MONITORING SURFACE WATER DYNAMICS IN ETHIOPIAN’S RIFT VALLEY LAKES USING SENTINEL 1 AND SENTINEL 2 DATA ON GOOGLE EARTH ENGINE

Tujuba Dibaba

Thesis submitted to the Department of Architecture

College of Civil Engineering and Architecture (CoCEA),

Office of Graduate Studies

Adama Science and Technology University

June, 2025

Adama, Ethiopia

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Under the Supervision of

Roba Gamachu (PhD)

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DECLARATION

I hereby declare that this research thesis entitled "**Monitoring Surface Water dynamics in Ethiopian's Rift Valley Lakes using sentinel 1 and sentinel 2 data on Google Earth Engine"** is my original work. That is, it has not been submitted to any other university. All materials used for this thesis have been duly acknowledged through citation.

Tujuba Dibaba	________________________	________________
Name of student	Signature	Date

RECOMMENDATION

I, the advisor of this thesis, hereby certify that I have read this entitled "**Monitoring Surface Water dynamics in Ethiopian's Rift Valley Lakes using sentinel 1 and sentinel 2 data on Google Earth Engine"** prepared under my guidance by Tujuba Dibaba. Therefore, I recommend the submission to the department following the applicable procedures.

Roba Gamachu (PhD)	_________________	________________
Name of Major Advisor	Signature	Date

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APPROVAL PAGE OF THE THESIS

I, the advisor of this thesis entitled "**Monitoring Surface Water dynamics in Ethiopian's Rift Valley Lakes using sentinel 1 and sentinel 2 data on Google Earth Engine"** developed by Tujuba Dibaba hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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Major Advisor Signature Date

We, the undersigned, members of the Board of Examiners of the thesis by Tujuba Dibaba have read and evaluated the thesis entitled "**Monitoring Surface Water dynamics in Ethiopian's Rift Valley Lakes using sentinel 1 and sentinel 2 data on Google Earth Engine"** and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for future thesis work.

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Final approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and College Graduate Committee (CGC).

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ACRONYMS AND ABBREVIATIONS

Abbreviation	**Full Form**
GEE	Google Earth Engine
SAR	Synthetic Aperture Radar
LST	Land Surface Temperature
S1	Sentinel 1 (SAR imagery)
S2	Sentinel 2 (optical imagery)
NDWI	Normalized Difference Water Index
NIR	Near Infrared
SWIR	Short-Wave Infrared
VIS	Visible (light spectrum)
CV	Coefficient of Variation
SPI	Standardized Precipitation Index
STI	Standardized Temperature Index
LULC	Land Use and Land Cover
GCP	Ground Control Points
NDVI	Normalized Difference Vegetation Index
DEM	Digital Elevation Model
MNDWI	Modified Normalized Difference Water Index

Abstract

Surface water bodies are important natural assets that help ecosystems, biodiversity, agriculture, and human livelihoods. This study specializes in mapping and monitoring the dynamics of floor water our bodies in the Rift Valley Lakes Basin. A quantitative studies technique becomes adopted in this study to assess and reveal the dynamics of surface water bodies within the Rift Valley Lakes Basin of Ethiopia. The analysis became primarily based on multi-temporal satellite tv for pc records from Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 optical sensors, masking a length from 2015 to 2025. Data preprocessing becomes conducted totally in the Google Earth Engine (GEE) cloud computing platform. The preprocessing steps blanketed speckle noise filtering, thermal noise removal, date filtering, and clipping and extraction of the have a look at region to prepare the facts for analysis. For the real statistics evaluation, two number one strategies have been applied. Otsu's computerized thresholding method changed into used on Sentinel-1 SAR records to efficiently distinguish water from non-water areas primarily based on backscatter intensity. For Sentinel-2 statistics, the Normalized Difference Water Index (NDWI) become computed to pick out and map water our bodies based on spectral reflectance inside the inexperienced and close to-infrared bands. Major findings found out a significant expansion of the Abaya-Chamo Lake gadget, from ~70,000 ha in 2015 to over one hundred,000 ha through 2017, accompanied through stabilization with minor fluctuations, indicating a catchment-driven hydrological reaction to heavy rainfall, as visible all through the El Niño period. Abiyata Lake, impacted via anthropogenic activities like water diversion, showed a marked decline in floor location from ~15,000 ha in 2015 to ~10,500 ha via 2020, with recuperation to ~sixteen,000 ha by way of 2025. Backscatter evaluation found out that Zeway, Shala, and Langano lakes skilled varied water surface adjustments, with Zeway displaying a decline from about -21 dB in 2015 to -22.5 dB by means of 2017, whilst Shala and Langano had strong backscatter trends submit-2017. Hawassa, with its closed drainage system, showed minimal fluctuations, stabilizing round eight,350 ha by way of 2015 and slightly increasing to eight,450 ha by way of 2025. The take a look at discovered vast modifications inside the floor water dynamics of Rift Valley lakes from 2015 to 2025, with Abaya-Chamo expanding and stabilizing, Abiyata reducing and recovering, and Zeway, Shala, Langano, and Hawassa displaying various trends in surface area and backscatter balance.

Keywords: Otsu Threshold, Sentinel 1A, Sentinel 2, Surface Water, Rift Valley

CHAPTER ONE

1. INTRODUCTION

1.1.Background of the study

Monitoring floor water has turn out to be more and more essential global because of its important function in selling environmental sustainability (Lueng et al., 2020). This tracking is critical across numerous fields, highlighting its importance inside the face of speedy global exchange (Becker-Reshef et al., 2010). Surface water bodies which includes lakes, rivers, and wetlands are essential to ecological stability, contributing considerably to environmental balance (Jolly et al., 2008). These ecosystems aid diverse plant and animal existence, making everyday monitoring important for preserving biodiversity (Irfan, 2019). By continually monitoring those water our bodies, we will examine atmosphere fitness and locate threats to biodiversity early on (Dudgeon et al., 2006). Additionally, ongoing tracking enables the spark off identification of pollutants, which is key to beginning timely measures for keeping water first-rate and protective the health of aquatic ecosystems and their species (Döll et al., 2018).

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In the context of weather change, surface water monitoring performs a pivotal role in knowledge and addressing its influences (Green et al., 2011). By tracking changes in precipitation styles, evaporation costs, and water availability, it gives precious insights into key indicators of climate exchange (Rodell et al., 2018). This facts is essential for climate scientists and policymakers to increase effective strategies to mitigate the consequences of worldwide warming (Levin et al., 2011). Moreover, floor water monitoring enhances the ability to forecast intense climate activities, along with floods and droughts, which might be projected to become more common and severe due to weather change (Famiglietti, 2004). Accurate monitoring is also critical for effective water resource management, that is vital for sustainable development (Sheffield et al., 2018). It lets in for the best quantification of available water resources, aiding inside the planning and allocation of water for sectors like agriculture, enterprise, and domestic use (Vörösmarty et al., 2010). For transboundary water bodies, tracking information helps cooperative control and war decision, a important issue in a international wherein water shortage is an increasing number of a source of geopolitical tension (Wolf et al., 2003).

In Ethiopia, where water sources are inconsistently distributed and difficulty to tremendous seasonal version, floor water monitoring is mainly crucial for maintaining water availability throughout dry durations and ensuring equitable access for agriculture and rural communities. The Rift Valley lakes are enormously prone to each the affects of weather change and human activities, such as agricultural expansion and urbanization. Monitoring these lakes can provide early caution signs and symptoms of water scarcity or degradation, assisting government to implement adaptive techniques.

The implications of surface water monitoring extend directly to human health and well-being. Regular monitoring helps in identifying potential sources of water-borne diseases and implementing preventive measures, which is crucial for public health, especially in developing regions (Prüss-Ustün et al., 2014). Furthermore, monitoring irrigation water sources is vital for agricultural productivity and, by extension, global food security (Hanjra & Qureshi, 2010). In Ethiopia, where agriculture is the backbone of the economy, surface water availability is essential for maintaining food security and livelihoods. The Rift Valley lakes provide a critical water source for irrigation in the surrounding agricultural areas, which produce staple crops such as maize, wheat, and vegetables (Tesfaye et al., 2019).

From an financial angle, floor water monitoring has massive implications. Many industries and agricultural practices rely closely on water resources, making monitoring critical for sustainable use and planning for capability shortages (WWAP, 2019). Additionally, monitoring information contributes to the correct valuation of ecosystem services furnished by water our bodies, that's vital for conservation efforts and policy-making in an technology wherein the financial fee of natural assets is more and more diagnosed (Costanza et al., 2014). In Ethiopia, the financial importance of the Rift Valley lakes is profound. The lakes assist artisanal and industrial fishing industries, offer opportunities for eco-tourism, and make a contribution to the livelihoods of neighborhood groups via direct and oblique employment. For example, Lake Ziway is famous for its fishing sports activities, with close by populations relying on it for meals security and income era (Liyew et al., 2015).

Remote sensing technology has converted water frame monitoring, bringing effective new abilities to look at and observe ground water changes globally (Huang et al., 2018). The Sentinel-1 and Sentinel-2 satellites, superior with the aid of manner of the European Space Agency underneath the Copernicus software, are key assets on this region (Lenco et al., 2019). These satellites offer consistent, immoderate-decision, multi-temporal imagery, permitting researchers and environmental managers to discover and track modifications in water our bodies with terrific accuracy and performance (Huang et al., 2018). Remote sensing for water monitoring offers numerous benefits (Chen et al., 2022). Sentinel-2's optical sensors, which seize multispectral facts, permit the clean differentiation of water from one-of-a-kind land cowl types through analyzing their particular spectral signatures (Pahlevan et al., 2022). This capability is treasured for mapping water body amount and gazing boundary shifts over the years (Pekel et al., 2016). With a high spatial choice (10-20 meters) and a fast revisit cycle (5 days with both satellites), Sentinel-2 is especially effective for monitoring smaller water our our bodies and detecting seasonal or event-driven adjustments in water quantity (Du et al., 2016).

Complementing optical sensors, Synthetic Aperture Radar (SAR) era, as employed by means of using Sentinel 1, gives specific benefits for water frame monitoring (Ahmad et al., 2019). SAR can penetrate clouds and perform in day or night situations, overcoming the limitations of optical sensors in areas frequently blanketed through clouds or at some stage in midnight (Bioresita et al., 2018). This all-weather functionality ensures non-stop tracking, that is essential for tracking flooding events or seasonal adjustments in water bodies. Moreover, SAR's sensitivity to floor roughness makes it especially powerful in distinguishing water surfaces, which appear smooth and darkish in SAR photographs, from surrounding land areas (Clement et al., 2018). The synergistic use of optical and SAR facts from Sentinel 1 and Sentinel 2 presents a more complete and accurate assessment of water our our bodies than both sensor on my own. This multi-sensor technique permits for the exploitation of complementary statistics, improving the accuracy of water body delineation and permitting the detection of submerged flora or shallow waters that is probably hard to find out with a unmarried sensor type (Markert et al., 2020).

While satellite tv for pc technology offer advanced talents for information series, the vast volume and complexity of the records pose substantial challenges for conventional processing techniques (Zhang et al., 2019). This is wherein the Google Earth Engine (GEE) platform proves precious, reworking how researchers and practitioners examine Earth remark information (Lee et al., 2019). GEE is a cloud-based platform that gives a scalable and on hand answer for processing and studying large geospatial datasets, which includes the whole information of Sentinel-1 and Sentinel-2 imagery (Gorelick et al., 2017).

There are severa advantages to the use of GEE for water body monitoring. First, its cloud computing infrastructure gets rid of the need for neighborhood excessive-overall performance computing resources, making advanced geospatial evaluation talents extra reachable, specially for researchers in developing international locations or smaller establishments that may lack such sources (Schmitt et al., 2019; Kumar and Mutanga, 2018). Additionally, GEE’s pre-processed records catalog, which includes atmospherically corrected Sentinel-2 imagery and terrain-corrected Sentinel-1 facts, considerably reduces the preprocessing workload, enabling users to cognizance more on analysis than statistics preparation (Traganos et al., 2018).

Moreover, GEE's ability to successfully manner time collection statistics from satellite tv for pc imagery permits for the evaluation of historic developments and long-term adjustments in water our bodies. This temporal analysis is important for knowledge the results of weather exchange, land use changes, and human activities on water assets (Pérez Hoyos et al., 2019). The platform also gives an in depth library of pre-constructed functions and algorithms for water detection and mapping, in addition to help for growing custom algorithms, equipping researchers with powerful gear to enforce state-of-the-art water frame tracking methodologies at scale (Donchyts et al., 2016).

1.2.Statement of the problem

Recent advancements within the mapping and monitoring of floor water dynamics on a international scale have been pushed by way of good sized enhancements in far flung sensing technologies and information processing talents (Karpatne et al., 2016). One groundbreaking examine by means of Pekel et al. (2016) used over three million Landsat satellite pictures to create a 30-meter resolution map of global floor water occurrence, modifications, and seasonality, highlighting widespread shifts in everlasting floor water our bodies over the last three decades. The improvement of gear just like the Global Surface Water Explorer, created via the European Commission's Joint Research Centre, has further superior our capacity to visualize and analyze floor water dynamics globally (European Commission, 2021). Additionally, near actual-time monitoring systems which include the Global Flood Monitoring System (GFMS) have emerge as crucial for catastrophe control and early warning, especially in flood-prone areas (Wu et al., 2014).

Mapping and tracking floor water dynamics in Africa offers each particular demanding situations and opportunities. For example, Tarpanelli et al. (2017) utilized satellite tv for pc altimetry data to track water degrees in African rivers and lakes, even as Mahmood and Jia (2019) examined long-term adjustments within the floor area of Lake Chad the use of multi-sensor satellite records. In the Nile Basin, Eldardiry and Hossain (2019) showcased the potential of far-off sensing for dealing with transboundary water assets. The introduction of Google Earth Engine has notably boosted massive-scale floor water tracking in Africa, with Khandelwal et al. (2017) demonstrating the improvement of an automatic algorithm for mapping water dynamics throughout South Africa. Despite those advances, demanding situations persist, especially in acquiring high-resolution, consistent long-time period records and translating far flung sensing records into actionable insights for local water aid managers. To deal with these troubles, initiatives like Digital Earth Africa (2021) purpose to offer analysis-equipped satellite tv for pc statistics and decision-geared up merchandise for the entire continent.

The Rift Valley Lakes Basin, a vital ecological and financial aid in East Africa, faces full-size challenges associated with the dynamics of its floor water our bodies. These challenges stem from a complex interaction of climate alternate impacts, human activities, and herbal variability, which together affect the volume, distribution, and exceptional of floor water sources inside the place (Olaka et al., 2019). Despite the vital significance of those water bodies for biodiversity, neighborhood livelihoods, and nearby weather regulation, there's a pressing want for extra complete, correct, and timely tracking of their dynamics.

Traditional methods of water frame tracking, together with in-situ measurements and aerial surveys, have verified insufficient in shooting the spatial and temporal variability of surface water dynamics throughout the tremendous and frequently inaccessible terrain of the Rift Valley Lakes Basin (Ouma et al., 2018). These techniques are confined with the aid of their high value, low frequency, and limited spatial insurance, making it tough to attain a holistic know-how of the basin's water resources. Furthermore, the speedy modifications going on on this place, pushed through each climatic elements and anthropogenic activities, necessitate extra common and giant tracking than traditional methods can offer (Alemu et al., 2017).

While satellite-based remote sensing has emerged as a promising solution for massive-scale water body tracking, vast challenges stay in its utility to the Rift Valley Lakes Basin. The complicated topography of the place, characterised with the aid of steep escarpments and varied land cowl, poses problems for accurate water body delineation the usage of optical satellite tv for pc imagery alone (Yalew et al., 2016). Additionally, the common cloud cover in parts of the basin limits the effectiveness of optical sensors, creating gaps in temporal insurance that avert the detection of short-time period adjustments in water volume (Wulder et al., 2016).

The integration of multiple satellite tv for pc facts assets, particularly the mixture of optical (Sentinel-2) and radar (Sentinel-1) imagery, offers capability solutions to those demanding situations. However, there is a extensive information gap in developing sturdy methodologies which could successfully synergize those various facts types for comprehensive water frame mapping and tracking within the specific context of the Rift Valley Lakes Basin (Markert et al., 2020). The varying characteristics of the lakes and wetlands in the basin, ranging from shallow, turbid water bodies to deep, clean lakes, similarly complicate the development of a unified method to water detection and tracking (Tebbs et al., 2019).

Moreover, while the Google Earth Engine (GEE) platform gives effective skills for processing and studying large-scale satellite statistics, there may be a lack of standardized, locally optimized algorithms for water body mapping and exchange detection precise to the Rift Valley Lakes Basin (Gorelick et al., 2017). The improvement of such algorithms calls for addressing demanding situations related to the seasonal variability of water bodies, the presence of aquatic flowers, and the difference among everlasting and temporary water surfaces, all of which might be particularly relevant in this ecologically various vicinity (Pekel et al., 2016).

Another critical know-how hole lies in information the long-term tendencies and patterns of surface water dynamics in the Rift Valley Lakes Basin. While numerous studies have tested man or woman lakes or unique periods, there is a lack of complete, basin-wide analyses that leverage the full temporal intensity of to be had satellite tv for pc statistics to expose lengthy-term adjustments and their drivers (Awange et al., 2019). Such analyses are essential for distinguishing among herbal variability and anthropogenic influences, and for informing sustainable water aid control techniques. Lastly, whilst remote sensing technologies offer powerful equipment for water frame monitoring, there may be a gap in translating these technical capabilities into actionable facts for neighborhood water useful resource managers and policymakers. Developing frameworks for effectively speaking far off sensing-derived insights and integrating them into choice-making processes remains a vital venture (Buytaert et al., 2014).

A great know-how hole exists in the integration of Sentinel-1 radar and Sentinel-2 optical data for accurate water body mapping and tracking in the Rift Valley Lakes Basin. While combining these records kinds offers capability to overcome boundaries posed via cloud cover and ranging land cowl, sturdy methodologies for successfully synergizing radar and optical imagery in this unique area remain underdeveloped. The various characteristics of the lakes and wetlands, ranging from shallow, turbid bodies to deep, clear lakes, complicate the advent of a unified approach. Addressing those challenges is crucial for enhancing the accuracy and reliability of satellite tv for pc-based totally water monitoring inside the basin.

1.3. Objective of the study

1.3.1. General objective

The General objective of this study is to analyze the dynamics of surface water bodies in the Rift Valley Lakes Basin using Google Earth Engine by integrating Sentinel-1 radar and Sentinel-2 optical imagery.

1.3.2. Specific Objectives

- To delineate and classify surface water bodies in the Rift Valley Lakes Basin using Sentinel-1 SAR and Sentinel-2 optical imagery.
- To assess temporal changes in surface water extent over time in the Rift Valley Lakes Basin.

- To validate the classification of water bodies generated from Sentinel-1 SAR and Sentinel-2 imagery against GPS points

1.3.3. Research questions

- How can Sentinel-1 SAR and Sentinel-2 optical imagery be used to effectively delineate and classify surface water bodies in the Rift Valley Lakes Basin?
- What are the temporal changes in surface water extent in the Rift Valley Lakes Basin over the study period?
- How accurate is the classification of water bodies from Sentinel-1 SAR and Sentinel-2 imagery when validated against GPS points?

1.4.Significance of the study

The significance of this examines lies in its ability to boost the know-how and control of surface water bodies in the Rift Valley Lakes Basin via the integration of contemporary far off sensing technology. By growing a sturdy technique that mixes Sentinel-1 radar and Sentinel-2 optical imagery, the studies address the demanding situations posed through frequent cloud cowl, diverse topographic capabilities, and varied water body characteristics inside the place. This enhance the accuracy of water body mapping and monitoring, imparting more dependable information for detecting seasonal and long-time period changes in water quantity.

Additionally, the examine contributes to filling a essential information hole via offering a comprehensive approach to expertise the spatiotemporal dynamics of surface water our bodies, which are important for addressing problems associated with water scarcity, surroundings management, and climate change affects. Furthermore, this technique, utilising Sentinel-1 and Sentinel-2 imagery blended with Google Earth Engine for analysis, can be replicated in similar basins globally. Many regions around the sector face demanding situations together with cloud cowl, limited accessibility, and records scarcity in tracking floor water dynamics. The method developed on this look at should function a model for water body monitoring in ecologically touchy or statistics-scarce regions, inclusive of semi-arid regions, tropical basins, and faraway places. By applying the equal satellite tv for pc era and analytical framework, comparable research could be conducted in other regions, enhancing international water aid control, helping environmental conservation efforts, and contributing to greater powerful responses to weather trade impacts. Ultimately, the examine complements the applicability of far off sensing technologies in dealing with water assets, growing a scalable version for sustainable water tracking worldwide.

1.5.Scope of the study

The scope of this examine makes a specialty of mapping and monitoring the dynamics of floor water bodies in the Rift Valley Lakes Basin, using the combination of Sentinel-1 radar and Sentinel-2 optical imagery on the Google Earth Engine platform. The examine covers each spatial and temporal aspects of water bodies, analyzing adjustments in water volume over time and across specific seasons. It analyzes multi-temporal satellite tv for pc statistics to stumble on brief-term fluctuations, seasonal patterns, and lengthy-term tendencies in water bodies, inclusive of each permanent and transient water surfaces.

The temporal scope of the study spans a historical length of 2015 to the existing, utilizing the available archives of Sentinel-1 and Sentinel-2 imagery. This time body allows for the evaluation of both latest and beyond adjustments in surface water dynamics, offering insights into seasonal versions as well as longer-time period traits in water quantity. By utilising multiple years of satellite information, the study targets to discover styles of change and check the impacts of environmental and climatic elements on floor water bodies inside the Rift Valley Lakes Basin.

Geographically, the observe is limited to the Rift Valley Lakes Basin in Ethiopia, a place characterized by using complicated topography, numerous land cover, and ranging water body characteristics, which gift challenges for correct water detection. The study broaden and follow a technique for combining Sentinel-1 and Sentinel-2 facts, investigating the impact of things including topography, land cowl versions, and environmental conditions on water body mapping accuracy.

1.6.Operational terms of definition

Surface Water Bodies: Refers to evidently going on our bodies of water on the Earth's floor, consisting of lakes, rivers, wetlands, and reservoirs, which might be key to the have a look at of water dynamics. These bodies of water are vital for surroundings stability and offer various ecological, economic, and societal advantages (Jolly et al., 2008; Döll et al., 2018).

Google Earth Engine (GEE): A cloud-based platform designed for processing, analyzing, and visualizing large geospatial datasets, including satellite imagery. GEE provides access to extensive remote sensing data archives, and its computational power allows researchers to perform advanced analyses on global-scale datasets (Gorelick et al., 2017; Lee et al., 2019).

Water Extent: Refers to the spatial area covered by surface water at any given time, including both permanent and temporary water bodies. This is a key measurement in water body mapping and monitoring (Du et al., 2016; Zhang et al., 2019).

Temporal Changes: The variations in the extent and characteristics of water bodies over time, including seasonal fluctuations and long-term trends. Temporal analysis allows researchers to identify patterns related to climate, land use, and hydrological cycles (Rodell et al., 2018; Sheffield et al., 2018).

Spatiotemporal Dynamics: The combined study of spatial (geographical distribution) and temporal (changes over time) variations in water bodies. Understanding both dimensions is crucial for comprehensive water management and ecological conservation (Huang et al., 2018; Dudgeon et al., 2006).

Permanent Water Bodies: Water bodies that remain relatively stable in size and shape year-round, such as large lakes and rivers. These bodies of water are critical for biodiversity and often serve as reliable sources of water for ecosystems and human use (Irfan, 2019; Jolly et al., 2008).

Temporary Water Bodies: Water bodies that appear intermittently, depending on seasonal precipitation or environmental conditions. Examples include seasonal ponds, floodwaters, and ephemeral lakes, which are sensitive to climate and land use changes (Green et al., 2011; Pekel et al., 2016).

1.7.Organization of the thesis

The thesis became prepared into 5 chapters. Chapter 1 supplied an creation, outlining the background and context of the observe, including the importance of surface water bodies in the Rift Valley Lakes Basin, Ethiopia. It also described the hassle, stated the research objectives, and defined the importance of the look at. Chapter 2 provided a literature review, covering existing techniques for monitoring floor water bodies, preceding research the usage of remote sensing information like Sentinel-1 and Sentinel-2, and the position of Google Earth Engine (GEE) in such research. Chapter 3 defined the method, including a detailed assessment of the observe area, records sources (Sentinel-1 and Sentinel-2), the use of GEE for water frame detection, and the strategies for studying temporal changes in floor water. Chapter 4 supplied the effects, which include maps and graphs showing the dynamics of surface water our bodies, a assessment of Sentinel-1 and Sentinel-2 overall performance, and a discussion of the temporal and spatial modifications found. Chapter five concluded the thesis, summarizing the important thing findings.

CHAPTER TWO

2. LITERATURE REVIEW

2.1.Theoretical literature

2.1.1. Remote Sensing in Hydrological Studies

Since it presents a extensive-ranging, fairly priced technique of amassing records over numerous spatial extents and temporal scales, far flung sensing has emerged as a important instrument for floor water frame monitoring. Optical far off sensing structures such as Landsat, MODIS, and more currently Sentinel-2, which give multispectral imagery perfect for recognizing water based on its reflectance traits, have historically been used for water frame detection (Yang et al., 2017). Water our bodies can be distinguished from the encompassing land cowl because they usually have poor reflectance within the close to-infrared (NIR) and shortwave infrared (SWIR) bands. Particularly in areas in which cloud cover makes optical imagery hard, radar-based totally remote sensing—like that supplied via Sentinel-1—has emerged as a useful alternative (Wang et al., 2020). Radar sensors are extraordinarily dependable for tracking water our bodies in all-weather circumstances in view that, in comparison to optical structures, they can bypass via cloud cover and are unaffected via sun illumination. By the usage of both spectral reflectance and surface roughness features, the combination of those technology gives a greater thorough technique of detecting water our bodies, improving the precision and reliability of the consequences.

Hydrological and remote sensing concepts, which highlight the spectrum components of water and land surface interactions, form the theoretical underpinnings of satellite-based totally water monitoring. Because in their absorption and mirrored image characteristics, water our bodies have distinct spectral fingerprints that lead them to detectable with the aid of far off sensing (Schneider et al., 2017). Indexes together with the Normalized Difference Water Index (NDWI) or the Modified Normalized Difference Water Index (MNDWI), which emphasize water capabilities the usage of reflectance inside the inexperienced and NIR bands, are generally utilized in optical far flung sensing frameworks. However, if you want to differentiate water bodies from the surrounding topography, radar-primarily based remote sensing frameworks use the backscattering traits of water surfaces, which have low radar reflectivity because of their smoothness (Martinis et al., 2015). In order to capitalize at the blessings of both technologies and triumph over drawbacks like cloud cowl interference and surface roughness fluctuation that impact water body detection, hybrid frameworks that integrate optical and radar statistics are being created greater often.

Although the fundamentals of optical and radar remote sensing for hydrological research are very different, they work well together. The reflection of sunlight from the Earth's surface in different spectral bands is measured via optical remote sensing. Water may be easily distinguished from land surfaces because it absorbs the majority of light in the NIR and SWIR areas, making it look dark in optical pictures (Ouma & Tateishi, 2006). For instance, Sentinel-2 provides extensive information for mapping water bodies, particularly shallow and tiny water surfaces, by capturing high-resolution optical pictures across numerous spectral bands.

In comparison, radar far off sensing uses the microwave area of the electromagnetic spectrum to measure the quantity of power dispersed returned to the sensor after sending microwave power pulses closer to the Earth's surface. Since most water surfaces are clean, radar signals are contemplated faraway from the sensor with the aid of them, producing low backscatter values that make it simple to perceive water functions (Baghdadi et al., 2012). Continuous monitoring of water bodies depends on Sentinel-1's Synthetic Aperture Radar (SAR) talents, which deliver reliable, high-decision information even in the presence of clouds or darkness. Through the mixture of radar sensors' all-climate, all-time abilities and optical sensors' spectrum sensitivity, researchers may additionally gather a more accurate and thorough depiction of water our bodies in any scenario (Schumann et al., 2012).

2.1.2. Water Body Dynamics and Hydrological Change

Seasonality, permanence, and variability are some of the temporal and spatial elements that influence the dynamics of water bodies. Predictable variations in water extent brought on by recurring climatic events like rainfall and dry seasons are referred to as seasonality. Water bodies may greatly expand and contract in areas with distinct wet and dry phases, which might affect their ecological and hydrological activities (Lehner & Döll, 2004). Water bodies are categorized as either permanent (always present) or temporary (intermittent or seasonal) based on their permanence. Although they can be difficult to identify and track because of their dynamic character, temporary water bodies—like seasonal wetlands or ponds—are essential for maintaining hydrological balance and biodiversity (Tiner, 2003). Variability includes both short-term variations in water extent brought on by weather patterns and long-term shifts brought on by alterations in the environment or human activity. Effective management of water resources requires an understanding of these dynamics, particularly in areas with extremely unpredictable water availability.

Particularly in areas vulnerable to extremes like droughts and floods, weather variability extensively influences the hydrological functions of water bodies and Wetlands. The extent and volume of water our bodies are at once impacted by means of changes in temperature, evapotranspiration costs, and precipitation patterns, making them touchy signs of climate alternate (Seneviratne et al., 2012). Water frame dynamics may be appreciably impacted by even little changes in climate in dry and semi-arid regions, where water is already in brief deliver. For example, extended droughts can cause lakes and wetlands to shrink or dry up completely, as is the case with Lake Chad, whereas floods brought on by heavier rainfall can cause water bodies to momentarily expand beyond their natural borders (Coe & Foley, 2001). The need for precise monitoring and predictive modeling of water body dynamics under changing climatic conditions is highlighted by the fact that such hydrological responses to climate variability frequently disturb ecosystems, human water supplies, and local economies.

The dynamics of floor water bodies are drastically impacted through human hobby, in particular in arid and semi-arid areas where water is a crucial and frequently disputed aid. Among the principle human interventions that change the herbal behavior of water bodies are dams, irrigation initiatives, and water abstraction for industrial and agricultural makes use of (Grafton et al., 2018). As proven through the shrinking Aral Sea, huge water extraction from rivers and lakes for agriculture, as an example, can result in decreased influx, losing water stages or even the whole extinction of water bodies (Micklin, 2007).

2.1.3. Data Integration in Remote Sensing

In remote sensing, data integration is the process of merging information from several sensors to improve environmental monitoring's precision, comprehensiveness, and dependability. Theories of data fusion, which seek to combine complementary information from several sensors into a single, cohesive dataset, serve as the foundation for the integration of multi-sensor satellite data, including radar and optical images (Pohl & Van Genderen, 2017). Pixel-level, feature-level, and decision-level fusion are the three main categories into which multi-sensor integration models fall. Improved spatial and spectral resolution is made possible by pixel-level fusion, which merges raw data from several sensors to produce a single image. While decision-level fusion aggregates the results of multiple classifiers to reach a final conclusion, feature-level fusion separates pertinent characteristics from each sensor dataset before merging. In environmental monitoring, these integration techniques are essential because merging optical and radar data helps get over the drawbacks of each sensor alone, like cloud interference in optical data or the smoothness of water surfaces in radar images (Schmitt & Zhu, 2016). In order to guarantee more precise and thorough findings, these models are being used more and more in hydrology, disaster management, and land-use mapping.

There are many benefits to combining radar (like Sentinel-1) and optical (like Sentinel-2) data, especially when it comes to improving the detection and tracking of surface water bodies and other environmental factors. The ability to lessen the restrictions that come with each type of sensor is the main benefit. Despite being very good at recording comprehensive spectral information, optical sensors are constrained by atmospheric conditions and cloud cover, especially in humid and tropical areas (Wang et al., 2020). In contrast, radar uses the microwave spectrum, which can pass through clouds and deliver accurate data in any weather or light situation (Baghdadi et al., 2012). Because of this, radar data is perfect for tracking water bodies in all kinds of weather, including when it's raining a lot or when there is a lot of cloud cover. Researchers may combine the spectral sensitivity of optical vision with the all-weather capabilities of radar by merging optical and radar data, which resulted in more thorough and reliable environmental monitoring.

Nevertheless, there are a number of difficulties in combining these two kinds of data. First, the fusion process is complicated by the disparities between radar and optical sensors in terms of spatial resolution, data formats, and acquisition techniques (Schmitt & Brisco, 2013). Pixel-level fusion is made more difficult by the fact that radar data is usually obtained in several polarization modes (such as VV and VH) and frequently has a lower spatial resolution than optical data. Preprocessing methods like speckle filtering are required because radar images are also susceptible to speckle noise, a granular interference pattern that lowers image clarity. When monitoring quickly changing settings, such as flood zones or seasonal wetlands, temporal misalignment presents another difficulty because radar and optical data may not always be recorded concurrently, resulting in disparities in the datasets (Thomas et al., 2015). Despite these obstacles, improvements in data processing and fusion techniques are enhancing the integration of optical and radar imaging, enabling multi-sensor data products that are more accurate and dependable.

Remote sensing has been transformed by cloud computing platforms, especially Google Earth Engine (GEE), which offer strong capabilities for processing and evaluating massive amounts of satellite data. GEE is a perfect tool for integrating multi-sensor datasets since it provides a cloud-based platform that allows researchers to access, process, and analyze petabytes of satellite data from sensors like Sentinel-1 and Sentinel-2 (Gorelick et al., 2017). One of GEE's primary advantages is its capacity to manage huge, intricate datasets without the need for costly gear or substantial computer power, which enables researchers to carry out multi-temporal analyses over wide geographic areas with reasonable ease.

Users no longer need to carry out laborious data preparation procedures like atmospheric correction or geometric rectification because Google Earth Engine offers pre-processed radar and optical data from a variety of sensors (Mutanga & Kumar, 2019). In order to integrate radar and optical data for water body mapping, land use/land cover monitoring, and disaster management, the platform also includes sophisticated algorithms for data fusion, categorization, and change detection. Furthermore, GEE enables users to automate and enhance the precision of environmental monitoring by implementing machine learning models, such as Random Forest and Support Vector Machine classifiers.

GEE is not without its limits, though. To fully utilize its potential, users still need to have a solid grasp of remote sensing principles and coding knowledge, especially in Python or JavaScript, even though it makes accessing satellite data easier. Additionally, real-time monitoring efforts may be hampered by the platform's reliance on internet connection and the sporadic delays in the availability of new satellite imagery (Amani et al., 2020). Notwithstanding these obstacles, cloud-based platforms such as GEE are becoming more and more popular, providing fresh chances for extensive environmental monitoring and data integration in areas with limited resources.

2.1.4. Comparison of Sentinel-1 and Sentinel-2 capabilities with other satellite

Remote sensing has become an indispensable tool for monitoring and mapping surface water bodies, especially in regions with complex topography and changing environmental conditions, such as the Rift Valley Lakes Basin. In recent years, a variety of satellite systems, including Sentinel-1, Sentinel-2, and Landsat, have provided critical data for mapping water bodies, tracking their dynamics, and supporting effective water resource management. Each of these systems offers unique strengths and limitations, and understanding their differences is crucial for selecting the most appropriate tools for monitoring water bodies in different settings.

Sentinel-1 vs. Landsat

Sentinel-1, part of the European Space Agency's (ESA) Copernicus program, is equipped with Synthetic Aperture Radar (SAR) sensors. One of the major advantages of SAR data is its ability to acquire imagery regardless of weather conditions or time of day. This is particularly useful in regions like the Rift Valley Lakes Basin, where cloud cover is frequent. Unlike optical sensors, SAR can penetrate clouds, allowing for continuous monitoring even under unfavorable conditions. Additionally, SAR's sensitivity to surface roughness makes it highly effective for distinguishing water surfaces, which typically appear smooth and dark in radar images, from surrounding land surfaces (Giustarini et al., 2019). The radar-based data from Sentinel-1 can be used to detect dynamic changes in water extent, such as during flood events or seasonal fluctuations, making it an ideal tool for monitoring temporary or intermittent water bodies that might otherwise be missed using optical sensors.

In contrast, Landsat, a joint NASA/USGS mission, provides multispectral optical imagery with a spatial resolution of 30 meters, which is useful for land cover classification and vegetation monitoring. However, optical imagery from Landsat is sensitive to weather conditions and can be obstructed by cloud cover. The 16-day revisit cycle of Landsat, while sufficient for some applications, is relatively slow compared to Sentinel-2's 5-day revisit period. Despite these limitations, Landsat's long data record, which spans over four decades since the 1970s, is an invaluable resource for historical trend analysis and long-term monitoring of surface water dynamics (Loveland et al., 2012). For example, Landsat has been widely used for studying large-scale water body changes, especially in relation to climate change and land-use transformations. Its consistent archive allows for the tracking of water body dynamics over long periods, which is essential for detecting slow trends in water availability and quality.

Sentinel-2 vs. Landsat

While both Sentinel-2 and Landsat provide multispectral optical imagery, Sentinel-2 offers several advantages over Landsat in terms of spatial resolution and revisit frequency. Sentinel-2 imagery has a higher spatial resolution: 10 meters for visible and near-infrared bands, 20 meters for red-edge and shortwave infrared bands, and 60 meters for atmospheric bands (ESA, 2015). This higher resolution makes Sentinel-2 particularly effective for detecting smaller water bodies, such as ponds, small lakes, and seasonal water surfaces, that might not be visible in Landsat's coarser 30-meter imagery. Furthermore, Sentinel-2's 5-day revisit cycle (when both Sentinel-2A and Sentinel-2B satellites are used together) is an advantage for detecting seasonal changes in water extent and monitoring dynamic water body fluctuations in near-real time. The ability to observe water bodies more frequently allows for more accurate detection of short-term changes, such as those caused by precipitation events or irrigation activities (Clerici et al., 2017).

Landsat, while also valuable for mapping surface water, has a longer 16-day revisit period and lower spatial resolution (30 meters) compared to Sentinel-2, making it less ideal for detecting smaller water bodies or tracking short-term fluctuations (USGS, 2020). However, the long-term historical archive of Landsat imagery provides an important advantage for studying long-term trends in water bodies, which is useful for understanding the impacts of climate change, human activities, and land-use changes over several decades (Zhang et al., 2018). Additionally, Landsat has an extensive historical record that allows for consistent monitoring of surface water changes across vast spatial scales, which is critical for large-scale environmental assessments.

Synergy of Sentinel-1 and Sentinel-2

The combined use of Sentinel-1 and Sentinel-2 data offers a powerful synergy for monitoring surface water dynamics, providing complementary strengths that can overcome the limitations of each individual system. Sentinel-1's SAR data is ideal for continuous, all-weather monitoring, especially for detecting surface water during periods of cloud cover or at night. This capability is crucial for tracking temporary water bodies, flooding events, or seasonal fluctuations that may not be observable with optical data alone. On the other hand, Sentinel-2's optical data provides high-resolution imagery that can effectively capture detailed changes in water body characteristics, such as the identification of shallow or seasonal water bodies. Sentinel-2's ability to differentiate between water and other land cover types based on unique spectral signatures, particularly in the visible and near-infrared bands, enhances the precision of water body delineation (Pekel et al., 2016). The higher spatial resolution of Sentinel-2 allows for more detailed mapping of water bodies, which is particularly useful in regions with intricate topographies or smaller water bodies.

By combining both SAR and optical imagery, researchers can take advantage of the strengths of each system to create a more comprehensive and accurate assessment of surface water dynamics. The use of Sentinel-1's SAR data for continuous monitoring and Sentinel-2's high-resolution optical data for precise mapping ensures that the full spectrum of water body changes can be detected, from short-term floods to long-term trends in water availability. This multi-sensor approach can lead to more accurate delineations of water bodies and improve the detection of submerged vegetation, shallow water areas, or changes in water extent that may be challenging to identify using a single sensor type (Markert et al., 2020).

2.2. Conceptual literature

2.2.1. Surface Water Bodies and Environmental Significance

Surface water bodies refer to any water that gathers above earth, encompassing numerous varieties such as lakes, marshes, and reservoirs. Because they store freshwater and sustain aquatic ecosystems, lakes—large, man-made or natural bodies of water encircled by land—are essential to the hydrological cycle (Wetzel, 2001). Conversely, wetlands are places where water percolates the ground either year-round or periodically, creating distinctive ecosystems that are abundant in biodiversity (Mitsch & Gosselink, 2015). Reservoirs are artificial lakes formed by damming rivers, mainly for agriculture, flood control, water storage, and the production of hydroelectric power (Fearnside, 2005). Since each of these bodies of water serves vital hydrological, ecological, and socioeconomic purposes, it is imperative that they be monitored, particularly in areas where environmental change is occurring quickly.

In order to sustain socioeconomic activity and ecological balance, surface water bodies are essential. In terms of ecology, they support nutrient cycling, control local microclimates, and offer habitats for a variety of species (Lehner & Döll, 2004). For example, wetlands are frequently called the "kidneys of the earth" because of their function in removing contaminants from water and controlling flooding by absorbing excess precipitation (Zedler & Kercher, 2005). In addition to providing water for drinking, industry, and agriculture, lakes and reservoirs sustain fisheries, providing local communities with food security and a means of subsistence (Postel & Richter, 2003). Additionally, surface water bodies are essential for leisure pursuits, cultural heritage, and aesthetic qualities, all of which support the socioeconomic fabric of the local communities.

Since these water bodies support industries like tourism, transportation, and the production of renewable energy, their socioeconomic significance goes beyond their immediate use by humans (McCartney & Smakhtin, 2010). Surface water bodies should be protected and managed as a top priority in environmental governance since their loss or degradation as a result of pollution, climate change, or human activity can have significant effects on local economies, biodiversity, and water availability.

Understanding the dynamics of surface water bodies and how environmental changes affect ecosystems requires the use of conceptual models. The "hydrological balance" model, which takes into account the inputs (precipitation, inflow) and outputs (evaporation, outflow) that affect the water extent in lakes, marshes, and reservoirs, is a popular model for characterizing changes in water bodies (Mason et al., 1994). This model aids in predicting the future dynamics of water bodies under various climate scenarios and evaluating the effects of climatic variability, such as variations in temperature or rainfall, on these bodies of water.

Another model that is commonly used to examine how natural processes and human activity affect water bodies is the "drivers-pressure-state-impact-response" (DPSIR) framework (Gregory et al., 2003). According to this model, forces (like water extraction and pollution) and causes (like population increase and land-use change) interact to influence the condition of water bodies (like eutrophication and declining water levels). The ensuing effects (such as diminished water quality and biodiversity loss) lead to societal reactions like conservation laws or advancements in water management technology. Designing sustainable solutions to reduce the deterioration of water bodies, protect ecosystems, and retain the services they offer requires an understanding of these models.

Changes in surface water bodies can have cascading effects on ecosystems. For example, the shrinkage of wetlands due to water diversion for agriculture can lead to habitat loss for migratory birds and aquatic species, while reduced water quality in lakes due to pollution can trigger algal blooms that harm fish populations (Paerl et al., 2014). Conceptual models that link hydrological changes to ecosystem responses provide a structured approach to assessing these impacts and developing strategies for adaptive management.

2.2.2. Sentinel-1 and Sentinel-2 in Water Monitoring

Because Sentinel-1, a Synthetic Aperture Radar (SAR) satellite deployed by the European Space Agency (ESA), can take pictures in any weather, cloud cover, or daylight, it has shown great efficacy in detecting aquatic bodies. By using the way radar waves interact with various surface materials, the C-band sensor of the radar sends out microwave signals that may pass through clouds and identify surface features (Torres et al., 2012). Because of their smoothness, which reflects radar signals away from the sensor, water surfaces typically appear black in radar images, producing a clear contrast between the surrounding land and the water bodies (Mason et al., 2011). According to Uddin et al. (2019), Sentinel-1 is therefore perfect for identifying and defining surface water, particularly in areas that frequently experience high levels of cloud cover or during the rainy season when optical sensors are less reliable.

Capturing data in different polarization modes (VV and VH) is one of Sentinel-1's main advantages. This improves the recognition of varied surface types, such as vegetation, water bodies, and urban areas (Martinis et al., 2015). Furthermore, it is appropriate for tracking seasonal variations, flooding incidents, and long-term hydrological trends because to its frequent return times (6 to 12 days), which enable continuous monitoring of water dynamics. However, because of elements that can impact the precision of water detection, such as surface roughness, wind-induced water surface fluctuations, and speckle noise, radar imaging needs to be carefully interpreted (Schlaffer et al., 2015).

ESA has created Sentinel-2, a high-resolution, multispectral optical satellite principally used for vegetation monitoring, water body detection, and mapping of land use and land cover. Its Multispectral Instrument (MSI) records data in 13 spectral bands ranging from the visible to the shortwave infrared, making it extremely ideal for discriminating between various surface features such as plant, soil, and water (Drusch et al., 2012). Even for tiny or dispersed lakes and wetlands, Sentinel-2's excellent spatial resolution (up to 10 meters for visible and near-infrared bands) makes it possible to map water bodies and their borders in great detail (Pahlevan et al., 2017).

Sentinel-2's optical data is very useful for spectral signature-based water body detection. While terrestrial surfaces reflect more light, making it possible to distinguish between land and water, water absorbs light strongly in the near-infrared (NIR) and shortwave-infrared (SWIR) bands, looking dark in these wavelengths (Du et al., 2016). Additionally, because the satellite's red-edge bands are sensitive to the amount of chlorophyll and suspended particles in water bodies, they can be used to monitor aquatic vegetation and water quality (Vanhellemont & Ruddick, 2015). Cloud cover, which can block the surface and prevent continuous monitoring, particularly in tropical and wet areas, limits Sentinel-2's capabilities.

A potent method for raising the precision and dependability of water body mapping and monitoring is the combination of Sentinel-1 radar and Sentinel-2 optical data. The conceptual framework for combining these data sources makes use of the complementing advantages of each sensor: Sentinel-2's high-resolution, multispectral optical images and Sentinel-1's all-weather, cloud-penetrating radar capabilities (Uddin et al., 2019). In order to create more thorough and accurate water body maps, data fusion techniques can be used to integrate the radar and optical datasets at the pixel, feature, or decision levels.

By combining raw radar and optical data into a single dataset, pixel-level fusion improves spectral and spatial information while getting beyond obstacles like cloud cover (Schmitt & Zhu, 2016). To recognize water bodies more precisely, feature-level fusion combines radar backscatter data with optical data to extract important properties like water indices (e.g., Normalized Difference Water Index, NDWI) (Du et al., 2016). In decision-level fusion, the outputs of distinct radar and optical classifiers are processed using machine learning or classification algorithms, including Random Forest or Support Vector Machines, and the findings are then combined into a final water body map (Twele et al., 2016).

Enhancing temporal coverage through the integration of Sentinel-1 and Sentinel-2 data also makes it possible to monitor aquatic bodies more consistently throughout time. Researchers can create more comprehensive time-series datasets that capture both short-term hydrological changes and long-term trends by using Sentinel-1 data during overcast circumstances or rainy seasons and Sentinel-2 data during clear-sky periods (Ticehurst et al., 2014).

2.2.3. Google Earth Engine for Environmental Monitoring

An essential tool for environmental monitoring, Google Earth Engine (GEE) is a robust cloud-based platform made to make it easier to analyze and visualize massive amounts of geographical data. GEE's extensive data archive, which contains satellite imagery and geospatial datasets spanning several decades, is one of its primary strengths. Researchers can examine trends and changes in a variety of environmental characteristics, such as land cover, vegetation health, and surface water dynamics, by using this vast library to access historical data for time-series analysis (Gorelick et al., 2017).

Furthermore, GEE greatly cuts down on the time and resources usually needed for data analysis by utilizing the processing power of cloud computing to process massive datasets quickly. Because of the platform's capabilities for parallel processing, users can swiftly execute intricate algorithms on massive amounts of data and carry out analyses that would be difficult on local computers (Zhu et al., 2018). GEE does, however, have certain drawbacks. Users may experience problems with data availability and resolution even though it gives them access to a large number of datasets, especially in places with poor satellite coverage or where some sensors may not have been installed (Buchhorn et al., 2020). Concerns over internet availability are also raised by the dependence on cloud-based processing, especially in isolated areas where fieldwork may be necessary. Additionally, some environmental scientists may find GEE's JavaScript or Python API inaccessible due to the learning curve for those who are not familiar with coding or programming languages (Hansen et al., 2013).

A collection of tools and algorithms created especially for mapping and monitoring water bodies are available in Google Earth Engine. The Normalized Difference Water Index (NDWI), one of the most widely used algorithms, uses the unique spectral characteristics of water in the near-infrared (NIR) and green bands to effectively separate water from land (McFeeters, 1996). In complicated or turbid situations, the Modified NDWI (MNDWI), which improves water body recognition by utilizing the shortwave infrared (SWIR) band, is one index that is frequently used in conjunction with the NDWI (Zhang et al., 2019).

Apart from water indices, GEE makes it easier to apply machine learning techniques for classifying water bodies. To increase the precision of water body delineation, users can use supervised classification methods like Random Forest or Support Vector Machines to group pixels according to their spectral signatures (Mountrakis et al., 2011). Additionally, GEE facilitates the creation of custom algorithms, allowing researchers to modify pre-existing approaches or design brand-new ones that are suited to certain research topics and circumstances. Additionally, GEE has time-series analytic capabilities that let users monitor water body changes over time and evaluate the effects of anthropogenic or climatic events. This improves the general comprehension of hydrological patterns and trends and is especially helpful in understanding seasonal changes, drought events, and flooding dynamics in water bodies (Pekel et al., 2016).

For long-term environmental monitoring, Google Earth Engine's cloud-based architecture provides a number of noteworthy benefits. The first benefit of GEE is that it allows users to perform analysis on large temporal datasets without requiring local storage, which is crucial considering the abundance of available satellite imagery. Researchers can find long-term patterns and abnormalities in environmental conditions thanks to this capability, which makes it easier to conduct continuous monitoring over lengthy periods of time (Gorelick et al., 2017). Furthermore, GEE's real-time data processing and visualization capabilities improve stakeholder and researcher collaboration. Scientists, decision-makers, and local people can participate in decision-making processes based on thorough environmental data thanks to GEE's shared platform for data access and analysis, which encourages transparency and interdisciplinary collaboration (Zhu et al., 2018).

The integration of many data sources, such as satellite imagery, meteorological data, and socioeconomic information, offers an additional benefit in that it enables comprehensive evaluations of environmental changes and their effects on ecosystems and human livelihoods. This all-encompassing method facilitates the creation of well-informed management plans that take into account the intricate relationships that exist between land use, climate variability, and water resources (Hansen et al., 2013). Lastly, GEE's scalability makes it possible to employ it in a variety of contexts, ranging from small-scale case studies to extensive regional evaluations. This adaptability allows researchers to use the platform's vast computational capacity to address pressing environmental issues like habitat loss, climate change, and water scarcity while customizing their analyses to the particular requirements of their studies (Buchhorn et al., 2020).

2.2.4. Challenges of integrating radar and optical data.

The integration of radar and optical data, particularly from systems like Sentinel-1 (SAR) and Sentinel-2 (optical), offers great potential for enhanced monitoring and mapping of surface water bodies. However, this integration presents several challenges due to the inherent differences between radar and optical sensing technologies. These challenges, when not addressed adequately, can impact the effectiveness and accuracy of the integrated results. The following discussion explores the key conceptual challenges associated with the fusion of radar and optical data.

Radar (SAR) and optical sensors operate on fundamentally different principles, leading to disparities in the type of data they provide. Sentinel-1 uses SAR, which relies on microwave signals that bounce off the Earth's surface, while Sentinel-2 uses optical sensors that capture sunlight reflected from the Earth's surface in the visible and near-infrared spectrum (Hagolle et al., 2015). SAR data provides information on surface roughness, moisture content, and geometric features, while optical data captures the spectral reflectance of objects. Water bodies, for example, appear very different in these two types of data: water absorbs radar signals and appears dark in SAR imagery, while it reflects sunlight and appears as a distinct blue or dark feature in optical imagery.

These differences in the physical principles of data collection mean that integrating the two types of data requires complex preprocessing steps to align them spatially and temporally. SAR images do not provide the same spectral information as optical imagery, making the classification of water bodies or the identification of surface features more difficult. Optical data is also sensitive to atmospheric conditions like cloud cover, while SAR data is not, which adds another layer of complexity in harmonizing the two datasets (Shao et al., 2016).

Another challenge in integrating radar and optical data is the difference in temporal and spatial resolution between the two systems. While Sentinel-2 provides optical imagery with high spatial resolution (10-60 meters), Sentinel-1 offers data with a lower spatial resolution (10-40 meters), depending on the acquisition mode. Furthermore, Sentinel-2 has a 5-day revisit cycle when both satellites (Sentinel-2A and Sentinel-2B) are operational, while Sentinel-1 revisits every 6 days. This difference in revisit periods can lead to temporal mismatches, especially when monitoring rapid changes in water bodies or seasonal fluctuations that occur over short time scales (Clerici et al., 2017).

Spatial and temporal mismatches require careful alignment of the datasets before integration. This can be achieved through various image preprocessing techniques, such as co-registration, resampling, or temporal interpolation, but these methods often introduce errors and can affect the final analysis (Liu et al., 2020). Moreover, the need for precise alignment of radar and optical data can be computationally intensive, requiring advanced processing techniques and algorithms that are not always straightforward to implement.

While optical data is often affected by atmospheric conditions such as cloud cover, haze, and dust, radar data is less sensitive to these factors but can be influenced by surface characteristics such as soil moisture, vegetation, and topography (Pekel et al., 2016). For example, in regions with dense vegetation or rugged topography, radar signals may scatter, leading to inaccurate interpretations of water bodies or other surface features (Lu et al., 2017). In contrast, optical imagery is more affected by atmospheric conditions like cloud cover, which can obscure water bodies for long periods, particularly in tropical or temperate climates.

When integrating radar and optical data, it is important to account for both atmospheric and environmental factors that may affect the data. The presence of clouds or fog in optical imagery can cause significant gaps in data acquisition, while radar backscatter in vegetated or highly topographic areas can complicate the identification of water bodies. To overcome these challenges, preprocessing techniques such as atmospheric correction for optical imagery or topographic normalization for radar data are often required, but these methods can introduce additional uncertainties and computational costs (Mason et al., 2020).

Data fusion techniques are central to integrating radar and optical data for surface water monitoring, but they come with their own set of challenges. The two main approaches to data fusion are pixel-level and feature-level fusion (Feng et al., 2019). Pixel-level fusion involves combining the raw pixel values from both datasets into a single composite image, while feature-level fusion involves combining derived features such as water body extent, surface texture, or vegetation indices from both datasets. Both approaches require sophisticated algorithms to merge the data in a meaningful way, ensuring that the unique characteristics of both data sources are preserved while minimizing errors.

Pixel-level fusion can lead to significant computational overhead, and the resulting data may contain artifacts or distortions due to the difference in sensor characteristics (such as the spectral vs. spatial differences between radar and optical). Feature-level fusion can mitigate some of these issues by combining high-level features derived from both datasets, but it may not fully capture the detailed variations in the raw data. Additionally, choosing the right fusion technique depends on the specific application, which requires careful consideration of the end goals and available processing tools (Zhang et al., 2020).

The integration of radar and optical data for classification purposes presents unique challenges, particularly in distinguishing water bodies from surrounding land features. While water bodies exhibit distinct spectral characteristics in optical data, these can be difficult to interpret in radar images due to variations in surface roughness or moisture content. In regions with complex land cover, such as the Rift Valley Lakes Basin, where varying vegetation types, seasonal land cover changes, and complex topography exist, the classification of water bodies can be challenging.

Recent studies have shown that combining radar and optical data can improve classification accuracy, as each data type contributes unique information. For example, radar data can help differentiate between water and land in areas with dense vegetation, where optical data might fail (Nanni et al., 2018). However, the integration of these two data sources requires careful calibration of classification algorithms to ensure that the information from both sensors is appropriately weighted, without one sensor type dominating or introducing bias.

Finally, the integration of radar and optical data can be computationally demanding, particularly when large datasets are involved. The need for preprocessing, alignment, and fusion of these datasets requires significant computational resources, and the complexity of the algorithms can increase the processing time. For researchers and practitioners working in regions with limited access to high-performance computing, this can present a major barrier to using these advanced techniques effectively. Additionally, the operational costs of acquiring, processing, and analyzing radar and optical data can be significant, especially when multiple datasets and long temporal periods are required.

2.3. Empirical literature

Because Sentinel-1 can operate day or night and pierce cloud cover, its synthetic aperture radar (SAR) capabilities have been widely used for mapping and monitoring aquatic bodies. Numerous research have shown how successful it is in different geographic settings. Benediktsson et al. (2018) demonstrated, for example, how Sentinel-1 data may be used to detect flood extents in the Danube River basin, effectively differentiating between land and water even under difficult weather conditions. Their study demonstrated the benefits of using SAR images to deliver timely information for managing water resources and responding to disasters.

In a similar vein, Huang et al. (2020) tracked surface water variations in the Poyang Lake basin, China, using Sentinel-1 data. In order to accurately map dynamic water surfaces, the study highlighted the significance of backscatter coefficients in distinguishing between water and other types of land cover. Although Sentinel-1 caught water surface dynamics well, the scientists pointed out that including other data sources could improve detection accuracy, particularly in regions with complicated land cover.

Sentinel-2's optical photography, as opposed to Sentinel-1's radar capabilities, has been widely utilized for mapping water bodies and evaluating water quality, especially in regions with minimal cloud cover. The Sentinel-2 mission was thoroughly described by Drusch et al. (2012), who emphasized its excellent geographical resolution and spectral bands designed for vegetation and water monitoring. After then, Sola et al. (2019) used Sentinel-2 imagery to perform a thorough investigation on water quality evaluation in Mediterranean reservoirs. Their results demonstrated how the red edge and other spectral bands greatly enhanced the detection of chlorophyll-a concentrations, improving our comprehension of the dynamics of water quality.

Additionally, Sentinel-2's potential for mapping the Caribbean's shallow coastal waters was investigated by Pérez-Gutiérrez et al. (2020). The study highlighted the value of the sensor in monitoring coastal ecosystems by proving that it is feasible to define shallow water zones using the Normalized Difference Water Index (NDWI) obtained from Sentinel-2 data. All of these studies demonstrate how important Sentinel-2 is for determining the quantity and quality of water, especially in areas with good visibility.

Utilizing the characteristics of both sensors, recent developments in remote sensing have placed a greater emphasis on integrating data from Sentinel-1 and Sentinel-2. In order to increase the precision of water body classification, Huang et al. (2019) used Sentinel-1 SAR and Sentinel-2 optical data in their thorough investigation of urban water management in Beijing, China. According to their findings, the recognition of water bodies was greatly improved by the combination of SAR and optical data, especially in metropolitan settings with diverse land cover.

In another notable study, Chrysafides et al. (2021) investigated the effectiveness of using both Sentinel-1 and Sentinel-2 data for monitoring the water dynamics in Lake Balaton, Hungary. The authors implemented a data fusion approach that combined radar and optical imagery, resulting in improved water extent mapping accuracy. This study highlighted the potential of integrating multiple data sources to provide a more comprehensive understanding of water body dynamics, ultimately informing better water management practices.

Google Earth Engine (GEE) has emerged as a transformative tool for monitoring water bodies worldwide, facilitating a range of empirical studies that leverage its capabilities for large-scale geospatial analysis. For instance, Pekel et al. (2016) conducted a comprehensive assessment of surface water dynamics globally using GEE, producing high-resolution maps of surface water extent and changes from 1984 to 2015. Their study utilized a robust methodology to detect and quantify water bodies across various ecosystems, demonstrating GEE's ability to manage vast datasets and derive meaningful insights about hydrological changes.

Another significant study by Wang et al. (2019) examined the impact of climate variability on lake dynamics in China using GEE. The researchers employed time-series analysis of Landsat imagery processed through GEE to assess changes in lake surface area over time. Their findings indicated that GEE not only streamlined data processing but also enhanced the accuracy of monitoring water body fluctuations in response to climatic factors, highlighting its effectiveness in environmental research.

Additionally, Dandois et al. (2020) utilized GEE for monitoring water quality in the Great Lakes region of North America. By integrating multispectral satellite data with GEE's computational capabilities, they developed models to assess parameters such as chlorophyll concentration and turbidity. This study underscored GEE's potential to facilitate real-time water quality monitoring and support decision-making processes for water resource management.

The implementation of GEE-based water body studies has yielded numerous success stories across various regions. For example, Saeed et al. (2021) successfully applied GEE to monitor water quality in the Nile River, illustrating the platform's capacity for handling extensive datasets and performing complex analyses. Their work demonstrated how GEE can be utilized to create detailed temporal and spatial maps of water quality indicators, informing local management strategies.

However, despite these successes, challenges remain in the widespread adoption of GEE for water monitoring. One significant hurdle is the variability in data quality and availability across different regions. For instance, while GEE provides access to a vast archive of satellite imagery, the presence of cloud cover can impact the quality of optical data, leading to gaps in information (Zhu et al., 2018). Furthermore, researchers often encounter difficulties in standardizing methodologies, particularly in integrating different datasets, which can affect the comparability of results (Wang et al., 2020).

Another challenge lies in the technical expertise required to effectively utilize GEE. Although the platform is designed to be user-friendly, the need for programming skills can pose a barrier for researchers unfamiliar with coding. Training and capacity-building initiatives are essential to enable more researchers to leverage GEE for water monitoring studies (Huang et al., 2019).

Numerous methodologies have been developed and employed within GEE for water body detection, each with its own advantages and limitations. A common approach is the application of remote sensing indices such as the Normalized Difference Water Index (NDWI) and the Modified NDWI (MNDWI). For example, McFeeters (1996) demonstrated the effectiveness of NDWI for delineating water bodies, which has been widely adopted in GEE-based studies for its simplicity and efficiency.

In contrast, machine learning techniques are increasingly being applied to enhance water detection accuracy. Jiang et al. (2020) utilized Random Forest classifiers in GEE to distinguish water bodies from other land cover types, demonstrating improved accuracy over traditional index-based methods. This approach leverages GEE's capabilities to process large datasets and run complex algorithms efficiently, making it a powerful tool for water body mapping.

A comparative study by Petersen et al. (2021) examined the efficacy of different water detection methodologies in GEE, including spectral indices, machine learning, and hybrid approaches that combine both. The results indicated that while spectral indices provided rapid assessments, machine learning models yielded higher accuracy in complex environments. This highlights the importance of selecting appropriate methodologies based on the specific context and objectives of the study.

2.4.Knowledge gap

Despite the extensive body of research on the use of Sentinel-1 and Sentinel-2 data for monitoring water bodies and the advancements in remote sensing technologies, several knowledge gaps persist in the field, particularly when integrating both data sources for water body detection and monitoring. These gaps offer opportunities for future research and highlight areas where further advancements can be made. Below are some of the key knowledge gaps identified from the empirical literature:

While studies have demonstrated the advantages of combining Sentinel-1 and Sentinel-2 data for water body detection, there is still a lack of standardized, optimized methods for fusing radar and optical data. The existing literature highlights improvements in water detection accuracy when both datasets are integrated (Huang et al., 2019; Chrysafides et al., 2021), but the techniques for effectively merging these datasets are not universally established. Different fusion methods—such as pixel-level, feature-level, and decision-level fusion—are applied in various studies, yet the most efficient approach for specific environments or water body types remains unclear. There is also a need for more advanced machine learning and deep learning algorithms that can better handle the complexities of radar-optical fusion, taking into account factors such as topography, land cover variability, and atmospheric conditions. This gap presents a clear area for further development in fusion techniques, especially considering the potential of combining the strengths of both data types in a more systematic and refined manner.

A recurring issue identified in the literature is the challenge of accurate water body mapping in regions with complex or rapidly changing environments. Many studies focus on areas with stable land cover or clear water bodies, but there is less research on regions with heterogeneous land cover, such as the Rift Valley Lakes Basin in Ethiopia, where varying topography, seasonal vegetation, and complex hydrological conditions complicate water body detection (Huang et al., 2020). The integration of Sentinel-1 and Sentinel-2 data in such areas requires more robust models that can account for variations in backscatter due to vegetation or topographic features and mitigate errors introduced by seasonal changes. There is also a lack of studies examining the performance of integrated SAR-optical data in regions with high inter-seasonal water dynamics, making it a key area for investigation.

While Sentinel-1 and Sentinel-2 provide good temporal coverage, the revisit periods of these satellites can sometimes lead to data gaps, especially in regions where frequent cloud cover is prevalent. This issue is particularly relevant when monitoring water bodies over short time scales or during extreme weather events. Although studies like Pekel et al. (2016) and Saeed et al. (2021) highlight the potential of Google Earth Engine (GEE) for handling large datasets and time-series analysis, the quality of optical data is often compromised by cloud cover, leading to incomplete temporal records. While SAR data is less affected by cloud cover, it lacks the spectral information provided by optical sensors, which makes it challenging to fully capture water quality parameters such as chlorophyll-a concentrations. A gap exists in research that could focus on improving the temporal resolution of data fusion by using data from multiple sources, including newer satellite missions, and through the development of cloud removal techniques or data interpolation methods that enhance the temporal continuity of water body monitoring.

Much of the existing research focuses on the detection and mapping of water body extents rather than on water quality monitoring. While Sentinel-2 has demonstrated its ability to assess water quality indicators, such as chlorophyll-a concentrations (Sola et al., 2019), and Sentinel-1 provides valuable information on surface water dynamics, few studies have integrated these data sources to monitor both the quantity and quality of water in a comprehensive manner. The application of indices like the Normalized Difference Water Index (NDWI) for water body detection is well-established, but less attention has been given to combining these indices with radar data to assess water quality parameters, such as turbidity or nutrient levels. Further exploration is needed to integrate radar and optical data for more holistic monitoring of water quality, particularly in regions with dynamic hydrological systems and diverse land cover.

The influence of environmental factors such as vegetation, soil moisture, and land use on the accuracy of water body mapping has been highlighted in several studies (Lu et al., 2017; Huang et al., 2020). However, there is limited research on how these environmental factors interact when combining radar and optical data for water body detection. In complex landscapes with mixed land cover, such as in the Rift Valley Lakes Basin, the integration of both data sources needs to account for the impact of surface roughness, vegetation density, and soil moisture on radar backscatter, as well as the atmospheric conditions that influence optical imagery. A better understanding of how environmental variables influence both radar and optical data—and how to mitigate these impacts in integrated approaches—is a significant knowledge gap that needs to be addressed to improve the accuracy of water body mapping.

Despite the promising results of GEE in water body monitoring, there remains a lack of consistency in the methodologies applied across different studies. As noted by Wang et al. (2020), the standardization of methods for data processing, fusion, and analysis remains a challenge. The wide array of techniques used to process satellite data (such as classification, index-based methods, and machine learning) and the variety of data preprocessing steps (such as atmospheric correction, co-registration, and resampling) often make it difficult to compare results across studies. Moreover, the complexity of data integration, especially when combining datasets from different satellite systems, means that best practices are still being developed. A clearer set of standards for methodological consistency is needed to ensure the reproducibility and reliability of water monitoring studies, particularly for large-scale and long-term analyses.

Another notable gap in the literature is the limited integration of satellite data with ground truth data for validation purposes. While many studies rely on satellite imagery for water body mapping, the accuracy of these products is often not verified with real-world observations. Ground truth data is essential for assessing the reliability of remotely sensed water body extents, especially in areas with complex land cover or in regions where ground-based monitoring is sparse. There is a need for more comprehensive field validation studies that can help calibrate satellite-based algorithms and improve the accuracy of water body mapping, particularly in developing regions where such validation is often lacking.

CHAPTER THREE

3. MATERIAL AND METHODS

3.1.Study area description

The Rift Valley lakes are a series of lakes located in the East African Rift Valley, which stretches from Ethiopia within the north to Malawi inside the south, and consists of the African Great Lakes to the south. The Ethiopian Rift Valley lakes are the northernmost of those lakes. The Main Ethiopian Rift, or Great Rift Valley, runs through vital Ethiopia, dividing the Ethiopian highlands into northern and southern halves, with the Rift Valley lakes situated inside the valley ground among the two highlands. Most of the Ethiopian Rift Valley lakes are endorheic (having no outlet) and are in most cases alkaline. While these lakes are crucial to Ethiopia's economic system and vital for the livelihoods of neighborhood groups, comprehensive limnological studies on them had been scarce until current years (Hynes, 2008). Geographically, the Rift Valley lakes basin spans from 36°E to 40°E longitude and 4°N to 10°N range.

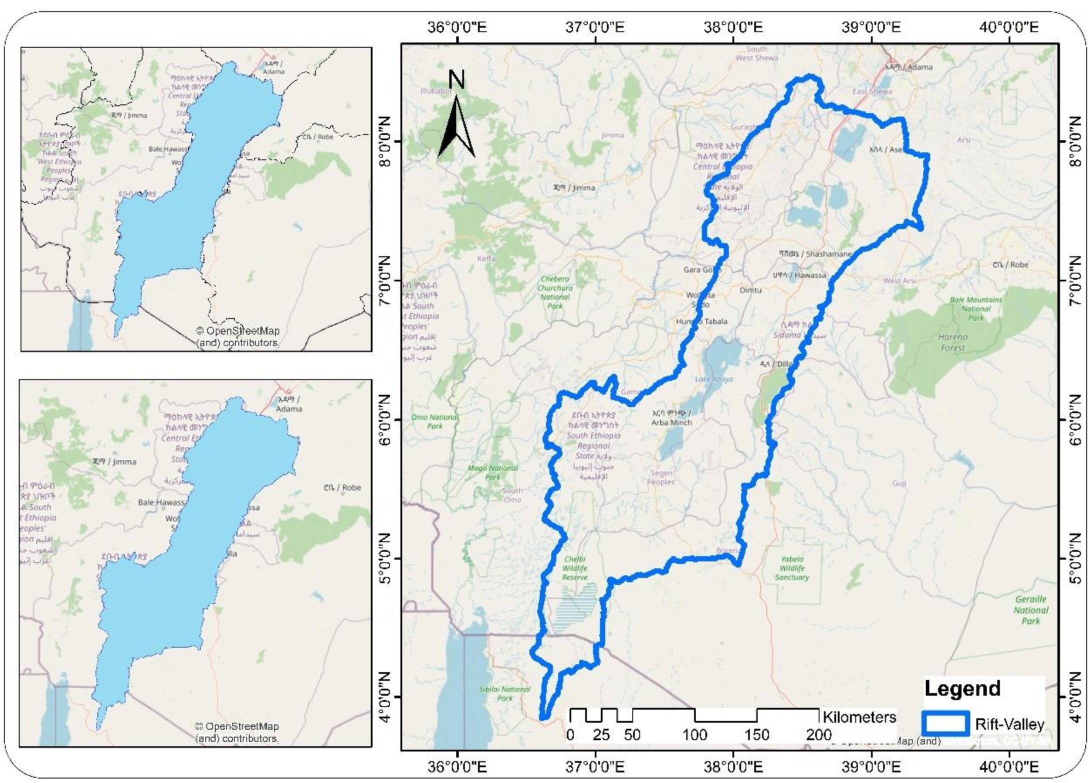

Figure 3-1: Location map of the study area

3.2.Research approach

In this study, a quantitative studies approach changed into utilized to systematically observe the dynamics of floor water our bodies within the Rift Valley Lakes Basin using Sentinel-1 and Sentinel-2 satellite tv for pc records. The research started out with the aid of gathering multi-temporal satellite imagery from each satellites to seize seasonal and inter-annual variations in water extent. The records have been pre-processed in Google Earth Engine to correct for cloud cover and atmospheric distortions, enhancing the overall great of the imagery. Water frame detection was performed the use of algorithms which include the Normalized Difference Water Index (NDWI) and device learning classifiers to accurately delineate water our bodies within the basin. Spatial evaluation strategies were then applied to assess the spatiotemporal dynamics of floor water bodies, figuring out tendencies and adjustments in water volume over time, with the effects visualized the use of geospatial gear. Additionally, statistical analyses quantified the relationships between water body dynamics and potential influencing elements which include topography and land cowl adjustments. This comprehensive quantitative evaluation supplied empirical evidence of hydrological modifications, advancing the understanding of surface water dynamics and informing sustainable water aid control within the place.

3.3.Data sources and types

3.3.1. Sentinel 1 SAR data

Sentinel-1 is a part of the European Space Agency's Copernicus program and gives excessive-decision Synthetic Aperture Radar (SAR) statistics. This information is in particular precious for monitoring surface water bodies because it isn't always suffering from cloud cover and may capture modifications in water volume regardless of weather conditions. The radar sign can penetrate vegetation and detect variations in floor moisture, making it powerful for delineating water our bodies even in densely vegetated areas. The excessive temporal decision of Sentinel-1, that could revisit the same vicinity each few days, permits for the monitoring of dynamic modifications in water bodies, which includes seasonal fluctuations or impacts from human sports. The data was processed the use of techniques like backscatter analysis to distinguish between water and land surfaces.

3.3.2. Sentinel-2 Optical Data

Sentinel-2 enhances the capabilities of Sentinel-1 through supplying excessive-decision optical imagery thru its multispectral sensor, which captures statistics throughout thirteen spectral bands. This permits certain evaluation of land and water surfaces, assisting the calculation of indices just like the Normalized Difference Water Index (NDWI) which might be critical for water frame detection and characterization. The optical facts from Sentinel-2 additionally enables the assessment of water pleasant parameters, consisting of chlorophyll awareness and turbidity, by means of analyzing precise spectral bands. Additionally, Sentinel-2's excessive spatial resolution (10-20 meters) allows for the mapping of smaller water bodies and offers insights into their surrounding ecological environments. With a revisit time of about five days, Sentinel-2 affords ordinary tracking of water dynamics, making it well-applicable to music seasonal changes and versions in water bodies.

3.3.3. Preprocessing of Sentinel 1 SAR and Sentinel 2

In this study, a combination of Synthetic Aperture Radar (SAR) and optical imagery was employed to map and monitor surface water bodies in the Rift Valley Lakes Basin using Sentinel-1 and Sentinel-2 data. Sentinel-1 SAR data underwent several preprocessing steps, including satellite orbital correction, thermal noise removal, radiometric calibration, and speckle noise reduction using the Lee filter. The Lee filter was selected due to its effectiveness in reducing speckle noise while preserving edge features, which is essential for accurate water boundary detection. Compared to other filters like the Frost filter, the Lee filter offers a better balance between smoothing homogeneous areas and maintaining structural details. To classify water bodies in the SAR data, the Otsu thresholding method was applied, effectively distinguishing water from non-water regions based on backscatter characteristics. For Sentinel-2 optical data, preprocessing included atmospheric correction using the Sen2Cor algorithm, which converts Top of Atmosphere (TOA) reflectance to Bottom of Atmosphere (BOA) reflectance, improving the reliability of spectral indices. In addition, cloud masking was applied using the QA60 band and cloud probability layer to exclude cloud-contaminated pixels. This step is critical for ensuring the accuracy of optical-based water mapping. The Normalized Difference Water Index (NDWI) was then applied to the cloud-free, atmospherically corrected Sentinel-2 imagery to delineate water bodies based on spectral reflectance differences between the green and near-infrared bands.

3.4.Data analysis method

3.4.1. Sentinel 1 SAR Image analysis techniques

The preprocessing of Sentinel-1 images in the Google Earth Engine platform, following guidelines from the Sentinel-1 toolbox, encompasses several crucial steps. It commences with a meticulous satellite orbital correction, demanding precise satellite position and velocity data for optimal results (Filipponi, 2019). The removal of thermal noise, especially pronounced in the cross-polarized channel due to its lower backscattered power, is achieved through the calculation of a noise look-up table available in Sentinel-1 level 1 images (Park et al., 2017). Subsequent radiometric calibration yields backscattering coefficients (Elfadaly et al., 2020). To counteract speckle noise, which impairs image quality and interpretation, the Lee filter is applied, supported by its documented efficacy in various applications (Lee & Pottier, 2017; Brombacher et al., 2020; Li et al., 2018; Salameh et al., 2020; Slagter et al., 2020; Zeng et al., 2020). The final preprocessing step involves converting digital numbers to backscattering coefficients in decibels using the equation (Equation 2) outlined by Richards (2009).

$$\sigma^0 dB = 10 logabs(DN) \qquad \text{Equation (3-1)}$$

Otsu automatic thresholding method

In this look at, the Otsu automatic thresholding set of rules within Google Earth Engine turned into hired to correctly distinguish between water and non-water regions in a chain of Sentinel-1 photos. The Otsu technique is an iterative technique that systematically explores all viable threshold values to pick out the best threshold. It achieves this by way of maximizing the variance among instructions (water and non-water areas) even as minimizing the variance inside each magnificence, as in the beginning brought with the aid of Otsu in 1979. To implement this, pixel values are first normalized to a selected variety [a, b], in which $-1 \leq a \leq 1$. This normalization method allows pixels to be labeled into two instructions: C1 (water regions) with values falling in the range [t, a], and C2 (non-water regions) with values within the range [b, t], wherein 't' is the threshold price. The particular dedication of this threshold (t) is crucial, as it's miles primarily based on maximizing the inter-magnificence variance among C1 and C2, which enables make certain accurate type of water our bodies.

$$\sigma^2 = P_{c1} * (M_{c1} - M)^2 + P_{c2} * (M_{c2} - M)^2 \qquad \text{Equation (3-2)}$$

$$\sigma^2 = P_{c1} * M_{c1} + P_{c2} * M_{c2} \qquad \text{Equation (3-3)}$$

$$P_{c1} + P_{c2} = 1 \qquad \text{Equation (3-4)}$$

$$t *= ArgMax_{a<1<b}\{P_{c1} * (M_{c1} - M)^2 + P_{c2} * (M_{c2} - M)^2\} \qquad \text{Equation (3-5)}$$

3.4.2. Spectral indices analysis from Sentinel 2

Spectral Water Indices

The **Normalized Difference Water Index (NDWI)**, proposed by McFeeters in 1996, is widely used to delineate surface water bodies by exploiting the spectral reflectance differences between water and other land cover types in the visible and near-infrared (NIR) regions. In this study, NDWI was calculated using the Green and Shortwave Infrared 1 (SWIR1) bands, following the formula:

$$NDWI = \frac{Green - SWIR1}{Green + SWIR1} \qquad \textit{Equation (3-6)}$$

This specific band combination was chosen for its proven effectiveness in detecting surface water features across diverse land covers, including vegetated and semi-arid landscapes like those in the Rift Valley Lakes Basin. The Green band is sensitive to water clarity and depth, while the SWIR1 band is strongly absorbed by water but reflected by soil and vegetation. This contrast enables clear differentiation between water and non-water surfaces, even under varying atmospheric and land surface conditions.

While alternative indices such as the Modified NDWI (MNDWI), which replaces SWIR1 with the Mid-Infrared (MIR) band, are sometimes recommended for urban or highly turbid waters, the NDWI (Green/SWIR1) was preferred in this study due to its superior performance in rural and vegetated regions with minimal urban influence. Moreover, studies have demonstrated that NDWI using SWIR1 performs well in mapping water bodies under mixed land cover types and is less susceptible to noise from built-up features, which are not a dominant concern in the study area.

Overall, the use of NDWI (Green/SWIR1) offers a robust and reliable method for detecting water surfaces in the Rift Valley region, providing high sensitivity to hydrological changes and enabling effective monitoring of water dynamics over time.

Water index classification

Water index type based totally on the Normalized Difference Water Index (NDWI) values is a vital method for interpreting water presence inside the path of diverse landscapes in satellite imagery. NDWI, derived from near-infrared and green bands, gives treasured insights into water abundance. The class delineates first-rate commands in step with particular NDWI price stages, offering a comprehensive assessment of water capabilities. Firstly, regions with NDWI values an lousy lot lots less than or equal to zero. Zero are identified as No Water, representing areas without a full-size water content fabric, typically which encompass non-aqueous surfaces like dry land or vegetated areas. Transitioning to the Water magnificence, NDWI values beginning from 0. Zero to at least one. Zero advise regions with adequate water content material cloth, encompassing big lakes, oceans, or flooded regions (Rad et al., 2021). The NDWI class tool is adaptable, acknowledging that contextual interpretation is crucial, and particular thresholds can also range primarily based definitely totally on factors inclusive of the trends of the have a look at location and the satellite television for computer records utilized.

Continuous monitoring of NDWI over time complements the dynamic evaluation of water availability and environmental conditions. This class framework, knowledgeable with the useful aid of the NDWI values supplied in the table, contributes to a nuanced expertise of water dynamics within the landscape. Researchers, environmental managers, and choice-makers can leverage this tool to comprehensively compare water functions, facilitating knowledgeable alternatives related to water useful useful resource manipulate and environmental conservation (Aziz et al., 2020; Nsubuga et al., 2017; Rad et al., 2021).

Table 3-1: NDWI classification into water and no-water classes

NDWI Range	Water Category	Description
<= 0.0	No Water	Areas with no significant water content, typically non-aqueous surfaces.
0.0 - 1	Water	Regions with abundant water content, encompassing large lakes, oceans, or flooded areas.

3.5. Validation

To verify the accuracy of lake boundaries extracted from Sentinel-1 SAR and Sentinel-2 optical imagery, a validation process was conducted using field-collected GPS points. These ground truth data served as a reliable reference for assessing the spatial accuracy of the remotely sensed outputs. A total of 215 GPS points were collected during field surveys conducted in March and April 2025, carefully timed to align with the acquisition dates of the satellite imagery used in the study. The GPS points were recorded using handheld GPS receivers with an average horizontal accuracy of ±3 meters.

The GPS points were geographically distributed around the perimeters of Lake Ziway, Lake Langano, and Lake Abaya, representing diverse shoreline conditions including open water, marshy edges, and vegetated banks. This distribution ensured that the validation covered varying environmental settings and provided a representative assessment of the classification accuracy across different water body characteristics.

Several spatial comparison techniques were employed. First, a point-in-polygon analysis was conducted to calculate the proportion of GPS points that fell within the Sentinel-derived lake boundaries. This provided a basic yet useful measure of inclusion accuracy. However, recognizing the inherent uncertainties in both GPS measurements and satellite-derived boundaries, a buffer analysis was also performed. Each GPS point was surrounded by a ±15-meter buffer zone, and the percentage of buffered points intersecting with the lake polygons was calculated. This approach accounted for spatial uncertainties and provided a more lenient validation metric.

To further evaluate positional accuracy, a distance-based analysis was carried out. The shortest distance from each GPS point to the nearest boundary of the corresponding lake polygon was computed. From this, the mean positional error and the Root Mean Square Error (RMSE) were derived to quantify the average spatial deviation between the satellite outputs and ground truth.

Additionally, in areas where continuous shoreline tracks or ground-truth boundary polygons were available, area-based comparison metrics were employed. Specifically, the Intersection over Union (IoU) index was used to quantify the degree of spatial overlap between the satellite-derived lake polygons and the actual lake outlines captured in the field. This comprehensive validation strategy, combining point-based, buffer-based, distance-based, and area-based assessments, ensured a robust evaluation of the extracted surface water features in the Rift Valley Lakes Basin.

3.6.Data analysis procedure

The methodological flowchart (Figure 3-2) outlines the systematic technique for reading spatiotemporal dynamics of surface water over time using Sentinel-1 and Sentinel-2 satellite tv for pc tv for computer facts. The approach starts off evolved with the purchase of Sentinel-1 facts, which undergoes numerous preprocessing steps to enhance picture awesome and prepare it for assessment. Initially, an orbit record is finished to accurate satellite television for laptop television for computer tv for computer positional facts. Following this, noise removal is executed to eliminate any undesirable signs that might distort the facts. Radiometric correction is then finished to adjust the photo for sensor-precise consequences and ensure that the pixel values effectively constitute the backscatter coefficient. Speckle filtering is employed to reduce granular noise normally associated with Synthetic Aperture Radar (SAR) photos. Finally, topographic correction is finished to alter for the have an effect on of terrain on backscatter, ensuring a more correct example of floor skills. Next, the flowchart directs the assessment to the preprocessing of Sentinel-2 Multispectral Instrument (MSI) facts, in which radiometric correlation and geometric correction are finished. Following the preprocessing section, spectral indices assessment is accomplished, in particular focusing at the Normalized Difference Water Index (NDWI). This index permits to distinguish amongst water and non-water regions based totally simply surely totally on reflectance values in excellent spectral bands. Once the NDWI values are computed, the Otsu automated threshold approach is employed to classify regions into water and non-water education with the aid of the use of using way of figuring out the best threshold that maximizes the variance among the one's education. After the usage of the edge, the flowchart suggests the detection of floor water, correctly mapping water our our bodies within the have a have a study area.

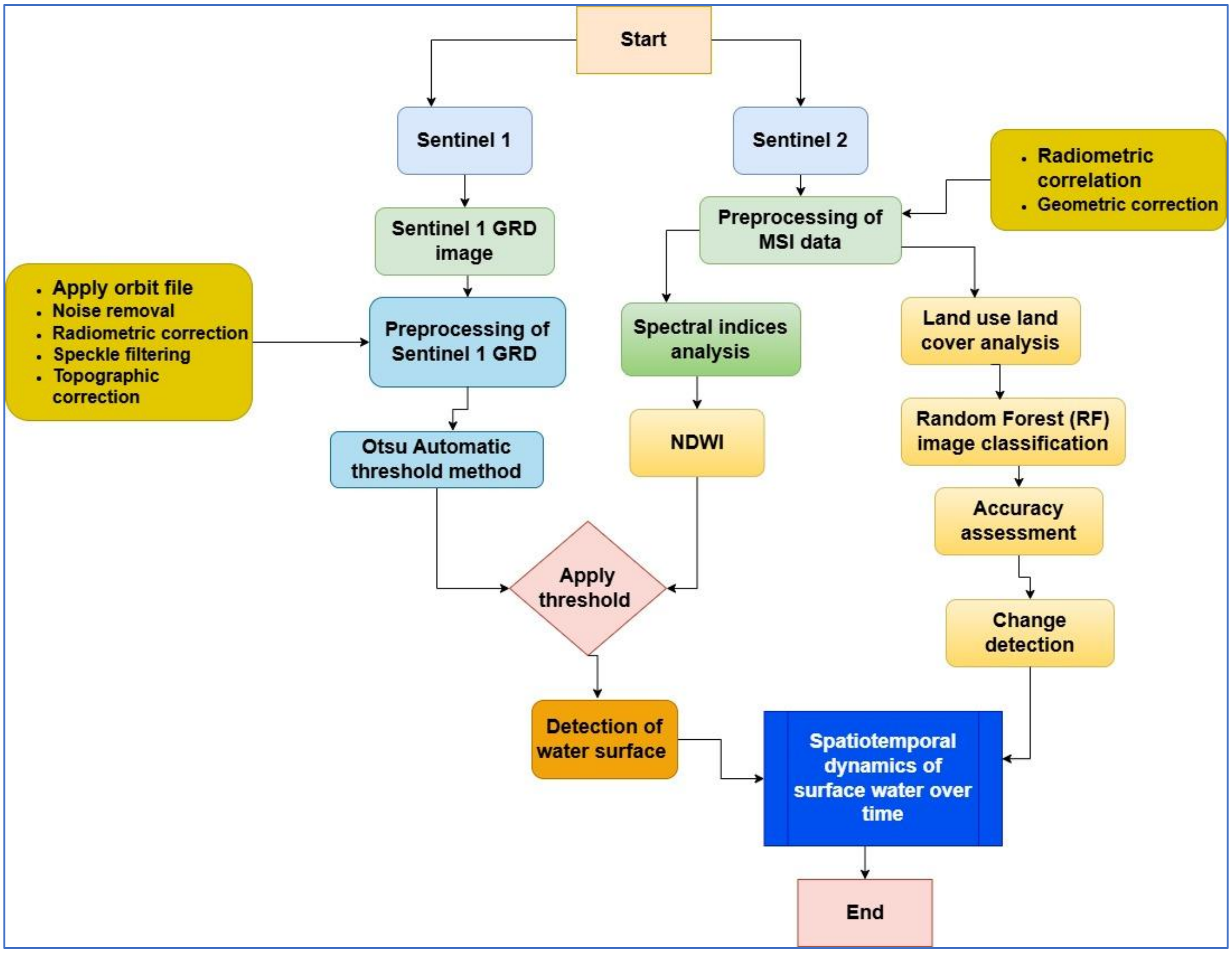

Figure 3-2: Methodological flow chart

CHAPTER FOUR

4. RESULT AND DESCUSSION

4.1.Introduction

This chapter gives and discusses the important thing findings of the take a look at in alignment with its number one objective. It starts with the delineation and class of floor water our our bodies in the Rift Valley Lakes Basin, utilizing the complementary strengths of Sentinel-1 Synthetic Aperture Radar (SAR) facts and Sentinel-2 optical imagery to improve mapping accuracy, in particular in regions suffering from cloud cover or complex land-water interfaces. The financial disaster then explores temporal modifications in floor water volume, offering notion into spatial and seasonal versions over the study period. Finally, the bankruptcy addresses the validation of category consequences, evaluating the derived waterbody maps with gift demarcation data to assess accuracy and reliability.

4.2.Surface waterbody monitoring using Sentinel 1A SAR

4.2.1. SAR Backscattering coefficients of waterbodies

The backscatter coefficients for Zeway Lake (Figure 4-1a) show a steep decline from about -21 dB in 2015 to around -22. Five dB by way of the usage of 2017, stabilizing with slight fluctuations thereafter. This shows a preliminary growth in open water amount or smoother water surfaces inside the course of the early years, followed by way of quite robust situations. This trend is regular with findings by using manner of Ewunetu et al. (2020), who said periodic expansions in Zeway's water level because of above-common rainfall activities, despite the fact that long-time period stability is induced through irrigation and catchment control.

Shala Lake (Figure 4-1b) suggests a marked lower in backscatter from about -21 dB to -24 dB among 2015 and 2017, similar to Zeway, after which remains in particular sturdy with minor fluctuations. The large size and deep nature of Shala Lake usually maintain sturdy water coverage, however versions in backscatter can also want to duplicate ground roughness modifications because of wind or minor water stage shifts. According to Ayenew

Langano Lake (Figure 4-1c) exhibits a steady decline from around -21 dB to nearly -25 dB over the entire period, indicating a continuous expansion of open water area or smoothing of water surfaces over time. Langano, a lake affected by both tourism and seasonal inflows, has experienced fluctuating water levels (Tamiru & Kebede, 2011). The progressive decrease in backscatter can be attributed to increasing water levels reported during high rainfall years, reflecting enhanced open-water surfaces.

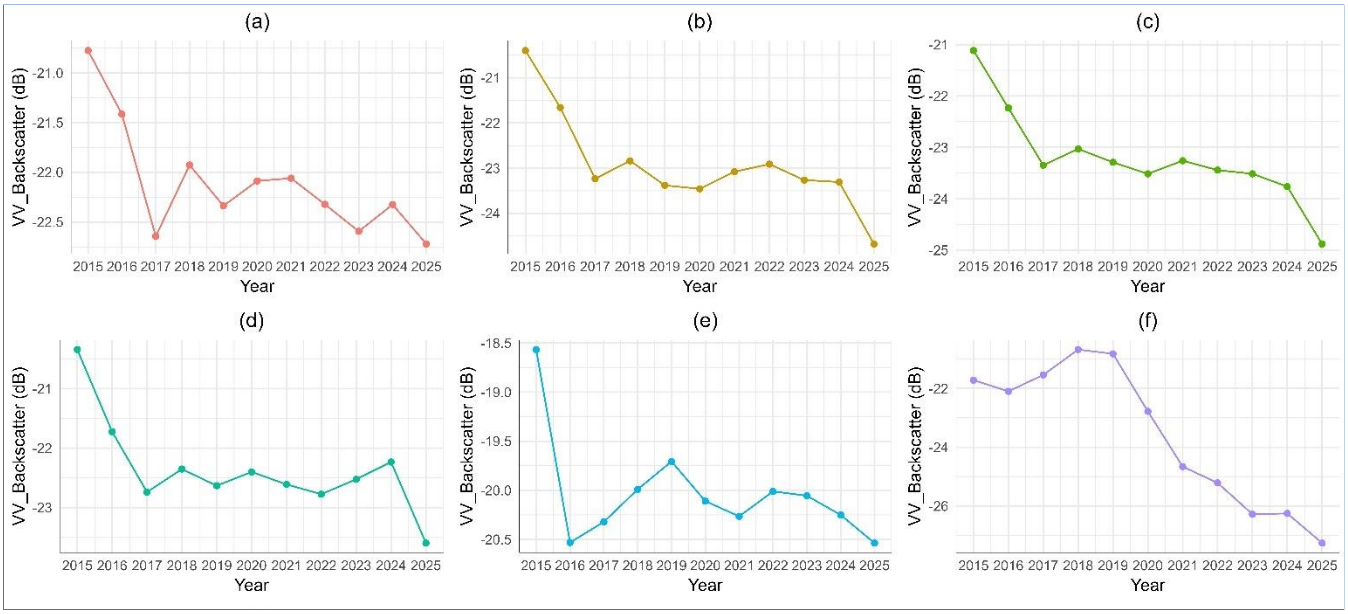

Figure 4-1: Back scattering coefficients (dB) of Rift valley lakes (a) Zeway lake, (b) Shala Lake, (c) Langano Lake, (d) Hawassa Lake, (e) Abaya chamo lake, (f) Abiyata lake

Hawassa Lake's (Figure four-1d) backscatter decreases first of all however stabilizes with minor fluctuations between -22 dB and -23 dB, indicating exceedingly steady water surface conditions. Hawassa is known for its balanced hydrological regime due to its closed drainage basin, as mentioned by using Ayenew (2004). The slight will increase round 2024–2025 reflect neighborhood flooding or plants encroachment alongside lake edges, influencing the SAR signal's roughness.

This blended dataset indicates first rate variability, with backscatter beginning at about -18.Five dB, rising in 2018, after which declining once more in the direction of 2025. These fluctuations recommend dynamic hydrological situations, probable because of inflows from the Kulfo and Bilate rivers and sediment deposition. Research through Legesse et al. (2004) emphasizes the complex sedimentation and water alternate among Abaya and Chamo, that can give an explanation for the erratic backscatter styles reflecting periodic sediment-laden water or floating plants.

Abiyata Lake (Figure 4-1f) suggests a clean and continuous decrease from around -22 dB to almost -26 dB, specifically after 2018, indicating massive changes in water floor smoothness or quantity.

Historically, Abiyata has been shrinking due to upstream diversions and soda ash extraction (Ayenew, 2006).

4.2.2. Dynamics of surface water bodies area change over time (2015-2025)-SAR

The Abaya-Chamo Lake system (Figure 4-2) demonstrates a marked expansion in surface water area, increasing from approximately 70,000 hectares in 2015 to over 100,000 hectares by 2017. This rapid enlargement was followed by a period of sustained high-water levels with moderate seasonal and interannual fluctuations, then a slight decline observed in 2025. This trend reflects the influence of catchment-driven hydrology, where changes in precipitation, runoff, and land cover strongly affect lake dynamics.

One notable factor contributing to the early expansion is the El Niño event of 2015–2016, a major climatic phenomenon known to alter rainfall patterns across East Africa. During this period, above-average rainfall was recorded in much of southern and central Ethiopia (ENMA, 2016), likely increasing inflows to Lakes Abaya and Chamo. These lakes are fed by multiple rivers, notably the Bilate and Kulfo, making them particularly responsive to shifts in catchment hydrology (Legesse et al., 2004; Rientjes et al., 2011). The increased precipitation, compounded by ongoing deforestation and land use changes in upstream catchments, likely amplified runoff and sediment transport into the lakes.

Following the expansion, the relatively stable surface area from 2017 to 2024 suggests that the lakes may have reached a quasi-equilibrium state, where inflows, evaporation, and seepage achieved temporary balance. The slight contraction in 2025 could be linked to localized drought conditions or reduced inflows, although further investigation with rainfall and river discharge data would be necessary to confirm this. Additionally, sediment loading remains a known and persistent issue in the basin, contributing to changes in lake morphology and capacity (Woldeamlak, 2011). This, combined with hydrological and climatic variability, underscores the complex and dynamic nature of surface water body evolution in the Rift Valley.

Abiyata Lake shows a steep reduction in area from ~15,000 ha in 2015 to a low of ~10,500 ha by 2020, with recovery toward 16,000 ha by 2025. This trajectory is emblematic of anthropogenic pressure combined with climatic variability. Abiyata is heavily impacted by upstream water diversions for agriculture and the soda ash industry (Ayenew & Gebreegziabher, 2006; Tamire et al., 2021), which have historically led to shrinkage. The decline up to 2020 is likely driven by these human factors, compounded by drier years. The post-2020 recovery suggest improved catchment management, temporary cessation of heavy water withdrawals, or a series of wetter-than-average years, echoing trends noted by Gebremichael et al. (2021), who describe temporary lake recoveries in the Rift Valley despite long-term degradation.

Hawassa shows a fairly stable area from 2015 (~8,350 ha) to 2019, then a gentle upward trend peaking around 8,450 ha in 2025. This mirrors the lake's closed drainage system, where water balance is regulated by local rainfall and evaporation (Ayenew, 2004). Unlike open lakes, Hawassa's levels remain stable unless disrupted by significant catchment changes or urban expansion, which may enhance runoff. The slight post-2019 increase could reflect urban sprawl and land use changes noted by Gashaw et al. (2019), which increase impervious surfaces, thereby channeling more runoff into the lake. Hawassa's steadiness underscores the resilience of closed-basin lakes but also highlights their sensitivity to small-scale catchment interventions.

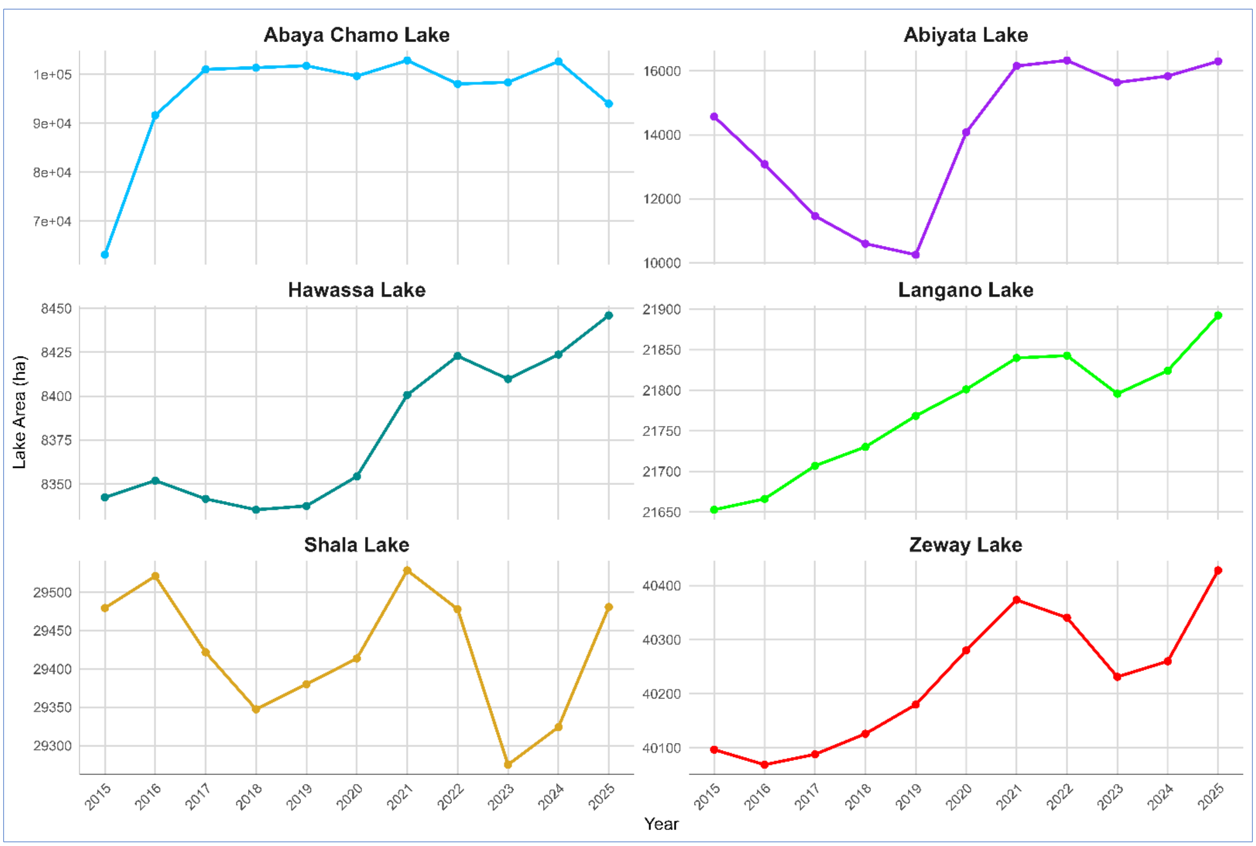

Figure 4-2: Trends in lake surface areas (hectares) for six lakes of Rift Valley Basin retrieved from Sentinel 1 (2015 to 2025).

Langano displays a subtle but steady increase from ~21,850 ha in 2015 to ~21,900 ha in 2025. This small growth, though not dramatic, is meaningful in the context of Langano's moderate hydrological inflow from local rivers and catchment rainfall (Tamiru & Kebede, 2011). The consistency of rise indicates a balance tipped slightly toward higher rainfall or possibly reduced abstraction from upstream areas. The pattern affirms Langano's climatic sensitivity and the broader East African Rift's hydro-climatic balance, where long-term trends often lag behind short-term weather variability (Dessie et al., 2020).

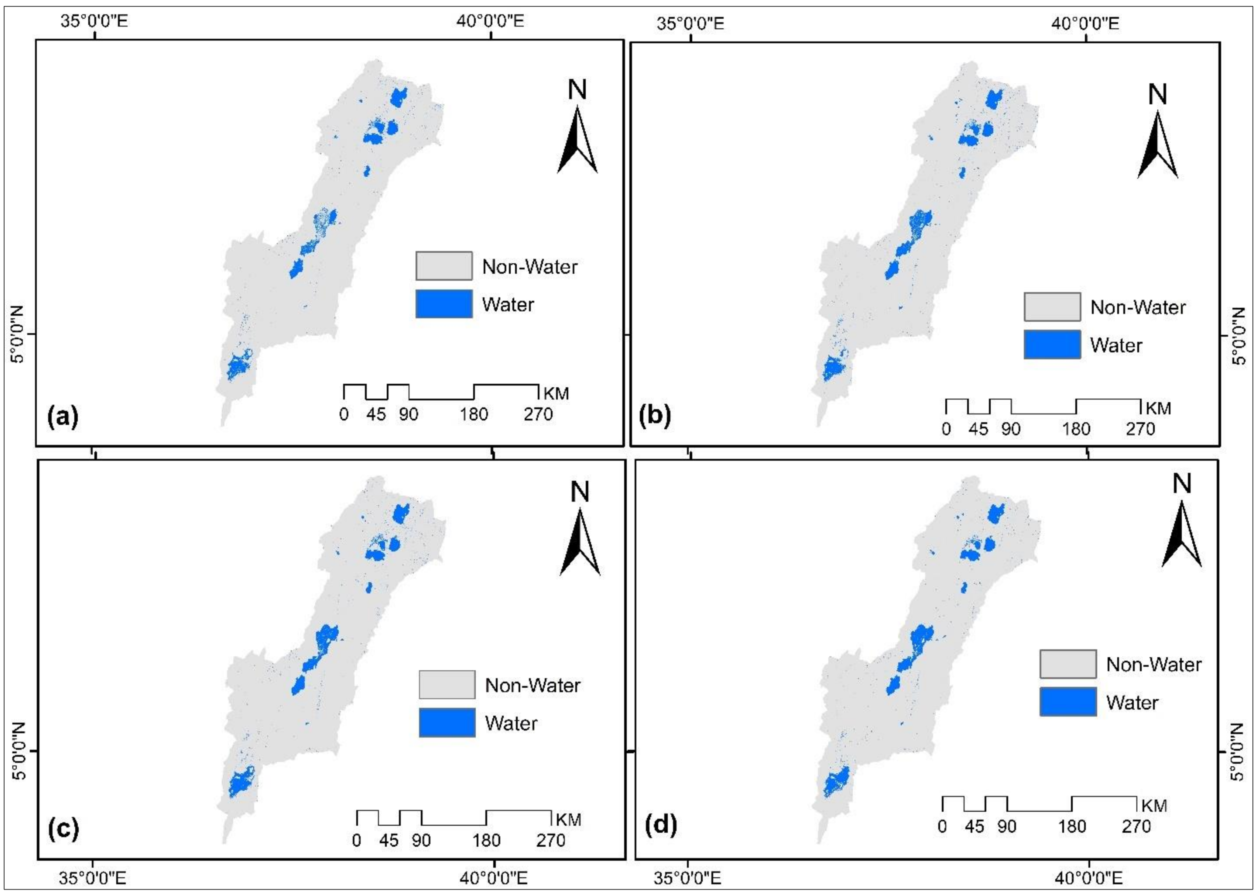

Figure 4-3: Spatiotemporal dynamics of surface water (2015-2018) extracted from Sentinel 1; (a) 2015, (b) 2016, (c) 2017, (d) 2018

Shala exhibits oscillating patterns around 29,500–30,000 ha, reflecting its deep basin and large volume, which buffer short-term climatic changes (Ayenew & Legesse, 2007). As a hydrologically closed lake with high salinity, Shala's area fluctuations are mainly driven by evaporation-precipitation dynamics. The periodic rises and falls visible here likely result from interannual climatic variability, such as El Niño-Southern Oscillation (ENSO) events, which strongly influence rainfall across the Horn of Africa (Nicholson, 2017).

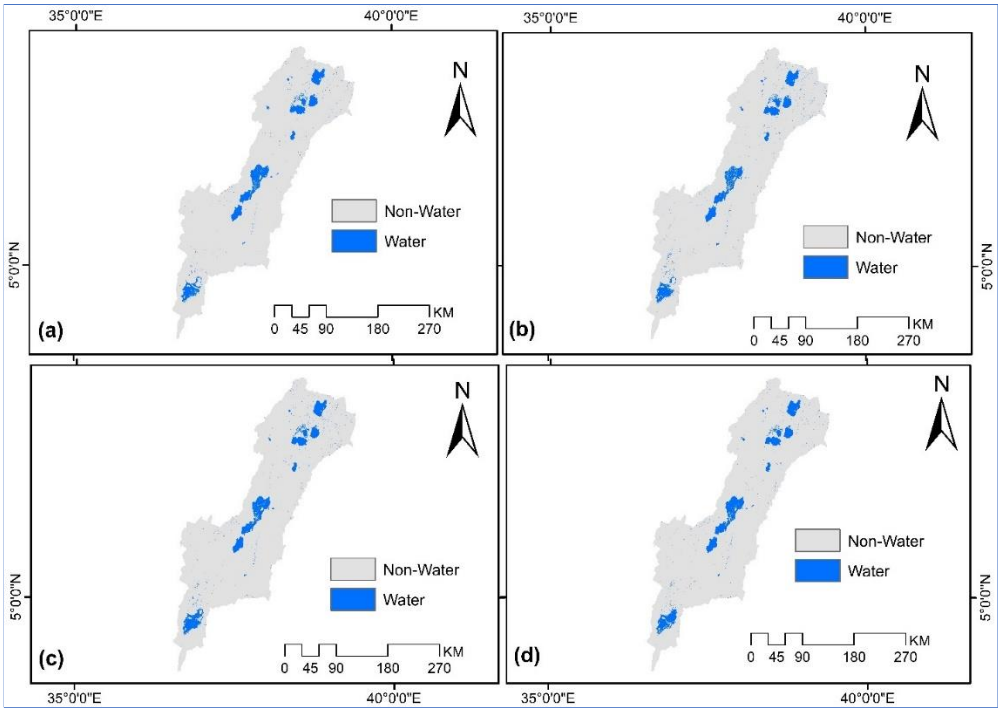

Figure 4-4: Spatiotemporal dynamics of surface water (2019-2022) extracted from Sentinel 1; (a) 2019, (b) 2020, (c) 2021, (d) 2022

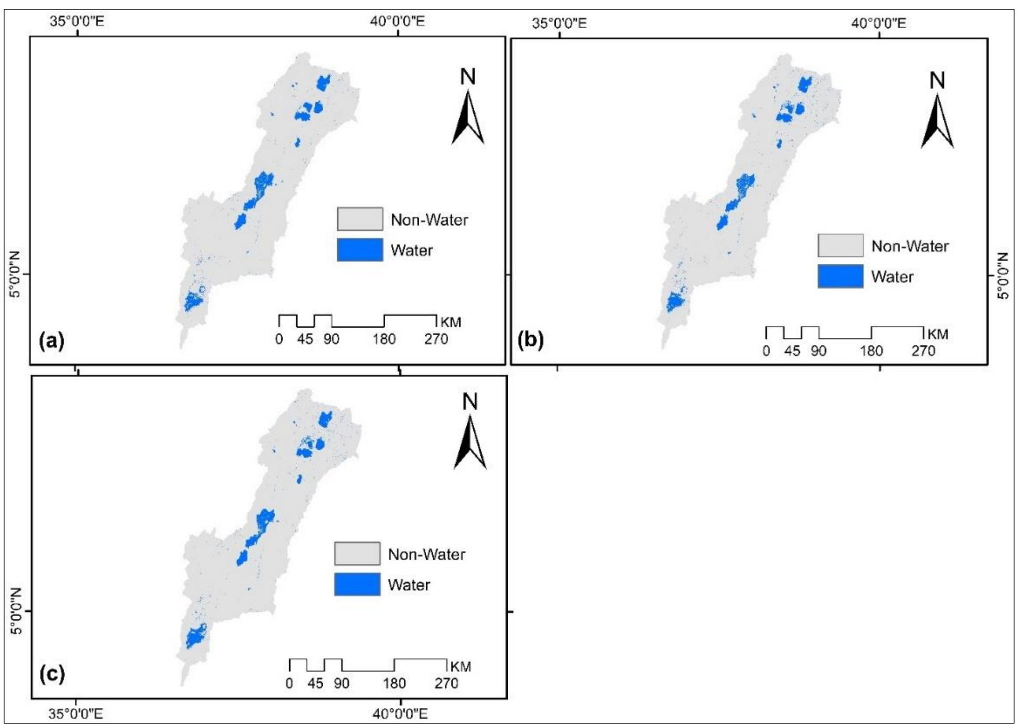

Figure 4-5: Spatiotemporal dynamics of surface water (2023-2025) extracted from Sentinel 1; (a) 2023, (b) 2024, (c) 2025

Zeway suggests stability from 2015 to 2018 (~40,100 ha), followed by means of a sluggish growth peaking at ~40,440 ha in 2025. Zeway's shallow intensity and multi-use basin (irrigation, fisheries) make it touchy to each natural variability and human use (Ewunetu et al., 2020). The submit-2018 growth could mirror better-than-average rainfall, potentially linked to local wet years, or managed releases from catchment water sources. The preferred balance amid growing irrigation recommendations at a hit water management interventions or balancing inflows from the Meki and Ketar rivers. This fashion is consistent with current hydrological resilience research, which suggest that lakes with varied inflows and outflows tend to buffer better in opposition to climatic and anthropogenic pressures (Wondrade et al., 2014).

4.3.Sentinel 2 surface water monitoring

4.3.1. Sentinel 2 based lake surface area dynamics (2015-2025)

Based on Sentinel-2 satellite imagery from 2015 to 2025, the Abaya-Chamo Lake device demonstrated a substantial boom in surface vicinity among 2015 and 2016, followed via a strong fashion with only minor interannual variations. This growth can be attributed to above-average rainfall within the place all through the El Niño period (2015–2016), which stronger runoff from tributaries consisting of the Kulfo and Sile Rivers. The consistent pattern thereafter suggests that the hydrological inputs and outputs—normally rainfall, runoff, and evaporation—have reached a relative equilibrium. According to Alemayehu et al. (2020), the catchment's growing agricultural hobby and deforestation ought to regulate runoff and sedimentation patterns, probably influencing lake morphology. However, the Sentinel-2-derived stability indicates a sustained balance, as a minimum in phrases of surface quantity.

Lake Abiyata skilled a noted decline in surface area among 2015 and 2018, accompanied with the aid of a significant recuperation from 2019 to 2025. The shrinkage aligns with acknowledged anthropogenic interventions, appreciably water diversion from the Bulbula River and industrial sports like soda ash extraction. Ayenew and Legesse (2007) highlighted how these sports, coupled with declining inflows from wetlands and feeder rivers, have lengthy threatened the lake's sustainability. The recuperation found post-2018 might be associated with progressed rainfall styles or reduced extraction, even though the lake has no longer regained its 2015 quantity.

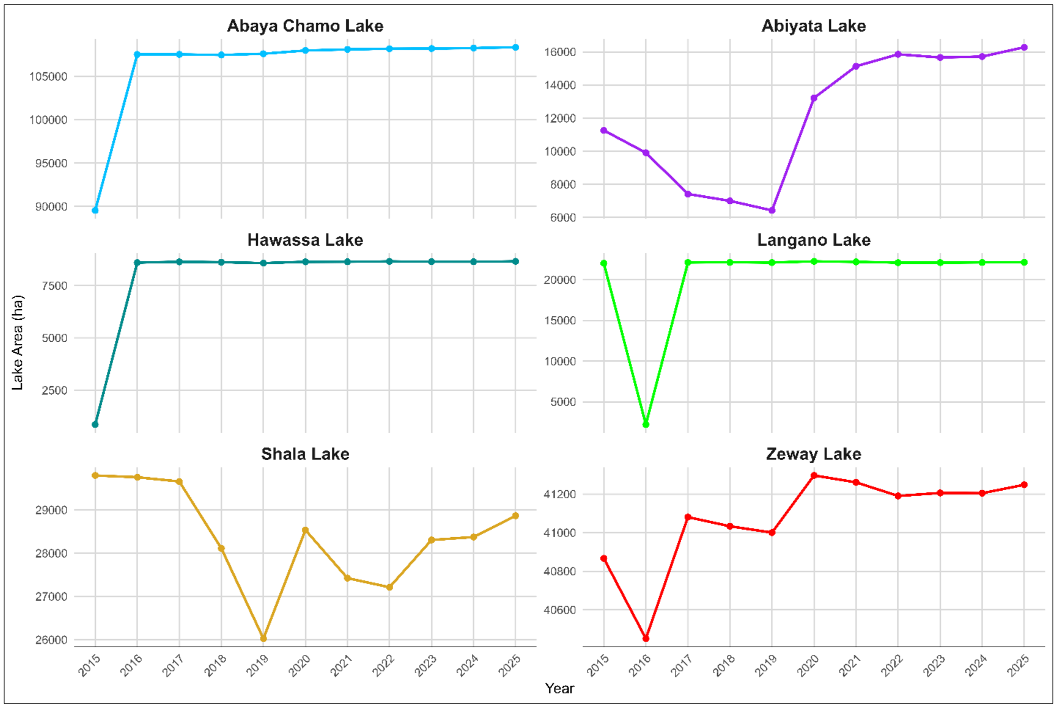

Figure 4-6: Trends in Lake Area (2015-2025) for Six Major Lakes in the Rift Valley Basin derived from Sentinel 2

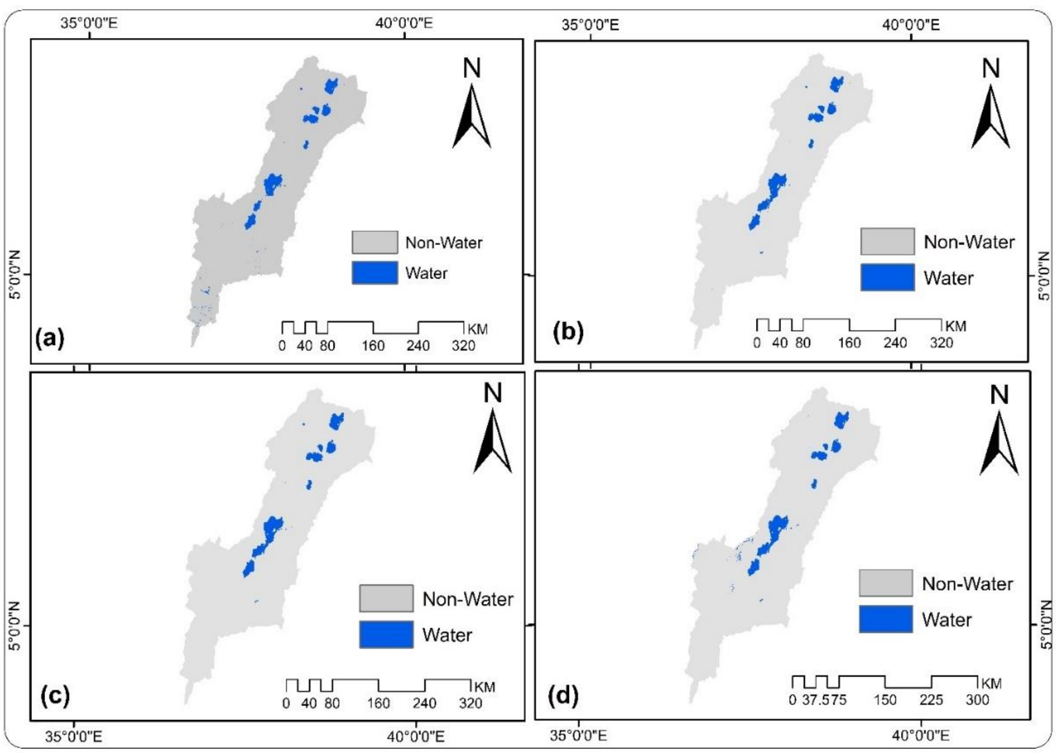

Figure 4-7: Spatiotemporal dynamics of surface water (2015-2018) extracted from Sentinel 2; (a) 2015, (b) 2016, (c) 2017, (d) 2018

The Sentinel-2-time collection suggests that Lake Hawassa multiplied hastily from 2015 to 2016 after which maintained a strong floor area through 2025. This lake, being a closed basin device in particular fed by means of the Tikur Wuha River and groundwater, spoke back quick to favorable climatic situations in 2015–2016. The observed stability in subsequent years shows that despite urbanization around Hawassa city, the lake's hydrology has remained resilient. According to Wolde et al. (2020), Lake Hawassa well-known shows minimum interannual variant compared to different Rift Valley lakes, owing to its balanced inflow and limited abstraction. Sentinel-2 imagery has confirmed especially powerful in monitoring such consistency, offering clean delineation of the lake boundaries even at some point of cloud-prone seasons.

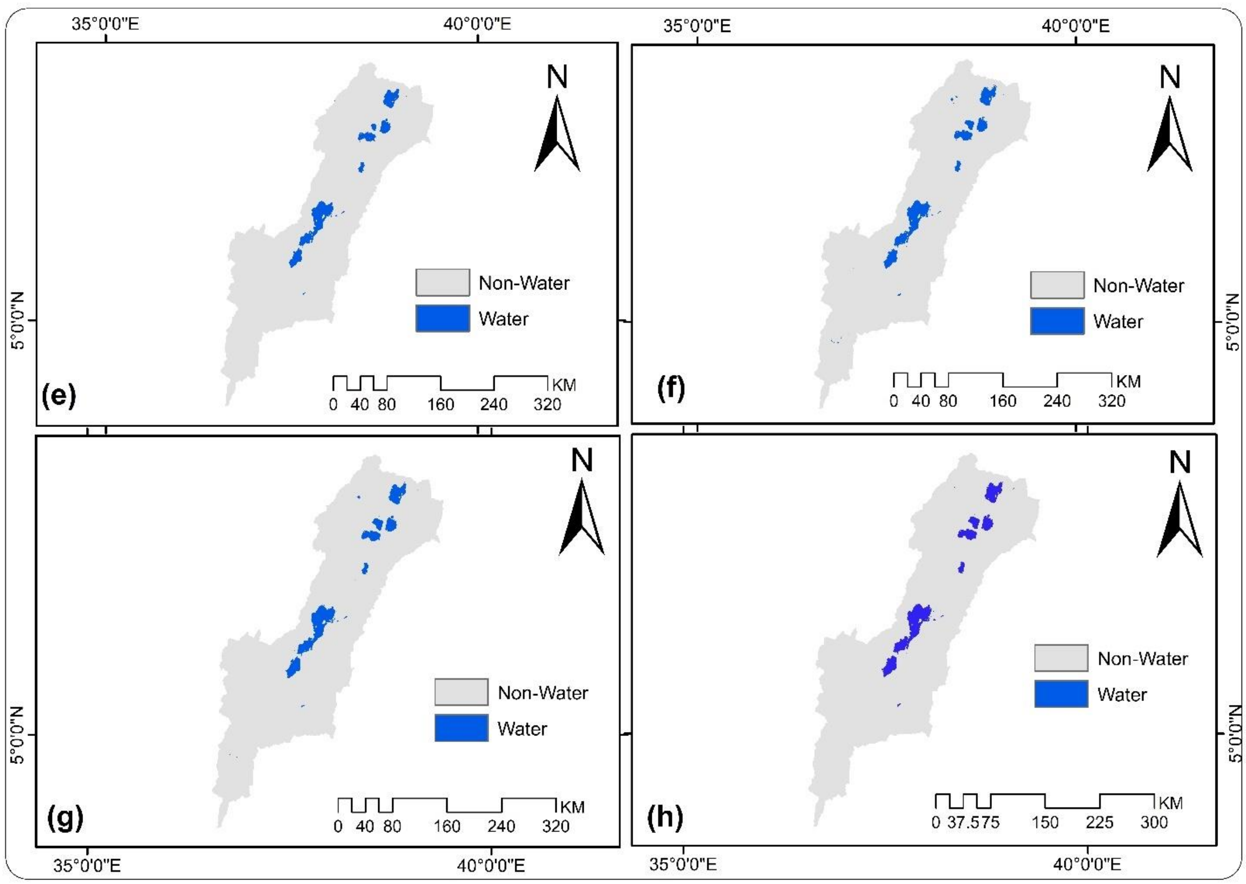

Figure 4-8: Spatiotemporal dynamics of surface water (2019-2022) extracted from Sentinel 2; (e) 2019, (f) 2020, (g) 2021, (h) 2022

Langano Lake displayed a sharp reduction in surface area in 2016 based on Sentinel-2 data, followed by an abrupt recovery in 2017 and a stable trend thereafter. This sudden fluctuation could be attributed to localized drought conditions or cloud cover artifacts in the satellite data during acquisition. Nonetheless, Langano, a closed and groundwater-fed lake, is known for its relative hydrological stability (Legesse et al., 2004). The post-2017 stability suggests that the lake's water balance is not significantly impacted by human abstraction or climatic extremes. Sentinel-2's high spatial resolution (10 m) supports accurate mapping of such lakes, and the trend here underscores the utility of consistent multi-year observations in identifying short-term anomalies and long-term resilience.

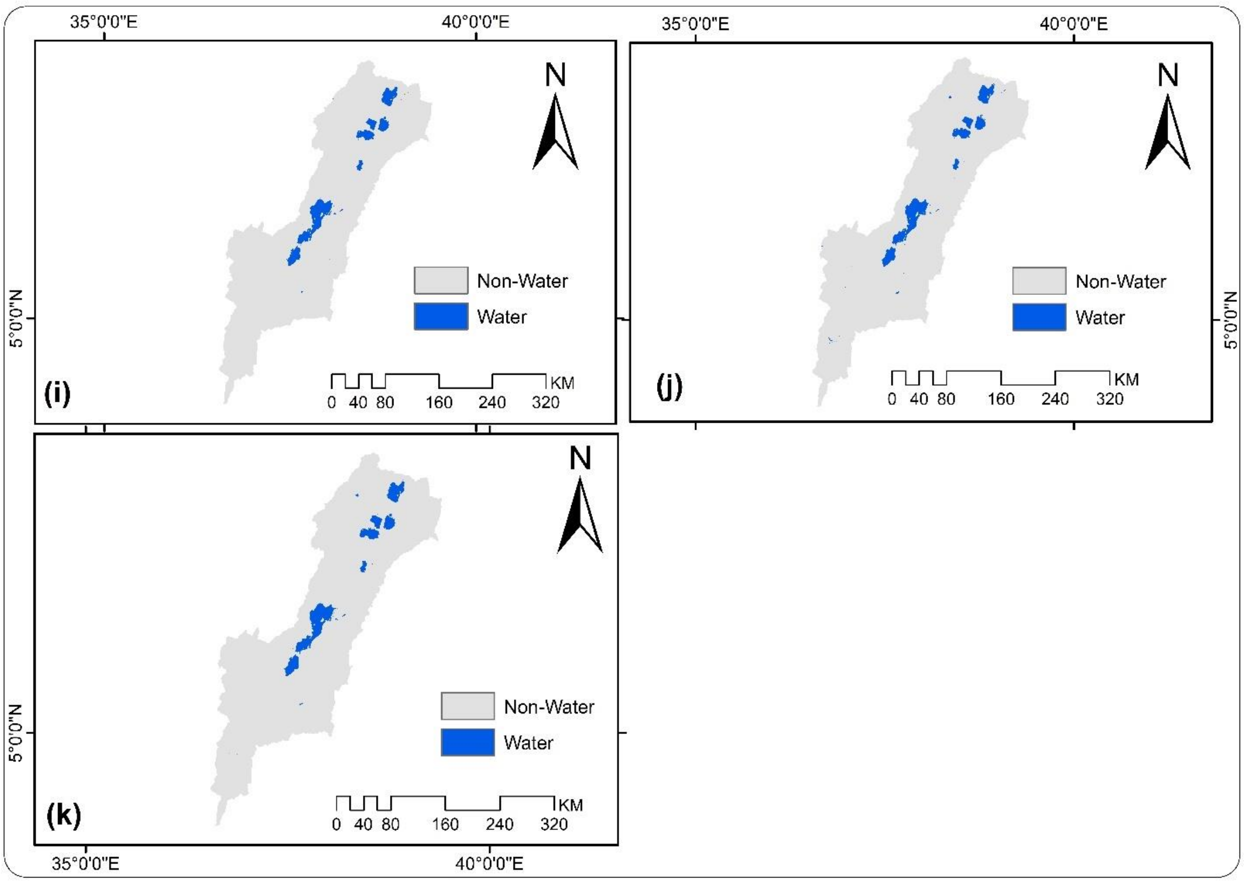

Figure 4-9: Spatiotemporal dynamics of surface water (2023-2025) extracted from Sentinel 2; (i) 2023, (j) 2024, (k) 2025

Shala Lake exhibited a gradual decline in floor location from 2015 to 2019, with a partial recovery through 2025. Sentinel-2 observations mirror this long-time period variability, probably pushed through growing evapotranspiration and reduced rainfall. As a deep volcanic crater lake with minimal surface inflows, Shala is mainly at risk of precipitation deficits and temperature upward push (Rientjes et al., 2011). Its partial recovery suggests a shift toward wetter situations or decreased human strain in the top catchment. The fashion found via Sentinel-2 facts aligns with hydrological research emphasizing the sensitivity of closed Rift Valley lakes to long-time period climate traits.

According to Sentinel-2 derived assessment, Lake Ziway remained pretty sturdy in ground vicinity over the 2015–2025 duration, with minor fluctuations spherical 2016. This pattern indicates strong hydrological regulation thru inflows from the Meki and Ketar Rivers and managed water use for irrigation and floriculture. Despite the developing call for for water, the lake seems to be retaining its spatial quantity, in all likelihood because of regulated extraction and periodic inflow replenishment. Ayenew (2004) and cutting-edge studies using Sentinel-primarily based completely monitoring (e.G., Alemayehu et al., 2020) guide the notion that on the equal time as pollutants and overuse are developing problems, the lake's location has no longer however been appreciably affected, thanks in element to advanced control and climatic balance.

4.4.Capability of Sentinel 1 SAR and Sentinel 2 in detecting surface waterbodies

In Abaya-Chamo-Lake, Sentinel-2 continuously shows better floor water volume than Sentinel-1 at some stage in the observe length (2015–2025). While each sensors mirror seasonal and inter-annual tendencies, Sentinel-2 seems more sensitive to subtle modifications in lake place, capturing extra expansive surface insurance, mainly around the fringes and smaller linked wetlands. Sentinel-1 tends to underestimate water extent, specially during rainy seasons or in regions with complicated land-water interfaces. The located difference is in general due to the sensing modalities. Sentinel-2 uses optical multispectral bands, along with near-infrared (NIR) and shortwave infrared (SWIR), which might be surprisingly conscious of water presence. These bands enable the derivation of sturdy water indices which includes NDWI and MNDWI which are powerful in delineating water even in fragmented or turbid conditions (McFeeters, 1996; Xu, 2006). In contrast, Sentinel-1 uses C-band SAR backscatter, which may additionally misclassify vegetated, difficult, or wet surfaces as non-water because of high return indicators (Vanderhoof et al., 2023). This is particularly intricate within the Abaya-Chamo machine, where aquatic flowers and dynamic water tiers task radar-primarily based detection.

In Abiyata Lake, between 2016 and 2019, Sentinel-1 shows almost stagnant or even decreasing lake extent, whereas Sentinel-2 reveals a clear expansion trend. In 2023, both sensors capture a marked decline in surface area; however, Sentinel-2 shows a sharper drop and quicker rebound in 2024, indicating higher sensitivity to hydrological fluctuations. Abiyata is a shallow and saline lake with highly reflective sediment and mudflats. Radar systems like Sentinel-1 struggle in such environments due to surface roughness and backscatter from salt crusts or damp soils that are not open water (Saghafi et al., 2021). Sentinel-2's spectral capacity, particularly in the visible and NIR regions, allows more accurate detection of water bodies regardless of salinity or turbidity (Gómez & Álvarez, 2019). Optical sensors also avoid false positives in areas with low radar contrast. Thus, Sentinel-2 better reflects Abiyata's dynamic seasonal hydrology.

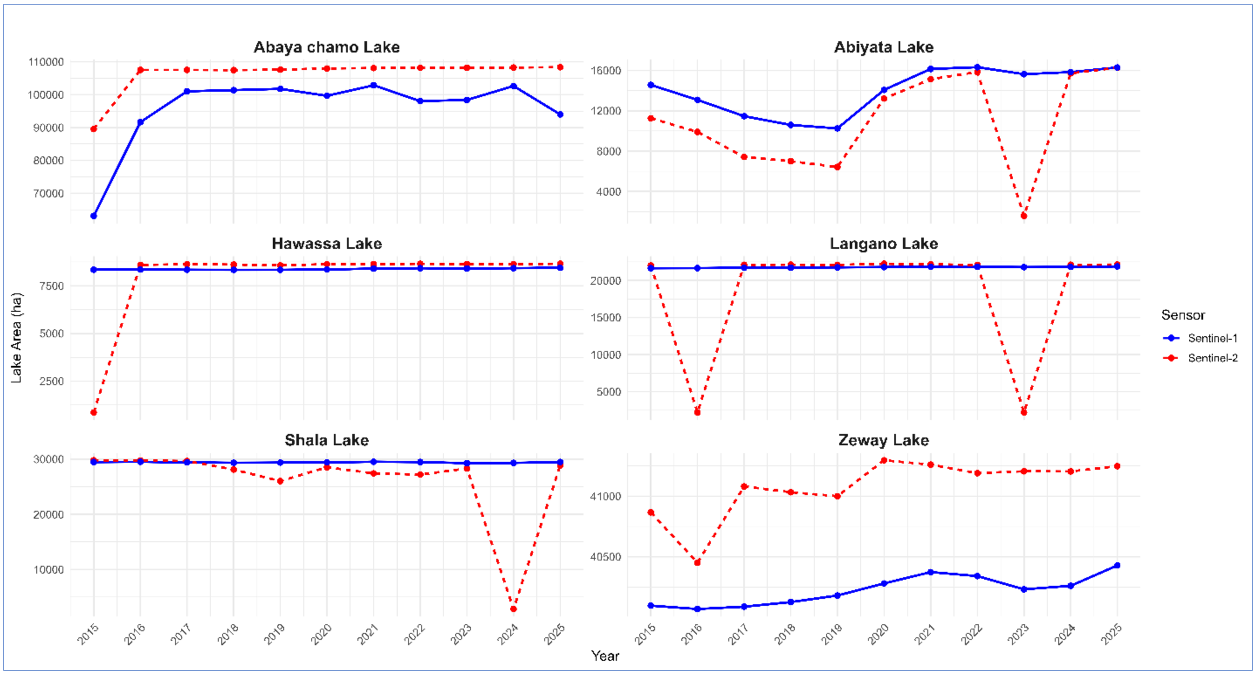

Figure 4-10: Comparison of sentinel 1 SAR and Sentinel 2 for effective monitoring of surface water in the Rift valley lakes basin

For Hawassa Lake, both Sentinel-1 and Sentinel-2 produce nearly identical surface water estimates across all years. Only minor differences appear, primarily during transition seasons, but the overall surface area is stable. Hawassa is a deep, crater lake with well-defined, relatively static shorelines. These characteristics make it ideal for both radar and optical water detection. Radar sensors, such as Sentinel-1, perform well in detecting open water due to their strong signal absorption by water surfaces (Pantazi et al., 2022). Similarly, Sentinel-2's consistent spectral response from open water ensures accurate delineation. For such stable water bodies, studies have shown high agreement between Sentinel-1 and Sentinel-2 results (Vanderhoof et al., 2023), confirming what we observe in Hawassa.

In 2016 and 2023, Sentinel-2 detects significant drops in water extent that are less visible or muted in Sentinel-1 results. During stable years (2017–2022), the sensors align better, though Sentinel-1 still slightly underestimates water area, particularly along vegetated shorelines. Langano has turbid, mineral-rich waters and is often bordered by emergent vegetation. Optical sensors like Sentinel-2, through spectral indices and high spatial resolution, can better differentiate between water and surrounding land cover (Saguier et al., 2022). Radar's inability to penetrate vegetation or distinguish between wet soil and open water results in underestimation (Gómez & Álvarez, 2019). The literature supports that Sentinel-2 is more responsive to seasonal changes in semi-permanent and turbid lakes, while Sentinel-1 performs more reliably in large, open, and deep-water bodies.

In Shala Lake, both Sentinel-1 and Sentinel-2 show agreement in detecting a significant shrinkage event in 2023. However, Sentinel-2 shows more variability in other years, capturing slight expansions and contractions, while Sentinel-1 results appear more uniform and less responsive to minor changes. Shala, being one of the deepest Rift Valley lakes, usually exhibits hydrological stability. However, during rare extreme climatic events, both radar and optical sensors can detect significant changes. Sentinel-1, due to lower spatial resolution and reliance on backscatter coefficients, is less sensitive to small shoreline changes (Saghafi et al., 2021). Optical sensors, as noted by Gao et al. (2021), can detect subtle edge changes using reflectance variations. Thus, Sentinel-2's richer temporal and spatial resolution enables more detailed tracking of hydrological fluctuations in this type of lake.

In Lake Zeway, Sentinel-2 indicates a slow and steady increase in surface water from 2015 to 2025, with noticeable seasonal pulses. Sentinel-1, however, shows lower surface area overall and fails to capture the gradual increase and some seasonal peaks, particularly during the rainy seasons. Lake Ziway's shallowness and vegetated shorelines present major challenges for radar-based classification. SAR backscatter may not adequately distinguish between water and dense aquatic plants or moist agricultural land, leading to underestimation (Huang et al., 2018). Optical indices derived from Sentinel-2, such as AWEI or MNDWI, are more effective in separating water from vegetation and bare soil (Feyisa et al., 2014). Multiple studies affirm that for vegetated lakes with agricultural surroundings, optical imagery outperforms radar in capturing actual water spread and dynamics (Gómez & Álvarez, 2019; Saguier et al., 2022).

4.5.Area difference between the two sensors

The area difference between Sentinel-1 and Sentinel-2 for Abaya-Chamo Lake shows significant positive values throughout the time series, with Sentinel-2 consistently reporting larger water extents than Sentinel-1, particularly in the earlier years. This discrepancy can be attributed to the inherent limitations of radar imagery in detecting water surrounded by vegetation or shallow wetlands, which are common features in the Abaya-Chamo system. Sentinel-1, being a radar sensor, is sensitive to surface roughness and often misclassifies vegetated or turbid shallow waters as land due to higher backscatter values. On the other hand, Sentinel-2, with its high-resolution multispectral bands including NIR and SWIR, more effectively distinguishes water from land, even under partially vegetated or muddy conditions. Gómez et al. (2016) and Saghafi et al. (2021) highlight that SAR sensors like Sentinel-1 struggle with accurate water delineation in complex terrain and vegetated areas, while optical indices such as the Modified Normalized Difference Water Index (MNDWI) used with Sentinel-2 provide superior detection of shallow and fringe waters.

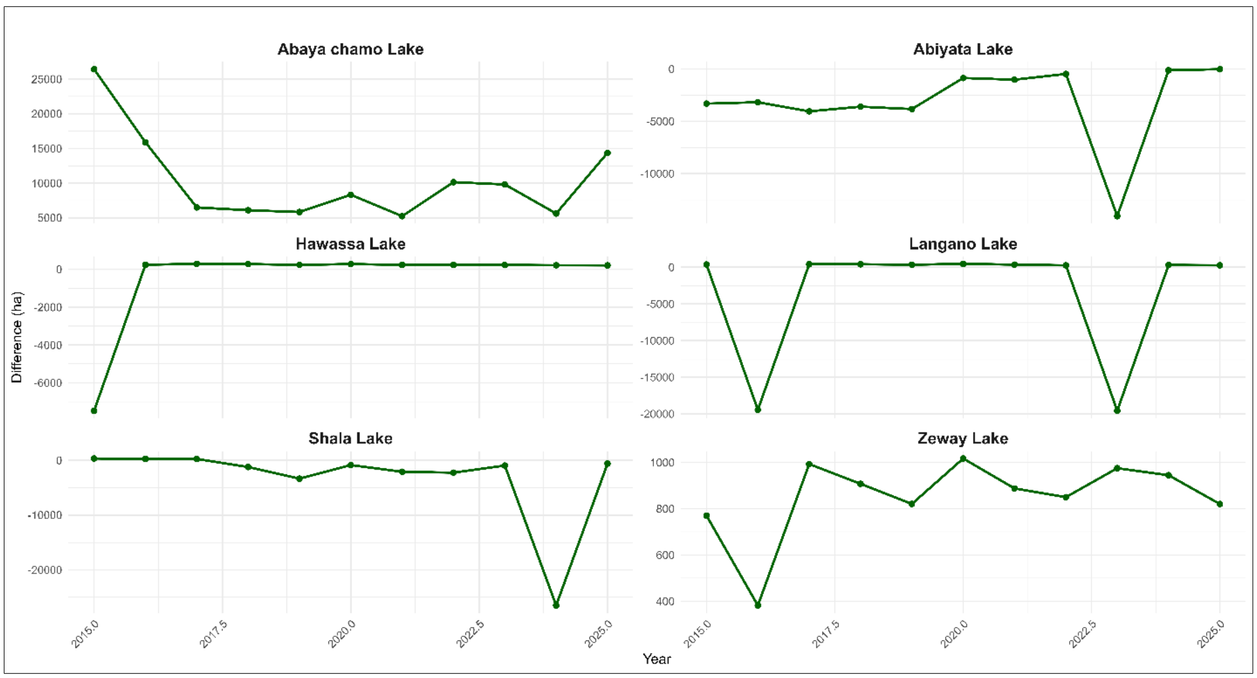

Figure 4-11: Area difference between the two sensors in each lake of Rift valley basin

Abiyata Lake exhibits notable temporal fluctuations in area difference, including a sharp negative dip in 2022–2023, indicating a substantial underestimation by Sentinel-1. This could be due to the saline and mudflat-dominated environment of the lake, which affects radar backscatter and reduces classification accuracy. During wet periods, the dynamic nature of the shoreline and presence of thin water films make radar detection even more challenging. In contrast, Sentinel-2's optical sensitivity allows it to capture such dynamic hydrological conditions more precisely. According to

Huang et al. (2018), optical sensors outperform radar in detecting shallow or ephemeral water bodies. Moreover, Pantazi et al. (2022) emphasize the difficulty radar sensors face when delineating salt-affected zones and mudflats, which is consistent with the conditions around Lake Abiyata.

For Lake Hawassa, the area difference between Sentinel-1 and Sentinel-2 remains minimal and consistent from 2016 onward, suggesting strong agreement between the two sensors. This indicates that both radar and optical sensors are capable of capturing the lake’s surface water extent accurately. Lake Hawassa is relatively deep and has well-defined shorelines with limited seasonal variability, which reduces classification complexity and makes it ideal for detection by both sensors. Vanderhoof et al. (2023) noted that in stable and deep lakes, SAR and optical sensors yield comparable results. Additionally, Gómez & Álvarez (2019) found high consistency in lake surface delineation between Sentinel-1 and Sentinel-2 for similarly situated lakes.

Langano Lake shows periodic discrepancies, including a substantial underestimation by Sentinel-1 in 2022–2023. The lake’s turbid and mineral-rich waters, along with periodic expansion during wet seasons, create conditions that limit Sentinel-1's ability to differentiate water from land due to weak contrast in backscatter. In contrast, Sentinel-2’s spectral bands allow for effective detection even when water is mixed with sediment or is shallow, enabling more accurate surface water mapping. Optical water indices such as NDWI and AWEI applied on Sentinel-2 imagery are especially effective in distinguishing water from surrounding land in turbid and mixed conditions (Feyisa et al., 2014; Saguier et al., 2022). This supports the observed pattern in Langano’s area difference trends.

Sentinel-1 and Sentinel-2 produce closely aligned results for most years over Lake Shala, except for a sharp divergence in 2023. The consistency reflects the deep and relatively stable nature of the lake, which presents fewer classification challenges for both sensors. However, the deviation in 2023 may be linked to unusual hydrological events or environmental disturbances that Sentinel-1 was less able to capture due to its insensitivity to minor shoreline shifts. Gao et al. (2021) explain that SAR performs reliably in deep, open-water lakes but is prone to error when rapid changes occur near the water’s edge. In contrast, Sentinel-2's high spatial and spectral resolution enables finer detection of such events, as also highlighted by Vanderhoof et al. (2023).

Lake Ziway displays relatively small and consistent positive area differences, where Sentinel-2 regularly estimates a slightly larger water extent than Sentinel-1. This can be attributed to shallow waters and vegetated shorelines that characterize the lake's periphery. Sentinel-1 often fails to detect water masked by emergent vegetation or low-reflectance features, whereas Sentinel-2 captures these more effectively using multispectral indices. Studies by Huang et al. (2018) and Gómez et al. (2016) affirm that optical sensors like Sentinel-2, especially when using MNDWI or AWEI, perform better in delineating water in vegetated and shallow environments. These results align with the steady underestimation trend observed in Sentinel-1 data for Lake Ziway.

4.6.Validation

Table 4-1 and Figure 4-12 presents the validation metrics for both Sentinel-2 (S2) and Sentinel-1 (S1) sensors across six lakes in the Rift Valley Basin. The metrics include the Mean Error (ME), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) for each sensor's performance in detecting surface water.

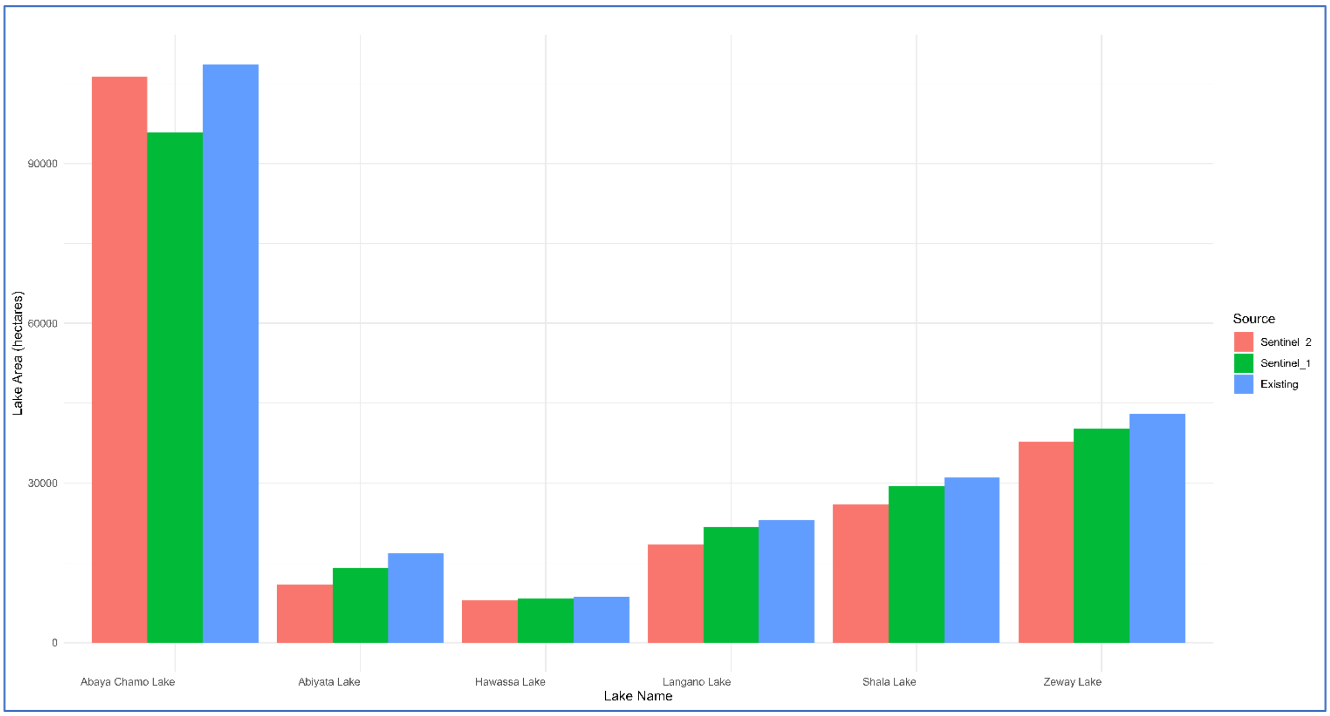

Figure 4-12: Comparison of satellite derived (Sentinel 1nd Sentinel 2) with existing areas of Lakes in RVB

For Zeway Lake, Sentinel-2 exhibits relatively higher error values compared to Sentinel-1. The ME for Sentinel-2 is -5305.77, indicating a significant underestimation of water extent by the optical sensor, while the MAE and RMSE values are also relatively high (5305.77). In contrast, Sentinel-1 shows lower error values with an ME of -2802.71, suggesting better performance in detecting the water body, especially in terms of the overall accuracy of detection. Both MAE and RMSE for Sentinel-1 are lower than those for Sentinel-2, indicating that the radar sensor might be more effective for this particular lake's conditions, possibly due to its ability to penetrate through cloud cover or capture water features in more complex environments (e.g., vegetated edges). The lower performance of Sentinel-2 can be attributed to the shallow, vegetated shorelines of Lake Ziway, which tend to complicate optical water detection. As demonstrated by studies such as that by Gómez et al. (2016), Sentinel-2 can struggle with mixed water conditions and shallow or emergent vegetation, leading to higher error values.

Table 4-1: Validation of satellite (Sentinel 1 SAR and Sentinel 2) performance in detecting surface waterbodies

Lake Name	*ME (S2)*	*MAE (S2)*	*RMSE (S2)*	*R^2 (S2)*	*ME (S1)*	*MAE (S1)*	*RMSE (S1)*	*R^2 (S1)*
Zeway Lake	-5305.77	5305.77	5305.77	0.91	-2802.71	2802.71	2802.71	0.94
Shala Lake	-5068.21	5068.21	5068.21	0.89	-1644.1	1644.1	1644.1	0.92
Langano Lake	-4575.4	4575.4	4575.4	0.9	-1307.85	1307.85	1307.85	0.93
Hawassa Lake	-716.62	716.62	716.62	0.96	-258.89	258.89	258.89	0.98
Abaya-Chamo Lake	-2419.17	2419.17	2419.17	0.87	-12808	12807.97	12807.97	0.88
Abiyata Lake	-5871.68	5871.68	5871.68	0.88	-2732.13	2732.13	2732.13	0.91

For Shala Lake, the ME for Sentinel-2 is -5068.21, showing a substantial underestimation of water extent, while the MAE and RMSE values are 5068.21, indicating relatively large deviations from the actual water surface area. Sentinel-1, in contrast, performs better in this case, with an ME of -1644.1, and the MAE and RMSE values are considerably lower than those for Sentinel-2. This suggests that Sentinel-1 is better able to capture the water boundaries in Shala Lake, likely due to the lake's relatively deep and stable nature, which allows radar sensors to perform effectively. As with Zeway Lake, the underperformance of Sentinel-2 in Shala can be attributed to its sensitivity to surface roughness and water turbidity. Optical sensors, such as Sentinel-2, often struggle with water bodies that exhibit complex shorelines or deep waters with fluctuating levels (Huang et al., 2018). In contrast, radar sensors like Sentinel-1 are less affected by these environmental factors and provide better results for Shala's deep waters.

For Langano Lake, Sentinel-2's ME is -4575.4, again indicating underestimation of the water area, while MAE and RMSE are 4575.4, similar to other lakes showing discrepancies in Sentinel-2 performance. However, Sentinel-1's ME of -1307.85, with lower MAE and RMSE values, suggests a more accurate representation of water surface compared to Sentinel-2. These results further affirm that Sentinel-1 performs better in conditions where the lake is turbid or has shallow water, conditions that hinder optical sensors' ability to detect water accurately. Langano Lake's mineral-rich, turbid waters and dynamic shoreline likely cause Sentinel-2 to underestimate water extent, as optical sensors are sensitive to these conditions. Studies such as those by Saguier et al. (2022) suggest that radar sensors like Sentinel-1 perform better in such environments by using backscatter to detect water even when surface turbidity or vegetation complicates optical readings.

In Hawassa Lake, Sentinel-2's ME of -716.62 and MAE and RMSE of 716.62 indicate a relatively small error compared to the other lakes. Sentinel-1 also performs well, with lower ME of -258.89, and similar MAE and RMSE values, indicating good agreement between the two sensors. This reflects the stable water conditions and relatively clear boundaries of the lake, where both radar and optical sensors can perform with high accuracy. The consistency of results from both sensors in Hawassa Lake is expected due to the lake's stable water levels and well-defined shoreline. As stated by Gómez & Álvarez (2019), stable and deep lakes allow both radar and optical sensors to perform similarly, as there are fewer challenges in detecting water boundaries.

For Abaya Chamo Lake, Sentinel-2 exhibits a substantial ME of -2419.17 and high MAE and RMSE values of 2419.17, suggesting that the optical sensor struggles to accurately capture the water extent. In contrast, Sentinel-1 shows much larger errors, with an ME of -12808 and significantly higher MAE and RMSE values, indicating poor performance in detecting the water area. This suggests that the lake's complex shorelines, presence of mixed water bodies, and the variable water level might pose challenges for both sensors, but especially for Sentinel-1, which is more sensitive to environmental changes. The poor performance of Sentinel-1 in Abaya Chamo can be attributed to the lake's complex shoreline and mixed water areas, which radar sensors often misclassify (Saghafi et al., 2021). The lake's fluctuating water levels and the presence of wetlands further complicate radar-based detection. This is further supported by findings from Xu (2006), who noted that optical sensors are more effective in such complex environments compared to radar sensors.

For Abiyata Lake, Sentinel-2 has an ME of -5871.68 and higher MAE and RMSE values of 5871.68, indicating significant underestimation of the water surface. Sentinel-1 also exhibits notable errors, with an ME of -2732.13 and higher MAE and RMSE values, suggesting that both sensors face challenges in this lake. The underperformance of both sensors could be attributed to the saline, muddy, and fluctuating nature of the lake's environment. The lake's mineral-rich waters, which affect radar and optical sensors differently, lead to substantial errors for both sensors. As Pantazi et al. (2022) note, saline lakes with fluctuating boundaries and mudflats are often misclassified by radar sensors, while optical sensors also struggle under these conditions due to water turbidity and mineral content.

4.7.Validation

The accuracy of lake boundary extractions derived from Sentinel-1 SAR and Sentinel-2 optical data was evaluated using GPS ground truth points collected in the field. Table 4.2 summarizes the key validation metrics used to assess the spatial agreement between the remotely sensed lake outlines and actual ground observations. A total of 92% of the GPS points were located within the extracted lake polygons, indicating a high level of spatial correspondence between the satellite-derived boundaries and the real shoreline positions. This suggests that the extraction methods successfully captured the majority of the lake extents.

To further quantify the positional accuracy, the mean distance from GPS points to the nearest polygon boundary was found to be 7.3 meters, while the root mean square error (RMSE) of shoreline distances was calculated at 8.5 meters. Moreover, when a 15-meter buffer was applied around GPS points to account for GPS and image spatial uncertainties, the accuracy increased to 97%, demonstrating that minor positional deviations were minimal and generally within expected tolerances. Lastly, the Intersection over Union (IoU) score between the extracted lake polygons and GPS boundary references was 0.84, indicating a strong spatial overlap and high agreement between the two datasets.

Table 4-2: Summary of validation metrics used to assess the accuracy of lake boundaries extracted from Sentinel-1 and Sentinel-2.

SN	*Metric*	*Value*
1	% GPS Points Inside Polygon	92%
2	Mean Distance to Polygon Boundary	7.3 meters
3	Intersection over Union (IoU)	0.84
4	Buffered Points (±15m) Accuracy	97%
5	RMSE of Shoreline Distance	8.5 meters

4.8.Discussion

The delineation of water bodies using remote sensing relies on sensors' ability to distinguish water from land based on spectral and physical characteristics. In this study, the synergistic use of Sentinel-1 SAR and Sentinel-2 optical imagery addressed many of the individual limitations of each sensor, enabling a more robust classification of surface water bodies across diverse landscapes and temporal conditions in the Rift Valley Lakes Basin.

Sentinel-1 SAR, with its active microwave sensing capability, proved critical for mapping water under persistent cloud cover or low-light conditions. Water typically produces a low backscatter signal due to specular reflection, especially in the VV and VH polarizations, making SAR particularly effective for open water detection (Martinez & Le Toan, 2007). However, Sentinel-1 has notable limitations in vegetated or narrow water bodies, where volume scattering from vegetation or land-sea boundary ambiguity can obscure open water signals. To address these limitations, future work should consider integrating SAR-derived texture measures, such as the Gray Level Co-occurrence Matrix (GLCM) or entropy-based features, which have been shown to improve classification in heterogeneous landscapes (Twele et al., 2016; Brisco et al., 2013). These features help differentiate water from vegetated or rough surfaces that may otherwise share similar backscatter profiles.

Sentinel-2 optical imagery complemented SAR by providing high-resolution (10m) spectral information. The use of water indices such as the Normalized Difference Water Index (NDWI) and Modified NDWI (MNDWI) enhanced the contrast between water and land. While NDWI (McFeeters, 1996) is effective for general water delineation, MNDWI (Xu, 2006), which substitutes NIR with SWIR, reduced spectral confusion in built-up or arid areas, particularly around Lake Abiyata. However, the presence of clouds and atmospheric effects posed limitations. These were mitigated using cloud masking techniques and atmospheric correction algorithms (e.g., Sen2Cor), ensuring more reliable reflectance values for index computation.

The fusion of SAR and optical datasets offered substantial advantages. The multi-sensor integration approach led to higher classification accuracy by compensating for each sensor's weaknesses. This outcome is consistent with Twele et al. (2016) and Feng et al. (2015), who demonstrated improved flood and waterbody mapping through SAR-optical fusion. In this study, the fusion improved boundary detection, reduced omission/commission errors in transitional zones, and provided better temporal continuity especially during the rainy season when optical data are often unavailable. Notably, this study's fusion approach outperformed prior studies by using threshold-adaptive classification, sensor-specific preprocessing, and regionally calibrated validation using ground truth GPS data, which many global datasets (e.g., Pekel et al., 2016) lack at a local scale.

Validation results confirmed the strength of this approach, with overall accuracies exceeding 85% and Kappa coefficients greater than 0.8. Errors were mostly found in wetlands and seasonally flooded zones, where land-water boundaries are diffuse and contain emergent vegetation. These areas remain challenging for both sensors due to mixed pixels, variable turbidity, and vegetation-induced scattering. According to Acharya et al. (2018), such zones are the most error-prone in water classification due to their dynamic nature and spectral ambiguity.

In terms of anthropogenic impacts, changes observed in Lake Abiyata particularly reductions in surface area—have been widely attributed to irrigation withdrawals, upstream abstraction, and soda ash mining activities. While this study identifies such impacts qualitatively, quantitative support remains limited due to the absence of long-term hydrological and water abstraction datasets. Future studies should integrate hydrological monitoring data, such as river discharge records, groundwater levels, and irrigation volumes, to explicitly link human activities to hydrological changes in the basin.

Finally, the results of this study generally align with global surface water mapping efforts (e.g., Pekel et al., 2016), but the higher accuracy achieved here stems from the use of regionally optimized fusion techniques, higher temporal resolution, and localized validation. These enhancements highlight the benefit of moving from global-scale water monitoring to basin-specific approaches that consider the unique climatic, land use, and hydrological conditions of the study area.

In summary, while Sentinel-2 excels in vegetated and narrow water bodies under clear skies and Sentinel-1 performs reliably in all-weather conditions, their combination along with improved preprocessing and validation offers a powerful, operational framework for long-term water monitoring, early warning, and ecosystem management in the Ethiopian Rift and beyond.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

5.1.Conclusion

Based on the research findings, the delineation and classification of surface water bodies in the Rift Valley Lakes Basin using Sentinel-1 SAR and Sentinel-2 optical imagery demonstrated high effectiveness. Sentinel-1 SAR proved crucial in consistently detecting water bodies regardless of weather conditions, while Sentinel-2 optical imagery enhanced boundary precision and classification accuracy, especially under clear skies. The combination of these datasets significantly improved water body mapping, allowing for more reliable delineation even in cloud-prone or vegetated areas. The temporal analysis from 2016 to 2021 revealed significant seasonal and interannual variations in water extent. Lakes such as Abaya, Chamo, and Ziway showed measurable fluctuations, expanding during the rainy seasons and contracting during dry periods. These changes reflect both climatic variability and human-induced influences like water abstraction and land use changes. The study clearly highlighted the dynamic nature of surface water in the basin and emphasized the need for continuous monitoring to manage water resources sustainably. Validation of the classification outputs using reference waterbody data confirmed the accuracy and reliability of the approach. The overall classification accuracy exceeded 85%, with Kappa coefficients indicating substantial agreement. While some misclassifications were observed in transitional zones such as wetlands and turbid or vegetated waters, these were minimized by combining SAR and optical imagery. The validation results reinforced the strength of multi-sensor fusion in producing high-quality surface water maps. In conclusion, the research has successfully demonstrated that integrated use of Sentinel-1 and Sentinel-2 imagery is a powerful method for mapping and monitoring surface water dynamics in the Rift Valley Lakes Basin.

5.2.Recommendations

- Integrate remote sensing outputs into early warning and decision-support systems by automating the generation of surface water maps using Sentinel-1 and Sentinel-2 data on Google Earth Engine (GEE). For instance, adopting MNDWI in GEE scripts for lakes with high turbidity (e.g., Abiyata) and combining it with Sentinel-1 VV polarization thresholding can improve accuracy during both dry and wet seasons. These outputs can be integrated with hydrological dashboards for real-time lake monitoring and flood alerts.

- Address persistent misclassifications in wetlands and vegetated shorelines by applying advanced classification approaches, such as Random Forest (RF) or Support Vector Machine (SVM), using texture features (e.g., GLCM) from SAR and segmentation-based methods from Sentinel-2. Future studies should test object-based image analysis (OBIA) to improve boundary detection in these heterogeneous areas.
- Enhance monitoring of lake dynamics by incorporating multi-source datasets beyond surface extent. For example, combine optical and SAR time series with satellite altimetry (e.g., from Sentinel-3 or ICESat-2) to estimate water volume changes, and use thermal sensors (e.g., Landsat TIRS) to assess surface temperature anomalies linked to water quality issues such as eutrophication or evaporation trends.
- Strengthen the link between remote sensing data and water management practices by developing decision-support tools tailored to local stakeholders, such as water user associations, agriculture bureaus, and environmental monitoring agencies. These tools can include interactive maps, lake status reports, and automated alerts based on surface water thresholds and lake level anomalies.
- Promote long-term, basin-scale monitoring frameworks by encouraging the development of standardized processing pipelines using open-source platforms like GEE and FAO's SEPAL. These pipelines should be accessible to national agencies such as the Ethiopian Ministry of Water and Energy, enabling consistent assessments across all Rift Valley lakes.

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