies. By harmonizing input data and ensuring methodological accuracy, the study resolves previous inconsistencies in water potential assessments. It also explicitly accounts for un-gauged catchments, often neglected in earlier models, through innovative spatial and hydrological techniques. This integration of modern datasets, advanced modelling approaches, and rigorous calibration represents a significant advancement over prior assessments, providing a robust foundation for sustainable planning and management of RVLB water resources.

4.2. WEAP MODEL FOR WATER RESOURCE SYSTEM ANALYSIS

4.2.1. Model description

The Water Evaluation and Planning System (WEAP) river basin model was developed by the Stockholm Environment Institute (SEI) in Boston, USA (Stockholm Environment Institute, 2015). and further upgraded with several improvements and input system arrangements with the work of different stakeholders. WEAP is comprehensive, straightforward, and easy to use, and attempts to assist rather than substitute for skilled planners. The data structure and level of detail may be customized to meet the requirements of a particular analysis and reflect the limits imposed by restricted data. A graphical interface facilitates the visualization of the physical features of the system and its layout within the catchment, and it operates on the basic principle of water balance accounting. Therefore, WEAP was selected to simulate the water resources of the Rift Valley Lake basin.

4.2.2. Hydrological model selection

The hydrological water balance models such as WEAP, SWAT, MIKE HYDRO Basin, and WatBal are the commonly used models to study integrated water resource management and planning analysis. In this study, the “Water Evaluation and Planning” (WEAP) model is applied to estimate the values of hydrological water balance elements. The soil moisture hydrological method in WEAP is one of the best soil moisture accounting hydrological methods that help easily separate, the surface runoff, interflow, base flow parts of the stream flow analysis (Romilly, 2011) and the volume and water levels of the lakes. It is a tool for integrated water resources planning that attempts to assist the planners and decision-making processes in providing a comprehensive, flexible and user-friendly framework for planning and policy analysis. It also gives the sub-catchment scale and stream scale water balance, which helps to separate the causes of changes, as natural and manmade, on the quantity and quality of water in the sub-basin. Therefore, this model will be used due to its appropriateness for the envisaged assignment that will help to implement the water allocation plan to improve the currently unregulated and excessive water abstractions in the sub-basin.

WEAP has four optional methods for analyzing the hydrological system in the basin unit. These methods are (1) the simplified coefficient of Rainfall Runoff, (2) Irrigation Demands versions of the FAO Crop Water Requirements Approach, (3) the Soil Moisture Method, and (4) the MABIA Method. We selected the soil moisture method because it accounts for the climatic, land use, and soil type effects of the basin to compute the stream flow with its three mean types (i.e., surface runoff, interflow, and base flow). The hydrological system in the basin unit can be analyzed using four different approaches in WEAP software. The soil moisture technique was selected for this study because it considers the basin's effects on climate, land use, and soil type while computing the stream flow with its three main categories (surface runoff, interflow, and base flow).

The Soil Moisture method is a one-dimensional, 2-compartment (or "bucket") empirical function that describes evapotranspiration, surface runoff, subsurface runoff (i.e., interflow and base flow), and deep percolation in a watershed unit. This method allows for the characteristics of land use and soil type impacts on processes. The deep percolation within the watershed unit can be transmitted to a surface water body as a base flow or directly to groundwater storage if an appropriate link is made between the watershed unit node and a groundwater node (Figure 5).

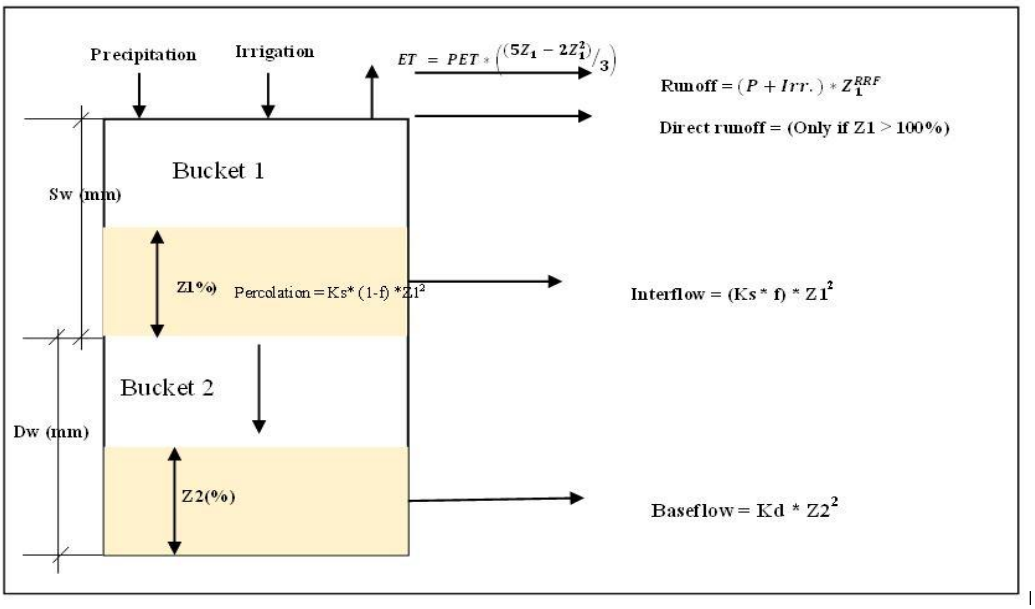


Figure 5: Conceptual diagram and equations incorporated in the Soil Moisture model

A watershed unit can be divided into N fractional areas representing different land uses or soil types, and a water balance is computed for each fractional area, j of N. Climate is assumed uniform over each catchment, and the water balance is given as,

$$\boldsymbol{Rd_j \frac{dz_{1,j}}{dt} = P_e(t) - PET(t)k_{c,j}(t)\left(\frac{5Z_{1,j} - 2Z_{1,j}^2}{3}\right) - P_e(t)Z_{1,j}^{RRF_j} - f_j K_{s,j} Z_{1,j}^2 - (1 - f_j)k_{s,j}Z_{1,j}^2} \text{----- eq 1}$$

Where z1,j = [1,0] is the relative storage given as a fraction of the total effective storage of the root zone, Rdj(mm) for land cover fraction, j. The effective precipitation, Pe, includes snowmelt from accumulated snowpack in the catchment. Due to this empirical functionality, the method requires land use and climatic inputs. In the land use input section, the software, takes the land use information of each catchment node as total area, percentage of area share for each land use and the Kc values of each land use type. The second major input is the climatic input, which requires Areal rainfall, Mean temperature, Humidity and Wind speed as a priority input.

4.2.3. Limitations of the WEAP model

WEAP cannot refer to values of decision variables established in previous allocation orders within the same time step, WEAP uses a one-dimensional lumped parameter

hydrologic Model to estimate monthly runoff, base flow, ET, groundwater recharge, and soil water storage.

4.3. MODEL INPUT DATA

4.3.1. Major catchments

Based on the hydrological units, major water resource development, and hydrological gauging stations, the basin was classified into 23 major watersheds. This watershed classification helps address the spatial variability of the input dataset as well as the calibrated parameters of the model (Figure 2). Accordingly, all the remaining input datasets of the model were organized based on these watersheds.

4.3.2. Land use data

After the acquisition of high-resolution images from the Sentinel-2 satellite, the images were processed to remove noises and artifacts using filtering, feature extraction was the next step to use for classification and then with semi-supervised classification the land use map was developed using GIS and finally outputs were evaluated to verify the accuracy. The land use map is developed as part of this study (Figure 2). Further rearrangement of the land cover was done to facilitate the model to account for the irrigation and rainfed cultivation water use differently. The information for irrigated area mapping, which is conducted as part of this study using NDVI imagery analysis, Google Earth survey, and ground truthing techniques was superimposed to the land use map and the share of the cropland divided into two as rainfed and irrigated cultivation. When calculating evapotranspiration using the soil moisture balance method, the impacts of land use and cover were represented by the Kc value. The Kc value for the dominant crop type was considered in the model according to the crop calendar for each major catchment. The Kc values for each land-use type were adopted from the FAO/EIAR reports and used as monthly data. Both the cropping calendar and Kc values differed between rainfed and irrigated areas.

4.3.3. Soil data

The soil type of the basin has been characterized using the soil data set compiled by the water and land resources center (WLRC, 2017). Soil data is used as an input for the WEAP model.

4.3.4. Stream flow and Lake Elevation data

Long-term monthly time series streamflow lake elevation data for model calibration and validation was obtained from the Ministry of Water and Energy (MoWE) and the Rift Valley Lakes Basin authority.

4.3.6. Climatic Data

Rainfall is a basic input in hydrological subsystem models. Climate data are present in each of the major catchments under consideration (Figure 6) and are utilized as inputs to programs that predict the hydrological response. The monthly time series annual rainfall data for each major catchment were retrieved from a gridded CHRIPS bias corrected precipitation product with a 4 km resolution for the years 1981 to 2022 because it requires monthly time series annual rainfall as the required input. Overlay analysis of Thiessen polygons surrounding each climatic grid point with a catchment layer was used to calculate areal precipitation over the catchment. Climatic datasets associated with each catchment, including temperature, wind, and relative humidity monthly time series, were arranged as input files for the model.

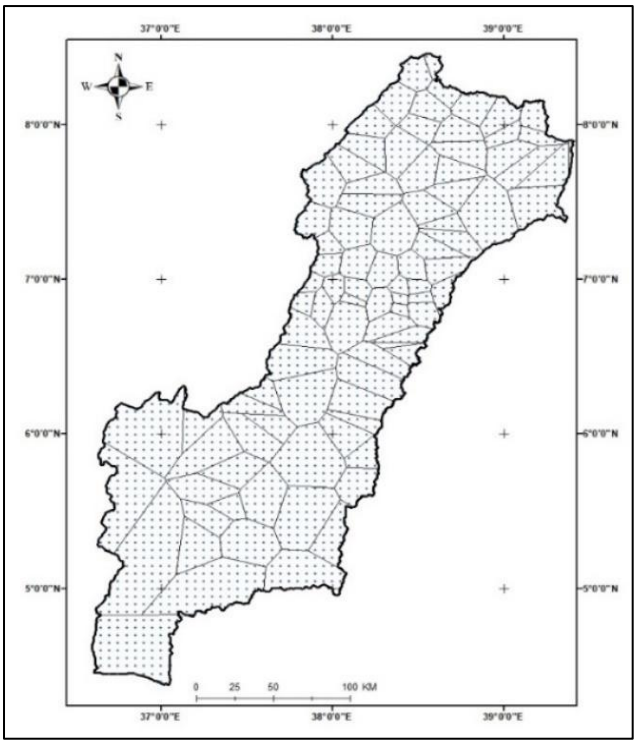


Figure 6: CHIRPS climate grid points and Theissen polygons over catchments

4.3.7. Evaporation Loss from Lakes

Evaporation of water from a water surface - like an open reservoir, a swimming pool, or similar - depends on water temperature, air temperature, air humidity and air velocity above the water surface. Therefore, the formula used for estimating the evaporative loss of water from the Lakes in RVLB is: - (engineering toolbox)

$$g_s = \Theta A (xs - x) / 3600 \quad \text{---------- eq 2}$$

Where: -

$\mathbf{g_s}$ = amount of evaporated water per second (kg/s)
Θ = (**25 + 19 v**) = evaporation coefficient (kg/m^{2}h)
v = velocity of air above the water surface (m/s)
A = water surface area (m^2)
$\mathbf{x_s}$ = *maximum humidity ratio of saturated air* at the same temperature as the water surface (kg/kg) (kg H_2O in kg Dry Air)
x = *humidity ratio air* (kg/kg) (kg H_2O in kg Dry Air)

4.4. WATER RESOURCES POTENTIAL ASSESSMENT

4.4.1. System Configuration and Model Set-Up

The schematization of the model includes existing water resource systems, mainly lakes, reservoirs, and rivers. Major catchments were established by considering the availability of gauging stations. Therefore, the model schematizes the surface water resource systems of the basin using 6 catchment nodes and 17 river nodes. The natural lakes were schematized using reservoir nodes. Eleven selected hydrological gauging stations were used for the calibration and validation of the model (Figure 7).

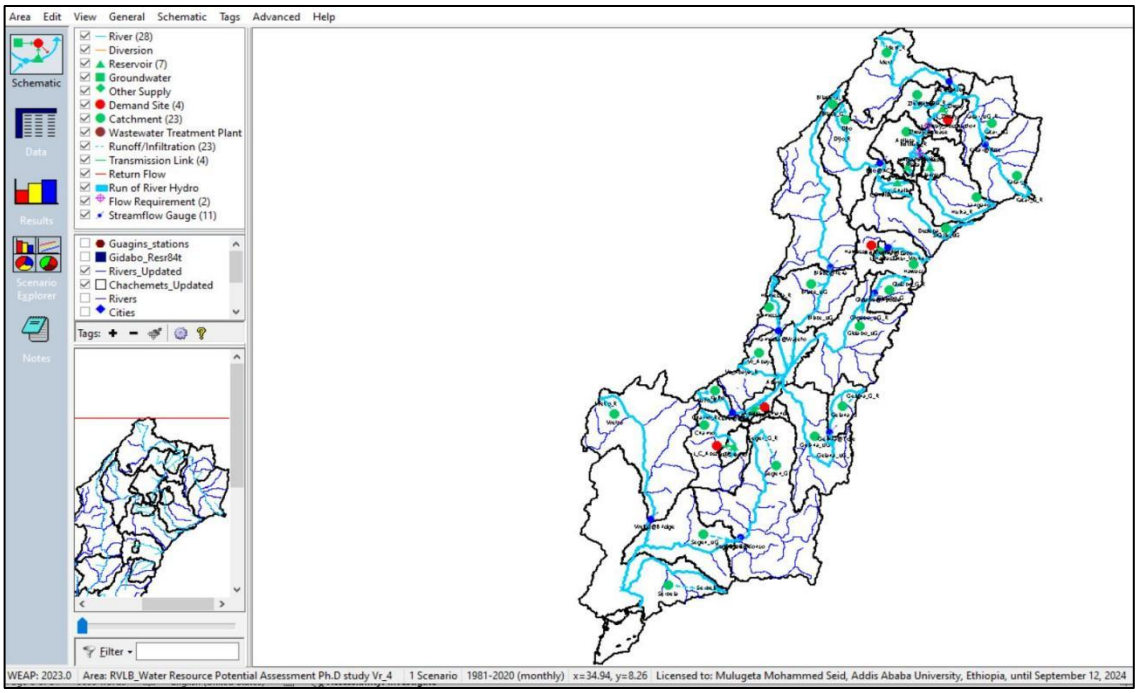


Figure 7: Model schematized configuration

4.4.2. Calibration and validation of the model

The WEAP model was calibrated based on historical stream flows using manual methods. The calibration was achieved by comparing the historical pattern of stream flows and simulated flows. Calibration involves changing runoff parameters, altering demand priorities, and modifying the operating rules of flow requirements to improve the fit between simulated and observed flows. Additionally, long-term gauge data of lake storage level, and annual direct abstraction data from Lakes (Lake Ziway: Pump inventory, discharge rates, irrigated area, irrigation water use data) are used for calibration. Even if all the assumptions made in the modeling were utterly correct, an exact fit between the simulation and observed flows is not to be expected. The three most sensitive runoff parameters, Soil Water Capacity (Sw), Runoff Resistance Factor (RRF), and Deep Conductivity (Kd), were adjusted to achieve calibration to stream flow. Other parameters including Crop coefficient (Kc), preferred flow direction (f), Root zone conductivity (Ks), Deepwater capacity (Dw), and Initials (Z1 and Z2) were also used in calibration. The Model is most sensitive to RRF. Thus, initial calibrations were focused on this parameter. Further refinements for base flow, the shape of the hydrograph, and the timing of peak flows were adjusted using the remaining parameters.

The performance of the calibration and validation process was evaluated using statistical performance indicators: coefficient of determination (R^2), Nash-Sutcliffe Efficiency (NSE), and percentage bias (PBIAS). The coefficient of determination (R^2) assesses how strong the linear relationship between simulated and observed datasets, and is heavily relied on by researchers when conducting trend analysis. It is used to check the fitness of simulated parameters with the observed ones. The Nash-Sutcliffe Efficiency (NSE) is used to evaluate how well the modeled stream flow matched the observed data. The NSE indicates how well a plot of observed versus simulated data fits to a 1:1 line. The PBIAS, on the other hand, calculates the relative volume difference between raw and observed rainfall volume. The Index of agreement (IA) represents the ratio of the mean square error and the potential error. The Standard Deviation Ratio (RSR) is calculated as the ratio of the Root Mean Squared Error (RMSE) and standard deviation of measured data. RSR varies from the optimal value of 0 to a large positive value. The formulas used for statistical performance are organized in Table 1, (Goshime, et al. 2021a)

Table 1:Statistical performance indicator formulas

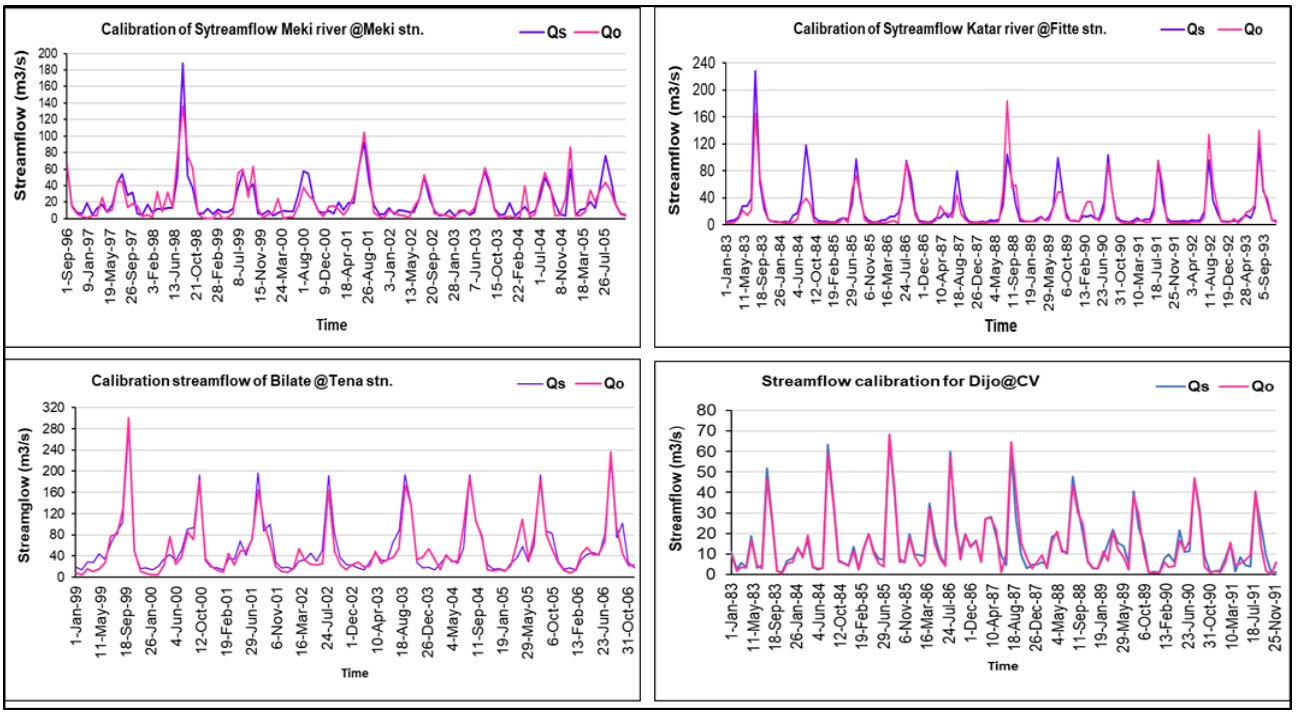
Performance Indicator	Equations	Best fit values	
Coefficient of determination	$R^2 = \frac{(\sum(Q_S - \overline{Q_S}) \times (Q_O - \overline{Q_O}))^2}{(\sum(Q_S - \overline{Q_S}))^2 \times (\sum(Q_O - \overline{Q_O}))^2}$	$0.70 < R^2 \leq 1$ $0.60 < R^2 \leq 0.70$ $0.5 < R^2 \leq 0.60$	Very Good Good Satisfactory
Nash-Sutcliffe coefficient of efficiency	$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{O,i} - Q_{S,i})^2}{\sum(Q_{O,i} - \overline{Q})^2}$	$0.75 < NSE \leq 1$ $0.65 < NSE \leq 0.75$ $0.5 < NSE \leq 0.75$	Very Good Good Satisfactory
Percentage of bias	$PBIAS = 100\left[\frac{\sum_{i=1}^{n}(Q_S - Q_O)}{\sum_{i=1}^{n}(Q_O)}\right]$	PBIAS < ±10 ±10 ≤ PBIAS < ±15 ±15 ≤ PBIAS < ±25	Very Good Good Satisfactory
Index of agreement	$IA = 1 - \frac{\sum_{i=1}^{n}(Q_O - Q_S)^2}{\sum_{i=1}^{n}(Q_o - \overline{Q_o})^2}$	$0.75 < IA \leq 1$ $0.65 < IA \leq 0.75$ $0.5 < AI \leq 0.75$	Very Good Good Satisfactory
standard deviation ratio	$RSR = \frac{\sqrt{\sum_{i=1}^{n}(Q_{O,i} - Q_{S,i})^2}}{\sqrt{\sum_{i=1}^{n}(Q_{O,i} - \overline{Q_S})^2}}$	RSR < 0.5 $0.5 \leq RSR \leq 0.6$ $0.6 \leq RSR \leq 0.7$	Very Good Good Satisfactory

***Where Q_S = simulated data, Q_O= observed data, Source: (Goshime, et al. 2021). ---------- eq 3**

Table 2 below presents the value of the performance evaluation measures for eleven gauging stations used for calibration. Once the catchment parameters are configured, the model's performance is further validated using the same gauging station stream flow data with different time series. Besides the statistical measures, the graphical representation of the monthly time series featuring simulated results versus observed data indicates the model's performance fit with the existing conditions, as shown in Figures 8 and 9.

Table 2: Statistical performance measures of calibration

Gauging stations	Calibration						validation					
	Time Range	R^2	NSE	PBIAS	IA	RSR	Time Range	R^2	NSE	PBIAS	IA	RSR
Meki @Meki	1996-2005	0.89	0.78	4.77	0.78	0.47	2007-2011	0.83	0.59	16.11	0.59	0.64
Katar @Fitte	1983-1993	0.87	0.76	2.13	0.76	0.49	1996-2000	0.89	0.66	-16.94	0.66	0.56
Bilate @Tena	1999-2006	0.85	0.74	-4.29	0.67	0.58	1989-1993	0.82	0.67	11.76	0.84	0.4
Dijo @CV	1983-1991	0.82	0.71	4.88	0.71	0.54	1998-2002	0.81	0.64	6.49	0.64	0.59
Gidabo @Aposto	1990-2000	0.93	0.85	3.63	0.7	0.55	1983-1988	0.83	0.7	-7.39	0.85	0.39
Kulfo @AM	1996-2003	0.88	0.84	-6.45	0.84	0.35	2004-2008	0.82	0.53	-15.17	0.53	0.61
Gelana @Tore	1991-1998	0.92	0.84	1.8	0.67	0.58	1999-2003	0.82	0.67	3.24	0.84	0.37
Hamessa @Wajefo	1992-1997	0.85	0.77	2.57	0.65	0.59	1984-1988	0.82	0.65	12.59	0.77	0.34
Weito @Bridge	1993-2002	0.83	0.74	2.57	0.65	0.59	2003-2007	0.82	0.65	-13.37	0.74	0.34
Segen @Konso	1997-2003	0.84	0.86	5.01	0.77	0.57	2004-2007	0.79	0.77	2.2	0.86	0.33
Tikurwiha @Dato	1990-2000	0.85	0.68	9.45	0.62	0.77	2003-2007	0.77	0.62	-13.52	0.68	0.53
L_Ziway Storage	2001-2010	0.89	0.63	10.05	0.63	0.56	2012-2015	0.81	0.59	7.05	0.53	0.55



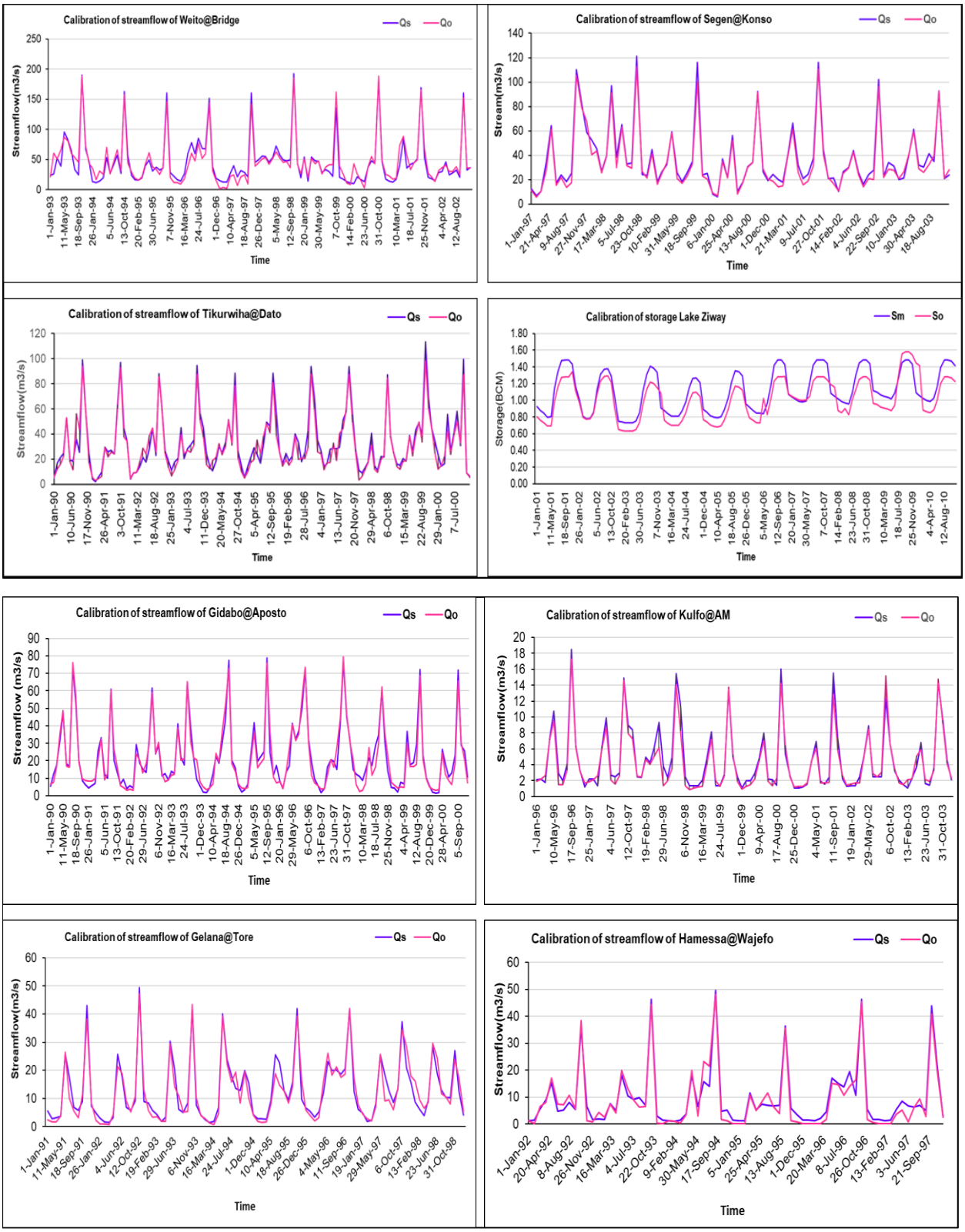


Figure 8: Graphical presentation of calibration

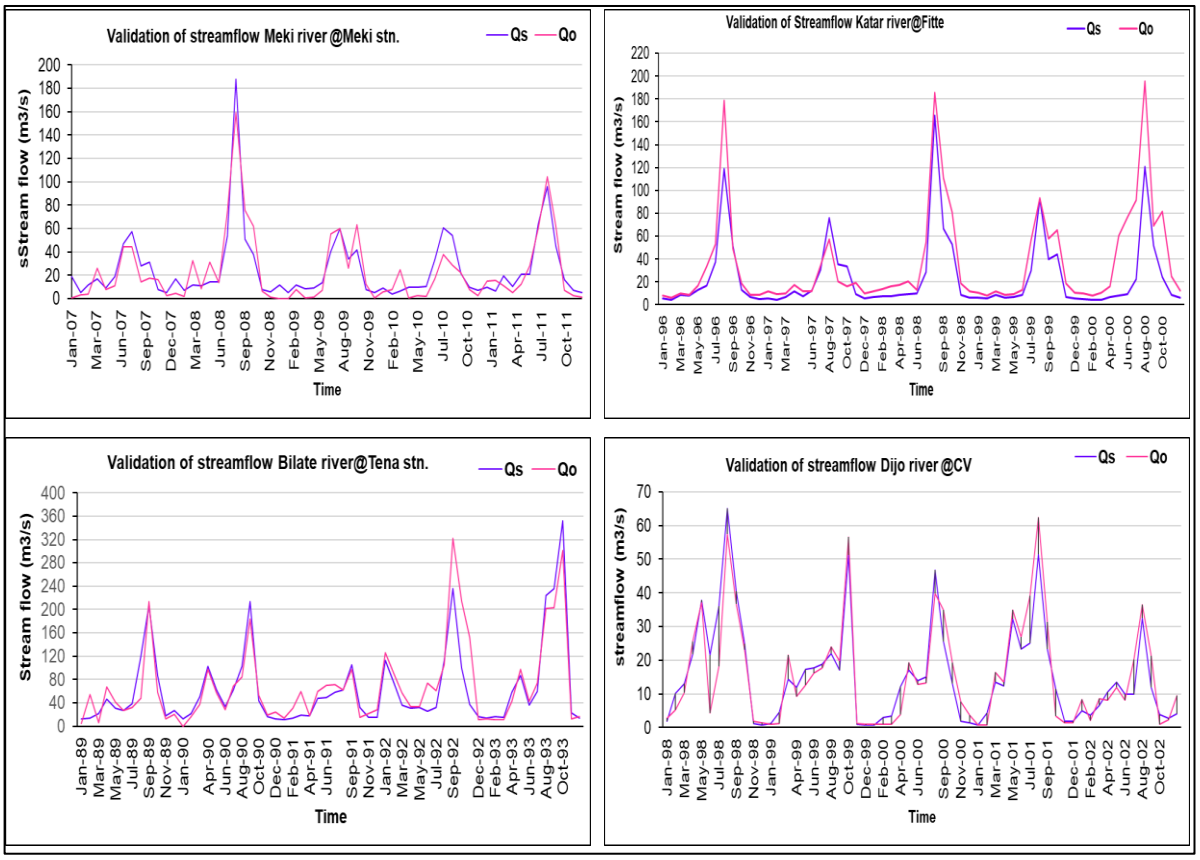


Figure 9: Graphical presentation of Validation

4.5. RESULTS

4.5.1. Water balance

Water balance is governed by the conservation of mass, and the rate of water entering a specified domain is equal to the rate of water leaving the same domain with any differences as changes in storage. The link between surface water, groundwater, soil moisture content, and the process of evapotranspiration has a critical importance in this water balance study. The basin-level water balance study tries to quantify each element of the hydrological cycle. It evaluates the hydrological elements by considering elements as one system. Precipitation, incoming water to the basin from the atmosphere is accounted as the inflow to the basin system. Evapotranspiration, surface runoff, and subsurface flow (Interflow, Base flow, and deep percolation) on the other side are counted as outflow from the basin system. The change between the soil moisture increments and reduction is considered a change in the storage of the system. Therefore, the balance between the right and left sides of the equation guarantees a correct annual balance of

water in the basin. Four interdependent hydrological basins the Ziway-Shala basin (14,477 km^2), the Hawassa basin (1,403 km^2), the Abaya-Chamo basin (18,118 km^2), and the Chew Bahir basin (19,029 km^2) are widely thought to be the focal points of the RVLB's hydrology. The main rivers usually originate on the elevated east and west edges of the Rift Valley and flow south into the terminal lakes. The terminal lakes have no surface flow, making the RVLB a hydrologically closed system. Although there isn't much information available right now to support either hypothesis, there may be groundwater outflows. Each subsystem of the RVLB undergoes a water balance study.

Ziway-Shalla sub-basin: The Ziway-Shalla sub-basin consists of four lakes, Ziway, Langano, Abijata and Shalla from which Abijata and Shalla are terminal Lakes, As shown in (Table 3), the subbasin obtains 12.27 BCM of annual rainfall from which 10.13 BCM is Evapotranspiration loss, and 2.15 BCM remains as surface runoff, baseflow, interflow and deep percolation. the balance analysis is done in not the hydrological year, hence the difference between inflow and outflow and the change in storage is non-zero.

Hawassa sub-basin: The Hawassa sub-basin consists of Hawassa Lakes, As shown in (Table 3), the sub-basin obtains 1.57 BCM of annual rainfall from which 1.33 BCM is Evapotranspiration loss, and 0.24 BCM remains as surface runoff, baseflow, interflow and deep percolation. the balance analysis is done in not the hydrological year, hence the difference between inflow and outflow and the change in storage is non-zero.

Abaya-Chamo sub-basin: The Abaya-Chamo sub-basin consists of two major lakes, Abaya and Chamo with Lake Chamo being a terminal Lake, As shown in (Table 3), the sub-basin obtains 18.49 BCM of annual rainfall from which 15.04 BCM is Evapotranspiration loss, and 3.45 BCM remains as surface runoff, baseflow, interflow and deep percolation.

Chewbahir sub-basin: The Chewbahir sub-basin has one lake, Chewbahir with two major rivers Weito and Segen flow to the Lake Chewbahir, Variations in river discharge can result in significant area changes for Lake Chew Bahir. The lowest point in the northeast is always wet, yet it frequently dries out. All of the water entering the lake evaporates because there is no outlet for it. Chew Bahir has changed over the last century from a swamp to shallow open water that reaches a maximum depth of 7.5 meters and has a surface area of up to 2,000 km^2. Because it is so salty, the water in Chew Bahir cannot be used for agriculture or residential uses. As shown in (Table 3), the sub-basin obtains 17.70 BCM of annual rainfall from which 14.90 BCM is Evapotranspiration loss, and 2.80 BCM remains as surface runoff, baseflow, interflow and deep percolation.

Table 3: Annual Water Balance of the sub-basins

Sub-basin	Inflow (BMC)	-	Outflow (BMC)	=	Change in storage (BMC)
	Precipitation	-	Evapotranspiration + Surface runoff + Interflow + Base flow+ deep percolation	=	Increase in soil moisture-Decrease in soil moisture
Ziway-Shall	12.27	-	10.13+1.24+0.40+0.25	=	4.13-3.56
	12.27		12.018		0.256
			0.26		0.26*
Hawassa	1.57	-	1.33+0.11+0.05+0.06	=	0.51-0.49
	1.569	-	1.553	=	0.016
			0.02	=	0.02*
Abaya_Chamo	18.49	-	15.04+2.03+0.62+0.42	=	5.20-4.81
	18.488	-	18.099	=	0.391
			0.39	=	0.39*
Chewbahir	17.7	-	14.90+1.24+0.68+0.47	=	4.66-4.24
	17.701	-	17.284	=	0.417
			0.42	=	0.42*

***** *The balance analysis is done in not the hydrological year, hence the difference between inflow and outflow and the change in storage is non-zero*

4.5.2. Renewable Water Resources of the Basin

The total renewable water resource of the basin is the sum of internal renewable water resources and external renewable water resources. Internal renewable water resources are defined as the long-term average annual flow of rivers and recharge of groundwater generated from indigenous precipitation for a given basin or region. On the other side, the external renewable water resources are part of the annual renewable water resources that are not generated in the basin. This includes inflow from upstream basins or regions (groundwater and surface water) and part of the water of border lakes. Since the basin is not interconnected with another basin system, the total renewable water resources are simply computed from the internal sources. It is the volume of water computed by separating the total evapotranspiration (41,316.06 MCM) of the basin from the total precipitation (50,031.29 MCM) of the basin. Accordingly, the total renewable water resource of the basin is estimated to be 8,637.19 MCM.

4.5.3. Surface water resources

Surface water is water within the hydrological system that includes all inland waters permanently or intermittently occurring on the Earth's surface in either liquid (rivers, lakes, reservoirs, swamps) or solid (glaciers, snow cover) conditions. The latter, however, was not considered, since it has no significant contribution to tropical countries like Ethiopia. The surface water of the RVL Basin accounts for two systems: Stream flow and

open water system (including renewable water at the lake, wetland, and floodplain). Although the model is configured with 23 catchments and a monthly time series of about 43 years (1981 -2022) to address spatial variability of rainfall-runoff interaction, the results of the surface water sources are presented based on the two surface water categories with a focus on the major rivers in the basin and lake water system.

Stream Flow-based Surface Water Sources

Stream flow is the central part of the surface water potential, commonly calculated at the outlet of the given hydrologic boundary. Surface water sources based on the flow of the RVLB stream are defined with 17 major rivers, which feed the lakes in the basin. Meki and Katar are the main sources of fresh water for Lake Ziway. Huluka is the main river that flows into Lake Langano. These two lakes are further interconnected with Lake Abijata (one of the terminal lakes) in the basin through the Bulbula and Horakalo rivers, respectively. The other terminal lake of the basin, Lake Shalla, receives water from the Dijo and Dedeba rivers. Tikurwiha River is the main source of Lake Hawassa, while Bilate, Gidabo, Gelana, Wajifo, Ginna and Kulfo are the main rivers feeding Lake Abaya, for Lake Chamo Sile, Sego and Gidole Rivers are the main sources fresh water. Weito and Segen rivers flow into Chewbahir, where there is no outlet, all water entering the lake is lost through evaporation. Over the past century, Chew Bahir has varied from swamp to shallow open water with a maximum depth of 7.5 m and a surface area of up to 2,000 km^2. Chew Bahir's water is so highly saline that it cannot be used for irrigation or domestic purposes. Figure 10, indicates the pattern and temporal distribution of the streamflow of gauged rivers in the basin.

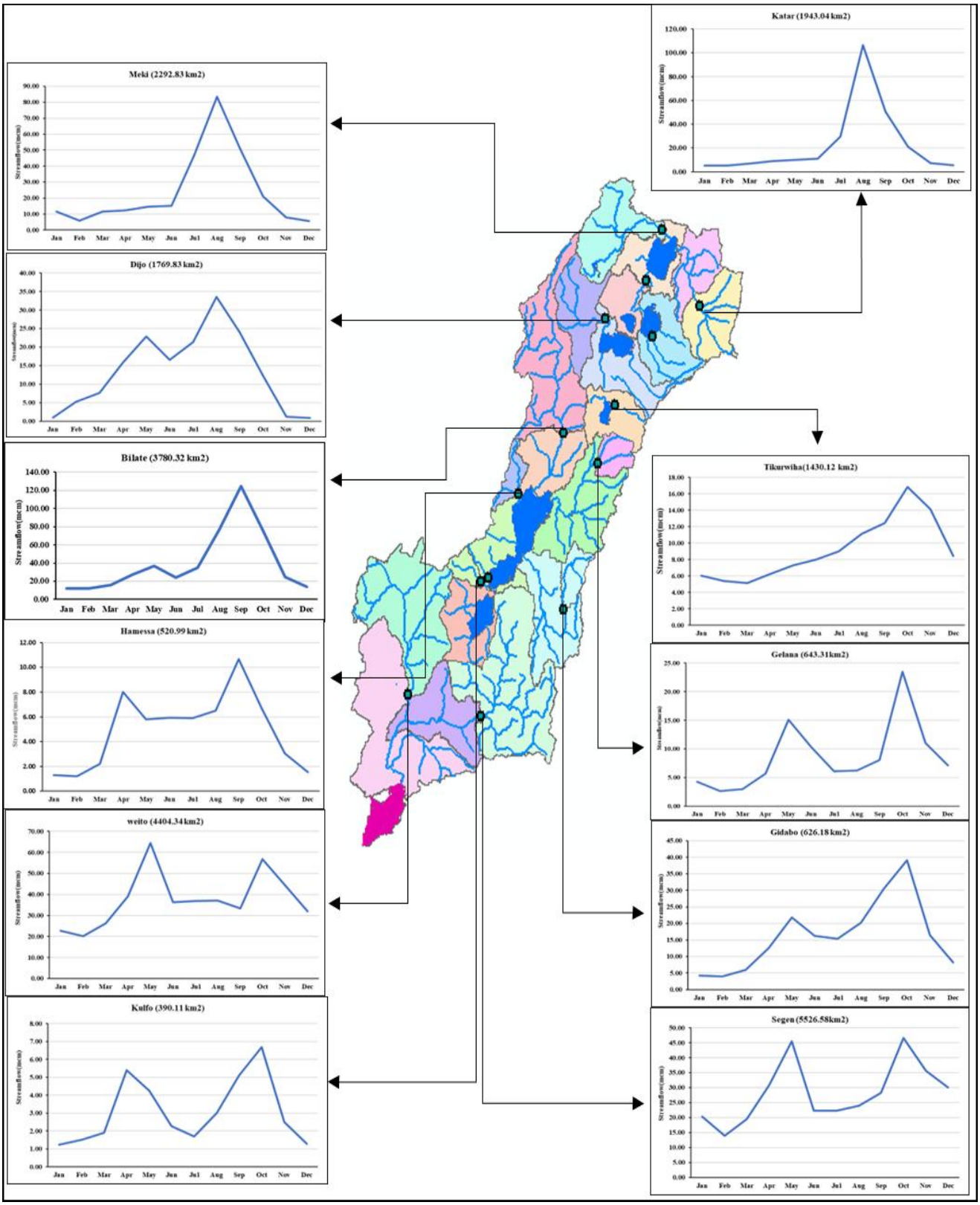


Figure 10: Spatial and temporal of flowrates at gauging stations

The Rift Valley Lake Basin has many rivers, which constitute the unique ecosystem of the basin. The rivers that feed these lakes provide vital water for agriculture, fishing, and other industries. Rivers in the Ethiopian Rift Lake Basin play a vital role in supporting the region's ecosystem and economy. These rivers provide important water resources for the lake and surrounding communities and contribute to the area's biodiversity.

Ziway-Shalla Sub-basin: Meki River of the major rivers in the sub-basin starts at the northern tip of the RVLB, primarily originating from the Gurage highlands. It flows eastward for 106 km before reaching Lake Ziway. Analyzing the surface water, the Meki River generates a stream flow of 322.08MCM from a catchment area of 2,292.83 km^2. At the river's outlet, there is a gauge that is used for model calibration and validation, as indicated in (Table 4), 47.10MCM is abstracted from the river along the course. Conversely, the Katar River begins at the Arsi highlands in the northwestern part of the RVLB and flows 106 km westward into Lake Ziway. It generates a streamflow of 533.28MCM from a catchment area of 3,390 km^2 and only 493.63MCM is estimated flow due to abstraction on the upstream.

The major rivers that enter Lake Langano are Hulka, Ejersa, Gedemso, and Lepis. Lepis River is the longest, spanning 66 km in the catchment area. The stream flow from this catchment area, which covers 2,020 km^2, amounts to 325.76 MCM, abstraction in the catchment is less as compared with other rivers. On the other hand, the Dijo River originates from the northwestern escarpments of the RVLB and flows 96.5 km into Lake Shalla, with a total stream flow of 169.56 MCM. The only ungauged catchment, Ziway catchment has a small stream size that flows into Lake Ziway, according to the water analysis result the 1,615 km^2 catchment area has a yield of 78.52 M annual streamflow. Bulbula and Harkelo Rivers are also the only rivers that supply Lake Abijata, Bulbula river flows the outflow from Lake Ziway while Harkelo supplies Lake Abijata carrying the outflow from Lake Langano, however, the stream flows balance the stream size originating from the catchment is considered.

Table 4: Water balance of Stream flows of Ziway-Shalla Sub-basin (MCM)

Rivers	Inter flow	Base Flow	Surface Runoff	Total Stream flow	Flow outlet	Abstractions
Meki	51.91	34.71	235.46	322.08	274.98	47.10
katar	76.77	11.16	445.36	533.28	493.63	39.65
Dijo	24.29	6.18	139.09	169.56	160.09	9.47
Ejersa/Hulka	13.41	23.13	289.23	325.76	324.64	1.12
Ziway_UG	20.36	0.52	57.64	78.52	71.28	7.24
Dedeba/Bisho	48.92	0.70	130.38	180.00	164.98	15.02

Bulbula/Harkelo	16.91	7.91	21.66	46.47	43.61	2.86
				1,655.68	**1,533.21**	

Temporally, the stream flow in the sub-basin follows the rainfall variability over the sub-basin. Most of the sub-basins have high flow in the rainy season. Due to these temporal and topographical characteristics of the river system, the dry season (Nov-May) flow in all catchments covers only 21% of the annual flow (Figure 11).

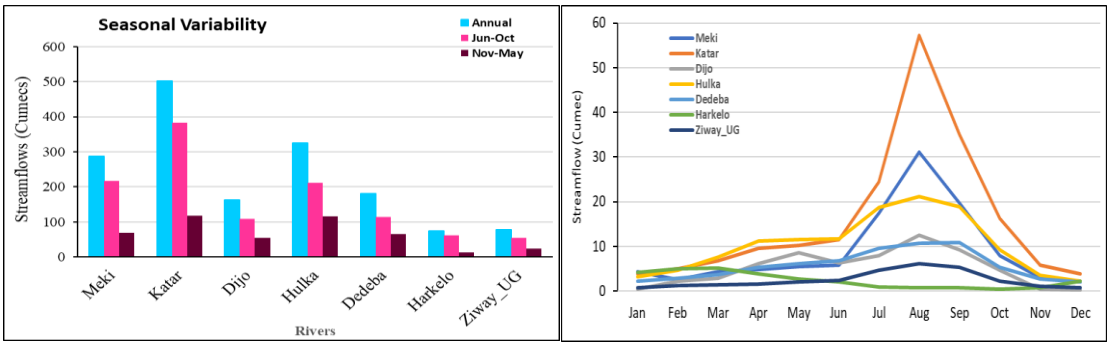


Figure 11: Seasonal variability of stream flow of sub-catchments in Ziway-Shalla sub-basin

Abaya - Chamo Sub-basin: Bilate River, situated in the southern part of Ethiopia, is a vital water source used for both agriculture and daily household needs. Originating from the Gurage highlands, the river flows southwards for a distance of 203 km until it reaches Lake Abaya. With a catchment area of 5,546 km^2, the river generates a stream of 909.66MCM from which 131.05MCM is abstracted on the upstream and 778.62MCM flows into Lake Abaya. The Gelana River begins in the Gedeo mountains in the eastern part of the RVLB. It flows west for 149km until it reaches Lake Abaya. The river's catchment area covers 3,129 km^2, and it is estimated that the streamflow is 541.5 M (Table 5). The Gidabo River, one of the longest rivers in the basin, originates in the Sidama Mountains in the eastern part of the RVLB. It flows for 108 km before reaching Lake Abaya. The catchment area for the Gidabo River is 3,552 km^2, and the estimated streamflow is 675.08M.

The Kulfo River originates in the southwestern part of the RVLB, specifically in the Gamo Mountains, and it flows into Lake Abaya. With a length of 39 km, the Kulfo River contributes 49.83M of streamflow to Lake Abaya. On the other hand, the Hamessa River originates from the Welayta Mountains and also flows into Lake Abaya, generates a

streamflow of 58.82MCM, covering a catchment area of 521 km^2. Within the West Abaya catchment, there are rivers such Harre, Shefe, Baso, Doshe, and Uraya, with Harre being the longest at 30 km. This catchment has an area of 1,339 km^2 and produces a total annual streamflow of 226.88M. These rivers are known for their unstable courses, and there are extensive banana farms along their banks and 77.14MCM of water is abstracted from these rivers. For Lake Chamo, Sego and Sille are the major supply rivers originating at the western highlands of Lake Chamo, the Streamflow generated is 283.61 M from 1,807 km^2 and 56.09MCM is abstracted mainly for irrigation.

Table 5: Water balance of Stream flows of Abaya - Chamo Sub-basin (MCM)

Rivers	Interflow	Base Flow	Surface Runoff	Total Stream flow	Flow outlet	Abstractions
Bilate	201.85	95.30	612.51	909.66	778.62	131.05
Hamessa	14.04	2.89	67.88	84.82	70.02	14.79
Gina	22.837	18.9	185.07	226.88	149.74	77.14
Kulfo	15.55	2.47	31.80	49.83	39.31	10.52
Sile	62.20	5.36	216.05	283.61	227.52	56.09
Gidabo	82.09	3.65	589.34	675.08	604.02	71.06
Gelana	98.81	19.92	422.78	541.50	475.60	65.90
				2,771.38	**2,344.82**	

The temporal distribution of the stream flow in the sub-basin follows the rainfall variability over the sub-basin. Most of the sub-basins have high flow in the rainy season. Due to these temporal and topographical characteristics of the river system, the dry season (Nov-Apr) flow in all catchments cover only 30% of the annual flow (Figure 12).

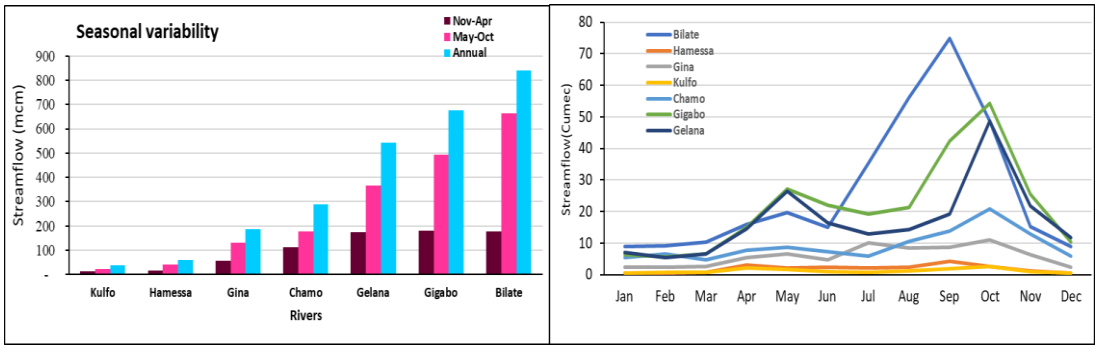


Figure 12: Seasonal variability of stream flow of sub-catchments in Abaya-Chamo sub-basin

Hawassa Sub-basin: Tikur-wiha is the major river that flows into Lake Hawassa, the river starts at the northeastern part of the RVLB, as shown in Table 6, the total stream flow size of the river is 129.06MCM from the total catchment 1,430 km^2 catchment area and 15.49MCM is abstracted.

Table 6: Water balance of Stream flows of Hawassa Sub-basin (MCM)

Rivers	Interflow	Base Flow	Surface Runoff	Total Stream flow	Flow outlet	Abstractions
Tikurwiha	**18.52**	**2.69**	**107.85**	**129.06**	**113.57**	**15.49**

Temporally, the stream flow in the sub-basin follows the rainfall variability over the sub-basin. The catchment has a high flow in the rainy season. Due to these temporal and topographical characteristics of the river system, the dry season (Nov-May) flow in the catchment covers only 42% of the annual flow (Figure 13).

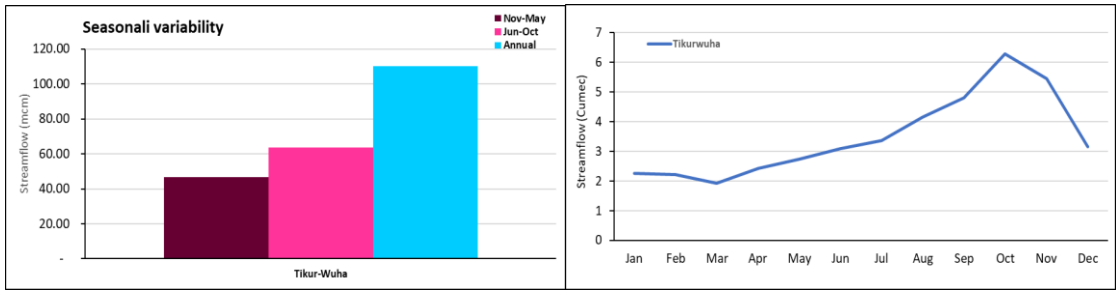


Figure 13: Seasonal variability of stream flow of sub-catchments in Hawassa sub-basin

Chewbahir Sub-basin: The Segen River, originating at the Plateau of the Netch-Sar National Park on the eastern side of Lakes Abaya and Chamo, is among the longest rivers in the basin. It flows 171 km south to Lake Chewbahir. The river is gauged at konso and it is used to calibrate the model. The total streamflow from the catchment area of 7,900 km^2 is estimated to be 468.72MCM (Table 7). Weito River, on the other hand, holds the record for being the longest river in RVLB, stretching 222 km. It starts at the junction mountains of South Omo, Gofa, and Gamo zones and flows south into Lake Chewbahir. The estimated streamflow from its catchment area of 4,404 km^2 is 528.80 MCM.

Table 7: Water balance of Stream flows of Chewbahir Sub-basin (MCM)

Rivers	Interflow	Base Flow	Surface Runoff	Total Stream flow	Flow outlet	Abstractions
Weito_	196.48	2.12	330.21	528.80	432.64	96.16
Segen	122.51	31.12	315.08	468.72	394.17	74.55
Serbela	124.16	204.29	594.47	922.91	785.74	137.17
				1,920.44	1,612.55	

Temporally, the stream flow in the sub-basin follows the rainfall variability over the sub-basin. The catchments have a high flow in the rainy season. Due to these temporal and topographical characteristics of the river system, the dry season (June - July) and (Nov – Feb) flow in all catchments cover only 38% of the annual flow (Figure 14).

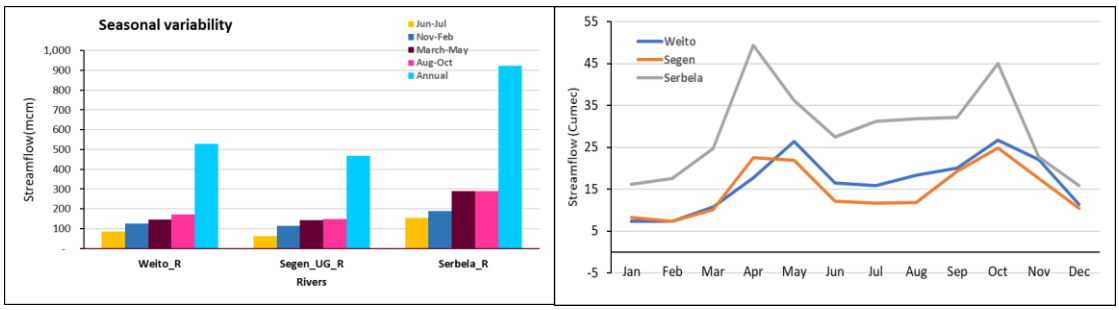


Figure 14: Seasonal variability of stream flow of sub-catchments in Chewbahir sub-basin

Lake-based Surface Water Resources

The Rift Valley Lakes of Ethiopia are a series of lakes in the Rift Valley extending from northeast to south in Ethiopia. These lakes include some old lakes, the deepest lakes, large lakes by area, and large lakes by volume. Many are freshwater biomes with high biodiversity, while others are alkaline biomes that harbor highly specialized organisms. Some of the lakes in the Ethiopian Rift Valley have no outlet and are mostly alkaline. These lakes are home to a wide variety of plants and animals, including fish, birds, reptiles and mammals. Some of the famous animals found in the Rift Valley lakes include hippos, crocodiles and flamingos. The Rift Valley lakes are very important to the Ethiopian economy. They provide drinking and irrigation water and are popular tourist destinations, attracting tourists from all over the world. The water resource of the Lakes is analyzed using the water balance approach. Table 8 indicates the volume and geometric descriptions of the Lakes.

Table 8: Lakes of the Rift Valley Basin

Lakes	Area (km2)	Volume (Bm3)	Mean Depth (m)	Max Depth (m)
Ziway	430.19	1.026	2.38	9
Abijata	87.30	0.615	7.04	76
Langano	231.13	1.917	8.30	46
Shalla	313.70	21.355	266.00	290
Hawassa	129.0	1.033	11.82	29
W_Abaya	1,154.19	9.084	7.87	86
Chamo	325.95	1.933	5.93	103

Lake Ziway: Lake Ziway is one of the freshwater lakes in the basin, with an area of 430 square kilometers, an average depth of 2.38m, and a maximum depth of 9m. It is a habitat for important bird and hippo populations and is also used for fish production. Lake Zwe is fed by two main rivers, flowing westward and southeastward respectively from the mountains on either side of the Great Rift Valley Mountains. It is the second-largest lake in the basin and is home to many endemic birds and a variety of wildlife. It is also one of the main sources of commercial fish farming in Ethiopia. The total drainage area of Ziway Lake is about 7297 square kilometers. The main source of water for the lake is the tributaries of the Maki and Qatar rivers. Small rivers on the west and east sides of the lake also have inflows. The average annual discharges of the Maki River, Katar River and the Little River around the lake are 288 MCM, 501 MCM and 78.5 MCM respectively. In addition, the average annual direct precipitation in the lake area is 41.16 million cubic meters, and the average annual inflow is 931.55 million cubic meters. On the other hand, the lake's evaporative losses, withdrawals, and discharges into the Bulbula River were 529 MCM, 153 MCM, and 241 MCM, respectively, making the lake's positive water storage change 0.8 MCM, which is good for the lake to absorb and resist climate changes and the effects of overabsorption upstream of tributaries and maintain water levels. (Desta et al. 2020; Goshime et al. 2021b), Reported similar findings.

Lake Langano: Lake Langano which is also a freshwater lake, relatively experienced less seasonal and inter-annual water level variability. Since the level of Lake Abijata is only a few meters lower than that of Lake Langano, the Lake flows towards Lake Abijata to the south through the Harakalo River. The upstream catchment area of Lake Langano is 2,020km2 and contributes a mean annual inflow of 328.97 MCM. Rainfall in the lake area contributes a mean annual water of 17.68 M. The total inflow to the lake system, thus, becomes 346.65MCM. The outflow of Langano Lake consists of evaporation from the Lake surface and outflows through the Harakalo River. Their mean annual volume accounts for 228.62MCM and 70.85MCM, respectively. Deduction of these mean annual outflows from the mean annual inflows gives a positive annual change in storage of 5.18MCM. Thus, the lake water balance confirms that the water level is stable against the long-year climate variability. Since there is no significant abstraction from the lake, its water level has not been affected by human activities in the system (Table 9).

Lake Abijata: Lake Abijata is a terminal lake and the principal sources of water are Lakes, Ziway and Langano, through Bulbula and Harakalo Rivers, respectively. The lake supports a wide variety of wildlife and migrant birds (Wagaw et al, 2019). The fluctuation of its principal water sources, its final position in the drainage area, and its shallow depth make Lake Abijata more sensitive to climate and human interventions. Since Lake Ziway

contributes about 80% of the inflow water to Lake Abijata, the abstraction from this lake and its feeder rivers, Meki and katar will have a very significant effect on the water conditions of Lake Abijata. The current lake water balance shows that the total volume of Lake Abijata is 384.14MCM, where 241.18MCM is contributed from Lake Ziway through Bulbula River, 74.59MCM from Lake Langano through Harakalo River, from the catchment 61.39MCM and 6.97MCM from mean annual rainfall over the lake. Deduction of the mean annual lake evaporation 384.14MCM and overflow in high water conditions gives a negative mean annual stored water change of 0.36MCM, which indicates the continuous reduction of water level of the Lake that improves only during high water flows in the flood season (Table 9). Due to the effect of uncontrolled abstraction issues over the lake area and feeder rivers, the Lake is in serious natural water balance threat.

Lake Shalla: Lake Shalla is the deepest lake in the Basin with a depth of about 266m. It is separated from Abijata by a volcanic caldera rim. Lake Shalla, along with neighboring Lake Abijata, is part of the Lake Abijata–Shalla National Park, where more than 300 species of birds have been recorded. A hot spring situated in the lake's northeastern corner is a popular attraction. The Lake is highly alkaline which makes direct water abstraction for irrigation and other uses impossible. Lake Shalla does not have direct interconnection with other lakes with its surface water. However, since it is the lowest lake among the lakes in the basin, there is a greater probability for a sub-surface water flow interaction. Although it is not interconnected with the rest of the lake catchment system, Lake Shalla has a river network that flows into it. The two main rivers, Dijo and Dedeba, feed this lake with mean annual inflows of 162.56MCM and 180MCM, respectively. The rainfall over the lake surface having an area of 311km2, accounts for 29MCM of inflows, which makes the total mean annual inflows to the lake 372.56MCM. The mean annual inflows and outflows of the lake balance with a negative 0.65MCM mean annual changes of stored water (Table 9). Since Lake Shalla is a deep lake, the effect of this recurrent mean annual reduction of 0.65MCM did not show a change in the water level and Lake surface area.

Lake Hawassa: Situated at the center of the Rift Valley Lakes Basin (RVLB), Lake Hawassa boasts an area of 87 km2. With a length of 16 km, a maximum width of 9 km, and a maximum depth of 10 m, the lake rests at an elevation of 1,681 m above sea level. Lake Awasa's accessibility has made it one of the most studied lakes in the Ethiopian Rift Valley Lake system by scientists. The main river, Tikurwiha, feeds Lake Hawassa with mean annual inflows of 131.53MCM. The rainfall over the lake surface having an area of 87.43 km2, accounts for 9.90MCM of inflows, which makes the total mean annual

inflows to the lake 141.43MCM. This makes the water balance analysis limited to carrying out the analysis of the difference between the inflows to the lake and evaporation plus abstraction from the lake; according to which the mean annual water volume of the Lake is estimated at 141.43MCM. The mean annual inflows and outflows of the lake balances with a negative 0.35MCM mean annual changes of stored water (Table 9).

Lake Abaya: Lake Abaya is positioned near Lake Chamo, east of the Guge mountains, in the main Ethiopian Rift. The lake covers an area of 1,162 square kilometers and boasts a length and width of 60 and 20 kilometers, respectively. Furthermore, it has a maximum depth of 13.1 meters and is located at an elevation of 1,175 meters above sea level. The lake is fed by three primary rivers: the Bilate, Gidabo, and Gelana Rivers. The lake and its surrounding savanna are home to a variety of birdlife and wildlife, and they are also a vital fishing area for the local population. The only outflow of Lake Abaya is through the lower reaches of the Kulfo River, which is situated at an elevation of 1,190 m. The riverbed acts as a spillway during times of high lake levels, releasing excess water into Lake Chamo. The elevation difference between the two lakes is 62 m, with Lake Abaya being higher than Lake Chamo. The outflow from Lake Abaya is crucial for maintaining the hydrological balance of the Abaya-Chamo Lake basin. It helps regulate the water levels in the lakes and prevents them from becoming too saline. Additionally, the outflow provides a source of water for irrigation and drinking in the surrounding area.

Lake Abaya is the widest lake in the basin and the main source of water for the lake is the tributaries of the Bilate, Gidabo, Gelana, Hamessa and Kulfo rivers. Small rivers on the west sides of the lake also have inflows. As shown in (Table 9), the total discharge that flows into Lake Abaya is 2,469.90 MCM. In addition, the average annual direct precipitation in the lake area is 131.14 MCM, On the other hand, the lake's evaporative losses, withdrawals, and discharges into Lake Chamo were 2126.20MCM, 156.57 MCM, and 174 MCM, respectively, making the lake's positive water storage change 13.44 MCM, which is good for the lake to absorb and resist climate changes and the effects of overabsorption upstream of tributaries and maintain water levels. The results are consistent with previous studies. Findings are in line with previous study reports (Abdi and Gebrekristos, 2022; Asfwossen Asrat, 2009; Teffera et al., 2019)

Lake Chamo: Occupies an area of 3,17 km2. The lake has a maximum length and width of 32 km and 13 km, respectively, reaches a maximum depth of 14 m, and is situated at an elevation of 1,110 m above sea level. Lake Chamo is primarily fed by the Kulfo River and the overflow from Lake Abaya.

The main source of water for Lake Chamo are the tributaries of the Sile, Sego, and Gidole rivers. Small rivers on the southeast sides of the lake also have inflows. The total discharge that flows into the lake is 289.64 MCM. In addition, the average annual direct precipitation in the lake area is 34.66 MCM, On the other hand, the lake's evaporative losses, withdrawals, and discharges into Lake Chamo were 274.54, and 44.01 MCM, respectively, making the lake's positive water storage change 5.73 MCM (Table 9), which is good for the lake to absorb and resist climate changes and the effects of overabsorption upstream of tributaries and maintain water levels. The results are consistent with previous studies. The results are in line with previous study reports (Abdi & Gebrekristos, 2022; Eyerus Nigussie, 2021; Hailemicael Mezgebe & Solomon, 2011; Teffera et al., 2019)

Other smaller lakes: Other smaller lakes in the basin have not yet been given adequate attention by most of the studies including researchers. Lake Chitu: is a small lake found adjacent to Lake Shalla. It is one of the crater lakes in RVLB located at an altitude of 1540 masl between. The lake has an area of 0.8 km^2 and a maximum depth of 21m. Unlike for the other major lakes; it is hardly possible to analyze the water balance for this Lake since the required measured data are not available. Lake Tinishu Abaya; is found at an altitude of 1894m.a.s.l between 394683N and 827730E. The total area of the lake was estimated at 12.5 km^2. According to the information from the local people, the lake has become shallow with the shrinking of its area in recent years.

Water level fluctuations of the lakes are also analyzed with seasonal and annual variability of water balance components. Lake Ziway, the lake water level shows a 1m change from the end of September, 1636.2 to the end of May, 1635.8masl. Annually, the lake water fluctuates from 1635masl in dry years to 1636.8m in wet years. It provides a 2m active water depth in the lake when the frequency of occurrence of the lower and upper water levels for the last four decades (1981 -2020) is analyzed (Figure 14). For Lake Abijata water level has reduced to a point where it cannot even satisfy the evaporation (environmental) requirement. The climate sensitivity is further pronounced when the long-term water level change is considered. The drop and recovery time vary based on the severity and magnitude of climatic variations. Seasonally, the Lake Langano water level shows a 1m change from the end of September, 1,581.25 to the end of May, 1,580.25masl. Annually, the lake water fluctuates from 1,579 m,a.s.l during dry years to 1,581m in the wet years. Lake Hawassa's water level fluctuates between 1,672m to 1,680m. Moreover, Lake Abaya's water level has fluctuated from 1,166 m.a.s.l in Dec to 1,170.5 m.a.s.l in Sep. and Lake Chamo fluctuates between 1,102 – 1,109 masl.

Table 9: Annual water balance of the Rift Valley Lakes (MCM)

Lakes	Water balance	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Ziway	Rainfall	0.76	1.16	2.24	3.40	3.46	4.15	6.64	5.84	3.85	2.03	0.45	0.21	34.17
	Inflow	27.31	19.17	32.03	42.53	43.34	52.61	128.63	257.41	147.71	94.39	27.07	18.19	890.40
	Evaporation	79.23	80.42	57.14	36.16	27.57	21.15	20.95	18.63	16.56	34.59	60.49	76.66	529.53
	Abstraction	10.62	9.68	10.62	13.71	14.17	13.71	14.17	14.17	13.71	14.17	13.71	10.62	153.05
	Outflow	6.77	4.44	4.72	3.40	2.58	3.47	20.41	84.35	56.49	41.20	8.47	4.89	241.18
	Changes in storage	-68.56	-74.21	-38.21	-7.34	2.49	18.44	79.74	146.11	64.80	6.46	-55.15	-73.77	0.80
Abijata	Rainfall	0.19	0.21	0.47	0.77	0.71	0.89	1.28	1.13	0.84	0.38	0.07	0.04	6.97
	Inflow	0.29	0.32	2.78	2.86	4.60	7.65	8.82	9.68	5.69	5.52	6.96	6.24	61.39
	Inflow from Lake Ziway	6.77	4.44	4.72	3.40	2.58	3.47	20.41	84.35	56.49	41.20	8.47	4.89	241.18
	Inflows from Lake Langano	11.15	12.04	13.71	9.85	7.30	5.55	2.37	1.84	1.82	1.17	1.75	6.06	74.59
	Evaporation	56.84	51.60	44.26	27.81	22.40	19.78	22.94	20.71	15.07	22.40	33.13	47.57	384.50
	Changes in storage	-38.45	-34.59	-22.58	-10.92	-7.21	-2.22	9.94	76.28	49.76	25.86	-15.88	-30.34	-0.36
Langano	Rainfall	0.22	0.23	1.55	1.79	1.78	1.81	2.29	2.21	1.97	1.62	1.15	1.06	17.68
	Inflow	10.38	10.32	19.03	26.93	28.50	31.08	52.65	55.36	47.80	31.70	9.64	5.60	328.97
	Evaporation	37.27	39.78	31.79	17.59	12.87	12.56	14.85	13.12	11.40	16.24	27.40	35.75	270.62
	Outflow	13.33	12.81	10.75	6.27	4.51	4.56	3.15	1.06	0.91	1.31	3.17	9.03	70.85
	Changes in storage	-40.00	-42.04	-21.96	4.86	12.91	15.77	36.94	43.38	37.45	15.76	-19.78	-38.12	5.18
Shalla	Rainfall	0.75	1.27	2.39	3.38	3.44	3.30	4.43	4.20	3.67	1.43	0.43	0.32	29.00
	Inflow	6.92	12.18	17.50	29.66	39.24	34.25	47.11	62.38	52.44	26.43	8.22	6.24	342.56
	Evaporation	52.09	48.94	40.98	24.15	18.59	16.84	19.92	18.60	15.46	26.95	39.52	50.17	372.21
	Changes in storage	-44.42	-35.49	-21.09	8.90	24.10	20.70	31.61	47.97	40.64	0.90	-30.87	-43.61	-0.65
Hawassa	Rainfall	0.32	0.27	0.69	1.21	1.21	0.94	1.30	1.10	1.17	1.17	0.35	0.17	9.90
	Inflow	8.88	6.65	5.62	6.75	7.83	8.84	10.17	11.49	13.34	23.56	18.55	9.84	131.53
	Evaporation	17.17	18.10	16.18	9.16	6.82	7.33	9.67	9.24	7.72	7.62	11.83	16.52	137.35
	Abstraction	0.35	0.36	0.34	0.38	0.47	0.35	0.33	0.32	0.38	0.30	0.43	0.43	4.42
	Changes in storage	-7.97	-11.17	-9.87	-1.20	2.22	2.45	1.80	3.35	6.79	17.12	7.07	-6.52	-0.35
Abaya	Rainfall	3.68	4.34	9.07	21.56	21.24	10.12	11.01	10.30	12.02	18.15	7.01	2.66	131.14
	Inflow	68.25	57.01	74.09	144.89	223.74	159.26	215.46	278.01	391.91	449.68	184.29	92.16	2338.76
	Evaporation	357.10	342.96	279.61	95.26	45.53	84.84	134.64	138.21	106.93	94.72	164.78	281.63	2126.20
	Abstraction	0.00	0.00	0.00	39.18	39.13	39.11	39.15	0.00	0.00	0.00	0.00	0.00	156.57
	Outflow	0.54	0.18	0.41	1.35	7.19	6.97	10.58	24.15	44.85	57.60	18.82	1.36	174.00
	Changes in storage	-285.16	-281.61	-196.46	71.20	199.45	84.54	91.83	150.09	297.00	373.11	26.52	-186.81	13.14
Chamo	Rainfall	1.10	1.61	2.76	6.16	5.30	2.33	1.98	2.15	2.47	5.41	2.27	1.11	34.66
	Inflow	14.24	16.15	12.27	19.88	23.52	19.00	15.66	28.47	36.08	55.55	33.27	15.52	289.61
	Evaporation	30.24	23.39	19.79	10.52	10.65	18.50	21.65	19.44	24.43	23.08	34.80	38.04	274.54
	Abstraction	0.74	0.77	0.38	0.97	2.87	2.12	0.62	4.26	6.56	15.48	8.19	1.06	44.01
	Changes in storage	-15.64	-6.40	-5.14	14.55	15.30	0.70	-4.63	6.93	7.56	22.41	-7.44	-22.47	5.73

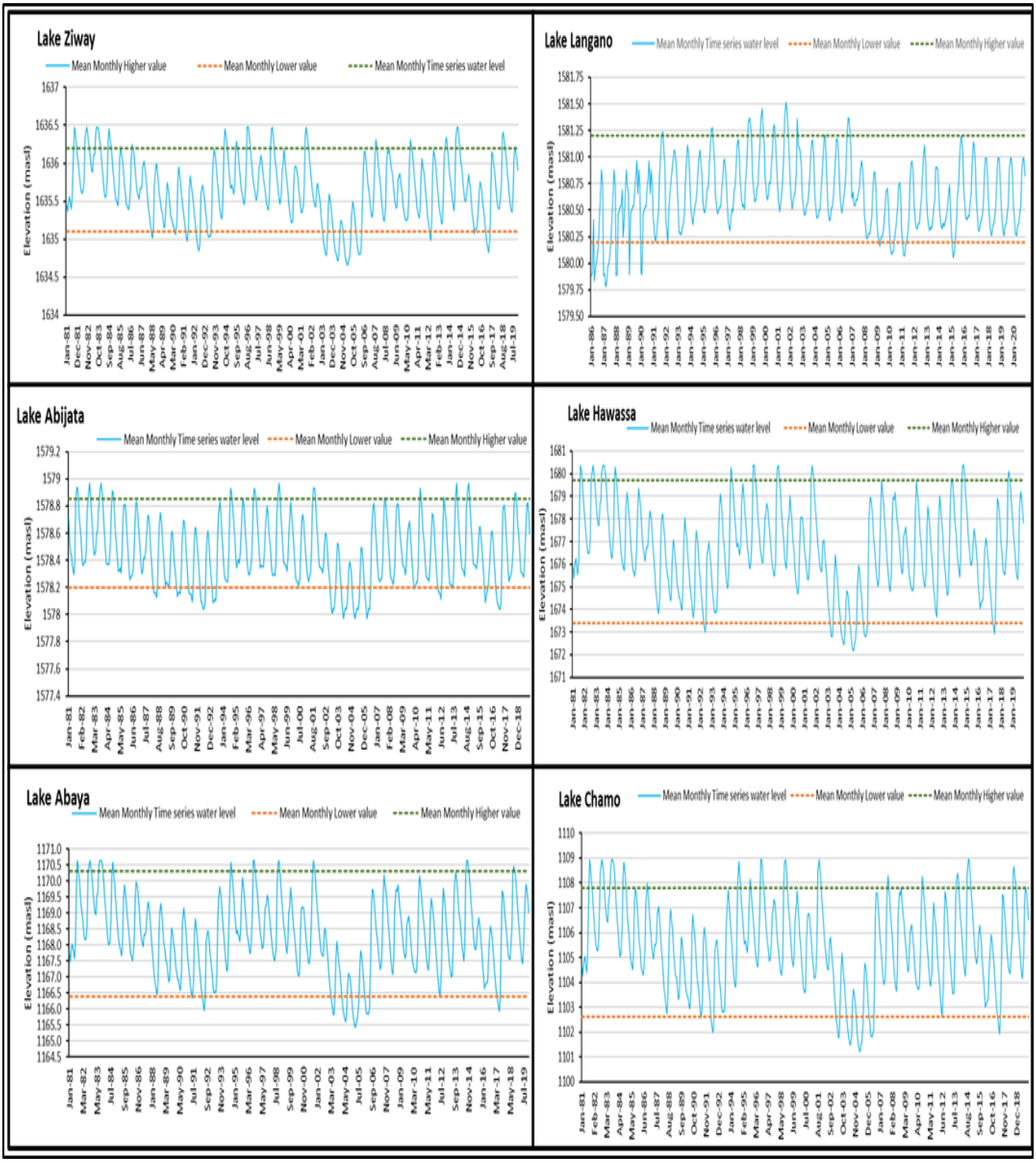


Figure 15: Water level fluctuation of Lakes

4.5.4. Total surface water resource potential of the RVLB

As indicated in Table 10, the basin has an annual renewable potential surface water resource of 6,534MCM and 358MCM, which can be abstracted as stream flow from the river network system and lake water system respectively. Lakes can serve as a storage facility to manage the time variability of the surface water resources. However, Abijata, Shalla and Chewbahir lakes have high concentrations of alkaline and fluoride, which limits the abstraction of water for domestic, irrigation and other related uses. Thus, storage facilities in the upper sections of the tributary rivers are highly required for efficient use of the surface water.

Table 10: Total surface water resource potential of the basin

Lake System	Available water from Lake (MCM)	Available water from Streams (MCM)	Total Available Surface Water Potential (MCM)
Lake Ziway	153.05	890.40	1,043.45
Lake Langano		328.97	328.97
Lake Abijata		377.16	377.16
Lake Shalla		258.00	258.00
Lake Hawassa	4.42	131.53	135.95
Lake Abaya	156.57	2,338.76	2,495.33
Lake Chamo	44.01	289.61	333.62
Lake Chewbahir		1,920.44	1,920.44
Total	**358.05**	**6,534.86**	**6,892.91**

4.6. DISCUSSIONS

The Rift Valley Lake Basin has many rivers, which constitute the unique ecosystem of the basin. The rivers that feed these lakes provide vital water for agriculture, fishing, and other industries. Rivers in the Ethiopian Rift Lake Basin play a vital role in supporting the region's ecosystem and economy. These rivers provide important water resources for the lake and surrounding communities and contribute to the area's biodiversity. The total surface water flow into the lakes of the basin is estimated to be 6.48BCM which is higher than the master plan study report of 5.3BCM (Halcraw and GIRDC, 2009) and 5.6BCM reported by (Ermias Mekonin, 2019) but, lower than the 7.83BCM reported by (MoWIE, 2018) and according to the (OIDA, 2018) report, the surface water resource potential of the 21,155km^2 catchment area which is part of the RVLB found in the Oromia state administrative boundary is 6.47BCM, as compared with the estimate of this study it is much higher.

The results also compared with previous study reports which were conducted at major catchments level for instance Meki River has 10.2 m^3/s average annual flow which is higher than the 8.96m^3/s reported by (Halcraw and GIRDC, 2009), 8.73m^3/s reported by (Goshime et al. 2021a) and 8.86 m^3/s reported by (OIDA, 2018) but, lower than the 11.28 m^3/s reported by (Bunta & Abate, 2021). For katar Catchment, the Katar River has an estimated average annual streamflow of 16.9m^3/s, which is higher than the 12.47m^3/s reported by (Halcraw and GIRDC, 2009), 13.66 reported by (Goshime, et al. 2021a), and 12.88 m^3/s reported by (OIDA, 2018). Dijo River has an estimated 5.38m^3/s average annual flow which is comparable to 5.72 m^3/s reported by (Halcraw and GIRDC, 2009). Bilate River has 28.58m^3/s flow which is comparable to the 27m^3/s reported by (Aklilu Megebo, 2020), Tikur wiha has an estimated average annual flow of 4.09m^3/s which is also comparable to 3.64m^3/s reported by (Abiot and Dwarakish, 2020). Segen River has 29.27 m^3/s which is lower than the 38.3m^3/s reported by (Ashenafi Kifle, 2016), Kulfo and Hamessa Rivers have 1.58m3/s and 2.69m^3/s average annual streamflow respectively which is lower than the 2.82 m^3/s and 3.06m^3/s streamflow reported by (Halcraw and GIRDC, 2009). Deviations are caused mainly due to the methodology, data used for calibration, model input data variations, different assumptions used, different study objectives and the time difference when the studies are conducted.

4.7. CONCLUSIONS

The Water Evaluation and Planning (WEAP) is used for the hydrological analysis, calibrated and validated with time series stream gauge data obtained from MoW and RVLB authority office. The model performance was tested using statistical performance indicators, such as coefficient of determination, Nash-Sutcliffe Efficiency, and percentage bias, used to evaluate the model's accuracy in simulating stream flows, and the results revealed that the RSQ ranges from 0.83 – 0.93, NSE ranges from 0.68 – 0.86, PBIAS ranges from-9.45 to -1.85, RSR ranges 0.35 – 0.59 and IA ranges from 0.62 – 0.84. At basin level water balance, the basin receives 50.03BCM total mean annual precipitation, of which 83% (41.32BCM) evaporates back into the atmosphere. Since the basin water flows to the lakes: Ziway, Langano, Abijata, Shall, Hawassa, Abaya, Chamo and Chewbahir, it does not have any water leaving the basin through the river as outflow. The remaining 8.64CM becomes the renewable water source of the basin that can be accessed in the form of surface or subsurface water sources. The available surface water for abstraction was further evaluated based on type, space, and time distribution. Accordingly, a total of 358MCM is available as lake water abstraction, and 6,534MCM is available as stream flow water, making it a total surface water flow of 6,892MCM available for any abstraction use in the basin. Considering the temporal distribution of the

surface water sources, 79 % is available in the rainy season, June–October, and 21% during the dry period, November–May for the Ziway-Shall sub-basin, 70 % is available in the rainy season, May–October, and 70% during the dry period, November – April for Abaya-Chamo sub-basin, 62% is available in the rainy season, March-May and August – October (because it has binomial rainfall regime) and 38% during the dry period, June-July and November - February for Chewbahir sub-basin. The remaining Hawassa sub-basin receives, 58% of the surface water sources during the rainy season May – October. The water level and capacity of the lakes in the basin were characterized using a detailed water balance analysis. The positive change in storage value at Lake Ziway, Langano, Abaya and Chamo was an indication that there is water level stability and temporal increment in lake level. On the contrary, lakes, Abijata, Shalla and Hawassa, show a negative change in storage, which leads to a continuous water volume drop from the lakes. Unlike Lake Abijata, the drop in water volume for Lake Shalla (which has a higher depth of about 260m) was not significant enough for surface area shrinkage. The main lakes of the basin are climate-sensitive lakes. Especially, Lake Abijata, with its terminal, shallow and alkaline nature, is highly sensitive to climate change and over-abstraction on the two upstream lakes and their feeder rivers. Particularly Meki and Ketar rivers supply is crucial since 82% of the inflows to Lake Abijata are contributed from the Lake Ziway subsystem who fed by these rivers.

The results of this study support sustainable water resource management and decision-making in RVLB. Water resource assessment with spatial and temporal distribution is a basis for improving efficient and sustainable water use. Furthermore, to improve future attempts to regulate the water resource development in the Rift Valley Lakes Basin, this study gives the spatial and temporal distribution of water resources available. The findings of this study, along with additional research on water resource assessment, can help to advise policy-makers about optimized water allocation planning in the basin. The climate sensitivity is further pronounced when the long-term water level change is considered. The water level drops during unfavorable climate scenarios and attempts to recover during years with above-average rainfall. The drop and recovery time vary based on the severity and magnitude of climatic variations

CHAPTER 5: MULTI SPECTRAL REMOTE SENSING FOR IRRIGATED AREA MAPPING

5.1. INTRODUCTION

Irrigation plays a key role in increasing crop production, especially in areas where water is scared (Yin et al., 2016). Irrigated agriculture is the main user of the available water resources. About 70% of the total water withdrawals and 60-80% of total consumptive water use are consumed in irrigation(Huffaker, 2008). Imposing sustainable water conservation policies at the core requires quantifying the spatial extent of the irrigated areas. Currently, the extent of irrigated areas on a global scale is principally derived from country-level statistics and remains uncertain. Although national statistical data gives the list of irrigated areas and water use, these data may lack precision especially when irrigation is not reported by the farmers and irrigated areas are mostly being estimated at the project level to calculate the cropping intensity (Kaini, Gardner, et al., 2020). To address the need for a precise large-scale mapping of irrigated areas, remote sensing provides a powerful tool for mapping irrigated areas (Hajj et al., 2013). With the availability of several operational cost-free and open access satellites (e.g., Landsat, Sentinels), remote sensing has been widely used for monitoring and managing crops from the field level to large domains (Ndikumana et al., 2018).

Irrigation extent mapping using optical satellite data has been explored in several studies using various methodologies to distinguish between irrigated and rain-fed crops(Xiang et al., 2019). Nevertheless, these methods are developed based on a similar principle that the phenological differences between irrigated and non-irrigated crops (e.g., growth rate, greenness) are detectable by the vegetation spectral information derived from satellite optical sensors. Most of the prior studies using optical data tend to classify irrigated/non-irrigated areas only for one specific crop type. The transferability of the methods based on optical data is further limited in humid regions due to the cloud cover, and the marginal difference in crop phenology between irrigated and rain-fed crops(Maselli et al., 2020).

Climate change and variability is also having a high impact on the irrigated area with spatial and temporal variability of available water resources, resulting in the inconsistency of the estimation of the irrigated area with time.(Kaini, Nepal, et al., 2020). The current challenge to mapping irrigated areas is that existing data sets differ in their results and accurately mapping irrigated areas still represents a challenge for land use classification. This is because approaches that are restricted to statistics alone are hard to

verify and may include errors. Additionally, there are discrepancies between official statistics and remote-sensing-based data, indicating that the irrigated area might be underestimated or overestimated by the official statistics. The politicized nature of data reports and different definitions of irrigated areas contribute to these discrepancies. Furthermore, better inventorying and investigation of irrigated areas are needed to improve water resource management and sustainable land use(Zhu et al., 2014a). Hence the outcomes of this study are useful in addressing the challenges explained above on estimating the current irrigated area using newly established multispectral imagery data analysis with ground truth verification procedures.

The Rift Valley Lakes Basin (RVLB) is one of the twelve major river basins in Ethiopia. The RVLB is considered a high priority because it is an area of significant ecological and environmental interest, with a system of lakes and wildlife parks and reserves, having substantial areas of productive rainfed agricultural land and good rangelands. The RVLB is primarily an agricultural basin and agriculture will continue to be an important part of the economy. According to the master plan study report, the potential of irrigation in the basin was estimated to be 153,000, of which 22,000 ha was under irrigation (Halcrow and GIRD, 2009). The traditional measuring unit irrigated land area in most of the parts in Ethiopia uses “qurt” which is approximately 0.25ha, and the database organized at district and regional levels is based on the traditionally estimated way, however, it lacks precision and the reported data are inflated. The first national database for the irrigated area estimated using GPS measurement in Ethiopia was reported by (MoWR, 2002) as 1.97Mha,(Awulachew et al., 2007, 2010) also reported the irrigated area in Ethiopia as 0.107Mha and 0.64 Mha, and based on the (CSA, 2016) report irrigated area is 1.82Mha while MoA reported on the same year the irrigated area is 2.7Mha (MoA et al., 2016). According to the assessment conducted by IWMI using the NDVI-MODIS method, the irrigated area in Ethiopia is estimated to be 1.35Mha (Chandrasekharan et al., 2021) and in a very recently published review paper, the irrigated area in Ethiopia is 2.47Mha (Belachew, et al 2022). As a result, there is no uniform and credible inventory of the current irrigated area in Ethiopia especially in the study area.

All discrepancies and inconsistent reports generated regarding the actual current irrigated areas in Ethiopia are mainly due to the lack of use of standard and precise techniques of measurement. This will have an impact on the sustainable and efficient utilization and planning of water resources. Hence, determining the precise quantification of the irrigated area helps with water resource planning, sustainable and efficient utilization of water and land resources, mitigating climate change and variability and optimizing water allocation.

Therefore, this study will assess the current irrigated area of the Ethiopian Rift Valley Lakes Basin, so that irrigation water use will be estimated based on the results and other additional data (major crops growing, agroecology, LGP, cropping pattern and cropping calendar) for optimized water resource planning. The study also uses multispectral satellite imagery data and new techniques for the assessment of irrigated areas, and results of the remote sensing techniques are compared and evaluated based on ground truthing.

5.2. IRRIGATED AREA MAPPING METHODOLOGIES

5.2.1. Normalized difference of vegetation Index (NDVI)

Relationships between the NDVI time series and vegetation activities have been well-established theoretically and empirically. The NDVI curve properties and characteristics can generate a set of metrics (Such as on-set of greening, senescence, the timing of maximum NDVI, growing season length, etc) that measure the timing and magnitude of NDVI response and summarize the spatial and temporal distribution of crop growth and phenology, therefore being used widely as an input for classification.

Recently developed methodologies are used for irrigated area mapping. Ready-made images of raw data were downloaded cost-free at high resolutions (10x10m spatial and 5 days of temporal resolution): Sentinel. Available raw data consists of different reflection bands that can be composed into a "normal" photo (RGB image), but the infra-red (and thermal band) gives more information about vegetation growth (Zanter, 2015). More specifically, the ratio of the infra-red and red bands results in the Normalized Difference Vegetation Index (NDVI). This ratio is widely used to identify green areas in a landscape. Inspired by the published studies (Thenkabail & Wu, 2012), NDVI is used as a measure to validate and identify irrigated land in RVLB.

For this reason, Sentinel-2 images with fine resolution (10mx10m) have been used with the ability to identify individual plots in several grid cells. To calculate the NDVI of satellite images taken by Sentinel-2A, Band 4 (Red Band) and Band 8 (Near Infrared Band) were used for the analysis. NDVI is a standardized index considering the ratio of the infra-red and red-band results (Liu & Huete, 1995)

$$\mathbf{NDVI} = \frac{(\boldsymbol{B8}-\mathbf{B4})}{(\mathbf{B8}+\mathbf{B4})} \qquad \text{---------- eq 4}$$

Where:

NDVI = Normalized Difference Vegetation Index

B8 = Near-Infrared Band
B4 = Red Band

Three years (2020 – 2022) Sentinel-2 images of a 15-day time series are downloaded from the Copernicus open access hub at levels S2A and S2B. Levels-S2A and S2B for Sentinel data refer to the at-top of the atmosphere reflectance with geometric corrections including ortho-rectification and spatial registration. The sentinel imagery is based on tile/grid and the kmz gridding/tilling file was downloaded from the sentinel hub and overlaid with the basin boundary, rainfall regime and LULC in ArcGIS that the exact dry season or irrigation time of the basin was identified. Figure 16 shows the steps followed in irrigated area mapping in this study.

5.2.2. Enhanced Vegetation Index (EVI)

The EVI method is a spectral index that is used to map irrigated areas. The EVI is a modified version of the NDVI that is more sensitive to changes in vegetation caused by irrigation. Similar procedures as the NDVI were followed regarding the data management except the additional band which is B2(Blue). The EVI is calculated from satellite imagery using the following formula: (Matsushita et al., 2007a)

$$\boldsymbol{EVI = 2.5 * \left(\frac{(B8 - B4)}{(B8 + 6 * B4) - (7.5 * B2 + 1)}\right)} \quad \text{---------- eq 5}$$

Where:
B2: Blue
B4: Red
B8: Visible and Near Infrared (VNIR)

The EVI is a more sensitive measure of vegetation greenness and it takes into account the absorption of light by water vapor in the atmosphere. This makes the EVI more reliable for mapping irrigated areas, especially in areas with high levels of atmospheric water vapor.

5.2.3. Land use classification (LULC)

Image classification procedures such as geometric correction, visual interpretation, identifying training sites, supervised classification, maximum likelihood ground truthing, and accuracy assessment were followed for LULC irrigated area mapping. To support classification algorithms in interpreting input data patterns and producing reliable outcomes, specific training data is necessary. The training dataset was created in this study by delineating polygon features representing areas irrigated by commercial farms,

state farms, riparian cash crop-producing farmers, irrigated areas around the lakes, and center pivots visible in high-spatial-resolution imagery data from the sentinel-2 imagery with (10x10m) spatial resolution.

5.2.4. Accuracy Assessment

The accuracy assessment consists of validation through ground truth data, comparison with existing irrigation products, and statistical data analysis. for overall accuracy (OA), kappa Coefficient, F1 score, and coefficient of determination (R^2).

$$\mathbf{OA} = \frac{\textbf{Number of sampling classes classified correctly}}{\textbf{Number of refernce sampling classes}} \quad \text{---------- eq 6}$$

$$\mathbf{K} = \frac{\textbf{\% overall correct value} - \textbf{\% correct agreement to observed values}}{\textbf{Total number of class} - \textbf{\% correct agreement to observed values}} \quad \text{--------- eq 7}$$

A field survey was conducted for validation of the irrigated area during the image accusation time in line with the cropping calendar of the study area. Sample sites were clustered based on the type of irrigation (modern and traditional), irrigation technology (pressurized, gravitational), irrigation scale (large, medium, small, and micro), source of water (river, lake, and groundwater), irrigated and non-irrigated farms. Based on the above parameters set, 996 sample sites were selected and data were collected, including time of sowing/planting, growth stage (initial, vegetative maturity, and senescence), canopy cover, type of crop, variety, date of harvesting, area, greenness (qualitative), and source of water. The irrigated area was measured using GPS. Figure 16 shows the steps followed in irrigated area mapping in this study.

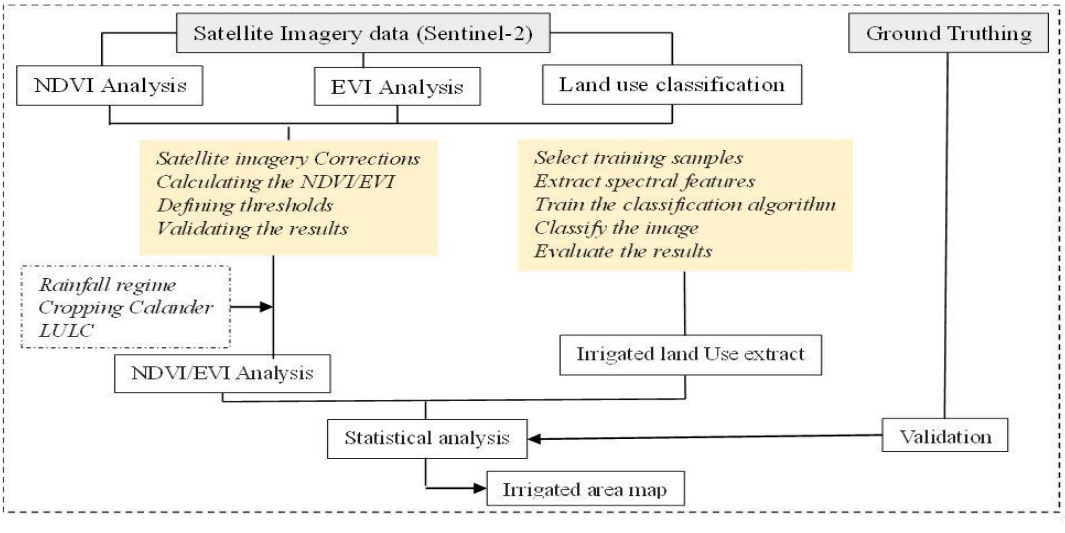


Figure 16: Flowchart of irrigated area mapping

5.3. RESULTS

Irrigated area mapping is a crucial aspect of agricultural management and planning. The use of remote sensing techniques such as NDVI, EVI, and land use classification methods has proven to be effective tools in accurately mapping and monitoring irrigated areas. As shown in Figure 17, the rainfall regime of the study area is bimodal, with the main season being during July- September and the second rainfall (Belg) in March-May (Berhanu et al., 2014). and the cropping calendar for the rainfed agricultural practice follows the two seasons of rainfall, however, the rainfall of the "Belg" season does not meet the crop water requirements of the crops and farmers use supplemental irrigation. Therefore, irrigation is practiced from October – June in the basin.

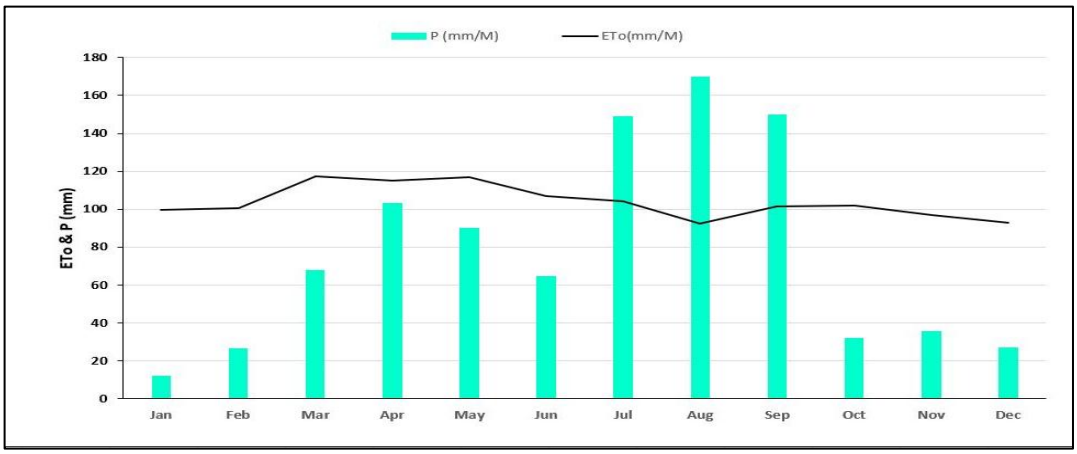


Figure 17: Rainfall and ETo of the RVLB

5.3.1. Irrigated area mapping based on NDVI analysis

There is no specific NDVI value set for irrigated area classification, irrigated areas can have varying levels of vegetation density depending on the type of crops grown, growth stage, and the irrigation system efficiency. Therefore, based on the above factors and the NDVI trend analysis results, the threshold NDVI values were set to be 0.2 – 0.6. For this study, three years (2020-2022) of Sentinel-2 images with fine temporal and spatial resolutions are used that enable to identification of individual plots in several grid cells. To calculate the NDVI of satellite images taken by Sentinel-2, Band 4 (Red Band) and Band 8 (Near Infrared Band) were used for the analysis. Figure 18 shows the peak NDVI values during 1-10 January 2020, 2021, and 2022. Accordingly, as shown in Table 11 the current irrigated area in RVLB is 109,173 ha.

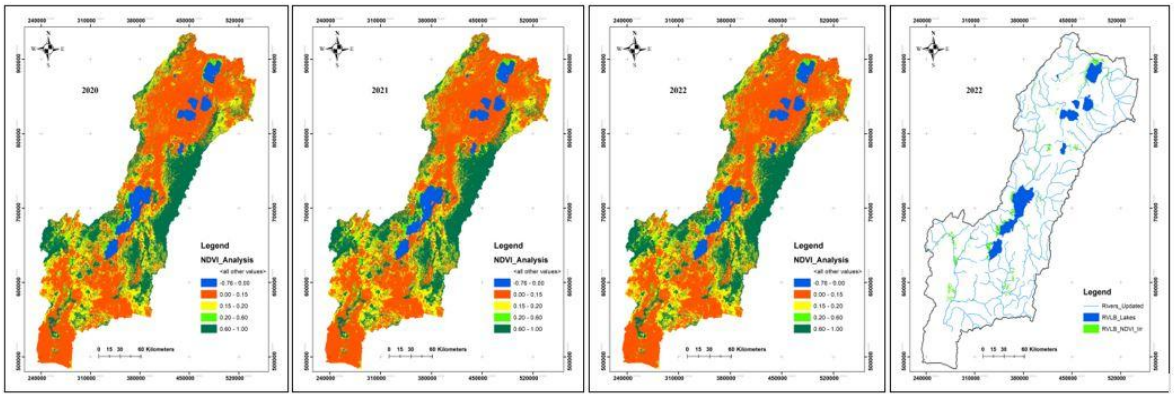


Figure 18: RVLB_NDVI irrigated area map

As shown in Figure 19, the trend of NDVI values spikes following the rainfall, and in most parts of the RVLB irrigation is practiced during October – February. At that time, the NDVI values from the imagery data analysis showed consistent greenness in the cultivated area even though there was not rainfall, greenness was observed due to irrigation. Supplemental irrigation is also practiced from March to May. Results go in line with reports from(Chandrasekharan et al., 2018) as NDVI and Rainfall in rainfed agriculture areas NDVI and pick rainfall overlap were used to identify the irrigation time.

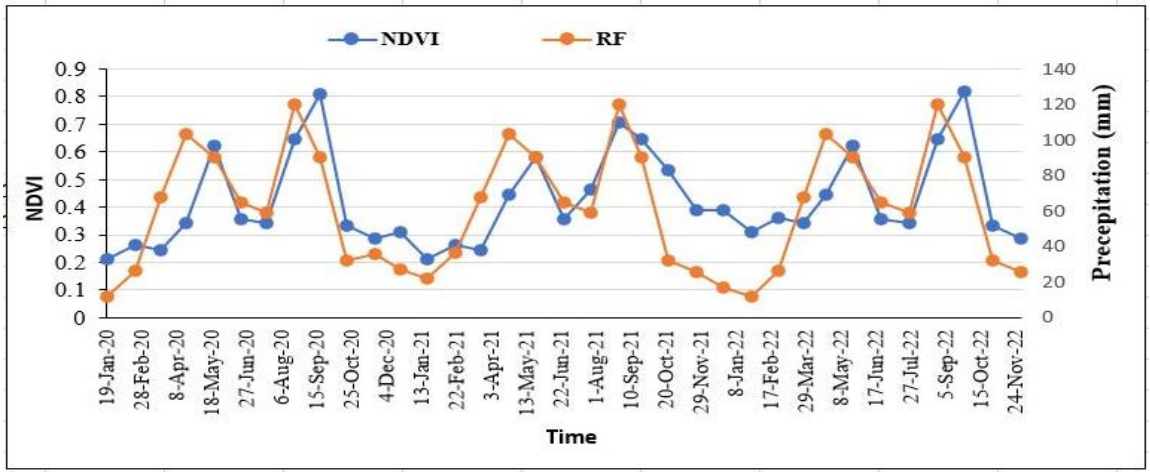


Figure 19: NDVI annual time series vs rainfall data

5.3.2. Irrigated area mapping based on EVI analysis

The Enhanced Vegetation Index (EVI) is a vegetation index designed to improve the sensitivity of satellite sensors to changes in vegetation coverage. It is estimated using satellite imagery in the near-infrared (NIR), red, and blue spectral regions. EVI is used in irrigated area mapping to evaluate and track the strength and vitality of vegetation in irrigated areas. It is feasible to distinguish and identify irrigated areas from non-irrigated areas by comparing the EVI values over time in a given area. Due to improved vegetation growth and enhanced greenness brought about by irrigation, irrigated areas typically have higher EVI values. Compared to other vegetation indices, EVI offers a more accurate depiction of vegetation health since it considers both the canopy structure and chlorophyll content.

The EVI values set for irrigated area classification are considering the type of crops, growth stage, and the irrigation systems. Therefore, the threshold EVI values were set to be 0.20 – 0.60, as shown in Figure 20, which shows the peak NDVI values during 1-10 January 2020, 2021 and 2022. Based on the image analysis using the EVI method, Table 11 indicated the current irrigated area in RVLB is 101,130 ha.

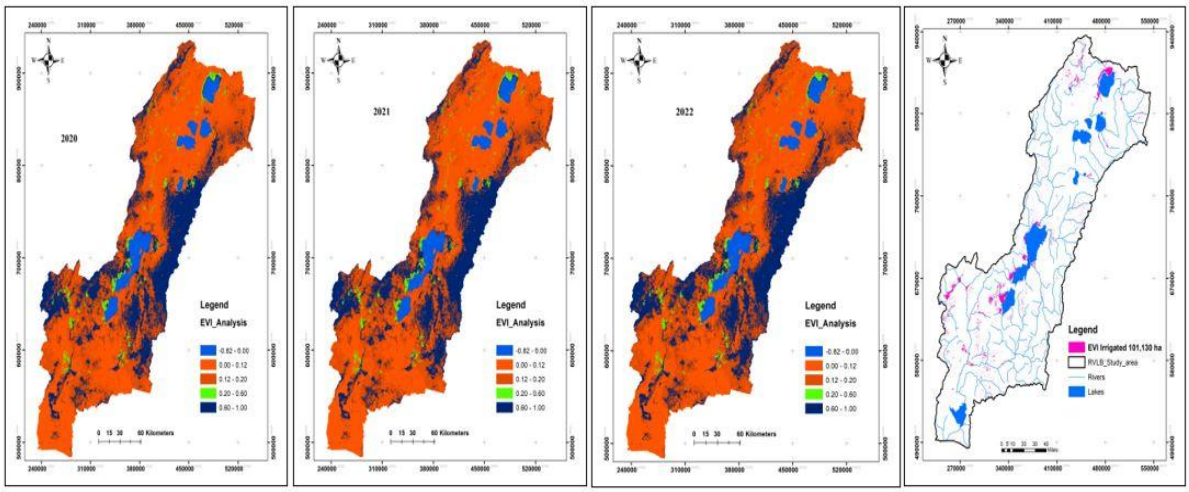


Figure 20: RVLB_EVI irrigated area map

Figure 21 exhibits an identical pattern with a sharp peak in greenness around May and September, followed by a rapid decline. While irrigated fields exhibit slightly larger EVI, possibly due to constant availability of moisture, the EVI value range 0.2 - 0.6 is observed consistently during October – May due to the irrigation practice. Findings are in line with previous studies (Zuo et al., 2023).

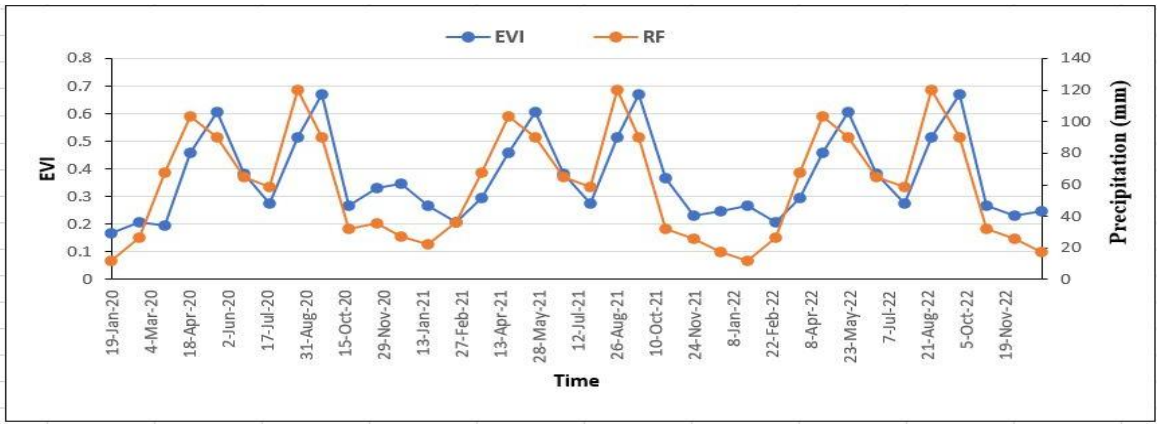


Figure 21: EVI time series vs rainfall data

5.3.3. Irrigated area extract of the Land Use Classification

The selection of training samples considered commercial farms, riparian farmers, irrigated areas around lakes, and center pivots. A signature file was created with the

addition of training samples for other land use types, and the classification of the remaining areas was done using the selected algorithm. The accuracy of the classification depends on the quality and number of training samples used, as well as the choice of the classification algorithm. Supervised land classification has been successfully used in many studies to identify irrigated areas and other land cover types (Hassan et al., 2016). Polygon features representing the irrigated areas of the training samples for the irrigated area visible in high-spatial-resolution imagery data from the Sentinel-2 imagery were used to create the training dataset for land classification. Accordingly, as shown in Table 11, the irrigated area is the estimated area found to be 103,474 ha (Figure 22), and both the imagery data analysis approaches have relatively close results.

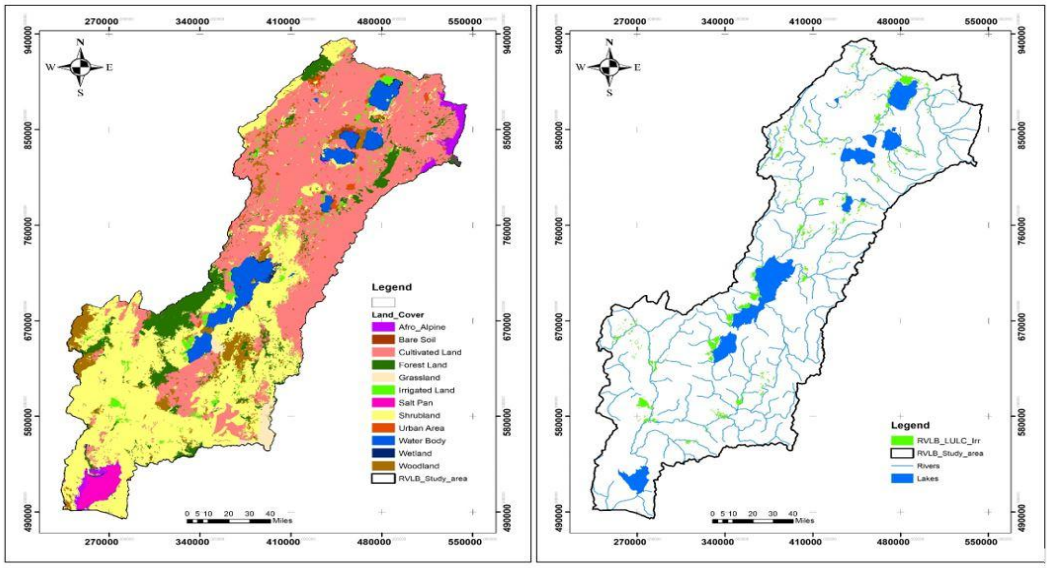


Figure 22: RVLB_LULC irrigated area map

Table 11: Irrigated areas computed by NDVI, EVI, and LULC analysis

Major Catchments	Irrigated area estimated (KM2)			
	NDVI_ Analysis	EVI	LULC	Mean
Abijata	14.83	13.73	26.00	18.23
Bilate	132.13	122.39	131.70	121.13
Chamo	90.57	83.90	85.03	83.15
Dijo	29.26	27.10	27.56	29.12
Gelana	16.29	15.09	0.57	9.57
Gidabo	28.31	26.23	53.66	31.59
Hamessa	2.22	2.05	1.35	5.59

Hawassa	47.60	44.10	49.44	52.78
Katar	29.38	27.21	25.16	26.45
Meki	63.08	58.44	66.48	63.51
Langano	14.78	13.69	41.28	19.11
Segen	114.25	105.84	116.67	105.92
Serbela	51.21	47.43	76.73	63.66
Shalla	31.62	29.29	20.77	23.49
Weito	152.42	141.19	83.39	120.98
W_Abaya	163.79	151.72	137.14	140.62
Ziway_UG	109.99	101.89	92.54	99.90
Total Area	1,091.73	1,011.30	1,035.47	1,014.81

*NDVI=Normalized Difference Vegetation Index, EVI= Enhanced Vegetation Index, and LULC = Land use and Land Cover

5.3.4. Intercomparison of outputs

Based on the validation sample points, the outputs of the irrigated area mapping methodologies were compared to each other, accordingly, the NDVI analysis was able to perform better in areas where vegetation is scattered or not denser, around Meki, Ziway, along the Bilate and Katar rivers. The EVI method was able to identify irrigated areas with highly denser vegetation with diverse crops and forest areas such as the Gurage mountains, around the Lake Abaya, Langano, Dijo, Segen and Weito catchments.

NDVI is more sensitive at lower vegetation levels because it's designed to capture the contrast between the red and near-infrared reflectance that is characteristic of green vegetation. When vegetation is sparse, there's a significant difference between the amount of red and near-infrared light reflected, resulting in a moderate NDVI value. As vegetation becomes denser, the difference between red and near-infrared reflectance decreases, making changes in NDVI less noticeable(Huang et al., 2021). Therefore, NDVI is a powerful tool for distinguishing areas with sparse vegetation from those with dense vegetation. The EVI is more sensitive to the Near-Infrared (NIR) B2. As a result of the penetrating properties of the NIR band, EVI is more responsive to canopy structural variations, including Leaf Area Index (LAI), canopy type, and canopy architecture. This sensitivity to canopy structure makes EVI particularly useful in areas with high biomass, where changes in vegetation structure over the growth season can be significant(Matsushita et al., 2007b). Therefore, EVI tends to have stronger growth season peaks as it can capture these structural changes more effectively than NDVI. This makes EVI a powerful tool for monitoring vegetation in irrigated areas, where changes in canopy structure can indicate changes in water availability or crop health.

5.3.5. Accuracy assessment

Ground truthing for validation and accuracy assessment was conducted, and a systematic sampling technique was chosen for validation points. 996 sample points were selected in three years based on irrigated cluster areas considering the accessibility to water sources (lakes, rivers, and reservoirs), crop diversity, and cropping Calendar.

Evaluation metrics indicators were used to evaluate the performance of the irrigated area mapping techniques, as indicated in Table 12, the mean overall accuracy was 0.82, with a kappa coefficient of 0.76 and an F1-score of 0.86 with the highest and lowest overall accuracy observed in 2020 (0.86) and 2022 (0.76), respectively. The coefficient of determination (r^2) provides the portion of total variation explained between the ground truth data and remote sensing analyzed data. R^2 was 0.81, 0.86, and 0.94 in the consecutive three-year evaluation, respectively, with a mean value of 0.87, which suggests a strong agreement between GT and the multispectral remote sensing data analysis results. Results are in line with reports of previous studies (Xiang et al., 2020).

Table 12: Accuracy assessment indicator

Indicator	Year			
	2020	**2021**	**2022**	**Mean**
R^2	0.81	0.86	0.94	0.87
Overall Accuracy	0.86	0.85	0.76	0.82
Kappa Coefficient	0.76	0.78	0.75	0.76
F1-Score	0.84	0.85	0.83	0.84
Irrigated Samples	151.8	203.6	163.8	173
None irrigated samples	178.2	147.4	151.2	159
Total Samples	330	351	315	332

5.4. DISCUSSION

Satellite remote sensing offers tremendous potential for routine monitoring of irrigation due to the synoptic nature of the data and readily available archives of imagery. Various research and studies suggested that finer spatial and temporal resolution imagery of Sentinel-2 Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) data is adequately efficient to identify the irrigated land in a vast geographical location (Chance et al., 2017). As new methods for identification and estimation of existing irrigated land in the basin, remote sensing technologies have been applied and of course, integrated with other data acquisition techniques for the better and more reliable building of the dataset. High-resolution remote sensing analysis and

mapping technique is used to identify the irrigated land covered. The data available at different spatial and temporal resolutions provide daily global coverage of observations to detect unique multitemporal, spectral vegetation signatures for mapping. The "sentinel-2" imagery data are currently available with enhanced vegetation sensitivity with minimal influence from the atmosphere, view and sun angles, clouds, and inherent non-vegetation influences of canopy, background, and litter.

Irrigated area information generated from NDVI, EVI and LULC is 1,091.73km^2, 1,011.30km^2 and 1,035.47km^2 respectively, compared with FAO WaPOR portal report of LCC 2022 report on irrigated area (774.03km^2), the results of this study are higher, and deviation is mainly due the methodology difference and the resolution of the data used, the FAO WaAPOR report used a 100m spatial resolution data. In comparison to NDVI, EVI, and LULC techniques, irrigated area is estimated for RVLB, and the multispectral remote sensing data analysis results from maps agreed with irrigated area mapping to ground truthing with r^2 of 0.81, 0.86, and 0.94 in the consecutive three years evaluation respectively with a mean value of 0.87. (Xiang et al., 2020; Zhu et al., 2014b) have reported supporting the findings. Evaluation metrics indicators were also used to evaluate the performance of the irrigated area mapping techniques, the mean overall accuracy was 0.82, with a kappa coefficient of 0.76 and an F1-score of 0.86 with the highest and lowest overall accuracy observed in 2020 (0.86) and 2022 (0.76), respectively. The best irrigation patterns are seen in the Meki, Katar, Dijo, Bilate, Chamo, Hawassa, and West Abaya catchments, where comparatively big farms have similar irrigation patterns. However, the maps for the Gigabo, Gelana, and Weito catchments have shown inconsistent results.

5.5. Conclusion

It can be concluded that the source data of Sentinel-2 had a fine spatial resolution (10x10 m2), which could explain the substantial precision in irrigated area mapping. We compared the spatial distribution of NDVI, EVI, and LULC with the spatial distribution of the historical precipitation or rainfall regimes to assess the consistency of the spatial distribution of irrigated areas in those three maps, assuming that irrigation would be practiced during the offseason and associated with peak NDVI and EVI values. metrics indicators were used to evaluate the performance of the irrigated area mapping techniques and the coefficient of determination quantified the correlation in geospatial information, whereas the autoregression model identified the strength of the relationship between geospatial variables. These geospatial analysis techniques provide effective exploratory tools for comparing geospatial information derived from raster maps with differences in spatial resolution and classification methods. Further research is needed in the field of

irrigation mapping to obtain a more realistic picture of water abstraction and accurate estimates of irrigated areas. Recent advances in the availability of remote sensing tools through the EU Copernicus system promise to improve irrigation mapping. In addition, better inventory and studies of irrigated areas are needed to improve global and regional water cycles and promote sustainable land use. Furthermore, to improve future attempts to regulate irrigation development in the Rift Valley Lakes Basin, this study gives the spatial extent and distribution of currently irrigated areas. The findings of this study, along with additional research on potential irrigable area assessment, can help to advise policy-makers and investors about potential future irrigation development in the basin.

CHAPTER 6: WATER DEMAND ESTIMATIONS

6.1. INTRODUCTION

Measuring the amount of water used in different sectors within a river basin strengthens decision-making for water management, evaluates and strengthens the viability of plans, scenarios, and strategies, and addresses spatial detail, consistency, trend analysis, allocation, and managing water scarcity. This promotes economic development, improves water resource management, and strengthens water security and sustainability (Santos et al., 2023). Estimating the water use demand of different sectors in a river basin involves understanding the needs of those who use the resources. The main sectors utilizing the basin water resources are typically agriculture, drinking water, animal husbandry, and industries. Water demand for each of the water use sectors will be analyzed based on empirical and conceptual equations. It will be done based on disaggregated or highly aggregated consumption of water evolving in all sectors of the study area. For each sub-basin, four so-called demand nodes will be defined. Each demand node has a specific water user: domestic, industry, livestock, and irrigated agriculture. These water users can take water from surface water and groundwater. Optimal water resource development planning also requires a thorough analysis of current and future predictions of different water uses/demands of the basin (Langsdale and Cardwell, 2022). Estimating the available and usable water is critical work in any water resource study and design project. However, it is challenging to provide a robust and accurate quantification of water use and distribution for better water resource management and planning. This study aims to estimate the water use by different sectors, including water supply and irrigation sectors.

The Rift Valley Lakes Basins (RVLB), cradles of biodiversity and engines of economic development, face an acute water challenge temporally. Balancing the competing demands of diverse sectors within these fragile ecosystems necessitates a deep understanding of their water footprint. Accurately estimating water use across critical sectors, including irrigation, livestock, industry, domestic, and environmental, is not merely a technical exercise, but a vital first step towards sustainable water management and long-term prosperity. Rift Valley lakes support diverse ecological services, where expansive farmlands depend on irrigation. Yet, estimating irrigation water use precisely is crucial for several reasons. Inefficient irrigation practices lead to significant water losses through evaporation, seepage, and runoff, risking both farmer livelihoods and overall water security (Awulachew et al., 2010). Precise water use estimations enable targeted interventions such as improved irrigation technologies and water pricing strategies to promote efficient water use and optimize crop yields (Ayalew et al., 2022).

Furthermore, understanding irrigation water demands is essential for informing future infrastructure projects and ensuring equitable water allocation across competing sectors.

The increasing populations surrounding the Rift Valley Lakes rely heavily on their waters for daily needs. Estimating domestic water use is crucial. It allows for the assessment of access to safe and clean water for communities, highlighting vulnerable areas and guiding targeted interventions to improve sanitation and hygiene practices (Santos et al., 2023). It also enables the efficient planning and distribution of water resources to meet present and future domestic needs, minimizing water shortages and ensuring public health. The Rift Valley lakes are precious ecosystems packed with biodiversity, and their ecological health depends on maintaining adequate water flows, lake volumes and quality (JICA, 2012). Estimating environmental water requirements, the water needed to sustain ecosystems and ecological processes. It allows for the quantification of water needed for maintaining healthy habitats and ensuring the survival of aquatic species. Furthermore, it enables the implementation of measures to mitigate the negative impacts of human activities such as water abstraction and pollution on the environment (Yang et al., 2005).

Estimating water use across the sectors in the Rift Valley Lakes Basins of Ethiopia is not simply a technical undertaking, but a strategic one. It is the cornerstone for informed water management decisions that ensure sustainable water use, safeguard both human and environmental needs, and pave the way for a prosperous future for all stakeholders. Armed with precise water use data, policymakers, resource managers, and communities can navigate the complex water challenge of these vital ecosystems, ensuring their continued survival and contribution to Ethiopia's development.

6.2. WATER DEMAND ESTIMATION METHODS

6.2.1. Water Demand Data and Analysis

Water demand for each of the water use sectors is analyzed based on empirical and conceptual equations. It is done based on disaggregated consumption of water evolves in all sectors of the study area. For each major catchment, demand nodes were established. Each demand node has a specific water user: irrigation, domestic, industry, livestock and the environment. Optimal water resource development planning also requires a thorough analysis of current and future predictions of different water demands of the basin. The inventory of current demand covers spatial, temporal, quantity and quality aspects of uses in the basin. The water uses in the basin are categorized as water demand which includes consumptive uses in irrigated agricultural production, livestock demand, domestic

demand, which includes all municipal uses in an urban and rural area, industrial uses and environmental uses.

6.2.2. Irrigation Water Requirement

Input data required for estimation of irrigation water requirement, climate data, precipitation, actual crop evapotranspiration (ETc), cropping pattern and calendar and adopted irrigation efficiency. The irrigation water demand is estimated using CROPWAT-8 software considering cropping patterns, crop scheduling, crop water requirements, and irrigation efficiencies. By combining the monthly effective rainfall and actual crop evapotranspiration, the actual irrigation water requirements are estimated.

$$IR_{net} = CWR - Rf_{eff} \quad \text{---------- eq 8}$$

$$GIR = (IR_{net} / Ea) * A \quad \text{---------- eq 9}$$

Where:

NIR = Net Irrigation Requirement
Ea = Overall Irrigation efficiency
A crop = Area coverage in a season (ha)

For the projected water demand to be estimated the potential irrigated area, projected livestock population, projected rural and urban population and the industrial expansion extent are the main input parameters.

Irrigated area assessment and water demand

Current irrigated area mapping

The current irrigated area is estimated using a multi-spectral imagery data analysis as discussed in Chapter 5; accordingly, the estimated irrigated area data is used for estimating the current irrigation water requirement

Potential irrigation area identification

Potential irrigation area is a suitable land resource for irrigation, which could be irrigated by a fully or partially, controlled irrigation system, which can be accomplished by surface, or pressurized irrigation system. Thus, this study referred to irrigation as the process by

which water is abstracted from a river a well or a lake by a diversion/pumping system and distributed over the potential irrigation area for agricultural production. Assessment of the potential irrigable areas is conducted based on combinations of suitability of topography, and soil characteristics such as soil depth, texture and drainage.

The soil suitability classes by texture and assigned codes for the identified soil classes either distinctively or in combinations are presented in Table 13 below. Possible matrixes of the soil depths, soil texture, topography, and drainage, land slope ranges of the sub-basin have then been analyzed to identify the potentially irrigable land as S_1, S_2, S_3, N_1, or N_2 based on likely combinations of parameters shown in the following table. The following criterion for land evaluation for surface irrigation has also been adopted.

Table 13: Criteria of Land Evaluation for Irrigation

Code Values	Soil Depth (cm)	Slope (%)	Drainage Condition	Stoniness (%)	Texture
1	>200	0-3	Well-drained (W)	< 1	Silt loam, sandy clay, and clay loam
2	120-200	3-5	Moderate (M)	1-3	Sandy loam, loam, silty clay loam, silty clay
3	60-120	5-8	Imperfect (S)	3-15	Loamy sand – clay
4	30-60	8-15	Excessive (E)	15-50	Sand, clay
5	<30	> 15	Poorly drained	> 50	Sand, gravel

Ranges of Codes for Combinations of Conditional Assessments of Suitability of Land for irrigation

Land Suitability Class	S_1	S_2	S_3	CNS					PNS	
Texture	1	1-2	1-3	1-3	1-3	1-3	4	4	5	5
Drainage	1	1-2	1-2	1-2	1-3	4	1-4	1-4	1-4	5
Soil Depth	1-2	1-2	1-3	1-3	1-4	1-4	1-3	1-4	1-5	1-5
Stoniness %	1-3	1-3	1-3	1-4	1-4	1-4	1-3	1-4	1-5	1-5
Slope	1-2	1-3	1-4	1-4	1-4	1-4	1-3	1-4	1-5	1-5

**Source: National Guidelines for Small Scale Irrigation Development in Ethiopia, SSIGL 2, MoA, 2018*

The land suitability groupings, in general, have been considered into five land suitability classes based on FAO's classification of potential productivity levels: S_1 is highly suitable, S_2 is moderately suitable, S_3 is marginally suitable, N_1 is currently not suitable and N_2 is permanently not suitable (FAO, 1976). The overall model framework of land suitability evaluation procedures, mapping and assessment of irrigation potential are shown in Figure 23, a flow chart that shows the demand and supply side of the irrigation system

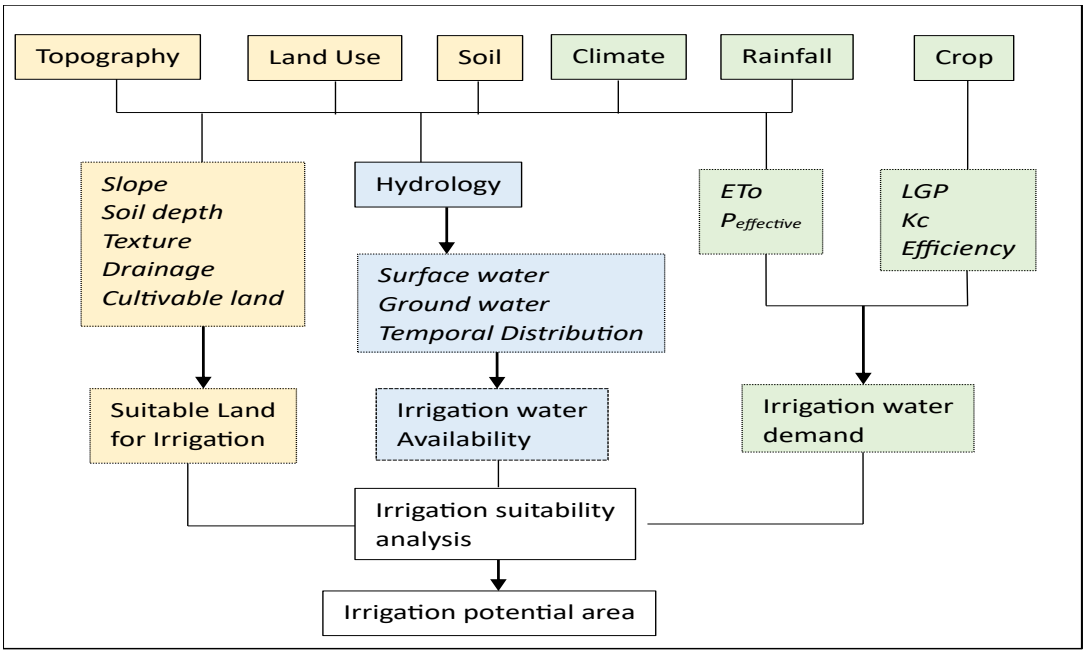


Figure 23: Flowchart for potential irrigation area

Projected irrigation water demand

In this study, the future demand for irrigation water is estimated to be based on three different scenarios. The first scenario is irrigated area expansion and the second scenario is climate change's impact on irrigation water demand and the final scenario is the adoption of improved technologies.

6.2.3. Domestic Water Demand:

Domestic water use is water used for indoor and outdoor household purposes in the home every day which includes drinking, preparing food, bathing, washing clothes and dishes, flushing toilets and uncounted uses such as watering the lawns and garden. The domestic water demand studies with the water balance study enable us to estimate how much water is supplied to consumers in each catchment. The current water demand is estimated using a simple empirical formula as the daily per capita water demand and population as input data obtained from the CSA and the GTP -II documents.

Projected population and water demand

The population projection for the proposed planning years was made based on the Central Statistical Agency Reports forecasted the population of Ethiopia from 2014 to 2021 (CSA, 2021). The population projections for the planning period are based on the projected growth rate proposed by the CSA. The method of population projection for the future period is selected by examining the growths of the community that have occurred between recent censuses. Accordingly, if the rate of growth is constant in the successive census, the simple arithmetic mean method is selected to project the future period's population. Geometric methods are mostly applicable for growing towns and cities having a scope of expansion. This method is based on the assumption that the percentage increase in the population remains constant. By simple arithmetic methods, Population projections for future periods are estimated using the equation below. Population data source https://data.humdata.org/dataset/cod-ps-eth?

$$\boldsymbol{D_{wd} = \sum_{w=1}^{w}\left[\left[P_w^u(1+\mu_w^u)^n\right]K_w^u\right] + \left[\left[P_w^R(1+\mu_w^R)^n\right]K_w^R\right]}\text{---------- eq 10}$$

Where:

D_{wd} = projected domestic water demand of the whole basin
P_w^u&P_w^R = Urban and rural population in a catchment
μ_w^u&μ_w^R = Urban and rural population growth rates
n = the time interval b/n the base year and forecast year
δ = the rate of rural population immigration
K_w^u & K_w^R = Urban and rural per capita water use quota

The amount of water needed (known as the "Per Capita Demand") is estimated based on the actual service needs of the population in both urban and rural areas. Although reliable data on domestic water demand was not available, recommendations from studies were used to estimate the current and future demand in both rural and urban areas. A study by the Ministry of Water Resources and Energy (MoWR, 2006) found that per capita water demand is expected to increase in the coming decades, as shown in Table 14 and is used for this study.

Table 14: Projected per capita domestic water demands

Settlement	Per capita water demand, l/c/d	
	2035	2050
Rural	40	50
Urban: <20,000 population	60	70
Urban 20,000-50,000 population	70	80
Urban: 50,000-100,000 population	80	90
Urban: 100,000-1,000,000 population	100	110
Urban: >1,000,000 population	120	130

**Source: Assessment of National Water Use and Demand Forecast, MOWIE, 2020*.

6.2.4. Industrial Water Demand

The current and future industrial water demand estimation requires knowledge of the size of consumers and unit water demands using different datasets, methods and tools. Both primary and secondary data are employed in this study that includes, unit and total water demands, sources and mode of water supply, type, and extent of scale of industries existing in the study area. Therefore, the current and future annual water demand estimates for industrial uses will be determined at administrative regions and hydrologic units. Data collection and analysis methods are by review of the Rift Valley Lakes Basin master plan, other previous study reports, and federal plans of the four regions in the Basin, and collection of water billing records of the industries.

Projected industrial water demand

The projected water demand is estimated using:

$$I_{wd} = \sum_{w=1}^{w} W_w(1 + r_w)^n \quad \text{---------- eq 11}$$

Where:

I_{wd} = industrial water use

W_w= current industrial water use

r_w = the annual growth rate of industrial water use calculated by the change tendency in the past years

n = the time interval b/n forecast and base year

6.2.5. Livestock Water Demand:

Current livestock water demand

Livestock water use is one of the major water abstraction categories that have significant implications on the basin water balance. Livestock water use per head varies with the type of animal, climate and animal-husbandry practices. Therefore, the livestock water demand in the basin will be computed using the water use rate of the different categories of animals per climatic condition and the number of livestock in the basin. Accordingly, the estimation mainly depends on livestock census data from the Central Statistics Authority (CSA) or records in the Wereda offices and studies on the water use rate of different livestock categories including cattle, small ruminants, equines and poultries. The volume of water livestock consumes is dependent on weather, diet, management of livestock, type of species and between species. Water demand for livestock will be estimated by multiplying the tropical livestock unit (TLU) and unit water requirement for each livestock. (Sileshi et al., 2003.)

$$LWD = PCWD \ X \ LP \text{---------- eq 12}$$

Where:

LWD is Livestock Water Demand(l/d)
PCWD = Per-capita water consumption (l/d)
LP is livestock population (number)

Projected Livestock population and water demand

The projected water demand for livestock depends on the rate of growth of the livestock population each year, as well as the type of animal. The estimation is based on data from the Government offices and the Central Statistics Authority. Table 15 summarizes the annual growth and mortality (off-take) rates of livestock and their water demands. The projected water demand for livestock in the next 15 and 30 years is estimated for each catchment. These estimates consider current trends and expected population growth, as well as future changes in livestock production.

Table 15: Annual growth and mortality (off-take) rates of livestock and their water demands

Livestock	Annual Growth rate (%)	Annual Off-take (%)	Average water demand (lit/h/d)	
			Normal weather	Hot weather
Cattle	0.29	0.07	25	30
Sheep	1	0.3	5	5
Goats	1.08	0.35	5	5

Horses	0.029	0.02	12	20
Mules	0.029	0.02	12	20
Donkeys	0.029	0.02	12	20
Poultry	2.5	-	0.22	0.4

**Source: MoWIE, 2020 Revised version of National Water Use and Demand Forecast*

6.2.6. Ecological/Environmental Water Demand:

Environmental demands include the water required to sustain aquatic ecosystems, flows needed for ecological conservation, and water needed to maintain minimum lake levels. Water allocation, therefore, will include provisions for maintaining the sustainability of freshwater ecosystems, including the need to maintain minimum in-stream flows and to anticipate the impact of hydrologic modifications on downstream environments. Environmental (instream) flows are flows that are left in, or released into, a river system with the specific purpose of managing some aspect of its condition. Their purpose could be as general as the maintenance of a 'healthy' riverine ecosystem, or as specific as enhancing the survival chances of a threatened fish species. They could be targeting the river channel, lakes and their surface waters, groundwater, the estuary, linked wetlands or floodplains, the riparian zone, and/or any of the plant and animal species associated with any of these system components(King et al., 2008).

According to policies incorporating environment conservation and protection requirements as integral parts of water resources management is necessary for sustainable development and to maintain the ecological services as well as the natural channel habitat associated with the historic flow regimes of the Basin Rivers. Quantifying the amount of water needed for environmental flow demand in water resource allocation modeling involves determining the water quantity and quality requirements that will ensure the ecological functioning of the river and recharging groundwater aquifer. There are different methodologies used for EFR calculation which range from general water resources planning to the setting of detailed plans for managed hydraulic structures (Xin et al., 2011). The environmental flow requirement (EFR) is calculated by using Indicators of Hydrologic Alteration (IHA) software.

6.2.7. Input data

Agronomy and Agroecological data

Crop coefficient, cropping pattern and length of growing period (LGP) are the required inputs to estimate the irrigation water requirement of major crops growing in the basin.

To calculate the water requirement of the individual crop, appropriate crop coefficients Kc have been used, which represent the relationship between the reference crop water requirement and evapotranspiration ETo. Accordingly, the crop coefficients were referred from different research works of literature and adopted with a monthly weighted value of them for each crop and their growth stages. In the case of crop LGP, the required data were collected from the field for dominant crop varieties and also referred to different agronomy guidelines (Allen et al., 1998). In the following Table 16, the crop coefficient and length of the growing period for each of the considered crops are presented.

Table 16: Crop coefficient and length of the growing period used for CWR computation

Crop	Kc				LGP, in days				
	Initial	Dev.	Mid	Late	Initial	Dev.	Mid	Late	Total
Onion	0.5	0.75	1.05	0.85	20	35	40	25	120
Potato	0.45	0.75	1.15	0.9	25	30	45	30	130
Kale	0.7	0.7	1	0.95	30	60	60	30	180
Tomato	0.45	0.75	1.15	0.9	20	30	40	20	110
Banana	0.5	1	1.1	1	30	60	180	95	365
Papaya	0.9	1	1.1	0.9	60	80	90	60	290
Green Pepper	0.35	0.7	1.05	0.9	25	35	40	20	120
Pepper (Red)	0.35	0.7	1.05	0.9	25	35	40	30	130
Cabbage	0.5	0.75	1	0.95	20	30	35	25	110
Sugarcane	0.45	0.85	1.15	0.75	30	60	180	95	365
Beetroot	0.45	0.8	1.12	0.95	15	25	30	20	90
Inset	0.6	0.8	0.9	0.7	60	90	120	95	365
Garlic	0.4	0.6	0.8	0.5	25	50	50	25	150
Carrot	0.7	0.85	1.05	0.95	15	30	30	15	90

**Source: FAO Irrigation and Drainage P 56; MOA, 2018 SSIGL Irrigation Agronomy Guideline,*

According to the MoA 2016 newly established agroecological zones, the RVLB has six agroecological classifications and fourteen sub-agroecological zones (Figure 24).

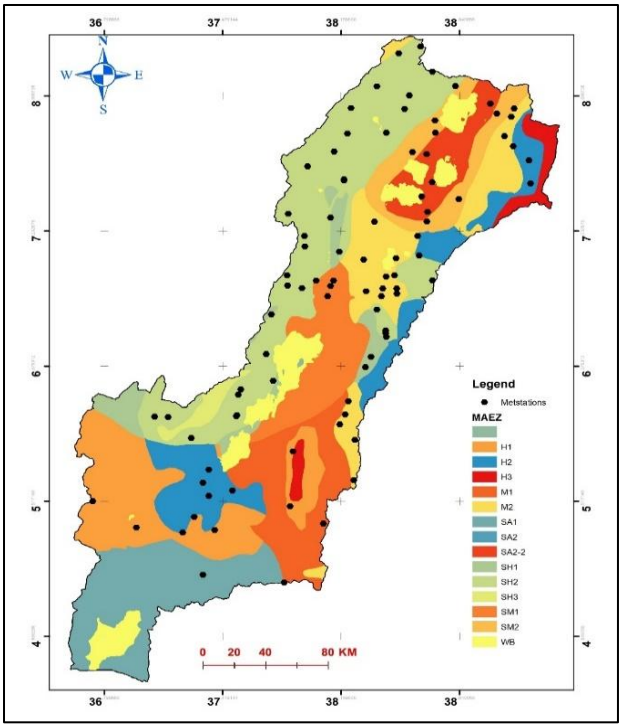


Figure 24: AEZ and meteorological stations in RVLB

Climate data

The data input for the CROPWAT 8 software includes meteorological data such as precipitation, maximum and minimum air temperature, sunshine hours, wind speed and relative humidity. The reference evapotranspiration was highly influenced by the Agroecology, based on the rainfall regime and agroecological zoning of the basin the reference evapotranspiration (ETo) was calculated, in Table 17. The irrigation water requirement is then calculated, considering the effective rainfall, and irrigation efficiency for gross demand.

Table 17: Monthly average ETo (mm) of AEZ of the RVLB

Months	Monthly ETo of Sub-Agro ecological zones in the Rift Valley Lakes basin (mm/month)					
	Hot to warm humid lowlands	Cold to very cold humid sub-Afroalpine	Hot to warm moist lowlands	Tepid to cool moist mid highlands	Hot to warm semi-arid lowlands	Tepid to cool sub-humid mid highlands
Jan	110	88	125	114	148	105
Feb	115	88	132	112	132	109
Mar	137	101	149	134	165	126
Apr	117	130	137	146	124	126
May	149	100	144	126	142	122
Jun	129	88	139	115	141	107
Jul	145	87	143	108	137	105

Aug	124	82	131	100	136	89
Sep	134	86	140	107	151	104
Oct	142	86	131	112	153	109
Nov	115	85	116	105	140	103
Dec	108	83	123	108	143	100

Domestic water use data

The basis for estimating domestic water use is the population and per capita water use rate. The current total population of the basin as projected based on CSA 2007 census data (Table 19) has been estimated to be 17.8 million. Table 18 shows the per capita daily water use data set at the GTP-II based on the size of the population in urban areas, towns and cities.

Table 18: Urban categories according to GTP II

City Level	Population size	Per capita water use target at the end of GTP II, l/c/d
1	>1,000,000	100
2	100,000-1,000,000	80
3	50,000-100,000	60
4	20,000-50,000	50
5	<20,000	40

**Source: GTP-II plans, strategic document for water sector development*

Table 19: Projected population of the RVLB

NAME	Population		Total population
	Urban	Rural	
Abijata	59,639.33	259,375.94	319,012.82
Bilate	749,038.87	3,257,696.21	4,006,731.77
Chamo	127,138.81	552,954.33	680,092.02
Dijo	39,464.84	171,632.08	211,096.07
Gelana	265,685.02	1,155,512.39	1,421,196.75
Gidabo	540,624.79	2,351,281.09	2,891,908.25
Hamessa	68,303.12	297,060.31	365,362.59
Hawassa	213,302.74	927,686.44	1,140,988.94
Katar	184,169.74	800,988.19	985,157.30
Langano	123,547.51	537,331.25	660,879.37
Meki	142,369.95	619,194.42	761,564.90
Segen	171,556.12	746,126.63	917,684.58
Serbela	36,622.48	159,278.24	195,901.02
Shalla	147,723.48	642,474.09	790,197.39
W_Abaya	178,320.96	775,545.23	953,865.87
Weito	180,432.59	784,742.25	965,176.78
Ziway	102,429.61	445,482.61	547,911.16
	3,330,369.96	**14,484,361.69**	**17,814,727.57**

Livestock population data

To estimate the livestock water demand, the following inputs were required: Livestock population; i.e., livestock number by type of species availed from Zona livestock and fishery development offices and Central Statistics Agency. The CSA data are mainly indicated at the Wereda level which is not adequate for this analysis and estimates (Table 20).

Table 20: Livestock population of the RVLB, 2022

Name	Cattle	Sheep	Goats	Horses	Mules	Donkeys	Camels	Poultry	Beehives
Abijata	464,347	153,746	168,925	17,509	1,322	105,620		248,888	7,069
Bilate	3,167,163	647,701	629,618	65,640	5,694	394,288		1,888,183	185,145
Chamo	343,347	136,822	113,117	15,429	2,023	10,002	289	170,151	13,886
Dijo	450,707	186,906	181,649	15,250	949	114,085	-	345,882	26,429
Gelana	1,109,529	429,506	365,378	50,478	4,258	23,555	1,050	412,363	48,773
Gidabo	3,513,516	1,048,542	747,287	145,520	9,239	138,469	11,457	1,883,808	283,276
Hamessa	220,363	50,476	45,001	1,852	498	11,063		145,555	14,494
Hawassa	781,145	172,571	140,413	17,682	622	42,206	-	399,310	22,710
Katar	453	54,312	14,335	24,494	1,055	677	4,653	34,704	3,358
Langano	571,391	211,799	102,594	46,145	1,344	93,885	795	227,530	15,502
Meki	2,291,662	684,282	501,034	121,345	6,315	379,864		1,063,796	119,514
Segen	727,597	561,135	547,736	75,417	6,986	51,182	56,535	336,872	126,646
Serbela	835,202	2,804,358	214,266	2,202	33,129	24,970	524,636	195,831	37,051
Shalla	887,288	322,422	118,119	72,136	1,586	134,067		322,520	27,336
W_Abaya	666,667	255,577	206,382	27,598	2,495	13,270		268,256	22,960
Weito	991,496	1,159,516	286,887	24,902	19,652	33,315	170,469	477,657	55,033
Ziway	638,700	214,968	263,813	23,142	2,400	151,259	1,718	363,234	8,537

6.3. RESULTS AND DISCUSSION

6.3.1. Current water demand

The current water demand estimation is based on the existing data of the irrigated area, urban and rural population, livestock population and Industries of the RVLB

Current Irrigation water demand

The mean daily ETo for all the different AEZs in the study area was 4.09 mm. The irrigation water demand is estimated for two irrigation cycles, the first-round irrigation starts from October to the end of January, second round irrigation from early February to the end of May, specifically to the Ziway-Shalla sub-basin, Hawassa sub-basin and Abaya-Chamo sub-basin, however for the Chewbahir sub-basin the irrigation cycles are June-September and December-March. The current estimated irrigation water demand is found to be 1,045MCM. As indicated in Figure 25, the demand reaches its peak in December (241.81MCM) and January (266.78MCM) while the lowest demand is in June (38.99 MCM) is also summarized in Figure 20. Thus, the average water demand per ha

is 9,643.73 m^3. In estimating the current gross irrigation water demand the analysis considered the weighted average irrigation efficiency of the current irrigation system data which is estimated at 40%.

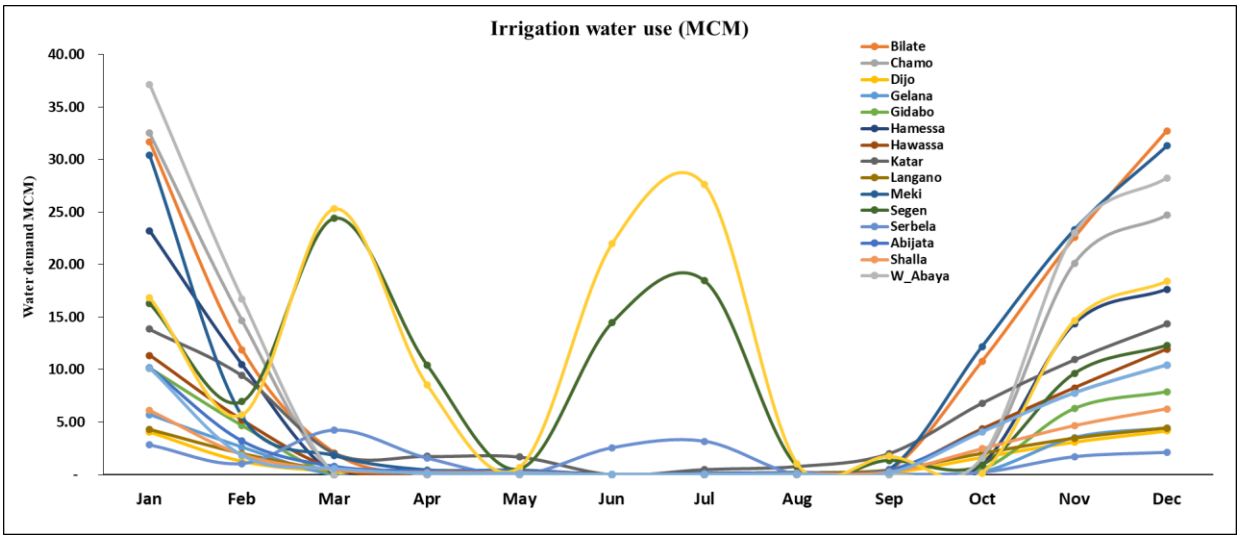


Figure 25: Irrigation Water Demand Distribution

Current Livestock water demand

The livestock population was obtained mainly from Woreda livestock and fishery development offices and from CSA to compute their water uses based on the number, types, and water use rates of different livestock categories. The future water uses were then forecasted based on the growth of the livestock population in the agricultural sector. Livestock water requirement varies between species and depends on the type and quality of feed, climate, livestock growth stage, and others. Studies with poultry have shown an increase in water consumption due to increases in the fat, protein, salt, or potassium contents in the diet. In general, the water requirement is largely correlated with the type and quality of animal feed. The current livestock water demand for the sub-basin was computed based on the population and average livestock water intake rate per head per day. The average water intake rate values for each species were adopted from Table 21.

Table 21: Livestock water use rate in liters per head per day

Livestock	Average water demand (lit/h/d)	
	Normal weather	Hot weather
Cattle	25	30
Sheep	5	5

Goats	5	5
Horses	12	20
Mules	12	20
Donkeys	12	20
Camels	30	20
Poultry	0.22	0.4
Beehives	11	11

**Source: (Richard M., 1995)*

According to the study, the total annual current livestock water requirement of the basin is 229.46 MCM. As shown in Table 22, the highest consumption demand is for the cattle group which accounts for about 78.3% of the total livestock demand. The share of annual water requirement for sheep is 7.96%, Goats4.56%, Poultry0.52%, Horses 2.96%, Donkeys 5.45 and Mule 0.25%.

Table 22: Current Livestock water demand

Sub-basin	Water Demand (MCM)								
	Cattle	Sheep	Goats	Horses	Mules	Donkeys	Camels	Poultry	Beehives
Abijata	4.66	0.28	0.31	0.10	0.01	0.62	-	0.03	0.03
Bilate	31.79	1.18	1.15	0.38	0.03	2.30	-	0.21	0.74
Chamo	3.45	0.25	0.21	0.09	0.01	0.06	0.00	0.02	0.06
Dijo	4.52	0.34	0.33	0.09	0.01	0.67	-	0.04	0.11
Gelana	11.14	0.78	0.67	0.29	0.02	0.14	0.01	0.05	0.20
Gidabo	35.27	1.91	1.36	0.85	0.05	0.81	0.10	0.21	1.14
Hamessa	2.21	0.09	0.08	0.01	0.00	0.06	-	0.02	0.06
Hawassa	7.84	0.31	0.26	0.10	0.00	0.25	-	0.05	0.09
Katar	0.00	0.10	0.03	0.14	0.01	0.00	0.04	0.00	0.01
Langano	5.74	0.39	0.19	0.27	0.01	0.55	0.01	0.03	0.06
Meki	23.00	1.25	0.91	0.71	0.04	2.22	-	0.12	0.48
Segen	7.30	1.02	1.00	0.44	0.04	0.30	0.52	0.04	0.51
Serbela	8.38	5.12	0.39	0.01	0.19	0.15	4.79	0.02	0.15
Shalla	8.91	0.59	0.22	0.42	0.01	0.78	-	0.04	0.11
W_Abaya	6.69	0.47	0.38	0.16	0.01	0.08	-	0.03	0.09
Weito	9.95	2.12	0.52	0.15	0.11	0.19	1.56	0.05	0.22
Ziway	6.41	0.39	0.48	0.14	0.01	0.88	0.02	0.04	0.03
Total	177.27	16.60	8.48	4.36	0.58	10.06	7.04	0.99	4.09

Current Domestic water demand

As indicated in Table 24, the urban categories by the population size and proposed service levels collected from the woredas and the current water supply coverage are mapped in Figure 26.

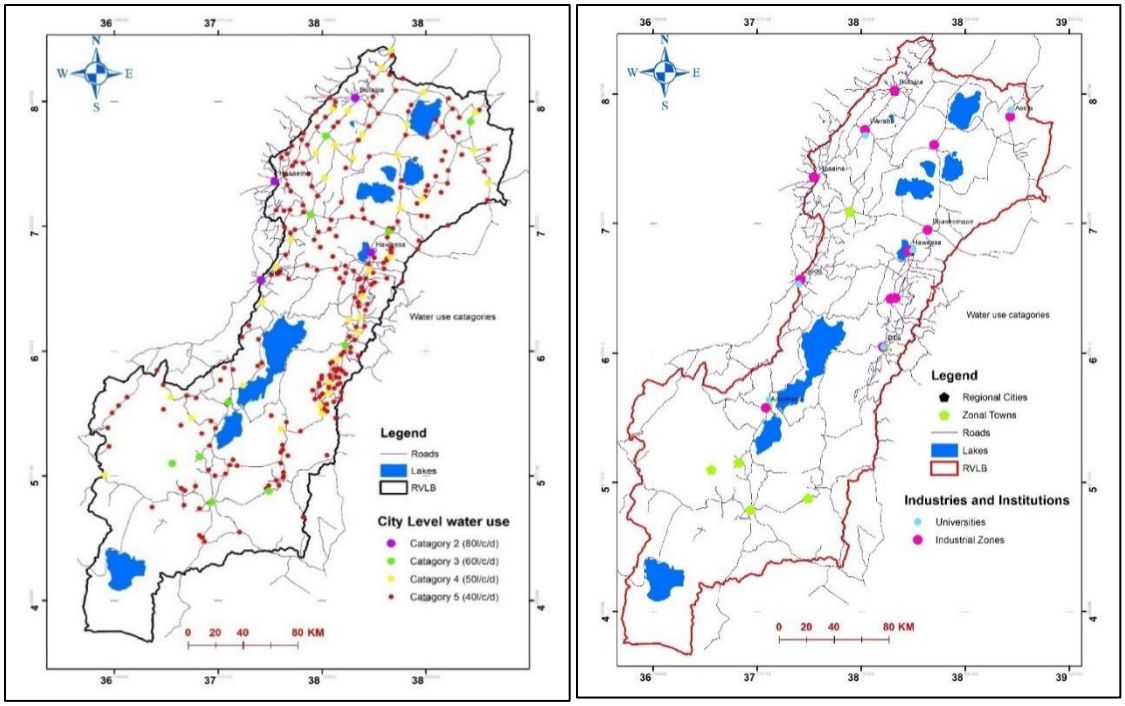


Figure 26: Water use Categorical map of towns and Industrial zones of RVLB

As shown in Figure 26 towns are categorized according to their consumption rates under category 1,2,3, and 4. The category range data is used to estimate the water demand of the urban and rural areas. Table 23 shows the water use of the major catchments; accordingly, the total domestic water demand of the basin is 63.53MCM for urban and 87MCM for rural areas making it a total of 150.53MCM of water annually.

Table 23: Domestic water demand of the RVLB

NAME	Total population	Population		Water use (MCM)	
		Urban	Rural	Urban	Rural
Abijata	319,013	59,639	259,376	1.33	1.56
Bilate	4,006,732	749,039	3,257,696	14.35	19.57
Chamo	680,092	127,139	552,954	2.00	3.32
Dijo	211,096	39,465	171,632	0.61	1.03
Gelana	1,421,197	265,685	1,155,512	5.07	6.94
Gidabo	2,891,908	540,625	2,351,281	9.57	14.12
Hamessa	365,363	68,303	297,060	1.09	1.78
Hawassa	1,140,989	213,303	927,686	4.63	5.57
Katar	985,157	184,170	800,988	3.54	4.81
Langano	660,879	123,548	537,331	2.03	3.23
Meki	761,565	142,370	619,194	2.75	3.72
Segen	917,685	171,556	746,127	4.26	4.48
Serbela	195,901	36,622	159,278	1.53	0.96

Shalla	790,197	147,723	642,474	2.41	3.86
W_Abaya	953,866	178,321	775,545	2.56	4.66
Weito	965,177	180,433	784,742	3.51	4.71
Ziway	547,911	102,430	445,483	2.28	2.68
Total	**17,814,728**	**3,330,370**	**14,484,362**	**63.53**	**87.00**

Current Industrial water demand

Thus, as the major industries located in the basin have not properly recorded water consumption data their water uses were estimated indirectly based on the data from similar industrial water use. Thus, the current industrial water use estimate is summarized in Table 24.

Table 24: Current industrial water uses in the basin

NAME	Name of the industries	Number	Water use rate (m3/year)	Total Water use (m3/year)	Source of water
Abijata	Bulbula Agro-Industrial Park	50	60,000	760,100	GW
Dijo	Flour (Grain Milling) companies	11	19,200	243,232	GW
Gidabo	Awada Industrial Zone	50	15,000	190,025	GW
	Yirgalem Ago-Industrial Park	10	288,000	3,648,482	GW
	Beza Water Bottling	1	216,000	2,736,362	GW
	South Water Bottling	1	205,000	2,597,010	GW
	Dilla Agro_ Processing industrial park	10	96,000	1,216,161	GW
Hawassa	BGI Ethiopia	1	11,400	144,419	GW
	Moha PLC	1	7,400	93,746	GW
	Food processing companies	5	19,200	243,232	GW
	Hawassa Textile factory	1	100,000	1,266,834	GW
	Industrial Zone (Textile)	50	350,000	4,433,919	GW
	Tabor Ceramic factory	1	42,000	532,070	GW
	Etab Soap and Detergent factory	1	38,000	481,397	GW
	Guts agro Industries	1	25,000	316,709	GW
	Tsehay Garment	1	5,000	63,342	GW
	Animal feed processing	1	4,625	58,591	GW
	Awasa flour S.Co	1	6,000	76,010	GW
	G-Agri pack plc	1	2,000	25,337	GW
	General Plastic Packing company	1	2,000	25,337	GW
	Zerihun Textile	1	3,200	40,539	GW
	Other companies	20	9,000	114,015	GW
Katar	Asela Malt Barley factory	1	10,000	126,683	GW
	Flour (Grain Milling) companies	10	19,200	243,232	GW
	Bokoji water Bottling	1	160,000	2,026,935	GW
	Oda water Bottling	1	140,000	1,773,568	GW
Meki	Timber Factory	1	10,000	126,683	GW
	Desta Garment	1	6,000	76,010	GW
Shalla	Selam water bottling	1	225,000	2,850,377	GW
	Tractor assembly factory	1	15,000	190,025	GW
	Flour (Grain Milling) companies	5	19,200	243,232	GW
	Small industries	1	9,000	114,015	GW
W_Abaya	Arbaminch Textile factory	1	100,000	1,266,834	Lake

Ziway	Adami Tulu Pest side factory	1	50,000	633,417	Lake

The estimate of total water use takes into account the water lost from the current water supply methods. In principle, the magnitude of the loss of water depends on numerous parameters that include the age and length of the distribution pipe, operating pressure, number of connections and maintenance services offered to the system. As the exact value of loss could not be quantified, often it is reported as a percent of the entire demand and its value fluctuates from 5-30% (MoWIE, 2020). In this study real water loss percentages that varied from 15% were adopted according to the data measurements and water utility offices with the size of population and time as proposed by current assessment and previous studies are used for estimation of current water loss.

Environmental water demand

Environmental flow

Environmental water demand is estimated based on Lotic systems of running water stream flow order and the volume and depth of the lake as it is essential to provide necessary life-supporting nutrients and space for living organisms inhabiting these aquatic systems. Hence, the environmental water flow to maintain biodiversity in the RVLB ranges from 0.07 – 1.46m^3/s with an average flow of 0.58m^3/s (Figure 27).

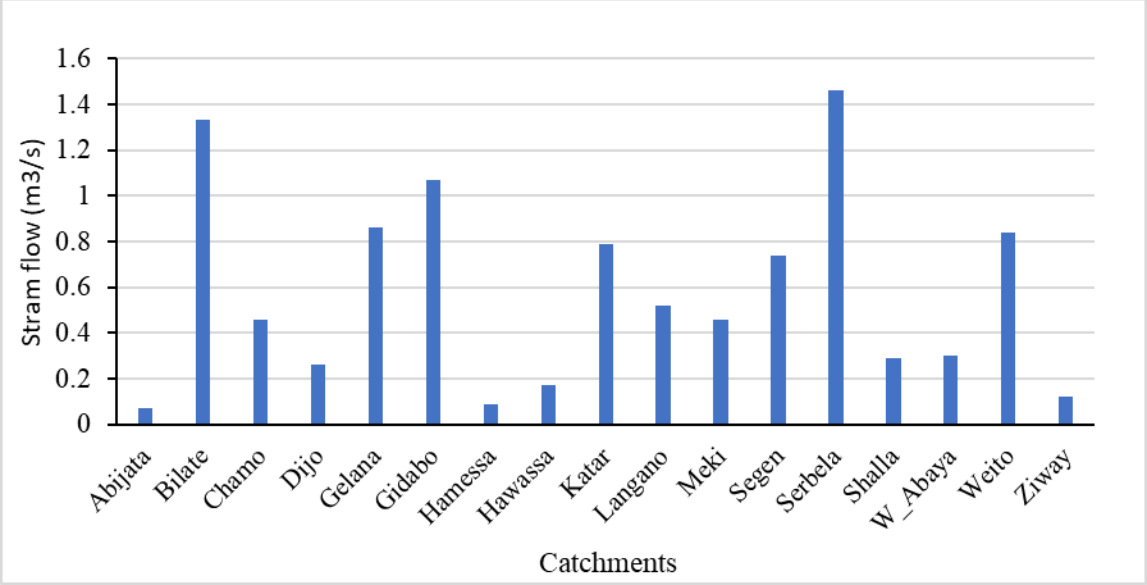


Figure 27: Environmental flows

Environmental Lake Water Levels

Trying to balance a swinging lake level is analogous to determining the optimal water level in a lake: too high and fish struggle and wetlands drown; too low and shorelines crumble and critical habitats dwindle. Finding the right threshold requires understanding natural cycles, respecting life's diversity, considering human needs, and adapting to a changing environment. For the RVLB, the threshold lake water level is set based on the volume of water required to maintain the annual fish production in the lakes, for specific lakes additional criteria are also considered such as minimum flow for downstream lakes, minimum elevation for boat transport, and aquatic bird habitat. In a $2m^3$ of water with a conservative estimate of 0.01 kg of fish, the threshold elevation for the RVL is presented below in Table 25.

Table 25: Threshold Lake elevation (m.a.s.l)

Lake	Fish production (tone/year)	Storage (MCM)	Threshold lake level(masl)
Ziway	4,850	970.00	1636.20
Langano	1,300	260.00	1581.00
Hawassa	3,645	729.00	1679.00
Abaya	4,120	824.00	1170.00
Chamo	4,500	900.00	1108.00

6.3.2. Overall current water demand estimate

As indicated in Table 26, the current overall water demand is estimated by integrating all the sectoral demands and it's found to be 1,796.34 MCM. The highest demand is from Blate with 226.05 MCM annual demand followed by the Weito and Meki catchments and the Dijo catchment has least annual water demand of 31.50 MCM. The irrigation water demand takes 58% share with the livestock demand share of 13% the Agricultural water demand holds 71% total share of the demand which makes it the highest of all the sectors. Domestic water demand accounts for up to 8% share while the industrial water demand is only 4%. To keep the ecology safe and sustainable the environmental water demand is up to 17% of the demand (Figure 28).

Table 26: Summary of all current water use in the sub-basin in MCM

Catchments	Irrigation Demand (MCM)	Livestock Demand (MCM)	Domestic Water Use (MCM)	Industrial Water Use (MCM)	Environmental water use (MCM)	Total (MCM)
Abijata	37.83	6.03	2.89	1.55	2.32	**50.63**
Bilate	112.12	37.80	33.92	0.23	41.98	**226.05**

Chamo	93.41	4.14	5.33	0.23	14.48	**117.59**
Dijo	15.13	6.10	1.64	0.50	8.13	**31.50**
Gelana	16.61	13.30	12.01	0.23	27.08	**69.22**
Gidabo	29.49	41.71	23.69	21.19	33.75	**149.84**
Hamessa	66.72	2.54	2.87	0.23	2.94	**75.31**
Hawassa	42.04	8.90	10.20	16.15	5.50	**82.80**
Katar	64.15	0.34	8.35	8.51	25.06	**106.41**
Langano	18.03	7.23	5.25	0.23	16.29	**47.03**
Meki	106.17	28.73	6.46	0.41	14.35	**156.13**
Segen	116.59	11.17	8.74	0.23	23.44	**160.17**
Serbela	19.45	19.20	2.49	0.23	46.15	**87.52**
Shalla	22.70	11.07	6.27	6.93	9.00	**55.97**
W_Abaya	106.75	7.91	7.22	2.58	9.34	**133.81**
Weito	142.62	14.88	8.23	0.23	26.44	**192.40**
Ziway	35.39	8.41	4.96	1.29	3.93	**53.98**
Total	**1,045.19**	**229.46**	**150.53**	**60.97**	**310.19**	**1,796.34**
Max	**142.62**	**41.71**	**33.92**	**21.19**	**46.15**	**226.05**
Min	**15.13**	**0.34**	**1.64**	**0.23**	**2.32**	**31.50**
Avg.	**61.48**	**13.50**	**8.85**	**3.59**	**18.25**	**105.67**
Total	**1,045.19**	**229.46**	**150.53**	**60.97**	**310.19**	**1,796.34**

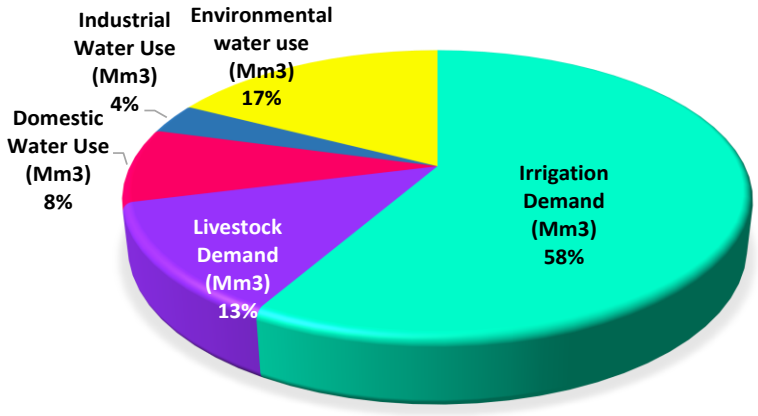


Figure 28: Distribution of water demand among sectors

As shown in Figure 29, comparing the supply and demand of the catchments, in most of the catchments the demand seems to be less than the available surface water, however, some catchments have higher demand than the surface water available within the catchment, Abijata, Ziway UG and Hamessa catchments are the catchments with higher water demand than the supply. This is mainly due to some specific reasons, Abijata, for instance, large commercial and farmers' land is irrigated directly from Bulbula River, which is a river that overflows water from Lake Ziway to Lake Abijata, the same holds

for Ziway _UG and Hamessa Catchments where the irrigated farms are getting water from Lake Ziway and Lake Abaya by pumping meanwhile the demand estimation was catchment based though they get supply outside the catchments.

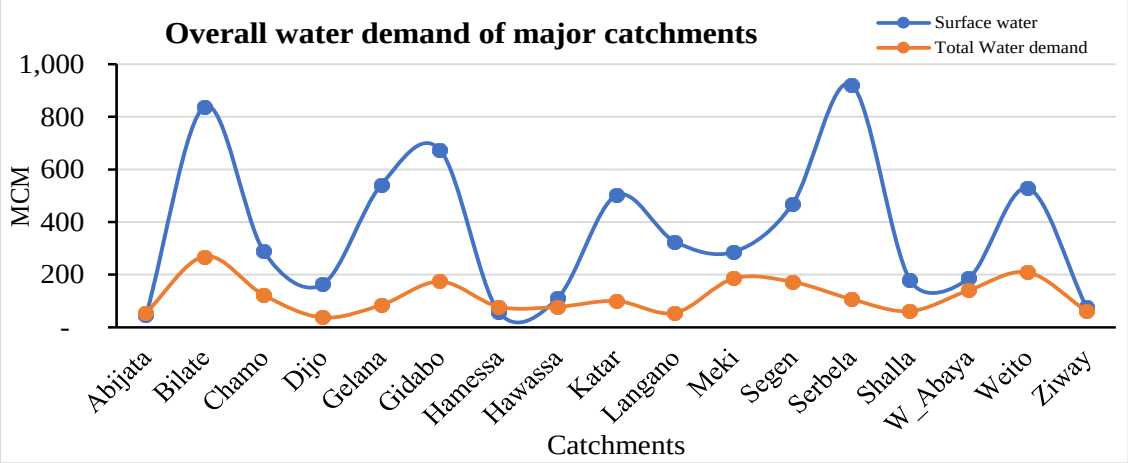


Figure 29: Spatial distribution of water demand and supply of major catchments

Considering the temporal distributions of the demand and supply the surface water resource available in the basin stultifies the demand in most of the months, however, during the peak time of irrigation in December and January the demand of the basin surpasses the supply. In January the demand is maximum with 329 MCM monthly demand followed by December (304 MCM) while the surface water supply during these months is 216 MCM and 250 MCM, showing a deficit of water. (Figure 30)

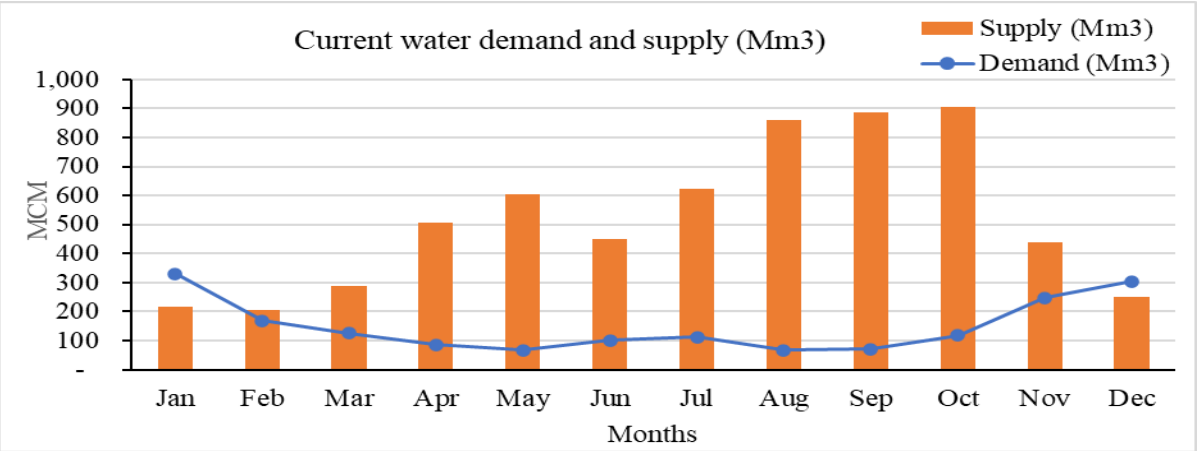


Figure 30: Temporal distribution of Water demand and supply

6.3.3. Projected water demand

Climate and Rainfall Projections

Dynamical downscaling was employed using regional climate models (RCMs) under the Coordinated Regional Climate Downscaling Experiment for Africa (CORDEX-Africa). The CORDEX-Africa dataset provided high-resolution (0.44° × 0.44°) climate projections, including temperature and precipitation, under multiple Representative Concentration Pathways (RCPs), such as RCP4.5 and RCP8.5. Climate data spanning historical (1981–2020) and future periods (2021–2035 and 2035–2050) were used to evaluate trends in rainfall and temperature variability. RCM outputs were dynamically downscaled to capture localized climate variations, incorporating topographic and land-use features. Bias correction techniques were applied to align model outputs with observed climatic data for enhanced accuracy.

Projected Water Demand Estimations

Water demand projections were categorized into key sectors: domestic, agricultural, industrial, and environmental. Projected climate variables (temperature and rainfall) were integrated with water demand drivers, such as population growth, urbanization, and economic activities, to estimate future demands. The Water Evaluation and Planning (WEAP) system was utilized, integrating downscaled climate data to simulate changes in water availability and demand under different scenarios. CORDEX-Africa data inputs were combined with local demographic, land-use, and economic datasets to align demand estimates with regional realities.

Projected irrigation water demand

Based on the stated classifications of soil depth, texture, drainage pattern, and topographic parameters in the methodology section, five land classes that are potentially suitable as well as unsuitable for surface irrigation were presented and classified. The finding depicts the land's suitability regardless of the potential availability and source of water. However, the actual irrigable area is identified in a more detailed approach considering the availability of water sources from surface, groundwater or others like runoff water harvesting systems with its temporal distribution for availability (Table 27).

Table 27: Summary of Land Suitability Results for Surface Irrigation in RVLB

Land Suitability	Area (Km^2)	Remark
S1	2,316.62	These classes are potentially suitable irrigable lands
S2	13,184.03	

S3	5,775.30	
N1	967.72	Suitable under some interventions like bench terraces
N2	48.61	Permanently not suitable
Total	**22,292.27**	
Other	**30,152.88**	
	52,445.15	**Total area of the sub-basin**

Out of these all categories, potentially suitable irrigable land that has favorable to suitable soil and site characteristics without considering the irrigation water availability categorized in S1, S2, and S3 classes have a total area coverage of about 21,275.95 km2 which is about 40% of the total land resource in the sub-basin (i.e., 52,445 km^2), However considering the irrigation water availability with its temporal distribution, the suitable irrigation potential area is 2,304 km^2. (Figure 31)

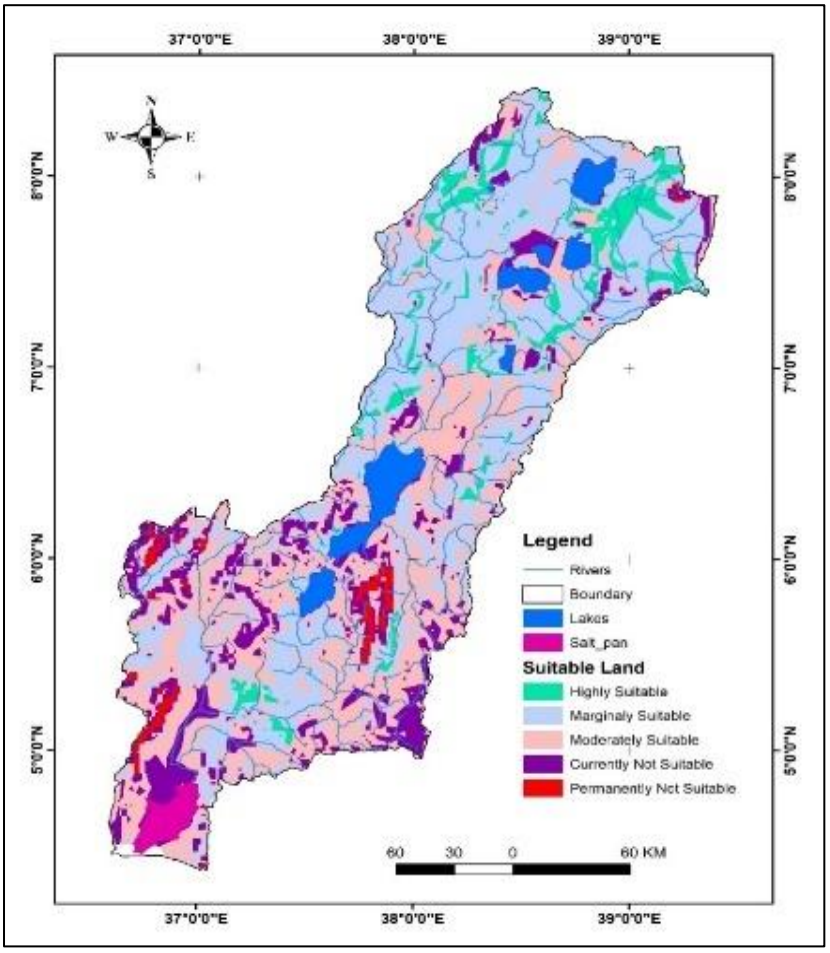


Figure 31: Land suitability for irrigation

Scenario I: Irrigated area expansion (IAE)

The potential irrigation area determined in the planning years 2035 and 2050 is the basis for estimating the predicted irrigation water requirement. The area expansion for irrigated agriculture in the basin is predicted to rise by approximately 56% to 162,570 in 2035 and 113% (230,400 ha) throughout the projected 30 years, using the current/existing 108,380ha as a basis (2022). 21,275.95 km2 of land could be suitable for irrigation, according to the suitability analysis. Nevertheless, the basin's water supply can only support development across an area of 230,400 km^. As a result, according to this scenario, the irrigation water demand will range from 1,567 MCM in 2035 to 2,272 MCM in 2050 (Figure 32).

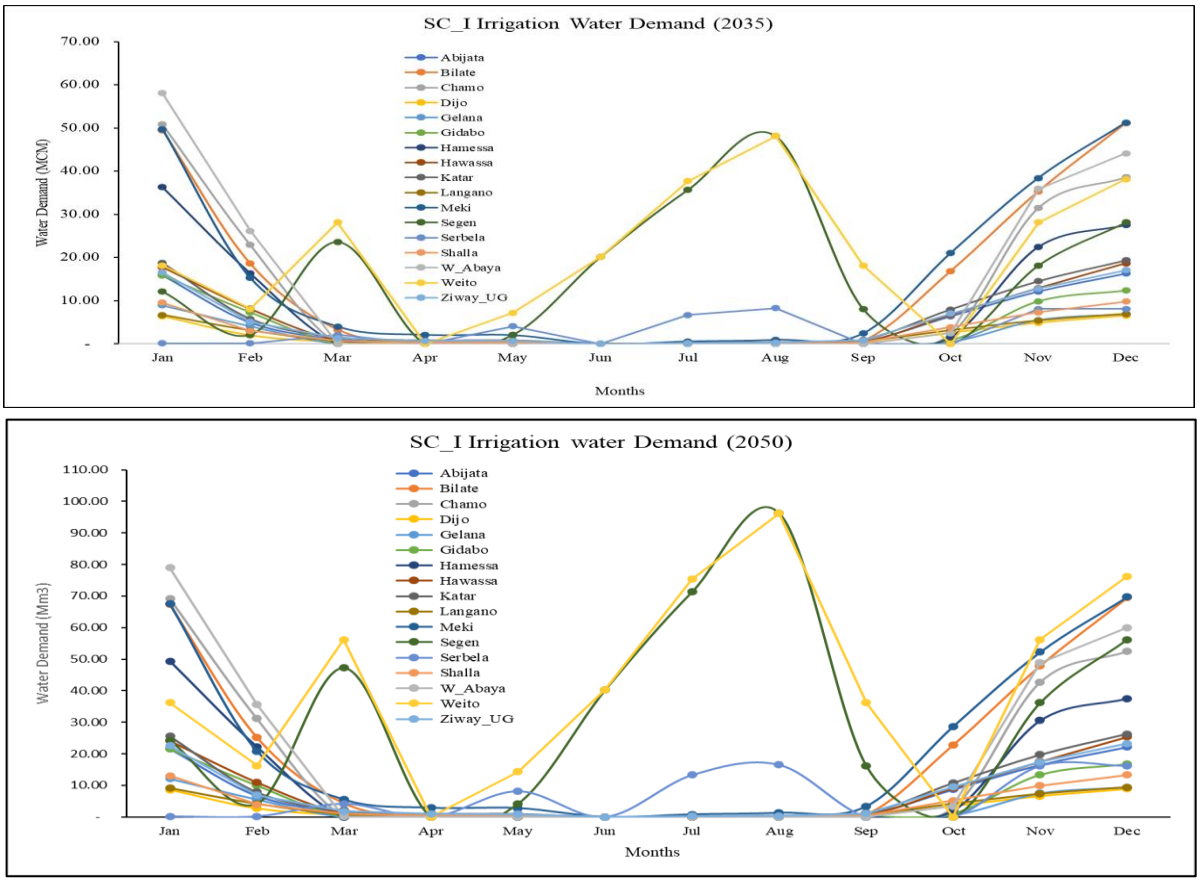


Figure 32: Irrigation water demand of Scenario I

Scenario II: Climate change impact on irrigation water demand with expanded irrigated area (CC)

Based on the downscaled climate data analysis, the trend of rainfall has shown fluctuation with small increments and decrements while temperature has shown increments. The two parameters (Rainfall and temperature) are the basic inputs for irrigation water demand. Bias-corrected downscaled CHIRPS climate data is used for the projected ETo estimation of the basin and the mean daily ETo ranges from 4.09 to 5.01 which shows a small increment in the mean daily ETo value. There is also an increment in the effective rainfall which impacts the irrigation water demand, However, the total irrigation water demand estimated under the climate change and irrigated area expansion scenario increases. Accordingly, the irrigation water demand is 1,877.10 MCM and 2553.165 MCM for the planning years 2035 and 2050 respectively (Figure 33).

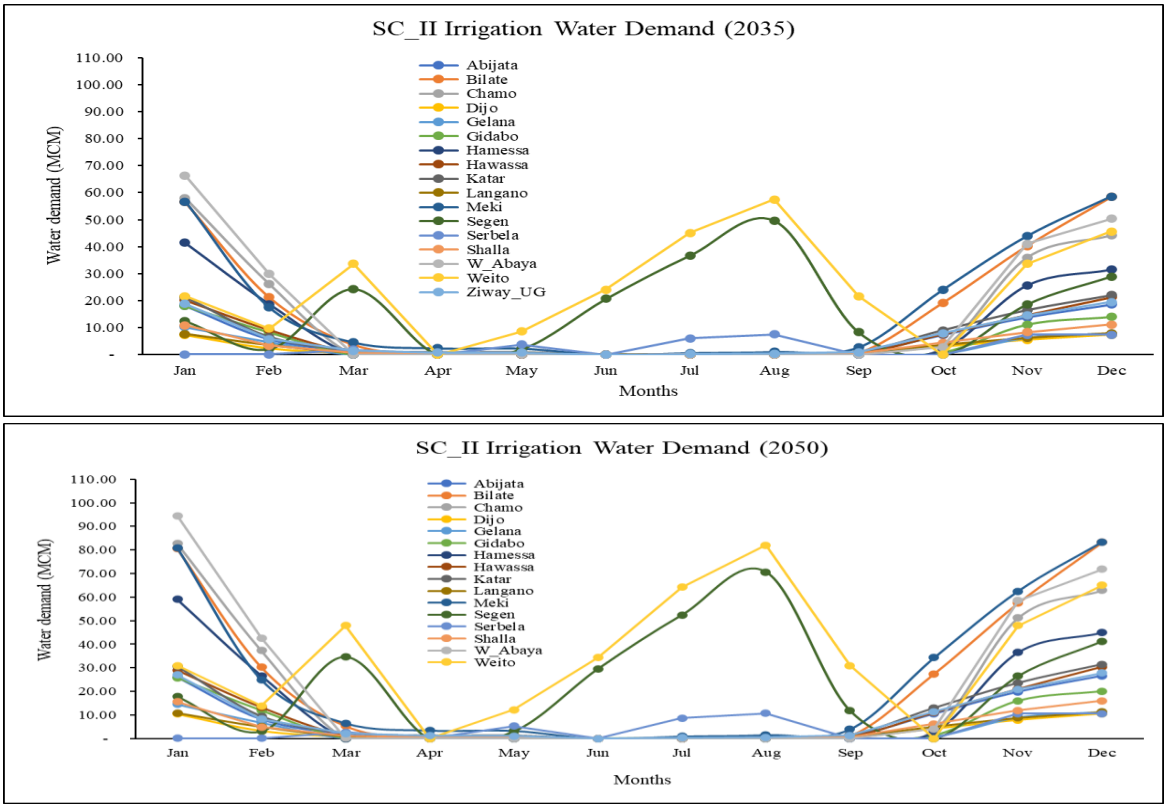


Figure 33: Irrigation water demand of scenario II

Scenario III: Using Advanced Irrigation Technologies (AIT)

The weighted average of irrigation efficiency is predicted to increase up to 58% as a result of the incorporation of contemporary irrigation technology (pressurized irrigation, pipe systems, and water saving) combined with the expansion of the irrigation area. Due to the higher availability of water conserved, the increased irrigation efficiency will result in a larger area under irrigation. There are two possible increases to the irrigated area: 76,225 hectares in 2035 and 103,680 ha in 2050. Water conservation could reach 45% with the implementation of contemporary irrigation systems and increased efficiency. In this scenario, the irrigation water demand is 1,126.59 MCM in 2030 and 1,532.36 MCM in 2050 (Figure 34).

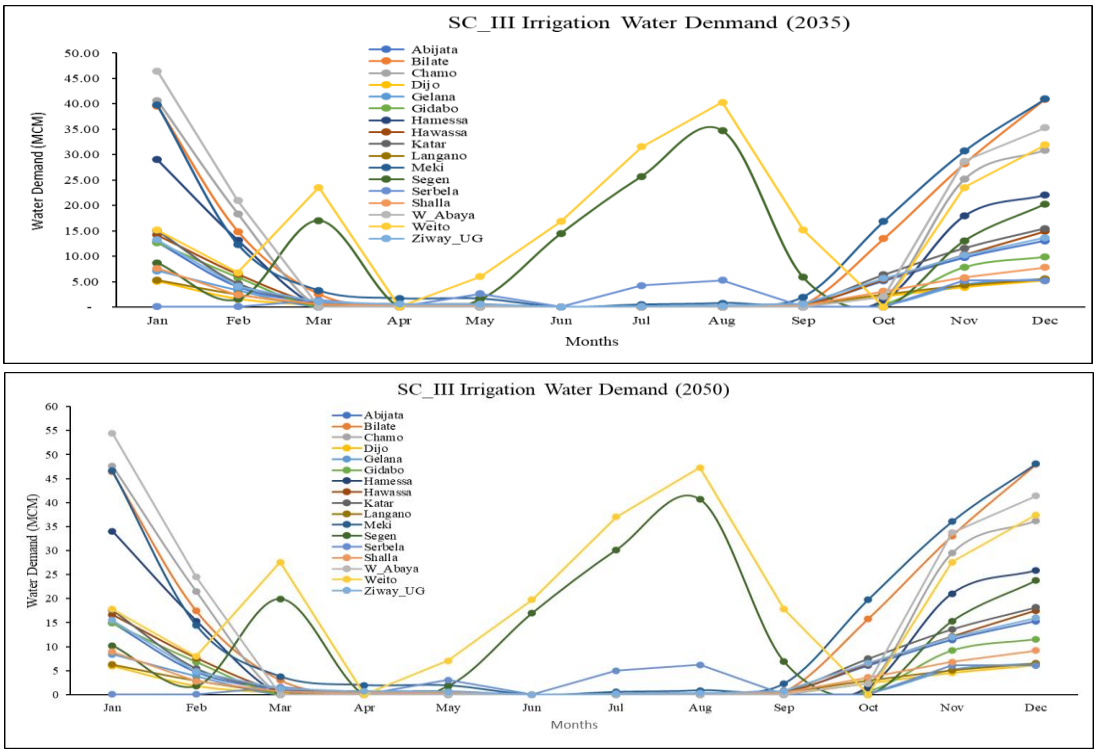


Figure 34: Irrigation water demand of scenario III

Projected Livestock water demand

The projected livestock water demand of the basin is estimated to be 238.38 MCM and 247.29 MCM for the planning years 2035 and 2050. Forecasted water consumption of livestock for the next fifteen years intervals are estimated for each major catchment. The

population projection and livestock water demand forecast from 2035 to 2050 for the basin are presented in Figure 35.

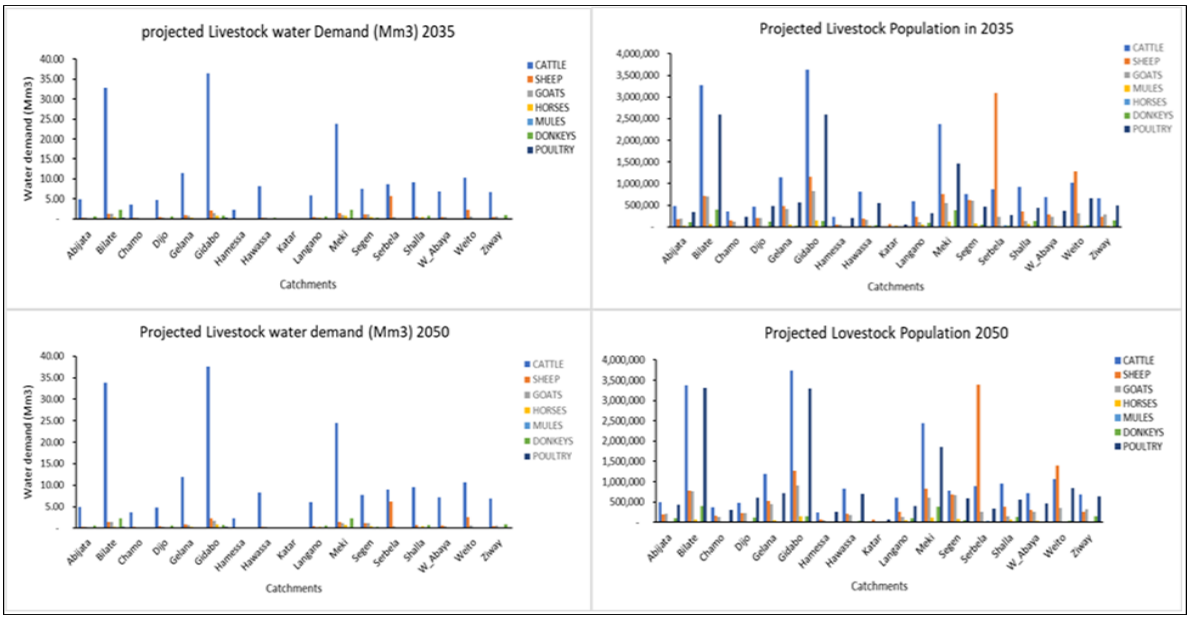


Figure 35: Projected Livestock water demand

Projected Domestic water demand

Estimating household water demand is essential for efficient planning and management of water resources. These estimates take into account variables including socioeconomic status, climatic change, and population growth. One method makes use of per capita water use, which impacts income. An alternative approach is assessing a community's value orientation while taking into account its aspirations for better living conditions and water conservation practices. Water authorities can forecast future demand and put conservation plans or infrastructure improvements into action to guarantee a sustainable water supply by knowing these elements. The population projection of the basin is estimated to reach 22,828,185 in 2035 and 28,754,550 in 2050 planning years, accordingly the projected water demand is estimated to be 211.71 MCM and 285.46 MCM in 2035 and 2050 planning years respectively. (Figure 36).

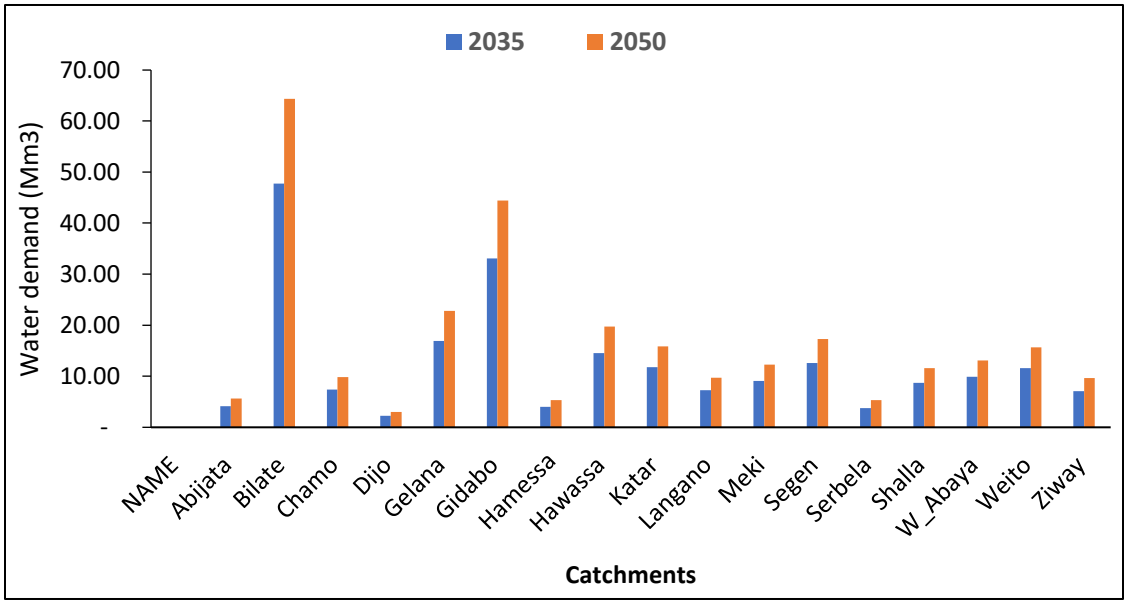


Figure 36: Projected domestic water demand

Projected Industrial water demand

The projected industrial water demand is estimated to be 41.55MCM and 60.98MCM for the planning years 2035 and 2050 respectively.

6.3.4. Overall projected water demand

Finally, after estimating each water use at the catchment level both for rural and urban areas of different sectors, the total projected water use estimate of the basin is summarized in Table 28. Based on the scenarios the projected demand ranged from 1,628.23 MCM to 2,378.74 MCM in 2035 and it ranged from 2126.09 MCM to 3,146.89 MCM.

Table 28: The overall projected water demand of the basin

Planning year	Projected water demand (MCM)			
	Irrigation (Scenario based)	Livestock	Industry	Domestic
2035	1,126.59 - 1,877.10	238.38	182.91	221.71
2050	1,532.36 – 2,553.16	247.29	304.86	285.46

As seen in Figure 37, When the supply and demand of the catchments are compared, most of the catchments appear to have less demand than the available surface water; however, six of the seventeen catchments have higher demand than the surface water available

within the catchment; Ziway UG, Hawassa, Meki, Segen, West Abaya, and Hamessa catchments have higher water demand than the supply. This is mostly due to several unique factors, including some catchments that have pumped irrigation farms adjacent to surrounding lakes, but the fundamental issue is that projected demands exceed supply, necessitating strategic interventions.

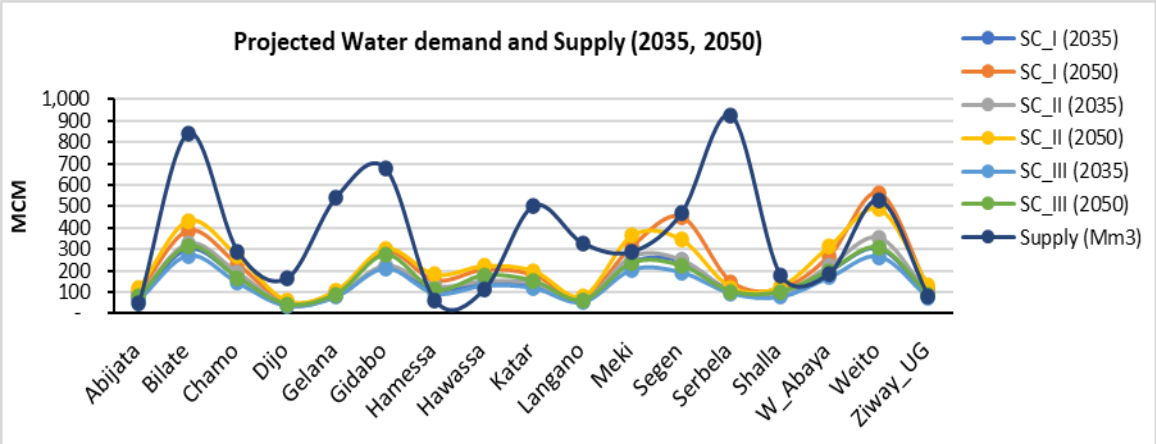


Figure 37: Water demand and supply of the catchments in RVLB

Considering the temporal distributions of demand and supply, the surface water resource available in the basin meets the demand in most months; but, during the peak irrigation season of November-February, the basin's demand exceeds its supply (Figures 38 and 39).

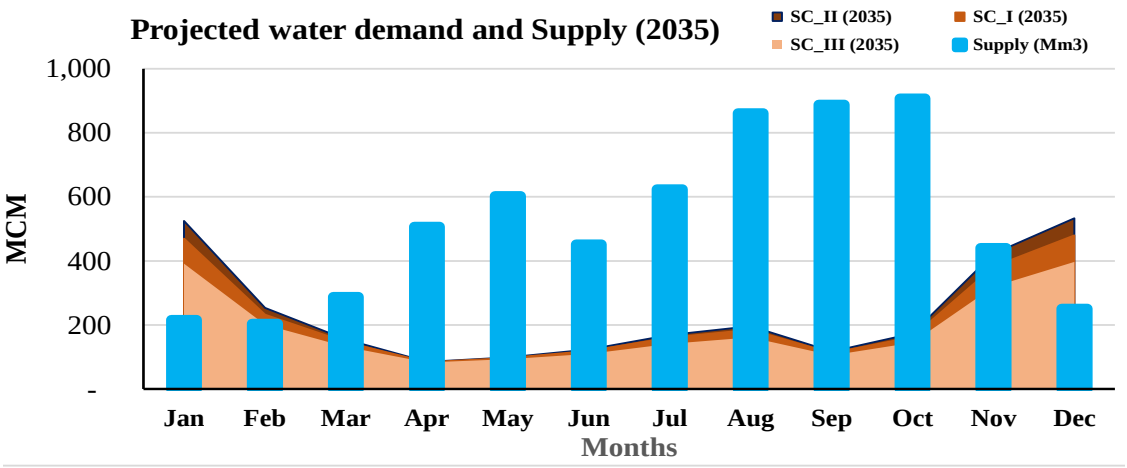


Figure 38: Projected overall water demand 2035

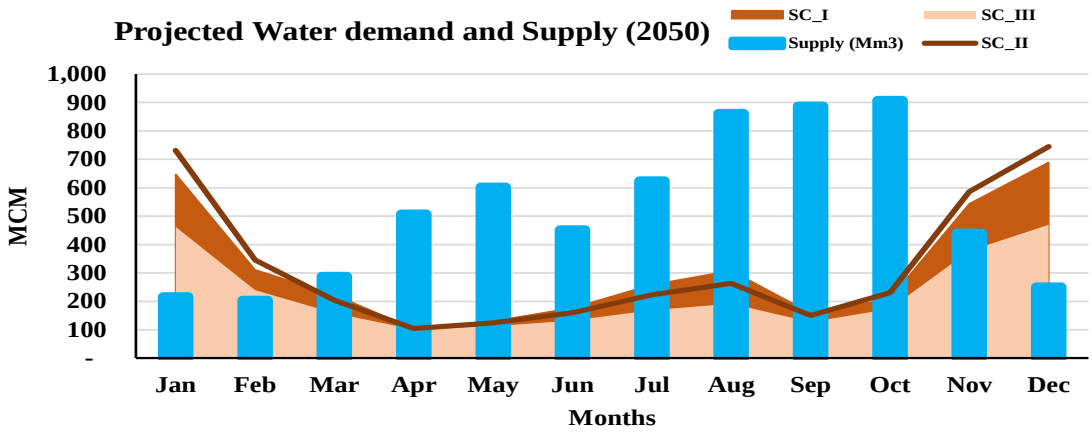


Figure 39: Projected overall water demand in 2050

The irrigation water demand share ranges from 59% to 67% which makes the agricultural water demand share range 69% - 75% of the total share of the demand which makes it the highest of all the sectors. Domestic water demand accounts for up to 7% - 9% share while the industrial water demand ranges from 6% - 8% for the 2035 planning year. Similarly, for the 2050 planning year, the projected water demand estimation results indicated that the agricultural water demand holds the highest share with a range of 67% to 76%, followed by Domestic and industrial water demand. For the environmental demand for sustainability and safety of the ecology, the demand ranges from 8% - 14% (Figure 40).

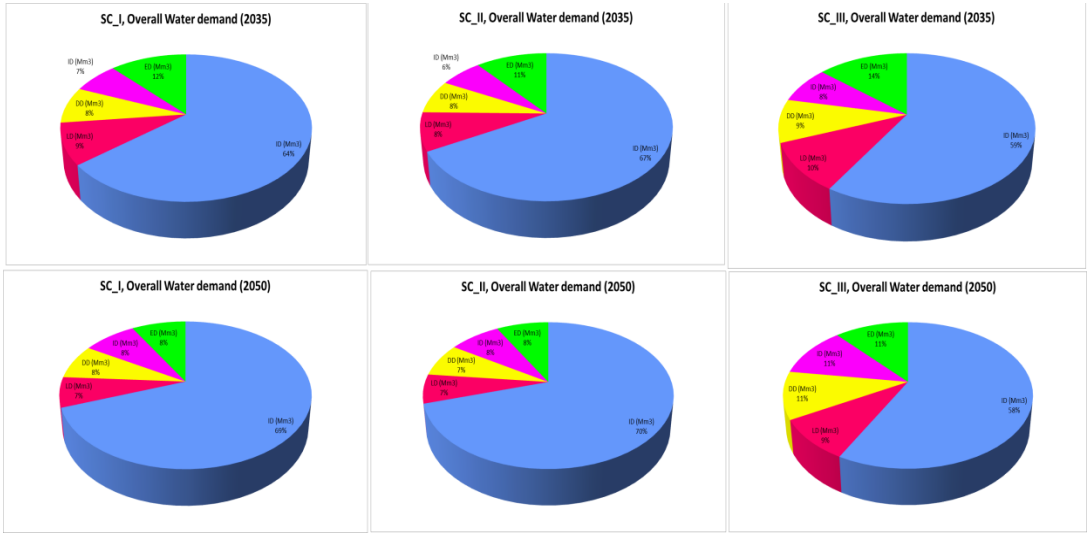


Figure 40: Scenarios for Projected water demand in RVLB

6.5. CONCLUSION

The current total population of the basin is estimated to be 17.8 million. Thus, in the basin, current water use is estimated as irrigation water demand is 1,045.19 MCM/year for the 108,380-ha irrigated area, the domestic water demand (Urban and rural area) is 150.53 MCM/year and industrial 27.76MCM/year, for livestock the water demand is 229.46MCM/year for the 45.87 million total livestock population and for the environment the estimated water demand is 310.19MCM/year. Thus, the total current water demand is 1,796.34MCM/year. The potential irrigable area in the basin is 230,400 ha, the projected population for the planning years of 2035 and 2050 is 22.83 and 28.75 million respectively with 25% and 30% urban population for each year, the projected Livestock population will be 48.10 million and 53.44 million for the planning years of 2035 and 2050 respectively.

The current overall water demand is estimated by integrating all the sectoral demands and it's found to be 1,796.34 MCM. The highest demand is from Blate with 226.05 MCM annual demand followed by Weito and Meki catchments and the Dijo catchment has least annual water demand of 31.50 MCM. The irrigation water demand takes 58% share with the livestock demand share of 13% the Agricultural water demand holds 71% total share of the demand which makes it the highest of all the sectors. In January the demand is maximum with 329 MCM monthly demand followed by December (304 MCM) while the surface water supply during these months is 216 MCM and 250 MCM, showing a deficit of water. The total projected water use estimate of the basin is summarized in. Based on the scenarios the projected demand ranged from 1,628.23 MCM to 2,378.74 MCM in 2035 and it ranged from 2126.09 MCM to 3,146.89 MCM. When the supply and demand of the catchments are compared, most of the catchments appear to have less demand than the available surface water; however, six of the seventeen catchments have higher demand than the surface water available within the catchment; Ziway UG, Hawassa, Meki, Segen, West Abaya, and Hamessa catchments have higher water demand than the supply. This is mostly due to several unique factors, including some catchments that have pumped irrigation farms adjacent to surrounding lakes, but the fundamental issue is that projected demands exceed supply, necessitating strategic interventions. Considering the temporal distributions of demand and supply, the surface water resource available in the basin meets the demand in most months; but, during the peak irrigation season of November-February, the basin's demand exceeds its supply.

6.6. RECOMMENDATIONS

Development of storage infrastructure, such as reservoirs and recharge systems, to capture excess runoff during the rainy season for use during the dry season; implementation of water-saving technologies (e.g., drip irrigation), reduction of losses in distribution systems, and the promotion of water-use efficiency across all sectors; adoption of drought-resistant crops and adjustment of planting schedules to align with water availability and establishing basin-wide water-sharing agreements, seasonal allocation planning, and incentives for efficient water use are the proposed strategic interventions for the RVLB. The feasibility of these strategies varies based on the basin's constraints. Combining water storage, demand management, and alternate cropping patterns appears most viable, provided sufficient investment and stakeholder collaboration. Managed aquifer recharge and policy reforms offer long-term benefits but require more substantial institutional and technical capacity.

CHAPTER 7: WATER RESOURCE SYSTEM PERFORMANCE EVALUATION

7.1. INTRODUCTION

A water system framework regularly comprises surface water including streams, lakes, and reservoirs, groundwater, harvested rainwater, ice meltwater and desalinated water. Wastewater deals with treatment that can be reused for various purposes, including irrigation, industrial processes, or replenishing surface or groundwater. The water resource system also incorporates infrastructures including dams, wells, trenches, and water treatment and distribution systems that catch store, treat, and convey water. Ecology and legal and institutional frameworks also play significant roles in the water resource system (Loucks and Van Beek, 2017).

Performance evaluation of water resources systems involves assessing various aspects of the system to ensure it is functioning optimally and sustainably. Evaluating the availability and sustainability of water resources is crucial. This includes assessing surface water (rivers, lakes, reservoirs), groundwater, and rainwater. Physical Performance assessment involves assessing the physical infrastructure of the water system, including the condition of pipes, pumps, treatment facilities, and storage facilities, another main aspect of the system performance is the Operational Performance which includes evaluating the efficiency of the system's operation, such as the effectiveness of water treatment processes, the reliability of water supply, and the system's resilience to disturbances evaluating water losses in the system, including real losses such as leakage from the network and overflows at the utility's reservoirs and irrigated farms (Wan Rosely and Voulvoulis, 2024).

Water shortage has always been a great challenge and decision makers always investigate different policies and scenarios to overcome this challenge. However, in water resources systems these investigations can be efficient only if the policymakers and decision-makers have integrated perspectives of the whole system. In the past decades, simulation and optimization techniques have been useful in analyzing water resource systems. Although there have been extensive improvements in optimization techniques and their applications in water resources specifically in reservoir operation, simulation techniques can make it possible to better evaluate the system and impose different management decisions. Therefore, developing a simulation model that can provide a better understanding of complex and dynamic systems and makes it possible to perform analysis

and impose policies on the system is the focus of many studies especially in the field of system analysis (Ahmad and Simonovic, 2000).

Water productivity in river basins is a critical aspect of sustainable water management, with far-reaching implications for agriculture, ecosystems, and human well-being. As water resources become increasingly scarce and demands grow, optimizing water productivity is essential for ensuring food security, economic development, and environmental sustainability. The water productivity of a river basin has profound implications for various sectors and stakeholders in a river basin. Efficient water use in agriculture is vital for maximizing crop yields while minimizing water consumption (Chatigny et al., 2007). Improving water productivity enables farmers to produce more food with less water, contributing to food security and economic prosperity. Maintaining adequate water flows within river basins is crucial for supporting diverse ecosystems, including wetlands, forests, and aquatic habitats. Enhancing water productivity helps preserve ecosystem health and biodiversity, promoting resilience to climate change and human disturbances. River basins facing water scarcity challenges can benefit from improved water productivity, which reduces pressure on finite water resources. By using water more efficiently, communities can meet their water needs while preserving water for environmental and future generations (Frisvold and Duval, 2024).

Among many simulation techniques, System Dynamics (SD)- first introduced by Forrester in 1964- with its dynamic, feedback-based and object-oriented structure has proved to be a helpful tool in modeling complex systems. However, the application of SD in water resources and hydrology was started in the 1990s. Thereafter, many researchers have applied this approach to water resources systems and investigated the impacts of different scenarios on the system. For example, Ahmad and Simonovic (2000) developed an SD model and simulated different reservoir operation scenarios for flood management.

In optimization techniques, the performance evaluation of water resources systems is inherent in the objective functions, constraints and eventually the results; whereas, in simulation methods, this assessment should be done separately. One way to assess the impacts of different policies and scenarios on systems is to use performance indices. Although there were studies before the 1980s in this area, (Hashimoto et al., 1982) are considered basic studies. (Hashimoto et al., 1982) introduced reliability, resiliency and vulnerability as three important performance indices in performance evaluation of water resources systems. In the literature, many studies used definitions similar to (Hashimoto

et al., 1982) definitions; however, in some other studies, resiliency and vulnerability are defined using different estimators (Moys et al., 1986).

The RVLB is a critical water resource supporting diverse ecosystems, agricultural activities, industrial operations, and the potable water needs of the surrounding population. However, the basin faces numerous challenges, including variable rainfall patterns, increasing water demand due to population growth, industrial development, climate change impacts, and potential contamination from agricultural runoff and industrial discharge. These challenges necessitate a comprehensive evaluation of the water resource system to ensure sustainable management and optimal usage. Hence, the primary objective of this study is to evaluate the water resource system of the basin using WP, resilience, reliability, and vulnerability indicators. The evaluation provides insights into the current state of the water resource system and identifies areas requiring intervention to enhance sustainability.

Resilience assesses the ability of the water resource system to recover from disturbances such as droughts, floods, and pollution incidents, reliability measures the water supply's consistency in meeting the demands of various stakeholders, including households, agriculture, and industry and Vulnerability identifies the susceptibility of the water resource system to potential threats such as climate change, over-extraction, and contamination. The study analyses historical data on water flow, precipitation, quality, availability, usage patterns, supply disruptions socioeconomic conditions, infrastructure robustness, and environmental pressures to evaluate the system's capacity to maintain functionality under adverse conditions.

7.2. WATER RESOURCE SYSTEM PERFORMANCE INDICATORS

7.2.1. Water productivity

Water productivity and water use efficiencies are the most affecting factors mainly in irrigation water use. Any changes in irrigation water management practices or using modern irrigation technologies will alter irrigation water consumption. As a result, analyzing and modeling the temporal and spatial characteristics of the basin's WP and WUE will be one of the fundamental steps for defining the many scenarios for alternate water allocation strategies. The procedure will include the collection and analysis of relevant water productivity models, as well as geographical and water usage efficiency

variable data sets for various scale irrigation schemes and commercial and private farms (Schewe et al, 2013)

Increasing WP is important for water resources management. WP can be described as an economic output per unit water use amount. How to quantify the coordination of multiple factors that affect WP, how to reveal the relationship between economic output and water use amount under different scenarios, and how to scientifically evaluate the efficiency of water allocation schemes are particularly important (Wang et al., 2017).

WP measures how the system converts water, together with other resources, into goods and services. It is defined as the ratio of net benefits from the crop, forestry, fishery, livestock and other mixed agricultural systems to the amount of water used in the production process (Molden et al. 2010). The benefits can be measured with various terms including physical mass (Kg), economic value (monetary) and nutritional value (calorie). The water input, denominator in the WP equation, also has a set of choices depending on the purpose of the examination and the availability of data. For example, irrigation diversion, gross/net inflow, evapotranspiration, and precipitation can all be used to calculate WP indicators.

These variations give WP assessment flexibility and robustness as a tool to measure the efficiency of water use. The assessments of WP could be carried out using various approaches and combining a range of datasets. Because crops dominate agricultural production and are the biggest water consumers, we gave them more attention in the WP assessment. In some basins, where livestock and fisheries are important contributors, we also included them. The basic equation to calculate WP is:

$$WP = \frac{Output\ from\ water\ use}{Water\ input} \text{---------- eq 13}$$

Physical water productivity

WP is affected by Agroecology, field management cropping pattern irrigation water management therefore data will be collected considering these factors. Datasets come from sources such as field monitoring, surveys, official statistics, weather stations, remote sensing imagery, and literature reviews. Various datasets of different spatial scales from the field, through sub-catchments, to the basin will be combined in the assessment from institutions in the project area. For this particular study, the water productivity of major

crops grown in the basin will be evaluated. The water-productivity analysis considers the physical accounting of water with yield or economic yield to indicate how much value is obtained from the use of water. Productivity data and cropping patterns of the major crops is collected from the Wereda offices and used for analysis. For the basin, physical (kg/m3) water productivity will be calculated using the formula:

WP = Output/Q---------- eq 14

Where: WP is the water productivity (kg/m3 or $/m3), Output is the output of irrigated agriculture, crop yields (ton), the power generated (kWh) or its value converted into monetary units, and Q is water resources supplied or consumed, m^3.

WaPOR Satellite imagery Biomass water productivity

Satellite imagery and remote sensing technologies have revolutionized the way to assess water productivity at large scales. Remote sensing technologies provide detailed information about land cover, crop health, and water availability, which are crucial for determining water productivity. For this study, the WaPOR water productivity assessment data is used to evaluate the performance of the river basin validated with ground truthing data. The FAO WaPOR data portal is a public domain free data source. The WaPOR is gross biomass water productivity produced seasonally for the years 2020, 2021 and 2022, the data is downloaded from the website of the FAO WaPOR and used for evaluation of the water productivity of the river basin.

7.2.2.RRV techniques as indicators for water system performance

Reliability

The ability of existing and proposed water resource systems to operate satisfactorily under the wide range of possible future demands and hydrologic conditions is an important system characteristic. The likely performance of water resource systems is

often described by the mean and variance of benefits, pollutant concentrations, or some operating variables.

There are several definitions of reliability and resilience available in the literature. The basic notions of the mathematical theory of reliability are the reliability function and the availability function. The reliability function defines the probability that the system has not entered state NS until a given time, while the availability function defines the probability that the system is in state S at a given time. In practical applications, reliability is the term used to represent the probability of the system being in state S, either in a single time instant or in a time interval (Hashimoto et al. 1982). Reliability denotes a system's output state or status by the random variable X_t at time t, where t takes on discrete values 1, 2, 3..., In general, the possible values of X_t can be partitioned into two sets 'S', the set of all satisfactory outputs, and 'F', the set of all unsatisfactory(failure) outputs. At any time, t the system output is assumed to be an element of one of these sets. The reliability of a system will be evaluated by the frequency or probability that a system is satisfactory. The ranges from 0 to 1, as the reliability value is closer to 1 shows the system is more reliable.

$$\alpha = \mathbf{Prob}[X_t \in S] \quad \text{---------- eq 15}$$

Where:

α=Reliability

X_t=System output at time t

S=Satisfactory state

Resiliency

Resiliency describes how quickly a system is likely to recover or bounce back from failure once failure has occurred. If failures are prolonged events and system recovery is slow, this may have serious implications for system design. One would like to design systems that can rapidly recover and return to a satisfactory state. Resiliency may be given a mathematically precise definition.

Let TF be the time a system's output remains unsatisfactory after a failure. The resiliency of a system can be defined as the inverse of the expected value of TF. To derive a mathematical expression for that expected value, Let

$Z_t = 1 \quad X_t \in S \qquad\qquad Z_t = 0 \quad X_t \in F$

Then $\left(\frac{1}{n}\right)\sum_{t=1}^{n} Z_t$ is the fraction of time from period t = 1 to t = n that the system output or performance is satisfactory. In the long run, this fraction approaches the probability of the performance being sufficient, and hence equals system reliability:

$$\lim_{n\to\infty}\left(\frac{1}{n}\right)\sum_{t=1}^{n} Z_t = \alpha \text{---------- eq 16}$$

Let W_t indicate a transition from a satisfactory to an unsatisfactory state:

$W_t = 1 \qquad X_t \in S \qquad X_{t+1} \in F \qquad W_t = 0 \qquad$ Otherwise

In the long run, the mean value of W_t will equal the probability of the system being in the set S in some period t and going to the set F in the following period:

$$\rho = Prob\{X_t \epsilon S, X_{t+1} \epsilon F\} = \lim_{n\to\infty}(1/n)\sum_{t=1}^{n} W_t \text{---------- eq 17}$$

The average stopover time in the unsatisfactory or failure states during an n-period experiment is:

TF = A/B

Where A is the total time in F and B is the number of times the process went into F. Hence

$$T_F = \frac{1}{n}\sum_{t=1}^{n}(1 - Z_t)\left(\frac{1}{n}\sum_{t=1}^{n} W_t\right)^{-1} \text{---------- eq 18}$$

As n approaches infinity, the average sojourn time TF will approach its mean value (1 - α)/ρ. Thus, the expected length of time that the system's output or performance remains unsatisfactory once it becomes unsatisfactory equals

$$E(TF) = \frac{1-\alpha}{\rho} \text{---------- eq 19}$$

This defines the average number of periods a failure is expected to last once it has occurred. The inverse of this is the system's average recovery rate will be the measure of resiliency:

$$\gamma = \frac{\rho}{1-\alpha} = \frac{Prob\{X_t \epsilon S \text{ and } X_{t+1} \epsilon F\}}{Prob\{X_t \epsilon F\}} \text{---------- eq 20}$$

In the long run, the number of transitions from satisfactory states in S to unsatisfactory states in F must equal the number of transitions in the reverse direction:

$$\textbf{Prob } \{X_t \in S \text{ and } X_{t+1} \in F\} = \textbf{Prob } \{X_t \in F \text{ and } X_{t+1} \in S\} \text{ ---------- eq 21}$$

Hence $\boldsymbol{\gamma}$ is equivalent to the average probability of a recovery from the failure set in a single time step:

$$\boldsymbol{\gamma} = \frac{\textbf{Prob}\{X_t \in F \text{ and } X_{t+1} \in S\}}{\textbf{prob}\{X_t \in F\}} = \textbf{Prob } \{X_{t+1} \in S \mid X_t \in F\} \text{ ---------- eq 22}$$

Note that if the occurrence of a failure Xt ∈ F and a subsequent success Xt+1 ∈S are probabilistically independent events, then, /would reduce to Prob {Xt+1 ϵ S}, which will be the measurement of reliability. The value ranges from 0 to 1, as the resilience value is closer to 1 shows the system is more resilient.

Vulnerability

Vulnerability refers to the likely magnitude of a failure if one occurs. Even when the probability of failure is small, attention should be paid to the possible consequences of failure. Attempts to maximize system reliability are attempts to make a system's operation failure-free. Still, few systems can be made so large or so redundant that failures are impossible but not economical. It is important to realize that efforts to maximize system efficiency and reliability can increase a system's vulnerability to costly failure. The unsatisfactory and severe outcome that occurs in a sojourn into the set of unsatisfactory states F. Then e_j equals Prob {xj, corresponding to S_j, is the most severe outcome in a sojourn in F}. One reasonable metric for overall system vulnerability would be the expected maximum severity of a sojourn into the set of unsatisfactory states:

$$\boldsymbol{\nu} = \sum_{j \epsilon F} \mathbf{S_j e_j} \text{---------- eq 23}$$

Note: The value ranges from 0 to 1, as the fractional value is closer to 1 showing the system is more vulnerable.

7.3. RESULTS

7.3.1. Water productivity of the RVLB

There is no clear-cut value as good or bad performance for a river basin in terms of WP Hence the WP can be influenced by the crop type, variety, soil type, agronomic practices (input use) irrigation technologies, climate, farming practices source of water and energy consumption, however, it can be evaluated relative to similar basins and its attainable potential. Based on the productivity of the major crops grown in the basin the cropping patterns, irrigated area and irrigation water use, the weighted average of the water productivity of the catchment is calculated. As indicated in Table 29, the water productivity of the river basin ranges from 0.71 to 1.58 kg/m3 with a mean value of 1.13kg/m^3. Catchments with high intensity of irrigation such as the Ziway, Meki, lower Katar, Bilate, lower Gidabo, W_Abaya, Chamo and Hamessa have comparability lower water productivity indicating there is wastage of water as the result of poor irrigation efficiency. The irrigation water use efficiency of the basin is very low as reported by (Hirpa et al., 2023). As reported by (Bashe et al., 2024), The WP of Koga na d Fincha irrigation schemes are 0.5 kg/m^3 and 4.31 kg/m^3 respectively, it can be seen that the WP of the RVLB is lower as compared to Fincha. The lower water productivity performance could be due to excess water use and mismanagement of the irrigation water applied.

Table 29: Water productivity of the major crops in RVLB

Major Catchments	Irrigated Area (ha)	Water use (MCM)	Water productivity (kg/m3)	Dominant crops growing in the catchment
Abijata	3,788.63	37.83	1.03	Onion, Tomato, kale, Cabbage, Pepper, Potato Papaya
Ziway	13,029.66	112.12	1.14	
Meki	9,012.22	93.41	1.14	
Katar	1,515.45	15.13	0.71	
Shalla	1,550.61	16.61	1.03	
Dijo	2,753.03	29.49	1.03	
W_Abaya	6,437.30	66.72	1.23	Banana, Carrot, Cabage, Tomato, Peper, Onion
Chamo	4,634.60	42.04	1.23	
Gelana	4,429.53	64.15	1.20	
Gidabo]	1,399.13	18.03	1.20	
Hamessa	11,723.09	106.17	1.23	
Weito	11,360.61	116.59	1.27	Onion
Serbela	2,107.67	19.45	1.08	
Segen	2,273.18	22.70	0.97	
Bilate	10,299.69	106.75	1.18	Onion, Potato, Tomato, Banana, Kale, Cabbage

Langano	18,157.88	142.62	1.00	Sugarcane, Onion, Tomato, Potato
Hawassa	3,907.70	35.39	1.58	Sugarcane, Potato, Onion, cabbage

The Water Productivity Portal (WaPOR) database provides valuable information on water productivity for major crops in Ethiopia. The database utilizes remote sensing data and hydrological modeling to estimate crop water productivity at various spatial scales. While specific water productivity values may vary depending on factors such as location, soil type, and management practices, the WaPOR database offers valuable insights into water use efficiency and crop production in Ethiopia. This data is used to indicate the spatial distribution of the WP of the basin; accordingly, WaPOR Biomass water productivity analysis indicated the water productivity of the river basin ranges from 1.3 – 2.89kg/m^3 this is in fact after the biomass water productivity needs conversion with biomass index factor to get the economic yield water productivity (Figure 41). Serbela and Segen catchments have lower water productivity of <1.3 kg/m^3 and <1.9kg/m^3 this is mainly because the catchments have low yield productivity and less tradition of irrigated agriculture as compared to the central and upper part of the RVLB. Areas where high intensity of irrigated agriculture practices have a high-water productivity range of 2.38 – 2.84 kg/m^3 of Biomass production per applied cubic of water.

As compared to other basins and irrigation schemes the performance of the RVLB in terms of water productivity is low with an average WP of 1.13kg/m3. This is mainly due to poor irrigation efficiencies, and mismanagement of the agricultural inputs (improved seed, recommended fertilizer rates, paste and disease management, weeding and cultivation). Mekonin Ayana, (2020), Hove conducted similar studies in different basins in Ethiopia, and their conclusions resemble with findings of this study. For improved water productivity irrigation water applications should consider, the slope/topography of the land/furrow, the stream size/discharge, soil type and its infiltration rate, along with the CWR of the crop and climatic conditions, using advanced irrigation technologies also improve the WP not only physical but also in terms of quality of production.

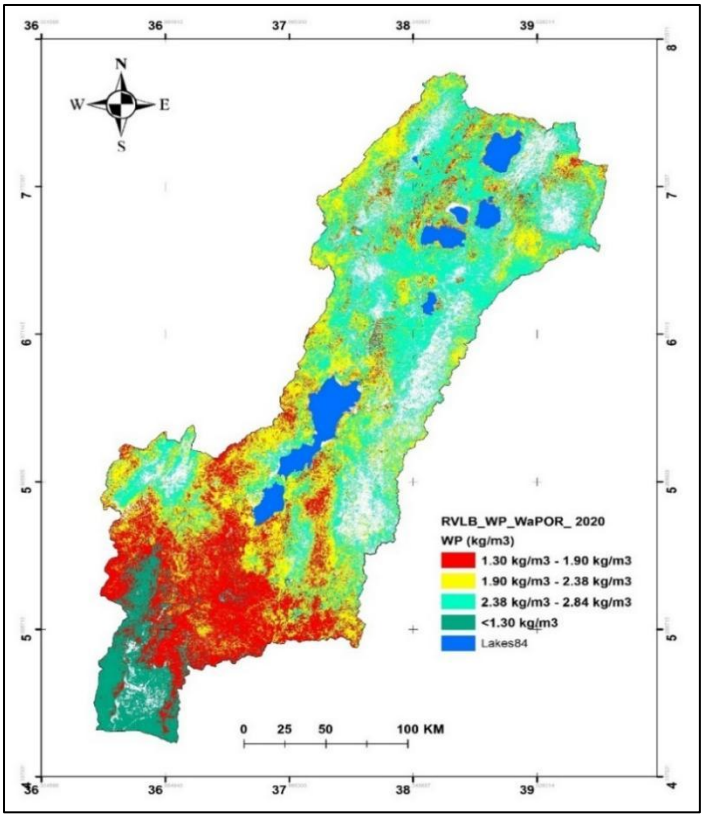


Figure 41: Biomass Water productivity of the RVLB 2020

7.3.2. Resilience, Reliability and Vulnerability of the RVLB

Thus, the construction of Gidabo reservoirs in the basin in addition to the existing lakes. There is also a Dijo reservoir under construction with six more reservoirs under study condition, thus scenarios are established to evaluate the water resource system performance of the basin with the combination of the possible scenarios.

- Scenario I: The existing water resources systems (Lakes and Gidabo reservoir) existing demand
- Scenario II: Dijo reservoir added to the system with projected demand
- Scenario III: Meki, Gelana, Ropi, Bezo, lyanda and Haro reservoirs added to the system with projected demand

This study aims to simulate the RVLB water resources system and to evaluate the performance of the system under each scenario. To better understand the results and evaluate the scenarios the basin is divided into four sub-basins: (1) Ziway-Shalla Subs-basin that includes Lake Ziway, Lake Langano, Lake Abijata, Lake Shalla and Meki, Dijo reservoirs, (2) Hawassa Sub-basin that includes lake Hawassa and, (3) Abaya-Chamo Sub-basin that includes Lake Abaya, lake Chamo and Gidabo, Gelana and Ropi reservoirs, and (4) Chewbahir Sub-basin that includes lake Chewbahir and Bezo, Lyanda, and Haro reservoirs. The water demand distribution in the basin in the present is shown in Figure 42.

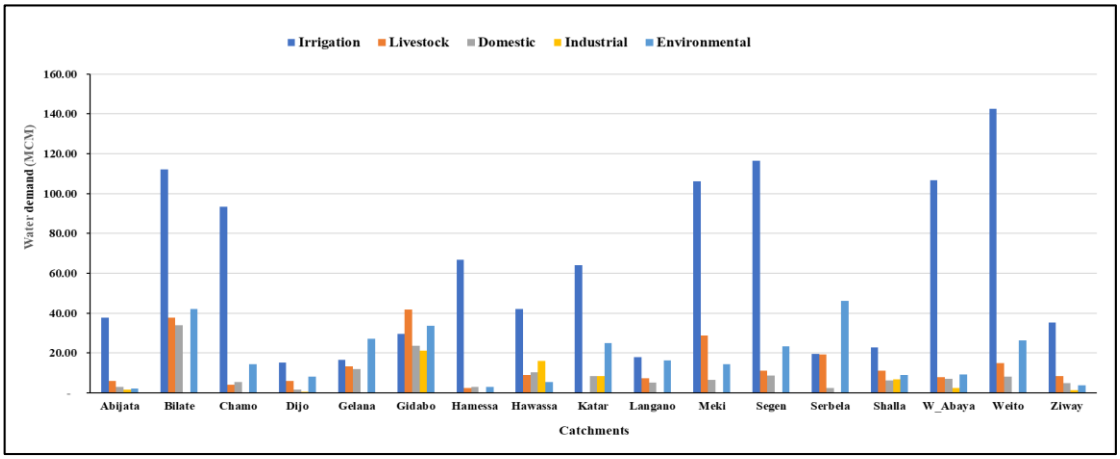


Figure 42: Water Demand distribution in the subsystems

WEAP Model

The WEAP model is used to analyze the water resources available in the base. The model uses input data such as climate, rainfall, land use, and soil data for the hydrologic analysis. The model was calibrated and validated using observed gauge data (chapter 4).

System dynamics model

The System Dynamics approach is used to simulate the water demand and supply interaction using Vensim DSS 10.1.3. The SD modeling is carried out in three main stages; first, system elements and interrelationships among them are determined, which results in the diagram which is called Causal Loop Diagram (CLD). Then, using state, rate and auxiliary variables the Stock Flow Diagram (SFD) of the system in the software

is sketched. Finally, the mathematical formulation for each element is provided. The typical SFD for the RVLB is shown in Figure 43

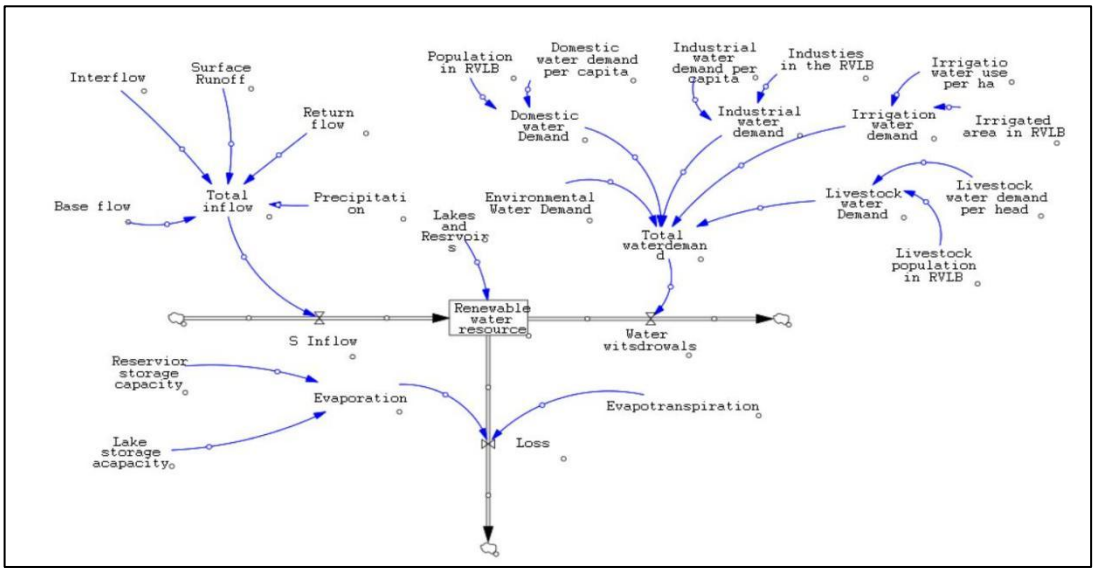


Figure 43: Stock flow diagram of the water resource system of the RVLB

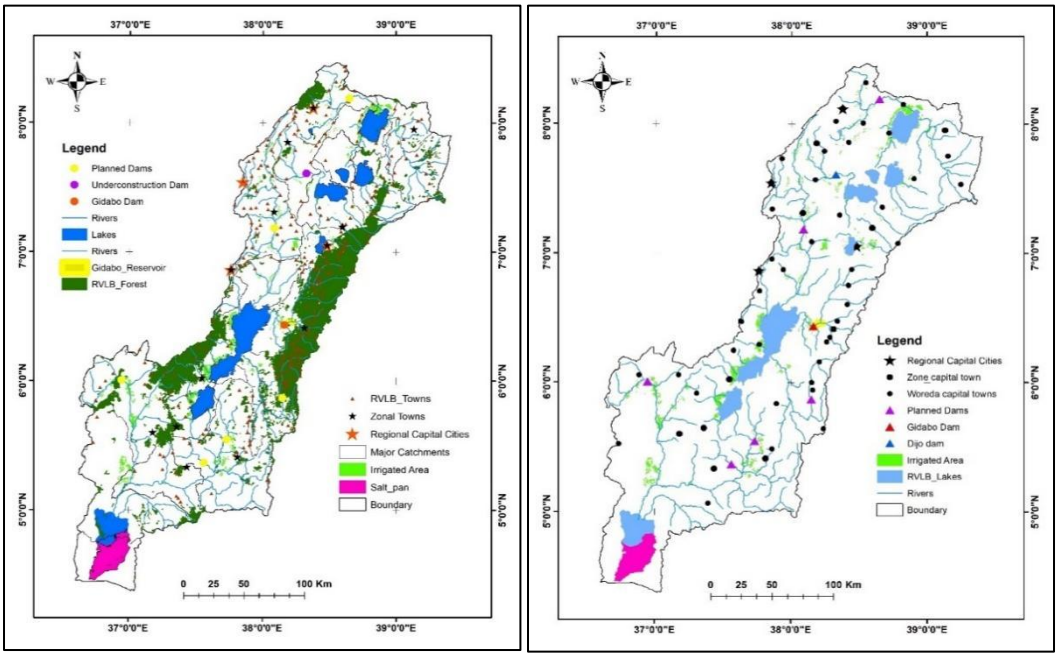


Figure 44: Water resource system of the RVLB

SD Model Results

As presented in Chapter 4 the available water on lakes for abstraction is 358 MCM, for this SD model only water available on lakes and reservoirs is considered and the current water demand abstracted from the lakes is 400.64 MCM. The result of the simulation for the whole system under three scenarios and the present condition is shown in Table 33, Scenario I considers the live storage of Gidabo dam there is only a 3MCM deficit (Table 34), however with a projected demand for irrigated area expansion and population increase but only Gidabo and Dijo reservoirs are added to the system the deficit will be 219MCM, in scenarios I and III the deficit will be reduced to 3 and 19MCM with the planned additional six reservoirs added to the system. Weights assigned for basins are based on the water demand in them and the threshold is chosen to be $e_m = 0.10$. which means if the e is above the threshold value the system is not in a satisfactory state. Accordingly, the RVLB is not in a satisfactory state in Scenario II condition as the e value is 0.34.

Table 30: SD model results for the system under different scenarios (in MCM/yr).

	Scenario I	Scenario II	Scenario III
Demand	400.64	652.12	652.12
Supply	398.00	433.00	633.00
Deficit	3	219	19
e	0.01	0.34	0.03

Performance assessment

As shown in Table 31, the reliability of the RVLB, is 0.75, with system resilience of 0.67 and vulnerability is 0.25 generally the current status (Scenario I) can be considered as satisfactory, however, there is room for improvement for the system. In Scenario II the system performs worse with only 0.58 reliability and the system resilience of 0.29 and the basin will be highly vulnerable (0.42). With all the proposed reservoirs implemented (Scenario III), the system performance will be improved up to 0.83 reliability and 0.80 resiliency and the system vulnerability could be lower to 0.17. (Jood and Abrishamchi, 2012) conducted a water resource system performance using the RRV approach for the Aras River basin in Iran, their findings the system reliability was up to 0.96 with vulnerability lower up to 0.1. In another study conducted by (Yassin and McCartney, 2012) for the Koga and Gomit reservoirs in Ethiopia, the reliability of the Koga reservoir is 0.992 for irrigation and 0.948 for hydropower, while the reliability of the Gomit reservoir is 0.95 for irrigation.

Table 31: Water resource system performance of the RVLB

	Reliability (α)	Resiliency (γ)	Vulnerability (V)
Scenario I	0.75	0.67	0.25
Scenario II	0.58	0.29	0.42
Scenario III	0.83	0.80	0.17

7.4. CONCLUSIONS

Maximizing water productivity in river basins is essential for sustainable water management, food security, and environmental conservation. By optimizing water use efficiency across various sectors, communities can enhance resilience, promote economic development, and ensure the long-term viability of water resources. Adopting appropriate estimation techniques and implementing targeted interventions can help realize the full potential of water productivity within river basins, leading to positive outcomes for both people and the environment.

The water resource system of the RVLB comprises seven lakes 13 major rivers, and the Gidabo reservoir, the basin has also covered four regional states thirteen zonal capital towns and fifty-two Wereda capital towns with a total urban population of 3.33 million. As discussed in Chapter 4 the basin has a total of 358MCM available as lake water abstraction, and 6,534MCM is available as stream flow water from which 70.25% is available during the rainy season and the water demand of the basin as discussed in Chapter 6, the basin has a total water demand of 1,796.34MCM/year where the pick demand is from November to March, with this data as input, this study it has evaluated the water resource system of the basin with respect to its water productivity, reliability, resiliency and vulnerability, results showed that the water productivity of the river basin ranges from 0.7kg/m^3 to 1.58kg/m^3 with an average value of 1.13kg/m^3 the water productivity of the basin has been also evaluated using the Biomass water productivity using the WaPOR data from the FAO webpage according to the WaPOR data the WP ranges from 1.3 – 2.89 kg/m^3 this is in fact after the biomass water productivity needs conversion with biomass index factor to get the economic yield water productivity. Serbela and Segen catchments have lower water productivity <1.3 kg/m^3 and <1.9kg/m^3 this is mainly the catchments have low yield productivity and less tradition of irrigated agriculture as compared to the central and upper part of the RVLB. Areas where high intensity of irrigated agriculture practices have a high-water productivity range of 2.38 – 2.84 kg/m^3 of Biomass production per applied cubic of water.

the reliability of the RVLB, is 0.75, with system resilience of 0.67 and vulnerability is 0.25 generally the current status (Scenario I) can be considered unsatisfactory, and, there should be improvement for the system. In Scenario II the system performs worse with only 0.58 reliability and the system resilience of 0.29 and the basin will be highly vulnerable (0.42). With all the proposed reservoirs implemented (Scenario III), the system performance will be improved up to 0.83 reliability and 0.80 resiliency and the system vulnerability could be lower to 0.17. Therefore, it is recommended more dams be constructed in the RVLB to regulate the temporal distribution of the water resource system, it should also be considered for subbasin water transfer, it is also necessary to improve the water use efficiency and sustainable utilization of water resources.

7.5. RECOMMENDATIONS

To improve water productivity in the basin, it is recommended to adopt drought-resilient and high-value crops while replacing traditional irrigation methods with efficient systems like drip and sprinkler irrigation. Utilize technologies such as weather data and soil moisture sensors to optimize irrigation schedules, and invest in maintaining irrigation infrastructure. Enhance soil and water conservation through practices like reduced tillage, cover cropping, contour farming, and rainwater harvesting. Use fertilizers effectively in conjunction with irrigation to minimize waste and improve yields. Provide education on water-efficient farming practices and support research on innovative techniques. Encourage water-saving technologies through pricing mechanisms or subsidies, and develop policies for integrated water resource management. Implement climate-resilient systems for water monitoring and management. Implementing these strategies will enhance water productivity in the RVLB by improving resource efficiency, reducing wastage, and promoting sustainable agricultural practices. These recommendations can serve as a framework for policymakers, farmers, and stakeholders to work collaboratively toward long-term water and food security in the basin

CHAPTER 8: MULTI-OBJECTIVE OPTIMIZATION IN WATER RESOURCES ALLOCATION USING NSGA-II APPROACH.

8.1 INTRODUCTION

In a river basin, the economy, ecological services and way of life all depend heavily on water. Water is a valuable resource for agriculture and it is a foundation of the economy. River basins also support a range of livelihoods such as farming, transportation, tourism, and fishing. The ecosystem of river basins supports the biodiversity of the area and it is also essential to the provision of wildlife habitats, and the preservation of wetlands (IUCN, 2020). The distribution of water resources within a river basin is vital because it affects livelihood and the environment. Water resources in a basin must be allocated efficiently to protect biodiversity, ecological balance, and ecosystem health as a whole. Authorities can promote the resilience of these ecosystems and prevent future environmental deterioration by carefully controlling the distribution of water to meet the needs of wetlands, forests, and aquatic habitats (Li et al., 2022b).

The distribution of water resources plays a crucial role in addressing the various demands of the human populations living in the river basin. The demand for water resources from agriculture, urbanization, and population increase significantly strain these supplies. Assuring residential, industrial, and agricultural needs while preventing over-extraction and depletion requires the implementation of effective allocation mechanisms. Better water management can reduce tensions between various industries over water consumption, improve water efficiency, and support the basin's long-term viability. Furthermore, tackling the effects of climate change such as modified precipitation patterns and heightened frequency of extreme weather events highlights how urgent it is to allocate water resources in river basins thoughtfully and adaptively (Tickner et al., 2017).

Optimization methods are designed to provide the ‘best’ values of system design and operating policy variables – values that will lead to the highest levels of system performance. These methods, combined with more detailed and accurate simulation methods, are the primary ways we have, short of actually building physical models, of estimating the likely impacts of particular water resources system designs and operating policies. This chapter introduces and illustrates some of the art of optimization model

development and uses in analyzing water resources systems. The modelling methods introduced in this chapter are extended in subsequent chapters (Daniel et al., 2005).

8.2 METHODOLOGY

8.2.1 Conceptual framework

The model is a comprehensive water resources management tool to manage how water resources can be optimally allocated to achieve better efficiency, equity and sustainability. The model consists of 3 main parts: (1) available water resources, (2) water demand and projections; and (3) multi-objective optimization of water resources allocation with tradeoffs between efficiency, equity and sustainability. In terms of a river basin system, the designed water allocation model concerns the case of entire water supply insufficiency and tackles the problem that the limited water should be optimally distributed to subbasins by the river basin authorities and then to different sectors.

Figure 45 shows the construction of a conceptual framework and a feasible mechanism for the proper distribution of water. The model aims to provide optimal water allocation methods by taking into account the concepts of environmental sustainability, economic benefit, and equity. The equity-based principle pertains to the equitable distribution of water among economically independent groups, and policies may influence the allocation of water. To maximize economic return, the water resource is distributed fairly across all sectors under the economic benefit allocation concept. Following the environmental sustainability principle, water is supplied to reduce ecological damage as a result of water use. To maximize fairness, environmental sustainability, and economic benefit efficiency, this study develops a multi-objective programming approach.

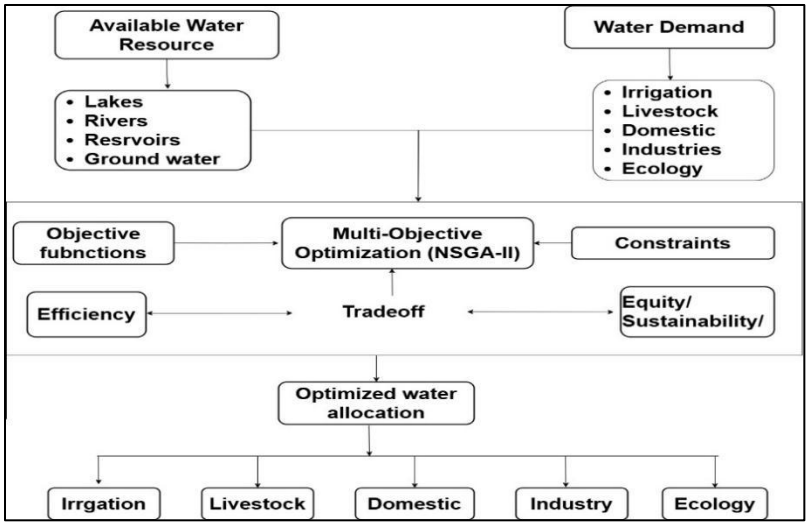


Figure 45: Conceptual framework demand nodes of the RVLB

8.2.2 Objective functions

Objective function $f_1(x)$: Maximization of mean economic benefit efficiency.

Over the years, a variety of strategies for financial gains of water resources have been studied (Divakar et al., 2011; Griffin, 2006). The net economic benefits of agricultural water can be calculated by using a demand function in conjunction with the residual imputation approach, which calculates the economic benefits of domestic water usage. These procedures, however, are complex and include a huge number of parameters. The average yearly economic benefit per unit of water use is used to more accurately and efficiently calculate the net economic benefits of various water applications.

The first aim function is to achieve maximum economic efficiency for a calendar year with established hydrological conditions. Economic benefit is relatively straightforward to quantify and is widely used in complex water resource allocation systems. In real-world scenarios, one sector's use of water may have an impact on another. Agriculture, residential use, industry, livestock, and ecology have all been considered to help estimate water demands and allocate water resources more effectively. In this study, gross economic interest is used to measure efficiency. The first objective function represented by equation 24, estimated the basin’s economic benefit efficiency.

$$\boldsymbol{maxf_{sB} = \sum_{t=1}^{T} \sum_{i=1}^{n} \sum_{j=1}^{m} \left(NEB_{i,j} \times q_{i,j}^{t} \right)}$$ ---------- eq 24

Where:

f_{SB} refers to system economic benefit efficiency

$NEB_{i,j}$ refers to the net economic benefit per unit of water quantity of j^{th} sector in i^{th} catchment;

$q_{it,j}$ refers to the water allocated to the j^{th} sector in the i^{th} catchment in t^{th} time;

T refers to the total number of months during calculation;

i refers to the total number of water intakes;

j refers to the total number of water user sectors

Objective function $f_2(x)$: Maximizing the water allocation equity

Equity refers to fair and just access to water and the benefits derived from its utilization. The concept of equitable water distribution amongst sectors serves as the basis for allocating water resources and is also the primary concern for achieving water sustainability. The Gini coefficient, devised by the Italian economist Gini, is extensively employed to evaluate the level of disparity in the distribution of income. Furthermore, other than assessing the equality of income distribution in the economic society, it may also be employed to inspect the equity of distribution in other fields, such as the balance of water and soil. Recently, the Gini coefficient has been employed to quantify the inequality in land and water usage. The Gini coefficient of water allocation has been applied to water allocation equity within a multi-objective decision-making system (Deng et al., 2022; Hu et al., 2016).

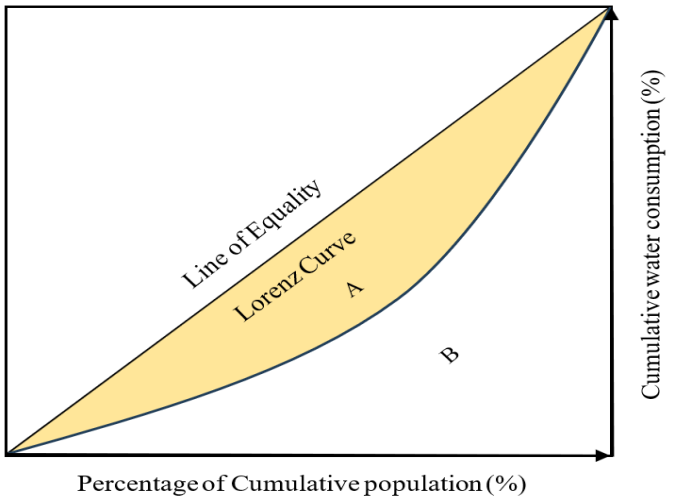


Figure 46: Lorenz curve for water allocation

In this study, the Lorenz Curve is a graphical representation of the distribution of water consumption (demand) within a population. It plots the cumulative percentage of total water consumption by the cumulative percentage of the population. If there were perfect equality, the Lorenz Curve would be a 45-degree line from the origin (this is called the line of equality). The more the Lorenz Curve deviates from this line, the higher the level of inequality. The Gini Coefficient quantifies inequality based on the Lorenz Curve. It measures the area between the line of equality and the Lorenz Curve, divided by the total area under the line of equality equation 25.

Mathematically, the **Gini Coefficient (G)** is:

$$G = \frac{A}{A+B} \text{ ---------- eq 25}$$

Where:

- A is the area between the line of equality and the Lorenz Curve.
- B is the area under the Lorenz Curve.

The Gini Coefficient ranges from 0 to 1, where 0 represents perfect and 1 represents perfect inequality. The steps followed to Calculate the Gini Coefficient are (a) Rank the population from lowest to highest water consumption. (b) calculate the cumulative percentages of water consumption and population for each group. (c) plot the Lorenz Curve using the cumulative population on the x-axis and cumulative water consumption

on the y-axis. (d) calculate the area between the line of equality and the Lorenz Curve. (e) use the formula to calculate the Gini Coefficient (Figure 46). Equation 26 represents the average Gini coefficient between the percentage of cumulative population and the cumulative water consumption and equation 27 represents the average Gini coefficient between the available water resource and the cumulative percentage of water consumption.

$$CPG_{av} = \sum_{t=1}^{T} \frac{CPG_t}{T} = 1 - \sum_{t=1}^{T} \sum_{i=1}^{n} \frac{(WPC_{it} + WPC_{i-1,t}) \times (PPC_{it} + PPC_{i-1t})}{T} \quad \text{---------- eq 26}$$

$$CWG_{av} = \sum_{t=1}^{T} \frac{CWG_t}{T} = 1 - \sum_{t=1}^{T} \sum_{i=1}^{n} \frac{(WPC_{it} + WPC_{i-1,t}) \times (WRC_{it} + WRC_{i-1t})}{T} \quad \text{----------eq 27}$$

Where:

CPG_{av} = the average of CPG,

CPG_t = the CPG in t^{th} time,

T = the total number of months during calculation;

n = to the total number of catchments,

$WPC_{i,t}$ = cumulative percentage of available water resources in i^{th} catchment in t^{th} time

$PPC_{i,t}$ = the cumulative percentage of water consumption (population) in i^{th} catchment in t^{th} time

CWG_{av} = the average of CWG,

$CWG_{i,t}$ = CWG in t^{th} time,

$WRC_{i,t}$ Cumulative percentage of available water resources in the i^{th} time and it is equivalent to zero in the initial stage.

The second objective function is to minimize the comprehensive Gini coefficient to consider the impacts of various indexes on water consumption.

$$f_2(x) = min\left((\omega_1 \times CPG_{av}) + (\omega_2 \times CWG_{av})\right) \quad \text{---------- eq 28}$$

Where: $f_2(x)$ denotes the comprehensive Gini coefficient, $\omega_i (i = 1, 2,)$ denotes the weighting coefficient and the sum of $\omega_i (i = 1, 2,)$ is equivalent to one. The impacts of

population and available water resources on water consumption can be viewed as equally important. Hence, ω_i(i = 1, 2,) are equal to ½.

8.2.3 Constraints

The upper and lower limits of the constraints are based on the thresholds of the Lake levels and maximum downstream releases as presented in equations 29 -33.

1. Water availability constraints

$$\sum \boldsymbol{q_{ij}^t} \leq \boldsymbol{AW_i^t} \qquad \forall_{ij} \text{ ---------- eq 29}$$

Where: $q_{t\ i,j}$ refers to j^{th} water use sector in i^{th} catchment in t^{th} time, AW_i^t represents the available water in i^{th} water-intake in t^{th} time.

2. Lake storage capacity constraints

$$\boldsymbol{V_{k\,min}^t \leq V_k^t \leq V_{k\,max}^t} \text{---------- eq 30}$$

Where: $V^t_{k,\,min}$ refers to the lower bound of k^{th} Lake in t^{th} time, (the threshold); $V^t_{k,\,max}$ refers to the upper bound of k^{th} reservoir in t^{th} time, usually the maximum storage capacity below the normal storage water level in the non-flood season and the flood-control water level in the flood season, respectively.

3. Lake abstraction discharge constraints

$$\boldsymbol{y_{ik}^t \leq q_{\max ij}^t} \text{---------- eq 31}$$

Where $y^t_{i,j}$ refers to the discharge of the k^{th} Lake in i^{th} catchment in t^{th} time; $q^t_{max\ i,k}$ refers to the discharge capacity of the k^{th} Lake in i^{th} catchment in t^{th} time.

4. Water demand constraints

$$\boldsymbol{q_{ij}^t \leq D_{ij}^t} \text{---------- eq 32}$$

Where: $D^t_{i,j}$ denotes the water demand of the j^{th} water use sector in i^{th} catchment in t^{th} time

5. Non-negative constraints

$$q_{ij}^t \geq 0$$

$$\boldsymbol{y_{ij}^t \geq 0} \text{ ---------- eq 33}$$

8.2.4 Global model

The comprehensive framework that combines the objective function and constraints to define the optimization problem. It provides a unified mathematical representation of what aim to achieve (objective function) and the limitations or conditions that must be satisfied (constraints).

$$\text{Objective function} \quad \begin{cases} maxf_{sB} = \sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{j=1}^{m}\left(NEB_{i,j} \times q_{i,j}^{t}\right) \\ minf_2(x) = (\omega_1 \times CPG_{av}) + (\omega_2 \times CWG_{av}) \end{cases}$$

$$\text{Subjected to} \quad \begin{cases} \sum q_{ij}^{t} \leq AW_i^t \\ V_{j\,min}^{t} \leq V_j^t \leq V_{j\,max}^{t} \\ y_{ij}^{t} \leq q_{\max ij}^{t} \\ q_{ij}^{t} \leq D_{ij}^{t} \\ q_{ij}^{t} \geq 0 \\ y_{ij}^{t} \geq 0 \end{cases}$$

Where: $f_1(x)$and $f_2(x)$are the objective functions, $q^t_{i,j}$ refer to the design variables and the remaining formulas are the constraints.

8.3 OPTIMIZATION ALGORITHM

The Non-Dominated Sorting Genetic Algorithm approach II (NSGA-II) is a widely recognized and resilient method for multi-objective optimization (MOO) that has achieved significant accomplishments in various practical scenarios. Introduced by (Deb et al., 2002), NSGA-II has emerged as a standard for assessing the efficiency of other algorithms for multi-objective optimization (MOP) because of its ability to effectively tackle intricate optimization problems with numerous objectives that conflict with each other. NSGA-II is characterized by its elitist and diversity-preserving techniques. The algorithm utilizes a rapid, non-dominated sorting method to categorize solutions into distinct fronts according to their dominant relationships. The sorting method guarantees that solutions without any inferior aims are given higher priority than those with compromised performance. NSGA-II improves diversity preservation by integrating the

calculation of crowding distance, which quantifies the concentration of solutions in the goal space. This strategy ensures a diverse range of options on the Pareto front, avoiding early convergence to a less optimal set of answers. The effectiveness of NSGA-II arises from its capacity to achieve a balance between the speed of convergence and the preservation of diversity. It effectively directs the search towards the Pareto front, while also preserving a varied collection of answers, guaranteeing that the algorithm does not become stuck in suboptimal solutions. NSGA-II is a versatile and powerful tool that can effectively address a wide range of multi-objective optimization problems in various fields such as engineering, science, and other subjects.

Water resource management has made considerable use of the evolutionary technique to develop optimal solutions to challenging multi-objective optimization situations because of the aforementioned benefits. Consequently, this study uses NSGA-II to trade off equity and efficiency. Figure 47 illustrates the NSGA-II algorithm flowchart. 500, 300, 85%, and 0.01% were allocated to the population size, number of maximal generations, crossover probability, and mutation rate, respectively. It was observed that a rigorous trial-and-error procedure is used to select the NSGA-II's parameters to produce results that will converge.

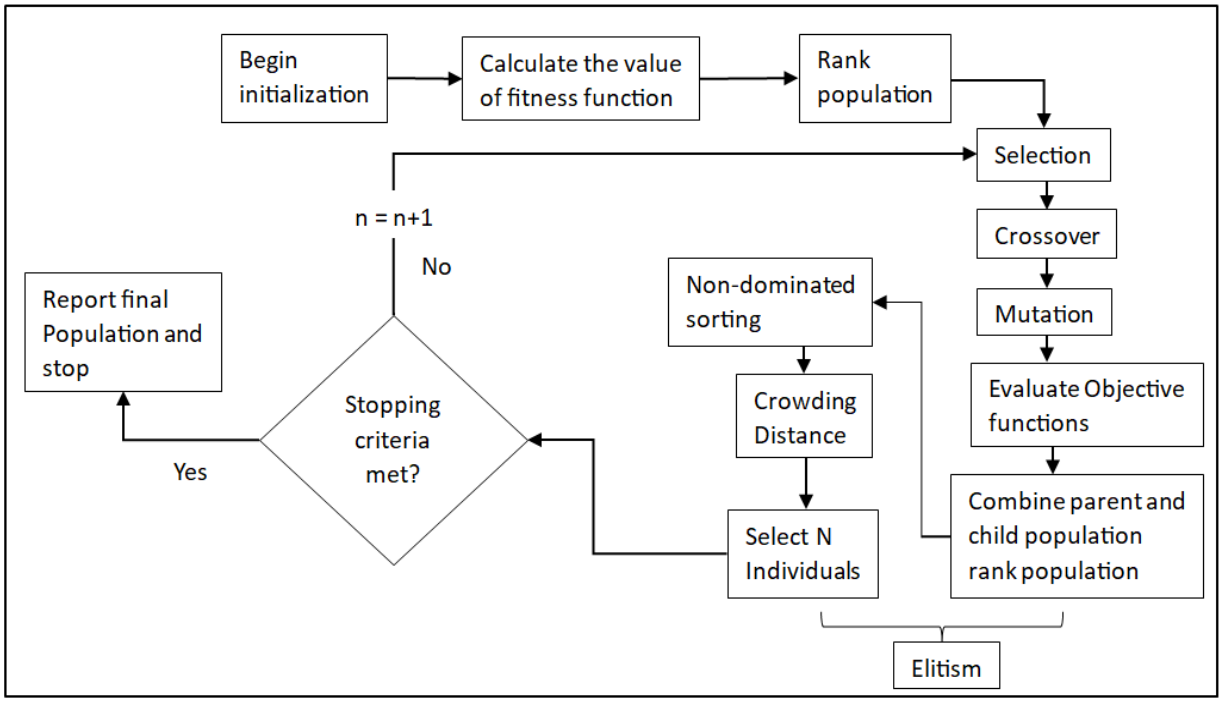


Figure 47: Flowchart of NSGA-II

8.4 DECISION-MAKING PROCEDURES

In the Pareto front, relationships are typically trade-off-oriented. Finding a balance point between optimized goals is critical. Finding a solution that is acceptable to each target with the least amount of variation was done in this study.

8.4.1. Fast Nondominated Sorting

A basic method of identifying members of the first nondominated front in a population is to compare each candidate to every other solution in the group to determine if it is dominated by others.

8.4.2. Crossover

Crossover in NSGA-II is a genetic operator used to combine the genetic information of two parent solutions to generate new offspring for the next generation. It's a key mechanism that allows the algorithm to explore new areas of the solution space, potentially leading to better and more diverse solutions. In NSGA-II, the most common crossover technique is Simulated Binary Crossover (SBX). This method simulates the single-point crossover of binary strings in a real-numbered space. The SBX operator works by choosing a random crossover point and exchanging the segments of the parent solutions to create two new offspring. The probability of crossover, along with the distribution index, determines how close the offspring will be to their parents. The process of crossover in NSGA-II typically involves the selection of Parent Solutions, crossover point determination, creation of offspring, and evaluation and Selection.

8.4.3. Mutation

Mutation in NSGA-II is a crucial operator that introduces diversity into the population by randomly altering the genes of individuals. In NSGA-II, the most commonly used mutation operator is the polynomial mutation. This operator works by adding a polynomial distributed noise to the gene values, which helps in exploring the search space more effectively. Mutation in NSGA-II is a mechanism that helps maintain genetic diversity and prevents premature convergence, thereby enhancing the algorithm's ability to find a well-distributed set of Pareto-optimal solutions.

8.4.4. Crowding distance

Crowding distance in NSGA-II is a measure used to estimate the density of solutions surrounding a particular solution in the population. It is an important concept in multi-objective optimization as it helps maintain diversity in the solution set. For each solution, the crowding distance is calculated by considering the average distance of two points on either side of this point along each of the objectives. The crowding distance essentially estimates how crowded an individual solution's neighborhood is. A larger crowding distance implies that the solution is in a less crowded region, which is preferred during the selection process. When selecting solutions to form a new population, NSGA-II prefers solutions with a larger crowding distance. This ensures a uniform spread of solutions along the Pareto front.

$$\boldsymbol{CD} = \frac{f_m(x_{i-1}) - f_m(x_{i+1})}{f_m(x_{max}) - f_m(x_{min})} \text{---------- eq 34}$$

8.4.5. Average variability

The average variability is the average value of the slopes of the lines connecting any point except endpoints with two adjacent points. Suppose the average variability of f_1 and f_2 is $d_1^{(i)}$ and $d_2^{(i)}$, respectively. Let K be the number of Pareto solution sets, which can be sequenced in order. $f_1^{(i)}$ is the value of the first objective function of the ith Pareto solution, i $\in$ {1, 2, . . . K}; $f_2^{(i)}$ is the value of the second objective function of the ith Pareto solution, i $\in$ {1, 2, . . . K}, then the average change rate of the above two objectives is:

$$\boldsymbol{d_1^{(i)}} = \frac{1}{2}\left(\frac{f_2^{(i+1)} - f_2^{(i)}}{f_1^{(i+1)} - f_1^{(i)}} + \frac{f_2^{(i)} - f_2^{(i-1)}}{f_1^{(i)} - f_1^{(i-1)}}\right), \boldsymbol{i} \in \{\mathbf{2}, \mathbf{3}, \ldots \boldsymbol{K} - \mathbf{1}\} \text{---------- eq 35}$$

$$\boldsymbol{d_2^{(i)}} = \frac{1}{2}\left(\frac{f_1^{(i+1)} - f_1^{(i)}}{f_2^{(i+1)} - f_2^{(i)}} + \frac{f_1^{(i)} - f_1^{(i-1)}}{f_2^{(i)} - f_2^{(i-1)}}\right), \boldsymbol{i} \in \{\mathbf{2}, \mathbf{3}, \ldots \mathbf{K} - \mathbf{1}\} \text{---------- eq 36}$$

Where: $k_1^{(i)}$ and $k_2^{(i)}$ refer to the average change rate of the first objective and the second objective, respectively. Especially, when s is equal to 1 or K, the average change rate is:

The equations you provided seem to be calculating the average change rate of two objective functions, f_1 and f_2, across a set of Pareto solutions:

- The first equation calculates the average change rate of the first objective function, f_1, to the second objective function, f_2. This is done by averaging the rate of change of f_1 to f_2 between the $(i+1)^{th}$ and i^{th} solutions and the i^{th} and $(i-1)^{th}$ solutions.
- The second equation does the same but for the second objective function, f_2, to the first objective function, f_1.

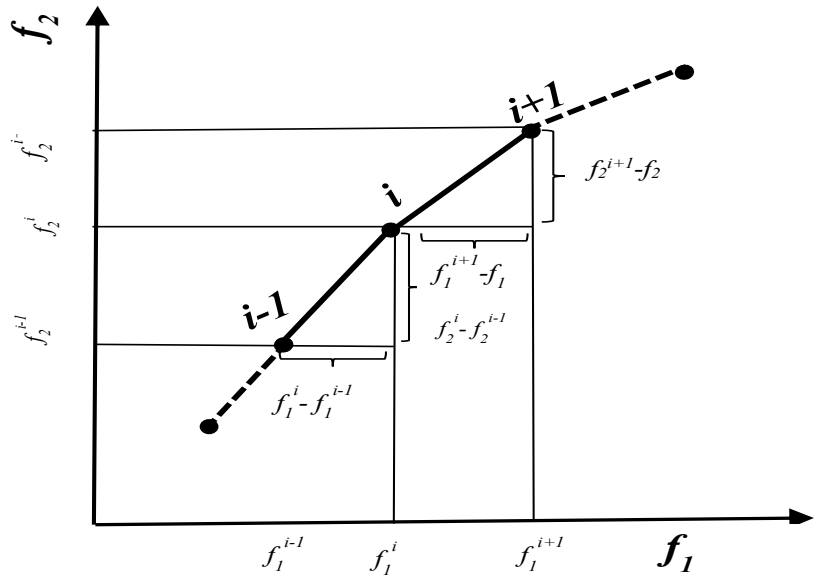


Figure 48: Average change rate of objective functions on the Pareto solutions

For the endpoints of the Pareto front (i = 1 and K), the average variability of $d_1^{(1)}$, $d_2^{(1)}$, $d_1^{(K)}$ and $d_2^{(K)}$ is defined as follows:

$$d_1^1 = \frac{f_1^2 - f_1^1}{f_2^2 - f_2^1},\ d_2^1 = \frac{f_2^2 - f_2^1}{f_1^2 - f_1^1},\ d_1^k = \frac{f_1^k - f_1^{k-1}}{f_2^k - f_2^{k-1}},\ d_2^k = \frac{f_2^k - f_2^{k-1}}{f_1^k - f_1^{k-1}}$$ ---------- eq 37

8.4.6. Sensitivity ratio

The sensitivity ratio is the ratio of the two average variabilities of a certain Pareto non-inferior solution to the corresponding value of the objective function in the Pareto front. The sensitivity ratio of the Pareto non-inferior solution whose number is m (δ_1^i) is defined as the ratio of average variability ($k_1^{(i)}$) to the corresponding value of objective function f_1, and δ_2^i is defined as the ratio of the average variability ($k_2^{(i)}$) to the corresponding value of objective function f_2. Then, based on the above results, the sensitivity ratios are calculated by

$$\delta_1^i = \frac{k_1^i}{p^i}, i \in \{1, 2, \ldots, K\}$$ ---------- eq 38

$$\delta_2^i = \frac{k_2^i}{C^i}, i \in \{1, 2, \ldots, K\}$$ ---------- eq 39

Where:

- δ_1^i = sensitivity ratios of f_1
- δ_2^i = sensitivity ratios of f_2

For the convenience of comparison, the above results need to be dimensionless. The value of the sensitivity ratio reflects the sensitivity degree of the average variability of certain objective function values as the function values change. When the functions of the MOP are performance functions, i.e., quantity, efficiency, cost, etc., the sensitivity ratio is similar to the performance-price ratio. For comparison in the next step, the sensitivity ratio must be non-dimensional.

Let ε_1^i and ε_2^i be the results of δ_1^i and δ_2^i then, the sensitivity analysis is done using equations 38 and 39 for both objective functions respectively.

$$\varepsilon_1^i = \frac{\delta_1^i}{\sum_{i=1}^{k} \delta_1^i}, i \in \{1, 2, \ldots, k\}$$ ---------- eq 40

$$\varepsilon_2^i = \frac{\delta_2^i}{\sum_{i=1}^{k} \delta_2^i}, i \in \{1, 2, \ldots, k\}$$ ---------- eq 41

Where: ε_1^i and ε_2^i refer to the dimensionless sensitivity ratios of the first objective and the second objective, respectively.

8.4.7. Bias degree based on sensitivity ratio

The bias degree is the degree of bias for different objective functions, and the value range is (0,1). Suppose K is the set of numbers of the Pareto non-inferior solutions in X. ω_1^i and ω_2^im is the bias degrees of the Pareto non-inferior solution for objective functions f_1 and f_2, respectively, whose number is i in the Pareto non-inferior solutions.

$$\omega_1^i = \frac{\varepsilon_1^i}{\varepsilon_1^i + \varepsilon_2^i}, i \in \{1, 2, \ldots, K\}$$ ---------- eq 42

$$\omega_2^i = \frac{\varepsilon_2^i}{\varepsilon_1^i + \varepsilon_2^i}, i \in \{1, 2, \ldots, K\}$$ ---------- eq 43

Where: ω_1^i and ω_2^i refer to the preference degrees of i^{th} Pareto solution for the first objective and the second objective, respectively

8.5 RESULTS

8.5.1 Current and projected water demand

As shown in Table 32, the total current water demand, calculated by integrating all sectoral demands, is estimated at 1,796.34 MCM. The projected demand is expected to range from 1,628.23 MCM to 2,378.74 MCM by 2035 and from 2,126.09 MCM to 3,146.89 MCM by 2050.

Table 32: Current and projected water demand of RVLB

	year	Water use in (MCM)						
		Irrigation			Livestock	Industry	Domestic	Ecology
		SC_I	SC_II	SC_III				
Current	2022	1,045.19			229.46	60.97	150.53	310.19

Projected	2035	1,685.47	1,907.26	1,336.30	238.38	182.91	211.71	310.19
	2050	2,604.42	2,719.61	1,566.90	247.29	304.86	285.46	310.19

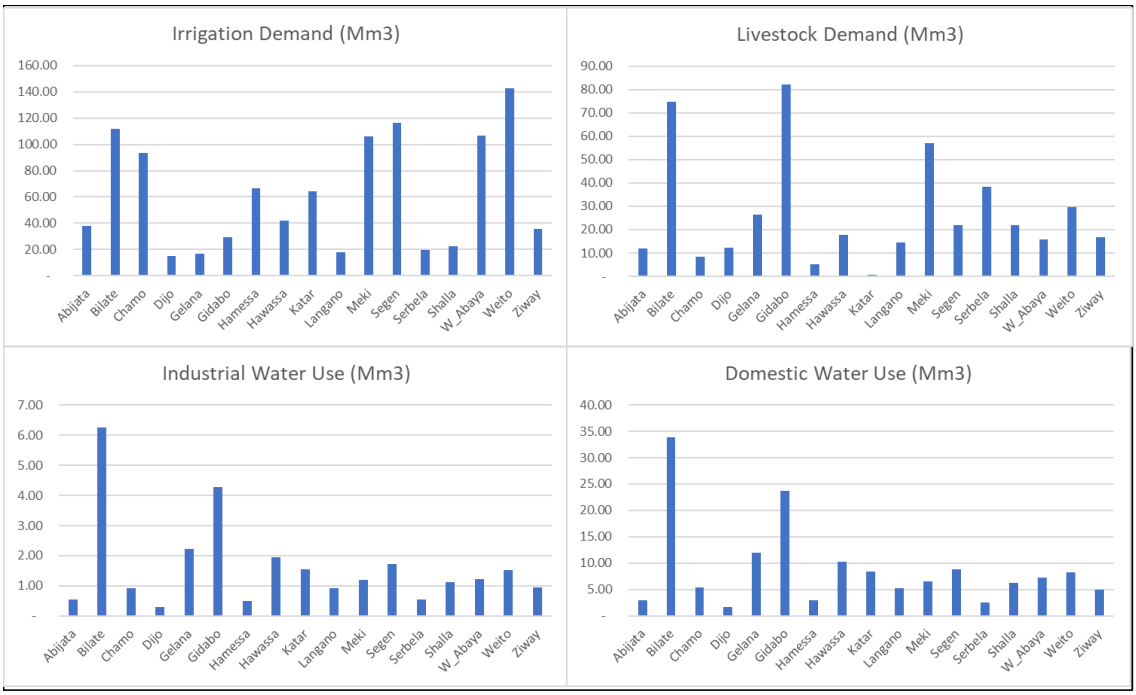


Figure 49: Water demand of the sectors in RVLB

8.5.2. Non-inferior pareto front solutions

The Rift Valley Lakes Basin's monthly water allocation plan was optimized for a calendar year using the NSGA_II. The model, solved using the NSGA-II algorithm in Python, used the runoff time series and water demand data of each major catchment as input. The ideal Pareto front, or non-inferior solution set, between two objective functions is shown in Figure 50. It suggests a favourable correlation between Economic return and the Gini coefficient. A lower Gini coefficient value denotes better water allocation equity, and a higher economic return value denotes more efficient use of available water resources. Hence, the superior efficiency objective matches the inferior equity objective, and the value of the Gini coefficient increases with the growth of economic return, translating to a worse equity condition. The trade-off between economic return and equality reveals how incompatible efficiency and equity are when it comes to allocating water resources. To effectively manage water allocation, decision-makers should analyze the Pareto front by examining trade-offs, where each point represents a viable plan. It is important to

emphasize the endpoints to understand the maximum potential of each objective when the other is excluded. Engaging stakeholders is vital, involving policymakers, local communities, environmental advocates, and industry representatives to identify priorities, assess objectives, and promote social equity. The rationale behind the chosen plan should be communicated, highlighting trade-offs and stakeholder contributions. Additionally, systems for monitoring and addressing concerns during execution should be implemented. Starting with small-scale trials helps assess feasibility, and regular evaluations based on new data, feedback, or shifting priorities should guide necessary adjustments.

20 Pareto set of equity and economic return objectives with even distribution is taken to analyze the correlation between different Gini coefficients, i.e., CPG and CWG, and comprehensive Gini coefficient. Similar studies have been conducted in China by Tian et al, (Tian et al., 2019). (Liu et al, 2019, He et al, 2022, Yin et al, 2021).

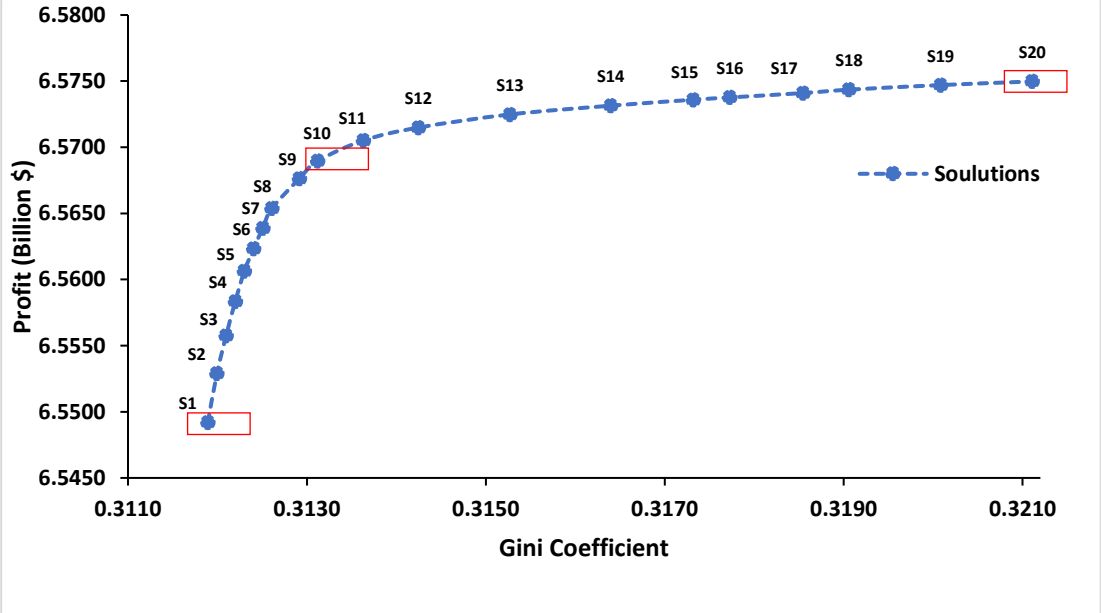


Figure 50: The Pareto fronts of the optimal water allocation

Table 33: Min and max values on the Pareto front of objective functions

	f_1 (Gin Coefficient)	f_2 (Billion USD)
Min	0.3119	6.549
Max	0.3211	6.575

8.5.4 Optimized allocation

Table 33 presents the minimum and maximum values for the two objectives on the Pareto front. The minimum Gini coefficient is 0.312, corresponding to a total economic interest of $6.549B, while the maximum Gini coefficient is 0.321, associated with a total economic interest of $6.575B. These values indicate that the best equity outcome aligns with the least efficient outcome, highlighting a conflict between the two objectives. When the study area aims for maximum economic output efficiency, i.e., optimizing for the highest monetary return, solution S_1 is the ideal choice. Conversely, if the goal is to achieve the best equity, focusing on minimizing the Gini coefficient, solution S_{20} should be selected. However, both solutions S_1 and S_{20} prioritize only one objective, either efficiency or equity, without balancing the two. A similar study by Deng et al, (Deng et al., 2022) in the Han River basin, China, demonstrated successful outcomes using an optimization model, and the results of this study show similarly favorable results.

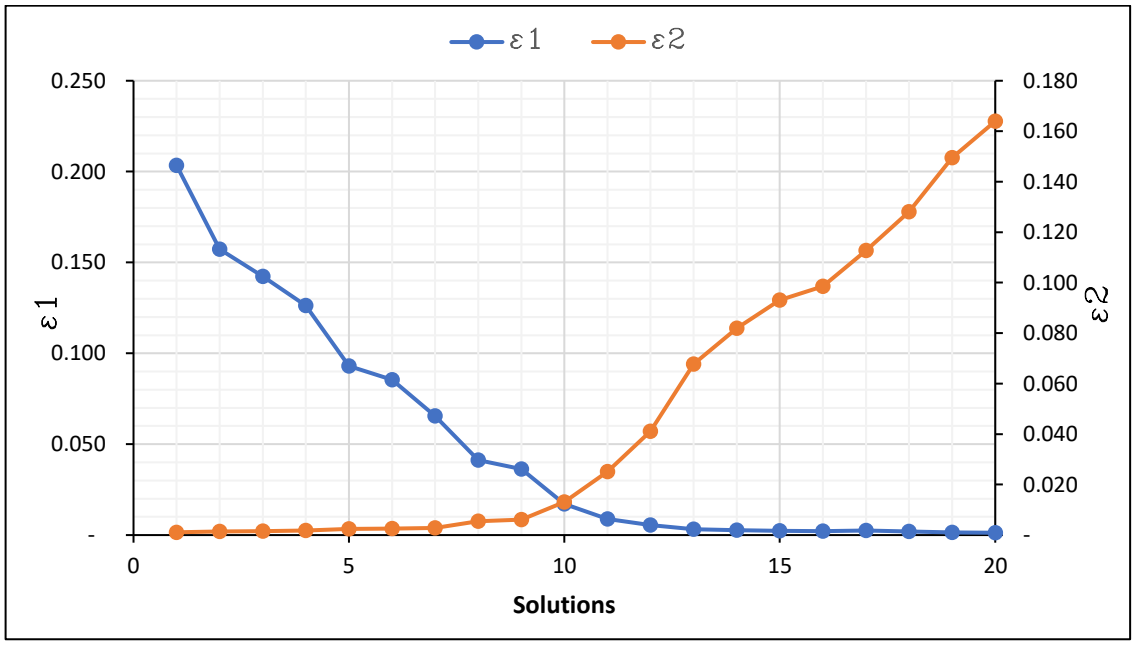


Figure 51: Distribution of the dimensionless sensitivity ratio

As shown in Table 34, based on the dominance relationship derived from the sensitivity ratio, no solution dominates another, resulting in a new subset of non-dominated solutions. These solutions are used as inputs to calculate the preference degree of each Pareto non-inferior solution for different objective functions. The results of the preference degrees are shown in Figure 51. These quantitative indices help decision-makers make

more efficient trade-offs. For example, if the goal is to minimize f_1, solution S_1 can be chosen, as it is preference degree for f_1 is 0.995, while for f_2 it is only 0.005. Similarly, if the aim is to maximize f_2, S_{20} is ideal, with a preference degree of 0.992 for f_2 and just 0.008 for f_1. For decision-makers who value both objectives equally, S_{10} is recommended, as it is preference degree for f_1 (0.566) is closest to that for f_2 (0.434) among all non-inferior solutions. The new subset of Pareto non-inferior solutions, based on the sensitivity ratio, not only narrows down the selection but also provides a quantitative evaluation, making decision-making more convenient.

Table 34: The non-inferior solution set based on sensitivity ratio with preference degree

Solution	ω_1	ω_2	Solution	ω_1	ω_2
S1	0.995	0.005	S11	0.261	0.739
S2	0.991	0.009	S12	0.117	0.883
S3	0.989	0.011	S13	0.046	0.954
S4	0.986	0.014	S14	0.032	0.968
S5	0.975	0.025	S15	0.025	0.975
S6	0.970	0.030	S16	0.022	0.978
S7	0.960	0.040	S17	0.022	0.978
S8	0.884	0.116	S18	0.015	0.985
S9	0.855	0.145	S19	0.010	0.990
S10	0.566	0.434	S20	0.008	0.992

Therefore, based on the optimal solution (S_{10}), the water allocation scheme for the RVLB should be as presented in Table 35. Based on the scenarios and optimized allocation the current water allocation for irrigation should be 55.28% of the remaining 44.72%% water should be allocated to the other sectors with the livestock share being 13.14% and domestic demand taking its 7.75% share. For the planning years of 2035 and 2050 on Scenario III the irrigation demand share is declining with the use of modern irrigation technologies urbanization and industry expansion the demand share of both sectors is going to increase.

Table 35 : Optimized water allocation for RVLB

Sector	Current Demand (%)	Projected Demand (%)					
		Scenario I		Scenario II		Scenario III	
		2035	2050	2035	2050	2035	2050
Irrigation	55.28%	64.12%	69.41%	72.56%	72.48%	50.84%	41.76%
Livestock	13.14%	7.25%	3.59%	4.43%	2.57%	11.67%	12.81%
Industry	6.56%	5.14%	5.12%	2.32%	4.10%	9.56%	14.34%

Domestic	7.75%	6.23%	4.61%	3.42%	3.58%	10.66%	13.82%
Ecology	17.27%	17.27%	17.27%	17.27%	17.27%	17.27%	17.27%

8.6. CONCLUSION

The model, implemented in Python and solved using the NSGA-II algorithm, used runoff time series data and water demand series for each major catchment as inputs. The current overall water demand in the Rift Valley Lakes Basin (RVLB) is estimated by integrating sectoral demands, resulting in a total of 1,796.34 MCM. Projections indicate that water demand will range from 1,628.23 MCM to 2,378.74 MCM in 2035 and from 2,126.09 MCM to 3,146.89 MCM in 2050. The RVLB aims to maximize economic efficiency by identifying allocation schemes yielding the highest economic returns. The study approach identified Pareto front solutions that represent trade-offs between economic returns and equitable water distribution. As an extreme solution, for maximum efficiency (economic return), solution S_1 (0.995, 0.005) with highest economic return, poorest equity was optimal and for maximum equity (minimum Gini coefficient), solution S_{20} (0.008, 0.992) was preferred, sacrificing economic efficiency. For a balanced solution, S_{10} (0.566, 0.434) was selected as the most balanced, providing a trade-off between economic efficiency and equity with preference degrees closer to equal values. Based on the optimized allocation scenarios, current water allocation should prioritize irrigation at 55.28%, with the remaining 44.72% allocated to other sectors, including 13.14% for livestock and 7.75% for domestic needs. For the planning years of 2035 and 2050 under Scenario III, irrigation demand is expected to decline due to modern irrigation technologies, while urbanization and industrial expansion will increase their respective demand shares.

In 2035 and 2050, the total water demand in the RVLB is projected to range from 2,279.49 MCM to 2,850.45 MCM and from 2,714.70 MCM to 3,867.41 MCM, respectively, reflecting a significant increase compared to the 2022 base year. Notably, agricultural and domestic water demands are expected to rise during these periods. A conflict between efficiency, equity, and sustainability in water resource allocation emerges as the Gini coefficient increases with economic benefits, resulting in reduced equity but higher monetary returns. Solutions S_1 (0.995, 0.005) and S_{20} (0.008, 0.992) represent two extreme outcomes, each optimizing a single objective at the expense of the other. However, when both objectives, economic efficiency (f_1) and equity (f_2), are equally important, solution S_{10} (0.566, 0.434) is recommended. This balanced trade-off offers the smallest gap between preference degrees, making S_{10} an ideal choice for equitable and efficient decision-making. Projections for 2035 and 2050 necessitate adjusting allocation

strategies to accommodate urbanization and industrial growth. This study highlights the importance of efficient water use in agriculture by promoting improved water management practices and adopting modern irrigation methods to reduce agricultural water demand, allowing more resources to be allocated to other sectors. The implementation of a multi-objective optimization model is crucial to balancing economic efficiency and equity in water distribution, ensuring sustainable and fair resource utilization.

CHAPTER 9: CONCLUSION AND RECOMMENDATIONS

9.1. CONCLUSION

This study provides a comprehensive analysis of water resource availability, demand, and management. The research highlights the basin's potential to support economic growth and ecological sustainability, despite challenges such as water scarcity, inefficient use, and environmental degradation. Key findings include the basin's limited water resource potential due to climatic variability and human pressures, the inefficiencies in current irrigation practices, and the pressing need for optimized allocation strategies.

The research developed an innovative multi-objective water allocation model using the NSGA-II approach, which successfully balances economic efficiency, equity, and sustainability. It also evaluated the performance of the water resource system based on resilience, reliability, and vulnerability, demonstrating the need for infrastructure development and sustainable practices. By employing advanced techniques like WEAP modelling and remote sensing, the study filled data gaps, enabling better resource estimation and planning. The findings underscore that without strategic interventions, the RVLB faces long-term risks to water security, agricultural productivity, and ecosystem health, which are exacerbated by climate change and population growth.

The study's insights call for a paradigm shift in water resource management in the RVLB. Policies must transition from sector-specific approaches to holistic and integrated frameworks that address competing demands. Strategic interventions must prioritize investments in infrastructure, technological innovation, and institutional reforms to ensure sustainable use of limited resources. The adoption of optimization models in policy planning can guide equitable allocation while enhancing economic efficiency and environmental resilience. By addressing the interconnected challenges of water scarcity, ecosystem degradation, and socio-economic demands, Ethiopia can harness the RVLB's potential to drive sustainable development and improve the livelihoods of millions dependent on its resources.

9.2. RECOMMENDATIONS

Findings highlight critical policy implications essential for sustainable water resource management. Policymakers are advised to adopt integrated water resource management

(IWRM) strategies that harmonize economic, social, and environmental goals while promoting cross-sectoral collaboration. Ensuring equity in water distribution should also be a priority through frameworks designed to provide fair access for marginalized groups and address regional disparities. Incorporating advanced optimization models such as NSGA-II into decision-making processes can help evaluate trade-offs and synergies among efficiency, equity, and sustainability. Climate resilience and sustainability should be integrated into water management policies, encouraging investments in water-saving technologies and sustainable irrigated agriculture. Preserving aquatic ecosystems and biodiversity should also be central objectives, supported by mandates for maintaining environmental flows. Transparent and participatory governance is crucial to engaging all stakeholders, it can reduce conflicts and improve decision-making. Building the capacity of water managers and policymakers is also vital for effectively implementing advanced methodologies, complemented by public awareness campaigns to promote water conservation. Economic incentives such as equitable pricing and subsidies for water-efficient technologies, paired with robust monitoring and feedback systems, are vital for adaptive and effective water management policies. These strategies collectively provide a comprehensive pathway to achieving equitable, efficient, and sustainable water resource management.

Effective water resource management in the Rift Valley Lakes Basin (RVLB) requires addressing discrepancies in resource potential and ensuring sustainable utilization. The WEAP model, with its flexible and comprehensive planning framework, should be utilized for hydrological analysis, supported by accurate calibration and validation using historical data and performance indicators. Developing storage facilities in the tributary river's upper sections is essential to optimize surface water usage, particularly in regions affected by high levels of alkalinity and fluoride in lakes. Advanced technologies such as multispectral remote sensing (e.g., NDVI and EVI) should be employed to map and monitor irrigated areas, combined with ground truth verification to enhance data accuracy. Standardized measurement techniques will reduce discrepancies in irrigated area data, providing reliable inputs for sustainable water planning, land use, and optimized allocation. Efficient irrigation technologies and water pricing strategies can further reduce losses and boost crop yields, while domestic water use estimation and livestock demand assessment are vital for guiding sanitation, hygiene, and agricultural planning.

Quantifying environmental water requirements is critical for ecosystem health and mitigating human impacts. Reservoir construction and improved irrigation management

practices can help regulate distribution, address rising demand, and enhance system resilience against droughts and floods. Sustainable practices considering topography, soil types, and crop water needs should be prioritized, along with multi-objective optimization models to balance economic efficiency and equity in water distribution. Continued research on water resource and demand assessments is recommended to support policy-making and enhance future development efforts in the RVLB. These strategies collectively aim to improve water resource management, ensure sustainability, and foster long-term growth in the region.

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ANNEXE

Python Code for Multi-Objective optimization

```
import numpy as np
from deap import base, creator, tools, algorithms

# Problem-specific constants
NUM_OBJECTIVES = 2  # Example: Bi-objective optimization
NUM_VARS = 10       # Number of variables in the problem

# Parameters for NSGA-II
POP_SIZE = 500
MAX_GEN = 300
CROSS_PROB = 0.85
MUT_RATE = 0.0001

# Define the problem
creator.create("FitnessMulti", base.Fitness, weights=(-1.0,) *
NUM_OBJECTIVES)
creator.create("Individual", np.ndarray, fitness=creator.FitnessMulti)

# Define toolbox
toolbox = base.Toolbox()
toolbox.register("attr_float", np.random.rand)
toolbox.register("individual", tools.initRepeat, creator.Individual,
toolbox.attr_float, n=NUM_VARS)
toolbox.register("population", tools.initRepeat, list, toolbox.individual)

# Define evaluation function
def evaluate(individual):
    # Example objective functions
    f1 = sum(individual)  # Dummy objective 1
    f2 = sum(x**2 for x in individual)  # Dummy objective 2
    return f1, f2

toolbox.register("mate", tools.cxSimulatedBinaryBounded, low=0.0, up=1.0,
eta=20.0)
toolbox.register("mutate", tools.mutPolynomialBounded, low=0.0, up=1.0,
eta=20.0, indpb=MUT_RATE)
toolbox.register("select", tools.selNSGA2)
toolbox.register("evaluate", evaluate)

# Main loop
def main():
    population = toolbox.population(n=POP_SIZE)
    hof = tools.ParetoFront()

    stats = tools.Statistics(lambda ind: ind.fitness.values)
    stats.register("avg", np.mean, axis=0)
    stats.register("std", np.std, axis=0)
    stats.register("min", np.min, axis=0)
    stats.register("max", np.max, axis=0)
```

```
    algorithms.eaMuPlusLambda(population, toolbox, mu=POP_SIZE,
lambda_=POP_SIZE,
                              cxpb=CROSS_PROB, mutpb=MUT_RATE, ngen=MAX_GEN,
                              stats=stats, halloffame=hof, verbose=True)

    return population, stats, hof

if __name__ == "__main__":
    pop, stats, hof = main()



import numpy as np
from deap import base, creator, tools, algorithms

# Define the problem: maximize f1, minimize f2
creator.create("FitnessMulti", base.Fitness, weights=(1.0, -1.0))  # (1.0)
for maximizing f1, (-1.0) for minimizing f2
creator.create("Individual", list, fitness=creator.FitnessMulti)

# Define the toolbox
toolbox = base.Toolbox()
toolbox.register("attr_float", np.random.uniform, 0, 1)
toolbox.register("individual", tools.initRepeat, creator.Individual,
toolbox.attr_float, n=2)
toolbox.register("population", tools.initRepeat, list, toolbox.individual)

# Objective functions
def evaluate(individual):
    x, y = individual
    f1 = min_o1 + (max_o1 - min_o1) * x  # Scale x to range of f1
    f2 = min_o2 + (max_o2 - min_o1) * y  # Scale y to range of f2
    return f1, f2

# Genetic operators
toolbox.register("mate", tools.cxSimulatedBinaryBounded, low=0.0, up=1.0,
eta=20.0)
toolbox.register("mutate", tools.mutPolynomialBounded, low=0.0, up=1.0,
eta=20.0, indpb=0.0001)
toolbox.register("select", tools.selNSGA2)
toolbox.register("evaluate", evaluate)

# Main function
def main():
    population = toolbox.population(n=500)
    hof = tools.ParetoFront()

    stats = tools.Statistics(lambda ind: ind.fitness.values)
    stats.register("avg", np.mean, axis=0)
    stats.register("std", np.std, axis=0)
    stats.register("min", np.min, axis=0)
    stats.register("max", np.max, axis=0)

    algorithms.eaMuPlusLambda(population, toolbox, mu=500, lambda_=500,
cxpb=0.85, mutpb=0.0001, ngen=300, stats=stats, halloffame=hof, verbose=True)
```

```
        return population, stats, hof

# Run the optimization
if __name__ == "__main__":
    pop, stats, hof = main()

    # Extract and print Pareto front solutions
    print("\nPareto front solutions:")
    for i, sol in enumerate(hof):
        f1, f2 = sol.fitness.values
        print(f"Solution {i+1}: f1 = {f1:.4f}, f2 = {f2:.4f}")

    # Plot the Pareto front
    import matplotlib.pyplot as plt
    o1_values = [ind.fitness.values[0] for ind in hof]
    o2_values = [ind.fitness.values[1] for ind in hof]

    plt.scatter(o1_values, o2_values, color='blue', label='Pareto Front
Solutions')
    plt.plot(o1_values, o2_values, color='blue')
    plt.xlabel('Objective 1 (O1)')
    plt.ylabel('Objective 2 (O2)')
    plt.title('Non-Inferior Pareto Front Solutions')
    plt.legend()
    plt.grid(True)
    plt.show()
```

```
import numpy as np
import matplotlib.pyplot as plt

# Objective value ranges
min_o1, max_o1 = 6.549, 6.575
min_o2, max_o2 = 0.3119, 0.3211

# Generate 20 linearly spaced values within the range for O1
o1_values = np.linspace(min_o1, max_o1, 20)

# Calculate corresponding O2 values based on a linear relationship
# Here, we assume a linear decrease in O2 as O1 increases to generate the
Pareto front
o2_values = min_o2 + (max_o2 - min_o2) * (o1_values - min_o1) / (max_o1 -
min_o1)

# Combine O1 and O2 values into pairs
pareto_solutions = list(zip(o1_values, o2_values))

# Print the solutions
for i, sol in enumerate(pareto_solutions):
    print(f"Solution {i+1}: O1 = {sol[0]:.4f}, O2 = {sol[1]:.4f}")

# Plot the Pareto front
plt.scatter(o1_values, o2_values, color='blue', label='Pareto Front
Solutions')
plt.plot(o1_values, o2_values, color='blue')
```

```
plt.xlabel('Objective 1 (O1)')
plt.ylabel('Objective 2 (O2)')
plt.title('Non-Inferior Pareto Front Solutions')
plt.legend()
plt.grid(True)
plt.show()
```

The generated solutions are:

```
Solution 1:  O1 = 6.5490, O2 = 0.3119
Solution 2:  O1 = 6.5504, O2 = 0.3124
Solution 3:  O1 = 6.5518, O2 = 0.3129
Solution 4:  O1 = 6.5532, O2 = 0.3134
Solution 5:  O1 = 6.5545, O2 = 0.3139
Solution 6:  O1 = 6.5559, O2 = 0.3144
Solution 7:  O1 = 6.5573, O2 = 0.3149
Solution 8:  O1 = 6.5587, O2 = 0.3154
Solution 9:  O1 = 6.5601, O2 = 0.3159
Solution 10: O1 = 6.5615, O2 = 0.3164
Solution 11: O1 = 6.5629, O2 = 0.3169
Solution 12: O1 = 6.5643, O2 = 0.3174
Solution 13: O1 = 6.5657, O2 = 0.3179
Solution 14: O1 = 6.5671, O2 = 0.3184
Solution 15: O1 = 6.5685, O2 = 0.3189
Solution 16: O1 = 6.5699, O2 = 0.3194
Solution 17: O1 = 6.5713, O2 = 0.3199
Solution 18: O1 = 6.5727, O2 = 0.3204
Solution 19: O1 = 6.5741, O2 = 0.3209
Solution 20: O1 = 6.5750, O2 = 0.3211
```

Monthly Areal Rainfall of the Rift Valley Lakes Basin (MCM)

Major Catchments	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Sum
Abijata	19.07	32.20	67.80	91.79	96.06	97.50	154.12	145.30	108.25	35.20	9.48	5.42	862.20
Bilate_G	101.91	180.49	378.63	479.03	539.08	471.97	671.98	684.61	615.75	295.09	73.06	56.07	4,547.66
Bilate_UG	49.39	79.75	159.26	238.50	248.62	170.64	221.34	223.70	215.73	167.55	68.47	35.48	1,878.44
Chamo	51.95	83.55	167.21	346.83	290.06	142.69	110.16	138.57	174.59	274.79	129.97	71.62	1,981.98
Dijo	42.93	72.62	152.13	201.80	219.77	200.68	293.37	278.25	238.35	94.28	23.56	18.10	1,835.83
Gelana_G	14.00	18.66	55.97	132.12	120.95	48.94	35.39	43.75	63.45	103.73	44.16	14.01	695.12
Gelana_UG	54.07	72.07	216.22	510.38	467.23	189.04	136.72	168.99	245.10	400.71	170.58	54.13	2,685.23
Gidabo_G	20.97	28.58	64.57	98.40	104.37	66.80	83.18	85.66	93.90	88.10	31.66	20.28	786.47
Gidabo_UG	93.84	123.17	267.67	500.48	507.96	299.70	327.23	346.03	420.45	431.95	170.69	85.91	3,575.07
Hamessa	13.88	18.37	36.02	67.28	73.78	55.60	69.49	63.24	49.45	44.54	18.76	12.06	522.45
Hawassa	39.18	57.48	130.56	189.75	194.19	149.18	196.43	191.67	185.43	148.14	56.36	30.79	1,569.17
Katar_G	35.59	68.28	151.27	203.82	195.62	190.48	321.57	327.62	237.13	119.65	32.49	17.96	1,901.48
Katar_UG	26.49	50.83	112.62	151.75	145.64	141.82	239.42	243.92	176.55	89.08	24.19	13.37	1,415.70
Kulfo	13.44	16.00	28.40	57.92	60.53	34.22	39.25	38.99	37.66	48.35	24.06	10.95	409.76
Langano	25.19	39.84	84.37	117.31	115.90	108.66	170.16	173.00	138.19	65.78	19.57	10.94	1,068.92
Meki	41.62	80.45	175.59	190.89	229.21	233.68	418.63	383.15	258.49	81.77	19.61	19.06	2,132.14
Segen_G	119.34	176.84	459.22	942.41	676.81	251.55	199.28	248.23	372.64	735.83	358.30	188.33	4,728.79
Segen_UG	48.74	58.91	188.33	464.64	254.46	68.42	59.35	58.54	144.05	305.23	131.83	68.19	1,850.70
Serbela	184.72	312.23	650.43	877.68	732.54	508.82	548.12	544.52	533.37	595.27	305.32	186.51	5,979.54
Shalla_UG	54.92	92.69	174.62	247.18	251.73	240.90	323.51	306.82	267.92	104.40	31.74	23.03	2,119.47
W_Abaya	46.11	54.90	97.43	198.75	207.68	117.42	134.68	133.77	129.22	165.90	82.56	37.56	1,405.97
Weito	140.07	214.51	463.80	834.23	675.26	398.56	343.90	369.26	510.26	606.97	380.10	204.82	5,141.74
Ziway_UG	23.26	60.17	106.77	123.54	150.18	141.41	255.57	232.74	157.75	55.42	17.36	8.39	1,332.58

Mean Monthly Temperature of the Rift valley lakes basin (ºC)

Major Catchments	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Abijata	17.05	17.80	18.89	18.62	18.09	16.87	15.55	15.51	16.15	16.31	16.69	16.51
Bilate_G	17.71	18.48	19.42	18.53	17.54	15.88	14.93	15.08	15.88	16.51	17.15	17.12
Bilate_UG	19.83	20.66	21.78	20.89	19.61	18.05	17.13	17.42	18.36	18.77	19.50	19.32
Chamo	19.80	20.63	21.31	19.91	18.52	17.60	16.87	17.20	18.31	18.21	18.89	19.06
Dijo	18.09	18.84	19.90	19.34	18.58	17.19	16.00	16.06	16.73	17.07	17.64	17.50
Gelana_G	19.85	20.46	21.07	19.80	18.36	17.28	16.39	16.69	17.92	18.12	18.67	19.00
Gelana_UG	19.85	20.46	21.07	19.80	18.36	17.28	16.39	16.69	17.92	18.12	18.67	19.00
Gidabo_G	18.80	19.58	20.61	19.70	18.44	17.09	16.11	16.41	17.39	17.58	18.31	18.26
Gidabo_UG	18.80	19.58	20.61	19.70	18.44	17.09	16.11	16.41	17.39	17.58	18.31	18.26
Hamessa	20.52	21.42	22.46	21.38	19.92	18.74	17.77	18.03	19.02	19.22	19.94	19.87
Hawassa	18.13	19.04	20.30	19.75	18.72	17.11	16.07	16.32	17.20	17.27	17.82	17.59
Katar_G	14.89	15.72	16.86	16.78	16.38	15.46	13.85	13.80	14.47	14.21	14.25	14.28
Katar_UG	14.89	15.72	16.86	16.78	16.38	15.46	13.85	13.80	14.47	14.21	14.25	14.28
Kulfo	19.80	20.63	21.31	19.91	18.52	17.60	16.87	17.20	18.31	18.21	18.89	19.06
Langano	16.71	17.52	18.81	18.62	17.97	16.79	15.34	15.38	16.23	16.14	16.36	16.18
Meki	16.13	17.04	18.30	18.37	17.97	17.01	15.43	15.30	15.71	15.71	15.75	15.50
Segen_G	23.19	23.70	24.35	22.75	21.26	20.45	19.96	20.42	21.80	21.71	22.14	22.46
Segen_UG	24.74	25.28	25.94	24.23	23.33	23.07	22.63	23.24	24.59	23.99	23.94	24.00
Serbela	26.88	27.32	28.07	26.32	25.65	25.41	24.91	25.43	26.76	26.51	26.26	26.27
Shalla_UG	17.05	17.80	18.89	18.62	18.09	16.87	15.55	15.51	16.15	16.31	16.69	16.51
W_Abaya	19.80	20.63	21.31	19.91	18.52	17.60	16.87	17.20	18.31	18.21	18.89	19.06
Weito	21.33	22.02	22.66	21.00	19.93	19.42	18.92	19.37	20.49	20.08	20.47	20.64
Ziway_UG	17.12	18.04	19.42	19.62	19.28	18.54	16.87	16.64	17.01	16.87	16.79	16.44

Mean Monthly Actual Evapotranspiration of the Rift Valley lakes Basin (MCM)

Major Catchments	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Abijata	70.60	60.73	64.02	59.93	59.63	55.05	56.65	65.33	69.59	77.81	78.70	75.53
Bilate_G	354.24	323.69	348.42	319.78	311.61	275.36	269.97	288.21	303.41	350.70	356.28	360.51
Bilate_UG	137.43	118.77	123.64	114.85	117.17	107.87	104.91	113.40	117.83	131.99	144.54	146.11
Chamo	139.08	127.81	144.83	141.77	149.47	138.71	123.27	125.48	125.81	136.89	151.51	147.20
Dijo	146.84	127.56	134.93	124.92	124.46	112.71	112.29	125.20	133.84	149.75	155.72	154.07
Gelana_G	46.26	43.58	48.69	45.41	46.37	42.14	41.61	43.41	45.07	46.99	46.53	46.69
Gelana_UG	178.10	167.01	186.01	173.92	178.60	162.84	157.52	164.24	170.53	178.08	180.09	180.37
Gidabo_G	48.55	44.18	49.35	45.95	46.63	42.84	43.12	45.85	46.93	48.85	49.24	50.14
Gidabo_UG	260.89	237.98	263.64	242.88	245.00	208.31	208.46	220.21	225.51	255.13	260.26	267.81
Hamessa	36.92	33.63	37.03	34.55	34.95	32.33	32.83	35.72	37.18	40.40	39.46	38.64
Hawassa	123.57	107.32	112.76	105.62	105.90	95.31	94.55	103.31	110.11	120.14	125.95	128.62
Katar_G	136.04	117.35	124.74	121.84	122.38	109.79	110.18	123.20	131.12	141.44	143.94	142.11
Katar_UG	99.17	85.86	91.06	88.25	87.95	78.43	78.12	87.57	93.78	101.34	103.56	102.91
Kulfo	29.02	26.69	29.82	27.84	28.33	26.34	26.55	28.25	29.54	31.70	30.88	30.41
Langano	51.88	47.42	54.51	52.75	53.99	50.10	49.66	52.73	53.43	55.60	54.94	53.99
Meki	148.73	134.68	149.42	143.26	138.42	124.80	126.52	141.44	151.64	177.20	168.79	158.75
Segen_G	360.36	324.05	344.07	332.65	357.27	337.82	336.48	343.35	340.18	363.48	366.63	368.47
Segen_UG	132.40	125.46	141.51	141.87	155.59	143.66	135.32	136.68	137.00	145.18	140.25	134.69
Serbela	362.39	345.16	405.27	395.00	426.98	409.49	417.51	438.43	456.18	465.57	397.47	366.07
Shalla_UG	164.33	142.85	150.88	140.86	140.02	127.87	128.41	143.88	151.99	170.17	175.45	173.01
W_Abaya	102.30	92.08	102.34	98.86	105.75	85.96	85.50	90.84	94.66	101.68	116.27	110.40
Weito	339.41	328.12	377.42	352.34	359.50	333.44	335.86	351.36	358.13	363.35	336.42	333.80
Ziway_UG	97.54	86.29	95.54	92.41	90.51	83.46	95.02	99.02	107.31	125.11	117.16	106.14

Land Use Land Cover of the Rift valley lakes Basin (%)

Major catchments	Cultivated Land	Forest Land	Grassland	Shrubland	Woodland	Bare Soil	Water Body	Wetland	Salt Pan	Afro_Alpine	Urban Area	Irrigated Land
Abijata	63.17%	0.19%	0.00%	2.15%	10.61%	4.65%	13.34%	1.99%	0.00%	0.55%	0.95%	2.38%
Bilate_G	74.98%	1.38%	0.00%	13.31%	6.45%	0.00%	0.00%	0.00%	0.00%	0.02%	1.51%	2.36%
Bilate_UG	49.54%	1.28%	0.00%	38.64%	6.61%	0.00%	0.54%	0.88%	0.00%	0.06%	0.07%	2.37%
Chamo	22.75%	15.75%	1.19%	34.15%	3.54%	0.00%	17.32%	0.28%	0.00%	0.01%	0.33%	4.68%
Dijo	89.01%	1.96%	1.50%	2.11%	3.22%	0.00%	0.00%	0.00%	0.00%	0.07%	0.58%	1.54%
Gelana_G	66.50%	10.27%	0.00%	12.10%	11.13%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Gelana_UG	15.46%	9.97%	0.00%	71.58%	2.10%	0.00%	0.49%	0.36%	0.00%	0.03%	0.00%	0.01%
Gidabo	98.10%	0.00%	0.00%	0.48%	0.37%	0.00%	0.00%	0.00%	0.00%	0.00%	0.07%	0.98%
Gidabo_UG	55.61%	1.37%	0.00%	36.46%	1.99%	0.00%	1.00%	1.77%	0.00%	0.03%	0.20%	1.56%
Hamessa	83.48%	7.23%	0.00%	5.26%	2.33%	0.00%	0.05%	0.05%	0.00%	0.00%	1.41%	0.18%
Hawassa	69.22%	5.53%	0.00%	7.19%	4.02%	0.31%	6.20%	1.19%	0.00%	0.00%	2.87%	3.47%
Katar_G	68.36%	7.49%	1.55%	0.72%	0.68%	0.00%	0.00%	0.00%	0.00%	20.11%	1.08%	0.00%
Katar_UG	87.75%	1.66%	0.21%	3.43%	0.00%	0.00%	0.08%	0.30%	0.00%	2.84%	2.03%	1.71%
Kulfo	13.11%	83.78%	0.00%	1.77%	0.70%	0.00%	0.00%	0.00%	0.00%	0.43%	0.21%	0.00%
Langano	65.04%	14.70%	0.00%	1.56%	2.79%	0.05%	11.06%	0.53%	0.00%	1.24%	0.98%	2.05%
Meki	62.64%	12.91%	0.37%	15.95%	0.62%	0.00%	0.45%	0.15%	0.00%	0.00%	4.04%	2.87%
Segen_G	21.05%	3.48%	9.50%	51.83%	12.98%	0.00%	0.02%	0.03%	0.00%	0.09%	0.02%	1.01%
Segen_UG	11.82%	6.57%	0.00%	72.77%	6.21%	0.00%	0.00%	0.00%	0.00%	0.03%	0.02%	2.58%
Serbela	4.01%	2.93%	0.00%	74.23%	4.56%	0.00%	0.00%	0.26%	11.63	0.97%	0.03%	1.36%
Shalla	71.83%	2.96%	0.00%	6.15%	2.35%	0.12%	12.03%	0.81%	0.00%	0.40%	2.47%	0.88%
W_Abaya	16.32%	34.60%	0.00%	34.97%	1.63%	0.00%	0.52%	0.58%	0.00%	0.22%	0.95%	10.21%
Weito	7.50%	14.50%	0.00%	66.12%	9.93%	0.00%	0.00%	0.00%	0.00%	0.05%	0.02%	1.89%
Ziway_UG	55.25%	1.55%	2.00%	4.08%	1.30%	0.00%	25.96%	2.62%	0.00%	0.09%	1.28%	5.85%

ABOUT THE AUTHOR

Mulugeta Mohammed Seid was born on April 18, 1983, in Asmara, Eritrea, to Ethiopian parents. In 1992, the family relocated to Mekelle. In July of 2007, he graduated with a Bachelor of Science in Agricultural Engineering from Hawassa University in Ethiopia. In 2009, he began working as a junior researcher in the irrigation water management research program at the Ethiopian Institute of Agricultural Research at Wondogenet Research Center. In July 2015, he completed his master's degree in water resource engineering and management at Hawassa University. He conducted experimental research activities on drainage, water harvesting, and irrigation water management. The primary goals of research activities are to increase water productivity, improve water use efficiency, and develop technology for the agricultural sector. The author has also worked as an independent irrigation engineer consultant and has studied and designed irrigation schemes. In his career as a researcher, the author has held positions as director of the Wondogenet research center, coordinator of research teams at Wondogenet, national coordinator of irrigation water and drainage research, and deputy director of the soil and water research directorate at the EIAR headquarters in Addis Ababa. To pursue his doctorate in hydraulic engineering, the author enrolled at Addis Abeba University AAiT in 2018. He studied the Rift Valley Lakes Basin to find an optimal water allocation model that would improve water productivity. The author researched the basin's hydrology, its irrigated areas, the water demands of its various industries, and the effectiveness of the basin's water resource system to create an optimal water allocation plan that strikes a balance between environmental sustainability, equity, and economic efficiency. The author has extensive research experience, study and design water-related projects and good leadership skills. The author is married and has three children.