Impacts of Land Use/Land Cover Change on Sediment Yield and Stream flow to Rift Valley Lakes Basin, A Case Study on Lake Ziway, Ethiopia.

Alazar Abdulkadir Tube

A Thesis Submitted to the Department of Water Resources Engineering, College of Civil Engineering and Architecture Presented in Partial Fulfillment of the Requirement for the Degree of Master's in Water Resources Engineering (Hydraulic Engineering)

School of Post Graduate Studies

Adama Science and Technology University

October, 2025

Adama, Ethiopia

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DECLARATION

I hereby declare that this Master Thesis entitled **"**Impacts of Land Use/Land Cover Change on Sediment Yield and Stream flow to Rift Valley Lakes Basin, A Case Study on Lake Ziway, Ethiopia**"** is my original work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials used for this thesis have been duly acknowledged through appropriate citations.

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I, the advisor of this thesis, hereby certify that I have read and revised version of the thesis entitled **"**Impacts of Land Use/Land Cover Change on Sediment Yield and Stream flow to Rift Valley Lakes Basin, A Case Study on Lake Ziway, Ethiopia**"** prepared under my guidance by Alazar Abdulkadir Tube submitted in partial fulfillment of the requirements for the degree of masters of science in Water Resources Engineering (Specialization in Hydraulic Engineering). Therefore, I recommend the submission of a revised version of the thesis to the department following the applicable procedures.

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APPROVAL SHEET

I, the advisor of the thesis entitled "Impacts of Land Use/Land Cover Change on Sediment Yield and Stream flow to Rift Valley Lakes Basin, A Case Study on Lake Ziway, Ethiopia" and developed by Alazar Abdulkadir Tube, hereby certify that the recommendations and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Major Advisor	Signature	Date

We, the undersigned members of the Board of Examiners of the thesis by Alazar Abdulkadir Tube, have read and evaluated the thesis entitled "Impacts of Land Use/Land Cover Change on Sediment Yield and Stream flow to Rift Valley Lakes Basin, A Case Study on Lake Ziway, Ethiopia" and examined the candidates during the open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Water Resources Engineering (Specialization in Hydraulic Engineering).

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Finally, 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 School Graduate Committee (SGC).

Department Head	Signature	Date
School Dean	Signature	Date
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LIST OF ACRONYMS

95PPU:	95% Prediction Uncertainty
CFSR:	Climate Forecast System Reanalysis
CRV:	Central Rift Valley (Ethiopia)
DEM:	Digital Elevation Model
FAO:	Food and Agriculture Organization
GIS:	Geographic Information System
HRU:	Hydrologic Response Unit
LULC:	Land Use/Land Cover
MoWE:	Ministry of Water and Energy (Ethiopia)
NMA:	National Meteorological Agency (Ethiopia)
NASA:	National Aeronautics and Space Administration
NSE:	Nash–Sutcliffe Efficiency
ONRS:	Oromia National Regional State
PBIAS:	Percent Bias
P-factor:	Percentage of observed data within 95PPU
R^2:	Coefficient of Determination
R-factor:	Thickness of 95PPU band relative to data variance
RS:	Remote Sensing
SNNPRS:	Southern Nations, Nationalities, and Peoples' Region
SUFI-2:	Sequential Uncertainty Fitting version 2
SWAT:	Soil and Water Assessment Tool
SWAT-CUP:	SWAT Calibration and Uncertainty Programs

ABSTRACT

This study investigates the impacts of Land use/land cover change on sediment yield and stream flow in the Lake Ziway watershed, Ethiopia. Land Use/Land cover changes in this region have been driven by rapid population growth, urbanization, and agricultural expansion, which have significantly altered the natural landscape. The research employs the Soil and Water Assessment Tool (SWAT) model to analyze hydrological responses to these land use/land cover (LULC) changes over the past few decades. The methodology involves multiple steps, including LULC classification using high-resolution Sentinel-2 imagery, hydrological model setup, and calibration using historical streamflow data from the Meki and Ketar gauging stations. The SWAT model is particularly effective for simulating hydrological processes, allowing for detailed analysis of water flow and sediment transport across the watershed. The result indicates that significant spatial variability in sediment yield within the lake Ziway catchment in respond to LULC change. The highest sediment yields were recorded in sub-basins characterized by steep slopes and intensive agricultural practices, with values exceeding sustainable thresholds. These findings suggest that certain areas are highly susceptible to erosion, which can lead to increased sedimentation in Lake Ziway, impacting water quality and aquatic ecosystems. The study also highlights the critical relationship between land cover dynamics and hydrological responses, emphasizing the necessity for integrated watershed management approaches. The insights gained from this research underline the importance of implementing targeted soil and water conservation measures, particularly in high-risk erosion zones. In conclusion, this study underscores the significance of integrating LULC dynamics with hydrological modeling for effective watershed management. Recommendations for future actions include adopting sustainable land management practices, enhancing monitoring efforts, and developing policies that address the impacts of land cover change. By prioritizing these strategies, it is possible to mitigate the adverse effects of sediment yield and improve the overall health of the Lake Ziway ecosystem.

Key Words: Lake Ziway, SWAT, SWAT-CUP, Runoff, Sediment

1. INTRODUCTION

1.1 Background

Land use and land cover change (LULC) has emerged as one of the most significant drivers of global environmental transformation. While **land cover** refers to the observable physical and biological surface features of the Earth—such as vegetation, water bodies, bare soil, and built-up areas—**land use** describes the human purposes or activities associated with a specific land type, including agriculture, settlement, grazing, and conservation. Thus, **land use change** represents a shift in human activities or management practices on the land, whereas **land cover change** may occur due to both **natural processes** (e.g., erosion, flooding, wildfire) and **anthropogenic actions** (e.g., deforestation, urbanization, agricultural expansion).

Globally, land use change is recognized as one of the main factors altering ecosystem structure, hydrological processes, and climatic conditions (Aloui et al., 2023; Gadissa et al., 2018). Rapid expansion of agriculture and settlement areas has accelerated soil erosion, reduced vegetation cover, and disrupted natural water cycles, leading to increased sediment yield and declining water quality in many watersheds. In this context, understanding the dynamics of land use and land cover change is fundamental for sustainable watershed and lake management, particularly in sensitive environments such as Ethiopia's Central Rift Valley, where land degradation directly affects lakes like Ziway through enhanced sedimentation and nutrient loading (Yuan & Forshay, 2019; Zhang et al., 2019).

Land cover change (LCC) is a locally pervasive and globally significant environmental trend and has become a process of paramount importance to the study of global environmental change (Demessie, 2015). LCC is a widespread phenomenon and has contributed to the existing high rate of soil erosion and land degradation in the highlands of Ethiopia. Specifically, it has significant eco-hydrological impacts on soil physical and hydrological properties (Teferi et al., 2013). Land use planning and management are closely related to the sustainability of water resources as changes of land use are linked with amount of water through relevant hydrological processes. The effect of the land cover changes has impact on the stream flow of the watershed by changing the magnitude of surface runoff and ground water flow. The change in land use controls the water yields of surface

streams and groundwater aquifers and thus the amount of water available for both ecosystem function and human use. Land Cover change plays a significant role in water quality and quantity and there is a great need to integrate land change science, hydrology and water resources management in future research initiatives. (Hari Krishna et al., 2014). Land cover change strongly influences seasonal stream flow and alters the annual hydrograph of river flow in the basins (Guo et al., 2008). The potential effects on water resources due to land cover change and global climate change in the past few decades have been of great concern. Land clearing, agricultural activities, construction, mining, urban and industrial development, and similar activities can have a major impact on the quantity and rate of surface runoff, and on the rates of erosion and sediment transport that take place. The knowledge on how land cover change influence watershed hydrology will enable local governments and policy makers to formulate and implement effective and appropriate response strategies to minimize the undesirable effects of future land cover change or modifications. Given that impacts of land use/cover change on water resources are the result of complex interactions between diverse site-specific factors and offsite conditions, standardized types of responses will rarely be adequate. General statements about land–water interactions need to be continuously questioned to determine whether they represent the best available information and whose interests they support in decision-making processes (FAO, 2002).

Land cover (LC) changes have a profound impact on hydrological processes such as sediment yield and stream flow, particularly in regions with dynamic ecosystems and agricultural intensification. The Ethiopian Rift Valley, home to a series of lakes, is one such region where human activities have significantly altered the natural landscape. Among the Rift Valley lakes, Lake Ziway, located in the central part of Ethiopia, is a key resource for local communities and plays a critical role in the regional water cycle, agriculture, and biodiversity.

However, in recent decades, the catchment area of Lake Ziway has experienced significant changes in land cover due to rapid population growth, urbanization, agricultural expansion, and deforestation. These alterations have, in turn, affected the hydrology of the lake's watershed, leading to changes in sediment yield and stream flow patterns that pose serious environmental and socio-economic challenges.

Lake Ziway is one of the largest lakes in the Ethiopian Rift Valley, situated at an elevation of approximately 1,636 meters above sea level. It covers an area of about 430 square kilometers and

is an important water resource for the surrounding communities, which depend on the lake for drinking water, irrigation, and fishing. The lake is also a critical habitat for various species of fish, birds, and other aquatic organisms, making it ecologically significant. The major rivers that feed into Lake Ziway include the Meki and Ketar Rivers, which drain the surrounding watershed that spans approximately 3,000 square kilometers (Mekonnen et al., 2020).

Lake Ziway and its tributary rivers are part of the complex hydrological system of the Rift Valley, which is characterized by seasonal variations in rainfall, evaporation, and runoff. The lake serves as both a source and a sink for water in the region, receiving inflow during the rainy season and contributing to downstream water supplies and evaporation. As such, understanding the hydrological processes within the lake's catchment is critical for managing water resources, especially in the face of increasing pressures from both climate change and anthropogenic activities.

Over the past several decades, the catchment area of Lake Ziway has undergone significant changes in land use and land cover. These changes have been driven primarily by population growth, agricultural expansion, and urbanization. As the population of the surrounding area has increased, the demand for agricultural land, water resources, and infrastructure has intensified, leading to widespread deforestation, conversion of natural landscapes to agricultural lands, and the expansion of settlements.

Agricultural expansion has been particularly pronounced in the highland areas surrounding Lake Ziway. These areas, which were once covered by forests and grasslands, have been converted to croplands for the cultivation of crops such as maize, wheat, and barley. In addition, the intensification of livestock grazing has contributed to land degradation and soil erosion in some areas. The conversion of natural vegetation into agricultural land has reduced the protective cover of the soil, leading to increased vulnerability to erosion, especially during the rainy season (Teshome et al., 2021). This erosion results in the transport of soil particles into the rivers that feed Lake Ziway, contributing to an increase in sediment yield.

1.2 Statement of the Problem

Over the past few decades, the **catchment area of Lake Ziway** in the Ethiopian Rift Valley has undergone extensive **land use and land cover (LULC) changes**, driven by rapid population growth, agricultural expansion, urban development, deforestation, wetland conversion, and small-scale irrigation projects (Tadesse et al., 2022; Alemayehu et al., 2023; Worku et al., 2023). Such land cover transitions have been observed in many Ethiopian watersheds, where cropland and settlement areas have expanded at the expense of forests, grasslands, and wetlands, leading to altered hydrological processes, increased soil erosion, and enhanced sediment transport (Gebremedhin et al., 2023; Tesfaye et al., 2023). In the Lake Ziway basin, these changes are likely to have **increased sediment yield** and **modified streamflow regimes**, with implications for the lake's water quality, ecological balance, and availability of water for irrigation, fisheries, and local communities.

Sedimentation is a significant problem in many Ethiopian lakes and reservoirs, where accelerated soil erosion from upstream catchments contributes to the reduction of water storage capacity and the degradation of water quality (Mekonnen et al., 2021; Teshome et al., 2023). For instance, in the Fincha Watershed (Upper Blue Nile Basin), mean annual soil loss increased from ~32.51 t ha^{-1} in 1989 to ~41.20 t ha^{-1} in 2019 due to changes in land use, highlighting the potential for similar processes in Lake Ziway (Worku et al., 2023). Likewise, studies in other Rift Valley sub-basins, such as the Megech and Akaki watersheds, demonstrate that LULC changes can significantly alter streamflow patterns, increasing peak flows during the wet season and reducing base flows in the dry season, which can exacerbate sediment transport and impact downstream water availability (Desta et al., 2022; Tesfaye et al., 2023).

Despite the recognized importance of Lake Ziway for **regional water supply, irrigation, fisheries, biodiversity, and socio-economic activities**, there is a **paucity of integrated studies** that examine the combined effects of LULC changes on **both sediment yield and streamflow dynamics** within the lake's catchment (Tadesse et al., 2022; Gebremedhin et al., 2023). Most existing studies focus on either land cover change or hydrological impacts separately, and few directly address the unique conditions of the Lake Ziway basin or the broader Rift Valley lakes system (Mekonnen et al., 2021; Worku et al., 2023). This lack of integrated research limits

understanding of how LULC change may threaten the ecological integrity of Lake Ziway, reduce water storage capacity, and compromise water availability for irrigation, fisheries, and other community needs.

Given these challenges, it is crucial to assess the **hydrological impacts of land cover changes** in the Lake Ziway catchment. Such assessment provides a basis for quantifying **sediment yield, streamflow alteration, and their implications for lake sustainability**, enabling the development of evidence-based **water resources management and soil conservation strategies** (Teshome et al., 2023; Alemayehu et al., 2023). Therefore, this study aims to **analyze the impacts of LULC changes on sediment yield and streamflow into Lake Ziway**, employing **remote sensing, GIS, and hydrological modeling approaches** to understand the broader ecological and socio-economic implications for the Rift Valley lakes system. By addressing this research gap, the study will provide critical insights to support **sustainable watershed management**, mitigate sedimentation, and maintain the lake's water quality, volume, and ecosystem services.

1.3 Objectives:

1.3.1 General Objectives

The general objective of the study was to assess the impacts of land use/land cover changes on sediment yield and stream flow in the catchment of Lake Ziway, Ethiopia.

1.3.2 Specific Objectives:

- To detect Land cover dynamics for in the watershed of Lake Ziway for the future period of 2035-2050.
- Modeling the stream flow & sediment yield by using soil and water Assessment Tool (SWAT) in the Lake Watershed.
- To evaluate the response of stream flow & sediment yield due to the land cover Change (LCC) changes on sediment yield in the major rivers (Ketar, and Meki Rivers) feeding into Lake Ziway dynamics in the watershed.
- To recommend sustainable land management practices that could mitigate the adverse impacts of LC changes on sediment yield and stream flow

1.4 Research questions

1. How has Land cover in the Lake Ziway watershed changed over the past 40 years?
2. How can SWAT model simulate stream flow & sediment yield in the watershed?
3. What impact does land use and land cover change would have on stream flow and sediment yield of the watershed?
4. What land and water management practices can be implemented to reduce the negative impacts of LC changes on sediment yield and stream flow?

1.5 Significance of the Study

The study on the impacts of land cover (LC) changes on sediment yield and stream flow dynamics in the Lake Ziway catchment is significant for several reasons, both in terms of environmental conservation and socio-economic development. Given the vital role that Lake Ziway plays in the local ecosystem and the livelihoods of surrounding communities, understanding how changes in land use affect sediment transport and water flow is critical for sustainable management. This study offers both scientific and practical value, with implications for policy, land use planning, water management, and conservation efforts.

1.6 Scope of the study

The scope of this study focuses on assessing the impacts of Land cover (LC) changes on sediment yield and stream flow dynamics in the catchment area of Lake Ziway, located in the Ethiopian Rift Valley. The research will primarily concentrate on understanding how the alteration of Land Cover patterns in the surrounding catchment influences the hydrological processes, particularly sediment transport and water flow, which in turn affects the ecological and socio-economic health of the lake.

2. LITERATURE REVIEW

2.1 Overview of Land Use Land Cover Change

According to the (FAO, 2002), land refers to a specific area of the Earth's terrestrial surface that includes all the features of the biosphere located just above or below it. This encompasses elements such as the local climate near the surface, soil types, landforms, surface water bodies like rivers, lakes, swamps, and marshes, as well as shallow sediment layers and groundwater reserves. It also includes the presence of plant and animal life, patterns of human settlement, and the physical impacts of both historical and current human activities, such as terraces, water management structures, roads, and buildings.

Land use and land cover are distinct concepts, as noted by Rawat and Kumar (2015). **Land cover** refers to the physical and biological characteristics of the Earth's surface and immediate subsurface. This includes vegetation types, soil, biodiversity, water bodies, groundwater, and man-made features like buildings and roads. In contrast, **land use** describes how these physical features are utilized by humans, reflecting the activities and intentions behind their use (Rawat & Kumar, 2015). Meyer and Turner (1994) further clarify this distinction by defining land cover as the physical, chemical, or biological classification of the land surface—such as forest, grassland, or built-up areas—while land use refers to the purposes or functions these areas serve, such as residential living in buildings, livestock grazing on grasslands, or recreational use of forests.

LULC change is a change in the aerial extent of land use or land cover type. It is a shift in an extent and management constitutes land use and land cover. LULC change can be categorized into LULC conversion and LULC modification. LULC conversion is the change of one land cover or land use type to another. For instance: the expansion of urban and cultivated land at the expense of forests due to deforestation. On the other hand, LULC modification indicates the maintenance of land cover or land use type in the face of change in its attributes. Modification involves the alterations of structure, function without a whole change from one land use or land cover type to another (Kassa Tadele, 2009).

2.2 Land Use and Land Cover Change in Ethiopia

Land Use and Land Cover (LULC) change in Ethiopia has received increasing scholarly attention due to its significant implications for environmental sustainability, agricultural productivity, and socio-economic development. The country has experienced extensive LULC transformations driven by a combination of human activities and natural factors. Numerous studies indicate that rapid population growth and agricultural expansion are among the leading causes of LULC change. For example, in the Dedo Watershed of southwest Ethiopia, cultivation areas expanded significantly between 1984 and 2017, primarily due to increasing population pressure and resettlement activities (Anteneh, 2022). Similarly, urbanization has emerged as a dominant factor, particularly in rapidly growing cities like Addis Ababa, where built-up areas increased by over 25% from 2000 to 2020, leading to substantial reductions in agricultural and vegetated lands (Ayenachew & Abebe, 2024). Institutional and policy-related factors have also played a role. Weak governance, inadequate land use regulations, and unsustainable land management practices have contributed to land degradation and deforestation in various regions, such as the Abaminus Watershed in northwest Ethiopia (Debie et al., 2022).

The environmental impacts of these changes are multifaceted. One major consequence is the alteration of hydrological cycles and increased soil erosion, which undermines the productivity of agricultural land and threatens water resources. A study in the upper Blue Nile Basin, for instance, found that conversion of forests and grasslands to farmlands led to higher runoff and sedimentation, significantly affecting ecosystem stability (Negese, 2021). Furthermore, LULC changes have resulted in biodiversity loss, especially in ecologically sensitive areas such as the Chebera Churchura National Park, where agricultural encroachment has fragmented habitats and reduced wildlife populations (Yadeta et al., 2022). In terms of ecosystem services, the Central Rift Valley experienced a loss valued at over USD 62 billion between 1973 and 2020, mostly due to declines in provisioning and cultural services (Mekuria et al., 2021). Regional studies further support these trends. In the Adama District, cultivated land and settlements expanded rapidly between 1990 and 2020, while forest cover declined, driven largely by urban expansion and the demand for fuelwood (Masha et al., 2023). Likewise, in the Jarmet wetland ecosystem, wetland areas declined sharply from 1986 to 2015 due to farmland expansion, influenced by demographic pressures and the need for food production (Teshome & Nigatu, 2024).

2.3 Application of RS and GIS for Land Use Land Cover Assessment

Remote Sensing (RS) and Geographic Information Systems (GIS) have become essential tools for analyzing Land Use and Land Cover (LULC) changes due to their capability to provide spatially explicit, timely, and multi-temporal data over large geographic areas. The integration of RS and GIS allows for efficient mapping, monitoring, and modeling of LULC dynamics, especially in regions where ground-based observations are limited or infeasible. According to Belay and Mengistu (2019), satellite imagery has been instrumental in detecting significant LULC transformations in Ethiopia over the past few decades, particularly due to agricultural expansion and deforestation. The use of Landsat imagery in combination with GIS techniques enables researchers to classify land cover types and assess their changes over time. For instance, Gashaw et al. (2018) employed multi-temporal Landsat data and GIS-based change detection techniques to evaluate LULC dynamics in the Andassa watershed and found a significant decline in forest cover and an increase in agricultural land over three decades.

Moreover, the integration of RS and GIS has proven useful for identifying the spatial drivers of LULC changes and for informing sustainable land management policies. As demonstrated by Tadesse et al. (2021), applying supervised classification algorithms such as Maximum Likelihood in RS platforms can yield high classification accuracy when supported by ground truth data. This is particularly important for policy-making and planning in rapidly changing landscapes. In addition, RS and GIS tools have facilitated predictive modeling and scenario analysis. For example, Yirsaw et al. (2017) used the CA-Markov model integrated with GIS to project future LULC scenarios in the Upper Blue Nile Basin, highlighting the potential impacts of current land management practices on future land use patterns. These tools also support ecosystem service assessment, as RS-derived data can quantify land degradation, carbon storage, and water resource alterations, which are directly linked to LULC changes (Bewket & Abebe, 2013).

The versatility of RS and GIS is also reflected in their application across diverse ecological zones. In arid and semi-arid regions of Ethiopia, such as the Rift Valley, GIS-based LULC mapping has revealed ongoing wetland degradation and loss of grazing lands due to anthropogenic pressures (Kidane & Stahlmann, 2012). Furthermore, RS techniques are increasingly being enhanced with machine learning and cloud-based platforms like Google Earth Engine, improving the speed and

accuracy of LULC classification (Dibaba et al., 2020). Overall, the combined application of RS and GIS in LULC studies not only enhances spatial and temporal analyses but also provides critical insights into human-environment interactions, resource use, and land degradation trends. This makes them indispensable tools for researchers, planners, and decision-makers aiming to ensure sustainable land resource management.

2.4 Impact of Land Use Land Cover on Sediment Yield

Land Use and Land Cover (LULC) changes are widely recognized as major drivers influencing sediment yield in river basins, particularly in developing countries like Ethiopia where land use dynamics are rapidly evolving. The conversion of forests and grasslands into cultivated and built-up areas typically leads to increased surface runoff, reduced infiltration, and consequently, higher sediment loads in river systems (Bewket & Teferi, 2009). Numerous watershed-scale studies in Ethiopia have confirmed that agricultural expansion and deforestation are the primary contributors to elevated sediment yield. For instance, in the Chemoga watershed, land conversion between 1957 and 2002 resulted in a significant increase in soil erosion and sediment delivery, with cultivated lands showing the highest sediment contribution due to poor conservation practices and slope cultivation (Meshesha et al., 2012). Similarly, in the Lake Tana Basin, significant land use shifts from forest and shrubland to farmland over a 30-year period were found to substantially increase sediment yield and degrade water quality (Gebremicael et al., 2019).

The relationship between LULC change and sediment yield has also been effectively modeled using hydrological models such as SWAT (Soil and Water Assessment Tool), which integrates spatial land cover data with hydrologic and sediment processes. For example, Adimassu et al. (2014) applied SWAT in the northern highlands of Ethiopia and demonstrated that areas with dense vegetation cover exhibited lower sediment yield, whereas degraded cultivated areas contributed the highest sediment outputs. The spatial distribution of sediment yield was closely linked to land use types and slope steepness, highlighting the critical role of land management in erosion control. Furthermore, climate variability may exacerbate the sedimentation problem, but studies consistently point out that anthropogenic LULC change has a more direct and dominant impact. In the Nashe watershed, for instance, Getahun and Gebre (2015) concluded that land use changes alone accounted for over 65% of the variation in sediment yield over a 30-year period.

Therefore, LULC changes, particularly deforestation and unsustainable agriculture, significantly increase sediment yield and pose serious challenges for soil productivity, reservoir capacity, and aquatic ecosystems. The evidence strongly underscores the need for integrated land and water management strategies that promote sustainable land use, afforestation, and soil conservation practices to mitigate sedimentation and its impacts on hydrological systems.

2.5 Hydrological Models

2.5.1 Concepts of Hydrological Models

Hydrological models are essential tools used to simulate the movement, distribution, and quality of water within a catchment or watershed system. These models help in understanding the behavior of hydrologic processes and predicting responses to natural or anthropogenic changes such as climate variability and land use modifications (Beven, 2012). Hydrological models can be broadly categorized into three types: empirical (black-box), conceptual (lumped), and physically-based (distributed) models. Empirical models rely on statistical relationships derived from observed data and are useful where process understanding is limited (Chow et al., 1988). Conceptual models, on the other hand, represent the hydrological cycle as interconnected reservoirs (e.g., soil moisture, groundwater) and simulate flow between them using simplified governing equations (Refsgaard & Storm, 1995). Physically-based models, such as MIKE SHE or SWAT, use mathematical representations of physical processes like infiltration, evapotranspiration, and surface runoff, and often require extensive data input for calibration and validation (Arnold et al., 1998).

Each modeling approach has its own strengths and limitations. While empirical models are easy to use and require fewer data, they lack transferability and process representation. Conceptual models strike a balance between complexity and practicality, making them suitable for regional applications with moderate data availability. Physically-based models offer the highest level of detail but are data-intensive and computationally demanding (Singh & Woolhiser, 2002). The selection of an appropriate hydrological model depends on the research objective, scale of the study, data availability, and the hydrological complexity of the catchment. Increasingly, hybrid models that integrate empirical, conceptual, and physical elements are being explored to improve accuracy and applicability across diverse hydrological conditions (Abbaspour, 2015). Furthermore, advancements in remote sensing and GIS have greatly enhanced the spatial

representation of hydrological models, making them more robust for flood forecasting, water resource management, and climate change impact assessment (Immerzeel & Droogers, 2008).

2.5.2 Hydrological Model Classification

Hydrological models are classified based on their conceptual structure, spatial representation, temporal resolution, and the processes they simulate. A common classification divides hydrological models into empirical (or black-box), conceptual (or lumped), and physically-based (or distributed) models (Singh & Woolhiser, 2002). Empirical models rely entirely on statistical correlations between inputs and outputs without explicitly representing the underlying physical processes, making them useful for prediction when process understanding or data is limited (Chow et al., 1988). Conceptual models represent the hydrological system using simplified reservoirs or stores (e.g., soil moisture, groundwater), linking them via mathematical equations that approximate the key hydrological processes. These models operate at the catchment scale and typically use lumped parameters, which simplifies computation but may limit spatial accuracy (Beven, 2012). Physically-based models simulate hydrologic processes explicitly based on physical laws such as conservation of mass and energy, using spatially distributed data on soil, land use, topography, and climate (Refsgaard & Storm, 1995). These models, like SWAT, MIKE SHE, or HEC-HMS, are well-suited for detailed watershed analyses but require extensive data and computational resources (Abbaspour, 2015).

In addition to these primary types, hydrological models are also categorized by their temporal resolution, such as event-based models, which simulate single storm events, and continuous models, which simulate long-term hydrological processes over months or years (Singh, 1995). Another axis of classification considers spatial scale: lumped models treat the watershed as a single unit with averaged parameters, semi-distributed models divide the watershed into sub-basins, and fully distributed models represent spatial variability at fine grid scales (Beven, 2012). Recent advancements have focused on hybrid models that combine empirical, conceptual, and physically-based approaches to leverage the strengths of each type and improve model reliability and applicability across different contexts (Gupta et al., 2008). Overall, the choice of model classification depends on study objectives, available data, and computational capacity.

Beyond the traditional classifications, hydrological models are also distinguished by their primary purpose and the scale of application. For example, water quality models focus not only on flow but also on the transport and transformation of pollutants within the watershed, integrating sediment and nutrient dynamics with hydrological processes (Abbaspour et al., 2015). Similarly, urban hydrological models are tailored to simulate the altered hydrological responses caused by impervious surfaces, stormwater drainage systems, and human infrastructure, often requiring integration with hydraulic models to capture flood risks in urban environments (Chen et al., 2018). Models like SWMM (Storm Water Management Model) specialize in such urban applications (Rossman, 2010).

Another dimension of classification arises from the level of uncertainty representation in hydrological modeling. Some models incorporate uncertainty analysis explicitly through stochastic or probabilistic approaches, recognizing the variability and errors in input data, model structure, and parameter estimation (Beven, 2006). These include ensemble modeling techniques and Bayesian inference frameworks that provide probabilistic forecasts rather than single deterministic outputs, improving decision-making under uncertainty (Vrugt et al., 2008).

Moreover, advances in machine learning and data-driven approaches have led to the development of hybrid or purely data-driven hydrological models that complement or substitute traditional physical models. These approaches use techniques such as artificial neural networks, support vector machines, and random forests to model complex, nonlinear hydrological processes without requiring detailed physical inputs (Dawson & Wilby, 2001; Nearing et al., 2020). While promising in terms of predictive performance and adaptability, these models sometimes lack interpretability and physical consistency, which remains a critical limitation for their application in policy and resource management.

Finally, the classification can also consider model flexibility and adaptability, where some hydrological models are designed as modular platforms allowing users to customize process representations, parameterizations, and input data according to the specific needs of a study (e.g., the HYPE model, Lindström et al., 2010). Such modularity supports multi-disciplinary applications, coupling hydrology with ecology, agriculture, and socio-economic models for integrated watershed management.

2.5.1 Criteria for Hydrological Model Selection

Selecting an appropriate hydrological model is a critical step that profoundly influences the success and reliability of hydrological studies and water resources management. The decision is often complex and must consider multiple interrelated criteria to ensure the model's suitability for the intended purpose. One of the foremost considerations is the objective of the modeling exercise—whether it is flood forecasting, water resources planning, environmental impact assessment, sediment transport analysis, or climate change impact studies. Each objective demands different levels of detail, accuracy, and model capabilities (Singh & Woolhiser, 2002).

Scale and resolution are equally important. Models must be compatible with the spatial extent of the study area and the temporal scale of interest. For small catchments or event-based studies, simpler or lumped models might suffice, while large river basins or studies involving spatial heterogeneity require distributed models that incorporate variations in topography, soil, land use, and climate inputs (Beven, 2012). Temporal resolution also varies, ranging from hourly or daily time steps for flood simulation to monthly or annual for long-term water balance or climate studies.

A crucial practical criterion is data availability and quality. Physically-based and distributed models typically demand high-resolution input data, including digital elevation models (DEMs), soil properties, land cover maps, and meteorological observations (temperature, rainfall, evapotranspiration). In regions where such data are scarce or unreliable, conceptual or empirical models may provide more robust and feasible alternatives (Abbaspour, 2015). Furthermore, the calibration and validation data—usually streamflow or groundwater measurements—must be sufficient in quantity and quality to allow for model parameterization and performance assessment (Gupta et al., 1998).

Model complexity should be balanced with the capability of the modeler and the computational resources available. Overly complex models can lead to over-parameterization, making calibration difficult, reducing transparency, and potentially compromising predictive reliability due to equifinality issues where different parameter sets produce similar results (Beven, 2006). Conversely, overly simplistic models might omit critical processes or fail to capture essential system behaviors, reducing usefulness in decision-making.

Computational efficiency and user-friendliness also affect model selection. Some hydrological models require significant computational power and expert knowledge to implement and interpret, which might not be feasible for all users or organizations. Models with well-documented user interfaces, active user communities, and comprehensive technical support are preferable, especially in operational or educational contexts (Reed et al., 2004).

Another important factor is the model's capability to incorporate uncertainty and sensitivity analysis. Hydrological processes are inherently variable and uncertain due to natural variability and data limitations. Models that enable formal uncertainty quantification (e.g., through Monte Carlo simulations, Bayesian frameworks, or ensemble approaches) provide more reliable and informative outputs for risk-based decision-making (Vrugt et al., 2008). Sensitivity analysis helps identify which parameters most influence model outcomes, guiding data collection and calibration efforts effectively.

In addition to technical and scientific criteria, stakeholder engagement and end-user requirements can drive model choice. Participatory modeling approaches emphasize selecting models that are transparent, interpretable, and communicable to non-experts, ensuring broader acceptance and usability in policy and management decisions (Hermann et al., 2011).

Finally, the integration potential of the model with other environmental, socio-economic, or climate models may be decisive for comprehensive watershed management or climate adaptation studies. Models that support modularity, open-source code, or standard data formats facilitate coupling with GIS, remote sensing data, and other modeling frameworks (Lindström et al., 2010).

2.6 Soil and Water Assessment Tool (SWAT) Model

The Soil and Water Assessment Tool (SWAT) is a comprehensive, semi-distributed, process-based hydrological model developed by the United States Department of Agriculture's Agricultural Research Service (USDA-ARS) to assess the impact of land management practices on water, sediment, and agricultural chemical yields in large, complex watersheds (Arnold et al., 1998). SWAT simulates the water balance using climate, soil, topography, land use, and land management data. It divides the watershed into sub-basins and further into Hydrologic Response Units (HRUs)—areas with unique combinations of land use, soil, and slope characteristics—allowing it

to represent spatial heterogeneity without requiring a fully distributed model structure (Neitsch et al., 2011). The core water balance equation in SWAT accounts for components such as precipitation, surface runoff, evapotranspiration, infiltration, percolation, lateral flow, and return flow, making it suitable for long-term simulation under varying land use and climate scenarios.

SWAT's integration with Geographic Information Systems (GIS), particularly through ArcSWAT and QSWAT interfaces, enables spatial data processing, visualization, and scenario generation for land use and management changes. This makes it a valuable decision-support tool for watershed management, soil erosion control, agricultural planning, and water quality modeling (Gassman et al., 2007). For example, it has been extensively applied in Ethiopian river basins such as the Blue Nile, Awash, and Omo-Gibe to evaluate the effects of deforestation, agricultural expansion, and soil conservation practices on streamflow, sediment yield, and nutrient loading (Setegn et al., 2009; Betrie et al., 2011; Mengistu et al., 2019). The model supports simulation at daily, monthly, or annual time steps and is capable of representing human interventions such as irrigation, reservoirs, crop rotation, and fertilizer application, making it ideal for integrated catchment management and climate-smart agriculture assessments.

One of the notable strengths of SWAT is its ability to simulate nonpoint source pollution**,** particularly the transport of nitrogen, phosphorus, and pesticides, and its integration with water quality models such as QUAL2E or MODFLOW when groundwater interaction is essential. Additionally, recent developments such as SWAT+ have introduced more flexible spatial representation, improved water routing, and enhanced management operation capabilities, overcoming some limitations of the classic model structure (Bieger et al., 2017).

However, despite its robustness, SWAT is not without challenges. The model calibration and validation process can be demanding, requiring extensive data on hydrology, meteorology, and land management practices. To address uncertainty and parameter sensitivity, tools such as SWAT-CUP (SWAT Calibration and Uncertainty Program) are commonly used (Abbaspour, 2015). The quality of model outputs is highly sensitive to input data accuracy and resolution, especially in data-scarce environments like many parts of sub-Saharan Africa. Additionally, the HRU approach, while useful for capturing variability, can obscure spatial connectivity and overgeneralize hydrological processes in heterogeneous terrains (Liu et al., 2019).

Despite these challenges, SWAT remains one of the most widely accepted models for scenario-based watershed planning, policy analysis, and ecosystem service valuation. It has been applied in thousands of peer-reviewed studies worldwide, underpinning research on land degradation, sedimentation, and the effectiveness of soil and water conservation practices under changing climatic conditions (White et al., 2011). Its adaptability, openness, and broad community support continue to make SWAT a cornerstone in watershed hydrological modeling.

2.6.1 Calibration and Validation of SWAT Model

Calibration and validation are critical processes in ensuring the reliability and predictive accuracy of the Soil and Water Assessment Tool (SWAT) model. Calibration involves adjusting model input parameters to match simulated outputs with observed data, while validation tests the model's performance using independent data not used in calibration (Abbaspour, 2015). These procedures help to account for uncertainties and variability in model inputs such as climate, land use, soil properties, and management practices. Typically, calibration and validation are performed using historical streamflow, sediment, or water quality data at daily, monthly, or annual time steps, depending on the study objective and data availability (Arnold et al., 2012). A widely used tool for this purpose is SWAT-CUP (SWAT Calibration and Uncertainty Program), which supports several calibration algorithms, including SUFI-2, GLUE, ParaSol, and MCMC, allowing for both parameter optimization and uncertainty analysis (Abbaspour, 2015). Among these, SUFI-2 (Sequential Uncertainty Fitting Ver. 2) is preferred for its balance between accuracy and computational efficiency, especially in data-scarce regions.

Performance of the model during calibration and validation is assessed using statistical metrics such as the Nash–Sutcliffe Efficiency (NSE)**,** Coefficient of Determination (R^2)**,** Percent Bias (PBIAS), and the Root Mean Square Error (RMSE)**.** A model is generally considered satisfactory when NSE > 0.5, R^2 > 0.6, and PBIAS falls within ±25% for streamflow and ±55% for sediment yield (Moriasi et al., 2007). However, acceptable thresholds can vary depending on watershed characteristics and data resolution. In Ethiopian watersheds, where observed data are often limited or inconsistent, modelers sometimes rely on regionalization techniques, remote sensing datasets, or literature-based parameter ranges to support calibration efforts (Mengistu et al., 2019; Betrie et al., 2011). Furthermore, sensitivity analysis is performed before calibration to identify the most

influential parameters, such as CN2 (Curve Number), SOL_K (saturated hydraulic conductivity), and ALPHA_BF (baseflow alpha factor), which greatly affect flow and sediment simulations.

Despite its strengths, the SWAT model's calibration process can be time-consuming and complex, particularly in heterogeneous basins with multiple land uses and human interventions. Modelers must also be cautious of overparameterization, which can reduce model robustness and lead to equifinality—where different parameter sets produce similar results (Beven & Freer, 2001). Nonetheless, successful calibration and validation are crucial for applying SWAT to scenario analysis, policy development, and integrated watershed management. When properly calibrated, SWAT provides a powerful tool for predicting the impacts of land use change, soil conservation, and climate variability on water resources.

3. MATERIALS AND METHODS

3.1 Study Area Description

3.1.1. Location

Lake Ziway watershed located in the central rift valley (CRV) of Ethiopia encompasses an area of 7148 km2, falling between gradients 7˚22'36"N and 8˚18'21"N latitude and 37˚53'40"E and 39˚28'9"E longitude (Figure 1). It is at 160 km south of the capital-Addis Ababa. The watersheds of the two principal rivers, Meki and ketar Rivers, feeding Lake Ziway lay in two administrative regions of Ethiopia, 73.6% in Oromia National Regional State (ONRS) and the remaining part in Central Region of Ethiopia (CRE). The watershed stretches from edges of the Gurage Mountains in the west to the Arsi Mountains in the east Kalsido et al., 2020). The watershed includes the rift floor, two escarpment areas, two major river inlets the Katar and Meki Rivers, and one river outlet the Bulbula River. The Meki River originates in the highlands of Gurage and travels a distance of about 100 km from the highlands at an altitude of 3600 m to 1636 m before draining into the Lake Ziway.

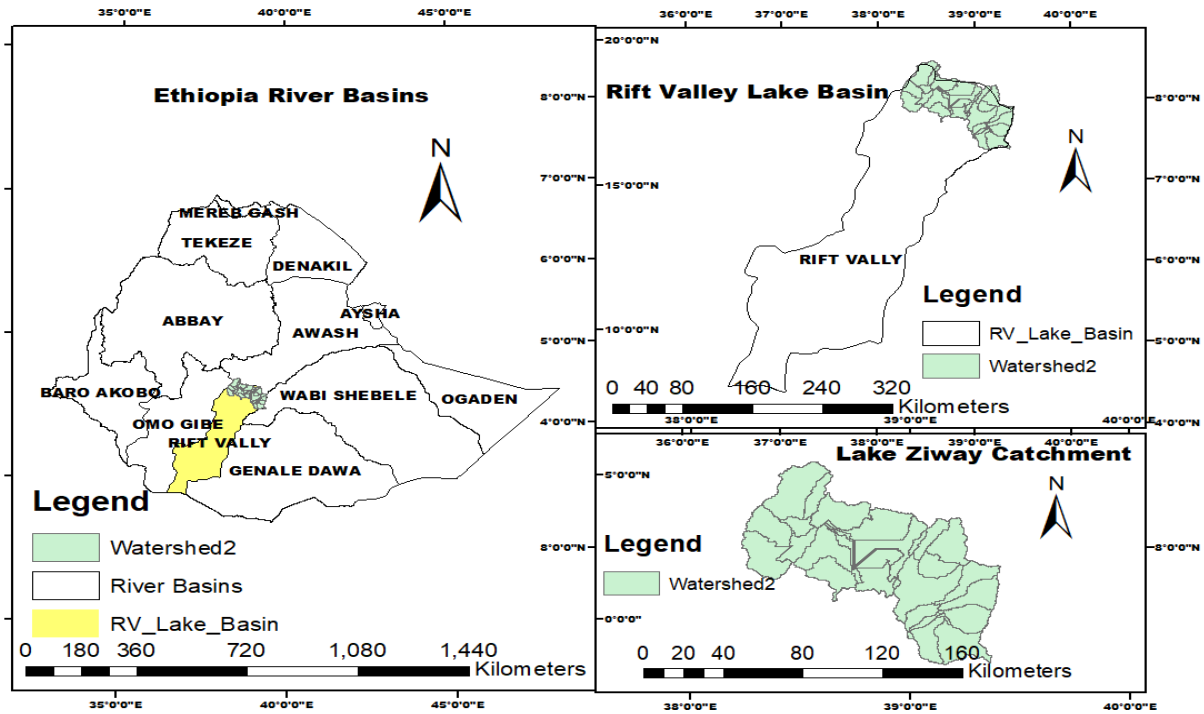


Figure 3. 1 Location of the study area.

3.2 Materials and Software Tools

To accomplish the study's goal of evaluating the influence of LULC change on the hydrological responses of the large Ziway lake watershed, the following tools and software were utilized. Spatial data, including soil and land use data, were processed using the Geographic Information System (GIS) 10.4, which also served as an interface for the SWAT hydrology model. The LULC image categorization and creation were obtained from Sentinel 2-10m . The watershed's sediment output and hydrological components were simulated, evaluated, and analyzed using the Soil and Water Assessment Tool (SWAT) 2012. In order to provide land use update files for SWAT simulation scenarios, multi-year land use data was processed using the SWAT-CUP software. Model sensitivity analysis, calibration, validation, and uncertainty analysis of SWAT model simulation were conducted using the sequential Uncertainty Fitting-2 (SUFI-2) algorithm, one of the five37 uncertainty analysis techniques included in the SWAT Calibration and Uncertainty Program (SWAT-CUP) software.

3.3 Hydrological Model Data Input and Sources

Watershed description input data is needed for the hydrological models. Weather data, hydrological data, topography (DEM), soil maps, and property and LULC maps are a few of the most crucial input data. These statistics were gathered from several sources.

3.3.1 Weather data

The SWAT hydrological model, which simulates the hydrology of watersheds, depends on weather data as its primary input. For the years 1990–2010, the Ethiopian Meteorological Institute of (EMI) provided data on daily precipitation, maximum and minimum temperatures, relative humidity, wind speed, and solar radiation at 11 meteorological stations located within and surrounding the study watershed: Arata, Ziway, Meraro, Ogolcho, Sagure, and Adamitulu, Ketar Genet, Bekoji SF, Koshe, Butajira, and Meki. The Climate Forecast System Reanalysis (CFSR) database and the National Aeronautics and Space Administration's (NASA) Power Data Access Viewer were the sources of the extra weather data.

Table 3. 1 *Weather Stations in and around the study area*

Station Name	Latitude	Longitude	Elevation	Parameter				
				RHMD	PCP	SLR	TMP	WND
Arata	7.9828	39.0594	1777	No	Yes	No	No	No
Ziway	7.9333	38.7	1640	Yes	Yes	Yes	Yes	Yes
Meraro	7.45	39.3667	2940	Yes	Yes	Yes	Yes	Yes
Ogolcho	8.0398	39.0182	1682	No	Yes	No	Yes	Yes
Sagure	7.46	39.09	2480	No	Yes	No	Yes	No
Adamitulu	7.8555	38.7028	1653	No	Yes	No	Yes	No
KitereGenet	7.8333	39.1	2400	No	Yes	No	No	No
BekojiSF	7.5333	39.25	2388	Yes	Yes	No	Yes	Yes
Koshe	8.0065	38.5253	1878	No	Yes	No	Yes	No
Butajira	8.15	38.3667	2000	No	Yes	No	Yes	No
Meki	8.173884	38.79347	1662	No	Yes	No	No	No

3.3.2 Streamflow data

The SWAT hydrological model must be calibrated, validated, and subjected to sensitivity analysis using the streamflow data. The Ministry of Water and Energy of Ethiopia (MoWE)'s hydrology department provided the daily streamflow data for the large Meki watershed at the Meki Village station for the years 1990-2010.

3.3.3 Digital elevation model data

The Digital Elevation Model (DEM) serves as a digital representation of the topographic surface, which is fundamental for hydrological analyses such as watershed delineation and drainage pattern evaluation. In this study, the DEM was utilized to derive key watershed parameters, including slope length, slope gradient, and stream network characteristics such as channel length, slope, and width, as well as various hydrological parameters. The DEM, with a spatial resolution of 12.5 meters, was obtained from the Alaska Satellite Facility (https://vertex.dac.asf.alaska.edu). This dataset was employed as a primary input in the Soil and Water Assessment Tool (SWAT) hydrological model to delineate the study area into multiple sub-watersheds and subsequently into Hydrologic Response Units (HRUs), thereby facilitating detailed hydrological simulation and analysis.

3.3.4 Soil data

One of the spatial input data needed for the physical-based hydrological models that simulate streamflow and sedimentation is soil data. According to (Zhang et al., 2020), the hydrological models require a soil map and a database table of soil characteristics, including soil hydrologic group, maximum rooting depth of the soil profile, moist bulk density, soil texture, soil saturated hydraulic conductivity, grain size percentage, texture class, and soil available water for various soil layers. Hydrological modelling relies heavily on the properties and map of the soil. Soil physical characteristics and knowledge of these data are necessary for predicting runoff, sediment yield, and LULC consequences. The specific physical and chemical characteristics of the soils are necessary for the SWAT hydrological model to function. Therefore, to identify the kind of soil in the study region, the soil map and data were acquired from the Food and Agriculture Organization (FAO) and the Ministry of Water and Energy (MoWE) using the Harmonized World Soil Database (HWSD) of soil classification (FAO, 2002).

In order to integrate the soil map with the SWAT model, a user soil table database containing the physical and chemical properties of soil was created using the SWAT user soil template (Excel extension) and imported into the SWAT user soil database because the soil data for the Ethiopian catchment is not available in the SWAT user soil database.

3.3.5 Land use and land cover

Land conservation, sustainable development, and water resource management all benefit from information gleaned from land use and land cover data. Evapotranspiration, groundwater infiltration, and overland runoff are all impacted by LULC change (Tewabe & Fentahun, 2020). When evaluating how watershed characteristics react to changes in land use over various time periods, the LULC data is crucial. Along with the soil and slope map, it is one of the key inputs for the SWAT model to determine the Hydrological Response Units (HRUs) of watersheds.

Land Use/Land Cover (LULC) data for the study area were derived from Sentinel-2 satellite imagery, which provides high-resolution multispectral data at a spatial resolution of 10 meters. The imagery was obtained through **https://scihub.copernicus.eu/** the Copernicus Open Access Hub . The LULC classification was carried out based on spectral reflectance patterns, and each land cover class was assigned a unique grid code corresponding to specific land use types such as agricultural land, forest, grassland, water bodies, urban areas, and barren land.

These classified LULC grid codes were then reclassified according to the requirements of the Soil and Water Assessment Tool (SWAT) model, which uses a predefined land use lookup table to interpret land cover types for hydrological simulations. The reclassification process involved mapping the Sentinel-2 LULC classes to SWAT land use codes to ensure accurate representation of land surface processes within the model. This LULC dataset played a crucial role in defining Hydrologic Response Units (HRUs) by influencing parameters such as evapotranspiration, surface runoff, infiltration, and sediment transport across different land use categories.

3.3.6 LULC change detection analysis

The method of identifying which LULC class is changing to the other is called LULC change detection. It involves analyzing spatiotemporal multi-temporal information to determine how land use classes have changed throughout time. A categorization comparison of land cover statistics was used in this investigation. Between the years 2017–2020 and 2020–2024, the areal coverage of classified LULC maps for the specified periods was computed, and the areal change was measured. The difference between two subsequent LULC maps, such as the area of LULC 2017 minus the area of LULC 2020, was used to calculate the absolute change in LULC classes.

The rate of LULC change across the study period was calculated by dividing the LULC area difference between two periods, while a LULC change between each period was also produced to comprehend the spatiotemporal fluctuations in the LULC classes.

This study aimed to analyze and project Land Use/Land Cover (LULC) changes within the **Lake Ziway watershed** for the years **2035** and **2050** using a **trend-based extrapolation approach**. The prediction was based on the observed trends between **2017**, **2020**, and **2024**. The approach assumes that the recent LULC dynamics will continue into the future under a "business-as-usual" (BAU) scenario, a technique widely applied in LULC projection studies (Mas, 2004; Eastman, 2016; Pontius et al., 2008). Sentinel-2 Multispectral Instrument (MSI) images with a **10 m spatial resolution** were acquired from the **Copernicus Open Access Hub** (https://scihub.copernicus.eu/) for the years **2017**, **2020**, and **2024**.

3.3.7 Image Preprocessing

All preprocessing and analyses were conducted in **ArcGIS 10.4**. Atmospheric correction was applied using the **Dark Object Subtraction (DOS)** method to convert Top-of-Atmosphere reflectance to surface reflectance (Chavez, 1996). The images were clipped to the **Lake Ziway**

watershed boundary, which was delineated from the DEM using the **Hydrology** toolbox. Band composition and layer stacking were performed to prepare multispectral composites.
A visual inspection was conducted to verify geometric alignment and remove residual clouds or haze.

3.3.8 LULC Change Detection (2017–2024)

Land Use/Land Cover (LULC) change detection was conducted using the **post-classification comparison technique**. This method involves comparing independently classified maps from different years (2017, 2020, and 2024) to identify transitions among LULC categories. It is one of the most reliable approaches because it minimizes the effects of atmospheric and sensor differences between image dates (Singh, 1989).

The classified maps were overlaid in **ArcGIS 10.4** using the **"Raster Calculator"** and **"Tabulate Area"** tools to determine the spatial extent and direction of change for each land cover type. For each time interval (2017–2020 and 2020–2024), the area occupied by each LULC class was measured in hectares, and the gain or loss of land was computed by comparing the corresponding class areas across the two periods. The **magnitude of change** was calculated by subtracting the earlier year's area from the later year's area. A positive value indicates an **increase** in that land cover type, while a negative value shows a **decrease**.

In addition, the **percentage change** for each class was determined by dividing the change in area by the total watershed area and multiplying by 100. This helped to identify the dominant trends, such as expansion of cultivated and built-up areas or reduction in forest and grassland cover. The results of the change detection analysis were summarized in tables and maps to visualize the spatial distribution and direction of LULC transformations within the Lake Ziway watershed from 2017 to 2024.

3.4 Hydrological Model Setup and Simulation

3.4.1 SWAT model setup

The semi-distributed SWAT model is the most effective at forecasting sediment output and hydrology under land use changes. In large, complex watersheds with shifting soil, land-use, and management conditions over extended periods of time, the SWAT model is a physically-based model created to forecast the effects of land management practices on water, sediment, and agricultural chemical yields (J. G. Arnold, 2012).

There are several sub-basins inside a basin. Additionally, sub-basins are separated into hydrological response units (HRUs) according to the slope classes, land-use kinds, and soil types' homogeneity. In order to simulate hydrological processes, the SWAT model needs input data on topography, soil, and land use in addition to hydro-meteorological data. Watershed delineation, the Hydrologic Response Unit (HRU), sensitivity analysis, model calibration, and validation are all included in the SWAT model setup. In order to evaluate the effect of LULC on hydrological responses, a SWAT model for the vicinity of Ziway Lake watersheds was established using the SWAT-2012 interface compatible with Arc GIS 10.4 (Arc SWAT 2012).

3.4.2 Watershed delineation

Watershed delineation represents the initial and fundamental step in the development of the SWAT model. Prior to this, all necessary spatial input datasets—including the Digital Elevation Model (DEM), soil, and land use/land cover (LULC) data—were prepared and projected into the UTM Zone 37 coordinate system to ensure spatial alignment within ArcGIS 10.4. The delineation process was carried out using the ArcSWAT extension, which operates as an interface within the ArcGIS environment. A DEM with a spatial resolution of 12.5 meters was utilized to delineate the watershed and its respective sub-watersheds.

The delineation procedure consists of five main stages: setting up the DEM, defining stream networks, identifying inlets and outlets, selecting the watershed outlet, and calculating sub-basin parameters. Following the DEM setup and projection, the model automatically generates flow direction and flow accumulation grids. A key input during this process is the threshold drainage area, which determines the minimum upstream area required to initiate a stream. A smaller threshold value results in a more detailed drainage network, leading to a higher number of sub-

basins and Hydrologic Response Units (HRUs), whereas a larger threshold produces a more generalized network with fewer subdivisions.

Weather data

The SWAT model requires daily climate data—including precipitation, maximum and minimum temperatures, relative humidity, solar radiation, and wind speed—for effective watershed simulation. However, most meteorological stations within the study area, with the exception of Ziway, Meraro, and Bekoji, lacked complete records for relative humidity, solar radiation, and wind speed. To address this data gap, the model's built-in Weather Generator (WGN) module was employed to simulate the missing climatic variables based on available measured data.

Using the WGN functionality within SWAT, relative humidity, solar radiation, and wind speed were synthetically generated for the stations with incomplete records. These generated datasets were then integrated into the SWAT climate database, enabling the model to assign complete weather inputs across all meteorological stations used in the simulation.

3.5 Sensitivity Analysis, Calibration, and Validation

Physically based hydrological models are capable of simulating continuous hydrological processes, thereby supporting the planning, development, and management of water resources. For such models to be reliable tools for decision-making in watershed management, their outputs must be scientifically valid and robust. Consequently, conducting sensitivity analysis, calibration, validation, and uncertainty assessment is essential to ensure the credibility of the model results. In the context of SWAT modeling, it is crucial that input parameters fall within acceptable uncertainty ranges to maintain the integrity of the simulation outputs. To achieve this, the SWAT Calibration and Uncertainty Procedures (SWAT-CUP) software, utilizing the Sequential Uncertainty Fitting algorithm (SUFI-2) developed by Abbaspour et al. (2015), was employed. This tool facilitated the sensitivity analysis, model calibration, validation, and uncertainty quantification, ensuring the model's outputs are suitable for informed decision-making in watershed management and water resource planning.

3.5.1 Sensitivity analysis

Sensitivity analysis is a fundamental process used to evaluate how changes in model input parameters affect the model output. It serves as a critical step in identifying influential parameters that are necessary for effective model calibration. Hydrological models, especially complex ones like SWAT, involve numerous parameters influenced by spatial variability, measurement uncertainties, and incomplete representation of physical processes. Consequently, many parameter values are not precisely known. To ensure that the model accurately replicates real-world conditions, it is essential to optimize internal parameters to achieve a satisfactory agreement between observed and simulated data. Sensitivity analysis helps identify which parameters have the most significant impact on the variability of the model output, thereby guiding the calibration process.

In the SWAT model, sensitivity analysis is particularly important for predicting streamflow and other hydrologic components. According to Shawul et al. (2019), this process is used to assess the effect of various parameters on total flow prediction. SWAT offers two primary approaches for sensitivity analysis: the One-Factor-At-a-Time (OAT) method and Global Sensitivity Analysis, each providing different levels of insight into parameter influence and interaction.

3.5.2 Calibration and validation

Model calibration refers to the process of adjusting model parameters to minimize the discrepancy between simulated outputs and observed data under the same set of conditions. This process is essential for improving the model's accuracy and ensuring its predictions are consistent with real-world measurements. Typically, calibration assumes a linear relationship between observed and simulated values, whereby all the variance is attributed to the simulated outputs, while the observed data are considered error-free. However, this assumption does not always hold in practice, as observational data often contain uncertainties and measurement errors.

In the context of the SWAT model, calibration can be performed using either manual or automatic methods, both of which are supported within SWAT or the SWAT-CUP software package (Abbaspour et al., 2015). Manual calibration involves iterative adjustment of input parameter values by the modeler, aiming to align the simulated outputs within an acceptable range of the

observed data. Conversely, automatic calibration utilizes numerical optimization algorithms to systematically minimize an objective function, such as the Nash–Sutcliffe Efficiency or Root Mean Square Error, making it a more rigorous and computationally efficient approach to parameter estimation. In this study, the semi-automated Sequential Uncertainty Fitting version 2 (SUFI-2) algorithm, which is one of the uncertainty analysis techniques integrated within the SWAT-CUP tool, was employed for the calibration and validation of streamflow at the Meki gauging station.

3.5.3 Uncertainty analysis

The performance of model calibration and the extent to which uncertainties are addressed can be evaluated using two key statistical metrics—**P-factor** and **R-factor**—within the Sequential Uncertainty Fitting version 2 (SUFI-2) algorithm implemented in SWAT-CUP. The **P-factor** represents the percentage of observed data enveloped by the 95% prediction uncertainty (95PPU) band, thereby reflecting the degree to which the model accounts for all uncertainties. A higher P-factor indicates better model performance in capturing observed variability. The **R-factor**, on the other hand, quantifies the thickness of the 95PPU band relative to the standard deviation of the measured data. It serves as an indicator of the quality and sharpness of the calibration. Lower R-factor values suggest narrower uncertainty bounds and a more precise model output, provided the P-factor remains high (Abbaspour et al., 2015).

In SUFI-2, uncertainty in model parameters encompasses all sources of uncertainty, including those from input data (e.g., precipitation), model structure, parameter estimates, and observational data. The strength of the uncertainty analysis is evaluated based on how effectively the 95PPU band captures observed data. This uncertainty range is computed using Latin hypercube sampling at the 2.5th percentile (L95PPU) and the 97.5th percentile (U95PPU), thereby excluding the most extreme 5% of simulations.

3.6 Model Performance Evaluation

To evaluate the performance of the model during calibration and validation periods, both graphical and statistical methods were employed. **Graphical methods** provide a visual comparison between simulated and observed values, offering an initial qualitative assessment of the model's

performance. Meanwhile, **statistical techniques** offer a quantitative evaluation of the agreement between model predictions and observed data.

In this study, three widely accepted statistical indicators were used to assess the SWAT model performance: the **Coefficient of Determination (R^2)**, **Nash–Sutcliffe Efficiency (NSE)**, and **Percent Bias (PBIAS)**.

The **Coefficient of Determination (R^2)** represents the squared correlation between observed and simulated values. It quantifies how well variations in the observed data are captured by the model and is calculated based on the ratio of the covariance of observed and simulated data to the product of their standard deviations (Krause et al., 2005). The value of R^2 ranges from 0 to 1, where values closer to 1 indicate a stronger correlation and better model performance, while values near 0 suggest weak agreement between the simulated and observed datasets. It can be computed using the following formula:

$$R^2 = \left(\frac{\sum (O_i - \overline{O})(P_i - \overline{P})}{\sqrt{\sum (O_i - \overline{O})^2} \sqrt{\sum (P_i - \overline{P})^2}} \right)^2$$

Nash–Sutcliffe Efficiency (NSE) is a dimensionless performance indicator used to assess the predictive power of hydrological models. It quantifies how closely the simulated results match the observed data by comparing the residual variance (model error) to the variance of the measured data (Nash & Sutcliffe, 1970). An NSE value of 1 indicates a perfect match between observed and simulated data, while a value of 0 indicates that the model predictions are as accurate as the mean of the observed values. A negative NSE value suggests that the model is less accurate than simply using the mean of the observed data as a predictor.

$$\text{NSE}=1-\frac{\sum_{i=1}^{n} (\text{WSEo-WSEs})\text{^}2}{\sum_{i=1}^{n} (\text{WSEo-WSEmean})\text{^}2}$$

Percent Bias (PBIAS) is a statistical measure used to evaluate the average tendency of the simulated data to either overestimate or underestimate the observed values. A positive PBIAS value suggests that the model tends to underestimate the observed data, while a negative PBIAS value indicates an overestimation. An optimal PBIAS value is zero, meaning perfect agreement

between simulated and observed data. The closer the PBIAS value is to zero, the more accurate the model's performance (Gupta, 1999)

$$\text{PBIAS (\%)} = \frac{\sum_{i=1}^{n}(\text{Yi(Obs)-Yi(sim)})*100}{\sum_{i=1}^{n}(\text{Yi(Obs)}}$$

Where Yi(Obs) and Yi(Sim) are observed and simulated respectively.

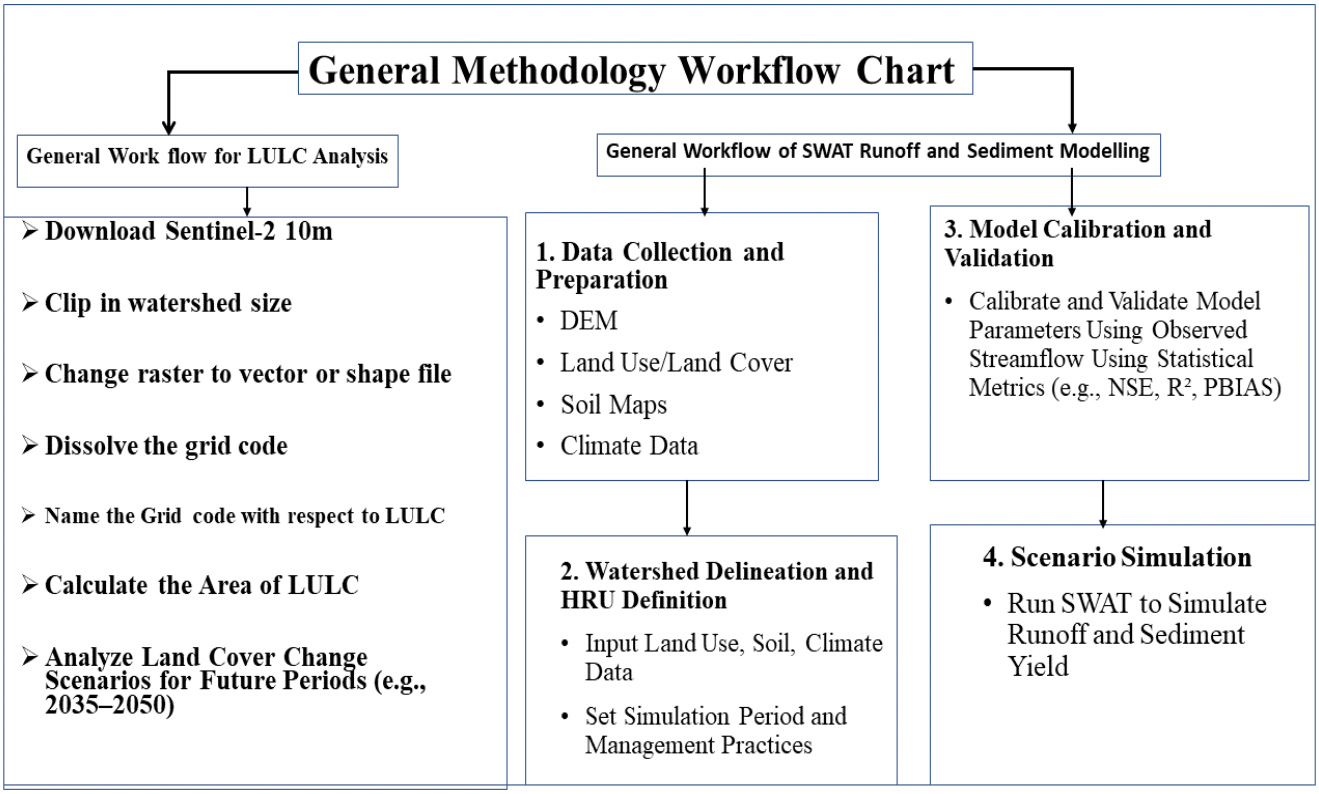


Figure 3. 2 General Methodology Workflow Chart

4. RESULTS AND DISCUSSIONS

4.1 Data Quality Analysis

4.1.1 Homogeneity Analysis

To ensure the reliability and consistency of the rainfall datasets used in the hydrological modeling, homogeneity analysis was performed for all meteorological stations using the **RAINBOW** software tool. A suite of standard statistical tests—including the **Standard Normal Homogeneity Test (SNHT)**, **Buishand's Range Test**, **Pettitt's Test**, and the **Von Neumann Ratio Test**—were applied to detect any shifts or inconsistencies in the rainfall time series. Each test was evaluated at three confidence levels: **90%**, **95%**, and **99%**, providing a comprehensive assessment of data homogeneity. The results confirmed that the majority of the rainfall records were statistically homogeneous across all stations, thereby validating their suitability for use in subsequent hydrological simulations and analyses.

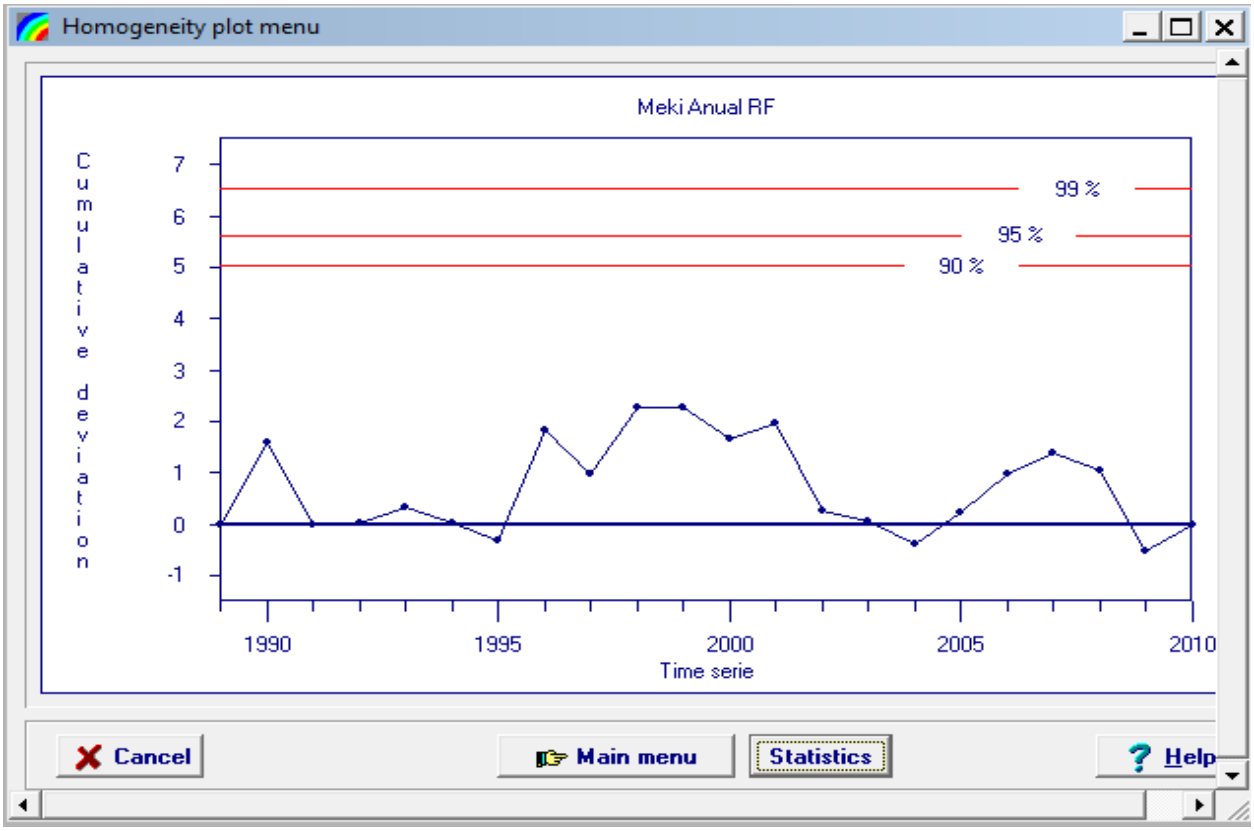


Figure 4. 1 Homogeneity test for Meki station

4.1.2 Filling of missed data

In the course of data preprocessing, the rainfall records from all meteorological stations were scrutinized for completeness. It was observed that the proportion of missing data for each station was less than 10% of the total dataset. According to hydrological data quality guidelines, when the percentage of missing data is below this threshold, the dataset can be considered sufficiently complete for use in modeling applications. Therefore, the rainfall records with less than 10% missing values were automatically adopted without interpolation or estimation and used directly in the hydrological analysis Hırca & Eryılmaz Türkkan, 2024; Wangwongchai et al., 2023. Therefore, in this study the missed data was less than 10%; for this data was automatically adopted.

4.2 Land Use Land Cover Change

4.2.1 Land Use Land Cover Classification of Lake Ziway Catchment

Land Use Land Cover (LULC) classification for the Lake Ziway catchment was derived from Sentinel-2 imagery at 10-meter spatial resolution. The classified raster dataset was reclassified based on Sentinel-defined grid codes, which correspond to specific land cover classes. This classification was integrated into the SWAT model to represent the spatial distribution of land use types across the watershed, which significantly influences runoff generation and sediment transport processes. The distribution of land cover classes, represented by their Sentinel grid codes and corresponding areas is summarized as follows in Table 4.1 for the year 2017:

The Land Use Land Cover (LULC) results for the Ziway Catchment in 2017 indicate a diverse distribution of land types, reflecting the catchment's ecological and socioeconomic significance. The largest share of land is occupied by cropland, totaling approximately **489,273.56 hectares**, which highlights the predominance of agricultural activities in the area. This extensive agricultural land use could be attributed to the fertile soils and favorable climatic conditions around Ziway, making it a key region for both subsistence and commercial farming.

Following cropland, **rangeland** accounts for about **144,619.37 hectares**, suggesting a substantial area used for pastoral activities and livestock grazing. This extensive rangeland may support the livelihoods of pastoral communities, yet its size could also reflect pressures from overgrazing and

land degradation if not properly managed. The **built-up area**, covering **44,265.81 hectares**, shows significant human settlement and urban expansion, likely driven by population growth and development along major roads and in towns near Lake Ziway.

Water bodies occupy **43,693.38 hectares**, largely represented by Lake Ziway and surrounding wetlands. This water resource plays a vital role in supporting irrigation, domestic use, and biodiversity. However, the relatively modest extent of **flooded vegetation** (**2,795.04 hectares**) might indicate seasonal or degraded wetland conditions, possibly due to land encroachment or water abstraction. Similarly, **trees** cover **27,975.20 hectares**, which may reflect natural forest remnants or agroforestry practices. While this represents a moderate green cover, it may not be sufficient for ecological balance given the dominance of farmland.

Lastly, **bare ground** comprises only **418.59 hectares**, suggesting limited areas of exposed soil or degraded land. Overall, the LULC analysis shows that the catchment is intensively used for agriculture, with some pressure on natural and semi-natural land covers such as trees and wetlands. These results can inform land management strategies to balance productivity with environmental sustainability in the region. These classified LULC categories are critical for understanding hydrological responses and informing effective watershed management practices in the SWAT modeling framework.

Table 4. 1 Land Use Land Cover Classification of Lake Ziway Catchment for the year 2017

LULC	Area (ha)	Area (%)
Water	43,693.38	5.8%
Trees	27,975.20	3.7%
Flooded vegetation	2,795.04	0.4%
Crops	489,273.56	65.0%
Built Area	44,265.81	5.9%
Bare ground	418.59	0.1%
Rangeland	144,619.37	19.2%
Total	**753,040.94**	

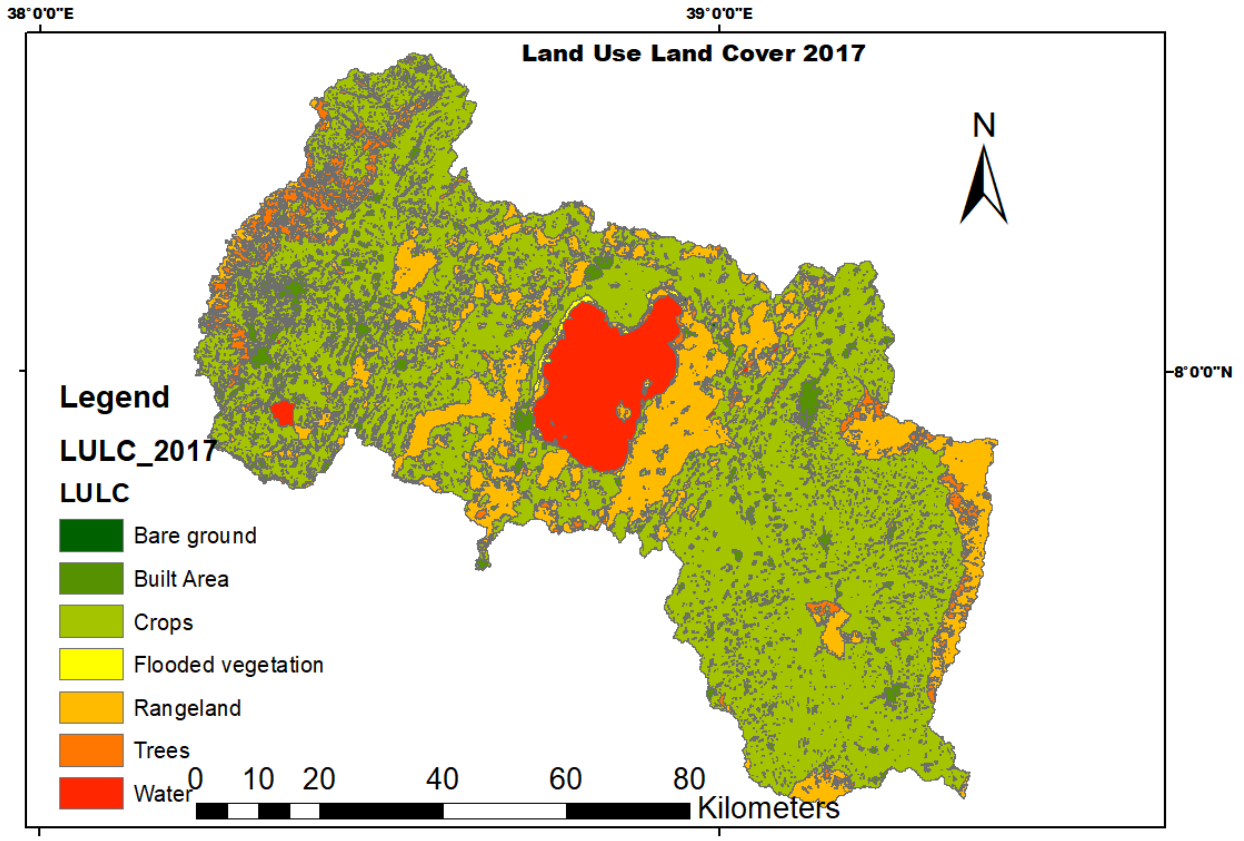


Figure 4. 2 Land Use 2017 for the Lake Ziway Catchment

In the Year 2020 of LULC for Ziway Catchment, Cropland continues to dominate the catchment, slightly decreasing from **489,273.56 ha in 2017** to **486,409.71 ha in 2020**, a net loss of about **2,863.85 ha**. This small decline may indicate either a shift of agricultural land to other uses (e.g., urban expansion) or land degradation. However, cropland remains the primary land use, emphasizing the region's dependence on agriculture.

Rangeland also shows a slight decrease, dropping from **144,619.37 ha** to **132,192.64 ha**, a reduction of about **12,426.73 ha**. This decline could be due to conversion into cropland or built-up areas, potentially reducing available grazing areas and threatening pastoralist livelihoods. **Built-up areas** increased significantly from **44,265.81 ha** in 2017 to **53,170.23 ha** in 2020—an increase of **8,904.42 ha**. This notable growth suggests rapid urban expansion or infrastructure development, possibly due to population growth, migration, or improved economic opportunities near towns and roads.

Water bodies expanded modestly, from **43,693.38 ha** to **45,751.97 ha**, an increase of **2,058.59 ha**. This could reflect seasonal changes, higher rainfall, or water level increases in Lake Ziway. However, it may also suggest waterlogging or expansion of irrigation reservoirs. **Flooded vegetation** rose from **2,795.04 ha** to **4,481.76 ha**, a gain of **1,686.72 ha**. This could indicate either the recovery of wetland areas or seasonal flooding effects. It's a potentially positive sign for wetland restoration, but further investigation is needed to confirm the cause.

Tree cover increased slightly from **27,975.20 ha** to **30,793.89 ha**, adding **2,818.69 ha**, suggesting reforestation, afforestation efforts, or growth of plantation forests. This is encouraging for environmental stability and biodiversity if it reflects natural regeneration or conservation initiatives. **Bare ground**, on the other hand, decreased significantly from **418.59 ha** to just **88.06 ha**, showing a **reduction of 330.53 ha**. This may indicate reduced land degradation or successful soil conservation efforts.

Table 4. 2 Land Use Land Cover Classification of Lake Ziway Catchment for the year 2020

LULC 2020	Area (ha)	Area (%)
Water	45,751.97	6.08%
Trees	30,793.89	4.09%
Flooded vegetation	4,481.76	0.60%
Crops	486,409.71	64.61%
Built Area	53,170.23	7.06%
Bare ground	88.06	0.01%
Rangeland	132,192.64	17.56%
Total	**752,888.26**	

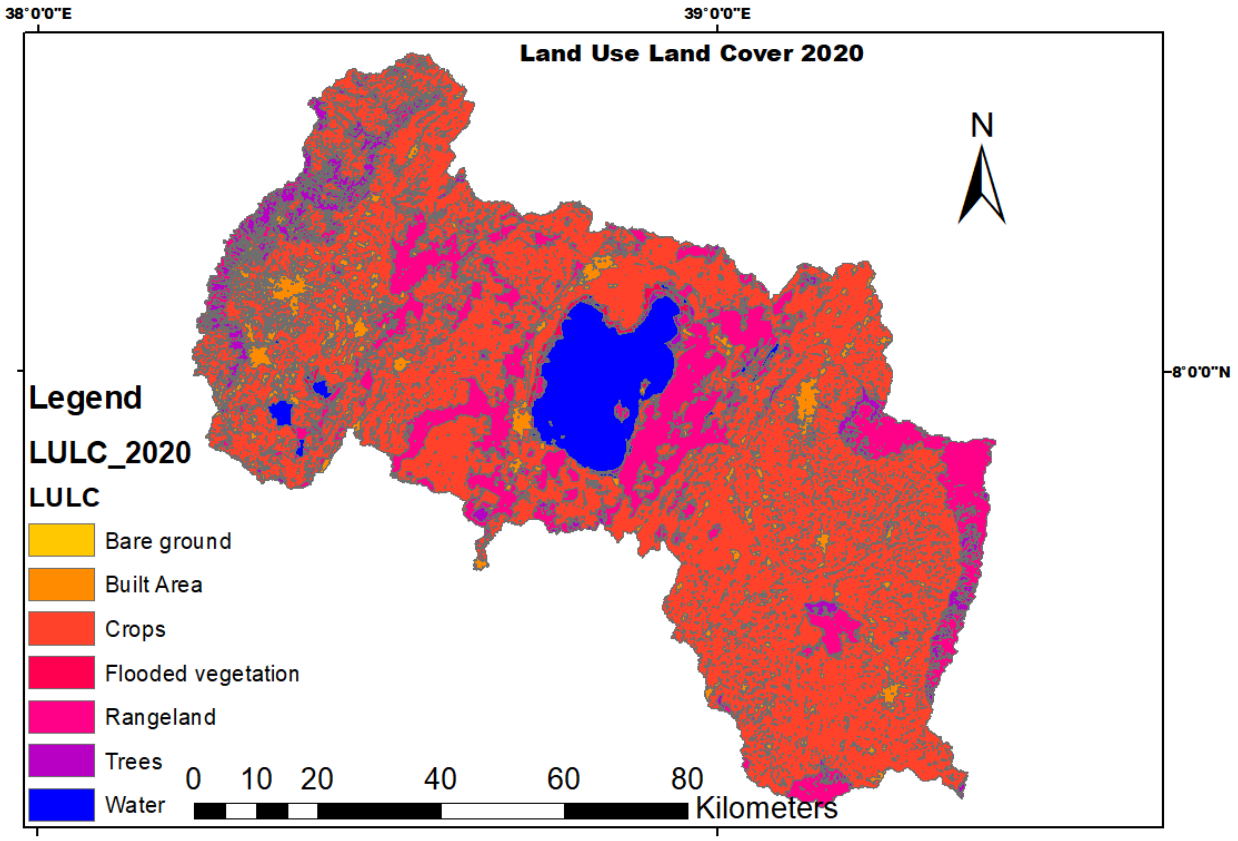


Figure 4. 3 Land Use 20*20* for the Lake Ziway Catchment

In 2024, the **Ziway Catchment** continues to be primarily dominated by **cropland**, which occupies approximately **464,679.56 hectares**, accounting for **61.78%** of the total area. This large share reflects the ongoing reliance on agriculture as the central land use activity, likely supporting both local livelihoods and regional food supply. Following cropland, **rangeland** covers about **140,324.53 hectares** (**18.65%**), indicating significant space still dedicated to grazing and livestock production.

Next in line is the **built-up area**, which has expanded to **62,961.49 hectares** (**8.37%**). This marks a notable urban footprint, possibly driven by population growth, infrastructure development, and peri-urban expansion around towns like Ziway. **Water bodies**, primarily Lake Ziway and associated wetlands, occupy **45,350.80 hectares** (**6.03%**), emphasizing the catchment's hydrological importance for agriculture, drinking water, and ecological balance.

Tree cover accounts for **35,981.94 hectares** (**4.78%**), suggesting moderate vegetation presence, which could be from forests, plantations, or agroforestry systems. **Flooded vegetation** is relatively limited at **2,816.10 hectares** (**0.37%**), hinting at seasonal wetlands or riverbank vegetation that may fluctuate with water levels. Finally, **bare ground** is minimal, covering just **96.40 hectares** (**0.01%**), which may indicate successful vegetation cover and minimal land degradation.

Table 4. 3 Land Use Land Cover Classification of Lake Ziway Catchment for the year 2024

LULC 2024	Area (ha)	Area (%)
Water	45,350.80	6.03%
Trees	35,981.94	4.78%
Flooded vegetation	2,816.10	0.37%
Crops	464,679.56	61.78%
Built Area	62,961.49	8.37%
Bare ground	96.40	0.01%
Rangeland	140,324.53	18.65%
Total	**752,210.81**	100.00%

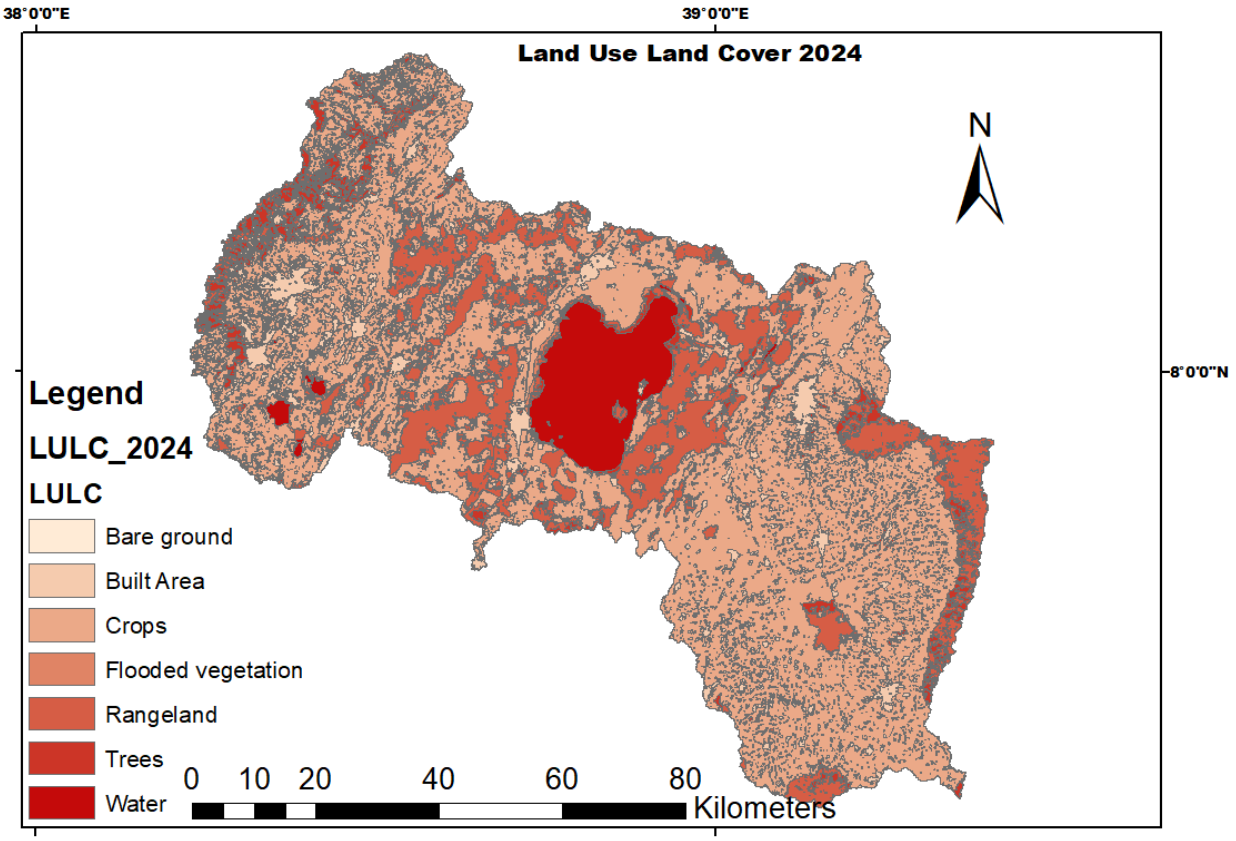


Figure 4. 4 Land Use 20*20* for the Lake Ziway Catchment

4.3 Analysis of Land Use Changes

4.3.1 LULC Change: 2017 to 2020

Between 2017 and 2020, **built-up areas** increased significantly by **8,904.42 ha** (+**20.1%**), reflecting expanding settlements and infrastructure development. **Tree cover** also grew by **+10.1%**, possibly due to reforestation programs or natural regrowth. Notably, **flooded vegetation** rose sharply by over **+60.3%**, likely tied to higher rainfall or hydrological shifts in the catchment.

Meanwhile, **cropland** declined slightly (**-0.60%**), indicating some conversion of agricultural land to other uses, possibly urban expansion. **Rangeland** experienced a moderate drop (**–8.6%**), which may be due to encroachment or changes in land management. Interestingly, **bare ground** decreased by nearly **–79.0%**, suggesting land rehabilitation or vegetative cover improvements. **Water bodies** expanded modestly by **+4.7%**, likely due to hydrological variation.

Table 4. 4 Area changes from 2017 to 2020

LULC Class	2017 Area (ha)	2020 Area (ha)	Change (ha)	% Change
Water	43,693.38	45,751.97	**2,058.59**	**4.70%**
Trees	27,975.20	30,793.89	**2,818.69**	**10.10%**
Flooded vegetation	2,795.04	4,481.76	**1,686.72**	**60.30%**
Crops	489,273.56	486,409.71	**–2,863.85**	**–0.6%**
Built Area	44,265.81	53,170.23	**8,904.42**	**20.10%**
Bare ground	418.59	88.06	**–330.53**	**–79.0%**
Rangeland	144,619.37	132,192.64	**–12,426.73**	**–8.6%**
Total	**753,040.94**	**752,888.26**	**–152.68**	**≈0.0%**

4.3.2 LULC Change: 2017 to 2024

Over the longer term (2017–2024), **built-up areas surged** by over **+18,695.68 ha**, marking a **+42.2%** increase strong evidence of urban growth. **Tree-covered areas** rose by **+28.6%**, a positive trend that might point to afforestation efforts, agroforestry, or better land management.

On the other hand, **cropland shrank** by **–24,594.00** (**–5.0%**), possibly indicating land use conversion to urban or residential areas. **Flooded vegetation** showed only a marginal increase (**+0.8%**), suggesting relatively stable seasonal wetland dynamics over time. **Rangeland** saw a slight decline of **–5.7%**, while **bare ground** nearly vanished (**–77.0%**), again implying positive vegetative recovery or land use stabilization. **Water bodies** increased by about **+3.8%**, showing some stability in surface water availability.

Table 4. 5 Area changes from 2017 to 2024

LULC Class	2017 Area (ha)	2024 Area (ha)	Change (2017–2024) (ha)	% Change (2017–2024)
Water	43,693.38	45,350.80	**1,657.42**	**3.80%**
Trees	27,975.20	35,981.94	**8,006.74**	**28.60%**
Flooded vegetation	2,795.04	2,816.10	**21.06**	**0.80%**
Crops	489,273.56	464,679.56	**–24,594.00**	**–5.0%**
Built Area	44,265.81	62,961.49	**18,695.68**	**42.20%**
Bare ground	418.59	96.4	**–322.19**	**–77.0%**
Rangeland	144,619.37	140,324.53	**–8,294.84**	**–5.7%**
Total	**753,040.94**	**752,210.81**	**–830.13**	**≈0.0%**

4.3.3 LULC Change: 2020 to 2024

From 2020 to 2024, the **urban footprint continued to expand**, with built areas increasing by **+9,791.26 ha** (**+18.4%**). **Tree cover** also rose by **+16.9%**, continuing the upward trend possibly due to deliberate conservation actions or natural processes.

However, **cropland experienced a more noticeable decline**, losing -**21,730.15 ha** (**-4.5%**), which reinforces concerns over shrinking agricultural zones. **Flooded vegetation** reduced sharply by **–1,665.66** (**-37.2%**), potentially reflecting drought effects or drainage. **Rangeland** rebounded modestly (**+6.1%**), indicating restoration or less pressure from grazing. **Bare ground** saw a slight increase (**+9.5%**), which may suggest localized disturbances. **Water bodies** slightly decreased (**–0.9%**), possibly due to seasonal fluctuation or water extraction.

Table 4. 6 Area changes from 2020 to 2024

LULC Class	2020 Area (ha)	2024 Area (ha)	Change (ha)	% Change (2020–2024)
Water	45,751.97	45,350.80	**–401.17**	**–0.9%**
Trees	30,793.89	35,981.94	**5,188.05**	**16.90%**
Flooded vegetation	4,481.76	2,816.10	**–1,665.66**	**–37.2%**
Crops	486,409.71	464,679.56	**–21,730.15**	**–4.5%**
Built Area	53,170.23	62,961.49	**9,791.26**	**18.40%**
Bare ground	88.06	96.4	**8.34**	**9.50%**
Rangeland	132,192.64	140,324.53	**8,131.89**	**6.10%**
Total	**752,888.26**	**752,210.81**	**–677.45**	**≈0.0%**

4.3.4 Prediction of Land Use Land Cover

Several recent studies have used multi-temporal LULC datasets to compute annual change rates (hectares/year) and project trends into the future. For example, (Gebrehiwot et al., 2024) calculated annual change rates for various land cover classes over three decades in the Upper Tekeze River Basin and used these data to inform future land use planning. (Delgado et al., 2025) mapped change over thirty years (1990-2020) in southern coastal Peru, derived area changes per year, and projected land cover extents to 2030 using Markov-CA models.

To predict the land use and land cover (LULC) for the years 2035 and 2050, we first calculate the annual change for each LULC class based on the differences observed from 2020 to 2024. This is done by dividing the total change in area (in hectares) by the number of years (4) to obtain the annual change. Next, we use this annual change to estimate the area for 2035 by multiplying the annual change by 11 (the number of years from 2024 to 2035) and adding it to the area in 2024. Similarly, we predict the area for 2050 by multiplying the annual change by 26 (the number of years from 2024 to 2050) and adding that to the area in 2024. This method allows us to extrapolate the trends observed in recent years, providing an estimate of future land use patterns for each class.

Calculate Annual Change:

For each LULC class, calculate the annual change based on the data from 2020 to 2024.

$$\textbf{Annual Change} = \frac{\text{Change (ha)}}{Number\ of\ Years}$$

Step 2: Calculate Annual Change Between Each Period

Annual Change 2017−2020 = $\frac{\textbf{Area2020}-\textbf{Area2017}}{\textbf{3}}$

Annual Change 2020−2024 = $\frac{\textbf{Area2024}-\textbf{Area2020}}{\textbf{4}}$

Step 3: Compute the Average Annual Change (2017–2024)

Average Annual Change 2017−2024 = $\frac{\textbf{Annual Change2017}-\textbf{2020}+\textbf{Annual Change2020}-\textbf{2024}}{\textbf{2}}$

Predict for 2035:

Use the annual change to estimate the area for the year 2035 (11 years from 2024).

Predicted Area2035=Area2024+(Average Annual Change×11)

Predict for 2050:

Use the annual change to estimate the area for the year 2050 (26 years from 2024).

Predicted Area2050=Area2024+(Average Annual Change×26)

Predicted LULC for 2035 and 2050

Table 4. 7 Predicted LULC for 2035 and 2050 from the Scenarios of 2017, 2020, and 2024\

LULC	2017 Area (ha)	2020 Area (ha)	2024 Area (ha)
Water	43,693.38	45,751.97	45,350.80
Trees	27,975.20	30,793.89	35,981.94
Flooded vegetation	2,795.04	4,481.76	2,816.10
Crops	489,273.56	486,409.71	464,679.56
Built Area	44,265.81	53,170.23	62,961.49
Bare ground	418.59	88.06	96.4
Rangeland	144,619.37	132,192.64	140,324.53

Table 4. 8 Future Predicted LULC for 2035 and 2050

LULC	Annual Change (2017-2020)	Annual Change (2020-2024)	Average Annual change (2017-2024)	Predicted LULC 2035	Predicted LULC 2050
Water	686.19667	-100.2925	292.9520833	48573.27292	52967.55417
Trees	939.56333	1297.0125	1118.287917	48283.10708	65057.42583
Flooded vegetation	562.24	-416.415	72.9125	3618.1375	4711.825
Crops	-954.6167	-5432.538	-3193.577083	429550.2121	381646.5558
Built Area	2968.14	2447.815	2707.9775	92749.2425	133368.905
Bare ground	-110.1767	2.085	-54.04583333	-498.1041667	-1308.791667
Rangeland	-4142.243	2032.9725	-1054.635417	128723.5404	112904.0092

4.4 SWAT Model Simulation

4.4.1 Streamflow sensitivity analysis

Sensitivity analysis plays a crucial role in accurately predicting streamflow within a given watershed model. It serves as a key approach for determining the most influential parameters that require adjustment during the calibration, validation, and uncertainty assessment phases of the SWAT model (J. G. Arnold, 2012; Moriasi, 2007). Sensitivity analysis was conducted using the SWAT-CUP tool to identify the most influential parameters affecting streamflow simulation in the Lake Ziway catchment. The analysis aimed to determine which parameters exert the greatest impact on model output, thereby guiding the calibration and uncertainty analysis processes. Ten parameters were selected based on their relative sensitivity rankings and influence on streamflow dynamics.

Parameter Name	t-Stat	P-Value
9:R__SURLAG.bsn	0.030721946	0.975504166
8:R__GW_REVAP.gw	0.031962522	0.974515336
7:R__HRU_SLP.hru	0.033066913	0.973635088
6:R__CH_K2.rte	-0.277435587	0.781566108
5:R__SOL_K(..).sol	0.821367309	0.411848266
4:V__GWQMN.gw	-0.529631456	0.596614410
3:V__GW_DELAY.gw	-2.186492297	0.029265790
23:R__SOL_AWC(..).sol	-1.523589942	0.128275246
22:R__REVAPMN.gw	0.965101269	0.334984146
21:R__EVRCH.bsn	-1.284767802	0.199498287
20:R__SURLAG.bsn	1.552945477	0.121100758
2:V__ALPHA_BF.gw	0.347891098	0.728075761
19:R__EVLAI.bsn	1.950233306	0.051734911
18:R__TIMP.bsn	0.877964308	0.380406019
17:R__ESCO.bsn	-0.074102328	0.940960093
16:R__HRU_SLP.hru	-1.215402740	0.224814998
15:R__SLSUBBSN.hru	3.327873975	0.000942930
14:R__CH_N2.rte	2.069645336	0.039024511
13:R__CH_K2.rte	0.588366339	0.556565486

Figure 4. 5 Streamflow sensitive parameters Lake Ziway Catchments

In the calibration process, several key parameters influencing surface runoff, groundwater flow, soil water processes, and channel routing were selected to improve streamflow simulation. These include r__CN2.mgt, v__ALPHA_BF.gw, v__GW_DELAY.gw, v__GWQMN.gw, r__SOL_K().sol, r__CH_K2.rte, r__CH_N2.rte, r__HRU_SLP.hru, r__SLSUBBSN.hru, r__GW_REVAP.gw, r__RCHRG_DP.gw, r__REVAPMN.gw, r__SURLAG.bsn, r__SOL_AWC().sol, r__ESCO.bsn, r__TIMP.bsn, r__EVLAI.bsn, r__EVRCH.bsn, and r__USLE_P.mgt, .These parameters collectively represent hydrological processes such as infiltration, surface runoff generation, baseflow, groundwater–surface water interaction, and evapotranspiration dynamics. Table 4.10 below presents the sensitive parameters along with their type, name, and fitted range values used during the sensitivity analysis.

Table 4. 9 Sensitive parameters for Lake Ziway Catchments

Parameter Name	Lower Range	Upper Range	Parameter Name	Lower Range	Upper Range
r__CN2.mgt	-0.753932	0.428776	r__SOL_K().sol	-134.20908	63.116341
v__ALPHA_BF.gw	0.626363	1.244537	r__CH_K2.rte	140.698227	292.79953
v__GW_DELAY.gw	198.441696	413.030701	r__CH_N2.rte	0.0623	0.196188
v__GWQMN.gw	132.612137	296.550018	r__SLSUBBSN.hru	-0.744253	0.051845
r__SOL_K().sol	-478.1944	-119.373466	r__HRU_SLP.hru	0.591499	11.447498
r__CH_K2.rte	100.64077	153.659576	r__ESCO.bsn	0.122726	0.942094
r__HRU_SLP.hru	7.684844	31.046122	r__TIMP.bsn	-0.213478	0.336008
r__GW_REVAP.gw	-0.012347	0.100365	r__EVLAI.bsn	1.63403	9.416494
r__SURLAG.bsn	2.098217	5.091477	r__SURLAG.bsn	6.550764	23.720177
r__RCHRG_DP.gw	0.108524	0.921121	r__EVRCH.bsn	0.223476	0.58642
r__USLE_P.mgt	-0.302458	0.291022	r__REVAPMN.gw	619.910217	1131.22961
			r__SOL_AWC().sol	5.803955	11.1155

4.4.2 Calibration and Validation

Streamflow calibration for the Meki watershed was conducted at the Meki village gauging station using the SUFI-2 algorithm within the SWAT-CUP interface. The simulation began with a two-year warm-up period (1990–1991) to initialize the model and stabilize its internal state variables, thereby reducing the impact of uncertain initial conditions. The calibration phase was carried out on a monthly time scale for the period 1992–2008 for the number of simulations 500, during which sensitive hydrological parameters—identified through prior sensitivity analysis—were iteratively adjusted within their defined allowable ranges. The goal was to minimize the discrepancy between simulated and observed streamflow data.

Once calibration was complete, the model was validated using independent streamflow data for 2009–2010, without modifying the previously calibrated parameter values. Model performance was assessed using key statistical indicators: the coefficient of determination (R^2), Nash–Sutcliffe Efficiency (NSE), and Percent Bias (PBIAS). These metrics were applied to evaluate how well the model replicated observed monthly streamflow patterns. The results indicate satisfactory performance of the SWAT model in simulating streamflow for both calibration and validation periods. Based on study using **Moriasi et al. (2007 & 2015)** performance rating benchmarks, the **Meki** and **Ketar** watershed SWAT model performance can be interpreted in terms of **R^2**, **NSE**, and **PBIAS**, focusing on the **"satisfactory"** threshold for **streamflow simulation**. These results demonstrate the model's reliability in capturing the hydrological behavior of the Meki watershed using both static and dynamic land use conditions.

Table 4. 10 Calibration and Validation performance for the model

Watershed	Period	R^2	NSE	PBIAS (%)
Meki	Calibration (1992–2008)	0.45	0.56	-30
	Validation (2009–2010)	0.51	0.58	-28
Ketar	Calibration (1992–2005)	0.56	0.61	-24.6
	Validation (2006–2007)	0.60	0.64	-25.2

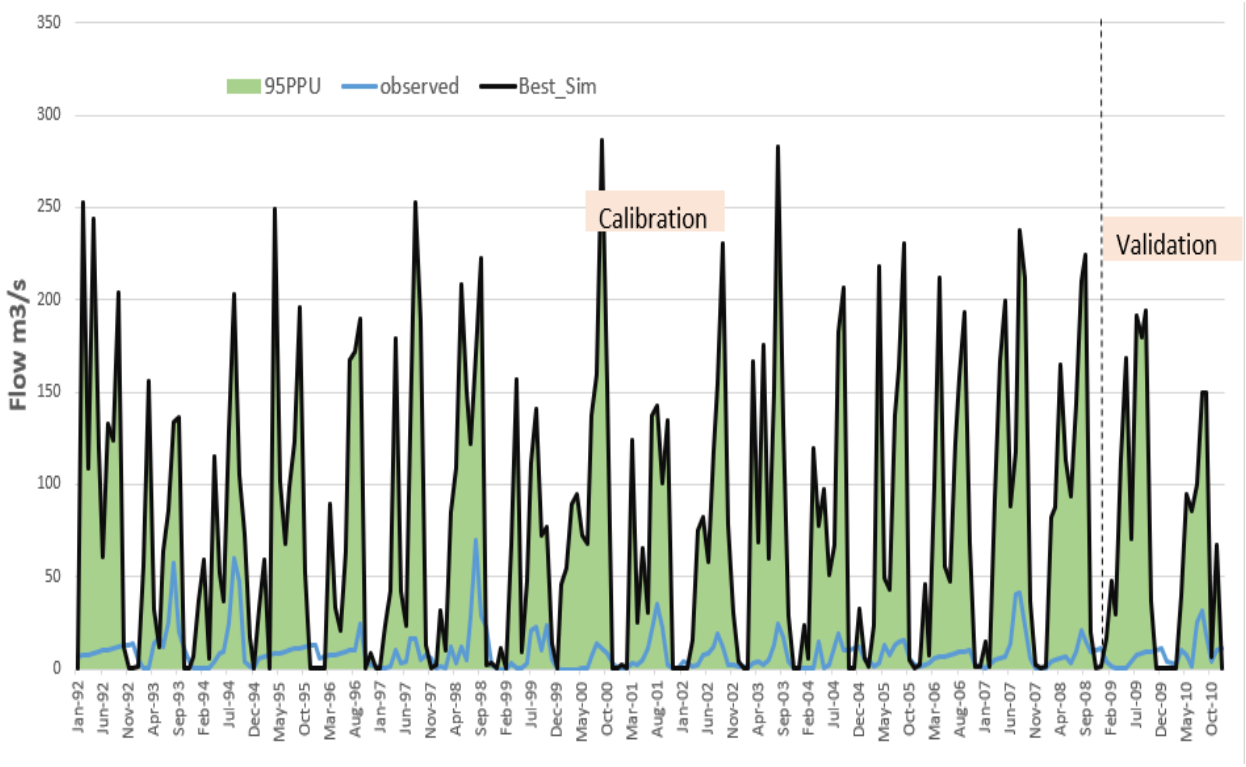


Figure 4. 6 Calibration and validation of stream flow of Meki river

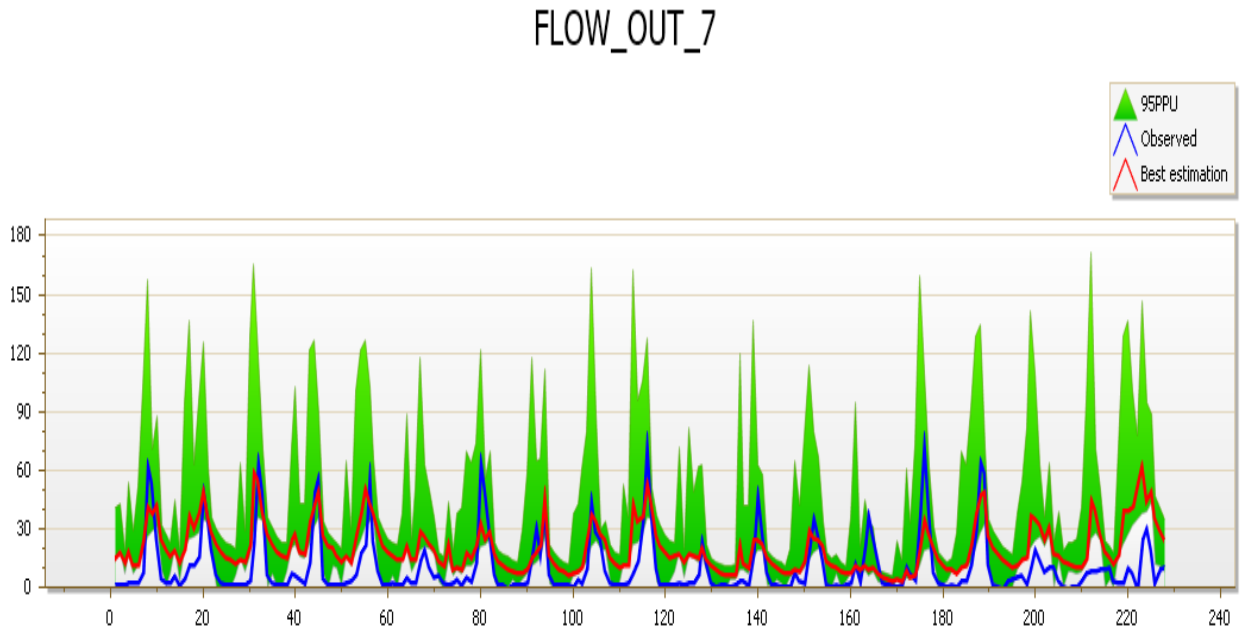


Figure 4. 7 Calibration of stream flow of Ketar River

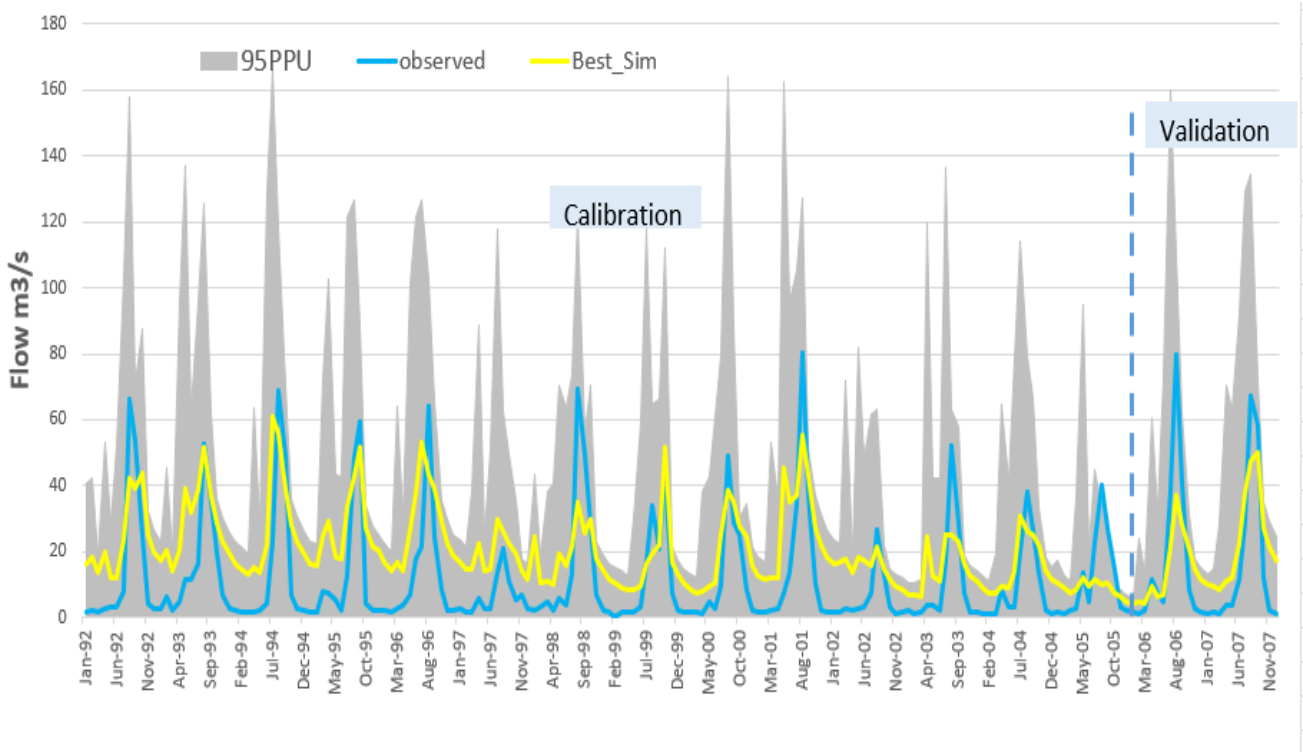


Figure 4. 8 Calibration and validation of stream flow of Ketar River

Ketar Watershed: SWAT performed **good** in both calibration and validation (R^2 = 0.56–0.60, NSE = 0.61–0.64, PBIAS ~ –25%). This indicates that the model reliably captures hydrological processes and sediment transport. While **Meki Watershed:** SWAT performance is **satisfactory** (R^2 = 0.45–0.51, NSE = 0.56–0.58, PBIAS ~ –28%). While slightly lower, it still provides a reasonable estimate of sediment loads. Differences in watershed characteristics such as land use, soil types, topography, and vegetation cover can significantly influence model performance. For instance, the Meki watershed may have more complex land use patterns or varied topography compared to the Ketar watershed, leading to greater uncertainty in model predictions. This is consistent with findings from studies in Ethiopia, where variations in watershed characteristics affected model outcomes (Gadissa, *T* et al., 2018).

4.5 Sediment Yield Estimation

Following the successful calibration and validation of streamflow at the Meki village gauging station using the SUFI-2 algorithm within the SWAT-CUP framework, the model was employed to simulate and assess sediment yield for the entire Lake Ziway catchment. The validated

hydrological parameters provided a reliable foundation for estimating sediment transport dynamics across the watershed, enabling the evaluation of spatial and temporal patterns of sediment yield under both current and projected land use conditions.

A total of 30 subbasins were delineated within the Lake Ziway catchment during the SWAT model setup. This subbasin delineation allowed for a detailed spatial representation of hydrological processes across the watershed, enabling the assessment of streamflow and sediment yield at a sub-watershed level. The delineation served as a fundamental step for simulating distributed hydrologic responses and identifying critical source areas of sediment contribution within the catchment.

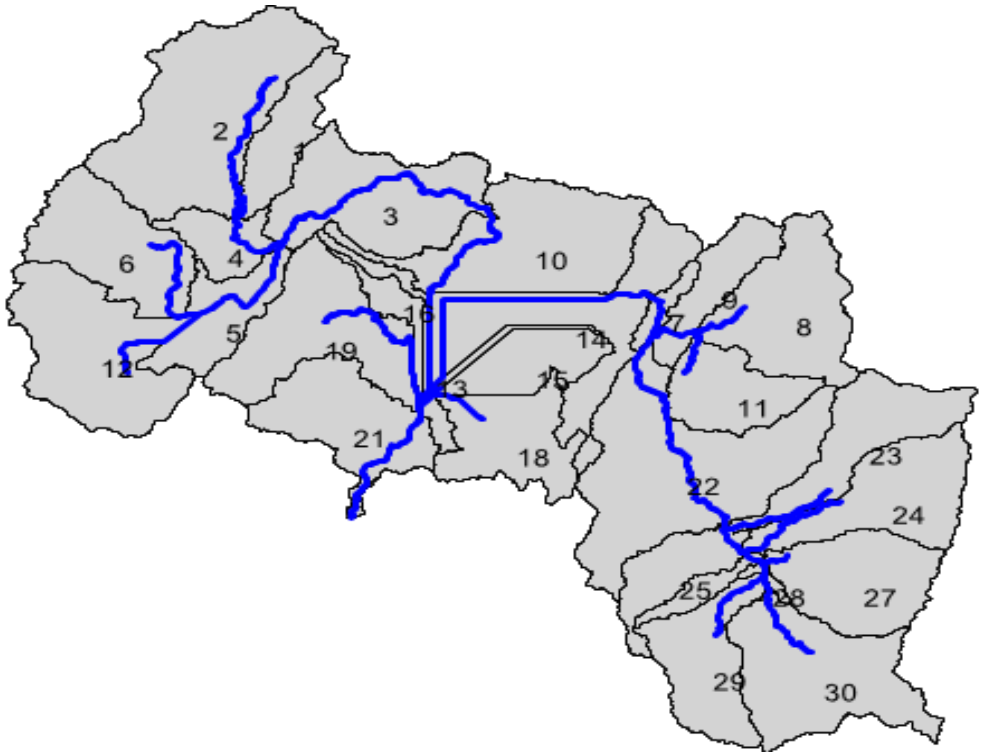


Figure 4. 9 Subbasins for Lake Ziway Catchment delineated

4.5.1 Average Annual Sediment Yield (1990–2010)

The average annual sediment yield (SYLD) from the 30 sub-basins draining into Lake Ziway between 1990 and 2010 shows significant spatial variability, highlighting that certain sub-basins contribute disproportionately to the total sediment inflow. Sub-basin 6 emerges as the highest sediment producer with 173.70 t/ha, followed by sub-basin 12 with 117.36 t/ha, while sub-basins

such as 3, 13, 14, 15, 16, and 17 exhibit very low sediment yields, some close to zero. This pattern indicates the presence of sediment hotspots likely driven by a combination of steep topography, highly erodible soils, intensive agricultural practices, and potentially inadequate soil conservation measures. Conversely, low-contributing sub-basins may be characterized by flatter terrain, better soil cohesion, forest or grassland cover, and existing erosion control practices.

The observed variability underscores the need for targeted watershed management, as controlling erosion in a few high-contributing sub-basins can substantially reduce overall sediment loads to Lake Ziway. High sediment inflows from sub-basins 6, 12, 2, 27, 24, and 30 are likely to accelerate siltation, reduce water storage capacity, and degrade water quality in the lake. Therefore, implementing terraces, vegetative buffers, reforestation, and sustainable agricultural practices in these hotspot sub-basins is crucial. These findings align with global hydrological studies, where sediment yields are strongly influenced by topography, land use, soil type, and conservation practices, emphasizing that accurate modeling and management strategies should focus on sub-basins with the highest sediment contributions to optimize sediment control efforts.

Table 4. 11 Average Annual Sediment Yield from different Sub-basins Surrounding the Lake Zeway

Average Annual Sediment Yield from the Year (1990-2010)					
Sub-Basin	SYLDt_ha	Sub-Basin	SYLDt_ha	Sub-Basin	SYLDt_ha
1	25.0387	11	16.1462	21	7.9572
2	28.499	12	117.364	22	9.3053
3	0.7082	13	0	23	13.7017
4	7.5023	14	2.4676	24	22.8076
5	6.5598	15	2.8044	25	6.1556
6	173.6962	16	2.6239	26	4.251
7	3.4077	17	0.6852	27	25.1286
8	20.6527	18	8.8742	28	15.0663
9	4.5896	19	3.7531	29	14.2089
10	1.0127	20	6.0878	30	21.0783

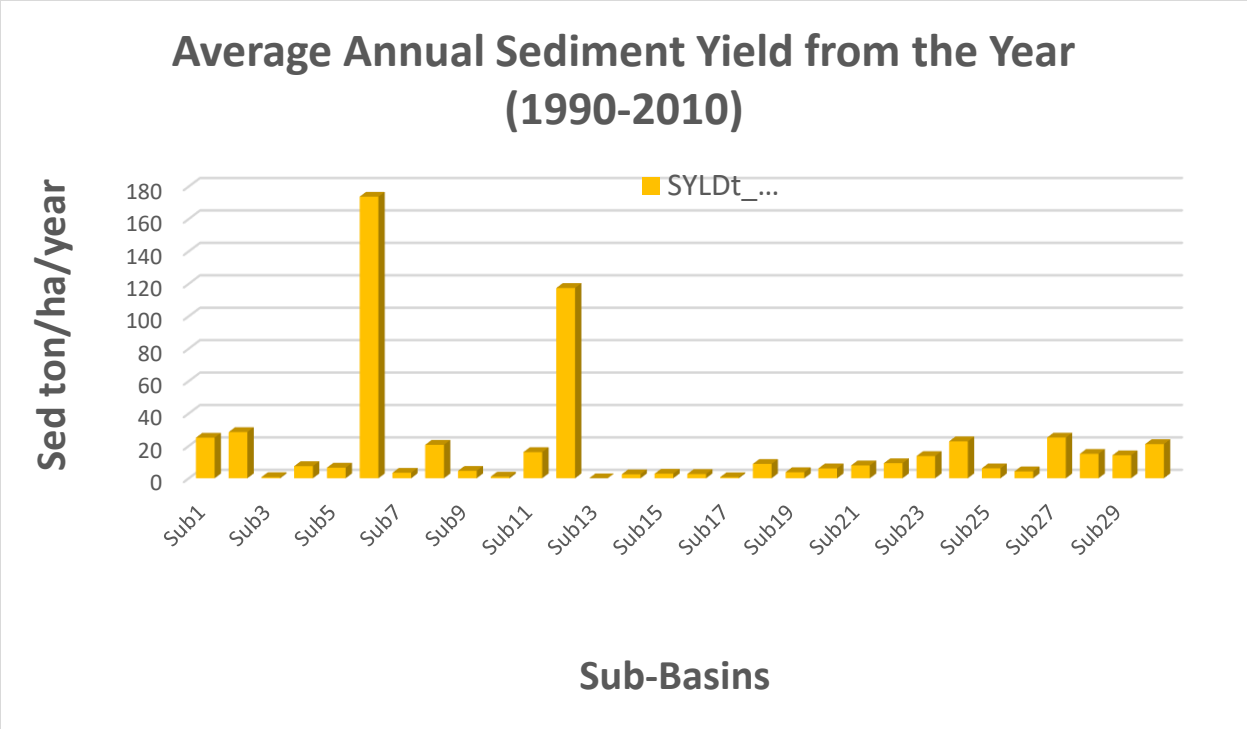


Figure 4. 10 sediment yield distribution in Sub-basins

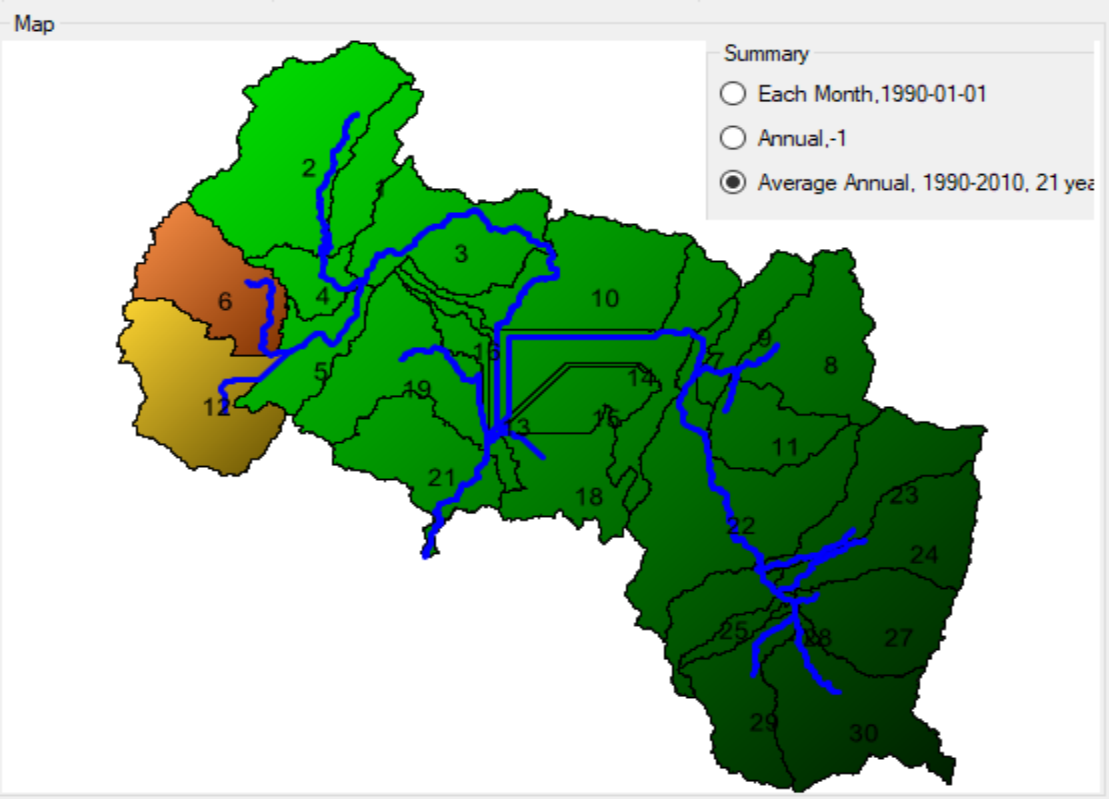


Figure 4. 11 Map shows the sediment distributions in the sub-basins

4.6 Discussions

The analysis of average annual sediment yield (SYLDt/ha/year) over a 21-year simulation period (1990–2010) using the SWAT model provided key insights into the spatial distribution and intensity of soil erosion across the Lake Ziway catchment. The sediment yield values varied considerably among the 30 delineated sub-basins, highlighting the heterogeneity of land cover, topography, land use practices, and hydrological responses within the watershed.

4.6.1 Analysis of Sediment Yield Results

The analysis of average annual sediment yield (SYLD) from the 30 sub-basins draining into Lake Ziway during 1990–2010 indicates substantial spatial variability, which can be categorized into **high, moderate, and low sediment yield sub-basins**.

High Sediment Yield Sub-basins:
Sub-basins such as 6 (173.70 t/ha) and 12 (117.36 t/ha) are identified as high sediment yield areas. These sub-basins contribute disproportionately to the total sediment inflow to Lake Ziway. The elevated sediment yield is likely due to steep slopes, highly erodible soils, intensive agricultural practices, and minimal soil and water conservation measures. These areas represent critical hotspots where erosion control interventions are essential to reduce sediment loading to the lake.

Moderate Sediment Yield Sub-basins:
Sub-basins including 1, 2, 24, 27, 28, and 30, with sediment yields ranging approximately from 15 to 28 t/ha, fall into the moderate category. These sub-basins contribute a significant, yet not dominant, portion of the total sediment inflow. Sediment production in these areas is influenced by a combination of moderate slope, agricultural activities, and partial vegetation cover. Management strategies in these sub-basins, such as buffer strips along streams and improved land use practices, can further reduce sediment transport.

Low Sediment Yield Sub-basins:
Sub-basins such as 3, 13, 14, 15, 16, and 17, with sediment yields below 5 t/ha, represent low sediment yield areas. These sub-basins are less prone to erosion due to flatter terrain, cohesive soils, forest or grassland cover, and potentially effective conservation practices. Although their

contribution to total sediment inflow is minimal, maintaining existing land cover and conservation measures is important to prevent future increases in sediment production.

The SWAT model is widely used and able to identify sediment source areas (critical/source/catchment hotspots) and to simulate sediment transport to reservoirs when appropriately set up and calibrated. However, reviews by Aloui etal also show SWAT studies vary in quality depending on data, parameterization, and regional conditions, so good performance in one sub-catchment doesn't guarantee equal performance in another without careful calibration and uncertainty analysis.

4.6.2 Comparison with previous Lake Ziway / Rift Valley studies

Several SWAT and field studies in the Lake Ziway / Rift Valley region report **typical sediment yields** in the range of a few to a few tens of tones per hectare per year, depending on watershed condition and the sub-basin considered. For example, Bunta & Abate (2021) reported ~**13.12 t ha^{-1} yr^{-1}** for the Meki watershed; other SWAT-based studies for parts of the Ziway basin present values that are often in the low-to-mid tens of t ha^{-1} yr^{-1} for high-erosion areas. These published ranges make your **173 and 117 t ha^{-1}** values stand out as **anomalously high** relative to common findings for the same region.

Regional syntheses and basin studies (Aga 2018; Gadissa et al.) document large spatial variability and identify Meki and Ketar tributaries as major contributors to lake siltation — but the literature generally reports annual sediment yields for problematic sub-catchments in the order of single digits to a few tens of t ha^{-1} (and aggregated fluxes often reported in t km^{-2} or total tones to the lake). Your highest sub-basins exceed typical published per-hectare values by an order of magnitude or more. Published classification thresholds used in several Ethiopian SWAT studies classify erosion intensity roughly as: **low** (0–11 t ha^{-1} yr^{-1}), **medium** (11–18), **high** (18–30), and **very high** (>30). By that scheme, sub-basins 6 and 12 are extremely beyond "very high."

The simulated average annual sediment yields (1990–2010) show strong spatial variability across the Lake Ziway catchment, with two sub-basins (6 and 12) exhibiting exceptionally high per-hectare yields (≈174 and 117 t ha^{-1} yr^{-1}, respectively). Published SWAT and field studies in the Ziway and Rift Valley basin typically report sediment yields for problematic sub-catchments in the order of single to tens of tones per hectare per year. Thus, the magnitudes observed in sub-

basins 6 and 12 are anomalous compared to regional results and should be verified. Possible explanations include model-setup artifacts (units reporting, small HRU areas, or uncalibrated sediment parameters), or very intense localized erosion (gullying, bare soils, steep slopes) that may not be well captured in the cross-checked literature. Prior to management decisions, we therefore recommend targeted model diagnostics and field verification in these sub-basins; if confirmed, conservation priority should be assigned to these areas and a mix of hill-slope BMPs and in-stream sediment controls implemented to reduce sediment flux to Lake Ziway.

A recent study by Negasa (2023) used runoff plots and measured sediment contributions from different land-cover types in the Lake Ziway watershed found that **cultivated land produces the highest sediment losses**, while forest and grassland produce far less; the study provides measured sediment-loss magnitudes from plot-scale experiments and shows strong land-use control on sediment export. This confirms the common pattern you see where agricultural sub-basins (if sub-basins 6 or 12 are heavily cropland) are likely to produce disproportionately high yields.

Aga (2018) applied SWAT and river SSC sampling in the Ziway basin and validated modeled basin-scale sediment flux with bathymetric and SSC data. Typical SWAT-derived sub-catchment yields in these regional studies commonly range from **single-digit to a few tens of t ha^{-1} yr^{-1}** for many sub-catchments; very high values (>100 t ha^{-1} yr^{-1}) are not typical at the basin scale unless there are severe, localized gully or bank-failure processes. This makes the **~174 and ~117 t ha^{-1} yr^{-1}** in your table unusually large relative to MDPI-reported basin results, and therefore worth closer checking and field validation.

Another study by Leta et al., (2023), emphasize that SWAT results are sensitive to land-use/soil inputs and to calibration against observed flow/SSC or bathymetry. Typical "hotspot" thresholds used in these papers treat yields >30 t ha^{-1} yr^{-1} as very high. Many Springer articles use SWAT+SUFI-2 calibration and then run BMP scenarios to show realistic reductions (often tens of percent). Your highest values greatly exceed the "very high" threshold used in these studies, suggesting either genuine severe erosion or a model/setup artifact (units, small HRU area, parameterization).

Other regional studies by Turdu et al., (1999) on lake bathymetry and long-term siltation observations for multiple basin studies (including bathymetric reconstructions and sediment-core

based assessments) confirm that Lake Ziway has experienced substantial sedimentation and that the **upper watershed (intensive cultivation + exposed volcanic soils)** is the main source. Those studies provide basin-scale support for prioritizing upland cultivated areas, but they do not usually report universal per-hectare yields exceeding 100 t ha^{-1} yr^{-1} across sizeable sub-basins without identifying extreme local processes (deep gullies, landslides, channel bank collapse).

The spatial pattern and magnitudes of simulated sediment yield across Lake Ziway sub-basins are broadly consistent with previous regional studies that identify cultivated uplands as the dominant sediment source (runoff-plot and SWAT studies). However, the model results show two sub-basins (Sub-Basin 6 and 12) with exceptionally high per-hectare yields (~174 and ~117 t ha^{-1} yr^{-1}), values which exceed typical basin-scale reports in the literature (commonly single to a few tens t ha^{-1} yr^{-1}). Similar SWAT studies by Aga et al., (2018) emphasize that such large magnitudes require careful verification against observed suspended-sediment or bathymetric data and a check of model settings (units, HRU area, USLE parameters, channel erosion representation). Therefore, we recommend targeted model diagnostics and field validation (runoff plots / SSC or bathymetry) before prioritizing interventions in these sub-basins.

4.6.3 Key Observations and Interpretation

The sediment yield data from the Lake Ziway catchment reveals critical insights into the state of erosion and soil management across the 30 sub-basins. Here are the key observations and interpretations based on the results:

Significant Variability in Sediment Yield

The sediment yield across the sub-basins exhibited considerable spatial variability, indicating differences in topography, land cover, and hydrological response. Sub-basins such as 6 and 12 showed extremely high sediment yields, suggesting active erosion processes likely due to steep slopes and intensive land use practices. Similar spatial heterogeneity in sediment generation has been reported in various studies where sub-basin characteristics and rainfall intensity were found to be dominant controlling factors (Aloui et al., 2023; Zhang et al., 2019). This implies that the hydrological and geomorphological conditions of each sub-catchment play a vital role in determining sediment production potential.

The analysis of sediment yield across the 30 sub-basins draining into Lake Ziway reveals substantial spatial variability. Sub-basins 6 and 12 are the highest contributors, producing 173.70 t/ha and 117.36 t/ha annually, while sub-basins such as 3, 13, 14, 15, 16, and 17 contribute below 5 t/ha. This variability highlights that sediment inflow is dominated by a few hotspots, emphasizing the need for spatially targeted interventions rather than uniform watershed management.

Erosion Risk and Land Use Practices

High sediment-yield sub-basins are likely influenced by steep slopes, erodible soils, and intensive agricultural practices with limited soil conservation measures. Moderate-yield sub-basins (15–28 t/ha) are partially affected by cultivation and land disturbances, whereas low-yield areas benefit from flatter terrain, natural vegetation, or existing conservation structures. These patterns indicate a strong link between **erosion risk and land use practices**, underlining the importance of sustainable land management in controlling sediment generation.

Implications for Water Quality

Elevated sediment transport from these sub-basins can cause lake siltation, reduced water depth, and degradation of aquatic habitats. The inflow of sediment also affects the turbidity and nutrient balance of the receiving water body, as shown in comparable studies from the Yellow River and Mediterranean basins (Zhang et al., 2019; Aloui et al., 2023). Such degradation has long-term implications for the sustainability of Lake Ziway and its surrounding ecosystem, where increased sedimentation has been observed to reduce water storage capacity and impair fisheries (Gadissa et al., 2018). Sediment from high- and moderate-yield sub-basins contributes to siltation, reduced storage capacity, and turbidity in Lake Ziway. Excessive sediment inflow can carry nutrients and pollutants, further degrading water quality and impacting aquatic ecosystems. Effective management of these sub-basins is therefore crucial to maintain both the **quantity and quality of water resources** in the lake.

Importance of Monitoring and Adaptive Management

Given the observed variability and the role of land use in driving sediment production, continuous monitoring and adaptive watershed management strategies are essential. The application of SWAT in other catchments has proven effective for identifying critical source areas and guiding erosion

control interventions (Oduor et al., 2023). Implementing soil and water conservation measures—such as terracing, vegetative buffer strips, and controlled grazing—can substantially reduce sediment delivery to the lake. Thus, ongoing calibration and monitoring of sediment yield dynamics are crucial for maintaining the hydrological integrity of Lake Ziway and ensuring sustainable land–water resource management.

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This study effectively utilized the Soil and Water Assessment Tool (SWAT) model to evaluate the hydrological and sediment transport processes within the Lake Ziway catchment in Ethiopia. The research highlighted significant disparities in sediment yield across the 30 sub-basins, revealing that Sub-basin 6 and Sub-basin 12 exhibited the highest sediment yields, approximately 173.6962 and 117.364 t/ha/year, respectively. These findings indicate that these areas are likely characterized by steep slopes, reduced vegetation cover, or high surface runoff, making them hotspots for soil erosion. Conversely, sub-basins such as 3, 9, 14, 15, 16, 19, 25, and 26 demonstrated minimal sediment yields, suggesting effective land management practices and protective vegetative cover.

The analysis of land use and land cover changes over the years 2017, 2020, and 2024 revealed a significant transformation of the landscape, marked by the expansion of cropland and built-up areas at the expense of natural vegetative covers. This shift underscores the increasing anthropogenic pressure driven by population growth and agricultural intensification, which may exacerbate erosion and sedimentation issues in the watershed.

Given the variability in sediment yield, the results emphasize the necessity for spatially targeted soil and water conservation measures, particularly in high-risk erosion zones. Strategies such as reforestation, contour farming, and the establishment of buffer strips should be prioritized to mitigate sediment loss and protect water quality in Lake Ziway. Additionally, this study provides a foundation for future land use prediction scenarios for 2035 to 2050, utilizing LULC modeling tools to forecast landscape evolution under current development trajectories and climate variability.

In summary, this research demonstrates the utility of integrated hydrological modeling and land use analysis in understanding the complex interactions between land use dynamics and watershed behavior. The SWAT model has proven to be a reliable tool for simulating streamflow and sediment yield, offering a scientific basis for sustainable land and water resource management in the Lake Ziway basin. The insights gained from this study can significantly aid local authorities,

environmental agencies, and policymakers in formulating strategic interventions to curb land degradation, ensure water security, and safeguard the long-term health of the Lake Ziway ecosystem.

5.2 Recommendations

Based on the findings of this study, several recommendations can be made to enhance soil and water management practices in the Lake Ziway catchment. These recommendations focus on addressing the identified challenges related to sediment yield, land use changes, and overall watershed health.

1. ***Implement Targeted Soil and Water Conservation Practices***

To mitigate high sediment yields in critical sub-basins such as Sub-basin 6 and Sub-basin 10, targeted soil and water conservation measures are essential. This includes:

- **Reforestation and Afforestation**: Restoring native vegetation can stabilize soils, reduce erosion, and enhance biodiversity. Planting trees along slopes and in riparian zones can significantly decrease surface runoff.
- **Contour Farming**: Encouraging farmers to adopt contour farming techniques can help reduce soil erosion by following the natural contours of the land, which slows down water runoff and encourages water infiltration.
- **Terracing**: In areas with steep slopes, implementing terracing can effectively reduce erosion and improve water retention.

2. **Enhance Agricultural Practices**

To promote sustainable agricultural practices that reduce sediment yield and enhance productivity, the following strategies should be considered:

- **Crop Rotation and Diversification**: Encouraging farmers to diversify their crops can improve soil health, reduce pest cycles, and enhance resilience to climate variability.
- **Cover Cropping**: Implementing cover crops during the offseason can protect soils from erosion, improve soil fertility, and enhance moisture retention.

- **Reduced Tillage**: Promoting no-till or reduced-till farming practices can help maintain soil structure and organic matter, leading to improved soil health and reduced erosion.

3. **Strengthen Community Engagement and Education**

Involving local communities in sustainable land management practices is crucial for the long-term success of conservation efforts. Recommended actions include:

- **Training Programs**: Establish training sessions to educate farmers on best practices in soil conservation, sustainable agriculture, and the importance of maintaining vegetative cover.
- **Community-Based Monitoring**: Encourage community involvement in monitoring soil and water quality, which can lead to increased awareness and stewardship of local resources.
- **Incentives for Sustainable Practices**: Provide financial incentives, such as subsidies or grants, to encourage farmers to adopt environmentally friendly practices.

4. **Develop Comprehensive Watershed Management Plans**

A holistic approach to watershed management is essential for addressing the complexities of sediment yield and land use changes. Recommendations include:

- **Integrated Watershed Management Plans**: Develop and implement comprehensive plans that consider hydrology, land use, and community needs. These plans should incorporate stakeholder input and address issues such as pollution, sedimentation, and habitat loss.
- **Monitoring and Adaptive Management**: Establish a robust monitoring framework to assess the effectiveness of implemented strategies. Use adaptive management principles to adjust approaches based on ongoing assessments and changing conditions.

5. Utilize Advanced Modeling and Prediction Tools

To better understand future land use dynamics and their potential impacts on sediment yield, the following recommendations should be pursued:

- **Scenario Planning**: Use modeling tools, such as CA-Markov or Land Change Modeler (LCM), to create scenarios for future land use changes. This can help anticipate potential impacts on hydrology and sediment yield.
- **Climate Change Considerations**: Integrate climate change projections into watershed management plans to prepare for potential shifts in precipitation patterns and their effects on erosion and water quality.

6. Promote Research and Collaboration

Continuous research and collaboration among stakeholders can foster innovation and improve management practices. Recommended actions include:

- **Collaborative Research Initiatives**: Encourage partnerships between universities, government agencies, and NGOs to conduct research on best practices for soil and water management tailored to local conditions.
- **Knowledge Sharing Platforms**: Create platforms for sharing knowledge, research findings, and successful case studies among local authorities, farmers, and conservation groups.

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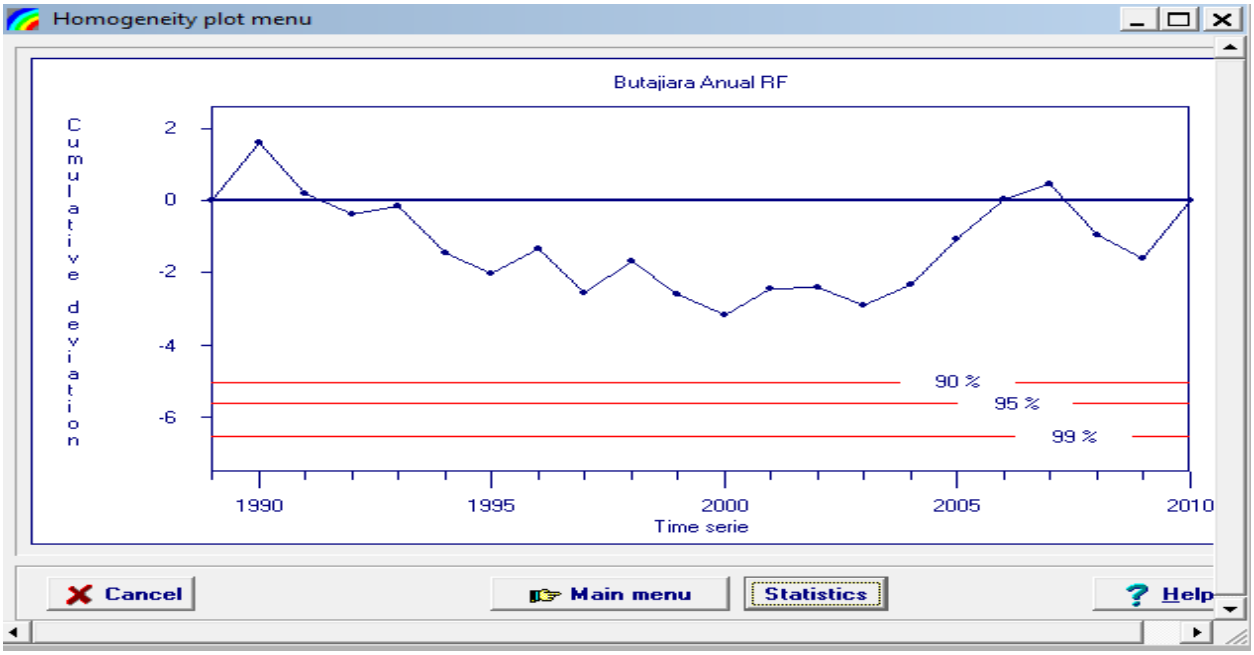
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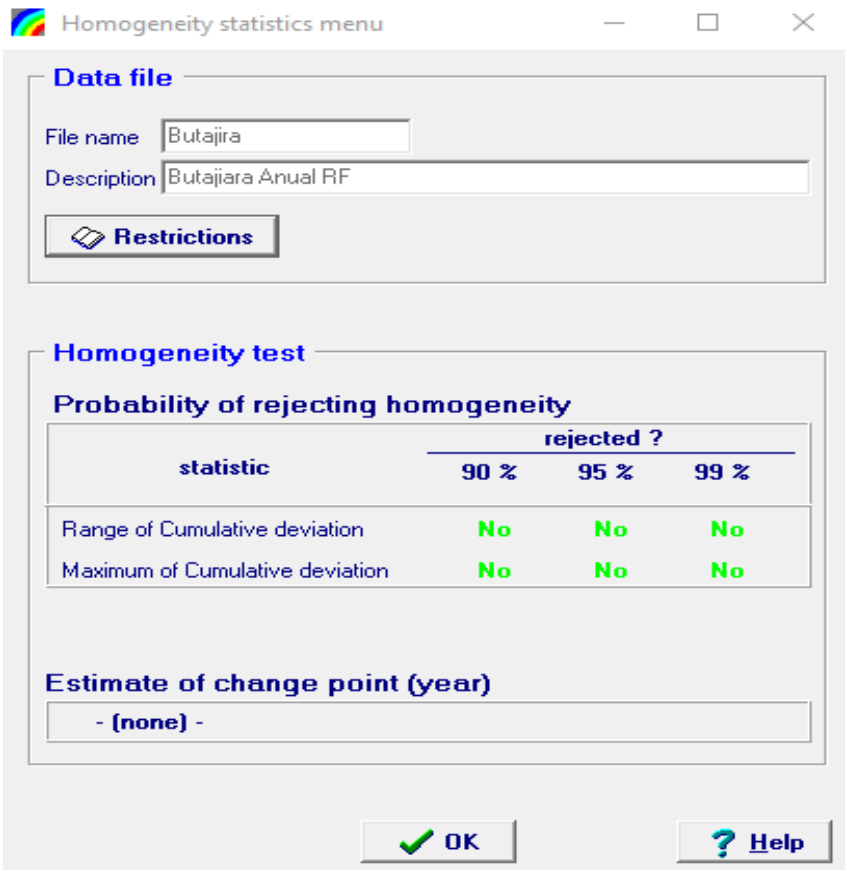
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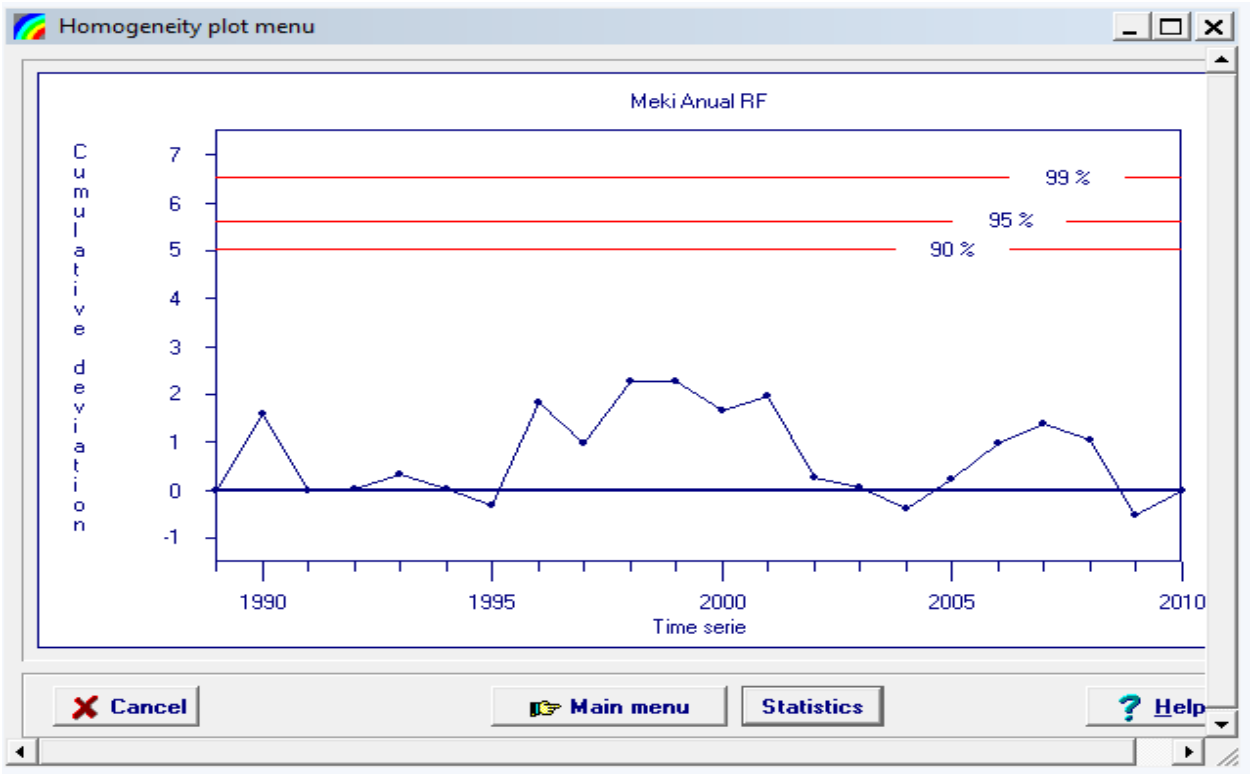
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Appendices

Appendix A: Homogeneity Analysis for the stations







Homogeneity statistics menu

Data file

File name: Meki

Description: Meki Anual RF

Restrictions

Homogeneity test

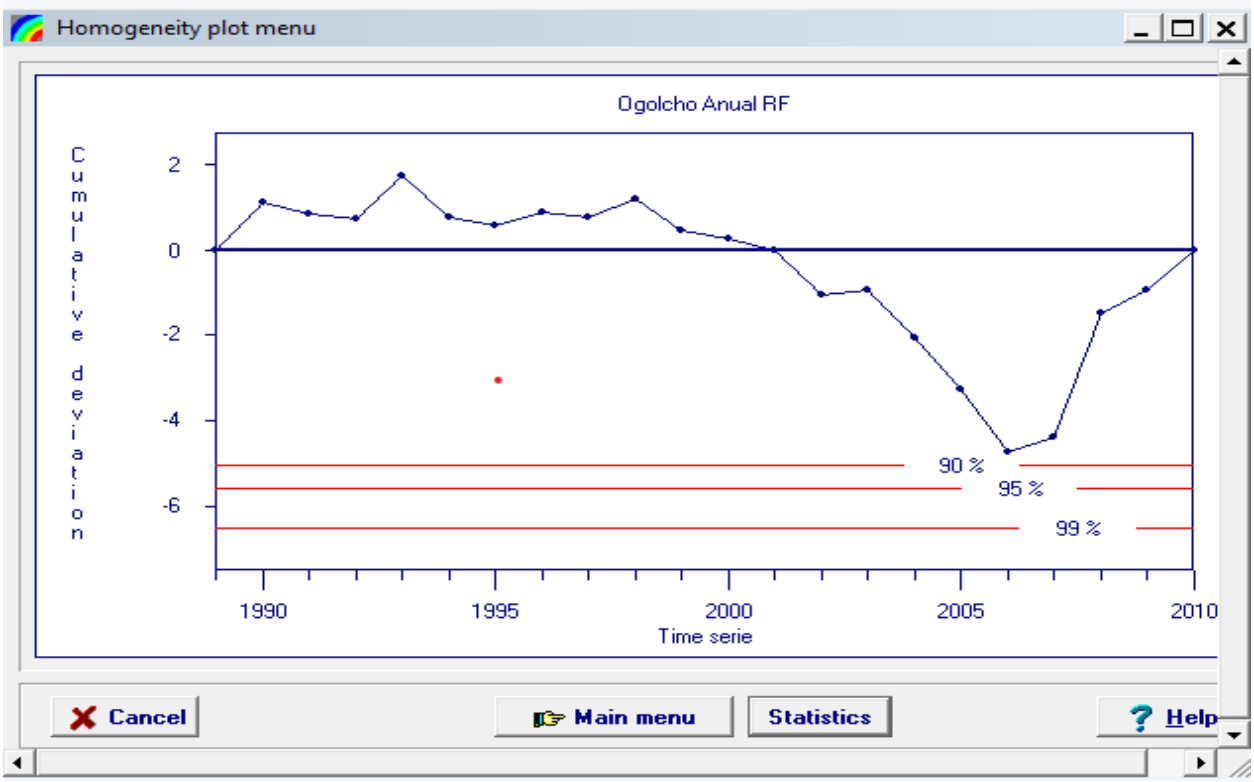
Probability of rejecting homogeneity

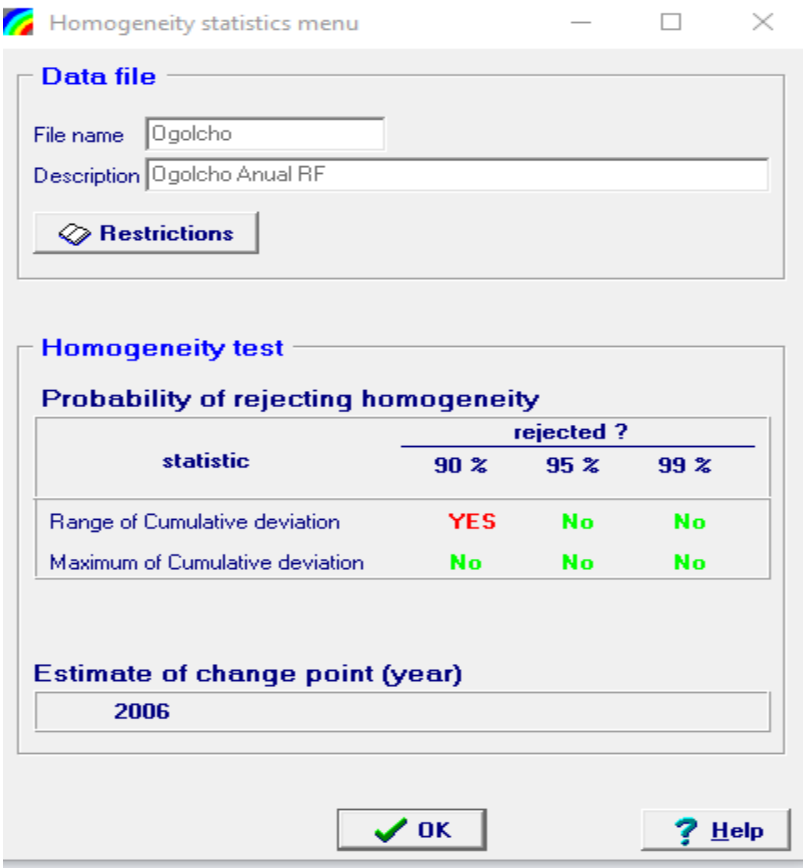
statistic	rejected ? 90 %	95 %	99 %
Range of Cumulative deviation	No	No	No
Maximum of Cumulative deviation	No	No	No

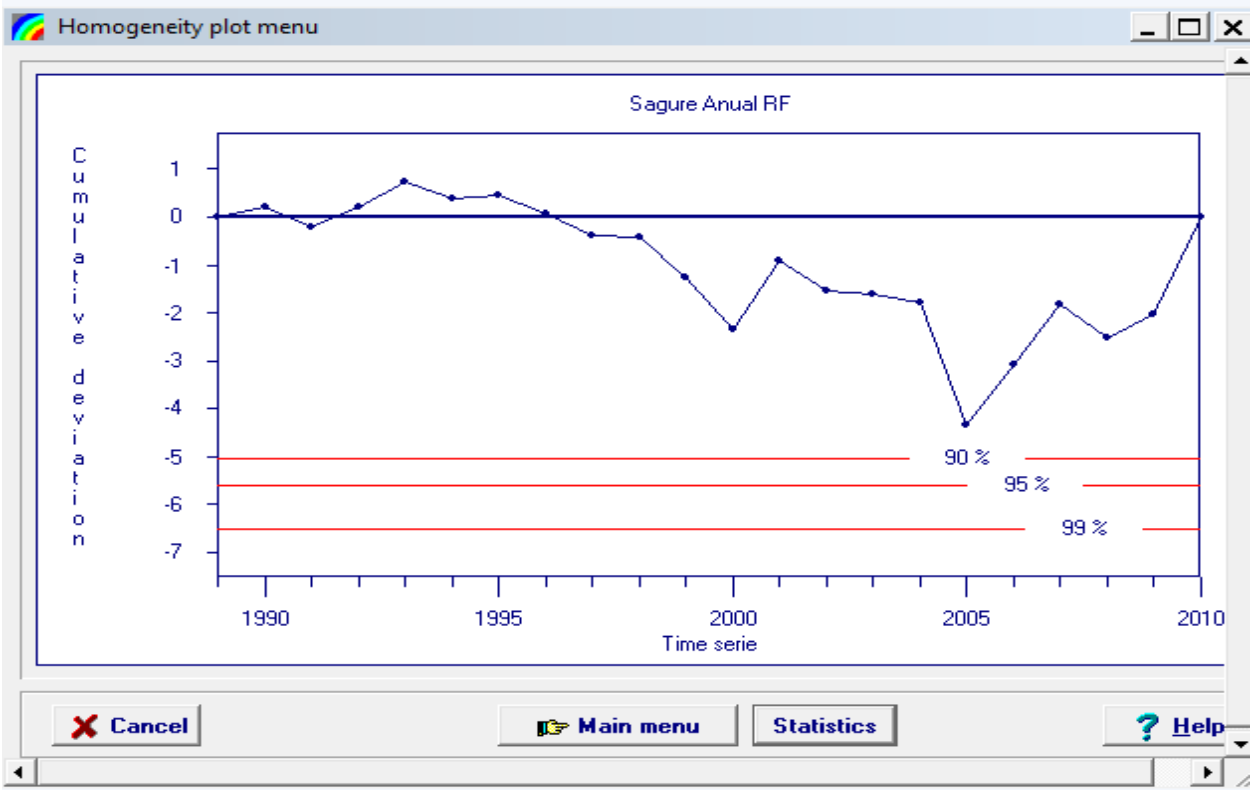
Estimate of change point (year)

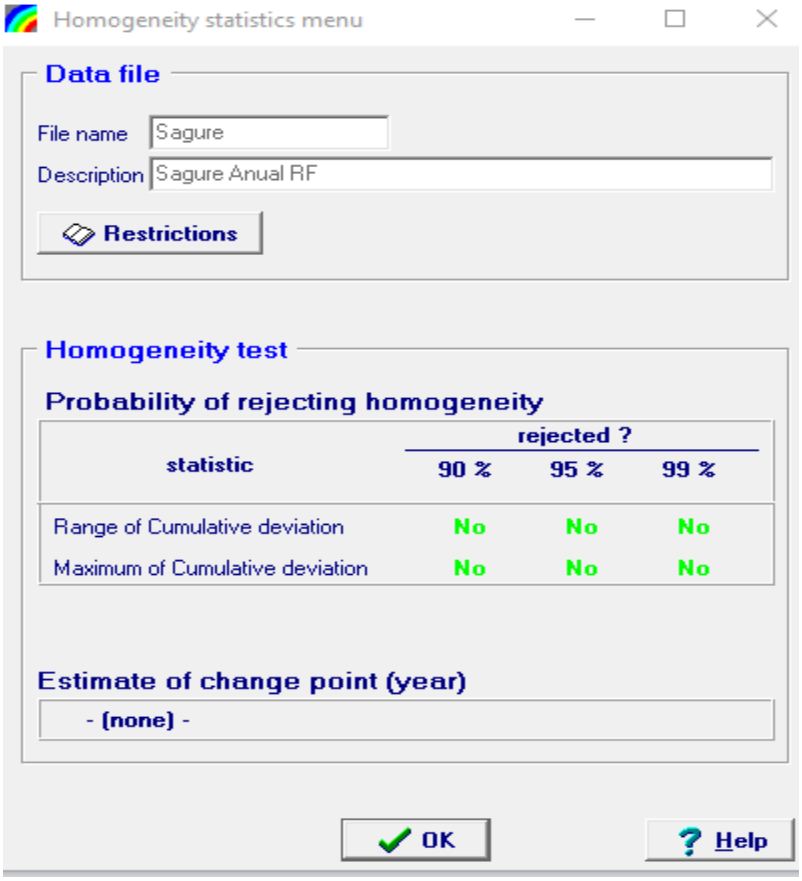
- (none) -

OK Help


Homogeneity plot menu
Ogolcho Anual RF
Cumulative deviation
2
0
-2
-4
-6
90 %
95 %
99 %
1990
1995
2000
2005
2010
Time serie
Cancel
Main menu
Statistics
Help


Homogeneity statistics menu
Data file
File name
Ogolcho
Description
Ogolcho Anual RF
Restrictions
Homogeneity test
Probability of rejecting homogeneity
statistic
rejected ?
90 %
95 %
99 %
Range of Cumulative deviation
YES
No
No
Maximum of Cumulative deviation
No
No
No
Estimate of change point (year)
2006
OK
Help

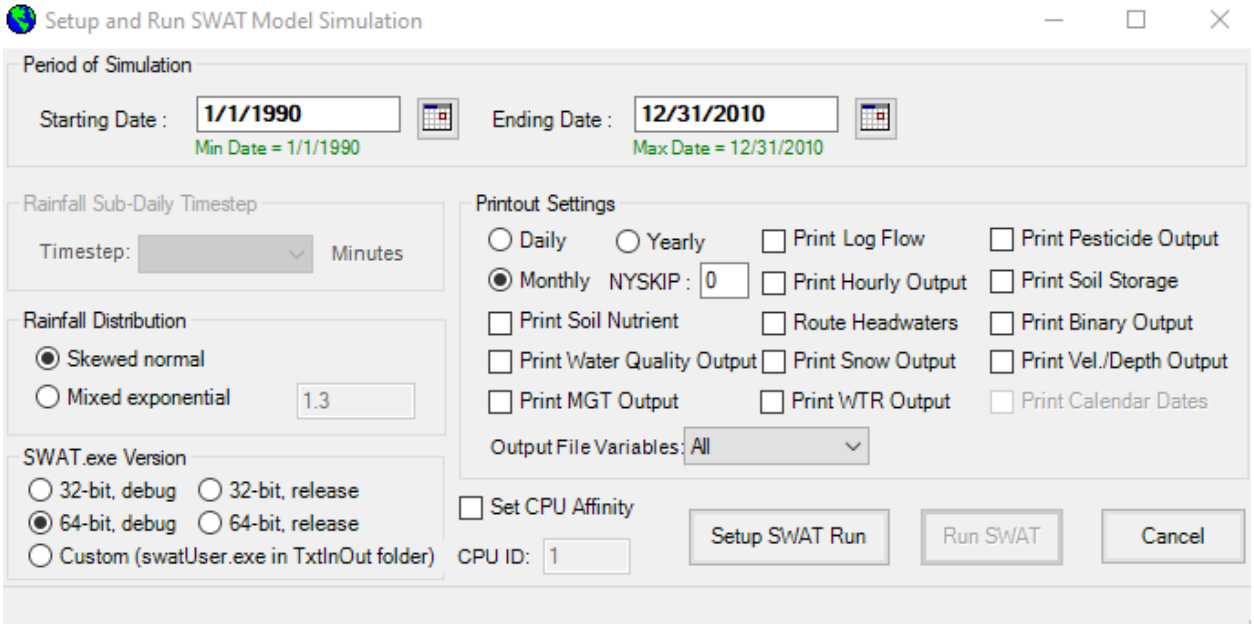

Homogeneity plot menu
Sagure Anual RF
Cumulative deviation
1
0
-1
-2
-3
-4
-5
-6
-7
90 %
95 %
99 %
1990
1995
2000
2005
2010
Time serie
Cancel
Main menu
Statistics
Help

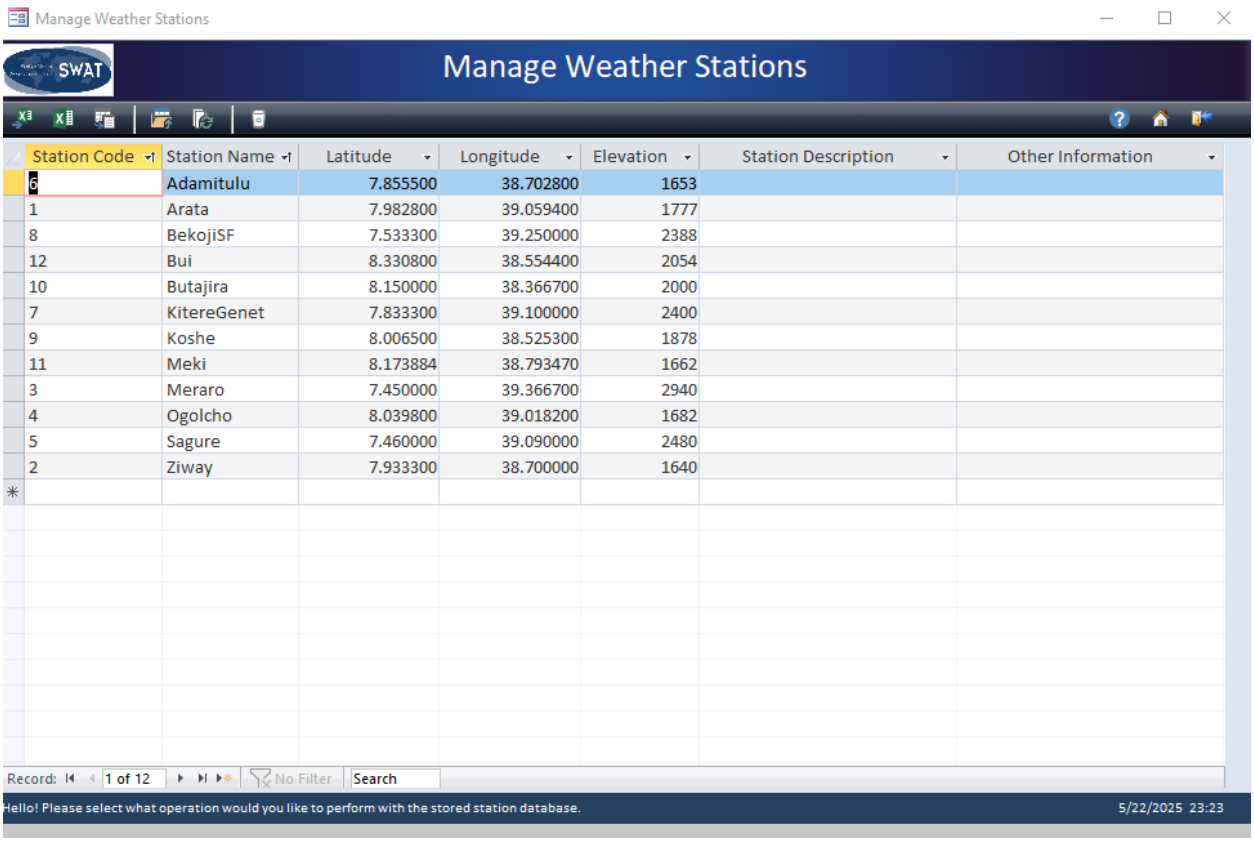

Homogeneity statistics menu
Data file
File name
Sagure
Description
Sagure Anual RF
Restrictions
Homogeneity test
Probability of rejecting homogeneity
statistic
rejected ?
90 %
95 %
99 %
Range of Cumulative deviation
No
No
No
Maximum of Cumulative deviation
No
No
No
Estimate of change point (year)
- (none) -
OK
Help

Appendix B: Sentinel-2 10m LULC Classification

Value	Name	Description
1	Water	Areas where water was predominantly present throughout the year; may not cover areas with sporadic or ephemeral water; contains little to no sparse vegetation, no rock outcrop nor built up features like docks; examples: rivers, ponds, lakes, oceans, flooded salt plains.
2	Trees	Any significant clustering of tall (~15 feet or higher) dense vegetation, typically with a closed or dense canopy; examples: wooded vegetation, clusters of dense tall vegetation within savannas, plantations, swamp or mangroves (dense/tall vegetation with ephemeral water or canopy too thick to detect water underneath).
4	Flooded vegetation	Areas of any type of vegetation with obvious intermixing of water throughout a majority of the year; seasonally flooded area that is a mix of grass/shrub/trees/bare ground; examples: flooded mangroves, emergent vegetation, rice paddies and other heavily irrigated and inundated agriculture.
5	Crops	Human planted/plotted cereals, grasses, and crops not at tree height; examples: corn, wheat, soy, fallow plots of structured land.
7	Built Area	Human made structures; major road and rail networks; large homogenous impervious surfaces including parking structures, office buildings and residential housing; examples: houses, dense villages / towns / cities, paved roads, asphalt.
8	Bare ground	Areas of rock or soil with very sparse to no vegetation for the entire year; large areas of sand and deserts with no to little vegetation; examples: exposed rock or soil, desert and sand dunes, dry salt flats/pans, dried lake beds, mines.
9	Snow/Ice	Large homogenous areas of permanent snow or ice, typically only in mountain areas or highest latitudes; examples: glaciers, permanent snowpack, snow fields.
10	Clouds	No land cover information due to persistent cloud cover.
11	Rangeland	Open areas covered in homogenous grasses with little to no taller vegetation; wild cereals and grasses with no obvious human plotting (i.e., not a plotted field); examples: natural meadows and fields with sparse to no tree cover, open savanna with few to no trees, parks/golf courses/lawns, pastures. Mix of small clusters of plants or single plants dispersed on a landscape that shows exposed soil or rock; scrub-filled clearings within dense forests that are clearly not taller than trees; examples: moderate to sparse cover of bushes, shrubs and tufts of grass, savannas with very sparse grasses, trees or other plants.

Appendix C: Setup and Run Swat Model





SWAT model simulation Date: 5/14/2025 12:00:00 AM Time: 00:00:00
MULTIPLE HRUs LandUse/Soil/Slope OPTION THRESHOLDS : 0 / 0 / 0 [%]
Number of HRUs: 609
Number of Subbasins: 29

	Area [ha]	Area[acres]	
Watershed	460057.8281	1136825.8962	
	Area [ha]	Area[acres]	%Wat.Area
LANDUSE:			
Forest-Evergreen --> FRSE	15297.1250	37799.9607	3.33
Agricultural Land-Row Crops --> AGRR	260250.3125	643091.5347	56.57
Residential --> URBN	40812.8594	100850.6162	8.87
Wetlands-Non-Forested --> WETN	80.2031	198.1859	0.02
Range-Grasses --> RNGE	95149.7344	235119.7511	20.68
Water --> WATR	45302.6719	111945.1673	9.85
Forest-Deciduous --> FRSD	2817.0469	6961.0637	0.61
Winter Pasture --> WPAS	347.8750	859.6165	0.08
SOILS:			
ET1267	64489.8438	159357.6284	14.02
ET931	41521.0313	102600.5443	9.03
ET1187	18582.4219	45918.0936	4.04
ET1266	3197.8906	7902.1476	0.70
ET1137	25520.9219	63063.4740	5.55
ET1185	77428.5781	191329.8880	16.83
ET1189	1927.4844	4762.9103	0.42
ET1258	1.5000	3.7066	0.00
ET416	12053.2969	29784.2992	2.62
ET1064	28224.9844	69745.3476	6.14
ET1154	700.8594	1731.8586	0.15
ET955	41636.8906	102886.8386	9.05