Schriftenreihe Umweltingenieurwesen
Agrar- und Umweltwissenschaftliche Fakultät

Band 115

Dissertation

Megersa Kebede Leta

Modeling Optimal Operation of Nashe Hydropower Reservoir under Land Use Land Cover Changes in Blue Nile River Basin, Ethiopia

PROFESSUR **Wasserwirtschaft**

Universität Rostock Traditio et Innovatio

Universität Rostock

Traditio et Innovatio

ISBN 978-3-86009-548-5
https://doi.org/10.18453/rosdok_id00004427

Schriftenreihe Bd. 115 **Umweltingenieurwesen** ▪ Wasserwirtschaft

Schriftenreihe Umweltingenieurwesen

Band 115

Dissertation

Megersa Kebede Leta

Modeling Optimal Operation of Nashe Hydropower Reservoir under Land Use Land Cover Changes in blue Nile River Basin, Ethiopia

Professur

Wasserwirtschaft

Agrar- und Umweltwissenschaftliche Fakultät

Universität Rostock

Traditio et Innovatic

Dissertation

HERAUSGEBER

Prof. Dr.-Ing. habil. Jens Tränckner
Universität Rostock
Agrar- und Umweltwissenschaftliche Fakultät
Professur Wasserwirtschaft
18051 Rostock

CIP-KURZTITELAUFNAHME

Dissertation Megersa Kebede Leta
Universität Rostock
Agrar- und Umweltwissenschaftliche Fakultät
Rostock, 2023

BEZUGSMÖGLICHKEITEN

Universität Rostock
Agrar- und Umweltwissenschaftliche Fakultät
Professur Wasserwirtschaft
Satower Straße 48, 18059 Rostock
Tel.: 0381/498-3461, Fax: 0381/498-3462

ISBN 978-3-86009-548-5
https://doi.org/10.18453/rosdok_id00004427

Universität Rostock
Professur Wasserwirtschaft

Foreword

Water and land are precious and limited resources and highly interdependent. Worldwide, there is an alarming trend of land use land cover change from natural and near natural systems to agricultural, urban industrial or traffic usages. This has dramatic ecological, social and economic consequences.

With regard to water, there is a direct link to hydrology and water pollution. Although the interdependencies are well understood from the conceptual point of view, they are rarely quantified in prognostic assessment in terms of What-If-Scenarios. This applies even more for emerging economies where land use planning is often vague and/or has low binding force. The future development of land use and land cover (LULC) is in those case mainly driven by land use specific demands and according availabilities (e.g. slope, distance to water courses and agglomerations etc.). Forecasting in those conditions becomes more a stochastic problem based on experience from the past rather than the targeted development of probable scenarios.

If probable land use land cover changes (LULCC) overlap with hydrologic consequences and – like in this study – operation of large reservoirs for energy production (including international implications due to the conflict with Egypt on Nile flow), forecasting and derivation of measures is much more than a scientific challenge.

Mr. Leta addressed this issue by developing a methodological concept that combines the forecast of LULCC with a hydrologic model and a consecutive reservoir control model. The clever combination of different open-access modelling tools and their parametrization based on monitoring data provides not only an insight in the probable future development of land use, water balance, flow and even energy production potential. It enables also the targeted development of desired future conditions. In our increasingly complex interaction of natural, social, economic and even political systems, the availability of those holistic and deterministic assessment tools is mandatory for rational and sustainable management.

Prof. Dr.-Ing. habil. Jens Tränckner

Universität Rostock

Traditio et Innovatio

Aus der Professur für Wasserwirtschaft
der Agrar- und Umweltwissenschaftlichen Fakultät

MODELING OPTIMAL OPERATION OF NASHE HYDROPOWER RESERVOIR UNDER LAND USE LAND COVER CHANGES IN BLUE NILE RIVER BASIN, ETHIOPIA

Dissertation
For obtaining the academic degree
Doctor of Engineering (Dr.-Ing.)

Agrar- und Umweltwissenschaftlichen Fakultät
Universität Rostock

Submitted by: **Megersa Kebede Leta, MSc**

Scientific Advisors:

Prof. Dr.-Ing. habil. Jens Tränckner, Faculty of Agriculture and Environmental Sciences, University of Rostock, 18051 Rostock, Germany.

Prof. Dr.-Ing. Tamene Adugna, Faculty of Civil and Environmental Engineering, Jimma Institute of Technology, Jimma University, Jimma, Ethiopia.

Reviewers:

Prof. Dr. Jens Tränckner
Universität Rostock, Agrar- und Umweltwissenschaftlichen Fakultät, Wasserwirtschaft

Prof. Dr. Mekonen Ayana
Adama Science and Technology University Ethiopia, Department of Water Resources

Prof. Dr. Michael Nones
Institute of Geophysics Polish Academy of Sciences, Poland, Hydrology and Hydrodynamics Department

Year of submission: January 2023
Year of defense: September 2023

Abstract

The availability and distribution of water resources for economic development in the watershed have been affected by land use land cover (LULC) changes. The LULC changes have significant effects on hydrology and reservoir operations by altering the hydrological components of the watershed. The Nashe watershed is the upstream part of the Blue Nile River basin and one of the most significant potential areas for various socio-economic developments. The purpose of the study was to analyze the impacts of historical and future LULC change on hydrological components and optimal reservoir operations for managing water resources in relation to hydropower generation. The historical and future LULC scenarios were developed using the ERDAS Imagine model and Land Change Modeler respectively. In this study, agricultural land was the largest LULC occupying an area of 44% in 1990, 50.4% in 2005, and 61.2% in 2019 over the past thirty years and predicted to occupy an area of 73% in 2035 and 73.2% in 2050 over the coming thirty years. Therefore, according to the transition probability matrix, the largest LULC change in the Nashe watershed was the conversion of forest land, range land, and grass land to agricultural land and urban area.

The Soil and Water Assessment Tool (SWAT) model was applied to assess the impacts of LULC change on the hydrological processes under varying LULC changes. The findings of the study demonstrated that the SWAT model performance indicators were within an acceptable range, and the model performed well in simulating the hydrological processes of the watershed. In the Nashe watershed, the development of agricultural land and the reduction of forest cover were the major contributors to the increase in surface runoff and decline in groundwater flow. Compared to the baseline, the wet and dry season surface runoff have increased by 6.96% and 11.17%, respectively, under the current LULC. The potential future LULC change scenarios were predicted to result in moderate increases in surface runoff while decreasing groundwater flow, lateral flow, and evapotranspiration in comparison to the baseline scenario.

To model and optimize the operation of the Nashe hydropower reservoir, a modeling framework that integrates the SWAT model and the HEC-ResPRM optimization model was used. The HEC-ResPRM reservoir operation optimization model was utilized to reproduce the optimal hydropower reservoir storage, release, water level, and hydropower generation. In comparison to the status of the Nashe actual hydropower reservoir operation, the current optimized operation demonstrated a significant

increase in power storage, pool level, release, and power generation. Similar results indicate that under the 2035 and 2050 LULC scenarios, the optimized hydropower reservoir operation policy shows an increasing trend compared to the current actual and optimized reservoir operations. In general, the findings demonstrated the importance of using an integrated simulation-optimization approach to investigate the effects of LULC changes on hydrological processes and consequently available water resources in the optimal operation of hydropower reservoirs. Therefore, decision-makers and land use planners should pay close attention to LULC change as one of the major drivers of change in the watershed's hydrology and reservoir operation.

Zusammenfassung

Die Verfügbarkeit und Verteilung von Wasserressourcen für die wirtschaftliche Entwicklung in der Wasserscheide wurde durch Änderungen der Landnutzung Landbedeckung (LULC) beeinflusst. Die LULC-Änderungen haben erhebliche Auswirkungen auf die Hydrologie und den Reservoirbetrieb, indem sie die hydrologischen Komponenten der Wasserscheide verändern. Die NasheWasserscheide ist der stromaufwärts gelegene Teil des Einzugsgebiets des Blauen Nils und eines der bedeutendsten potenziellen Gebiete für verschiedene sozioökonomische Entwicklungen. Der Zweck der Studie bestand darin, die Auswirkungen historischer und zukünftiger LULC-Änderungen auf hydrologische Komponenten und den optimalen Reservoirbetrieb für die Bewirtschaftung von Wasserressourcen in Bezug auf die Wasserkrafterzeugung zu analysieren. Die historischen und zukünftigen LULC-Szenarien wurden mit dem ERDAS Imagine-Modell bzw. dem Land Change Modeler entwickelt. In dieser Studie war landwirtschaftliches Land die größte LULC, die in den letzten dreißig Jahren eine Fläche von 44 % im Jahr 1990, 50,4 % im Jahr 2005 und 61,2 % im Jahr 2019 einnahm und voraussichtlich eine Fläche von 73 % im Jahr 2035 und 73,2 % im Jahr 2050 einnehmen wird in den kommenden dreißig Jahren. Daher war gemäß der Übergangswahrscheinlichkeitsmatrix die größte LULC-Änderung in der Nashe-Wasserscheide die Umwandlung von Waldland, Weideland und Grasland in landwirtschaftliche Flächen und städtische Gebiete.

Das Modell des Soil and Water Assessment Tool (SWAT) wurde angewendet, um die Auswirkungen von LULC-Änderungen auf die hydrologischen Prozesse bei unterschiedlichen LULC-Änderungen zu bewerten. Die Ergebnisse der Studie zeigten, dass die Leistungsindikatoren des SWAT-Modells in einem akzeptablen Bereich lagen und das Modell bei der Simulation der hydrologischen Prozesse der Wasserscheide gute Leistungen erbrachte. In der Nashe-Wasserscheide trugen die Ausweitung der landwirtschaftlichen Flächen und die Verringerung der Waldbedeckung am stärksten zum Anstieg des Oberflächenabflusses und zum Rückgang des Grundwasserflusses bei. Im Vergleich zum Ausgangswert ist der Oberflächenabfluss in der Regen- und Trockenzeit für den aktuellen LULC um 6,96 % bzw. 11,17 % gestiegen. Es wurde vorhergesagt, dass die potenziellen zukünftigen LULC-Änderungsszenarien zu einer moderaten Zunahme des Oberflächenabflusses führen, während die Grundwasserströmung, die seitliche Strömung und die Evapotranspiration im Vergleich zum Basisszenario abnehmen.

Um den Betrieb des Wasserkraftreservoirs Nashe zu modellieren und zu optimieren, wurde ein Modellierungsrahmen verwendet, der das SWAT-Modell und das HEC-ResPRM-Optimierungsmodell integriert. Das HEC-ResPRM-Reservoir-Betriebsoptimierungsmodell wurde verwendet, um die optimale Speicherung,

Freisetzung, den Wasserstand und die Wasserkrafterzeugung des Wasserkraftreservoirs zu reproduzieren. Im Vergleich zum Status des tatsächlichen Betriebs des Nashe-Wasserkraftreservoirs zeigte der aktuelle optimierte Betrieb eine signifikante Steigerung der Energiespeicherung, des Beckenpegels, der Freisetzung und der Stromerzeugung. Ähnliche Ergebnisse weisen darauf hin, dass unter den LULC-Szenarien 2035 und 2050 die Betriebsstrategie für optimierte Wasserkraftreservoirs einen zunehmenden Trend im Vergleich zum aktuellen tatsächlichen und optimierten Reservoirbetrieb zeigt. Im Allgemeinen zeigten die Ergebnisse, wie wichtig es ist, einen integrierten Simulations-Optimierungs-Ansatz zu verwenden, um die Auswirkungen von LULC-Änderungen auf hydrologische Prozesse und folglich verfügbare Wasserressourcen beim optimalen Betrieb von Wasserkraftreservoirs zu untersuchen. Daher sollten Entscheidungsträger und Landnutzungsplaner der LULC-Änderung als einer der Hauptursachen für Änderungen in der Hydrologie und dem Reservoirbetrieb der Wasserscheide große Aufmerksamkeit schenken.

Acknowledgments

First and foremost, my passionate, eternal love and admiration go directly to the almighty God for his never-ending love, limitless care, health, and strength throughout my entire life and for granting me the capability to proceed successfully. You have given me the power to believe in my passion and pursue my dreams. Thank you, Lord Jesus Christ.

I would like to express my heartfelt appreciation and gratitude to my main supervisor **Prof. Dr.-Ing. habil. Jens Tränckner** for providing me the opportunity to pursue my PhD under his supervision. My utmost word of thanks goes to him for his constructive supports, invaluable and in-depth comments, suggestions, advice, and consistent guidance throughout the research period to bring the thesis to the current product. I am genuinely thankful to him for being patient with me, understanding, and willingness to answer all my inquiries.

I am also delighted to express my profound thanks to **Prof. Dr.-Ing. Tamene Adugna**, my co-supervisor, for devoting his significant time, constructive comments, valuable recommendations, and systematic guidance of the research. Thanks are due to all staffs of the institute of Hydrology and Water Management at the University of Rostock for their friendly cooperation and hospitality. I want to thank Dr.-Ing. Muhammed Waseem and Motuma Shiferaw for their continuous encouragement throughout the research period to all the academic and non-academic matters.

I would like to extend my recognition to the Ethiopian Meteorological Agency, the Ethiopian Ministry of Water, Irrigation, and Electricity and the Ethiopian Electric Power for their cooperation in providing data for the research. My sincere gratitude also goes to the Horo and Abay Chomen woredas agricultural offices and the community for their assistance during my field survey and data collection process. My genuine acknowledgment also goes to the government of Ethiopia for funding this PhD scholarship under the program of ECBP (Engineering Capacity Building Program). I would also thank DAAD (Deutscher Akademischer Austauschdienst) for providing me a scholarship during my study.

Most importantly, I would like to thank my beloved wife, **Dame Miresa**, for her loving support, endless patience, encouragement, and all the innumerable sacrifices that she has made on my behalf, especially during my absence. Words cannot express how grateful I am to you in the course of producing this thesis. My sons **Kayo Megersa** and

Raga Megersa also deserve my appreciation for their patience while I have been busy pursuing my research. They have been the source of my courage, happiness, and unwavering inspiration. Even though I used to spend family time for research and would frequently be away when they most needed me, they had always been supportive of my work.

I am grateful to my entire parents for always being there for me knowing that they always held me in their thoughts and praying for me from the first day of my life and they are always behind my success. I cannot end my acknowledgment without conveying my special thanks to my lovely late father, **Kebede Leta**, to whom this work was dedicated, not only for his continuous encouragement until his end day, but also for the long-term investment of his resources on my education. There are no proper words to convey and express my gratitude for your wisdom. **Dad**, your advice and words will ring in my mind and stay with me for the rest of my life. **Abbaa Koo** losing you is great heartbreak for me and I will never forget you until I will come to you.

Finally, I would like to forward heartfelt thanks for those who deserve it, for their assistance, guidance, and contributed a lot for the success of my study during the long journey from the beginning to the final achievement.

May God Bless You ALL!

Dedication

Dedicated to my beloved late father, **Kebede Leta**

Without you, I would never have been able to write this chapter of my life.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

95PPU	95 percent prediction uncertainty
BAU	Business-as-usual
BCM	Billion cubic meter
BNRB	Blue Nile River Basin
CA	Cellular automata
DEM	Digital Elevation model
DHSVM	Distributed Hydrology Soil Vegetation Model
DWSM	Dynamic Watershed Simulation Model
ERDAS	Earth Resource Data Analysis System
ETM+	Enhanced thematic mapper plus
FAO	Food and agriculture organization
FGD	Focus group discussion
GCP	Ground control point
GERD	Grand Ethiopian Renaissance Dam
GIS	Geographic information system
GPS	Global positioning system
GUIs	Graphical user interfaces
HEC-DSS	Hydrologic Engineering Center-Data Storage System
HEC–HMS	Hydrologic Engineering Center-Hydrologic Modeling System
HEC-PRM	Hydrologic Engineering Center-Prescriptive Reservoir Model
HEC-ResPRM	Hydrologic Engineering Center-Reservoir Evaluation System Perspective Reservoir Model
HEC-ResSIM	Hydrologic Engineering Center-Reservoir System Simulation
HRU	Hydrologic response unit
HSPF	Hydrologic Simulation Program-FORTRAN
LCM	Land change modeler
LULC	Land use land cover change

MC	Markov chain
MCM	Million cubic meter
MFL	Maximum flood level
MIKE-SHE	MIKE-system Hydrologic European
MLC	Maximum likelihood classification
MLP	Multilayer Perceptron
MLP-NN	Multilayer Perceptron Neural Network
MOL	Minimum operating level
MoWIE	Ministry of Water, Irrigation, and Energy
MW	Megawatt
NSE	Nash-Sutcliffe Efficiency
OFWE	Oromia Forest and Wildlife Enterprise
OLI_TIRS	Operational Land Imager-Thermal Infrared Sensor
OWWDSE	Oromia Water Works Design and Supervision Enterprise
PBIAS	Percent Bias
RS	Remote sensing
SDDP	Stochastic Dual Dynamic Programming
SimWeight	Similarity-weighted instance-based machine learning tool
SUFI-2	Sequential Uncertainty Fitting-2
SWAT	Soil and Water Assessment Tool
SWAT-CUP	Soil and Water Assessment Tool- Calibration Uncertainty Program
SWIM	Soil and Water Integrated Model
TGMMS	TerrSet Geospatial Monitoring and Modeling System
TM	Thematic mapper
TPM	Transition Probability Matrix
USGS	United States Geological Survey

1. Introduction

1.1. Background

Water is the most important and valuable natural resources for sustaining life, development, and the environment in order to achieve long-term economic, environmental, and social growth. Land is another natural resource that peoples use for a variety of purposes. As a result, water availability along with sustainable land use is the basis for long-term socio-economic development and environmental conservation, particularly in the areas that experience water challenges [1]. Land use land cover (LULC) change is closely connected to water demand and hydrology. The LULC changes are increasingly being recognized and have adverse influences at the global, regional, and local levels of spatial and temporal environmental change in catchments [2–5]. Changes in the LULC are inevitable worldwide and prevalent in developing countries, which are characterized by agriculture-dependent economies and rapidly growing populations [4,6].

In Africa, the rapid changes of LULC are mainly due to population growth, expansion of agricultural land, and other human and nature-induced factors. The agriculture in East Africa is predominantly rain-fed, making rural livelihoods and food security particularly vulnerable to changes in water availability [7]. Furthermore, Ethiopia, where agriculture has been the mainstay of the economy and ensures people's well-being, has perceived significant LULC changes towards the rapid expansion of agricultural land at the expense of forests and other LULC types [8]. Agriculture has gradually expanded in various regions of the highlands of Ethiopia from gently sloping areas to the steeper slopes of the adjacent mountains. This is due to the high population density (about 88% of the Ethiopians live in highland areas) and their dependency on subsistence agriculture. The Ethiopian highlands, which account for 45% of the country's total area, are plagued by significant LULC change and land degradation issues [4].

Human drivers are the primary drivers of LULC changes in Ethiopia mainly population growth, which is manifested mostly through the expansion of agricultural lands, even in areas where cultivation is almost impossible, and urban expansions [4,6]. Therefore, understanding the types, drivers, and implications of LULC change is an important indicator for resource base analysis to develop effective and sustainable strategies and to have informed planning decisions. The LULC change drivers having direct environmental repercussions and predicting future LULC status in the watershed is expected to be significant for land use planning, management, and sustainable water resources [9]. However, the stochastic change in nature, as well as the dynamics of natural and socio-economic variables, make analyzing and predicting future LULC change a challenge.

The historical and current LULC used in this study predicts the future LULC condition based on a Business-as-Usual (BAU) scenario and driver variables [10,11]. The drivers of LULC change selection play a key role in the modeling of LULC changes. In the current study, topographic factors (slope and elevation), socio-economic data (population density), and human–geographic or proximity data (distance from roads, distance from urban areas, and distance from streams) were the main driver variables of LULC change. Therefore, detecting past LULC change and scenario-based LULC predictions at different time scales (i.e., short and long-term) will help policymakers, land use planners, environmentalists, conservation planners, practitioners, and other stakeholders in examining the past, current, and future effects of LULC change [9,10].

In Ethiopia, the conversion of LULC from natural vegetation to farmlands, grazing lands, human settlements, and urban centers is common [4,6,8,11,12]. Correspondingly, in order to effectively manage LULC and water resources in a watershed, the historical and current impacts of LULC change dynamics as well as the possible future consequences need to be evaluated [10].

Land use land cover models can be used to identify the location and magnitude of change, predict LULC change based on past changes, and examine explanatory variables. To simulate and predict the future LULC change, a variety of land use models have been developed, mainly through the integration of remote sensing (RS) data and geographic information system (GIS) data including, but not limited to, Cellular Automata (CA), Markov Chain model (MC), Cellular Automata-Markov chain (CA-MC), Multi-Layer Perception Markov Chain (MLP-MC), Artificial Neural Network, Land Change Modeler (LCM), Binary Logistic Regression Algorithm, System dynamic simulation, system dynamic modeling, CLUE, cellular and agent-based models or a hybrid of the two are some of the models developed to analyze and predict LULC change dynamics [2,13,14].

The Land Change Modeler (LCM) model incorporates a cellular automata-markov chain (CA-MC) based multi-layer perceptron-neural network (MLP-NN) to predict future LULC maps. The model forecasts future LULC maps based on relative transition potential maps, which anticipate a cell's transition from one LULC to another based on presence of a driving forces and suitability of the transition area[15]. The transition probability matrices between LULC classes were determined using a MC, based on the transition results of MLP-NN, and the LULC map was predicted using CA [10,11]. CA-MC is used to model both temporal change and spatial distribution of land uses by combining a stochastic model (CA) (an open configuration that can easily be integrated with knowledge-driven models) and a technique (MC) (modeling spatio-temporal dynamics with better accuracy results) [2,16,17]. The MLP-NN uses artificial intelligence to provide a better understanding of the land transformation process [16]. MLP-NN is an efficient approach that uses a supervised backpropagation algorithm to simulate and predict LULC change and has good performance to generalize the transition potential [17].

The MLP-NN-CA-MC model is an effective hybrid model that has been tested by a number of researchers to simulate future LULC and predict its effects on the environment, natural resources, and landscape formation [18]. Many studies have applied the LCM to analyze and predict LULC change around the world, such as the Upper Siem Reap River in Cambodia [18], Neka Watershed in Iran [19], and the Des Plaines River watershed in the United States [20]. In Ethiopia, only a few studies have attempted to model the future trends of LULC changes [10,11,21,22].

The relationship between LULC change and hydrological components has been investigated all over the world, and the results have been utilized to forecast future LULC implications on water resources [23]. It has been clearly demonstrated that LULC has a significant impact on water availability by changing the magnitudes of the hydrological components. The hydrological response is more sensitive to LULC dynamics [4,6]. Hydrological responses to LULC changes depend on the scale of the changes, the land use type, and the location of the changes within a watershed [24]. At the watershed scale, the hydrological components distribution spatially is smaller than at the sub-watershed scale. The uneven spatial distribution of watershed management interventions in sub-watersheds was mainly responsible for this typical scale effect. In three different basins in South Africa, Warburton et al. [24] found that land use changes have a strong influence on stream flows at the sub-catchment scale than at the catchment scale and that different land use patterns influence rainfall partitioning into base flows in different ways.

In addition, to estimate the future implications of LULC changes on hydrological responses, it is also necessary to understand the impact of historical LULC changes on the hydrological regime. Predicting and assessing future watershed hydrology throughout time is important for achieving long-term water resource sustainability [1]. Therefore, thorough evaluations of the effects of LULC changes on hydrological responses are vital for water resource planning and management in particular, as well as the entire watershed in general [25]. Nowadays, due to the competing demands of various stakeholders, rapid population growth, industrialization, hydropower development, irrigation, urbanization, and land degradation, effective water resources planning and management are increasingly recognized as critical for sustainable economic growth and poverty reduction in developing countries [26].

The previous studies in different parts of the country, particularly the Blue Nile River basin, have revealed remarkable LULC dynamics caused by human activities that affect the water resources of the basin. In East Africa, Guzha et al. [7] found that forest cover loss increased annual flows and surface runoff. Similarly, most studies in Ethiopia indicate that increasing agricultural areas resulted in increased annual and seasonal stream flow. A study by Welde and Gebremariam [25] in the Tekeze watershed (Northern Ethiopia) presented the impact of LULC dynamics change increased the stream flow. According to Gebremicael et al. [27], the increase in water bodies was basically due to the construction of different dams throughout the basin. According to the findings, changes in LULC have decreased groundwater flow while increasing surface runoff. Similarly, Shawul et al. [28] found that LULC changes in the watershed were responsible for increasing surface runoff and groundwater decrease in the upper awash basin.

Hydrological modeling has the capability of representing a complex LULC system efficiently and used to analyze the dynamic water balance of a catchment that takes into account the spatio-temporal properties of watersheds [29]. Hydrological models are especially useful tools for assessing water resources since they can simulate historical watershed management strategies and predict the possible implications of LULC changes on hydrological circumstances [3]. Many models for watershed hydrology have been developed for a variety of purposes, and as a result, they have a variety of forms [30], but the major challenge to their adoption, particularly in developing countries, has been the availability of temporal and spatial data [31].

Hydrologists frequently employ fully distributed and semi-distributed hydrological models to analyze complicated hydrological processes. Fully distributed models are capable of capturing the spatial distribution of input variables. The fully distributed hydrological models are data-intensive, require high-quality data, are difficult to configure, and require more simulation and calibration time. In areas where data is scarce (hydrologically remote areas), the performance of these models is quite low [30,32]. Semi-distributed hydrological models aggregate meteorological variables and physical parameters into sub-basins, are easy to set up, require less time, and are often used in watersheds with limited data [33].

In various studies [4,6,9,34–36], the SWAT model applications have been widely used to simulate and predict the influence of LULC changes on the hydrology of catchment areas across the world in large and complex watersheds (https://www.card. iastate.edu/ swat articles/) and in Ethiopia to large and small river basins. Similarly, in the Nile basin countries, the SWAT hydrological model has been applied to large and small river basins [37].

The Soil and Water Assessment Tool (SWAT) model is a physically based, semi-distributed simulation model that can analyze the impact of LULC change on hydrological regimes in watersheds with varying topography, climate, soils, land use, and management over long time periods [38]. The SWAT model uses spatially non-explicit hydrological response units (HRUs) as the smallest spatial unit to discretize a watershed, making them less data-intensive in comparison to raster based models [30]. It is a comprehensive model for simulating hydrology in watersheds of almost any size and complexity over a long-term and continuous process[39].

The purpose of water resource planning and management is to ensure that water supply is distributed according to the temporal and spatial distribution of supply and demand through water regulation and distribution systems. However, the distribution of water resources varies through time and space, which has an impact on the development of water infrastructure [40]. Reservoir systems are commonly used to manage water resources in river basins through reducing high flows and increasing low flows for smoothing out the hydrological fluctuation and making water accessible when and where it is required to meet the temporal and spatial variability of water demand [41,42]. Due to social, economic, environmental concerns, public services, reservoir operations with consideration has attracted global attention in order to extend their useful life and benefits.

The operation of a reservoir is one of the most challenging issues facing water resource planners and managers, involving numerous decision variables, multiple objectives, as well as considerable risks and uncertainties [43–45]. In an ideal world, water resource management would assess all competing water demands and attempt an equitable allocation of water to meet all uses and demands. However, in practice, this is rarely attainable. Additionally, the significant challenge is that hydropower reservoir operation depends on the amount and timing of stream flow, which is in turn influenced by LULC patterns in the watershed [26,39,41]. Hydrological conditions are the primary drivers of reservoir management and have a direct impact on operational decisions due to their variable and uncertain structure.

The LULC change and hydropower generation have a long-term relationship and interact with one another [46]. The fluctuations in spatio-temporal stream flow will affect reservoir inflow, which would affect reservoir operation and hydropower generation. Future changes in LULC will almost certainly continue to influence stream flow patterns, which may pose significant challenges for reservoir management. As a result, it is imperative to predict stream flow and hydropower generation in the face of changing LULC [46,47]. The effects of LULC variations on hydropower reliability are particularly detrimental to developing countries [48]. Therefore, the evaluation of hydropower generation and reservoir operation under LULC change can play a significant role by providing baseline and future hydropower production evidences in the particular hydropower plant.

In reservoir operation, the way in which releases are controlled is called the operating rules. A rule curve, also known as a rule level, specifies how much storage should be maintained in a reservoir at different times of the year and the reservoir state (current reservoir capacity and inflow to the reservoir) in order to meet various demands. It is impossible to develop a single objective satisfying all interests, all adversaries, and all political and social viewpoints [43]. Therefore, the relative priority of multiple uses may be incorporated into the release decision, and in the event of a shortage, the higher priority needs are met first [26,42,49]. Despite the fact that reservoirs are built to serve a wide range of functions, the majority of the country's reservoirs lack a pre-determined, up-to-date, and real-time reservoir operation policy that benefits all basin users [50]. In general, most reservoirs around the world are managed by established operating rules that are often derived during the design stage through modeling approaches. Generating reservoir rule curves based on current and future inflow, which is predicted to be influenced by LULC change, results in the creation of new optimum rule curves for planning future events.

As a result, effective reservoir management necessitates the development of optimal policies for managing storage and discharges while maximizing benefits [51]. The optimal rule curves developed by the model under the future inflow situations may demonstrate a significantly better performance compared to the current rule curves as conducted by Prasanchum and Kangrang [52] in Lampao Dam in northeast Thailand for optimal reservoir rule curves under land use changes. The study by Guo et al. [46] on the responses of hydropower generation and sustainability to changes in reservoir policy, climate, and land use under uncertainty of the Xinanjiang reservoir in China shows that increasing reservoir inflows will increase hydropower generation in the future under land use change scenario. Labadie [53] comprehensively reviewed the state-of-the-art in reservoir system optimization and suggested guidelines for future study, as well as suggesting that the focus should be changed from the single reservoir optimization to multiple reservoir optimizations.

The Nile basin is the world's longest river and a vital resource for the economies of eastern and northeastern Africa. The water resource of the Blue Nile River basin is the source of water for many people living in the basin and further downstream [50]. In developing countries like Ethiopia, there are enormous surface and subsurface water resources, however, only a limited portion of them are developed throughout the year to meet national economic and social development goals. Ethiopia has a significant water resource potential, with twelve major river basins, with 80 to 90% of the total surface water resources found locally in the four river basins: the Blue Nile, Baro Akobo, Tekeze, and Omo Gibe (Table 1.1) [54]. The country's entire surface water resource is estimated to be over 123 BCM, and its groundwater resource is expected to be around 2.6 BCM. Even though the country has reasonably good water and land resources, they have yet not been developed or managed effectively due to significant problems and a variety of factors with water resources [40].

The Blue Nile River basin countries are characterized by rapid population growth, extensive poverty, and political instability. Additionally, Sub-Saharan Africa is home to over 2.4 billion people and is the region with the most spatially and temporally unevenly distributed water resources. On the other hand, Ethiopia is Africa's second most populated country in the region [55]. Although the Blue Nile River basin is Ethiopia's largest river in terms of volume of discharge, has vast hydropower development potential, and suitable topography for power generation, hydropower development has been low. The total hydroelectric power generation potential of the country is about 45,000 MW. The Blue Nile River basin has the potential to generate 17,000 MW out of the aforementioned hydroelectric potential, which accounts for 38% of the country’s total hydropower generation potential. Ethiopia has one of the lowest levels of per capita electricity consumption in the world. As of May 2010, there were only three small hydroelectric dams in the Blue Nile River basin in Ethiopia. In addition, the Beles and Nashe hydropower projects have recently started operations with different power generation capacities [54] as indicated in figure 1.1. This increases the basin's total contribution of electric power.

As a result of the hydroelectric power plants currently under development, including the Grand Ethiopian Renaissance Dam (GERD) on the Blue Nile River near the Ethiopia-Sudan border in western Ethiopia, hydroelectric generation in the country is likely to increase in the near future [56]. This hydropower dam will be Africa's largest hydropower project and expected to produce a maximum of 6000 MW of hydroelectric power when completed [56]. This would be a significant improvement over Ethiopia's existing hydroelectric power and for exporting to neighboring countries. However, transboundary rivers might bring cooperation or conflict [50]. Water resources system analysis, which focuses on management approaches for the sustainable and optimal use of water resources, can help with conflict resolution by allowing for a better understanding of the conflicts and cooperation options [50,57].

Digna et al. [44] investigated the optimal operation of the Eastern Nile system using a Genetic Algorithm, as well as the benefits of water resource development distribution. The findings of the study support the argument that GERD development has a good influence on the Eastern Nile riparian countries of Ethiopia, Sudan, and Egypt, as long as the three countries agree to manage the system cooperatively. Various studies, however, have contested the GERD's long-term economic, sectoral, resource, and social consequences [58–60]. To assist sustainable land and water development, scientific study on LULC and hydrological processes is required to meet increasing water demands and tensions in shared water resources such as the Nile basin [29].

Table 1.1. The surface water resource potential of Ethiopia.

No.	Basin Name	Catchment Area (km^2)	Annual Runoff (BM^3)	Gross Hydropower Production Potential (GWh/year)	Terminus
1	Blue Nile (R)	199,812	54.5	78820	Mediterranean
2	Wabi-Shebele (R)	202,220	3.4	5440	Indian Ocean
3	Genale-Dawa (R)	172,259	6	9270	Indian Ocean
4	Awash (R)	110,000	4.9	4470	Within the country
5	Tekeze (R)	82,350	8.2	5980	Mediterranean
6	Baro-Akobo (R)	75,912	23.23	13765	Mediterranean
7	Omo-gibe (R)	79,000	16.6	36560	Lake Turkana
8	Ogaden (D)	77,120	0	-	-
9	Denkele (D)	64,380	0.86	-	Within the country
10	Rift Valley Lakes (L)	52,000	5.3	800	Chew Bahir
11	Mereb (R)	5,900	0.72	-	Sudanese wetland
12	Ayisha (D)	2,223	0	-	-

R-River, D-Dry, L- Lake

Different reservoir operation models have been developed and employed for planning studies, the formulation and evaluation of alternative strategies for managing water management challenges, feasibility studies of proposed construction projects, and re-operation of existing reservoir systems. The two basic modeling applications in system analysis of reservoir operations, including hydropower generation problems are optimization and simulation [50,53]. Optimization models are extensively utilized for hydropower reservoir operations over a variety of time scales, from seasonal planning to daily, hourly, and real-time operations. The ability to search for the optimum policy from an infinite number of possible operation policies defined by decision variables is one of the advantages of employing optimization models [42]. Simulation models use pre-established logical rules to simulate reservoir operation decisions for successful reservoir operations [61].

Simulation models can assess alternatives to reflect a realistic scenario system, whereas optimization models can limit the range of viable alternative scenarios. By minimizing overall penalty functions in designated areas throughout the water resource network, optimization algorithms have been utilized to address water resource management problems and find the optimal rule curves, optimize storage, and release [41]. The traditional optimization algorithms that are used to optimize reservoir operations include Linear Programming, Non-Linear Programming, Dynamic Programming, Quadratic Programming, and simulation models [42,53]. However, these optimization approaches have limitations when dealing with complex reservoir systems. Linear optimization approaches are effective for large-scale systems with many variables, but they demand that all relations between variables in constraints and objectives be linear [62].

Non-linear programming is useful in dealing with non-linearity, but it requires that all relationships be differentiable, which may not always be the case for complex problems involving non-concave, non-convex, discontinuous, and non-differentiable functions. The Non-linear programming has a slow rate of convergence, resulting in high computational time and cost, as well as the tendency of convergence to local optima [50,63]. Dynamic programming can deal with non-linear objective functions, constraints, and the continuity of the function. However, one of the dynamic programming difficulties is dimensionality, or the processing of multiple state variables is one of its limitations. Recently, reservoir operation has been investigated using a combination of simulation and optimization models to perform optimal decisions [41].

As a result, the Hydrologic Engineering Centre Reservoir Evaluation System Perspective Reservoir Model (HEC-ResPRM), a combination of simulation and optimization model was being used in the study. In reservoir system analysis, the HEC-ResPRM addresses the constraints of conventional optimization techniques by dealing with non-linear, discontinuous, non-convex, and multi-functions [63]. HEC-ResPRM is an optimization or operating purpose-driven model for reservoir system operations. The model offers some degree of flexibility in illustrating operational strategies because it allows users to specify the penalty functions and their weights [44,64]. The HEC-ResPRM is compatible with Arc-GIS shapefiles, which can be used as a background layer to facilitate better representation of the physical system. This assists in the proper layout of the stream alignment following the background map, as well as the addition of project elements such as stream reaches, reservoirs, and computation points to the proper locations on the stream alignment.

Therefore, the HEC-ResPRM reservoir optimization model has been used to formulate the effects of LULC change on the operation of the reservoir [64]. Although only a few researchers have investigated the impact of LULC change on stream flow and the application of various optimal reservoir operating techniques, the majority of them have conducted it separately. SWAT and HEC-ResPRM were combined to evaluate the optimal operation of the Tekeze reservoirs in the Eastern Nile [64]. Climate change scenarios were simulated in that study, however, changes in LULC were ignored in future socio-economic development scenarios. Similarly, Anand et al. [1] combined the SWAT with a genetic optimization algorithm to optimize reservoir operation in the Ganga River basin. G/Mariam [45] developed a simulation model for the Tekeze dam reservoir in Ethiopia, intending to determine the optimal operation policy for producing hydroelectric power and to meet the requirements of downstream users of the dam.

The Nashe watershed is the tributary of the Blue Nile River basin and has enormous potential for hydropower, irrigation, and other development activities, however, there is inadequate information about the impact of LULC change on the hydrological process. Furthermore, the primary concern in the Nashe watershed is the increase of agricultural lands at the expense of forest, range land, and grass land [10]. In general, LULC change is a fundamental problem in the country [8]. As a result, to establish the framework for sustainable land management throughout spatio-temporal scales, it is vital to study LULC changes as well as the driving causes behind these changes. However, as far as the author's understanding, no study has assessed in the study area with respect to long-term spatial and temporal variability, as well as the potential impacts of LULC dynamics for both historical and future periods on hydrology.

Similarly, the spatio-temporal variation of the LULC is expected in the future, yet no study has attempted to simulate the future LULC dynamics effect on the operation of the Nashe reservoir. Likewise, there is no substitute for studying the impact of LULC change on hydropower generation in Ethiopia, where hydropower provides more than 90% of the country's electricity. There was a clear general lack of modeling on the integrated impact of LULC and reservoir operation of the watershed. Hence, it is essential to study the LULC change effects on past (historical) and future water resources under different LULC change periods and their effects on the optimization of reservoir operation. Therefore, understanding and determining the impacts of different time periods of individual LULC on the hydrological processes and reservoir operation in the watershed and prioritization of the sub-basins will contribute to identifying strategies for the hydrological water balance components of the watershed.

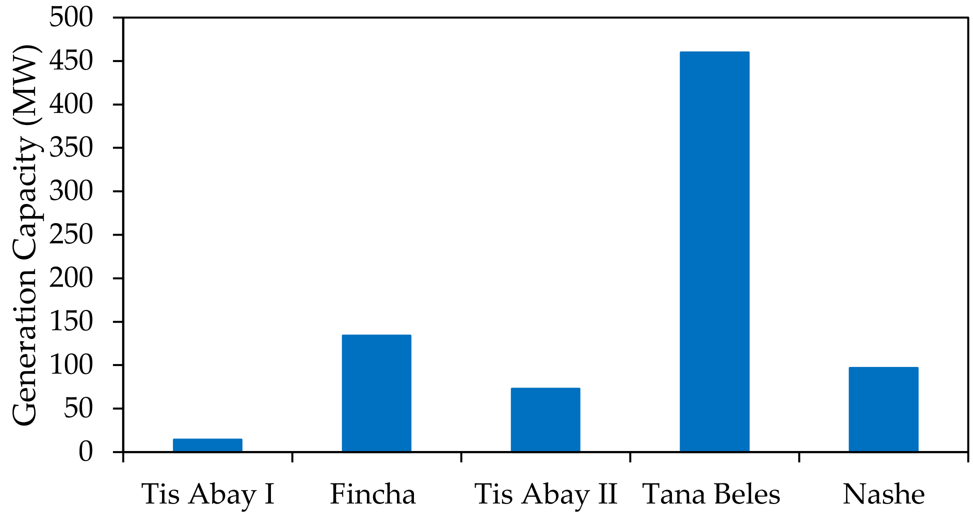


Figure 1.1. Hydropower projects in the Blue Nile River basin (Ethiopia)

1.2. Objectives of the research

The main purpose of this study was to investigate and predict the long-term spatial and temporal potential impacts of historical and future LULC changes on hydrological processes and hydropower reservoir operation in the Nashe watershed of the Blue Nile River basin in Ethiopia, East Africa. Towards the main objective, the following specific objectives were pursued:

- To investigate the extent and change of LULC dynamics of the past from Landsat imagery using ERDAS Imagine and predicting the future LULC change in the Nashe watershed using Land Change Modeler in TerrSet.
- To identify and assess the major driving factors and explore the implications on the land use land cover changes in the Nashe watershed.
- To analyze the spatial and temporal hydrological impacts attributed to different historical and potential future LULC changes at watershed and sub-watershed levels.
- To develop LULC scenarios in order to better understand the contribution of individual changes in the water balance dynamics of the watershed within the basin at various spatial and temporal scales.

- To assess the impacts of LULC changes on the existing and future hydropower generation of the Nashe reservoir operation.
- To derive the optimal hydropower reservoir operation level, storage, and operation guide curve for optimal power production under LULC change by applying the optimization model.

1.3. Structure of the thesis

The thesis was organized into six chapters and based on three papers (Figure 1.2). From the introduction and main body of the thesis to the conclusions and proposed directions, the overall flow follows the research process.

Chapter 1: presents a general introduction in which the research background, the state of the art, the research objectives, and the structure of the dissertation were elaborated.

Chapter 2: is based on paper 1 and describes the concepts of land use land cover changes, data types and sources, methods for LULC data acquisition, land use land cover classification, accuracy assessment, driver variables of land use land cover changes, quantification of the areal extent of LULC changes, and analysis made at watershed and sub-watershed levels. A detailed transitions probability matrix, rate of change, validation of the model, and change detection analysis was conducted and the future land use land cover prediction was described in this chapter. The mapping of historical and current LULC images obtained from Landsat imagery and classified using the ERDAS imagine model and identifying the potential drivers of LULC changes were elaborated. The future LULC prediction based on the classified historical satellite imagery using LCM integrated into TerrSet with MLP-NN and CA-Markov chain was described (Figure 1.2).

Chapter 3: is based on paper 2 and presents the assessment of the long-term effects of historical and future land use land cover changes on hydrological parameters. This chapter also addresses the description of the hydrological, meteorological, and spatial data used for this study and the methodology that has been employed for historical and future LULC change scenarios in the Nashe watershed. It further discusses the processing and preliminary analysis of the input data for the models. Describes hydrological modeling in the context of LULC change. It highlights water resources management, discusses guidelines for model selection, and describes the selected hydrological models for this research. Watershed hydrological modeling, including sensitivity analysis, calibration, and validation in the context of sustainable water resources was described. This chapter also focuses on the setup and calibration of the SWAT hydrological model at the Nashe watershed, mainly to investigate the effects of historical and future LULC change on Nashe hydropower reservoir inflows. The performance of the selected hydrological models was assessed through sensitivity analysis, calibration, validation, and uncertainty analysis. It also presents the spatial and temporal simulations of hydrological responses to LULC changes at watershed and sub-watershed scales and the contribution of individual LULC classes to water balance components (Figure 1.2).

Chapter 4: This chapter is based on paper 3 and presents the research methodology combining GIS, statistical, hydrological models, and reservoir simulation-optimization models. This section describes the details of the selected hydrological and reservoir optimization models. The reservoir inflow-outflow under land use land cover change and reservoir optimization operations were presented in this chapter. The main results from the combined watershed and LULC change model to estimate flow and the combined reservoir simulation-optimization model to generate optimal rule curves of reservoir systems in the study area were outlined. The chapter discusses the results of current and future hydropower reservoir optimal operations on reservoir storage, release, pool level, and hydropower generation. Generally, this chapter describes hydropower reservoir optimal operation using the HEC-ResPRM optimization network flow monthly model (Figure 1.2).

Chapter 5: This chapter presents the discussions about the combined results of the three consecutive papers with regard to the initially formulated research objectives.

Chapter 6: Finally, this chapter describes the conclusions from the thesis, recommendations, and perspectives on possible future research developments in the watershed.

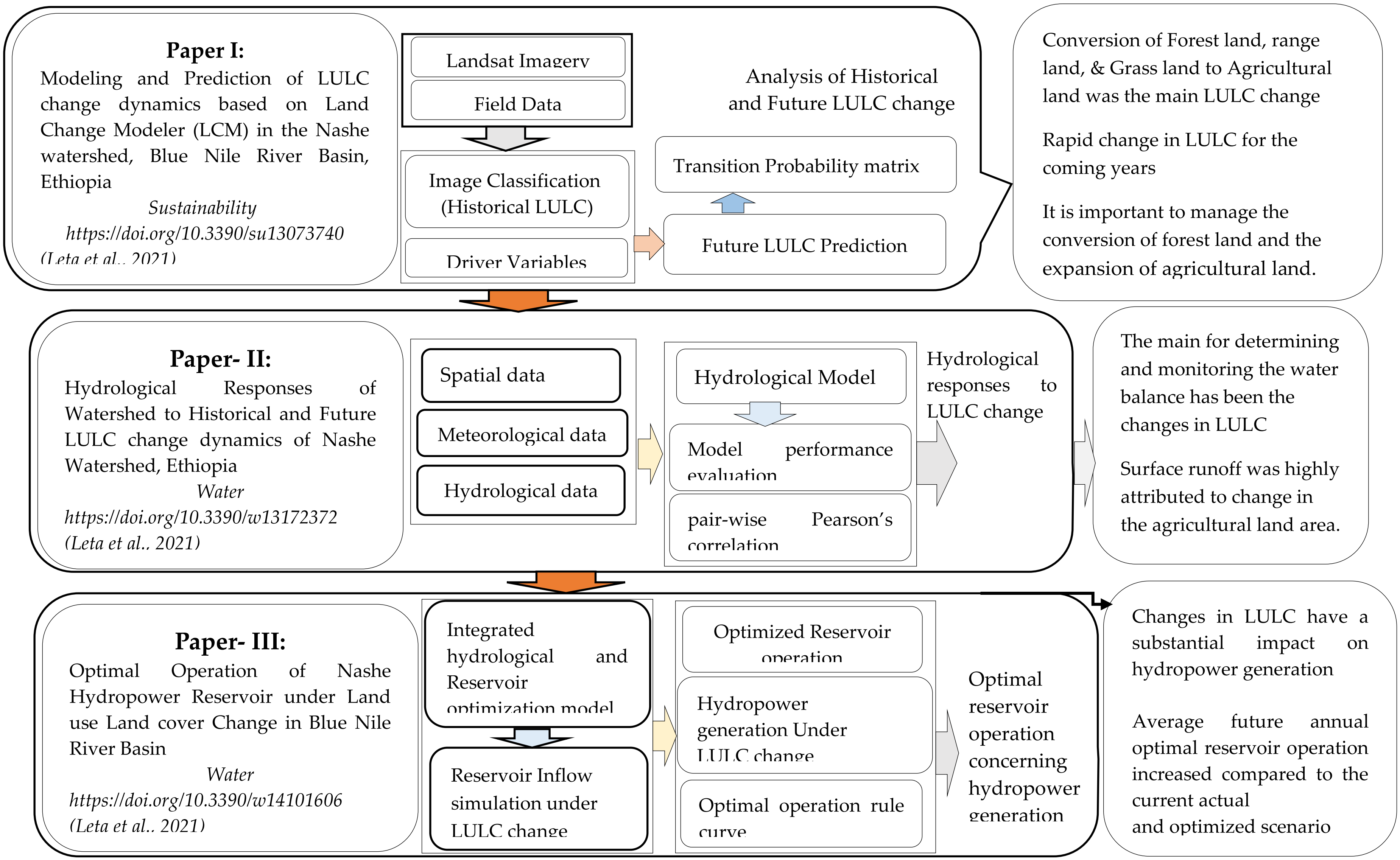


Figure 1.2. Structure of publications

References

1. Anand J, Gosain AK, Khosa R. Prediction of land use changes based on Land Change Modeler and attribution of changes in the water balance of Ganga basin to land use change using the SWAT model. Sci Total Environ. 2018;644:503–19. https://doi.org/ 10.1016/j.scitotenv.2018.07.017
2. Kafy AA, Naim MNH, Subramanyam G, Faisal A Al, Ahmed NU, Rakib A Al, Kona MA, Sattar GS. Cellular Automata approach in dynamic modelling of land cover changes using RapidEye images in Dhaka, Bangladesh. Environ Challenges. 2021;4 (January):100084. https://doi.org/10.1016/j.envc.2021.100084
3. Lu Z, Zou S, Qin Z, Yang Y, Xiao H, Wei Y, Zhang K, Xie J. Hydrologic Responses to Land Use Change in the Loess Plateau: Case Study in the Upper Fenhe River Watershed. Adv Meteorol. 2015;2015(2013).
4. Gashaw T, Tulu T, Argaw M, Worqlul AW. Modeling the hydrological impacts of land use/land cover changes in the Andassa watershed, Blue Nile Basin, Ethiopia. Sci Total Environ. 2018;619–620:1394–408. https://doi.org/ 10.1016/j. scitotenv. 2017 .11.191
5. Jalloh A, Nelson GC, Thomas TS, Zougmore R, Roy-Macauley H. West African agriculture and climate change: a comprehensive analysis. (IFPRI Research Monograph). IFPRI issue Br. 2013;(August).
6. Gebremicael TG, Mohamed YA, Van der Zaag P. Attributing the hydrological impact of different land use types and their long-term dynamics through combining parsimonious hydrological modelling, alteration analysis and PLSR analysis. Sci Total Environ. 2019;660:1155–67. https://doi.org/ 10.1016/j. scitotenv. 2019.01.085
7. Guzha AC, Rufino MC, Okoth S, Jacobs S, Nóbrega RLB. Impacts of land use and land cover change on surface runoff, discharge and low flows: Evidence from East Africa. J Hydrol Reg Stud. 2018;15(May 2017):49–67.
8. Hassen EE., Assen M. Land use/cover dynamics and its drivers in Gelda catchment, Lake Tana watershed, Ethiopia. Environ Syst Res. 2017;6(1).
9. Wang SW, Munkhnasan L, Lee WK. Land use and land cover change detection and prediction in Bhutan's high altitude city of Thimphu, using cellular automata and Markov chain. Environ Challenges. 2021;2(November 2020).
10. Leta MK, Demissie TA, Tränckner J. Modeling and prediction of land use land cover change dynamics based on land change modeler (LCM) in Nashe watershed, upper blue nile basin, Ethiopia. Sustainability 2021,13, 3740. https://doi.org/10.3390/ su13073740

11. Girma R, Fürst C, Moges A. Land use land cover change modeling by integrating artificial neural network with cellular Automata-Markov chain model in Gidabo river basin, main Ethiopian rift. Environ Challenges. 2022;6(December 2021): 100419. https://doi.org/10.1016/j.envc.2021.100419

12. Belihu M, Tekleab S, Abate B, Bewket W. Hydrologic response to land use land cover change in the Upper Gidabo Watershed, Rift Valley Lakes Basin, Ethiopia. HydroResearch. 2020;3:85–94. https://doi.org/10.1016/j.hydres.2020.07.001

13. Regasa MS, Nones M, Adeba D. A Review on Land Use and Land Cover Change in Ethiopian Basins. Land. 2021;10(585):1–18.

14. Al Rakib A Al, Akter K, Rahman M,… SA-1st ISR, 2020 U. Analyzing the pattern of land use land cover change and its impact on land surface temperature: a remote sensing approach in mymensingh, Bangladesh. AcademiaEdu. 2020;(December). https://www.academia.edu/download/65116756/NS_09.pdf

15. Aburas MM, Ho YM, Ramli MF, Ash'aari ZH. Improving the capability of an integrated CA-Markov model to simulate spatio-temporal urban growth trends using an Analytical Hierarchy Process and Frequency Ratio. Int J Appl Earth Obs Geoinf. 2017;59(March 2017):65–78.

16. Dey NN, Al Rakib A, Kafy A Al, Raikwar V. Geospatial modelling of changes in land use/land cover dynamics using Multi-layer perception Markov chain model in Rajshahi City, Bangladesh. Environ Challenges. 2021;4(May):100148. https://doi. org/10.1016/j.envc.2021.100148

17. Mishra VN, Rai PK. A remote sensing aided multi-layer perceptron-Markov chain analysis for land use and land cover change prediction in Patna district (Bihar), India. Arab J Geosci. 2016; http://dx.doi.org/10.1007/s12517-015-2138-3

18. Chim K, Tunnicliffe J, Shamseldin A, Ota T. Land use change detection and prediction in upper Siem Reap River, Cambodia. Hydrology. 2019;6(3).

19. Shooshtari SJ, Gholamalifard M. Scenario-based land cover change modeling and its implications for landscape pattern analysis in the Neka Watershed, Iran. Remote Sens Appl Soc Environ. 2015;1:1–19. http://dx.doi.org/10.1016/ j.rsase. 2015.05.001

20. Wilson CO, Weng Q. Simulating the impacts of future land use and climate changes on surface water quality in the Des Plaines River watershed, Chicago Metropolitan Statistical Area, Illinois. Sci Total Environ. 2011;409(20):4387–405. http://dx.doi.org/ 10.1016/j.scitotenv.2011.07.001

21. Kura AL, Beyene DL. Cellular automata Markov chain model based deforestation modelling in the pastoral and agro-pastoral areas of southern Ethiopia. Remote

Sens Appl Soc Environ. 2020;18(May):100321. https://doi.org/ 10.1016/j. rsase. 2020. 100321

22. Tadese S, Soromessa T, Bekele T. Analysis of the Current and Future Prediction of Land Use/Land Cover Change Using Remote Sensing and the CA-Markov Model in Majang Forest Biosphere Reserves of Gambella, Southwestern Ethiopia. Sci World J. 2021;2021.
23. Aboelnour M, Gitau MW, Engel BA. Hydrologic response in an urban watershed as affected by climate and land-use change. Water (Switzerland). 2019;11(8):1–23.
24. Warburton ML, Schulze RE, Jewitt GPW. Hydrological impacts of land use change in three diverse South African catchments. J Hydrol. 2012;414–415:118–35. http://dx. doi.org/10.1016/j.jhydrol.2011.10.028
25. Welde K, Gebremariam B. Effect of land use land cover dynamics on hydrological response of watershed: Case study of Tekeze Dam watershed, northern Ethiopia. Int Soil Water Conserv Res. 2017;5(1):1–16. http://dx.doi.org/10.1016/j.iswcr. 2017. 03.002
26. Zhou C, Sun N, Chen L, Ding Y, Zhou J, Zha G, Luo G, Dai L, Yang X. Optimal operation of cascade reservoirs for flood control of multiple areas downstream: A case study in the upper Yangtze River Basin. Water (Switzerland). 2018;10(9).
27. Gebremicael TG, Mohamed YA, Betrie GD, van der Zaag P, Teferi E. Trend analysis of runoff and sediment fluxes in the Upper Blue Nile basin: A combined analysis of statistical tests, physically-based models and landuse maps. J Hydrol. 2013; 482: 57–68. http://dx.doi.org/10.1016/j.jhydrol.2012.12.023
28. Shawul AA, Chakma S, Melesse AM. The response of water balance components to land cover change based on hydrologic modeling and partial least squares regression (PLSR) analysis in the Upper Awash Basin. J Hydrol Reg Stud. 2019;26 (August):100640. https://doi.org/10.1016/j.ejrh.2019.100640
29. Gebrekristos ST. Understanding catchment processes and hydrological modelling in the Abay/Upper Blue Nile basin, Ethiopia. DISSERTATION Submitted in fulfilment of the requirements of the Board for Doctorates of Delft University of Technology. 2015. 189 p.
30. Neitsch S., Arnold J., Kiniry J., Williams J. Soil & Water Assessment Tool Theoretical Documentation Version 2009. Texas Water Resour Inst. 2011;1–647.
31. Gassman PW, Sadeghi AM, Srinivasan R. Applications of the SWAT Model Special Section: Overview and Insights. J Environ Qual. 2014;43(1):1–8.
32. Waseem M, Kachholz F, Tränckner J. Suitability of common models to estimate

hydrology and diffuse water pollution in North-eastern German lowland catchments with intensive agricultural land use. Front Agric Sci Eng. 2018; 5(4):420–31.

33. Jajarmizadeh M, Harun S, Salarpour M. An Assessment on Base and Peak Flows Using a Physically-Based Model. Res J Environ Earth Sci. 2013;5(2):49–57.

34. Leta MK, Demissie TA, Tränckner J. Hydrological Responses of Watershed to Historical and Future Land Use Land Cover Change Dynamics of Nashe Watershed, Ethiopia. Water (Switzerland). 2021;13(17).

35. Dile YT, Daggupati P, George C, Srinivasan R, Arnold J. Introducing a new open source GIS user interface for the SWAT model. Environ Model Softw. 2016;85:129–38. http://dx.doi.org/10.1016/j.envsoft.2016.08.004

36. Megersa K, Ankit Ch, Tamene A. Stream Flow and Land Use Land Cover Change in Finchaa Hydropower, Blue Nile Basin, Ethiopia. Int J Civil, Struct Environ Infrastruct Eng Res Dev. 2017;7(5):1–12.

37. Van Griensven A, Ndomba P, Yalew S, Kilonzo F. Critical review of SWAT applications in the upper Nile basin countries. Hydrol Earth Syst Sci. 2012;16(9): 3371–81.

38. Roth V, Nigussie TK, Lemann T. Model parameter transfer for stream flow and sediment loss prediction with SWAT in a tropical watershed. Environ Earth Sci. 2016;75(19):1–13.

39. Kangrang A, Prasanchum H, Hormwichian R. Active future rule curves for multi-purpose reservoir operation on the impact of climate and land use changes. J Hydro-Environment Res. 2019;24(February):1–13. https://doi.org/10. 1016/j.jher. 2019.03.001

40. Belete MA. Modeling and Analysis of Lake Tana Sub Basin Water Resources Systems, Ethiopia. Dissertation zur Erlangung des akademischen Grades Doktor der Ingenieurwissenschaften (Dr.-Ing.) an der Agrar- und Umweltwissens chaftl ichen Facultät der Universität Rostock. 2013;1–108.

41. Choi Y, Lee E, Ji J, Ahn J, Kim T, Yi J. Development and evaluation of the hydropower reservoir rule curve for a sustainable water supply. Sustain. 2020; 12 (22):1–11.

42. Lu B, Li K, Zhang H, Wang W, Gu H. Study on the optimal hydropower generation of Zhelin reservoir. J Hydro-Environment Res. 2013;7(4):270–8. http://dx.doi.org/ 10.1016/j.jher.2013.01.002

43. Zhang J, Liu P, Wang H, Lei X, Zhou Y. A Bayesian model averaging method for

the derivation of reservoir operating rules. J Hydrol. 2015;528(January):276–85. http:// dx.doi.org/10.1016/j.jhydrol.2015.06.041

44. Digna RF, Castro-Gama ME, van der Zaag P, Mohamed YA, Corzo G, Uhlenbrook S. Optimal operation of the Eastern Nile System using Genetic Algorithm, and benefits distribution of water resources development. Water . 2018; 10(7).

45. G/mariam M. Modeling of Tekeze Hydropower Reservoir Operation with HEC – ResSim. Msc thesis,. 2012;(April). Addis Ababa University, Addis Ababa, Ethiopia

46. Guo Y, Fang G, Xu YP, Tian X, Xie J. Responses of hydropower generation and sustainability to changes in reservoir policy, climate and land use under uncertainty: A case study of Xinanjiang Reservoir in China. J Clean Prod. 2020;281 (xxxx):124609. https://doi.org/10.1016/j.jclepro.2020.124609

47. Leta MK, Demissie TA, Tränckner J. Optimal Operation of Nashe Hydropower Reservoir under Land Use Land Cover Change in Blue Nile River Basin. Water 2022, 14, 1606. https://doi.org/10.3390/w14101606

48. Falchetta G, Kasamba C, Parkinson SC. Monitoring hydropower reliability in Malawi with satellite data and machine learning. Environ Res Lett. 2020;15(1).

49. Azizipour M, Ghalenoei V, Afshar MH, Solis SS. Optimal Operation of Hydropower Reservoir Systems Using Weed Optimization Algorithm. Water Resour Manag. 2016;30(11):3995–4009. http://dx.doi.org/10.1007/11269-016-1407-6

50. Mulat AG. WATER RESOURCE SYSTEM MODELING OF EASTERN NILE RIVER BASIN. PhD Dissertation submitted to Graduate School of Addis Ababa Doctor of Philosophy , PhD. 2015;(June).

51. Paliwal V, Ghare AD, Mirajkar AB, Bokde ND, Lorenzo AEF. Computer modeling for the operation optimization of mula reservoir, upper godavari basin, India, using the jaya algorithm. Sustain. 2020;12(1):1–21.

52. Prasanchum H, Kangrang A. Optimal reservoir rule curves under climatic and land use changes for Lampao Dam using Genetic Algorithm. KSCE J Civ Eng. 2018;22(1):351–64.

53. Labadie JW. Optimal Operation of Multireservoir Systems: State-of-the-Art Review. J Water Resour Plan Manag. 2004;130(2):93–111.

54. Abay Basin Authority. The Federal Democratic Republic of Ethiopia, Abbay Basin Authority. The Great Ethiopian Rennaisance Dam. 2016;(June):1–46.

55. UNDESA. UNDESA (United Nations Department of Economic and Social Affairs). Back to our Common Futur Sustain Dev 21st Century Proj. 2013;39. http://sustainabledevelopment.un.org/content/documents/UN-DESA_Back_

Common_ Future_En.pdf

56. EEPCo. Ethiopian Electric Power - Power Sector Development Powering Africa. 2014; https://www.eep.com.et/en/eep-history/

57. Mirchi A, Watkins D, Madani K. Modeling for watershed planning management, and decision making. Chapter 6. In: Vaughn, J.C (Ed.), Watersheds: Management, Restoration and Environmental Impact. Nova Science Publishers, Hauppauge, NY, USA. Watersheds Manag Restor Environ. 2010;

58. Abdelhady D, Aggestam K, Andersson D-E, Beckman O, Berndtsson R, Palmgren KB, Madani K, Ozkirimli U, Persson KM, Pilesjö P. The Nile and the Grand Ethiopian Renaissance Dam: Is There a Meeting Point between Nationalism and Hydro solidarity? J Contemp Water Res Educ. 2015;155(1):73–82.

59. Arjoon D, Mohamed Y, Goor Q, Tilmant A. Hydro-economic risk assessment in the eastern Nile River basin. Water Resour Econ. 2014;8:16–31. http://dx.doi.org/10.1016 /j.wre.2014.10.004

60. Mulat AG, Moges SA. Assessment of the Impact of the Grand Ethiopian Renaissance Dam on the Performance of the High Aswan Dam. J Water Resour Prot. 2014;06(06):583–98.

61. Zeng X, Hu T, Guo X, Li X. Water Transfer Triggering Mechanism for Multi-Reservoir Operation in Inter-Basin Water Transfer-Supply Project. Water Resour Manag. 2014;28(5):1293–308.

62. Li F-F, Shoemaker CA, Wei J-H, Fu X-D. Estimating Maximal Annual Energy Given Heterogeneous Hydropower Generating Units with Application to the Three Gorges System. J Water Resour Plan Manag. 2013;139(3):265–76.

63. Nicklow J, Reed P, Savic D, Dessalegne T, Harrell L, Chan-hilton A, Karamouz M, Minsker B, Ostfeld A, Singh A, Zechman E. State of the Art for Genetic Algorithms and Beyond in Water. J Water Resour Plann Manag. 2010;136(August):412–32.

64. Abera FF, Asfaw DH, Engida AN, Melesse AM. Optimal operation of hydropower reservoirs under climate change: The case of Tekeze reservoir, Eastern Nile. Water (Switzerland). 2018;10(3).

2. Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed, Blue Nile River Basin, Ethiopia

This chapter was published in:
Sustainability; 27 March 2021; Volume 13, 3740
https://doi.org/10.3390/su13073740

Abstract: Change of land use land cover (LULC) has been known globally as an essential driver of environmental change. Assessment of LULC change is the most precise method to comprehend the past land use, types of changes to be estimated, the forces and developments behind the changes. The aim of the study was to assess the temporal and spatial LULC dynamics of the past and to predict the future using Landsat images and LCM (Land Change Modeler) by considering the drivers of LULC dynamics. The research was conducted in Nashe watershed (Ethiopia) which is the main tributary of the Blue Nile River basin. The total watershed area is 94,578 ha. The Landsat imagery from 2019, 2005, and 1990 was used for evaluating and predicting the spatio-temporal distributions of LULC changes. The future LULC image prediction has been generated depending on the historical trends of LULC changes for the years 2035 and 2050. LCM integrated in TerrSet Geospatial Monitoring and Modeling System assimilated with MLP and CA-Markov chain have been used for monitoring, assessment of change, and future projections. Markov chain was used to generate transition probability matrices between LULC classes and cellular automata were used to predict the LULC map. Validation of the predicted LULC map of 2019 was conducted successfully with the actual LULC map. The validation accuracy was determined using the Kappa statistics and agreement/disagreement marks. The results of the historical LULC depicted that forest land, grass land, and range land were the most affected types of land use. The agricultural land in 1990 was 41,587.21 ha which increased to 57,868.95 ha in 2019 with an average growth rate of 39.15%. The forest land, range land, and grass land declined annually with rates of 48.38%, 19.58%, and 26.23%, respectively. The predicted LULC map shows that the forest cover will further degrade from 16.94% in 2019 to 8.07% in 2050, while agricultural land would be expanded to 69,021.20 ha and 69,264.44 ha in 2035 and 2050 from 57,868.95 ha in 2019. The findings of this investigation indicate an expected rapid change in LULC for the coming years. Converting the forest area, range land, and grass land to other land uses, especially to agricultural land, is the main LULC

change in the future. Measures should be implemented to achieve rational use of agricultural land and the forest conversion needs to be well managed.

Keywords: land change modeler; Landsat images; modeling LULC change; multilayer perceptron; TerrSet

2.1. Introduction

Land use land cover (LULC) change occurs under a variety of pressure and it is the result of changes or modifications in the intensity of an existing LULC type to determine the location and nature of the land use change. The changes of LULC have been perceived as worldwide environmental change drivers in the watershed that are very sensitive to LULC dynamics [1]. A dynamic LULC offers an inclusive sympathetic of the interactions and relations that are crucial for sustainable land resource management [2]. At global and local levels, the changes of LULC are driven by anthropogenic and natural processes at different spatio-temporal levels. The LULC changes are dynamic, non-linear human-nature interactions that are significant land surface conversions and involve complex processes. The LULC change trajectory worldwide for the past 300 years has been categorized by gains in agriculture and losses in forests [3,4]. According to the FAO [5], LULC changes are associated with the change of forest land to agricultural expansion, urbanization, and deforestation.

The LULC changes were broadly assessed in various areas of the world, for instance, Europe and USA [6], South America [7], Asia, and Africa [8], Ethiopia [9,10]. In Africa, the expansion of agricultural land influenced by rapid population growth has been recognized as a primary driver of LULC. Many developed countries including Europe and the United States practiced massive deforestation because of agricultural expansion and industrialization until the early 19th century [11]. Urbanization dynamics and urban growth are usually linked to demographic factors mostly in developing countries [12]. The landscape has been intensely changed due to socio-economic and political changes that occurred in the first half of the 19th century in Europe [11]. The decrease in agricultural land at the expenditure of increased urban areas and water bodies in Europe is another strong trend [13].

The dynamics of LULC intensities and rates are changing because they are highly associated with the overexploitation of natural resources. The natural variability issues like climate change, soil conditions, and terrain characteristics have also accounted for land use changes [14]. Therefore, the integration of natural and human factors in LULC dynamics have become a significant issue throughout the world in efficient land use. The assessment of LULC change and the drivers that have direct consequences on the natural environment and human societies are the focus of the current scientific examination of scientists [15]. In order to develop sustainable strategies and to have informed planning decisions, understanding the drivers and dynamics of LULC change is crucial. The LULC change driving forces can be direct or indirect for change over time and space; this was incorporated to provide an estimate of future scenarios [16].

The drivers' assessment and predicting their future LULC status in the watershed is expected to have an essential contribution for land use planning management and sustainable water resources. The use of historical satellite imageries are used to effectively monitor and analyze LULC change [17]. Future LULC change analysis and prediction are often complicated for the change of nature and the dynamic of natural and socio-economic variables. The prediction of forthcoming LULC dynamics in areas where the economic condition depends upon agriculture has a profound impact. The LULC model developed in this study predicts a future LULC state based on a business-as-usual scenario. Therefore, understanding the earlier and current LULC changes and simulating for the future is vital for the management of land and water resources of the basin [18,19].

Models of land change are useful tools for environmental and other types of research concerning LULC change [20]. The magnitude and location are the two important issues of LULC that have been considered in the modeling. LULC change assessment models are either dynamic or static, non-spatial or spatial, deductive or inductive, pattern-based or agent-based [21,22]. Modeling the LULC process is to properly calibrate and validate the model for predicting future changes [23]. The LCM embedded in the TerrSet model has been utilized to inspect the historical and to predict the future changes of LULC of the watershed. The model is strong due to its dynamic projection proficiency, suitable calibration, and capability to simulate several types of land cover [24,25]. LCM evaluates changes of the land use of two different periods, determines the changes, visualizes changes, and presents the results with various maps and graphs.

The model predicts future LULC images based upon MLPNN (Multi-Layer Perceptron neural networks) and CA-Markov Chain (CA-MC) [26]. The transition potential of pixel to change into another class determination is through MLP drivers of change [27]. The

MC model is stochastic, which requires pairs of LULC images to derive the transition potential into the future predictions based on the amount of historical change [28,29]. The blend of CA-MC can simulate the spatio-temporal dynamics of LULC change. The model predicts transitions of a cell from one LULC to another depending on physical and socio-economic data [30,31]. The model validation process is the accuracy assessment of prediction and contrast made between the predicted and observed land cover maps. Therefore, to assess the change drivers of the past and to simulate for the future, the validated data have been used.

Remote sensing data particularly Landsat images provide suitable possibility for LULC change monitoring, particularly for developing countries where geospatial technologies are not well developed [32]. In Africa, around 40% of the population were living in urban centers as of 2014. Between 2013 and 2050 the African population is projected to increase by 115% and the urban residents' percentage has been projected to reach 56% by 2050 [33]. In Europe, between 1990 and 2006 the population grew up by 146% [34] as per the study was conducted in 24 European countries. Currently, in Europe around 73% of the population lives in urban areas and it is estimated to be over 80% by 2050 [33]. The availability of resources as well as their dynamics and management varies considerably from area to area, especially in Ethiopia. Ethiopia is highly vulnerable to environmental changes induced by natural and anthropogenic activities [35].

Due to changes of LULC, Ethiopia experienced serious environmental problems including soil erosion, land degradation, loss of soil fertility, and deforestation [36]. The Blue Nile River basin (BNRB) is the most varied and a highly important river basin in Ethiopia [37,38]. Nashe watershed is the tributary of the Basin that faced LULC change driven by population growth, urbanization, agricultural land expansion, deforestation, overgrazing, expansion of industrial activities, and political dynamics. The analysis of LULC change in the Nashe watershed, its drivers, and prediction of future land use change are vital for understanding the dynamics of human environment interactions and environmental management interventions. Therefore, it is very important to assess and predict the LULC changes based on the historical data using Landsat images and Land Change Modeler. The following research questions were addressed: (i) what was the trend of LULC change within the study area in the past (1990–2019) and which LULC classes were mostly affected? (ii) What growth and change patterns can be expected in the future? (iii) What are the major driving factors of LULC change in the watershed?

The above research questions are so significant and addressed in this study watershed since a dramatic socio-economic change with expected enormous effect on the land use is undergoing and this will influence various hydrological processes. Thus, especially in the BNRB, those changes need to be predicted in time for environmental management in this area in an effective and sustainable manner. The study findings are utilized to provide empirical evidence on patterns and rates and identify major driving forces of LULC dynamics at watershed level and improve policies in land use within the framework of sustainable land use planning in relation to future changes or development.

2.2. Materials and Methods

2.2.1. Study Area

The Blue Nile River Basin (BNRB) is the main stream of the Nile basin and is located within the western and central part of Ethiopia between latitudes 7° 45′ and 12° 45′ N and longitudes 34° 05′ and 39° 45′ E. The BNRB consists of the major part of Ethiopia and covers an area of 157,000 km^2. The basin is located within the region of Oromia, Amhara, and Benishangul-Gumuz of Ethiopia. The basin has three main seasons: a main rainy season which occurs between June and September, a dry season from October to January, and a short rainy season between February and May. The basin mean yearly rainfall ranges within 800–2000 mm and increases with altitude. The Nashe watershed is the major tributary from the left bank within the BNRB of Ethiopia which is situated at about 300 km from Addis Ababa. The sub-basin lies in between 9° 35′ and 9° 52′ N latitudes and 37° 00′ and 37° 20′ E longitudes (Figure 2.1).

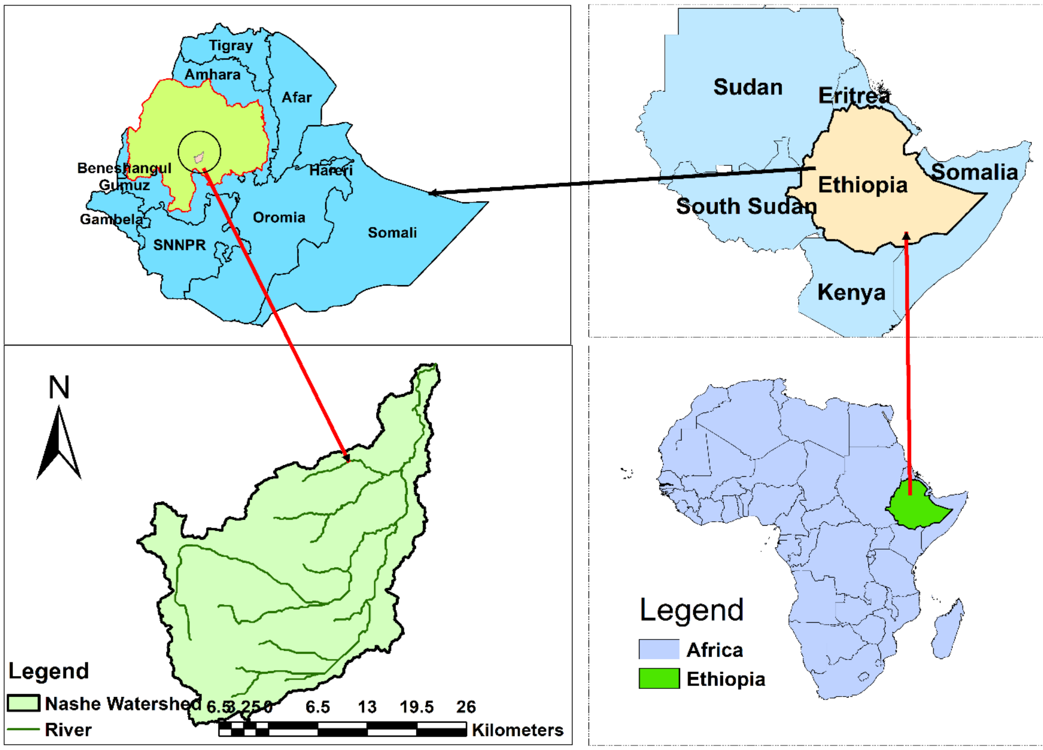


Figure 2.1. Map of the study area.

The watershed area varies in elevation from 1600 m in the lower plateau under the escarpment to the hills and ridges of the highland climbing to over 2500 m. The annual average rainfall of the Nashe watershed ranges from 1200 mm to 1600 mm (depending on data from five weather stations); June, July, August, and September are the main rainy season of the catchment. The observed average temperature of the catchment is 22 °C. The watershed area is categorized by intensive irrigable lands at the downstream, large water potential sites at the upstream, and also with high head of hydropower potential. Agriculture is the leading financial activity in the watershed and the main source of livelihood for the local population.

2.2.2. Data Types and Sources

The important spatial data required for the study were Digital Elevation Model, Landsat Images, and field data. The three Landsat images used were downloaded from the USGS (http://glovis.usgs.gov/, accessed on 2 January 2017) (Table 2.1) and DEM was obtained from the Ethiopian Ministry of Water, Irrigation and Energy (MoWIE). The collected 30 m spatial resolution of DEM was used to delineate the watershed, to develop elevation, and to generate the slope of the watershed. The analysis was performed using the TM Landsat-5 from 1990, ETM+ Landsat-7 from 2005, and OLI_TIRS Landsat-8 from 2019. The images were acquired in January, which corresponds to the dry season in Ethiopia when a clear sky period occurs to obtain images with Zero clouds and avoid extreme differences in the land cover reflectance dataset. The global positioning system (GPS) measurements were taken during fieldwork to verify and confirm the information gathered through remote sensing at each ground control point (GCP). The LULC types were noted and for reference purposes, photographs were also taken.

Table 2.1. Details of Landsat images data used for the analysis of land use and land cover (LULC) in the study area.

Satellite Sensor	Path/Row	Acquisition Date	User Bands	Spatial Resolution	Year
Landsat 5 TM	169/053 170/053	January, 1990	1–5, 7	30 m	1990
Landsat 7 ETM+	169/053 170/053	January, 2005	1–5, 7, and 8	30 m, 15 m	2005
Landsat 8 OIL	169/053 170/053	January, 2019	1–7, 9, and 8	30 m, 15 m	2019

The coordinates of each location selected were marked with GPS, and these points were verified in Google Earth. During the field survey and data collection, socio-economic survey methods such as interviews with key informants, discussions with focus groups, and participatory field observation were conducted. The socio-economic data collected were utilized to get information on historical land use change, socio-economic status, and the driving factors that change the land use in the watershed. For key informant interview and focus group discussion three representative sub-watersheds (upper, middle, and lower) were selected depending on the agro-ecological conditions and proximity of the locations to reservoirs in the catchment. The key informants were selected purposely based on their experience, position, and responsibilities from various social groups including elders, community leaders, and local natural resource experts. A total of six focus group discussions were conducted in different Kebeles selected from two in each of the upper, middle, and lower parts of the watershed. Each focus group discussion comprises six members drawn from the members of the community. They include elderly farmers, vulnerable groups, youth, local community leaders, and natural resource experts.

2.2.3. Land Use Land Cover Change Assessment

2.2.3.1. Image Classification

The classification of images is to categorize automatically all pixels from the Landsat images into LULC classes to extract useful thematic information [39]. For image classification, the data of ground truth were gathered on the field and satellite image verification. After pre-processing the satellite images, the supervised classification was implemented using maximum likelihood classification (MLC) technique to produce image classification. The MLC method is the widely used algorithm for supervised satellite image classification [40]. The method has a strong theoretical foundation and the ability to accommodate varying data, LULC types, and satellite systems [28]. The approach of supervised classification is adopted as it preserves the basic land cover characteristics through statistical classification techniques [41]. In classifying the 1990, 2005, and 2019 images, reference data were gathered from images of Google Earth and through interviews from concerning body of the corresponding time periods. In this study, six separable LULC were considered (Table 2.2).

Table 2.2. Major land use land cover types used and their descriptions.

LULC Types	Description
Agricultural Land	Includes areas used for perennial and annual crops, irrigated areas, scattered rural settlements, and commercial farms (sesame cultivations and sugarcane plantations).
Forest Land	Areas covered with dense trees (deciduous forests, evergreen forests, mixed forests).
Range Land	Includes areas covered with small trees, less dense forests, bushes, and shrubs. These areas are less dense than forests.
Grass Land	Areas covered by grasses are usually used for grazing and those remain for some months in a year.
Urban Area	Areas of commercial areas, urban and rural settlements, and industrial areas.
Water Body	Areas covered by rivers, streams, and reservoirs

To accomplish classification of image in multi-temporal approach and for mapping purposes, the ERDAS Imagine 2015 and ArcGIS 10.3 software were used, respectively. For each LULC, as many as possible training samples were selected throughout the entire image, based on the composite images, as well as Google Earth images. For classification, verification, and validation of the classified images, the training data were used.

2.2.3.2. Accuracy Assessment

Accuracy assessment tells us to what extent the ground truth is represented on the equivalent classified image. Since land use maps derived from image classification usually contain some errors, the accuracy of classification results obtained must be assessed. Assessing the classification accuracy provides the degree of confidence in the results and the subsequent change detection [40]. For accuracy assessment, the classified map was compared with ground truth data. For 1990 and 2005, the reference points were collected from Google Earth, original Landsat images, interviews, group discussions, previous reports, and maps. For the 2019 image, Google Earth, field observation, original Landsat images, interviews, and group discussions of random reference points in different LULC types were recorded from the field survey conducted by using GPS.

The common and most effective method used to measure the accuracy of the classified image from remotely sensed imagery is an error/confusion matrix [42]. The confusion matrix provides overall accuracy, user accuracy, producer accuracy, and kappa statistics. Kappa coefficient was determined by using Equation (1) [43]. According to Mishra and Rai [21], a kappa coefficient value below 0.4 shows poor agreement, a value between 0.4 and 0.8 depicts a moderate agreement, and a value greater than 0.8 shows a strong agreement.

$$K = \frac{N\sum_{i=1}^{r} Xii - \sum_{i=1}^{r}(Xi+) * (X+i)}{N^2 - \sum_{i=1}^{r}(Xi+) * (X+i)} \tag{1}$$

$$K = \frac{(\text{Total} * \text{sum of correct}) - \text{sum of all the (row total} * \text{column total)}}{\text{Total squared} - \text{sum of all the (row total} * \text{column total)}} \tag{2}$$

Where r-rows number in the matrix, Xii-number of observations in row i and column i (the diagonal elements), X + i and Xi+ -the marginal totals of row i and column i, respectively, and N -observations number.

2.2.3.3. Land Use Land Cover Change Drivers

Driving factors influence LULC changes. LULC changes are driven by natural and human activities [10]. The regionally differing main drivers have great impact on many environmental aspects [44]. Provided that drivers of past changes are sustained, they can be expected to be influential forces in the future. LULC change simulation studies have used topographic, socio-economic data, and distance driver variables [45,46]. Elevation, slope, population density, distance from roads, distance from streams, distance from urban areas, and evidence likelihood rasters were considered as the potential driver variables. Distance from roads, distance from streams, population density, and distance from urban areas were set as dynamic variables to express the varying as they change over time.

The evidence likelihood is an empirical probability of change in the LULC categories between an earlier and a later map [47]. It is used to transform categorical variables, such as change from one land cover class to another into numerical values. The significance of driver variables was tested using Cramer's V and P values which measure strength of the correlation between two variable classes. Cramer's V value is a coarse statistic measure of the association strength or dependency between variables, and it ranges from 0.0 to 1.0 in value. Generally, variables with a total Cramer's V value greater than 0.15 are considered useful and those with a score over 0.4 are considered good [48,49]. The Cramer's V does not assure a strong performance of the variables, since it cannot represent the scientific pre-requisites and the multifaceted nature of the relationships. It simply helps to determine whether or not to include the particular variable as a driving factor of LULC change [50].

2.2.4. LULC Change Prediction and Validation

2.2.4.1. LULC Prediction

The LCM (Land Change Modeler) embedded in the TerrSet Geospatial Monitoring and Modeling System (TGMMS) software was used for prediction of future LULC for a specified year based on the classified historical satellite images. The LCM determines how the factors influence future LULC change, how much land cover change took place between earlier and later LULC, and then calculates a relative amount of transitions [51]. It was widely tested and used to predict change for the analysis and modeling of impacts on biodiversity using multiple land cover categories [46]. The module provides changes of the LULC assessment as losses and gains to each LULC category. LCM produces two simulated maps, i.e., soft projection and hard projection. In hard predictions, a simulated map is developed for the prediction year, in which each pixel is allocated to a specific land use category [52]. Whereas, the soft prediction is a projected map created to show the vulnerability in which each pixel is allocated a value from 0 to 1. The smaller value indicates less vulnerability to change and the high value shows high susceptibility to change [52]. Similarly, the model is used for analyzing, predicting, and validating the predicted LULC change [53].

The trend variations of LULC changes for the years 1990, 2005, and 2019 were analyzed to predict future years of the watershed. The future land use scenarios were based on recent trends, historical land use information, and anticipated future changes. The LCM uses the change analysis tab, the transition potentials tab, and the change prediction tab. The change rates were determined through the change analysis tab, along with the transition potential maps to simulate the future scenario. The LCM module allows three different approaches to produce maps of transition potential based on the individual sub-models and associated explanatory variables: multi-layer perceptron (MLP) neural network, logistic regression, and a similarity-weighted instance-based machine learning tool (SimWeight) [47]. The MLP estimates accurately the land that would be estimated to change from the image of later date to the specified simulation date based on the projection. From the approaches, the performance of MLP is stronger when modeling the relationship between non-linear land change and the explanatory variables. It is more flexible and dynamic compared to the others when multiple transition types are modeled [47].

The TerrSet model uses CA-MC which is a stochastic modeling process to simulate the future changing over time from past changes [54]. It predicts the spatial structure of various LULC categories and scenarios based on the TPM [31,55]. To predict LULC change, the Markov matrix model depends on the Bayes equation (Equation (3) that evaluates the change by comparing the initial (T1) and the second land cover (T2) [47].

$$S_{(t+1)} = P_{ij} * S_{(t)} \tag{3}$$

$$\mathrm{Pij} = \begin{bmatrix} \mathrm{P11} & \mathrm{P12} \ldots & \mathrm{P1n} \\ \mathrm{P21} & \mathrm{P22} \ldots & \mathrm{P2n} \\ \ldots & \ldots \quad \ldots & \ldots \\ \mathrm{Pn1} & \mathrm{Pn2} \ldots\ldots & \mathrm{Pnn} \end{bmatrix} \tag{4}$$

Where $0 \leq \mathrm{Pij} < 1$ and $\sum_{j=1}^{n} \mathrm{Pij} = 1$, (i, j = 1, 2… n). The cellular automata model can be expressed by the following equation:

$$S_{(t,t+1)} = f[S(t),N] \qquad (5)$$

where $S_{(t)}$ and $S_{(t+1)}$ are the system status at times t and t + 1, respectively, N-cellular field, t and t+1 are the different times, f-transformation rule of cellular states in local space, S-the set of limited and discrete cellular states, Pij-the transition probability matrix in a state.

The CA-Markov considers constraints and factors to prepare a single map of suitability [28,51,56]. The model prepares the probability transition matrix and transition probability areas. The probability transitional matrix contains the changing probability of an individual LULC class to other classes. The transitional area matrix contains the pixel number that is expected to change from each LULC class over the specified time frame [48].

2.2.4.2. Model Validation

Validation is simply a procedure to assess the quality of the predicted LULC map against a reference map [57]. The images of Landsat for 1990 and 2005 were utilized to simulate the 2019 LULC image. The comparison of simulated LULC image with the actual map was developed. The LULC of the 1990 and 2005 years were provided to calibrate LCM, and the model was validated by simulating the recent LULC map of 2019. The validation process in LCM involves a cross-tabulation in a three-way comparison between the later land cover map (2005), the predicted land cover map (2019), and the actual map (2019). The module validation in the LCM model was used to assess statistically the quality of the predicted 2019 LULC image against the 2019 reference image [57].

The map shows areas where the model correctly predicted called hits, areas where the model predicted change but it actually did not occur called false alarms, and occasions where the model was unable to predict it, but areas are changed in reality, called misses. After the model prediction capacity was verified between the 1990 and 2005 time periods for 2019, the simulation process was repeated to project the 2035 and 2050 maps using 2005 and 2019 classified maps. The other method is the kappa coefficient calculation between the predicted map and actual land use map [58]. However, the original kappa coefficient does not distinguish between the quantification and location error, delimiting its expressiveness. This can be resolved by calculating cause dependent

K-indices, Kno (kappa for no information), Klocation (kappa for location), Kstandard (kappa for standard), and KlocationStrata (kappa for stratum-level location) [58].

The overall agreement of the projected and reference map indicates the Kappa for no information (Kno). The location kappa (Klocation) is used to compute the spatial accuracy in the overall landscape, because of the correct assignment values in each category between the simulated and reference map [59]. The ratio of inaccurately allocations by chance to the correct assignments is kappa for standard (Kstandard) [53]. The kappa for stratum level location (KlocationStrata) is a quantification of the spatial accuracy within pre-identified strata, and it indicates how well the grid cells are situated within the strata [47]. The blend of Kstandard, Kno, Klocation, and Klocation strata scores is considered for a comprehensive evaluation of the overall accuracy both in terms of location and quantity. Additionally, the statistics considered are AgreementQuantity, AgreementChance, AgreementGridCell, DisagreementGridCell, and DisagreementQuantity to know exactly how strong the agreement is between the simulated map and the base map (Table 2.3).

Table 2.3. Possible ranges of map comparison and level of agreement of kappa values.

No.	Values	Strength of Agreement
1	<0	Poor
2	0.01–0.40	Slight
3	0.41–0.60	Moderate
4	0.61–0.80	Substantial
5	0.81–1.00	Almost Perfect

The DisagreementQuantity and DisagreementGridCell constituents are crucial to understand the simulated model [57]. This sort of validation method gives the idea about the level of agreement or disagreement between projected and actual LULC maps [49]. The two most important differences between the two categorical maps are in terms of quantity (changes or persistence) and allocation. Disagreement by quantity is the variation between two images because of an imperfect combination in the overall proportions of LULC categories. The allocation disagreement is the distinction between two images caused by an imperfect combination among the spatial allocations of all land cover map categories [53].

2.2.5. Analysis of Land Use Land Cover Change

The change of LULC assessment was computed using the LCM model. Different LULC categories of quantitative assessment, net change of LULC categories, and the contributors to the net change experienced by each LULC class are the three sections of results identified in the LCM. Change analysis was performed by using the classified maps (1990, 2005, and 2019) and the predicted LULC (2035 and 2050) to demonstrate the pattern of changes [58]. The LULC dynamics in each study period were assessed using the numerical values extracted from the classified images. To acquire the change pattern, the images classified from consecutive periods were cross-tabulated and compared to each other. The probability matrix was done between 1990 and 2005, 2005 and 2019, 2019 and 2035, 2035, and 2050 using LCM. The change percentage [35] and the rate of change were determined [41] for LULC categories by using Equations (6) and (7), respectively, to determine the amount of the changes experienced between the periods of the different LULC categories.

$$\text{Percent of change} = \frac{\text{Ay}-\text{Ax}}{\text{Ax}} * 100 \quad (6)$$

$$\text{Rate of change (ha/year)} = \frac{Ay - Ax}{T} \quad (7)$$

Where Ax is the area of LULC (ha) of an earlier land cover image, A_y is the area of LULC (ha) of a later land cover image, T is the time interval between Ax and A_y in years.

2.3. Results and Discussions

2.3.1. Accuracy Assessment of the Classified Images

The assessment of accuracy was performed for LULC change analysis by generating confusion/error matrix in each LULC category of 1990, 2005, and 2019 classified maps. The overall accuracy, kappa statistics, producer's and user's accuracy have been used for assessment. The kappa statistics and overall accuracy of classified images show 91.43%, 87.59%, 85.71%, and 0.93, 0.90, and 0.88 for the years 2019, 2005, and 1990, respectively (Table 2.4). The more recent LULC map accuracy results were higher and these may be related to a higher spatial resolution of satellite images.

The accuracy assessment of LULC is required in any study using remote sensing Landsat data for the historical LULC. According to Sitthi et al. [61], LULC map accuracy is quantified by creating an error matrix or a confusion matrix, which compares the classified map with a reference classification map. The results of the study is consistent with some other studies conducted by Temesgen et al. [41] in Dera District, Abate [36] in Borena Woreda, Gashaw et al. [10] in Blue Nile basin, Wubie et al. [9] in Gumera, Araya and Cabral [62] in Portugal, Wnek et al. [11] in Poland, Slovakia, and Czechia, and Rimal et al. [63] in India. The accuracy of this study shows that the result is within the range of accuracies, in which Land Change Modeler and Landsat images were used [55,63].

Table 2.4. Accuracy assessment of classified LULC maps for 1990, 2005, and 2019.

	LULC Types	AL	FL	RL	GL	UL	WB	UA (%)
1990	Agricultural Land (AL)	**86**	0	3	5	0	1	90.53
	Forest Land (FL)	0	**78**	6	0	1	0	91.76
	Range Land (RL)	1	4	**67**	3	0	0	89.33
	Grass Land (GL)	4	3	0	**56**	5	2	80.00
	Urban Land (UL)	0	4	4	2	**50**	0	83.33
	Water Body (WB)	0	0	0	4	0	**51**	92.73
	PA (%)	94.51	87.64	83.75	80.00	89.29	94.44	
	K = 85.71%; OA = 0.88							
	LULC Types	AL	FL	RL	GL	UL	WB	UA (%)
2005	Agricultural Land	**89**	2	4	4	1	0	89.00
	Forest Land	0	**81**	4	3	2	0	90.00
	Range Land	3	4	**72**	0	1	0	90.00
	Grass Land	5	0	1	**54**	1	4	83.08
	Urban Land	0	1	0	2	**52**	0	94.55
	Water Body	1	0	0	2	0	**47**	94.00
	PA (%)	90.82	92.05	88.89	83.08	91.23	92.16	
	K = 87.59%; OA = 0.90							
	LULC types	AL	FL	RL	GL	UL	WB	UA (%)
2019	Agricultural Land	**100**	0	1	3	1	0	95.24
	Forest Land	2	**84**	4	0	0	0	93.33
	Range Land	1	4	**63**	2	0	0	90.00
	Grass Land	2	1	4	**57**	0	1	87.69
	Urban Land	0	0	1	2	**57**	0	95.00
	Water Body	0	0	0	2	0	**48**	96.00
	PA (%)	95.24	94.38	86.30	86.36	98.28	97.96	
	K = 91.43%; OA = 0.93							

UA: User's Accuracy, PA: Producer's Accuracy, K: Kappa Statistics, OA: Overall Accuracy.

2.3.2. LULC Change Analysis

The change of the LULC analysis was through evaluation of gains, net change, and losses experienced by different categories using change analysis in LCM. The evaluation of spatial and temporal changes between various classes during the period 1990, 2005, and 2019 was analyzed (Figure 2.2 and Table 2.5). The from–to transformations were summarized as loss, gain, and net change of LULC in Figure 2.3 and Figure 2.4. The gain of LULC for each class was determined from the result of persistence and the total column value, whereas the loss is from total row and the persistence.

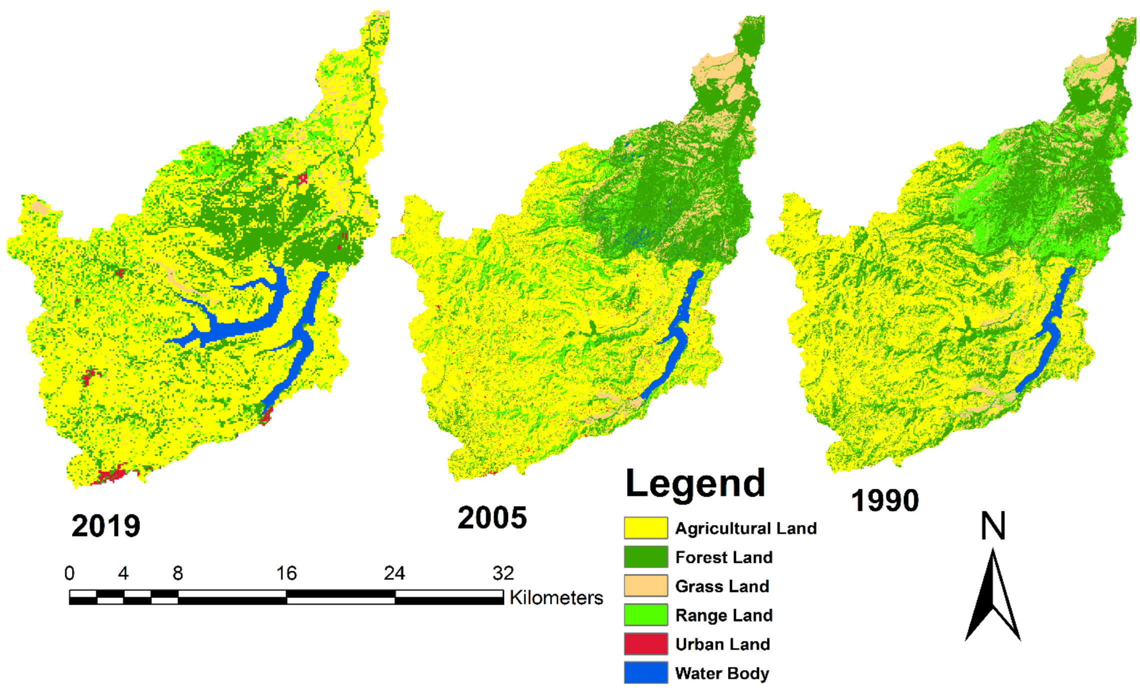


Figure 2.2. The LULC of the Nashe watershed in 1990, 2005, and 2019.

Table 2.5. The area coverage of LULC, percent, and rate of changes in the Nashe watershed between 1990, 2005, and 2019.

LULC Types	**Area**						**Change**								
	1990		**2005**		**2019**		**1990–2005**			**2005–2019**			**1990–2019**		
	Ha	%	Ha	%	Ha	%	Ha	%	Rate of Change (ha/Year)	Ha	%	Rate of Change (ha/Year)	Ha	%	Rate of Change (ha/Year)
Agricultural Land	41,587.2	44.0	47,658.5	50.4	57,869.0	61.2	6071.3	14.6	404.8	10,210.5	21.4	680.7	16,281.7	39.2	561.4
Forest Land	31,033.9	32.8	26,579.3	28.1	16,019.1	16.9	–4454.6	–14.4	–297.0	–10,560.2	–39.7	–704.0	–15,014.8	–48.4	–517.8
Grass Land	9443.4	10.0	7964.7	8.4	6966.0	7.4	–1478.8	–15.7	–98.6	–998.6	–12.5	–66.6	–2477.4	–26.2	–85.4
Range Land	10,637.8	11.3	9835.5	10.4	8555.0	9.1	–802.4	–7.5	–53.5	–1280.5	–13.0	–85.4	–2082.9	–19.6	–71.8
Urban Land	471.1	0.5	882.6	0.9	1084.0	1.2	411.5	87.3	27.4	201.4	22.8	13.4	612.9	130.1	21.1
Water Body	1404.6	1.5	1657.6	1.8	4085.0	4.3	253.0	18.0	16.9	2427.4	146.4	161.8	2680.4	190.8	92.4
Total	**94578**	**100**	**94578**	**100**	**94578**	**100**									

The percentage and rate of change were calculated using Equations (6) and (7), respectively.

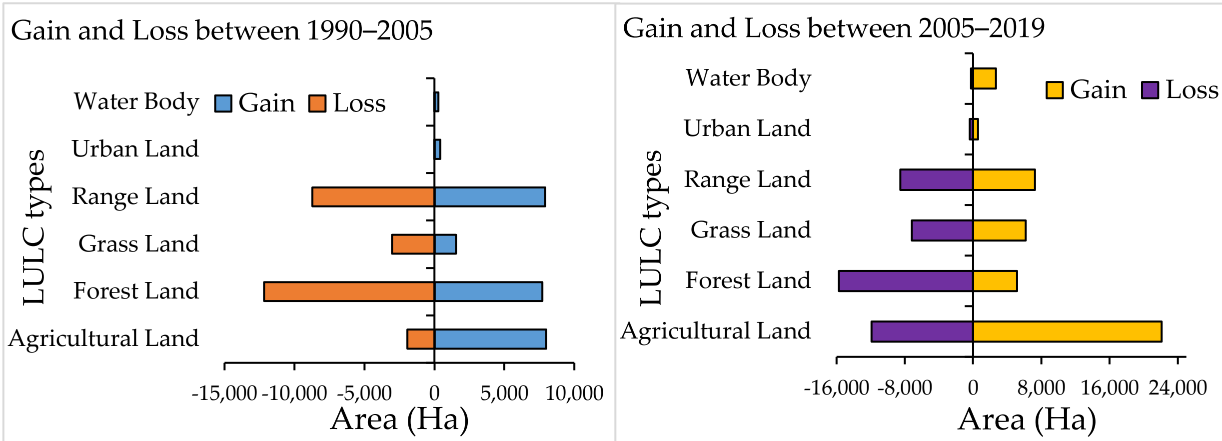


Figure 2.3. Gain and loss area of the land use land cover class in 1990–2005 and 2005–2019

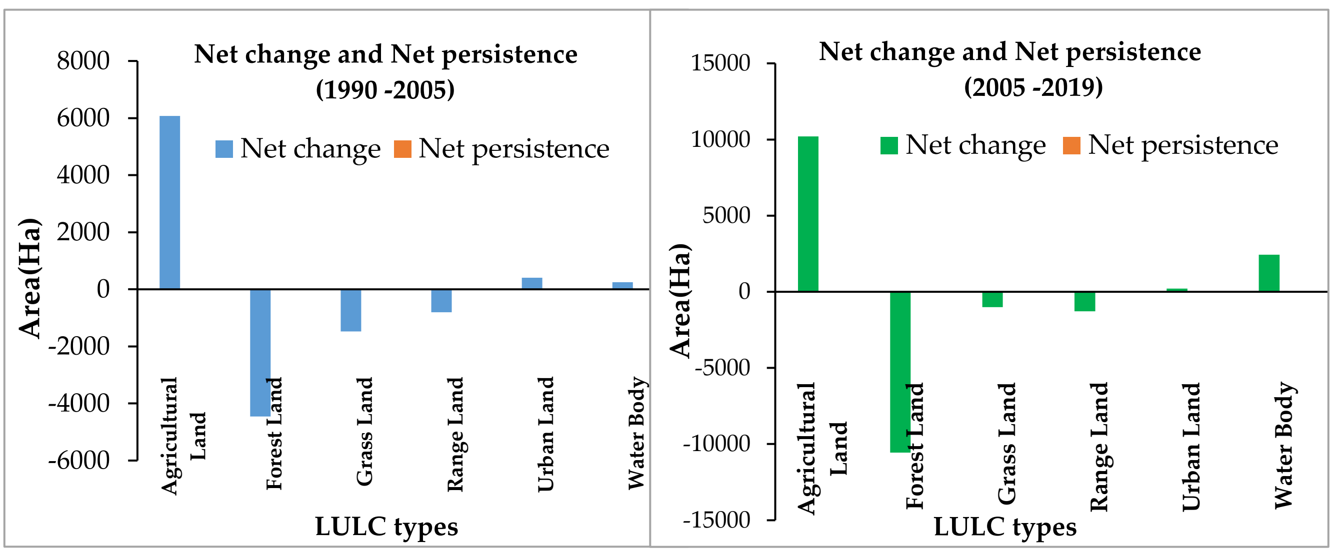


Figure 2.4. Net change and net persistence area of LULC class of the study periods

The agricultural land is the dominant LULC type of the watershed which covered 44.00% of the study area in 1990, 50.40% in 2005, and 61.19% in 2019 (Table 2.5). The changes in LULC have influenced forest distribution in the study area. The forest land area, which is also the largest part of land use class, has significantly decreased. Similarly, according to the least prevalent types of land use, the urban areas and water body increased from 1990 to 2019. The significant increase of agricultural land, water body, urban land, and the sharp decline of forest land in the watershed were the major transformations observed. Although forest land, range land, and grass land experienced reduction in coverage throughout the study periods, the greatest reduction rate was observed in forest land. To mitigate the rapid rates of LULC conversions at watershed, the application of integrated watershed management strategies, managing the rapid population growth, afforestation of degraded or deforested areas, and reducing the dependency of locals on forest products is critically important. The findings of the study are consistent with other studies conducted in Ethiopia by Solomon et al. [64] in Birr and Upper Didesa watersheds of the Blue Nile basin, and as outlined Temesgen et al. [41] for Dera district of northwestern Ethiopia, where the agricultural land increased significantly and the forest land was shrinking.

2.3.3. Driver Variables of LULC Change

The driver variables influencing changes are based on spatial analysis and added to the model either as static or dynamic components [47]. The LULC prediction in the watershed was based on change in a driver's impact. In this study, socio-economic data, topography, and proximity factors were selected to analyze the LULC change. Before the drivers are added to the model, the selected driver variables were tested for their explanatory value using Cramer's V and P values (Table 2.6). The Cramer's V value does not give decisive proof that a particular variable explains the change in land use. It is rather a more intuitive tool that can be utilized to understand the significance that a particular variable has in influencing change.

Table 2.6. Cramer's V and p-value for each of the explanatory variables.

Driver Variables	Cramer's V	p-Value
Elevation	0.2967	0.0000
Slope	0.0094	0.0000
Population density	0.3261	0.0000
Distance_from_Urban	0.1547	0.0000
Distance_from_stream	0.2158	0.0000
Distance_from_road	0.1391	0.0000
Evidence Likelihood	0.4472	0.0000

Evidence likelihood is used for the determination of the relative frequency of pixels of different LULC types within the areas of change. It is recommended in cases where there are low Cramer's V values. The obtained result for evidence likelihood is considered as a good. In this study, it is a quantitative measure of the frequency of change between agricultural land and all other land classes (also called disturbance).

From Table 2.6, it was observed that the variable such as elevation, population density, distance from urban areas, distance from stream, and distance from road are considered as useful variables of transitions. Variables such as slope have low Cramer's V values, and it shows that the effect of slope on LULC change in the study area is not critical. The variables with good Cramer's V value show that they are the most explanatory variables for LULC change. All driver variables were used to model the transitions in this study. The elevation and slope are recognized as the imperative topographic factors affecting LULC change. Topography has effects on the spread and extent of urban distribution, forest, and range land conversion to agricultural land. Khoi and Murayama [65] found that deforestation decreases with the increase of the slope gradient. The other driver variables such as distance from stream, distance from urban areas, population density, and distance from roads also play an important role in land use change, as each provides convenience to residents to access resources.

2.3.4. Transition Probability Matrix (TPM)

Transition potential modeling is assessing the likelihood of LULC change from one class to another depending on the suitability transition of area and the presence of driving forces [66]. The TPM records the probability of each land use class to change into the other class. The LULC changes of the future predictions are utilized through the probability of the transition matrix [67]. The transition probability matrices produced by the model between LULC types during the periods 1990–2005 and 2005–2019 were depicted in Table 2.7. The spatio-temporal LULC change assessment between the earlier and later land cover maps were cross-tabulated. The cross-tabulation is used to determine the amounts of change and conversions between different land cover maps. In the table of cross-tabulation shown in Table 2.7, the bolded frequencies along the transition probability matrix of the diagonal confirm the probability of LULC class remaining unchanged (persistence) from the earlier to the later land cover map. Whereas, the off-diagonal frequencies express the possibility of a given LULC experiences changes from one to another. The change analysis is depends on the changes in LULC between time 1 and time 2 [28].

Table 2.7. Transition area matrix (ha) of LULC between 1990–2005 and 2005–2019.

	LULC Types	2005						
		AL	FL	GL	RL	UL	WB	Total
1990	Agricultural Land	**39,662.13**	302.16	179.91	1121.71	321.25	0.06	41,587.21
	Forest Land	5214.82	**18,856.81**	292.80	6429.98	59.35	180.12	31,033.88
	Grass Land	2001.18	617.60	**6419.75**	372.33	32.42	0.12	9443.40
	Range Land	778.37	6783.15	1072.00	**1911.17**	0.74	92.39	10,637.83
	Urban Land	1.98	0.13	0.18	0.00	**468.79**	0.01	471.10
	Water Body	0.01	19.44	0.00	0.28	0.00	**1384.91**	1404.64
	Total	47,658.49	26,579.30	7964.65	9835.47	882.55	1657.60	94,578.05
	LULC Types	2019						
		AL	FL	GL	RL	UL	WB	Total
2005	Agricultural Land	**35,763.83**	4299.68	1181.79	4196.23	349.90	1867.06	47,658.48
	Forest Land	12,051.96	**10,869.35**	1360.03	1708.26	167.12	422.57	26,579.30
	Grass Land	4673.21	913.15	**802.00**	1317.94	20.25	238.11	7964.65
	Range Land	5021.16	3101.81	212.67	**1314.36**	51.83	133.64	9835.47
	Urban Land	337.82	14.09	9.28	15.25	**494.75**	11.37	882.55
	Water Body	20.97	221.04	0.26	2.92	0.13	**1412.28**	1657.60
	Total	57,868.95	16,019.13	6966.01	8554.95	1083.98	4085.03	94,578.05

The agricultural land which is the highest class has 39,662.13 ha with the probability of remaining as agricultural land in 1990–2005. The conversion of forest land, range land, and grass land was the major contributing land use for the agricultural land. The minimum loss of LULC category was observed from water body to grass land and urban land. Although in urban land there was minimum or no conversion to range land and water body. In 2005–2019 the highest class loss was the change of forest land to agricultural land by 12,051.96 ha.

In 2005–2019, especially since 2012, a dam on Nashe River was built for irrigation and hydropower purposes. The water body has increased. The displacement of communities occurred from their land during the expansion of hydropower projects and the displacement caused land scarcity. The lowland areas of the watershed was covered with forests, range lands, and grass lands before 1990 even before 2005. Currently, however, a great decline of forest cover is occurring because of urbanization and agricultural land expansion. In recent times, the expansion of urban areas has been continuously increasing at the highest rate.

The findings of the study show that urban area increase was consistent with other research findings in Africa [8] and Ethiopia [9,10]. The studies in some parts of Europe, for example, [13] in Slovakia, [62] in Portugal, and [11] in Poland, Slovakia, and Czechia, reported an increase in urban areas at the expense of agricultural land. Similarly, a study in China reported that the urban built-up land expansion from conversion of cultivated land [68]. Riad et al. [12] revealed that effective urban planning is needed to address the multiple challenges and competing interests of urban environments for the rapid increase in urban built-up area with scarce land and water resources on the urban edge.

2.3.5. Validation of the Model

The agreement of the two categorical maps was measured by using validation module. In order to assess the accuracy, validation of the model is necessary. Validation is significant as it allows to determine the quality of the predicted land cover map with actual map. A comparison was made between the actual and simulated LULC map of 2019 so as to validate the predicted map. The less effective simulated LULC class is water body as the projected map was from the maps before construction of the dam and the actual LULC map is from after the construction. The validation results between the simulated and actual LULC test summary of the model are presented in Table 2.8.

Table 2.8. LULC change prediction validation based on the actual and projected 2019 LULC.

LULC Category	Projected		Actual	
	Area (Ha)	**Area (%)**	**Area (Ha)**	**Area (%)**
Agricultural Land	54,161.90	57.27	57,868.95	61.19
Forest Land	20,384.75	21.55	16,019.13	16.94
Range Land	9388.67	9.93	6966.01	7.37
Grass Land	8288.78	8.76	8554.95	9.05
Urban Land	608.90	0.64	1083.98	1.15
Water Body	1745.06	1.85	4085.03	4.32
Total	**94,578.05**	**100.00**	**94,578.05**	**100.00**

The achieved k-indices were compiled in Table 2.9. The model is regarded to be validated if the Kstandard (overall kappa) score exceeds 70% [22]. The values of k-index greater than 80% show good agreement between the projected and actual LULC map that exceeds the minimum acceptable standard [47]. Here, all indices are greater than 80%, showing a good overall agreement and projection ability of the model.

Table 2.9. The k-index values of the simulated LULC map of 2019.

Index.	Value
Kno	0.9026
Klocation	0.9213
KlocationStrata	0.8836
Kstandard	0.8743

The values of AgreementChance, AgreementQuantity, AgreementGridCell, Disagreement Grid Cell, and Disagreement Quantity in Table 2.10 provide statistical agreement information between the simulated map and the reference map. Namely, Disagreement GridCell and DisagreementQuantity constituents are crucial to recognize the model simulated outputs [57].

Table 2.10. The validation result analysis (agreement/disagreement component values).

Agreement/Disagreement	Value	Value (%)
Agreement Chance	0.1629	16.29
Agreement Quantity	0.3335	33.35
Agreement GridCell	0.4254	42.54
Disagreement GridCell	0.0269	2.69
Disagreement Quantity	0.0513	5.13

The disagreement between the two maps is generally low and this is mainly due to quantity errors (0.0513) rather than allocation errors (0.0269). The agreement measures show overall good agreement between the actual and simulated map (92.81%). The result shows that in the study area the model has higher ability to predict the LULC changes in location than in quantity. This indicates the good capacity of the model in simulating future LULC states and an accurate specification of location.

According to the Wang et al.[55], the model was validated by comparing the map of observed LULC of 2019 with the predicted LULC map of 2019 using the statistics of kappa index. For accuracy assessment measurement in a number of studies, kappa coefficient is still considered as a vital tool [61]. The LULC change model performance is different for different study areas because of varied environmental features and situations of the individual study area [62,63].

2.3.6. Future LULC Prediction

The LULC change of the future has been predicted for the years 2035 and 2050. The future probable percentages of changes in LULC for the periods of 2019–2035 and 2035–2050 were analyzed by transition probabilities matrix. The quantity of change and the spatial distribution are the two aspects of LULC prediction in LCM that are provided by Markov chain and MLP neural network, respectively [69]. The simulated future LULC images of the watershed obtained from the LCM were shown in Figure 2.5. Similarly, the area coverage, percentage, and rate of change were provided in Table 2.11. Generally, the LULC change increase or decrease was provided in Figure 2.6.

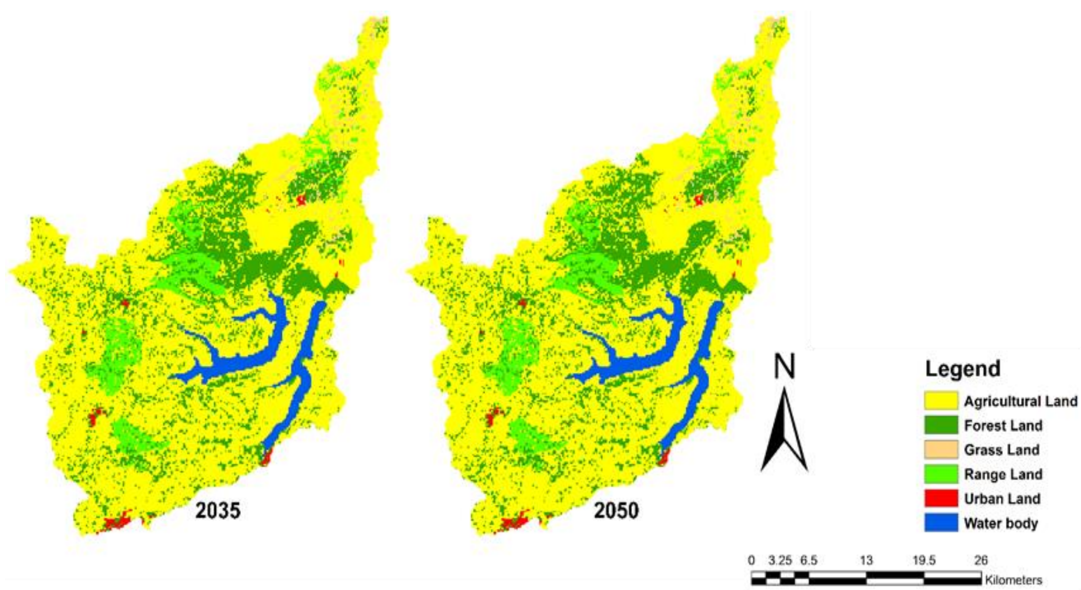


Figure 2.5. The predicted 2035 and 2050 LULC of the watershed.

Table 2.11. The area coverage of LULC, percent, and rate of changes in the Nashe watershed between 2019, 2035, and 2050.

LULC Types	Area						Change					
	2019		2035		2050		2019–2035		2035–2050		2019–2050	
	Ha	%	Ha	%	Ha	%	Ha	%	Ha	%	Ha	%
Agricultural Land	57,869.0	61.2	69,021.2	73.0	69,264.4	73.2	11,152.3	19.3	243.2	0.4	11,395.5	20.0
Forest Land	16,019.1	16.9	11,759.0	12.4	7636.1	8.1	–4260.1	–26.6	–4123.0	–35.1	–8383.1	–52.3
Grass Land	6966.0	7.4	2336.8	2.5	2392.7	2.5	–4629.2	–66.5	55.9	2.4	–4573.4	–65.7
Range Land	8555.0	9.1	4929.3	5.2	6749.8	7.1	–3625.7	–42.4	1820.5	36.9	–1805.2	–21.1
Urban Land	1084.0	1.2	1893.5	2.0	3612.9	3.8	809.6	74.7	1719.3	90.8	2528.9	233.3
Water Body	4085.0	4.3	4638.2	4.9	4922.3	5.2	553.2	13.5	284.1	6.1	837.3	20.5
Total	**94,578**	**100**	**94,578**	**100**	**94,578**	**100**						

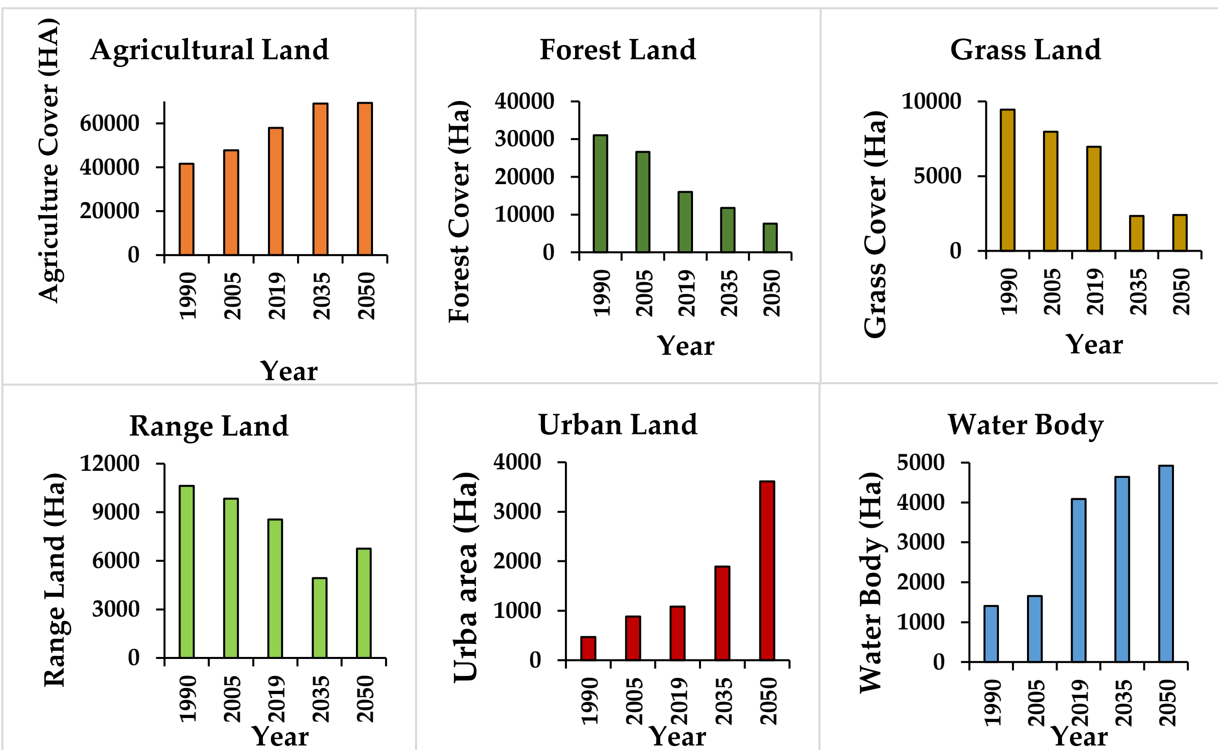


Figure 2.6. Land use land cover change in 1990–2050.

Significant changes were observed from the change analysis result in LULC change between 1990 and 2050. Agricultural land will be the predominant LULC type. It was seen from the result as the area of agricultural land increment from 61.19% in 2019 to 72.98% in 2035 and 73.24% in 2050. Agricultural land increased significantly from 1990 to 2035 and then slowly from 2035 to 2050 (Figure 2.7 and Table 2.11). Similarly, a continuous increment was also observed in urban areas and water bodies from the 2019 to 2050 periods. The development of infrastructure, industry, and housing have taken place and are expected to take place around the watershed, therefore, the urban land will increase. The urban coverage around watershed totaled 1.15% in 2019, which is predicted to reach 2.00% and 3.82% by 2035 and 2050, respectively. The graphical demonstration of the area covered by six LULC classes for past years (1990, 2005, and 2019) and for the future years (2035 and 2050) are shown in Figure 2.8.

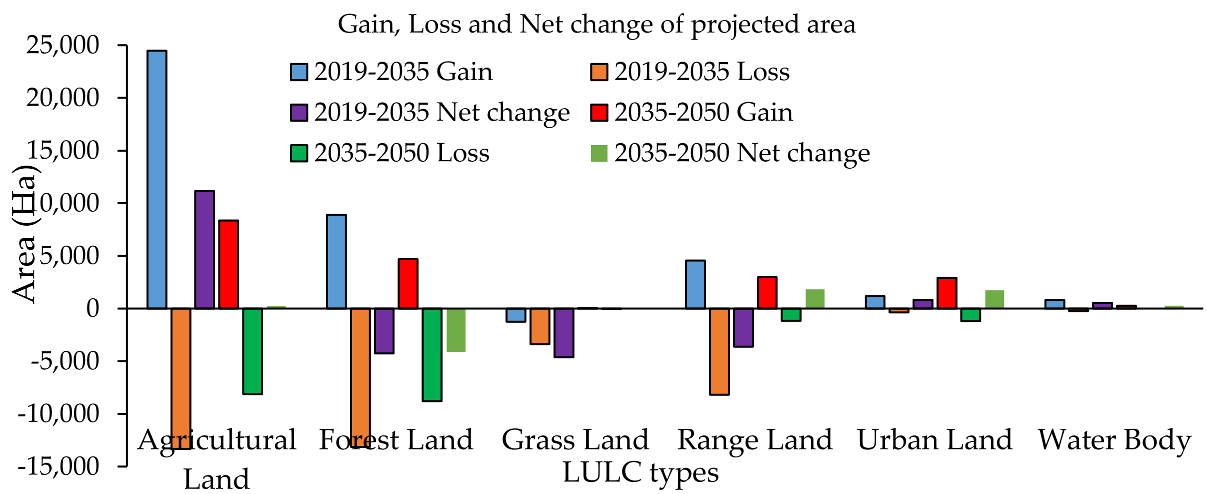


Figure 2.7. The gain, loss, and net change of the projected LULC area (2019, 2035, and 2050).

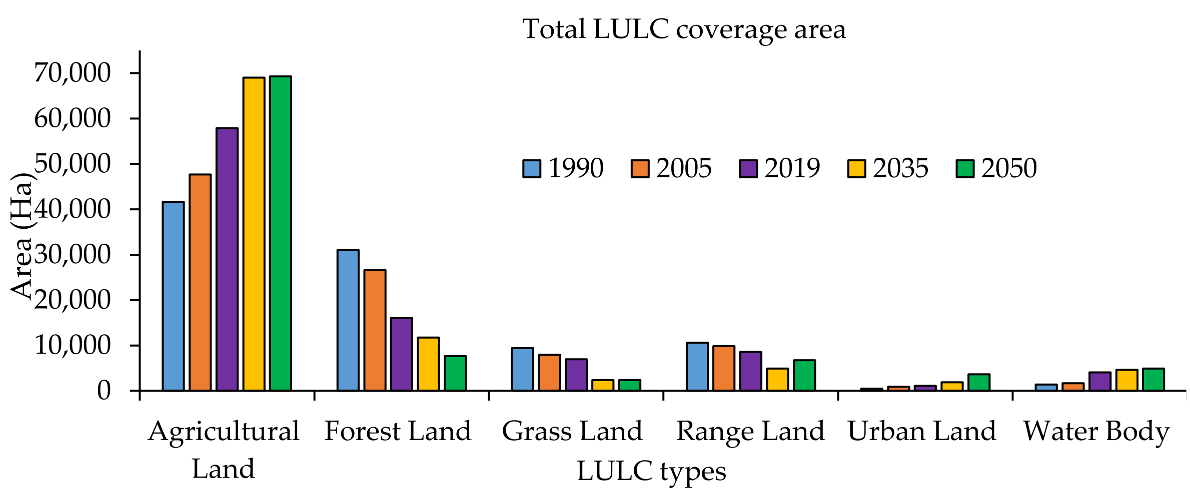


Figure 2.8. Historical and predicted land use land cover change area coverage.

The forest land and range land show a decreasing trend from 2019 to 2035. Unfortunately, the grass land, range land, and agricultural land will slightly increase from 2035 to 2050. This might be due to the limited area of land for different purposes. The major contributing factors to LULC change were the expansion of hydropower and irrigation projects, mostly at the downstream, for expansion of a sugar factory. The scarcity of jobs and urban expansions in the catchment amplified the socio-economic activities for LULC changes. In the watershed, the downstream and partly at the upstream areas, which were previously covered by forests and range lands, have been converted to agricultural land and commercial crop farms.

Forest reduction also occurred as a result of using charcoal and firewood as the energy source for most of the people living around the watershed, who depend on fuel wood. Additionally, most of the evacuated population during the construction of Nashe and Amerti projects were involved in converting the forest land to agriculture and settlement. Illegal and unplanned settlements by the local people to expand agriculture and settlement also contributed to destruction of forest land, range land, and grass land. Thus, the forest conversion needs to be controlled and well-managed, and a reasonable land use plan should be developed in an organized way. The expansion of one LULC type occurs at the detriment of other LULC classes [70]. Currently, the government has given more emphasis to the plantation trees program. Hence, in the country, many of the areas that were deforested might become covered by plants again. In the future prediction of LULC scenarios, the change of the area in the transition matrix was determined as indicated in Table 2.12.

Table 2.12. Transition area matrix (ha) of LULC between 2019–2035 and 2035–2050.

LULC Types		**2035**						
		AL	FL	GL	RL	UL	WB	Total
2019	Agricultural Land	**44,533.17**	6988.39	77.18	3731.99	385.73	2152.50	57,868.95
	Forest Land	11,991.32	**2864.52**	508.76	337.33	122.17	195.03	16,019.13
	Grass Land	1897.14	650.99	**3593.18**	648.95	26.04	149.71	6966.01
	Range Land	3745.42	4286.30	60.93	**371.37**	13.30	77.64	8554.95
	Urban Land	319.97	27.64	2.31	21.40	**702.63**	10.04	1083.98
	Water Body	86.07	166.48	0.25	0.11	0.00	**3832.13**	4085.03
	Total	69,021.20	11,759.00	2336.80	4929.30	1893.53	4638.21	**94,578.05**

LULC Types		2050						
		AL	FL	GL	RL	UL	WL	Total
2035	Agricultural Land	**60,912.11**	4365.93	27.74	515.43	3200.00	0.00	69,021.20
	Forest Land	8798.27	**2959.71**	0.00	1.03	0.00	0.00	11,759.00
	Grass Land	0.57	1.07	**2335.16**	0.00	0.00	0.00	2336.80
	Range Land	245.57	309.40	0.00	**3774.33**	0.00	600.00	4929.30
	Urban Land	1200.00	0.00	0.00	0.00	**693.53**	0.00	1893.53
	Water Body	0.00	0.00	0.00	0.00	0.00	**4638.21**	4638.21
	Total	69,264.44	7636.05	2392.65	6749.77	3612.85	4922.29	**94,578.05**

The study shows that agricultural land experienced the largest increase from the historical analysis to the projections. The conversion of other land uses to agricultural land might be mainly associated with the land demand for crop production to satisfy the food demand of the increasing human population, deforestation for household energy consumption, construction of materials, and loss of land productivity. This may cause serious environmental impacts unless proper environmental management strategies are planned and implemented. As per the analysis in the entire watershed, the urban area was increased. This increase was assumed to be closely associated with the rise of infrastructure to accommodate the increasing population. To minimize land degradation, it is necessary to apply management measures such as soil and water conservation technologies, family planning, and promotion of agricultural land use intensification in the study watershed. The future land use land cover change plan for the study area should be made in advance and needs to be incorporated at policy level.

A Multilayer Perceptron neural network and CA-Markov modeling in LCM-based analysis was combined with GIS, and remote sensing technologies was used to perform the analysis of the LULC change. The performance of the MLPNN-CA-MC in LCM for the LULC pattern was not assessed previously over this study watershed as far as the authors are aware. Additionally, analyses regarding the dynamics of LULC changes and their drivers are not conducted in the study area. Therefore, in this study, the LULC dynamics of the historical and future LULC were assessed using Landsat images and LCM by using the drivers of LULC dynamics. Consequently, this study will also help to assess the performance of the MLPNN-CA-MC approach over the watershed area. The future LULC is somewhat known in some parts of Ethiopia but not in the study area. The LCM embedded in the TGMMS model was successfully used by different researchers in other areas and it confirmed that LCM, based on MLPNN-CA-MC, is a capable model for the assessment and prediction of LULC change, urban growth, and the validation of results [9,21,57,63,71,72].

Generally, the patterns of LULC change in the past almost three decades shows forest land decreased at an average rate of 48.38%. The results showed that the agricultural land gained the most area compared to the other LULC types. However, at the expense of forest LULC categories, agricultural land is expanding at an average rate of 39.15% (1990–2019). From the temporal patterns of the changes between 1990 and 2019, forest land decreased at a higher rate. The other affected LULC types were range land and grass land. The urban land and water body LULC classes gained trends in the study.

Simulation analysis was conducted for the years of 2035 and 2050 based on historical LULC change data from 1990–2005, 2005–2019, and 1990–2019, which were used as a baseline. Similar to the historical analysis of LULC change, the predicted results of forest, grass, and range land classes were registered net loss in the area from 1990 to 2035. Whereas, the range land and grass land smoothly gained from 2035–2050. The predicted results of the year 2035 and 2050 show an increase in agriculture, water body, and urban land. Therefore, future land use activities ought to be based on proper land use development and land regulation to reduce the enduring adverse impact of LULC changes. Riad et al. [12] confirmed that effective urban planning is needed to address the multiple challenges and competing interests of urban environments for rapid increase in urban built up area on scarce land.

Lennert et al. [72] indicated that agricultural land expansion, both for commercial and crop production is the main driver of LULC change. The rate of crop land expansion is increasing whereas forests, grass land, shrub land, and other lands are decreasing in the world. This study finding is in agreement with results from previous studies that confirm the major driver of LULC change [9,10,21,57,62,63,72]. OFWE [73] reported that weak law enforcement and growth of population are fundamental drivers of deforestation. The other driving force for agricultural land expansion is probably government policy [72]. On the other hand, the major underlying driving forces are Demographic, Economic, Technological, Institution, policy, and biophysical factors were identified by the key informant and FGDs of the study. Agricultural expansion, firewood extraction, settlement expansion, land tenure policy, and infrastructure development were also the top LULC change drivers revealed from key informant interviews and FGDs. Similarly, Focus group discussants noted that farmers have been practicing subsistence farming with inappropriate land management practices and very low additional farm inputs.

2.4. Conclusions

The present study was carried out to understand the changes in the historical and predicted land use land cover patterns from the year 1990 to 2050. The integrated approach including remote sensing, GIS, and a MLPNN-based CA-MC model was used to understand the spatio-temporal dynamics of LULC and prediction of future LULC change in Nashe watershed, Ethiopia. The conclusions drawn from the research findings were the following.

The multitemporal satellite imagery data were used for informed decision-making in LULC change, providing the potential information required for monitoring and evaluating of LULC changes. The precision of the data from the remotely sensed imagery classified based on the maximum likelihood classification method with high resolution image of Landsat was checked through an error matrix and it yielded an acceptable result that was further processed for analysis.

To validate the model, the projected 2019 LULC map was compared with 2019 actual LULC map. After successful model validation, the LULC map for the years 2035 and 2050 were simulated by considering the business-as-usual scenario and driver variables. In this procedure, we used 1990–2005 and 2005–2019 LULC data as a baseline and current scenario for comparison. Its validation showed a strong correlation between the simulated LULC map and satellite-derived map, which proved the simulation model's reliability.

The rapid and massive changes of LULC in the watershed may have serious environmental impacts. The analysis of LULC change shows that forest cover has been decreasing, as well as the high increasing rate of urban area and agricultural land. The predicted LULC situation show that this cover would continue in the future. This will increase vulnerability of the watershed to landslides, soil loss, gully erosion, worsened air pollution, and impact the hydrology of the studied watershed in particular and the Blue Nile River basin in general.

Therefore, suitable and timely management measures must be taken by policy decision makers to enable sustainable development and to protect the watershed in order to reduce the severity of the changes. Settlement expansion, agricultural expansion, firewood extraction, land tenure policy, and infrastructure development were the top LULC change drivers. Moreover, to ensure a better environmental condition, this kind of study revealed a significant prospective to contribute towards the sustainable environmental planning and management system of an area at the local and global levels.

Finally, it can be concluded that the projected conditions may be reversed, which is very important to reduce the enduring adverse impact of LULC changes on the watershed hydrological components through the announced nationwide tree planting, implementing the strategy of climate resilient green economy, and formulating the local and regional scale policies required for sustainable development. However, the tree plantation alone does not guarantee increasing vegetation cover, continuous monitoring and managing the planted trees are equally important for the effectiveness of afforestation programs. Future studies incorporating the assessment of land use land cover change impacts on the hydrological parameters of the watershed would be helpful for better management of the watershed.

References

1. FAO. Watershed Management in Action: Lessons Learned from FAO Field Projects; Food & Agriculture Organization: Rome, Italy, 2017; pp. 5–6.
2. Mmbaga, N.E.; Munishi, L.K.; Treydte, A.C. How dynamics and drivers of land use/land cover change impact elephant conservation and agricultural livelihood development in Rombo, Tanzania. J. Land Use Sci. 2017, 12, 168–181, doi: 10.1080/ 1747423X.2017.1313324.
3. Pérez-Vega, A.; Mas, J.F.; Ligmann-Zielinska, A. Comparing two approaches to land use/cover change modeling and their implications for the assessment of biodiversity loss in a deciduous tropical forest. Environ. Model Softw. 2012, 29, 11–23, doi: 10.1016/j. envsoft.2011.09.011.
4. Kolb, M.; Mas, J.F.; Galicia, L. Evaluating drivers of land-use change and transition potential models in a complex landscape in Southern Mexico. Int. J. Geogr. Inf. Sci. 2013, 27, 1804–1827, doi:10.1080/13658816.2013.770517.
5. FAO. Climate Change and Food Security: Risks and Responses; Food & Agriculture Organization: Rome, Italy, 2015.
6. Manakos, I.; Braun, M. Land Use and Land Cover Mapping in Europe; Springer: Berlin/Heidelberg, Germany, 2014.
7. Lee, J.E.; Lintner, B.R.; Boyce, C.K.; Lawrence, P.J. Land use change exacerbates tropical South American drought by sea surface temperature variability Land use change exacerbates tropical South American drought by sea surface temperature variability. Geophys. Res. Lett. 2011, 38, 19.
8. Gibbs, H.K.; Ruesch, A.S.; Achard, F.; Clayton, M.K.; Holmgren, P.; Ramankutty, N.; Foley, J.A. Tropical forests were the primary sources of new agricultural land in the 1980s and 1990s. Proc. Natl. Acad. Sci. USA 2010, 107, 1–6.
9. Wubie, M.A.; Assen, M.; Nicolau, M.D. Patterns, causes and consequences of land use / cover dynamics in the Gumara watershed of lake Tana basin, Northwestern Ethiopia. Environ. Syst. Res. 2016, 5, 1–12.
10. Gashaw, T.; Tulu, T.; Argaw, M.; Worqlul, A.W. Evaluation and prediction of land use/land cover changes in the Andassa watershed, Blue Nile Basin, Ethiopia. Environ. Syst. Res. 2017, 6, 1–15.

11. Wnek, A.; Kudas, D.; Stych, P. National level land-use changes in functional urban areas in Poland, Slovakia, and Czechia. Land 2021, 10, 1–16.

12. Riad, P.; Graefe, S.; Hussein, H.; Buerkert, A. Landscape and urban planning landscape transformation processes in two large and two small cities in Egypt and Jordan over the last five decades using remote sensing data. Landsc. Urban Plan 2020, 197, 103766, doi:10.1016/j.landurbplan.2020.103766.

13. Tarasovičová, Z.; Saksa, M.; Blažík, T.; Falťan, V. Changes in agricultural land use in the context of ongoing transformational processes in Slovakia. Agriculture (Pol'nohospodárstvo) 2013, 59, 49–64.

14. Serra, P.; Pons, X.; Saurí, D. Land-cover and land-use change in a Mediterranean landscape: A spatial analysis of driving forces integrating biophysical and human factors. Appl. Geogr. 2008, 28, 189–209.

15. Tiwari, A.; Suresh, M.; Rai, A.K. Ecological planning for sustainable development with a green technology : GIS. Int. J. Adv. Res. Comput. Eng. Technol. 2014, 3, 636–641.

16. Behera, M.D.; Borate, S.N.; Panda, S.N.; Behera, P.R.; Roy, P.S. Modelling and analyzing the watershed dynamics using Cellular Automata (CA)-Markov model—A geo-information based approach. J. Earth Syst. Sci. 2012, 121, 1011–1024.

17. Yirsaw, E.; Wu, W.; Shi, X.; Temesgen, H.; Bekele, B. Land use/land cover change modeling and the prediction of subsequent changes in ecosystem service values in a coastal area of China, the Su-Xi-Chang region. Sustainability 2017, 9, 1–17.

18. Sohl, T.L.; Sleeter, B.M. Land-use and land-cover scenarios and spatial modeling at the regional scale. US Geol. Surv. 2012, 2012–3091, 4, doi: 10.3133/fs20123091.

19. Wang, S.; Zhang, Z.; Wang, X. Land use change and prediction in the Baimahe Basin using GIS and CA-Markov model. IOP Conf. Ser. Earth Enviro. Sci. 2014, 17, 13–18.

20. Paegelow, M.; Camacho Olmedo, M.T.; Mas, J.F.; Houet, T.; Pontius, R.G. Land change modelling: Moving beyond projections. Int. J. Geogr. Inf. Sci. 2013, 27, 1691–1695.

21. Mishra, V.N.; Rai, P.K. A remote sensing aided multi-layer perceptron-Markov chain analysis for land use and land cover change prediction in Patna district (Bihar), India. Arab. J. Geosci. 2016, 9, 1–18, doi: 10.1007/s12517-015-2138-3.

22. Zadbagher, E.; Becek, K.; Berberoglu, S. Modeling land use/land cover change using remote sensing and geographic information systems: Case study of the Seyhan Basin, Turkey. Environ. Monit. Assess. 2018, 190, 1–15.

23. Noszczyk, T. A review of approaches to land use changes modeling. Hum. Ecol. Risk Assess. 2018, 25, 1377–1405, doi:10.1080/10807039.2018.1468994.

24. Memarian, H.; Kumar Balasundram, S.; Bin Talib, J.; Teh Boon Sung, C.; Mohd Sood, A.; Abbaspour, K. Validation of CA-Markov for simulation of land use and cover change in the Langat Basin, Malaysia. J. Geogr. Inf. Syst. 2012, 4, 542–554.

25. Regmi, R.R.; Saha, S.K.; Balla, M.K. Geospatial analysis of land use land cover change predictive modeling at Phewa Lake watershed of Nepal. Int. J. Curr. Eng. Technol. 2014, 4, 2617–2627.

26. Wu, Q.; Li, H.-Q.; Wang, R.-S.; Paulussen, J.; He, Y.; Wang, M.; Wang, B.-H.; Wang, Z. Monitoring and predicting land use change in Beijing using remote sensing and GIS. Landsc Urban Plan. 2006, 78, 322–333.

27. Mas, J.F.; Kolb, M.; Paegelow, M.; Camacho Olmedo, M.T.; Houet, T. Inductive pattern-based land use/cover change models: A comparison of four software packages. Environ. Model Softw. 2014, 51, 94–111, doi:10.1016/j.envsoft.2013.09.010.

28. Eastman, J.R. IDRISI Selva Tutorial; 17th Version; IDRISI Production: Worcester, MA, USA, 2012; pp. 30–45, 51–63.

29. Shooshtari, S.J.; Gholamalifard, M. Scenario-based land cover change modeling and its implications for landscape pattern analysis in the Neka Watershed, Iran. Remote Sens. Appl. Soc. Environ. 2015, 1, 1–19, doi:10.1016/j.rsase.2015.05.001.

30. Tong, S.T.Y.; Sun, Y.; Yang, Y.J. Generating a future land-use change scenario : A case study of the Little Miami River Watershed, Ohio. J. Environ. Inform. 2012, 19, 108–119.

31. Li, S.H.; Jin, B.X.; Wei, X.Y.; Jiang, Y.Y.; Wang, J.L. Using CA-Markov model to model the spatiotemporal change of land use/cover in fuxian lake for decision support. ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 2015, 2, 163–168.

32. Adepoju, M.O.; Millington, A.C.; Tansey, K.T. Land use/land cover change detection in metropolitan Lagos (Nigeria): 1984–2002. In Prospecting for Geospatial

Information Integration, Proceedings of the ASPRS Annual Conference, Reno, NV, USA, 1–5 May 2006; ASPRS: Bethesda, MD, USA, 2006.

33. United Nations. World Urbanization Prospects: The 2014 Revision, United Nations Department of Economic and Social Affairs/Population Division; United Nations: New York, NY, USA. 2014..

34. Triantakonstantis, D.; Stathakis, D. Examining urban sprawl in Europe using spatial metrics. Geocarto Int. 2015, 30, 1–21, doi:10.1080/10106049.2015.1027289.

35. Ebrahim, E.H.; Mohamed, A. Land use/cover dynamics and its drivers in Gelda catchment, Lake Tana watershed, Ethiopia. Environ. Syst. Res. 2017, 6, 1–13.

36. Abate, S. Journal of Sustainable Development in Africa. J. Sustain. Dev. Africa. 2011, 13, 87–107.

37. Yalew, S.G.; Mul, M.L.; van Griensven, A.; Teferi, E.; Priess, J.; Schweitzer, C.; van Der Zaag, P. Land-use change modelling in the upper blue nile basin. Environments 2016, 3, 1–16.

38. Haregeweyn, N.; Tsunekawa, A.; Poesen, J.; Tsubo, M.; Meshesha, D.T.; Fenta, A.A.; Nyssen, J.; Adgo, E. Comprehensive assessment of soil erosion risk for better land use planning in river basins: Case study of the Upper Blue Nile River. Sci. Total Environ. 2017, 574, 95–108, doi:10.1016/j.scitotenv.2016.09.019.

39. Al-sharif, A.A.A.; Pradhan, B. Monitoring and predicting land use change in Tripoli Metropolitan City using an integrated Markov chain and cellular automata models in GIS. Arab. J. Geosci. 2014, 7, 4291–4301.

40. Samal, D.R.; Gedam, S.S. Optimal ground control points for geometric correction using genetic algorithm with global accuracy. Eur. J. Remote Sens. 2015, 48, 85–99.

41. Temesgen, G.; Amare, B.; Abraham, M. Evaluations of land use/land cover changes and land degradation in Dera District, Ethiopia: GIS and Remote Sensing Based Analysis. Int. J. Sci. Res. Environ. Sci. 2014, 2, 199–208.

42. Lucia, M.-B.; Lyons, M.B.; Phinn, S.R.; Roelfsema, C.M. Trends in remote sensing accuracy assessment approaches in the context of natural resources. Remote Sens. 2019, 11, 1–16.

43. Jenness, J.: Wynne, J.J. Cohen's Kappa and Classification Table Metrics 2.0: An ArcView 3. X Extension for Accuracy Assessment of Spatially EXPLICIT models. 2005. http://www.treesearch.fs.fed.us/pubs/25707.

44. Megersa, K.L.; Tamene, A.D.; Sifan, A.K. Impacts of land use land cover change on sediment yield and stream flow. Int. J. Sci. Technol. 2017, 6, 763–781.

45. Khoi, D.D. Spatial Modeling of Deforestation and Land Suitability Assessment in the Tam Dao National Park Region, Vietnam Spatial Modeling of Deforestation and Land Suitability Assessment in the Tam Dao National Park Region, Vietnam. Ph.D. Thesis, University of Tsukuba, Tsukuba, Japan, January 2011.

46. Mas, J.F.; Pérez-Vega, A.; Clarke, K.C. Assessing simulated land use/cover maps using similarity and fragmentation indices. Ecol. Complex. 2012, 11, 38–45.

47. Eastman, J.R. TerrSet Geospatial Monitoring and Modeling System—Manual. www.clarklabs.org (accessed on 2 January 2016).

48. Eastman, J.R. IDRISI Terrset Manual; IDRISI Production: Worcester, MA, USA, 2016.

49. Islam, K.; Rahman, M.F.; Jashimuddin, M. Modeling land use change using cellular automata and artificial neural network: The case of Chunati wildlife sanctuary, Bangladesh. Ecol. Indic. 2018, 88, 439–453, doi:10.1016/j.ecolind.2018.01.047.

50. Hasan, S.; Shi, W.; Zhu, X.; Abbas, S.; Khan, H.U.A. Future simulation of land use changes in rapidly urbanizing South China based on land change modeler and remote sensing data. Sustainability 2020, 12, 4–6.

51. Clark, L. Clark Labs. http://www.clarklabs.org (accessed on 2 January 2015).

52. Ayele, G.; Hayicho, H.; Alemu, M. Land use land cover change detection and deforestation modeling: In Delomena district of Bale Zone, Ethiopia. J. Environ. Prot. 2019, 10, 532–561.

53. Kim, I.; Jeong, G.; Park, S.; Tenhunen, J. Predicted land use change in the Soyang River Basin, South Korea.In Proceedings of the TERRECO Science Conference, Garmisch-Partenkirchen, Germany, 2–7 October 2011; pp. 17–24.

54. Fathizad, H.; Rostami, N.; Faramarzi, M. Detection and prediction of land cover changes using Markov chain model in semi-arid range land in western Iran. Environ. Monit. Assess. 2015, 187, 1–12.

55. Wang, S.Q.; Zheng, X.Q.; Zang, X.B. Accuracy assessments of land use change simulation based on Markov-cellular automata model. Procedia Environ. Sci. 2012, 13, 1238–1245, doi:10.1016/j.proenv.2012.01.117.

56. Singh, S.K.; Mustak, S.; Srivastava, P.K.; Szabó, S.; Islam, T. Predicting spatial and decadal LULC changes through cellular automata Markov chain models using earth observation datasets and geo-information. Environ. Process. 2015, 2, 61–78.

57. Wang, W.; Zhang, C.; Allen, J.M.; Li, W.; Boyer, M.A.; Segerson, K.; Silander, J.A. Analysis and prediction of land use changes related to invasive species and major driving forces in the state of Connecticut. Land 2016, 5, 25.

58. Mosammam, H.M.; Nia, J.T.; Khani, H.; Teymouri, A.; Kazemi, M. Monitoring land use change and measuring urban sprawl based on its spatial forms: The case of Qom city. Egypt J. Remote Sens. Sp. Sci. 2016, 20, 103–116, doi:10.1016/j.ejrs.2016.08.002.

59. Nadoushan, M.A.; Soffianian, A.; Alebrahim, A. Predicting urban expansion in arak metropolitan area using two land change models. World Appl. Sci. J. 2012, 18, 1124–1132.

60. Viera, A.J.; Garrett, J.M. Understanding interobserver agreement: The kappa statistic. Fam. Med. 2005, 37, 360–363.

61. Sitthi, A.; Nagai, M.; Dailey, M.; Ninsawat, S. Exploring land use and land cover of geotagged social-sensing images using Naive Bayes Classifier. Sustainability 2016, 8, 921.

62. Araya, Y.H.; Cabral, P. Analysis and modeling of urban land cover change in Setúbal and Sesimbra, Portugal. Remote Sens. 2010, 2, 1549–1563.

63. Rimal, B.; Keshtkar, H.; Haack, B. Land use / land cover dynamics and modeling of urban land expansion by the land use / land cover dynamics and modeling of urban land expansion by the integration of cellular automata and Markov chain. Int. J. Geo Inf. 2018, 7, 154.

64. Solomon, G.G.; Bewket, W.; Gärdenäs, A.I.; Bishop, K. Forest cover change over four decades in the Blue Nile Basin, Ethiopia: Comparison of three watersheds. Reg. Environ. Chang. 2014, 14, 253–266.

65. Khoi, D.D.; Murayama, Y. Forecasting areas vulnerable to forest conversion in the tam Dao National Park region, Vietnam. Remote Sens. 2010, 2, 1249–1272.

66. Maguire, D.J.; Batty, M.; Goodchild, M.F. GIS, Spatial Analysis, and Modeling, 1st ed.; ESRI Press: Redlands, CA, USA, 2005.

67. Pontius, G.R.; Malanson, J. Comparison of the structure and accuracy of two land change models. Int. J. Geogr. Inf. Sci. 2005, 19, 243–265.

68. Han, H.; Yang, C.; Song, J. Scenario simulation and the prediction of land use and land cover change in Beijing, China. Sustainability 2015, 7, 4260–4279.

69. Hepinstall, J.A.; Alberti, M.; Marzluff, J.M. Predicting land cover change and avian community responses in rapidly urbanizing environments. Landsc. Ecol. 2008, 23, 1257–1276.

70. Cheruto, M.; Kauti, M.; Kisangau, P.; Kariuki, P. Assessment of land use and land cover change using GIS and remote sensing techniques. A case study of makueni county Kenya. J. Remote Sens. GIS 2016, 5, 1–6.

71. Kosal, C.; Tunnicliffe, J.; Asaad, S.; Ota, T. Land use change detection and prediction in upper Siem Reap River, Cambodia. Hydrology 2019, 6, 64.

72. Lennert, J.; Farkas, J.Z.; Kovács, A.D.; Molnár, A.; Módos, R.; Baka, D.; Kovács, Z. Measuring and predicting long-term land cover changes in the functional urban area of Budapest. Sustainability 2020, 12, 1–20.

73. Oromia Forest and Wildlife Enterprise (OFWE), Farm Africa and SOS Sahel Ethiopia. Bale Mountains Eco-Region Reduction of Emission from Deforestation and Forest Degradation (REDD+) Project-Ethiopia. https://s3.amazonaws.com/ CCBA/Projects/ Bale_ Mountains Eco-region Reductions of Emissions from Deforestation and Forest Degradation.

3. Hydrological Responses of Watershed to Historical and Future Land Use Land Cover Change Dynamics of Nashe Watershed, Ethiopia

This chapter was published in:
Water; 29 August 2021; Volume 13, 2372
https://doi.org/10.3390/w13172372

Abstract: Land use land cover (LULC) change is the crucial driving force that affects the hydrological processes of a watershed. The changes of LULC have an important influence and are the main factor for monitoring the water balances. The assessment of LULC change is indispensable for sustainable development of land and water resources. Understanding the watershed responses to environmental changes and impacts of LULC classes on hydrological components is vigorous for planning water resources, land resource utilization, and hydrological balance sustaining. In this study, LULC effects on hydrological parameters of the Nashe watershed, Blue Nile River basin were investigated. For this, historical and future LULC change scenarios in the Nashe watershed were implemented into a calibrated Soil and Water Assessment Tool (SWAT) model. Five LULC scenarios have been developed that represent baseline, current, and future periods corresponding to the map of 1990, 2005, 2019, 2035, and 2050. The predicted increase of agricultural and urban land by decreasing mainly forest land will lead till 2035 to an increase of 2.33% in surface runoff and a decline in groundwater flow, lateral flow, and evapotranspiration. Between 2035 and 2050, a gradual increase of grass land and range land could mitigate the undesired tendency. The applied combination of LULC prognosis with process-based hydrologic modeling provide valuable data about the current and future understanding of variation in hydrological parameters and assist concerned bodies to improve land and water management in formulating approaches to minimize the conceivable increment of surface runoff.

Keywords: hydrologic response; LULC change; surface runoff; SWAT model; water balance

3.1. Introduction

Land use land cover (LULC) change influences different fundamental features and processes such as hydrological, geomorphological, land productivity, and associated water resource systems in watersheds [1]. Changes of LULC have both long-term and short-term temporal and spatial impacts on watershed hydrology [2–4]. Topography and soil properties are more likely to result in short-term hydrologic variations. However, long-term changes like urbanization and deforestation, on the other hand, cause reductions in evapotranspiration and water recycling, which may result in reduced rainfall. Rainfall to runoff conversion is a complex, non-linear, time and space variable process. Runoff estimation in a watershed based on rainfall distribution is one of the most frequent analyses in hydrology [5]. LULC change may have an effect on the quality, quantity, distribution, and timing of water changes, which could affect a variety of water resource operations and managements, such as hydropower generation, irrigation, flood risk reduction, navigation, and a combination of these future water resource developments [6,7]. Therefore, it is important to investigate the impacts of LULC change on the hydrology of the catchment in order to address water resource operation and management issues.

To manage LULC and water resources effectively in a watershed, it is necessary to assess the historical, present, and potential future LULC dynamics [8]. The relations between LULC change and hydrological components have been conducted around the world and used to predict the impacts of future LULC on water resources [9,10]. Prediction and assessment of future watershed hydrology through advanced tools over a long period are very important to attain sustainable water resources at the catchment scale [11,12]. Modeling LULC change is used to identify where the change has, or will potentially occur [13]. Different hydrological simulation models are currently being utilized to simulate and project the impacts of LULC change on hydrological processes including Soil and Water Assessment Tool (SWAT), MIKE-system Hydrologic European (MIKE-SHE), Hydrologic Simulation Program-FORTRAN (HSPF), Dynamic Watershed Simulation Model (DWSM), Soil and Water Integrated Model (SWIM), and Distributed Hydrology Soil Vegetation Model (DHSVM) [14,15].

The simulation of various hydrological components and long-term temporal scales, at watershed and sub-watershed levels, from small to large watershed sizes, and also the modeling of openness, readily and freely available data, minimum data input requirements from watersheds with poor data, and availability of graphical user interface are some of the significant factors considered in selecting the appropriate model to achieve the objectives of the study in the Nashe watershed [16]. Different model reviews conclude that SWAT can model the desired hydrological processes in more detail than many other watershed models [15] and simulates stream flow better than other hydrological models [17]. It is comprehensively used in Europe [18], North America [16], Australia [19], and Africa [20]. By testing it in different environments [14], the dynamic character of surface hydrological parameters in response to change of LULC can be indicated.

In several studies, SWAT is distinctively utilized for investigating the impacts of LULC change on hydrological processes in small and large watersheds [21–23]. It is also commonly used for modeling and analyzing hydrological processes in the context of changing LULC and land management, with high efficiency [24]. One study in the Wami River Basin, Tanzania [25] has been successfully performed in East Africa. In this region, factors such as soil type, seasonal rainfall, topography, social, political, demographic as well as economic issues together lead to great fluctuations in LULC, and these patterns are estimated to continue in the future [26]. Similarly, Baker and Miller [20] conducted in East African watershed using the SWAT model for assessment of water resources under land use impact and demonstrated an increment in surface runoff and decline in groundwater recharge.

Accordingly, SWAT was implemented for this study based on the criteria specified for the Nashe watershed. Generally, SWAT is physically based, a spatially semi-distributed, daily time step parameter model designed to simulate all relevant parameters of a watershed, such as surface runoff, groundwater, soil water, and lateral flow [27,28]. The studies conducted on the hydrological processes of watershed based on LULC change shows marked increase in rainy season flow and surface runoff potential in a given watershed that corresponds to the expansion of agricultural land and urban area at the decline of forest cover [2,29,30]. Tekalegn et al. [31] in Lake Tana and Beles watershed, Dibaba et al. [32] in Finchaa watershed, Galata et al. [33] in Hangar watershed, Ethiopia, and Karamage et al. [34] in Rwanda have described the surface runoff increase because of the agricultural land expansion and decrease of forest covers.

Likewise, groundwater flow decrease and surface runoff increase were also presented in Olifants basin South Africa, due to agricultural land and urban area expansion at the expenditure of range lands [24]. It is also reported by Santos et al. [35] in northeast Portugal, increases of lateral flow, evapotranspiration and decreases of surface runoff, and flow of groundwater due to LULC change and afforestation scenario. In another study conducted by Megersa et al. [36] in Ethiopia, Finchaa watershed, it was shown that surface runoff increment due to agricultural expansion and afforestation reduced surface runoff generation.

From African sub-Saharan countries, in Ethiopia, water resources are abundant for domestic use, production of agriculture, and hydropower generation. The available plentiful water resource potential is not being properly realized and translated into development because the country has significant problems related to water resources, such as flooding, deforestation, drought, land degradation, financial resources, and extreme hydrological variability [29]. The Blue Nile River basin is one of the utmost diverse and significant river basins in Ethiopia. The Basin is serving as the largest tributary to the Nile River basin, which is the basic water resource for the region and continent. It also contributes more than 60–70% of water to the Nile River, flowing through Sudan and Egypt [30]. The lower riparian areas of Sudan and Egypt contribute insignificant amount to the Nile flow. Water from Ethiopian plateaus, particularly the Blue Nile River basin has historically benefited downstream consumers in Egypt and Sudan in a variety of ways. Such benefits are now threatened due to dramatic changes in upstream land, water, and livestock management practices [37].

The Nashe watershed is the most productive area and contributes a large amount of water to the Blue Nile River basin. Human-induced land degradation has occurred in the watershed, primarily as a result of agricultural expansion and urbanization [38]. Additionally, the fundamental problem in the Nashe watershed is the expansion of agricultural areas and urbanization at the expense of range land, forest land, and grass land and this will also be expected to continue in the future [8]. Many people have been displaced and moved to available land areas within the watershed since the construction of the Nashe dam and have started agricultural activities on steep and marginal areas within and around the Nashe watershed which may have caused LULC changes. Some of these people relocated to urban areas and caused rapid urban expansion in the watershed [8].

As far as the author's understanding, this is the first study focusing on watershed hydrology depending on historical and future LULC change effects on hydrological responses in the Nashe watershed, Ethiopia. Therefore, the study aimed to explore the historical and potential future LULC change impacts on the hydrological processes in the Nashe watershed, Blue Nile River basin, Ethiopia. The following specific objectives were pursued to achieve the main objective: (i) to quantify and analyze the different characteristics of LULC change impacts on hydrological parameters at various Spatio-temporal scales; (ii) To develop LULC scenarios to explore the LULC change effect on hydrological parameters of the watershed.

To overcome this objective, LULC scenarios were developed depending on historical and potential future data to analyze the impacts of LULC change on water resources of the watershed. The findings obtained contribute useful information towards the enhancement of the current comprehension of hydrological parameter variation. Similarly, the findings are instructive for water resource planning and management measures aimed at reducing the negative effects of LULC change in the Nashe watershed.

The structure of this paper is as follows: The introduction of the study including the objective is described in the first section. The second section presents the study area including the data sets, hydrological modeling, sensitivity analysis, model calibration and validation, and model performance evaluation. In Section 3, a discussion of the most relevant results for land use land cover change, hydrological model performance evaluation, and hydrological responses to land use land cover change are provided. Finally, the conclusions of the study are described in Section 4.

3.2. Materials and Methods

3.2.1. Description of the Study Watershed

The Nashe catchment is the sub-basin of the Blue Nile River basin, which is located in Oromia Regional state, Ethiopia. Geographically, the watershed is found between 9° 35′ and 9° 52′ N latitudes and 37° 00′ to 37° 20′ E longitudes (Figure 3.1). The watershed has an area of 94578 km^2 and administratively the area belongs to two woredas, Abay Chomen Woreda and Horo Woreda. The Nashe River valley starts on the highland plateau North-East of Shambu town and runs from west to east and then in the Northern direction. The valley elevation is above 2200 m, with the encompassing edges extending to over 2500 m. The watershed area varies in elevation from 1600 m in the lower plateau under the escarpment to hills and ridges of the highland, climbing to over 2500 m. The major sources of the Nashe River are the streams of Himane, Lege Ferso, and Abuna that drain swampy areas in the region of Bone Muleta. These streams form the Aseti River flow north and then south into the Nashe Valley.

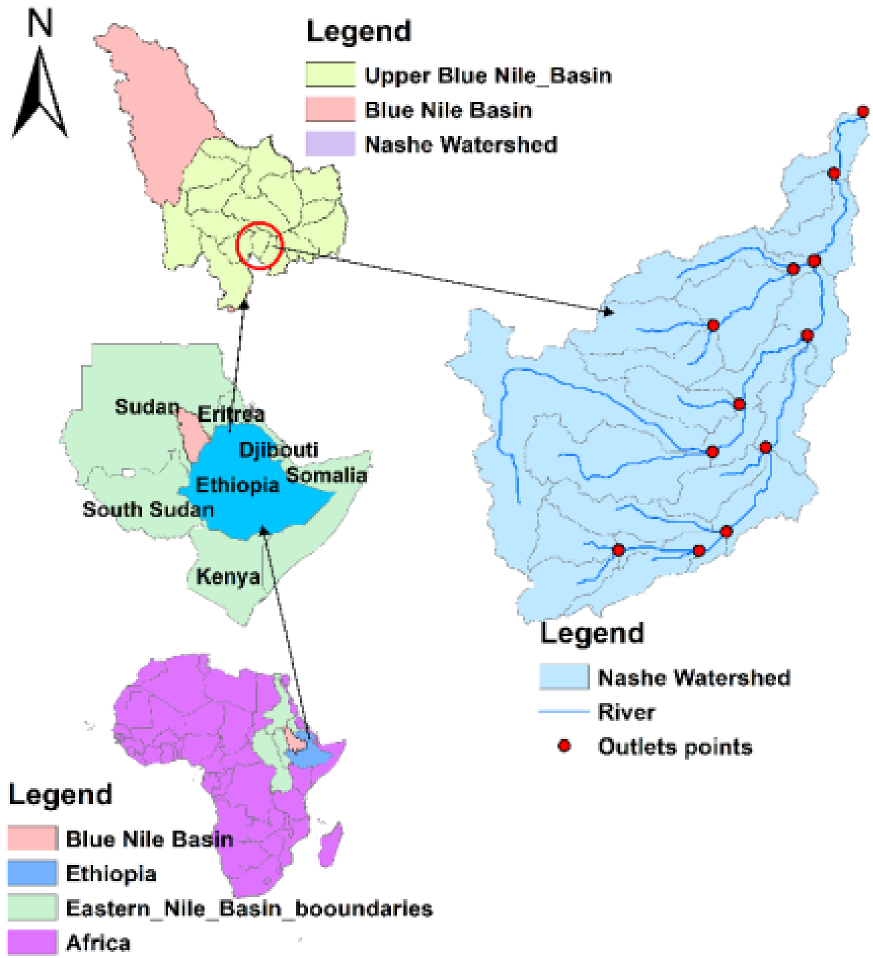


Figure 3.1. Location map of the study area.

In the Nashe Swamp, the Aseti River meets the Babo Stream, which flows from the west. From this point downstream, the water is referred to as the Nashe River. The Nashe watershed rainfall varies from the maximum of 1600 mm per annum in the southern and western areas to 1200 mm per annum in the northern lowland areas, with June to September being the main rainy season. The average maximum and minimum temperature of the watershed ranges between 20.18–27.38°C and 8.92–12.63°C respectively. The average monthly rainfall and temperature features of the stations in the study watershed are depicted in Figure 3.2. The LULC categories of the watershed include forest land, range land, agricultural land, grass land, urban area, and water body. The soil types of the watershed include Haplic Alisols, Rhodic Nitosols, Haplic Arenosols, and Chromic Luvisols. A thick series of Mesozoic sedimentary layers covering the Precambrian foundation complex, largely overlain by Tertiary and Quaternary volcanic deposits dominates the geology of the area. Agriculture is the utmost significant economic activity and the major source of livelihood for the population and crop production is particularly concentrated in the main rainy season.

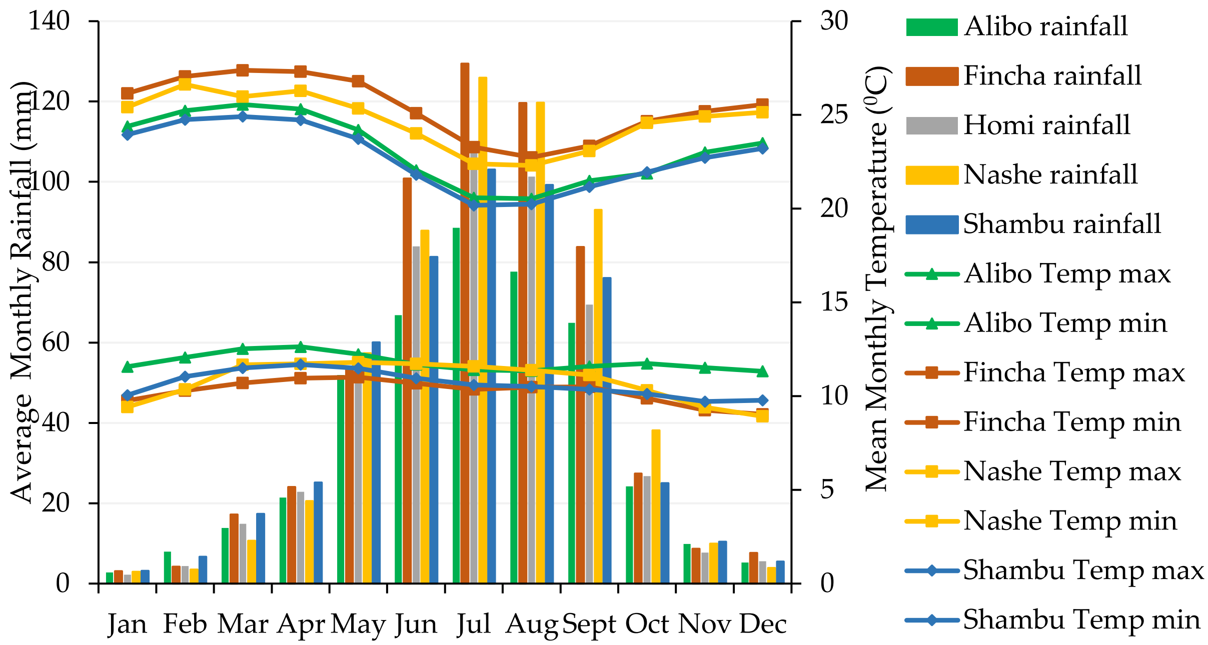


Figure 3.2. Monthly average rainfall and temperature features of the stations in the Nashe watershed.

3.2.2. Model Input Data

The required input data for the SWAT model incorporates a Digital Elevation Model (DEM), LULC maps, soil data and map, weather data, and hydrological data. Generally, the input data used in this study are summarized in Table 3.1. The DEM was the first input data in the SWAT model. It was utilized to compute the hydrological parameters of the catchment such as the direction of flow, flow accumulation, stream network generation, watershed delineation, sub-basin definition, and hydrologic response units (HRUs) setup. The DEM was also utilized to derive the slope gradient, slope length of terrain, and the network of the stream attributes such as channel length, slope, and width of sub-basin parameters. The DEM (Elevation), slope, and classified sub-basins of the watershed are depicted in Figure 3.3.

Table 3.1. Input data description used in the SWAT model.

Data Types	Research Data	Resolution/ Period	Sources
Spatial data	Digital Elevation Model (DEM)	30m	The shuttle radar topographic mapping obtained from the Ministry of Water, Irrigation, and Energy, Ethiopia
	Land Use Land cover	30 m/ (1990, 2005, 2019, 2035, and 2050)	Derived from Landsat images (Landsat-5, Landsat-7, and Landsat-8) and Predicted by Land change modeler model [8]
	Soil	1:50,000	Ministry of Water, Irrigation, and Energy (MoWIE), Ethiopia
Meteorological data	Daily observed weather data	1985–2019	National Meteorological Agency, Ethiopia
Hydrological data	Daily stream flow	1985–2008	Ministry of Water, Irrigation, and Energy (MoWIE), Ethiopia

Land use land cover is also an indispensable input data influencing the hydrological responses of the watershed. The historical LULC images were obtained from Landsat images and classified using supervised classification in Earth Resource Data Analysis System (ERDAS) imagine model. The future LULC was predicted based on the classified historical satellite images using Land Change Modeler (LCM) integrated TerrSet model. Therefore, the classified historical LULC data for three time periods (1990, 2005, and 2019) and the two time periods (2035 and 2050) predicting LULC were conducted in detail by Leta et al. [8] and utilized in this study (Figure 3.4). The maps were utilized independently in the assessment of hydrological parameters in the watershed. The LULC classes of the watershed are agricultural land, forest land, grass land, range land, urban area, and water body [8].

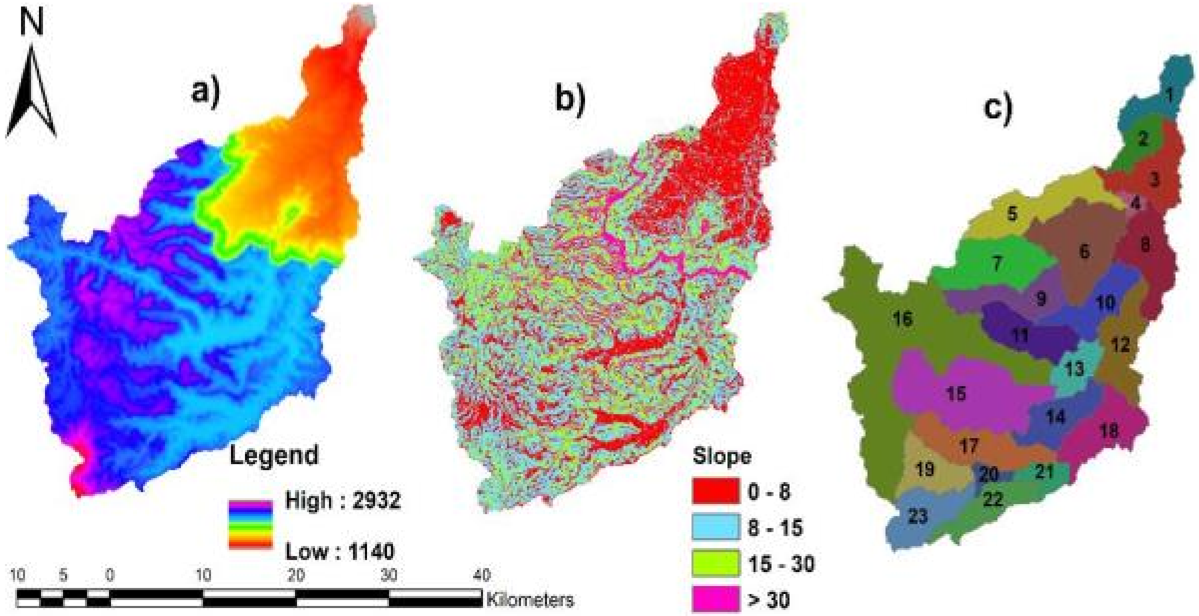


Figure 3.3. The DEM (Elevation) (m) (a), Slope (%) (b), and Sub-basins (c) of the Nashe watershed.

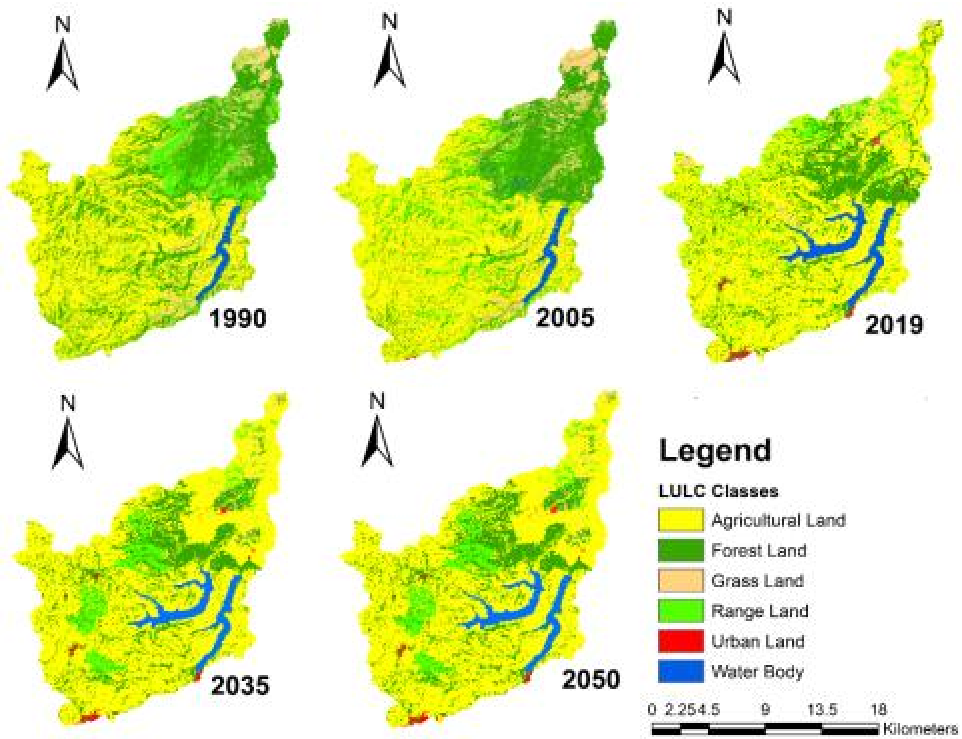


Figure 3.4. The Land use land cover of the study watershed.

The necessary soil properties (physical and chemical parameters of the soils) required by SWAT were obtained from the Oromia Water Works Design and Supervision

Enterprise (OWWDSE), literature, and from the design and feasibility study document of Finchaa Amarti Nashe Hydropower project. Therefore, using the collected parameters, the classified soil is adapted in the way the SWAT model requires. There are nine types of soil in the study watershed. Eutric Cambisols, Haplic Alisols, Haplic Arenosols, Rhodic Nitosols, Chromic Luvisols, Eutric Vertisols, Water, Eutric Leptosols, and Dystric Vertisols (Figure 3.5). The dominant soil type of the watershed is Haplic Alisols (47.01%) following Rhodic Nitosols (31.77%).

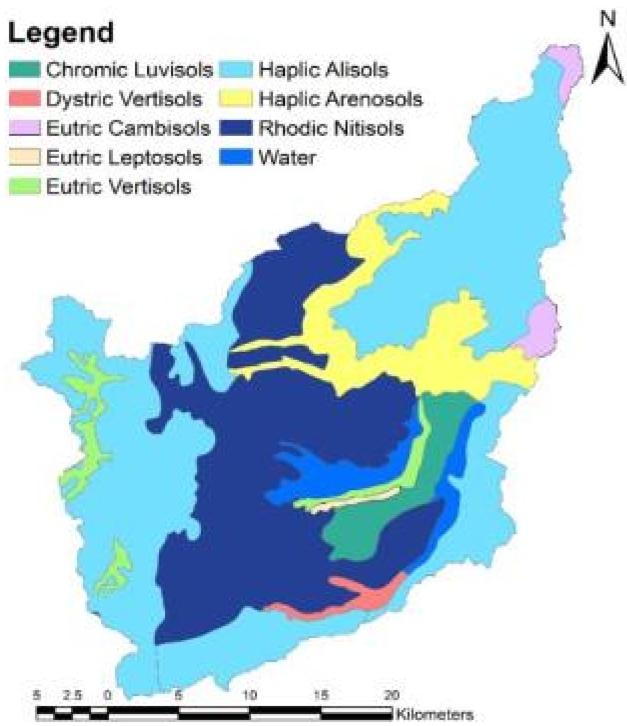


Figure 3.5. The soil types of the Nashe watershed.

Historically, long-term daily weather data is required for the hydrological SWAT model. Therefore, the weather data were collected for five stations (Alibo, Finchaa, Homi, Nashe, and Shambu) within and nearby stations of the watershed. SWAT uses five types of daily weather data as input: precipitation, temperature (minimum and maximum), solar radiation, wind speed, and humidity. The missing data values of the weather were filled with the use of Xlstat (a Micro soft excel extension complete and user-friendly data analysis and statistical solution). The consistency of data and homogeneity were also checked utilizing the double mass curve. The daily recorded hydrological (stream flow) data measured at the gauging station was utilized for the SWAT model calibration and validation.

3.2.3. Hydrological Modeling

The Hydrological SWAT model was developed to analyze the effect of land use land cover, management on water, and sediment at a watershed level at daily, monthly, and annual time increments. The SWAT model with spatially and temporally dispersed parameters was used to compute the LULC change effect on hydrological responses with changing soils, LULC, and slope [39]. There are two major hydrologic cycle phases in the SWAT simulation; the land and routing (channel-based) phase. The land phase simulates the quantity of water, nutrients, sediment, and pesticides delivered by surface runoff from each sub-basin to the corresponding main channel [40,41].

The hydrologic cycle of the land phase is simulated depending on the equation of water balance in each hydrological response unit (Equation (8). In the SWAT model, the water balance is the foundation and driving force for all hydrological processes [13]. The routing phase controls stream processes such as movement of water, transport of sediment, and nutrient loading through the channel network until they reach the watershed's outlet. SWAT calculates runoff volumes using the Soil Conservation Service Curve number method, lateral flow and percolation using the kinematic storage routine method, potential evapotranspiration using the Penman-Monteith equation, and peak runoff rate using the modified rational method.

Depending on the extent of the watershed and the detail of available geographical input data, the SWAT model splits a watershed into several sub-basins, which are further divided into smaller areas denoted as HRUs. HRUs are a composition of homogeneous land use, soil, slope, and management characteristics [16,17,42]. The SWAT model forecasts the effects of LULC changes on different hydrological parameters in the watershed at the HRUs and sub-watershed levels [42,43]. The SWAT divides the Nashe watershed depending on topographical data information into 23 sub-watersheds that were in turn divided into a total of 321 HRUs based on their soil type, land use land cover, and slope. The hydrologic response unit (HRU) was defined using the multiple land use/soil/slope technique, with a land use of 5%, a soil of 10%, and a slope of 10% threshold. By using these thresholds, land uses, soils, and slopes with smaller areas than their respective thresholds were integrated into larger land use, soil, and slope respectively by an area-weighted scheme.

$$SWt = SWo + \sum_{i=1}^{n}(Rday - QSurf - Ea - Wseep - Qgw) \qquad (8)$$

where SWt: final soil water content (mm H_2O); SWo: initial water content (mm H_2O); Rday: precipitation on day i (mm H_2O); Qsurf: surface runoff on day i (mm H_2O); Ea: evapotranspiration on day i (mm H_2O); Wseep: water entering the vadose zone from the soil profile on day i (mm H_2O); Qgw: return flow on day i (mm H_2O); and t: time (days).

3.2.4. Sensitivity Analysis

The method of identifying the most significant parameters for the model is known as sensitivity analysis [16]. A model's performance is only truly acceptable after a sensitivity analysis has been conducted. In this study, SUFI-2 (Sequential Uncertainty Fitting-2) algorithm, which is the interface of SWAT-CUP (Soil and Water Assessment Tool- Calibration Uncertainty Program), was used to accomplish sensitivity analysis [18]. The flow parameters were tested and the influential sensitive parameters were selected and used for further analysis. The t-stat and p-value statistics from the model provided the measure and significance of sensitivity respectively. Therefore, a lesser p-value and a larger t-stat in absolute value indicate the sensitive parameters [18,44,45].

Table 3.2. Performance evaluation measurements for stream flow simulation.

Performance Rating	NSE	PBIAS	R^2
Unsatisfactory	NSE ≤ 0.5	PBIAS ≥ ±25	$R^2 < 0.50$
Satisfactory	0.5 < NSE ≤ 0.65	±15 ≤ PBIAS < ±25	$0.50 < R^2 < 0.70$
Good	0.65 < NSE ≤ 0.75	±10 ≤ PBIAS < ±15	$0.70 < R^2 < 0.80$
Very good	0.75 < NSE ≤ 1	PBIAS < ±10	>0.80

3.2.5. Model Calibration and Validation

The method of adjusting input model parameters to ensure that simulations match with observations, within the recommended ranges, so that prediction uncertainty is reduced, is known as model calibration. Whereas, the progression of affirming the calibrated parameters by evaluating them with an independent set of data without making any further modifications to the model parameters, is validation [16,46]. The model calibration and uncertainty analysis were also conducted in the SWAT-CUP program using the SUFI-2 algorithm. The uncertainty was determined by the 95PPU (95% prediction Uncertainty) band computed at the 97.5% and 2.5% levels of the variable output [18]. The 95PPU was computed through the method of Latin Hypercube sampling, which restricts 5% of the bad simulations.

The two measurements used to analyze the quality of uncertainty analysis are the p-factor and the r-factor. The p-factor is a proportion of measured data bracketed by the 95PPU that ranges from 0 to 1, with 1 being the optimal result. The r-factor ranges between 0 to infinity, and it is the average thickness of the 95PPU band to the standard deviation of the corresponding measured data [44,47–49]. Twenty-four years (1985–2008) of flow data were used for the calibration and validation. The first two years (1985–1986) were considered the model's warm-up period. The period between 1987 and 1999 was utilized for calibration, whereas the period between 2000 and 2008 was used for model validation.

3.2.6. Model Performance Evaluation

The model performance evaluation was conducted to determine the consistency of simulated data compared to the measured data during the calibration and validation periods [45,50]. When simulating stream flow, the model's performance was evaluated graphically and with different objective function values. The various indicators used to assess the performance of the SWAT model and to test the goodness of fit between monthly simulated and observed values are: Nash-Sutcliffe Efficiency (NSE); designates the degree of fitness of observed and simulated data, Percent Bias (PBIAS): a measure of how much the observed variable is either underestimated or overestimated, coefficient of determination (R^2): a measure of the consistency of simulated and observed data, as depicted in Equations (9–11). The objective functions for the calibrated and validated model were compared to the performance statistics ratings for monthly time steps to determine the performance of the model (Table 3.2).

$$\mathrm{NSE} = 1 - \left[\frac{\sum_{i=1}^{n}(\mathrm{Qoi} - \mathrm{Qsi})^2}{\sum_{i=1}^{n}(\mathrm{Qoi} - \overline{\mathrm{Q}}\mathrm{o})^2}\right] \quad (9)$$

$$\mathrm{PBIAS} = 100 * \left[\frac{\sum_{i=1}^{n}(\mathrm{Qoi} - \mathrm{Qsi})}{\sum_{i=1}^{n}\mathrm{Qoi}}\right] \quad (10)$$

$$R^2 = \frac{[\sum_{i=1}^{n}(Qsi - \overline{Q}s)(Qoi - \overline{Q}o)]^2}{\sum_{i=1}^{n}(Qsi - \overline{Q}s)^2 \sum_{i=1}^{n}(Qoi - \overline{Q}o)^2} \quad (11)$$

Where; Qsi is the simulated stream flow, Qoi is the observed stream flow, $\overline{Q}o$ is the mean observed stream flow, $\overline{Q}s$ is the mean simulated stream flow.

3.2.7. Model Application for Scenario Simulation

Assessing the LULC change impact in the watershed on hydrological processes is substantial for the management of water resources [24,51]. Therefore, the calibrated and validated model with 1990, 2005, 2019, 2035, and 2050 LULC maps were utilized to reveal the effects of LULC variations on watershed hydrology. The simulated results were used to assess the effects of LULC change at the watershed level and to determine the involvement of individual changes at the sub-basin scale. A fixing–changing method was used in this study to explore the impacts of LULC change [21]. The model was run with a change in the LULC maps, while the remaining model parameters from calibrated model and other SWAT inputs were constant. The method has been conducted by many researchers in different parts of the world [2,20,24,31,51,52].

The trend and future LULC change influences on watershed hydrological responses for the period 1990–2050 were evaluated using scenario-based simulation. Five kinds of LULC scenarios were established in this study, representing three periods, i.e., baseline, current, and future LULC conditions. The first two scenarios considered as a baseline were the LULC map corresponding to the years 1990 and 2005. The third scenario represents the current LULC, which corresponds to 2019. The fourth and fifth scenarios represent potential future LULC change that is projected for 2035 and 2050 under Business as Usual Scenario (Figure 3.4). The variations in LULC classes and hydrological components were assessed using the pair-wise Pearson's correlation method [51]. In this study, the pair-wise Pearson correlation matrix was applied to develop linear correlations between dependent variables (hydrological components) and independent variables (land use land cover classes).

3.3. Results and Discussions

3.3.1. Land Use Land Cover Change

The classified, predicted, and analyzed LULC change of the Nashe watershed for the period of 1990 to 2050 is shown in Figures 3.4 and 3.6 respectively. The assessment of

LULC change shows that forest cover, range land, and grass land has been decreasing. However, high increasing rate of urban areas and agricultural land is also demonstrated. Similarly, an increase in grass land and range land occurred from 2035 to 2050. From the result, it is evident that changes occurred in all LULC classes [8]. According to Leta et al. [8], details about the historical and future LULC change analysis and the main drivers of the change of LULC in the Nashe watershed were conducted.

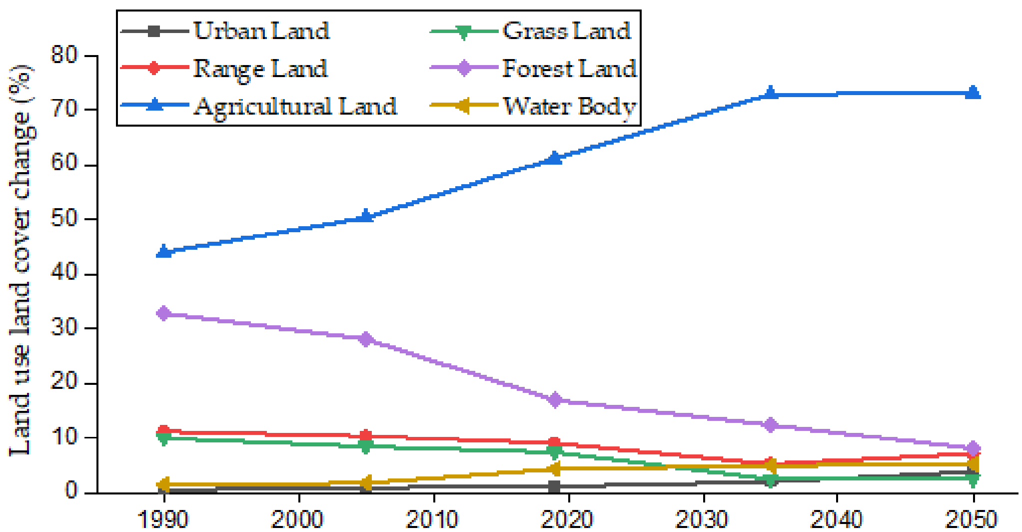


Figure 3.6. Historical and predicted land use land cover dynamics in the Nashe watershed.

3.3.2. Hydrological Model Performance Evaluation

3.3.2.1. Sensitivity Analysis

In this research, the nine most influential sensitive parameters selected (p-value < 0.05) [53] were identified for the watershed and ranked according to their sensitivity based on the t-stat and p-value (Table 3.3). The sensitivity analysis indicated the overall importance of the nine parameters in determining the stream flow at the study area. The top three most sensitive parameters in the order of sensitivity are CN2.mgt, GW_DELAY.gw, and SOL_K (...).Sol. The parameters include those governing sub-surface, surface hydrological processes, soil, and stream routing.

Table 3.3. Sensitive flow parameters and their rank.

Parameters Name	Description	Sensitivity			Parameter Value		
		t-Stat	p-Value	Rank	Min	Max	Fitted
r__RCHRG_DP.gw	Deep aquifer percolation fraction	−0.54	0.04	9	0	1	0.837
r__SLSUBBSN.hru	Average slope length (m)	−0.83	0.03	8	0	150	76.98
r__SOL_AWC (...).sol	Soil available water capacity (mm H_2O/ mm soil)	−0.96	0.03	7	−25	25	−12.1
v__GWQMN.gw	Threshold depth of water in shallow aquifer required for return flow(mm)	−1.17	0.01	6	0	5000	1921
v__CH_N2.rte	Manning's roughness coefficient for the main channel	1.96	0.00	5	0	1	0.524
v__ALPHA_BF.gw	Base flow alpha factor for bank storage	2.68	0.00	4	0	1	0.367
r__SOL_K (...).sol	Saturated hydraulic conductivity (mm/hour)	7.23	0.00	3	−25	25	17.15
v__GW_DELAY.gw	Groundwater Delay from soil to channels(days)	−8.21	0.00	2	0	500	19.02
r__CN2.mgt	SCS runoff curve number	13.13	0.00	1	−25	25	−16.31

3.3.2.2. Calibration and Validation

After finding the sensitive parameters on stream flow simulation it is important to identify key parameters and the parameter precision required for calibration [54]. To simulate the hydrological components of the watershed, the model validation proficiency was conducted using the calibrated parameters. The calibration of the model was implemented for the time period of 1987–1999 and validated for the period 2000–2008; the period from 1985–1986 was considered as the spin-up period. The data of stream flow has been calibrated and validated with the observed weather data and LULC scenarios of various time periods. Niraula et al. [55]proposed calibration and validation of the model to assess the effects of LULC change.

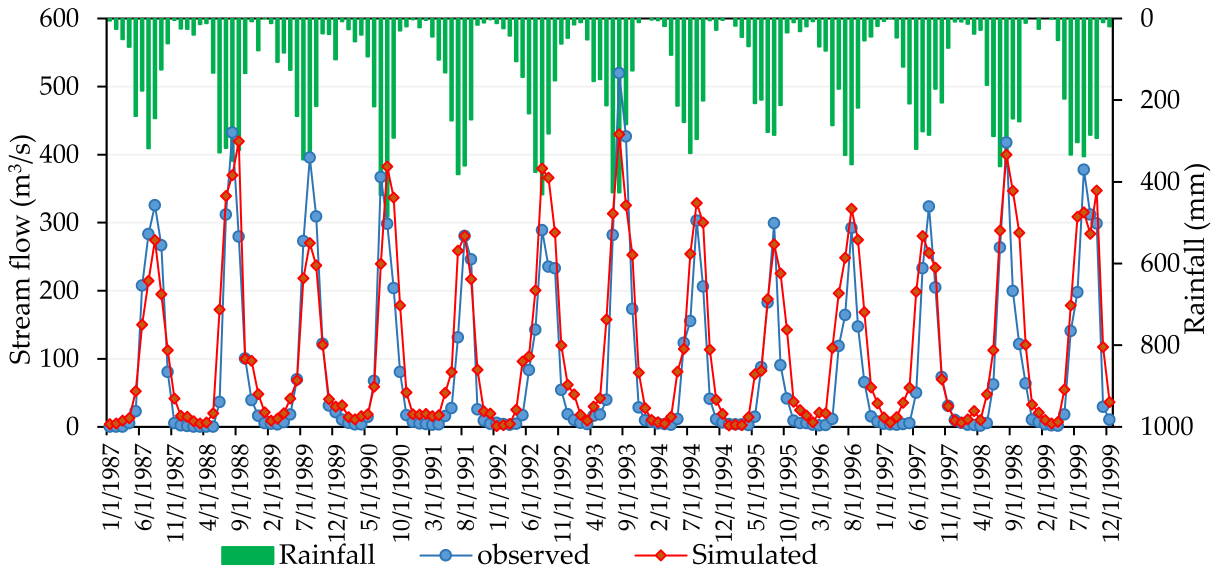
Figure 3.7a and b demonstrate the visual contrast of time series observed and simulated stream flow on a monthly basis to investigate the similarity of stream flows in the watershed through the calibration and validation periods. Moriasi et al. [45] depicted that graphical comparison and statistical indices can assess the efficiency of the calibrated and validated parameters. During the calibration and validation period, the simulated flow values are marginally less than the observed value at peak flow months. But the simulated flow is slightly greater than the observed value at low flow months. Generally, the model underestimates mean monthly stream flow (Figure 3.7). The simulated and observed graphical comparison shows a good agreement both in calibration and validation results.

3.3.2.3. Model Efficiency

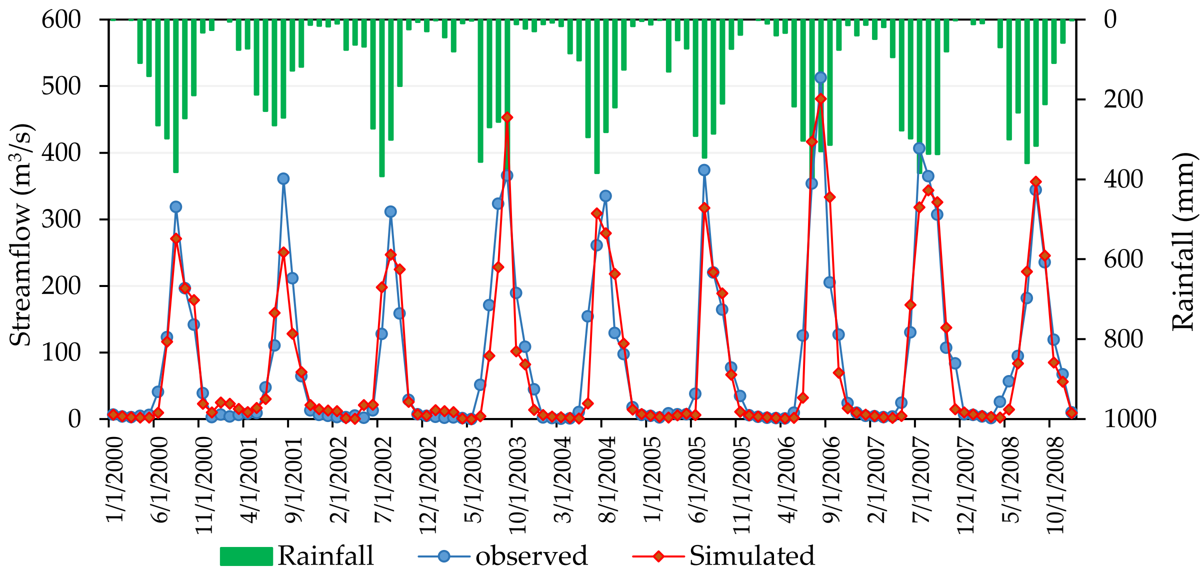
The evaluation of simulated and observed stream flow computed through the statistical values of objective functions are in the acceptable range (Table 3.4) based on the performance assessment criteria (Table 3.2). Therefore, the performance indices obtained indicated a good performance rate of the model in simulating the impacts of LULC changes [36]. Thus, depending on the model performance indicator results, it can be justified that the model is applicable specifically for the Nashe watershed and in general for Blue Nile River basin. The PBIAS of the study shows a small bias towards underestimation in both calibration and validation. However, depending on the result, no significant model over or underestimation was found, since the obtained values are in the recommended range.

Table 3.4. Stream flow calibration and validation model performance values of Nashe watershed.

Index	**R^2**	**NSE**	**PBIAS**	**p-Factor**	**r-Factor**
Calibration	0.80	0.76	3.03	0.83	0.74
Validation	0.85	0.80	1.28	0.80	0.69



(a)



(b)

Figure 3.7. Average monthly stream flow (a) Calibration and (b) Validation of the SWAT model for the Nashe watershed.

3.3.3. Hydrological Responses to Land Use Land Cover Change

3.3.3.1. Seasonal Hydrology of the Watershed

The LULC change effect on the hydrological components of the watershed was mainly analyzed annually, seasonally, and monthly basis. LULC classes from different time periods were utilized independently to analyze the change of LULC effect on the hydrological parameters of the Nashe watershed. For seasonal analysis, seasons in

Ethiopia are categorized into three seasons in the year based on the rainfall magnitudes. The season of short rain (February to May), followed by the wet season lasts from June to September. The other season is the dry season, which lasts from October to January and can be generally characterized over the majority of the country. The hydrological components variability due to LULC change was assessed based on these three rainfall seasons. Similarly, the hydrological parameters to the LULC dynamics were also reflected in the peak flow and base flow in the Nashe watershed.

The well-known components of water balance are surface runoff, groundwater, lateral flow, water yield, and evapotranspiration [43,56,57]. According to the findings, it was observed that more than 80% and 40% of the surface runoff and groundwater occurs during the wet season for all LULC time periods, while less than 10% of the surface runoff occurs during the dry and short rainy seasons (Figure 3.8). Over Ethiopia, heavy rainfall (June to September) creates high seasonal flows and surface runoff. The reason might be that the surface runoff was more susceptible in summer than in other seasons. The LULC change from 2019 to 2035 increases the surface runoff in the wet season by 2.15% (5.48 mm). Similarly, when the LULC changed from 2035 to 2050 the surface runoff decreased by 1.41% (3.67 mm) in the same season.

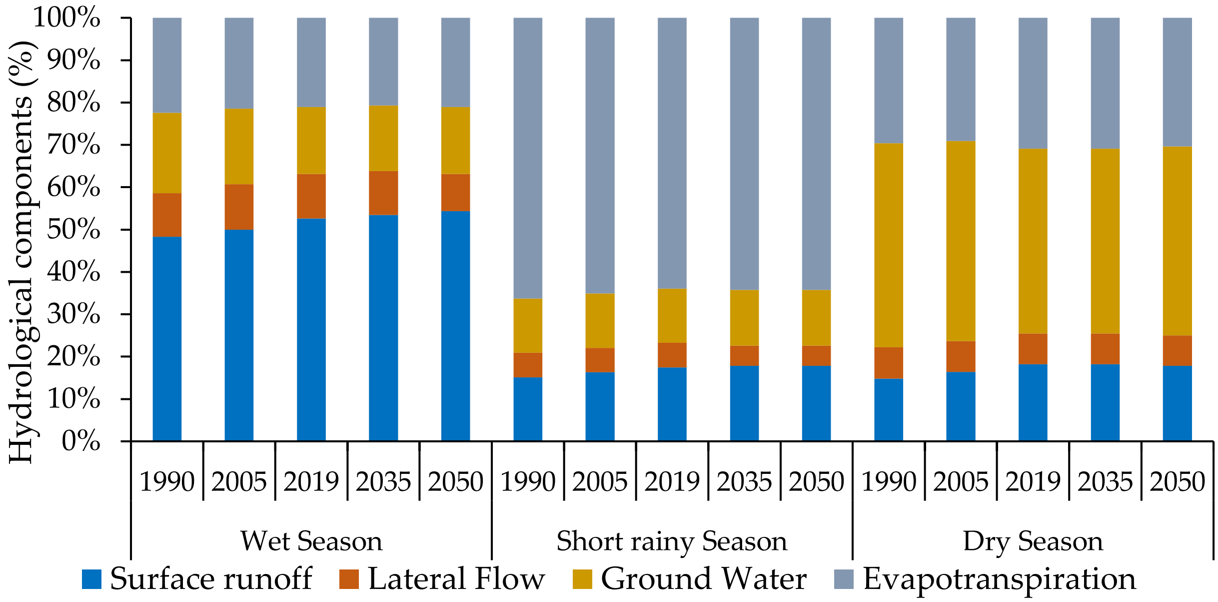


Figure 3.8. Seasonal hydrological components of the Nashe watershed.

In the season of short rain, the surface runoff increased by 1.17 mm (4.23%), and in the dry season by 0.57 mm (2.0%) for the period of 2019–2050. The change in the hydrologic components due to LULC change decreased in the dry period, which mostly comes from base flow and increases runoff during the wet seasons, which is supplied from surface runoff [1]. The surface runoff decline can be accredited to increased infiltration [58]. The observed and simulated mean monthly stream flow shows that there was not much difference between them according to hydrological data.

The agricultural coverage and urban area expansion and extraction of forest land, range land, and grass land strongly influences surface runoff, peak flow, and base flow following rainfall events [8]. This causes alteration in soil moisture conditions and the water amount that percolates into the groundwater storage. Because infiltration diminishes with an increase in impervious surface, urban area growth normally increases high stream flow and decreases low stream flow. Similarly, a reduction in forest land reduces infiltration and evapotranspiration rates, resulting in a reduction in base flow and an increase in impervious surface covers [2,24]. Evapotranspiration was highest in the period from February to May and reached minimum values from the months of October to January.

Therefore, the result of this research is generally in agreement with the fact that agricultural land has less evapotranspiration than forest land [51,59]. Mango and Melesse [60] found that alteration of forest to agriculture and grass land increased peak flows and declined dry season flows in the Upper Mara watershed, affecting water scarcity during low flows. In general, the annual and seasonal watershed hydrology show an increasing or decreasing trend throughout the study period based on the trend of LULC change categories. According to studies conducted by [24,25,34,61,62], the rise in surface runoff and decline of groundwater and evapotranspiration was attributed to the increase of agricultural area and urban areas at the expense of forest cover using the SWAT model.

3.3.3.2. Hydrological Responses to Land Use Land Cover Scenarios

The LULC scenarios were conducted using constant weather data and the variations of hydrological components were exclusively attributable to LULC change. The simulated surface runoff for the potential future LULC scenarios was higher than those of the baseline and current land uses because of further LULC changes (Table 3.5). The future scenario (LULC 2035) yields higher surface runoff and lower groundwater flow in comparison to the other scenarios.

Table 3.5. Average annual hydrological components (mm) and percentage changes in the Nashe watershed.

Hydrologic Components	LULC Scenarios					Changes (%)			
	1990	2005	2019	2035	2050	1990–2005	2005–2019	2019–2035	2035–2050
Surface runoff	288.15	292.04	311.02	318.26	314.56	1.35	6.50	2.33	−1.16
Lateral flow	69.24	67.88	67.67	65.40	60.61	−1.96	-0.31	−3.35	−7.32
Groundwater	171.59	166.99	147.20	143.72	152.89	−2.68	−11.85	−2.36	6.38
Water Yield	528.98	526.02	526.86	527.96	528.06	−0.56	0.16	0.21	−0.02
Evapotranspiration	284.11	283.06	279.26	277.11	275.81	−0.37	−1.34	−0.77	−0.47

The average surface runoff of the catchment was increased by 7.94%, 10.45%, and 9.17% in 2019, 2035, and 2050 respectively, compared to the baseline scenario (1990). In contrast, the average annual lateral flow of the watershed declined by 2.27%, 5.55%, and 18.24% in 2019, 2035, and 2050 in relation to the baseline scenario (1990) (Figure 3.9). The continued increase of agricultural land and urban areas and extraction of forest cover, range land, and grass land will further increase the annual surface runoff in 2035. Unfortunately, the surface runoff will decrease from 2035 to 2050 due to the gradual increase of grass land and range land starting from the year 2035. The finding of the study is consistent with [24], from the three hydrologic parameters studied (surface runoff, groundwater, and base flow), surface runoff was the utmost affected by LULC changes.

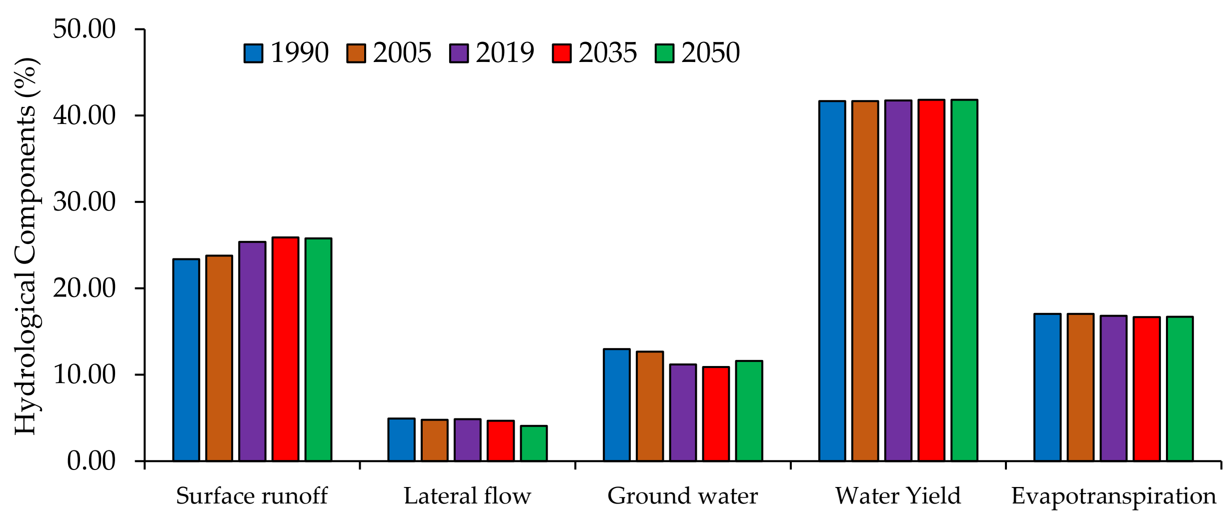
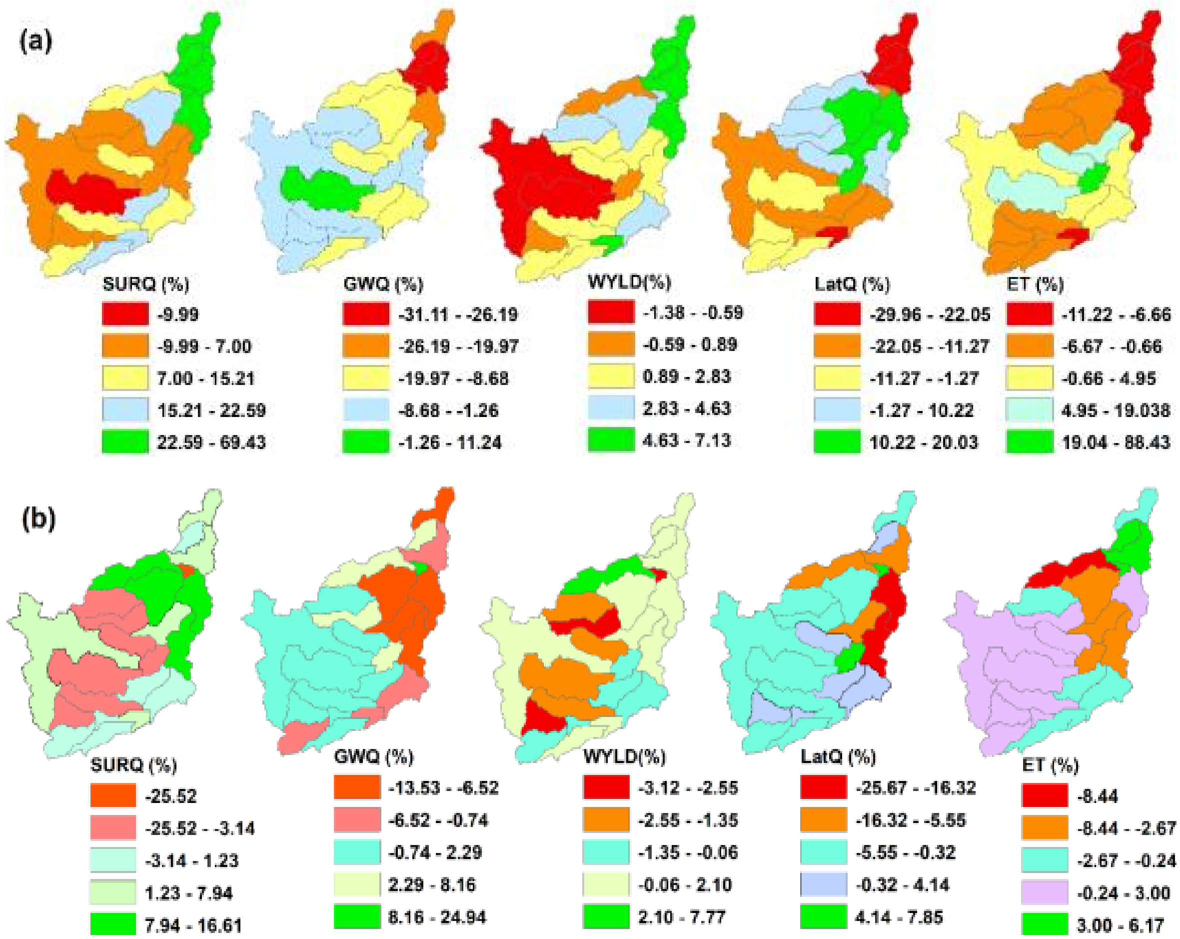


Figure 3.9. Average annual hydrological components under land use land cover scenarios.

3.3.3.3. Spatial Analysis of Watershed Hydrology to LULC Changes

The change of hydrological response amount and direction in each of the sub-basins were assessed from 1990–2050 LULC data as shown in Figure 3.10 (a) 1990–2019, (b) 2019–2035, and (c) 2035–2050. Warburton et al. [4] indicated the impact of LULC changes on hydrological parameters at different spatio-temporal scales. Investigating the spatial LULC change impact on the hydrology of the watershed at the sub-basins level allows to define the degree of vulnerability of local water resources [63]. The spatial distribution expansion in agricultural land and urban areas is proved by the positive correlation with surface runoff. The correlations among LULC categories, the water balance components, and between the groups of variables have been shown by the correlation matrix (Table 3.6).



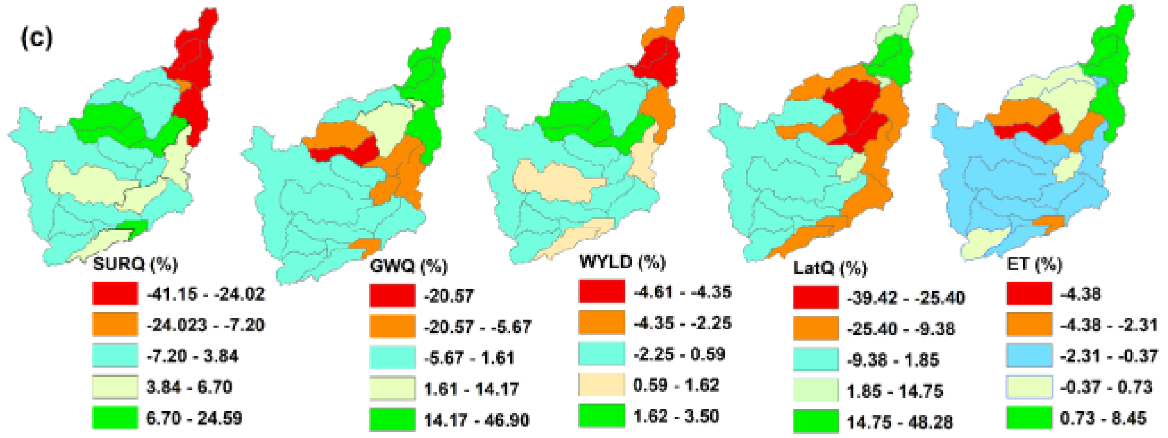


Figure 3.10. Spatial distribution of hydrological components at the sub-basin level (a) 1990–2019, (b) 2019–2035, (c) 2035–2050.

Similarly, surface runoff increased more in sub-basins characterized by higher urban development and increment of irrigation projects downstream of the watershed. Aduah et al. [64] found that surface runoff is very highly susceptible to urbanization and LULC changes have significant effects on hydrological processes. A very strong positive Pearson correlation factor of 0.97 was found between surface runoff and agricultural land (Table 3.6). A strong negative correlation was also found between surface runoff and forest land. Changes in rainfall are the dominant factor that induces changes in water balance components.

Table 3.6. Pair-wise Pearson correlation coefficients for land use, land cover classes, and hydrological components between 1990 and 2050 time periods.

	SurfQ [1]	**LatQ**	**GWQ**	**WYLD**	**ET**	**AGRL**	**FRST**	**GRSL**	**RNGL**	**UrbL**	**WatB**
SurfQ[1]	1.00										
LatQ	−0.60	1.00									
GWQ	−0.97	0.41	1.00								
WYLD	−0.38	0.86	0.24	1.00							
ET	−0.96	0.79	0.88	0.57	1.00						
AGRL	0.97	−0.74	−0.89	−0.52	−0.99	1.00					
FRST	−0.96	0.79	0.89	0.60	1.00	−0.98	1.00				
GRSL	−0.89	0.78	0.78	0.51	0.95	-0.97	0.93	1.00			
RNGL	−0.92	0.57	0.87	0.27	0.90	−0.95	0.88	0.96	1.00		
UrbL	0.71	−0.99	−0.53	−0.82	−0.87	0.84	−0.86	−0.87	−0.69	1.00	
WatB	0.99	−0.70	−0.94	−0.48	−0.98	0.97	−0.99	−0.89	−0.88	0.79	1.00

[1] SurfQ: surface runoff, LatQ: lateral flow, GWQ: groundwater flow, WYLD: water yield, ET: evapotranspiration, AGRL: agricultural land, FRST: forest land, GRSL: grass land, RNGL: range land, UrbL: Urban land, WatB: water body.

The evapotranspiration spatial distribution increment matches with the areas detected to be covered by forest land. This agreement was approved by the maximum correlation coefficient of 1.00. Similarly, evapotranspiration is the main water availability determinant in the watershed since it negatively influences surface runoff. The surface runoff for the 1990–2019 time period decreased only in sub-basin 15 (Figure 3.10a) among all other sub-basins. From 1990 to 2035, surface runoff is the most significant increase in hydrological components occurring mainly in the downstream and central parts of the watershed. For the period of 2035–2050, the minimum surface runoff and water yield happened at downstream of the watershed. The maximum surface runoff occurred in sub-basin 13 and the surrounding areas. Whereas, sub-basin 7 has the least amount of surface runoff (Figure 3.10c).

Previous studies reported that the LULC change impact on water balance components, such as evapotranspiration reduced from plant transpiration due to the decline of forest areas, simultaneously increasing surface runoff, particularly during the rainy season [65,66]. The slopes of the watershed in some parts of the downstream and northeastern part of the catchment are very high and steep. An increase in slope length and steep slopes combined with a decrease in forest cover, grass land, and range land increased surface runoff. Furthermore, the rainy season's peak flow mostly occurs in July and August, resulting in significant surface runoff volumes due to saturated soils. The watershed's maximum monthly discharges occurred in 2050, while the minimum flow occurred in 1990 (Figure 3.11) and most monthly peak flows happened in July and August. This causes flooding in some areas of the watershed, particularly downstream of the watershed. The scenarios generated a moderate increase in average annual stream flow for all future time periods due to projected increased surface runoff.

Generally, the increase of surface runoff in wet seasons may result in flooding and a decline in the dry season may affect water scheme practices. Additionally, water resource planners and managers should consider LULC change scenarios while planning and designing hydropower and irrigation projects. The impact of historical and future LULC change on hydrological components based on scenario analysis was not conducted in the Nashe watershed. Therefore, the outcomes found in this study offer concerned bodies a way to improve the LULC changes towards increasing forest land to modify surface runoff that contributes to wet season flow, and infiltration that supplies groundwater from which base flow contributed will be increased.

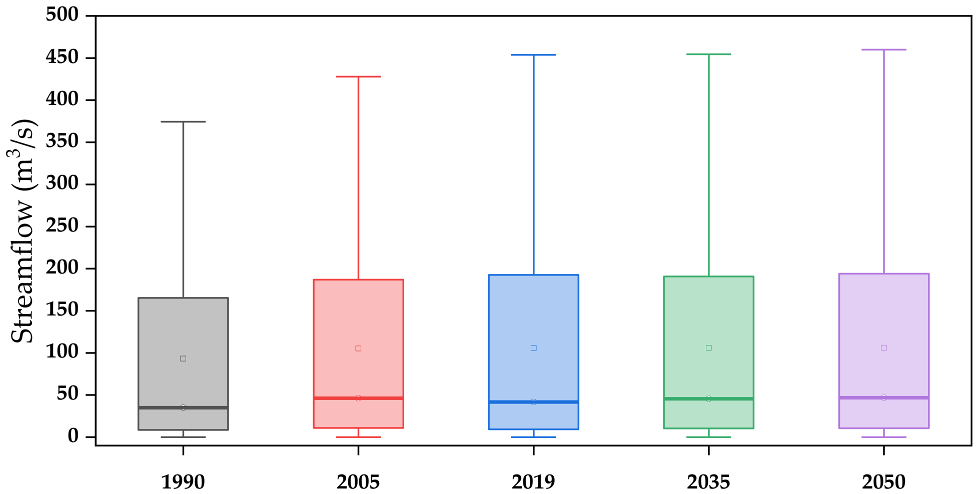


Figure 3.11. The stream flow of the watershed for different LULC time periods.

3.4. Conclusions

The investigation was conducted to analyze the effect of LULC changes on different hydrological processes of the Nashe watershed, Blue Nile River basin, Ethiopia. For different LULC time periods, the SWAT was utilized to simulate historical and future continuous fluctuations in stream flow through time.

The findings lead to the following conclusions:

- Stream flow, which is the key hydrological parameter for water resources planning and management in the basin, changed due to LULC change. Droughts and floods which influence hydropower and irrigation production, may increase more frequently and last longer as a consequence of LULC change.
- For all time periods, LULC scenarios resulted in a modest increment in average annual stream flow which can be utilized as an input for reservoir operation in hydropower and irrigation projects.
- The relation of LULC categories and hydrological components revealed that the surface runoff was highly attributed to change in the agricultural land area with a higher correlation coefficient.
- The increase of surface runoff and decrease of groundwater simulated during the wet season in the Nashe watershed of the Blue Nile River basin may lead to increasing extreme weather events, sedimentation, runoff, siltation, and water shortages may occur during the dry season and obstruct socio-economic development in Ethiopia.

- Forest land coverage increase is important for decreasing surface runoff and wet season flow, and increasing lateral flow, groundwater, and dry season flow. The appropriate management strategy should be prepared based on the commonly LULC change including afforestation in high-risk areas, such as downstream areas in the Northeastern regions of the watershed.
- The study showed that LULC change will affect the operation of the Nashe hydropower reservoir. Additionally, the predicted LULC changes might affect the land use projects within and outside the Nashe watershed and Blue Nile River basin, including the GERD (Grand Ethiopian Renaissance Dam). Therefore, it is substantial to reduce the enduring adverse impact of LULC changes on the hydrological response of the Blue Nile River basin tributaries by formulating and implementing land use management interventions that are essential for sustainable land use resources in Ethiopia.
- The decline of groundwater and surface runoff increase could pose a significant problem for agriculture and may increase the need for irrigation in the dry season. As a result, water storage in reservoirs, in addition to beside natural solutions may become more relevant.
- Understanding the impacts of potential LULC dynamics and how they influence watershed hydrology will allow planners and concerned bodies to formulate strategies to reduce adverse impacts of future LULC dynamics. The findings of the study may aid stakeholders and policy makers to make better decisions about water resources and land management in the future.
- Suitable management systems should be implemented, and it is necessary to have long-term water resource plans to minimize the flooding, soil erosion, and sedimentation caused by the change of LULC. Furthermore, proper conservation measures of water and soil are highly necessary and should be flexible and adaptable to changing insights on the impacts.

References

1. Zhang, L.; Nan, Z.; Yu, W.; Ge, Y. Hydrological Responses to Land-Use Change Scenarios under Constant and Changed Climatic Conditions. Environ. Manag. 2016, 57, 412–431.
2. Gashaw, T.; Tulu, T.; Argaw, M.; Worqlul, A.W. Modeling the hydrological impacts of land use/land cover changes in the Andassa watershed, Blue Nile Basin, Ethiopia. Sci. Total Environ. 2018, 619–620, 1394–1408, doi:10.1016/j.scitotenv.2017.11.191.
3. Marhaento, H.; Booij, M.J.; Rientjes, T.H.M.; Hoekstra, A.Y. Attribution of changes in the water balance of a tropical catchment to land use change using the SWAT model. Hydrol. Process. 2017, 31, 2029–2040.
4. Warburton, M.L.; Schulze, R.E.; Jewitt, G.P.W. Hydrological impacts of land use change in three diverse South African catchments. J. Hydrol 2012, 414–415, 118–135, doi:10.1016/j.jhydrol.2011.10.028.
5. Pang, S.; Wang, X.; Melching, C.S.; Feger, K.H. Development and testing of a modified SWAT model based on slope condition and precipitation intensity. J. Hydrol. 2020, 588, 125098, doi:10.1016/j.jhydrol.2020.125098.
6. Hyandye, C.B.; Worqul, A.; Martz, L.W.; Muzuka, A.N.N. The impact of future climate and land use/cover change on water resources in the Ndembera watershed and their mitigation and adaptation strategies. Environ. Syst. Res. 2018, 7, 1–24, doi: 10.1186/s40068-018-0110-4.
7. Elfert, S.; Bormann, H. Simulated impact of past and possible future land use changes on the hydrological response of the Northern German lowland " Hunte" catchment. J. Hydrol. 2010, 383, 245–255, doi:10.1016/j.jhydrol.2009.12.040.
8. Leta, M.K.; Demissie, T.A.; Tränckner, J. Modeling and prediction of land use land cover change dynamics based on land change modeler (LCM) in Nashe watershed, upper blue nile basin, Ethiopia. Sustainability 2021, 13, 3740, doi: 10.3390/ su13073740.
9. Aboelnour, M.; Gitau, M.W.; Engel, B.A. Hydrologic response in an urban watershed as affected by climate and land-use change. Water 2019, 11, 1–23.

10. Maetens, W.; Vanmaercke, M.; Poesen, J.; Jankauskas, B.; Jankauskiene, G.; Ionita, I. Effects of land use on annual runoff and soil loss in Europe and the Mediterranean: A meta-analysis of plot data. Prog. Phys. Geogr. 2012, 36, 599–653.
11. Anand, J.; Gosain, A.K.; Khosa, R. Prediction of land use changes based on Land Change Modeler and attribution of changes in the water balance of Ganga basin to land use change using the SWAT model. Sci. Total Environ. 2018, 644, 503–519, doi:10.1016/j.scitotenv.2018.07.017.
12. Verma, S.; Bhattarai, R.; Bosch, N.S.; Cooke, R.C.; Kalita, P.K.; Markus, M. Climate Change Impacts on Flow, Sediment and Nutrient Export in a Great Lakes Watershed Using SWAT. Clean-Soil Air. Water. 2015, 43, 1464–1474.
13. Gayathri, D.K.; Ganasri, B.P.; Dwarakish, G.S. A Review on Hydrological Models. Aquat. Procedia. 2015, 4, 1001–1007.
14. Tegegne, G.; Park, D.K.; Kim, Y.O. Comparison of hydrological models for the assessment of water resources in a data-scarce region, the Upper Blue Nile River Basin. J. Hydrol. Reg. Stud. 2017, 14, 49–66, doi:10.1016/j.ejrh.2017.10.002.
15. Waseem, M.; Kachholz, F.; Tränckner, J. Suitability of common models to estimate hydrology and diffuse water pollution in North-eastern German lowland catchments with intensive agricultural land use. Front Agric. Sci. Eng. 2018, 5, 420–431.
16. Arnold, J.G.; Moriasi, D.N.; Gassman, P.W.; Abbaspour, K.C.; White, M.J.; Srinivasan, R.; Santhi, C.; Harmel, D.R.; van Griensven, A.; Liew, W.M.; et al. Swat: Model Use, Calibration, And Validation. Trans. ASABE 2012, 55, 1491–1508.
17. Gassman, P.W.; Sadeghi, A.M.; Srinivasan, R. Applications of the SWAT Model Special Section: Overview and Insights. J. Environ. Qual. 2014, 43, 1–8.
18. Abbaspour, K. SWAT-Calibration and Uncertainty Programs (CUP). Neprash technology ca: http://www.neprashtechnology.ca/wp-content/uploads/2015/06/ User manual_SwatCup.pdf.
19. Shrestha, M.K.; Recknagel, F.; Frizenschaf, J.; Meyer, W. Assessing SWAT models based on single and multi-site calibration for the simulation of flow and nutrient loads in the semi-arid Onkaparinga catchment in South Australia. Agric. Water Manag. 2016, 175, 61–71, doi:10.1016/j.agwat.2016.02.009.

20. Baker, T.J.; Miller, S.N. Using the Soil and Water Assessment Tool (SWAT) to assess land use impact on water resources in an East African watershed. J. Hydrol. 2013, 486, 100–111, doi:10.1016/j.jhydrol.2013.01.041.
21. Wagner, P.D.; Kumar, S.; Schneider, K.; Earth, S. An assessment of land use change impacts on the water resources of the Mula and Mutha Rivers catchment upstream of Pune, India. Hydrol. Earth Syst. Sci. Discuss. 2013, 10, 1943–1985.
22. Saddique, N.; Mahmood, T.; Bernhofer, C. Quantifying the impacts of land use/land cover change on the water balance in the afforested River Basin, Pakistan. Environ. Earth Sci. 2020, 79, 1–13, doi: 10.1007/s12665-020-09206-w.
23. dos Santos, F.; de Oliveira, R.; Di Lollo, J. Effects of Land Use Changes on Stream flow and Sediment Yield in Atibaia River Basin—SP, Brazil. Water 2020, 12, 1711, doi: 10.3390/w12061711.
24. Gyamfi, C.; Ndambuki, J.M.; Salim, R.W. Hydrological responses to land use/cover changes in the Olifants Basin, South Africa. Water 2016, 8, 588.
25. Twisa, S.; Kazumba, S.; Kurian, M.; Buchroithner, M.F. Evaluating and predicting the effects of land use changes on hydrology in Wami river basin, Tanzania. Hydrology 2020, 7, 1–18.
26. Keenan, R.J.; Reams, G.A.; Achard, F.; de Freitas, J.V.; Grainger, A.; Lindquist, E. Dynamics of global forest area: Results from the FAO Global Forest Resources Assessment 2015. For. Ecol. Manag. 2015, 352, 9–20, doi:10.1016/j.foreco.2015.06.014.
27. Rafiei, V.; Ghahramani, A.; An-Vo, D.A.; Mushtaq, S. Modelling hydrological processes and identifying soil erosion sources in a tropical catchment of the great barrier reef using SWAT. Water 2020, 12, 2179.
28. Krajewski, A.; Sikorska-Senoner, A.E.; Hejduk, L.; Banasik, K. An Attempt to Decompose the Impact of Land Use and Climate Change on Annual Runoff in a Small Agricultural Catchment. Water Resour. Manag. 2021, 35, 881–896, doi: 10.1007/s11269-020-02752-9.
29. Kebede, W.; Tefera, M.; Habitamu, T.; Alemayehu, T. Impact of Land Cover Change on Water Quality and Stream Flow in Lake Hawassa Watershed of Ethiopia. Agric. Sci. 2014, 5, 647–659.

30. Khadr, M. Forecasting of meteorological drought using Hidden Markov Model (case study: The upper Blue Nile river basin, Ethiopia). Ain. Shams. Eng. J. 2016, 7, 47–56, doi:10.1016/j.asej.2015.11.005.

31. Tekalegn, W.A.; Elagib, N.A.; Ribbe, L.; Heinrich, J. Hydrological responses to land use/cover changes in the source region of the Upper Blue Nile Basin, Ethiopia. Sci. Total Environ. 2017, 575, 724–741, doi:10.1016/j.scitotenv.2016.09.124.

32. Dibaba, W.T.; Demissie, T.A.; Miegel, K. Watershed hydrological response to combined land use/land cover and climate change in highland ethiopia: Finchaa catchment. Water 2020, 12, 1801.

33. Galata, A.W.; Demissei, T.A.; Leta, M.K. Watershed Hydrological Responses to Changes in Land Use and Land Cover at Hangar Watershed, Ethiopia. Iran. J. Energy Environ. 2020, 11, 1–7.

34. Karamage, F.; Zhang, C.; Fang, X.; Liu, T.; Ndayisaba, F.; Nahayo, L.; Kayiranga, A.; Nsengiyumva, J.B. Modeling rainfall-runoff response to land use and land cover change in Rwanda (1990–2016). Water 2017, 9, 147.

35. Santos, R.M.B.; Fernandes, L.F.S.; Cortes, R.M.V.; Pacheco, F.A.L. Hydrologic impacts of land use changes in the Sabor river basin: A historical view and future perspectives. Water 2019, 11, 1464.

36. Megersa, K.L.; Tamene, A.D.; Sifan, A.K. Impacts of Land Use Land Cover Change on Sediment Yield and Stream Flow . Int. J. Sci. Technol. 2017, 6, 763–781.

37. Kitila, G.; Gebrekidan, H.; Alamrew, T. Soil quality attributes induced by land use changes in the Fincha'a watershed, Nile Basin of western Ethiopia. Sci. technol. Arts. Res. J. 2018, 5, 16.

38. Gebrehiwot, S.G.; Bewket, W.; Gärdenäs, A.I.; Bishop, K. Forest cover change over four decades in the Blue Nile Basin, Ethiopia: Comparison of three watersheds. Reg. Environ. Chang. 2014, 14, 253–266.

39. Gumindoga, W.; Rientjes, T.H.M.; Haile, A.T.; Dube, T. Predicting stream flow for land cover changes in the Upper Gilgel Abay River Basin, Ethiopia: A TOPMODEL based approach. Phys. Chem. Earth. 2014, 76–78, 3–15, doi:10.1016/j.pce.2014.11.012.

40. Sith, R.; Nadaoka, K. Comparison of SWAT and GSSHA for high time resolution prediction of stream flow and sediment concentration in a small agricultural watershed. Hydrology 2017, 4, 27.

41. Banasik, K.; Hejduk, L.; Krajewski, A.; Wasilewicz, M. The intensity of siltation of a small reservoir in Poland and its relationship to environmental changes. Catena 2021, 204, 105436, doi:10.1016/j.catena.2021.105436.

42. Kushwaha, A.; Jain, M.K. Hydrological Simulation in a Forest Dominated Watershed in Himalayan Region using SWAT Model. Water Resour. Manag. 2013, 27, 3005–3023.

43. Ghoraba, S.M. Hydrological modeling of the Simly Dam watershed (Pakistan) using GIS and SWAT model. Alexandria Eng. J. 2015, 54, 583–594, doi:10.1016/j.aej.2015.05.018.

44. Khalid, K.; Ali, M.F.; Rahman, N.F.A.; Mispan, M.R.; Haron, S.H.; Othman, Z.; Bachok, M.F. Sensitivity Analysis in Watershed Model Using SUFI-2 Algorithm. Procedia Eng. 2016, 162, 441–447, doi:10.1016/j.proeng.2016.11.086.

45. Moriasi, D.N.; Gitau, M.W.; Pai, N.; Daggupati, P. Hydrologic and water quality models: Performance measures and evaluation criteria. Trans. ASABE 2015, 58, 1763–1785.

46. Vilaysane, B.; Takara, K.; Luo, P.; Akkharath, I.; Duan, W. Hydrological Stream Flow Modelling for Calibration and Uncertainty Analysis Using SWAT Model in the Xedone River Basin, Lao PDR. Procedia Environ. Sci. 2015, 28, 380–390, doi: 10.1016/j. proenv. 2015.07.047.

47. Abbaspour, K.C.; Vaghefi, S.A.; Srinivasan, R. A guideline for successful calibration and uncertainty analysis for soil and water assessment: A review of papers from the 2016 international SWAT conference. Water 2017, 10, 6.

48. Gholami, A.; Habibnejad Roshan, M.; Shahedi, K.; Vafakhah, M.; Solaymani, K. Hydrological stream flow modeling in the Talar catchment (central section of the Alborz Mountains, north of Iran): Parameterization and uncertainty analysis using SWAT-CUP. J. Water Land Dev. 2016, 30, 57–69.

49. Smarzyńska, K.; Miatkowski, Z. Calibration and validation of SWAT model for estimating water balance and nitrogen losses in a small agricultural watershed in central Poland. J. Water Land Dev. 2016, 29, 31–47.

50. Sao, D.; Kato, T.; Tu, L.H.; Thouk, P.; Fitriyah, A.; Oeurng, C. Evaluation of different objective functions used in the sufi-2 calibration process of swat-cup on water balance analysis: A case study of the pursat river basin, cambodia. Water 2020, 12, 1–22.

51. Yan, B.; Fang, N.F.; Zhang, P.C.; Shi, Z.H. Impacts of land use change on watershed stream flow and sediment yield: An assessment using hydrologic modelling and partial least squares regression. J. Hydrol. 2013, 484, 26–37, doi: 10.1016/ j.jhydrol. 2013.01.008.

52. Tankpa, V.; Wang, L.; Awotwi, A.; Singh, L.; Thapa, S.; Atanga, R.A.; Guo, X. Modeling the effects of historical and future land use/land cover change dynamics on the hydrological response of Ashi watershed, northeastern China. Environ. Dev. Sustain. 2020, 23, 7883–7912, doi: 10.1007/s10668-020-00952-2.

53. Whittaker, G.; Confesor, R.; Di Luzio, M.; Arnold, J.G. Detection of over parameterization and overfitting in an automatic calibration of SWAT. Trans. ASABE 2010, 53, 1487–1499.

54. Boufala, M.; El Hmaidi, A.; Chadli, K.; Essahlaoui, A.; El Ouali, A.; Taia, S. Hydrological modeling of water and soil resources in the basin upstream of the Allal El Fassi dam (Upper Sebou watershed, Morocco). Model. Earth Syst. Environ. 2019, 5, 1163–1177, doi: 10.1007/s40808-019-00621-y.

55. Niraula, R.; Meixner, T.; Norman, L.M. Determining the importance of model calibration for forecasting absolute/relative changes in stream flow from LULC and climate changes. J. Hydrol. 2015, 522, 439–451, doi:10.1016/j.jhydrol.2015.01.007.

56. Makhtoumi, Y.; Li, S.; Ibeanusi, V.; Chen, G. Evaluating water balance variables under land use and climate projections in the upper choctawhatchee River Watershed, in Southeast US. Water 2020, 12, 1–33.

57. Nasiri, S.; Ansari, H.; Ziaei, A.N. Simulation of water balance equation components using SWAT model in Samalqan Watershed (Iran). Arab. J. Geosci. 2020, 13, 1–15.

58. Benegas, L.; Ilstedt, U.; Roupsard, O.; Jones, J.; Malmer, A. Effects of trees on infiltrability and preferential flow in two contrasting agroecosystems in Central America. Agric. Ecosyst. Environ. 2014, 183, 185–196, doi:10.1016/j.agee.2013.10.027.

59. Santos, D.V.; Laurent, F.; Abe, C.; Messner, F. Hydrologic response to land use change in a large basin in eastern Amazon. Water 2018, 10, 1–19.

60. Mango, L.M.; Melesse, A.M.; McClain, M.E.; Gann, D.; Setegn, S.G. Land use and climate change impacts on the hydrology of the upper Mara River Basin, Kenya: Results of a modeling study to support better resource management. Hydrol. Earth Syst. Sci. 2011, 15, 2245–2258.

61. Belihu, M.; Tekleab, S.; Abate, B.; Bewket, W. Hydrologic response to land use land cover change in the Upper Gidabo Watershed, Rift Valley Lakes Basin, Ethiopia. HydroResearch 2020, 3, 85–94, doi:10.1016/j.hydres.2020.07.001.

62. Shawul, A.A.; Chakma, S.; Melesse, A.M. The response of water balance components to land cover change based on hydrologic modeling and partial least squares regression (PLSR) analysis in the Upper Awash Basin. J. Hydrol. Reg. Stud. 2019, 26, 100640, doi:10.1016/j.ejrh.2019.100640.

63. Abe, C.A.; Lobo, F.D.L.; Dibike, Y.B.; Costa, M.P.D.F.; Dos Santos, V.; Novo, E.M.L. Modelling the effects of historical and future land cover changes on the hydrology of an Amazonian basin. Water 2018, 10, 932.

64. Aduah, M.S.; Jewitt, G.P.W.; Toucher, M.L.W. Assessing impacts of land use changes on the hydrology of a lowland rainforest catchment in Ghana, West Africa. Water 2017, 10, 9.

65. Panday, P.K.; Coe, M.T.; Macedo, M.N.; Lefebvre, P.; de Almeida Castanho, A.D. Deforestation offsets water balance changes due to climate variability in the Xingu River in eastern Amazonia. J. Hydrol. 2015, 523, 822–829, doi:10.1016/ j.jhydrol. 2015.02.018.

66. Dias, L.C.P.; Macedo, M.N.; Costa, M.H.; Coe, M.T.; Neill, C. Effects of land cover change on evapotranspiration and stream flow of small catchments in the Upper Xingu River Basin, Central Brazil. J. Hydrol. Reg. Stud. 2015, 4, 108–122.

4. Optimal Operation of Nashe Hydropower Reservoir under Land Use Land Cover Change in Blue Nile River Basin

This chapter was published in:
Water; 17 May 2022; Volume 14, 1606
https://doi.org/10.3390/w14101606

Abstract: Changes in LULC (land use land cover), which significantly influence the spatial and temporal distribution of hydrological processes and water resources in general, have a substantial impact on hydropower generation. The utilization of an optimization approach in order to analyze the operation of reservoirs is an important concern in the planning and management of water resources. The SWAT (Soil and Water Assessment Tool) and the HEC-ResPRM (Hydrologic Engineering Center reservoir evaluation system Prescriptive Reservoir Model) were combined to model and optimize the Nashe hydropower reservoir operation in the Blue Nile River basin (BNRB). The stream flow into the reservoir was determined using the SWAT model, considering the current and future impacts of LULC changes. The HEC-ResPRM model has been utilized in order to generate the optimal hydropower reservoir operation by using the results of the SWAT calibrated and validated stream flow as input data. This study proposes a method for integrating the HEC-ResPRM and SWAT models to examine the effects of historical and future land use land cover change on the watershed's hydrological processes and reservoir operation. Therefore, the study aimed to investigate the current and future optimal reservoir operation scenarios for water resources management concerning hydropower generation under the effect of LULC changes. The results reveal that both the 2035 and 2050 LULC change scenarios show the increased operation of hydropower reservoirs with increasing reservoir inflows, releases, storage, and reservoir elevation in the future. The effects of LULC change on the study area's hydrological components reveal an increase in surface runoff until 2035, and its decrease from 2035 to 2050. The average annual reservoir storage and elevation in the 2050 LULC scenario increased by 7.25% and 2.27%, respectively, when compared to the current optimized scenario. Therefore, changes in LULC have a significant effect on hydropower development by changing the total annual and monthly reservoir inflow volumes and their seasonal distribution. Reservoir operating rule curves have been commonly implemented in the operation of hydropower reservoirs, since they help operators to make essential, optimal decisions with available stream flow. Moreover, the generated future reservoir rule curves can be utilized as a reference for

the long-term prediction of hydropower generation capacity, and assist concerned authorities in the successful operation of the reservoir under the impact of LULC changes.

Keywords: HEC-ResPRM; hydropower; LULC change; optimization; reservoir operation; storage

4.1. Introduction

Reservoirs are the most critical infrastructure components for integrating management and development of water resources through impounding water and controlling stream flow [1,2]. The management of water resources has become a primary issue in today's fast developing world, and the global economy's development is hampered by the continuous increase in water demand and the limited supply of water resources [3]. The most common reservoir purposes that regulate water resources through changing natural stream flow include flood control, hydropower production, irrigation, water supply, recreation, navigation, and fisheries [4–7]. Due to a lack of optimal operation policies, the majority of reservoirs are unable to serve their intended purposes, even though they are designed to serve a variety of purposes [8]. Furthermore, reservoir development aims to alleviate regional problems of water scarcity via re-distribution of water resources with temporal variability and spatial heterogeneity [9].

The operation of a reservoir is very challenging for water resource planners and managers; it involves numerous, intricately linked variables, such as storage, power production, hydrological, environmental, institutional, political, as well as the uncertainty of reservoir inflow and stochastic fluctuation of water demands [10–13]. Historical and future LULC changes will alter the pattern, intensity, and frequency of rainfall events, influencing regional and global stream flows and water resource reliability, which may cause significant challenges for reservoir management [14–17]. Therefore, changes in LULC have a significant impact on the distribution and timing of water changes, which affect a variety of water resource operations and managements, including the operation rule curves in addition to the capacity of basins to generate hydropower [14,18,19]. The uncertainties of land use changes have directly impacted the inflows and water resource management in reservoirs.

Land Change Modeler (LCM) has been used to predict future LULC, and estimate historical and future LULC changes. As a result, in a given watershed, estimating and predicting stream flow and hydropower generation in the face of changing LULC is crucial for effective water management and decision-making. Consequently, the effects of LULC changes on hydrological processes must be considered in the management and planning of water resources so that measures can be made to adapt future LULC scenarios [20,21]. Various hydrological simulation models are currently being used to simulate and predict the effects of LULC change on hydrological processes, such as the following: Hydrologic Simulation Program-FORTRAN (HSPF), MIKE-system Hydrologic European (MIKE-SHE), Soil and Water Integrated Model (SWIM), Distributed Hydrology Soil Vegetation Model (DHSVM), Soil and Water Assessment Tool (SWAT), Dynamic Watershed Simulation Model (DWSM), and Hydrologic Engineering Center Hydrologic Modeling System (HEC–HMS) [14,15,22,23]. For any hydrological response evaluation and stream flow predictions, it is essential to select the proper model.

The significant factors considered in selecting the appropriate model to achieve the objectives of the study are the following: the ability to simulate hydrological components, efficiency, long-term temporal scaling, flexibility, continuous-time modeling, ease of utility, performance demonstrated through numerous validation studies using readily available data, model complexity, ability to simulate for small to large scale watersheds, freely available, and widely used modeling for assessing the impacts of LULC changes on water resources [23–26]. Based on the criteria outlined here and after a thorough literature review, the SWAT model was selected for analyzing and predicting the stream flow. The hydrological SWAT model is widely used to model and analyze the stream flow simulations that were affected by the uncertainties of LULC changes into the reservoir [24,27–29]. Similarly, various model reviews found that the SWAT can model the desired hydrological processes in more detail than many other watershed models, and can better replicate stream flow than other hydrological models [22].

In reservoir system analysis, the basic modeling approaches utilized to provide quantitative information that can improve operational water management are descriptive simulation, prescriptive optimization, and hybrid models [30]. Optimization algorithms have been used to solve water resource management problems, and to find the best rule curves, optimize the storage and release by minimizing total penalty functions at designated locations throughout the water resource network [31,32]. The descriptive simulation models describe reservoir system performance under a given set of control actions [30,33]. Simulation models simulate decisions of reservoir operations in predefined logical rules, resulting in good reservoir operation but with an inability to optimize the solution [34]. Therefore, recently, a combination of optimization and simulation models (hybrid models) has been applied to reservoir operation in order to address these problems [35,36].

According to Fayaed et al. [12], a review of optimization and simulation models used in resolving essential concerns in reservoir systems emphasized that reservoir optimization is the most crucial element. Reservoir operation rule curves are the utmost popular tool used to determine the rate of water release and storage, by considering the interests of the reservoir stakeholders, inflows, stored water volume, release capacity, current reservoir level, water demands, and downstream constraints [20]. Therefore, developing a rule curve is one type of proper management system frequently used for reservoir operation [37]. In order to achieve the best potential system performance in reservoir operation, decisions on releases and storage must be made over, time while taking into account the variations [7,35,38].

A combination of simulation and optimization models, the Hydrologic Engineering Centre Reservoir evaluation system Perspective Reservoir Model (HEC-ResPRM) of the US Army Corps of Engineers, was utilized in this study for reservoir optimization. The HEC-ResPRM prescriptive reservoir model is a network flow, monthly based optimization model that determines the optimal releases and storage for multi-reservoir systems over time by minimizing the total penalties in the system [39,40]. In this study, the HEC-ResPRM model was selected above the other optimization models, since it integrates simulation and optimization modeling, and overcomes the limitations of traditional optimization techniques. According to Faber and Harou [41], the HEC-ResPRM was applied to optimize multi-objective reservoir systems in the Mississippi Headwaters. Prasanchum and Kangrang [16] investigated the effect of land use change in the future using the Soil and Water Assessment Tool (SWAT) hydrologic model to assess the future inflow, and the GA optimization algorithm, as one of the popular algorithms due to its random search capability and near-global optimal values, to optimize the reservoir operation rules.

There are a few studies in East Africa that look at the impact of land use land cover change on hydropower production [42]. However, the studies conducted are primarily focused on the effects of the LULC change on past and predicted hydropower generation. The findings suggest that yearly hydropower generation capacity will increase significantly [42,43]. In developing countries, rapid economic development can result in LULC changes within a watershed reservoir [44]. Ethiopia, like many other developing countries, has been grappling with fundamental environmental problems such as LULC change, soil erosion, and water resource degradation, and these are very serious in the highland parts of the country [14]. The main source of renewable energy in developing countries, particularly in Sub-Saharan countries, is affected by LULC changes and their associated impacts. Hydropower is the most widely used renewable energy source in many African power systems [45]. The African population and energy demands are increasing rapidly; the hydropower plants and their share of electricity production are developing gradually. Ethiopia has a potential energy source in the country, with plenty of water and a suitable topographical aspect for the establishment of hydropower projects.

The Blue Nile River basin is one of Ethiopia’s twelve major river basins. The Nashe watershed is a tributary of the Blue Nile River Basin and the upper watershed of the Grand Ethiopian Renaissance Dam (GERD), Africa’s largest dam. It began operation since February 2022. The goal of the Ethiopian government with the construction of the GERD is to increase the power generation capacity of the country without affecting its downstream users. Similarly, the GERD was expected to help with meeting the increasing domestic electricity demand, exporting electricity to neighboring countries for regional integration, in addition to economic benefits and fisheries growth.

The Blue Nile River basin is politically significant, important for regional economic development, and environmental sustainability, since it is a transboundary basin shared by Ethiopia, Sudan, and Egypt. The Blue Nile River basin is one of the international river basins with the potential for water conflicts between riparian countries [46]. In order to address the growing demand for energy and economic growth, each of the basin countries is developing water resource projects unilaterally [47,48]. McCartney and Menker Girma [49] argue that unilateral management restricts the potential benefits from transboundary water resources, which can be expanded beyond shared water system management. Consequently, one feature of the conflicts in the Blue Nile River basin is that downstream countries have a high dependency on the water generated from upstream countries.

The effects of the GERD on downstream users have been investigated in different studies. For example, Arjoon et al. [50] developed a hydro-economic model based on the Stochastic Dual Dynamic Programming (SDDP) model in order to examine the positive and negative effects of the GERD on Sudan and Egypt. The findings revealed that the GERD would provide significant irrigation and hydropower benefits for Egypt, Sudan, and Ethiopia under cooperative management. Similarly, according to the findings, the GERD would also have a key role in decreasing hydrological uncertainty during low flow periods. However, according to research by Jeuland et al. [48], non-cooperative management reduces Egypt's total flow compared to cooperative management. Furthermore, the study by Mulat and Moges [51] estimates a 12% and 7% decline in electricity generation from the High Aswan Dam (HAD) during filling and after the GERD is operational, respectively.

A high level of cooperation, especially during reservoir filling, may help Sudan and Egypt to minimize negative consequences. In general, a basin-wide cooperative agreement can help to manage the risks to downstream users. The Blue Nile River basin has a tremendous hydropower production potential that can be fully realized through cooperative water resource development and management. Effective management strategies are becoming more critical as Ethiopia's River Basins become increasingly stressed. Therefore, it is crucial to assess the reservoir operation of the Nashe hydropower reservoir based on historical and predicted LULC changes.

The performance of the HEC-ResPRM in combination with the SWAT model for the LULC pattern was not assessed previously over this watershed study nor in Ethiopia, as far as the authors are aware. Similarly, no study has been conducted on this watershed in order to determine the extent of historical and future land use land cover change effects on the watershed's hydrological processes and reservoir operation. In fact, one of the previous studies investigated the performance of optimization algorithms (HEC-ResPRM) on the Tekeze Reservoir in the Eastern Nile, taking into consideration climate change scenarios [39,40]. Thus, this research presents a novel method for combining the HEC-ResPRM model with the SWAT model in order to assess the effects of historical and future land use land cover change on the watershed hydrological processes and reservoir operation. As a result, a hybrid methodology is provided in this study as a simulation-optimization framework to investigate the Nashe reservoir operation under various LULC change scenarios.

Therefore, this study was carried out to investigate the impact of individual LULC changes on reservoir operation, as LULC changes in the study watershed are now increasing at an astonishing rate [52]. Furthermore, assessing the perspectives of individual land use land cover changes in hydrological components is critical for long-term water and land resource management. The aims of the study were as follows: (1) to assess the impact of historical and future LULC change on reservoir inflow using Soil and Water Assessment Tool (SWAT); (2) to assess the hydropower generation of Nashe reservoir operation considering the LULC change; and (3), to develop new reservoir operation guide curves for the Nashe hydropower reservoir system in order to increase yearly energy production under the LULC change, using the optimization-simulation model.

4.2. Materials and Methods

4.2.1. Description of the Study Watershed

The Nashe River originates from a long and wide river valley in the high mountainous area of Ethiopia. The land relief is up-down, with a low ridge separating the Nashe River from the adjacent river basins. The Nashe dam site is located in the central Ethiopian highlands, about 300 km northwest of the capital of Ethiopia, Addis Ababa, on the Nashe River (Figure 4.1). The Nashe River basin is located on the plateau, with an average altitude of 2200 m. The watershed plateau is characterized by a hilly topography interspersed with high mountain ranges, volcanic cones, and deep gorges. The Nashe River has a sharp drop of about 600 m at the Nashe cliff, forming a fall and torrents. The river basin has a sub-tropical climate with distinct dry and wet seasons. The Nashe hydropower plant, which has a reservoir located on the left side bank of the Blue Nile River basin, is the principal tributary, and is mainly utilized for electricity generation for the country. The Nashe dam was developed by building a homogeneous earth-fill dam across the Nashe River, with a height of 38 m, crest length of 1000 m, and a crest elevation of 2235 m. The total water storage capacity of the reservoir is 448 million cubic meters (MCM), of which 85 MCM is dead storage and 363 MCM is live storage.

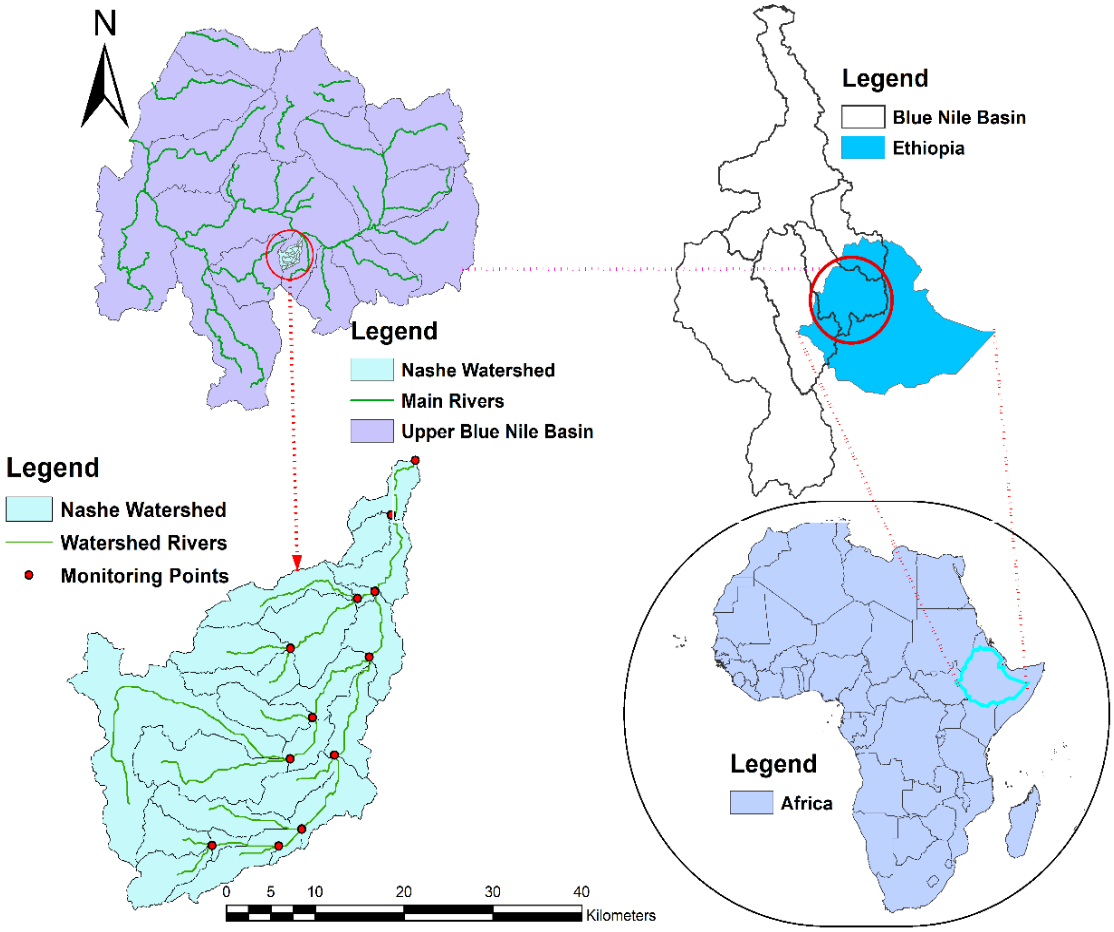


Figure 4.1. Map of the study area.

The watershed is geographically found between 9° 35′ and 9° 52′ N latitudes and 37° 00′ and 37° 20′ E longitudes. The purpose of the Nashe reservoir is primarily for hydropower production, with a total installed capacity of 97 MW in two 48.5 MW Pelton turbines installed at an elevation of 1614 masl (meters above sea level) at the surface powerhouse. The project is aimed to irrigate 6000 ha of land area downstream of the watershed for sugar cane cultivation. The annual mean temperature and rainfall of the watershed are 22 °C and range from 1200 mm to 1600 mm, respectively. Agricultural land and Haplic Alisols are the dominant LULC and soil types of the watershed, respectively.

4.2.2. Input Data Sets

4.2.2.1. Hydrological and Meteorological Data

In order to achieve the research goal, it is critical to have relevant and appropriate data before the simulation and optimization of any model [53]. The historical, current, and future hydrological data corresponding to LULC change scenarios have been investigated. The observed stream flow data of the watershed was used for comparison with the simulation results. The SWAT2012 hydrological model was used to examine the historical and future stream flow of the watershed, considering LULC changes. The necessary input data used for the SWAT model to simulate the stream flow of the watershed were DEM (Digital Elevation Model), weather data (rainfall, temperature, wind speed, relative humidity, and solar radiation), land use land cover data, soil data, and observed stream flow data.

The results of these hydrological simulations are instead used as input into an optimization model that determines the optimal reservoir operations given a time series of reservoir inflows. The reservoir's stream flow prediction has been carried out by changing LULC maps, while the remaining model parameters from the calibrated model and other SWAT inputs remain constant. The observed historical stream flow data, soil, and DEM of the Nashe watershed were collected from the Ministry of Water, Irrigation, and Energy, Ethiopia. The weather data were obtained from the Meteorological Service Agency, Ethiopia.

4.2.2.2. Reservoir Data

The following data is typically required when using the HEC-ResPRM model to perform the reservoir operation: elevation-area-storage curve, historical reservoir storage and water surface level, reservoir outlet capacities, outflow-energy generation relationship, power production, background map of the watershed, and flow time series. The calibrated and validated SWAT model was used to estimate reservoir inflow data for the Nashe watershed [24]. The background map is helpful for setting up the model and visualizing its spatial layout, whereas the physical data is utilized to develop model constraints and allow the model to calculate penalties.

Therefore, the inflow data were first configured in the HEC-DSS (Hydrologic Engineering Center- Data Storage System) for efficient storage and retrieval of scientific input and output time series data. The historical flow time series data was collected from the Ministry of Water, Irrigation, and Energy of Ethiopia. The background map of the study area was extracted by importing the geo-referenced GIS data map of the watershed area using ArcGIS. The other required reservoir data were collected from the Ethiopian Electric Power.

4.2.3. Land Use Land Cover Change Scenarios

Changes in land use land cover affect a catchment's hydrological cycle through altering rainfall, evaporation, and runoff. The impact of LUCC on surface runoff has been related to land use types. The LULC types are one of the input parameters of the SWAT model. One of the most important factors influencing surface runoff generation is LULC change within a watershed [24,29,54]. In order to investigate the spatio-temporal dynamics of LULC and to predict future LULC change in the Nashe watershed, an integrated method that includes remote sensing, GIS, and a Multi-Layer Perceptron Neural Network-based Cellular Automata-Markov Chain model was employed by Leta et al. [14]. The historical LULC maps developed from Landsat images for the years 1990, 2005, and 2019 (Figure 4.2) were utilized as the base map and imported into the TerrSet model's Land Change Modeler (LCM) interface to develop the future LULC maps and change scenarios for the years 2035 and 2050 [14] (Figure 4.3).

The potential LULC change in the watershed was examined using the LCM TerrSet software [14,55]. According to Leta et al. [14], the accuracy of the classified map was compared to ground truth data, and the model was validated for the predicted LULC by simulating the recent LULC map of 2019. The percentage changes of the historical and future LULC change were conducted by Leta et al. [14] and adopted in this study. Based on available land use maps, LCM is extensively used to simulate the projection of LULC changes between two periods. The comprehensive framework of the study is depicted in Figure 4.4.

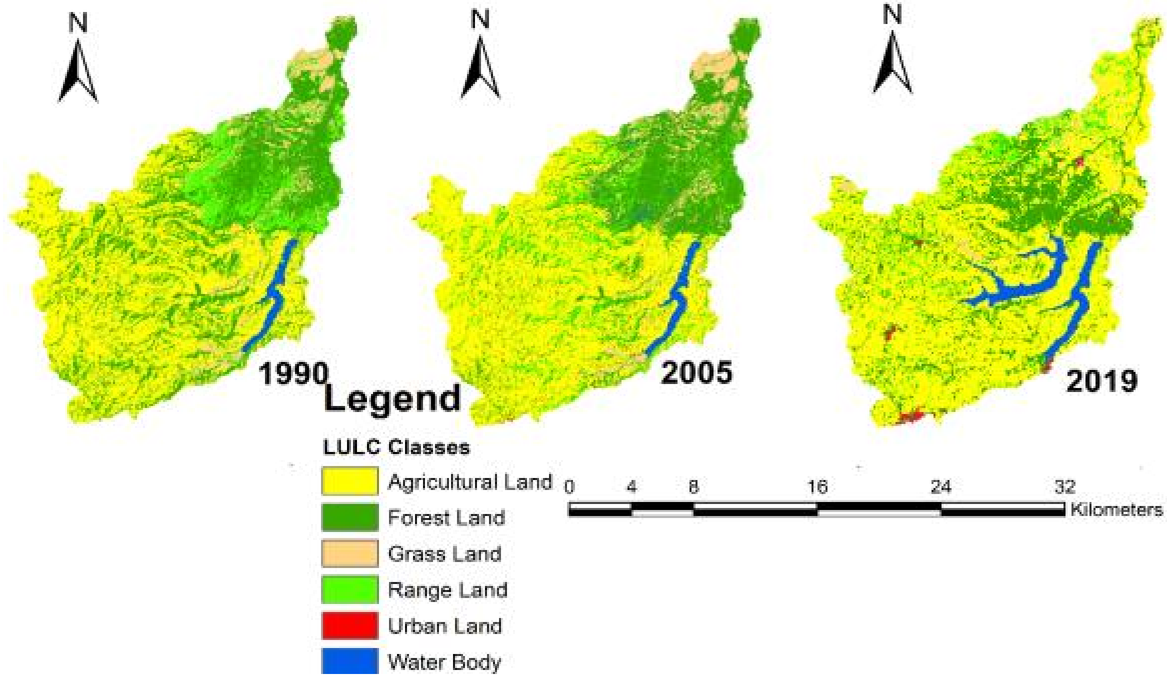


Figure 4.2. Current and historical land use land cover of the Nashe watershed.

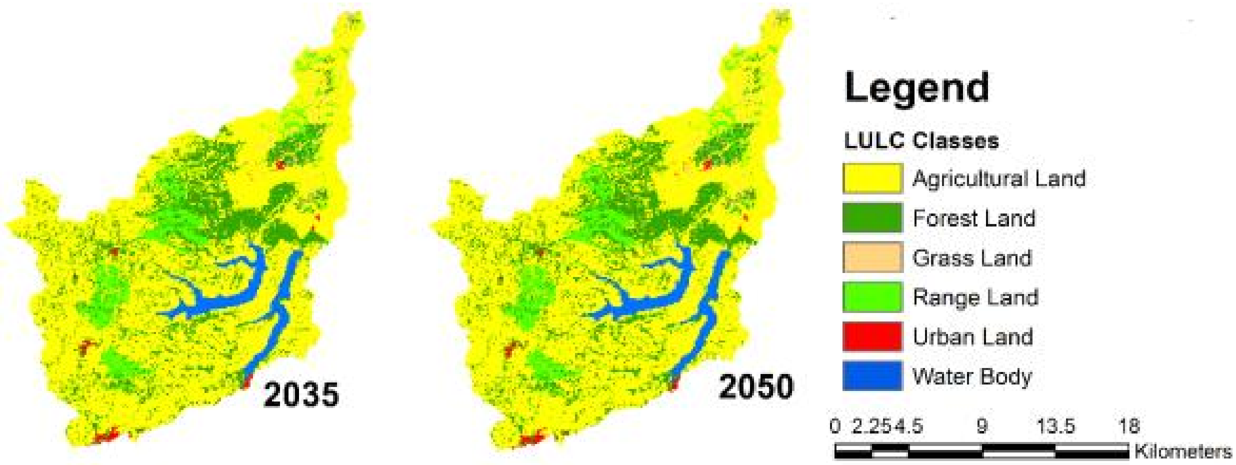


Figure 4.3. Predicted land use land cover of the Nashe watershed.

The LULC results between 1990 and 2050 revealed a significant change. From 2035 to 2050, agricultural lands, urban areas, and water bodies were predicted to increase continuously. However, compared to the result of the previous change, the rate of agricultural land expansion is lower. This might be due to the limited area of land available for the agricultural land expansion. Furthermore, the distances from urban areas and water bodies could also be another possible reason.

The LULC types of the study watershed include agricultural land, forest land, grass land, range land, water body, and urban areas. Essentially, transition potential maps were developed and processed, after which the data were linked from the current time LULC map to the predicted time. The SWAT model was used to examine the existing and future stream flow of the reservoir using current and future LULC maps as inputs.

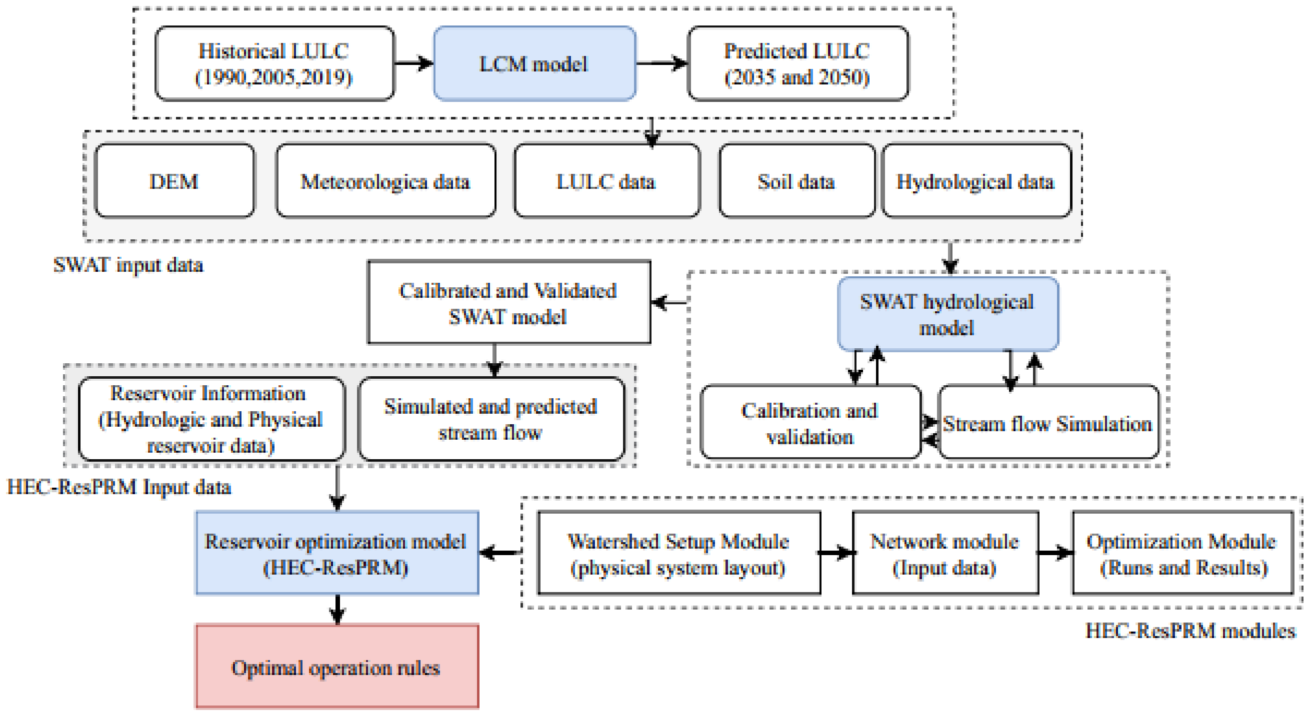


Figure 4.4. Framework of simulation-optimization model for reservoir operation.

4.2.4. Model Development

4.2.4.1. SWAT Hydrological Model

The Soil and Water Assessment Tool is a hydrological model that has been used for investigations of hydrological processes, reservoir operation, assessing the impact of LULC change, climate change on water resources, and for evaluating the effects of land management practices at the level of a watershed that operates over a daily period of time [24,54,56,57]. Precipitation, evapotranspiration, surface runoff, peak runoff, percolation, lateral flows, transmission losses, and groundwater flows are the primary components required in the surface and groundwater hydrology assessed by the SWAT. In order to simulate the future inflow projections and analyze the LULC change impact on the stream flow utilized as an input for reservoir operation, this study applied the SWAT hydrological model.

It is crucial to consider the impact of different parameters on how much the model simulates the hydrological processes in a watershed. The method of identifying the most substantial parameters for the model is by using sensitivity analysis. The sensitive parameters should be identified in order to improve the hydrological model's calibration. The most sensitive parameters identified by Leta et al. [24] were adopted in this study. The SWAT splits the watershed into hydrologic response units (HRUs) based on topography, each of which has homogeneous land use, soil properties, slope, and estimates the relative effects of soil and LULC changes within each hydrologic response unit (HRU) [24,54].

The flow in each HRU is further simulated according to the hydrologic cycle equation (Equation (8). The watershed of the Nashe has been divided into 23 sub-basins and 321 hydrological response units. The sensitivity analysis, model calibration, and validation were conducted to adjust and confirm the parameters in order to optimize the agreement between the observed and simulated stream flow of the Nashe watershed. In order to assess the goodness of the SWAT hydrological model in the Nashe watershed, the coefficients of determination (R^2), Nash–Sutcliffe efficiency (NSE), and percent bias (PBIAS) were implemented. Detailed information about model input, sensitivity analysis, calibration, validation, and model performance assessment has been given by Leta et al. [24].

4.2.4.2. HEC-ResPRM Model Description and Setup

The HEC-ResPRM, a hybrid reservoir system optimization operation developed by Hydrologic US Army Corps of Engineering Centers, has been implemented to support planners, operators, and managers with reservoir operation planning and decision making. The HEC-ResPRM modeling platform was developed to facilitate the joint development and use of simulation and optimization models in reservoir system planning and management, by coupling the HEC-PRM (Hydrologic Engineering Center-Prescriptive Reservoir Model) in graphical user interfaces (GUIs) shared with HEC-Res (common interface to both HEC-ResSIM and HEC-ResPRM) [58].

The HEC-ResPRM model stores and retrieves input and output time series data using HEC-DSS. The system is characterized as a network of nodes (reservoirs and junctions) and conveyance links with gain/loss coefficients characterize the system. The optimization problem represented by a network flow system implemented in the HEC-ResPRM model with costs associated with the flow can be described as follows:

$$\text{Minimize:} \qquad \sum_{k}^{n} C_k Q_k \tag{12}$$

$$\text{Subject to:} \qquad \sum Q_k - \sum a_k Q_k = 0 \qquad \text{(For all nodes)} \tag{13}$$

$$L_k \leq Q_k \leq U_k \qquad \text{(For all arcs)} \tag{14}$$

where n is the total number of network arcs; Ck is unit cost, weighting factor for flow along arc k; Qk is flow along arc k; ak is multiplier (gain) for arc k; Lk is lower bound on flow along the arc k; and Uk is upper bound on flow along the arc k.

The arcs represent the outflow and inflow links in the reservoir system, whereas the node represents a river and reservoir, or channel junctions in this case. Equation (12) depicts the objective function of the flow network optimization model, which minimizes the cost of the flow network. Equation (13) represents model constraints and the continuity equation at each node of the flow network. Equation (14) represents the model constraint, and the maximum and minimum flow constraints at each arc.

The reservoir simulation model is based on the water balance for tracking the movement of water through a reservoir-stream system [59], which fluctuates from time to time. The HEC-ResPRM model allows modelers to create penalty functions that reflect system objectives by relating storage or flow with cost or benefit that derive the solution to the optimization problem. Penalty functions combine a penalty (cost) or reward (negative penalty) with the designated levels of storage or flow. The penalty functions characterize the relative economic, social, environmental, and political penalties linked to the failure to achieve operational goals (storage, pool level, and power production). As a result of unavailable cost data, making penalty functions that reflect costs is a complex economic activity in this study. Therefore, the two categories of penalty functions expressed in the Nashe watershed were storage and flow.

In this study, the constraint values for reservoirs are the lower and upper bounds of reservoir storage. Penalty functions for hydropower releases and storage were established when the inflow time series was specified and reservoir constraints were added. Consequently, as long as the volume of the reservoirs is between the MFL (maximum flood level) and the MOL (minimum operating level), the cost of storage will be zero; if these values are exceeded or not reached, then penalties are applied in the Nashe watershed. The penalties applied in this study were done by changing the shape or magnitude of penalty curves, and by changing the initial and ending reservoir storage volumes.

4.2.5. Reservoir Optimization Operation

An effective reservoir operation requires policies that optimize releases from the reservoir or storage volume in order to achieve the desired objectives, such as maximizing power generation or minimizing operation costs. The reservoir's water yield is determined by the stream flow flowing into the reservoir in each time period, since the model's principle is predicated on water balance [59]. Mostly, throughout the process of water balance determination, the storage capacity must be determined first, then the water release can be computed using the standard operating rule curves. The rule curves consist of lower and upper limits to guide the release to different water demand target levels. Decisions about reservoir operation would be more challenging due to the uncertainty of inflow caused by the impacts of LULC change.

The power generation requirement can be expressed in various hydropower rules as a relationship between storage and seasons; it can also be directly expressed as an external time series in some circumstances. If the available water is greater than the upper rule curve level, water is discharged from the reservoir into the downstream river; if it is below the lower rule curve, a reduction in supply is required to maintain the water level at the conservation zone. The management of the reservoir for maximum efficiency using basic tools to release water following reservoir rule curves for which LULC change relationships have been studied [60], including improved reservoir rule curves that are appropriate for the dynamics of the hydrological environment in the future [61].

Therefore, the available water in the reservoir should be managed between the upper and lower rule curve levels. The Nashe hydropower reservoir has three major water management zones, which are the inactive (dead storage) zone, the conservation zone, and the flood control zone. In this study, the two boundary rule curves (upper and lower) are used to define the operational zones of the Nashe reservoir that yield greater energy generation. Basically, three types of rule curves, the lower rule curve, upper rule curve, and operating rule curve, were developed and used in operating a reservoir. The operation of the Nashe hydropower reservoir was investigated in this study under three LULC scenarios (2019, 2035, and 2050). Optimization was attempted using alternative options for the three scenarios in order to establish the dynamic features of the reservoir and to determine the optimal solution that could generate maximum energy.

4.3. Results and Discussion

4.3.1. Reservoir Inflow under Land Use Land Cover Change

Land use land cover change has an impact on stream flow, which is a critical hydrological response used in water resource management planning and environmental assessments [62]. The influences of LULC change on annual, seasonal, and monthly stream flow were investigated with regard to the baseline period of 1990, and 2005 for the current (2019) and future (2035 and 2050) LULC changes. Multiple land use transitions in the watershed were projected using the Land Change Modeler integrated TerrSet model [14]. The stream flow corresponding to the individual LULC variations was simulated using the SWAT hydrological model. The SWAT model was calibrated and validated from 1987 to 1999, and from 2000 to 2008, respectively, on a monthly basis.

The model result shows a strong correlation between the simulated and observed stream flows for the calibration and validation periods, as depicted in Figure 4.5. A detailed investigation of SWAT model performance utilizing graphical and statistical evaluation was presented by Leta et al. [24]. The study conducted by Leta et al. [24] on the hydrological responses of the watershed to historical and future LULC changes of the Nashe watershed, proved the efficacy of the SWAT model to simulate stream flow under varying time periods of LULC changes. The calibrated and validated SWAT model was simulated using inputs of the soil data, DEM, weather data, and projected LULC data, in order to simulate future reservoir inflow. The results of the hydrological SWAT model make it possible to recognize future trends in the inflow into the reservoir, which has the effect of improving the reservoir rule curves in the future. As a result, the future reservoir inflow variation as a function of LULC change was projected using the calibrated SWAT model.

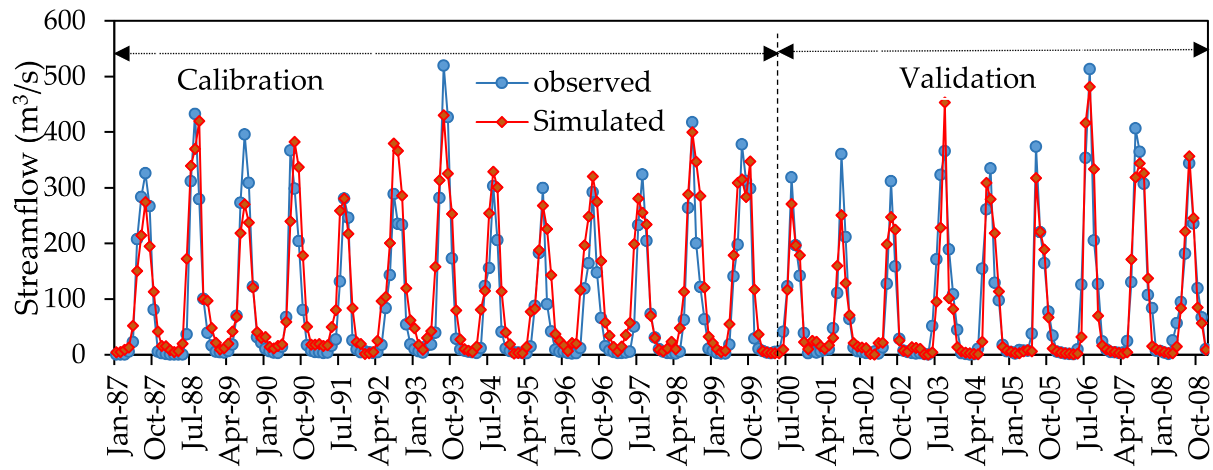


Figure 4.5. Observed and simulated average monthly stream flow of the Nashe watershed.

The average annual changes of stream flow show 1.15%, 1.36%, and 1.62% in 2019, 2035, and 2050, respectively, with respect to the historical (2005) simulated stream flow. Consequently, the results indicate that the average annual future stream flow into the reservoir shows an increasing trend for all time periods. The trend of increment and decline depend upon the rate of LULC changes. Mostly, the stream flow slightly decreased in the short rainy season and showed an increasing trend for the other seasons in the watershed. In particular, during the high rainfall season between June and September, the stream flow accounts for more than 70% of the total, whereas it is below 10% in the short rainfall season.

Figure 4.6 depicts the average monthly percentage change of current and predicted hydropower reservoir inflow patterns under LULC change impacts. The results are in agreement with the results of the study conducted by Sajikumar and Remya [63] on the impact of land use land cover change on inflow characteristics. The average monthly stream flow change shows a maximum increase of 2.43% in 2050 and a maximum decrease of 1.74% in 2019. The trend of monthly stream flow shows that, individually, there was an increasing trend from August to February and a decreasing tendency from March to July.

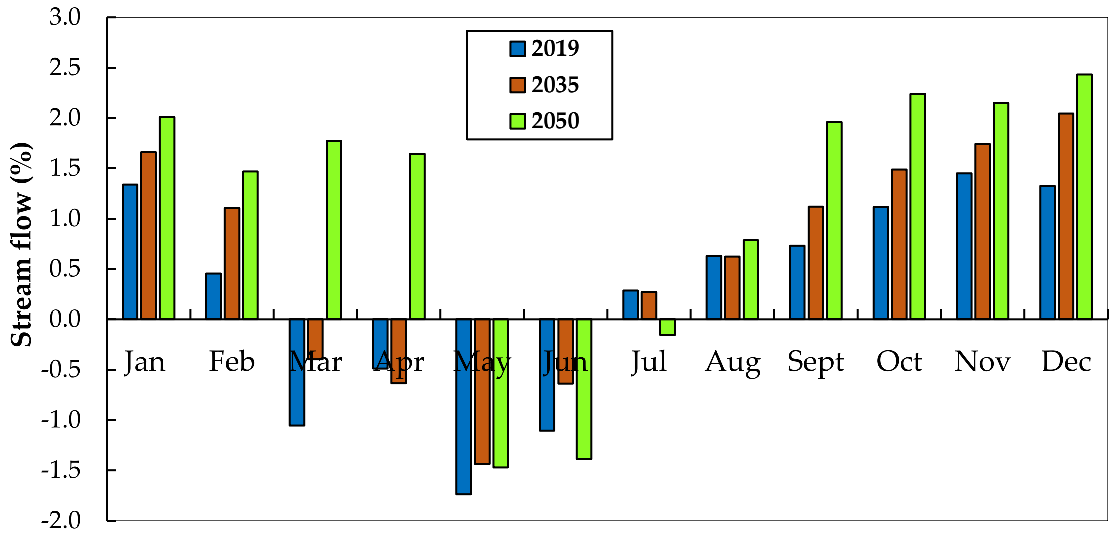


Figure 4.6. Average monthly stream flow change under land use land cover scenarios.

4.3.2. Reservoir Operation

In this study, the operation of the hydropower reservoir of the Nashe was performed under current and future trends. The foremost purpose of the Nashe hydropower reservoir construction on the Nashe River was to generate hydropower energy, which will help to substantially meet the energy requirements of the country. Furthermore, the dam produces a managed flow throughout the year, in contrast to the fluctuating seasonal flows that existed prior to dam construction. This has resulted in significant potential for downstream irrigation operations, which would improve the performance of downstream activities that were not investigated in this study as a result of unavailable diversion structure data. Operational decisions have to be made in order to reasonably balance the effects on the storage capacity and water releases between reservoirs and users throughout the time periods that further affect power generation.

The HEC-ResPRM optimization operation model used the SWAT model simulated stream flow to determine the storage, elevation (pool level), and hydropower generation of the reservoir system. The optimization model was employed under current conditions (2012–2019) after the Nashe hydropower reservoir was constructed to assess the performance of the reservoir operating model in the future. The comparison between the current optimized and actual values of the Nashe hydropower reservoir operation is presented with respect to the dynamics of current flows, elevation, storage, and power production. According to the results, the optimized hydropower reservoir operation (storage and pool level) values exhibited an increase when compared to the current actual reservoir operation status (Figures 4.7 and 4.8).

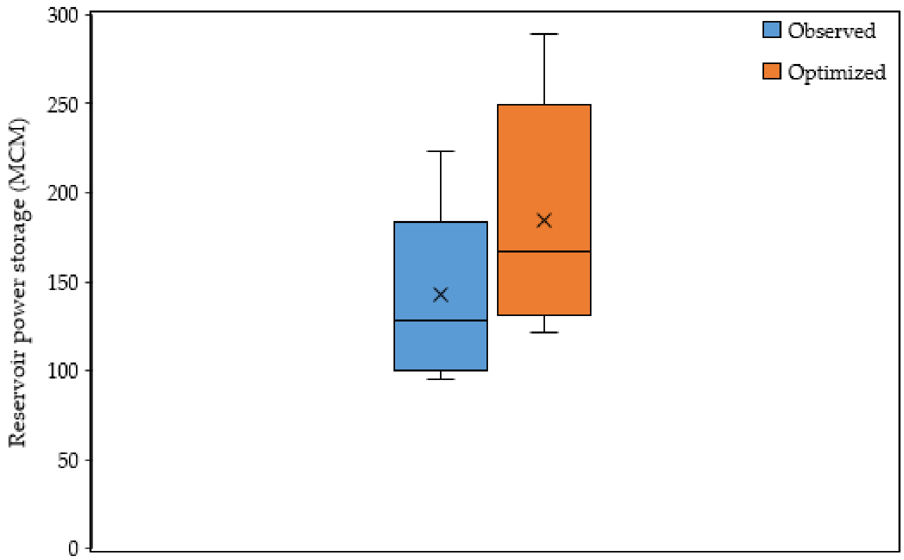


Figure 4.7. Average monthly current observed and optimized power storage of the Nashe reservoir.

The aim of performance measures is to provide a mechanism to compare the effectiveness of the reservoir system in accomplishing specific objectives quantitatively for different operating plans. In addition to the current reservoir operation, optimization strategies for the sole purpose of hydropower generation are frequently used in the area of water resources management [18]. The average annual optimized reservoir power storage and reservoir pool level increased by 10.58 MCM and 3.12 m, respectively. Figure 4.9 shows the associated optimal hydropower generation compared to the actual hydropower output. As can be seen, optimized operation performs better. Since the total volume passing the turbines is generally the same in both operation scenarios, the add-on for power supply is mainly generated by an increased storage level, and with that, an increased water head.

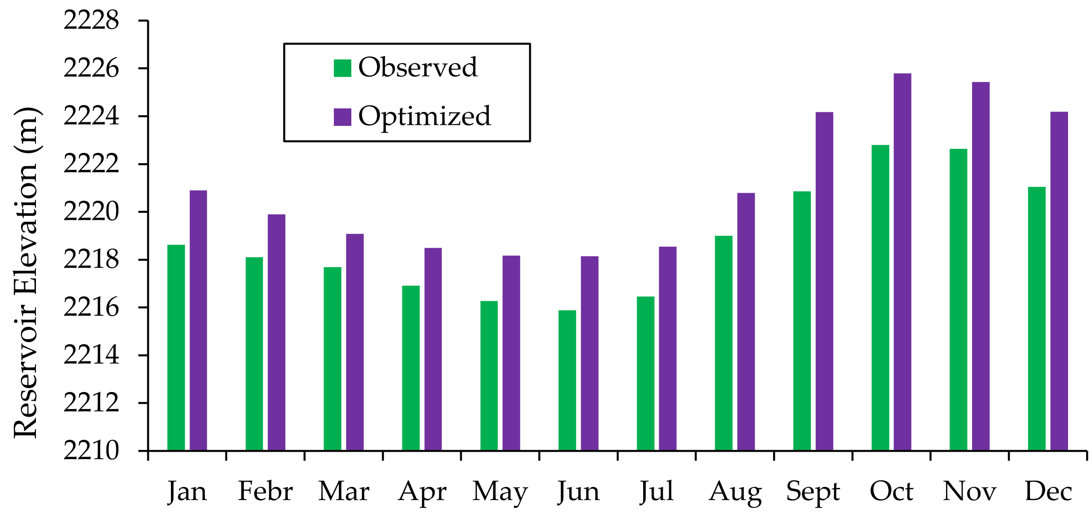


Figure 4.8. Average monthly current observed and optimized elevation of the Nashe reservoir.

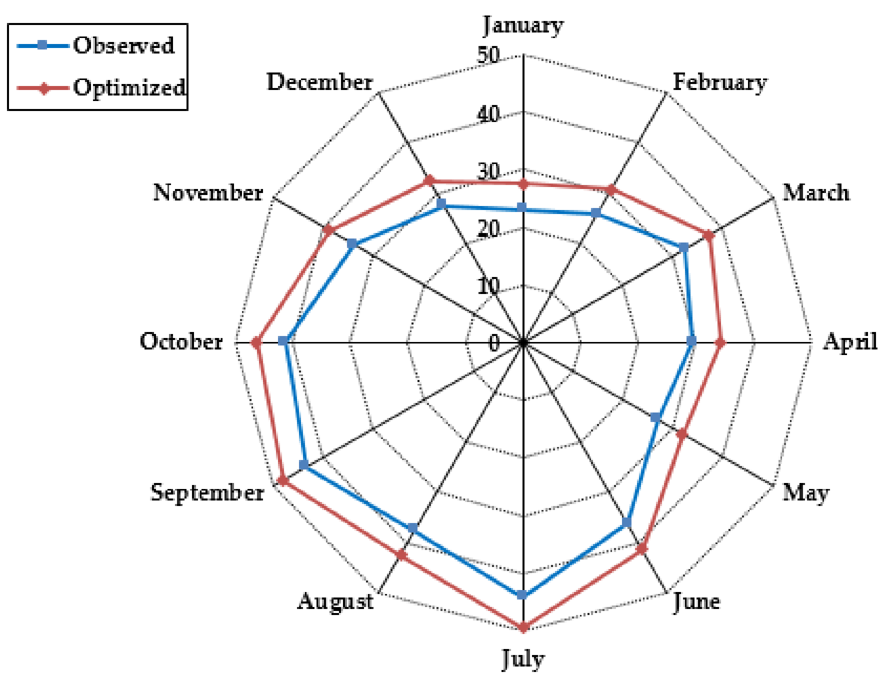


Figure 4.9. Average monthly current observed and optimized power generated of the Nashe reservoir.

4.3.3. Hydropower Generation under Land Use Land Cover Changes

4.3.3.1. Reservoir Inflow and Outflow

The average simulated total inflows to the study hydropower reservoir show an increasing trend, as per the inflow prediction model under all LULC change scenarios. Inflows are also a limiting factor for mean hydropower. Releases (outflows) are used for the watershed optimization model to determine reservoir storage, water levels, and power generation. Similarly, the releases from the reservoir are utilized to assess the objective function for reservoir optimization, and depend on the water availability in the reservoir, prevailing users, and projected reservoir inflow. The surplus water release and water shortage, as well as the average annual shortage, were determined using the released water from the reservoir.

The optimization model was applied for the Nashe hydropower reservoir in order to generate the monthly optimal releases to meet the target demand of the watershed under LULC scenarios for the time periods of 2019, 2035, and 2050. In order to avoid the significant penalties associated with high releases, the model optimizes hydropower release using pre-release before high inflows. Thus, the reservoir release decisions are based on specified storage zones defined by elevation, and on a set of rules that specify the aims and constraints governing releases when the storage level falls within each zone. Therefore, the increased inflow in the development scenarios resulted in an accordingly adapted water release.

Correspondingly, the increased reservoir inflow also increases the reservoir outflow in all future periods, producing more energy from hydropower. According to Kangrang et al. [28], excess water release while increasing stream flow to produce more energy was demonstrated on active future rule curves for multipurpose reservoir operation under the effect of LULC changes. As depicted in Figure 4.10, the results of optimal reservoir operation, including inflows and reservoir release, were compared to those of the current period. The volume of reservoir inflow begins to increase in May and reaches its maximum in July, but afterward begins to decrease significantly from October, following the decline of rainfall. In addition to variations in mean monthly inflows and outflows, seasonal and annual distributions of inflows and outflows have also been investigated.

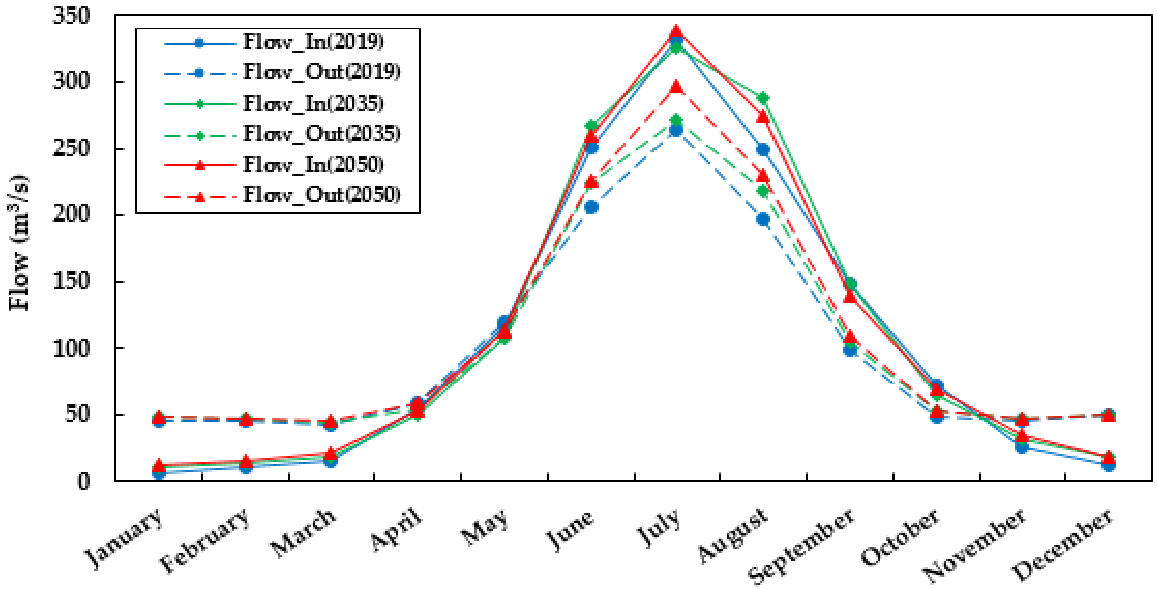


Figure 4.10. Average monthly reservoir inflow and optimized outflow under LULC changes.

The increased outflow in the Nashe watershed will increase the inflow to the Grand Ethiopian Renaissance Dam. Thus, the downstream users also benefited from the increased stream flow in the future. Zhang et al. [64] found similar results following analysis of the inter-annual and decades scale stream flow variations of the GERD. Reservoir development, according to Soleimani et al. [9], intends to relieve regional water scarcity problems through the redistribution of water resources with temporal variability and spatial heterogeneity. Besides greater net benefits with increasing storage in Ethiopia, floods and droughts will be reduced, and the hydrological uncertainties will be nullified, particularly during low flow periods.

During the season of rain, the water volume flowing into the reservoir is typically at its maximum, making it difficult to control the excessive outflow. Similarly, as depicted in Figure 4.10, average outflow values were also highest during the wet season, mostly in June, July, and August, while decreasing in the other seasons. The high runoff season of the study area begins mostly in June and ends in September. From November to April, it is the only base flow that flows into the reservoir. Similarly, during this time period, the outflow exceeds the inflow. From the results, it was observed that the average maximum monthly reservoir inflow ranges between 320 m^3/s and 350 m^3/s in 2019, 2035, and 2050.

The average monthly optimal reservoir inflow and releases (outflow) in the 2050 LULC change scenario are greater than the other scenarios in all time periods. Generally, plentiful rainfall in the wet season increased both the Nashe reservoir inflow and outflow. During the short rainy season, the difference between the inflows and outflows was minimal, especially in April and May. According to Guo et al. [15], future land use land cover changes will almost definitely continue to alter stream flow patterns, posing considerable reservoir management challenges.

4.3.3.2. Reservoir Storage and Elevation

The desired storage, which was determined by applying the HEC-ResPRM model for hydropower generation, is a variable in the reservoir operation optimization model. The storage capacity of a reservoir varies, depending on inflow and outflow variations. However, the increment of reservoir inflow is the main factor for increasing reservoir storage. Therefore, the specified reservoir storage for the various operating strategies was achieved using the three time period (2019, 2035, and 2050) optimization scenarios. The reservoir optimization model results revealed a significant increase in predicted mean annual hydropower reservoir storage under the 2035 and 2050 LULC change scenarios of the Nashe watershed. The maximum average monthly optimum reservoir storage shows 289 million cubic meter (Mm^3) in 2019, 307 Mm^3 in 2035, and 313 Mm^3 in 2050 (Figure 4.11).

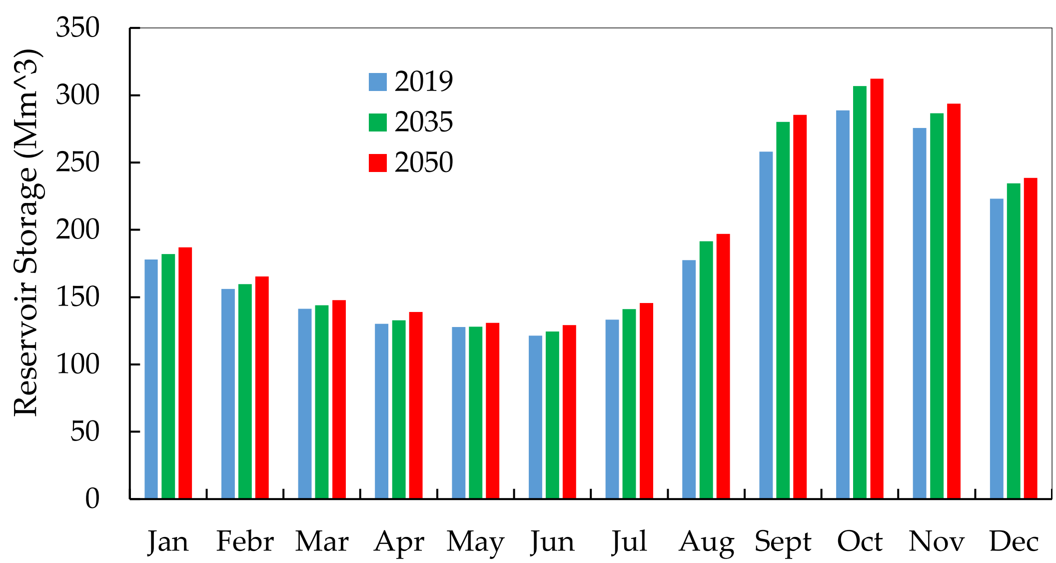


Figure 4.11. Average monthly current optimized and future reservoir storage of Nashe reservoir.

The optimum reservoir storage occurred between September to December, with peak storage in October. The optimized future storage volumes for the reservoir within scenarios are greater than the current actual and optimized reservoir operations. However, most of the average storage volumes are close to the optimized current reservoir storage operation, especially during dry and short rainy seasons. Likewise, the storage volumes for the 2035 LULC scenario maximum volume are more comparable to the 2050 future scenario operation. According to [65,66] investigations, the optimum reservoir storage obtained by using the optimization algorithm for the reservoir should be better than the currently used operational storage for optimizing annual hydropower production. Figure 4.11 illustrates the average monthly reservoir storage results derived by the HEC-ResPRM optimization model for operations in 2019, 2035, and 2050.

In order to generate more head and hence more energy, the first scenario requires greater amounts of water storage within the reservoir relative to the second scenario. Furthermore, the findings depicted that the reservoir storage declined from the middle of February, and reached a minimum storage level in June. During this month, it helps to release more water volume in order to prepare for the next main rainy season. However, the simulation process determines the reservoir at each time step and the resulting downstream flows by considering the reservoir storage balance equation while keeping the system in balance. In conclusion, based on the results of the optimization approach, power storage generation could be optimized, and should not result in significant water shortages in most of the years (Figures 4.11 and 4.12).

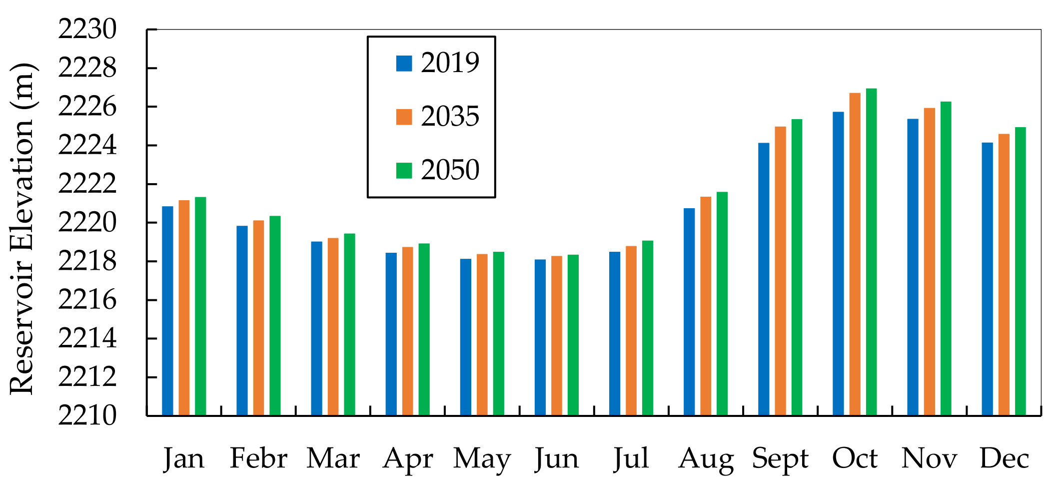


Figure 4.12. Average monthly current optimized and future reservoir elevation of the Nashe reservoir.

Nevertheless, it is recommended to further decrease the spill of water during the wet season to avoid shortages of water in the following year. Therefore, the results show that the maximum reservoir storage in scenarios is more than the historical projected operations. This finding is in agreement with Lu et al. [1], Azizipour et al. [4], and He et al. [67] in their indications for the optimal levels of release and optimal volumes of storage in different parts of the world. The impacts of the change in LULC on the Nashe hydropower reservoir operation through the use of optimization models reveal a positive impact on the reservoir storage and its pool level. The major features of the reservoir pool define the volume of storage and the surface area at each level.

The Nashe hydropower reservoir pool level contains the relationship of the elevation-storage-area curve. The average monthly maximum and minimum reservoir levels for the future vary between 2226.76 m and 2227.01 m, and 2218.34 m and 2218.40 m, respectively, for the 2035 and 2050 LULC change scenarios, respectively. The results of reservoir elevation between operations in 2019, 2035, and 2050 were compared and are illustrated in Figure 4.12. From the results, it was observed that the optimized pool level is greater than the current optimal reservoir levels of the Nashe hydropower reservoir.

Similar to reservoir storage, the reservoir pool level remains at a high level every year from September to December. However, the reservoir reaches a maximum level in October, near the end of the rainy season. In general, the findings show that the reservoir system has appropriate storage distributions and water allocations for the entire period. Hydropower generation is a priority when available water is above average and increased hydropower generation is required [6]. The reservoir authority and policymakers could use the various possible operational storage and elevation rules to assist them in developing efficient and long-term guidelines for several competing issues.

4.3.3.3. Reservoir Power Generation

The change in the hydropower generation caused by the LULC changes in the future scenarios (2035 and 2050) was explored by utilizing the current LULC scenario (2019) as a point of comparison. The optimization operation model employed the future stream flow data simulated by the SWAT hydrological model, and observed power production as input to develop the Nashe reservoir’s future power generation. The average annual power generation from the Nashe reservoir under different LULC time period scenarios (currently optimized and future), including the actual operation of the reservoir, is depicted in Figure 4.13. Therefore, Figure 4.13 shows that 2050 reservoir operation leads to improved power generation compared to the observed, optimized, 2035, and 2050 scenarios.

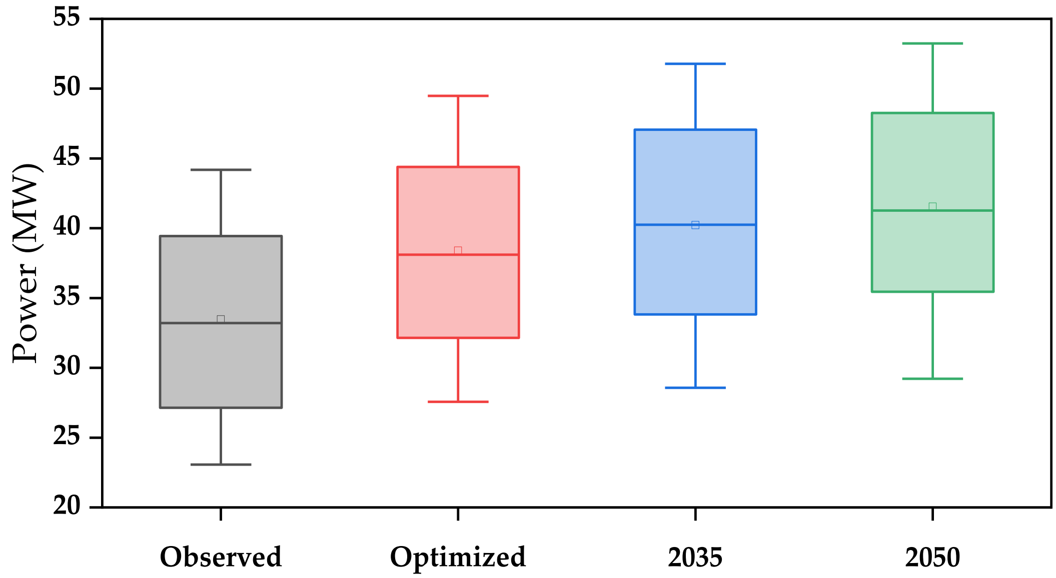


Figure 4.13. Boxplots of monthly hydropower generation of the Nashe watershed under different scenarios.

The findings propose that the outcomes of the future scenario optimization model are the most promising for increasing energy development. However, the fluctuations in power generation over time suggest that LULC changes have an impact on reservoir performance for energy production. Furthermore, the average annual energy production utilizing the HEC-ResPRM model for the 2035 and 2050 time periods is higher than that of the current actual and optimized energy generation of the reservoir. In comparison to the reservoir's optimal operation in 2019; the average hydropower generation increased by 4.83%, and 8.32% for 2035 and 2050, respectively. As a result, when compared to earlier periods, this indicates a gradually increasing trend. Generally, there are no significant variations between the scenarios in terms of hydropower potential generation.

The results of the hydropower generation are consistent with the results of the stream flow simulation. The trend of average annual stream flow and hydropower generation shows an increment in each of the future LULC time period scenarios due to the close relationship between hydropower generation and stream flow. Optimal hydropower occurs mostly during the rainy season under all scenarios, as a result of the increased inflow and water release. Between October and April, reservoir inflow decreases, resulting in a significant reduction in hydropower generation. In contrast, the increment of inflow from May to September contributes to a high pre-water level.

In all scenarios, the months of October to January, considered as dry months for the watershed, are projected to have a considerable increase in hydropower generation. Additionally, the peak value of hydropower generation is detected mostly in the wet season, especially in July, with minimum power generation happening in January. Similarly, the reason for a significant increment in inflow during the rainy period is that it encourages water impoundment, resulting in higher power output. Consequently, when the reservoir accumulates a high amount of water during the wet season, a high water level can be reached in the dry season, providing a larger water head for hydropower generation. Generally, reservoir management is expected to be affected by changes in the spatial and temporal availability of water at reservoir locations [68].

4.3.4. Optimal Operating Rule Curves

The operating rules for the reservoir system under this investigation were derived from the time series for reservoir storage and pool level generated by the optimization model during the entire period. It is necessary to obtain an appropriate guideline for effective reservoir storage and release balance, taking into consideration the objectives of the project for reservoir operation. Rule curves could be expressed in a number of ways, including water surface elevation or storage volume with respect to time of the year. The HEC-ResPRM optimization model was utilized to operate the current and future reservoir rule curves of the Nashe hydropower reservoir. Reservoir operation rule curves are the most frequent techniques used to determine the pace at which water is released and stored depending on currently existing information, such as the current status of storage volume and forecasted inflow [20]. Future optimal rule curves are required for operating reservoir under uncertainty situation. The optimization results for the storage volume (Figure 4.14a) and pool level (Figure 4.14b) indicate that the 2035 and 2050 future scenarios rule curves are slightly higher than the current curves.

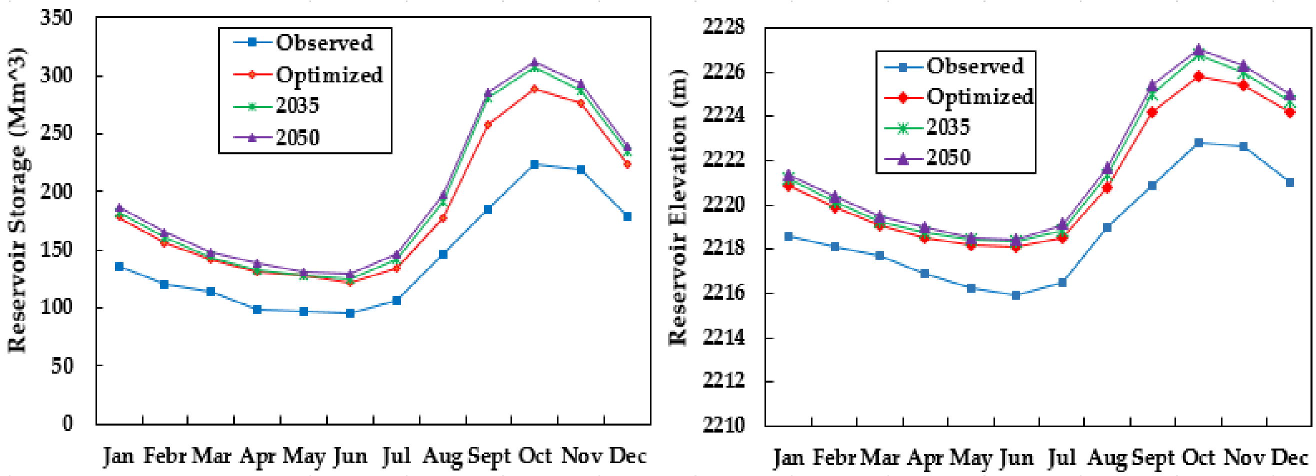


Figure 4.14. Nashe reservoir mean monthly power storage (a) and pool level (b) rule curves for current and future time periods.

Figure 4.14 shows the optimal rule curves for the 2035 and 2050 scenarios in comparison to the existing rule curves. The rule curve features are based on the quantity of the inflow, which is ascribed to rainfall patterns and reservoir operation in proportion to monthly energy requirements. The power rule curves of the future scenarios also follow similar tendencies, but are higher compared to current optimized and efficient rule curves, with uneven power distribution from month to month. The 2050 LULC scenario rule curve shows the highest average power storage, reservoir level, power production, and total energy. According to [65,66], the optimal operating rules for reservoirs should be better than the current random operational rules using an optimization algorithm for annual hydropower production.

The reservoir operation focuses on the upper rule curves throughout the rainy season, since the volume of water flowing into the reservoir is very high, and is necessary to control the excess release reservoir operation focuses on the lower rule curves in the event of lower-than-average rainfall, resulting in low flow. The reservoir always wants to release more water than that entering the pool when the reservoir's pool elevation is above the guide curve in flood control, and releases less water than that entering the pool when below the guide curve in conservation. In addition, the reservoir will be able to withstand the excessive volume of water that might finally lead to a flood, since it has more space to reserve excess amounts of water without an overflow situation.

Therefore, rule curves are crucial in order to control the effects of flash floods through dams. As a result, these curves can be suggested to be guidelines for reservoir operation, ensuring that all water demands are satisfied on a monthly basis. In general, all demands are satisfied as long as the reservoir's current water levels and storage fall between the upper and lower rule curves. The water level in the Nashe reservoir is generally in the conservation zone, which is a safe zone for power generation, and reduces risks to dam safety and other structures. Therefore, the curves show the desired storage levels in the reservoir during the operation of reservoirs to satisfy the demands of hydropower production, environmental release, and flood protection.

The optimized model rule curve indicates that the maximum reservoir water level is about 2227.01 masl (Figure 4.14b), while the full reservoir level is 2230 masl. The study by Prasanchum and Kangrang [16] proved that the new rule curves can be helpful when connected to the simulation model, and this could prevent water shortages in the future. The long-term average elevation, storage, and hydropower capacity obtained in this study can be used as a rule curve under the uncertainty due to land use land cover change. Generally, in the Nashe watershed, decisions based on reservoir operating rule curves are critical to achieving seasonally and annually balanced water release, as well as protecting reservoir downstream areas from flooding.

4.4. Conclusions

In this study, the LULC changes from the Land Change Modeler, which represent the current and future prediction scenarios, were assessed in order to determine the base and future inflows into the Nashe hydropower reservoir. As a result, the calibrated and validated SWAT model was utilized to generate LULC change-driven stream flow, which was then used as an input for modeling optimal reservoir operation. The reservoir optimization model has been utilized to develop optimal hydropower reservoir operation policies (storage and releases) for the Nashe hydropower reservoir, using a combination of the SWAT and the HEC-ResPRM optimization algorithm; this was implemented in order to meet the target storage and maximize reservoir capacity to generate hydropower under current and future LULC conditions. The following conclusions were reached as a result of the study's key contribution:

- The estimated optimal reservoir operations for all scenarios have distinct values but follow similar tendencies. This indicates that the seasonal hydropower generation is affected by stream flow and that the future inflow from the reservoir area is substantially more susceptible to future LULC changes. The optimal rule curves that were developed perform significantly better under future inflow scenarios compared to current rule curves, which allow the reservoir to be more effective and appropriate in terms of water release and storage for future scenarios to generate more energy.

- The optimal solution could maintain a higher level of water in the reservoir, and the optimized policy may increase hydropower generation during the wet season, while also increasing the possibility of water accessibility during the following dry season.

- The possibility of improved water resource utilization in the future, particularly with vigorous operating rules that consider optimization and uncertainty, can be utilized as a guide for the future operation of hydropower planning. The development of appropriate reservoir operating rules is critical for planning and management, particularly from the perspective of LULC change.

- The findings are intended to provide information to policymakers, water resource managers, and other interested stakeholders so that future development in the Nashe watershed of the Blue Nile River basin can be more effective.

- Furthermore, the findings suggest that the methodology utilized in this research can be used to evaluate and optimize current systems, as well as emphasize the importance of using predicted land use land cover change as an assessment tool for reservoir management in the future.

- Generally, changes in LULC have an impact on the quantity of water available for energy generation in hydropower reservoirs. Land use land cover changes can cause soil deterioration (silting), which can affect both the watershed and the reservoir level as a result of sediment transport, and thus exacerbate the negative effects of climate change.

- As a result, it is essential to perform studies that take into account a variety of variables in order to produce accurate scenarios for the future availability of water resources for hydropower generation and to define regulations for flexible reservoir operation.

References

1. Lu, B.; Li, K.; Zhang, H.; Wang, W.; Gu, H. Study on the optimal hydropower generation of Zhelin reservoir. J. Hydro-Environ. Res. 2013, 7, 270–278. https://doi.org/ 10.1016j.jher.2013.01.002.

2. Yazdi, J.; Moridi, A. Interactive Reservoir-Watershed Modeling Framework for Integrated Water Quality Management. Water Resour. Manag. 2017, 31, 2105–2125. https://doi.org/10.1007/s11269-017-1627-4.

3. Xu, M.; Li, C.; Wang, X.; Cai, Y.; Yue, W. Optimal water utilization and allocation in industrial sectors based on water footprint accounting in Dalian City, China. J. Clean. Prod. 2018, 176, 1283–1291. https://doi.org/10.1016/j.jclepro.2017.11.203.

4. Azizipour, M.; Ghalenoei, V.; Afshar, M.H.; Solis, S.S. Optimal Operation of Hydropower Reservoir Systems Using Weed Optimization Algorithm. Water Resour. Manag. 2016, 30, 3995–4009. https://doi.org/10.1007/s11269-016-1407-6.

5. Birhanu, K.; Alamirew, T.; Dinka, M.O.; Ayalew, S.; Aklog, D. Optimizing Reservoir Operation Policy Using Chance Constraint Nonlinear Programming for Koga Irrigation Dam, Ethiopia. Water Resour. Manag. 2014, 28, 4957–4970. https://doi.org/ 10.1007/s11269-014-0770-4.

6. Yang, T.; Gao, X.; Sellars, S.L.; Sorooshian, S. Improving the multi-objective evolutionary optimization algorithm for hydropower reservoir operations in the California Oroville-Thermalito complex. Environ. Model Softw. 2015, 69, 262–279. https://doi.org/10.1016/j.envsoft.2014.11.016.

7. Chou, F.N.-F.; Wu, C.-W. Stage-wise optimizing operating rules for flood control in a multi-purpose reservoir. J. Hydrol. 2015, 521, 245–260. https://doi.org/10.1016/j. jhydrol.2014.11.073.

8. Daniel, A. Water Use and Operation Analysis of Water Resource Systems in Omo Gibe River Basin. Master's Thesis, Addis Ababa University, Addis Ababa, Ethiopia, 2011 May.

9. Soleimani, S.; Bozorg-Haddad, O.; Loáiciga, H.A. Reservoir Operation Rules with Uncertainties in Reservoir Inflow and Agricultural Demand Derived with Stochastic Dynamic Programming. J. Irrig. Drain. Eng. 2016, 142, 04016046. https://doi.org/ 10. 1061/ (ASCE) ir.1943-4774.0001065.

10. Feng, M.; Liu, P.; Guo, S.; Gui, Z.; Zhang, X.; Zhang, W.; Xiong, L. Identifying changing patterns of reservoir operating rules under various inflow alteration scenarios. Adv. Water Resour. 2017, 104, 23–36. https://doi.org/10.1016/j.advwatres.2017.03.003.
11. Sangiorgio, M.; Guariso, G. NN-Based Implicit Stochastic Optimization of Multi-Reservoir Systems Management. Water 2018, 10, 303. https://doi.org/10.3390/w10030303.
12. Fayaed, S.S.; El-Shafie, A.; Jaafar, O. Reservoir-system simulation and optimization techniques. Stoch. Hydrol. Hydraul. 2013, 27, 1751–1772. https://doi.org/10.1007/s00477-013-0711-4.
13. Zhou, J.; Jia, B.; Chen, X.; Qin, H.; He, Z.; Liu, G. Identifying Efficient Operating Rules for Hydropower Reservoirs Using System Dynamics Approach—A Case Study of Three Gorges Reservoir, China. Water 2019, 11, 2448. https://doi.org/10.3390/ w11122448.
14. Leta, M.; Demissie, T.; Tränckner, J. Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed, Upper Blue Nile Basin, Ethiopia. Sustainability 2021, 13, 3740. https://doi.org/ 10.3390/ su13073740.
15. Guo, Y.; Fang, G.; Xu, Y.-P.; Tian, X.; Xie, J. Responses of hydropower generation and sustainability to changes in reservoir policy, climate and land use under uncertainty: A case study of Xinanjiang Reservoir in China. J. Clean. Prod. 2020, 281, 124609. https:// doi.org/10.1016/j.jclepro.2020.124609.
16. Prasanchum, H.; Kangrang, A. Optimal reservoir rule curves under climatic and land use changes for Lampao Dam using Genetic Algorithm. KSCE J. Civ. Eng. 2017, 22, 351–364. https://doi.org/10.1007/s12205-017-0676-9.
17. Asadieh, B.; Afshar, A. Optimization of Water-Supply and Hydropower Reservoir Operation Using the Charged System Search Algorithm. Hydrology 2019, 6, 5. https:// doi.org/10.3390/hydrology6010005.
18. Fan, J.-L.; Hu, J.-W.; Zhang, X.; Kong, L.-S.; Li, F.; Mi, Z. Impacts of climate change on hydropower generation in China. Math. Comput. Simul. 2018, 167, 4–18. https://doi. org/10.1016/j.matcom.2018.01.002.

19. Paliwal, V.; Ghare, A.D.; Mirajkar, A.B.; Bokde, N.D.; Lorenzo, A.E.F. Computer Modeling for the Operation Optimization of Mula Reservoir, Upper Godavari Basin, India, Using the Jaya Algorithm. Sustainability 2019, 12, 84. https://doi.org/ 10.3390/ su12010084.

20. Zhang, J.; Liu, P.; Wang, H.; Lei, X.; Zhou, Y. A Bayesian model averaging method for the derivation of reservoir operating rules. J. Hydrol. 2015, 528, 276–285. https://doi. org/10.1016/j.jhydrol.2015.06.041.

21. Zuo, D.; Xu, Z.; Yao, W.; Jin, S.; Xiao, P.; Ran, D. Assessing the effects of changes in land use and climate on runoff and sediment yields from a watershed in the Loess Plateau of China. Sci. Total Environ. 2016, 544, 238–250. https://doi.org/10.1016/j. scitotenv.2015.11.060.

22. Waseem, M.; Kachholz, F.; Tränckner, J. Suitability of common models to estimate hydrology and diffuse water pollution in North-eastern German lowland catchments with intensive agricultural land use. Front. Agric. Sci. Eng. 2018, 5, 420–431.

23. Kumari, N.; Srivastava, A.; Sahoo, B.; Raghuwanshi, N.S.; Bretreger, D. Identification of Suitable Hydrological Models for Stream flow Assessment in the Kangsabati River Basin, India, by Using Different Model Selection Scores. Nonrenewable Resour. 2021, 30, 4187–4205. https://doi.org/10.1007/s11053-021-09919-0.

24. Leta, M.K.; Demissie, T.A.; Tränckner, J. Hydrological Responses of Watershed to Historical and Future Land Use Land Cover Change Dynamics of Nashe Watershed, Ethiopia. Water 2021, 13, 2372. https://doi.org/10.3390/w13172372.

25. Zhang, L.; Meng, X.; Wang, H.; Yang, M. Simulated Runoff and Sediment Yield Responses to Land-Use Change Using the SWAT Model in Northeast China. Water 2019, 11, 915. https://doi.org/10.3390/w11050915.

26. Anand, J.; Gosain, A.K.; Khosa, R. Optimisation of Multipurpose Reservoir Operation by Coupling Soil and Water Assessment Tool (SWAT) and Genetic Algorithm for Optimal Operating Policy (Case Study: Ganga River Basin). Sustainability 2018, 10, 1660. https://doi.org/10.3390/su10051660.

27. Megersa, K.; Ankit, C.; Tamene, A. Stream Flow and Land Use Land Cover Change in Finchaa Hydropower, Blue Nile Basin, Ethiopia. Int. J. Civil. Struct. Environ. Infrastruct Eng. Res. Dev. 2017, 7, 1–12.

28. Kangrang, A.; Prasanchum, H.; Hormwichian, R. Active future rule curves for multi-purpose reservoir operation on the impact of climate and land use changes. J. Hydro-Environ. Res. 2019, 24, 1–13. https://doi.org/10.1016/j.jher.2019.03.001.

29. Lin, B.; Chen, X.; Yao, H.; Chen, Y.; Liu, M.; Gao, L.; James, A. Analyses of land use change impacts on catchment runoff using different time indicators based on SWAT model. Ecol. Indic. 2015, 58, 55–63. https://doi.org/10.1016/j.ecolind.2015.05.031.

30. Labadie, J.W. Optimal Operation of Multireservoir Systems: State-of-the-Art Review. J. Water Resour. Plan. Manag. 2004, 130, 93–111. https://doi.org/10.1061/(asce)0733-9496 (2004)130:2(93).

31. Rozos, E. An assessment of the operational freeware management tools for multi-reservoir systems. Water Supply 2018, 19, 995–1007. https://doi.org/10.2166/ws. 2018. 169.

32. Choi, Y.; Lee, E.; Ji, J.; Ahn, J.; Kim, T.; Yi, J. Development and Evaluation of the Hydropower Reservoir Rule Curve for a Sustainable Water Supply. Sustainability 2020, 12, 9641. https://doi.org/10.3390/su12229641.

33. Ozkaya, A.; Zerberg, Y. Water storage change assessment in the Seyhan Reservoir (Turkey) using HEC-ResSim model. Arab. J. Geosci. 2021, 14, 1–12.

34. Zeng, X.; Hu, T.; Guo, X.; Li, X. Water Transfer Triggering Mechanism for Multi-Reservoir Operation in Inter-Basin Water Transfer-Supply Project. Water Resour. Manag. 2014, 28, 1293–1308. https://doi.org/10.1007/s11269-014-0541-2.

35. Chou, F.N.-F.; Linh, N.T.T.; Wu, C.-W. Optimizing the Management Strategies of a Multi-Purpose Multi-Reservoir System in Vietnam. Water 2020, 12, 938. https:// doi. org/10.3390/w12040938.

36. Ehteram, M.; Koting, S.B.; Afan, H.A.; Mohd, N.S.; Malek, M.A.; Ahmed, A.N.; El-Shafie, A.H.; Onn, C.C.; Lai, S.H.; El-Shafie, A. New Evolutionary Algorithm for Optimizing Hydropower Generation Considering Multireservoir Systems. Appl. Sci. 2019, 9, 2280. https://doi.org/10.3390/app9112280.

37. Nourani, V.; Rouzegari, N.; Molajou, A.; Hosseini, B.A. An integrated simulation-optimization framework to optimize the reservoir operation adapted to climate change scenarios. J. Hydrol. 2020, 587, 125018.https: //doi.org/10.1016/j.jhydrol. 2020.125018.

38. Nandalal, K.D.W.; Bogardi, J.J. Dynamic programming based operation of reservoirs: Applicability and limits. Dyn. Program Based Oper. Reserv. Appl. Limits. 2013, 31, 1–130.

39. Ashrafi, S.; Ashrafi, S.; Moazami, S. Developing Self-adaptive Melody Search Algorithm for Optimal Operation of Multi-reservoir Systems. J. Hydraul. Struct. 2017, 3, 35–48.

40. Abera, F.F.; Asfaw, D.H.; Engida, A.N.; Melesse, A.M. Optimal Operation of Hydropower Reservoirs under Climate Change: The Case of Tekeze Reservoir, Eastern Nile. Water 2018, 10, 273. https://doi.org/10.3390/w10030273.

41. Faber, B.A.; Harou, J.J. Multi-objective optimization of reservoir systems using HEC-ResPRM. Restoring Our Nat Habitat. In Proceedings of the 2007 World Environmental and Water Resources Congress, Tampa, Florida, United States, May 15–19, 2007, pp. 1–14.

42. Khare, D.; Patra, D.; Mondal, A.; Kundu, S. Impact of land use/land cover change on run-off in the catchment of a hydro power project. Appl. Water Sci. 2015, 7, 787–800. https://doi.org/10.1007/s13201-015-0292-0.

43. Bahati, H.K.; Ogenrwoth, A.; Sempewo, J.I. Quantifying the potential impacts of land-use and climate change on hydropower reliability of Muzizi hydropower plant, Uganda. J. Water Clim. Chang. 2021, 12, 2526–2554. https://doi.org/ 10.2166/ wcc. 2021. 273.

44. Nguyen, A.; Cochrane, T.; Pahlow, M. A Framework to Assess the Reliability of a Multipurpose Reservoir under Uncertainty in Land Use. Water 2021, 13, 287. https://doi.org/10.3390/w13030287.

45. Falchetta, G.; Kasamba, C.; Parkinson, S.C. Monitoring hydropower reliability in Malawi with satellite data and machine learning. Environ. Res. Lett. 2019, 15, 014011. https://doi.org/10.1088/1748-9326/ab6562.

46. Samaan, M.M. The Win-Win-Win Scenario in the Blue Nile's Hydropolitical Game: Application on the Grand Ethiopian Renaissance Dam; GESIS-Leibniz-Institut für Sozialwissenschaften: Mannheim, Germany, 2014.

47. Goor, Q.; Halleux, C.; Mohamed, Y.; Tilmant, A. Optimal operation of a multipurpose multireservoir system in the Eastern Nile River Basin. Hydrol. Earth Syst. Sci. 2010, 14, 1895–1908. https://doi.org/10.5194/hess-14-1895-2010.

48. Jeuland, M.; Wu, X.; Whittington, D. Infrastructure development and the economics of cooperation in the Eastern Nile. Water Int. 2017, 42, 121–141. https://doi.org/ 10.1080/ 02508060.2017.1278577.

49. McCartney, M.P.; Girma, M.M. Evaluating the downstream implications of planned water resource development in the Ethiopian portion of the Blue Nile River. Water Int. 2012, 37, 362–379. https://doi.org/10.1080/02508060.2012.706384.v.

50. Arjoon, D.; Mohamed, Y.; Goor, Q.; Tilmant, A. Hydro-economic risk assessment in the eastern Nile River basin. Water Resour. Econ. 2014, 8, 16–31. https://doi.org/ 10.1016/ j.wre.2014.10.004.

51. Mulat, A.G.; Moges, S.A. Assessment of the Impact of the Grand Ethiopian Renaissance Dam on the Performance of the High Aswan Dam. J. Water Resour. Prot. 2014, 6, 583–598. https://doi.org/10.4236/jwarp.2014.66057.

52. Yesuph, A.Y.; Dagnew, A.B. Land use/cover spatiotemporal dynamics, driving forces and implications at the Beshillo catchment of the Blue Nile Basin, North Eastern Highlands of Ethiopia. Environ. Syst. Res. 2019, 8, 21. https://doi.org/ 10.1186/s40068-019-0148-y.

53. Fang, H.; Bin, H.T.S.; Zeng, X.; Wu, F.Y. Simulation-optimization model of reservoir operation based on target storage curves. Water Sci. Eng. 2014, 7, 433–445.

54. Megersa, K.L.; Tamene, A.D.; Sifan, A.K. Impacts of Land Use Land Cover Change on Sediment Yield and Stream Flow. Int. J. Sci. Technol. 2017, 6, 763–781.

55. Ansari, A.; Golabi, M.H. Prediction of spatial land use changes based on LCM in a GIS environment for Desert Wetlands-A case study: Meighan Wetland, Iran. Int. Soil Water Conserv. Res. 2018, 7, 64–70. https://doi.org/10.1016/j.iswcr.2018.10.001.

56. Buakhao, W.; Kangrang, A. DEM Resolution Impact on the Estimation of the Physical Characteristics of Watersheds by Using SWAT. Adv. Civ. Eng. 2016, 2016, 1–9. https://doi.org/10.1155/2016/8180158.

57. Liu, Y.; Wang, W.; Hu, Y.; Cui, W. Improving the Distributed Hydrological Model Performance in Upper Huai River Basin: Using Stream flow Observations to Update the Basin States via the Ensemble Kalman Filter. Adv. Meteorol. 2016, 2016, 1–14. https://doi.org/10.1155/2016/4921616.

58. USACE. HEC-ResPRM Prescriptive Reservoir Model-Quick Start Guide. U.S.; Army Corps of Engineers, Institute for Water Resources, Hydrologic Engineering Center: Davis, CA, USA, 2011.

59. Zhao, T.; Zhao, J. Optimizing Operation of Water Supply Reservoir: The Role of Constraints. Math. Probl. Eng. 2014, 2014, 1–15. https://doi.org/10.1155/2014/853186.

60. Jothityangkoon, C.; Hirunteeyakul, C.; Boonrawd, K.; Sivapalan, M. Assessing the impact of climate and land use changes on extreme floods in a large tropical catchment. J. Hydrol. 2013, 490, 88–105. https://doi.org/10.1016/j.jhydrol.2013.03.036.

61. Zhou, Y.; Guo, S. Incorporating ecological requirement into multipurpose reservoir operating rule curves for adaptation to climate change. J. Hydrol. 2013, 498, 153–164. https://doi.org/10.1016/j.jhydrol.2013.06.028.

62. Srivastava, A.; Kumari, N.; Maza, M. Hydrological Response to Agricultural Land Use Heterogeneity Using Variable Infiltration Capacity Model. Water Resour. Manag. 2020, 34, 3779–3794. https://doi.org/10.1007/s11269-020-02630-4.

63. Sajikumar, N.; Remya, R. Impact of land cover and land use change on runoff characteristics. J. Environ. Manag. 2015, 161, 460–468. https://doi.org/10.1016/ j.jenvman.2014.12.041.

64. Zhang, Y.; Erkyihum, S.T.; Block, P. Filling the GERD: Evaluating hydroclimatic variability and impoundment strategies for Blue Nile riparian countries. Water Int. 2016, 41, 593–610. https://doi.org/10.1080/02508060.2016.1178467.

65. Wu, Y.; Chen, J. Estimating irrigation water demand using an improved method and optimizing reservoir operation for water supply and hydropower generation: A case study of the Xinfengjiang reservoir in southern China. Agric. Water Manag. 2013, 116, 110–121. https://doi.org/10.1016/j.agwat.2012.10.016.

66. Loucks, D.P.; van Eelco, B. Water resource systems planning and analysis-An Introduction to Methods, Models, and Applications. Adv. Water Resour. 2016, 4, 146.

67. He, Y.; Xu, Q.; Yang, S.; Liao, L. Reservoir flood control operation based on chaotic particle swarm optimization algorithm. Appl. Math. Model. 2014, 38, 4480–4492. https://doi.org/10.1016/j.apm.2014.02.030.

68. Gu, W.; Shao, D.; Tan, X.; Shu, C.; Wu, Z. Simulation and Optimization of Multi-Reservoir Operation in Inter-Basin Water Transfer System. Water Resour. Manag. 2017, 31, 3401–3412. https://doi.org/10.1007/s11269-017-1675-9.

5. Discussions

5.1. Land use land cover changes detection

The LULC change of the Nashe watershed was investigated over 60 years (1990–2050), including historical and future LULC scenarios. The historical LULC (1990, 2005, and 2019) was determined using a synergy of Landsat imageries, geographic information system (GIS), focus group discussions, an interview with key informants, and intensive land use mapping (ground truth) with GPS and processed with the ERDAS Imagine software utilizing supervised classification with the maximum likelihood classifier technique. To determine the correctness of the classified image, the accuracy assessment was carried out. The overall classification accuracies and Kappa coefficients acquired were significantly higher than the substantial range (≥ 80%), ensuring a high degree of acceptance [1,2].

Change in LULC is important and essential for economic development and social advancement, but it frequently comes at a high environmental cost [3]. The patterns of LULC vary dramatically around the world, depending on culture, traditions, and purposes. The findings indicate that there have been significant changes and conversions of LULC in the Nashe watershed, with periodic variations. Over the past thirty years (1990–2019), the study watershed has undergone significant landscape changes with a variety of modifications. The changes observed in the Nashe watershed included a significant increase in agricultural land, water bodies, and urban areas, as well as a substantial loss of forest cover, range land, and grass lands. Throughout the studied time periods, agricultural land was the largest LULC type in the watershed, followed by forest land.

The agricultural land expanded by 14.6% and 21.4% during the first period (1990–2005) and the second period (2005–2019) respectively. In the first period, urban land exhibited the highest increase of 87.3% followed by water body (18%). The increase in water bodies dominated the second period (146.4%) due to the construction of a dam on the Nashe River during this time period. The main land use types that have experienced the greatest detrimental change and are being transformed into agricultural land are forest land, range land, and grass land. In general, the patterns of LULC change over the last nearly three decades demonstrate that forest land has been reduced at a pace of 48.38% on average.

Identifying the main driver variables is quite helpful in understanding the root causes of LULC change patterns in any watershed. The LULC change drivers in the Nashe watershed are due to topography, proximity (human-geographic), and socio-economic development of the area. The extent and scale of urbanization, and the conversion of forest and range land to agricultural land are all primarily influenced by topography and proximity. In general, the fast-growing population has a direct impact on LULC patterns with an average annual rate of about 2.61% according to (the World Population Review 2021) has a direct impact on LULC patterns [2,4].

To identify systematic transitions among the LULC categories, a change detection methodology based on the transitional probability matrix has been used. In general, the watershed's LULC experienced considerable alterations from one category to another [5]. The LULC change models are crucial tools to determine and comprehend the phenomenon of LULC [6]. The LCM model was used to predict the future LULC and validated by comparing the observed and predicted LULC maps using the kappa statistics index. The future LULC for the years 2035 and 2050 was predicted after a successful simulation of LULC changes in 2019 based on Business-as-Usual (BAU) scenarios. The LCM change analysis module was used to perform the LULC change analysis by evaluating gains, losses, net change, and swap (simultaneous gain and loss of a specific LULC over a given time) for the respective study period.

The forecasted LULC results for 2035 and 2050 show a significant increase in agricultural land, water bodies, range land, and urban areas with a simultaneous decrease in forest land. Generally, from the change analysis result, significant dynamics of the LULC were observed between 1990 and 2050 in the Nashe watershed. The findings on agricultural land , urban land expansion, and forest area reduction are comparable with earlier studies conducted in Ethiopia by Gashaw et al. [7] in the Upper Blue Nile basin, Gebresilassie [8] in the Lake Tana basin, and Girma et al. [9] in the Gidabo River basin.

However, the rate of agricultural land expansion has been reduced between 2035 and 2050 as most of the cultivable land is already in use and the expansion limit in the highlands has practically been reached. Similarly, this is owing to the rugged terrain, steep slopes, water bodies, and urban areas that are unsuitable for farming. Understanding the most important current causes and assessing the future impact of LULC change is critical for proper watershed planning and sustainable land resource management [5,10]. Therefore, developing and implementing a reasonable land use policy can assist to reduce the threat of natural resource degradation while also promoting sustainable development.

5.2. Impacts of land use land cover change on hydrological responses

The most essential factor influencing a watershed's hydrological process and determining its characteristics is the LULC change [11,12]. Evaluating the effects of LULC changes on hydrological variability at the watershed and sub-watershed levels reveals the extent of vulnerable sub-basins, which is critical for the development of effective watershed management measures. However, the impacts of changing LULC on the hydrological response have not been uniform across space and time [13]. The study found that, the spatial variability in hydrological components rate changes was lower at the watershed scale than at the sub-watershed scale. Similarly, the analysis identified sub-watersheds in the catchment that are highly susceptible to surface runoff and other hydrological components. The historical, current, and future LULC scenarios were used independently to investigate the effects of LULC changes on the hydrological responses in the watershed [14].

The Soil and Water Assessment Tool model was calibrated and validated using stream flow data from the Nashe watershed. Before using the simulations for scenario analysis, the flow parameters were adjusted based on the sensitivity analysis, keeping the model parameters within reasonable ranges and minimizing uncertainties. Any model used to generate stream flows will unavoidably have certain uncertainties since hydrological models are approximate representations of real-world hydrological processes. Uncertainty prevails in every aspect of optimizing water resource management. The randomness of hydrological processes, the uncertainty of input data and model parameters, and errors in the model structure all contribute to uncertainty in hydrological models. Data processing techniques such as appropriate image processing and ground truth were applied to reduce uncertainty in input data such as LULC. However, sensitivity analysis can help to reduce the uncertainty in the parameter space. It can be concluded that there is a good agreement between the measured and the simulated monthly stream flow for both the calibration and validation periods.

The impacts of LULC change on the hydrological regime were analyzed under the LULC scenario following calibration, validation, and uncertainty analysis using the

SWAT model. As a result, it is recognized that changes to the LULC would have a significant impact on a number of hydrological processes. In an uncertain future, a scenario-based LULC change simulation can assist in assessing the potential implications of LULC change on water resources [15]. The results of the SWAT model on mean annual and seasonal hydrological components of the watershed areas were associated with changes in LULC patterns [16]. The consequences of LULC change analysis revealed that the development of agricultural land and urban areas, as well as the decline of vegetation cover, have resulted in an increase of surface runoff over the Nashe watershed.

In comparison to the baseline, the watershed mean annual lateral flow and groundwater flow decreased in the current period and were predicted to decrease in the future as well. Throughout the study period, surface runoff was the most significant increase in hydrological components, mainly in the watershed's downstream and central areas. However, range lands and grass lands, will start to recover beginning from 2035 to reduce the undesirable trend, and groundwater flow increased, whilst surface runoff and lateral flow decreased. Even though the hydrology has changed significantly between the baseline, current, and future LULC scenarios, the seasonal patterns of high and low flows have remained consistent. The increasing surface runoff and decreasing groundwater and evapotranspiration would result in increased stream flow, mostly during the wet season.

Although increasing wet season stream flow may increase downstream water availability, it may also increase flooding, erosion, sedimentation, and a decrease in the dry season may influence water system practices. As a result, it is suggested that various best management practices (e.g., filter strips, stone/soil bunds, contouring, terracing, reforestation, or a combination of two or more scenarios) be implemented that are specific to the site topography, land use, soil, and climate conditions and should reflect the reality of the study area. Additionally, management practices should always be adopted from the Ethiopian community-based participatory watershed development guideline [17] and the Ethiopian guidelines for development agents on soil water conservation [18]. To be agro-ecologically appropriate, all of the selected scenarios should make use of resources that are readily available in the area. The findings of this study were consistent with previous studies [7,11,19–21], which found significant variation in the hydrological components of the watershed as a result of LULC change.

The pair-wise Pearson correlation approach was used to study the relationship between individual LULC types (agricultural land, grass land, range land, forests, water bodies, and urban areas) and hydrological components (surface runoff, groundwater flow, evapotranspiration, and lateral flow). Using the hydrological model and pair-wise Pearson correlation to examine the influence and contribution of each LULC variation on the hydrological responses of the watershed could be a promising method [12,22,23]. According to the analysis, all hydrological components were strongly associated with the majority of LULC types. Surface runoff has been positively correlated with changes in agricultural land, whereas groundwater, evapotranspiration, and lateral flow have been negatively correlated. However, surface runoff has a significant negative association with forest cover, while lateral flow, groundwater flow, and evapotranspiration show positive correlations. Because of its negative impact on surface runoff, evapotranspiration is the main determinant of water availability in the watershed. The variations of hydrological responses (surface runoff, groundwater, and evapotranspiration) were directly proportional to the magnitude of land-use change. The increased surface runoff was due to increased agricultural land and urban areas at the expense of forest land with respect to the base line time period.

Above all, the considerable correlation between hydrological components supports the general relationships between various hydrological components, such that increasing one hydrological component increases the quantity of others while decreasing the quantity of others. The estimated results were in agreement with those reported in studies by Woldesenbet et al. [12] in Ethiopia's Upper Blue Nile basin and Bossa et al. [24] in West Africa, which indicated a substantial positive association between agricultural areas and mean annual surface runoff. Quantifying the impact of LULC changes on stream flow is critical for transboundary water management at the river basin scale. The results of the study provided significant information on the relative contribution of certain LULC to improving a specific water balance component, which is critical for implementing sustainable water resource management strategies.

Generally, according to the analysis, water bodies, urban areas, and agricultural land have expanded while forest land has decreased in the watershed, which could place further pressure on water availability by increasing water extraction for a variety of purposes. The method utilized in this study correlated changes in LULCs to hydrological components, providing tangible information that would help stakeholders and decision-makers to make important choices regarding land and water resource planning and management. Therefore, since forest cover has a negative impact on surface runoff, reforestation management scenarios should be investigated by converting croplands and range lands in steep slope areas to plantation forests. Similarly, applying appropriate management practices on degraded areas and sloppy lands could enhance groundwater recharge and surface runoff, which washes the topsoil into the reservoirs. In the long run, this contributes to maintaining land, water, and the lifespan of the reservoir.

5.3. Optimal operation of hydropower reservoir under LULC change

Optimization models are used to determine the optimal approach to satisfy various reservoir system management goals for planning and real-time operation. However, determining the optimal operating strategy for a reservoir to ensure that water is used more effectively is a typical challenge when modeling the water resources system. Sustainable management of water resources depends on optimizing reservoir operations. The HEC-ResPRM is a reservoir operation optimization model that minimizes penalty functions at defined locations in the water resource network to prescribe optimal flow and storage values over time [25]. Based on a given priority of the system objectives and provided inflow time series, the HEC-ResPRM model uses network flow optimization to suggest an estimate of the best possible outcome for the system [26].

The SWAT and HEC-ResPRM optimization models were used in this study to generate the optimal reservoir operation of the watershed under current and future LULC scenarios for the Nashe hydropower reservoir. As a result, to assess hydropower reservoir operation, the SWAT model was simulated with inputs from projected LULC maps to generate future reservoir water inflows at the watershed. Consequently, the average annual future stream flow to the hydropower reservoir under the 2035 and 2050 LULC scenarios demonstrates that the result has been increased compared to the baseline and the current period. In the future, the increased reservoir inflow would also result in increased reservoir outflow. However, the rate of LULC changes determines the trend of stream flow increment and decline.

Hydropower generation is dependent on available water resources, which are influenced by patterns of LULC in the watershed. As a result, due to the close relationship between hydropower generation and stream flow, the trajectory of hydropower generation indicates an increment in each of the future LULC time period scenarios. According to Welde and Gebremariam [11], LULC changes in Ethiopia's Tekeze dam catchment increased the mean annual stream flow. Similarly, the study by Obahoundje et al. [27] revealed that the increasing conversion of vegetative land to agricultural land and urban areas had increased stream flow and benefited Bui hydropower generation in Ghana. In general, the Nashe hydropower reservoir inflow and outflow increased throughout the wet season, but the disparity between inflows and outflows was minor during the short rainy season. The increased outflow from the Nashe watershed will improve the Blue Nile River basin's water resources, which will benefit the country and downstream water users in general.

The operating rules for the system under consideration were derived using the time series for the inflow, elevation, and storage generated by the HEC-ResPRM for the entire period. Reservoir operation rules are intended to get appropriate guidelines and manage the reservoir system so that the release is in the best interests of the system objectives while remaining consistent with specific inflow and existing storage levels. The HEC-ResPRM optimization technique associated with the reservoir simulation model was used to define the adaptive optimal rule curves, making reservoir rule curves an appropriate strategy for long-term reservoir operation [26]. When compared to the current rule curves, the optimal rule curves developed by the model perform significantly better under future inflow scenarios.

The current optimized and future optimal rule curves considered the impact of LULC change. Since the stream flow into the reservoir is affected by LULC changes, the stream flow data from the past does not correspond to the future situation. Normally, the existing reservoir rule curves were generated from observed historical stream flow data, which is appropriate only for stream flow situations in the past to present. Creating reservoir rule curves using the future stream flow, which is expected to be impacted by LULC changes, makes the new rule curves optimal for dealing with events that will occur in the future.

In general, reservoir operating rule curve-based decisions about the operation of the reservoir in the Nashe watershed are crucial to ensure seasonally and annually balanced water release while also safeguarding the downstream areas of the reservoir from flooding. Even though hydropower production has a non-linear relationship with storage and water level, optimum reservoir operation significantly increases power production by storing the higher inflow volume to inflow deficiency periods. The elevation difference allows more water to be conserved during the rainy season for energy production during the dry season [28].

Therefore, if operators and water managers adopt proper reservoir operation techniques to store and utilize the wet season flow for the dry seasons, the potential for hydropower generation in the Nashe hydropower reservoir was predictable to increase. In comparison to existing reservoir operations, the reservoir optimization model demonstrated a considerable increase in expected hydropower reservoir storage volumes and elevation under the 2035 and 2050 LULC change scenarios of the Nashe watershed. According to [29,30] investigations, the optimum reservoir storage determined by utilizing the optimization algorithm for the reservoir could be better than the currently employed operational storage for optimizing annual hydropower generation.

The rainy season, particularly July, shows the highest levels of hydropower generation, with January indicating the lowest levels. In general, the optimal storage, pool level, and power generation of the Nashe hydropower reservoir change as a result of LULC change impacts. The study by Wu and Chen [29] examined the optimal reservoir operating rules using an optimization model and advocated that the optimal reservoir operating rules derived through the use of the optimization model were better than the currently used operational policy for optimizing annual hydropower production. The use of an optimization model to assess the effects of the LULC change reveals a positive impact on the Nashe hydropower reservoir operation. As a result, the optimal reservoir operation established in this study may provide decision-makers and reservoir operators with useful and instructive information for the efficient operation of the Nashe reservoir.

5.4. Management of Nashe and other similar watersheds in Ethiopia

Water resource issues are inherently complicated. The world's water challenges are not homogeneous, continuous, or steady across time. The complexity of water management, combined with increased uncertainty caused by socio-economic developments and LULC change, restricts the efficiency of integrated planning and management approaches to water resource systems. The principal element that directly affects watershed hydrology is LULC and understanding its effects is critical for land use planning and water resource management. Since the LULC change is related to the hydrological cycle and hydropower production, rapid changes in LULC have been identified as one of the most important factors affecting water availability and resulting in both positive and negative consequences for society [31]. The effects have already been assessed in Europe [32], Africa [33], and China [2].

The design, planning, and operation of reservoirs are important part of water resource development initiatives. Water resource management, based on water availability and hydropower production, is a major concern for the future of countries that are heavily reliant on hydropower. Hydropower is the world's most abundant renewable energy source, accounting for up to 65% of all renewable sources and about 16.5% of electric generation sources [34]. As a result of the dynamics of land use land cover changes in hydrological processes make these countries extremely vulnerable.

The upstream countries of the Nile basin possess hydropower potential, while the downstream countries have abundant irrigable fertile soil. Although hydropower does not directly consume water, its generation frequently conflicts with other uses, because its release schedule does not always correspond to the timing of water use by other activities. Due to the problem of water resources management, cooperation among riparian countries is required for the development of water resources for hydropower generation and irrigation. Ethiopia's hydropower development, which is located upstream of the Nile basin and contributes a larger percentage of the Nile flow, is not well received by most downstream countries, which rely entirely on the Nile basin. Therefore, water resources system analysis, which focuses on management techniques for the sustainable and optimal use of water resources, can contribute to conflict resolution by better understanding conflicts and opportunities for cooperation. Nowadays, water resource system planning and management are strongly reliant on the use of systems approach and system analysis methodologies to develop and solve water resource management problems.

In this study, increased stream flows in the current and future LULC scenarios compared to the baseline scenario hydrological regime, as well as a decrease in vegetation cover in the future scenarios, indicating that management interventions in the watershed are required. To manage the hydrology and environment of the Nashe and similar watersheds in Ethiopia and in the world in general, it is suggested that an integrated and adaptive management strategy should be used [35]. As a result, efficient management of a watershed's water resources necessitates an understanding of the amount of water that can be abstracted and supplied under various conditions. Forest rehabilitation should also be prioritized in agriculturally dominated areas. Generally, to maximize water production and quality, proper watershed management strategies should be applied.

References

1. Dey NN, Al Rakib A, Kafy A Al, Raikwar V. Geospatial modelling of changes in land use/land cover dynamics using Multi-layer perception Markov chain model in Rajshahi City, Bangladesh. Environ Challenges. 2021;4(May):100148. https://doi. org/10.1016/j.envc.2021.100148

2. Wang SW, Munkhnasan L, Lee WK. Land use and land cover change detection and prediction in Bhutan's high altitude city of Thimphu, using cellular automata and Markov chain. Environ Challenges. 2021;2(November 2020).

3. Devi AB, Deka D, Aneesh TD, Srinivas R, Nair AM. Predictive modelling of land use land cover dynamics for a tropical coastal urban city in Kerala, India. Arab J Geosci. 2022;15(5):1–19.

4. Naikoo MW, Rihan M, Ishtiaque M, Shahfahad. Analyses of land use land cover (LULC) change and built-up expansion in the suburb of a metropolitan city: Spatio-temporal analysis of Delhi NCR using landsat datasets. J Urban Manag. 2020;9(3): 347–59. https://doi.org/10.1016/j.jum.2020.05.004

5. Leta MK, Demissie TA, Tränckner J. Modeling and prediction of land use land cover change dynamics based on land change modeler (LCM) in Nashe watershed, Upper Blue Nile Basin, Ethiopia. Sustainability 2021, 13,3740. https://doi.org/10. 3390/su 13073740.

6. Jahanishakib F, Mirkarimi SH, Salmanmahiny A, Poodat F. Land use change modeling through scenario-based cellular automata Markov: improving spatial forecasting. Environ Monit Assess. 2018;190(6).

7. Gashaw T, Tulu T, Argaw M, Worqlul AW. Modeling the hydrological impacts of land use/land cover changes in the Andassa watershed, Blue Nile Basin, Ethiopia. Sci Total Environ. 2018;619–620:1394–408. https://doi. org/10.1016/ j. scitotenv. 2017. 11.191

8. Gebresilassie AT. Modeling the Impact of Climate and Land Use/Land Cover Change on Hydrological Responses in Lake Tana Basin, Ethiopia [Internet]. Addis Ababa University; 2020. Presented in Fulfillment of the Requirements for the Degree of Doctor of Philosophy (Ph.D.) in Water Resources Engineering and Management

9. Girma R, Fürst C, Moges A. Land use land cover change modeling by integrating artificial neural network with cellular Automata-Markov chain model in Gidabo river basin, main Ethiopian rift. Environ Challenges. 2022;6(December 2021): 100419. https://doi.org/10.1016/j.envc.2021.100419

10. Regasa MS, Nones M, Adeba D. A Review on Land Use and Land Cover Change

in Ethiopian Basins. Land 2021,10, 585.1–18. https://doi. org/10.3390/land10060585

11. Welde K, Gebremariam B. Effect of land use land cover dynamics on hydrological response of watershed: Case study of Tekeze Dam watershed, northern Ethiopia. Int Soil Water Conserv Res. 2017;5(1):1–16. http://dx.doi. org/10.1016/ j.iswcr. 2017. 03.002
12. Woldesenbet TA, Elagib NA, Ribbe L, Heinrich J. Catchment response to climate and land use changes in the Upper Blue Nile sub-basins, Ethiopia. Sci Total Environ. 2018;644:193–206. https://doi.org/10.1016/j.scitotenv.2018.06.198
13. Birhanu A, Masih I, van der Zaag P, Nyssen J, Cai X. Impacts of land use and land cover changes on hydrology of the Gumara catchment, Ethiopia. Phys Chem Earth. 2019;112(January):165–74. https://doi.org/10.1016/j.pce.2019.01.006
14. Leta MK, Demissie TA, Tränckner J. Hydrological Responses of Watershed to Historical and Future Land Use Land Cover Change Dynamics of Nashe Watershed, Ethiopia. Water 2021, 13, 2372. https://doi.org/10.3390/w13172372.
15. Cao M, Zhu Y, Quan J, Zhou S, Lü G, Chen M, Huang M. Spatial Sequential Modeling and Predication of Global Land Use and Land Cover Changes by Integrating a Global change Assessment Model and Cellular Automata. Earth's Future. 2019;7(9):1102–16.
16. Talib A, Randhir TO. Climate change and land use impacts on hydrologic processes of watershed systems. J Water Clim Chang. 2017;8(3):363–74.
17. Desta L, Carucci V, Wendem-Ageňehu A, Abebe Y. Community-Based Participatory Watershed Development: A Guideline: Ministry of Agriculture and Rural Development, Addis Ababa, Ethiopia. 2005. 1–74 p.
18. Hurni H, Berhe W, Chadhokar P, Daniel D, Gete Z, Grunder M, Kassaye G. Soil and Water Conservation in Ethiopia: Guidlines for Development Agents. 2nd ed.; Centre for Development and Environment (CDE): Bern, Switzerland; Bern Open Publishing (BOP): University of Bern, Bern, Switzerland,. 2016. 1–134 p. http://link. springer. com/10.1007/BF02987717
19. Shrestha B, Cochrane TA, Caruso BS, Arias ME. Land use change uncertainty impacts on stream flow and sediment projections in areas undergoing rapid development: A case study in the Mekong Basin. L Degrad Dev. 2018;29(3):835–48.
20. Berihun ML, Tsunekawa A, Haregeweyn N, Meshesha DT, Adgo E, Tsubo M, Masunaga T, Fenta AA, Sultan D, Yibeltal M, Ebabu K. Hydrological responses to land use/land cover change and climate variability in contrasting agro-ecological environments of the Upper Blue Nile basin, Ethiopia. Sci Total Environ. 2019;689

(June):347–65. https://doi.org/10.1016/j.scitotenv.2019.06.338

21. Tekalegn WA, Elagib NA, Ribbe L, Heinrich J. Hydrological responses to land use/cover changes in the source region of the Upper Blue Nile Basin, Ethiopia. Sci Total Environ. 2017;575:724–41. http://dx.doi.org/10.1016/j.scitotenv.2016.09.124

22. Shi ZH, Ai L, Li X, Huang XD, Wu GL, Liao W. Partial least-squares regression for linking land-cover patterns to soil erosion and sediment yield in watersheds. J Hydrol. 2013;498:165–76.

23. Yan B, Fang NF, Zhang PC, Shi ZH. Impacts of land use change on watershed stream flow and sediment yield: An assessment using hydrologic modelling and partial least squares regression. J Hydrol. 2013;484:26–37. http://dx.doi.org/10.1016/j.jhydrol.2013.01.008

24. Bossa AY, Diekkrüger B, Agbossou EK. Scenario-based impacts of land use and climate change on land and water degradation from the meso to regional scale. Water (Switzerland). 2014;6(10):3152–81.

25. O' Connell s, Harou J. "HEC- PRM, Prescriptive Reservoir Model", Institute for Water Resources, Hydrologic Engineering Center (HEC), US Army Corps, Quick Start Guide, Davis, California, USA. 2011;

26. USACE. HEC-ResPRM Prescriptive Reservoir Model-Quick Start Guide. U.S. Army Corps of Engineers, Institute for Water Resources, Hydrologic Engineering Center, Davis, CA. 2011;(July).

27. Obahoundje S, Ofosu EA, Akpoti K, Kabo-bah AT. Land use and land cover changes under climate uncertainty: Modelling the impacts on hydropower production in Western Africa. Hydrology. 2017;4(1).

28. Leta MK, Demissie TA, Tränckner J. Optimal Operation of Nashe Hydropower Reservoir under Land Use Land Cover Change in Blue Nile River Basin. Water 2022, 14, 1606. https://doi.org/10.3390/w14101606.

29. Wu Y, Chen J. Estimating irrigation water demand using an improved method and optimizing reservoir operation for water supply and hydropower generation: A case study of the Xinfengjiang reservoir in southern China. Agric Water Manag. 2013;116:110–21. http://dx.doi.org/10.1016/j.agwat.2012.10.016

30. Loucks DP, Eelco van B. Water resource systems planning and analysis-An Introduction to Methods, Models, and Applications. Vol. 4, Advances in Water Resources. 2016. 146 p.

31. Silva V de PR da, Silva MT, Singh VP, de Souza EP, Braga CC, de Holanda RM, Almeida RSR, de Assis Salviano de Sousa F, Braga ACR. Simulation of stream

flow and hydrological response to land-cover changes in a tropical river basin. Catena. 2018;162(November):166–76.

32. Guse B, Pfannerstill M, Fohrer N. Dynamic Modelling of Land Use Change Impacts on Nitrate Loads in Rivers. Environ Process. 2015;2(4):575–92.

33. Op de Hipt F, Diekkrüger B, Steup G, Yira Y, Hoffmann T, Rode M, Näschen K. Modeling the effect of land use and climate change on water resources and soil erosion in a tropical West African catchment (Dano, Burkina Faso) using SHETRAN. Sci Total Environ. 2019;653:431–45. https:// doi.org/ 10.1016/ j.scitotenv. 2018.10.351

34. Guerrero JVR, Escobar-Silva E V., Chaves MED, Mataveli GAV, Bourscheidt V, Oliveira G de, Picoli MCA, Shimabukuro YE, Moschini LE. Assessing land use and land cover changes in the direct influence zone of the Braço Norte Hydropower Complex, Brazilian Amazonia. Forests. 2020;11(9):1–13.

35. Homa ES, Brown C, McGarigal K, Compton BW, Jackson SD. Estimating hydrologic alteration from basin characteristics in Massachusetts. J Hydrol. 2013; 503:196–208. http://dx.doi.org/10.1016/j.jhydrol.2013.09.008

6. Conclusions and Perspectives

6.1. Conclusions

To achieve sustainable watershed management, this research was conducted in the Nashe watershed with the goal of understanding the LULC (historical and future) change with their driving forces and thoroughly investigating the long-term dynamics of LULC change impacts on hydrological responses and operation of hydropower reservoir. The following main conclusions can be inferred based on the results of the study.

- The Nashe watershed encompasses land and water resources that have the potential to provide many regional and national socio-economic benefits. Water resources in the watershed area are becoming increasingly important due to increasing agricultural, hydropower, industrial, domestic, and environmental needs. Therefore, understanding the LULC change as well as the associated hydrological processes at various spatial and temporal dimensions is indispensable for improved water resources management in the watershed.
- Analyzing LULC change dynamics requires the mapping of multi-temporal satellite imagery, which provides data for estimating potential future LULC changes and assessing potential repercussions.
- The fundamental drivers of LULC change in the study watershed were identified as being rapid population growth, topographic features, and proximity variables. Expansion of urban land, agricultural expansion, firewood extraction, climate variability, land tenure policies, use of trees for construction, and infrastructure development were the main drivers of LULC change observed during the field observation.
- The integrated use of land change modeler, hydrological model, reservoir optimization model, and statistical tools was considered as it ensured that multiple LULC classes were spatially simulated to provide up-to-date information on the impact of LULC change on hydrological processes and hydropower reservoir operation. The modeling methodology developed in this study contributes to a scientific understanding of the impact of LULC change on hydrological responses and hydropower reservoir operation reliability.

Modeling historical and future LULC is crucial for effective land use planning and natural resources management.

- In this study, the majority of systematic transitions, gains, losses, and persistence were analyzed using a transition matrix and multi-temporal LULC changes in the study watershed. According to the LULC analysis, a significant expansion of agricultural land and urban area happened in the watershed. The trend of increasing agricultural land and urban areas while forest cover decreasing is expected to continue in the future time periods unless effective management measures are implemented.
- The model parameter sensitivity analysis identified nine most sensitive parameters affecting the surface, sub-surface, soil, and stream routing processes of the watershed. The parameters were adjusted based on the sensitivity analysis to maintain the model parameters within reasonable ranges and reduce the uncertainty in the simulations before being further used for the scenario analysis. On the other hand, model calibration and validation have shown that the observed stream flow was simulated quite satisfactorily at gauging stations.
- The effects of LULC changes on surface runoff, groundwater flow, lateral flow, and water yield are very noteworthy in the annual, seasonal, and monthly average values. The LULC changes had increased the annual, wet season flow, and surface runoff while decreasing the dry season flow, groundwater flow, lateral flow, and evapotranspiration. A combined technique of hydrological modeling and pair-wise Pearson's correlation analysis was used to study the influence and contribution of individual LULC variations on hydrological processes.
- The relationship between hydrological components and LULC classes revealed that surface runoff was strongly related to changes in agricultural land, as evidenced by a higher correlation coefficient. Similarly, forest land had a positive correlation with groundwater flow, evapotranspiration, and lateral flow, whereas, it had a severe negative correlation with surface runoff. The positive effects indicate that the forest land increases the groundwater flow, evapotranspiration, and lateral flow. Whereas the negative effects show that the forest land decreases the surface runoff. However, in the long term, the negative and positive effects offset each other in the watershed, particularly at the sub-

watershed level. In general, understanding the individual effects of LULC change and their consequent impacts on hydrological components could help concerned bodies to develop more effective and sustainable land use planning and water resource management strategies in the study watershed.

- The stream flow, which is the fundamental hydrological parameter for water resources planning and management in the watershed has been changed due to the LULC change. The study has shown that the current LULC scenario has significantly increased the stream flows in the Nashe watershed as compared to the baseline scenario. The future period LULC scenarios had significantly more total reservoir inflows compared to the historical and current simulations, which has several implications for future hydropower reservoir planning and operations. Generally, the increase in the area of agricultural land and urban area was mainly responsible for the substantial increase in stream flow.
- The reservoir optimization model was used to generate optimal hydropower reservoir operation policies for the Nashe hydropower reservoir to maximize reservoir capacity to generate hydropower under current and future LULC circumstances. As a result, the future scenarios result in optimum reservoir operation policies that significantly exceed those observed currently. In addition, the optimized policy may amplify the generation of hydropower during the flood season, as well as increase the likelihood of accessibility of water for the subsequent dry season.
- The reservoir optimization modeling approach would provide a better understanding of current and future conditions of optimal hydropower reservoir operation by incorporating water storage, water surface elevation, release, and power generation. The generated optimal rule curves outperform current rule curves under future inflow scenarios, allowing the reservoir to be more effective and appropriate in terms of water release and storage for future scenarios that generate more energy.
- In general, it has been shown that, the historical, current, and also the future LULC change scenarios have significant effects on hydropower generation. Furthermore, the importance of LULC distribution in land use planning and management should be emphasized as it has a significant impact on reservoir performance indicators. Changes in the LULC and their hydrological

consequences are considered as a hotspot and key issues in hydrological research. In order to ensure the sustainability of water resources, the LULC condition of the area needs to be managed effectively.

- The approach used in this study can be applied to any watershed as a decision-support tool to make better planning and management decisions for land, water resource, and reservoir in the future to optimize power generation. The findings are envisioned to update policymakers, water resource managers, and other concerned stakeholders so that future development in the Blue Nile River basin can be more effective.

6.2. Perspectives

This study assessed the trends, drivers, future LULC dynamics, and the impacts of LULC changes on hydrological processes and hydropower reservoir operation in the Nashe watershed. The modeling study was used in operating the Nashe hydropower reservoir under the effect of hydrological processes and LULC change. As a result, depending on the findings of the study, the following recommendations and directions for future research have been outlined to improve the outcome for future perspectives of Nashe water resource management.

The availabilities of LULC data (historical and predicted), hydrological data (stream flow), weather data, and reservoir data (historical reservoir storage and water surface level, outflow-energy generation relationship) are essential for the development of water resource management in the watershed. Data accessibility and quality should be prioritized significantly more when using hydrological and reservoir optimization models. Similarly, the lack of pertinent and adequate observed data revealed some of the difficulties that the Nashe watershed confronts. However, an improved understanding of LULC change dynamics allows for more reliable information for hydrological processes and reservoir operations in the watershed. Therefore, it is strongly recommended to improve the hydrological and hydropower monitoring system in the watershed.

The SWAT model was used to simulate the hydrological regime of the Nashe watershed, according to statistical analysis and hydrographs of the simulated and observed stream flow obtained through calibration and validation. However, in this study, the model was calibrated and validated using only stream flow data at a single gauging station outlet of the watershed. Therefore, it is suggested that future studies evaluate the value of employing multisite stream flow gauges to validate hydrological modeling; hence, more stream flow gauges are necessary in the interior part of catchments.

Nowadays, climate change and its consequences are becoming a hot issue in different anthropogenic and natural systems in a variety of ways. This study has not considered the climate change effects. Throughout the simulation period, a fixing-changing approach was considered in this study, such an assumption can influence hydrological processes and hydropower generation projections in the watershed. Hence, further refinement is recommended in the Nashe watershed to couple LULC change with climate change scenarios in order to evaluate changes in hydrological responses as well as their implication on hydropower generation. In addition, multiple hydrologic models, climatic models, and reservoir optimization models should be used in future studies to provide more precise results in the Nashe watershed hydropower reservoir operation.

In the study watershed, the expansion of agricultural land and urban area has increased surface runoff while decreasing the groundwater flow. The increase in surface runoff could further increase erosion and sedimentation. It is important to take measures against further expansion of agricultural land at the expense of forest land and range land which avert undesirable LULC changes and thereby reduce its negative impact on hydrological processes.

Land use land cover changes, including the predicted LULC changes associated with the effects of soil erosion and sediment yield, which are required to evaluate the Nashe hydropower reservoir operation were not investigated in this study. Sediment modeling, which was left out from this study due to lack of data, is very important in the Nashe watershed. The installation of sediment gauges inside catchments will also enable the accurate determination of the spatial and temporal variability of water resources and sediment yield. Further studies were recommended to attempt watershed reservoir systems with different LULC to analyze the potential sources of soil erosion for prioritization, sediment yield, and evaluation of best management practices in the watershed and their impacts on the reservoir indicators. In addition, to minimize the predicted future impact of LULC changes on the hydrology of the catchment, appropriate and integrated approaches for land use planning and management need to be developed and implemented.

In general, the study showed that the LULC changes could affect the land use projects within and outside the Nashe watershed and the Blue Nile River basin, including the GERD (Grand Ethiopian Renaissance Dam) and the downstream countries of the users of the Blue Nile River basin. As a result, it is essential to reduce the long-term detrimental effect of LULC changes on the hydrological response of the tributaries of the Blue Nile River basin in particular, and the country as a whole, by formulating and implementing appropriate land use management interventions.

Planning professionals, practitioners, researchers, and farmers can better formulate and implement sound measures to reduce adverse future potential impacts and develop management approaches by understanding how changes in LULC influence stream flow and subsequently optimization of water resources. Similarly, the recently introduced nationwide green legacy of planting trees in Ethiopia may also help in reducing the surface runoff, wet season flow, and increasing groundwater, and dry season flow if properly implemented and monitored. They have positive effects on riparian buffer zones in order to fight against sediments and nutrient emissions from entering river basins. Furthermore, the implementation of a climate-resilient green economy strategy and the formulation of local and regional scale plans for sustainable development could essentially curb the negative impact of LULC changes.

Curriculum Vitae

Personal Information

Full Name	Megersa Kebede Leta
Sex	Male
Date of Birth	03.03.1989 G.C
Nationality	Ethiopian

Summary

- Highly self-motivated academic researcher with demonstrated research expertise in hydrology and water resources engineering
- Integrated academic achievement with administrative skills and capable of motivating and organizing others for research works with good interpersonal communication skills.
- Advanced competence in field work and in integrated hydrological modeling
- Experience in process designing and experimental setup with a knack of using programming tools
- Concrete practical and theoretical foundation

Education

October 2019 to present	**PhD student**, Institute of Hydrology and Water Management, University of Rostock, Germany
October, 2013 – November, 2015	**Master of Science (MSc)** in Hydraulic Engineering from Jimma University, Jimma Institute of Technology, Ethiopia
October, 2007 – June, 2011	**Bachelor of Science (BSc)** in Water Supply and Environmental Engineering from Arba Minch University, Arba Minch Institute of Technology, Ethiopia

Professional career

October, 2020 –Present	**Assistance Professor**, Jimma University, Jimma Institute of Technology
November,2015–September, 2020	**Lecturer**, Jimma University, Jimma Institute of Technology
October, 2012–October, 2015	**Assistant Lecturer**, Jimma University, Jimma Institute of Technology

September,2011–September, 2012 **Graduate Assistance II**, Arba Minch University, Arba Minch Institute of Technology

Scientific work

- **Leta, M.K.**, Waseem, M., Rehman, K., Tränckner, J. *(2023).* Sediment yield estimation and evaluating the best management practices in Nashe watershed, Blue Nile Basin, Ethiopia. *Environ Monit Assess* **195**, 716. https://doi.org/10.1007/s10661-023-11337-z
- **Leta, M.K.**; Demissie, T.A.; Tränckner, J. (2022). Optimal Operation of Nashe Hydropower Reservoir under Land Use Land Cover Change in Blue Nile River Basin. Water, 14, 1606. https://doi.org/ 10.3390/ w14101606
- **Leta, M.K.**; Demissie, T.A.; Tränckner, J. (2021). Hydrological Responses of Watershed to Historical and Future Land Use Land Cover Change Dynamics of Nashe Watershed, Ethiopia. Water, 13, 2372. https://doi.org/10.3390/w13172372
- **Leta, M.K.**; Demissie, T.A.; Tränckner, J. (2021). Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed, Upper Blue Nile Basin, Ethiopia. Sustainability, 13, 3740. https://doi.org/10.3390/su13073740
- **Leta, M.K.**; Demissie, T.A.; Waseem, M. (2021). Analysis of Hydrological Characteristics of Blue Nile Basin, Nashe Watershed. Appl. Sci. , 11, 11791. https://doi.org/10.3390/app 112411791
- **Leta MK**, Ebsa DG, Regasa MS. (2022). Parameter Uncertainty Analysis for Streamflow Simulation Using SWAT Model in Nashe Watershed , Blue Nile River Basin , Ethiopia. Appl Environ Soil Sci.;2022:19. https://doi.org/10.1155/2022/1826942
- Waseem, M., Ahmad, S., Ahmad, I., Wahab, H., Leta, M.K., (2023). Urban flood risk assessment using AHP and geospatial techniques in swat Pakistan. SN Appl. Sci. 5, 215. https://doi.org/10.1007/s42452-023-05445-1
- Teshome, D.S.; **Leta, M.K.**; Taddese, H.; Moshe, A.; Tolessa, T.; Ayele, G.T.; You, S. Watershed Hydrological Responses to Land Cover Changes at Muger Watershed, Upper Blue Nile River Basin, Ethiopia. Water 2023, 15, 2533. https://doi.org/10.3390/w15142533
- Waseem, M.; Mutahir Ullah Ghazi, S.; Ahmed, N.; Ayaan, M.; **Kebede Leta, M**. Rainwater Harvesting as Sustainable Solution to Cope with Drinking Water Scarcity and Urban Flooding: A Case Study of Public Institutions in Lahore, Pakistan. Civil Eng 2023, 4, 638–656. https://doi.org/10.3390/civileng4020037

- Waseem, M.; Iqbal, F.; Humayun, M.; Umais Latif, M.; Javed, T.; **Kebede Leta, M.** Spatial Assessment of Soil Erosion Risk Using RUSLE Embedded in GIS Environment: A Case Study of Jhelum River Watershed. Appl. Sci. 2023, 13, 3775. https://doi.org/10.3390/app13063775
- Sher, S.; Waseem, M.; **Leta, M.K.** Review of Techniques for the Removal of Polycyclic Aromatic Hydrocarbons from Produced Water. Environments 2023, 10, 40. https://doi.org/10.3390/ environments10030040
- Abbas, S.; Waseem, M.; Yaseen, M.; Latif, Y.; **Leta, M.K.**; Khan, T.H.; Muhammad, S. Spatial-Temporal Seasonal Variability of Extreme Precipitation under Warming Climate in Pakistan. Atmosphere 2023, 14, 210. https:// doi.org/ 10.3390/ atmos14020210
- Merga, D.D.; Adeba, D.; Regasa, M.S.; **Leta, M.K**. (2022). Evaluation of Surface Water Resource Availability under the Impact of Climate Change in the Dhidhessa Sub-Basin, Ethiopia. Atmosphere, 13, 1296. https://doi.org/10.3390/atmos13081296
- Abbas, S.; Yaseen, M.; Latif, Y.; Waseem, M.; Muhammad, S.; **Kebede Leta, M.**; Sher, S.; Ali Imran, M.; Adnan, M.; Khan, T.H. (2022). Spatiotemporal Analysis of Climatic Extremes over the Upper Indus Basin, Pakistan. Water, 14, 1718. https://doi.org/10.3390/w14111718
- Ilyas, M.; Ahmad, A.; Riaz, A.; Khan, F.A.; Sher, S.; Waseem, M.; Ali, S.Z.; Badrashi, Y.I.; Waqas, H.A.; Seitz, H.; Shahzada, K; **Leta, M.K.** (2022). Review of Modeling Techniques for Analysis and Assessment of RC Beam-Column Joints Subjected to Seismic Loads. *Materials*, *15*, 7448. https://doi.org/ 10.3390/ ma15217448
- Kabeto, J.; Adeba, D.; Regasa, M.S.; **Leta, M.K.** (2022). Groundwater Potential Assessment Using GIS and Remote Sensing Techniques: Case Study of West Arsi Zone, Ethiopia. Water, 14, 1838. https://doi.org/ 10.3390/w14121838
- Yaseen, M.; Latif, Y.; Waseem, M.; **Leta, M.K.**; Abbas, S.; Akram Bhatti, H. (2022). Contemporary Trends in High and Low River Flows in Upper Indus Basin, Pakistan. Water, 14, 337. https://doi.org/ 10.3390/ w14030337
- Anjum, M.N.; Irfan, M.; Waseem, M.; **Leta, M.K**.; Niazi, U.M.; ur Rahman, S.; Ghanim, A.; Mukhtar, M.A.; Nadeem, M.U. (2022). Assessment of PERSIANN-CCS, PERSIANN-CDR, SM2RAIN-ASCAT, and CHIRPS-2.0 Rainfall Products over a Semi-Arid Subtropical Climatic Region. Water, 14, 147. https://doi.org/10.3390/w14020147

- Ali, S.; Cheema, M.J.M.; Waqas, M.M.; Waseem, M.; **Leta, M.K.**; Qamar, M.U.; Awan, U.K.; Bilal, M.; Rahman, M.H.u. (2021). Flood Mitigation in the Transboundary Chenab River Basin: A Basin-Wise Approach from Flood Forecasting to Management. Remote Sens., 13, 3916. https://doi.org/ 10.3390/ rs13193916
- Ali, M.G.; Ali, S.; Arshad, R.H.; Nazeer, A.; Waqas, M.M.; Waseem, M.; Aslam, R.A.; Cheema, M.J.M.; **Leta, M.K.**; Shauket, I. (2021). Estimation of Potential Soil Erosion and Sediment Yield: A Case Study of the Transboundary Chenab River Catchment. Water, 13, 3647. https://doi.org/10.3390/w13243647
- Mohiuddin, M.; Ali, J.; **Leta, M.K**.; Waseem, M.; Irshad, M.; Hussain, Z. (2021). Estimation of Iodine Leaching in Soil Amended with Organic and Inorganic Materials Using HYDRUS 1-D Model. Sustainability, 13, 10967. https://doi.org/10.3390/su131910967
- Sher, S.; Waseem, M.; Waqas, M.M.; Rehman, K.; Ilyas, M.; Waqas, H.A.; **Kebede Leta, M.** (2022). An Integrated Hydrological Modelling Approach to Evaluate the Capacity of Keenjhar Lake by Using STELLA. Hydrology, 9, 90. https://doi.org/10.3390/hydrology9050090
- Mohsin Waqas, M.; Waseem, M.; Ali, S.; **Kebede Leta, M**.; Noor Shah, A.; Khalid Awan, U.; Hamid Hussain Shah, S.; Yang, T.; Ullah, S. (2021). Evaluating the Spatiotemporal Distribution of Irrigation Water Components for Water Resources Management Using Geo-Informatics Approach. Sustainability, 13, 8607. https://doi.org/10.3390/su 13158607
- **M. K. Leta** (2020). Land Suitability Assessment of Surface Irrigation Potential in Gilgel Gibe, Omo Gibe Basin, Ethiopia. Journal of Water Sciences & Environment Technologies ISSN: 2508-9250. JOWSET, 2020 (05), N°1, 513-524.
- A. W. Galata, T. A. Demissei, **M. K. Leta** (2020). Watershed Hydrological Responses to Changes in Land Use and Land Cover at Hangar Watershed, Ethiopia. Iranian (Iranica) Journal of Energy & Environment. Doi: 10.5829/ijee.2020.11.01.13.
- Dereje Gizaw, **Megersa Kebede** (2019). Spatial and Temporal Distribution of Sediment Yield-Case Study Nashe, Blue Nile Basin, Ethiopia. Journal of Water Sustainability 2(2019) 23-35. DOI: 10.11912/jws.2019.9.2.23-34.
- W. Takala Dibaba, **M. Kebede Leta** (2019). Assessment the Potential Impacts of Urbanization: Case of Jimma City. Iranian (Iranica) Journal of Energy & Environment. Doi: 10.5829/ijee. 2019.10.03.06.

- Lencho Takele, **Megersa Kebede** (2019). Stream flow modeling of upper Awash River basin using Soil and Water Assessment Tool. Appl. J. Envir. Eng. Sci. 4 N°4(2018)456-466
- **Megersa Kebede Leta** and Wakjira Takala Dibaba (2019). Assessment of Physico-Chemical Parameters of Awetu River, Jimma, Oromia, Ethiopia. Journal of Water Sustainability 1 (2019) 13-21.
- **Megersa K. Leta**, Tamene A. Demissie, Sifan A. Koriche (2017). Impacts of Land Use Land Cover Change on Sediment Yield and Stream Flow: A Case of Finchaa Hydropower Reservoir, Ethiopia. International Journal of Science and Technology Volume 6 No. 4.
- **Megersa Kebede Leta**, Dr. Ankit Chakravarti (2017). Sediment Yield Assessment and Mitigation Measures in Finchaa Watershed, Ethiopia. International Journal of Engineering Research & Technology (IJERT), ISSN: 2278-0181.
- **Megersa Kebede**, Ankit Chakravarti & Tamene Adugna (2017). Stream Flow and Land Use Land Cover Change in Finchaa hydropower, Blue Nile Basin, Ethiopia. International Journal of Civil, Structural, Environmental and Infrastructure Engineering Research and Development (IJCSEIERD) ISSN (P): 2249-6866; ISSN (E): 2249-7978.

Conference papers

- **Leta, M.K.**; Demissie, T.A.; Tränckner, J. Evaluation of the impacts of land use land cover change on hydrology. A case study in Nashe watershed. *Environ. Sci. Proc.*2021. Presented at the 6th International Electronic Conference on Water Sciences (ECWS-6), Online, 15–30 November 2021.
- **Leta, M.K.**; Demissie, T.A.; Tränckner, J. Potential impacts of historical and future land use land cover changes on hydrological responses of Nashe watershed. International Sopot Youth Conference 2022 entitled Where the World is Heading, 10 June 2022.
- **Leta, M.K.**; Demissie, T.A.; Tränckner, J. Water resources assessment under the effect of land use land cover change in Nashe watershed, Blue Nile River basin. Poster presentation on *3rd IAHR Young Professionals Congress (29 November – 1 December 2022).*
- **Leta, M.K.**; Demissie, T.A.; Tränckner, J. Optimizing Reservoir Operation for Hydropower Generation under Land Use Land Cover Changes in the Blue Nile Basin of Ethiopia: Nashe Reservoir. VII INTERNATIONAL SOPOT YOUTH CONFERENCE 2023 entitled "Where the World is Heading?"- Sopot, June 16, 2023 - Institute Of Oceanology Polish Academy Of Sciences Ul. Powstancow Warszawy 55, Sopot, Poland

In dieser Reihe bisher erschienen

Band I
10. DIALOG Abfallwirtschaft MV
– Von der Abfallwirtschaft zur Energiewirtschaft.
Tagungsband, erschienen im Juni 2007, ISBN 987-3-86009-004-6

Band II
Ellen-Rose Trübger
Entwicklung eines Ansatzes zur Berücksichtigung der ungesättigten Zone bei der Grundwassersimulation von Feuchtgebieten.
Dissertation, erschienen im August 2007, ISBN 978-3-86009-006-0

Band III
René Dechow
Untersuchungen verschiedener Ansätze der Wasserhaushalts- und Stofftransportmodellierung hinsichtlich ihrer Anwendbarkeit in Stickstoffhaushaltsmodellen.
Dissertation, erschienen im September 2007, ISBN 978-3-86009-016-9

Band IV
Carolin Wloczyk
Entwicklung und Validierung einer Methodik zur Ermittlung der realen Evapotranspiration anhand von Fernerkundungsdaten in Mecklenburg-Vorpommern.
Dissertation, erschienen im September 2007, ISBN 978-3-86009-009-1

Band 5
1. Rostocker Bioenergieforum.
Bioenergieland Mecklenburg-Vorpommern.
Tagungsband, erschienen im Oktober 2007, ISBN 978-3-86009-013-8

Band 6
Kulturtechniktagung 2007.
Ostseeverschmutzung und Flächenentwässerung.
Tagungsband, erschienen im Januar 2008, ISBN 978-3-86009-018-3

Band 7
Enrico Frahm
Bestimmung der realen Evapotranspiration für Weide (Salix spp.) und Schilf (Phragmites australis) in einem nordostdeutschen Flusstalmoor.
Dissertation, erschienen im Mai 2008, ISBN 978-3-86009-023-7

Band 8
Jenny Haide
Methode zur Quantifizierung der Einflüsse auf Vorgangsdauern lohnintensiver Arbeiten am Beispiel von Pflasterarbeiten.
Dissertation, erschienen im Juni 2008, ISBN 978-3-86009-024-4

Band 9
11. DIALOG Abfallwirtschaft MV
Chancen und Risiken für die deutsche Abfallwirtschaft im Ausland.
Tagungsband, erschienen im Juni 2008, ISBN 978-3-86009-029-9

Band 10
Stefan Cantré
Ein Beitrag zur Bemessung geotextiler Schläuche für die Entwässerung von Baggergut.
Dissertation, erschienen im Juni 2008, ISBN 978-3-86009-032-9

Band 11
Birgit Wüstenberg
Praxis der Standortwahl von Sportboothäfen im Küstenbereich Mecklenburg-Vorpommerns und Entwicklung einer Bewertungsmethode als Planungshilfe.
Dissertation, erschienen im Juli 2008, ISBN 978-3-86009-033-6

Band 12
André Clauß
Erhöhung der Trinkwasserversorgungssicherheit in Havarie- und Krisensituationen durch neue Handlungsalgorithmen sowie Einbeziehung bisher ungenutzter Ressourcen am Beispiel von Bergbaugrubenwasser.
Dissertation, erschienen im September 2008, ISBN 978-3-86009-037-4

Band 13
Peter Degener
Sickerwasserkreislauf zur Behandlung von Sickerwässern der aerob-biologischen Restabfallbehandlung (Restabfallrotte).
Dissertation, erschienen im Oktober 2008, ISBN 978-3-86009-043-5

Band 14
2. Rostocker Bioenergieforum
Innovationen für Klimaschutz und wirtschaftliche Entwicklung.
Tagungsband, erschienen im Oktober 2008, ISBN 978-3-86009-044-2

Band 15
7. Rostocker Abwassertagung
Fortschritte auf dem Gebiet der Abwasserentsorgung.
Tagungsband, erschienen im November 2008, ISBN 978-3-86009-045-9

Band 16
Christian Noß
Strömungsstrukturen kleiner naturnaher Fließgewässer unter Berücksichtigung von Turbulenztheorie und Dispersionsmodellen.
Dissertation, erschienen im Januar 2009, ISBN 978-3-86009-054-1

Band 17
Ralf Schröder
Entwicklung von Möglichkeiten zur Messung der N2-Übersättigung sowie Methoden zur Reduzierung der Schwimmschlammbildung.
Dissertation, erschienen im Februar 2009, ISBN 978-3-86009-055-8

Band 18
Elmar Wisotzki
Bodenverfestigungen mit Kalk-Hüttensand-Gemischen.
Dissertation, erschienen im April 2009, ISBN 978-3-86009-059-6

Band 19
Ramez Mashkouk
Untersuchungen zur Adsorption und biologischen Aktivität an Aktivkohlefilter unter den Bedingungen der Wasseraufbereitung im Wasserwerk Rostock.
Dissertation, erschienen im April 2009, ISBN 978-3-86009-060-2

Band 20
Torsten Birkholz
Handlungserfordernisse und Optimierungsansätze für kommunale Ver- und Entsorgungsunternehmen im Zusammenhang mit demografischen Veränderungen im ländlichen Raum aufgezeigt an einem Beispiel in Mecklenburg-Vorpommern.
Dissertation, erschienen im Mai 2009, ISBN 978-3-86009-061-9

Band 21
12. DIALOG Abfallwirtschaft MV
Aktuelle Entwicklungen in der Abfallwirtschaft.
Tagungsband, erschienen im Juni 2009, ISBN 978-3-86009-062-6

Band 22
Thomas Fritz
Entwicklung, Implementierung und Validierung eines praxisnahen Verfahrens zur Bestimmung von Biogas- bzw. Methanerträgen.
Dissertation, erschienen im Oktober 2009, ISBN 978-3-86009-065-7

Band 23
3. Rostocker Bioenergieforum
Bioenergie – Chance und Herausforderung für die regionale und globale Wirtschaft.
Tagungsband, erschienen im Oktober 2009, ISBN 978-3-86009-065-8

Band 24
Muhammad Mariam
Analyse von Gefahrenpotenzialen für die Trinkwasserversorgung der Stadt Rostock unter besonderer Berücksichtigung von Schadstoffausbreitungsvorgängen in der Warnow.
Dissertation, erschienen im Februar 2010, ISBN 978-3-86009-078-7

Band 25
Manja Steinke
Untersuchungen zur Behandlung von Abwässern der Fischverarbeitungsindustrie.
Dissertation, erschienen im Juni 2010, ISBN 978-3-86009-085-5

Band 26
13. DIALOG Abfallwirtschaft MV
Die Kreislauf- und Abfallwirtschaft im Wandel. Wohin gehen die rechtlichen und technischen Entwicklungen?
Tagungsband, erschienen im Juni 2010, ISBN 978-3-86009-087-9

Band 27
4. Rostocker Bioenergieforum
Zukunftstechnologien für Bioenergie
Tagungsband, erschienen im Oktober 2010, ISBN 978-3-940364-12-8

Band 28
Dirk Banemann
Einfluss der Silierung und des Verfahrensablaufs der Biomassebereitstellung auf den Methanertrag unter Berücksichtigung eines Milchsäurebakteriensiliermittel
Dissertation, erschienen im Januar 2011, ISBN 978-3-86009-087-9

Band 29
14. DIALOG Abfallwirtschaft MV
Abfall als Wertstoff- und Energiereserve
Tagungsband, erschienen im Juni 2011, ISBN 978-3-940364-18-0

Band 30
5. Rostocker Bioenergieforum
Tagungsband, erschienen im November 2011, ISBN 978-3-940364-20-3

Band 31
8. Rostocker Abwassertagung
Erhöhung der Effektivität von Abwasserentsorgungsanlagen
Tagungsband, erschienen im November 2011, ISBN 978-3-86009-120-3

Band 32
6. Rostocker Bioenergieforum
Tagungsband, erschienen im Juni 2012, ISBN 978-3-940364-27-2

Band 33
Ishan Machlouf
Untersuchungen zur Nitratelimination bei der Trinkwasseraufbereitung unter Berücksichtigung syrischer Verhältnisse
Dissertation, erschienen im März 2013, ISBN 978-3-86009-204-0

Band 34
Ralph Sutter
Analyse und Bewertung der Einflussgrößen auf die Optimierung der Rohbiogasproduktion hinsichtlich der Konstanz von Biogasqualität und -menge
Dissertation, erschienen im März 2013, ISBN 978-3-86009-202-6

Band 35
Wolfgang Pfaff-Simoneit
Entwicklung eines sektoralen Ansatzes zum Aufbau von nachhaltigen Abfallwirtschaftssystemen in Entwicklungsländern vor dem Hintergrund von Klimawandel und Ressourcenverknappung
Dissertation, erschienen im Mai 2013, ISBN 978-3-86009-203-3

Band 36
7. Rostocker Bioenergieforum
Tagungsband, erschienen im Juni 2013, ISBN 978-3-86009-207-1

Band 37
Markus Helftewes
Modellierung und Simulation der Gewerbeabfallaufbereitung vor dem Hintergrund der Outputqualität, der Kosteneffizienz und der Klimabilanz
Dissertation, erschienen im Oktober 2013, ISBN 978-3-86009-402-0

Band 38
Jan Stefan Riha
Detektion und Quantifizierung von Cyanobakterien in der Ostsee mittels Satellitenfernerkundung
Dissertation, erschienen im Oktober 2013, ISBN 978-3-86009-403-7

Band 39
Peter Helmke
Optimierung der Verarbeitungs-, Gebrauchs- und Entsorgungseigenschaften eines naturfaserverstärkten Kunststoffes unter Berücksichtigung automobiler Anforderungen
Dissertation, erschienen im November 2013, ISBN 978-3-86009-404-4

Band 40
Andrea Siebert-Raths
Modifizierung von Polylactid (PLA)für technische Anwendungen
Verfahrenstechnische Optimierung der Verarbeitungs- und Gebrauchseigenschaften
Dissertation, erschienen im Januar 2014 ISBN 978-3-86009-405-1

Band 41
Fisiha Getachew Argaw
Agricultural Machinery Traffic Influence on Clay Soil Compaction as Measured by the Dry Bulk Density
Dissertation, erschienen im Januar 2014 ISBN 978-3-86009-406-8

Band 42
Tamene Adugna Demissie
Climate change impact on stream flow and simulated sediment yield to Gilgel Gibe 1 hydropower reservoir and the effectiveness of Best Management Practices
Dissertation, erschienen im Februar 2014 ISBN 978-3-86009-407-5

Band 43
Paul Engelke
Untersuchungen zur Modellierung des Feststofftransports in Abwasserkanälen: Validierung in SIMBA®
Dissertation, erschienen im Februar 2014 ISBN 978-3-86009-408-2

Band 44
16. DIALOG Abfallwirtschaft MV
Aktuelle Entwicklungen in der Abfall- und Ressourcenwirtschaft
Tagungsband, erschienen im April 2014, ISBN 978-3-86009-410-5

Band 45
8. Rostocker Bioenergieforum, 19.-20. Juni 2014 an der Universität Rostock
Tagungsband, erschienen im Juni 2014, ISBN 978-3-86009-412-9

Band 46
Abschlussbericht Projekt CEMUWA – Climate protection, natural resources management and soil improvement by combined Energetic and Material Utilization of lignocellulosic agricultural WAstes and residues
Projektbericht, erschienen im September 2014, ISBN 978-3-86009-413-6

Band 47
8. Rostocker Baggergutseminar, 24.-25. September 2014 in Rostock
Tagungsband, erschienen im September 2014, ISBN 978-3-86009-414-3

Band 48
Michael Kuhn
Mengen und Trockenrückstand von Rechengut kommunaler Kläranlagen
Dissertation, erschienen im Oktober 2014 ISBN 978-3-86009-415-0

Band 49
8. Rostocker Abwassertagung, 10.-11. November 2014 in Rostock
Tagungsband, erschienen im November 2014, ISBN 978-3-86009-416-7

Band 50
Mulugeta Azeze Belete
Modeling and Analysis of Lake Tana Sub Basin Water Resources Systems, Ethiopia
Dissertation, erschienen im Dezember 2014 ISBN 978-3-86009-422-8

Band 51
Daniela Dressler
Einfluss regionaler und standortspezifischer Faktoren auf die Allgemeingültigkeit ökologischer und primärenergetischer Bewertungen von Biogas
Dissertation, erschienen im Mai 2015 ISBN 978-3-86009-424-2

Band 52
9. Rostocker Bioenergieforum, 18.-19. Juni 2015 in Rostock
Tagungsband, erschienen im November 2014, ISBN 978-3-86009-425-9

Band 53
Nils Engler
Spurenelementkonzentrationen und biologische Aktivität in NaWaRo-Biogas-fermentern
Dissertation, erschienen im September 2015 ISBN 978-3-86009-427-3

Band 54
Thomas Schmidt
Möglichkeiten der Effizienzsteigerung bei der anaeroben Vergärung von Weizenschlempe
Dissertation, erschienen im Oktober 2015 ISBN 978-3-86009-428-0

Band 55
Thomas Dorn
Principles, Opportunities and Risks associated with the transfer of environmental technology between Germany and China using the example of thermal waste disposal
Dissertation, erschienen im Dezember 2015 ISBN 978-3-86009-429-7

Band 56
Uwe Holzhammer
Biogas in einer zukünftigen Energieversorgungsstruktur mit hohen Anteilen fluktuierender Erneuerbarer Energien
Dissertation, erschienen im Dezember 2015 ISBN 978-3-86009-430-3

Band 57
17. DIALOG Abfallwirtschaft MV
Aktuelle Entwicklungen in der Abfall- und Ressourcenwirtschaft,
15. Juni 2016 in Rostock,
Tagungsband, erschienen im Juni 2016, ISBN 978-3-86009-432-7

Band 58
10. Rostocker Bioenergieforum, 16.-17. Juni 2016 in Rostock
Tagungsband, erschienen im Juni 2016, ISBN 978-3-86009-433-4

Band 59
Michael Friedrich
Adaptation of growth kinetics and degradation potential of organic material in activated sludge
Dissertation, erschienen im Juli 2016 ISBN 978-3-86009-434-1

Band 60
Nico Schulte
Entwicklung von Qualitätsprüfungen für die haushaltsnahe Abfallsammlung im Holsystem
Dissertation, erschienen im Juli 2016 ISBN 978-3-86009-435-8

Band 61
Ullrich Dettmann
Improving the determination of soil hydraulic properties of peat soils at different scales
Dissertation, erschienen im September 2016 ISBN 978-3-86009-436-5

Band 62
Anja Schreiber
Membranbasiertes Verfahren zur weitergehenden Vergärung
von feststoffreichen Substraten in landwirtschaftlichen Biogasanlagen
Dissertation, erschienen im Oktober 2016 ISBN 978-3-86009-446-4

Band 63
André Körtel
Entwicklung eines selbstgängigen statischen Verfahrens zur biologischen Stabilisierung und Verwertung organikreicher Abfälle unter extrem ariden Bedingungen für Entwicklungs- und Schwellenländer, am Beispiel der Stadt Teheran
Dissertation, erschienen im Oktober 2016 ISBN 978-3-86009-447-1

Band 64
Ayman Elnaas
Actual situation and approach for municipal solid waste treatment in the Arab region
Dissertation, erschienen im Oktober 2016 ISBN 978-3-86009-448-8

Band 65
10. Rostocker Abwassertagung, Wege und Werkzeuge für eine zukunftsfähige Wasserwirtschaft im norddeutschen Tiefland, 8. November 2016 in Rostock
Tagungsband, erschienen im November 2016, ISBN 978-3-86009-449-5

Band 66
Gunter Weißbach
Mikrowellen-assistierte Vorbehandlung lignocellulosehaltiger Reststoffe
Dissertation, erschienen im November 2016 ISBN 978-3-86009-450-1

Band 67
Leandro Janke
Optimization of anaerobic digestion of sugarcane waste for biogas production in Brazil
Dissertation, erschienen im Mai 2017 ISBN 978-3-86009-454-9

Band 68
11. Rostocker Bioenergieforum, 22.-23. Juni 2017 in Rostock
Tagungsband, erschienen im Juni 2017, ISBN 978-3-86009-455-6

Band 69
Claudia Demmig
Einfluss des Erntezeitpunktes auf die anaerobe Abbaukinetik der Gerüstsubstanzen im Biogasprozess
Dissertation, erschienen im Juli 2017, ISBN 9978-3-86009-456-3

Band 70
Christian Koepke
Die Ermittlung charakteristischer Bodenkennwerte der Torfe und Mudden Mecklenburg-Vorpommerns als Eingangsparameter für erdstatische Berechnungen nach Eurocode 7 / DIN 1054
Dissertation, erschienen im Juni 2017, ISBN 978-3-86009-457-0

Band 71
Sven-Henning Schlömp
Geotechnische Untersuchung und Bewertung bautechnischer Eignung von Müllverbrennungsschlacken und deren Gemischen mit Böden
Dissertation, erschienen im Juni 2017, ISBN 978-3-86009-458-7

Band 72
Anne-Katrin Große
Baggergut im Deichbau – Ein Beitrag zur geotechnischen Charakterisierung und Erosionsbeschreibung feinkörniger, organischer Sedimente aus dem Ostseeraum zur Einschätzung der Anwendbarkeit
Dissertation, erschienen im Juni 2017, ISBN 978-3-86009-459-4

Band 73
Thomas Knauer
Steigerung der Gesamteffizienz von Biogasanlagen durch thermische Optimierung
Dissertation, erschienen im Juli 2017, ISBN 978-3-86009-460-0

Band 74
Mathhar Bdour
Electrical power generation from residual biomass by combustion in externally fired gas turbines (EFGT)
Dissertation, erschienen im August 2017, ISBN 978-3-86009-468-6

Band 75
Johannes Dahlin
Vermarktungsstrategien und Konsumentenpräferenzen für Dünger und Erden aus organischen Reststoffen der Biogasproduktion
Dissertation, erschienen im September 2017, ISBN 978-3-86009-469-3

Band 76
Sören Weinrich
Praxisnahe Modellierung von Biogasanlagen
Systematische Vereinfachung des Anaerobic Digestion Model No. 1 (ADM1)
Dissertation, erschienen im März 2018, ISBN 978-3-86009-471-6

Band 77
18. DIALOG Abfallwirtschaft MV
Aktuelle Entwicklungen in der Abfall- und Ressourcenwirtschaft
Tagungsband, erschienen im Juni 2018, ISBN 978-3-86009-472-3

Band 78
12. Rostocker Bioenergieforum
Tagungsband, erschienen im Juni 2018, ISBN 978-3-86009-473-0

Band 79
Tatyana Koegst
Screening approaches for decision support in drinking water supply
Dissertation, erschienen im Juni 2018, ISBN 978-3-86009-474-7

Band 80
Liane Müller
Optimierung des anaeroben Abbaus stickstoffhaltiger Verbindungen durch den Einsatz von Proteasen
Dissertation, erschienen im September 2018, ISBN 978-3-86009-475-4

Band 81
Projektbericht Wasserwirtschaft
KOGGE – **Ko**mmunale **G**ewässer **G**emeinschaftlich **E**ntwickeln
Ein Handlungskonzept für kleine urbane Gewässer am Beispiel der Hanse- und Universitätsstadt Rostock
Projektbericht, erschienen im September 2018, ISBN 978-3-86009-476-1

Band 82
Adam Feher
Untersuchungen zur Bioverfügbarkeit von Mikronährstoffen für den Biogasprozess
Dissertation, erschienen im Oktober 2018, ISBN 978-3-86009-477-8

Band 83
Constanze Uthoff
Pyrolyse von naturfaserverstärkten Kunststoffen zur Herstellung eines kohlenstoffhaltigen Füllstoffs für Thermoplasten
Dissertation, erschienen im November 2018, ISBN 978-3-86009-478-5

Band 84
Ingo Kaundinya
Prüfverfahren zur Abschätzung der Langzeitbeständigkeit von Kunststoffdichtungsbahnen aus PVC-P für den Einsatz in Dichtungssystemen von Straßentunneln
Dissertation, erschienen im Dezember 2018, ISBN 978-3-86009-484-6

Band 85
Eric Mauky
A model-based control concept for a demand-driven biogas production
Dissertation, erschienen im Januar 2019, ISBN 978-3-86009-485-3

Band 86
Michael Kröger
Thermochemical Utilization of Algae with Focus on hydrothermal Processes
Dissertation, erschienen im Februar 2019, ISBN 978-3-86009-486-0

Band 87
13. Rostocker Bioenergieforum
Tagungsband, erschienen im Juni 2019, ISBN 978-3-86009-487-7

Band 88
12. Rostocker Abwassertagung
Tagungsband, erschienen im September 2019, ISBN 978-3-86009-488-4

Band 89
Philipp Stahn
Wasser- und Nährstoffhaushalt von Böden unter Mischkulturen und Trockenstress
Dissertation, erschienen im Juli 2019, ISBN 978-3-86009-489-1

Band 90
BioBind: Luftgestützte Beseitigung von Verunreinigungen durch Öl mit biogenen Bindern
Projektbericht, erschienen im September 2019, ISBN 978-3-86009-490-7

Band 91
Jürgen Müller
Die forsthydrologische Forschung im Nordostdeutschen Tiefland: Veranlassung, Methoden, Ergebnisse und Perspektiven
Habilitation, erschienen im Oktober 2019, ISBN 978-3-86009-491-4

Band 92
Marcus Siewert
Bewertung der Ölhavarievorsorge im deutschen Seegebiet auf Grundlage limitierender Randbedingungen – Ein Beitrag zur Verbesserung des Vorsorgestatus
Dissertation, erschienen im November 2019, ISBN 978-3-86009-492-1

Band 93
Camilo Andrés Wilches Tamayo
Technical optimization of biogas plants to deliver demand oriented power
Dissertation, erschienen im Februar 2020, ISBN 978-3-86009-493-8

Band 94
Robert Kopf
Technisches Benchmarking mit Standortqualifikationsstudie biochemischer Energieanlagenprojekte (Beispiel Biogas)
Dissertation, erschienen im Februar 2020, ISBN 978-3-86009-494-5

Band 95
14. Rostocker Bioenergieforum und 19. DIALOG Abfallwirtschaft MV
Tagungsband, erschienen im Juni 2020, ISBN 978-3-86009-507-2
DOI: https://doi.org/10.18453/rosdok_id00002650

Band 96
Safwat Hemidat
Feasibility Assessment of Waste Management and Treatment in Jordan
Dissertation, erschienen im Juli 2020, ISBN 978-3-86009-509-6

Band 97
Andreas Heiko Metzing
Verdichtung von ungebundenen Pflasterdecken und Plattenbelägen - Untersuchungen zur Lagerungsdichte des Fugenmaterials
Dissertation, erschienen im Juli 2020, ISBN 978-3-86009-510-2
DOI: https://doi.org/10.18453/rosdok_id00002742

Band 98
Ying Zhou
Research on Utilization of Hydrochars Obtained by the Organic Components of Municipal Solid Waste
Dissertation, erschienen im November 2020, ISBN 978-3-86009-515-7

Band 99
Mathias Gießler
Ein prozessbasiertes Modell zur wirtschaftlich-technischen Abbildung von Abwasserunternehmen – Beispielhafte Anwendung für eine ländliche Region mit Bevölkerungsrückgang
Dissertation, erschienen im November 2020, ISBN 978-3-86009-516-4
DOI: https://doi.org/10.18453/rosdok_id00002790

Band 100
Dodiek Ika Candra
Development of a Virtual Power Plant based on a flexible Biogas Plant and a Photovoltaic-System
Dissertation, erschienen im Dezember 2020, ISBN 978-3-86009-518-8
DOI: https://doi.org/10.18453/rosdok_id00002814

Band 101
Thomas Zeng
Prediction and reduction of bottom ash slagging during small-scale combustion of biogenic residues
Dissertation, erschienen im Dezember 2020, ISBN 978-3-86009-519-5

Band 102
Edward Antwi
Pathways to sustainable bioenergy production from cocoa and cashew residues from Ghana
Dissertation, erschienen im Dezember 2020, ISBN 978-3-86009-520-1
DOI: https://doi.org/10.18453/rosdok_id00002818

Band 103
Muhammad Waseem
Integrated Hydrological and Mass Balance Assessment in a German Lowland Catchment with a Coupled Hydrologic and Hydraulic Modelling
Dissertation, erschienen im Januar 2021, ISBN 978-3-86009-521-8
DOI: https://doi.org/10.18453/rosdok_id00002884

Band 104
Martin Rinas
Sediment Transport in Pressure Pipes
Dissertation, erschienen im März 2021, ISBN 978-3-86009-538-6
DOI https://doi.org/10.18453/rosdok_id00003915

Band 105
15. Rostocker Bioenergieforum
Tagungsband, erschienen im Juni 2021, ISBN 978-3-86009-524-9
DOI https://doi.org/10.18453/rosdok_id00003024

Band 106
Jan Sprafke
Potenziale der biologischen Behandlung von organischen Abfällen zur Sektorenkopplung
Dissertation, erschienen im Oktober 2021, ISBN 978-3-86009-527-0
DOI https://doi.org/10.18453/rosdok_id00003118

Band 107
Mingyu Qian
The Demonstration and Adaption of the Garage - Type Dry Fermentation Technology for Municipal Solid Waste to Biogas in China
Dissertation, erschienen im Oktober 2021, ISBN 978-3-86009-528-7

Band 108
Haniyeh Jalalipour
Sustainable municipal organic waste management in Shiraz, Iran
Dissertation, erschienen im November 2021, ISBN 978-3-86009-526-3
https://doi.org/10.18453/rosdok_id00003116

Band 109
Michael Cramer
Umgang mit stark verschmutzem Niederschlagswasser aus Siloanlagen
Dissertation, erschienen im Dezember 2021, ISBN 978-3-86009-530-0
https://doi.org/10.18453/rosdok_id00003358

Band 110
16. Rostocker Bioenergieforum und 20. DIALOG Abfallwirtschaft MV
Tagungsband, erschienen im Juni 2022, ISBN 978-3-86009-535-5
DOI: https://doi.org/10.18453/rosdok_id00003615

Band 111
Fachtagung Wasserwirtschaft – Gute Stadt-Land-Beziehungen für eine nachhaltige Entwicklung in MV
Tagungsband, erschienen im Juni 2022, ISBN 978-3-86009-538-6
DOI: https://doi.org/10.18453/rosdok_id00003915

Band 112
Zelalem Abera Angello
Selection of Optimal Pollution Management Strategy for the Little Akaki River, Ethiopia, Based on Determination of Spatio-temporal Pollutant Dynamics and Water Quality Modeling
Dissertation, erschienen im Oktober 2022, ISBN 978-3-86009-542-3
https://doi.org/10.18453/rosdok_id00003948

Band 113
Qahtan Thabit
Hybrid waste Incineration – Solar Parabolic System with Thermal Energy Recovery in Sea wate Disalination in MENA Region
Dissertation, im Druck, ISBN 978-3-86009-545-4
https://doi.org/10.18453/rosdok_id00004181

Band 114
17. Rostocker Bioenergieforum
Tagungsband, erschienen im Juni 2023, ISBN 978-3-86009-547-8
https://doi.org/10.18453/rosdok_id00004269