

Institut für Natur- und Ressourcenschutz

Christian-Albrechts-Universität zu Kiel

Modeling the Dynamics of Long-Term Variability of Hydro-Climatic Processes and Associated Extreme Events in the Rift Valley Lakes Basin, Ethiopia

Dissertation

Zur Erlangung des Doktorgrades der Mathematisch- Naturwissenschaftlichen Fakultät

der Christian-Albrechts-Universität zu Kiel

Vorgelegt von

M.Sc. Ayenew Desalegn Ayalew

geboren am 27. April 1986

Kiel, 2024

Dekan: Prof. Dr. Frank Kempken

Erste Gutachterin: Prof. Dr. Nicola Fohrer

Zweite Gutachterin: Prof. Dr. Natascha Oppelt

Prüfer: PD Dr. Paul Wagner

Leiter der Prüfungskommission: Prof. Dr. Florian Dünckmann

Tag der mündlichen Prüfung: 14.03.2025

Abstract

Over the past four decades, the hydrological systems of the Earth have witnessed significant transformations, driven by a complex interplay of anthropogenic, hydro-climatic, and geological factors. Hydro-climatic processes are central to Earth's water resources and climate systems, and the demands on these resources have increased with global socio-economic development. Understanding the long-term variability of these processes is crucial for effective water resource management, climate adaptation, and disaster risk reduction.

The Rift Valley Lakes Basin in Ethiopia is experiencing profound transformations in land use patterns, attributed to population growth, urbanization, and agricultural expansion. Concurrently, the region faces increasingly unpredictable climate dynamics that lead to changes in the hydrological system, disrupting ecosystems and livelihoods. Therefore, addressing the following research questions is crucial for sustainable water resource management and planning. 1) What are the key hydro-climate variables influencing hydrologic systems in the Rift Valley Lakes Basin? 2) How do long-term variations in land use and climate dynamics influence the hydrological processes in the region? 3) Why are water bodies in the upper part of the basin experiencing significant water loss and drying, while those in the lower part of the basin are showing substantial increases in water levels? This study presents a comprehensive analysis of land use and climate dynamics, hydrological change, and driving factors in the Rift Valley Lakes Basin by employing an ensemble machine learning algorithm, hydrologic modeling, change point analysis, an indicators of hydrological alteration (IHA) method, and bathymetry surveys. A Random Forest (RF) ensemble machine learning algorithm, along with a confusion matrix, was employed for land use classification and change analysis; the hydrologic model Soil and Water Assessment Tool (SWAT+) was parameterized for gauged watersheds and extended to ungauged watersheds through multisite regionalization techniques. The SWAT+ model exhibited good performance in simulating daily streamflow across all watersheds, as indicated by measurable metrics including Kling–Gupta efficiency (KGE), Nash–Sutcliffe efficiency (NSE), and Percent bias (PBIAS).

The findings reveal a significant shift in land use patterns from 1989 to 2019. The agricultural land area witnessed a marked increase of 27.5%, settlement increased by 0.8%, and barren land increased by 0.4%, whereas natural vegetation, wetlands, water bodies, and grasslands experienced declines of 24.5%, 1.6%, 0.5%, and 2.1%, respectively. Notably, the initial decade of the study period exhibited the most pronounced changes in land use dynamics, which can be

attributed to the agricultural expansion policy that was implemented in order meet the increasing demand for food of a rapidly growing population. Simultaneously, a discernible shift in climate trends was observed during the 1980s. Over the past four decades, rainfall exhibited a non-significant decreasing trend, whereas temperature displayed a significant upward trend. The drivers underpinning these land use dynamics are multifaceted, encompassing rapid population growth, agricultural expansion policies, and the variability of climatic conditions.

This study also addresses the pivotal question of how land use and land cover (LULC) transformations, when coupled with climate dynamics, modulate the hydrological cycle and water availability within the basin, and it meticulously dissects the consequential implications for water resource management and sustainability. The change of water balance components was evaluated across all hydrologic response units and marked spatial-temporal variability in water flux has been observed within the studied watersheds. Notable findings include a decrease in the percentages of precipitation, evapotranspiration (ET), and infiltration as well as an upward trend in surface runoff during the period 2000-2005 compared to the baseline period (1989-2000). Moreover, we observed significant shifts in runoff seasonality, associated with increasing deforestation and agricultural expansion, resulting in a decline in low flows and an increase in peak flows. The results revealed that LULC transformations, resulting from a growing population, coupled with climate variability, exert a substantial pressure on the hydrologic system of the basin. Remarkably, the relative contribution of LULC changes outweighed that of climate variability throughout the study period.

Moreover, substantial shifts in lake inflows and levels were observed over the past four decades. In the southern part of the basin lakes have expanded in area, depth, and volume, while in the northern part of the basin lakes have experienced significant reductions. Lake Chamo experienced a noteworthy expansion, increasing its area by 30 km², depth by 4.4 m, and volume by $7.8 \times 10^8 \text{ m}^3$ in the last four decades. In stark contrast, Lake Abijata witnessed a reduction of 68% in area and a depth decrease of 1.6 meters. During this transformative period, lake mean annual rainfall declined by 6.5% and 2.7% for Lake Abijata and Chamo Lake, respectively. Actual evapotranspiration decreased by 2.9% in Lake Abijata but increased slightly, up to 0.5%, in Lake Chamo. Surface inflow to Lake Abijata decreased by 12.5%, while Lake Chamo experienced 80.5% increase in surface inflow. Sediment depth in Lake Chamo also increased by 0.6 m. The evolving hydrological regime of Lake Chamo is primarily driven by surface runoff and sediment influx, largely attributed to anthropogenic influences. In contrast, the

hydrological regime of Lake Abijata is significantly impacted by water abstraction from its feeding rivers and lakes for industrial and irrigation purposes.

This research contributes to a broader understanding of Earth's hydro-climatic systems. It advances scientific knowledge by shedding light on the intricate mechanisms that underlie long-term variability, ultimately enhancing our capacity to predict and respond to future hydro-climatic challenges. This study provides a holistic understanding of the complex and data-limited hydrological systems within Ethiopia's Rift Valley Lakes and also presents potential driving factors. The knowledge derived from this study holds relevance beyond this specific region, offering valuable insights for addressing similar challenges in hydrological systems worldwide.

Zusammenfassung

In den letzten vier Jahrzehnten haben sich die hydrologischen Systeme der Erde durch ein komplexes Zusammenspiel von anthropogenen, hydroklimatischen und geologischen Faktoren erheblich verändert. Hydroklimatische Prozesse sind von zentraler Bedeutung für die Wasserressourcen und Klimasysteme der Erde, und die Anforderungen an diese endlichen Ressourcen sind mit der globalen sozioökonomischen Entwicklung gestiegen. Das Verständnis der langfristigen Variabilität dieser Prozesse ist entscheidend für eine wirksame Bewirtschaftung der Wasserressourcen, die Anpassung an Klimaveränderungen und die Verringerung des Katastrophenrisikos.

Das Rift Valley Lakes Basin in Äthiopien erlebt einen tiefgreifenden Wandel der Landnutzungsmuster, der auf Bevölkerungswachstum, Verstädterung und landwirtschaftliche Expansion zurückzuführen ist. Gleichzeitig ist die Region mit einer zunehmend unvorhersehbaren Klimadynamik konfrontiert, die das hydrologische System verändert und die Ökosysteme und Lebensgrundlagen beeinträchtigt. Daher ist die Beantwortung der folgenden Forschungsfragen für eine nachhaltige Bewirtschaftung der Wasserressourcen von entscheidender Bedeutung: 1) Welches sind die wichtigsten hydroklimatischen Variablen, die die hydrologischen Systeme im Rift Valley Lakes Basin beeinflussen? 2) Wie beeinflussen langfristige Variationen in der Landnutzung und Klimadynamik die hydrologischen Prozesse in der Region? 3) Warum kommt es in den Gewässern im oberen Teil des Einzugsgebiets zu erheblichem Wasserverlust und Austrocknung, während in den Gewässern im unteren Teil des Einzugsgebiets ein erheblicher Anstieg der Wasserstände zu verzeichnen ist? Diese Studie stellt eine umfassende Analyse der Landnutzungs- und Klimadynamik, des hydrologischen Wandels

und der treibenden Faktoren im Rift Valley Lakes Basin vor, indem sie hydrologische Modellierung, die Analyse von Veränderungspunkten, Indikatoren für hydrologische Veränderungen (IHA) und bathymetrische Untersuchungen integriert. Ein hydrologisches Modell (SWAT+) wurde erfolgreich für Wassereinzugsgebiete mit Pegelaufzeichnungen parametrisiert und durch standortübergreifende Regionalisierungstechniken auf unbeobachtete Wassereinzugsgebiete erweitert. Für die Klassifizierung der Landnutzung und die Analyse von Veränderungen wurde ein Machine-Learning-Algorithmus nach dem Zufallsprinzip (Random Forest, RF) in Kombination mit einer Konfusionsmatrix verwendet. Das Modell SWAT+ zeigte eine gute Leistung bei der Simulation des täglichen Abflusses in allen Wassereinzugsgebieten, wie robuste Gütemaße wie die Kling-Gupta-Effizienz (KGE), die Nash-Sutcliffe-Effizienz (NSE) und die prozentuale Abweichung (PBIAS) zeigen.

Die Ergebnisse zeigen, dass sich die Landnutzungsmuster zwischen 1989 und 2019 deutlich verändert haben. Die landwirtschaftliche Nutzfläche nahm um 27,5% zu, die Siedlungsfläche um 0,8% und die Ödlandfläche um 0,4%, während die natürliche Vegetation, Feuchtgebiete, Gewässer und Grasland um 24,5%, 1,6%, 0,5% bzw. 2,1% abnahmen. vor allem Im ersten Jahrzehnt des Untersuchungszeitraums war die Dynamik der Landnutzung am stärksten ausgeprägt. Gleichzeitig wurde in den 1980er-Jahren eine erkennbare Veränderung der Klimatrends beobachtet. In den letzten vier Jahrzehnten war bei den Niederschlägen ein nicht signifikanter Abwärtstrend zu verzeichnen, während die Temperatur einen signifikanten Aufwärtstrend aufwies. Die dieser Landnutzungsdynamik zugrundeliegenden Faktoren sind vielschichtig und umfassen ein schnelles Bevölkerungswachstum, eine Politik der landwirtschaftlichen Expansion und die Variabilität der klimatischen Bedingungen.

Diese Studie befasst sich auch mit der zentralen Frage, wie Veränderungen in Landbedeckung und Landnutzung (land use and land cover, LULC) in Verbindung mit der Klimadynamik den hydrologischen Kreislauf und die Wasserverfügbarkeit im Einzugsgebiet beeinflussen, und untersucht die sich daraus ergebenden Auswirkungen auf die Bewirtschaftung der Wasserressourcen und die Nachhaltigkeit. Die Veränderung der Wasserhaushaltskomponenten wurde für jede hydrologische Reaktionseinheit bewertet, und innerhalb der untersuchten Wassereinzugsgebiete wurde eine ausgeprägte räumlich-zeitliche Variabilität des Abflusses beobachtet. Zu den Ergebnissen gehören ein Rückgang der prozentualen Anteile von Niederschlag, Evapotranspiration (ET) und Infiltration sowie ein Anstieg des Oberflächenabflusses während des Interventionszeitraums (2000-2005) im Vergleich zum

Basiszeitraum (1989-2000). Darüber hinaus wurden erhebliche Verschiebungen in der Saisonalität des Abflusses beobachtet, die mit zunehmender Entwaldung und der

Ausweitung der Landwirtschaft einhergingen und zu einem Rückgang der Niedrigwasserabflüsse und einem Anstieg der Spitzenabflüsse führten. Das Ergebnis zeigt, dass die durch die wachsende Bevölkerung ausgelösten Veränderungen der Landnutzung in Verbindung mit Klimaschwankungen einen erheblichen Einfluss auf die Veränderung des hydrologischen Systems des Einzugsgebiets haben. Dabei war der relative Beitrag der Veränderungen der Landnutzungsformen während des gesamten Untersuchungszeitraums größer als der der Klimaschwankungen.

Die Forschungsergebnisse zeigen auch, dass sich die Zuflüsse und Wasserstände der Seen in den letzten vier Jahrzehnten erheblich verändert haben. Im südlichen Teil des Einzugsgebiets haben sich die Seen in Bezug auf Fläche, Tiefe und Volumen vergrößert, während im nördlichen Teil des Einzugsgebiets ein erheblicher Rückgang der Seen zu verzeichnen war. Der Chamo-See erfuhr eine bemerkenswerte Vergrößerung: seine Fläche nahm um 11,86 km² zu, seine Tiefe um 4,4 m und sein Volumen um $7,8 \times 10^8$ m³. Im starken Gegensatz dazu verringerte sich die Fläche des Abijata-Sees um 68% und seine Tiefe um 1,6 m. In diesem Zeitraum verringerte sich der durchschnittliche jährliche Niederschlag für den Abijata-See um 6,5% und für den Chamo-See um 2,7%. Die tatsächliche Evapotranspiration ging im Abijata-See um 2,9% zurück, während sie im Chamo-See leicht anstieg (bis zu 0,5%). Der Oberflächenzufluss zum Abijata-See ging um 12,5% zurück, während der Chamo-See einen Anstieg des Oberflächenzuflusses um 80,5% verzeichnete. Die Sedimenttiefe im Chamo-See nahm ebenfalls um 0,6 Meter zu. Das sich verändernde hydrologische System des Chamo-Sees wird in erster Linie durch den erhöhten Oberflächenabfluss und Sedimenteintrag bestimmt, die größtenteils auf anthropogene Einflüsse zurückzuführen sind. Im Gegensatz dazu wird das hydrologische System des Abijata-Sees durch die Wasserentnahme aus den ihn speisenden Flüssen und Seen für Industrie- und Bewässerungszwecke erheblich beeinträchtigt.

Diese Forschung trägt zu einem umfassenderen Verständnis der hydroklimatischen Systeme der Erde bei. Sie erweitert den wissenschaftlichen Kenntnisstand, indem sie die komplizierten Mechanismen beleuchtet, die der langfristigen Variabilität zugrunde liegen, und erweitert dadurch die Möglichkeiten zur Vorhersage und Reaktion auf künftige hydroklimatische Herausforderungen. Die Studie ermöglicht ein ganzheitliches Verständnis der komplexen und wenig erforschten hydrologischen Systeme in den Seen des Rift Valley in Äthiopien und zeigt

auch potenzielle Einflussfaktoren auf. Die gewonnenen Erkenntnisse sind über diese Region hinaus von Bedeutung und bieten wertvolle Einblicke für die Bewältigung ähnlicher Herausforderungen in hydrologischen Systemen weltweit.

Table of Contents

Abstract.....	<i>i</i>
Zusa mmenfassung	<i>iii</i>
1. General Introduction	1
1.1. Background.....	1
1.2. Basin Description	3
1.2.1. Topography	6
1.2.2. Climate	6
1.2.3. Land use land cover.....	7
1.2.4. Soils	8
1.2.5. Geology	9
1.2.6. Water Resources	10
1.2.7. Ecosystem Services.....	13
1.2.8. Demographic Characteristics	14
1.3. Motivation.....	14
1.4. Introduction of Hydrological Modeling	17
1.5. Importance of Hydrological Models	19
1.6. Hydrological Modeling Ungauged Catchments	23
1.7. Thesis Structure and Flowchart.....	27
2. Land use change and climate dynamics in the Rift Valley Lakes Basin, Ethiopia	30
Abstract:.....	30
2.1. Introduction.....	31
2.2. Material and Methods	33
2.2.1. Study area Description	33
2.2.2. Data Acquisition and Processing	34
2.2.3. Methodology	35
2.2.4. Land Use Classification and Accuracy Assessment.....	36
2.2.5. LULC Change Dynamics	38
2.2.6. Climate Patterns and Change Point Analysis.....	39
2.3. Result and Discussion.....	41
2.4. Land Use Classification and Accuracy Assessment	41
2.5. LULC Change Dynamics.....	45
2.6. Climate Pattern and Abrupt Shift Detection	48
2.7. Climate Pattern and Variability.....	52
2.8. Discussion.....	56
2.9. Summary & Conclusion	59
3. Hydrological responses to land use and land cover change and climate dynamics in the Rift Valley Lakes Basin, Ethiopia	61
Abstract.....	61
3.1. Introduction.....	62

3.2. Materials and Methods	64
3.2.1. Study Area Description.....	64
3.2.2. Spatial and Hydro-climatic Data.....	67
3.2.3. Methodology	67
3.3. Results and Discussion	71
3.3.1. Model Performance	71
3.3.2. LULC Change.....	74
3.3.3. Climate Dynamics.....	76
3.3.4. Water Balance Change Analysis	77
3.3.5. Attribution of LULC and Climate Dynamics on the Hydrology Processes.....	79
3.4. Discussion.....	80
3.5. Summary and Conclusions.....	82
4. Unveiling Hydrological Dynamics in Data-Scarce Regions: Experiences from the Ethiopian Rift Valley Lakes Basin.....	84
4.1. Introduction.....	85
4.2. Materials and Methods	86
4.2.1. Study Area Discerption.....	86
4.2.2. Spatial and Hydroclimatic Data	88
4.2.3. Methodology	89
4.3. Results and Discussions.....	97
4.3.1. Lake Water Balance Analysis	97
4.4. Discussion.....	112
4.5. Summary and Conclusions.....	115
5. General Conclusion and Summary.....	116
6. Outlook	122
7. References.....	124
8. Acknowledgments	144
9. Declarations	146

List of Tables

Table 2-1: List of acquired data used in this study	35
Table 2-2: Land use classes based on the FAO Classification System	37
Table 2-3: Land use transition matrix	38
Table 2-4: Quality of the land use classifications	42
Table 2-5: Temporal quantitative change of land use	45
Table 2-6: Speed and trend of land use change.....	47
Table 2- 7: Transfer matrix of land use.....	48
Table 3-1: List and sources of spatial and hydro-climatic data used for this study	67
Table 3-2: Calibration parameters and the upper and lower boundaries used for calibration..	69

Table 3-3: Scenarios for quantifying attribution analysis	71
Table 3-4: Daily and annual average model performances	72
Table 3-5: Conversion matrix of LULC in% area.....	76
Table 3-6: Climate variability trend test	76
Table 3-7: Attribution analysis of LULC and climate dynamics in a changing hydrology process	80

List of Figures

Figure 1-1: Topography of Rift Valley Lakes Basin.....	5
Figure 2-2: Flowchart of the methods	36
Figure 2-3: Spatio-temporal distribution map of land use	43
Figure 2-4: The spatial dynamics of land use change.	46
Figure 2-5: Spatio-temporal variability of rainfall	49
Figure 2-6: Spatio-temporal variability of temperature	50
Figure 2-7: Rainfall of the homogeneous regions of the Rift Valley Lakes Basin	51
Figure 2-8: Temperature for the homogeneous regions of the Rift Valley Lakes Basin	52
Figure 2-9: Innovative trend analysis of temperature over the Rift Valley Lakes Basin.....	53
Figure 2-10: Change point detection (1970-2018).....	54
Figure 2-11: Onset and offset analysis across Rift Valley Basin.	55
Figure 2-12: Wet and Dry Spells in all Regions of Rift Valley Basin	56
Figure 3-1: Topography of the Ethiopian Rift Valley Lakes Basin	66
Figure 3-2: Flow duration curves of simulated (Qsim) and observed (Qobs).	73
Figure 3-3: Hydrograph of simulated (Qsim) and observed (Qobs)	74
Figure 3-4: LULC maps in 1989 and 2009 and change	75
Figure 3-5: Change of spatio-temporal distribution of change of rainfall and ET.....	77
Figure 3-6: Spatio-temporal distributions change of water balance components	78
Figure 3-7: Flow duration curves for the base line and interference periods.....	79

1. General Introduction

1.1. Background

The Earth's terrestrial surface and climate have undergone significant change over the past three decades (Song et al., 2018, Nicholson, 2001, Gutman et al., 2004, Pielke Sr et al., 2002). The Earth's surface water resources have undergone substantial changes due to the human induced change of land use and vegetation patterns and the management of surface water and groundwater systems (Gerten et al., 2007, Rost et al., 2008). The rapidly growing population and rising food demands have caused a drastic global irrigation expansion (Siebert et al., 2015). In the Global South, the water demand for agricultural irrigation is ever increasing for economic development increase with population. However, rapid urbanization and economic development are likely to be the main drivers for increasing water demands worldwide (Wada et al., 2017). Global precipitation patterns are changing associated with ocean-atmospheric circulation (Gu and Adler, 2013, Liu et al., 2017). The sea levels are rising due to global warming (Church et al., 2008, Douglas, 1991, Shukla et al., 2017). Streamflow is changing across the world due to deforestation, urbanization, and agricultural expansion (Asadieh and Krakauer, 2017, Milly et al., 2005). Global groundwater is also depleting due rapid population growth and economic development (Wada et al., 2010, Konikow and Kendy, 2005, Kundzewicz et al., 2007). Recurrent occurrences of hydro-climate extreme events are increasing (Zwiers et al., 2013, Easterling et al., 2000); and global wetlands and lakes ecosystems are changing (Prigent et al., 2001, Mitsch and Wu, 2018). These prominent changes are driven by a combination of natural variability and human-induced factors (Wada et al., 2010, Vörösmarty et al., 2010).

Ethiopia is located at the Horn of Africa, and it covers an area of approximately 1,104,300 km². This makes Ethiopia one of the largest countries in Africa by land area. The population of Ethiopia is approximately 127 million (UN, 2023). The country is known for its diverse geography, which includes highlands, plateaus, valleys, deserts, and lowlands. Ethiopia's climate is diverse due to its varying topography, and as a result, the annual rainfall varies significantly across different regions of the country. The amount of rainfall can vary widely depending on the specific location and altitude (Gummadi et al., 2018). The central and northern highlands of Ethiopia receive the highest amount of annual rainfall ranging from 800 to 2,400 mm (Conway, 2000). The Rift Valley region, which runs through the country from north to south, receive annual rainfall ranges from 600 to 1,200 mm. Lowland areas, such as the eastern

and southeastern parts of Ethiopia, receives less annual rainfall ranging from 200 to 500 mm (Gummadi et al., 2018), leading to arid or semi-arid conditions. The western mountains and highlands of Ethiopia, particularly in the border areas with Sudan and South Sudan, can receive substantial annual rainfall of more than 1,500 mm (Fazzini et al., 2015b). Certain desert areas, like the Danakil Depression in the northeast, receive very little rainfall, often less than 100 mm per year (Chiozzi et al., 2018).

Agriculture is a crucial sector, employing 90% of the population and contributing a substantial share to the country's GDP (50%) (Solomon et al., 2021). The country has a predominantly agrarian economy, and agriculture contributes to both subsistence farming and export-oriented production. Major crops include coffee, teff (*Eragrostis tef*), cereals, pulses, oilseeds, and flowers. Livestock farming is also an important subsector next to crop production (Negassa et al., 2012).

Ethiopia possesses ample water resources (Sadoff, 2008, Faures et al., 2001). It has 12 major river basins, numerous lakes, springs, adequate annual precipitation, and substantial groundwater resources (Haile and Kasa, 2015, Awulachew et al., 2007). The total renewable water resources are estimated to be 124.6 billion m³ annually (Amenu, 2013, Amenu et al., 2013). Surprisingly, merely a fraction, less than 2 percent, of these resources are currently utilized. The availability of renewable freshwater is approximated to be 1,900 m³/capita (MoWR, 2002, Awulachew et al., 2007). Despite having abundant water resources, the country faces significant water-related challenges due to an uneven distribution and inadequate infrastructure for water storage, management, and distribution, particularly during dry seasons (Ngoran et al., 2015). A substantial portion of the population lacks access to clean and safe drinking water. This leads to health issues and an increased risk of waterborne diseases (Simane et al., 2016). Ethiopia is also vulnerable to the impacts of climate change, including changes in rainfall patterns and increased frequency of droughts and floods (Bezu, 2020, Burka et al., 2023). These changes affect water availability, agricultural production, and the overall livelihood of the society. The capacity for effective water resource management, including data collection, policy implementation, and enforcement are limited in many areas of the country.

Ethiopia is home to several major river basins that play a crucial role in the country's water resources, agriculture, and overall development. Some of the most significant river basins in Ethiopia are the Blue Nile River, Awash River, Omo River, Baro Akobo, Tekeze, Genale-Dawa, Mareb, Wabe Shebelle, Rift Valley lakes, Ogaden, Denakil, and Ayisha. The Rift Valley

lakes, Awash Ogaden, Denakil, and Ayisha are internal drainage basins, while the others are transboundary rivers with neighboring countries, which can lead to conflicts over water usage and management. The most notable example is the Grand Ethiopian Renaissance Dam (GERD) on the Nile River, which has sparked tensions between Ethiopia, Sudan, and Egypt. The Nile River is one of the longest rivers in the world, originating from Lake Tana in Ethiopia. This study is conducted on the Rift Valley Lakes of Ethiopia.

1.2. Basin Description

The Rift Valley Basin is a prominent geographical feature in East Africa. It is part of the East African Great Rift System, a tectonic plate boundary where the African Plate is slowly splitting into two separate plates: the Nubian Plate (to the west) and the Somali Plate (to the east) (Chorowicz, 2005a, Michon et al., 2022). This geological activity has created a series of valleys, escarpments, and fault lines, resulting in distinct topographic characteristics. The Rift Valley Basin is located geographically between 36°00' and 40°00' E and 4°00' and 9°00' N, transects the uplifted Ethiopian plateau over a distance of 1000 km and extends southward from the Afar depression to Kenya, across the broad basins of Ziway-Shalla, Aawassa, Abaya-Chamo, and Segen. It has an area of 55,050 km² and is characterized by a semi-arid and sub-humid to humid climate in the Rift Valley floor and highlands, respectively. The basin contains a range of natural habitats, including lakes, wetlands, forests, grasslands, and savannahs. Comprising a network of interconnected lakes and rivers, this basin serves as a lifeline for millions of people, supporting agriculture, industry, and ecosystems. Seven large lakes are located in the Rift Valley floor and are fed by large perennial rivers that originate on both sides of the ridges.

The Ziway-Shalla subbasin constitutes a significant component within the broader Rift Valley Lakes basin. It is geographically located between 7°00' N and 8°30' N and 38°07' E and 39°30' E. It covers an area of 14,477 km². It comprises four significant lakes, namely Ziway, Shalla, Abijata, and Langano, along with their primary contributing rivers Meki, Katar, Bulbula, Horakelo, Huluka, Lepis, Gudemso, Kersa, and Jirma. Shalla and Lake Abijatas are receiving lakes, i.e., there is no surface water outlet from these lakes.

The second subbasin, Hawassa subbasin, is the smallest subbasin geographically located 38°16' E to 38°43' E and 6°52' N to 7°14' N. The Lake Hawassa subbasin covers an area of 1,436 km². The subbasin comprises one major Rift Valley Lakes, Lake Hawassa, and its only tributary is Tikur Wuha River.

The third subbasin, Abaya-Chamo subbasin, is found between 5°24' to 8°7' N and 37°17' to 38°38' E, covering an area of approximately 18,023.25 km². The subbasin contains six main watersheds, which are drained by rivers Bilate, Gidabo, Gelana, Hamessa-Guracha, Sille-Chamo, and Kulfo and two large lakes, Abaya and Chamo. The flow of these rivers and other seasonal streams plays a crucial role in maintaining the water levels of Lake Abaya and Chamo. Lake Abaya is the largest lake in the Rift Valley Lakes Basin, while Chamo is the third largest lake, following lake Abaya and Zeway.

The Segen subbasin is one of the four sub-basins of the Rift Valley Lakes Basin. The sub-basin's area is 19,029 km², primarily drained by the River Weito and River Segen catchments. This subbasin faces significant challenges due to water scarcity and conflicts between investors, upstream irrigation water users, and downstream pastoralists. Despite these challenges, the subbasin is vital for its wetland resources, suitable land for irrigation, and a popular tourist destination. To develop an effective management plan, it is essential to have a comprehensive understanding of the various resources of the subbasin, including its socioeconomic, physical, and biological characteristics.

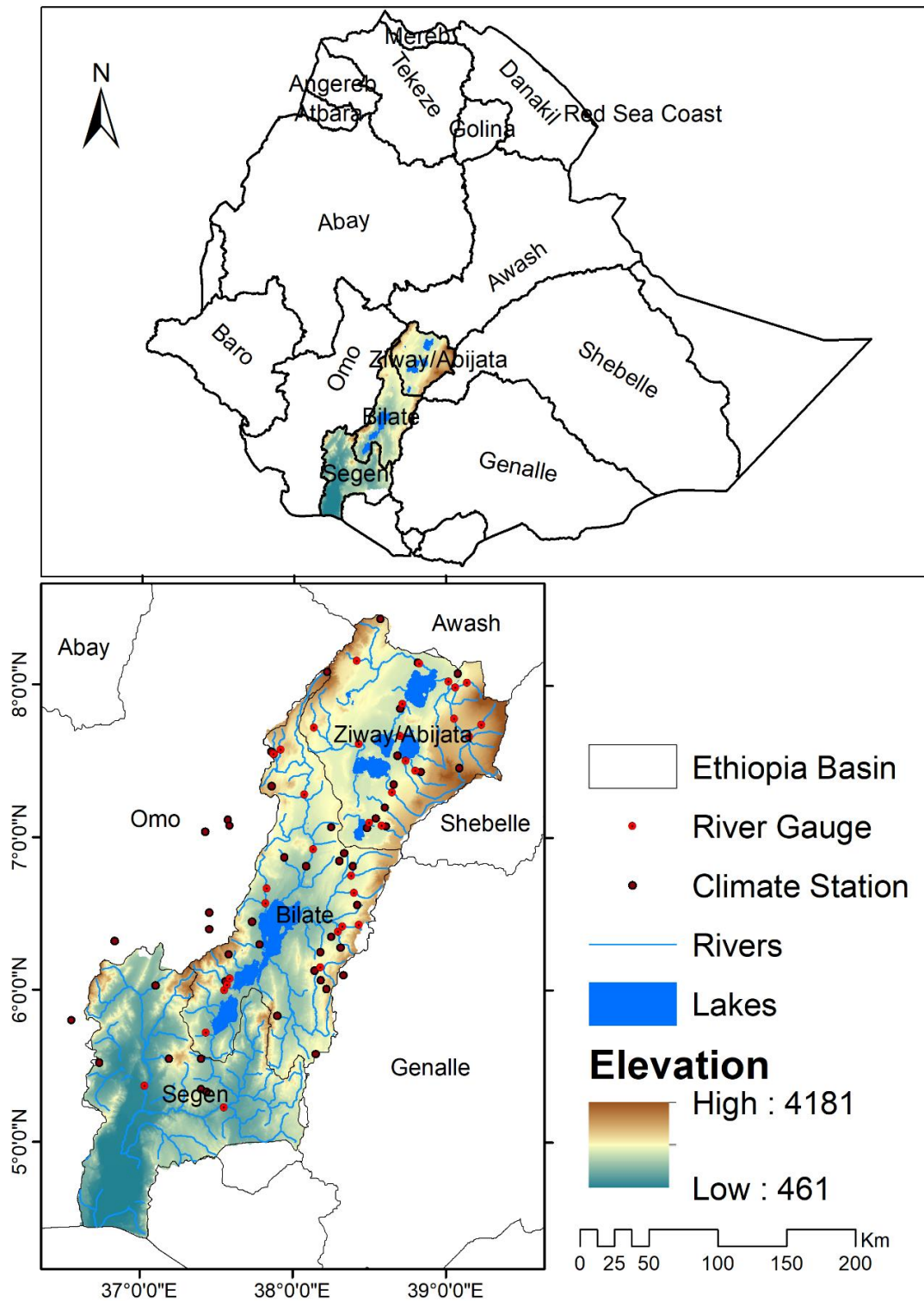


Figure 1-1: Topography of Rift Valley Lakes Basin as well as the river network, river gauge, and climate stations used for modeling on the selected subbasins (*Geospatial data is obtained from Ethiopian Ministry of water irrigation and electric city*).

1.2.1. Topography

The Ethiopian Rift Valley is characterized by a series of deep, elongated depressions or valleys, which run in a north-south direction. Steep cliffs and escarpments often flank these valleys, creating a dramatic and picturesque landscape (Fig. 1-1). Along the edges of the rift valleys, cliffs or escarpments mark the abrupt transition from the low-lying valley floor to the higher plateaus surrounding the rift. These plateaus are generally at higher altitudes than the valley floors and are characterized by more gentle slopes. They can vary in elevation and often provide fertile agricultural land.

The Ethiopian Rift Valley is also known for its volcanic activity. Within and around the rift, there are several prominent volcanic peaks. Beyond the Rift Valley itself, the topography extends to the Ethiopian Highlands, a vast region of elevated plateaus, rugged mountains, and high peaks. These highlands are a significant part of Ethiopia's topography and include some of the country's tallest mountains. Some of these, like Chilalo Mountain (4,056 masl), Galama Mountain (4,153 masl), and Kaka Mountain (4,167 masl), are located along the eastern side, while Gurage highlands (3,500 - 3,609 masl), Gughe Mountain (3547 masl) and Amaro Mountains (3,200 masl) are located along the western side of the rift. They have played a significant role in shaping the landscape. These volcanic peaks often have distinct cone-shaped profiles and are a result of past eruptions.

1.2.2. Climate

The climate in the Ethiopian Rift Valley is diverse and can vary significantly depending on the specific location within the valley and the highlands. This variation in altitude leads to diverse microclimates within the valley. The Indian summer monsoon and north-southward movement of the Intertropical Convergence Zone (ITCZ), which brings moisture to the region, influence rainfall patterns in the basin. The western side of the valley, particularly the highlands, tends to receive more rainfall and has a more temperate climate compared to the eastern side. The Rift Valley Lakes Basin experiences distinct wet and dry seasons. The main rainy season varies across the subbasins.

The upper part of the Rift Valley Lakes Basin, the Ziway-Shalla subbasin, is characterized by three distinct seasons. Between June and September, the long rainy season takes place, known as Kiremt. This period is influenced by the seasonal migration of the ITCZ, which is situated north of Ethiopia during this time (Nicholson, 2018). Wet season or Kiremt rain accounts for 50-70% of the annual rainfall.

The dry season (Bega) lasts from October to February when the ITCZ moves south. Finally, the spring (Belg, small rain) season occurs from March to May, accounting for approximately 20-30% of the total annual rainfall (Kassie et al., 2014a). The mean annual rainfall ranges from 600 mm in the vicinity of the rift floor to 1200 mm at the high margins. The mean annual temperature ranges from 15°C in the highland areas to 20°C in the lowlands. Evaporation ranges from more than 2200 mm in the rift floor to less than 1000 mm in the highlands (Melesse et al., 2009).

The middle part of the basin, the Abaya-Chamo Basin, experiences a semi-humid to semi-arid subtropical climate, with an annual average temperature of approximately 20°C in the rift floor and slightly lower temperatures in the surrounding highlands. The average yearly temperature ranges from 13°C to 24.2°C, and the seasonal variation is not pronounced. Depending on local topography and location, mean annual rainfall ranges from 951 mm to 1653 mm. The rainfall cycle is markedly bimodal, with two distinct wet seasons: from March to June (Belg) and from July to October (Kiremt). The dry season (Bega) lasts from November to February.

The lower part of the basin, the Segen subbasin, falls under the bimodal rainfall region and experiences two main rainy seasons: the main rainy season (March to May, MAM) and the short rainy season (September to November, SON)). The MAM contributes more than 40% of the annual total rainfall. The annual rainfall ranges from 400 mm in the dry lowlands to 2000 mm in the mountain regions, with an average of about 500 mm per year. The mean annual temperature ranges from 22°C to 24°C. The climate of the subbasin can be categorized as a semi-arid tropical lowland climate.

1.2.3. Land use land cover

The land use and land cover in the Ethiopian Rift Valley varies significantly due to its diverse topography, climate, and human activities. Moreover, it is dynamic and subject to change due to factors like population growth, agricultural practices, and land management policies (Garedew et al., 2009a). However, much of the Ethiopian Rift Valley is characterized by fertile soils and a favorable climate, making it a key agricultural region. Agriculture is a dominant land use, with crops such as maize, teff, wheat, coffee, and various fruits being cultivated (Mekuria et al., 2021a). The agricultural production is dominated by mixed farming. Irrigated agriculture is mainly vegetable and fruit production, predominantly practiced around the numerous lakes and rivers in the region. In addition to large scale growing crops, local communities in the Rift Valley engage in horticulture and subsistence farming.

Some areas within the Rift Valley maintain their natural vegetation, especially in less populated or protected regions. This includes woodlands, savannas, shrublands, communal and conservation plantations, and agro-forestry, which provide habitats for wildlife. The natural forest vegetation in the area varies depending on altitude. The majority of the vegetation in the subbasin is categorized as woodland and savannas dominated by acacia-euphorbia woodland, riverine vegetation, bushland, shrub, and herbaceous species (including grassland). Acacia tree species are dominant in the basin and are an important means of livelihood for the local people. As the population has grown, urban and settlement areas have expanded within the Rift Valley Basin. Cities like Awassa, and smaller towns have developed, leading to an increase in infrastructure and residential land use (Kinfu et al., 2019).

1.2.4. Soils

The soils of the Rift Valley Basin are diverse and exhibit variations depending on factors such as topography, climate, and geological characteristics (Fig. 1-1).

The soils in the Ziway-Shalla subbasin consist mainly of Eutric and Chromic Cambisols, which are young soils with poorly developed horizons but are well drained and relatively fertile. On the hills and foot slopes, there are Haplic and Chromic Luvisols, which show evidence of clay translocation, are well drained, relatively fertile, deep, and fine to medium textured. On the flatter plains, there are dark cracking clays that are poorly drained but fertile. Just to the west of Lake Ziway, the soils are again Luvisols with patches of Leptosols associated with the incised Meki River. Around Lake Ziway, the soils are Vitric Andosols, which are derived from volcanic materials and generally well-drained, deep, and medium to coarse textured. There are also Calcaric and Eutric Fluvisols developed from recent alluvial deposits, which are imperfectly drained, deep, and fine to medium textured, and associated with the Meki delta. On the Arsi plateau, the soils are primarily Luvisols, but there are appreciable areas of Rhodic Nitisols, which are soils with a uniform clay distribution and a nuggety structure, well-drained, fertile, deep, and fine to medium textured. There are also some areas of Vertisols. Around Lake Shala, Abiyata, and Langano, the soils are Haplic Solonetz, which are sodic soils, with a small area of Cambisols between lakes Abiyata and Shalla. The soil types found in the Awassa subbasin are Eutric Vertisols, Chromic Vertisols, Eutric Fluvisols, Vitric Andosols, Mollic Andosols, Humic Glycels, Pellic Vertisols, Chromic Luvisols, and Orthic Luvisols.

In Abaya-Chamo subbasin, the dominant soil types in the mid to highland areas of the basin are Nitisols, Andosols, Luvisols, and Vertisols, while Fluvisols are predominant in the rift floor

and areas around the lakes. The Bilate watershed to the west is mainly composed of Cambisols, Fluvisols, and Leptosols. Meanwhile, the western hills are largely made up of Nitisols. There are also small areas of Fluvisols and Vertisols near the alluvial fans surrounding lakes Abaya and Chamo located in the south. The majority of the southern uplands, including the Gamo Gofa hills and Konso area, consist of Cambisols with a few small patches of Nitisols around Karat Konso.

The Chew Bahir Subbasin has two main soil types: Fluvisols and Cambisols. Recent fluvial deposits on a periodically flooded alluvial plain form the Fluvisols. The soil profiles are highly stratified, with deep layers that are dark brown, brown or dark yellowish brown, and have a fine to coarse texture. They have weak to moderate fine and medium sub-angular blocky structures, and some layers have massive structures. The soil is loose or very friable when moist, and non-sticky to sticky and non-plastic to plastic when wet. The Fluvisols are mostly well to moderately well drained, but some areas are poorly to very poorly drained due to flooding. The Cambisols, on the other hand, are characterized by well to moderately drained soil that is deep to very deep. The soil is dark brown and has a clay or silty clay texture. It has weak to moderate medium and coarse sub-angular blocky structures and is friable when moist. The Cambisols are very sticky to sticky and very plastic to plastic when wet (Francis and Lowe, 2015, Zewdu et al., 2017).

1.2.5. Geology

The Rift Valley Basin region is composed of Pre-Cambrian basement gneisses and granites, which are mostly covered by newer volcanic basalts and ignimbrites (Lemenkova, 2022). River valleys feature alluvium, while the major lakes are surrounded by lacustrine deposits (Laury and ALBRITTON JR, 1975).

The Ziway-Shalla subbasin is mainly composed of Pliocene ignimbrites with tuff and pumice interbedded throughout (Bonnefille et al., 1986). Basalt is only found extensively around the margins of the area. The northern region has several recent (Pliocene to Holocene) volcanoes, resulting in layers of lava, ash, and pumice. These volcanoes are mixed with lacustrine siltstones and sandstones near the northern lakes. Lake Ziway lies in the central main Ethiopian rift, which is covered by Holocene Lake deposits. The Pliocene– pleistocene strata can be observed at the scarps of the faults where the Wonji Fault Belt (WFB) is well developed. Gademotta and Mt. Aluto have thick deposits of volcanic rocks. The Bofa Basalt is only present next to the fault scarp on the eastern side of Mt. Aluto, with Gademotta Rhyolite overlaying it according to geothermal borehole data. Rhyolitic volcanoes may have existed at that time, with similar

rhyolite found to the east of Lake Ziway. Ogolcho Basalt, Adami Tulu Basaltic Pyroclastics, and Kulumusa highly welded Tuff overlie Gademotta Rhyolite with intercalation of lake sediments in Holocene volcanic activities. The rift floor basalts and rhyolite volcanoes along the WFB developed lakes and/or swamps (Le Turdu et al., 1999).

The basin floor of the central part of the main Ethiopian Rift Valley includes Lake Abijata-Langano-Shala and its surrounding areas, making up the flat floor of the Lake Ziway area. The basin floor consists mostly of Holocene lacustrine deposits, but the Wonji Fault Belt (WFB) cuts through these sediments in some parts, creating a step-like topography. The distribution of Lake Abijata and Lake Langano is affected by these faults. Lake Shalla was formed by a volcanic eruption and is a caldera (Zenebe, 2009). The lowest geological unit in the region is rhyolitic tuff, which outcrops at Munesa on the escarpment east of Lake Langano (Lamb, 2001).

In the Abaya-Chamo subbasin, pre-Cambrian basement rocks appear as migmatized gneisses and occasional granites and granodiorites, forming high ground with recent alluvium in the valley bottoms. In some areas, alkaline early Tertiary basalts occupy the highest ground and often overlie the basement. Around the northern lakes, these volcanic rocks are inter-bedded with lacustrine siltstones and sandstones. The most recent deposits are alluvial, located around Lake Chamo and Abaya. Different processes result in Quaternary sediments in various positions. Alluvial deposits of gravels, sands, and silts form alluvial fans where rivers enter Lake Abaya. A large delta of the Bilate River is found on the northern, while a large alluvial plain can be seen on its western shores to the north of Lake Chamo. The area of Hamassa River near Humbo Volcanic Field (North of Lake Abaya) comprises the sediments of Quaternary basalts. Non-welded pumice and tuff deposits produced by voluminous rhyolitic eruptions of the Late Pleistocene to Holocene are found west of Chamo Lake. Rhyolite lavas cover an area of 265 km² on the northern and northeastern shores of Lake Abaya. The obsidians of the Korke Seluwa Volcano are rich in crystals dominated by plagioclase with less abundant Fe-clino pyroxene and Fayalite (Corti, 2009, Berhe et al., 1987).

1.2.6. Water Resources

The Rift Valley Lake Basin is endowed with a rich array of water resources. This region, characterized by its geological features, contains numerous lakes and water bodies, which collectively contribute to its water resources. It is known as the Lakes District, containing a chain of eight main lakes lying on the rift floor (Fig. 1-1). The total surface area of open waters,

including wetlands, of the basin was 4,558.14 km² in 1989, which is 60% of the total area of open waters resources of Ethiopia.

The Ziway-Shalla subbasin is a unique closed system in Ethiopia's Rift Valley, encompassing Lake Ziway, Lake Langano, Lake Shalla, and Lake Abijata. This subbasin accounts for 29% of the total surface water potential of the Rift Valley Lakes basin, with an annual potential of 1,553 mm³/year (Kebede, 2023). Lake Ziway and Lake Langano are connected to Lake Abijata via the Bulbula and Horakelo Rivers, respectively. Lake Shalla generally remains separate but can transfer water to Lake Abijata during high flow conditions.

The groundwater recharge in the Ziway-Shalla subbasin varies, with the eastern highlands providing 146 mm³/year and the western areas contributing 286 mm³/year. The central lowlands receive 119 mm³/year. However, the overuse of water resources, particularly from Lake Ziway, poses significant risks, with declining water levels in Lake Abijata since the mid-1980s attributed to unsustainable water abstractions associated with irrigation (Ayenew, 2008, Belete et al., 2015b).

In the Hawassa subbasin, Lake Hawassa is fed by runoff from various streams, including the Wesha and Werka Rivers, and runs through the Cheleleka Wetland, which has an approximate surface area of 34 km². This wetland, located 8 km northeast of Lake Hawassa, plays a crucial role in regulating water flow to the lake. The Tikur Wuha River, with an average monthly flow rate of 6-7 m³/s, drains the wetland into Lake Hawassa (Lencha et al., 2021).

The Abaya-Chamo subbasin features Lake Abaya, the largest lake in the Rift Valley Basin, with an area of approximately 1,094 km² (Yohannes, 2003). Lake Abaya is fed by major rivers such as the Bilate, Gelana, Gidabo, Hare, Baso, and Hamassa Rivers, and it is characterized by moderately saline and alkaline waters. The lake's overflow enters Lake Chamo through the Kulfo River. Lake Chamo receives water from rivers including Sille, Argoba, Wezeka, and Sego. Both lakes are highly impacted by biophysical changes in their catchments, influenced by factors like irrigation, land use changes, and sediment load (Tiruneh, 2005). Table 1-1 provides a comprehensive overview of all key aspects, including surface and groundwater details, environmental sensitivities, and river linkages.

Table 1-1: Overview of water resources in Rift Valley Basin

Subbasin	Lake/ Wetland	Linked Rivers	Area (km ²)	Annual Water Potential (mm ³ /year)	Special Characteristics
Ziway-Shalla	Lake Ziway	Bulbula River	440	1553	Linked to Lake Abijata; highly sensitive to water resource changes
	Lake Langano	Horakelo River	230	-	Linked to Lake Abijata; lacks surface outlets
	Lake Shalla	-	329	-	Generally separate; some water transfer to Lake Abijata during high flow
	Lake Abijata	Bulbula and Horakelo Rivers	205	-	Receives water from Ziway and Langano during high flow; water levels declining due to unsustainable use
	-	-	-	Groundwater Recharge: 551 mm ³ /year (varies by region)	Groundwater Availability: Varies: Eastern Highlands (146 mm ³ /year recharge, 7 mm ³ /year availability), Central Lowlands (119, 6), Western Areas (286, 14)
Hawassa	Lake Hawassa	Tikur Wuha River (from Cheleleka Wetland)	1400	-	Receives runoff from multiple streams; peak levels in Oct-Nov; Tikur Wuha River has an average flow of 6-7 m ³ /s
	Cheleleka Wetland	Wesha, Werka, and Butara Rivers	34	-	Regulates flow to Lake Hawassa; formerly a lake; peak flow two weeks before Lake Hawassa
Abaya-Chamo	Lake Abaya	Bilate, Gelana, Gidabo, Hare, Baso, and Hamassa Rivers	1094	-	Largest lake in Rift Valley; moderately saline and alkaline; prone to overflow during floods; permanent brown color due to suspended material
	Lake Chamo	Sille, Sego, Argoba, Kulfo, and Wezeka Rivers	348	-	More sensitive to climate change than Lake Abaya due to seasonal rainfall; dependent on biophysical changes in the catchment area

1.2.7. Ecosystem Services

The Ethiopian Rift Valley Lakes Basin provides a wide range of ecosystem services that are vital for the well-being of both human societies and the environment. Some key ecosystem services provided by this basin according to the four Ecosystem Service (ESS) groups include:

Provisioning

The lakes, springs, groundwater, and rivers within the basin serve as a significant source of freshwater for domestic, agricultural, and industrial use (Pascual-Ferrer et al., 2014). The lakes in the Rift Valley Basin are also known for their abundant fish populations (Janko, 2014), providing income and a source of food for local community (Zenebe et al., 1998). In addition, the fertile soils around the lakes and rivers in the basin are highly suitable for agriculture purposes (Hengsdijk and Jansen, 2006, Scholten, 2007). The water resources are used for irrigation, enabling the cultivation of crops such as maize, teff, and coffee, which are essential for local food security and economic development (Sime and Aune, 2018).

Regulating

Wetlands and forests in the basin play a role in carbon storage and sequestration, helping to mitigate climate change (Mesfin et al., 2020). They also regulate local climate patterns and contribute to temperature and humidity regulation (Mekuria et al., 2021b). Apart from regulating the climate, wetlands and marshes act as natural buffers, reducing flood risks and improving water quality through natural filtration (Sissay, 2003a, Desta, 2021, Bezabih and Mosissa, 2017).

Supporting

The basin's diverse ecosystems, including lakes, wetlands, and forests, support a rich variety of plant and animal species (Sissay, 2003a). These habitats provide breeding grounds for fish, support migratory birds, and contribute to overall biodiversity conservation (Elias et al., 2019a).

Cultural

The basin holds cultural and spiritual significance for many indigenous communities (Geleta et al., 2023, Desta, 2021). It is often associated with traditional practices and beliefs, contributing to cultural heritage and identity (Mekuria et al., 2021a). Tourism generates income for local communities through activities like birdwatching, boating, and eco-tourism. The scenic beauty

of the Rift Valley lakes, combined with their diverse wildlife, attracts tourists and nature enthusiasts (Gobena, 2008, Ali, 2016). Some of the top spots to visit in this region include Lake Ziway and its surrounding islands, the numerous lodges located along the shores of Lake Langano, Lake Abjata and its diverse bird population, the Aluto Langano geothermal sites, and the hot springs located in Shalla and Langano (Zekarias and Gelaw, 2023).

The unique ecosystems found in the basin provide opportunities for scientific research and environmental education (Seid et al., 2022, Mulat, 2013). They serve as living laboratories for studying ecology, hydrology, soil and water conservation, and biodiversity.

1.2.8. Demographic Characteristics

The population of the Rift Valley Lake Basin is around 13.8 million (CAS, 2005). This is an increase from 7.3 to 9.8 million between 1992 and 2005 or an annual rate of increase of about 2.3%. Allowing this growth rate to continue will result in an increase of the population to 19.6 million by 2030. The current trends in population growth, distribution, and structure align with the overall level of socio-economic development in the basin. According to zonal population abstract (2014) data, the average family size is 5 persons with a growth rate of + 3%. The majority (84.74%) of the population is live in a rural area; mostly found in the highland. The average population density is about 167 persons/km². Rapid population growth has caused population pressure over the available resources and service facilities as well. The rural population density is 365 per km² in the west and 5.17 per km² in the east.

1.3. Motivation

1.3.1. Research gaps

The Rift Valley Basin is facing rapidly changing hydrologic conditions due to both natural and human activities. The existing body of knowledge indicates a significant research gap in understanding of the hydrological system and hydro-climatic processes in the study area. Sedimentation is also an emerging problem, largely attributed to deforestation and agricultural expansion (Hengsdijk and Jansen, 2006, Ayenew, 2007). Additionally, concerns have been raised about the impact of climate change on water availability and the ecosystems within the basin (Gizachew and Shimelis, 2014).

The water level in the upper Rift Valley is significantly falling due to excessive abstraction of water for irrigation, industrial, and other uses (Hulluka et al., 2023). Meanwhile, in the lower

Rift Valley, water levels are rising, and new streams and lakes are emerging. This large hydrological change may be attributed to increased surface runoff and sediment load resulting from changing land use and land cover. Active tectonic faults could also be contributing to regional groundwater flow connections. As a result of these challenges, the government initiated a basin master plan in 2008 (Francis and Lowe, 2015).

The current cropping system, which relies on subsistence agriculture, cannot ensure food security. To address this issue, the government has proposed developing around 31,000 hectares of small- and large-scale irrigation projects within the basin. According to the National Water and Irrigation Policy and its accompanying strategies, irrigation development must be economically feasible, socially equitable, technically efficient, and environmentally sound. However, many irrigation schemes fail due to a lack of understanding of the basin's hydrological systems.

There is growing pressure on water resources (Hulluka et al., 2023, Mohammed et al., 2024, Benvenuti et al., 2002), and hydrological data on water levels, inflows, and outflows for many lakes is either missing or fragmented, making it difficult to assess long-term trends and water balances (Pascual-Ferrer et al., 2013, Gelagay, 2017, Peppia et al., 2023, Abraham et al., 2021). Research in the region often focuses on specific drivers or areas, neglecting broader hydrological interactions and trends, which limits a comprehensive understanding (Hulluka et al., 2023, Abraham et al., 2018, Belete et al., 2015a, Desta and Lemma, 2017).

The region is also experiencing an increased frequency of hydro-meteorological extremes, such as floods and droughts, exacerbated by climate change and human-induced factors (Lambe and Kundapura, 2023). Research highlights the urgent need for basin-specific studies to assess the effects of land use and climate change on hydrological responses (Abdule et al., 2024, Aragaw and Kura, 2024, Mummed and Seleshi, 2024, Besha et al., 2024, Luo et al., 2024). Soil erosion and severe soil loss are emerging issues (Dagne et al., 2023). Sedimentation from catchment erosion could reduce lake storage capacity and affect water quality in the Ethiopian Rift Valley lakes. Increased turbidity and nutrient levels, such as nitrates and soluble reactive phosphorus, have been observed in both Lake Abaya and Lake Chamo, contributing to eutrophication (Dagne et al., 2023).

Despite the changing hydrology, there are a lot of disorganized and even contradicting publications on the status of water level fluctuation and the spatio-temporal pattern of the morphology Rift Valley lakes.

This situation calls for comprehensive action to ensure the sustainable management of the Rift Valley lakes and their watersheds. Thus, it is important to investigate the trend in water level fluctuation using up-to-date data on the spatio-temporal coverage of the lakes and the driving forces.

1.3.2. Research questions

This research aims to address these challenges by exploring the interrelationship between land use, climate dynamics, and hydrological responses in the Rift Valley Basin.

In this dissertation, the following main research questions are addressed:

- (i) How have land use land cover (LULC) and climate dynamics evolved over the past decades in the Rift Valley Basin?**
- (ii) How has the changing hydrology responded to LULC and climate dynamics in the Rift Valley Basin?**
- (iii) Why is the hydrological response to the LULC and climate dynamics different in the upper and lower parts of the Rift Valley Basin?**
- (iv) How can an integrated hydrological modeling approach be effective in evaluating the main driving factors for changing hydrology in a data-scarce region?**

The Rift Valley Basin faces significant hydrological changes, driven by natural and anthropogenic factors. Land use/land cover changes, climate dynamics, and human activities such as irrigation and deforestation are reshaping the hydrological processes within the basin. These factors are exacerbating sedimentation, affecting lake storage, and leading to more frequent hydro-meteorological extremes. Moreover, there is scarcity of hydrological data, making it difficult to fully understand the long-term impacts of these changes. The integrated hydrological modeling approach offers a potential solution for assessing water resource dynamics in such data-scarce regions.

1.4. Introduction of Hydrological Modeling

Hydrological modeling is essential for comprehending water cycle dynamics, predicting hydrologic components, managing watersheds, and mitigating environmental impacts (Fowler et al., 2021). These models aid in planning and managing water resources by providing insights based on factors like data availability, spatial resolution, computational efficiency, and model robustness. Recent research underscores the importance of choosing models that align with specific project requirements, as model types differ in how they handle physical processes, spatial representation, and temporal scales (Clark et al., 2015, Shrestha et al., 2024). Using classifications similar to those by (Wagener and Wheater, 2006), contemporary studies categorize hydrological models based on structure (empirical, conceptual, physics-based, and hybrid), spatial configuration (lumped, semi-distributed, and distributed), process type (deterministic or stochastic), and scale, which allows for improved model selection tailored to various hydrological challenges (Addor and Melsen, 2019, Blöschl et al., 2019). This approach has proven valuable in supporting sustainable water resource management and informed decision-making.

In catchment hydrology, it is practically impossible to measure every aspect of the hydrological system due to the high spatial heterogeneity of catchments and the inherent limitations of current measurement techniques. These constraints, alongside the need to extrapolate limited measurement data across space and time, have driven the use of hydrological models (Addor & Melsen, 2019; Blöschl et al., 2019). Despite their utility, these models face uncertainties in prediction accuracy, which can impact confidence in their results and their applicability in management decisions (Gupta and Govindaraju, 2023).

Hydrological models like Soil and Water Assessment Tool (SWAT) and its enhanced version, SWAT+, are widely utilized models that assist scientists and resource managers in understanding watershed processes and making informed decisions (Bieger et al., 2017b). These models are particularly valuable for predicting and managing water availability, quality, and flow patterns in response to climate change, land use, and management practices (Kumar and Jayakumar, 2020).

To effectively apply these models, it is crucial to understand the underlying runoff processes that shape hydrograph behavior. The shape of a river flow hydrograph is influenced by various physiographic and meteorological factors. Physiographic characteristics such as catchment size,

shape, slope, and storage capacity significantly affect hydrograph behavior, which hydrological models aim to simulate accurately. Larger and more elongated catchments produce distinct hydrograph shapes due to varying flow paths and storage capacities, which models like SWAT utilize to improve predictions. Steeper slopes and higher drainage densities lead to quicker runoff responses, affecting the rising limb of hydrographs, an important factor that hydrological models account for (Arash et al., 2023). A catchment's ability to retain water influences peak flow timing; greater storage results in delayed peak discharges, a consideration that models must incorporate for accuracy (Tarasova et al., 2024). Meteorological variables, including rainfall intensity, duration, and distribution, also play a crucial role in the models (Zhou et al., 2019). Intense and prolonged rainfall events significantly alter hydrograph shapes, particularly during larger runoff events, which is essential for hydrological models to predict effectively (Morgenstern et al., 2024). Variations in temperature and vegetation cover impact potential evapotranspiration, subsequently affecting streamflow responses, an aspect that models must account for to enhance reliability (Bati et al., 2023). It is important to consider that human activities and land use changes can also modify hydrological responses, potentially altering flood behaviors and hydrograph shapes, which models should reflect for effective watershed management (Meyer et al., 2022).

Dynamics of Stormwater Flow

The dynamics of stormwater flow, especially during intense rainfall events, involve various processes that are crucial to consider for effective hydrological modeling. Understanding these processes allows models to simulate and predict runoff behavior accurately.

Overland Flow Dynamics

Horton overland flow occurs when rainfall intensity exceeds soil infiltration capacity, leading to a thin layer of water flowing overland. Research indicates that overland flow is prevalent in tropical rainforest catchments, where it can dominate storm flow during high-intensity events (Birch et al., 2021). Modeling these conditions helps anticipate flood risks in vulnerable areas. Another type of overland flow is saturated overland flow, which occurs when the soil becomes saturated, particularly at the foot of hills or mountains. Studies show that saturation overland flow significantly contributes to storm flow under varying rainfall conditions, which hydrological models must incorporate to simulate flood events accurately (Birch et al., 2021).

Subsurface Flow Mechanisms

Unsaturated subsurface flow, driven by suction head gradients, can occur as a matrix or macropore flow. The flow dynamics are influenced by soil moisture conditions and hydraulic conductivity, which affects lateral subsurface flow, critical factors for hydrological models (Liang and Uchida, 2022). The second subsurface flow mechanism is perched subsurface flow, which occurred where the saturated hydraulic conductivity is lower than the overlying layer. This flow can lead to localized saturation and increased runoff. Understanding these mechanisms is also essential for accurately modeling hydrological responses (Liang and Uchida, 2022).

Groundwater Flow and Drainage

Groundwater flow, characterized by its large storage volume and slower dynamics, plays a crucial role in base flow contributions to hydrographs. This aspect is essential for understanding the overall hydrological cycle and drainage systems, which models like SWAT strive to represent accurately (Zhang et al., 2020, Tigabu et al., 2024). The complexity of urban environments complicates modeling efforts, necessitating advanced methods to accurately represent flow dynamics, thereby ensuring effective water resource management (Gironás et al., 2010).

1.5. Importance of Hydrological Models

Hydrological models are essential for water resource planning, development, and management. Choosing an appropriate model depends on factors like data availability, spatial representation, computational cost, and model robustness. Generally, hydrological models are classified by their structural characteristics (metric, conceptual, physics-based, and hybrid), spatial representation (lumped, semi-distributed, and distributed), process types (deterministic or stochastic), as well as time and spatial scales (Wheater et al., 1993). Each model type has unique attributes, and researchers must address issues like parameter identifiability, including the equifinality problem, which is often managed by reducing the dimensionality of the parameter space (Beven, 2016).

Hybrid models are particularly effective in addressing these complexities. They leverage the parameterization efficiency of metric models, which statistically characterize observational data, and incorporate prior knowledge to test hypotheses about the structure of hydrological

components (Fenicia et al., 2016). Such hybrid models combine process-driven and data-driven approaches, making them well-suited for complex catchment characteristics (Xu et al., 2024). Many models regarded as "physics-based" are actually hybrid physical-based conceptual models, like recent SWAT versions, which simplify the model structure by conceptualizing some physical processes. This approach can improve parameter identifiability, though models still often involve high-dimensional parameter spaces (Arnold et al., 2018, Mizukami et al., 2019). Additionally, primarily conceptual models may incorporate physical-based components to ease calibration, such as when a hydrodynamic channel model is driven by outputs from a conceptual hillslope model (Ajami et al., 2017).

In water resource management, the applications of hydrological models are diverse, including event-based modeling, water balance modeling, and continuous streamflow modeling (Alemayehu and Tesfaye, 2024). The number of parameters and state variables needed for model calibration varies significantly with model complexity (Li et al., 2018b). Selecting the most suitable model for a specific watershed is challenging due to the unique characteristics of each watershed, and field testing can be invaluable in guiding researchers toward the best model for their objectives (Tilahun et al., 2023). Key criteria for model selection include the scale of the study, data availability, watershed characteristics, hydroclimatic conditions, and the intended application of the model (Qiu et al., 2023).

The model choice is further influenced by climatic conditions and watershed features. Different climates, such as tropical or temperate, require tailored models to capture variations in rainfall patterns and runoff responses (Morgenstern et al., 2024). For instance, Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed to model sequential data. LSTM networks have shown effectiveness in diverse catchment conditions, adapting to local climatic variations (Morgenstern et al., 2024). Furthermore, terrain, land use, and river networks significantly impact model performance and should be incorporated to enhance model accuracy (Alexander et al., 2023).

The decision between short-term and long-term predictions also impacts the model selection (Rajab et al., 2023). Data availability, particularly the availability of historical rainfall and runoff data, is crucial for training models, especially in regions with limited observations (Morgenstern et al., 2024). Advanced models, like deep learning and hybrid approaches, offer improved accuracy but require substantial data and careful configuration. Conversely, traditional models remain relevant in certain contexts where data is scarce or computational

resources are limited. Thus, selecting an appropriate hydrological model involves carefully considering the specific water management objectives, watershed characteristics, and data availability. Model accuracy also hinges on calibration and validation with observed field data, which are essential for reliable predictions (Dile et al., 2018).

In summary, criteria for model selection generally include the model's ability to represent specific hydrological processes, sensitivity to input data, computational requirements, and ease of use (Xia et al., 2022).

Soil and Water Assessment Tool (SWAT)

The Soil and Water Assessment Tool (SWAT) is a comprehensive modeling framework developed by the USDA Agricultural Research Service to evaluate the effects of land management practices on water, sediment, and agricultural chemical yields across diverse watersheds (Arnold et al., 2012; Gassman et al., 2014). SWAT's design supports long-term simulations, making it particularly effective for assessing hydrological responses to land use changes and climate variability (Bieger et al., 2017).

SWAT is a conceptual, physical-based, continuous model operating on a daily time step. It is designed to predict the impact of watershed management practices on hydrology, sediment, and water quality in both gauged and ungauged watersheds (Blöschl et al., 2013). The model includes several components: weather generation, hydrology, sediment transport, crop growth, and nutrient and pesticide subroutines (Arnold et al., 2012). To simulate water quality and quantity accurately, SWAT requires specific data on topography, weather (e.g., precipitation, temperature), hydrograph features (e.g., groundwater reserves, channel routing, ponds, reservoirs, sedimentation patterns), soil properties (e.g., composition, moisture, nutrient content, temperature, erosion potential), crops, vegetation, and agronomic practices (e.g., tillage, fertilization, pest control) (Abbaspour et al., 2015).

The model represents a watershed by dividing it into subbasin, further subdividing each into hydrologic response units (HRUs), which are determined by overlaying digitized soil, slope, and land use maps to find regions of similarity. For each HRU, SWAT simulates processes such as soil water balance, groundwater flow, lateral flow, channel routing (main and tributary), evapotranspiration, crop growth, nutrient uptake, pond and wetland balances, soil pesticide degradation, and in-stream transformation of nutrients and pesticides (Slater et al., 2019). Hydrologic components within SWAT include surface runoff, infiltration, evapotranspiration,

lateral flow, tile drainage, percolation/deep seepage, consumptive use through pumping (if applicable), shallow aquifer contribution to streamflow (baseflow), and recharge through seepage from surface water bodies (Abbaspour et al., 2015; Arnold et al., 2012).

SWAT has been successfully applied in various contexts, such as estimating sediment yield in the Salma Dam watershed, demonstrating its capability to handle complex hydrological scenarios (Sadiqi, 2019). The model also effectively evaluates the impacts of land use and cover changes on water quality and quantity (Getachew and Manjunatha, 2022). SWAT has also been used to assess the effects of urbanization and agricultural expansion on hydrological processes (Li et al., 2019). Despite its strengths, SWAT is not designed for detailed flood routing, which limits its application in scenarios requiring precise flood event simulations. This highlights the need for complementary models in flood-prone areas.

Soil and Water Assessment Tool (SWAT+)

The revised version of the Soil and Water Assessment Tool (SWAT+) enhances the modeling of hydrological processes and watershed management. This new version introduces significant improvements over its predecessor, SWAT, particularly in spatial representation and process dynamics. Among the key enhancements: SWAT+ allows for the definition of landscape units, improving the representation of spatio-temporal dynamics in hydrological modeling (Bieger et al., 2017b). It effectively simulates water balance components and their spatial distribution (Barresi Armoa et al., 2023). It also includes improved process dynamics, incorporating new functionalities for routing flow across landscape units, which enhances the modelling of hydrological fluxes, especially in lowland areas (Bieger et al., 2017b). The updated model also includes mechanisms for better in-stream phosphorus retention and remobilization, addressing previous shortcomings in phosphorus modeling (Wallington and Cai, 2023). It also has enhanced capabilities for modeling basin-scale processes, offering a 5-step model setup verification workflow using SWATdoctR (Plunge et al., 2024). This tool helps to identify errors in the SWAT+ model setup process and supports decision-making processes with accurate model setups. SWAT+ improves code development, data analysis, and visualization in water resources modeling (Bieger et al., 2017c). It offers also more flexibility in defining management schedules and routing constituents. While SWAT+ offers advanced capabilities, challenges remain in accurately representing extreme hydrological events, indicating a need for ongoing refinement in model development.

SWAT+ has been successfully applied in various studies, such as: Integrated Water Resource Management: Research has demonstrated its effectiveness in evaluating different management scenarios to optimize water resources (Mirzaei et al., 2023). Ecosystem Services Assessment: SWAT+ has been utilized to assess the impacts of land use changes on ecosystem services, providing insights for sustainable land management practices (González-Ramírez and Parés-Sierra, 2019).

Application of SWAT in the Rift Valley Basin, Ethiopia

The Soil and Water Assessment Tool (SWAT) has been effectively applied in the Rift Valley Basin of Ethiopia across multiple hydrological, environmental, and land management studies. This model has become widely used in the region for watershed management and hydrological assessments, enabling researchers to investigate critical issues such as land use change impacts on water quality and sedimentation in lakes (Gashaw et al., 2022, Seyoum et al., 2022, Dinku and Kebede, 2023, Beza et al., 2024). SWAT has proven especially useful in simulating streamflow within the Lake Ziway watershed, aiding in the assessment of seasonal variations in water availability and the projected effects of climate change on local hydrological processes (Demmsie, 2021, Aragaw et al., 2021).

Additionally, SWAT has been applied to model water quality in various watersheds of the basin, providing insights into the influence of land use practices and natural processes on water conditions (Truneh et al., 2024). The model has also enabled researchers to assess the potential impacts of climate change on hydrology and water resources, supporting efforts to anticipate and mitigate climate-related changes in water availability (Aragaw et al., 2023, Zena et al., 2024, Mohammed et al., 2020, Mersha et al., 2023).

The application of SWAT in the Rift Valley Basin of Ethiopia has significantly advanced the understanding of regional hydrological processes, water quality, and the effects of climate change and land use. SWAT's versatility and ability to simulate various scenarios make it a valuable tool for researchers and policymakers aiming to promote sustainable water resource management in the area.

1.6. Hydrological Modeling Ungauged Catchments

Hydrological modeling in ungauged catchments has gained significant attention due to the lack of direct measurements in many basins worldwide, which hampers the prediction of water

dynamics (Blöschl et al., 2013). The need for reliable models in such areas has led to the development and refinement of methodologies to address the unique challenges posed by ungauged catchments. In recent years, the hydrologic community has focused on better understanding ungauged catchments hydrological systems, with a concerted effort under initiatives like the Prediction in Ungauged Basins (PUB) program. This initiative synthesized methods to improve prediction accuracy, foster parameter transfer methods, and advance process-based modeling (Hrachowitz et al., 2013).

Particular emphasis has been placed on predicting hydrological responses in ungauged catchments, transferring model parameters from similar gauged basins (Parajka et al., 2013) and assessing the impact of environmental changes on catchment responses (Li et al., 2018a). These methods include regionalization techniques, where model parameters are transferred based on physical and hydrological similarity, and distributed hydrological models, which help predict responses at interior catchment points despite limited direct observations (BEVEN et al., 2015). Additionally, studies have integrated climate and land use change scenarios to evaluate future catchment response, an approach increasingly essential in understanding resource dynamics under environmental shifts (Li et al., 2018).

The key challenges in modeling ungauged catchments include data scarcity, parameter uncertainty, and regional variability (Sivapalan, 2018). Without historical streamflow and climate data, calibrating and validating models becomes challenging, leading to high uncertainty in predictions (Hrachowitz et al., 2013). Additionally, catchments often exhibit unique characteristics based on their geography, land cover, and climate, which complicates the direct transfer of model parameters from one basin to another (Razavi and Coulibaly, 2017). Understanding and overcoming these challenges is fundamental to developing reliable hydrological models for ungauged regions.

Methods for Modeling in Ungauged Catchments

Regionalization Approaches

Regionalization involves transferring parameters or model structures from gauged to ungauged catchments based on their similarities. Recent studies have advanced this field by identifying effective methods for parameter transfer, particularly in using hydrological similarity indices.

These indices quantify catchment similarity through physical attributes like climate, soil, and topography (Vormoor et al., 2018).

Parameter Transfer Based on Proximity

Proximity-based approaches have been widely used due to their simplicity, where parameters from geographically close catchments are transferred to ungauged catchments (Guo et al., 2021a). While effective in some cases, these approaches may struggle in areas with significant climatic or physiographic variability (Akstinis et al., 2022).

Hydrological Signature Regionalization

Regionalizing hydrological signatures such as flow duration curves or base flow indices has proven useful. These signatures allow the model to capture specific flow characteristics, improving accuracy over single-criterion methods (Guntu et al., 2020).

Statistical and Data-Driven Models

Data-driven models, including regression models and machine learning, are increasingly popular in ungauged catchments due to their flexibility and reduced dependence on site-specific data (Mosavi et al., 2021). Regression models correlate streamflow with catchment characteristics such as slope, area, and precipitation. Beven (2016) have found regression models to be effective when robust regional datasets are available, although they may lack flexibility for complex hydrological responses. Machine learning models like random forests and artificial neural networks have shown promising results in simulating streamflow to understand hydrological responses in ungauged basins (Feng and Koch, 2024). These models utilize available proxy data to predict streamflow, often achieving higher accuracy than traditional approaches, especially when hybridized with physical models (Wu et al., 2019).

Rainfall-Runoff Models

Rainfall-runoff models are widely used for ungauged basins due to their capability to simulate water balance processes with limited data requirements. Common models in this category include conceptual models like the HBV (Hydrologiska Byråns Vattenbalansavdelning) (Seibert and Bergström, 2022) and distributed models like SWAT (Soil and Water Assessment Tool). Conceptual Models: The HBV model, for instance, is commonly used due to its

simplified structure, which allows parameter transfer across basins. Studies by Seibert and Vis (2012) indicate that such models can be adapted for ungauged catchments, although they may require calibration to match local conditions. Distributed Models: Distributed models such as TOPMODEL and SWAT allow for greater spatial variability, though they require significant parameter assumptions when data is scarce (Singh and Devi, 2022). TOPMODEL, which represents spatial variability in groundwater flow, has been applied successfully in ungauged catchments using generalized parameter sets (Guo et al., 2021b).

The SWAT model was initially developed by the USDA to predict the impact of land management on water, sediment, and agricultural chemical yields in large, complex watersheds with varying conditions (Arnold et al., 2012). SWAT's structure enables it to use GIS-based land use and soil maps, topography, and meteorological datasets, making it particularly suitable for ungauged basins when data transfer techniques are applied. The donor watershed approach leverages information from gauged basins (donor watersheds) that exhibit hydrological and physical similarities to the ungauged target catchment. This regionalization technique allows for parameter transfer, improving SWAT's ability to simulate hydrological processes in data-scarce regions (Blöschl et al., 2013).

One of the main challenges when using SWAT in ungauged catchments is parameter uncertainty. Since SWAT requires detailed parameters for calibration, including soil properties, land use, and streamflow data, applying it in ungauged basins requires either extensive assumptions or alternative estimation methods. Without direct calibration data, predictions often contain substantial uncertainty, which affects model performance and reliability in representing actual hydrological processes (Abbaspour et al., 2015). It is also highly sensitive to the spatial heterogeneity of land use, soil type, and topography. In ungauged catchments, obtaining detailed spatial data can be challenging, leading to assumptions that may compromise model precision. For instance, hydrological responses in mountainous or varied terrains often differ significantly from lowland or homogeneous areas, making direct parameter transfer from donor watersheds potentially inaccurate unless adjusted (Guse et al., 2016).

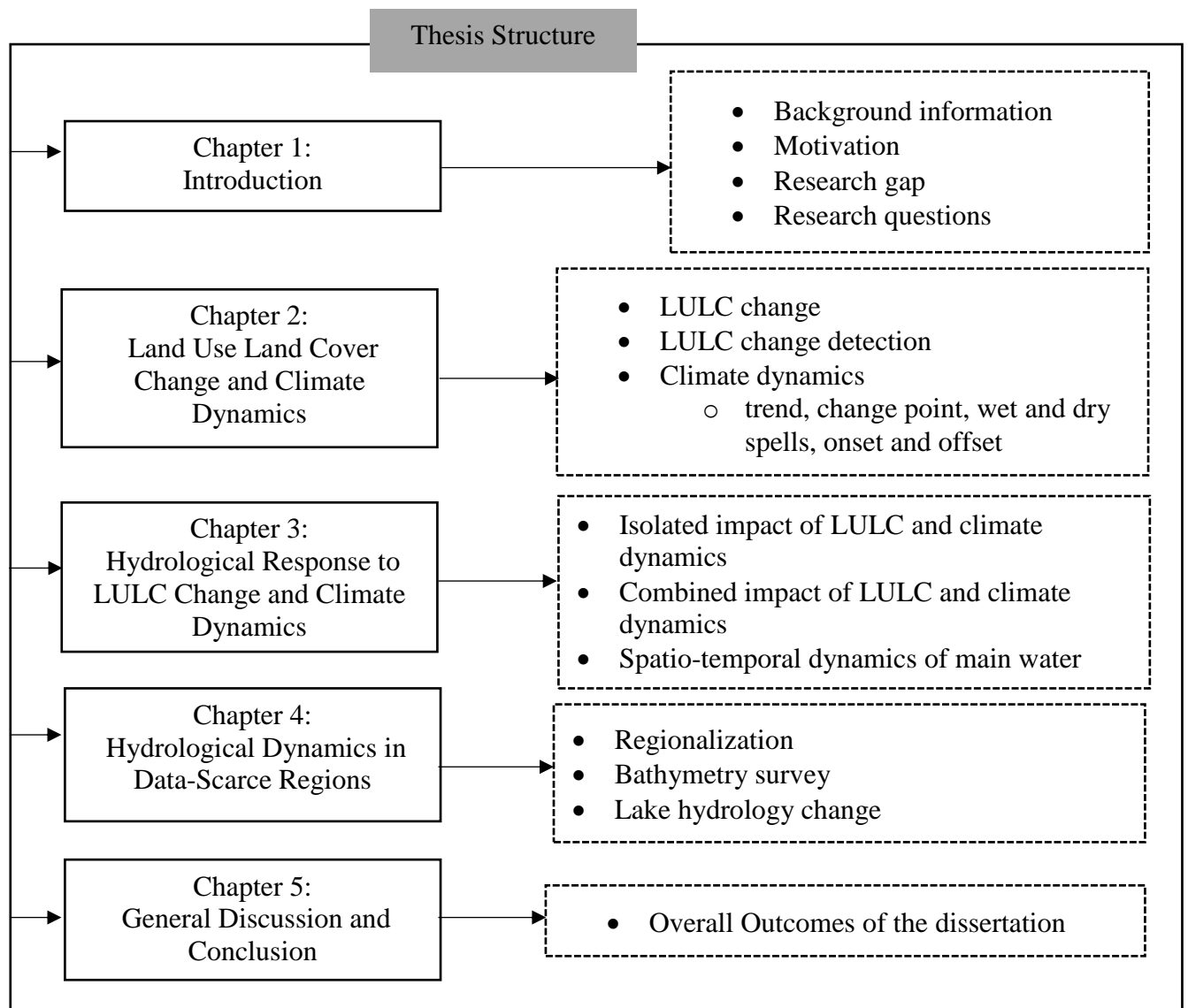
Applications of SWAT in Ungauged Catchments

Several studies have used SWAT in large, ungauged basins by transferring parameters from nearby gauged basins. Many studies leveraged donor watersheds to calibrate SWAT in ungauged sections of the basin, successfully estimating streamflow and runoff patterns that closely matched observed conditions in similar gauged parts (Sisay et al., 2017, Nkonge, 2017,

Tegegne and Kim, 2018, Meng et al., 2020, Qi et al., 2020). The multi-criteria regionalization approach has also been tested in boreal mid-Norway, and where it was found that using hydrological signatures for the parameter transfer improved model calibration and validation (Hailegeorgis and Alfredsen, 2016). In India, researchers explored the application of SWAT in ungauged catchments in transferring parameters from a variety of donor catchments with similar climate and land use conditions (Swain and Patra, 2017, Sisay et al., 2017). The study found that while SWAT could reasonably predict base flow, peak flow estimates were less reliable due to differences in stormwater runoff patterns. This highlighted the need for multi-criteria regionalization that specifically accounts for high flow conditions. In the arid Wabi Shebele basin in Ethiopia, Dile et al. (2020) used satellite-derived soil moisture and temperature data to simulate hydrological conditions using SWAT, achieving relatively accurate runoff estimates despite the lack of gauging stations in the catchment. A study by Tegegne and Kim (2018) in the Blue Nile Basin demonstrated that selecting donor catchments based on similarity in climate, soil properties, and topography significantly improved SWAT model accuracy in ungauged watersheds. Their results indicate that aligning specific hydrological signatures, such as runoff and baseflow ratios, provides better predictions for the ungauged basin.

1.7. Thesis Structure and Flowchart

The PhD thesis is divided into five chapters. The first chapter is the general introduction that includes background information, the state of art, the description of the study area, and the motivation of the research that explains the derived research questions. The second chapter deals with LULC change and climate dynamics in the basin. In the third chapter, the hydrological response to LULC change, and climate dynamics has addressed. The fourth chapter focuses on unveiling hydrological dynamics in data-scarce regions: A comprehensive integrated approach in the Rift Valley Lakes Basin. The last chapter focuses on the general discussion and conclusion of the overall outcomes of the dissertation.



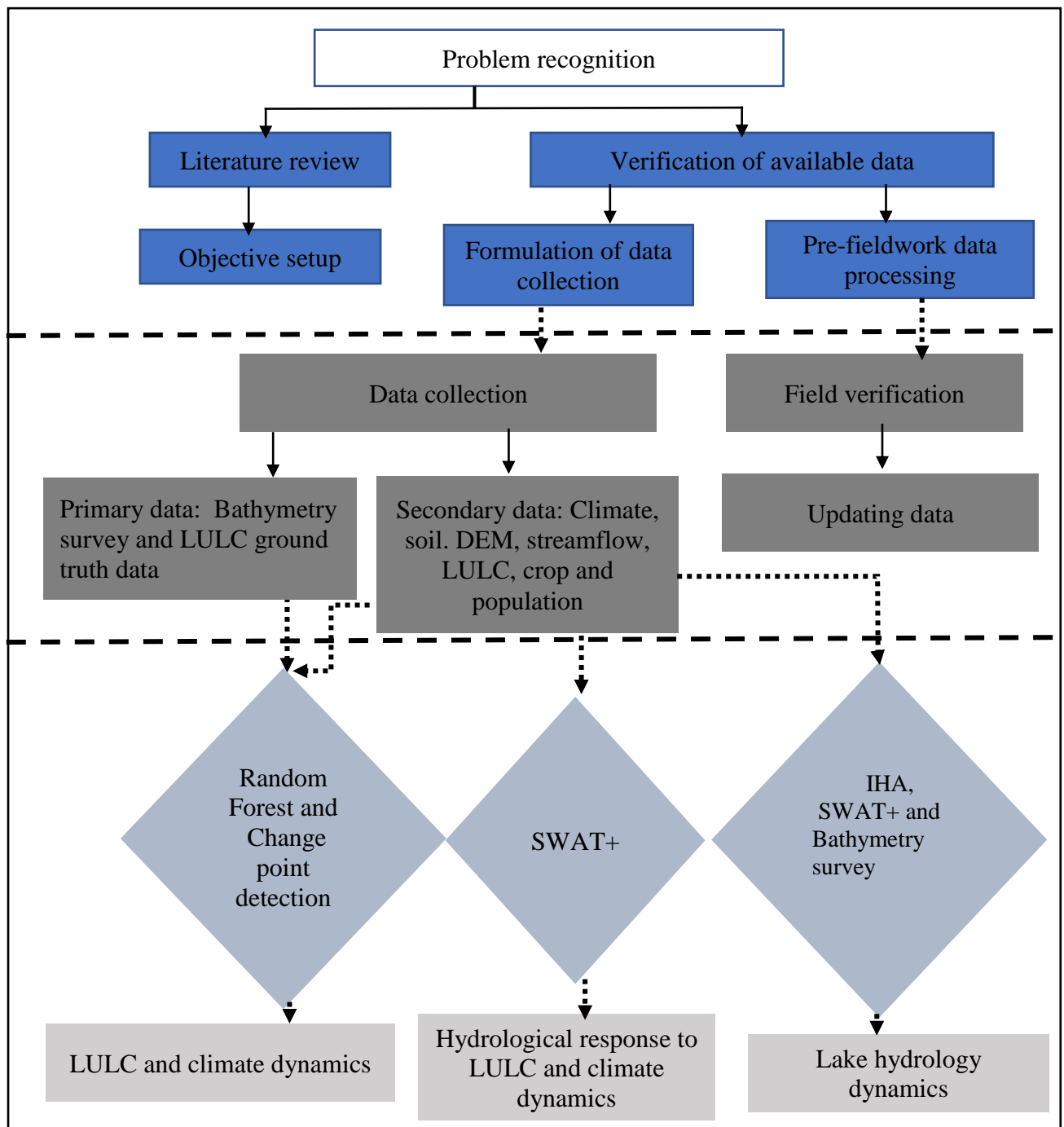


Figure 1-2: Methodological framework employed for modeling the dynamics of long-term variability of hydro-climatic processes and associated extreme events in the Rift Valley Lakes Basin, Ethiopia.

2. Land use change and climate dynamics in the Rift Valley Lakes Basin, Ethiopia

Ayenew D. Ayalew, Paul D. Wagner, Dejene Sahlu, and Nicola Fohrer

Department of Hydrology and Water Resources Management, Institute for Natural Resource Conservation, Kiel University, D-24118 Kiel, Germany

Address to correspondence author: Ayenew Desalegn, Department of Hydrology and Water Resources Management, Institute of Natural Resource Conservation, CAU, D-24118 Kiel, Germany, E-mail: ayalew@hydrology.uni-kiel.de

Journal of Environmental Monitoring and Assessment Environ Monit Assess (2022) 194:791, <https://doi.org/10.1007/s10661-022-10393-1>.

Received: 28 January 2022 / Accepted: 12 August 2022/Published online: 15 September 2022

Abstract:

Land use and climate dynamics have a pronounced impact on water resources, biodiversity, land degradation, and productivity at all scales. Thus, in this study, we present the spatio-temporal dynamics of land use change and climate aiming to provide scientific evidence about gains and losses in major land use categories and associated drivers; and significant and homogeneity of climate change. To this end, Landsat images and historical climate data have been used to determine the dynamics. In addition, population census data and land use policy have been considered to assess the potential drivers of land use change. The spatio-temporal land use dynamics have been evaluated using a transition matrix and dynamics index. Likewise, shifts in the climate data were analyzed using change point analysis, and three homogenous climate zones have been identified using principal component analysis. The results show that, from 1989 to 2019, the areal percentage of agricultural land increased by 27.5%, settlement by 0.8%, and barren land 0.4% while the natural vegetation, wetland, water body, and grassland decreased by 24.5%, 1.6%, 0.5%, and 2.1%, respectively. The land use dynamics have been stronger in the first decade of the study period. An abrupt shift of climate has occurred in the 1980s. In the last four decades, rainfall has shown a not significant decreasing trend. However, a significant increasing trend has been observed for temperature. Rapid population growth, agricultural expansion policy, and climate variability have been identified as the underlying drivers of land use dynamics.

Keywords: Land use dynamics; Random Forest; principal component analysis; change point analysis; climate dynamics; Rift Valley.

2.1. Introduction

The earth's terrestrial surface and climate have been changed considerably over the past decades because of urbanization, deforestation and agricultural expansion (Winkler et al., 2021, Luyssaert et al., 2014). In the past, recognition of the importance of the natural environment for human well-being has been less influential in maintaining sustainable development and poverty alleviation strategies (Jane et al., 2014, Vira, 2015).

In Rift Valley Lakes Basin, the economy is depending on small-scale rainfed cultivation. However, this low yield traditional cereal mono-cropping system did not fulfil the food demand of a rapidly growing population after the 1980s'. As a result, farmers have recently intensified agriculture as a response to the pressure from food-deficit resulting from low yields (Malmberg and Tegenu, 2007, Garedew et al., 2009b).

Several studies have been conducted to analyze the impact of climate change on water resources in the Rift Valley Lakes Basin (Alemayehu et al., 2006, Legesse and Ayenew, 2006a, Awulachew et al., 2007, Van Halsema et al., 2011a, Jansen et al., 2007b). Gisbert (2010) investigated that most researchers understand that water resources have been diminished due to reduction of rainfall over the Rift Valley. Moreover, the decreasing in rainfall has been investigated in the study area (Matewos and Tefera, 2020, Kassie et al., 2014b). However, a few scholars disagree on the reduction of rainfall over the last 50 years (Ayenew, 2004b, Gebrechorkos et al., 2019). These disagreements within the scientific community result in difficulties for decision makers and planners. Therefore, scientific evidences are required to understand the nature of climate and land use change dynamics in the Rift Valley Lakes Basin.

The study of land use and climate dynamics is critical for proper planning, management and utilization of natural resources. Traditional methods ,pixel-based (unsupervised and supervised classification), for gathering and analysis of geographic, demographic, and environmental data are not adequate for multi-complex environmental studies (Maktav et al., 2005), since many environmental issues exist that require handling multi-disciplinary data sets. Multi-spectral remote sensing data can be used to monitor the dynamics of land use (Saatchi et al., 1997, Thenkabail et al., 2005, Lei et al., 2021, Wagner et al., 2013), but is constrained by weather conditions, topographic complexity and heterogeneity of LULC (Wagner et al., 2013, Wilken et al., 2017). Moreover, parametric classifiers like maximum likelihood (ML) depend on a predefined data model, and the performance of these classifiers depends on how well the data

match the predefined model (Pal and Mather, 2004). Therefore, other non-parametric classification methods have been proposed to overcome this problem (Gislason et al., 2006, Benediktsson et al., 1992, Benediktsson, 1990). Among non-parametric classifiers, random forest (RF), support vector machines (SVM), and artificial neural networks (ANN) are the most common machine learning algorithms that are used to classify remote sensing data. Past studies have shown that remote sensing integrated with machine learning algorithms is a vital and efficient tool to develop and understand the biophysical change of the earth and to detect heterogenic land use (Wang et al., 2006, Steinhausen et al., 2018). Machine-learning algorithm classifiers often show a higher classification accuracy for mapping heterogeneous land use (Adam et al., 2014, Gong et al., 2013, Christovam et al., 2019). In particular, ensemble classifiers have been proposed (Benediktsson et al., 1992, Hansen et al., 1990, Kuncheva, 2003). Random Forests is a decision tree-type ensemble classifier. The algorithm is highly data adaptive (Bauer and Kohavi, 1999), and computationally less intensive. Therefore, Random Forest has been selected to detect land use change in this study.

Apart from land use change analysis, the spatio-temporal variability of climate has been evaluated aiming at detecting both, climate and land use changes in the basin, as well as to derive scientific evidences for decision makers, water resources and land use planners, and other stakeholders. The basin is a monsoon-dominated region, where almost all agricultural communities rely on the monsoon summer rainfall for their livelihood. However, the increasing variability of rainfall and considerable change in the duration, intensity and frequency of rainfall, rainfall periods (wet and dry spells), onset and offset of rainfall have become a big concern. Change in the monsoonal rainfall characteristics, especially the variability of onset/offset and wet/dry spells, and its adverse effect on agricultural activities have gained attention by agronomists and agricultural development agents, because the onset/offset (length of rain) and the wet/dry spells affect farmer's crop and livestock. However, there is no scientific investigations of the rainfall characteristics in the basin. Moreover, most people, including the scientific community, perceived that the Rift Valley Lakes Basin has a homogenous climate regime. Also, climate and climate change impact studies in the basin have no common results, conclusions and recommendations. Therefore, decision makers, water resources planners, development agents, agronomists and other stakeholders are not able to take decisions e.g., with regard to climate change adaptation, mitigation, and disaster risk reduction. Likewise, many recent studies indicate that there is a substantial and dynamic LULC change in the upper part of the basin (Elias et al., 2019b, Desta and Fetene, 2020b, Kidane et al., 2012); but there are no

comprehensive scientific evidences of LULC change in the lower and central part of the basin. To address these research gaps, homogeneous climate regions, spatio-temporal variability for each homogeneous region, and the land use dynamics are analyzed.

2.2. Material and Methods

2.2.1. Study area Description

The Great Rift Valley (GRV) is a 4,000 km long fault line that stretches from the Red Sea to Mozambique's and Zambia Valley. It is the single largest geographical feature in Africa and it transects the countries of Ethiopia, Kenya, Uganda, Rwanda, Burundi, Zambia, Tanzania, Malawi, and Mozambique (Gregory, 2018). The study has been conducted in the Ethiopian part of the Rift Valley Lakes Basin located between 36°00' and 40°00' E and 4°00' and 9°00' N. It extends from the Afar depression southwards to Kenya across the broad basins of Abijata-Ziway, Abaya-Chamo, and Segen (Fig. 2-1) and has an area extent of 55,050 km².

The basin is characterized by a complex and rugged topography. Based on the digital elevation model (USGS) data, the valley floor altitude ranges from 500–1700 m above sea level and it is bounded by western and eastern escarpments with altitudes of up to 4181 m above sea level.

The basin contains lakes, wetlands, forests, grasslands, and savannah which provide a range of ecosystem services e.g., as a natural habitat for a diversity of birds, fishes, and wildlife species. It contains over 500 bird species of African, European, Arabian, and Asian origin and 33 fish species (Sissay, 2003b). In particular, many lakes of the region are a focal point for internationally important numbers of wildfowl and waders as well as rare or endangered species. In addition, Bird Life International has identified it as one of the important bird habitats in the world (Pascual-Ferrer et al., 2008).

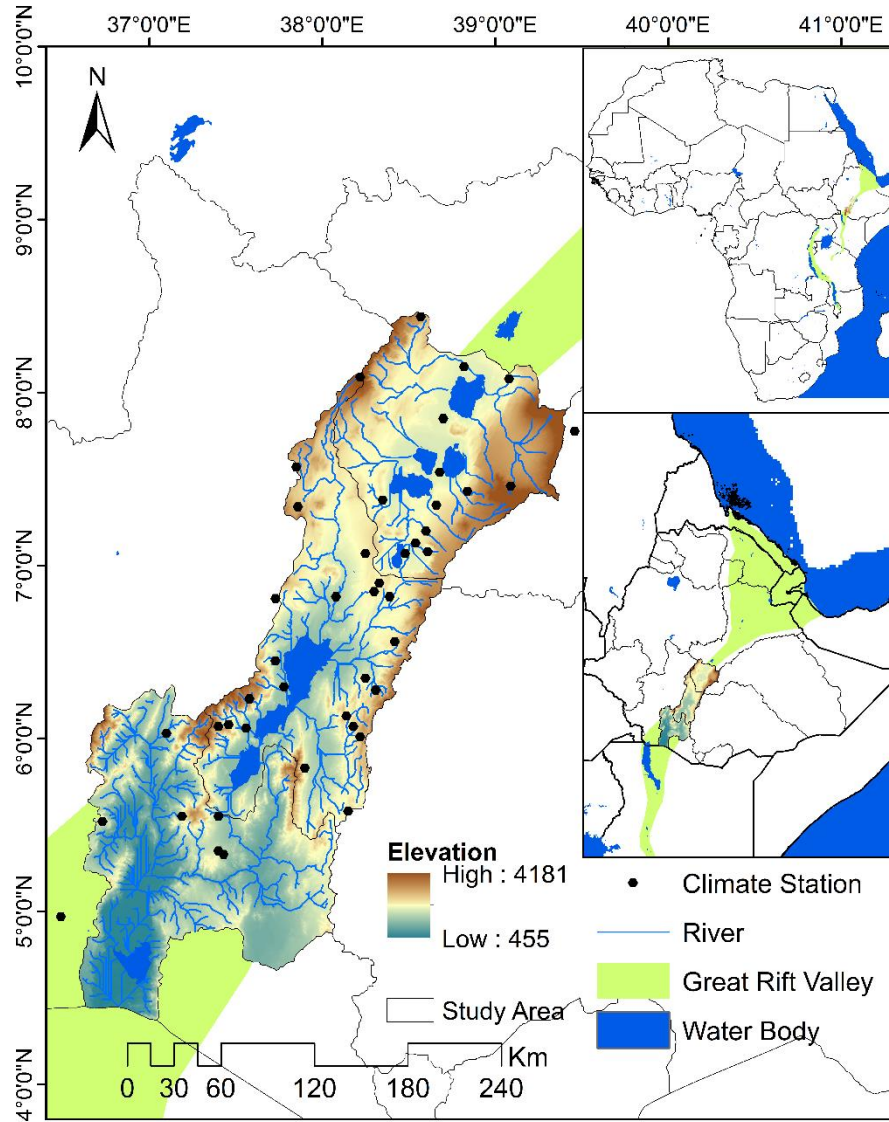


Figure 2-1: Ethiopia Rift Valley Lakes Basin with reference to Ethiopia and Africa.

2.2.2. Data Acquisition and Processing

Time series of daily and monthly rainfall and temperature data for 44 stations have been used to evaluate spatio-temporal climate patterns and climate variability in the basin from 1951 to 2019. Landsat satellite data are widely used for LULC classification and analysis (Abdullah et al., 2015, Jiménez et al., 2018) due to their free availability and the good temporal and spatial coverage. In this study, post-monsoonal (23 January to 3 March), georeferenced Landsat images with a cloud coverage less than 10% have been employed, since satellite images are more likely to be affected by seasonal cloud cover from April to November. Since the study area is large eight Landsat scenes are needed to cover it. Histogram contrast matching has been performed to mosaic these Landsat scenes together using histMatch function of the R package “RSToolbox” (Leutner et al., 2017). In addition, other ancillary data like the stream network, the basin

boundary, the Ethiopia Basin boundary, the African country boundary, the Great Rift Valley boundary, a DEM and water bodies have been obtained from the Ministry of Water Irrigation and Electricity (MoWIE). Ground truth information of land use has been collected during a field survey for the year 2019 and from Google Earth images for classification and accuracy assessment. Crop data has also been used to identify the type of crops and cropping system. Finally, population census data has been considered to evaluate the correlation between LULC change and rapidly growing population. The major data sets used in this study are presented in Table 2-1.

Table 2-1: List of acquired data used in this study

Platform	Sensor	Resolution(m)	Acquisition Date	Sources
Landsat-5	TM	30	Feb 18,1989	http://earthexplorer.usgs.gov
Landsat-5	TM	30	Feb 25,1999	http://earthexplorer.usgs.gov
Landsat-5	TM+	30	Mar 03,2009	http://earthexplorer.usgs.gov
LANDSAT_8	OLI	30	Jan 23,2019	http://earthexplorer.usgs.gov
Crop data	-	-	2005/6-2019/20	CSA
Climate	-	-	1951-2019	NMA
Population	-	-	1987-2019	CSA

“OLI - Operational Land Imager, TM - Thematic Mapper, TM+ - Enhanced Thematic Mapper plus, NMA - Ethiopian National Meteorological Agency, CSA - Ethiopian Central Statistical Agency

2.2.3. Methodology

Flowchart of the Methods

The general study design is shown in Fig. 2-2. All calculations have been carried out in the R programming environment, which is available from the Comprehensive R Archive Network (<http://cran.r-project.org/>). Random Forest ensemble machine learning algorithms has employed for Land Use Land Cover (LULC) classification Following the identification of homogenous climate region via cluster analysis, spatio-temporal climate patterns and variability have been evaluated using Innovative trend analysis (ITA), and an analysis of change points, onset/offset of rainfall and wet/dry spells.

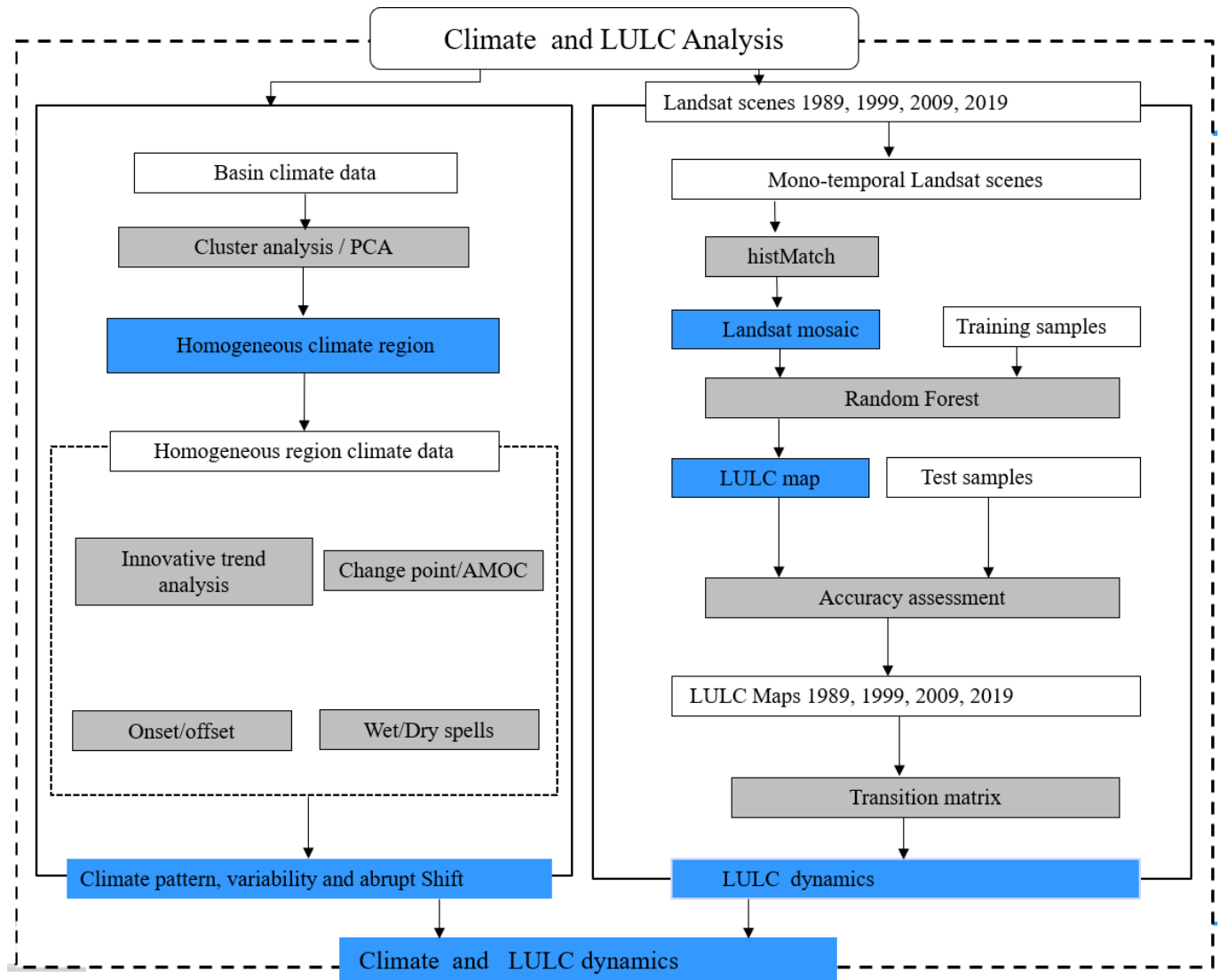


Figure 2-2: Flowchart of the methods

2.2.4. Land Use Classification and Accuracy Assessment

The criteria for determining land use classes are not uniform throughout the world, and the definitions of classification types also differ among different classification systems (Zhang et al., 2011). In this study, the Food and Agriculture Organization Land Cover Classification System (FAOLCCS) is adopted to establish an effective link between remote sensing land use information and the literature (Table 2-2).

Table 2-2: Land use classes based on the FAO Classification System

Land use class	FAO Classification System
Water body	Water body: Lakes, Streams, Canals, Reservoirs, ponds
Agriculture land	Cropland, Paddy field, Cropland/Other Vegetation Mosaic
Wood land	Scattered large trees
Grass land	Herbaceous, Herbaceous with Sparse Tree/Shrub
Forest	Broadleaf Evergreen Forest, Broadleaf Deciduous Forest, Needle leaf Evergreen Forest, Needle leaf Deciduous Forest, Mixed Forest, Tree Open, Mangrove
Shrub	Shrub, Sparse vegetation
Settlement	Residential, Co mmercial and Services, Industrial, Transportation, Co mmunications, and Utilities and Built-up Land.
Wetland	Forested Wetland and No forested Wetland
Barren Land	Bare area, consolidated (gravel, rock); Bare area, unconsolidated (sand)
Alpine	grasses, sedges, forbs, cushion plants, mosses, and lichens of alpine climate

Various classification methods have been developed to extract essential information from Landsat imageries. Since the launch of the first land observation satellite Landsat-1 in 1972, many classifiers e.g., maximum likelihood, and in recent years, machine learning algorithms have been used for classification. Among, pixel-based ensemble machine learning algorithms Random Forest (RF) has been selected for this study. Because of its versatility, RF has been used in a wide range of earth science applications including modeling of forest cover (Betts et al., 2017), spatio-temporal land use modeling (Araki et al., 2018), land-cover classification (Nitze et al., 2015), wetland identification (Berhane et al., 2018, Maxwell et al., 2016), and object-oriented land use mapping (Kavzoglu, 2017). For this work, random forests (Breiman, 2001) supervised classification approach was applied to produce land use classifications for the years 1989, 1999, 2009, and 2019 in R (Team et al., 2020). This algorithm uses decision trees and selects the best solution through voting/averaging. The number of trees required to maintain a certain level of accuracy has been assessed by several authors, and the minimum number of trees for optimal classification varies between 100 to 300 trees (Lawrence et al., 2006). For this study, depending on the quality of satellite images, several polygons have been created for each year. The number of polygons for the year 1989, 1999, 2009, and 2019 are 448, 294, 736, and 640, respectively. Polygons of each year have been split equally for training and testing sample and then ten random points has been created for each training and testing polygons. Each classification has been carried out with 200 decision trees using the extracted spectral

information from the training points. The accuracy of each year classification has been determined and evaluated with the test data using confusion matrices, overall, user's, and producer's accuracies (Story et al., 1986).

2.2.5. LULC Change Dynamics

Land Use Transition Matrix

To quantify the spatio-temporal land use dynamics, the classifications have been compared with the help of a transition matrix (Singh et al., 2017). The transition matrix consists of rows of previous land use categories (T1) and a column of recent land categories (T2) (Table 2-3). A_{ij} denotes the land area that experiences transition from category i to category j . The entire diagonal indicates unchanged areas. The area of the land use in category i in time T1 (A_{i+}) is the sum of A_{ij} over all j . Likewise, the area of the land use in category j in time T2 (A_{+j}) is the sum of A_{ij} over all i . In addition, the loss area has been determined as the difference between the row total and the persistence land use area ($A_{i+} - A_{ii}$). Similarly, the gains have been calculated as the difference between the columns total and the persistence land use area ($A_{+j} - A_{jj}$).

Table 2-3: Land use transition matrix

		T2					
		L1	L1	...	Ln	A_{i+}	Loss
T1	L1	A_{11}	A_{11}	...	A_{1n}	A_{1+}	$A_{1+} - A_{11}$
	L2	A_{11}	A_{22}	...	A_{2n}	A_{2+}	$A_{2+} - A_{22}$

	Ln			...	A_{nn}	A_{n+}	$A_{n+} - A_{nn}$
	A_{+j}			...	A_{+n}		
	Gain			...	$A_{+n} - A_{nn}$		

Trend and Rate of Change

This study adopted the single dynamic index to evaluate the change of speed and trend of regional land use (WANG et al., 2001, Yi et al., 2013), and is defined as

$$K = \frac{(A_r - A_p)}{A_p} * \frac{1}{T} * 100, \quad (1)$$

Where, A_r and A_p are the area of a certain land use category at the end (recent) and beginning (past) of the research period, respectively, and T is number of years between the two land use maps.

Also the transfer rate among land use categories for the research period has been evaluated using the integrated land use dynamic index (Qingqing et al., 2012) that reflects the overall change of all land categories formulas follows:

$$K_{total} = \frac{\sum_1^n |A_{ri} - A_{pi}|}{2 \sum_1^n A_{pi}} * \frac{1}{T} \times 100, \quad (2)$$

where, A_{ri} and A_{pi} are the area of a certain land use category of the recent and past land use map, respectively, T is the year difference between the recent and past land use maps, and n is the number of land use categories. K_{total} , is the annual integrated change index of area change of all land use categories.

2.2.6. Climate Patterns and Change Point Analysis

Climate dynamics and homogeneous regions

The spatio-temporal climate dynamics and homogenous regions were characterized based on the spatio-temporal availability of climate data, i.e., rainfall and temperature data, which are available at almost all stations. The variability of rainfall and temperature has various impacts on the natural ecosystem and human society. Consequently, many climatological studies are based on the analysis of rainfall characteristics (Rao et al., 1990, Rao et al., 2016, de Oliveira et al., 2014), and temperature (da Silva, 2004, Vincent et al., 2005). The spatial pattern and variability of rainfall and temperature over the Rift Valley Lakes Basin has been investigated for the 44 years of data (1950s-2019) using Principal Component Analysis (PCA). In particular, it is an objective partitioning method and widely used across various research studies for cluster analysis to identify homogeneous rainfall regions (Terassi and Galvani, 2017, Teodoro et al., 2016, Oliveira-Júnior et al., 2017). The concepts and the algorithms used to execute a cluster analysis with PCA are inherently different. The PCA can be computed either using eigendecomposition or singular value decomposition (SVD). Since our data matrix is huge, it was hard to compute the eigenvalues of the covariance matrix using eigendecomposition, which sometimes causes round-off errors. However, singular value decomposition (SDV) is a stable computational method often used to compute PCAs of a dataset by truncating the less important basis vectors in the original SVD matrix. It involves a reduction of data dimensionality, and is

primarily used to explain mutual dependence and variance of huge series of data (Praus, 2005). Among other statistical tools, SVD is considered a simple, precise, and robust method for dealing with the correlation between fields and the preferred method for numerical accuracy (Bretherton et al., 1992). It extracts the most significant modes of variability in comparison to other statistical techniques (Wallace et al., 1992). The dimension of the data is reduced by projecting it into the space spanned by the Principal Components (PCs). To that end, we calculate the eigenvectors of the variance matrix via SVD. The data were centered and scaled to explain the amount of variation (Becker et al., 1988) using the open-source statistical software R.

Climate Change Point Analysis

An abrupt climate change occurs when the climate system is forced to cross some threshold, thereby triggering a transition to a new state at a rate that is determined by the climate system itself and which is faster than the cause (Alley et al., 2002). In the field of data mining, abrupt change can be seen as a sudden change in a data series. Statistical analysis has proven to be a useful technique to detect climatic patterns and changes in the past (Khapalova et al., 2013). Change-point analysis is a widely used statistical approach to detect the change points in a data series, that are defined as a point at which the parameters' mean, variance, or trend of a distribution change abruptly (Beaulieu et al., 2012, Vu et al., 2019b). It has been shown to have the potential to detect abrupt shifts (Zhao et al., 2012). Recently, especially in earth system sciences, change-point analysis has been applied to detect changes in temperature (Croitoru et al., 2012, Shirvani and Climatology, 2017), precipitation (Khapalova et al., 2013, Xie et al., 2018), and changes of the river water level (Wong et al., 2006). Therefore, for this study, change point analysis has been chosen as analytic tool to detect abrupt shift and dynamics in 44 years of rainfall for Region II (central part of study area) and Region III (southern part of study area) and 66 years of rainfall for Region I (Northern part of study area) and 55 years of temperature datasets. Popular algorithms for change point analysis as implemented in the R package *strucchange* (Zeileis et al., 2002), *breakpoints* (Zeileis et al., 2002) and Bayesian (Wang et al., 2018) were tested in this study. Break and Bayesian change point analysis have been found very suitable for our dataset. Break point analysis has been used to detect the optimal positioning and number of change points for the dataset. The critical change point in mean has been accessed using at most one change point ("AMOC") method (Hinkley, 1970) with the `cpt.mean()` function and the dynamics of the time series have been detected using Bayesian change point analysis Method (Sung et al., 2017).

Onset and Offset of Rainfall

To identify the onset and offset of the wet season we apply a method proposed by Liebmann et al. (2012), which is widely applicable for rainfall seasonality analysis across Africa. As described in Liebmann et al. (2012), initially the start (d_i) and end (d_f) of the wet season has been computed from the annual cumulative of the dataset. Secondly, the onset and offset has been determined from daily cumulative rainfall anomaly in the range of the window ($d_i - 30$ to $d_f + 30$), where the minimum (maximum) daily cumulative rainfall was considered as onset and offset. The value 30 refers to the maximum shift of onset and offset in days. A moving window was used to extract the start and end of rainfall from the time series data using onset package in R (Becker et al., 1988).

Wet and Dry Spells

Wet and dry spells have been extracted from the baseline period (1983-2018) to evaluate the space and time variability of wet and dry spells. The simplest way to define the onset of the wet spell would be to find the first wet day with rainfall above a given threshold (Lau and Yang, 1997, Liebmann and Marengo, 2001, Nieto-Ferreira and Rickenbach, 2011) and considering the persistence of precipitation and the occurrence of dry spells or wet spells. This method agrees well with the planting in rain-fed agriculture (Tadross et al., 2005, Marteau et al., 2011). In this study, a wet spell is defined as three consecutive days with precipitation greater than 1 mm; and a dry spell is defined as three consecutive days with precipitation less than 1 mm (Froidurot and Diedhiou, 2017, Bichet and Diedhiou, 2018).

2.3. Result and Discussion

2.4. Land Use Classification and Accuracy Assessment

The accuracy assessment for the four land use maps is shown in Table 2-4. The overall accuracies of 92.0, 93.3, 93.1, and 94.9% for the years 1989, 1999, 2009, and 2019, respectively, indicate excellent classification accuracy for the majority of land use classes, indicating that the land use maps are suitable for the subsequent analysis and change detection as proposed by (Pontius Jr, 2000). User accuracies range from 83.5% to 99.7%.

Table 2-4: Quality of the land use classifications

		LANDSAT 5 TM		LANDSAT 5 TM+	LANDSAT8 OII
Indicators	Classes	1989	1999	2009	2019
Overall Accuracy		92.3	93.3	93.1	94.9
User Accuracy	Barren land	91.2	95.8	94.7	95.0
	Agriculture	89.6	94.7	97.67	96.2
	Alpine	87.7	97.5	93.8	97.1
	Forest	96.3	98.0	96.3	96.7
	Grass	93.3	83.5	93.3	91.1
	Settlement	84.9	86.6	90.0	89.2
	Shrub	96.7	92.5	91.9	93.3
	Water	99.7	98.8	99.7	97.8
	Wetland	85.8	94.3	93.3	94.7
	Woodland	98.2	89.1	83.7	94.3

The classification has been validated using ground truth obtained from a field survey (2020) and google earth image (1986-2019). This showed that the water class was better distinguished and grass class was poorer distinguished than other classes. The water bodies, mainly lakes are large water areas which are usually easy to detect. Whereas, grass was difficult to distinguish from agricultural land. The high level of classification accuracy for these classes could be attributed to the large number of training samples, selected remotely sensed data, dry season, and image-processing (contrast adjustment and histogram equalization) and classification approach.

The resulting land use maps of the four years 1989, 1999, 2009, and 2019 shown in Figure 2-3 have overall ten land use classes. Most parts of the basin area are used for agriculture land. Agricultural production is dominated by mixed farming.

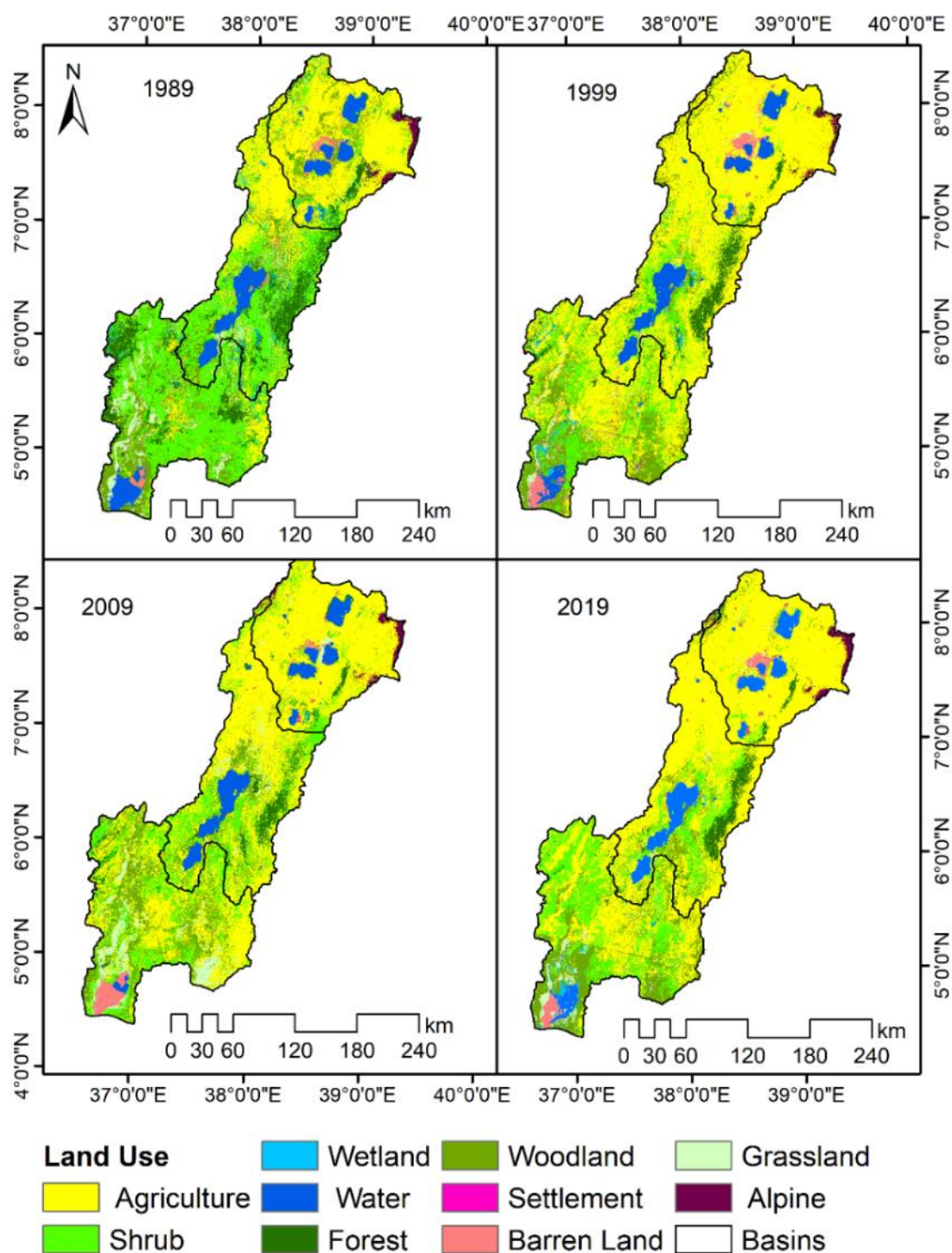


Figure 2-3: Spatio-temporal distribution map of land use

Cereal-cereal crop rotation is the usual practice in the Rift valley; but sowing pulses preceding to cereals (like maize-haricot bean rotation) and inter-crops (cereal with pulse) are becoming more common (Burayu et al., 2006). A 2015 / 2016 crop and livestock production report of CSA (CSA, 2016) showed that the irrigated agriculture is mainly vegetable and fruit production predominantly practiced along the rivers and lakes. Different types of crops are being grown in the basin including grain crops, cereals, ensete (false banana, Ethiopian banana, pseudo-

banana), root crops, fruits, coffee, chat, sugarcane, oilseeds, vegetables, and pulses. Ensete is the dominant crop followed by grain crops, cereals, and root crops.

Semi-natural vegetation is the second most dominant land use class of the basin characterized by dry evergreen mountain forest, evergreen shrub and Acacia Woodland. It varies distinctively with the altitude, and above 3,000 m the dominant vegetation type is afro-alpine and sub-afro-alpine ericaceous shrub and dispersed clumps of highland bamboo (*Arundinaria alpina*) around valley bottoms and springs. The basin also contains eight major lakes which lie in the rift floor and are fed by large perennial rivers originating from either side of the mountainous ridges. The largest of these lakes is Lake Abaya (1137.82 km²) that accounts for 36.8% of the water body area. Other major lakes include Lake Chew Bahir (462.1 km²), Zway (415.9 km²), Chamo (307.7 km²), Shale (300.4 km²), Langano (229.16 km²), Awassa (91.7 km²), and Abijata (68.4 km²), comprising 14.9%, 13.4%, 9.94%, 9.7%, 7.4%, 3%, and 2.2% of the total lake area, respectively.

The individual class percentage area change statistics of each class in the four periods are summarized in Table 2-5, and show that agricultural area had the largest share in all periods of the total land use categories followed by vegetation (forest, woodland, shrub and alpine). Except agriculture, settlement and barren land, other land use classes faced a major decline during the last three decades. The study also revealed that there was about 27.5% areal percentage increase of agricultural area, 0.4% barren, 0.8% settlement at the cost of 24.5% vegetation, 1.6% wetland, 0.5% water body, and 2.1% grassland from 1989 to 2019. These values signify the rapid land use change driven by agricultural expansion that exerts pressure on non-agricultural areas, in particular vegetation lands and wetlands. Expansion of the already existing agricultural land through rapid deforestation of woodland, shrub land, grass land, wetland, and forest units all combined together led to its continuous expansion throughout the basin. Shrubland and forest land, the two most impacted sub-classes, lost 14.9% and 7.8% of the total land area, respectively, over the last three decades.

Table 2-5: Temporal quantitative change of land use

Class	Area (%)				Change (%)
	1 989	1999	2009	2019	1989-2019
Agriculture	30.89	45.60	54.00	58.40	27.51
Alpine	1.09	1.00	1.00	1.10	0.01
Barren	1.48	1.00	1.60	1.90	0.42
Forest	11.19	7.50	3.70	3.40	-7.79
Grass	4.60	7.90	4.70	2.50	-2.1
Settlement	0.02	0.20	0.40	0.80	0.78
Shrub	30.87	19.10	18.80	15.90	-14.97
Water	6.08	5.80	5.00	5.60	-0.48
Wetland	2.20	0.60	0.30	0.60	-1.6
Woodland	11.58	11.30	10.50	9.80	-1.78

2.5. LULC Change Dynamics

The spatial land use dynamics presented in Figure 2-4, show maximum changes in the first and second decade of the study period. Spatially, the dynamics were particularly strong in the Southern part of the basin. Traditionally, grazing was dominant in this part of the basin, so that there was no cultivation practice before 1990. However, after 2000 cultivation practices have become common in the area due to rapid population growth and the community adopt crop cultivation systems. As a result, the land use change is very strong in this region in all periods. In addition, land use change is observed in the central part Abijata- Ziway and Nechisar National Parks due to agricultural expansion, illegal settlement and tree cutting for fuel.

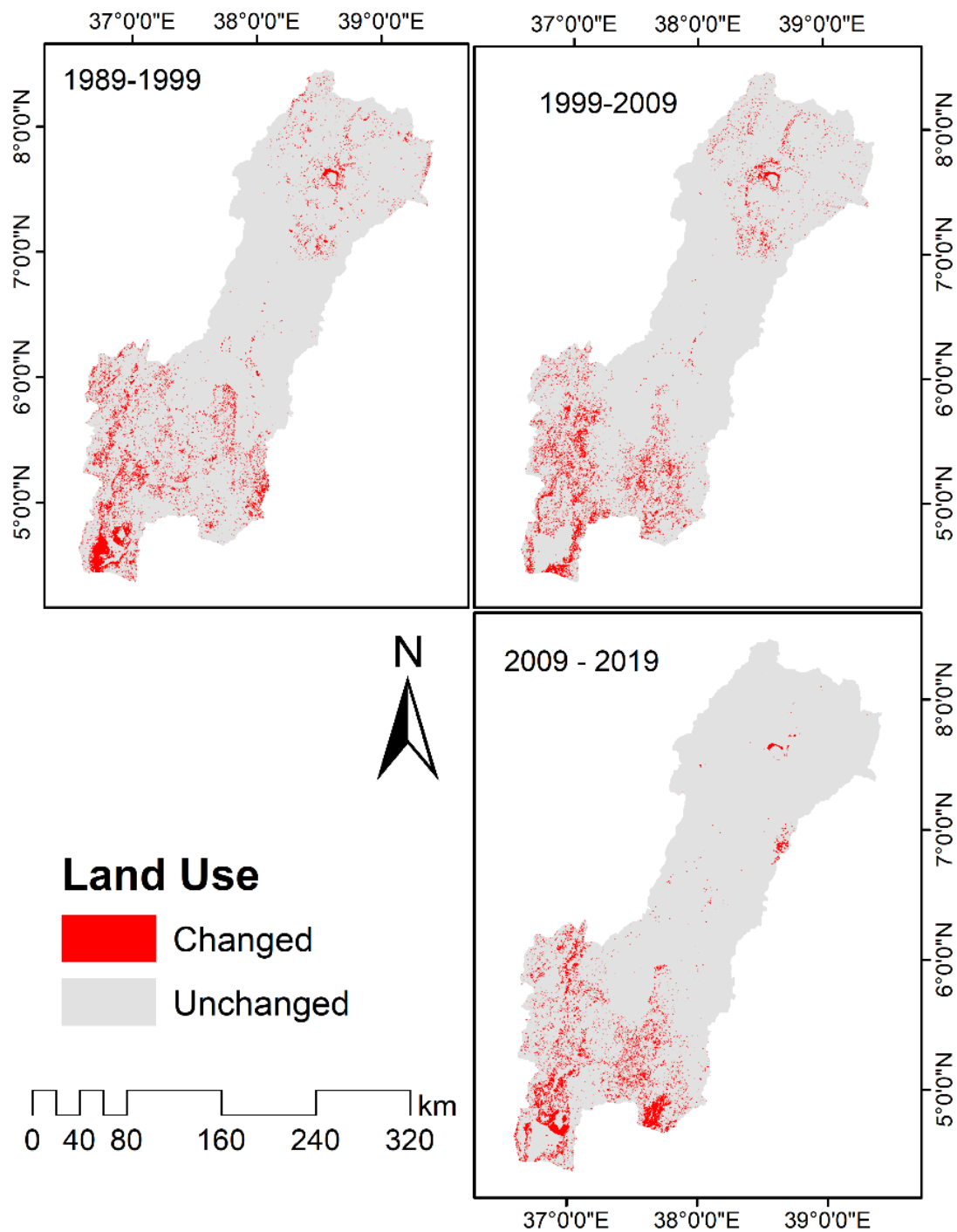


Figure 2-4: The spatial dynamics of land use change show stronger changes in the southern part of the study area.

The land use dynamic index during the periods of 1989-1999, 1999-2009 and 2009–2019 is shown in Table 2-6. It underlines that there was a strong land use change in the first decade of the study period. The maximum land use dynamic index was in settlement, up to 148.5% followed by wetland (-7.4%), grassland (7.0%), agriculture (4.8%), and shrub land (-3.8%). For most classes land use dynamics were strongest in the first decade. Only settlement and water

had the maximum index in the last decade (2009-2019). The integrated dynamic index (K) value was 1.8, 0.5 and 0.1 for time period (1989-1999), (1999-2009) and (2009-2019), respectively; and confirms that the land use change was strongest for the first decade and decreased in the latter two decades.

Table 2-6: Speed and trend of land use change

Class	Single dynamic index (%)		
	K (1989-1999)	K (1999-2009)	K (2009-2019)
Agriculture	4.8	0.9	0.8
Alpine	-0.8	-0.2	0.7
Barren land	-3.3	3.0	-0.4
Forest	-3.3	-2.6	-0.2
Grass land	7.0	-2.0	-2.9
Settlement	75.3	95.0	148.5
Shrub	-3.8	-0.2	-0.7
Water	-0.6	-0.6	1.0
Wetland	-7.4	-2.7	1.6
Woodland	-0.2	-0.1	-0.2

Furthermore, the overall temporal dynamics of land conversion ('from-to') has been evaluated. The land transfer index (Table 2-7) shows that the majority of the land use has been changed into agriculture between 1989 and 2019. The maximum land transformation was observed in wetland as only 0.6% of its original cover remained unchanged. Water, alpine, agriculture, and settlement have relatively high shares of persistent land use (>65%).

Table 2- 7: Transfer matrix of land use

	Class	2019									
		Agriculture	Alpine	Barren	Forest	Grass	Settlement	Shrub	Water	Wetland	Wood
1989	Agriculture	90.6	0.7	0.3	0.4	0.9	0.3	3.0	0.1	0.2	3.7
	Alpine	26.0	66.2	0.0	0.6	0.1	0.00	6.7	0.0	0.0	0.2
	Barren	30.9	0.0	20.8	0.2	7.5	1.2	9.6	14.7	0.4	14.7
	Forest	44.0	0.4	0.1	19.4	0.6	0.1	28.1	0.9	0.6	5.9
	Grass	45.9	0.0	1.1	0.3	18.7	0.4	8.8	0.1	0.9	23.8
	Settlement	0.0	0.0	0.0	0.0	0.0	99.3	0.8	0.0	0.0	0.0
	Shrub	49.2	0.2	0.2	3.1	1.2	0.1	31.6	0.3	0.3	13.9
	Water	0.8	0.0	11.4	0.0	3.7	0.0	0.2	82.5	0.3	1.1
	Wetland	73.1	0.3	0.1	4.6	0.3	0.2	15.6	1.2	0.6	4.1
	Wood	52.9	0.0	0.6	0.2	3.4	0.7	9.4	1.0	2.8	29.2

2.6. Climate Pattern and Abrupt Shift Detection

Construction of homogeneous climatic regions

The principal component analysis (PCA) suggests three main homogenous rainfall regions and three main rainfall regimes (Figure 2-5). The vector lines grouped together show a high correlation between weather stations and are considered as a homogeneous climate zone. The points show the temporal variability at a monthly time scale. Region I is the upper part of the basin which is formed by 11 stations, Region II is the central part of the basin which is formed by 15 stations, and Region III is the lower part of the basin and formed by 18 stations according to their pertinence degrees.

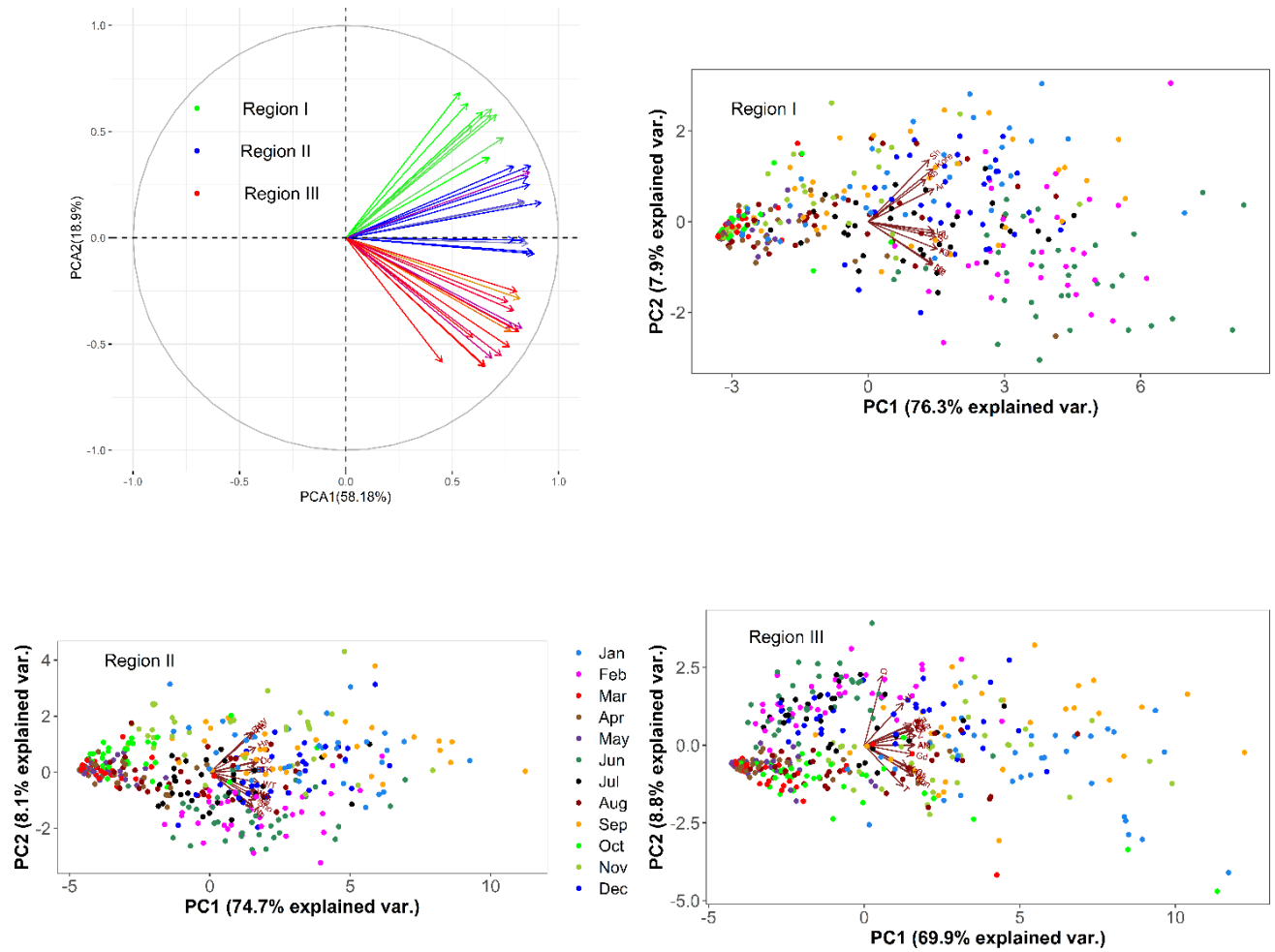


Figure 2-5: Spatio-temporal variability of rainfall. The PCA plot of the first two PCs of the data set explains 80% of the variation, colored by month of the respective data.

The first two PCs are explaining more than 80% of the total variability in the dataset. They have a standard deviation of the principal components greater than 1 providing a good incite of the variability of rainfall and temperature. The rainfall variability is high during the transition periods, i.e., spring and autumn. Likewise, the PCA shows that there is a high temporal variability of temperature (Figure 2-6). Especially, its variation is very high during the wet season and is mainly associated with changes of cloud cover.

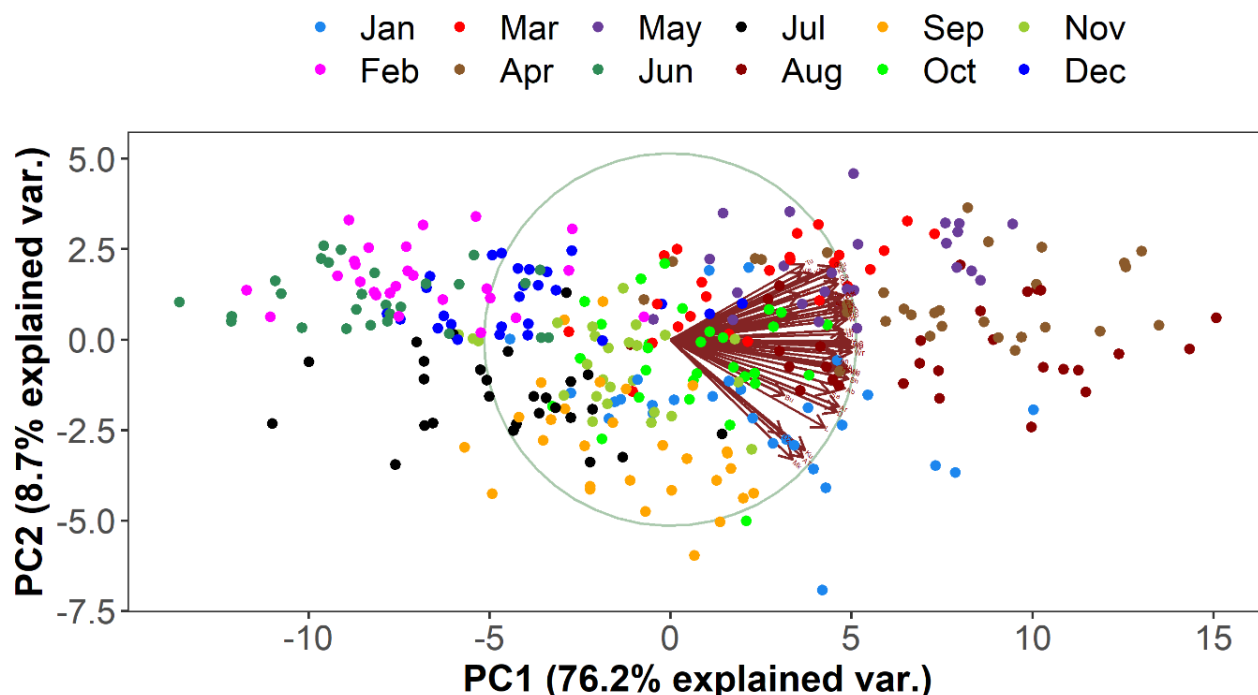


Figure 2-6: Spatio-temporal variability of temperature: The PCA plot of the first two PCs of the data set explains 80% of the variation, colored by month of the respective data.

As can be seen in Figure 2-7 and 2-8, the rainfall and temperature patterns over the basin are heterogeneous in space and time. Region I is characterized by lower volumes of annual average precipitation ranging from 400 mm to 860 mm with one peak in August. Region II is characterized by a higher volume of annual precipitation ranging from 704 mm to 1200 mm with a bimodal climate pattern with peaks in April and August. Likewise, Region III is characterized by a bimodal rainfall pattern with peaks in April and October. It receives an average annual precipitation ranging from 500 to 1100 mm with maximum rainfall in April. Three seasons can be distinguished based on precipitation for region I & III and two seasons for region II. Region I has summer (June-Sept), spring (March – May) and winter (October – February) seasons. Similarly, Region III has spring (March-July), summer (August – November) and winter (December – February). However, Region II has a long summer (March – October) with a little break in June and a winter season (November – February).

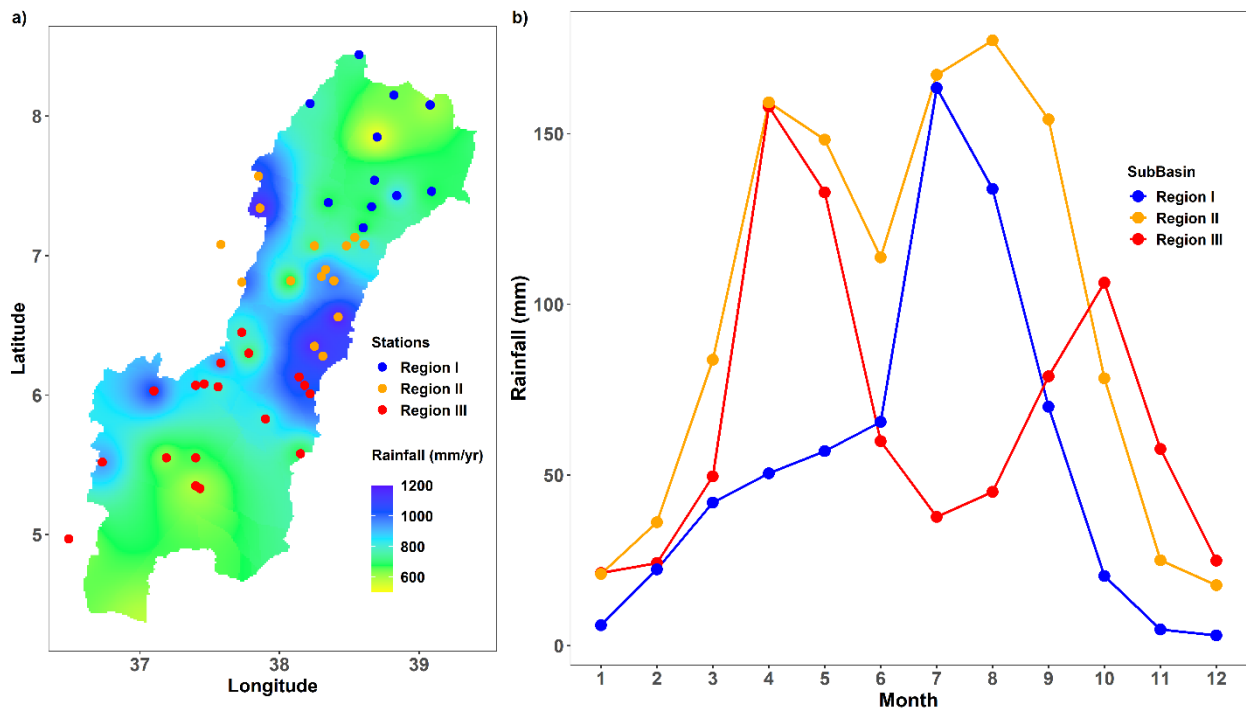


Figure 2-7: Rainfall of the homogeneous regions of the Rift Valley Lakes Basin: a) the spatial distribution of rainfall over the basin interpolated using inverse distance weighting (IDW); b) the temporal pattern of rainfall for each region.

Distinct patterns in the seasonal temperature were also identified (Fig. 2-8). The intra-annual, inter-seasonal as well as the diurnal temperature variability is very high in the entire basin. The temperature also varies widely throughout the basin, from the hottest on rift floor to frost-prone in the Afro-alpine zone. The maximum seasonal average temperature is occurring during dry season for all climate zones. This variation from 10°C to 36°C is mainly due to differences in elevation and cloud cover. The southern part of the Rift valley is lower, warmer, and drier than other parts of the basin.

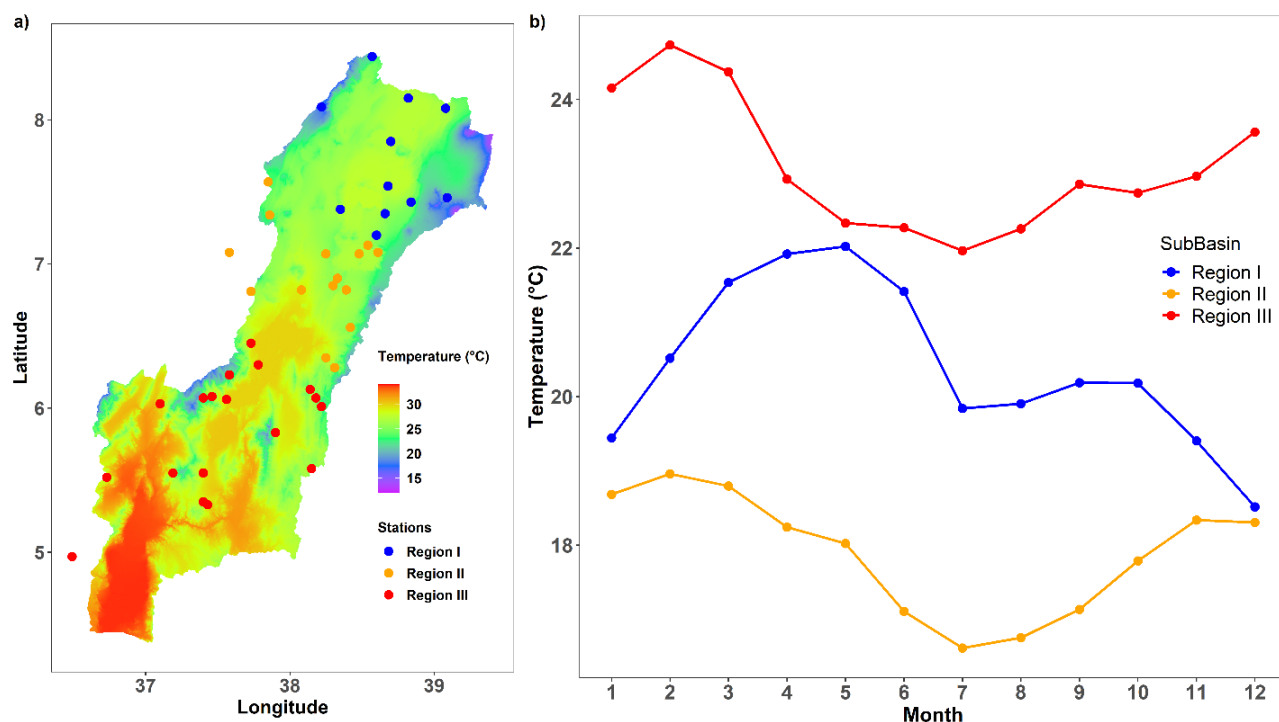


Figure 2-8: Temperature for the homogeneous regions of the Rift Valley Lakes Basin a) the spatial distribution of long term annual average temperature; b) the annual average temperature cycle obtained from the available weather stations.

2.7. Climate Pattern and Variability

Trend Analysis

The trend of an annual total rainfall and temperature series has been evaluated for the study area (Fig. 2-9). The ITA method has been applied to the annual rainfall time series of the three regions and to the annual average temperature time series of the whole study area. ITA provided visual inspection with quantitative trend slopes distinctively for low, medium, and high sub-values of the time series with physical interpretations. With regard, rainfall records have insignificant decreasing trends in low, medium, and high values for Region I and Region II and insignificant increasing trends in low value of Region III. In contrary to rainfall, temperature records have significantly strong increasing tendency in low, medium, and high values along the basin.

As a confirmation of the results of the ITA method, the significance of the trend has been verified with the Mann–Kendall test. The p value of the rainfall data was larger than 0.05 (ranging from 0.125 to 0.514). Therefore, with regard to the 5% significance level, no

significant trend in the rainfall data can be identified. However, the p values for temperature show a highly significant trend with p values below the standard 0.05 (ranging between 2.38×10^{-7} and 0.00096).

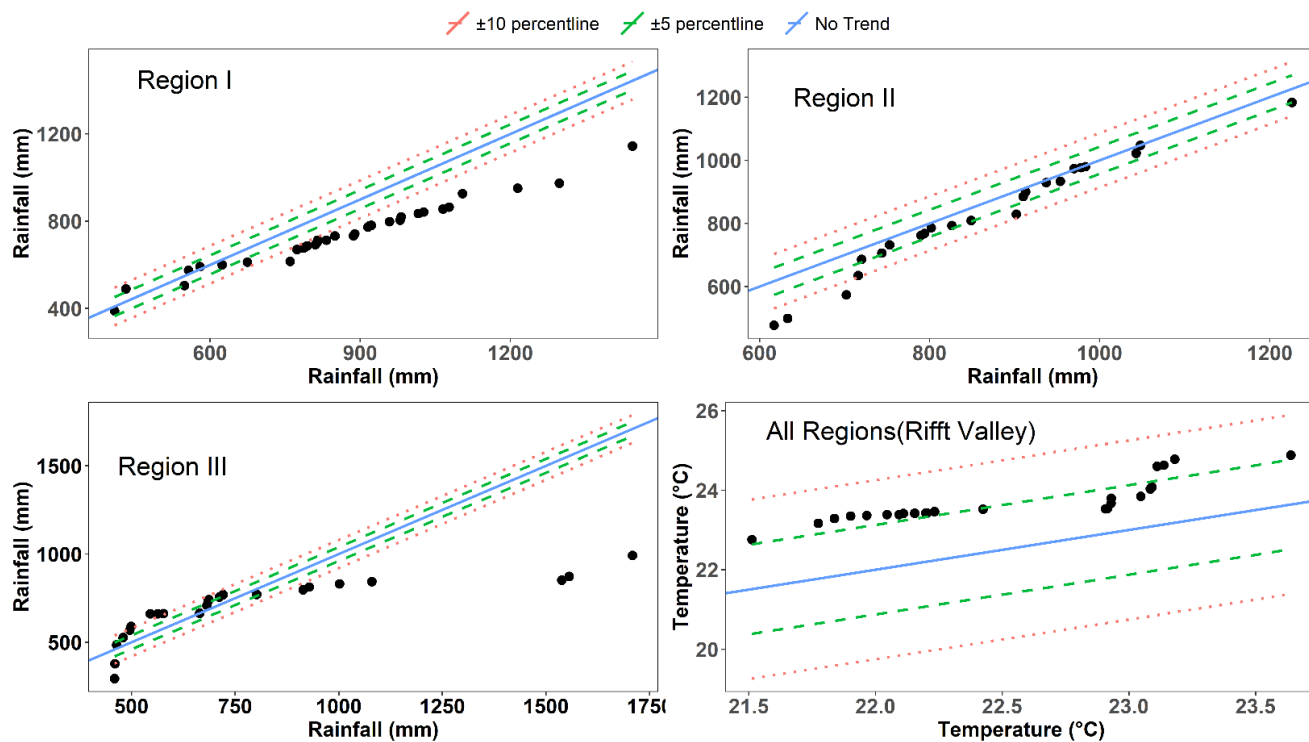


Figure 2-9: Innovative trend analysis of temperature over the Rift Valley Lakes Basin.

Climate dynamics and change point detection

The change point analysis presented in Figure 2-10, shows that there is an abrupt shift in rainfall and temperature over the Rift Valley Lakes Basin. The change point analysis results revealed that rainfall has shifted downward after the year 1983. Apparently, the rainfall of Region I was very dynamic from the year 1954 to 1970 with maximum probability of 0.784 of a change in mean and posterior means. And the climate was stable from 1970 to 1980 and again the region has experienced dynamic change from 1981 to 1992 and becomes stable after 1992. Likewise, Region II has experienced a decrease after a change point from the 1980s until 2015 and more recently, a large increase was observed. A moderate dynamic variation was observed before the change point as well. In Region III, after a change point in the mid-1980s, decreased posterior mean values have been maintained. Before 1983 the variation was very dynamic. In summary, the rainfall variation was highly dynamic before the 1980s and became more stable after the middle of the 1980s.

Likewise, a change point analysis has been performed for temperature for the entire basin, and the result revealed that an abrupt upward shift has occurred in 1980s. The posterior mean value of temperature was stable before the 1980 and from 1990 to 2010. However, from 1980 to 1990 and after 2010 it was very dynamic. The dynamics of temperature in the basin was mainly associated with the length of wet season and cloud cover. In fact, sunny days prevail during most of the year in almost the entire basin. The alternation of cloudy and clear sky conditions results in ample temperature differences and the annual temperature amplitude is limited and seems to be controlled by the intertropical circulation and the monsoon pattern rather than by elevation (Fazzini et al., 2015a).

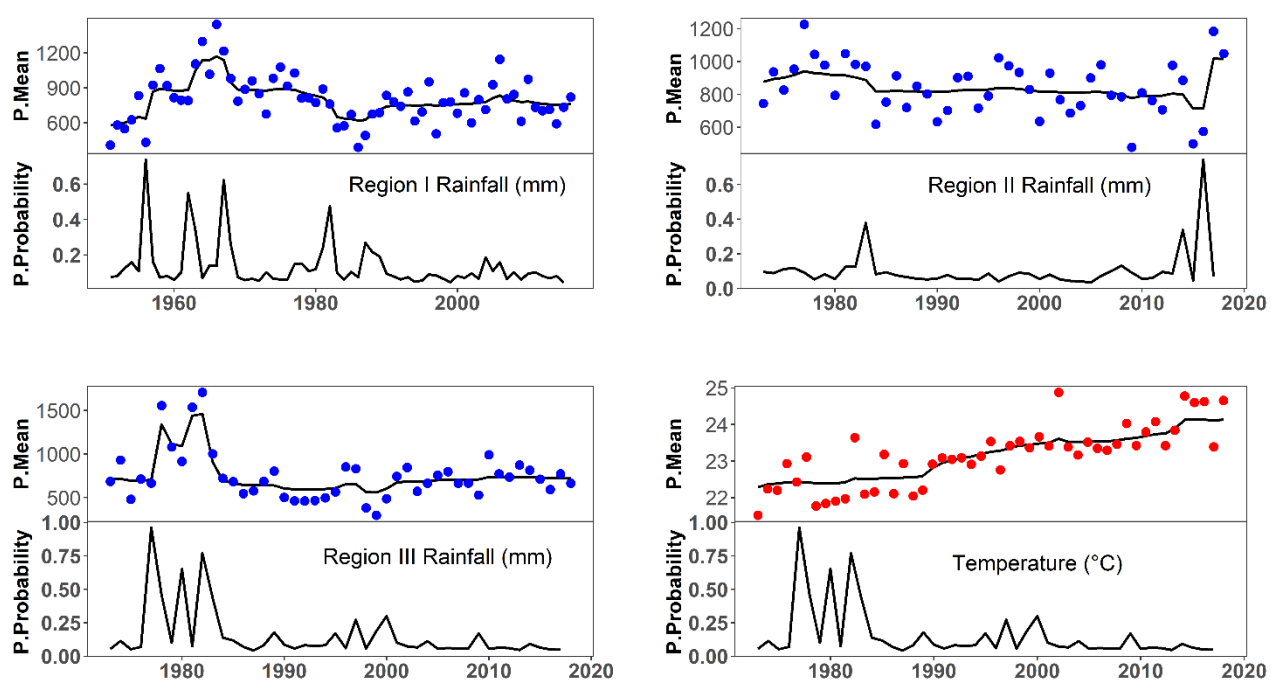


Figure 2-10: Change point detection (1970-2018): Estimated posterior mean (P. Mean), display the data along with the posterior means of each position and posterior probabilities (P. Probability), displays the proportion of iterations resulting in a change point at each position.

Onset and Offset of the rainy season

The result for the analysis of onset and offset of the rainy season are presented in Figure 2-11. Along with the mean of the 36 years long record, we show the maximum and minimum difference to the mean to visualize the variability of onset and offset from the mean. Thus, the long-term mean onset of the rainy season in Region I is in the second week of June and the rainy season ends in the last week of September. The onset is varying from mid-May to end of June and the offset is varying from the first week of September to the first week of November.

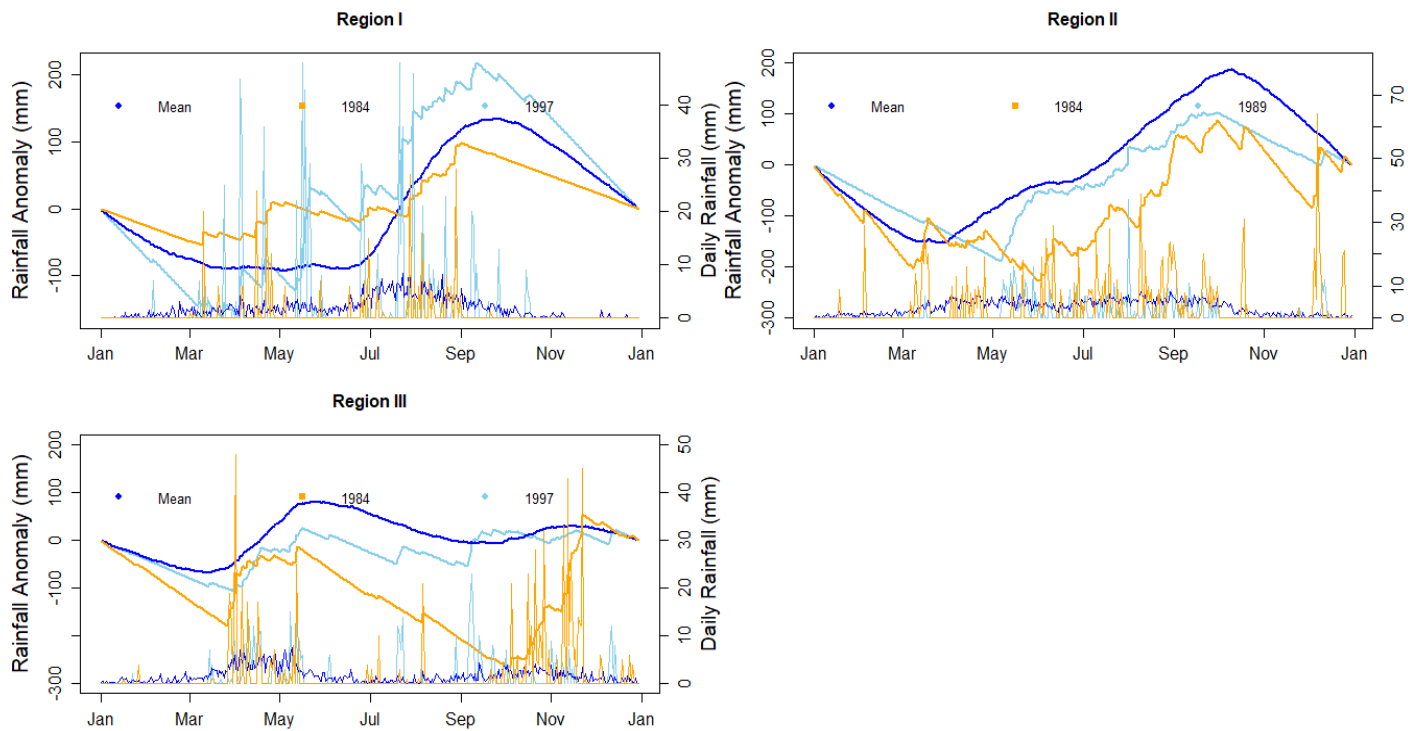


Figure 2-11: Onset and offset analysis across Rift Valley Basin using the daily cumulative rainfall anomaly based on a 30 days moving window.

Likewise, the onset of rainfall in Region II varies from the second week of March to the last week of April and the offset is varying from the last week of September to the last week of October. Its long term mean onset is in the third last week of March and the offset is in the last week of October. It has a long rainy season with a short break in June. In Region III of the basin, the first onset is varying from first week of February to the first week of April and the offset is varying from the second week of May to the last week of June. The second onset is varying from last week of August to mid-October and the offset is varying from the second week of September to the last week of November. The second long-term mean of onset and offset is the last week of September and the third week of November, respectively. However, the long-term mean of onset and offset of the first rainy season is mid-March and end of May, respectively. The long-term mean of onset and offset of the second wet season of Region III is the last week of September and the end of November, respectively. Both the onset and offset of the basin shows insignificant decreasing trends. These reveal that the rainfall starts earlier and lasts earlier. i.e., the wet season is shifting.

Wet and dry spells

The temporal patterns of the wet and dry spells in wet season of each region of the Rift Valley Basin are shown in Figure 2-12. The highest number of dry and wet spell days were observed in 1984 at Region III (151 days) and in 2001 at Region II (100 days), respectively. Region II experienced the longest wet spells compared to the other regions and Region I experienced the longest dry spells. There is high spatio-temporal variability of dry and wet spells across the basin (Figure 2-12). The Mann Kendall trend test indicates that no significant changes have been found for both, wet and dry spells in all regions of the basin; as the p values of wet and dry spells are larger than 0.05 (ranging from 0.219 to 0.836).

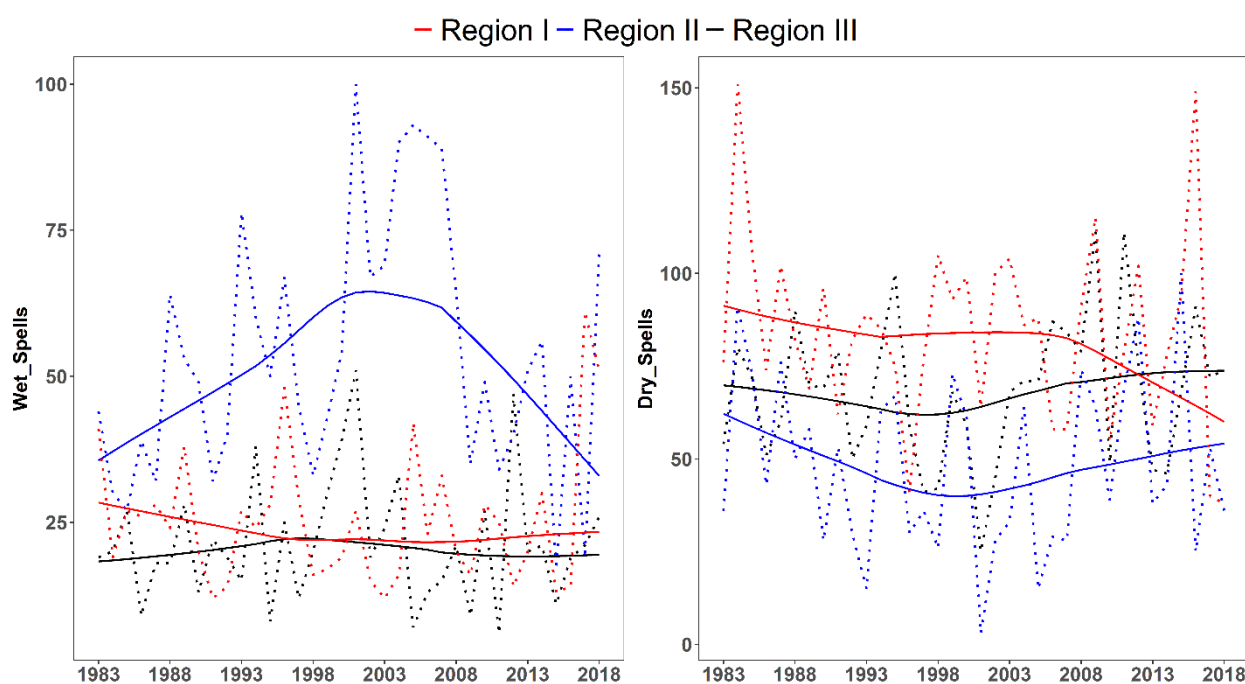


Figure 2-12: Wet and Dry Spells in all Regions of Rift Valley Basin

The variation of wet and dry spells is mainly associated with south-northward migration of the ITCZ resulting in longer wet spells in Region II and long dry spells in Region I.

2.8. Discussion

The rapid expansion of agriculture and decline of vegetation for the first two decades is mainly linked to the civil war between the socialist Dergue regime and Ethiopian People republic democratic front (EPRDF) in 1990/1991. During the war and after the fall of the Dergue regime, people used the natural vegetation land illegally for agriculture and settlement. In addition, after

the present government took power in 1991, it has embarked upon a new national land policy and agricultural expansion land use policy that promotes farming and the development of rural infrastructure aimed to raise food production and ensuring national food security (ARD, 2004). This has led to rapid reduction of the natural vegetation cover and rapid increase of agricultural land during the last three decades. Moreover, harvesting of trees for firewood and charcoal is another important activity reducing tree density of vegetation cover. Pronounced urban area increase resulted mainly from migration of people from rural to urban areas (Bundervoet, 2018) due to continuing ecological destruction, drought, famine, and war (Ezra, 2003) and the lack of necessary social infrastructures. An alarming decline of surface water areas in Region I of the basin can be linked to high abstraction of water from the lakes and the tributaries feeding the reservoirs for irrigation and industry (Jansen et al., 2007b, Legesse and Ayenew, 2006b). Especially the National Economic Development Strategy (NEDS) emphasizes the need for the agricultural sector to enhance food self-sufficiency, ensure food security at the household level, and for agriculturally led industrial development aggravating agricultural expansion. Due the fact that the subsistence agricultural system cannot assure food security, the government supported the development of irrigation systems that have higher water use efficiencies. In this regard, the government has put forward more than 31,000 ha small- and large-scale potential irrigation development projects in the basin. All these together put pressure on water resources in the basin. Contrarily, the area coverage of water resources has increased in Region III of the basin. This might be due to high surface runoff and sediment load associated with deforestation, and/or linkages of groundwater flow. Scientific evidences showed that the Ethiopian Refit Valley is an active tectonic and seismic region (Chorowicz, 2005c, Stamps et al., 2008b, Ring, 2014, Saria et al., 2014, Saria et al., 2006). This active tectonic movement faults might have created regional linkages of groundwater flow. However, this subject requires further investigation.

Apart from population growth and national land policy, high inter-annual climate variability has impacts on land use dynamics especially on water and wetland. The surface area of water and wetland has been decreased noticeably in the land use map of 2009, which is mainly associated with a reduction of annual rainfall in 2008/2009 and water abstraction e.g. for irrigation and industrial water use (Ayenew et al., 2008, Jansen et al., 2007b).

The onset, offset, wet spells, and dry spells are varying across the basin. Three homogenous climatological regions can be identified. The spatio-temporal variations of rainfall in the Rift Valley Lakes Basin are due to variations of topography and the north-south ward movement of

the ITCZ. The ITCZ oscillates annually between a southward location of 15°S in January and a northward location of 15°N in July (Diro et al., 2011c). The ITCZ arrives between the first week of February and the first week of April in Region III and will persist until end of May. Likewise, it arrives to Region II from second week of March to last week of April and persist until the last week of September to the last week of October. The ITCZ continues to move northward and arrives in Region I between mid-May and the end of June and persists until the first week of September to the first week of November. After the first week of September to the first week of November it starts to move back southward (Diro et al., 2009b, Lashkari et al., 2021a, Korecha and Barnston, 2007b). This gives rise to the bimodal rainfall pattern in Region II and Region III and the monomodal pattern in Region I of the basin. The variation of onset and offset window is depending on the weakening and strengthen of subtropical high-pressure systems (Dyer et al., 2022, Lashkari et al., 2021b). Various previous studies have investigated that the Ethiopian summer rainfall is affected by the variation of equatorial pacific sea surface temperature (SST) and its teleconnection with summer rainfall (Gleixner et al., 2017, Diro et al., 2011b, Korecha and Barnston, 2007b, Gissila et al., 2004b, Block and Rajagopalan, 2007b).

Apart from the spatio-temporal climate variability over the basin, also an abrupt climate shift has been identified in 1980s'. Many scientists have identified abrupt shifts of climate worldwide and the mechanisms behind the climate shift (Dansgaard et al., 1993, Johnsen et al., 1992, Broecker and Change, 2006, Clement and Peterson, 2008, Marotzke, 2000, Overpeck and Cole, 2006) and the implications of abrupt change for the future (Alley et al., 2003, Palmer et al., 2011). They have investigated the possible reasons for abrupt changes include global warming takes, melting of ice caps and glaciers, increased precipitation and other inflows of fresh water to the North Atlantic Ocean that weaken or shut down thermohaline circulation, resulting in cooling of the North Atlantic Ocean. This change in ocean circulation could disrupt the transfer of moisture eastward to Ethiopia, where the study area is located. Another possible explanation of the change point is the changing vegetation cover over the study area. The role of natural vegetation and savanna grass change on modifying the climate at local as well as at global level has been well documented (Da Silveira Lobo Sternberg and Biogeography, 2001, Holm et al., 2014, Sud and Fennessy, 1982). Therefore, rapid decline of vegetation cover might have led to the abrupt shift of climate over the basin. Also, insignificant decreasing rainfall trends and significant increasing temperature trends have been observed in the basin. These findings are in agreement with other studies in the basin and in other basins in Ethiopia (Tigabu et al., 2020, Ayenew, 2004c, Kassie et al., 2014b, Viste et al., 2013). Future climate change in the basin

may alter the wet and dry soil conditions, length of winter and summer, and crop yield, i.e., it may affect LULC patterns in the basin. Moreover, as climate is a significant driver of land degradation processes, future climate change can result in further LULC change (Smith et al., 2020, Sunderland and Rowland, 2019).

2.9. Summary & Conclusion

The land use pattern has changed significantly between 1989 and 2019 in the Rift Valley Lakes Basin. The agricultural land maintained the largest area share, followed by vegetation and water body. Moreover, the agricultural, barren land, and settlement share of land increased by 27.5%, 0.4% and 0.8%; vegetation land, wetland, grass land, and waterbody decreased by 24.5%, 1.6%, 2.1% and 0.5 respectively from 1989 to 2019.

The analysis of the land use dynamic degree showed that the dynamics of wetland change was the largest during 1989–2019 followed by grass land, and vegetation. Water areas, agricultural land, settlement area were persistent land use classes. These changes can be related to sustained and ongoing population growth. The rapid population growth associated with a dependency on rural economy contribute to the ongoing land use changes. Deforestation, overgrazing, agricultural expansion, water body declination becomes the emerging issues of the basin.

Water bodies are substantially declining in upper part of the basin because of high abstraction for irrigation, industrial, and other uses. However, in the lower part of the basin, the water bodies are increasing. The water area dynamics index (k) for the last decade (2009 – 2019) showed positive values. This is due to the appearance of a new lake near to south of Lake Chamo with a surface area of 10.45 km². In addition, the expanding of area of Lake Abaya and Chamo has its own contribution. Even though, further investigation is required, this study also thought the increasing of surface runoff and sediment load associated with deforestation has big contribution. Secondly, few studies have investigated that the major flow systems and groundwater flux into the lakes are controlled strongly by Rift faults (Ayenew, 2001). Therefore, the increasing of water in the lower part of the basin might be linked with active tectonic movement faults, and groundwater movement.

In addition to agricultural expansion, cutting tree for fuel and illegal settlement are also the main cause for deforestation of the basin. Apart from population growth and national land policy, highly inter-annual variability of rainfall has impacts on land use dynamics especially on water and wetland areas. Increasing agricultural production to meet rapidly growing food

demand through strength agricultural intensification policy while safeguarding vital ecosystem services and promoting social equality, lies at the heart of sustainable development.

The Rift Valley Lakes Basin is characterized by three climate zones and regimes and its summer (June–September) climate pattern controlled by several climatological features in the lower and upper troposphere (Hastenrath, 2012, Li and Hsu, 2018). These include the seasonal northward movement of the ITCZ, persisting over Ethiopia; formation of heat lows over the Sahara and Arabian landmasses; establishment of subtropical high pressure over the Azores, St. Helena, and Mascarene; southerly/southwesterly cross-equatorial moisture flow from the southern Indian Ocean, central tropical Africa, and the equatorial Atlantic; upper-level TEJ flowing over Ethiopia; and low-level jet (Somali jet) (Fekadu, 2015, Segele et al., 2009). The upper part (Region I) of the basin has a mono-modal rainfall pattern with low rainfall amount relative to other parts of the basin, while the middle (Region II) and lower part (Region III) of the basin have bi-modal rainfall patterns. The rainfall is highly variable both in space and time but its change is not significant. However, change of temperature is significant and highly variable both in space and time. Furthermore, climate variability is explained via onset, offset, and wet spell and dry spell of rainfall. All of them are highly variable within the window; and the window is varying from region to region in the basin. Currently, there is no well-organized onset and offset information dissemination system for farmers and other users. Since many crop seeds will damage if they wait more days in the soil and farmers obliged to sow two or three times during late of onset. Not only, is knowing of the length of wet season really important to select type of crop to grow. Very commonly farmers grow the same crop type each year based on their own indigenous knowledge, rather considering the onset and offset information of rainfall. This might have high impact on agricultural system and yield.

The change point analysis also well investigated the abrupt shift of climate, occurred in 1980s, across the basin. It also clearly identified the dynamic nature of climate over the basin. The abrupt shift and dynamicity of climate is linked with change in global ocean-atmosphere circulation (Hastenrath, 2012, Li and Hsu, 2018, Nicholson and lakes, 2019).

Developing adequate land use policy frameworks, enforcement regulations, and land use management plans could be effective to reduce the impact of land use change on ecosystem services. Diversification of climate adaptation strategies could be more effective in coping up climate variability impacts as the study area consists of various climate zone. To this end, the findings of this study, which shows the spatio-temporal dynamics of land use and climate

change could greatly enhance the awareness of concerned decision makers to devise relevant strategies for mitigation and adaptation of future climate and land change impacts in the basin.

3. Hydrological responses to land use and land cover change and climate dynamics in the Rift Valley Lakes Basin, Ethiopia

¹Ayenew D. Ayalew, ¹ Paul D. Wagner, Tibebe B. Tigabu, ³ Dejene Sahlu, and ¹ Nicola Fohrer

¹ *Department of Hydrology and Water Resources Management, Institute for Natural Resource Conservation, Kiel University, D-24118 Kiel, Germany*

² *Department of Land, Air and Water Resources, University of California, Davis, USA*

³ *Institute of Disaster Risk Management and Food Security Studies, Bahir Dar University*

Address to correspondence author: Ayenew Desalegn, Department of Hydrology and Water Resources Management, Institute of Natural Resource Conservation, CAU, D-24118 Kiel, Germany, E-mail: ayalew@hydrology.uni-kiel.de

Journal of Water and Climate Change (2023) 14 (8): 2788–2807,
<https://doi.org/10.2166/wcc.2023.138>.

Received: 01 March 2023/ Accepted: 26 June 2023/Published online: 14 August 2023

Abstract

Due to the rapid socio-economic development in the world, the pressures on water resources are increasing. Evaluating and understanding the hydrological processes and response to land use and land cover (LULC) change and climate dynamics is important for sustainable water resources development and management in a country. Therefore, it is important to address how does land use and land cover change, in combination with climate dynamics, affect the hydrologic cycle and water availability in a given basin, and what are the implications for water management and sustainability. To understand the change of spatial temporal water fluxes, the hydrologic model SWAT+ (Soil and Water Assessment Tool+) was applied to five selected watersheds within the basin. Four scenarios were developed using a combination of two climate periods (1980-2000, and 2001-2018) and two LULC maps (1989 and 2009) to evaluate the relative contribution of climate, LULC and the combined impact. With regards to the objective functions Kling–Gupta efficiency (KGE), the Nash–Sutcliffe efficiency (NSE), Percent bias (PBIAS) and RMSE-observations standard deviation ratio (RSR) the SWAT+ model performed

very well for daily streamflow in all watersheds. The change of water balance components, which were mapped for each hydrologic response unit, indicated a considerable spatial temporal variation of water fluxes in the watersheds. The percentages of change of precipitation, ET, and infiltration have decreased; but surface runoff has increased in the interference period compared to the baseline period. We have also found significant shifts in runoff seasonality, which coincided with high deforestation and agricultural expansion resulting in a decrease in low flows and an increase in peak flows and evapotranspiration. LULC change associated with rapid population growth combined with climate variability contributes greatly to the changes of the hydrologic system in the basin. The relative contribution of LULC was higher than climate variability during the study period. This study provides a good insight into the combined and isolated impact of climate dynamics and LULC change on water resources advancing the understanding of interactions of LULC, climate and hydrology.

Keywords: SWAT+; Land use and land cover change; Climate dynamics; Hydrological response; Rift Valley

3.1. Introduction

Land use and land cover (LULC) and climate change are two main driving forces that lead to large variations in hydrological processes (Feng et al., 2014, Savary et al., 2009, Wang and Hejazi, 2011a). LULC is the main controlling factor of local hydrological processes and its change can influence both surface water hydrology and soil hydraulic properties (Wagner and Fohrer, 2019, Bormann et al., 2007, Savary et al., 2009, Tigabu et al., 2019). Different LULC types have different effects on the runoff processes and the rates of infiltration, erosion, and evapotranspiration (ET) (Baldyga et al., 2008, Hernández-Guzmán et al., 2008); so LULC does not only change the volume of surface and groundwater, but also it changes the way of regional water movement. The expansion of urbanization, agriculture and deforestation will decrease water retention and infiltration, increase surface runoff, and flood frequency (Wang and Hejazi, 2011b). In addition, climate change, especially change in precipitation and temperature, greatly affects terrestrial water resources (Cao et al., 2018). One of the most crucial components of the hydrological cycle, streamflow, can be impacted by climate change both directly via changes in precipitation and indirectly through change in temperature (Yang et al., 2019). Although climate change is expected to have a negative influence on water resources and freshwater ecosystems in almost every part of the world, the magnitude and nature of this impact vary (Wagner and Fohrer, 2019, IPCC, 2007, Lei et al., 2022, Mahmoodi et al., 2021b, Tigabu et al.,

2021). Few studies also indicate that the changing climate pattern will significantly affect East African communities (Bahaga et al., 2016, Bahaga et al., 2015, Ongoma and Chen, 2017, Takele et al., 2020). For instance, there has been an increase of 1.5°C of the daily maximum temperature in the central Rift Valley Basin over a period of 37 years (Jansen et al., 2007b); and associated ET is also expected to increase in the range of 3-4% (Gadissa et al., 2019). This will result in water loss in the basin and the effect will further be exacerbated if the temperature continues to increase. The effects of land cover and climate changes on the runoff of a basin are of great interest to water resource planners, managers, and decision-makers (Helmschrot and Flügel, 2002). However, many water resources impact studies, particularly in the Rift Valley Lakes basin, have focused on the long-term evaluation of the basin's water balance due to climate change only (Raju and Kumar, 2018, Alemayehu et al., 2006, Awulachew et al., 2007, Ayenew and Tilahun, 2008, Jansen et al., 2007b, Legesse and Ayenew, 2006a). Even though, LULC change is taking place at a rapid rate, and deforestation activities are having a major impact on water resources, analysis of its effect on hydrological processes remains limited in the basin. Several recent studies have estimated the impact of LULC on hydrological processes in various parts of the world (Dile et al., 2013, Hernandez et al., 2000a, Ma et al., 2009, Yang et al., 2014); few studies also have investigated the combined effect of climate and LULC change on hydrological processes (Hernandez et al., 2000a, Jingjing et al., 2017, Zhao et al., 2018). Climate and LULC change on streamflow (Pan et al., 2017, Roderick et al., 2014). As changes in water resources also feedback on changes in LULC (Wagner and Fohrer, 2019), quantitative and combined assessment of climate and LULC change impact on hydrological processes is important for a sustainable development of land and water resources.

There are three fundamental types of approaches for quantifying the impact of LULC and climate change on stream flow: hydrological modeling, sensitivity analysis, and time series analysis (empirical statistical approach) (Li et al., 2022). The empirical statistical approach is mainly based on trend and correlation analysis of time series data (Ahn and Merwade), which are easy to apply but they require a long-term time series of hydro-climatic data (Jiang and Wang, 2016). This type of methods may not be able to capture the exact physical characteristic of the hydrological system (Liu et al., 2012). Sensitivity analysis is mainly based on the water balance components within a basin and can be applied to stream flow (Zhang et al., 2015). This method allows to estimate the sensitivity of the stream flow to climate change using sensitivity indices with few data (Tu et al., 2015, Wang et al., 2012), but cannot directly quantify the effects of LULC, which limits its value (Asenso Barnieh et al., 2020). Hydrological modeling

approaches usually divide the whole study period into a base period and an interference period, and the simulation results for these periods are then compared to quantitatively distinguish the effects of climate change and human activities on streamflow. Models need to consider a variety of parameters, and considerable efforts to establish a suitable model for analysis (Tan et al., 2020).

Previous studies have associated streamflow change with high abstraction of water for irrigation and industries (Ayenew, 2002, Kebede et al., 1994, Zinabu and Elias, 1989), climate change (Belete et al., 2015a, Alemayehu et al., 2006, Jansen et al., 2007b, Van Halsema et al., 2011b), environmental degradation (Ayenew, 2004a), volcano-tectonics and sedimentation (Le Turdu et al., 1999, Street and Grove, 1979), frequent earthquakes(faults) (Ayalew et al., 2004b, Belay, 2009). These studies focused on single driven impact analysis and do not quantify the relative impact contribution of these drivers on stream flow. However, the rainfall-runoff relations within a watershed are mainly driven by the interplay of climate, LULC and soil (Hernandez et al., 2000b); and understanding these impacts requires an accurate assessment of the different conditions for a given hydrological system. Therefore, an integrated hydrologic model is used to quantify the relative contribution of climate and LULC change for the basin region under various scenarios, so that a deeper understanding of the relative and combined influence of climate and LULC change can be obtained. The main objective of this research is to understand and evaluate the hydrological response to climate change and LULC dynamics. We hypothesize that the combined impact of climate and LULC dynamics will be stronger in changing water fluxes than the isolated impacts.

3.2. Materials and Methods

3.2.1. Study Area Description

The Great Rift Valley (GRV) is a 4,000 km long fault line that stretches from the Red Sea to Mozambique's and Zambia Valley. It is the single largest geographical feature in Africa and it transects Ethiopia, Kenya, Uganda, Rwanda, Burundi, Zambia, Tanzania, Malawi, and Mozambique (Gregory, 2018). It is one of the most important basins in Ethiopia and occupies an area of 55,050 km².

The climate of the basin is heterogeneous in space and time. With arid, semi-arid, humid and semi-humid subbasins, it is characterized by low rainfall, high temperature, and high evapotranspiration. The basin is characterized by three climate regions. The Abijata-Ziway

subbasin which is characterized by low annual average rainfall ranging from 400 mm to 860 mm with one peak in August. The second basin, Abaya-Chamo subbasin, is characterized by relatively higher annual precipitation ranging from 704 mm to 1200 mm with a bimodal climate pattern with peaks in April and August. The Segen subbasin is characterized by a bimodal rainfall pattern with peaks in April and October and receives an average annual precipitation ranging from 500 to 1100 mm. The temperature varies throughout the basin ranging from 10°C to 36°C, the warmest on rift floor to frost-prone in the Afro-alpine zone. The southern part of the Rift Valley is lower in elevation, warmer, and drier than the other parts of the basin.

The current study has been conducted in the Ethiopian part of the Rift Valley Lakes basin located between 36°00' and 40°00' E and 4° and 9°00' N. It extends from the Afar depression southwards to Kenya across the broad basins of Abijata-Ziway, Abaya-Chamo, and Segen (Fig. 3-1). Five watersheds were selected within the basin which have relatively good data quality and that could exemplarily represent the entire basin. Meki and Katar are selected for a monomodal climate regime; and Bilate, Gelana and Gidabo watersheds are selected for a bimodal climate regime.

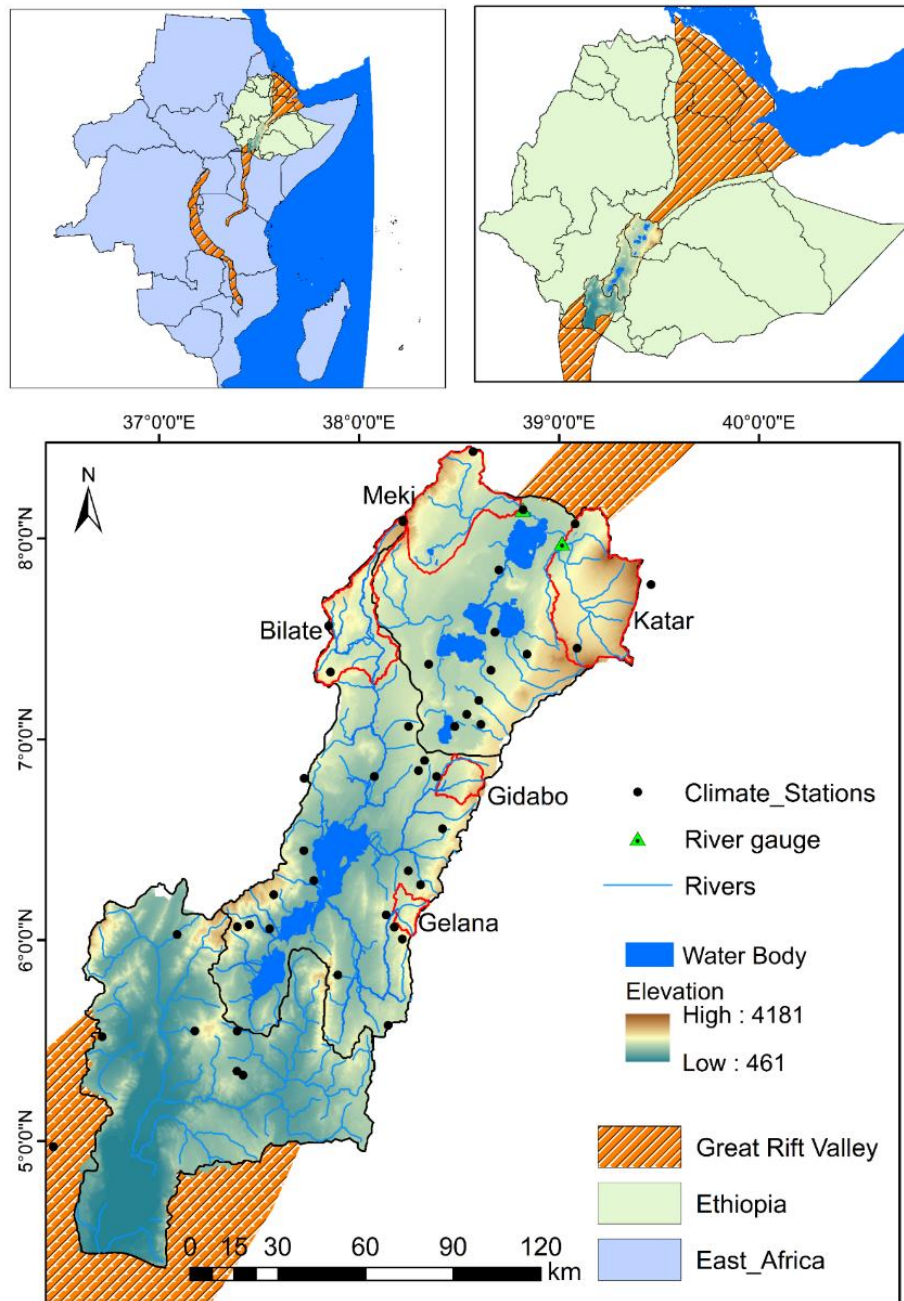


Figure 3-1: Topography of the Ethiopian Rift Valley Lakes Basin as well as the river network, river gauge, and the meteorological stations used for modeling.

The Ethiopian Rift Valley Lakes basin consists of a chain of lakes, streams, springs, and wetlands with unique hydrological characteristics. Based on the digital elevation model (USGS) data, the slope ranges from 0 to 161%. The slope class smaller than 2% accounts for about 7.1%, the slope class within the range of 2-4% accounts for about 19.5%; the slope class within the range of 4-8% accounts for about 72.0%, and the rest, 1.4% has a slope range

from 8-161% from the total area. Agricultural land is the most dominant land use followed by vegetation and water body.

3.2.2. Spatial and Hydro-climatic Data

The main hydrological characteristics of the basin have been acquired from the climate, topography, land use, and soil properties. Time series of climate data for 44 stations (1981-2018), LULC map of 1989 and 2009 in previous research (Ayalew et al., 2022b), stream flow (1983 – 2000), the Shuttle Radar Topography Mission digital elevation model (SRTM DEM) (30x30), and soil data were used for this study (Table 3-1). The SRTM DEM has been used, from which slope, river network, and watershed boundaries are obtained. Selected soil physical properties and the area coverage of each soil type were classified based on the requirements of the SWAT+ model.

Table 3-1: List and sources of spatial and hydro-climatic data used for this study

Data	Sensor	Resolution(m)	Access Date	Sources
Landsat-5	TM	30	Feb 18,1989 & Mar 03, 2009	http://earthexplorer.usgs.gov
STRM DEM		30	2014-09-23	http://earthexplorer.usgs.gov
Soil		30	2016	MoWIE
Stream flow		-	1980-2005	MoWIE
Climate		-	1980-2018	NMA

TM - Thematic Mapper, MoWIE- Ministry of water irrigation and electric city, NMA - Ethiopian National Meteorological Agency

3.2.3. Methodology

3.2.3.1. Hydrologic Model

The hydrological system and processes of this basin are modeled using the Soil and Water Assessment Tool Plus (SWAT+), a completely revised version of the SWAT model. It is more flexible than SWAT in terms of the spatial representation of interactions and processes within a watershed (Bieger et al., 2017a). Some algorithms used to calculate the processes, the structure and organization of the code, the input and output files and some parameters have been modified in the model (Bieger et al., 2017a).

SWAT+ simulates the hydrological processes from precipitation to streamflow using the water balance equation. The algorithm simulates a land and a water phase, in which the model

simulates soil water content, surface runoff, evapotranspiration, infiltration, percolation, and return flow on a daily basis (Moriiasi et al., 2015). The variable storage routing method was used for river routing and SCS curve number infiltration method was used. The Hargraves estimation equation was also used to calculate the potential evapotranspiration. The Hargreaves method is a potential ET estimator for data-scarce regions, requiring only minimum and maximum temperatures (de Sousa Lima et al., 2013b, Moeletsi et al., 2013b).

Apart from the spatial scale, depend on the concern of the analysis, SWAT+ simulates at daily time scales. Each term of the water balance equation has detailed physical processes that are interlinked in a harmony related to the atmosphere-vegetation-soil consortium. Further details of the model are available (<http://swatmodel.tamu.edu>) and literature (Bieger et al., 2017a, Arnold et al., 2018, Bieger et al., 2019).

Currently, SWAT+ is tested in few watersheds across the world, where the results from SWAT+ are favorable compared to the previous model version (Wagner et al., 2022); and SWAT+ is also capable to simulate streamflow (Bieger et al., 2019, Arnold et al., 2018, Wu et al., 2020). It can simulate the quantity and quality of surface and ground water resources from a hydrological response unit to basin scale. It is also suitable and capable to assess the long-term impact of climate change, land use change, and watershed management practices on water resources. It characterizes the spatial heterogeneity of a watershed, each watershed has been divided into multiple homogenous hydrological response units based on a unique combination of land use, slope, and soil characteristics (HRU) (Gassman et al., 2007). This spatial unit is assumed to respond similarly to hydrological inputs in SWAT+. In this study, the hydrological processes are evaluated from the outputs of HRU and watershed levels.

3.2.3.2. Model Parameterization, Calibration, and Validation

In the current research, local sensitivity analysis/ Morris' screening (one factor at a time [OAT]) was adopted for 18 parameters from which ten were found to be sensitive for streamflow in five watersheds (Table 3-2). Two of the watersheds (Katar and Meki) are from the monomodal rainfall region (R I) and three of the watersheds (Binate, Gidabo and Upper Gelana) belong to the bimodal rainfall region (R II). We found the same sensitive parameters for all watersheds, but different ranges due to different catchment characteristics and rainfall patterns. The largest changes in response to parameter perturbations were selected by combining the KGE (Gupta et al., 2009), the NSE (Nash and Sutcliffe, 1970), percent Bias (PBIAS), and RMSE-observations standard deviation ratio (RSR).

Table 3-2: Calibration parameters and the upper and lower boundaries used for calibration

Parameters	Description	Limit		Change	Fitted range			
		Min	Max		R I		R II	
					Min	Max	Min	Max
CN2	Condition II curve number	-15	+15	abschg ^a	-5	+5	-15	-10
Sol-Awc	Available water capacity of the soil layer (mm H2O/ mm soil)	-0.25	+0.25	abschg	-0.16	+0.15	-0.16	+0.15
ESCO	Soil evaporation compensation coefficient	0	1	absval ^b	0.01	0.3	0.01	0.15
SURLAG	Surface runoff lag Coefficient(days)	0	24	absval	0.1	10	0.1	10
PERCO	Percolation coefficient (mm H2O)	0	1	absval	0.01	0.5	0.01	0.3
LATQ_CO	Lateral flow contribution to reach (mm H2O)	0	1	absval	0.01	0.3	0.01	0.3
ALPHA_BF	Baseflow recession constant fast aquifer (days)	0	1	absval	0.01	0.6	0.01	0.3
k	Saturated hydraulic conductivity (mm h ⁻¹)	-45	+45	pctchg ^c	-10	+15	-10	+15
EPCO	Plant uptake compensation factor	0	1	absval	0.6	0.9	0.6	0.9
z	Soil depth (mm)	-45	+45	pctchg	-15	+0	-15	+0

where, R I and R II are regions of a basin having a mono modal and bimodal rainfall, respectively. a abschg^a adds an absolute value to the initial parameter value; b absval^b replaces the initial parameter value with an absolute value; c pctchg^c increases or decreases of the initial parameter value by the given percentage of the value.

The streamflow data at the watershed outlet (at the gauges) from 1980 to 2000 was split in to three periods for model warm-up (1980 to 1982), model calibration (1983 to 1994) and validation (1995 to 2000). For calibration, 5000 parameter sets were generated by Latin Hypercube Sampling (Soetaert and Petzoldt, 2010a) using the parameter ranges given in Table 3-2. The model configurations were evaluated for the same 5000 parameter sets. For each parameter set a model run was performed and the final parameter set was selected based on the best combined KGE, the NSE, and percent Bias (PBIAS) values, so that the KGE, NSE, PBIAS are used as an objective function in this research. The model was also examined during the validation period with the same parameter set. Calibration and validation were carried out in R using the packages FME for Latin Hypercube Sampling (Soetaert and Petzoldt, 2010a), hydroGOF for model evaluation (Zambrano-Bigiarini, 2014), and the packages zoo (Zeileis and

Grothendieck, 2005) and xts (Ryan and Ulrich, 2011a) for data processing. In addition to statistical performance evaluation, visual inspection of the hydrography and flow duration curve (FDC) could provide information about the overall qualitative match between measured and simulated streamflow. The performance evaluation is based on the daily temporal scale.

The annual average water balance analysis does not reflect the interannual variability of water balance components. The flow signals are averaged on an interannual scale and difficult to distinguish which flow signals are impacted in the annual water balance analysis. To avoid this limitation, we used FDC to evaluate the seasonal variation of streamflow for the baseline and interference periods. The shape of the curve is an index of the natural storage in the watershed, including the groundwater. Since the dry season flow consists entirely of return flow from the groundwater, i.e., the lower end of the FDC indicates the general characteristics of shallow aquifers. Therefore, flow signals were determined from the FDC based on the exceedance probability threshold. Here, low flow signals are defined as $\geq 75\%$ of the exceedance probability, while higher flow signals are defined as $\leq 20\%$ of the exceedance probability and the rest are mid-flow. The choices of thresholds for disaggregation were based on earlier studies (Pfannerstill et al., 2014, Yilmaz et al., 2008).

3.2.3.3. LULC Classification and Change Analysis

The land use has been classified using pixel-based ensemble machine learning algorithms Random Forest on R environment for the years 1989 and 2009 in previous research (Ayalew et al., 2022b). The spatio-temporal land use dynamics have been quantified and compared with the help of dynamics and transition matrix indexes (Singh et al., 2017).

3.2.3.4. Scenario Combinations

To evaluate the impacts of climate change and LULC on hydrological processes, scenario combination is often used when simulating the water balance components within the hydrological models (Guo et al., 2014). The result as shown in subsection 3.5, the baseline period (1980–2000) and the interference period (2001–2018) can be determined, and then, the scenarios for quantitative attribution analysis can be set as shown in Table 3-3.

Table 3-3: Scenarios for quantifying attribution analysis

Scenario	LULC	Climate data	Objective
S1	1989	1980-2000	Baseline period
S2	1989	2001-2018	contribution of climate change
S3	2009	1980-2000	contribution of LULC
S4	2009	2001-2018	combined impact

S1 is scenario regarded as the reference scenario, which uses the LULC and climate data in the baseline period. By comparing the simulation results under S1 and other scenarios (S2, S3, and S4), the contributions of climate changes and LUCC to water balance components (e.g., the runoff, lateral flow, percolation and ET) in a watershed has been quantified. The LULC data in the baseline period and climate data in the interference period are used to quantify the contribution of climate change (S1 and S2). Furthermore, to quantify the contribution of LULC, S3 is designed using the LULC data in the interference period and climate data in the baseline period. Also, S4 is designed to quantify the combined impacts of both climate change and LULC using the LULC and climate data in the interference period.

The relative contribution of climate change and LUCC to the water balance components was determined using the sensitive method:

$$\alpha_l = \frac{Q_2 - Q_1}{|Q_1 - Q_4|}$$

$$\alpha_c = \frac{Q_3 - Q_1}{|Q_1 - Q_4|}$$

$$\alpha_{com} = \frac{Q_4 - Q_1}{|Q_1 - Q_4|}$$

Where Q_1 , Q_2 , Q_3 , and Q_4 are the mean annual simulated surface runoff under S1, S2, S3, and S4 scenarios; and α_l , α_c and α_{com} denote the relative contributions of LUCC, climate variability and combined effect on the water balance components, respectively.

3.3. Results and Discussion

3.3.1. Model Performance

Model calibration and validation have been carried out for daily streamflow following the sensitivity analysis. The performance of the model run for each watershed was evaluated using

objective functions NSE, PBIAS, KGE, PBIAS, and RSR (Table 3-4). The statistical indices of the model showed that the model has strong predictive capability in all watersheds during both calibration and validation periods.

The SWAT+ model seems to overestimate the annual average ET ranges from 629.1 mm to 1053.0 mm, but other research showed also that the ET is very high over the basin (e.g. 985.5 mm/a (Meaza et al., 2019), 958.3 mm/a (Daniel and Abate, 2022), 900 mm/a (Billi and Caparrini, 2006). As a confirmation, the observed annual evaporation data from 2000 – 2018 was obtained from Arba Minch meteorological station and it shows that the evaporation ranges from 630 mm to 747 mm. This indicates that the model result is reliable.

Table 3-4: Daily and annual average model performances

Watershed	Method	Objective functions				Water balance components					
		KGE	NSE	PBIAS	RSR	Precip	Qsur	Qlat	Perco	ET	ΔS
Meki	Cal.	0.81	0.70	-1.6	0.54	872.7	92.3	20.8	13.6	742.4	3.7
	Val.	0.73	0.64	-2.4	0.68	865.5	85.6	31.3	10.8	732.4	5.5
Katar	Cal.	0.83	0.72	1.0	0.52	779.4	108.2	23.3	14.6	629.1	4.2
	Val.	0.72	0.66	1.4	0.65	776.2	105.2	22.4	10.3	635.3	3.2
Bilate	Cal.	0.81	0.71	-1.8	0.62	1144.3	141.6	53.7	40.4	905.2	3.3
	Val.	0.76	0.65	-3.4	0.68	1160.1	155.0	48.6	40.2	912.1	4.2
Gidabo	Cal.	0.79	0.65	-0.6	0.56	1097.4	200.6	73.4	28.3	789.7	5.4
	Val.	0.68	0.61	-1.2	0.69	1111.9	202.1	62.7	48.5	792.1	6.6
Gelana	Cal.	0.84	0.73	-0.4	0.52	1213.2	126.0	35.4	17.3	1033.2	1.4
	Val.	0.76	0.67	-0.6	0.61	1251.9	134.0	40.6	20.9	1053.0	3.5

* ΔS (Precip, Qsur, Qlat, Perco, and ET) is change in storage.

The FDC and hydrograph (Figure 3-2 & 3-3) also indicate that there is very good agreement between measured and simulated streamflow. The model is able to capture high, middle and low streamflow during the calibration period in all watersheds.

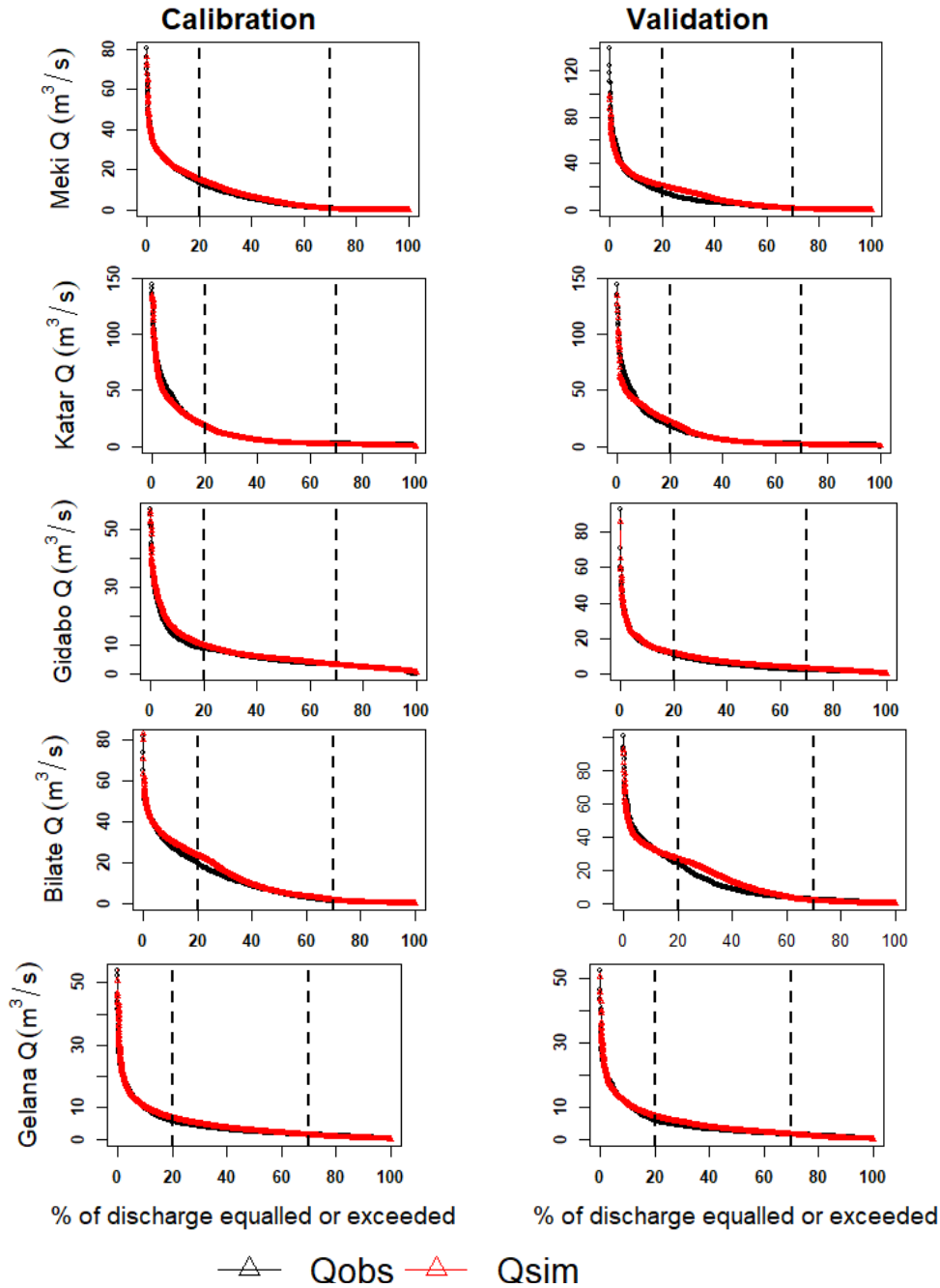


Figure 3-2: Flow duration curves of simulated (Q_{sim}) and observed (Q_{obs}) daily streamflow for the calibration and validation period.

However, the flow duration curve segment from 20% to 40% exceedance probability indicated an overestimation of streamflow by the model, especially in the Meki, Bilate and Gelana watersheds during the validation period. The model also underestimates high flows and low flows during validation period in all watersheds. Furthermore, as indicated in Table 3-2, the best model run was obtained with the base flow recession constant, $ALPHA_BF \leq 0.3$. This indicates that the groundwater flow response to changes in recharge is slow in the basin. The value of PERCO is also ≤ 0.5 which indicates that the water leaves the bottom of the root zone

quickly and reaches the shallow aquifer. The majority of the soil in the basin is sand and sandy loam which favor a fast percolation and groundwater recharge. The hydrologic response in the lateral flow is also fast, as values of LATQ_CO are ≤ 0.3 .

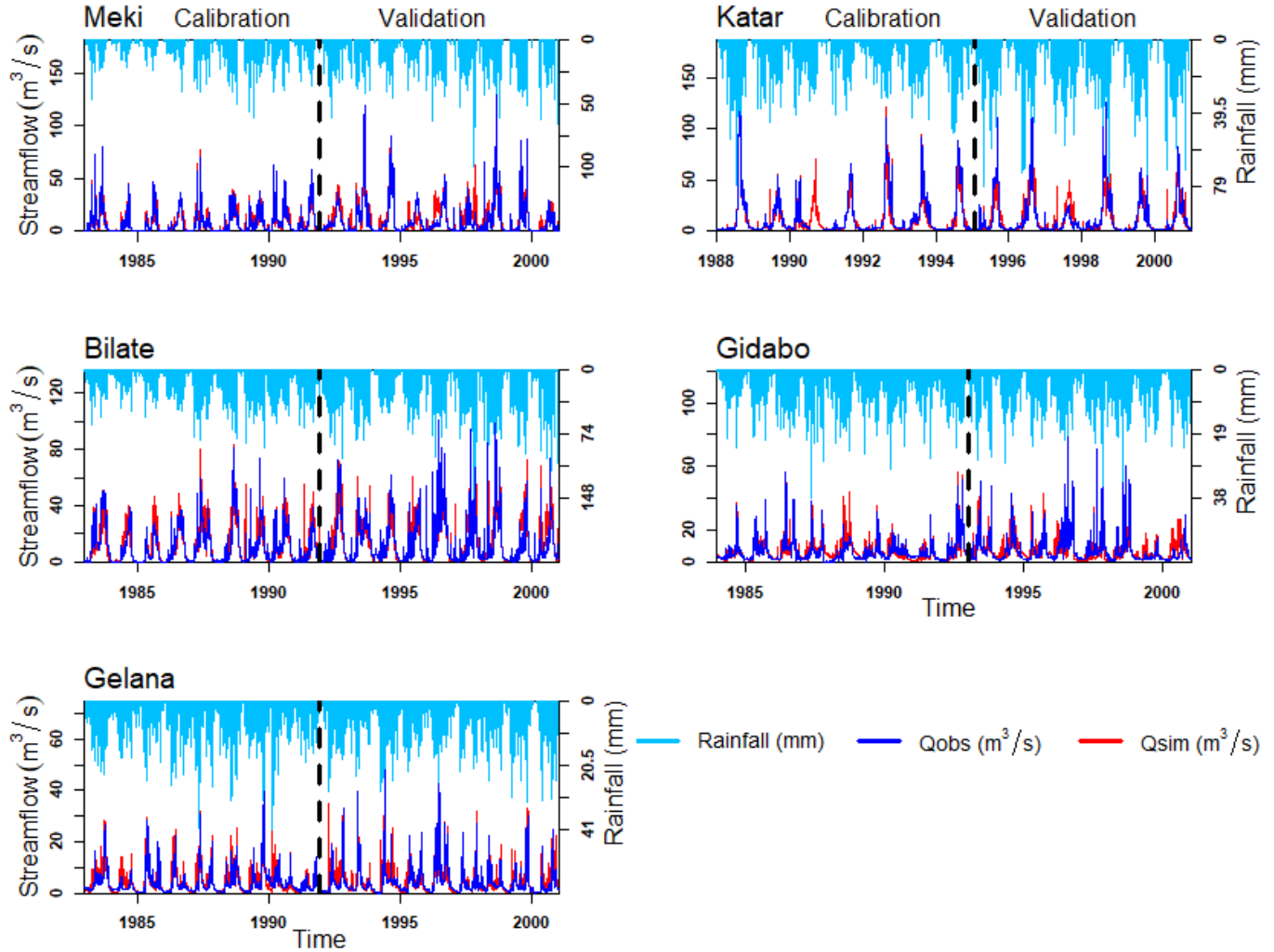


Figure 3-3: Hydrograph of simulated (Q_{sim}) and observed (Q_{obs}) daily streamflow for calibration and validation period.

3.3.2. LULC Change

The LULC map in 1989 and 2009 and percent of area change presented in (Figure 3-4 and Table 3-5) revealed that the area of agricultural land and settlement land had increased by 23.1% and 0.4% from the total land share, respectively; while the areas of shrub land, forest land, wetland and water bodies decreased by 13.0, 7.5%, 1.9% and 1.1% from the total land share, respectively (Ayalew et al., 2022b).

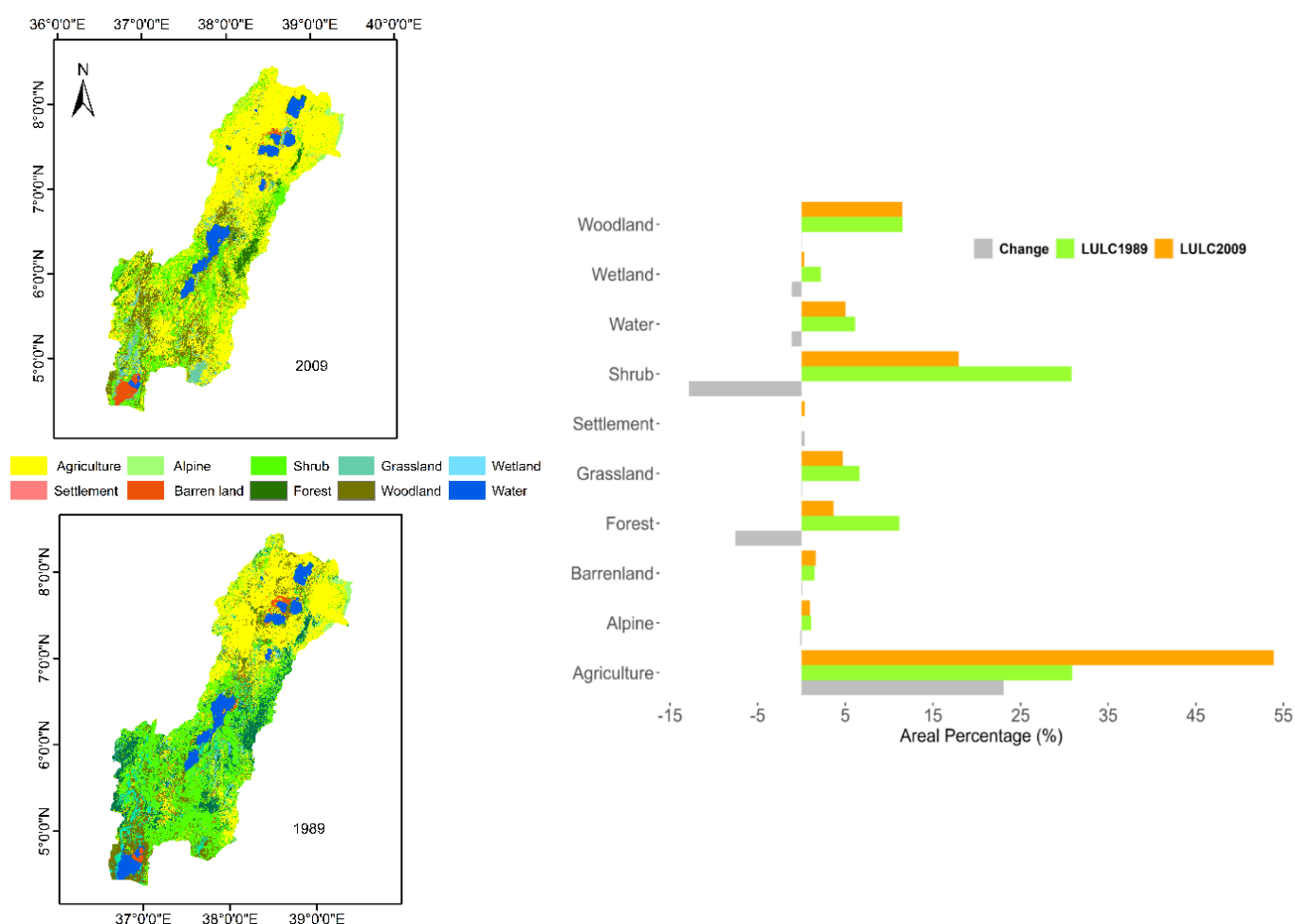


Figure 3-4: LULC maps in 1989 and 2009 and change

In addition, the overall temporal dynamics of land conversion ('from-to') has been evaluated as presented in Table 3 - 5. The LULC conversion matrix indicates that most land uses have changed to agricultural land. It is worth mentioning that the maximum land transformation was observed in wetland as only 2.3% of its original cover remained unchanged. Water, alpine, agriculture, and settlement have relatively high shares of persistent land use (>65%). Since different LULC types have different impacts on water balance components (like ET, surface runoff, lateral flow and percolation) of a watershed, these high transformations of LULC over the basin would have high effect on the water balance components.

Table 3-5: Conversion matrix of LULC in% area

2009												
1989	Class	Agriculture	Alpine	Barren	Forest	Grass	Settlement	Shrub	Water	Wetland	Wood	Total
	Agriculture	27.36	0.11	0.05	0.12	0.48	0.13	1.82	0.04	0.04	0.74	30.88
	Alpine	0.34	0.66	0.00	0.00	0.00	0.01	0.09	0.00	0.00	0.00	1.10
	Barren	0.49	0.00	0.23	0.01	0.03	0.02	0.31	0.19	0.00	0.20	1.48
	Forest	4.43	0.10	0.02	2.44	0.10	0.03	2.95	0.05	0.08	0.99	11.19
	Grass	1.88	0.00	0.05	0.02	1.45	0.01	0.55	0.00	0.00	0.67	4.62
	Settlement	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01
	Shrub	12.79	0.08	0.05	0.78	1.07	0.09	9.13	0.08	0.07	6.77	30.89
	Water	0.02	0.00	1.17	0.02	0.14	0.00	0.09	4.63	0.00	0.03	6.11
	Wetland	1.11	0.01	0.00	0.20	0.01	0.01	0.68	0.02	0.05	0.08	2.17
	Wood	5.59	0.00	0.05	0.07	1.45	0.05	2.26	0.04	0.01	1.99	11.53
	Total	54.02	0.97	1.60	3.67	4.72	0.37	17.89	5.04	0.25	11.48	100.0
Loss/gain	23.14	-0.14	0.13	-7.52	0.11	0.32	-13.0	-1.08	-1.92	-0.04		

3.3.3. Climate Dynamics

To evaluate the individual impact of LULC and climate dynamics on hydrological processes, we used the LULC and climate dynamics results from the previous research (Ayalew et al., 2022b). The dynamic nature of rainfall and temperature is different from 1998 to 2000 and 2001 to 2018; and combining the change point tests for precipitation and temperature, the middle year 2000 was regarded as the change point from 1980 to 2018. Therefore, in this study, years before 2000 were classified as the baseline period and years after 2000 were classified as the interference period. Then, the temporal trends of precipitation and temperature during these two periods could be obtained using the Mann–Kendall trend test. Different trends could be observed for these two climatic variables since 1980, and the annual changing rates of precipitation were not quite large rather temperature.

Table 3-6: Climate variability trend test

	Rainfall_Region I		Rainfall_Region II		Rainfall_Region III		Temperature	
	Base line	interference	Base line	interference	Base line	interference	Base line	interference
Tau	-0.147	-0.094	-0.0667	-0.123	0.133	0.157	0.39	0.6
P	0.38	0.5995	0.695	0.48411	0.415	0.3833	0.0144	0.000359

Precipitation showed an insignificant decreasing trend in both periods, with a p-value of the baseline period (ranging from 0.381 to 0.695) and interference period (ranging from 0.383 to 0.60) while temperature records have a significantly strong increasing tendency for interference

period and significant increasing trend for baseline period with a p-value of 0.00036 and 0.0144 with regard to the 5% significance level standard, respectively.

3.3.4. Water Balance Change Analysis

To understand the responses of hydrological processes to climate and LULC dynamics, the spatio-temporal variation in different water balance components (i. e., ET, surface runoff (Qsur), Lateral flow (Qlat), and Percolation (Perco)) at average annual time scales has been analyzed for the basin between 1980 and 2018 (Fig. 3-5 & 3-6). The results indicate that the spatio-temporal distribution of water balance components vastly varied across the basin. Compared to the baseline period, rainfall and evapotranspiration were decreased in all watersheds. The variation of change of annual average ET and rainfall ranges from -40% to 10% and - 20% to 5%, respectively across the watershed HRUs, with higher changes in the lower parts of the basin (Gidabo, Gelana and Bilate watersheds).

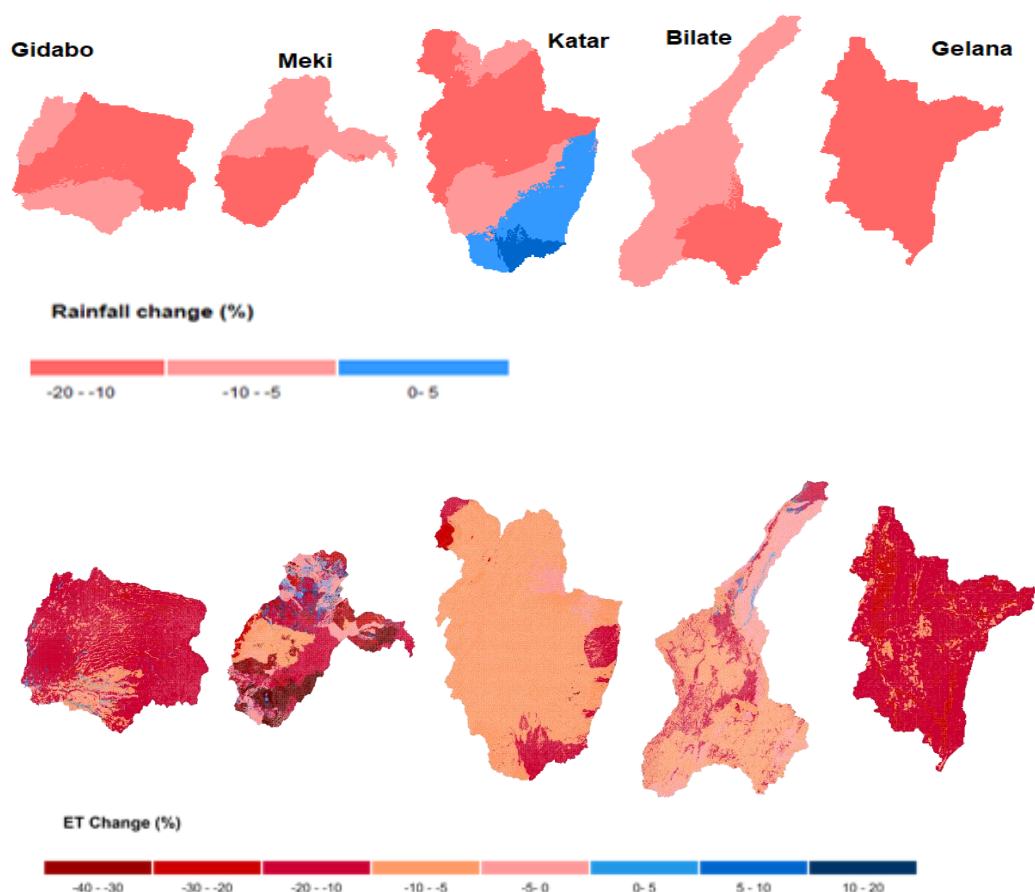


Figure 3-5: Change of spatio-temporal distribution of change of rainfall and ET during 1981-2018

]

The percolation varies across the basin with the annual average change value ranging from 7.8% to 13.14%, -4.47% to -16.51%, and -3.28% to -10.19%, respectively. High variation was observed in Bilate, Gelana and Gidabo watersheds. The variation of change of spatio-temporal distribution indicating that different watersheds have diverse runoff generating capacity (Fig. 3-6).

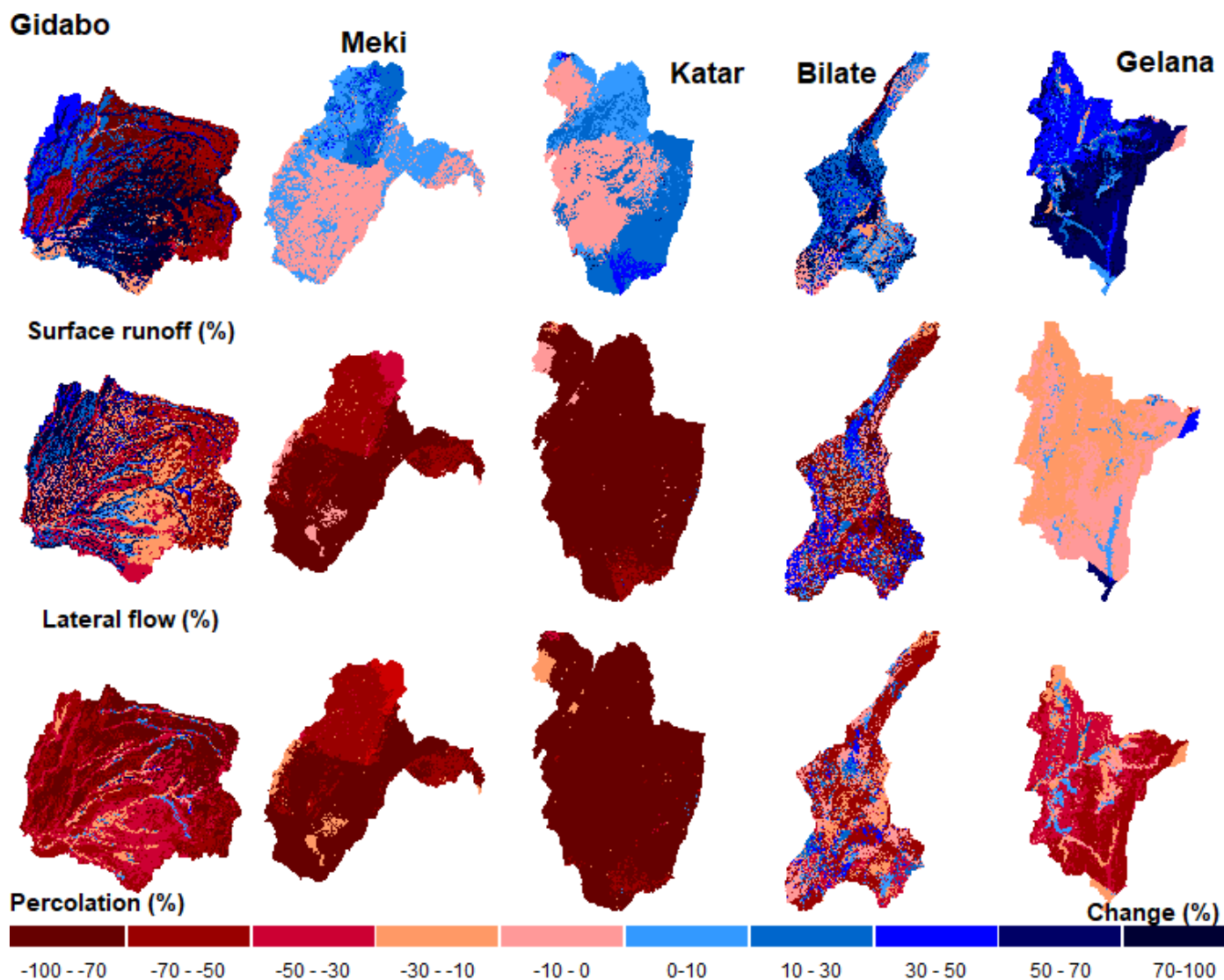


Figure 3-6: Spatio-temporal distributions change of water balance components (surface runoff, lateral flow and percolation)

The FDC illustrated in Figure 3-7 depicted also how flows changed within the two periods (1983-2000 and 2001-2018). High flows and low flows have changed in all watersheds. In all watersheds except Bilate, low flows (exceeded of 70% of the time) have decreased. Whereas, high flows (exceeded of 20% of the time) appear to have increased in all watersheds. In Bilate watershed, the full range of flows appears to have increased. In Bilate and Gelana watersheds,

the mid- range flows appear to have increased. However, in Meki, Katar and Gidabo watersheds, the mid- range flows appear to have decreased. As the FDC is plotted on a normal scale, even the modest difference between the two curves represents a pronounced increase in high and decrease in low flows (e.g., those that are exceeded 20% and 70% of the time). The rivers have experienced increases in high and decrease in low flows within the past two decades.

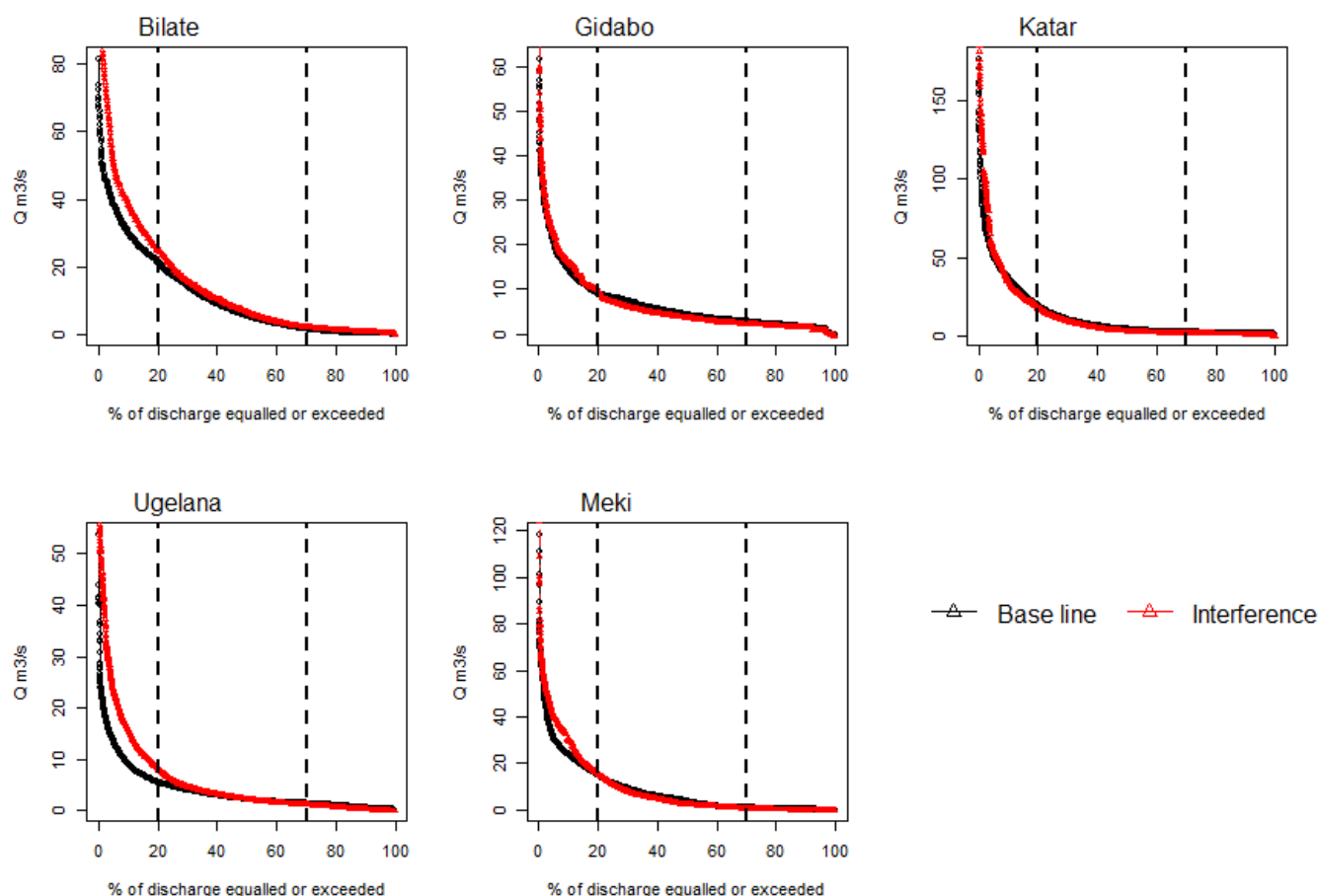


Figure 3-7: Flow duration curves for the base line and interference periods. Changes in flows are attributed to changes in LULC, as well as changes in rainfall.

3.3.5. Attribution of LULC and Climate Dynamics on the Hydrology Processes

Table 3-7 shows the evaluation of the LULC, climate dynamics, and combined impact on the water balance components during the study period. The result showed that change in LULC had a positive impact on surface runoff while having a negating infiltration and ET. Although climate dynamics positively influenced ET in all watersheds, and had a negative impact on surface runoff and infiltration. LULC had a greater relative contribution to changing surface

runoff than the combined and climate impact. Whereas the relative contribution of combined impact was greater in the changing of ET and infiltration.

Table 3-7: Attribution analysis of LULC and climate dynamics in a changing hydrology process

	Scenario	ET			Qsur			Qlat			Perco		
		Sim	Change (%)	RC (%)	Sim	Change (%)	RC (%)	Sim	Change (%)	RC (%)	Sim	Change (%)	RC (%)
Ugelana	S1	840.40			363.73			47.23			53.39		
	S2	856.25	1.89	37.61	358.10	-1.55	-58.83	47.04	-0.39	-6.67	53.20	-0.35	-2.86
	S3	802.30	-4.53	-90.44	376.03	3.38	128.76	44.67	-5.41	-92.00	47.84	-10.38	-84.87
	S4	798.27	-5.01	-100.0	373.28	2.63	100.0	44.45	-5.88	-100.0	46.85	-12.24	-100.0
Bilate	S1	745.08			267.833			36.467			81.27		
	S2	760.00	2.00	37.30	248.59	-7.19	-88.32	35.63	-2.31	-11.98	79.88	-1.72	-21.23
	S3	720.97	-3.24	-60.27	311.86	16.44	202.05	30.19	-17.22	-89.43	75.23	-7.44	-92.05
	S4	705.08	-5.37	-100.0	289.63	8.14	100.0	29.45	-19.25	-100.0	74.70	-8.08	-100.0
Gidabo	S1	698.88			307.884			62.329			122.014		
	S2	701.71	0.40	3.35	272.01	-11.65	-41.39	61.07	-2.03	-9.38	121.51	-0.41	-7.98
	S3	677.17	-3.11	-25.71	404.21	31.29	111.14	50.14	-19.56	-90.53	117.38	-3.80	-73.22
	S4	614.45	-12.08	-100.0	394.56	28.15	100.0	48.86	-21.61	-100.0	115.69	-5.19	-100.0
Katar	S1	505.08			151.839			52.82			81.101		
	S2	512.08	1.39	12.80	141.46	-6.84	-30.20	52.38	-0.84	-2.43	80.43	-0.83	-26.33
	S3	477.37	-5.49	-50.64	171.78	13.13	57.99	35.75	-32.32	-93.51	78.91	-2.70	-85.68
	S4	450.37	-12.05	-100.0	186.22	31.65	100.0	34.57	-34.85	-100.0	78.55	-3.15	-100.0
Meki	S1	652.59			109.813			35.858			45.923		
	S2	656.41	0.58	32.28	103.28	-5.96	76.21	32.19	-10.22	-18.63	41.69	-9.22	-23.47
	S3	643.57	-1.38	-76.29	118.10	7.54	-96.66	17.86	-50.20	-91.54	32.18	-29.92	-76.16
	S4	640.77	-2.38	-100.0	118.38	14.62	100.0	16.19	-54.84	-100.0	27.88	-33.12	-100.0

* Sim is simulated, RC is relative contribution, ET is Evapotranspiration, Qsur, surface runoff, Qlat is lateral flow and Perco is percolation.

* S1 = base line, S2= contribution of climate change, S3 = contribution of LULC and S4 = combined effect

3.4. Discussion

During the study period, vegetation area decreased by 20.70%, the water bodies decreased by 3%, the agriculture land increased by 23.14%; the barren land increased by 0.13%; the grass land increased by 0.11% and the settlement area increased by 0.32% from the total share of land. This high reduction of natural vegetation cover and rapid increase of agricultural land is

mainly associated with rapid population growth and agricultural expansion land use policy (ARD, 2004). In addition, harvesting of trees for firewood and charcoal is another important activity reducing tree density of vegetation cover. Especially, the National Economic Development Strategy (NEDS) emphasizes the need for the agricultural sector to enhance food self-sufficiency, ensure food security at the household level, and for agriculturally led industrial development-aggravating deforestation and agricultural expansion. Apart from population growth and national land policy, high inter-annual climate variability has impacts on land use dynamics especially on water and wetland. The surface area of water and wetland has been decreased noticeably in the land use map of interference period, which is mainly associated with a reduction of annual rainfall due to frequent drought occurrence; and water abstraction, e.g., for irrigation and industrial water use (Ayenew and Tilahun, 2008).

Apart from high inter-annual climate variability, the annual average rainfall has decreased in the interference period. This reduction of rainfall was mainly associated with a higher frequency of drought occurrence in the interference period than in the baseline period. The spatio-temporal variations of rainfall in the Rift Valley Lakes Basin mainly depend on the north–south ward movement of the ITCZ (Diro et al., 2009a, Korecha and Barnston, 2007a) and its magnitude is affected by the variation of equatorial pacific sea surface temperature (SST) (Block and Rajagopalan, 2007a, Diro et al., 2011a, Gissila et al., 2004a). The detail climate characteristics of the basin has been explained (Ayalew et al., 2022b).

Meanwhile, the decline of annual average ET in the watersheds is a result of LULC change, and climate change mainly attributed to the expansion of agricultural land at the cost of natural vegetation. Especially, the magnitude of change in ET is higher in the southern part of the basin, which was covered with vegetation in the base line period. Elsewhere, studies have shown that actual ET is generally greater for vegetated land than non-vegetated land, which is attributed to the loss of transpiration and to the reduction in soil moisture in non-vegetated LULC types due to the loss of vegetation cover (Chen et al., 2013, Tigabu et al., 2021). Moreover, forests have a much higher transpiration than other vegetation types, leading to a higher annual ET value (Yang et al., 2012).

The decrease of rainfall and the increase of temperature in the basin not only lead to the change of ET, but also due to change of infiltration and stream flow. Meanwhile, climate and LUCC dynamics not only affect ET, but also, they could affect the surface runoff and infiltration. The increase in surface runoff is primarily due to deforestation and urbanization, which results in

reduced infiltration. During the interference period, high deforestation resulted in greater surface runoff and lower infiltration. Urbanization leads to an increase in impervious areas, resulting in a decreased soil infiltration. With the reduction in base flow contribution to stream flow, the surface runoff increases, which can lead to more recurrent and severe flooding (Rose and Peters, 2001, Ehret et al., 2014, Massei and Fournier, 2012). The increase in streamflow is also attributed to decrease in water bodies and forest cover. It is worth mentioning that our study investigated a reduction in annual average ET caused by LULC change that was relatively larger in magnitude than the offsetting increase caused by climate variability, indicating that the LULC change played a dominant role affecting annual average ET.

The internal variability of stream flow was also evaluated using FDC. The result indicated that the frequency of high and low flow become increasing. The increasing of high flow during wet season was connected with deforestation and urbanization. Whereas the increasing of low flow frequency during dry season can be linked to irrigation abstraction (Wendemeneh et al., 2020), frequent drought and decrease of infiltration.

3.5. Summary and Conclusions

Land use/cover (LULC) and climate are significant environmental factors that influence hydrological processes in a watershed throughout. The present study attempts to understand and investigate the contribution of existing dynamics of climate and LULC on the hydrological processes of the Rift Valley Lakes Basin. Main water balance components were simulated using a semi-distributed Soil and Water Assessment Tool plus (SWAT+) model. The SWAT+ model performed well for daily stream flow during calibration and validation period.

The change of the main water balance components in the Rift Valley Lakes Basin was related to both climate and LUCC dynamics during the study period. Four scenarios were designed using combinations of two periods of climatic data (1980-2000 and 2000–2018) and two sets of land use maps (1989 and 2009).

This research investigates the individual and combined impact of land use change and climatic variations in the watersheds using a semi-distributed SWAT model. The results affirm that: individual impact of LULC change contributes to increase in the surface runoff and decrease in evapotranspiration (ET) and infiltration primarily due to increase in deforestation, urbanization and decrease in water bodies of the basin. The combined impact of climatic variations and land use change was higher on ET and infiltration; but the isolated impact of LULC was higher on

surface runoff. Generally, our result depicted that LULC change and climate dynamics can modify surface runoff, infiltration and ET in the Rift Valley Basin, and that surface runoff, infiltration and ET are important hydrological components subject to change with LULC and climate dynamics. As the changes in LULC and climate variability in the basin continue to increase, further significant change can be expected in the hydrological components. Thus, further investigations of the hydrological responses under future LULC and climate change scenarios are important for future sustainable land and water management strategies. The study provides insight to hydrological response to dynamics in climate and land use changes in Rift Valley Basin in recent decades. The results of this study can be beneficial to the authorities, decision-makers, water resource engineers and planners for the best water resource management approaches in the perspective of LULC change and climate change of a heterogeneous climate region as that of Rift Valley Basin. This method can be applied to other regions, and for a comprehensive understanding of future scenarios of LULC and climate change should be combined. By doing so, a more holistic approach can be achieved.

4. Unveiling Hydrological Dynamics in Data-Scarce Regions: Experiences from the Ethiopian Rift Valley Lakes Basin

¹Ayenew D. Ayalew, ¹Paul D. Wagner, ²Dejene Sahlu, and ¹Nicola Fohrer

¹Department of Hydrology and Water Resources Management, Christian-Albrechts-University, Kiel, Germany

²Institute of Disaster Risk Management and Food Security Studies, Bahir Dar University

Email: ayalew@hydrology.uni-kiel.de

Abstract: The hydrological system of Rift Valley Lakes in Ethiopia has recently experienced changes since the past two decades. Potential causes for these changes include anthropogenic, hydro-climatic and geological factors. The main objective of this study was to utilize an integrated methodology to gain a comprehensive understanding of the hydrological systems and potential driving factors within a complex and data-scarce region. To this end, we integrated a hydrologic model, change point analysis, indicators of hydrological alteration (IHA), and bathymetry survey to investigate hydrological dynamics and potential causes. A hydrologic model (SWAT+) was parameterized for the gauged watersheds and extended to the ungauged watersheds using multisite regionalization techniques. The SWAT+ model performed very good to satisfactory for daily streamflow in all watersheds with respect to the objective functions, Kling–Gupta efficiency (KGE), the Nash–Sutcliffe efficiency (NSE), Percent bias (PBIAS). The findings reveal notable changes of lake inflows and lake levels over the past two decades. Lake Chamo experienced an increase in area by 30.1 km² (9.5%), in depth by 4.4 m (30.9%), and in volume by 7.8 x 10⁸ m³ (27.2%). In contrast, Lake Abijata witnessed an extraordinary 68% decrease in area and a depth decrease of 1.6 m (37.2%). During the impact period, the mean annual rainfall experienced a decrease of 6.5% and 2.7% over the Lake Abijata and the Chamo Lake, respectively. Actual evapotranspiration decreased by 2.9% in Lake Abijata but increased by up to 4.5% in Lake Chamo. Surface inflow to Lake Abijata decreased by 12.5%, while Lake Chamo experienced an 80.5% increase in surface inflow. Sediment depth in Lake Chamo also increased by 0.6 m (4.2%). The results highlight that the changing hydrological regime in Lake Chamo is driven by increased surface runoff and sediment intrusion associated with anthropogenic influences. The hydrological regime of Lake Abijata is affected by water abstraction from feeding rivers and lakes for industrial and irrigation purposes. This integrated methodology provides a holistic understanding of complex data scarce hydrological systems and potential driving factors in the Rift Valley Lakes in Ethiopia, which could have global applicability.

Keywords Hydrological change; IHA; Bathymetry; Lake Chamo; Lake Abijata; SWAT+; Rift Valley; Lake level.

4.1. Introduction

Continuous anthropogenic and natural activities are adversely altering the water resources from local to global scales (Flörke et al., 2018, Sivapalan et al., 2003). Changes of lake levels influence ecosystem services worldwide (Gownaris et al., 2015, Kolding and van Zwieten, 2012). In Eastern Africa, the Rift Valley Lakes are supporting eco-regions of great biodiversity, considered amongst the global 200 freshwater eco-regions of the world (O'Brien et al., 2018, Olson and Dinerstein, 2002). In this region, water resources play a crucial role for economic development through use of water for domestic supply, irrigation and industry, fishery, recreation and tourism (Cowx and Ogutu-Owhayo, 2019, Minale, 2020, White et al., 2002).

The Ethiopian Rift Valley Lakes Basin is known as the Lakes District, containing a chain of eight main lakes situated at the rift floor. The total surface area of open waters, including wetlands of the Rift valley was 3413 km² in 2019 which is 46% of total area of open waters resources of Ethiopia (Ayalew et al., 2022b). Most of these lakes are highly productive, contain indigenous populations of edible fish, and support a variety of aquatic and terrestrial wildlife (Tudorancea and Taylor, 2002). Currently, the hydrology of the Rift Valley Lakes is changing, i.e., water levels, areal extent, and volumes are altered, affecting ecosystem services and the communities. The situation has been aggravated recently due to increasing population density, excessive water abstraction and catchment land use changes (Billi and Caparrini, 2006, Legesse and Ayenew, 2006a). Because of high water abstraction for irrigation and industry, as well as climate change, the open water surface area has decreased by 2.1% in three decades (Ayalew et al., 2022b). The problem is getting worse since water abstractions is often carried out without a basic understanding of the complex hydrogeological system, and the fragile nature of the Rift ecosystem (Zinabu et al., 2002, Ayenew, 2002). The basin has become economically significant because of the development of flower and horticultural production, soda ash factory, tourism, and other human activities around the shores of the lakes. Despite the basin's significance as a vital component of the country's economy and ecological balance, the major challenge lies in the limited availability of accurate hydrological data. Previous hydrological studies conducted in the Rift Valley Lakes have predominantly focused on analyzing the impact of single drivers and have failed to provide a quantitative assessment of the respective contributions of land use and climate change on streamflow. For instance, some studies have primarily investigated the effects of high water abstraction for irrigation and industries (Kebede et al., 1994, Zinabu and Elias, 1989, Legesse and Ayenew, 2006a, Ayenew, 2002), environmental degradation (Ayalew

et al., 2004a, Meshesha et al., 2012, Ayenew, 2004a), volcano-tectonics, and sedimentation (Le Turdu et al., 1999, Street and Grove, 1979), bathymetry analysis (Awulachew, 1999) as well as the occurrence of frequent earthquakes and faults (Ayalew et al., 2004a, Ayenew, 2002, Belay, 2009). However, the hydrological system of the Rift Valley is very complex and processes within a basin are driven by the interplay of climate, LULC, topography, soil and human activities. Evaluating hydrological change typically involves assessing changes in the flow regime and water balance of a river, a lake or a reservoir. Therefore, to understand the hydrological system and driving forces that control the hydrological processes requires an integration approach. Flow regime analysis, trend analysis, time series analysis, and hydrological modeling are common methods used for hydrological change analysis (Wagener and Montanari, 2011, Hargreaves and Samani, 1985, Jain and Singh, 2019); and in regions with limited available hydrological data, the application of regionalization techniques is a commonly employed approach (Viglione et al., 2013, Pool et al., 2021, Pagliero et al., 2019).

The study aims to understand the changing hydrological systems and driving factors by integrating hydrological modeling, indicators of hydrological alteration (IHA), change point/break, and bathymetry survey analysis. We hypothesize that the changes in the hydrological regimes are associated with changes in high water abstraction, climate change and land use.

4.2. Materials and Methods

4.2.1. Study Area Discription

The Ethiopian Rift Valley Lakes Basin is located between 36°00' and 40°00' E and 4°00' and 9°00' N. It extends from the Afar depression southwards to Kenya across the broad basins of Abijata-Ziway, Abaya-Chamo, and Segen (Fig. 1). It is 55,050 km² large and one of the most important basins in Ethiopia. The basin is characterized by diverse landscape features and climate conditions. It has a complex hydrological system and encompasses numerous lakes, springs, wetlands, and rivers.

The climate of the basin is dominated by semi-arid climate (BSH) and tropical wet and dry climate (Aw/As) climate, which is characterized by low rainfall, high temperature, and high evapotranspiration. Three climate regions can be found in the basin (Ayalew et al., 2022b). The Abijata-Ziway subbasin which is characterized by low annual average rainfall ranging from 400 mm to 860 mm with one peak in August. The second basin, Abaya-Chamo subbasin, is

receives higher annual precipitation ranging from 704 mm to 1200 mm with a bimodal climate pattern with peaks in April and August. The third subbasin, Segen subbasin, is characterized by a bimodal rainfall pattern with peaks in April and October and receives an average annual precipitation ranging from 500 to 1100 mm. Temperatures within the basin exhibit a wide range, from 10°C to 36°C, with the warmest temperatures measured on the Rift Valley floor and frost-prone conditions in the Afro-alpine zone. The southern region of the Rift Valley is both lower in elevation and warmer and drier than the other areas of the basin.

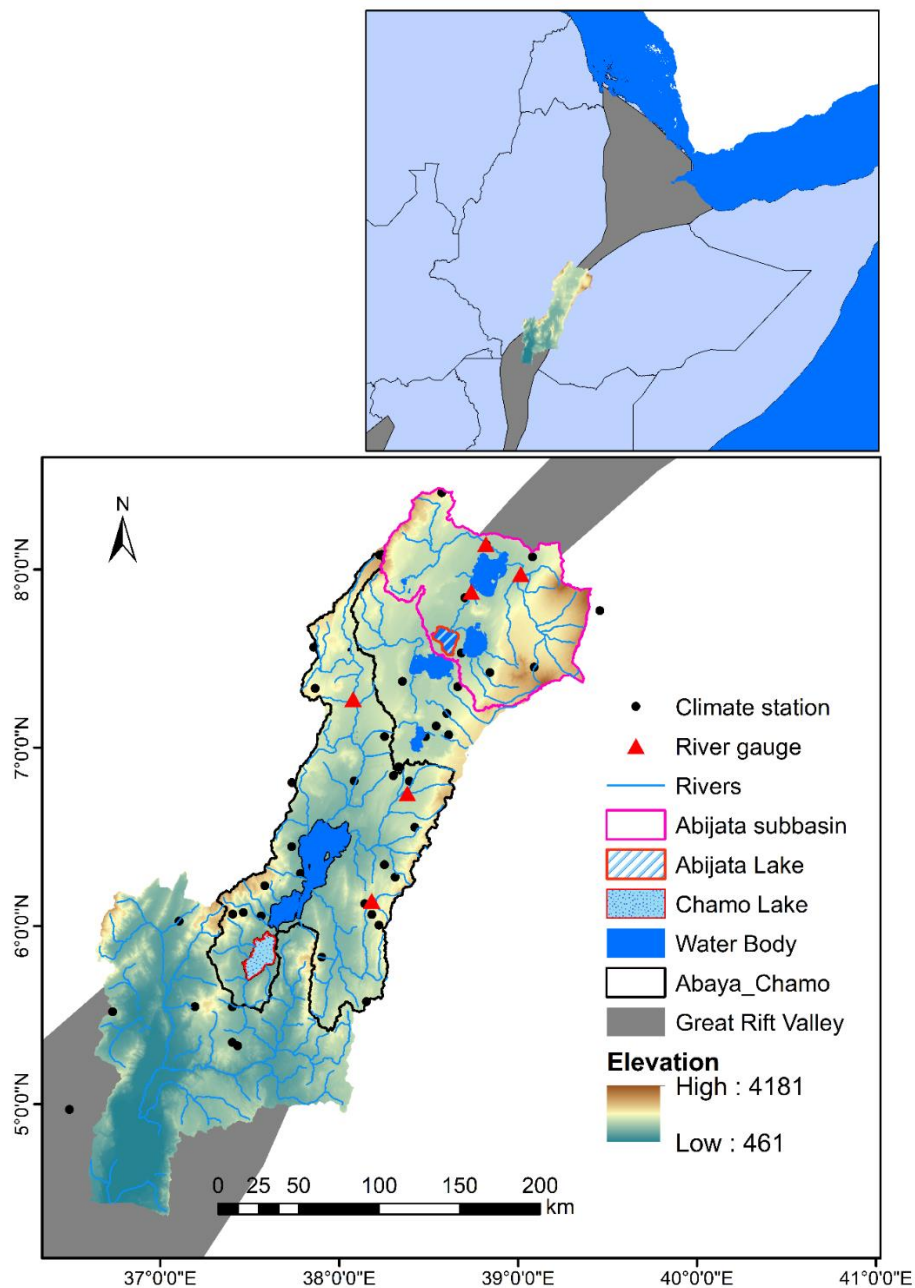


Figure 4-1: Topography of the Rift Valley Lakes Basin as well as the river network, river and climate stations used for modeling.

The basin is also characterized by a complex and rugged topography with active faults, volcanoes and hot springs (Stamps et al., 2008a). Based on the digital elevation model (USGS, 2023) data, the slope ranges from 0 to 161%. Agricultural land is the most dominant land use followed by semi-natural vegetation and water bodies. Two lakes were chosen from the basin as representative examples of its hydrological system, based on their degree of impact. Lake Abijata was selected as an example of a monomodal climate regime, while Lake Chamo was chosen to represent a bimodal climate regime. Lake Abijata is a terminal lake of the Ziway-Abijata subbasin and linked to Lake Ziway via the Bulbula River and to Lake Lugano via the Hurakolo River. Lake Chamo is a terminal lake for the Abaya-Chamo subbasin and linked with Lake Abaya via the Kulfo River.

4.2.2. Spatial and Hydroclimatic Data

The main hydrological characteristics of the basin have been acquired from the climate data, topography, land use, soil properties, streamflow, lake level and bathymetry survey (Table 4-1). Time series of climate data for 44 stations (1981- 2018), a georeferenced Landsat image (1999), bathymetry of Lake Chamo (1998 and 2021), streamflow of rivers (1987 – 2006), Lake level (1987-2015) the Shuttle Radar Topography Mission digital elevation model (SRTM DEM) (30x30) and soil data were used for this study. The SRTM DEM has been used, from which slope, river network, and watershed boundaries are obtained. Selected soil physical properties and the area coverage of each soil type were classified based on the requirements of the hydrologic model. The bathymetry survey data was used to calculate the change in volume, area and depth of a lake. It was also used to obtain information about sediment deposition in the lake.

Table 4-1: List of data and source used in this study

Data	Resolution (m)	Access Date	Sources
Landsat 5, Thematic Mapper	30	Feb 25,1999	http://earthexplorer.usgs.gov
STRM DEM	30	2014-09-23	Ministry of water irrigation and electricity
Soil	30	2016	
Stream flow	-	1987-2006	
Lake level	-	1987-2015	Ethiopian National Meteorological Agency
Climate (rainfall and temperature)	-	1987-2018	
Lake extent shape file		1999	
Bathymetry survey	-	1998 & 2021	AMU-VLIR-IUC

4.2.3. Methodology

4.2.3.1. Hydrological Regime Change Analysis

In this study, a common approach for analyzing hydrological regime change is utilized by combining a change point analysis and Indicators of Hydrological Alteration (IHA). The IHA can be used to assess and quantify changes in the natural flow regimes of rivers and streams. It provides a systematic way to analyze the impacts of human activities, e.g., dam construction and water withdrawals, on hydrology. A set of indicators are used to evaluate alterations in flow magnitude, frequency, duration, timing, and rate of change. Combining a change point analysis and IHA allows for a more robust and comprehensive analysis of hydrological regime change (Zhang et al., 2016, Vieceli et al., 2015, Vu et al., 2019a). Change point analysis is a statistical method that is used to detect changes in the mean or variance of a time series. We used it to identify breakpoints of the Lake level. Once the break points have been identified, IHA were used to evaluate the degree of alteration of the natural flow regime. The Range of Variability Approach (RVA), Environmental Flow Components (EFC), Flow Duration Curve (FDC), Box-and-Whisker (BAW), and Percentile analysis of the IHA were used to evaluate the alteration of the hydrological regime (Gunawardana et al., 2021, Song et al., 2020).

The Range of Variability Approach (RVA) evaluates hydrological alterations by analyzing 33 hydrological parameters, which are categorized into five groups which evaluate the magnitude, timing, frequency, duration, and rate of change (Richter et al., 1998, Shieh et al., 2007) (Table 4-2). Group 1: The 12-monthly mean flows were computed to determine the water level. Group 2: twelve parameters were used to explain the range of changes in annual extreme flows in magnitude and duration in daily, weekly, monthly, and seasonal cycles. Group 3: Julian dates for 1-day annual maximum and minimum were computed to determine the variation of timing of annual extreme flows that can be associated with extreme conditions. Group 4: four parameters are categorized in this group that refers to the frequency and duration of high and low pulses. The high pulses refer to periods within a year when the daily flows are above the 75th percentile of the data. The low pulses are periods within a year when the daily flows are below the 25th percentile of the data. Group 5: three parameters are also categorized in this group to understand the direction and magnitude of hydrological regime changes, including both positive and negative changes. These parameters are important because they capture the variability of hydrological flow over short periods, as high flow can cause erosion and sediment transport, while low flow pulses can lead to habitat degradation and changes in water quality.

Table 4-2: Hydrologic parameters used in the RVA, and their features

General group	Regime features	Streamflow parameters used in the RVA
Group 1: Median of monthly water condition indices	Magnitude, timing	The median monthly value for each month
Group 2: Yearly extreme water conditions indices	Magnitude, duration	1-day minimum 3-day minimum 7-day minimum 30-day minimum 90-day minimum 1-day maximum 3-day maximum 7-day maximum 30-day maximum 90-day maximum Number of zero days Base flow index
Group 3: Yearly extreme water conditions indices	timing	Date of minimum Date of maximum
Group 4: High and Low pulses indices	frequency and duration	Low pulse count Low pulse duration High pulse count High pulse duration
Group 5: Water condition changes indices	rate and frequency	Rise rate Fall rate Number of reversals

The calculation of pulse count and pulse duration was carried out through the utilization of the Indicators of Hydrological Alteration (IHA). A threshold for both high and low pulses is used. Pulse count represents the number of pulses exceeding the established threshold (here the median), while pulse duration indicates the time from the start to the end of a high or low pulse.

The uncertainty concerning pulse counts, determined by the threshold, stems from potential overcounting and undercounting of low and high pulses. This occurs due to the computation of the median for the data series, which includes both flood and drought years. The presence of flood and drought years in the data series influences the median value, consequently affecting the counted number of high and low pulses. Another threshold definition or other climate data will lead to different results.

In the annual average water balance, the flow signals are averaged and it is difficult to distinguish which flow signals affect the annual water balance. To avoid this limitation, we used FDC to evaluate the variation of streamflow for the pre-impacted and impacted periods. The shape of the curve is an index of the natural storage in the watershed, including the groundwater. Since the dry season flow consists entirely of return flow from the groundwater, i.e., the lower end of the FDC indicates the general characteristics of shallow aquifers. Therefore, flow signals were determined from the FDC based on the exceedance probability threshold. Here, low flow signals are defined as $\geq 75\%$ of the exceedance probability, while higher flow signals are defined as $\leq 20\%$ of the exceedance probability and the rest are mid flows. The choices of thresholds for disaggregation were based on earlier studies (Pfannerstill et al., 2014, Smakhtin, 2001).

4.2.3.2. Hydrologic Model

The Soil and Water Assessment Tool Plus (SWAT+), a completely revised version of the SWAT model (Arnold et al., 1998) was built to simulate water balance fluxes in a watershed. It is more flexible than SWAT in terms of the spatial representation of interactions and processes within a watershed (Bieger et al., 2017b). It simulates the hydrological processes from precipitation to streamflow using the water balance equation. There are two methods for channel routing currently implemented in SWAT+ (Muskingum and Variable Storage Routing (VSR)). In this study, the VSR, that is the standard method in SWAT+, was used for river routing. It provides a flexible representation of channel routing behavior using storage coefficients for each reach that depend on travel time and length of the time step (USDA-ARS 2024). It also considers the storage-discharge relationship for each reach, allowing for a better representation of channel routing processes (Pati et al., 2018). The Soil Conservation Service (SCS) Curve Number (CN) method was employed to estimate surface runoff. The Hargraves equation was used to calculate the potential evapotranspiration, which is commonly used in data scarce regions (de Sousa Lima et al., 2013a, Moeletsi et al., 2013a).

Currently, SWAT+ is tested in few watersheds across the world, where the results from SWAT+ are favorable compared to the previous model version (Wagner et al., 2022). It can simulate the quantity and quality of water resources from a hydrological response unit to a basin scale. SWAT is also suitable to assess the impact of climate change (Mahmoodi et al., 2021a), land cover change (Tigabu et al., 2019) and land use change (McGinn et al., 2021, Wagner et al., 2023), and watershed management practices on water resources (Mahmoodi et al., 2021c). Moreover, it has been proven capable of modeling in data-scarce regions (Tigabu et al., 2023,

Wagner et al., 2012). To depict the spatial heterogeneity of a watershed, each watershed is divided into multiple homogenous hydrological response units based on a unique combination of land use, slope, and soil characteristics (HRU).

4.2.3.3. Model Parameterization, Calibration, and Validation

Sensitive parameters were adopted from previous research (Ayalew Ayenew D et al., 2023) for streamflow simulation in two subbasins (Table 4-3). Lakes, which are located on the main channel network of the subbasin, are accounted for during modeling. The lakes' areal extent is used as input for the SWAT+ model. The default model parameters for the reservoirs are used, e.g., SWAT+ assumes an average depth of 10 m to calculate the volume of the lake. During the calibration process, the lake depth was modified using bathymetric data obtained from the Ethiopian Ministry of Water and Energy.

Table 2-3: Calibration parameters and the upper and lower boundaries used for calibration

Parameters	Description	Limit		Change	Fitted range & value					
		Min	Max		Lake Abijata			Lake Chamo		
					Min	Max	Value	Min	Max	Value
CN2	Condition II curve number	-15	+15	abschg ^a	-15	-5	-1.8	-15	-10	-11.8
Sol-Awc	Available water capacity of the soil layer (mm H2O/ mm soil)	-0.25	+0.25	abschg	-0.16	+0.15	-0.05	-0.16	+0.15	-0.12
ESCO	Soil evaporation compensation coefficient	0	1	absval ^b	0.01	0.5	0.34	0.01	0.5	0.21
SURLAG	Surface runoff lag Coefficient(days)	0	24	absval	0.1	10	6.7	0.1	10	8.4
PERCO	Percolation coefficient (mm H2O)	0	1	absval	0.01	0.95	0.91	0.01	0.3	0.17
LATQ_CO	Lateral flow contribution to reach (mm H2O)	0	1	absval	0.01	0.95	0.63	0.01	0.3	0.10
ALPHA_BF	Baseflow recession constant fast aquifer (days)	0	1	absval	0.01	0.6	0.27	0.01	0.3	0.07
k	Saturated hydraulic conductivity (mm h ⁻¹)	-45	+45	pctchg ^c	-10	+15	1.86	-10	+15	-3.7
EPCO	Plant uptake compensation factor	0	1	absval	0.6	0.9	0.8	0.6	0.9	0.85
z	Soil depth (mm)	-45	+45	pctchg	-15	+0	-3.7	-15	+0	-7.5
Lake depth	Average depth of a Lake (m)	10 (default)		absval	2.5	9	5.5	5	13	9.7

Where, a abschg^a adds an absolute value to the initial parameter value; b absval^b replaces the initial parameter value with an absolute value; c pctchg^c increases or decreases of the initial parameter value by the given percentage of the value.

The streamflow data at each outlet (at each gauge from 1987 to 2006 splatted in to three periods for model warm-up (one year), model calibration (1987 to 1995) and validation (1995 to 2006). For calibration, 5000 parameter sets were generated with Latin Hypercube Sampling (Soetaert and Petzoldt, 2010b) using the parameter ranges given in Table 2-3. The model configurations were evaluated for the same 5000-parameter sets. For each parameter set a model run was performed and the final parameter fitted range was selected based on the best combined $0.6 \leq \text{KGE} \leq 1$ (Gupta et al., 2009), $0.5 \leq \text{NSE} \leq 1$ (Nash and Sutcliffe, 1970), and percent Bias $-25 \leq (\text{PBIAS}) \leq 25$, and $0 \leq \text{RMSE-observations standard deviation ratio (RSR)} \leq 1$ values, so that the KGE, NSE, PBIAS and RSR were filtered within this range and the model runs were accepted within these range. The best optimal value (fitted value) has selected among the best value of KGE. During calibration and validation, the water balance (total amount, distribution through time), storm sequence (time lag or shift), and shape of hydrograph (rising limb, peak, recession) are considered as key components. Calibration and validation were carried out in R using the packages FME for Latin Hypercube Sampling (Soetaert and Petzoldt, 2010b), hydroGOF for model evaluation (Zambrano-Bigiarini, 2018), and the packages zoo (Zeileis and Grothendieck, 2005) and xts (Ryan and Ulrich, 2011b) for data processing.

In addition to statistical performance evaluation, visual inspection of the hydrography and flow duration curve (FDC) provide information about the overall qualitative match between measured and modeled streamflow.

4.2.3.4. Regionalization

A multisite (stepwise and pooled) regionalization method was applied to ensure that the model accurately represents the hydrological behavior of multiple locations and that the model can be used to make predictions for other locations. It improves the accuracy of the model by calibrating it with data from multiple sites (Hundecha et al., 2016). The method can also help to reduce uncertainty and improve the robustness of the model by taking into account the variability of hydrological conditions across different sites.

Hydrological processes are primarily controlled by rainfall, topography, soil characteristics, and land use, similarity between watersheds has been demonstrated prior to regionalization. The

stepwise calibration carried out on a nested class of sub-basins for the corresponding multiple gauging stations in the subbasin (Tsegaw et al., 2019). Multi-gauge calibration strategy involves calibrating all parameters of the model domain simultaneously against multiple streamflow gauges within the subbasin (Wi et al., 2014). This approach aims to look for suitable parameters that are able to produce satisfactory model results at all neighboring gauging stations in a single implementation of optimization. Therefore, pooled regionalization technique has been chosen for this study based on its ability to predict streamflow and calibration uncertainties. To do so, Bulbula assumed to be gauged watershed and Katar at Abura and Meki were assumed ungauged watersheds for validation (Figure 4-2). Likewise, Kulfo at Abaya has considered as gauged watershed and Bilate, Gidabo and Upper Gelana considered as ungauged watershed (Figure 4-2). The gauged stations are considered as the “donor” watershed, and the ungauged stations are considered as the ‘pseudo’ watersheds. The donor watersheds are used to parameterize and calibrate the SWAT+ model parameters. The pseudo-ungauged watersheds are used to test the calibrated model. In testing the model on the pseudo ungauged watersheds, the model was run with calibrated parameters for the same period and the model performance for donor and pseudo watersheds were evaluated using the objective functions KGE, NSE, PBIAS and RSR. If the developed model for the donor watershed performed sufficiently ($KGE \geq 0.5$, $NSE = 0.5$, $-25 \leq PBIAS \leq$ and $0 \leq RSR \leq 1$) for the pseudo watershed, the model is considered robust and was used for regionalization. The optimal values of parameters of each catchment were transferred to the nearest ungauged catchments and reach.

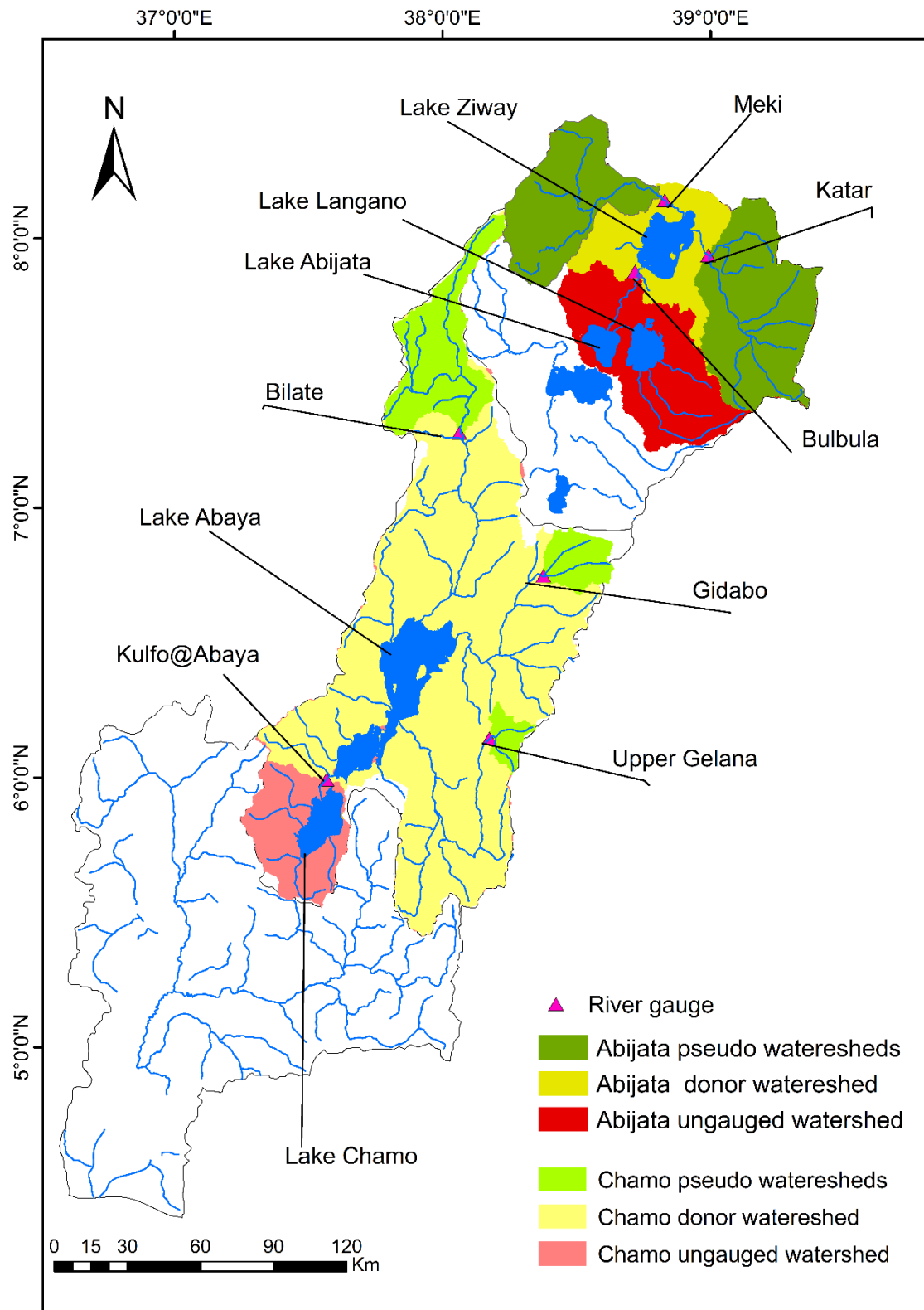


Figure 4-2: Multisite-pooled calibration technique to estimate flow of ungauged watersheds

4.2.3.5. Bathymetry Analysis

The Lake Chamo was surveyed using a Multibeam echosounder (MBES). It is sonar technology that uses a band of multiple beams to create a high-resolution 3D map of the lake bed. It is based on the principle of emitting a series of acoustic pulses and measuring the time it takes for the sound to travel to the lake bed and back. Although our hydrologic model was developed on two terminal lakes, Abijata and Chamo, we conducted a bathymetry survey only for Chamo Lake.

The survey was conducted during the dry season from 1 to 21 July 2021. Before the survey began, the surface elevation of the lake level was measured with a handheld GPS, which was at a level of 1110 m and used as the reference level. Following that, a continuous record of lake floor topography was measured with an MBES mounted on a motor boat at a constant speed of 5 km/h along predefined average traverse lines at 450 m spacing along a north-south direction. A crossing and recrossing survey was also performed in the same area to correct errors caused by potentially misleading reflections and variations in the speed of sound moving through the lake (Figure 4-3). To supplement the dataset produced by the echo sounder, zero depth coordinates were taken simultaneously with hand-held GPS along the lake's shoreline at shorter distances. Because there were no other obstacles, the true size of the lake was preserved during mapping using these border coordinates. The bathymetry data typically in the form of point data (XYZ) that represent the depth measurements at various locations within the lake was imported into Surfer20 to analyze the lake floor morphology in 2D and 3D, as well as depth, area, and volume.

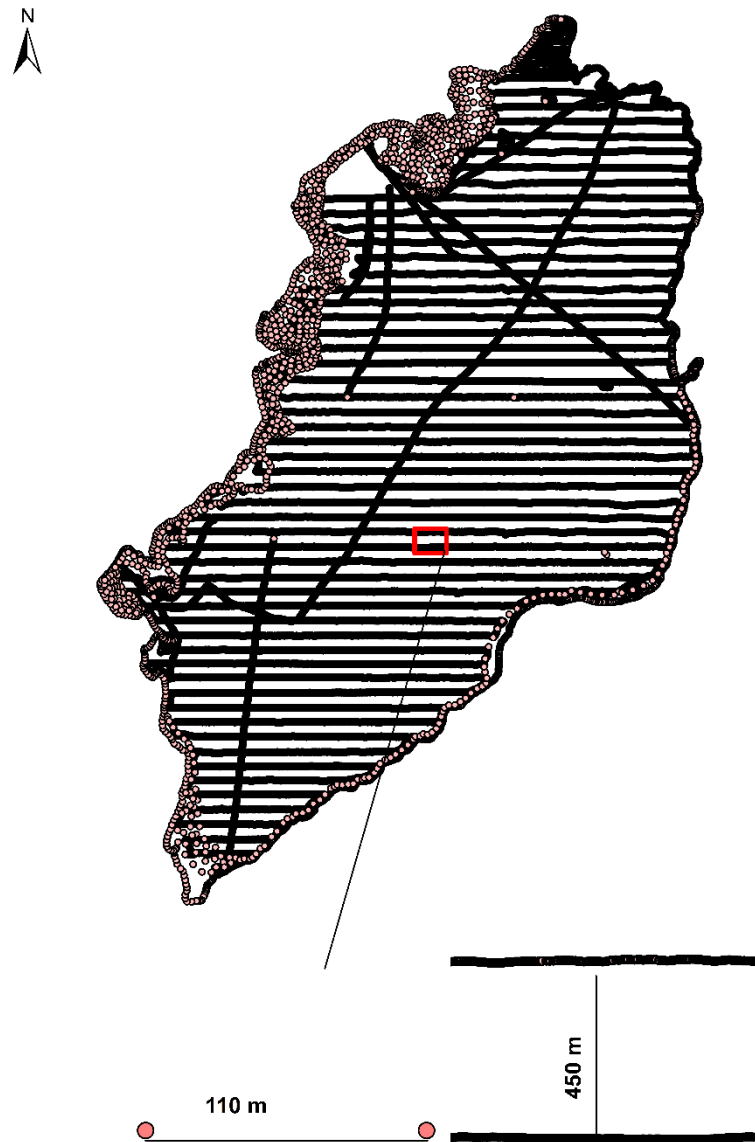


Figure 4-3: Bathymetry survey using multibeam echosounder (MBES) along predefined average traverse lines at 450 m spacing along a north-south direction and 110 m along east-west direction.

4.3. Results and Discussions

4.3.1. Lake Water Balance Analysis

4.3.1.1. Hydrological modeling and model performance

The hydrographs shown in Fig. 4-4 indicate that the SWAT+ model was successfully calibrated and validated for each ‘donor watershed’. Similarly, the hydrograph depicted in Fig. 4-5 signifies the model's success within each respective 'pseudo' watershed. The relationship between the simulated and observed streamflow based on the model is statistically summarized

in Table 4-4. The values of the objective functions indicate a strong goodness-of-fit for both ‘donor and pseudo watersheds.

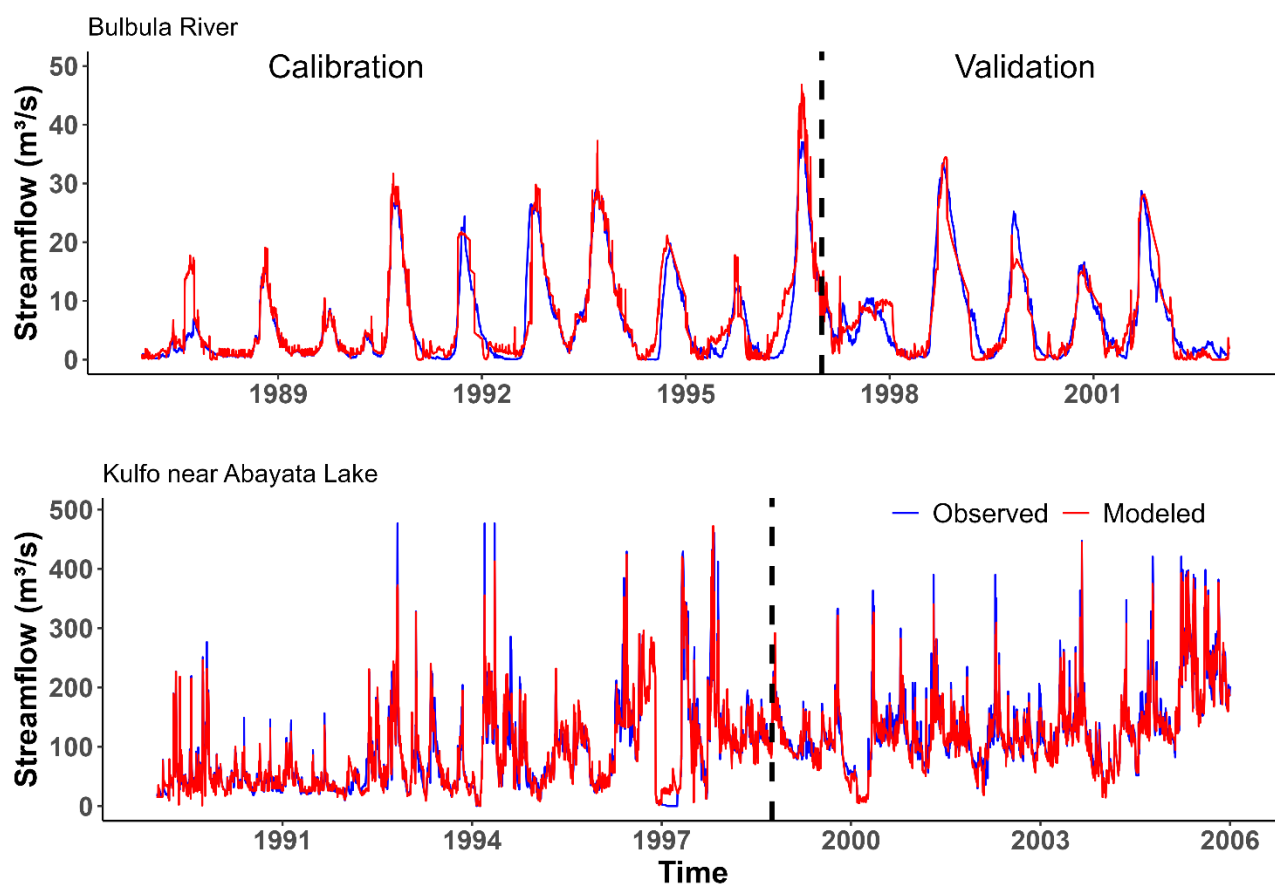


Figure 4-4: Hydrograph of modeled and observed daily streamflow for calibration and validation period of the donor watersheds.

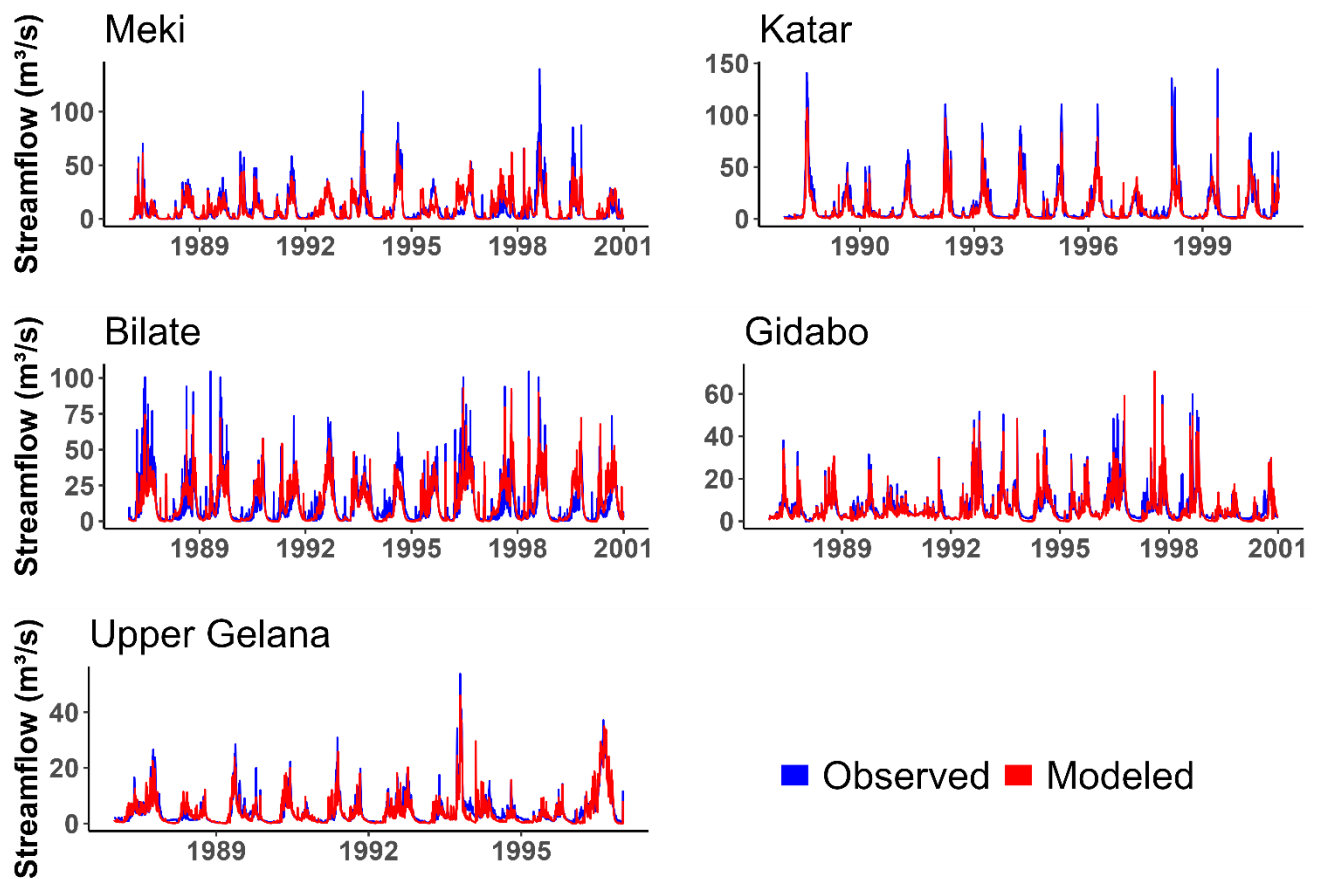


Figure 4-5: Hydrograph of modeled and observed daily streamflow of the 'pseudo' watersheds

Similarly, the FDC in Fig. 4-6 & 4-7 show that there is a good agreement between observed and the modeled discharge in both 'donor and pseudo' watersheds. Throughout the calibration and validation period, the model shows a slight overestimation of high, middle and low flows in Bulbul River. However, at Kulfo, high and low flows are slightly underestimated. The test of the regionalization approach shows that high flows were underestimated in all 'pseudo' watersheds.

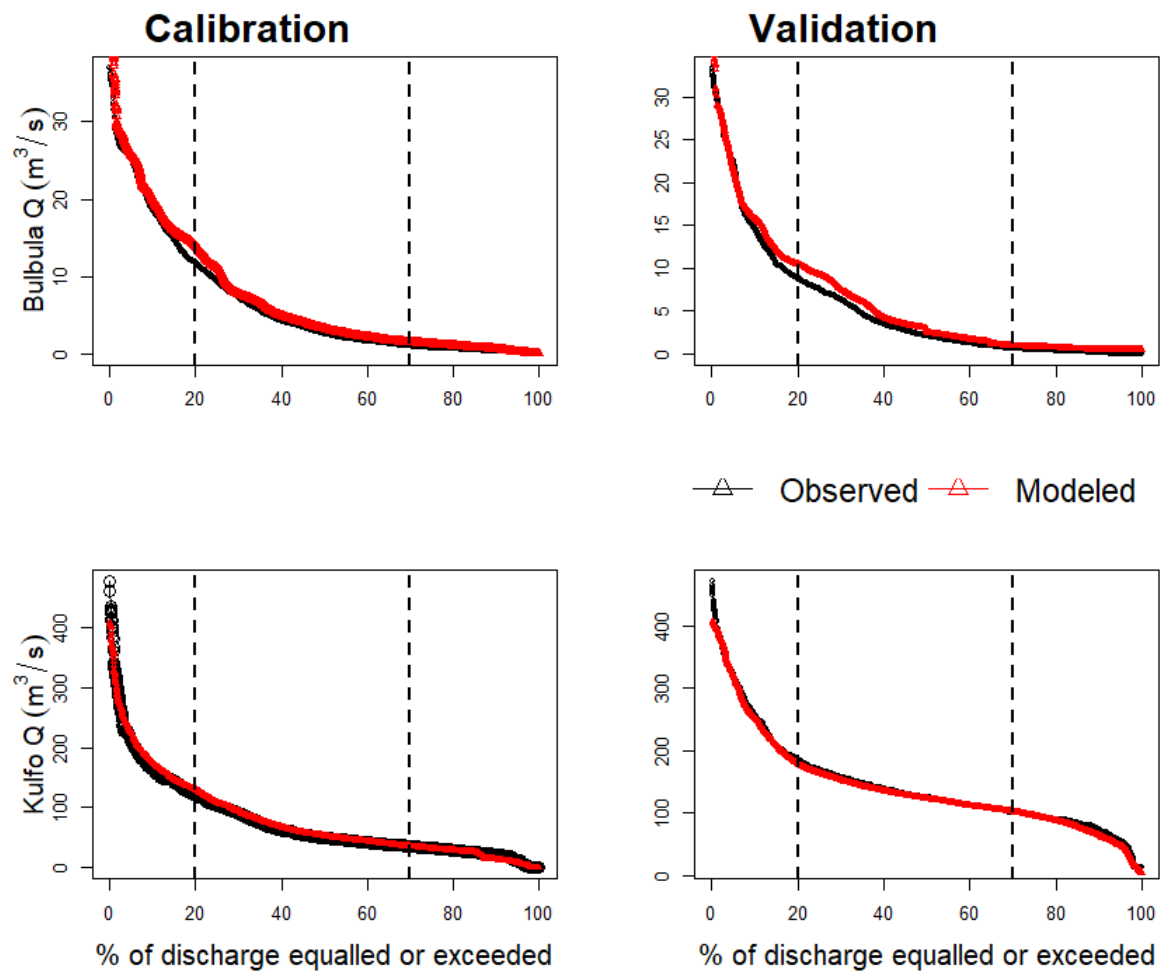


Figure 4-6: Flow duration curves of observed and modeled daily streamflow for the calibration and validation period of the ‘donor watersheds.

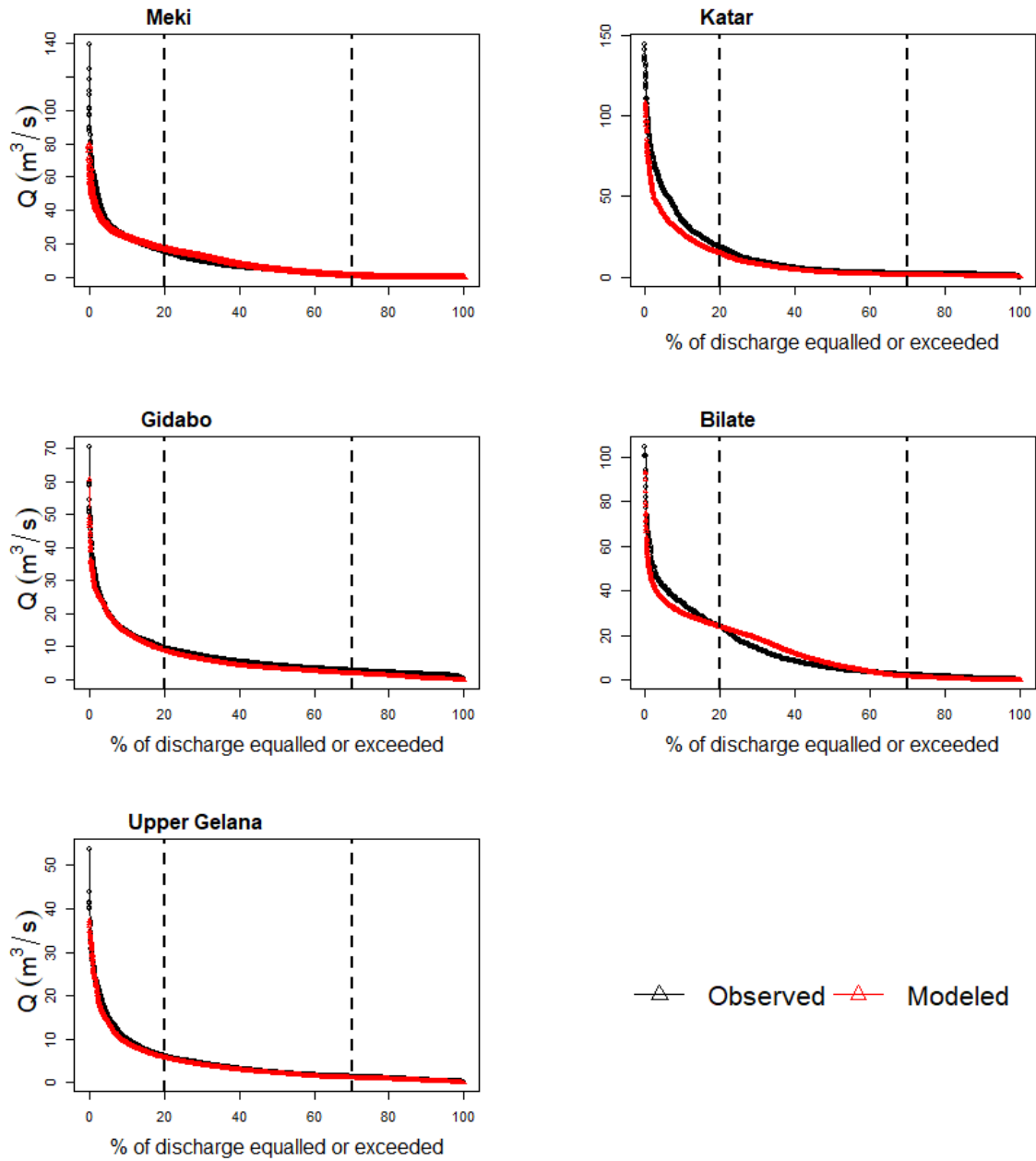


Figure 4-7: Flow duration curves of observed and modeled daily streamflow of the ‘pseudo watersheds.

Table 4-3: Model evaluation statistics of the daily SWAT+ for the calibration, validation and regionalization (1987-2000)

Watershed	Method	Objective functions			
		KGE	NSE	PBIAS	RSR
Bulbula (Donor)	Cal.	0.84	0.76	-2.1	0.51
	Val.	0.80	0.72	-5.4	0.53
Meki (Pseudo)	Test	0.71	0.63	9.2	0.69
Katar (Pseudo)	Test	0.75	0.64	10.7	0.67
Kulfo at Abayata (Donor)	Cal.	0.81	0.68	3.7	0.56
	Val.	0.78	0.63	7.6	0.68
Gidabo (Pseudo)	Test	0.70	0.59	+9.3	0.75
Upper Gelana (Pseudo)	Test	0.67	0.61	+11.8	0.73
Bilate (Pseudo)	Test	0.59	0.53	+14.3	0.78

4.3.1.2. Lakes water balance change

The water balance of Lake Abijata is controlled by rainfall and evaporation, water abstraction from the lake by the soda ash factory, inflow from Bulbula and Horakelo Rivers, and inflow from ungauged watersheds. The water balance of Lake Chamo is primarily controlled by evaporation and rainfall on the lake, inflow from Kulfo River, 40 springs, and inflow from ungauged watersheds (Sile and Elgo) (Table 4-6). We assumed that the groundwater flow and movement influence is negligible, following findings by Ayenew (2004). The result depicted that the surface runoff and evaporation increased in the impact period in both lakes. Abstraction increased in the Lake Abijata (Table 4-6). Changes in lake level and volume reflect variations in the inputs from rainfall, evaporation, abstraction and surface flow. Trends in the lake water levels in both lakes are highly variable. The Lake Abijata level decreased by 2 m due to large-scale water use for irrigation and soda abstraction in the catchment, significant changes have been recorded in the past few decades, and by 2021, the area of Lake Abijata had been reduced by about 68% as compared to year 1989 (Ayalew et. al, 2022) and 60% as compared to the year 2016 (Wagaw et al., 2019). Because irrigation is highly expanding and abstraction of water from Meki, Katar and Bulbula Rivers, and Lake Ziway for irrigation takes place year-round, its effect on water levels is increased during dry season (Getnet et al., 2014, Jansen et al., 2007a, Wagaw et al., 2019). The water balance of the lakes in Table 4-6 was determined by combining model output, including lake areal rainfall, evaporation, and inflow from both gauged and ungauged watersheds, with recorded data such as abstraction, depth, and spring inflow.

Table 4-4: Changes of the annual water balance components in million m³

Water Balance Components	Lake Abijata			Lake Chamo		
	Pre-impact period	Impact period	ΔV , million m ³ /y	Pre-impact period	Impact period	ΔV , million m ³ /y
Lake areal rainfall	103.3	96.6	-6.7	338.4	329.4	-9.0
Lake evaporation	240.7	233.9	-6.9	496.2	518.3	2.2
Gauged river inflow	238.3	208.4	-29.8	2184.3	3943.0	1758.7
Inflow from springs	-	-	-	5.3	4.1	-1.2
Ungauged river inflow	14.7	16.3	2.4	171.6	312.1	140.5
Lake outflow	-	-	-	-	-	-
Abstraction	5	13	8	-	-	-
Enclosure term*	110.6	74.4	-35.2	2203.4	4070.3	1886.8
Change in depth (m)	4.3	2.7	-1.6	14.2	18.6	4.4

* The enclosure term in this case is the water balance on the lake, which is determined by the difference between the input and output. The magnitude of this term depends on the amount of loss and gain.

4.3.1.3. Hydrological Alteration

The analysis of hydrological alterations was carried out on both Lake Abijata and Lake Abaya. The change point analysis presented in Fig.4-8 shows that there is an abrupt shift in lake level over the Rift Valley Lakes Basin. The change point analysis results revealed that the lake level has decreased after the year 2003. Lake Abaya has experienced a decrease after a change point from the 2000s until 2009 and more recently, a large increase was observed. Based on the change point analysis, three periods have identified, the pre-impact period (1985-2003), impact period (2003 to 2009) and post-impact period (2010 to 2015).

The environmental flow analysis in Fig. 4-8 depicted that the natural flow pattern has been disrupted. The magnitude and timing, duration, seasonality and frequency of high and low flows of the impacted periods have changed compared to the pre-impact period. The extreme low flow, low flow, small floods and large flood values for the impacted period have decreased in Lake Abijata, while they have increased in the Abaya Lake.

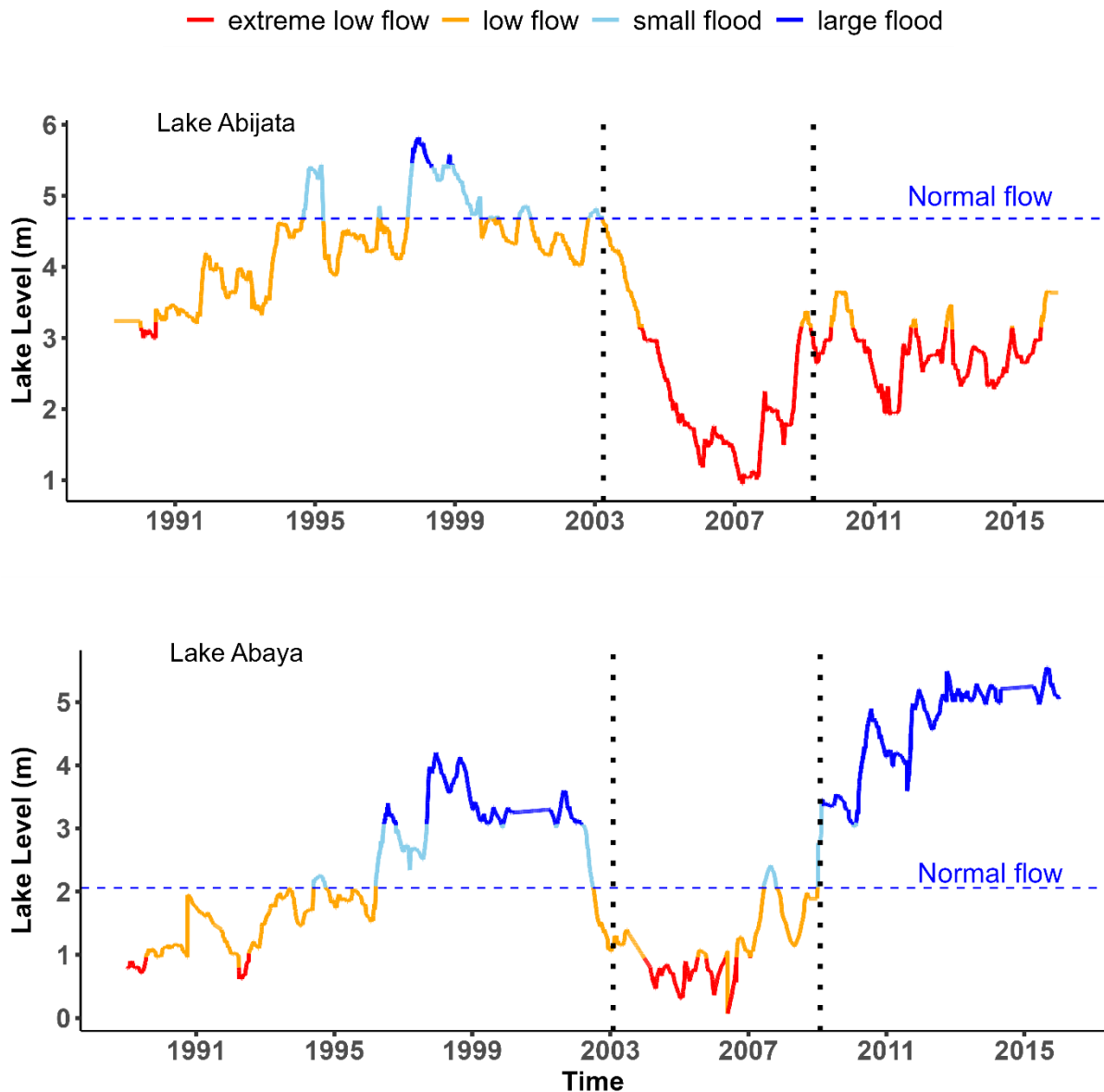


Figure 4-8: Environmental flow analysis of Lake Abijata and Abaya based on observed data

Fig. 4-9 depicts the monthly median and FDC plot of Lake Abijata and Abaya in the pre-impacted and impacted period. It is observed that the lake level and the natural regime have altered after the year 2002/2003 in both lakes. The Lake Abijata level exhibited a significant decrease during the pre-impacted period for all months, while the Lake Abaya level showed a significant increase during the impacted period in all months. The FDC showed an increase in the Lake Abaya level across all flow regimes (low, middle, and high) and a decrease in the Lake Abijata level. A high degree of alteration is observed in both lakes; but the hydrological regime of Lake Abaya has undergone a complete change, especially during the dry season (May to September). This is associated with a change of the rainfall pattern (Ayalew et al., 2022b).

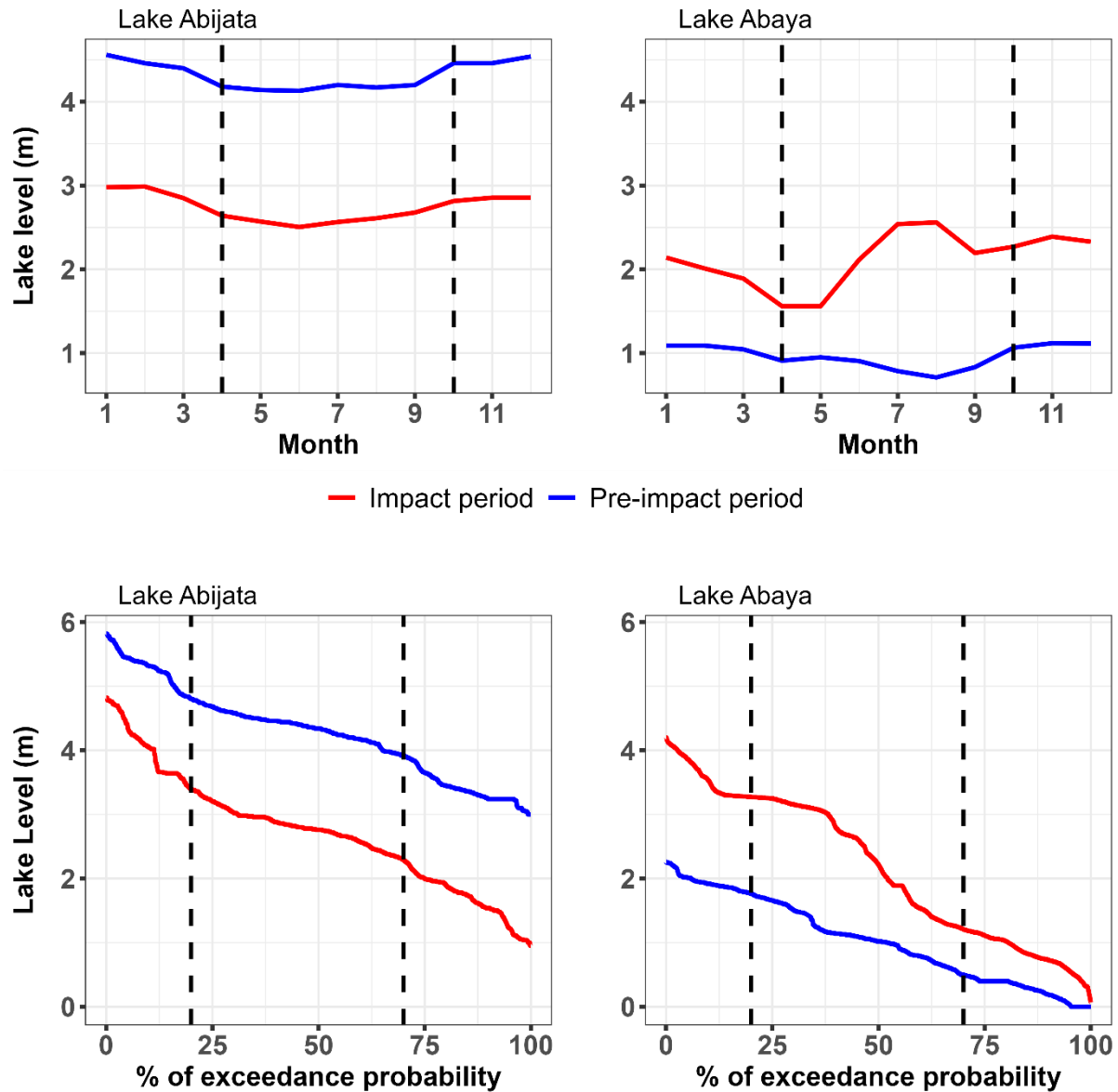


Figure 4-9: Monthly median and FDC analysis of pre-impacted and impacted period

Median of monthly flow (RVA Group 1) throughout the impact period indicates a decreasing trend compared with the pre-impact period in the Lake Abijata. The dispersion coefficients for the pre-impact period (ranging from 0.21 to 0.33) are mostly lower than those for the impact period (ranging from 0.3 to 0.49), indicating the higher flow fluctuations in the impacted period due to the irrigation expansion and soda ash factory. Whereas in Abaya Lake, median of monthly flow depicted an increasing trend compared with the pre-impact period. The dispersion coefficients for the pre-impact period (ranging from 1.18 to 1.68) are mostly lower than those for the impact period (ranging from 0.80 to 1.5), indicating that the higher flow fluctuations in the impacted period due high runoff are associated with high deforestation (Ayalew et al.,

2022a, Dessie and Kleman, 2007, Garedew et al., 2009c). The medians of annual 1-, 3-, 7-, 30, 90-day minimum and 1-, 3-, 7-, 30- and 90-day maximum for the impact period decrease significantly for Lake Abijata and significantly increase in the case of Abaya Lake. These results indicate that the daily, weekly, monthly and seasonal maximum/minimum flow cycles are negatively influenced by water abstraction for irrigation and factory in the case of Lake Abijata; and positively influenced by runoff increasing the case of Lake Abaya.

The median Julian dates for the annual 1-day minimum have shifted forward in the impacted period, moving from the 137th and 91st day in the pre-impact period to the 130th and 113th day in Lake Abijata and Abaya, respectively. Likewise, the median Julian dates for the annual 1-day maximum have also moved forward in the impact period, shifting from the 309th and 320th day to the 327th and 311st day in Lake Abijata and Abaya, respectively. The result also showed that there is no significant change on the medians of low, high pulse counts and base flow index in the impact period and in the pre-impact period, in both lakes (Figure 4-10).

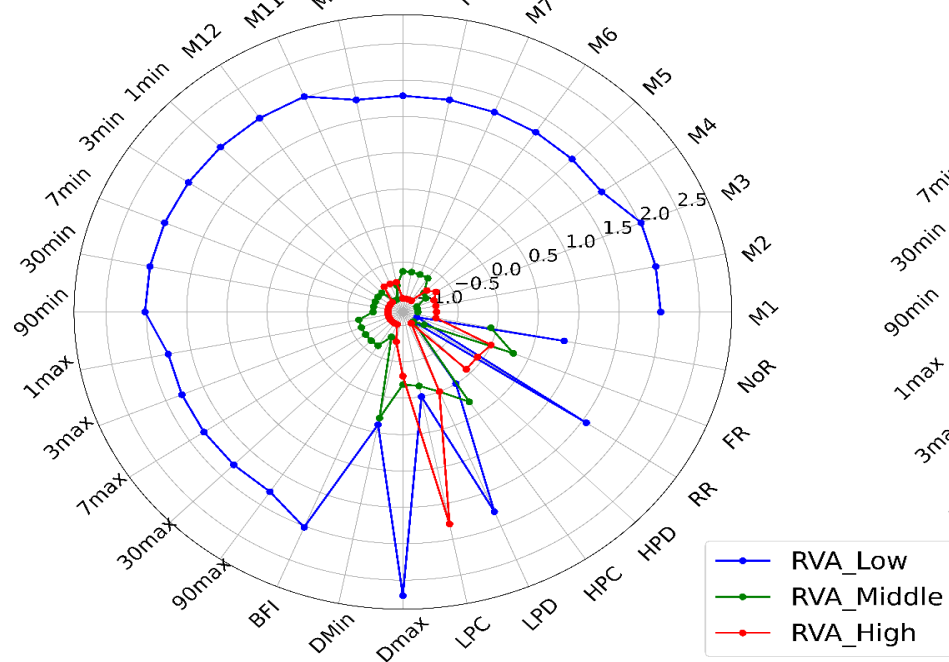
The medians of low pulse durations (increased from 2 to 47) and high pulse durations (increased from 64 to 140) in the impacted period are higher than those in the pre-impact period in Lake Abijata. However, the medians of low pulse durations (decreased from 125 to 36) and high pulse durations (increased from 208 to 223) in the impact period in Lake Abaya which indicates a high hydrologic alteration of low and high pulse durations. Median of high pulse durations have increased in both lakes, which is associated with increasing runoff during wet season.

The medians of rise rate and fall rate are the same as those in the pre-impact period in both Lakes except the number of reversals. The number of reversals is higher than in the pre-impacted period (decreased from 41 to 23) in Lake Abaya; and (decreased from 88 to 78) in Lake Abijata.

Considering all 33 parameters (Figure 4-10), the highest hydrologic alteration factors has occurred in low RVA category (ranging from 1 to 2.7) except fail rate and high pulse duration, which indicates annual parameter values more often fell inside the RVA target window than expected in Lake Abijata. Likewise, in this lake the second highest hydrologic alteration factors have occurred in high RVA category (ranging from -1 to -0.1) except low pulse count, which indicates annual parameter values less often fell inside the RVA target window than expected. High hydrologic alteration factor has also been observed in Lake Abaya which in the low RVA category (ranging from -1 to -0.1) except fail rate and low pulse duration, which indicates annual parameter values less often fell inside the RVA target window than expected. In this

lake also the second highest hydrologic alteration factor has occurred in high RVA category in group one and group two (ranging from 0.6 to 1.5), which indicates annual parameter values more often fell inside the RVA target window than expected.

Lake Abijata



Lake Abaya

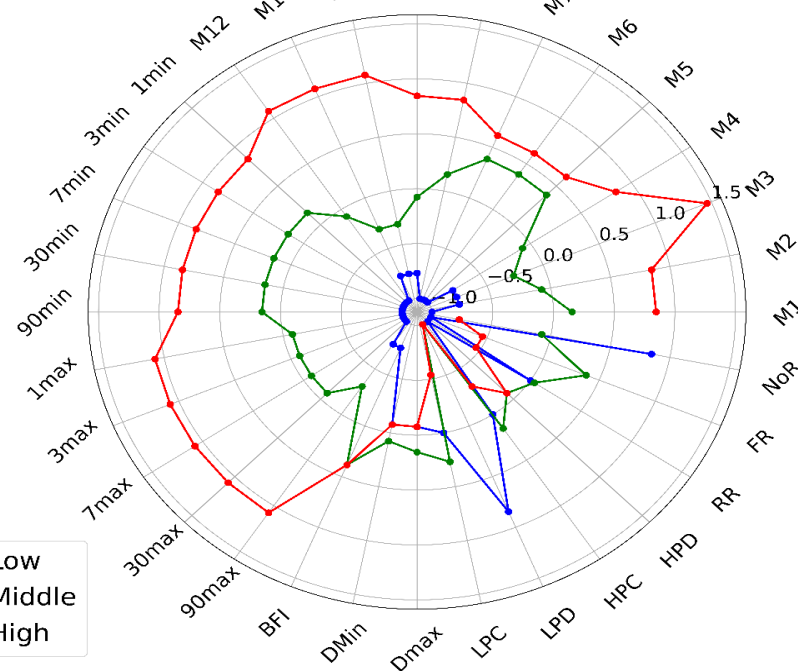


Figure 4-10: Hydrological alteration analysis using RVA

Where, 'M1', 'M2', 'M3', 'M4', 'M5', 'M6', 'M7', 'M8', 'M9', 'M10', 'M11', 'M12', '1min', '3min', '7min', '30min', '90min', '1max', '3max', '7max', '30max', '90max', 'BFI', 'DMin', 'Dmax', 'LPC', 'LPD', 'HPC', 'HPD', 'RR', 'FR', 'NoR' are 'January', 'February', 'March', 'April', 'May', 'June', 'July', 'August', 'September', 'October', 'November', 'December', '1_day_min', '3_day_min', '7_day_min', '30_day_min', '90_day_min', '1_day_max', '3_day_max', '7_day_max', '30_day_max', '90_day_max', 'Base_flow_index', 'Date_of_min', 'Date_of_max', 'Low_pulse_count', 'Low_pulse_duration', 'High_pulse_count', 'High_pulse_duration', 'Rise_rate', 'Fall_rate', 'Number_of_reversals'.

Generally, results indicate that the hydrological system is changing in both lake basins but responding differently to the changes. Changes in hydrology are mainly associated with human activity and climate change. Apparently, the changing hydrology for the impacted period (2003-2009) was worsen in the Lake Abijata and linked with frequent droughts and water abstraction. Despite the fact that the Lake Abijata's level increased during the post-impacted period, it remained lower than the lake level observed in the pre-impacted period. In contrast to the pre-impacted period, the water level of Lake Abaya increased during the post-impacted period.

4.3.1.4. Bathymetry analysis, Bathymetric Characteristics of Lakes

Morphometric characteristics and contour maps

Morphological parameters used to characterize the morphometry of the Lake Chamo, including area (A), Volume(V), maximum effective length (L_{me}), maximum width (W_{me}), mean width (W), maximum depth(d_{max}) and mean depth (d_{mean}), are summarized in Table 4-6. The values are presented with respect to the reference datum discussed in the methodology. The result is also compared with the bathymetry analysis of Awulachew (2001) conducted in 1998. The maximum depth increased by 4.4 m in the middle of the lake , the sediment thickness increased by about 0.6 m, the area increased by 30 km² and the volume increased by 7.8 x 10⁸ m³ within two decades (Figure 4-11).

Table 4-5: Morphometric characteristics of Lake Chamo

Parameter	Chamo Lake	
	This study (2021)	Awulachew (1998)
Altitude (m)	1110 (GPS)	1107(EMA 1: 50 000 maps)
Basin area, including lakes (km²)	18 599.8 (with Lake Abaya contribution)	18 599.8 (with Lake Abaya contribution)
A, including islands (km²)	346.76	316.72
Volume (m³)	4.12×10^9	3.24×10^9
L_{me} (km)	33.93 between 5°41'36"N and 37°28'40"E to 5°58'24"N and 37°35'56"E	33.50 between 5°42'00"N and 37°39'00"E to 5°58'00"N and 37°36'00"E
W_{me} (km)	16.07	15.5, perpendicular to L
W (km)	10.17	10.1
d_{max} (m)	18.6	14.2, near the middle
dmean (m)	11.38	10.23

The water depth distribution obtained using Kriging interpolation method in surfer20 is shown in Figure 4-11. A grid size of 110 m x 450 m bathymetric data was used to interpolate the depth distribution of the lake. The resulting depth estimates were plotted on a contour map to visualize the underwater topography of the lake, and we observed that the central region of the lake had the deepest parts.

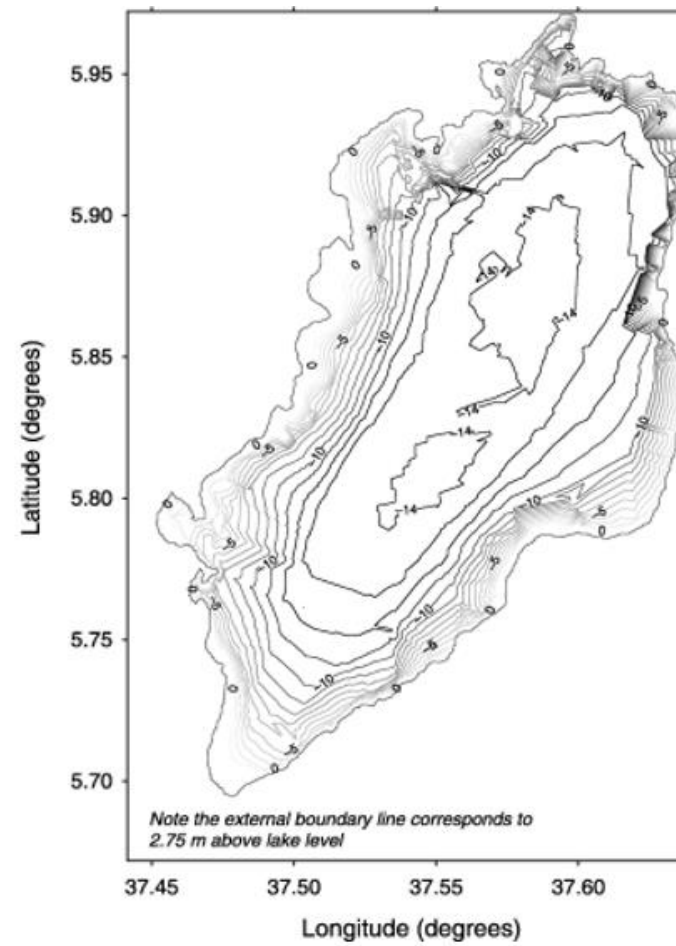
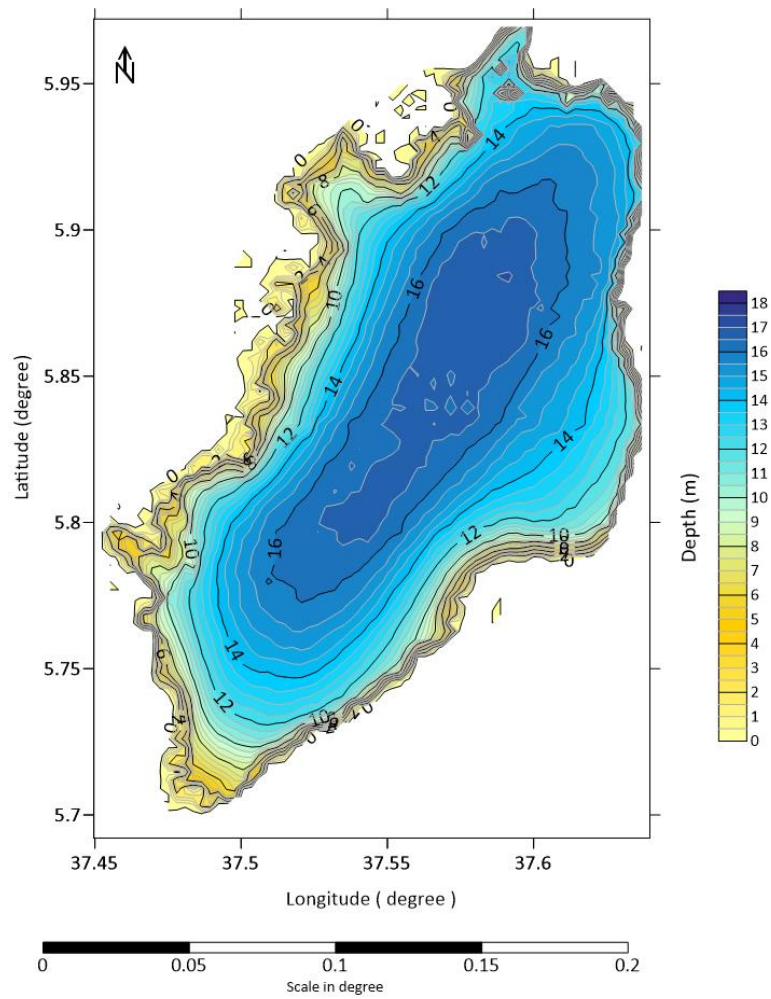


Figure 4-11: Bathymetric maps of Lake Chamo (a) bathymetry of this study (2021); (b) Bathymetry of Awulachew (1998)

4.3.1.5. Water level and storage change analysis

Fig. 4-12 a & b illustrates the changes in spatio-temporal patterns of Lake Chamo depth, area and storage over a span of 20 years (1998-2021), as indicated by the depth-area and storage analysis. Specifically, the lake has experienced an expansion, gaining an area of 30 km² (9.5%), and its volume has increased by 7.8 x 10⁸ m³ (27.2%) over the same period. As the maximum depth increased by 4.4 m (31%) and the lakebed level increased by 0.6 m (4.5%) possible factors that could contribute to such changes in lake size and volume are increased runoff and sedimentation from rivers or streams that flow into the lake due to land use change, deforestation. Another reason may be changes in the underlying geology of the area, such as changes in the flow of underground water and springs, that can contribute to changes in a lake's size and volume. These changes in size and volume could have significant ecological and environmental impacts on the lake and its surrounding area.

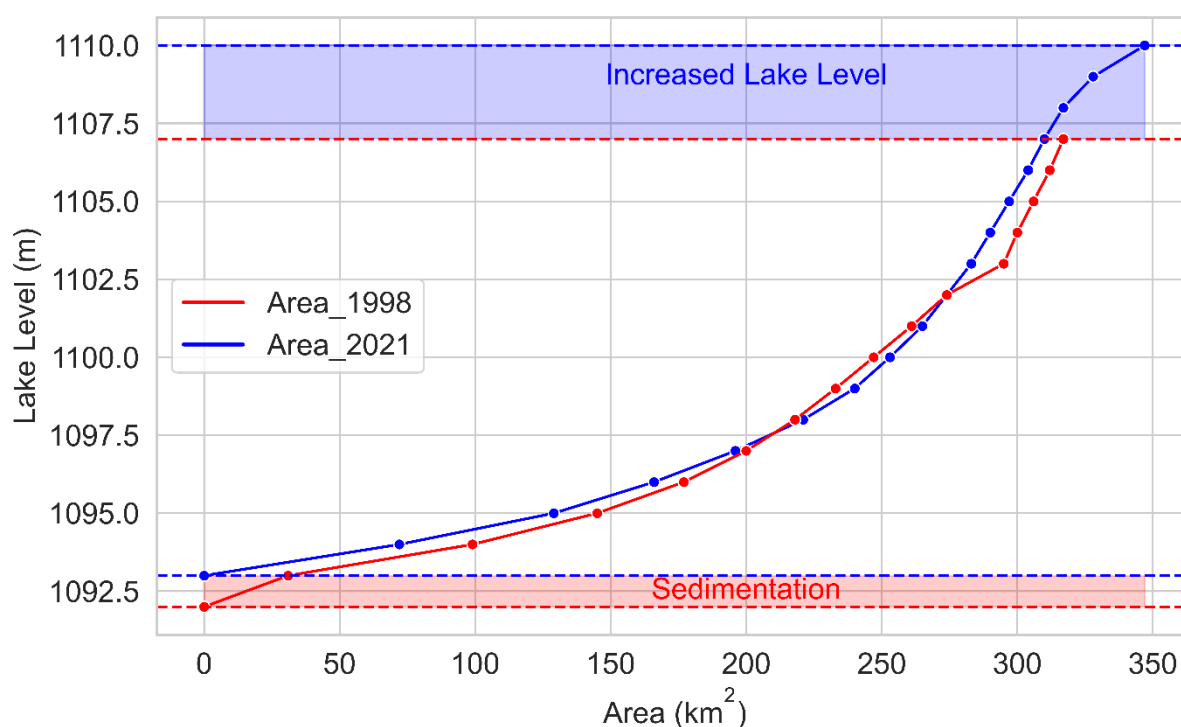


Figure 4-12a: Area-depth change analysis: blue color for the 2021; red color for 1998 (Awulachew (1998))

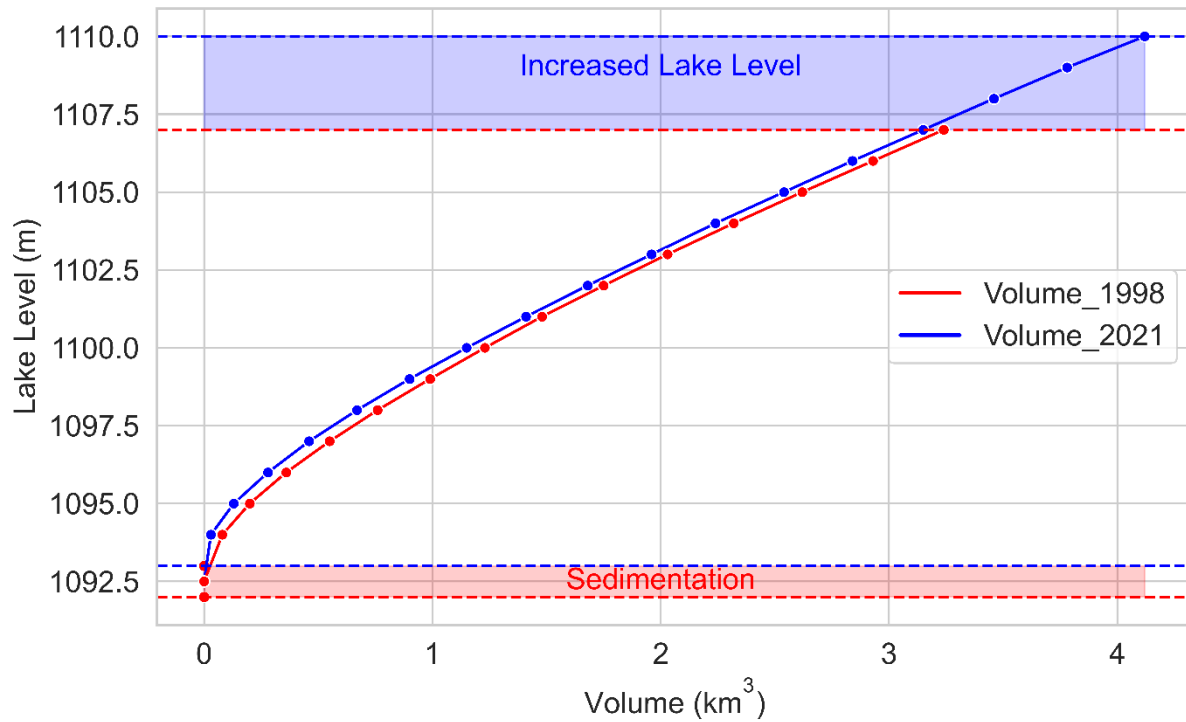


Figure 4-13b: Volume-depth change analysis: blue color for 2021; red color for 1998 (Awulachew (1998))

4.4. Discussion

In the context of the regionalization of model parameters, our hydrological model exhibited a performance level that aligns closely with the findings documented in the literature (Seibert, 1999, Beldring, 2002, Merz and Blöschl, 2004). Based on the evaluation using the objective functions NSE, KGE, PBIAS, and RSR, the pooled calibration technique showed a good performance. It exhibited a remarkable ability to accurately represent observed hydrological behavior, particularly for the closest pseudo watersheds (Gidabo, Upper Gelana, Meki, Katar, and Bilate). This phenomenon of varying performance across spatially related watersheds (also noted by Merz and Blöschl (2004), who attributed it to the interplay of spatial hydrologic variability and poor data quality. Seibert (1999) observed a decline in NSE runoff efficiency from 0.81 to 0.79 when transitioning from calibrated to regionalized parameters across 11 catchments and a decrease to 0.67 for a separate set of 7 catchments. Beldring (2002) also found an NSE of 0.68 for 141 gauged catchments and 43 catchments treated as ungauged, though approximately 20% of the latter group exhibited efficiencies below 0.3. Compared to this the maximum decline in model performance due to regionalization in our study is observed in the Bilate watershed with a decrease of the NSE from 0.68 (cal) /0.63 (val) in the donor watershed to 0.53 in the pseudo watershed (Table 4-3). In this case, the donor watershed (Chamo) is

dominated by semi-natural vegetation, whereas, the pseudo watershed (Bilate) has a larger share of agricultural land. It is evident that while regionalization allows for broader model applicability, the accuracy of predictions can vary significantly depending on contextual factors and the specific characteristics of the studied watersheds.

The study revealed significant changes in lake levels and inflows over the past two decades in the Rift Valley Lakes. Notably, Lake Chamo experienced substantial increases in area, depth, and volume, while Lake Abijata witnessed an extraordinary decrease in area and depth. The result revealed that significant shifts in the hydrological system of Lake Abijata and Lake Abaya after the year 2003. Substantial decreases in lake levels were observed in both lakes from 2003 to 2009. The lake levels recovered after 2009. In the post-impact period (2010-2015), the lake level of Lake Abaya showed an increase compared to both the pre-impact (1987-2003) and impact period (2003-2009). On the contrary, during the same period, the lake level of Lake Abijata showed a noticeable decreasing trend compared to the pre-impact period. According to Ayalew et al. (2022), the significant decline in water level during the impact period (2003-2009) was primarily attributed to prolonged drought affecting both lakes. A study by Street (1979) also investigated that many of the Rift Valley lake's water level fluctuations were associated with climate conditions rather than anthropogenic factors. However, recently the changing water level is also associated with anthropogenic activities (Alemayehu et al., 2006).

The Range Variable Approach (RVA) analysis also revealed that the river's flow regime has deviated significantly from its natural or historical patterns. The High-RVA and Middle-RVA values are negative in Lake Abijata, which indicates that the river's flow conditions are lower than what would be expected based on historical data. The negative value of high and middle, and the positive value of low level of Lake Abijata coincides with the time of high-water abstraction for soda production and water abstraction for irrigation from the upstream Lake Ziway. In the wet season, the time between May to September is a refilling period of the lake from large inflows from the Katar and Meki rivers. During the dry season (November to June), Ziway shows a net loss of storage due to high abstraction of water for irrigation. This high abstraction of water leads to shifts in the flow regime, and a positive value of low-RVA as observed. In Abaya Lake, the hydrological system responded reversely. The High-RVA and Middle-RVA values are positive, and the low-RVA value is negative. This indicates that the peak flow increased in the impact period during the wet season. Our previous work, Ayalew et al. (2023), showed an increasing surface runoff and decreasing infiltration and evaporation after 2000, which is associated with deforestation and agricultural expansion.

Lake Abijata is a terminal lake; it lacks any surface or groundwater outflow, making its water level and volume subject to changes in hydrological budget components such as rainfall, river inflow, and evaporation. However, recent development schemes in soda ash extraction and irrigation have also contributed to the drastic reduction of the lake level (Alemayehu et al., 2006). The main inflow is from the discharge from the Horakelo and Bulbula rivers, which are the outflows of lakes Langano and Ziway, respectively, and direct rainfall. The total river inflow decreased by 12.5%, which is associated with water abstraction for irrigation. As it is a terminal lake, the ways of water loss from the lake are evaporation and abstraction. Therefore, the main reason for hydrological regime change was water abstraction of feeding rivers for irrigation and water abstraction for industrial purposes from the lake followed by evaporation. Alemayehu et al. (2006) also state that abstraction of Lake Ziway for irrigation also has an influence on the level of Lake Abijata. Conversely, Lake Chamo experienced an increase in its water level during the post-impact period. The lake level increased by 4.4 m, and the lake bottom elevation increased by 0.6 m. This significant water level rise is mainly due to high surface runoff and sediment transportation. The total surface inflow increased by 80.5%, which is influenced by changes in Land Use and Land Cover, particularly deforestation and agricultural expansion, which resulted in higher runoff (Ayalew Ayenew D et al., 2023) and enhanced sediment transportation. In contrast to many East African terminal lakes, Lake Chamo has shown significant water level rise. These changes can be explained by change in Land Use and Land Cover (LULC) and climate change (Ayalew et al. 2023). Influence of human activities exerted a more significant impact compared to climate change. The hydrological regime of the lakes is affected by human-induced factors (mainly abstraction, urbanization, and deforestation) associated with rapid population growth. In the Northern part of the study area high water abstraction for irrigation and industry was the main driving factor for the changes hydrology. However, in the Southern part of the study area, high runoff and sedimentation associated with high deforestation are the main driving factors for the hydrological alterations (Ayalew et al. 2023). Even though further investigation is required, the changing hydrological system in the Rift Valley also might be linked to the geological setting. The Rift Valley is formed due to the divergent movement of tectonic plates, leading to the creation of a rift or crack in the Earth's crust. This tectonic activity results in the formation of grabens and horsts, additionally influencing the hydrological characteristics of the region (Scoon, 2018, Chorowicz, 2005b).

4.5. Summary and Conclusions

The Rift Valley Lakes in Ethiopia have experienced changes in their hydrological regime, due to anthropogenic and climate change. Integrating a physical based hydrologic model, break point analysis, indicators of hydrologic alteration (IHA) and bathymetry survey is a better approach to understand a dynamic and complex hydrological system and the potential driving factors. Indicators of hydrological alteration (IHA) were derived from lake level data that clearly showed the alterations of hydrological regime. Main water balance components were simulated using a semi-distributed Soil and Water Assessment Tool plus (SWAT+) model. Multisite regionalization techniques represent the hydrological behavior of multiple locations and that the model can be used to make predictions for other locations. The SWAT+ model performed well for daily stream flow during calibration and validation period. The pooled calibration approach showed a satisfactory performance in capturing observed hydrological behavior, both in ‘donor’ and ‘pseudo’ watersheds. The applied calibration technique was suitable for regionalization of model parameters as the rather small decrease of model performance in the pseudo ungauged watersheds showed.

The findings reveal notable changes over the past two decades. Lake Chamo experienced an increase in area by 11.86 km², depth by 4.4 meters, and volume by 7.8 x 10⁸ cubic meters. In contrast, Lake Abijata witnessed an extraordinary 68% decrease in area and a depth decrease of -1.6 meters. Mean annual rainfall decreased by 6.5% in Lake Abijata and 2.7% in Lake Chamo during the impacted period. Actual evapotranspiration decreased by 2.9% in Lake Abijata but increased by up to 0.5% in Lake Chamo. Surface inflow to Lake Abijata decreased by 12.5%, while Lake Chamo experienced an 80.5% increase in surface inflow. Sediment depth in Lake Chamo also increased by 0.6 meters.

The results of this study highlight on the changing hydrological regime in Lake Chamo, emphasizing the role of anthropogenic influences in increasing surface runoff and sediment intrusion. Conversely, the hydrological dynamics of Lake Abijata are primarily affected by water abstraction from the rivers and lakes that serve as its water sources, driven by industrial and irrigation demands. By examining these factors, this research offers valuable insights into the evolving hydrological systems of the Rift Valley Lakes in Ethiopia, contributing to a better understanding of the driving forces behind these changes.

The hydrological regime of Lake Chamo has experienced changes characterized by increased area, depth, and volume, primarily influenced by heightened surface runoff and sediment intrusion.

Lake Abijata has undergone significant changes in its hydrological regime, marked by a substantial decrease in area and depth, resulting from water abstraction for industrial and irrigation purposes from feeding rivers and lakes.

The findings emphasize the importance of understanding the driving factors behind hydrological changes in Rift Valley Lakes, particularly the influence of anthropogenic activities and climatic variations. Lake level changes, whether declining or increasing, have resulted from a combination of natural and human-induced factors. These changes can have significant impacts on ecosystems, human communities, and water availability. Mitigating the impacts of these changes requires sustainable water management practices, climate change adaptation strategies, and a holistic understanding of the interconnection of ecosystems and human activities.

Further research and monitoring efforts are necessary to deepen our understanding of the hydrological processes and identify effective management strategies to ensure the sustainable use and conservation of the Rift Valley Lakes in Ethiopia.

Acknowledgments: The German Academic Exchange Service (DAAD) and the Ethiopian Ministry of Education supported this research. Our grateful acknowledgment is also towards to Ethiopian Ministry of water resources for providing hydrological data; Ethiopian Meteorology Agency for providing meteorological data and Arba Minch University- Vlaamse Inter-universitaire Raad-Institutional University Cooperation (AMU-VLIR-IUC) program for funding the bathymetry survey conducted on Lake Chamo.

5. General Conclusion and Summary

The dynamics of long-term variability of climatic and LULC change, coupled with the increasing frequency and intensity of extreme weather events, pose significant challenges to water resource management, environmental sustainability, and societal resilience (Cao et al., 2022). The main driving factors of these changes are climate change and human activities (Wang et al., 2021). Climate change manifests as shifts in precipitation and temperature patterns, alterations in the timing and magnitude of runoff, and an increasing occurrence of extreme weather events (Trenberth, 2011). Therefore, understanding the long-term variability

of hydro-climatic processes and their interplay with extreme events becomes a scientific endeavor. This study focuses on modeling and analysis of the long-term variability and associated occurrence of extreme events in the Rift Valley Basin. By doing so, the past and present hydrological system in the face of changing land use and climate were evaluated. Addressing questions about how the hydrological systems are changing in the basin is not only of scientific interest but also of paramount importance for the environment, economies, and societal well-being in the basin.

The Rift Valley Basin is known as the District of Lakes and contains 80% of Ethiopia's lakes, with immense ecological significance and providing valuable ecosystem services. It is characterized by diverse climates and topographic features. Agriculture is the dominant land use, accounting for 58% followed by vegetation (30%) and water bodies (5.6%) from the total land share.

This research has investigated the connection among climate, LULC, and hydrological systems using an integrated approach (hydrological modeling, bathymetry survey, and statistical analysis). Apart from evaluating the pattern of LULC and climate, the isolated and combined impacts of climate change and LULC on main water fluxes have been evaluated. In this endeavor, it was possible to understand the hydrologic system through understanding the interconnection of factors influencing hydro-climatic variability.

The findings from this research have far-reaching implications. By elucidating the dynamics of hydro-climatic processes in the basin, it provides invaluable insights for water resource management, agricultural practices, disaster preparedness, and ecosystem conservation. Moreover, this research underscores the importance of long-term monitoring and modeling in assessing the sustainability of water resources and ecosystems in the face of climate variability and LULC change.

How have LULC and climate dynamics evolved over the past decades in the Rift Valley Basin?

The results revealed that the Rift Valley Lakes Basin has undergone substantial LULC changes over the study period. These changes include the conversion of natural vegetation into agricultural fields (12.2%), urban expansion (0.78%), deforestation (24.64%), and alterations in wetland areas (1.6%).

Various drivers underpin these changes, with population growth, agricultural expansion, urbanization, and infrastructure development playing pivotal roles (Ariti et al., 2015, Bekele et al., 2019). These human activities have significantly influenced the region's ecosystems (Mekuria et al., 2021a). Following human activities, agricultural expansion policy and climate change have played a great role in changing LULC (Desta and Fetene, 2020a).

The study has highlighted the consequences of these transformations on the disruption of hydrological systems and increased vulnerability to natural disasters like floods and landslides. Changes in LULC also have directly affected water resources in the Rift Valley. Changes in the area of water bodies and the drying wetlands have had implications for the quantity of available water. The alterations in LULC have had both negative and positive consequences on water resources.

The findings underline the urgency of effective conservation and land management strategies. Sustainable land use practices, reforestation efforts, and urban planning are critical to mitigating the negative impacts and fostering long-term resilience in the region. Effective policies and governance mechanisms are needed to balance the demands for economic development with the need to protect the environment and the rights of local communities. Collaboration among stakeholders, including government bodies, NGOs, and local communities, is vital for achieving sustainable land use in the Rift Valley.

The climate dynamics in the Rift Valley Lakes Basin are complex and highly influential in shaping the region's geography, ecology, and human activities. The climate patterns in this region exhibit variability due to the basin's diverse topography (Kassie et al., 2014c). Precipitation patterns in the basin are influenced by both the long and short rainy season, with the latter occurring in a shorter, more intense period. These precipitation patterns vary across the basin due to its size, topographical differences, and North-South movement of the ITCZ, leading to differing amounts of rainfall in different areas and years (Ademe and Eshetu, 2021, Hessebo et al., 2021). The basin's altitude range, from highlands to lowlands, also contributes to temperature gradient. Cooler temperatures in the highlands contrast with warmer conditions in the lowlands, impacting agriculture, ecosystems, and human settlement patterns.

The Rift Valley Lakes Basin has historically relied on a predictable pattern of rainfall. However, climate change has disrupted this pattern, leading to increased variability in rainfall, with periods of drought and intense rainfall becoming more common (Tullu, 2024). Rising temperatures are a key feature of climate change in the region. Higher temperatures have led to

increased evaporation rates from the lakes and have contributed to a warming trend that affects the local climate and ecosystems. Changes in rainfall patterns and temperature have altered the hydrology of the lakes and rivers. This has led to fluctuations in water levels, which can impact local agriculture, fisheries, and water availability for communities. Climate change also has increased the frequency and intensity of extreme weather events in the basin. These events, including drought and flooding, can have devastating impacts on local communities and infrastructure.

The region's unique ecosystems, including wetlands, grasslands, and aquatic habitats, are under stress due to climate change. Altered water levels and temperatures can disrupt these ecosystems, affecting both plant and animal species. Changes in temperature and rainfall can also influence the water quality of the lakes. This can have implications for aquatic life and the communities relying on the lakes for drinking water and fishing.

In conclusion, the Rift Valley Lakes Basin is experiencing notable effects of climate change, which are reshaping the region's environment and impacting the livelihoods of its inhabitants. These changes highlight the need for comprehensive climate adaptation and mitigation strategies that address water resource management, agriculture, and conservation efforts. Collaborative efforts between governments, conservation organizations, and local communities are essential to navigate the challenges posed by climate change in this ecologically and culturally significant region.

How has changing hydrology responded to LULC and climate dynamics in the Rift Valley Basin?

Hydrological changes in the basin are occurring due to a combination of LULC and climate changes. The interaction between LULC change and climate change has a substantial and multifaceted impact on the hydrology of the basin. These changes are closely intertwined and exacerbate each other's effects. Among the two factors, following the combined impact of LULC and climate change, LULC is observed to have a greater influence on the hydrological system of the basin. This is because the alteration of LULC, often driven by urbanization, agricultural expansion, and deforestation, directly affects local hydrology. Changes in vegetation, surface runoff patterns, and soil permeability can lead to increased surface water runoff and reduced groundwater recharge (Belihu et al., 2020). The region is experiencing shifts in temperature and precipitation patterns as a result of global climate change. This can lead to

altered evapotranspiration rates, changes in the timing and intensity of rainfall, and increased temperatures, all of which impact the water balance of the lakes and surrounding ecosystems.

Rising temperatures have led to increased evaporation from water bodies, while deforestation and drying wetlands have generally reduced evapotranspiration in some areas (Menna, 2017). Surface runoff has varied over time, with changes in precipitation patterns and LULC, where periods of intense rainfall can lead to flooding and soil erosion. However, urbanization and deforestation have also reduced the landscape's ability to absorb rainfall, further increasing runoff.

Groundwater recharge has decreased due to urban expansion and increased surface runoff, which reduces the natural infiltration of rainwater into aquifers. The hydrological response to these factors is complex, with LULC changes, such as deforestation and agricultural expansion, directly affecting runoff patterns, groundwater recharge, and water availability. These factors often exacerbate each other's impacts on the water system (Dessie & Suryabhagavan, 2019; Seyoum et al., 2021; Dinku et al., 2019).

Why is the hydrological response to LULC and climate dynamics different in the upper and lower parts of the Rift Valley Basin?

The Rift Valley Lakes have witnessed notable hydrological changes over time. The rising and declining of lake levels have been observed over time. In the southern part of the basin, the lake water level is increasing due to high surface runoff and sedimentation. In the northern part of the basin, the lake water level is declining due to the high abstraction of water from the rivers and lakes for irrigation and industrial use (Balcha et al., 2022). The high deforestation rate in the southern part of the basin has significantly altered surface runoff patterns, increasing the potential for flooding and erosion. These variations are influenced by different rainfall patterns, temperature differences, and land use practices across the basin, with lower areas being more vulnerable to runoff and sedimentation due to their flatter landscapes and proximity to agricultural areas. Such differences highlight the complex interplay between LULC, topography, and climatic influences that shape hydrological responses across the basin (Guta et al., 2021; Teshome et al., 2020; Gashaw et al., 2020). Therefore, the basin is experiencing hydrological changes primarily driven by the combined impact of abstraction, LULC change, and climate change. While all factors play a role, the interaction between them leads to more pronounced and far-reaching consequences.

How can an integrated hydrological modeling approach be effective in evaluating the main driving factors for changing hydrology in data-scarce region?

An integrated hydrological modeling approach, such as the combination of hydrological modeling with SWAT+, bathymetry surveys, and statistical analyses, can provide a comprehensive assessment of the main factors influencing hydrological changes. This approach enables the isolation and evaluation of the impacts of LULC change and climate changes on key water fluxes, such as runoff, evapotranspiration, and groundwater recharge. Through modeling, researchers can simulate various scenarios, understanding the potential effects of different land management practices or climate trends on water availability and ecosystem health.

Additionally, the integration of statistical and bathymetric data allows for more accurate assessments of lake water levels, flow patterns, and sedimentation. This research highlights the need for continuous monitoring and modeling to adapt to the ongoing changes and ensure sustainable water resource management in the basin. Despite some challenges, such as the lack of inflow data from ungauged catchments, this integrated approach supports stakeholders in making informed decisions for sustainable water resource management and resilience against climate impacts (Awulachew et al., 2020; Mekonnen et al., 2020).

The research on modeling the dynamics of long-term variability of hydroclimatic processes and associated extreme events in the Rift Valley Lakes Basin, Ethiopia, could contribute to the field of climate science and regional development. It equips policymakers, resource managers, and stakeholders with critical knowledge to make informed decisions in managing water resources, mitigating climate-related risks, and promoting resilience. This study underscores the need for continued research and proactive measures to address the challenges posed by a changing climate in vulnerable areas like the Rift Valley Lakes Basin.

This research is also a call to action. It underlines the urgency of managing water resources judiciously, adapting to the new normal of hydro-climatic variability, and fortifying resilience against the impacts of extreme events. The results of this study contribute to policymakers, environmental stewards, and communities around the world as they grapple with the challenges posed by dynamic and evolving hydro-climatic dynamics.

This study employed hydrological model, and statistical analysis and bathymetry survey to address these hydrological changes and their consequences. The bathymetry survey was

conducted only for one lake; for the future it would be of interest to conduct more bathymetry survey. Estimating inflows from ungauged catchments was challenging; a multisite calibration regionalization technique was applied but it was time consuming and laborious work. Therefore, continued monitoring and research efforts are crucial to better understand and adapt to the evolving hydrological dynamics of the Rift Valley Lakes Basin.

6. Outlook

The research findings on hydroclimatic processes in the Rift Valley Lakes Basin of Ethiopia underscore the importance of understanding long-term variability for sustainable water resource management. Policymakers and stakeholders can leverage insights into potential shifts in precipitation and runoff patterns to develop adaptive strategies that address water scarcity and mitigate flood risks, ensuring a reliable water supply for various sectors. Given the anticipated impacts of climate change, future studies should build upon existing modeling approaches to project hydroclimatic dynamics under different scenarios, enhancing preparedness for changing conditions. Moreover, the study's insights into extreme events like droughts and floods are crucial for disaster risk reduction efforts, informing the design of effective early warning systems and emergency response plans. Collaboration among meteorological agencies, disaster management authorities, local communities, researchers, and academic institutions is essential for implementing these strategies effectively. Additionally, understanding the ecological consequences of changing water levels is vital for conservation efforts, guiding initiatives that balance the needs of growing populations with environmental preservation. This holistic approach supports sustainable development planning, integrating socio-economic and environmental considerations for the region's future.

In the Rift Valley Basin, subbasins exhibit varying hydrological responses. In the upper part of the basin, there is evidence of water bodies decline, while in the lower part, new water bodies are appearing. This highlights the need for a detailed investigation into the connections between subbasins and the neighboring basins, groundwater flow, and the interactions between surface and groundwater systems.

The Soil and Water Assessment Tool (SWAT) and its enhanced version, SWAT+, struggles with the complex coupled interactions between atmospheric conditions and engineered systems, which are crucial during extreme weather events. This complexity limits the model's predictive capabilities for droughts and floods (King et al., 2023). These limitations stem from both model structure and external factors influencing hydrological processes. The limitations highlight the

need for improved modeling techniques and verification methods to enhance the accuracy of extreme event predictions. Both SWAT and SWAT+ also often fail to accurately simulate rain-on-snow (ROS) events, which are critical in cold climates (Farjad et al., 2017, Bouchard et al., 2024). This leads to misrepresentation of streamflow distributions, particularly during winter floods and summer droughts (Myers et al., 2021). Therefore, future work on improving the ability of SWAT+ to predict extreme events.

The Ethiopian Rift Valley is significantly affected by high erosion and sediment yield rates, driven by land use changes and climatic factors. Various studies highlight the severity of soil loss and its implications for land management and agricultural productivity. For example, the Boyo watershed experienced a mean annual soil loss increase from 15.5 t/ha/y in 1991 to 38.3 t/ha/y in 2020, with 74,147.25 tons of sediment reaching its outlet annually (Mathewos et al., 2024). In the Gidabo watershed, sediment yield increased by 24-43% due to land use changes and climate dynamics, indicating a critical need for targeted conservation strategies (Girma et al., 2023). For the upper Meki Sub-catchment, an annual soil loss of approximately 28.12 t/ha/y reported (Teku et al., 2024). The Ayigebire watershed shows an alarming annual soil loss of 47 t/ha/y, significantly exceeding the national tolerable limit (Abebe and Woldemariam, 2024). Research on suspended sediment dynamics in the southern Rift Valley revealed substantial variability in sediment concentration, influenced by seasonal vegetative cover and localized erosion processes (Tilahun et al., 2023). Despite these findings, some argue that improved land management practices could mitigate erosion impacts, emphasizing the importance of sustainable agricultural practices and reforestation efforts to restore degraded areas. However, the role of floodplains in sediment retention within the Rift Valley can be significant, as they act as sinks for sediment transported by rivers. This sediment trapping is essential for managing sediment flux and maintaining ecological balance in these regions. So, further work is crucial to investigate the role of floodplains in sediment retention.

7. References

- ABBASPOUR, K. C., ROUHOLAHNEJAD, E., VAGHEFI, S., SRINIVASAN, R., YANG, H. & KLØVE, B. 2015. A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model. *Journal of hydrology*, 524, 733-752.
- ABDULE, A. M., MULUNEH, A. & WOLDEMICHAEL, A. 2024. Modeling climate change projection and its impact on the streamflow in the Yadot watershed, Genale Dawa basin, Ethiopia. *Journal of Water Climate Change*, 15, 3487-3505.
- ABDULLAH, H. M., MAHBOOB, M. G., RAHMAN, M. M. & AHMED, T. J. I. J. E. 2015. Monitoring natural Sal forest cover in Modhupur, Bangladesh using temporal Landsat imagery during 1972–2015. 5, 1-7.
- ABEBE, T. G. & WOLDEMARIAM, A. 2024. Erosion spatial distribution mapping and sediment yield estimation using RUSLE and Arc GIS of Ayigebire watershed, North Shewa zone of Amhara region, Ethiopia. *Water-Energy Nexus*, 7, 124-134.
- ABRAHAM, T., LIU, Y., TEKLEAB, S. & HARTMANN, A. I. 2021. Quantifying the regional water balance of the Ethiopian Rift Valley Lake basin using an uncertainty estimation framework. *Hydrology Earth System Sciences Discuss*, 2021, 1-25.
- ABRAHAM, T., WOLDEMICHEALA, A., MULUNEHA, A. & ABATEB, B. 2018. Hydrological responses of climate change on Lake Ziway catchment, Central Rift Valley of Ethiopia. *J. Earth Sci. Clim. Change*, 9, 474.
- ADAM, E., MUTANGA, O., ODINDI, J. & ABDEL-RAHMAN, E. M. 2014. Land-use/cover classification in a heterogeneous coastal landscape using RapidEye imagery: evaluating the performance of random forest and support vector machines classifiers. *International Journal of Remote Sensing*, 35, 3440-3458.
- ADDOR, N. & MELSEN, L. 2019. Legacy, rather than adequacy, drives the selection of hydrological models. *Water resources research*, 55, 378-390.
- ADEME, F. & ESHETU, M. 2021. Spatial analysis of climate variability and change in the Great Ethiopian Rift Valley basins. *Journal of Environment Earth Science*, 11, 1-12.
- AHN, K.-H. & MERWADE, V. Quantifying the relative impact of climate and human activities on streamflow. *Journal of Hydrology*, 515, 257-266.
- AJAMI, H., SHARMA, A., BAND, L. E., EVANS, J. P., TUTEJA, N. K., AMIRTHANATHAN, G. E. & BARI, M. A. 2017. On the non-stationarity of hydrological response in anthropogenically unaffected catchments: an Australian perspective. *Hydrology Earth System Sciences*, 21, 281-294.
- AKSTINAS, V., ŠARAUSKIENĖ, D., KRIAUCIŪNIENĖ, J., NAZARENKO, S. & JAKIMAVIČIUS, D. 2022. Spatial and temporal changes in hydrological regionalization of lowland Rivers. *International Journal of Environmental Research*, 16, 1-14.
- ALEMAYEHU, A. & TESFAYE, A. 2024. The morphometric investigation of the Gelda watershed in the Lake Tana sub basin: implications for managing soil and water resources. *Modeling Earth Systems Environmental Earth Sciences*, 1-16.
- ALEMAYEHU, T., AYENEW, T. & KEBEDE, S. 2006. Hydrogeochemical and lake level changes in the Ethiopian Rift. *Journal of hydrology*, 316, 290-300.
- ALEXANDER, A. A., KUMAR, D. N., KNOBEN, W. J. & CLARK, M. P. 2023. Evaluating the parameter sensitivity and impact of hydrologic modeling decisions on flood simulations. *Advances in Water Resources*, 181, 104560.
- ALI, Y. 2016. Challenge and prospect of Ethiopian tourism policy. *Global Journal of Management Business Research: Real Estate, Event Tourism Management, Global Journals Inc.*, 16.
- ALLEY, R. B., MAROTZKE, J., NORDHAUS, W., OVERPECK, J., PETEET, D., PIELKE, R., PIERREHUMBERT, R., RHINES, P., STOCKER, T. & TALLEY, L. 2002. *Abrupt climate change: inevitable surprises*, National Academy Press.
- ALLEY, R. B., MAROTZKE, J., NORDHAUS, W. D., OVERPECK, J. T., PETEET, D. M., PIELKE, R. A., PIERREHUMBERT, R. T., RHINES, P. B., STOCKER, T. F. & TALLEY, L. D. J. S. 2003. Abrupt climate change. 299, 2005-2010.
- AMENU, K. 2013. *Assessment of water sources and quality for livestock and farmers in the Rift Valley area of Ethiopia: implications for health and food safety*, Sierke Verlag.
- AMENU, K., MARKEMANN, A. & VALLE ZÁRATE, A. 2013. Water for human and livestock consumption in rural settings of Ethiopia: assessments of quality and health aspects. *Environmental Monitoring Assessment* 185, 9571-9586.
- ARAGAW, H. M., GOEL, M. K. & MISHRA, S. K. 2021. Hydrological responses to human-induced land use/land cover changes in the Gidabo River basin, Ethiopia. *Hydrological Sciences Journal*, 66, 640-655.
- ARAGAW, H. M. & KURA, A. L. 2024. Hydrological response to land use/land cover changes in Ethiopian basins: a review. *Hydrological Sciences Journal*, 69, 986-996.

- ARAGAW, H. M., MISHRA, S. K. & GOEL, M. K. 2023. Assessing the impact of climate change on the hydrology of Gidabo river sub-basin, Ethiopian Rift Valley Lakes Basin. *Sustainable Water Resources Management*, 9, 65.
- ARAKI, S., SHIMA, M. & YAMAMOTO, K. 2018. Spatiotemporal land use random forest model for estimating metropolitan NO₂ exposure in Japan. *Science of The Total Environment*, 634, 1269-1277.
- ARD, I. 2004. Ethiopia Land Policy and Administration Assessment. Tech. Rep., USAID, United States Agency for International Development
- ARITI, A. T., VAN VLIET, J. & VERBURG, P. H. 2015. Land-use and land-cover changes in the Central Rift Valley of Ethiopia: Assessment of perception and adaptation of stakeholders. *Applied Geography*, 65, 28-37.
- ARNOLD, J. G., BIEGER, K., WHITE, M. J., SRINIVASAN, R., DUNBAR, J. A. & ALLEN, P. M. 2018. Use of decision tables to simulate management in SWAT+. *Journal of Water* 10, 713.
- ARNOLD, J. G., SRINIVASAN, R., MUTTIAH, R. S. & WILLIAMS, J. R. 1998. Large area hydrologic modeling and assessment part I: model development 1. *JAWRA Journal of the American Water Resources Association*, 34, 73-89.
- ASADIEH, B. & KRAKAUER, N. Y. 2017. Global change in streamflow extremes under climate change over the 21st century. *Hydrology Earth System Sciences*, 21, 5863-5874.
- ASENSO BARNIEH, B., JIA, L., MENENTI, M., ZHOU, J. & ZENG, Y. 2020. Mapping land use land cover transitions at different spatiotemporal scales in West Africa. *Sustainability*, 12, 8565.
- AWULACHEW, S. B., YILMA, A. D., LOULSEGED, M., LOISKANDL, W., AYANA, M. & ALAMIREW, T. 2007. *Water resources and irrigation development in Ethiopia*, IWMI.
- AWULACHEW, S. B. J. Z. J. 1999. Physical morphometric characteristics and capacity curves of Abaya and Chamo Lakes. 16, 26-37.
- AYALEW, A. D., WAGNER, P. D., SAHLU, D. & FOHRER, N. 2022a. Land use change and climate dynamics in the Rift Valley Lake Basin, Ethiopia. *Environmental Monitoring Assessment*, 194, 791.
- AYALEW, A. D., WAGNER, P. D., SAHLU, D. & FOHRER, N. 2022b. Land use change and climate dynamics in the Rift Valley Lake Basin, Ethiopia. *Environmental Monitoring Assessment*, 194, 791.
- AYALEW AYENEW D, WAGNER PAUL D, T., B. TIGABU,, SAHLU DEJENE, A. & NICOLA, F. 2023. Hydrological responses to land use and land cover change and climate dynamics in the Rift Valley Lakes Basin, Ethiopia. *Water and Climate Change*
- AYALEW, L., YAMAGISHI, H. & REIK, G. 2004a. Ground cracks in Ethiopian Rift Valley: facts and uncertainties. *Engineering Geology*, 75, 309-324.
- AYALEW, L., YAMAGISHI, H. & REIK, G. 2004b. Ground cracks in Ethiopian Rift Valley: facts and uncertainties. *Engineering Geology*, 75, 309-324.
- AYENEW, T. 2002. Recent changes in the level of Lake Abiyata, central main Ethiopian Rift. *Hydrological sciences journal*, 47, 493-503.
- AYENEW, T. 2004a. Environmental implications of changes in the levels of lakes in the Ethiopian Rift since 1970. *Regional environmental change*, 4, 192-204.
- AYENEW, T. 2004b. Environmental implications of changes in the levels of lakes in the Ethiopian Rift since 1970. *Regional environmental change*, 4, 192-204.
- AYENEW, T. 2007. Water management problems in the Ethiopian rift: Challenges for development. *Journal of African Earth Sciences*, 48, 222-236.
- AYENEW, T. 2008. The distribution and hydrogeological controls of fluoride in the groundwater of central Ethiopian rift and adjacent highlands. *J Environmental Geology*, 54, 1313-1324.
- AYENEW, T. & TILAHUN, N. 2008. Assessment of lake-groundwater interactions and anthropogenic stresses, using numerical groundwater flow model, for a Rift lake catchment in central Ethiopia. *Lakes Reservoirs: Research Management*, 13, 325-343.
- AYENEW, T., TILAHUN, N. J. L., RESEARCH, R. & MANAGEMENT 2008. Assessment of lake-groundwater interactions and anthropogenic stresses, using numerical groundwater flow model, for a Rift lake catchment in central Ethiopia. 13, 325-343.
- AYENEW, T. J. R. E. C. 2004c. Environmental implications of changes in the levels of lakes in the Ethiopian Rift since 1970. 4, 192-204.
- AYENEW, T. J. S. E. J. O. S. 2001. Numerical groundwater flow modeling of the Central Main Ethiopian Rift lakes basin. 24, 167-184.
- BAHAGA, T., KUCHARSKI, F., TSIDU, G. M. & YANG, H. 2016. Assessment of prediction and predictability of short rains over equatorial East Africa using a multi-model ensemble. *Theoretical applied climatology*, 123, 637-649.

- BAHAGA, T. K., MENGISTU TSIDU, G., KUCHARSKI, F. & DIRO, G. T. 2015. Potential predictability of the sea-surface temperature forced equatorial East African short rains interannual variability in the 20th century. *Quarterly Journal of the Royal Meteorological Society*, 141, 16-26.
- BALCHA, S. K., AWASS, A. A., HULLUKA, T. A., AYELE, G. T. & BANTIDER, A. 2022. Hydrological Simulation in a Rift-Bounded Lake System and Implication of Water Abstraction: Central Rift Valley Lakes Basin, Ethiopia. *Water*, 14, 3929.
- BALDYGA, T. J., MILLER, S. N., DRIESE, K. L. & GICHABA, C. M. 2008. Assessing land cover change in Kenya's Mau Forest region using remotely sensed data. *African Journal of Ecology*, 46, 46-54.
- BARRESI ARMOA, O. L., SAUVAGE, S., HOUSKA, T., BIEGER, K., SCHÜRZ, C. & SÁNCHEZ PÉREZ, J. M. 2023. Representation of Hydrological Components under a Changing Climate—A Case Study of the Uruguay River Basin Using the New Version of the Soil and Water Assessment Tool Model (SWAT+). *Water*, 15, 2604.
- BATI, H. G., AGUMASSIE, T. A., TEGAYE, T. A. & BELETE, M. D. 2023. Effects of landscape attributes and climate variables on catchment hydrology. *Environmental Systems Research*, 12, 9.
- BEAULIEU, C., CHEN, J., SARMIENTO, J. L. J. P. T. O. T. R. S. A. M., PHYSICAL & SCIENCES, E. 2012. Change-point analysis as a tool to detect abrupt climate variations. 370, 1228-1249.
- BECKER, R., CHAMBERS, J. & WILKS, A. J. C. S. S., PACIFIC GROVE, CA 1988. The New S Language. Wadsworth & Brooks/Cole.
- BEKELE, B., WU, W. & YIRSAW, E. 2019. Drivers of land use-land cover changes in the central rift valley of Ethiopia. *Sains Malays*, 48, 333-1345.
- BELAY, E. A. 2009. *Growing lake with growing problems: integrated hydrogeological investigation on Lake Beseka, Ethiopia*, Bonn, ZEF.
- BELDRING, S. 2002. Multi-criteria validation of a precipitation–runoff model. *Journal of Hydrology*, 257, 189-211.
- BELETE, M. D., DIEKKRÜGER, B. & ROEHRIG, J. 2015a. Characterization of water level variability of the main ethiopian rift valley lakes. *Hydrology*, 3, 1.
- BELETE, M. D., DIEKKRÜGER, B. & ROEHRIG, J. 2015b. Characterization of water level variability of the main ethiopian rift valley lakes. *J Hydrology*, 3, 1.
- BELIHU, M., TEKLEAB, S., ABATE, B. & BEWKET, W. 2020. Hydrologic response to land use land cover change in the Upper Gidabo Watershed, Rift Valley Lakes Basin, Ethiopia. *HydroResearch*, 3, 85-94.
- BENEDIKTSSON, J. A. 1990. *Statistical methods and neural network approaches for classification of data from multiple sources*. Purdue University.
- BENEDIKTSSON, J. A., SWAIN, P. H. J. I. T. O. S., MAN, & CYBERNETICS 1992. Consensus theoretic classification methods. 22, 688-704.
- BENVENUTI, M., CARNICELLI, S., BELLUOMINI, G., DAINELLI, N., DI GRAZIA, S., FERRARI, G., IASIO, C., SAGRI, M., VENTRA, D. & ATNAFU, B. 2002. The Ziway–Shala lake basin (main Ethiopian rift, Ethiopia): a revision of basin evolution with special reference to the Late Quaternary. *Journal of African Earth Sciences*, 35, 247-269.
- BERHANE, T. M., LANE, C. R., WU, Q., AUTREY, B. C., ANENKHONOV, O. A., CHEPINOGA, V. V. & LIU, H. 2018. Decision-tree, rule-based, and random forest classification of high-resolution multispectral imagery for wetland mapping and inventory. *Remote sensing*, 10, 580.
- BERHE, S. M., DESTA, B., NICOLETTI, M. & TEFERRA, M. 1987. Geology, geochronology and geodynamic implications of the Cenozoic magmatic province in W and SE Ethiopia. *Journal of the Geological Society*, 144, 213-226.
- BESHA, K. Z., DEMISSIE, T. A. & FEYESSA, F. F. 2024. Effects of land use/land cover change on hydrological responses of a watershed in the Central Rift Valley of Ethiopia. *Hydrology Research*, 55, 83-111.
- BETTS, M. G., WOLF, C., RIPPLE, W. J., PHALAN, B., MILLERS, K. A., DUARTE, A., BUTCHART, S. H. & LEVI, T. 2017. Global forest loss disproportionately erodes biodiversity in intact landscapes. *Nature*, 547, 441-444.
- BEVEN, K. 2016. Facets of uncertainty: epistemic uncertainty, non-stationarity, likelihood, hypothesis testing, and communication. *Hydrological Sciences Journal*, 61, 1652-1665.
- BEVEN, K., BATHURST, J., O'CONNELL, E., LITTLEWOOD, I., BLACKIE, J. & ROBINSON, M. 2015. Hydrological modelling. *Progress in modern hydrology: past, present future*, 216-239.
- BEZA, M., TATEK, E., CHALA, M. & MOSHE, A. 2024. Watershed hydrological responses to land use land cover changes at Bilata watershed, Rift Valley Basin, southern Ethiopia. *Water Practice Technology*, 19, 1455-1472.
- BEZABIH, B. & MOSISSA, T. 2017. Review on distribution, importance, threats and consequences of wetland degradation in Ethiopia. *International Journal of Water Resources Environmental Engineering*, 9, 64-71.

- BEZU, A. 2020. Analyzing impacts of climate variability and changes in Ethiopia: A review. *American Journal of Modern Energy*, 6, 65-76.
- BICHET, A. & DIEDHIOU, A. J. C. R. 2018. West African Sahel has become wetter during the last 30 years, but dry spells are shorter and more frequent. 75, 155-162.
- BIEGER, K., ARNOLD, J. G., RATHJENS, H., WHITE, M. J., BOSCH, D. D. & ALLEN, P. M. 2019. Representing the connectivity of upland areas to floodplains and streams in SWAT+. *JAWRA Journal of the American Water Resources Association*, 55, 578-590.
- BIEGER, K., ARNOLD, J. G., RATHJENS, H., WHITE, M. J., BOSCH, D. D., ALLEN, P. M., VOLK, M. & SRINIVASAN, R. 2017a. Introduction to SWAT+, a completely restructured version of the soil and water assessment tool. *JAWRA Journal of the American Water Resources Association*, 53, 115-130.
- BIEGER, K., ARNOLD, J. G., RATHJENS, H., WHITE, M. J., BOSCH, D. D., ALLEN, P. M., VOLK, M. & SRINIVASAN, R. 2017b. Introduction to SWAT+, a completely restructured version of the soil and water assessment tool. *JAWRA Journal of the American Water Resources Association*, 53, 115-130.
- BIEGER, K., ARNOLD, J. G., RATHJENS, H., WHITE, M. J., BOSCH, D. D., ALLEN, P. M., VOLK, M. & SRINIVASAN, R. J. J. O. T. A. W. R. A. 2017c. Introduction to SWAT+, a completely restructured version of the soil and water assessment tool. 53, 115-130.
- BILLI, P. & CAPARRINI, F. 2006. Estimating land cover effects on evapotranspiration with remote sensing: a case study in Ethiopian Rift Valley. *Hydrological sciences journal*, 51, 655-670.
- BIRCH, A. L., STALLARD, R. F., BUSH, S. A. & BARNARD, H. R. 2021. The influence of land cover and storm magnitude on hydrologic flowpath activation and runoff generation in steep tropical catchments of central Panama. *Journal of Hydrology*, 596, 126138.
- BLOCK, P. & RAJAGOPALAN, B. 2007a. Interannual variability and ensemble forecast of Upper Blue Nile Basin Kiremt season precipitation. *Journal of Hydrometeorology*, 8, 327-343.
- BLOCK, P. & RAJAGOPALAN, B. J. J. O. H. 2007b. Interannual variability and ensemble forecast of Upper Blue Nile Basin Kiremt season precipitation. 8, 327-343.
- BLÖSCHL, G., BIERKENS, M. F., CHAMBEL, A., CUDENNEC, C., DESTOUNI, G., FIORI, A., KIRCHNER, J. W., MCDONNELL, J. J., SAVENIJE, H. H. & SIVAPALAN, M. 2019. Twenty-three unsolved problems in hydrology (UPH)—a community perspective. *Hydrological sciences journal*, 64, 1141-1158.
- BLÖSCHL, G., SIVAPALAN, M., WAGENER, T., VIGLIONE, A. & SAVENIJE, H. 2013. *Runoff prediction in ungauged basins: synthesis across processes, places and scales*, Cambridge University Press.
- BONNEFILLE, R., ROBERT, C., LÉZINE, A.-M., PERINET, G., DELIBRIAS, G., ELENGA, C., HERBIN, J. & TIERCELIN, J.-J. 1986. Palaeoenvironment of Lake Abijata, Ethiopia, during the past 2000 years. *Geological Society, London, Special Publications*, 25, 253-265.
- BORMANN, H., BREUER, L., GRÄFF, T. & HUISMAN, J. A. 2007. Analysing the effects of soil properties changes associated with land use changes on the simulated water balance: A comparison of three hydrological catchment models for scenario analysis. *Ecological modelling*, 209, 29-40.
- BOUCHARD, B., NADEAU, D. F., DOMINE, F., ANCTIL, F., JONAS, T. & TREMBLAY, É. 2024. How does a warm and low-snow winter impact the snow cover dynamics in a humid and discontinuous boreal forest? Insights from observations and modeling in eastern Canada. *Hydrology Earth System Sciences*, 28, 2745-2765.
- BREIMAN, L. J. M. L. 2001. Random forests. 45, 5-32.
- BRETHERTON, C. S., SMITH, C. & WALLACE, J. M. J. J. O. C. 1992. An intercomparison of methods for finding coupled patterns in climate data. 5, 541-560.
- BROECKER, W. S. J. G. & CHANGE, P. 2006. Abrupt climate change revisited. 54, 211-215.
- BUNDERVOET, T. 2018. Internal Migration in Ethiopia.
- BURAYU, W., CHINAWONG, S., SUWANKETNIKOM, R., MALA, T. & JUNTAKOOL, S. J. K. A. J. 2006. Conservation tillage and crop rotation: win-win option for sustainable maize production in the dryland central Rift Valley of Ethiopia. 4, 48-60.
- BURKA, A., BIAZIN, B. & BEWKET, W. 2023. Drought characterization using different indices, theory of run and trend analysis in bilate river watershed, rift valley of Ethiopia. *J Frontiers in Environmental Science*, 11, 1098113.
- CAO, Y., NAN, Z., CHENG, G. & ZHANG, L. 2018. Hydrological variability in the arid region of Northwest China from 2002 to 2013. *Advances in Meteorology*, 2018.
- CAO, Z., WANG, S., LUO, P., XIE, D. & ZHU, W. 2022. Watershed ecohydrological processes in a changing environment: opportunities and challenges. *Water*, 14, 1502.
- CHEN, H., ZHU, Q., PENG, C., WU, N., WANG, Y., FANG, X., GAO, Y., ZHU, D., YANG, G. & TIAN, J. 2013. The impacts of climate change and human activities on biogeochemical cycles on the Q inghai-T ibetan P lateau. *Global change biology*, 19, 2940-2955.

- CHIOZZI, G., STIASSNY, M. L., ALTER, S. E., DE MARCHI, G., MEBRAHTU, Y., TESSEMA, M., ASMAMAW, B., FASOLA, M. & BELLATI, A. 2018. Fishes in the desert: mitochondrial variation and phylogeography of Danakilia (Actinopterygii: Cichlidae) and Aphanius (Actinopterygii: Cyprinodontidae) in the Danakil Depression of northeastern Africa. *Mitochondrial DNA Part A*, 29, 1025-1040.
- CHOROWICZ, J. 2005a. The east African rift system. *Journal of African Earth Sciences*, 43, 379-410.
- CHOROWICZ, J. 2005b. The east African rift system. *Journal of African Earth Sciences*, 43, 379-410.
- CHOROWICZ, J. J. J. O. A. E. S. 2005c. The east African rift system. 43, 379-410.
- CHRISTOVAM, L., PESSOA, G., SHIMABUKURO, M. & GALO, M. 2019. LAND USE AND LAND COVER CLASSIFICATION USING HYPERSPECTRAL IMAGERY: EVALUATING THE PERFORMANCE OF SPECTRAL ANGLE MAPPER, SUPPORT VECTOR MACHINE AND RANDOM FOREST. *International Archives of the Photogrammetry, Remote Sensing & Spatial Information Sciences*.
- CHURCH, J. A., WHITE, N. J., AARUP, T., WILSON, W. S., WOODWORTH, P. L., DOMINGUES, C. M., HUNTER, J. R. & LAMBECK, K. 2008. Understanding global sea levels: past, present and future. *Sustainability Science*, 3, 9-22.
- CLARK, M. P., NIJSSEN, B., LUNDQUIST, J. D., KAVETSKI, D., RUPP, D. E., WOODS, R. A., FREER, J. E., GUTMANN, E. D., WOOD, A. W. & BREKKE, L. D. 2015. A unified approach for process-based hydrologic modeling: 1. Modeling concept. *Water Resources Research*, 51, 2498-2514.
- CLEMENT, A. C. & PETERSON, L. C. J. R. O. G. 2008. Mechanisms of abrupt climate change of the last glacial period. 46.
- CONWAY, D. 2000. Some aspects of climate variability in the north east Ethiopian Highlands-Wollo and Tigray. *Sinet: Ethiopian Journal of Science*, 23, 139-161.
- CORTI, G. 2009. Continental rift evolution: from rift initiation to incipient break-up in the Main Ethiopian Rift, East Africa. *Earth-science reviews*, 96, 1-53.
- COWX, I. G. & OGUTU-OWHAYO, R. 2019. Towards sustainable fisheries and aquaculture management in the African Great Lakes. *Fisheries Management Ecology*, 26, 397-405.
- CROITORU, A.-E., DRIGNEI, D., HOLOBACA, I.-H., DRAGOTA, C. S. J. T. & CLIMATOLOGY, A. 2012. Change-point analysis for serially correlated summit temperatures in the Romanian Carpathians. 108, 9-18.
- CSA, R. J. S. B. 2016. The federal democratic republic of Ethiopia central statistical agency report on area and production of major.
- DA SILVA, V. D. P. R. J. J. O. A. E. 2004. On climate variability in Northeast of Brazil. 58, 575-596.
- DA SILVEIRA LOBO STERNBERG, L. J. G. E. & BIOGEOGRAPHY 2001. Savanna-forest hysteresis in the tropics. 10, 369-378.
- DAGNE, A., TADESSE, H. & TESHOME, K. 2023. Limnological features and water-quality changes of two Ethiopian Rift Valley lakes, Lake Abaya and Lake Chamo. *African Journal of Aquatic Science*, 48, 237-246.
- DANIEL, H. & ABATE, B. 2022. Effect of climate change on streamflow in the Gelana watershed, Rift valley basin, Ethiopia. *Journal of Water Climate Change*, 13, 2205-2232.
- DANSGAARD, W., JOHNSEN, S. J., CLAUSEN, H. B., DAHL-JENSEN, D., GUNDESTRUP, N., HAMMER, C., HVIDBERG, C., STEFFENSEN, J., SVEINBJÖRNSDOTTIR, A. & JOUZEL, J. J. N. 1993. Evidence for general instability of past climate from a 250-kyr ice-core record. 364, 218-220.
- DE OLIVEIRA, P. T., SILVA, C. M. S. E. & LIMA, K. C. J. A. S. L. 2014. Linear trend of occurrence and intensity of heavy rainfall events on Northeast Brazil. 15, 172-177.
- DE SOUSA LIMA, J. R., ANTONINO, A. C. D., DE SOUZA, E. S., HAMMECKER, C., MONTENEGRO, S. M. G. L. & DE OLIVEIRA LIRA, C. A. B. 2013a. Calibration of Hargreaves-Samani equation for estimating reference evapotranspiration in sub-humid region of Brazil. *Journal of Water Resource Protection*, 5, 1-5.
- DE SOUSA LIMA, J. R., ANTONINO, A. C. D., DE SOUZA, E. S., HAMMECKER, C., MONTENEGRO, S. M. G. L. & DE OLIVEIRA LIRA, C. A. B. 2013b. Calibration of Hargreaves-Samani equation for estimating reference evapotranspiration in sub-humid region of Brazil. *Journal of Water Resource Protection*, 2013.
- DEMMSIE, A. K. 2021. *Simulation of the Hydrological Impacts of Climate and Land Use/Cover Change on Tikur Wuha Watershed in Ethiopia*. National Institute of Technology Karnataka, Surathkal.
- DESSIE, G. & KLEMAN, J. 2007. Pattern and magnitude of deforestation in the South Central Rift Valley Region of Ethiopia. *Mountain research development*, 27, 162-168.
- DESTA, H. 2021. Local perceptions of ecosystem services and human-induced degradation of lake Ziway in the Rift Valley region of Ethiopia. *Ecological Indicators*, 127, 107786.
- DESTA, H. & FETENE, A. 2020a. Land-use and land-cover change in Lake Ziway watershed of the Ethiopian Central Rift Valley Region and its environmental impacts. *Land use policy*, 96, 104682.
- DESTA, H. & FETENE, A. J. L. U. P. 2020b. Land-use and land-cover change in Lake Ziway watershed of the Ethiopian Central Rift Valley Region and its environmental impacts. 96, 104682.

- DESTA, H. & LEMMA, B. 2017. SWAT based hydrological assessment and characterization of Lake Ziway sub-watersheds, Ethiopia. *Journal of Hydrology: Regional Studies*, 13, 122-137.
- DILE, Y. T., BERNDTSSON, R. & SETEGN, S. G. 2013. Hydrological response to climate change for gilgel abay river, in the lake tana basin-upper blue Nile basin of Ethiopia. *PloS one*, 8, e79296.
- DILE, Y. T., TEKLEAB, S., AYANA, E. K., GEBREHIWOT, S. G., WORQLUL, A. W., BAYABIL, H. K., YIMAM, Y. T., TILAHUN, S. A., DAGGUPATI, P. & KARLBERG, L. 2018. Advances in water resources research in the Upper Blue Nile basin and the way forward: A review. *Journal of Hydrology*, 560, 407-423.
- DINKU, M. B. & KEBEDE, H. H. 2023. Identification and mapping of surface irrigation potential in the data-scarce Jewuha watershed, Middle Awash River Basin, Ethiopia. *Hydrology Research*, 54, 1227-1245.
- DIRO, G., GRIMES, D., BLACK, E., O'NEILL, A. & PARDO-IGUZZUIZA, E. 2009a. Evaluation of reanalysis rainfall estimates over Ethiopia. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 29, 67-78.
- DIRO, G., GRIMES, D., BLACK, E., O'NEILL, A. & PARDO-IGUZZUIZA, E. J. I. J. O. C. A. J. O. T. R. M. S. 2009b. Evaluation of reanalysis rainfall estimates over Ethiopia. 29, 67-78.
- DIRO, G., GRIMES, D. I. F. & BLACK, E. 2011a. Teleconnections between Ethiopian summer rainfall and sea surface temperature: part I—observation and modelling. *Climate dynamics*, 37, 103-119.
- DIRO, G., GRIMES, D. I. F. & BLACK, E. J. C. D. 2011b. Teleconnections between Ethiopian summer rainfall and sea surface temperature: part I—observation and modelling. 37, 103-119.
- DIRO, G. T., GRIMES, D. & BLACK, E. 2011c. Large scale features affecting Ethiopian rainfall. *African climate and climate change*. Springer.
- DOUGLAS, B. C. 1991. Global sea level rise. *Journal of Geophysical Research: Oceans*, 96, 6981-6992.
- DYER, E., HIRONS, L. & TAYE, M. T. J. C. D. 2022. July–September rainfall in the Greater Horn of Africa: the combined influence of the Mascarene and South Atlantic highs. 1-21.
- EASTERLING, D. R., EVANS, J., GROISMAN, P. Y., KARL, T. R., KUNKEL, K. E. & AMBENJE, P. 2000. Observed variability and trends in extreme climate events: a brief review. *Bulletin of the American Meteorological Society*, 81, 417-426.
- EHRET, U., GUPTA, H. V., SIVAPALAN, M., WEIJS, S. V., SCHYMANSKI, S. J., BLÖSCHL, G., GELFAN, A. N., HARMAN, C., KLEIDON, A. & BOGAARD, T. 2014. Advancing catchment hydrology to deal with predictions under change. *Hydrology Earth System Sciences*, 18, 649-671.
- ELIAS, E., SEIFU, W., TESFAYE, B. & GIRMAY, W. 2019a. Impact of land use/cover changes on lake ecosystem of Ethiopia central rift valley. *Cogent Food Agriculture*, 5, 1595876.
- ELIAS, E., SEIFU, W., TESFAYE, B., GIRMAY, W. J. C. F. & AGRICULTURE 2019b. Impact of land use/cover changes on lake ecosystem of Ethiopia central rift valley. 5, 1595876.
- EZRA, M. J. G. 2003. Environmental vulnerability, rural poverty, and migration in Ethiopia: a contextual analysis. 63-91.
- FARJAD, B., GUPTA, A., RAZAVI, S., FARAMARZI, M. & MARCEAU, D. J. 2017. An integrated modelling system to predict hydrological processes under climate and land-use/cover change scenarios. *Water*, 9, 767.
- FAURES, J., ELIASSON, A., HOOGEVEEN, J. & VALLEE 2001. AQUASTAT-FAO's information system on water and agriculture. *GRID-Magazine of the IPTRID Network*.
- FAZZINI, M., BISCI, C. & BILLI, P. 2015a. The climate of Ethiopia. *Landscapes and landforms of Ethiopia*. Springer.
- FAZZINI, M., BISCI, C. & BILLI, P. 2015b. The climate of Ethiopia. *Landscapes landforms of Ethiopia*, 65-87.
- FEKADU, K. J. E. S. 2015. Ethiopian seasonal rainfall variability and prediction using canonical correlation analysis (CCA). 4, 112.
- FENG, J., YAN, D., LI, C., YU, F. & ZHANG, C. 2014. Assessing the impact of climatic factors on potential evapotranspiration in droughts in North China. *Quaternary International*, 336, 6-12.
- FENG, X. & KOCH, J. 2024. Combining vector and raster data in regionalization: A unified framework for delineating spatial unit boundaries for socio-environmental systems analyses. *International Journal of Applied Earth Observation Geoinformation*, 128, 103745.
- FENICIA, F., KAVETSKI, D., SAVENIJE, H. H. & PFISTER, L. 2016. From spatially variable streamflow to distributed hydrological models: Analysis of key modeling decisions. *Water Resources Research*, 52, 954-989.
- FLÖRKE, M., SCHNEIDER, C. & MCDONALD, R. I. 2018. Water competition between cities and agriculture driven by climate change and urban growth. *Nature Sustainability*, 1, 51-58.
- FOWLER, K. J., COXON, G., FREER, J. E., KNOBEN, W. J., PEEL, M. C., WAGENER, T., WESTERN, A. W., WOODS, R. A. & ZHANG, L. 2021. Towards more realistic runoff projections by removing limits on simulated soil moisture deficit. *Journal of Hydrology*, 600, 126505.
- FRANCIS, C. F. & LOWE, A. T. 2015. Application of strategic environmental assessment to the Rift Valley Lakes Basin master plan. *Monitoring Modelling Dynamic Environments*., 155-177.

- FROIDUROT, S. & DIEDHIOU, A. J. A. S. L. 2017. Characteristics of wet and dry spells in the West African monsoon system. 18, 125-131.
- GADISSA, T., NYADAWA, M., MUTUA, B. M. & BEHULU, F. 2019. Comparative assessment of the effect of climate change and human activities on streamflow regimes in Central Rift Valley Basin, Ethiopia. *American Journal of Water Resources* 7, 23-39.
- GAREDEW, E., SANDEWALL, M., SÖDERBERG, U. & CAMPBELL, B. M. 2009a. Land-use and land-cover dynamics in the central rift valley of Ethiopia. *Environmental management*, 44, 683-694.
- GAREDEW, E., SANDEWALL, M., SÖDERBERG, U. & CAMPBELL, B. M. 2009b. Land-use and land-cover dynamics in the central rift valley of Ethiopia. *Environmental management*, 44, 683-694.
- GAREDEW, E., SANDEWALL, M., SÖDERBERG, U. & CAMPBELL, B. M. 2009c. Land-use and land-cover dynamics in the central rift valley of Ethiopia. *Environmental management*, 44, 683-694.
- GASHAW, D. Y., SURYABHAGAVAN, K. V., NEDAW, D. & GUMMADI, S. 2022. Rainwater harvesting in Modjo watershed, upper Awash River Basin, Ethiopia through remote sensing and fuzzy AHP. *Geocarto International*, 37, 14785-14810.
- GASSMAN, P. W., REYES, M. R., GREEN, C. H. & ARNOLD, J. G. 2007. The soil and water assessment tool: historical development, applications, and future research directions. *Transactions of the ASABE*, 50, 1211-1250.
- GEBRECHORKOS, S. H., HÜLSMANN, S. & BERNHOFER, C. J. S. R. 2019. Long-term trends in rainfall and temperature using high-resolution climate datasets in East Africa. 9, 1-9.
- GELAGAY, H. S. 2017. Geospatial data sharing barriers across organisations and the possible solution for Ethiopia. *International Journal of Spatial Data Infrastructures Research*, 12, 62-84.
- GELETA, Y., HAILESLASSIE, A., SIMANE, B., ASSEFA, E. & BANTIDER, A. 2023. Mapping Community Perception, Synergy, and Trade-Off of Multiple Water Values in the Central Rift Valley Water System of Ethiopia. *Water*, 15, 2986.
- GERTEN, D., SCHAPHOFF, S. & LUCHT, W. 2007. Potential future changes in water limitations of the terrestrial biosphere. *Climatic Change*, 80, 277-299.
- GETACHEW, B. & MANJUNATHA, B. R. 2022. Impacts of Land-Use Change on the Hydrology of Lake Tana Basin, Upper Blue Nile River Basin, Ethiopia. *Global Challenges*, 6, 2200041.
- GETNET, M., HENGSDIJK, H. & VAN ITTERSUM, M. 2014. Disentangling the impacts of climate change, land use change and irrigation on the Central Rift Valley water system of Ethiopia. *Agricultural Water Management*, 137, 104-115.
- GIRMA, R., MOGES, A. & FÜRST, C. 2023. Integrated mOdeling of land degradation dynamics and insights on the possible future management alternatives in the Gidabo river basin, Ethiopian rift valley. *Land*, 12, 1809.
- GIRONÁS, J., ROESNER, L. A., ROSSMAN, L. A. & DAVIS, J. 2010. A new applications manual for the Storm Water Management Model(SWMM). *Environmental Modelling Software*, 25, 813-814.
- GISLASON, P. O., BENEDIKTSSON, J. A. & SVEINSSON, J. R. J. P. R. L. 2006. Random forests for land cover classification. 27, 294-300.
- GISSILA, T., BLACK, E., GRIMES, D. & SLINGO, J. 2004a. Seasonal forecasting of the Ethiopian summer rains. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 24, 1345-1358.
- GISSILA, T., BLACK, E., GRIMES, D. & SLINGO, J. J. I. J. O. C. A. J. O. T. R. M. S. 2004b. Seasonal forecasting of the Ethiopian summer rains. 24, 1345-1358.
- GIZACHEW, L. & SHIMELIS, A. 2014. Analysis and mapping of climate change risk and vulnerability in Central Rift Valley of Ethiopia. *African Crop Science Journal*, 22, 807-818.
- GLEIXNER, S., KEENLYSIDE, N. S., DEMISSIE, T. D., COUNILLON, F., WANG, Y. & VISTE, E. J. E. R. L. 2017. Seasonal predictability of Kiremt rainfall in coupled general circulation models. 12, 114016.
- GOBENA, A. 2008. *Assessment of ecotourism potentials for sustainable natural resources management in and around Abijata-Shala Lakes National Park in the central Ethiopian Rift Valley*. Addis Ababa University.
- GONG, P., WANG, J., YU, L., ZHAO, Y., ZHAO, Y., LIANG, L., NIU, Z., HUANG, X., FU, H. & LIU, S. 2013. Finer resolution observation and monitoring of global land cover: First mapping results with Landsat TM and ETM+ data. *International Journal of Remote Sensing*, 34, 2607-2654.
- GONZÁLEZ-RAMÍREZ, J. & PARÉS-SIERRA, A. 2019. Streamflow modeling of five major rivers that flow into the Gulf of Mexico using SWAT. *Atmósfera*, 32, 261-272.
- GOWNARIS, N. J., PIKITCH, E. K., OJWANG, W. O., MICHENER, R. & KAUFMAN, L. 2015. Predicting species' vulnerability in a massively perturbed system: The fishes of Lake Turkana, Kenya. *PLoS One*, 10, e0127027.
- GREGORY, J. W. 2018. *The great rift valley*, Routledge.
- GU, G. & ADLER, R. F. 2013. Interdecadal variability/long-term changes in global precipitation patterns during the past three decades: global warming and/or pacific decadal variability? *Climate dynamics*, 40, 3009-3022.

- GUMMADI, S., RAO, K., SEID, J., LEGESSE, G., KADIYALA, M., TAKELE, R., AMEDE, T. & WHITBREAD, A. 2018. Spatio-temporal variability and trends of precipitation and extreme rainfall events in Ethiopia in 1980–2010. *Theoretical Applied Climatology*, 134, 1315–1328.
- GUNAWARDANA, S. K., SHRESTHA, S., MOHANASUNDARAM, S., SALIN, K. R. & PIMAN, T. 2021. Multiple drivers of hydrological alteration in the transboundary Srepok River Basin of the Lower Mekong Region. *Journal of Environmental Management*, 278, 111524.
- GUNTU, R. K., MAHESWARAN, R., AGARWAL, A. & SINGH, V. P. 2020. Accounting for temporal variability for improved precipitation regionalization based on self-organizing map coupled with information theory. *Journal of Hydrology*, 590, 125236.
- GUO, Y., LI, Z., AMO-BOATENG, M., DENG, P. & HUANG, P. 2014. Quantitative assessment of the impact of climate variability and human activities on runoff changes for the upper reaches of Weihe River. *Stochastic environmental research risk assessment*, 28, 333–346.
- GUO, Y., ZHANG, Y., ZHANG, L. & WANG, Z. 2021a. Regionalization of hydrological modeling for predicting streamflow in ungauged catchments: A comprehensive review. *Wiley Interdisciplinary Reviews: Water*, 8, e1487.
- GUO, Y., ZHANG, Y., ZHANG, L. & WANG, Z. 2021b. Regionalization of hydrological modeling for predicting streamflow in ungauged catchments: A comprehensive review. *Wiley Interdisciplinary Reviews: Water*, 8, e1487.
- GUPTA, A. & GOVINDARAJU, R. S. 2023. Uncertainty quantification in watershed hydrology: Which method to use? *Journal of Hydrology*, 616, 128749.
- GUPTA, H. V., KLING, H., YILMAZ, K. K. & MARTINEZ, G. F. 2009. Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of hydrology*, 377, 80–91.
- GUSE, B., PFANNERSTILL, M., GAFUROV, A., FOHRER, N. & GUPTA, H. 2016. Demasking the integrated information of discharge: Advancing sensitivity analysis to consider different hydrological components and their rates of change. *Water Resources Research*, 52, 8724–8743.
- GUTMAN, G., JANETOS, A. C., JUSTICE, C. O., MORAN, E. F., MUSTARD, J. F., RINDFUSS, R. R., SKOLE, D., TURNER II, B. L. & COCHRANE, M. A. 2004. *Land change science: observing, monitoring and understanding trajectories of change on the earth's surface*, Springer Science & Business Media.
- HAILE, G. G. & KASA, A. K. 2015. Irrigation in Ethiopia: A review. *Academia journal of agricultural research*, 3, 264–269.
- HAILEGEORGIS, T. T. & ALFREDSEN, K. 2016. Multi-basin and regional calibration based identification of distributed precipitation–runoff models for hourly runoff simulation: calibration and transfer of full and partial parameters. *Hydrology Research*, 47, 239–259.
- HANSEN, L. K., SALAMON, P. J. I. T. O. P. A. & INTELLIGENCE, M. 1990. Neural network ensembles. 12, 993–1001.
- HARGREAVES, G. H. & SAMANI, Z. A. 1985. Reference crop evapotranspiration from temperature. *Applied engineering in agriculture*, 1, 96–99.
- HASTENRATH, S. 2012. *Climate dynamics of the tropics*, Springer Science & Business Media.
- HELMSCHROT, J. & FLÜGEL, W.-A. 2002. Land use characterisation and change detection analysis for hydrological model parameterisation of large scale afforested areas using remote sensing. *Physics Chemistry of the Earth, Parts A/B/C*, 27, 711–718.
- HENGSDIJK, H. & JANSEN, H. 2006. Agricultural development in the Central Ethiopian Rift valley: A desk-study on water-related issues and knowledge to support a policy dialogue. Plant Research International.
- HERNÁNDEZ-GUZMÁN, R., RUIZ-LUNA, A. & BERLANGA-ROBLES, C. A. 2008. Assessment of runoff response to landscape changes in the San Pedro subbasin (Nayarit, Mexico) using remote sensing data and GIS. *Journal of Environmental Science*, 43, 1471–1482.
- HERNANDEZ, M., MILLER, S. N., GOODRICH, D. C., GOFF, B. F., KEPNER, W. G., EDMONDS, C. M. & BRUCE JONES, K. Modeling runoff response to land cover and rainfall spatial variability in semi-arid watersheds. Monitoring Ecological Condition in the Western United States: Proceedings of the Fourth Symposium on the Environmental Monitoring and Assessment Program (EMAP), San Francisco, CA, April 6–8, 1999, 2000a. Springer, 285–298.
- HERNANDEZ, M., MILLER, S. N., GOODRICH, D. C., GOFF, B. F., KEPNER, W. G., EDMONDS, C. M. & BRUCE JONES, K. 2000b. Modeling runoff response to land cover and rainfall spatial variability in semi-arid watersheds. *Monitoring Ecological Condition in the Western United States*. Springer.
- HESSEBO, M. T., WOLDEAMANUEL, T. & TADESSE, M. 2021. Spatial and temporal climate variability and change in the bilate catchment, central Rift Valley lakes region, Ethiopia. *Physical Geography*, 42, 199–225.
- HINKLEY, D. V. 1970. Inference about the change-point in a sequence of random variables.

- HOLM, J. A., CHAMBERS, J. Q., COLLINS, W. D. & HIGUCHI, N. J. B. 2014. Forest response to increased disturbance in the central Amazon and comparison to western Amazonian forests. *11*, 5773-5794.
- HRACHOWITZ, M., SAVENIJE, H., BLÖSCHL, G., MCDONNELL, J. J., SIVAPALAN, M., POMEROY, J., ARHEIMER, B., BLUME, T., CLARK, M. & EHRET, U. 2013. A decade of Predictions in Ungauged Basins (PUB)—a review. *Hydrological sciences journal*, *58*, 1198-1255.
- HULLUKA, T. A., BALCHA, S. K., YOHANNES, B., BANTIDER, A. & NEGATU, A. 2023. groundwater research in the Ethiopian Rift Valley Lakes region. *Frontiers in Water*, *5*, 819568.
- HUNDECHA, Y., ARHEIMER, B., DONNELLY, C. & PECHLIVANIDIS, I. 2016. A regional parameter estimation scheme for a pan-European multi-basin model. *Journal of Hydrology: Regional Studies*, *6*, 90-111.
- IPCC 2007. Climate change 2007: The physical science basis.
- JAIN, S. K. & SINGH, V. P. 2019. *Engineering hydrology: an introduction to processes, analysis, and modeling*, McGraw-Hill Education.
- JANE, M.-G., MCGREGOR, J., AGARWALA, M., ATKINSON, G., BEVAN, P., CLEMENTS, T. J., DAW, T., HOMEWOOD, K., KÜMPEL, N. F. & LEWIS, J. 2014. Accounting for the impact of conservation on human well-being. London School of Economics and Political Science, LSE Library.
- JANKO, A. M. 2014. Fish production, consumption and management in Ethiopia. *International Journal of Economics Management*, *3*, 1-6.
- JANSEN, H., HENGSDIJK, H., LEGESSE, D., AYENEW, T., HELLEGERS, P. & SPLIETHOFF 2007a. Land and water resources assessment in the Ethiopian Central Rift Valley: Project: Ecosystems for water, food and economic development in the Ethiopian Central Rift Valley. Alterra.
- JANSEN, H., HENGSDIJK, H., LEGESSE, D., AYENEW, T., HELLEGERS, P. & SPLIETHOFF, P. 2007b. Land and water resources assessment in the Ethiopian Central Rift Valley: Project: Ecosystems for water, food and economic development in the Ethiopian Central Rift Valley. Alterra.
- JIANG, C. & WANG, F. 2016. Temporal changes of streamflow and its causes in the Liao River Basin over the period of 1953–2011, northeastern China. *Catena*, *145*, 227-238.
- JIMÉNEZ, A. A., VILCHEZ, F. F., GONZÁLEZ, O. N. & FLORES, S. M. J. S. 2018. Analysis of the land use and cover changes in the metropolitan area of Tepic-Xalisco (1973–2015) through landsat images. *10*, 1860.
- JINGJING, F., QIANG, H. & DENG FENG, L. 2017. Identification of impacts of climate change and direct human activities on streamflow in Weihe River Basin in Northwest China. *International Journal of Agricultural Biological Engineering*, *10*, 119-129.
- JOHNSEN, S., CLAUSEN, H., DANSGAARD, W., FUHRER, K., GUNDESTRUP, N., HAMMER, C., IVERSEN, P., JOUZEL, J. & STAUFFER, B. J. N. 1992. Irregular glacial interstadials recorded in a new Greenland ice core. *359*, 311-313.
- KASSIE, B., RÖTTER, R., HENGSDIJK, H., ASSENG, S., VAN ITTERSUM, M., KAHILUOTO, H. & VAN KEULEN, H. 2014a. Climate variability and change in the Central Rift Valley of Ethiopia: challenges for rainfed crop production. *The Journal of Agricultural Science*, *152*, 58-74.
- KASSIE, B., RÖTTER, R., HENGSDIJK, H., ASSENG, S., VAN ITTERSUM, M., KAHILUOTO, H. & VAN KEULEN, H. J. T. J. O. A. S. 2014b. Climate variability and change in the Central Rift Valley of Ethiopia: challenges for rainfed crop production. *152*, 58-74.
- KASSIE, B. T., RÖTTER, R., HENGSDIJK, H., ASSENG, S., VAN ITTERSUM, M., KAHILUOTO, H. & VAN KEULEN, H. 2014c. Climate variability and change in the Central Rift Valley of Ethiopia: challenges for rainfed crop production. *The Journal of Agricultural Science*, *152*, 58-74.
- KAVZOGLU, T. 2017. Object-oriented random forest for high resolution land cover mapping using quickbird-2 imagery. *Handbook of neural computation*. Elsevier.
- KEBEDE, E., MARIAM, Z. G. & AHLGREN, I. 1994. The Ethiopian Rift Valley lakes: chemical characteristics of a salinity-alkalinity series. *Hydrobiologia*, *288*, 1-12.
- KEBEDE, S. 2023. The State of the Water Resources in the Central Rift Valley
A Complex Hydroecosystem Under Threat *Investment for: The State of the Water Resources in the Central Rift Valley: A Complex Hydroecosystem Under Threat*.
- KHAPALOVA, E. A., JANDHYALA, V. K. & FOTOPOULOS, S. B. J. J. O. E. S. 2013. Change-point Analysis of Annual Mean Precipitation for Northern Tropical and Southern Latitudes of the Globe in the Past Century. *4*, 1-21.
- KIDANE, Y., STAHLMANN, R., BEIERKUHNEIN, C. J. E. M. & ASSESSMENT 2012. Vegetation dynamics, and land use and land cover change in the Bale Mountains, Ethiopia. *184*, 7473-7489.
- KINFU, E., BOMBECK, H., NIGUSSIE, A. & WEGAYEHU, F. 2019. The genesis of peri-urban Ethiopia: The case of Hawassa city. *Journal of Land Rural Studies*, *7*, 71-95.

- KING, K., BURGESS, M., SCHULTZ, E. T. & KNIGHTON, J. 2023. Forecasting hydrologic controls on juvenile anadromous fish out-migration with process-based modeling and machine learning. *Journal of Environmental Management*, 344, 118420.
- KOLDING, J. & VAN ZWIETEN, P. A. 2012. Relative lake level fluctuations and their influence on productivity and resilience in tropical lakes and reservoirs. *Fisheries Research*, 115, 99-109.
- KONIKOW, L. F. & KENDY, E. 2005. Groundwater depletion: A global problem. *Hydrogeology Journal*, 13, 317-320.
- KORECHA, D. & BARNSTON, A. G. 2007a. Predictability of june–september rainfall in Ethiopia. *Monthly weather review*, 135, 628-650.
- KORECHA, D. & BARNSTON, A. G. J. M. W. R. 2007b. Predictability of june–september rainfall in Ethiopia. 135, 628-650.
- KUMAR, A. U. & JAYAKUMAR, K. 2020. Hydrological alterations due to anthropogenic activities in Krishna River Basin, India. *Ecological Indicators*, 108, 105663.
- KUNCHEVA, L. I. J. I. T. O. F. S. 2003. " Fuzzy" versus" nonfuzzy" in combining classifiers designed by Boosting. 11, 729-741.
- KUNDZEWICZ, Z. W., MATA, L. J., ARNELL, N., DOLL, P., KABAT, P., JIMENEZ, B., MILLER, K., OKI, T., ZEKAI, S. & SHIKLOMANOV, I. 2007. Freshwater resources and their management.
- LAMB, H. F. Multi-proxy records of Holocene climate and vegetation change from Ethiopian crater lakes. *Biology and Environment: Proceedings of the Royal Irish Academy*, 2001. JSTOR, 35-46.
- LAMBE, B. T. & KUNDAPURA, S. 2023. Recent Changes in Hydrometeorological Extremes in the Bilate River Basin of Rift Valley, Ethiopia. *Journal of Hydrologic Engineering*, 28, 05023014.
- LASHKARI, H., JAFARI, M. J. M. & PHYSICS, A. 2021a. Annual displacement and appropriate index to determine ITCZ position in East Africa and the Indian Ocean regions. 133, 1111-1126.
- LASHKARI, H., JAFARI, M. J. T. & CLIMATOLOGY, A. 2021b. The role of spatial displacement of Arabian subtropical high pressure in the annual displacement of the ITCZ in East Africa. 143, 1543-1555.
- LAU, K. & YANG, S. J. A. I. A. S. 1997. Climatology and interannual variability of the Southeast Asian summer monsoon. 14, 141-162.
- LAURY, R. L. & ALBRITTON JR, C. C. 1975. Geology of Middle Stone Age archaeological sites in the main Ethiopian rift valley. *Geological Society of America Bulletin*, 86, 999-1011.
- LAWRENCE, R. L., WOOD, S. D. & SHELEY, R. L. J. R. S. O. E. 2006. Mapping invasive plants using hyperspectral imagery and Breiman Cutler classifications (RandomForest). 100, 356-362.
- LE TURDU, C., TIERCELIN, J.-J., GIBERT, E., TRAVI, Y., LEZZAR, K.-E., RICHERT, J.-P., MASSAULT, M., GASSE, F., BONNEFILLE, R. & DECOBERT, M. 1999. The Ziway–Shala lake basin system, Main Ethiopian Rift: influence of volcanism, tectonics, and climatic forcing on basin formation and sedimentation. *Palaeogeography, Palaeoclimatology, Palaeoecology*, 150, 135-177.
- LEGESSE, D. & AYENNEW, T. 2006a. Effect of improper water and land resource utilization on the central Main Ethiopian Rift lakes. *Quaternary international*, 148, 8-18.
- LEGESSE, D. & AYENNEW, T. J. Q. I. 2006b. Effect of improper water and land resource utilization on the central Main Ethiopian Rift lakes. 148, 8-18.
- LEI, C., WAGNER, P. D. & FOHRER, N. 2022. Influences of land use changes on the dynamics of water quantity and quality in the German lowland catchment of the Stör. *Hydrology Earth System Sciences*, 26, 2561-2582.
- LEI, C., WAGNER, P. D. & FOHRER, N. J. E. I. 2021. Effects of land cover, topography, and soil on stream water quality at multiple spatial and seasonal scales in a German lowland catchment. 120, 106940.
- LEMENKOVA, P. 2022. Seismicity in the Afar Depression and Great Rift Valley, Ethiopia. *Environmental Research, Engineering Management*, 78, 83-96.
- LENCHA, S. M., TRÄNCKNER, J. & DANANTO, M. 2021. Assessing the water quality of lake Hawassa Ethiopia—trophic state and suitability for anthropogenic uses—applying common water quality indices. *J International Journal of Environmental Research Public Health*, 18, 8904.
- LEUTNER, B., HORNING, N. & LEUTNER, M. B. J. R. F. F. S. C., VERSION 0.1 2017. Package ‘RStoolbox’.
- LI, T. & HSU, P.-C. 2018. *Fundamentals of tropical climate dynamics*, Springer.
- LI, X., TAN, L., LI, Y., QI, J., FENG, P., LI, B., LI LIU, D., ZHANG, X., MAREK, G. W. & ZHANG, Y. 2022. Effects of global climate change on the hydrological cycle and crop growth under heavily irrigated management—A comparison between CMIP5 and CMIP6. *Computers Electronics in Agriculture*, 202, 107408.
- LI, Y., GRIMALDI, S., PAUWELS, V. R. & WALKER, J. P. 2018a. Hydrologic model calibration using remotely sensed soil moisture and discharge measurements: The impact on predictions at gauged and ungauged locations. *Journal of hydrology*, 557, 897-909.

- LI, Y., PIAO, S., LI, L. Z., CHEN, A., WANG, X., CIAIS, P., HUANG, L., LIAN, X., PENG, S. & ZENG, Z. 2018b. Divergent hydrological response to large-scale afforestation and vegetation greening in China. *Science Advances*, 4, eaar4182.
- LIANG, W.-L. & UCHIDA, T. 2022. Performance and topographic preferences of dynamic and steady models for shallow landslide prediction in a small catchment. *Landslides*, 19, 51-66.
- LIEBMANN, B. & MARENGO, J. J. O. C. 2001. Interannual variability of the rainy season and rainfall in the Brazilian Amazon Basin. 14, 4308-4318.
- LIU, S., HUANG, S., HUANG, Q., XIE, Y., LENG, G., LUAN, J., SONG, X., WEI, X. & LI, X. 2017. Identification of the non-stationarity of extreme precipitation events and correlations with large-scale ocean-atmospheric circulation patterns: a case study in the Wei River Basin, China. *Journal of Hydrology*, 548, 184-195.
- LIU, Y., FU, B., LÜ, Y., WANG, Z. & GAO, G. 2012. Hydrological responses and soil erosion potential of abandoned cropland in the Loess Plateau, China. *Geomorphology*, 138, 404-414.
- LUO, Y., QIAO, X., DONG, Y., FENG, Z., ZHANG, J. & WANG, G. 2024. Characterization of hydrological response of the Dawen River Basin under land use change.
- LUYSSAERT, S., JAMMET, M., STOY, P. C., ESTEL, S., PONGRATZ, J., CESCHIA, E., CHURKINA, G., DON, A., ERB, K. & FERLICOQ, M. J. N. C. C. 2014. Land management and land-cover change have impacts of similar magnitude on surface temperature. 4, 389-393.
- MA, X., XU, J., LUO, Y., PRASAD AGGARWAL, S. & LI, J. 2009. Response of hydrological processes to land-cover and climate changes in Kejie watershed, south-west China. *Hydrological Processes: An International Journal*, 23, 1179-1191.
- MAHMOODI, N., KIESEL, J., WAGNER, P. D. & FOHRER, N. 2021a. Spatially distributed impacts of climate change and groundwater demand on the water resources in a wadi system. *Hydrology Earth System Sciences*, 25, 5065-5081.
- MAHMOODI, N., KIESEL, J., WAGNER, P. D. & FOHRER, N. 2021b. Spatially distributed impacts of climate change and groundwater demand on the water resources in a wadi system. *Hydrology Earth System Sciences*, 25, 5065-5081.
- MAHMOODI, N., WAGNER, P. D., KIESEL, J. & FOHRER, N. 2021c. Modeling the impact of climate change on streamflow and major hydrological components of an Iranian Wadi system. *Journal of Water Climate Change*, 12, 1598-1613.
- MAKTAV, D., ERBEK, F. & JÜRGENS, C. 2005. Remote sensing of urban areas. *International Journal of Remote Sensing*, 26, 655-659.
- MALMBERG, B. & TEGENU, T. 2007. Population pressure and dynamics of household livelihoods in an Ethiopian Village: an elaboration of the Boserup-Chayanovian framework. *Population and Environment*, 29, 39-67.
- MAROTZKE, J. J. P. O. T. N. A. O. S. 2000. Abrupt climate change and thermohaline circulation: Mechanisms and predictability. 97, 1347-1350.
- MARTEAU, R., SULTAN, B., MORON, V., ALHASSANE, A., BARON, C., TRAORÉ, S. B. J. A. & METEOROLOGY, F. 2011. The onset of the rainy season and farmers' sowing strategy for pearl millet cultivation in Southwest Niger. 151, 1356-1369.
- MASSEI, N. & FOURNIER, M. 2012. Assessing the expression of large-scale climatic fluctuations in the hydrological variability of daily Seine river flow (France) between 1950 and 2008 using Hilbert–Huang Transform. *Journal of Hydrology*, 448, 119-128.
- MATEWOS, T. & TEFERA, T. J. P. G. 2020. Local level rainfall and temperature variability in drought-prone districts of rural Sidama, central rift valley region of Ethiopia. 41, 36-53.
- MATHEWOS, M., WOSORO, D. & WONDRAGE, N. 2024. Quantification of soil erosion and sediment yield using the RUSLE model in Boyo watershed, central Rift Valley Basin of Ethiopia. *Heliyon*, 10.
- MAXWELL, A. E., WARNER, T. A. & STRAGER, M. P. 2016. Predicting palustrine wetland probability using random forest machine learning and digital elevation data-derived terrain variables. *Photogrammetric Engineering & Remote Sensing*, 82, 437-447.
- MCGINN, A. J., WAGNER, P. D., HTIKE, H., KYU, K. K. & FOHRER, N. 2021. Twenty years of change: Land and water resources in the Chindwin catchment, Myanmar between 1999 and 2019. *Science of the Total Environment*, 798, 148766.
- MEAZA, H., FRANKL, A., DEMISSIE, B., POESEN, J., ZENEBE, A., GEBRESAMUEL, G., ASFAHA, T. G., ANNYS, S., VAN EETVELDE, V. & JACOB, M. 2019. Water balance components of the potential agricultural grabens along the Rift Valley in northern Ethiopia. *Journal of Hydrology: Regional Studies*, 24, 100616.
- MEKURIA, W., DIYASA, M., TENGBERG, A. & HAILESLASSIE, A. 2021a. Effects of long-term land use and land cover changes on ecosystem service values: An example from the central rift valley, Ethiopia. *Land*, 10, 1373.
- MEKURIA, W., DIYASA, M., TENGBERG, A. & HAILESLASSIE, A. 2021b. Effects of long-term land use and land cover changes on ecosystem service values: An example from the central rift valley, Ethiopia. *Land*, 10, 1373.

- MELESSE, A. M., ABTEW, W. & DESSALEGNE, T. 2009. Evaporation estimation of Rift Valley Lakes: comparison of models. *Sensors*, 9, 9603-9615.
- MENG, F., SA, C., LIU, T., LUO, M., LIU, J. & TIAN, L. 2020. Improved model parameter transferability method for hydrological simulation with SWAT in Ungauged Mountainous Catchments. *Sustainability*, 12, 3551.
- MENNA, B. Y. 2017. Simulation of hydro climatological impacts caused by climate change: the case of hare watershed, southern rift valley of Ethiopia. *Hydrology: Current Research*, 8.
- MERSHA, A. N., BANTIDER, A., ALAMIREW, T., ALEMAYEHU, T. & ZEKEKE, G. 2023. Water Resources Management and Use in the Central Rift Valley Basin, Ethiopia.
- MERZ, R. & BLÖSCHL, G. 2004. Regionalisation of catchment model parameters. *Journal of hydrology*, 287, 95-123.
- MESFIN, D., SIMANE, B., BELAY, A., RECHA, J. W. & SCHMIEDEL, U. 2020. Assessing the adaptive capacity of households to climate change in the Central Rift Valley of Ethiopia. *Climate*, 8, 106.
- MESHESHA, D. T., TSUNEKAWA, A. & TSUBO, M. 2012. Continuing land degradation: cause–effect in Ethiopia's Central Rift Valley. *Land degradation development*, 23, 130-143.
- MEYER, J., NEUPER, M., MATHIAS, L., ZEHE, E. & PFISTER, L. 2022. Atmospheric conditions favouring extreme precipitation and flash floods in temperate regions of Europe. *Hydrology Earth System Sciences*, 26, 6163-6183.
- MICHON, L., FAMIN, V. & QUIDELLEUR, X. 2022. Evolution of the East African Rift System from trap-scale to plate-scale rifting. *Earth-Science Reviews*, 231, 104089.
- MILLY, P. C., DUNNE, K. A. & VECCHIA, A. V. 2005. Global pattern of trends in streamflow and water availability in a changing climate. *Nature*, 438, 347-350.
- MINALE, A. S. 2020. Water level fluctuations of Lake Tana and its implication on local communities livelihood, northwestern Ethiopia. *International Journal of River Basin Management*, 18, 503-510.
- MIRZAEI, A., VALIZADEH, N. & AZARM, H. 2023. Tools and Solutions for Watershed Management and Planning Under Climate Change. *Climate Change Impacts on Natural Resources, Ecosystems and Agricultural Systems*. Springer.
- MITSCH, W. J. & WU, X. 2018. Wetlands and global change. *Soil Management Greenhouse Effect*, 205-230.
- MIZUKAMI, N., RAKOVEC, O., NEWMAN, A. J., CLARK, M. P., WOOD, A. W., GUPTA, H. V. & KUMAR, R. 2019. On the choice of calibration metrics for “high-flow” estimation using hydrologic models. *Hydrology Earth System Sciences*, 23, 2601-2614.
- MOELETSI, M. E., WALKER, S. & HAMANDAWANA, H. 2013a. Comparison of the Hargreaves and Samani equation and the Thornthwaite equation for estimating dekadal evapotranspiration in the Free State Province, South Africa. *Physics Chemistry of the Earth, Parts A/B/C*, 66, 4-15.
- MOELETSI, M. E., WALKER, S. & HAMANDAWANA, H. 2013b. Comparison of the Hargreaves and Samani equation and the Thornthwaite equation for estimating dekadal evapotranspiration in the Free State Province, South Africa. *Physics Chemistry of the Earth, Parts A/B/C*, 66, 4-15.
- MOHAMMED, M., BIAZN, B. & BELETE, M. D. 2020. Hydrological impacts of climate change in Tikur wuha watershed, Ethiopian rift valley basin. *Environ Earth Sci*, 10, 28-49.
- MOHAMMED, M., BIRHANU, B. & ABEGAZ, F. 2024. Hydrological dynamics and water resource availability in the Rift Valley Lakes Basin (Ethiopia), using a WEAP model. *Water Practice Technology*, 19, 1473-1494.
- MORGENSTERN, T., GRUNDMANN, J. & SCHÜTZE, N. 2024. Flood Forecasting with Deep Learning LSTM-Networks: Relevance of Catchment Attributes in Regional Network Training. Copernicus Meetings.
- MORIASI, D. N., ZECKOSKI, R. W., ARNOLD, J. G., BAFFAUT, C., MALONE, R. W., DAGGUPATI, P., GUZMAN, J. A., SARASWAT, D., YUAN, Y. & WILSON, B. N. 2015. Hydrologic and water quality models: Key calibration and validation topics. *Transactions of the ASABE*, 58, 1609-1618.
- MOSAVI, A., GOLSHAN, M., CHOUBIN, B., ZIEGLER, A. D., SIGAROODI, S. K., ZHANG, F. & DINEVA, A. A. 2021. Fuzzy clustering and distributed model for streamflow estimation in ungauged watersheds. *Scientific Reports*, 11, 8243.
- MOWR 2002. Water Sector Development Program. Addis Ababa: Ethiopia.: Ethiopia: Ministry of Water Resources.
- MULAT, Y. 2013. Indigenous knowledge practices in soil conservation at Konso people, south western Ethiopia. *Journal of Agriculture Environmental Sciences*, 2, 1-10.
- MUMMED, B. A. & SELESHI, Y. 2024. Assessment of the effects of climate change on water balance components in the upper Erer subbasin, Ethiopia. *Heliyon*, 10.
- MYERS, T. A., SCOTT, R. C., ZELINKA, M. D., KLEIN, S. A., NORRIS, J. R. & CALDWELL, P. M. 2021. Observational constraints on low cloud feedback reduce uncertainty of climate sensitivity. *Nature Climate Change*, 11, 501-507.

- NASH, J. E. & SUTCLIFFE, J. V. 1970. River flow forecasting through conceptual models part I—A discussion of principles. *Journal of hydrology*, 10, 282-290.
- NEGASSA, A., RASHID, S., GEBREMEDHIN, B. & KENNEDY, A. 2012. Livestock production and marketing. *Food agriculture in Ethiopia: Progress policy challenges*, 159-189.
- NGORAN, S. D., DOGAH, K. E. & XUE, X. 2015. Assessing the impacts of climate change on water resources: The Sub-Saharan Africa perspective. *Journal of Economics Sustainable Development*, 6, 185-193.
- NICHOLSON, S. E. 2001. Climatic and environmental change in Africa during the last two centuries. *Climate research*, 17, 123-144.
- NICHOLSON, S. E. J. T. L., CLIMATOLOGY & LAKES, P. O. T. E. A. 2019. A review of climate dynamics and climate variability in Eastern Africa. 25-56.
- NIETO-FERREIRA, R. & RICKENBACH, T. M. J. I. J. O. C. 2011. Regionality of monsoon onset in South America: a three-stage conceptual model. 31, 1309-1321.
- NITZE, I., BARRETT, B. & CAWKWELL, F. 2015. Temporal optimisation of image acquisition for land cover classification with Random Forest and MODIS time-series. *International Journal of Applied Earth Observation and Geoinformation*, 34, 136-146.
- NKONGE, L. K. 2017. *Assessment of the Transferability of Swat Model Parameters from Gauged to Ungauged Sub-Watersheds for Streamflow Simulation in the Upper Tana Watershed, Kenya*. SEMATEC-JKUAT.
- O'BRIEN, G. C., DICKENS, C., HINES, E., WEPENER, V., STASSEN, R., QUAYLE, L., FOUCHY, K., MACKENZIE, J., GRAHAM, P. M. & LANDIS, W. G. 2018. A regional-scale ecological risk framework for environmental flow evaluations. *Hydrology Earth System Sciences*, 22, 957-975.
- OLIVEIRA-JÚNIOR, J. F. D., XAVIER, F. M. G., TEODORO, P. E., GOIS, G. D. & DELGADO, R. C. J. B. J. 2017. Cluster analysis identified rainfall homogeneous regions in Tocantins state, Brazil. 333-340.
- OLSON, D. M. & DINERSTEIN, E. 2002. The Global 200: Priority ecoregions for global conservation. *Annals of the Missouri Botanical garden*, 199-224.
- ONGOMA, V. & CHEN, H. S. 2017. Temporal and spatial variability of temperature and precipitation over East Africa from 1951 to 2010. *Meteorology Atmospheric Physic*, 129, 131-144.
- OVERPECK, J. T. & COLE, J. E. J. A. R. E. R. 2006. Abrupt change in Earth's climate system. 31, 1-31.
- PAGLIERO, L., BOURAOUI, F., DIELS, J., WILLEMS, P. & MCINTYRE, N. 2019. Investigating regionalization techniques for large-scale hydrological modelling. *Journal of hydrology*, 570, 220-235.
- PAL, M. & MATHER, P. M. J. F. G. C. S. 2004. Assessment of the effectiveness of support vector machines for hyperspectral data. 20, 1215-1225.
- PALMER, M. D., MCNEALL, D. J. & DUNSTONE, N. J. J. G. R. L. 2011. Importance of the deep ocean for estimating decadal changes in Earth's radiation balance. 38.
- PAN, S., LIU, D., WANG, Z., ZHAO, Q., ZOU, H., HOU, Y., LIU, P. & XIONG, L. 2017. Runoff responses to climate and land use/cover changes under future scenarios. *Water*, 9, 475.
- PARAJKA, J., VIGLIONE, A., ROGGER, M., SALINAS, J. L., SIVAPALAN, M. & BLÖSCHL, G. 2013. Comparative assessment of predictions in ungauged basins—Part 1: Runoff-hydrograph studies. *Hydrology Earth System Sciences*, 17, 1783-1795.
- PASCUAL-FERRER, J., CANDELA, L. & PÉREZ-FOGUET, A. Ethiopian Central Rift Valley basin hydrologic modelling using HEC-HMS and ArcSWAT. EGU General Assembly Conference Abstracts, 2013. EGU2013-10563.
- PASCUAL-FERRER, J., PÉREZ-FOGUET, A., CODONY, J., RAVENTÓS, E. & CANDELA, L. 2014. Assessment of water resources management in the Ethiopian Central Rift Valley: environmental conservation and poverty reduction. *International Journal of Water Resources Development*, 30, 572-587.
- PASCUAL-FERRER, J., SHIMELIS, S., FANTAYE, D. & PÉREZ FOGUET, A. Research on WASH sector, environment and water resources in the Central Rift Valley of Ethiopia. IV Congr s Universitat i Cooperaci  al desenvolupament: resums de posters i comunicacions. Universitat Aut noma de Barcelona, 12 al 14 de novembre de 2008. Bellaterra (Espan a), 2008. Universitat Aut noma de Barcelona (UAB). Servei de Publicacions, 1-11.
- PATI, A., SEN, S. & PERUMAL, M. J. J. H. E. 2018. Modified channel-routing scheme for SWAT model. 23, 04018019.
- PEPPA, M. V., SOLANO-CORREA, Y., MILLS, J. P. & HAILE, A. T. Rapid Mapping of Waterbody Variations in the Central Rift Valley, Ethiopia, Using the Digital Earth Africa Open Data Cube. IGARSS 2023-2023 IEEE International Geoscience and Remote Sensing Symposium, 2023. IEEE, 5359-5362.
- PFANNERSTILL, M., GUSE, B. & FOHRER, N. 2014. Smart low flow signature metrics for an improved overall performance evaluation of hydrological models. *Journal of Hydrology*, 510, 447-458.
- PIELKE SR, R. A., MARLAND, G., BETTS, R. A., CHASE, T. N., EASTMAN, J. L., NILES, J. O., NIYOGI, D. D. S. & RUNNING, S. W. 2002. The influence of land-use change and landscape dynamics on the climate system: relevance to climate-change policy beyond the radiative effect of greenhouse gases. *Philosophical*

- Transactions of the Royal Society of London. Series A: Mathematical, Physical Engineering Sciences*, 360, 1705-1719.
- PLUNGE, S., SCHÜRZ, C., ČERKASOVA, N., STRAUCH, M. & PINIEWSKI, M. 2024. SWAT+ model setup verification tool: SWATdoctR. *Environmental Modelling Software*, 171, 105878.
- PONTIUS JR, R. G. J. P. E. R. S. 2000. Comparison of categorical maps. 66, 1011-1016.
- POOL, S., VIS, M. & SEIBERT, J. 2021. Regionalization for ungauged catchments—lessons learned from a comparative large-sample study. *Water Resources Research*, 57, e2021WR030437.
- PRAUS, P. J. O. C. 2005. SVD-based principal component analysis of geochemical data. 3, 731-741.
- PRIGENT, C., MATTHEWS, E., AIRES, F. & ROSSOW, W. B. 2001. Remote sensing of global wetland dynamics with multiple satellite data sets. *Geophysical Research Letters*, 28, 4631-4634.
- QI, J., ZHANG, X., YANG, Q., SRINIVASAN, R., ARNOLD, J. G., LI, J., WALDHOLF, S. T. & COLE, J. 2020. SWAT ungauged: Water quality modeling in the Upper Mississippi River Basin. 584, 124601.
- QINGQING, Z., HAILIANG, X., JINGYI, F., PUJIA, Y. & PENG, Z. J. P. E. S. 2012. Spatial analysis of land use and land cover changes in recent 30 years in Manas River Basin. 12, 906-916.
- QIU, J., SHEN, Z. & XIE, H. 2023. Drought impacts on hydrology and water quality under climate change. *Science of The Total Environment*, 858, 159854.
- RAJAB, A., FARMAN, H., ISLAM, N., SYED, D., ELMAGZOUN, M., SHAIKH, A., AKRAM, M. & ALRIZQ, M. 2023. Flood Forecasting by Using Machine Learning: A Study Leveraging Historic Climatic Records of Bangladesh. *Water*, 15, 3970.
- RAJU, K. S. & KUMAR, D. N. 2018. Impact of climate change on water resources. *Clim. Chang. Model. Plan. Policy Agric*, 219-231.
- RAO, V., HADA, K. J. T. & CLIMATOLOGY, A. 1990. Characteristics of rainfall over Brazil: Annual variations and connections with the Southern Oscillation. 42, 81-91.
- RAO, V. B., FRANCHITO, S. H., SANTO, C. M. & GAN, M. A. J. I. J. O. C. 2016. An update on the rainfall characteristics of Brazil: seasonal variations and trends in 1979–2011. 36, 291-302.
- RAZAVI, T. & COULIBALY, P. 2017. An evaluation of regionalization and watershed classification schemes for continuous daily streamflow prediction in ungauged watersheds. *Canadian Water Resources Journal/Revue canadienne des ressources hydriques*, 42, 2-20.
- RICHTER, B. D., BAUMGARTNER, J. V., BRAUN, D. P. & POWELL, J. 1998. A spatial assessment of hydrologic alteration within a river network. *Regulated Rivers: Research Management: An International Journal Devoted to River Research Management*, 14, 329-340.
- RING, U. J. A. J. O. E. S. 2014. THE EAST AFRICAN RIFT SYSTEM. 107.
- RODERICK, M., SUN, F., LIM, W. H. & FARQUHAR, G. 2014. A general framework for understanding the response of the water cycle to global warming over land and ocean. *Hydrology Earth System Sciences*, 18, 1575-1589.
- ROSE, S. & PETERS, N. E. 2001. Effects of urbanization on streamflow in the Atlanta area (Georgia, USA): a comparative hydrological approach. *Hydrological Processes*, 15, 1441-1457.
- ROST, S., GERTEN, D., BONDEAU, A., LUCHT, W., ROHWER, J. & SCHAPHOFF, S. 2008. Agricultural green and blue water consumption and its influence on the global water system. *Water Resources Research*, 44.
- RYAN, J. A. & ULRICH, J. M. 2011a. xts: Extensible time series. *R package version 0.8-2*.
- RYAN, J. A. & ULRICH, J. M. 2011b. xts: Extensible time series. *R package version 0.8-2, 2011*.
- SAATCHI, S. S., SOARES, J. V. & ALVES, D. S. 1997. Mapping deforestation and land use in Amazon rainforest by using SIR-C imagery. *Remote Sensing of Environment*, 59, 191-202.
- SADIQI, S. S. 2019. Application of SWAT to estimate runoff and sediment yield of Salma Dam watershed in Afghanistan. *한국농공학회/학술대회초록집*, 2019, 26-26.
- SADOFF, C. 2008. Managing water resources to maximize sustainable growth: a World Bank water resources assistance strategy for Ethiopia. *Water P-Notes; No. 13*, © World Bank, Washington, DC. <http://hdl.handle.net/10986/11758> License: CC BY 3.0 IGO.”.
- SARIA, E., CALAIS, E., STAMPS, D., DELVAUX, D. & HARTNADY, C. J. J. O. G. R. S. E. 2014. Present-day kinematics of the East African Rift. 119, 3584-3600.
- SARIA, E., MBEDE, E., STAMPS, D., HERNANDEZ, S., CALAIS, E. & EBINGER, C. Kinematics of the East African Rift from GPS and earthquake slip vector data. AGU Fall Meeting Abstracts, 2006. G43B-1005.
- SAVARY, S., ROUSSEAU, A. N. & QUILBÉ, R. 2009. Assessing the effects of historical land cover changes on runoff and low flows using remote sensing and hydrological modeling. *Journal of Hydrologic Engineering*, 14, 575-587.
- SCHOLTEN, W. 2007. *Agricultural development and water use in the Central Rift Valley of Ethiopia: A rapid appraisal*. University of Twente.

- SCOON, R. N. 2018. The east African rift system. *Geology of National Parks of Central/Southern Kenya Northern Tanzania*, 19-28.
- SEGELE, Z. T., LAMB, P. J. & LESLIE, L. M. J. J. O. C. 2009. Seasonal-to-interannual variability of Ethiopia/Horn of Africa monsoon. Part I: associations of wavelet-filtered large-scale atmospheric circulation and global sea surface temperature. 22, 3396-3421.
- SEIBERT, J. 1999. Regionalisation of parameters for a conceptual rainfall-runoff model. *Agricultural forest meteorology* 98, 279-293.
- SEIBERT, J. & BERGSTRÖM, S. 2022. A retrospective on hydrological catchment modelling based on half a century with the HBV model. *Hydrology Earth System Sciences*, 26, 1371-1388.
- SEID, M., SIMANE, B., TEFERI, E. & AZMERAW, A. 2022. Determinants of farmers' multiple-choice and sustainable use of indigenous land management practices in the Southern Rift Valley of Ethiopia. *Current Research in Environmental Sustainability*, 4, 100158.
- SEYOU, W., TORA, E., KORE, K. & LEJEBO, F. 2022. Seasonal patterns: bovine trypanosomosis, *Glossina pallidipes* density, and infection in Rift Valleys of Gamo Zone, Southern Ethiopia. *Frontiers in Veterinary Science*, 9, 805564.
- SHIEH, C.-L., GUH, Y.-R. & WANG, S.-Q. 2007. The application of range of variability approach to the assessment of a check dam on riverine habitat alteration. *Environmental Geology*, 52, 427-435.
- SHIRVANI, A. J. T. & CLIMATOLOGY, A. 2017. Change point detection of the Persian Gulf sea surface temperature. 127, 123-127.
- SHRESTHA, P., SAMANIEGO, L., RAKOVEC, O., KUMAR, R., MI, C., RINKE, K. & THOBER, S. 2024. Toward improved simulations of disruptive reservoirs in global hydrological modeling. *Water Resources Research*, 60, e2023WR035433.
- SHUKLA, J., VERMA, M. & MISRA, A. 2017. Effect of global warming on sea level rise: A modeling study. *Ecological Complexity*, 32, 99-110.
- SIEBERT, S., KUMMU, M., PORKKA, M., DÖLL, P., RAMANKUTTY, N. & SCANLON, B. R. 2015. A global data set of the extent of irrigated land from 1900 to 2005. *Hydrology and Earth System Sciences*, 19, 1521-1545.
- SIMANE, B., BEYENE, H., DERESSA, W., KUMIE, A., BERHANE, K. & SAMET, J. 2016. Review of climate change and health in Ethiopia: status and gap analysis. *Ethiopian Journal of Health Development*, 30, 28-41.
- SIME, G. & AUNE, J. B. 2018. Sustainability of improved crop varieties and agricultural practices: A case study in the central rift valley of Ethiopia. *Agriculture*, 8, 177.
- SINGH, N. M. & DEVI, T. T. 2022. Regionalization methods in ungauged catchments for flow prediction: review and its recent developments. *Arabian Journal of Geosciences*, 15, 1019.
- SINGH, P., KIKON, N. & VERMA, P. 2017. Impact of land use change and urbanization on urban heat island in Lucknow city, Central India. A remote sensing based estimate. *Sustainable Cities and Society*, 32, 100-114.
- SISAY, E., HALEFOM, A., KHARE, D., SINGH, L. & WORKU, T. 2017. Hydrological modelling of ungauged urban watershed using SWAT model. *Modeling Earth Systems Environmental Earth Sciences*, 3, 693-702.
- SISSAY, L. 2003a. Biodiversity potentials and threats to the southern Rift Valley lakes of Ethiopia. *Wetlands of Ethiopia*, 18.
- SISSAY, L. J. W. O. E. 2003b. Biodiversity potentials and threats to the southern Rift Valley lakes of Ethiopia. 18.
- SIVAPALAN, M. 2018. From engineering hydrology to Earth system science: milestones in the transformation of hydrologic science. *Hydrology Earth System Sciences*, 22, 1665-1693.
- SIVAPALAN, M., BLÖSCHL, G., ZHANG, L. & VERTESSY, R. 2003. Downward approach to hydrological prediction. Wiley Online Library.
- SLATER, L. J., THIREL, G., HARRIGAN, S., DELAIGUE, O., HURLEY, A., KHOUAKHI, A., PROSDOCIMI, I., VITOLO, C. & SMITH, K. 2019. Using R in hydrology: a review of recent developments and future directions. *Hydrology Earth System Sciences*, 23, 2939-2963.
- SMAKHTIN, V. U. 2001. Low flow hydrology: a review. *Journal of hydrology*, 240, 147-186.
- SMITH, P., CALVIN, K., NKEM, J., CAMPBELL, D., CHERUBINI, F., GRASSI, G., KOROTKOV, V., LE HOANG, A., LWASA, S. & MCELWEE, P. J. G. C. B. 2020. Which practices co-deliver food security, climate change mitigation and adaptation, and combat land degradation and desertification? 26, 1532-1575.
- SOETAERT, K. & PETZOLDT, T. 2010a. Inverse modelling, sensitivity and Monte Carlo analysis in R using package FME. *Journal of statistical software*, 33, 1-28.
- SOETAERT, K. & PETZOLDT, T. 2010b. Inverse modelling, sensitivity and Monte Carlo analysis in R using package FME. *Journal of statistical software*, 33, 1-28.

- SOLOMON, R., SIMANE, B. & ZAITCHIK, B. F. 2021. The impact of climate change on agriculture production in Ethiopia: application of a dynamic computable general equilibrium model. *American Journal of Climate Change*, 10, 32-50.
- SONG, X.-P., HANSEN, M. C., STEHMAN, S. V., POTAPOV, P. V., TYUKAVINA, A., VERMOTE, E. F. & TOWNSHEND, J. R. 2018. Global land change from 1982 to 2016. *Nature*, 560, 639-643.
- SONG, X., ZHUANG, Y., WANG, X., LI, E., ZHANG, Y., LU, X., YANG, J. & LIU, X. 2020. Analysis of hydrologic regime changes caused by dams in China. *Journal of Hydrologic Engineering*, 25, 05020003.
- STAMPS, D. S., CALAIS, E., SARIA, E., HARTNADY, C., NOCQUET, J. M., EBINGER, C. J. & FERNANDES, R. M. 2008a. A kinematic model for the East African Rift. *Geophysical Research Letters*, 35.
- STAMPS, D. S., CALAIS, E., SARIA, E., HARTNADY, C., NOCQUET, J. M., EBINGER, C. J. & FERNANDES, R. M. J. G. R. L. 2008b. A kinematic model for the East African Rift. 35.
- STEINHAUSEN, M. J., WAGNER, P. D., NARASIMHAN, B., WASKE, B. J. I. J. O. A. E. O. & GEOINFORMATION 2018. Combining Sentinel-1 and Sentinel-2 data for improved land use and land cover mapping of monsoon regions. 73, 595-604.
- STORY, M., CONGALTON, R. G. J. P. E. & SENSING, R. 1986. Accuracy assessment: a user's perspective. 52, 397-399.
- STREET, F. A. & GROVE, A. 1979. Global maps of lake-level fluctuations since 30,000 yr BP. *Quaternary research*, 12, 83-118.
- SUD, Y. & FENNESSY, M. J. J. O. C. 1982. A study of the influence of surface albedo on July circulation in semi-arid regions using the GLAS GCM. 2, 105-125.
- SUNDERLAND, T. C. & ROWLAND, D. 2019. Forests, land use, and challenges to climate stability and food security. *Sustainable Food and Agriculture*. Elsevier.
- SUNG, J. H., CHUNG, E.-S., KIM, Y., LEE, B.-R. J. T. & CLIMATOLOGY, A. 2017. Meteorological hazard assessment based on trends and abrupt changes in rainfall characteristics on the Korean peninsula. 127, 305-326.
- SWAIN, J. B. & PATRA, K. C. 2017. Streamflow estimation in ungauged catchments using regionalization techniques. *Journal of Hydrology*, 554, 420-433.
- TADROSS, M., HEWITSON, B. & USMAN, M. J. J. O. C. 2005. The interannual variability of the onset of the maize growing season over South Africa and Zimbabwe. 18, 3356-3372.
- TAKELE, R., TESFAYE, K. & SIBIRY TRAORÉ, P. C. 2020. Seasonal Climate Predictability in Ethiopia: Review of best predictor sets for subseasonal to seasonal forecasting. *CCAFS Working Paper*.
- TAN, Y., GUZMAN, S. M., DONG, Z. & TAN, L. 2020. Selection of effective GCM bias correction methods and evaluation of hydrological response under future climate scenarios. *Climate*, 8, 108.
- TARASOVA, L., GNANN, S., YANG, S., HARTMANN, A. & WAGENER, T. 2024. Catchment characterization: current descriptors, knowledge gaps and future opportunities. *Earth-Science Reviews*, 104739.
- TEAM, R. C., BIVAND, R., CAREY, V. J., DEBROY, S., EGLEN, S., GUHA, R., HERBRANDT, S., LEWIN-KOH, N., MYATT, M. & NELSON, M. 2020. Package 'foreign'.
- TEGEGNE, G. & KIM, Y.-O. 2018. Modelling ungauged catchments using the catchment runoff response similarity. *Journal of hydrology*, 564, 452-466.
- TEKU, D., KESETE, N. & ABEBE, A. 2024. GIS based annual soil loss estimation with revised universal soil loss equation (RUSLE) in the upper Meki sub-catchment, rift valley sub-basin, Ethiopia. *Cogent Food Agriculture*, 10, 2311802.
- TEODORO, P. E., DE OLIVEIRA-JÚNIOR, J. F., DA CUNHA, E. R., CORREA, C. C. G., TORRES, F. E., BACANI, V. M., GOIS, G., RIBEIRO, L. P. J. M. & PHYSICS, A. 2016. Cluster analysis applied to the spatial and temporal variability of monthly rainfall in Mato Grosso do Sul State, Brazil. 128, 197-209.
- TERASSI, P. M. D. B. & GALVANI, E. J. C. 2017. Identification of homogeneous rainfall regions in the eastern watersheds of the State of Paraná, Brazil. 5, 53.
- THENKABAIL, P. S., SCHULL, M. & TURRAL, H. 2005. Ganges and Indus river basin land use/land cover (LULC) and irrigated area mapping using continuous streams of MODIS data. *Remote Sensing of Environment*, 95, 317-341.
- TIGABU, T. B., HÖRMANN, G., WAGNER, P. D., FOHRER, N. J. J. O. W. & CHANGE, C. 2020. Statistical analysis of rainfall and streamflow time series in the Lake Tana Basin, Ethiopia. 11, 258-273.
- TIGABU, T. B., VISSER, A., KADIR, T., ABUDU, S., CAMERON-SMITH, P. & DAHLKE, H. E. 2024. Optimization of the SWAT+ model to adequately predict different segments of a managed streamflow hydrograph. *Hydrological Sciences Journal*, 69, 1198-1217.
- TIGABU, T. B., WAGNER, P. D., HÖRMANN, G. & FOHRER, N. 2019. Modeling the impact of agricultural crops on the spatial and seasonal variability of water balance components in the Lake Tana basin, Ethiopia. *Hydrology Research*, 50, 1376-1396.

- TIGABU, T. B., WAGNER, P. D., HÖRMANN, G., KIESEL, J. & FOHRER, N. 2021. Climate change impacts on the water and groundwater resources of the Lake Tana Basin, Ethiopia. *Journal of Water Climate Change*, 12, 1544-1563.
- TIGABU, T. B., WAGNER, P. D., NARASIMHAN, B. & FOHRER, N. 2023. Pitfalls in hydrologic model calibration in a data scarce environment with a strong seasonality: experience from the Adyar catchment, India. *Environmental Earth Sciences*, 82, 367.
- TILAHUN, Z. A., BIZUNEH, Y. K. & MEKONNEN, A. G. 2023. The impacts of climate change on hydrological processes of Gilgel Gibe catchment, southwest Ethiopia. *Plos one*, 18, e0287314.
- TIRUNEH, A. T. 2005. Water quality monitoring in Lake Abaya and Lake Chamo region. *J Chemistry-Biology University of Siegen, University of Siegen*.
- TRENBERTH, K. E. 2011. Changes in precipitation with climate change. *Climate research*, 47, 123-138.
- TRUNEH, L. A., MATULA, S. & BĀŤKOVÁ, K. 2024. An analysis of the impacts of land use change on the components of the water balance in the Central Rift Valley sub-basins in Ethiopia. *Sustainable Water Resources Management*, 10, 77.
- TSEGAW, A. T., ALFREDSSEN, K., SKAUGEN, T. & MUTHANNA, T. M. 2019. Predicting hourly flows at ungauged small rural catchments using a parsimonious hydrological model. *Journal of Hydrology*, 573, 855-871.
- TU, X., SINGH, V. P., CHEN, X., CHEN, L., ZHANG, Q. & ZHAO, Y. 2015. Intra-annual distribution of streamflow and individual impacts of climate change and human activities in the Dongjiang River Basin, China. *Water Resources Management*, 29, 2677-2695.
- TUDORANCEA, C. & TAYLOR, W. D. 2002. *Ethiopian rift valley lakes*, Backhuys.
- TULLU, G. M. 2024. Spatiotemporal Rainfall Analysis of El Nino, Neutral and La Nina Years Across Belg and Kiremt Seasons Over Oromia Region Ethiopia. *Journal of Environmental Science Agricultural Research*, 2, 1-9.
- USGS 2023. 3D Elevation Program 1-Meter Resolution Digital Elevation Model (published 2014).
- VAN HALSEMA, G., KEDDI LENCHA, B., ASSEFA, M., HENGSDIJK, H. & WESSELER, J. 2011a. Performance assessment of smallholder irrigation in the Central Rift Valley of Ethiopia. *Irrigation and drainage*, 60, 622-634.
- VAN HALSEMA, G., KEDDI LENCHA, B., ASSEFA, M., HENGSDIJK, H. & WESSELER, J. 2011b. Performance assessment of smallholder irrigation in the Central Rift Valley of Ethiopia. *Irrigation drainage*, 60, 622-634.
- VIECELI, N., BORTOLIN, T. A., MENDES, L. A., BACARIM, G., CEMIN, G. & SCHNEIDER, V. E. 2015. Morphometric evaluation of watersheds in Caxias do Sul City, Brazil, using SRTM (DEM) data and GIS. *Environmental Earth Sciences*, 73, 5677-5685.
- VIGLIONE, A., PARAJKA, J., ROGGER, M., SALINAS, J., LAAHA, G., SIVAPALAN, M. & BLÖSCHL, G. 2013. Comparative assessment of predictions in ungauged basins—Part 3: Runoff signatures in Austria. *Hydrology Earth System Sciences*, 17, 2263-2279.
- VINCENT, L. A., PETERSON, T., BARROS, V., MARINO, M., RUSTICUCCI, M., CARRASCO, G., RAMIREZ, E., ALVES, L., AMBRIZZI, T. & BERLATO, M. J. J. O. C. 2005. Observed trends in indices of daily temperature extremes in South America 1960–2000. 18, 5011-5023.
- VIRA, B. 2015. Taking natural limits seriously: implications for development studies and the environment. *Development and Change*, 46, 762-776.
- VISTE, E., KORECHA, D., SORTEBERG, A. J. T. & CLIMATOLOGY, A. 2013. Recent drought and precipitation tendencies in Ethiopia. 112, 535-551.
- VORMOOR, K., HEISTERMANN, M., BRONSTERT, A. & LAWRENCE, D. 2018. Hydrological model parameter (in) stability—“crash testing” the HBV model under contrasting flood seasonality conditions. *Hydrological Sciences Journal*, 63, 991-1007.
- VÖRÖSMARTY, C. J., MCINTYRE, P. B., GESSNER, M. O., DUDGEON, D., PRUSEVICH, A., GREEN, P., GLIDDEN, S., BUNN, S. E., SULLIVAN, C. A. & LIERMANN, C. R. 2010. Global threats to human water security and river biodiversity. *Nature*, 467, 555-561.
- VU, T. T., KIESEL, J., GUSE, B. & FOHRER, N. 2019a. Analysis of the occurrence, robustness and characteristics of abrupt changes in streamflow time series under future climate change. *Climate Risk Management*, 26, 100198.
- VU, T. T., KIESEL, J., GUSE, B. & FOHRER, N. J. C. R. M. 2019b. Analysis of the occurrence, robustness and characteristics of abrupt changes in streamflow time series under future climate change. 26, 100198.
- WADA, Y., BIERKENS, M. F., DE ROO, A., DIRMEYER, P. A., FAMIGLIETTI, J. S., HANASAKI, N., KONAR, M., LIU, J., SCHMIED, H. M. & OKI, T. 2017. Human-water interface in hydrological modelling: current status and future directions. *Hydrology and Earth System Sciences*, 21, 4169-4193.
- WADA, Y., VAN BEEK, L. P., VAN KEMPEN, C. M., RECKMAN, J. W., VASAK, S. & BIERKENS, M. F. 2010. Global depletion of groundwater resources. *Geophysical research letters*, 37.

- WAGAW, S., MENGISTOU, S. & GETAHUN, A. 2019. Review of anthropogenic threats and biodiversity assessment of an Ethiopian soda lake, Lake Abijata. *African Journal of Aquatic Science*, 44, 103-111.
- WAGENER, T. & MONTANARI, A. 2011. Convergence of approaches toward reducing uncertainty in predictions in ungauged basins. *Water Resources Research*, 47.
- WAGENER, T. & WHEATER, H. S. 2006. Parameter estimation and regionalization for continuous rainfall-runoff models including uncertainty. *Journal of hydrology*, 320, 132-154.
- WAGNER, P., KUMAR, S., SCHNEIDER, K. J. H. & SCIENCES, E. S. 2013. An assessment of land use change impacts on the water resources of the Mula and Mutha Rivers catchment upstream of Pune, India. 17, 2233-2246.
- WAGNER, P. D., BIEGER, K., ARNOLD, J. G. & FOHRER, N. J. E. M. 2022. Representation of hydrological processes in a rural lowland catchment in Northern Germany using SWAT and SWAT+. *Hydrological Processes*, 36, e14589.
- WAGNER, P. D., FIENER, P., WILKEN, F., KUMAR, S. & SCHNEIDER, K. 2012. Comparison and evaluation of spatial interpolation schemes for daily rainfall in data scarce regions. *Journal of Hydrology*, 464, 388-400.
- WAGNER, P. D. & FOHRER, N. 2019. Gaining prediction accuracy in land use modeling by integrating modeled hydrologic variables. *Environmental Modelling Software*, 115, 155-163.
- WAGNER, P. D., KUMAR, S. & FOHRER, N. 2023. Integrated modeling of global change impacts on land and water resources. *Science of The Total Environment*, 892, 164673.
- WALLACE, J. M., SMITH, C. & BRETHERTON, C. S. J. J. O. C. 1992. Singular value decomposition of wintertime sea surface temperature and 500-mb height anomalies. 5, 561-576.
- WALLINGTON, K. & CAI, X. 2023. Updating SWAT+ to clarify understanding of in-stream phosphorus retention and remobilization: SWAT+ PR & R. *Water Resources Research*, 59, e2022WR033283.
- WANG, D. & HEJAZI, M. 2011a. Quantifying the relative contribution of the climate and direct human impacts on mean annual streamflow in the contiguous United States. *Water resources research*, 47.
- WANG, D. & HEJAZI, M. 2011b. Quantifying the relative contribution of the climate and direct human impacts on mean annual streamflow in the contiguous United States. *Water resources research*, 47.
- WANG, L., LI, Y., ZHENG, H., XU, T., OUYANG, Z., WANG, Z., JI, Z. & LIU, Y. 2012. Evaluating the effects of climate changes and LUCC on the hydrological processes using soil and water assessment tool models in Wangkuai Reservoir watershed in China. *Sensor Letters*, 10, 405-414.
- WANG, M., JIANG, S., REN, L., XU, C.-Y., MENZEL, L., YUAN, F., XU, Q., LIU, Y. & YANG, X. 2021. Separating the effects of climate change and human activities on drought propagation via a natural and human-impacted catchment comparison method. *Journal of Hydrology*, 603, 126913.
- WANG, S.-Y., LIU, J.-Y., ZHANG, Z.-X., ZHOU, Q.-B. & ZHAO, X.-L. J. A. G. S. 2001. Analysis on Spatial-Temporal Features of Land Use in China [J]. 6, 631-639.
- WANG, X., ERDMAN, C., EMERSON, J. W., WANG, M. X. & DNACOPY, S. 2018. Package 'bcp'. Version.
- WANG, Z., ZHANG, B., ZHANG, S., LI, X., LIU, D., SONG, K., LI, J., LI, F. & DUAN, H. 2006. Changes of land use and of ecosystem service values in Sanjiang Plain, Northeast China. *Environmental Monitoring and Assessment*, 112, 69-91.
- WENDEMENEH, D., AYANA, M. & HAILESLASSIE, A. 2020. Spatiotemporal variation of irrigation water quality at Bochessa Watershed in Central Rift Valley of Ethiopia. *African Journal of Environmental Science Technology*, 14, 70-82.
- WHITE, G. F., BRADLEY, D. J. & WHITE, A. U. 2002. Drawers of water: domestic water use in East Africa. *Bulletin of the World Health Organization*, 80, 63-73.
- WI, S., YANG, Y., STEINSCHNEIDER, S., KHALIL, A. & BROWN, C. 2014. Calibration approaches for distributed hydrologic models using high performance computing: implication for streamflow projections under climate change. *Hydrol. Earth Syst. Sci. Discuss*, 11, 10273-10317.
- WILKEN, F., WAGNER, P., NARASIMHAN, B. & FIENER, P. J. A. G. 2017. Spatio-temporal patterns of land use and cropping frequency in a tropical catchment of South India. 89, 124-132.
- WINKLER, K., FUCHS, R., ROUNSEVELL, M. & HEROLD, M. J. N. C. 2021. Global land use changes are four times greater than previously estimated. 12, 1-10.
- WONG, H., HU, B., IP, W. & XIA, J. J. J. O. H. 2006. Change-point analysis of hydrological time series using grey relational method. 324, 323-338.
- WU, C., HU, W., ZHOU, M., LI, S. & JIA, Y. 2019. Data-driven regionalization for analyzing the spatiotemporal characteristics of air quality in China. *Atmospheric Environment*, 203, 172-182.
- WU, J., YEN, H., ARNOLD, J. G., YANG, Y. E., CAI, X., WHITE, M. J., SANTHI, C., MIAO, C. & SRINIVASAN, R. 2020. Development of reservoir operation functions in SWAT+ for national environmental assessments. *Journal of Hydrology*, 583, 124556.

- XIA, W., ZHU, B., ZHANG, S., LIU, H., QU, X., LIU, Y., RUDSTAM, L. G., ANDERSON, J. T., NI, L. & CHEN, Y. 2022. Climate, hydrology, and human disturbance drive long-term (1988–2018) macrophyte patterns in water diversion lakes. *Journal of Environmental Management*, 319, 115726.
- XIE, P., WU, Z., SANG, Y.-F., GU, H., ZHAO, Y. & SINGH, V. P. J. J. O. H. 2018. Evaluation of the significance of abrupt changes in precipitation and runoff process in China. 560, 451-460.
- XU, H., WANG, H. & LIU, P. 2024. Identifying control factors of hydrological behavior through catchment classification in mainland China. *Journal of Hydrology*, 132206.
- YANG, L., WEI, W., CHEN, L. & MO, B. J. J. O. H. 2012. Response of deep soil moisture to land use and afforestation in the semi-arid Loess Plateau, China. 475, 111-122.
- YANG, X., REN, L., LIU, Y., JIAO, D. & JIANG, S. 2014. Hydrological response to land use and land cover changes in a sub-watershed of West Liaohe River Basin, China. *Journal of Arid Land*, 6, 678-689.
- YANG, Y., RODERICK, M. L., ZHANG, S., MCVICAR, T. R. & DONOHUE, R. J. 2019. Hydrologic implications of vegetation response to elevated CO₂ in climate projections. *Nature Climate Change*, 9, 44-48.
- YI, L., ZHANG, Z., WANG, X., LIU, B., ZUO, L., ZHAO, X. & WANG, J. J. T. O. T. C. S. O. A. E. 2013. Spatial-temporal change of major reserve resources of cultivated land in China in recent 30 years. 29, 1-12.
- YILMAZ, K. K., GUPTA, H. V. & WAGENER, T. 2008. A process-based diagnostic approach to model evaluation: Application to the NWS distributed hydrologic model. *Water resources research*, 44.
- YOHANNES, F. 2003. *Management of Lake Ziway Fisheries in Ethiopia*. Universitetet i Tromsø.
- ZAMBRANO-BIGIARINI, M. 2018. hydroGOF: Goodness-of-Fit Functions for Comparison of Simulated and Observed Hydrological Time Series, 2017. URL <https://CRAN.R-project.org/package=hydroGOF>. R package version 0.3-10.
- ZAMBRANO-BIGIARINI, M. J. Z. 2014. hydroGOF: Goodness-of-fit functions for comparison of simulated and observed hydrological time series. R package version 0.3-8. 10.
- ZEILEIS, A. & GROTHENDIECK, G. 2005. zoo: S3 infrastructure for regular and irregular time series. *arXiv preprint math/0505527*.
- ZEILEIS, A., LEISCH, F., HORNIK, K. & KLEIBER, C. J. J. O. S. S. 2002. strucchange: An R package for testing for structural change in linear regression models. 7, 1-38.
- ZEKARIAS, T. & GELAW, A. 2023. Impacts of land use/land cover change on wetland ecosystem services of Lake Abaya-Chamo Wetland, Rift Valley of Ethiopia. *Geology, Ecology, Landscapes landforms of Ethiopia*, 1-12.
- ZENA, K., ADUGNA, T. & FUFA, F. 2024. Climate and human activities impact on runoff and sediment yield in the central rift valley of Ethiopia. *Cogent Engineering*, 11, 2297511.
- ZENEBE, A. 2009. *Holocene paleoclimate reconstruction inferred from proxy records in speleothems from the Mechara karst area and lake archives from Tilo and Awassa lakes, Ethiopia*. Addis Ababa University.
- ZENEBE, T., AHLGREN, G. & BOBERG, M. 1998. Fatty acid content of some freshwater fish of commercial importance from tropical lakes in the Ethiopian Rift Valley. *Journal of fish biology*, 53, 987-1005.
- ZEWDU, S., SURYABHAGAVAN, K. & BALAKRISHNAN, M. 2017. Geo-spatial approach for soil salinity mapping in Sego Irrigation Farm, South Ethiopia. *Journal of the Saudi Society of Agricultural Sciences*, 16, 16-24.
- ZHANG, H., WANG, B., LAN, T., SHI, J. & LU, S. 2016. Change-point detection and variation assessment of the hydrologic regime of the Wenyu River. *Toxicological Environmental Chemistry*, 98, 358-375.
- ZHANG, H., WANG, B., LI LIU, D., ZHANG, M., LESLIE, L. M. & YU, Q. 2020. Using an improved SWAT model to simulate hydrological responses to land use change: A case study of a catchment in tropical Australia. *Journal of Hydrology*, 585, 124822.
- ZHANG, J.-H., FENG, Z. & JIANG, L.-G. J. R. S. 2011. Progress on studies of land use/land cover classification systems. 33, 1195-1203.
- ZHANG, Y., ENGEL, B., AHIABLAAME, L. & LIU, J. 2015. Impacts of climate change on mean annual water balance for watersheds in Michigan, USA. *Journal of Water*, 7, 3565-3578.
- ZHAO, F., XU, Z. & ZHANG, L. J. H. P. 2012. Changes in streamflow regime following vegetation changes from paired catchments. 26, 1561-1573.
- ZHAO, J., HUANG, S., HUANG, Q., WANG, H. & LENG, G. 2018. Detecting the dominant cause of streamflow decline in the loess plateau of China based on the latest budyko equation. *Water*, 10, 1277.
- ZHOU, Q., CHEN, L., SINGH, V. P., ZHOU, J., CHEN, X. & XIONG, L. 2019. Rainfall-runoff simulation in karst dominated areas based on a coupled conceptual hydrological model. *Journal of Hydrology*, 573, 524-533.
- ZINABU, G.-M. & ELIAS, D. 1989. Water resources and fisheries management in the Ethiopian rift valley lakes. *Sinet*, 12, 95-109.
- ZINABU, G., KEBEDE-WESTHEAD, E. & DESTA, Z. 2002. Long-term changes in chemical features of waters of seven Ethiopian rift-valley lakes. *Hydrobiologia*, 477, 81-91.

ZWIERS, F. W., ALEXANDER, L. V., HEGERL, G. C., KNUTSON, T. R., KOSSIN, J. P., NAVEAU, P., NICHOLLS, N., SCHÄR, C., SENEVIRATNE, S. I., ZHANG, X. & PRIORITIES, P. 2013. Climate extremes: challenges in estimating and understanding recent changes in the frequency and intensity of extreme climate and weather events. *Climate science for serving society: research, modeling*, 339-389.

8. Acknowledgments

Above all, I would like to express my gratitude to the almighty GOD for the boundless blessings and unseen guidance that have graced my journey. The completion of my thesis has been made possible through the collective efforts of numerous individuals, each offering their unique contributions and support.

I would like to express my deepest gratitude to my esteemed professor, Prof. Dr. Nicola Fohrer, for unwavering guidance, invaluable insights, and continuous support throughout the journey of my doctoral research. Prof. Dr. Nicola's dedication to fostering academic growth and commitment to excellence have been instrumental in shaping my understanding of the subject matter. I would also like to extend my heartfelt gratitude to my esteemed thank Dr. Paul D. Wagner, Dr. Dejene Sahlu and Dr. Tibebe B. Tigabu for their unwavering support, invaluable guidance, and profound expertise throughout the journey of my research. Their mentorship has been instrumental in shaping my understanding of the subject matter and refining the direction of my work.

Dr. Paul D. Wagner has consistently provided me with constructive feedback, enabling me to overcome challenges and grow as a researcher. His dedication to the project and commitment to my success have been truly inspiring. I am also thankful for the collaborative environment fostered by him which allowed me to explore innovative ideas and approach complex problems with confidence. This research would not have been possible without Dr. Paul D. Wagner's contributions, and I am deeply appreciative of his unwavering support and mentorship.

I would also like to express my gratitude to Dr. Katrin Bieger and Dr. Abeyou Wale for facilitating to connect with Prof. Dr. Nicola Fohrer. Without their invaluable assistance, I would not have had the opportunity to meet my esteemed professor.

I extend my sincere appreciation to the members of my dissertation committee, Prof. Dr. Frank Kempken (Dekan), Prof. Dr. Nicola Fohrer (first evaluator), Prof. Dr. Natascha Oppelt (second evaluator), Prof. Dr. Eileen Eckmeier (examiner), PD Dr. Paul Wagner (examiner), and Prof. Dr. Florian Dünckmann (head of the examination committee), for their valuable insights and constructive feedback, which significantly improved the quality of this work.

I am grateful to my colleagues and fellow researchers at Hydrology and Water resources management department of Kiel University whose discussions and solidarity provided an inspiring and stimulating research environment.

My heartfelt thanks go to my family for their boundless love, encouragement, and understanding during the demanding phases of this endeavor. Your unwavering belief in me was my constant motivation.

I would like to acknowledge the financial support provided by the German Academic Exchange Service (DAAD) and the Ethiopian Ministry of Education supported this research, which made this research possible.

My gratefully acknowledgment is also towards to Ethiopian Ministry of water resources for providing hydrological data; Ethiopian Meteorology Agency for providing meteorological data and Arba Minch University- Vlaamse Inter-universitaire Raad-Institutional University Cooperation (AMU-VLIR-IUC) program for funding the bathymetry survey conducted on Lake Chamo.

Last but not least, I want to express my gratitude to all the participants and individuals who generously contributed their time and knowledge to this study. Without their cooperation, this research would not have been feasible.

This dissertation represents the culmination of years of dedication and hard work, and I am deeply appreciative of everyone who played a role, no matter how small, in its completion.

9. Declarations

M.Sc. Ayenew Desalegn Ayalew

Statutory Declaration:

Herewith I declare on oath that the submitted dissertation under the title “Modeling the Dynamics of Long-Term Variability of Hydro-Climatic Processes and Associated Extreme Events in Rift Valley Lakes Basin, Ethiopia” has been authored independently and without illegitimate external help and that it has not been formerly submitted to another university department.

Kiel, 10.10.2023

Signature

Herewith I declare, that I am not subject to any pending case of public prosecution.

Kiel, 10.10.2023

Signature

Herewith I declare, that the dissertation complies with the conventions of proper academic practices as defined by the DFG.

Kiel, 10.10.2023

Signature