ASSESSING THE COMPOUND IMPACTS OF CLIMATE CHANGE AND LAND USE DYNAMICS ON FUTURE GROUNDWATER AVAILABILITY IN DRYLAND AREAS OF SRI LANKA

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Master of Science (Major Component of Research)

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Thesis submitted in partial fulfillment of the requirements for the degree

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DECLARATION

I declare that this is my work and this Thesis/Dissertation does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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Herath K.R.H.M.O.N Date

The above candidate has carried out research for the Master's Thesis/Dissertation under my supervision. I confirm that the declaration made above by the student is true and correct.

17/06/2025

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Dr. H.G.L.N. Gunawardhana Date

DEDICATION

This thesis is dedicated to my loving parents, whose blind love, unwavering encouragement, and countless sacrifices have been the backbone of my life and studies. Their unrelenting belief in me has provided me with the courage and determination to propel my academic and personal goals forward, even in the face of adversity. I am forever grateful to them for their patience, guidance, and virtues that they instilled in me.

I also dedicate this thesis to all those teachers and mentors who have taught, guided, and inspired me along the way, through my formative earliest years of schooling to this present moment. Their love for learning, their dedication to developing curiosity, and their willingness to share their expertise have shaped me for life in my intellectual and personal development. All of them have contributed to developing my mind, work habits, and aspirations.

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ABSTRACT

Climate change and land use and land cover (LULC) change are the primary challenges that disrupt the hydrological cycle, significantly impacting groundwater availability. While numerous studies have examined how these changes affect hydrological processes, a critical gap exists in understanding their combined impact on groundwater availability. This study addresses that gap by assessing the compound impacts of climate change and LULC change on groundwater resources in the Kumbukkan Oya catchment, a dryland area in southeastern Sri Lanka, where such research is currently lacking. The analysis uses hydrometeorological data, groundwater levels, borehole logs, and catchment characteristics such as land use, soil type, and elevation. Climate data were obtained from 1989 to 2011, while the groundwater level data and hydrological data were used from 2022 to 2024, at a mostly daily time step. Groundwater flow was then numerically modeled with MODFLOW, a three-dimensional numerical software for groundwater flow simulations. Projected future climate was obtained from the Coupled Model Intercomparison Project Phase 6 (CMIP6) using the CNRM-CM6-1-HR General Circulation Model (GCM) and downscaled to the local scale using a stochastic Random Forest (RF) machine learning algorithm. These were considered for the baseline period (1989–2011) and the future projection period (2030–2049) under the high-emission SSP5-8.5 scenario. Land use data of 2018 and projected for future conditions were employed in assessing LULC dynamics. The MODFLOW model was calibrated and validated using four monitoring wells. According to the result, the model captures the seasonal patterns of decline and recovery, particularly in the upstream, although some overestimation occurred in mid-catchment areas. Future projections indicate a decrease in seasonal rainfall compared to the baseline period, with reduced average rainfall but still frequent extreme events. The future period total rainfall will be 1,591 mm, which is a reduction of 220 mm from the observed total of 1,811 mm. Based on the projected results, groundwater levels are expected to decline by approximately 0.43 m to 0.65 m compared to observed conditions. Therefore, simulation reveals that the Kumbukkan Oya catchment has some extent of resilience in the groundwater level relative to the projected climate and land use change. However, localized tendencies in the fall in groundwater levels suggest the need for site-specific adaptation responses, particularly over vulnerable recharge zones. The study provides valuable insights to policymakers and water resource planners in developing sustainable groundwater management policy for Sri Lanka's dry regions in the context of future climatic uncertainty.

Keywords: Climatic alterations, Compound Impacts, Land use changes, MODFLOW, Random Forest

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LIST OF ABBREVIATIONS

CMIP	-	Coupled Model Intercomparison Project
CN	-	Curve Number
CORDEX	-	Coordinated Regional Downscaling Experiment
DEM	-	Digital Elevation Model
GCM	-	Global Climate Model
GFZ	-	German Research Centre for Geosciences
GIS	-	Geographic Information System
GRACE	-	Gravity Recovery and Climate Experiment
GWL	-	Ground Water Level
HC	-	Highland Complex
IQR	-	Interquartile Range
LULC	-	Land Use and Land Cover
ML	-	Machine Learning
MODIS	-	Moderate Resolution Imaging Spectroradiometer
NN	-	Neural Network
NWIS	-	National Water Information System
NWSDB	-	National Water Supply and Drainage Board
RCM	-	Regional Climate Model
RF	-	Random Forest
RS	-	Remote Sensing
SAR	-	Synthetic Aperture Radar
SMOS	-	Soil Moisture and Ocean Salinity
SSP	-	Shared Socioeconomic Pathways
SVM	-	Support Vector Machines
USGS	-	United States Geological Survey
VC	-	Vijayan Complex
WRB	-	Water Resources Board

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CHAPTER 1

INTRODUCTION

1.1 Background

Groundwater is one of the most valuable natural resources on Earth. Compared to surface water, it offers several advantages, such as higher quality, lower contamination levels, and minimized seasonal changes (UNESCO, 2022). Groundwater is also more evenly distributed across large areas and is often available where surface water is limited. Unlike surface water projects, which require large upfront capital investments, groundwater well fields can be developed over time. These advantages have contributed to the extensive utilization of groundwater for water supply.

Groundwater is a crucial resource for global water usage, especially in agriculture, which consumes the largest share. Out of the total water consumed globally, around 69% aids irrigation, which contributes nearly 40% of world food production. Domestic use is 22%, where water supply for drinking, house upkeep, and industry is about 9%. In Asia alone, 76% of groundwater is consumed annually for agriculture, showcasing the region's dependency on groundwater for food production. Ultimately, groundwater sustains significant global sectors, such as agriculture, domestic use, industrial use, and ecosystems (Aeschbach-Hertig & Gleeson, 2012; UNESCO, 2022).

Despite being a worldwide problem, groundwater depletion recently came to the spotlight. Aeschbach-Hertig & Gleeson (2012) noticed that some doubted its seriousness, citing that yearly groundwater withdrawals hover around 1,500 km^3, while global recharge is estimated at approximately 12,600 km^3. However, many regions still experience significant aquifer depletion. This is evident from rapid groundwater level (GWL) declines recorded in wells and, more recently, large-scale assessments using satellite gravity observations from the Gravity Recovery and Climate Experiment (GRACE) (Longuevergne et al., 2010). These findings confirm that over-extraction occurs routinely, regardless of adequate global recharge.

Groundwater depletion is primarily caused by climate change and land use changes (Marhaento et al., 2018; Neupane & Kumar, 2015; Sha et al., 2021). These changes modify the water cycle by altering surface conditions and atmospheric circulation patterns. Land Use and Land Cover (LULC) changes, such as deforestation or urbanization, affect land surface characteristics, which in turn impact infiltration and runoff. Meanwhile, climatic variations, including shifts in precipitation and temperature, directly influence groundwater recharge (UNESCO, 2022). Understanding climate change along with incremental LULC changes is synergistic, as these factors operate in complex interdependent ways. Therefore, studying the combined consequences of these factors on groundwater availability is more rational than assessing the impacts one at a time (Hao et al., 2018).

By the end of the 21st century, under most projected scenarios, global temperatures are expected to rise by more than 1.5°C above pre-industrial levels. The increase can only be limited to below 1.5°C if the world takes serious and immediate action to reduce greenhouse gas emissions and advances to low-carbon emissions. On the other hand, in scenarios where emissions continue to rise moderately or rapidly, global warming may exceed 2°C, leading to severe and widespread climate consequences (IPCC, 2023). Temperature changes will not be uniform and will persist beyond 2100. From 2016 to 2035, global temperatures are projected to increase by 0.3°C to 0.7°C compared to 1986–2005. In the tropics and subtropics, global temperature increases are projected to be greater than in mid-latitudes. Changes to the global water cycle will vary by region. Wet areas and seasons are likely to become wetter, while dry areas and seasons may become drier. However, some regions will not follow this pattern. The IPCC (2013) predicts heavier rainfall, heat waves, and extreme temperatures with over 90% confidence. Human activities, particularly greenhouse gas emissions, have altered the hydrological cycle over the past 50 years (Huntington, 2006; IPCC, 2023). These climate changes are having significant and widespread effects on groundwater resources, with implications for both quantity and quality.

Moreover, land use changes affect groundwater availability by altering natural water movement. In particular, groundwater serves as a reliable source for drinking, irrigation, and industrial uses in dryland regions (Pande & Moharir, 2021). However, rapid urbanization intensified the pressure on groundwater resources. Improving the capacity of groundwater for urbanization could lead to a lower water table, soil subsidence, and resultant degradation of groundwater quality. Also, the growth of cities introduces more impervious surfaces. The increase in infiltration and surface runoff can lead to shallower water tables and decrease recharge to groundwater (Siddik et al., 2022).

As indicated by the latest assessment report from the Intergovernmental Panel on Climate Change (IPCC, 2023), South Asia is one of the hotspots in the world for climate-induced hazards. By implication, this area, including Sri Lanka, is very seriously at risk regarding water security due to climate change. Also, in Sri Lanka, more than 60% of the population relies on agriculture as the primary source of livelihood, which makes the country extremely vulnerable to hydrological changes associated with climate change (Alahacoon et al., 2024). Among Sri Lanka's regions, the dry zone faces more vulnerability to future climate change. It has already seen a sharp decline in rainfall and high seasonality of annual precipitation, and groundwater, which is an important resource for agriculture, household, and ecosystem uses. Therefore, communities relying upon groundwater may face severe challenges in finding a reliable water supply. Accordingly, groundwater resources in the dryland areas of Sri Lanka need to be considered as possible interacting effects of climate change, together with those of the changes in LULC on the groundwater resources.

Figure 1.1 illustrates spatial variations in Sri Lankan groundwater yield in liters per minute (lpm), according to data collected from 1987 to 2017 by the Water Resources Board (WRB) Database. The majority of the island, particularly the North-Central, North-Western, and Uva provinces, shows low groundwater yields between 0 to 50 lpm, represented by red and orange colors. These regions indicate scarce groundwater resources, potentially creating difficulties for irrigation and domestic water consumption. As against these, the local zones, especially in parts of the Central, Southern, and Eastern provinces, record moderate to high yields (100–1,000+ lpm), characterized by green, cyan, and blue mottling. More significantly, few of the highest yields (2,000–4,000 lpm) are present and are usually scattered across specific zones of the south and central highlands that may relate to geologically or structurally enhanced conditions for aquifer storage and recharge. Overall, the map shows the availability of groundwater in Sri Lanka to be spatially heterogeneous, with the majority of the dry zone regions having low yields, which suggests the need for careful management of groundwater resources, particularly in vulnerable agricultural regions (WRB, 2017).

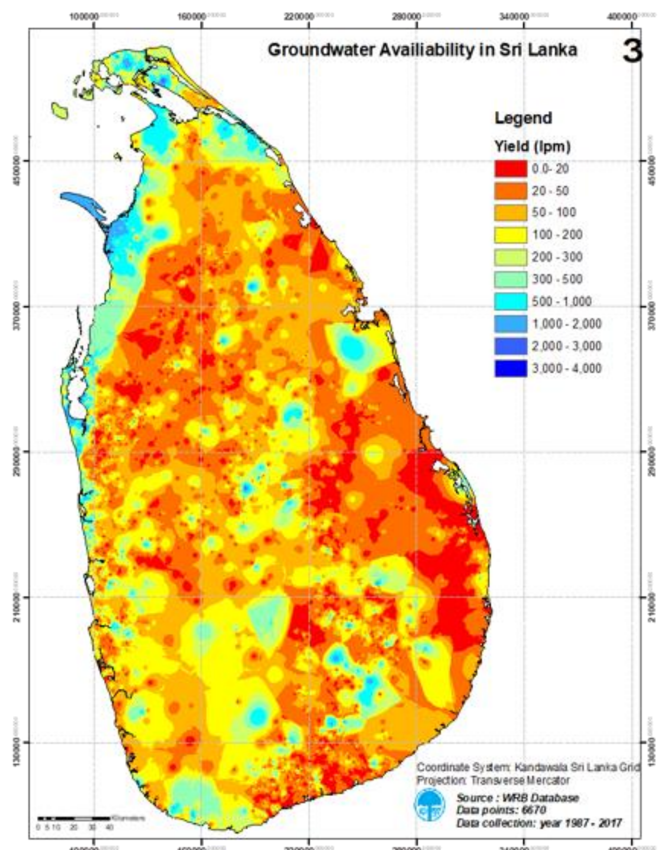

Figure 1.1: Spatial Distribution of the Groundwater in Sri Lanka based on Yield Rates (WRB, 2017)

1.2 Problem Statement

Sri Lanka's dry zone is a major vulnerability to groundwater security, attributable both to climate change and land use change. To assess the impacts of those changing factors on groundwater availability, the present study draws attention to the Kumbukkan Oya catchment, which is in the dry zone. The catchment has an average annual temperature of approximately 23°C throughout the year, and annual average rainfall of approximately 1,695 mm, principally received within the four to five months; and the pan evaporation of the area is approximately 1,100 mm (Irrigation Department of Sri Lanka (IDSL), 2020). As indicated in the map of drought presented by Sandamali et al. (2021), almost all of the catchment area suffers from moderate drought conditions. There are numerous climatic challenges in this catchment, with the primary causes of rainfall variability and prolonged droughts. Rainfall in the study area exhibits a high seasonal variability, with the majority occurring during the northeast monsoon. Climate change has intensified this pattern, which has an adverse effect on water scarcity and groundwater recharge.

Chena cultivation is widely engaged in Sri Lanka's dry zone, including within the Kumbukkan Oya catchment (Sandika & Withana, 2010). Kumbukkan Oya is an agricultural river basin, hence it is the primary livelihood of the community; therefore, long-term land uses have been altered through developments such as the expansion of paddy fields, chena cultivation, and large-scale plantations to the extent that they resulted in deforestation, as well as transformation of natural ecosystems to cultivated land. Because there has been greater demand for agricultural output as well as variable rainfall patterns, several farmers have relied on shallow and deep tube wells to obtain groundwater for irrigation (Sandhamali & Nanthakumaran, 2015) which has led to concerns over depletion, especially in areas where the extraction of groundwater is excessive.

1.3 Aim and Objectives of the Study

1.3.1 Aim of the Study

This study aims to use an integrated method of process-based physical model and machine learning technique to evaluate the effects of climate change and possible changes in LULC on groundwater aquifers in dryland areas of Sri Lanka.

1.3.2 Specific Objectives of the Study

- To develop a numerical groundwater flow model for groundwater flow simulation.
- To refine Global Climate Model (GCM) outputs to the local scale and assess future hydroclimatic variability.
- To evaluate the combined effects of climate change and potential LULC change effects on groundwater level variations.

1.4 Scope and Limitations

This research investigates the impacts of changes in climate and land use patterns on groundwater availability in dryland areas of Sri Lanka. The study will focus on the Kumbukkan Oya catchment. It incorporates the development of a simulation framework to represent the flow behavior of groundwater and future hydroclimatic trends to identify potential changes in groundwater resources. Historical and projected climate information, land use maps, and hydrological information are used to provide an estimate of how GWLs may respond to environmental changes over time. To estimate future GWL changes, the present precipitation data provided by the GCM were used to estimate future variations. Future land use variations are not considered in this study, instead, current land use conditions are used with minor changes to account for possible changes in future requirements. Population growth is important to consider when studying groundwater, as changing water demand and land use can have adverse effects on recharge and availability of groundwater. The impacts of urban expansion, intensification of agriculture, and deforestation vary the hydrological cycle, affecting groundwater storage. However, in this study, population growth is not considered.

1.5 Significance of Study

Over the last decade, there have been detailed studies about the effects of climate change and LULC transformation on surface water resources (Doble et al., 2012; Faridatul, 2018; Tan et al., 2022). While their compound effects on surface water resources have been explored extensively, few investigations have critically examined their effects on groundwater (Neupane & Kumar, 2015; Sha et al., 2021). This gap highlighted the need for the identification of the effects of the compound impacts of LULC change and climate change on the availability of groundwater. Additionally, this assessment is crucial in the development of long-term water management practices that contribute to mitigating the effects of drought by providing a constant groundwater supply. It permits attempts at improving groundwater recharge through practices such as artificial recharge, which are necessary for maintaining the aquifer levels. It also provides early warning systems in case there is a decrease in the aquifer level or pollution, where intervention can be made in time.

At the industrial level, knowing how much groundwater will be present in the future helps in planning water use. It supplies enough water for various industrial processes. This helps with having consistent operations. It also helps in distributing water evenly between industry, agriculture, and domestic consumption. This prevents overexploitation of groundwater resources. Such a pre-adoption measure serves to create a strategy that will ease the potential implications of water deficit and quality modification on production. Apart from the industries, effective groundwater management will also lead to cost savings through reducing exorbitant-cost emergency well or intake construction and/or alternative supply. Such an assessment will establish a baseline towards sustainability and resilience to the natural environment as well as the industrial system for meeting the demands caused by climate and land use change.

1.6 Arrangement of the Thesis

The thesis has been structured into five overall chapters, with each chapter emphasizing a crucial aspect of the research. The organization follows logical progression, from introducing the research problem to presenting methodologies, results, and conclusions.

The Introduction chapter provides a proper background to the research, outlining the significance and the dangers of climate change and land use changes. It clearly states the problem, sets out the aim and objectives, and outlines the research scope and limitations. The chapter concludes with an illustration of the importance of the research in understanding groundwater availability.

The second chapter, Literature Review, offers a thorough review of the research available on the subject. It begins with a description of the principal challenges faced in examining the impacts of climate change and land use changes on groundwater resources. It also explores the application of new technologies in compound impact assessment. The chapter further talks about selecting a suitable groundwater model and explaining different modeling approaches and applications. The chapter then ends by discussing methods to downscale GCM outputs at the local level, explaining model selection and outlining the selected model.

The third chapter, Materials and Methods, describes the study area and data collection procedure, including preliminary data analysis. It examines GWL variations in terms of rainfall and land use trends in the catchment. The chapter also provides a methodological flowchart, describing step-by-step groundwater model development. It includes conceptual model development, grid model development, and machine learning (ML) based downscaling of GCM outputs.

The fourth chapter, Results and Discussion, is where the results of the study are given. It starts with the results of the steady-state groundwater model and then proceeds to the transient model results. The chapter discusses the model results in detail, comparing them with observed data. Furthermore, it evaluates the effectiveness of the downscaling approach for GCM outputs and its impact on groundwater recharge projections.

The final chapter, Conclusion and Recommendations, summarizes the key findings of the study and provides recommendations for sustainable groundwater management. It discusses the broader implications of the research and suggests potential areas for future studies to enhance the understanding of groundwater response to climate and land use changes.

CHAPTER 2

LITERATURE REVIEW

This literature review was undertaken to develop a methodology for quantifying the compound impacts of climate change and land use dynamics on groundwater availability and to identify proper tools and models to be used in the research.

2.1 Overview

The primary precipitation source for groundwater recharge is rainfall. Available freshwater fills up underground aquifers via infiltration. Temporal and spatial variability in precipitation patterns, nevertheless, exerts a strong impact on the balance between precipitation and groundwater recharge. The relationship is also complicated by changes in precipitation intensity, frequency, and duration due to climate change (Faridatul, 2018). The temperature changes also influence groundwater by altering the evaporation rate from the surface water resources and soil, particularly in arid and semi-arid regions. The heightened evaporation rate causes additional water depletion from the surface water bodies and soils, thus decreasing groundwater recharge (Nkhonjera & Dinka, 2017). Additionally, the increasing temperature increases sea level, thereby accelerating the entry of seawater into the coastal aquifers, further contaminating freshwater resources with salts and thereby making such groundwater unfit for drinking or irrigation (Ranjan et al., 2006).

Also, groundwater recharge depends on natural landscapes, including forests, which help in the infiltration process. Forests, containing a complex root system and organic matter, allow water to infiltrate into soils. However, urbanization creates more impermeable surfaces, decreasing infiltration and increasing the rate of surface runoff. Because of that, less water can now infiltrate the aquifer, hence a diminished groundwater recharge rate. Furthermore, deforestation might disorganize the natural drainage patterns. Such disturbance would contribute to raising surface runoff and the frequency of flash flooding (Leonard et al., 2014). The elevation change may affect the location of recharge and discharge in an aquifer. Lower altitudes serve as discharge areas, while higher altitudes often serve as recharge areas. Changes in these areas may disrupt the balance between recharge and discharge. The pathways through which groundwater moves also depend on topography; generally, water flows towards lower altitudes from higher altitudes (Grinevskii, 2014).

Studying the relationship between climate change and LULC change helps in understanding the complex impact of the two processes on groundwater resources. Understanding changes as interconnected processes can help in designing more accurate measures to reduce or adapt the impact on the groundwater supply. Compound events, characterized by the simultaneity or consequence of two or more extraordinary events, have drawn significant attention in recent years since their impacts on socioeconomic and environmental systems have increased. Such events pair the extremes of weather events like heat waves, drought, and excessive rain, tend to have more impacts than individual events (Hao et al., 2018). The impacts of such compound events on groundwater have been addressed in several studies, underlining their complexity and broad range (Grinevskii, 2014; Ketabchi et al., 2016).

For example, the combination of drought and sea level rise is extremely risky, especially in the coastal areas. Droughts, along with low rainfall, lead to lower groundwater recharge. This decrease leads to the depletion of freshwater storage in aquifers. Simultaneously, droughts with rising temperatures can lead to an increase in the melting glaciers and an increase in the sea level. Rising sea level allows seawater encroachment into the aquifer and reduces the availability of freshwater (Guha & Panday, 2012). The opposite of this situation is intense and prolonged rain and rising sea level. It may result in increased groundwater recharge with surplus water seeping through the ground and into aquifers. Rising GWLs can introduce a variety of undesirable effects, including increasing the uplift forces on foundations and subsurface water structures, flooding low-lying buildings and subsurface tunnels, corroding into subsurface utility mains and cables, and reducing the quality of groundwater due to contaminants in shallow subsurface layers and inter-aquifer leakage (Gunawardhana et al., 2019).

Also, if we take altered precipitation patterns and agricultural expansion together, changes in precipitation patterns, namely the trend of fewer but more frequent rains, may result in spectacular changes in groundwater availability. This may result in a decrease in the infiltration rates as the soil is not given enough time to absorb the increased amount of water. In addition, increased rainfall intensity could also increase surface runoff further, thereby reducing the volumes infiltrating into aquifers (Doble et al., 2012).

However, catchment size does count when it comes to minimizing the impacts of climate change and LULC change on groundwater resources. For example, larger catchments, typically with heterogeneous topography and large areas of infiltration, are more resistant to changes in precipitation and are in a better position to sustain GWLs. For smaller catchments, especially in arid regions, precipitation variability is far greater; for such places, the condition of groundwater shifts at a greater speed (Guyasa et al., 2024). Also, several studies have indicated that the influence of LULC changes on groundwater resources becomes more significant as the size of the catchment decreases and exceeds the influence of climate change. Normally, the smaller catchment contains less total volume of water in the ground. Land use changes, like increases in paved areas for urbanization, decrease infiltration, so that in a smaller catchment, the total water that reaches the aquifer is decreased more vulnerable. Besides, in a small catchment, the totality of any land use changes compromises a greater fraction of the total area. If a development paves over a large part of the previous infiltration area, the percentage reduction is more drastic. Climate change effects, such as a change in precipitation, might be averaged out over a larger area. However, the reduction in localized rainfall is also more significant in a smaller catchment (Hung et al., 2020).

2.1.1 Challenges in Analysis of Climate Change and Land Use Dynamics on Groundwater Resources

Hydrological models are effective tools to understand how LULC and climate impact groundwater. Numerical models replicating hydrological processes, under land use and climate changes, can be integrated to explain the compound effects of warmer, drier climates and increasing urbanization on groundwater availability and recharge. However, the usage of conventional models makes it challenging to estimate such compound effects accurately because they simplify complex nonlinear interactions between climate change, LULC changes, and groundwater processes.

Reliable precipitation and aquifer characteristics data are more important for the precise estimation of groundwater recharge. Nevertheless, the scarcity of data, especially in developing regions, is leading to significant uncertainty. To model groundwater systems, hydrological models need to be used to simplify the variability in soil quality, plant cover, and aquifer geology. Inevitably, this simplification will lead to deviations from reality in many situations (Guyasa et al., 2024). Furthermore, climate is inherently variable; because of this, climate models can't project future climatic situations with total accuracy. Even while climate models try to account for this unpredictability, they may not include the whole range of all possible future circumstances. The precision of climate models is also exposed to influences from the assumptions and simplifications carried out during their development. In the study of compound events, the complexity of modeling the interaction among the different variables is a major problem. All the interactions are hardly possible to capture accurately, thus leading to uncertainty in the analyses and forecasts. The simulation of compound extremes using just historical data is difficult because climate change and other factors may change in intensity and frequency in the future. Because of this, scientists need to develop methods that will effectively forecast future changes in compound extremes based on these varying factors (Hao et al., 2018).

2.1.2 Utilizing Enhanced Technologies for Compound Impact Assessment

As previously mentioned, estimation of the effects produced by compound events on the hydrological cycle requires special methods. Here are some approaches that can be used. The Coordinated Regional Downscaling Experiment (CORDEX) project's Regional Climate Models (RCMs) can be used to analyse complex relationships between the components in the hydrological cycle and compound events. The CORDEX framework of downscaling, which produces high-resolution climate predictions from the GCMs, gives a fuller depiction of regional climatic conditions. Also, CORDEX RCMs can allow for the development of compound occurrences, such as sea-level rise, floods, and droughts, using temperature and precipitation changes as interactions. In addition, CORDEX RCMs can be used to estimate the level of uncertainty associated with these estimates, thus enabling better decision-making in water resource planning, management, and adaptation (Onyutha et al., 2019). Also, Remote Sensing (RS) data is widely applied to large and data-sparse catchments to help in hydrological modeling. RS data are available from government institutions, research institutions, and private agencies. Table 2.1 shows some of the most used sources of RS data for groundwater studies. By making use of RS data, researchers can trace the soil moisture change with time and assess the effects of compound events, such as droughts or extreme rainy events. RS technology can also be applied to monitor the alterations in the vegetation cover that will affect the rate of evapotranspiration and the amount of water remaining in the soil. Evaluating RS data of vegetation cover helps researchers to quantify the changes in vegetation and their impact on the hydrological cycle in response to compound events (Onyutha et al., 2019).

Table 2.1: Available RS Data Sets for Groundwater Studies

Source	Data Available
Gravity Recovery and Climate Experiment (GRACE) (https://podaac.jpl.nasa.gov/)	Monitoring groundwater storage changes
Soil Moisture and Ocean Salinity (SMOS) (https://earth.esa.int/eogateway/missions/smos)	Soil moisture monitoring, groundwater recharge estimation
Landsat (https://landsat.gsfc.nasa.gov/)	Map the places where groundwater recharge occurs and identify prospective groundwater zones.
Synthetic Aperture Radar (SAR) (https://earth.esa.int/eogateway/instruments/sar-ers)	It can be applied to detect land deformation related to groundwater extraction and subsidence.
Moderate Resolution Imaging Spectroradiometer (MODIS) (https://modis.gsfc.nasa.gov/data/)	Monitor land surface temperature, land use, and evapotranspiration.

Moreover, Advanced groundwater monitoring databases help to provide key data that are to be considered for the assessment of conditions of the groundwater and its response to stressors, which include compound events. For the analysis of the compound effects, research is conducted by collecting data including GWLs, precipitation, temperature, land use, and soil moisture. Then, the trends and patterns are analysed by using statistical and ML methods to see the relationships between groundwater conditions and multiple stressors. Historical data is then analysed to understand the impacts of past compound events. Finally, use Geographic Information Systems (GIS) and other visualization tools to map groundwater responses (Gogu et al., 2001). Table 2.2 provides an overview of some major local and global groundwater monitoring databases, with details on who developed them and their key features.

Table 2.2: Global and Local Groundwater Monitoring Databases

Database	Developer	Details
USGS National Water Information System (NWIS)	United States Geological Survey (USGS)	Comprehensive data on GWLs, quality, and usage across the U.S., including real-time and historical measurements.
Gravity Recovery and Climate Experiment (GRACE)	NASA and the German Research Centre for Geosciences (GFZ)	Satellite-based measurements of changes in groundwater storage globally.
National Water Supply and Drainage Board (NWSDB)	NWSBD, Sri Lanka	Provides data on GWLs, quality, and usage across various regions in Sri Lanka.
Water Resources Board (WRB)	WRB, Sri Lanka	Manages data related to groundwater resources, including levels, quality, and well information.

2.2 Groundwater Model Selection

Groundwater modeling is an effective tool that can aid in the analysis of most groundwater problems. The process starts with the conceptualization of physical problems. The second step of modeling involves mathematically representing the physical system. Typically, the results are the well-established groundwater flow and transport equations. These equations are typically simplified, under special characteristics of the site, to produce a set of equation subsets. It is only after knowing these equations and their respective boundaries and initial conditions that a model can be formulated. This is also known as a conceptual model for the area (El Alfy, 2014).

The groundwater flow models employed in this study attempted to define critical characteristics and behaviour of the groundwater system because the subsurface geology structures and processes cannot be directly observed. The models incorporate flow direction, distribution, and aquifer properties, and sediment or bedrock heterogeneity and anisotropy into mathematical equations (Becker, 2006; Ibrahim et al., 2024).

MODFLOW, MODPATH, Groundwater Vistas, GFLOW, FLOWPATH, AQUA3D, PEST, SUTRA, and MIKE-SHE can be used to quantify the groundwater flow as well as the prediction of water levels. Among these, MODFLOW is used most because it is highly documented, easy to use, and has lower computational demands (Akter & Ahmed, 2021; Basharat & Jawad, 2023; Itoua-Tsele et al., 2021; Kirubakaran et al., 2018; Paul Venance et al., 2021). Also, it easily couples with GIS technology, thereby enabling great visualization of the results in the spatial and temporal framework (Krause et al., 2007).

MODFLOW is a versatile numerical model that accurately simulates complex groundwater processes under both transient and steady-state flow conditions (Pathak et al., 2018). Unlike simple models, it accurately simulates nonlinear surface water-groundwater interactions, considering factors like evapotranspiration, recharge, and aquifer variable properties. It accurately functions even in data-scarce regions by assimilating heterogeneous datasets, such as RS data, and sensitivity analysis reduces uncertainty. In addition, MODFLOW has a holistic approach to simulating groundwater recharge, with the capacity to include precipitation, land use, and soil type, very useful in assessing groundwater availability under dynamic land use and climatic conditions. Based on the hydrogeological setting and availability of data of the study area, and the project objectives, the MODFLOW model was used for simulations.

2.2.1 Model Description

MODFLOW is a widely used three-dimensional finite difference groundwater model. It was developed by the USGS in 1984 to simulate the movement of groundwater, which is today's industry standard program. Therefore, the structure of MODFLOW is not rigid, and users can modify the code as per their requirements and needs. The following advancements, such as MODFLOW-2000, MODFLOW-2005, and the present MODFLOW-6, added new capabilities. MODFLOW can compute steady and transient hydraulic heads and steady and transient water discharge in a non-uniform aquifer system that may contain confined, unconfined, or both aquifer layers. It simulates interactions with outside forces like recharge, wells, drains, rivers, canals, and evapotranspiration. Because of its flexibility and effectiveness in calculations, it is now a standard tool for application in groundwater modeling for research and project use (Akter & Ahmed, 2021; Basharat & Jawad, 2023; Itoua-Tsele et al., 2021; Kirubakaran et al., 2018; Paul Venance et al., 2021). The governing three-dimensional flow (Equation 1) employed by MODFLOW was formulated by Darcy's Law and the conservation of mass law as:

$$\frac{\partial}{\partial x}\left(k_{xx}\frac{\partial h}{\partial x}\right)+\frac{\partial}{\partial y}\left(k_{yy}\frac{\partial h}{\partial y}\right)+\frac{\partial}{\partial z}\left(k_{zz}\frac{\partial h}{\partial z}\right)-W= S_s\frac{\partial h}{\partial t} \qquad \text{(Equation 1)}$$

where,

h is the hydraulic head,
K_{xx}, K_{yy}, and K_{zz} are hydraulic conductivity values along the x, y, and z coordinate axes,
W is any additional sources or sinks (like recharge or wells),
$\frac{\partial h}{\partial t}$ represents the variation in hydraulic head over time, and
Ss is the specific storage

2.3 Downscaling GCM Outputs for Local Scale

GCMs are critical to understanding and predicting climate change impacts on hydrological systems. GCMs provide large-scale climate variables like temperature, precipitation, and evaporation, which are the main inputs for hydrological models. These are utilized to project and assess long-term trends in groundwater recharge, availability, and potential stressors like droughts or floods. But, GCM outputs tend to be coarse-resolution but are often statistically or dynamically downscaled to provide local climate information to facilitate improved groundwater modeling (Amnuaylojaroen, 2023; Jain, 2014). The following section discusses the selection of a suitable GCM and a downscaling method.

2.3.1 Selection and Justification of a Suitable GCM

The purpose of the Coupled Model Intercomparison Project (CMIP) is to study and contrast climate models. The sixth phase of the project, that is, CMIP6, possesses the most advanced GCMs available today (Almazroui et al., 2020). Compared with their earlier counterparts, CMIP6 models can more accurately simulate different aspects of the monsoon, such as average and extreme rainfall patterns, and monsoon season variability. All the models differ in spatial resolution, parameterizations, and complexity. Some of the prominent models are CNRM-CM6-1, CNRM-CM6-1-HR, CNRM-ESM2-1, MPI-ESM1-2-HR, EC-Earth3, UKESM1-0-LL, and CESM2. (Jayaminda et al., 2023) compared various CMIP6 models' performances and determined that CNRM-CM6-1-HR and CNRM-ESM2-1 were the most suitable among the selected GCMs. Notably, there are two versions of the CNRM-CM6-1-HR model, with a high spatial resolution of 0.5° × 0.5°. Given that Sri Lanka is a small island in terms of size, the high-resolution version of CNRM-CM6-1-HR would be most suitable. Accordingly, the CNRM-CM6-1-HR model was selected for this study based on its suitability for representing regional climate patterns and its performance in previous evaluations.

A GCM model simulates the Earth's climate system by incorporating atmospheric, oceanic, and land surface processes to enable scientists to project future climate states under different greenhouse gas scenarios, such as the Shared Socioeconomic Pathways (SSP) combinations, to assess the possible impacts of different socio-economic and emission pathways. The main SSP types are categorized according to the different socioeconomic development, technological advancement, and mitigation. They are the low-emission scenario SSP1-2.6, the medium-emission scenario SSP2-4.5, and the high-emission scenario SSP5-8.5 (Almazroui et al., 2020). Under this study, the change of GWL is assessed under the compound impacts of climate change and land use patterns. Therefore, the use of the SSP5-8.5 scenario is appropriate since it is a high-emission worst-case pathway that helps in projecting the potential extreme impacts on groundwater systems.

2.3.2 Downscaling Techniques for Localized Climate Data

Using high-resolution RCMs, dynamic downscaling incorporates topography and land use to model local climatic processes. Dynamic downscaling provides physically realistic solutions but at a computational cost. By using historical records, statistical downscaling creates statistical links between local climate variables and the GCM outputs. Statistical downscaling is computationally cheap but assumes future climate relationships would be identical to past historical relationships (Jain, 2014). Besides, bias correction is mostly applied to bring GCM output into line with observed records before downscaling. These methods play an important role in improving the accuracy of climate projections used in groundwater modeling to ensure that future changes in groundwater recharge.

Dynamic downscaling is particularly good at modeling local climatic variability and extreme weather. However, it comes with serious shortcomings, including high computational demand, large calibration requirements, and dependence on coarse-resolution GCM boundary conditions, which can still make the results biased. For instance, RCMs require specialized expertise and long simulation times, making them inappropriate for most purposes (Xu et al., 2019). Given these limitations, statistical downscaling is similarly an ideal option as it is less computationally intensive. Statistical downscaling uses historical climate records to establish empirical relationships between GCM outputs and local climate variables. Statistical downscaling is less computationally demanding, more flexible, and is capable of handling bias correction as well, thus being a more viable option for localized climate impact assessments, such as groundwater availability assessments.

Statistical downscaling includes regression-based methods and weather generators (Jain, 2014). Weather generators use stochastic models to simulate daily climate variables while preserving observed statistical characteristics. Regression-based methods establish relationships between GCM outputs and local climate variables using methods like multiple linear regression, random forest, and artificial neural networks. These methods are effective in discovering nonlinear, complicated relationships and hence make ML an important tool to improve the prediction accuracy, as mentioned in Section 2.1.2 (Najafi et al., 2011; Sachindra et al., 2018).

2.4 Evaluating ML Algorithms for Climate Data Downscaling

For downscaling climate data, various ML algorithms can be employed, including Random Forest (RF), Support Vector Machines (SVM), Neural Networks (NN), and Linear Regression (Amnuaylojaroen, 2023; Hernanz et al., 2022; Hutengs & Vohland, 2016). Each of these algorithms has its strengths based on the characteristics of data and the problem at hand. However, RF stands out as the most suitable choice due to its ability to effectively handle complex, non-linear correlations between the predictors and outcome (Hutengs & Vohland, 2016). This is particularly important in climate data, where relationships are often non-linear. Furthermore, RF is an ensemble learning algorithm that increases strength through the process of averaging the predictions of many decision trees to avoid overfitting risk, most effective when dealing with noisy or high-dimensional data (Amnuaylojaroen, 2023; Hutengs & Vohland, 2016).

Compared with other algorithms like SVM or NN, RF requires minimal data preprocessing as it can handle input variables with varying scales and units without normalization. RF is also tolerant to noise and insensitive to outliers common in climate data, which makes its prediction more stable and reliable. It also handles multicollinearity well without needing complex feature selection (Hutengs & Vohland, 2016). Given these advantages, RF was selected as the optimal ML algorithm for downscaling climate data, as it offers the best balance of accuracy, robustness, and interpretability for the task at hand.

2.4.1 Model Description

RF is an ensemble ML algorithm that handles classification and regression tasks. It builds many decision trees and combines them into one tree to obtain more stable and accurate outputs.

Decision Trees:

A decision tree predicts an output (target variable) by splitting the data at each node. The mean of the target variable in each leaf node is the prediction for regression tasks, as demonstrated in (Equation 2):

$$y_i = \frac{1}{N_i} \sum_{j \in C_i} y_j \qquad \text{(Equation 2)}$$

where:

y_i is the predicted value for the i^{th} leaf node,
N_i is the number of data points in the i^{th} leaf node,
C_i is the set of data points in the i^{th} leaf node, and
y_j are the target values of the data points in the i^{th} leaf node

For classification, the prediction at each leaf node is typically the mode (most frequent) class in the node:

$$y_i = \ mode\ (C_i) \qquad \text{(Equation 3)}$$

Bootstrap Aggregating (Bagging):

RF uses an approach called bootstrapping, where it generates multiple random samples (with replacement) of the training set. Every decision tree in the forest is trained on a different bootstrap sample.

Let the original dataset be:

$$D = \{(x_1, y_1), (x_2, y_2), \dots \dots, (x_n, y_n)\} \qquad \text{(Equation 4)}$$

A bootstrap sample D^* of size n is created by sampling with replacement:

$$D^* = \{(x_{i_1}, y_{i_1}), (x_{i_2}, y_{i_2}), \dots \dots, (x_{i_n}, y_{i_n})\} \qquad \text{(Equation 5)}$$

where: $i_1, i_2, \dots\dots, i_n \in \{1, 2, \dots\dots, n\}$

Random Feature Selection:

Each tree split evaluates a randomly selected group of input variables (instead of using all features). This helps introduce variety among the trees in the forest. For each split, a random subset F of m features is selected from the total p features:

$$F \subseteq \{1, 2, \dots \dots, p\}, |F| = m \qquad \text{(Equation 6)}$$

where:

F is the subset of features considered for the split,
p is the total number of features, and
m is the number of features randomly selected

Making Predictions:

After training multiple decision trees, RF combines the predictions from each tree. The average of each tree's predictions is the RF's final forecast.

$$y_{RF} = \frac{1}{T}\sum_{t=1}^{T} y_t \qquad \text{(Equation 7)}$$

where:

y_{RF} is the final prediction from the RF,
T is the number of trees, and
y_t is the prediction from the t^{th} tree

The final prediction from the RF is the majority vote from all the trees:

$$y_{RF} = mode\ (y_{1,}, y_{2,\ldots\ldots\ldots\ldots,} y_t\ ) \qquad \text{(Equation 8)}$$

where:

y_t is the prediction from the t^{th} tree, and
$mode\ (y_{1,}, y_{2,\ldots\ldots\ldots\ldots,} y_t\ )$ is the most frequently predicted class across all trees

2.5 Estimation of Groundwater Recharge

The quantity of surface water that seeps into the permanent water table is known as groundwater recharge. Percolation can occur through direct interaction in the riparian zone or by percolation into the soil. It is the available water for long-term use and is significant for approximating groundwater resources. Since recharge cannot be measured directly, it must be quantified using various approaches. Deterministic modeling is an effective way of estimating groundwater recharge. It is a physical process of quantification of all the hydrological processes and the addition of the total water balance. Models such as TOPOG_IRM (Zhang et al., 1999), HELP3 (Jyrkama et al., 2002), and SWAT (Loukika et al., 2020) are employed to estimate recharge in the unsaturated zone.

Recharge is calculated using vegetation, climate, and hydrological factors. Since these models provide information on how recharge varies over space and time, they can be merged to improve groundwater flow modeling (Rushton & Ward, 1979). Most hydrologic models, including surface water and groundwater models, use the water budget method to quantify groundwater recharge (Priyantha et al., 2006). Therefore, we applied this method to the recharge assessment since it is extremely versatile. The fundamental equation for water balance of any catchment is given as in (Equation 9).

$$R = P - ET - RO \quad \text{(Equation 9)}$$

where,

R is the groundwater recharge,
P is the precipitation,
RO is the surface runoff, and
ET is the evapotranspiration

This water balance method is sensitive to measurement errors since it involves a lot of observational parameters. Therefore, in this research, this equation will be applied only to estimate recharge values that will serve as a first value input to MODFLOW before its calibration.

2.6 Summary of the Literature Review

According to the literature review, the groundwater resources of dryland regions like Sri Lanka come under growing pressure from the compound impacts of land use and climate change. Groundwater is a critical resource for agriculture, water supply, and ecosystem support in these regions, but its sustainability is increasingly threatened by shifting rainfall patterns, temperature rise, and land-cover alterations. Quantifying the compound impacts of these factors is important for efficient water resources management, but this is a difficult task due to the non-linear interaction among climatic variables, surface properties, and subsurface processes. The incompatibility of spatial and temporal scales between global climate model simulations and localized hydrological conditions is the key problem questioned in literature. Also, the limitations in the resolution and availability of long-term groundwater and land use data, as well as the unpredictability of future projections, complicate the assessment further.

To evaluate the compound effects of land use and climate change on groundwater availability in the Kumbukkan Oya, an integrated method will be used. Climate data downscaling will be achieved through ML methods, namely RF. The selected GCM for this study is CNRM-ESM2-1, which is part of the CMIP6 models and provides reliable simulations for South Asia. Future climate projections will be evaluated under the SSP5-8.5 scenario. Groundwater recharge will be approximated using a water balance approach with precipitation, evapotranspiration, and surface runoff. Groundwater flow simulations will be conducted using the MODFLOW modeling framework. This approach enables the simulation of historical, climate, and land use scenarios, providing a combined assessment of the implications of future changes in groundwater resources in the region.

CHAPTER 3

MATERIALS AND METHODS

In this chapter, the general approach followed to obtain the primary and specific objectives is explained. Apart from that, the study area and the data used for the analysis were discussed.

3.1 Study Area

Kumbukkan Oya catchment is in Sri Lanka's Uva and Eastern provinces, with most of it located in the Monaragala District (Figure 3.1). Covering 1,227 km², the catchment has an elevation range from the mean sea level to 1,400 m above sea level. The Kumbukkan Oya River flows for 116 km, supporting the largest irrigation system in Monaragala. Located at approximately 6.8°N and 81.5°E, catchment is essential for agriculture and water resources in the region. It irrigates about 2,000 acres of cultivated land and plays a vital role in agriculture and water management in the areas surrounding it (Rathnayaka, 2021).

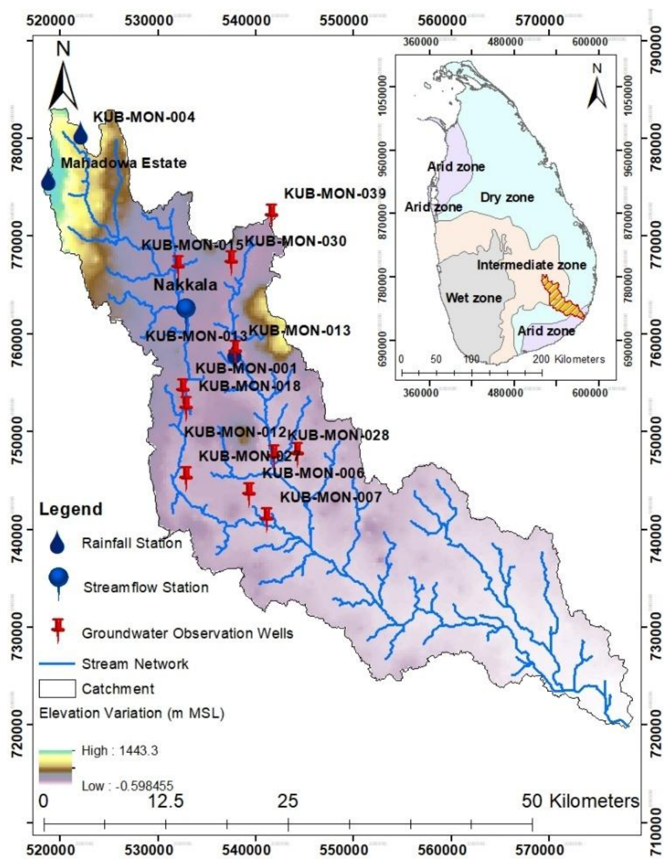

Figure 3.1: Kumbukkan Oya Catchment and the Locations of the Rainfall, Streamflow, and Groundwater Monitoring Stations

The geological formation map is attached to Appendix A. According to that, the area is covered by metamorphic rocks of two crustal complexes, namely the Highland Complex (HC) and Vijayan Complex (VC). Rocks of VC underlie approximately three-quarters of the area, while the rest is mainly HC. The borehole data attached to Appendix B show a heterogeneous geological makeup in the Kumbukkan Oya catchment, with a layering of soils over bedrock. The superficial deposits typically consist of topsoil, with underlying combinations of sand, clay, and gravel. Clay layers can serve to restrict the movement of groundwater. The deeper units consist of weathered rock and, in some cases, metamorphic bedrock. This geological heterogeneity, coupled with the rolling topography of the region, is expected to cause high spatial variation in groundwater levels and flow.

The Kumbukkan Oya catchment receives an annual rainfall of nearly 1,700 mm with distinct seasonal variations. The Northeast Monsoon (December–February) receives the highest portion, with 35.2% of the total rainfall, and is the most crucial season for surface water supply and groundwater recharge. It is followed by the Southwest Monsoon (May–September) with 27.4%, though the rain is relatively less in June and July. The Second Inter-Monsoon (October–November) contributes 21.3% with intense but brief rainfall. The First Inter-Monsoon (March–April) contributes the least with 16.1%. Figure 3.2 shows the rainfall pattern variation in the catchment.

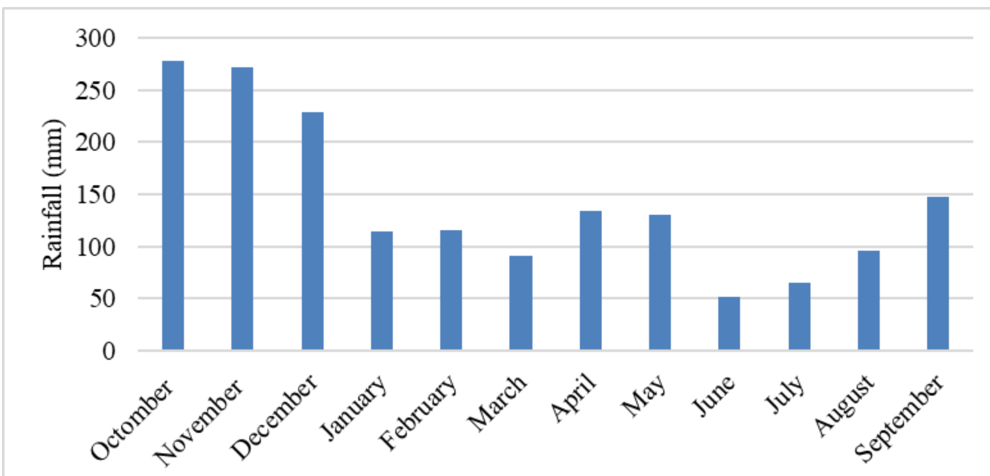

Figure 3.2: Monthly Rainfall Variation at Mahadowa Estate Rain Gauge in Kumbukkan Oya Catchment During the 1989 to 2011 Period

The catchment experiences wet periods from October to February, with particularly high rainfall observed during October to November, while dry during mid-year, from June and July. The groundwater recharge, the river flow properties, and water availability in the catchment are influenced by the seasonal pattern.

As evident from Figure 3.3, much of the catchment exhibits a GWL of 80–400 m, indicating relatively even groundwater availability over a large area. The higher GWL values are mostly restricted to the higher elevations of the catchment, possibly due to conditions like greater elevation, higher rainfall, and potentially more efficient aquifer properties.

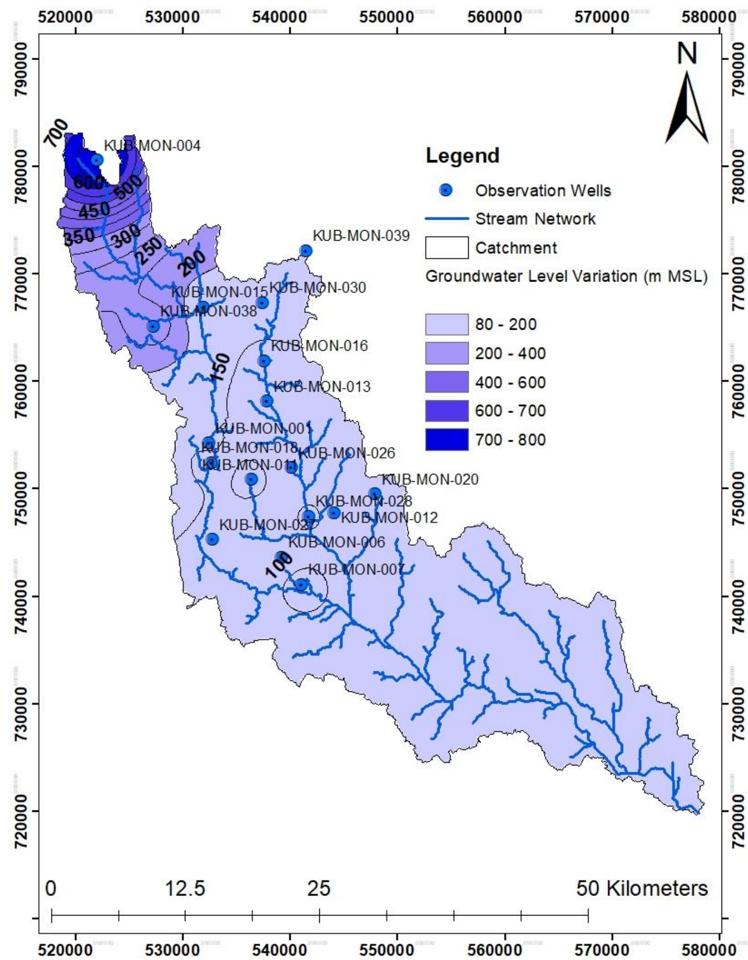

Figure 3.3: Spatial Variation of GWLs Estimated from the Observations in Kumbukkan Oya Catchment During the 2022 to 2024 Period

3.2 Data Collection

This process involved obtaining a comprehensive array of hydrological, meteorological, and geospatial data required for groundwater modeling and impact analysis within the study area. These data are gathered from various departments and organizations, including the Water Resources Board, Department of Meteorology, Irrigation Department, Survey Department, and international sources.

3.2.1 Data Requirement

The data requirement is illustrated in Table 3.1 below, outlines the specific data sets used with their respective sources, temporal coverage, and spatial or temporal resolutions.

Table 3.1: Data Requirement

Data Set	Source	Period	Resolution
DEM	Shuttle Radar Topography Mission (https://earthexplorer.usgs.gov/)	-	30 m x 30 m
Groundwater Data	Water Resource Board	2022/2024	Daily
Borehole Data	Water Resource Board	-	-
Rainfall Data	Département of Meteorology and Water Resources Board	1989/2011 And 2022/2024	Daily
Streamflow Data	Irrigation Department	2020/2024	Daily
Temperature Data	Département of Meteorology and through the website (https://power.larc.nasa.gov/data-access-viewer/)	1989/2011 And 2022/2024	Daily
Pan Evaporation	Hydrological Annual of Sri Lanka 2019/2020, published by the Ministry of Irrigation	2019/2020	Monthly
Soil Data	Harmonized World Soil Database (https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/)	-	-
Land Use Data	Survey Department	2018	1:100,000
Climate Data	Global Climate Model (https://www.ipcc-data.org/)	1989/2011 and 2030/2049	Daily

3.2.2 Preliminary Data Analysis

Groundwater Level Variation with Rainfall

To analyze the relationship of GWL with rainfall, a well was selected from the upstream zone (KUB_MON_004) shown in Figure 3.4, one from the midstream zone (KUB_MON_001) shown in Figure 3.5, and one from the downstream zone (KUB_MON_007) shown in Figure 3.6.

The plots suggest an overall positive relationship between the rainfall and GWL. There does appear to be some delay between the end of a rain event and the rise in GWL. That would be expected since time must elapse for water to seep downward through the soil into the aquifer.

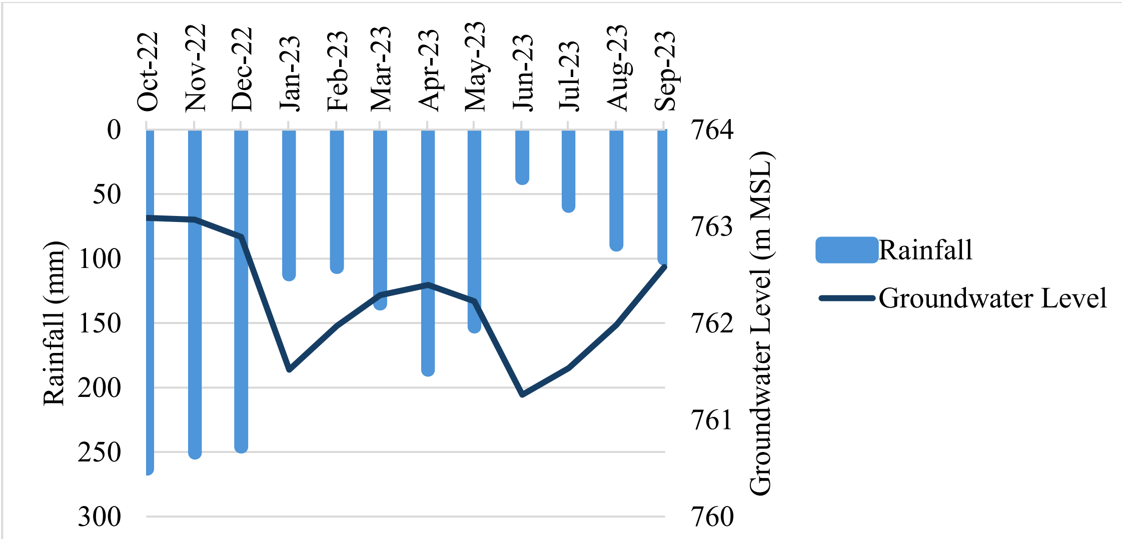

Figure 3.4: GWL Variation with Rainfall in the Catchment Upstream (KUB_MON_004 Well) During the 2022 to 2023 Period

Figure 3.4 illustrates a clear relationship between rainfall and GWL in the upstream part of the catchment. Following a period of decline from October to January, likely influenced by evapotranspiration and a lack of significant rainfall, the GWL exhibits a marked increase in response to rainfall events from February to April. This indicates that the aquifer is being effectively recharged by rainfall infiltration. However, a subsequent decline in GWL after April suggests that the aquifer is again experiencing a depletion.

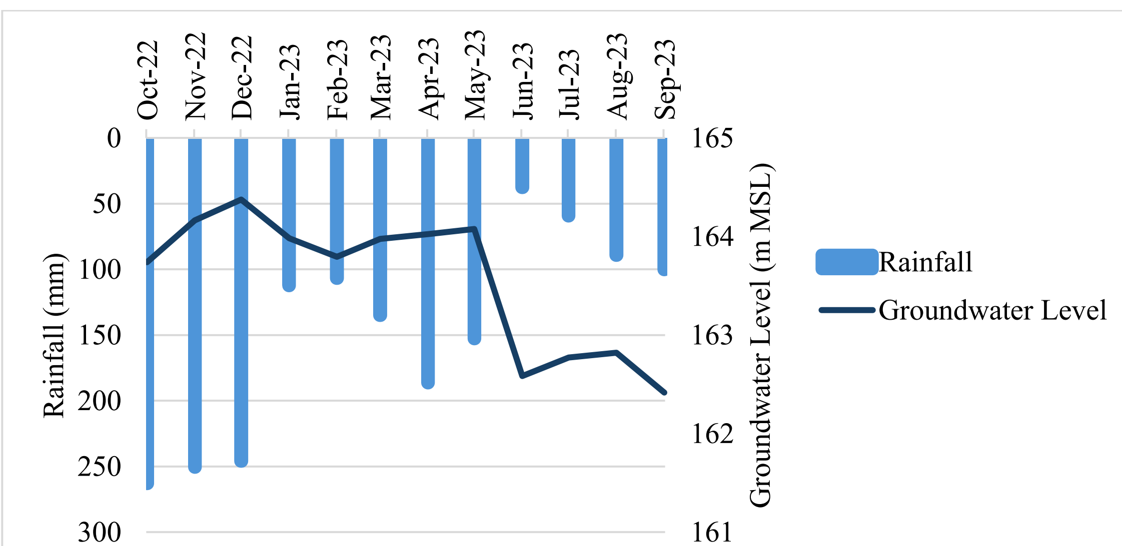

Figure 3.5: GWL Variation with Rainfall in the Catchment Midstream (KUB_MON_001 Well) During the 2022 to 2023 Period

The GWL in KUB_MON_001 is shown in Figure 3.5 follows a clear pattern. It first increases from October to November, which can be attributed to the lagged effect of past rainfall events. Further rainfall between November and March causes the GWL to rise further, showing aquifer recharge. After this March peak, the GWL remains stable until July, after which a consistent decrease is seen.

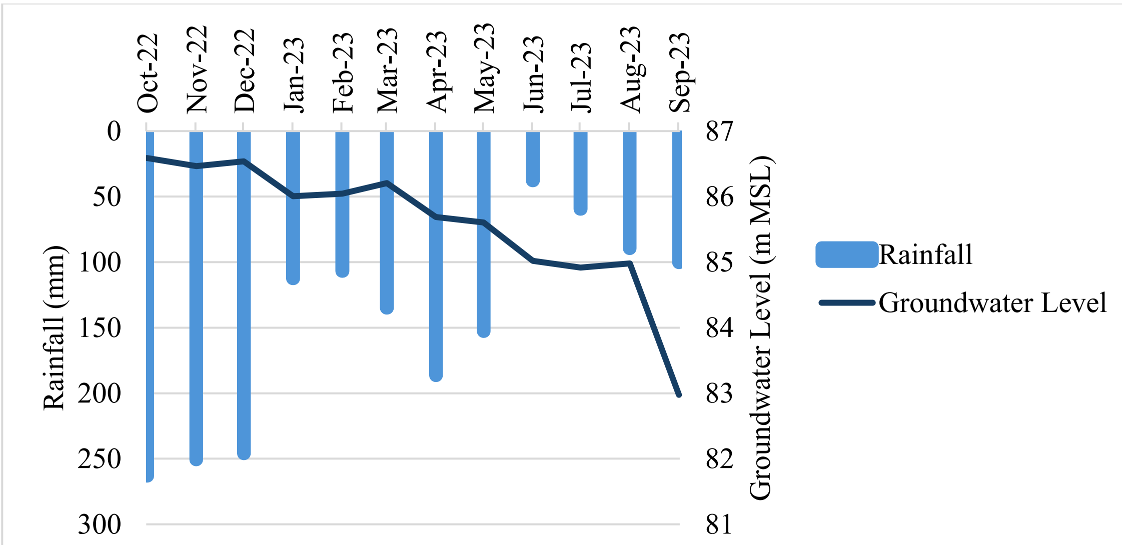

Figure 3.6: GWL Variation with Rainfall in the Catchment Downstream (KUB_MON_007 Well) During the 2022 to 2023 Period

The GWL in KUB_MON_007 exhibits distinct fluctuations in response to rainfall events, demonstrating a higher sensitivity to rainfall variations compared to previous locations. An initial decline from October to December, likely influenced by evapotranspiration and a lack of rainfall, is followed by a rise in response to rainfall events from December to March, indicating effective aquifer recharge. However, the GWL subsequently declines after March.

Land Usage in the Kumbukkan Oya Catchment

The land use classification of the catchment, as illustrated in Figure 3.7, derived from 2018 data (Appendix C), identifies the leading class as forest land, which covers 61% of the land. The extensive forest cover is primarily because the latter part of the catchment falls within Yala National Park, which is a conservation area that restricts deforestation and land conversion. Agricultural land use is 26%, reflecting the basin's primary role in supporting agricultural activity. Built-up land use is 6%, suggesting limited urbanization. The remaining land use classes comprise rocky areas (4%), water bodies (2%), and other areas (1%), comprising wetlands, bare lands, and sandy patches. The classification reflects the equilibrium of the basin between agricultural land use and natural ecosystems and recognizes it as an important area for groundwater recharge and ecological sustainability.

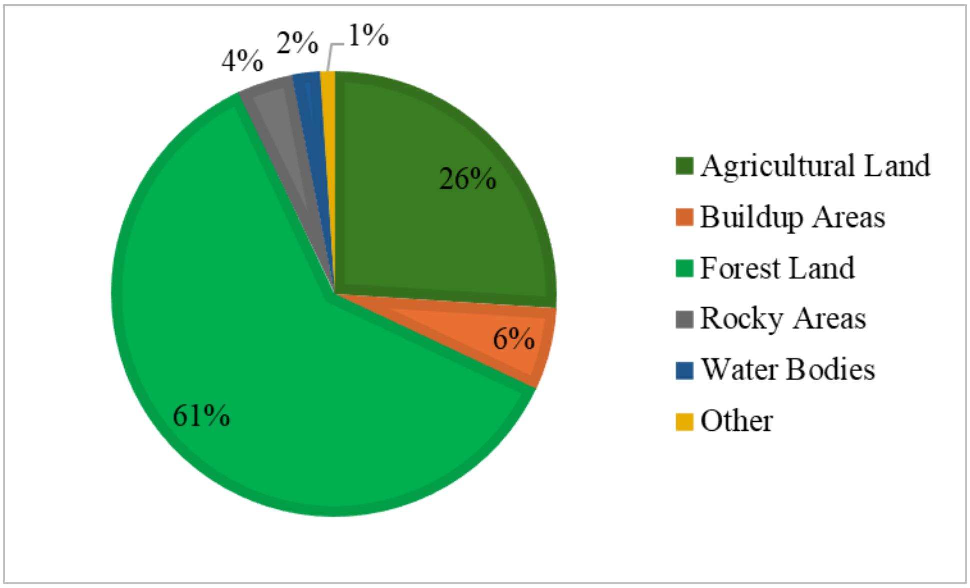

Figure 3.7: Land Use Types in Kumbukkan Oya Catchment Based on 2018 Land Use Map (Survey Department, 2018)

As previously mentioned, the latter part of the catchment belongs to Yala National Park, and most of the area is covered by forests since the park is a reserved. The middle part of the catchment is predominantly covered by agricultural land, with some built-up areas scattered throughout. The upper catchment has largely rocky terrain because the river is sourced from the Maduru Oya Hills. The bedrock exposure and steep slopes within the region form a thin soil cover, making the development of widespread vegetation challenging. However, where water supply and depth of soil are favorable, some areas in the upper catchment are utilized for agriculture. In addition, there is a rocky area towards the left boundary of the middle catchment.

Based on land use distribution, the catchment has been divided into four recharge zones, as shown in Figure 3.8, which will be used to quantify the effect of future land use dynamics on groundwater availability. As the Kumbukkan Oya catchment is not highly urbanized, negligible land use changes will likely take place between 2018 and 2049, a 31-year study period. Major land use alterations are less likely due to the relatively stable character of the catchment. Therefore, the projected land use changes will be relatively small and will exert relatively small effects on groundwater availability during the 2030–2049-time frame.

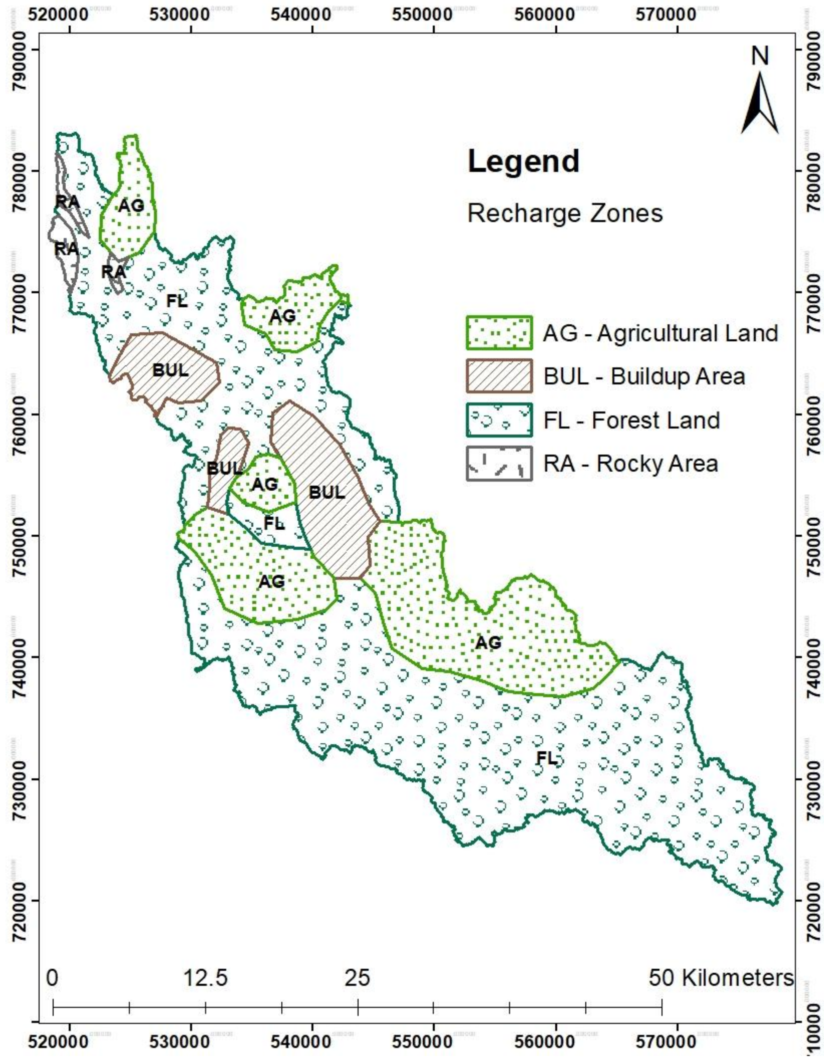

Figure 3.8: Spatial Distribution of Groundwater Recharge Zones in the Kumbukkan Oya Catchment Classified by Land Use Types

Using the available data, a comprehensive methodology flowchart has been created to achieve the three specific objectives. This methodology integrates various datasets, including precipitation, GWL, streamflow data, and DEM files, as well as the bias-corrected GCM data, to assess the compound impacts of climate change and land use dynamics on groundwater availability in the Kumbukkan Oya catchment.

3.3 Research Methodology

Based on the literature review, a comprehensive methodology was synthesized to evaluate the compound impacts of climate change and land use dynamics on groundwater availability in the Kumbukkan Oya catchment. The methodology adopted is illustrated in Figure 3.9 below.

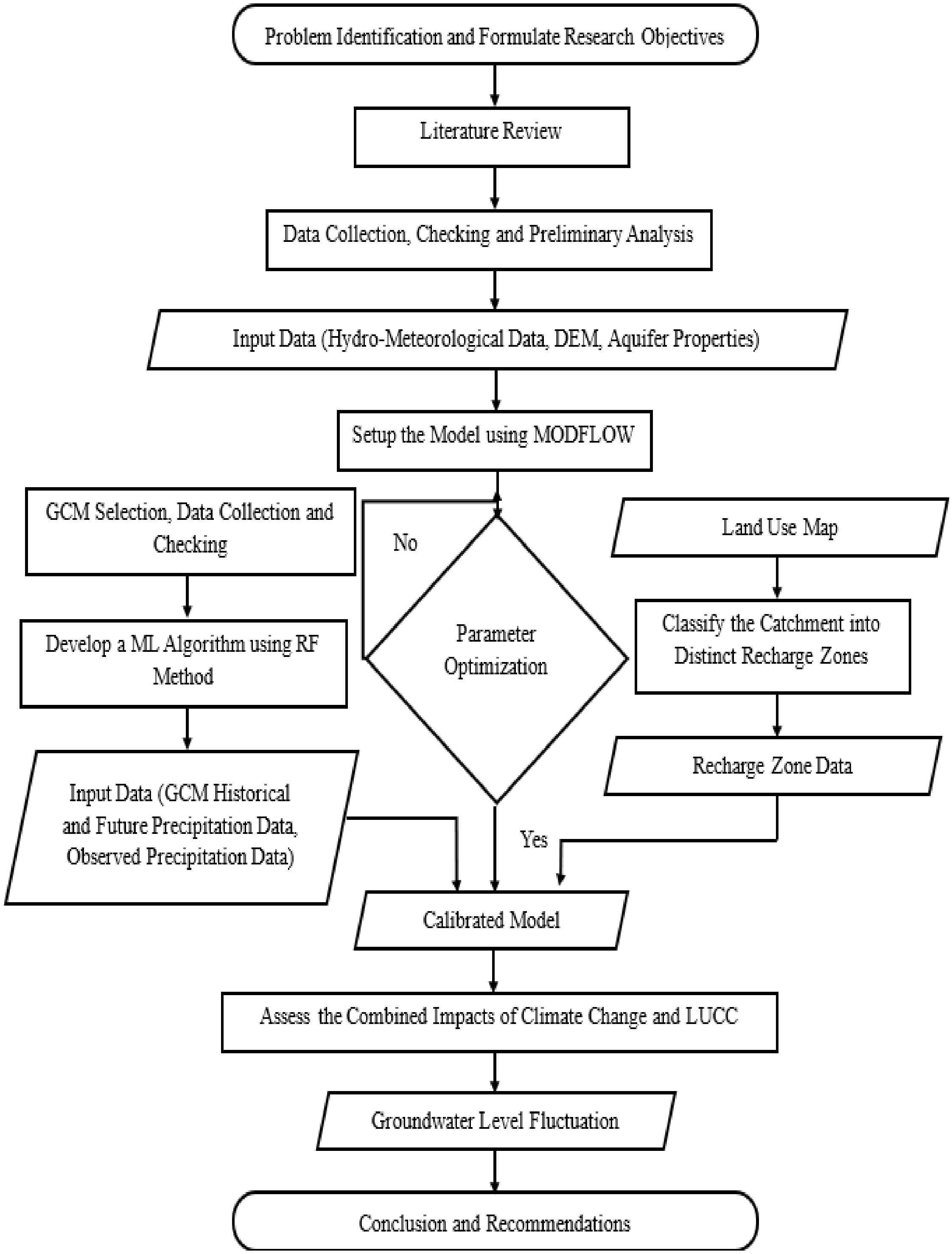

Figure 3.9: Methodology Flowchart

3.4 Development of the Groundwater Model

3.4.1 Conceptual Model

A conceptual model was formulated to create a groundwater flow model for approximately 1,227 km^2 of area under investigation. GIS functionality and the map module were employed to delineate multiple important elements such as lithology, groundwater monitoring data, and recharge. Inflow sources to the model are rainfall over the study area and subsurface flow from the upstream catchment. Outflows occur at the coastal boundary, where a constant head of 0 m was defined. The upstream boundary was also defined as a constant head, computed from GWLs at nearby observation wells (KUB-MON-004 and KUB-MON-039). Based on the GWL variations shown in the contour plot Figure 3.3, no-flow boundaries were defined on the east and west sections, excluding lateral groundwater flow. Layer properties such as hydraulic conductivity, specific yield, and specific storage were also added to the model setup.

3.4.2 Grid Model

Grid Preparation and Layer Discretization

The entire area of 1,227 km^2 was divided into a finite difference grid of cell size 250 m consisting of 266 columns, 280 rows, and 1 vertical layer. From the obtained geological data, the change in the geological profile with depth at each borehole location is demonstrated in Appendix B. The analysis shows that the upper layers, made up of different soils and weathered rock, are mostly confined to shallow depths. In contrast, the fractured rock or metamorphic rock layer extends over a much broader depth. Furthermore, the screen depths of all the boreholes fall within the fractured rock layer. Accordingly, the model was simplified by representing the geologic units as a main lithological unit that is analogous to the fractured rock/metamorphic rock unit.

Recharge

One of the most critical parameters in building the model is groundwater recharge. The recharge package allows an option to insert a recharge rate for the subject area. To calculate approximate values of recharge throughout the simulation time, the recharge-to-rainfall ratio was calculated. The calculation is as follows:

Long-term pan evaporation	=	1,100 mm
Long-term runoff	=	227.6 MCM
Long-term rainfall	=	1,652 mm

Using (Equation 9),

Groundwater Recharge	=	356.374 mm
Recharge/ Rainfall	=	0.22

With the above calculations, the recharge-to-rainfall ratio was computed to be approximately 22%. Then corresponding daily rainfall quantities were multiplied by this ratio to compute the corresponding daily recharge values. Thus, a file of time series of the daily recharge values was generated. This package was executed over the top layer of the active model.

Initial Condition

The initial conditions are significant in transient groundwater modeling because they constitute the foundation upon which the dynamic response of the system over time will be modeled. Therefore, final heads from the steady-state simulated heads were used as the initial GWLs for the transient model.

3.4.3 Selecting Simulation Intervals

The simulation was conducted using a daily time step, selected by available GWL observation data. The model was simulated using 164 intervals equating from 01-July-2023 to 12-Dec-2023.

3.5 Development of the ML Model for Downscaling

The observed data (1989–2011) consists of daily precipitation records, while the GCM data (1989–2011) represents precipitation data generated by the GCM for the same period. Additionally, the future GCM data spans the period from 2030 to 2049, which is considered the immediate future. This 20-year duration was selected because it gives more reliable estimates than long-term estimates. In climatology, forecasts for the near term are generally more dependable for short-term policy-making and water resource management, as they entail fewer of the uncertainties of extrapolations for remote times.

3.5.1 Data Processing

Input Variables (X): These are the factors that help the model make predictions. In this case,

- Precipitation_GCM: The precipitation data predicted by GCMs.
- Year, Month, Day: Time-related features that help the model account for patterns in precipitation over time, such as seasonal trends.

Target Variable (y): This represents the observed dataset used as the target variable for prediction. In this case, it's:

- Precipitation_Obs: The actual observed precipitation data.

The observed and GCM precipitation data are merged based on the date, and then new features (Year, Month, and Day) are extracted from the date.

3.5.2 Training and Testing

The data is split into two parts to train and evaluate the model.

Training Data: This is the data used to train the model. The model learns how the input (GCM data) and the output (observed precipitation) are related.

Testing Data: After training, this data is used to test how well the model performs. It helps to check whether the model can make accurate predictions on new data it has never seen before.

The data was split into training and testing datasets using the 80/20 rule, where 80% of the data was used for training and 20% for testing. The split was done using the train_test_split function from the sklearn.model_selection module with a constant random_state=42 for reproducibility. Although future forecasts are not directly included in the testing dataset, they were corrected using the trained model.

3.6 Assessment of Compound Impacts of Climate Change and LULC Change

As the final objective, the following task is to quantify the change in GWL owing to the cumulative impact of climate change and LULC changes. For this purpose, the groundwater numerical model developed during the first phase and climate data downscaled under the second goal will be employed.

The most problematic part is trying to quantify such changes precisely. In accordance with the model generated, groundwater recharge can be adapted to include considerations of the future impacts of climate and LULC changes. The model has been simulated for the baseline period from 01 July 2023 to 12 December 2023. To determine future changes, simulations will be run for the period 2030 to 2049. Estimation of the recharge during the future period is a critical process, for which the following steps have been followed.

3.6.1 Estimation of Recharge

The simplest way to estimate recharge taking account of land use change is to establish a function between precipitation and Curve Number (CN). This method allows for the indirect assessment of recharge variations by capturing the influence of different land use patterns on surface runoff and infiltration potential. As a first step, the percentage recharge from the calibrated model was computed using (Equation 10).

$$Recharge\,\% = \frac{R}{P} \qquad \text{(Equation 10)}$$

where,

R is the annual recharge in m, and
P is the annual precipitation of the calibrated model in m

Based on the final values, the recharge percentage is approximately 30% of the precipitation.

The next step is to calculate the average CN, based on the land use distribution illustrated in Figure 3.8. The corresponding calculation is detailed in Table 3.2.

Table 3.2: Curve Number (CN) Calculation for Kumbukkan Oya Catchment Based on Historical Land Use Data

Land Use Type	Area (A)		CN (United States Department of Agriculture, 1986)	A*CN
	km^2	%		
Forest	784	64	70	54,880
Agricultural	305	25	88	26,840
Buildup Areas	123	10	83	10,209
Rocky Area	15	1	89	1,335
Total	1,227			93,264
Average CN			76	

To estimate the daily groundwater recharge R_a for a land use type with Curve Number CN_1, given a daily precipitation amount P_a, is given in (Equation 11),

$$R_a = \frac{CN_1}{CN} \times P_a \qquad \text{(Equation 11)}$$

To project hypothetical CN values under future land use scenarios, four representative scenarios were established. Out of four scenarios three scenarios adhere to the assumption that forest cover will decrease in the future. Correspondingly, agricultural land and built-up areas are assumed to increase to replace the lost forest cover. And the remining one assume the forest cover will increase and buildup area going to be reduced. This gives a simplified but plausible means of estimating future CN values under assumed land use change. The corresponding calculation is given in Table 3.3.

Table 3.3: The Hypothetical CN Value Variation with the Future Land Use Change

Land Use Type	Area (A)		CN (United States Department Of Agriculture, 1986)	A*CN
	Km^2	%		
Scenario 1				
Forest	614	50	70	42,945
Agricultural	405	33	88	35,632
Buildup Areas	196	16	83	16,295
Rocky Area	12	1	89	1,092
Total	1,227			95,964
Average CN			78	
Scenario 2				
Forest	491	40	70	34,356
Agricultural	479	39	88	42,111
Buildup Areas	245	20	83	20,368
Rocky Area	12	1	89	1,092
Total	1,227			97,927
Average CN			80	
Scenario 3				
Forest	368	30	70	25,767
Agricultural	577	47	88	50,749
Buildup Areas	319	26	90	28,712
Rocky Area	12	1	89	1,092
Total	1,227			106,320
Average CN			87	
Scenario 4				
Forest	859	70	70	60,123
Agricultural	294	24	88	22,969
Buildup Areas	61	5	83	5,092
Rocky Area	12	1	89	1,092
Total	1,227			89,277
Average CN			73	

Following the United Nations Population Division's World Urbanization Prospects, World Bank staff estimates have projected a steady increase in the rural population from 1960 to 2023, as shown in Figure 3.10 below (WB, 2018). Additionally, according to a study by

Dey et al. (2024), the population of Sri Lanka is projected to increase between 2030 and 2060, based on the logistic growth model.

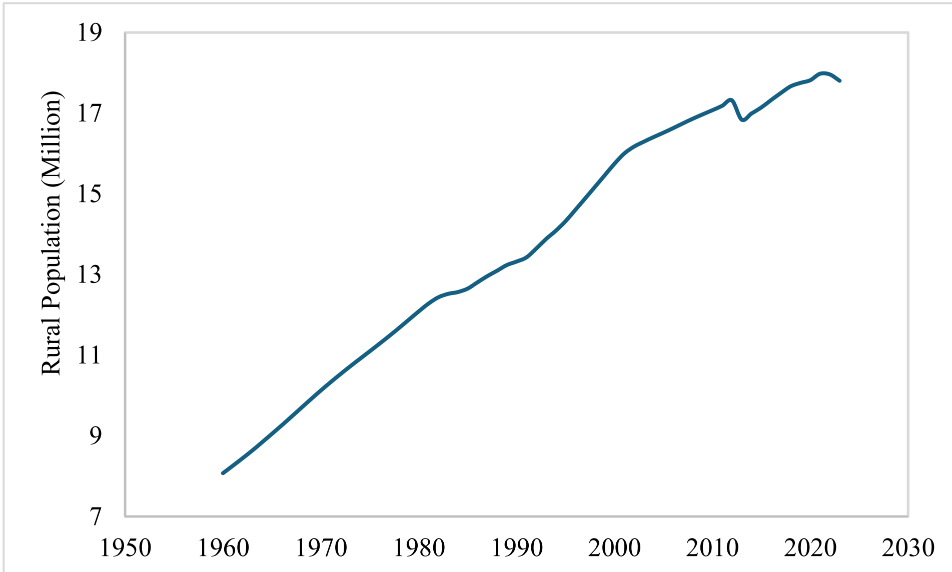

Figure 3.10: Rural Population in Sri Lanka from 1960 to 2023, based on World Bank Staff Estimates derived from the United Nations Population Division's World Urbanization Prospects (WB, 2018)

This historical trend, coupled with the projections of continued growth in the population from 2030 to 2060, forms the rationale for supposing that land use systems will change due to increasing demographic pressure. As the population grows, pressure on food production, shelter, and infrastructure is likely to mount, particularly in developing regions such as the Monaragala District. This will result in the conversion of forests to agricultural land and built-up areas, following trends commonly seen in rural catchments undergoing socio-economic change.

CHAPTER 4

RESULTS AND DISCUSSION

This chapter presents the results corresponding to each objective and provides a detailed discussion and interpretation of the findings about the study objectives.

4.1 Steady State Model

Development of the steady-state model is a requirement in transient groundwater modeling because initial conditions are a significant consideration in the accurate recreation of the dynamic behavior of the system as a function of time. Steady-state simulations provide a base or equilibrium condition for the groundwater system under constant recharge and discharge conditions.

4.1.1 Results and Analysis of Steady State Groundwater Flow Simulation

The hydraulic heads obtained from the steady-state model are employed as starting GWLs for the transient model for the transient simulation to begin from a physically consistent and realistic state. Figure 4.1 shows the result of the steady-state model, which models the groundwater system under an equilibrium condition.

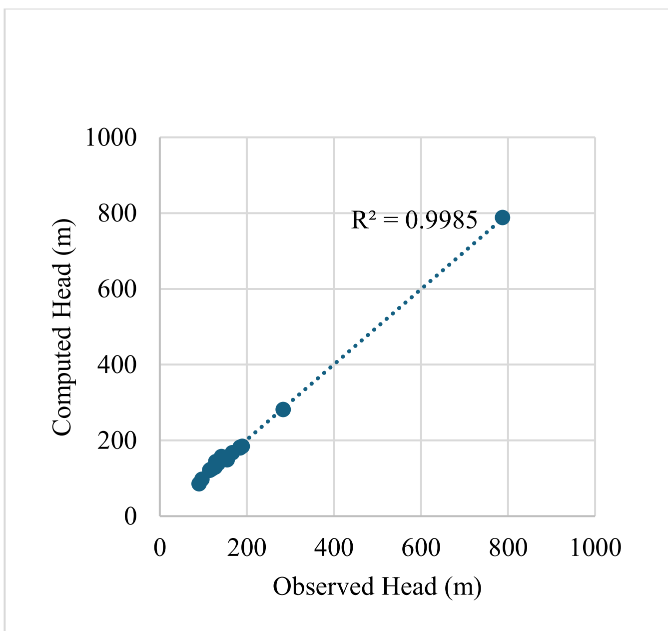

Figure 4.1: Computed Vs. Observed Head Values in Steady State Model

The groundwater model's performance demonstrates a high level of accuracy to observed conditions, as evidenced through high correlation among computed and observed values of groundwater head. The 1:1 line in the scatter plot is followed very closely by most data points, demonstrating close agreement between the observed and computed values. This indicates that the model is a good fit for the measured data. This is evident by a high value of the coefficient of determination (R^2), which is 0.9985. The model accuracy is consistent over the range of observed values, and this indicates that it is valid in simulating diverse groundwater head conditions. With good match, the calculated head values can be used as confidently as initial conditions for the transient groundwater model. This ensures that the transient model will begin its simulation from a realistic and well-established reference point, which will enhance the accuracy and reliability of its dynamic predictions.

4.2 Transient Model

A transient groundwater flow model was formulated to simulate temporal variations in GWLs across the study area. The model was verified and calibrated using observed GWL data from major monitoring wells to ensure reliability. The following section provides results of the transient simulation, recognizing spatial and temporal variations in groundwater recorded during the study. These results are then interpreted to conclude aquifer response, trends, and the suitability and performance of the model for various hydrological conditions.

4.2.1 Results and Analysis of Transient Groundwater Flow Simulation

To present the temporal changes of GWLs more easily to visualize, the transient model output is shown in hydrograph format. These graphs illustrate the ability of the model to depict the changes in GWLs over the simulation period. These plots directly chart GWL change, not values, to show the model's ability to capture temporal changes rather than accurate head elevations. The following figures give a sense of the system response to different recharge conditions and external forces, helpful in the evaluation of how well the model simulates observed groundwater behavior over time.

The GWL variation in the KUB_MON_004 well, as shown by Figure 4.2, at the upstream boundary, it compares observed and computed GWL variations with time. From June to October 2023, both exhibit a consistent decline, mirroring groundwater depletion, which is accurately represented by the model. Around October, GWL reaches its lowest point and then rises, suggesting recharge due to rainfall or reduced extraction. The model follows this trend quite closely from October to January 2024, with only minor deviations during the peak recovery in December, where calculated values somewhat overestimated observed rises. Despite such minor discrepancies, the model accurately reproduces seasonal variation and long-term groundwater flow. Such good correspondence between observed and calculated GWL changes suggests that the model is well calibrated and can be trusted to make future predictions.

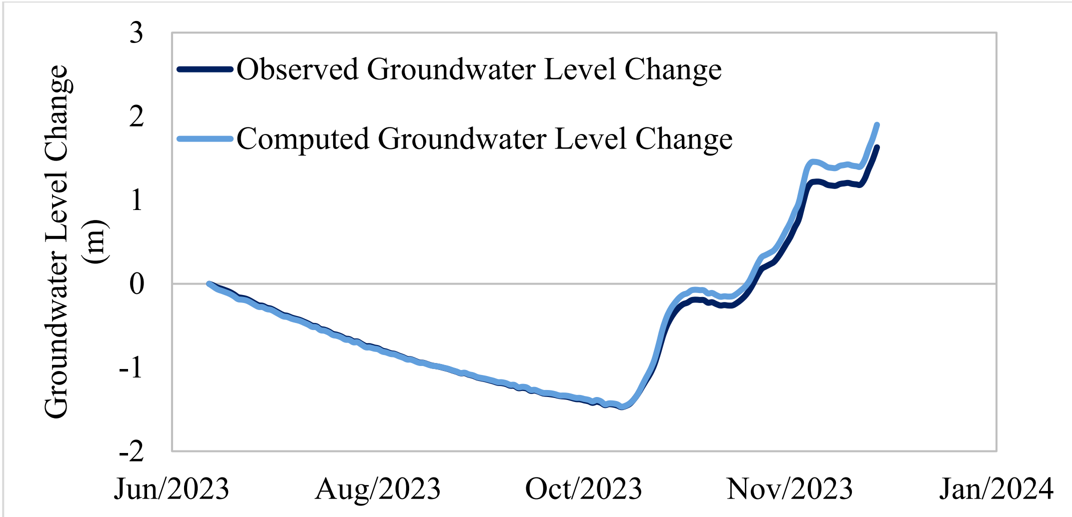

Figure 4.2: GWL Change at the Monitoring Well KUB_MON_004 Throughout the Transient Simulation Period

The GWL change in the KUB_MON_039 well, shown in Figure 4.3, located in the latter part of the upstream boundary, compares observed and computed GWL changes over time. From June to October 2023, in both data sets, there is a consistent drop, showing groundwater depletion that the model captures well with little oscillations. From October onwards, the GWL grows at a steep slope towards January 2024. Computed values follow the observed trend well, with small overestimates during the recharged peak period. Despite these slight differences, the model is good at simulating the seasonal patterns and overall groundwater behavior.

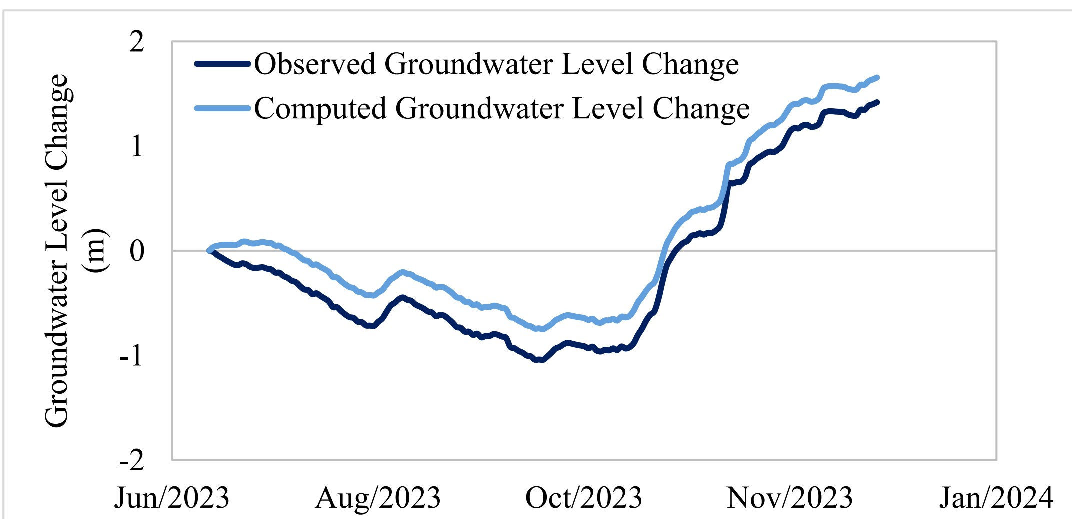

Figure 4.3: GWL Change at the Monitoring Well KUB_MON_039 Throughout the Transient Simulation Period

The provided Figure 4.4 represents the GWL changes at KUB_MON_015, which is in the upper, mid-section of the catchment. Both calculated and observed GWL changes show a general increasing trend from June 2023 to January 2024, indicating a rise in GWL. Between the two, there are some disparities. The observed GWL decreases slightly first, indicating depletion, while the calculated GWL remains unchanged. Both have a steep rise, but the model-calculated GWL is always greater than the observed one, indicating that the model could be overestimating GWL variations. Both show a steep rise simultaneously.

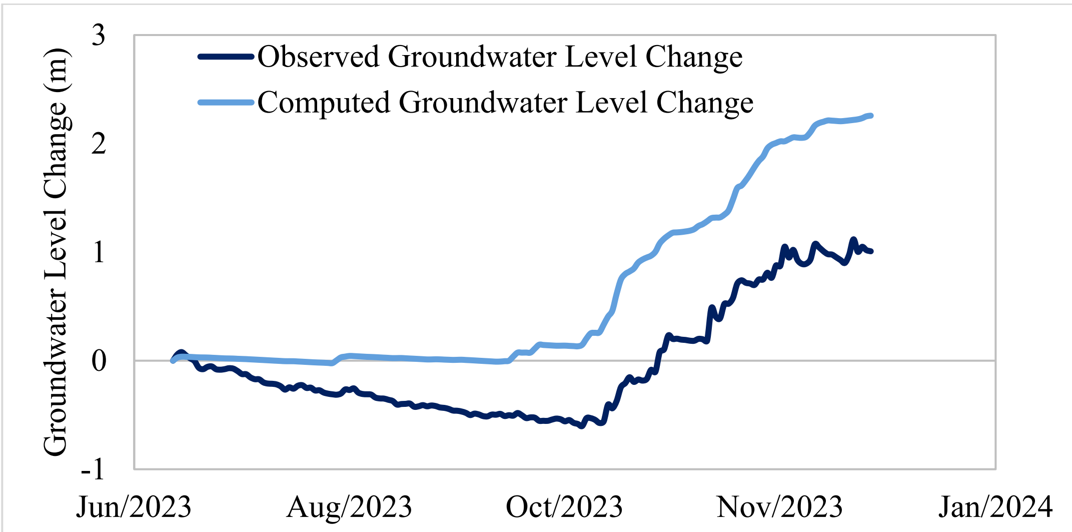

Figure 4.4: GWL Change at the Monitoring Well KUB_MON_015 Throughout the Transient Simulation Period

The GWL change in KUB_MON_028, shown in Figure 4.5, located in the middle of the catchment, reveals a similar pattern to KUB_MON_015, showcasing an overall increasing trend in both observed and computed GWLs from June 2023 to January 2024. The model's performance differs significantly. While the observed GWL decreases slightly at the start, the computed GWL remains relatively constant. Then both series are characterized by a steep growth, with the computed values consistently overestimating the changes observed, as though the amplitude of the recharge is being overestimated. Combined with the differences in the timing of the response magnitude, this reflects the challenges in suitably modeling groundwater processes within the inside of the catchment.

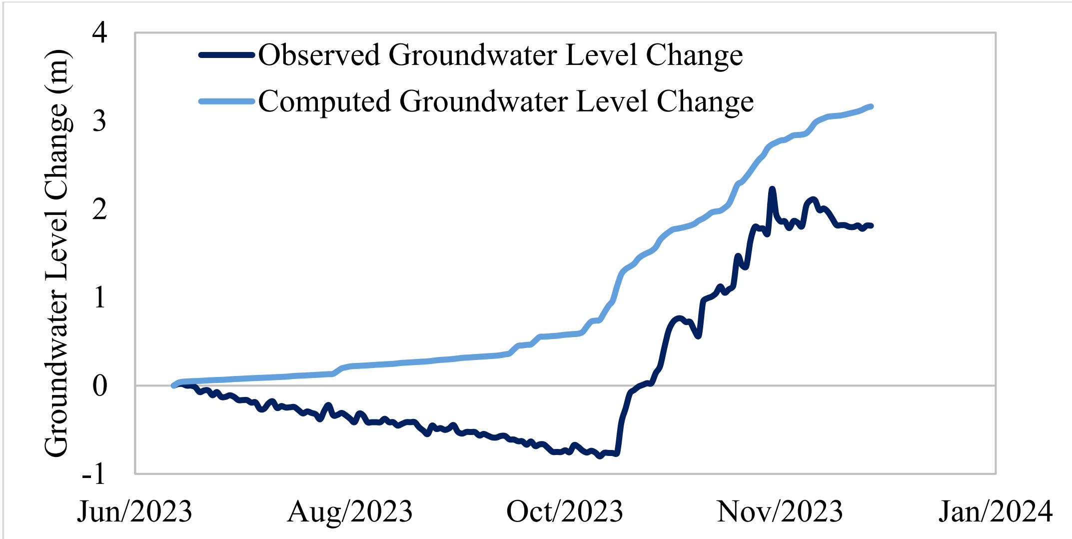

Figure 4.5: GWL Change at the Monitoring Well KUB_MON_028 Throughout the Transient Simulation Period

The GWL change across the four monitoring wells shows a similar pattern. June to October 2023, GWL decreased or remained constant. October 2023 to January 2024, GWL increased significantly, showing a recharge event or change in water balance. The initial decline was varied. KUB_MON_004 showed the maximum decline of approximately 2 m, while KUB_MON_039 declined by about 1 m. KUB_MON_015 and KUB_MON_028 showed the minimum declines, showing stability. In the rising phase, the maximum rise in KUB_MON_028 was more than 3 m. KUB_MON_015 increased by 2 m, and KUB_MON_004 increased by nearly 2 m. The least increase was that of KUB_MON_039, by around 1 m.

The model captured the general trend of decline and recovery but struggled with the magnitude. The model fits well in KUB_MON_004, especially during recovery. In KUB_MON_039, it underestimated both the decline and recovery. In KUB_MON_015, the model underestimated the increase in GWL, indicating possible issues with recharge or lateral flow. KUB_MON_028 also showed underestimation, with the model missing the sharp peak in observed data. The model performed well in the upstream part (KUB_MON_004 and KUB_MON_039), indicating it captured processes well there. However, in the mid-catchment (KUB_MON_015 and KUB_MON_028), the model had difficulty representing recharge and lateral flow.

4.2.2 Discussion of Transient Groundwater Flow Dynamics and Model Performance

As indicated in Figure 4.2 and Figure 4.3, in the upstream part of the catchment, computed GWLs follow the trend seen with small deviations, mainly in the peak recovery phase.

However, in the midstream section (Figure 4.4 and Figure 4.5), the computed values overestimate observed values throughout the simulation, while the initial decline is not well captured. The differences appear because of the site-specific conditions and can be due to local hydrological conditions. Among the likely causes are groundwater pumping, which was not accounted for because the data were limited. The annual amount of groundwater abstraction of the Monaragara District is estimated to be 4000 m^3/day (Villholth & Rajasooriyar, 2010), excluding the extraction from the private individual wells. If the drawdown is calculated using a model cell size of 250 m x 250 m is given in (Equation 12),

$$Drawdown\ (m) = \frac{Volume\ Extracted\ (m^3)}{Area\ (m^2) \times Specific\ Yield} \quad \text{(Equation 12)}$$

Let's assume a specific yield for sandy soil of 0.1, because for a sandy soil specific yield range in between 0.1 to 0.3 (Harter, 2004).

$$Drawdown\ (m) = \frac{4000}{250 \times 250 \times 0.1}$$

$$Drawdown\ (m) = 0.7\ m$$

Using a calculated annual groundwater drawdown of 4,000 m³/day and assuming an assigned specific yield value of 0.1 for sandy soil within a 250 m × 250 m model cell, the estimated drawdown would be approximately 0.7 m/day. This rate of abstraction is also consistent with the disparity reported between calculated and observed groundwater heads in the downstream region. Therefore, incorporation of this abstraction in the model could significantly reduce the disparity and improve computed GWL precision. Furthermore, the following Figure 4.6 explains this more.

According to Figure 4.6 KUB-MON-028 is in a built-up area, while KUB-MON-039 is in an agricultural area. KUB-MON-015 is located near an agricultural area. These wells show a noticeable overestimation in computed GWL (Figure 4.3, Figure 4.4, and Figure 4.5). This overestimation can be attributed to the impact of nearby land cover categories. In urban zones such as around KUB-MON-028, large groundwater abstraction for domestic and industrial use can lead to localized drawdown not fully captured by the model. Similarly, in agricultural areas such as those around KUB-MON-039 and KUB-MON-015, large abstraction of groundwater for irrigation can reduce actual water levels. If such land–use–specific pumping effects are not adequately simulated by the model, it may cause computed GWLs that are higher than the true field observed levels.

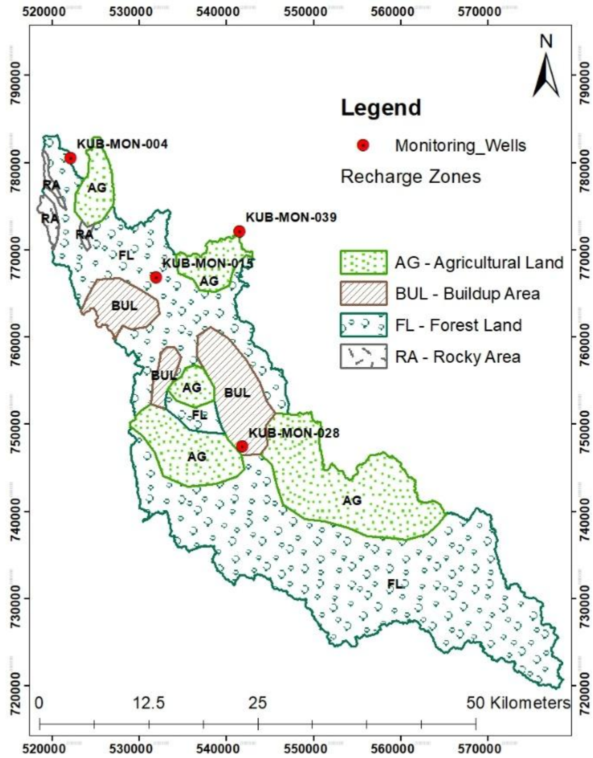

Figure 4.6: Spatial Distribution of Groundwater Recharge Zones in the Kumbukkan Oya Catchment with Monitoring Wells

In the model, the entire catchment is considered as a single recharge zone. Except for the upstream and downstream parts, no-flow boundaries have been given to the other two sides. But additional complexity can be introduced in the middle of the catchment due to the change in land use and varying recharge rates. Additionally, the influence of lateral outflows and inflows cannot be efficiently modeled, supporting further overestimation of GWLs. The above-mentioned problems are also responsible for the overestimation of GWLs.

Model assumptions and simplifications can also be the cause of these deviations. For example, MODFLOW assumes that aquifer properties, including hydraulic conductivity and storativity, are homogeneous. Aquifers in the real world are usually heterogeneous, and ignoring local variations in properties can lead to incorrect simulations. Also, boundary conditions such as no-flow boundaries may not be representative of actual conditions, especially when there are lateral inflows or outflows, which are not accounted for by the model. These assumptions might cause the model to overpredict GWLs.

Finally, data limitations make the problem even more difficult by creating difficulties in the optimization of model parameters. Limited or poor data makes it difficult to calibrate the model, leading to uncertainties in parameter values. In such a situation, the model can use approximations or default values, and the resulting GWL predictions will be inaccurate. These calibration issues, added to the inherent uncertainties in estimating model parameters, lead to overestimation of GWLs, especially in areas with complex hydrological interactions, such as the midstream section of the catchment.

4.3 Downscaling of GCM Outputs to the Local Scale

To assess future climate variability at the local scale, GCM outputs were bias-corrected and statistically downscaled using ML methods. This improves the spatial and temporal resolution of coarse GCM data to be more useful for hydrology. Observed climate records were used for training and validation to achieve improved accuracy of the downscaled projections. The following section presents the result of the downscaling process, observed and downscaled data comparisons, and the effectiveness of the approach applied in simulating local climate patterns.

4.3.1 Results of Downscaled Climate Projections and Precipitation Pattern Analysis

Only one observed rain gauging station was available that matched the data period with the GCM data. Due to limited data, the precipitation from both GCM and the single observation point was compared over time. Table 4.1 shows the long-term average monthly rainfall variation during a monsoon cycle.

Table 4.1: Long-term Monthly Average Rainfall Data During a Monsoon Cycle

Long-Term Average Monthly Precipitation (mm) [Based on the data from 1989 to 2011]			Long-Term Average Monthly Future Precipitation (mm) [Based on the data from 2030 to 2049]
Month	Observed	GCM	GCM
October	277.4	299.1	255.5
November	271.6	276.5	228.1
December	229.1	238.2	144.7
January	114.1	116.3	89.7
February	115.4	117.8	114.4
March	90.6	94.6	99.3
April	133.3	141.6	121.1
May	130.1	141.6	146.1
June	51.6	57.9	50.4
July	65.2	69.7	41.7
August	96.0	99.1	100.5
September	147.9	156.7	160.1

4.3.2 Discussion of Downscaled Climate Projections and Model Performance

The boxplot is a powerful tool to visualize trends, variability, and potential extreme changes in precipitation patterns at a glance. In the current analysis, it helps us determine whether future precipitation levels will be on the decline, highly variable, or witness more extreme events for water resource planning, agriculture, and groundwater management. The boxplot in Figure 4.7 compares the total values of the seasonal rainfall for historical (1989–2011) and future (2030–2049) periods across different monsoon seasons.

The boxplot shows a clear declining pattern of seasonal rainfall during all phases of the monsoon. Future precipitation levels are always below historical levels, indicating that climate change is perhaps to blame for lowering the overall amount of total seasonal rainfall. The median value of future period precipitation is lower, and that suggests seasons will become increasingly drier overall, potentially having severe impacts on water supply, agriculture, and groundwater recharge. This reduction of precipitation can be attributed to evolving monsoon trends, warmer temperatures with increasing evaporation, and changes in atmospheric moisture transport.

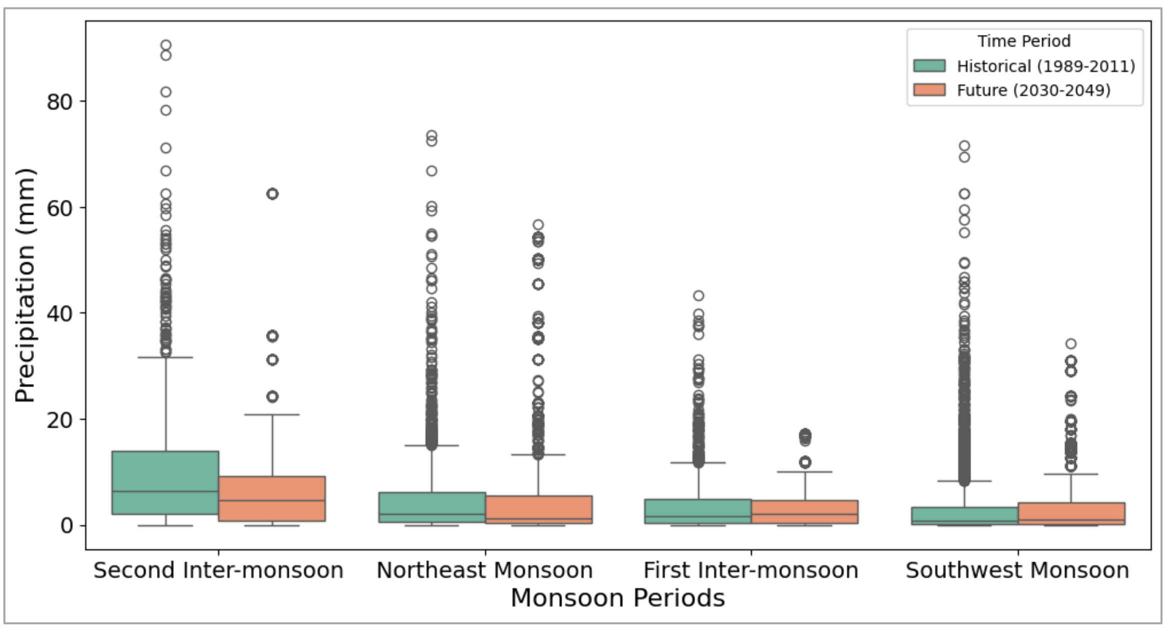

Figure 4.7: Comparison of Total Values of the Seasonal Rainfall for Historical (1989–2011) and Future (2030–2049) Periods Across Different Monsoon Seasons

Besides the general reduction in rainfall, the variability in precipitation also changes. The historical dataset shows a wider spread in rainfall values, with a greater interquartile range (IQR) and more outliers, which implies that rainfall in the past was more variable, as there was more frequent change between wet and dry. In contrast, the future dataset exhibits a more clustered distribution, i.e., rainfall amounts should be more uniform in each season, but at lower levels generally. Even with this decrease in variability, rainstorms are still prevalent in the future data set, as indicated by the presence of outliers. This means that even though overall rainfall may decrease, one or two intense storms or short periods of heavy rain can still occur, and they could be causing localized flash flooding and runoff problems.

A closer examination of the monsoon-specific trends suggests that the Second Inter-Monsoon and Southwest Monsoon periods, which used to get the maximum rainfall in the past, will experience significant decline in the future. However, the presence of extreme outliers in the future estimates suggests that although these intervals will be relatively dry, they have more intense rainfalls, which can lead to sudden water surplus. By comparison, the Northeast Monsoon and First Inter-Monsoon phases, which are historically lower rains, also experience a slight reduction in future rain, following the trend of becoming progressively drier across all the seasons. The decrease in the IQR during these seasons means the rains are more definite but of smaller quantities, and this can mean longer dry spell durations and increased dependence on stored water resources.

4.4 Compound Impact Assessment

This section aims to assess the compound impacts of climate change and potential LULC changes on fluctuations in GWLs. The assessment is based on three varying scenarios depicting varying combinations of future climate projections and LULC processes. Using these scenarios within the groundwater model, the analysis accounts for the interactive influence of both drivers, giving an integrated picture of their potential influences on groundwater resources. For this, two observation wells, KUB_MON_004 and KUB_MON_039, were selected to represent GWL variations. These two wells were selected based on their high performance and reliability throughout the transient model parameter optimization process.

4.4.1 Impact on the GWL - Scenario 1

For this study, the land use scenario was developed based on the possible future trends in the catchment. The land use is bound to change in the future due to increasing population and developmental activities. The forest cover, agricultural land, and built-up areas were assumed to decrease by 14%, increase by 8%, and decrease by 6%, respectively. These are reflective of the anticipated increase in agriculture and urban settlements in the years to come. The following graphs illustrate the alteration in GWLs because of land use changes described above.

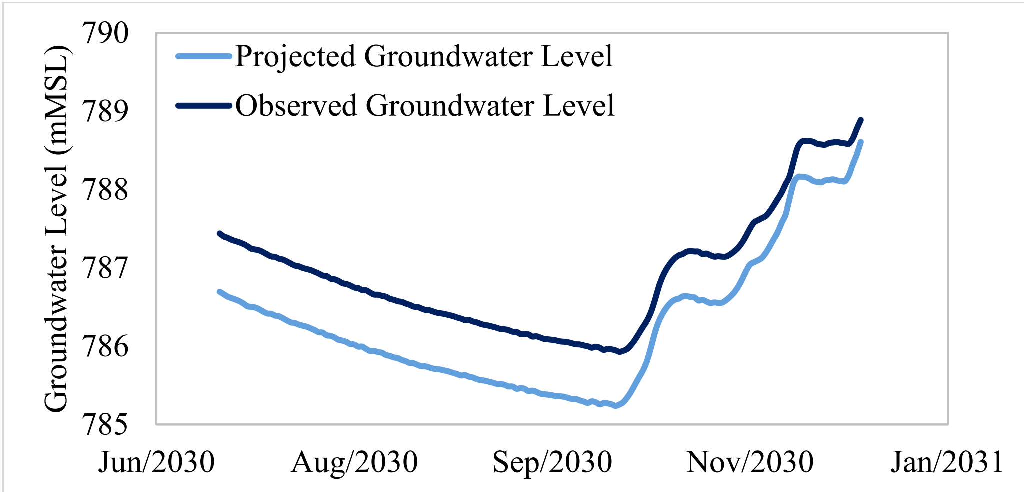

Figure 4.8: Comparison of Observed GWL in 2023 and Predicted GWL for 2030 at KUB_MON_004 Well in Scenario 1

Figure 4.8 shows the GWL variations between July and December in the years 2023 and 2030. The dark blue line represents observed GWL for 2023, and the light blue line represents projected GWL for 2030 in the future climate and land use change scenario. As evident, the whole period through, the GWL for 2030 remains lower than that of 2023. Both datasets follow the same seasonal trend, where GWL drops until around September before bouncing back. In 2030, the bounce back is delayed and less pronounced, indicating lower recharge capacity. This continuous gap between the two curves reflects growing stress on the aquifer system in the future. Results imply that groundwater availability may become increasingly limited over time, especially during drought times.

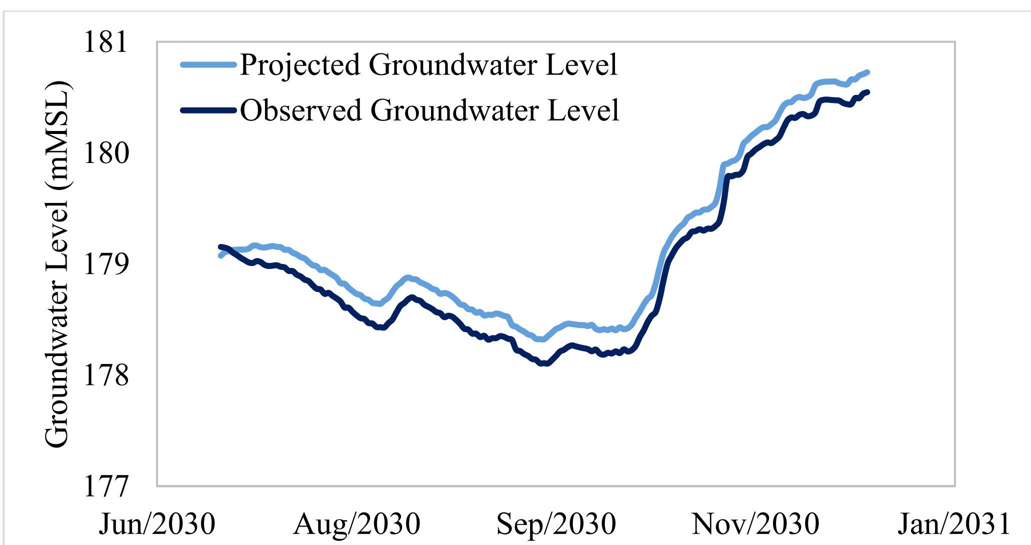

Figure 4.9: Comparison of Observed GWL in 2023 and Predicted GWL for 2030 at KUB_MON_039 Well in Scenario 1

Figure 4.9 shows the GWL trends at observation well KUB_MON_039 for the same periods as above. Here, the expected GWL is generally higher than the observed values. The main reason for this can be, according to Figure 4.3 computed GWL a bit higher than what was observed during the baseline period. However, both curves show a typical seasonal pattern, with the gradual decline of GWL from July to around mid-October, and its steady increase toward the end of the year.

4.4.2 Impact on the GWL - Scenario 2

In expectation of the coming urbanization and intensification of agriculture, the scenario sees a 24% reduction in forest cover, accompanied by a 14% increase in agricultural land and a 10% increase in built-up area. These projected changes are intended to capture the likely shift towards increased intensive use of land in the forthcoming years.

Comparing Figure 4.10 and Figure 4.11 representing Scenario 2, it is evident that there is no noticeable difference in GWL between Scenarios 1 and 2. Although there are slight differences in the trends, the overall GWL patterns and magnitudes are mostly the same for both cases. This implies that, in the period simulated, the changes due to the varied assumptions made in Scenario 1 and Scenario 2 do not produce substantial impacts on the GWL in the monitored wells.

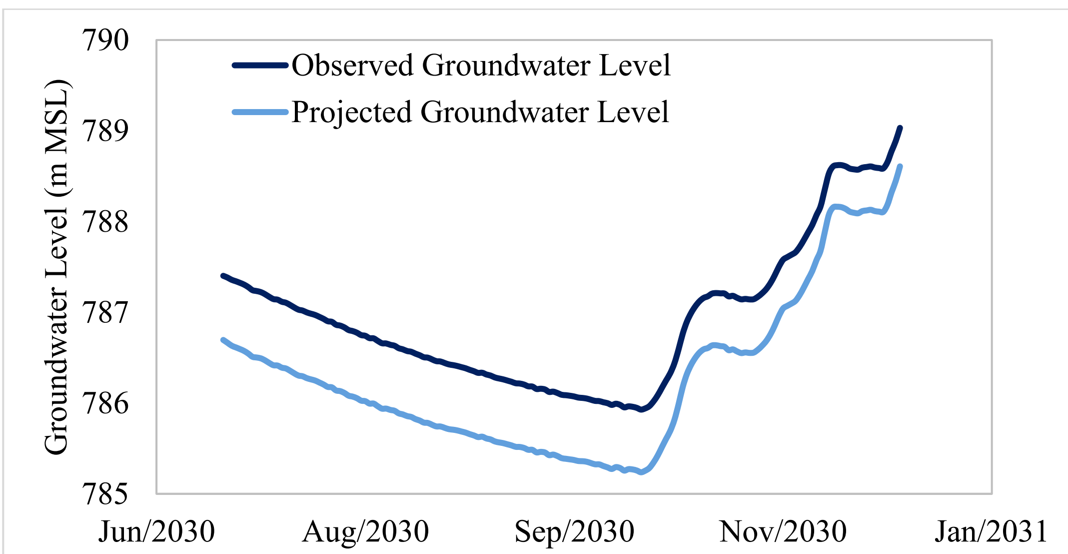

Figure 4.10: Comparison of Observed GWL in 2023 and Predicted GWL for 2030 at KUB_MON_004 Well in Scenario 2

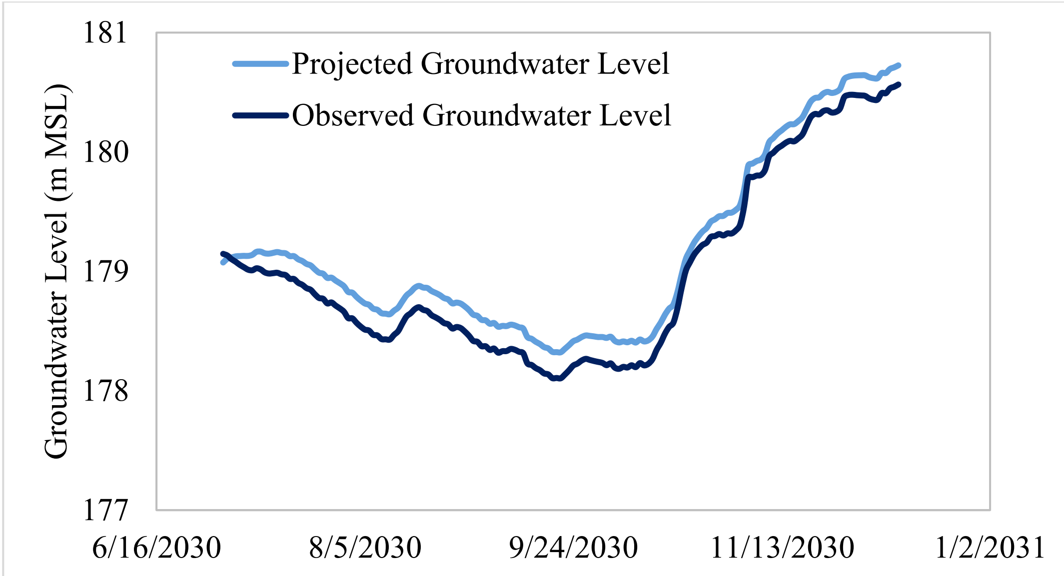

Figure 4.11: Comparison of Observed GWL in 2023 and Predicted GWL for 2030 at KUB_MON_039 Well in Scenario 2

4.4.3 Impact on the GWL - Scenario 3

Scenario 3 was designed to depict an increased pattern of land use change, driven by increased urbanization and agricultural expansion. Forest cover will decrease by 34%, agricultural land by 22%, and built-up land by 16%. With this expansion of urban areas, the average imperviousness of built-up areas is also likely to rise significantly, from 38% to 65%. Therefore, the CN for urbanized areas is higher than in the previous cases, indicating less infiltration and potentially more surface runoff. This situation indicates a more intense transition to agricultural and urban land use than in earlier scenarios.

Like Scenarios 1 and 2, Scenario 3 also has comparatively minor GWL changes, even with postulated more drastic land use changes. Even with 34% loss of forest cover, 22% increase in agricultural area, and 16% expansion in built-up area—along with a considerable increase in average imperviousness from 38% to 65%—the impact on GWLs is comparatively modest.

4.4.4 Impact on the GWL - Scenario 4

Scenario 4 assumes that forest cover is increased to 70%, while built-up areas decrease by 5%, or in essence, are halved from their current extent. Agricultural regions do not change much, with no meaningful variation projected. Unlike the other three scenarios, which assume less imperviousness due to less urban growth. The aim is to find out whether the decrease in impervious surfaces would be enough to make a difference in GWLs compared to the other alternative schemes.

Scenario 4 assumes an increase in forest cover up to 70%, a 5% reduction in built-up areas, and minimal change in agricultural land. Unlike the other three scenarios, which assume increased imperviousness due to urban expansion, this scenario examines the effect of reducing impervious surfaces. Yet, comparing the GWL fluctuations under all the scenarios, scenario 4 does not differ considerably from the other three. As in the other scenarios, the projected GWL is lower than the observations, suggesting the same trend irrespective of land use changes in this scenario.

This suggests that, during the period studied and under these conditions of catchment, the groundwater system expresses a degree of resilience towards these projected land use changes. Table 4.2 gives an overview of the changes in mean and maximum GWLs at selected observation wells under all three scenarios.

Table 4.2: Comparison of Observed and Projected Mean and Maximum GWLs Under the Three Different Scenarios

Scenario	**Observation Well**	**Mean GWL (m MSL)**		**Maximum GWL (m MSL)**	
		Observed	Projected	Observed	Projected
Scenario 1	KUB_MON_004	786.93	786.30	788.90	788.61
	KUB_MON_039	178.98	179.16	180.55	180.72
Scenario 2	KUB_MON_004	786.93	786.28	788.90	788.60
	KUB_MON_039	178.98	179.16	180.55	180.72
Scenario 3	KUB_MON_004	786.93	786.27	788.90	788.60
	KUB_MON_039	178.98	179.17	180.55	180.73
Scenario 4	KUB_MON_004	786.93	786.29	788.90	788.61
	KUB_MON_039	178.98	179.16	180.55	180.73

GWL analysis with the compound effects of climate change and LULC changes demonstrates spatially variable responses in the catchment, as observed in wells KUB_MON_004 and KUB_MON_039. For KUB_MON_004, there is a uniform decrease in both the mean and maximum GWL in each of the three scenarios. The mean GWL decreases from 786.93 m (previous) to 786.30 m in Scenario 1, and then further to 786.29 m in Scenario 4, which is a total of around 0.65 m decrease. Similarly, the maximum GWL decreases by up to 0.43 m. These decreases are hydrologically consistent with the hypothesized future conditions, including seasonal rainfall decrease and land use changes. These land use changes decrease vegetation cover and soil permeability, increasing surface runoff and decreasing infiltration and natural groundwater recharge. Additionally, the expansion of farmland would boost groundwater pumping for agriculture, further reducing the water table. The observed decline in rain makes this problem worse by reducing the amount of water present to be recharged during critical wet phases.

However, there is a slight increase in both mean and maximum GWL at KUB_MON_039, with the projected mean GWL rising from 178.98 m to 179.16 m across scenarios, and the maximum GWL increasing by approximately 0.17 m. This unusual trend may indicate localized model overestimation or suggest characteristics of an area with reduced hydrological sensitivity to rain and land use changes, possibly due to proximity to a constant head boundary, higher storage capacity, or recharge-dominated hydrogeology. However, given the regional decline in GWL recharge potential, this rise can also be justified as a model calibration deficiency. At the hydrologic level, this particularly highlights the importance of spatial heterogeneity in groundwater response to land use and climate drivers. While catchment-scale pressures are likely to decrease recharge and increase extraction, local hydrogeological conditions and model parameterization may modulate the direction and magnitude of GWL change. Hence, accurately capturing these spatial dynamics is of critical importance for successful groundwater management in future climate and land use situations.

One of the major limitations in the current arrangement of groundwater models is the assumption of a constant head boundary at the upstream end. During the simulation period, GWLs from two observation wells located near the upstream boundary were used to define this constant head. However, for compound impact analysis, the same boundary condition was utilized without updating it to reflect potential alterations in the upstream inflows or GWLs under future scenarios. Such a simplification may not accurately represent dynamic changes in the upstream hydrological condition, which can result in biased simulation results.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

This chapter provides the overall conclusion of the research and makes recommendations based on the findings. It begins briefly remembering the main objectives of the study and how they were achieved. It then summarizes the main findings, discusses their implications, and declares any limitations faced. Finally, it provides possible improvements and future research opportunities to allow the continuation of work in this area.

5.1 Conclusions

This study was carried out to analyze how climate change-induced LULC changes can affect groundwater availability in the arid zone of Sri Lanka, namely the Kumbukkan Oya catchment. To achieve this, the study aimed to develop a numerical groundwater flow model using MODFLOW and apply ML techniques to downscale climate projections to the local scale. Particularly, the aims were to simulate groundwater flow, analyze future climate variability from downscaled GCM outputs, and assess the compound impacts of climate and LULC changes on GWLs in the catchment. By integrating physical modeling and data-driven methods, the research sought to obtain implications for better management of groundwater resources in vulnerable dryland environments.

Construction of the steady-state model provided a robust platform from which transient groundwater simulations could be initiated. The model exhibited excellent correlation between calculated and observed groundwater head values, having an extremely high $R^2 = 0.9985$, which is indicative of good model calibration and accuracy. Within the transient model, system response to temporal recharge changes was investigated through GWL variations at four observation wells:

- KUB_MON_004: The model successfully replicated the decline and recovery of GWL with minor underestimation during periods of peak recharge. It performed best overall.
- KUB_MON_039: The model simulated observed behavior very well, though it tended to overpredict GWLs slightly during the recharge period.
- KUB_MON_015 and KUB_MON_028: Both locations showed differences. This means modeling shortcomings in mid-catchment dynamics. continuously and failed to simulate the initial loss. This suggests mid-catchment dynamics modeling deficiencies.

Generally, on all observation wells, there was a decrease in GWL between June and October 2023, followed by a sharp rise to January 2024—illustrative of recharge related to seasonal wet seasons. Overall, while the model demonstrated strong performance in upstream areas, it showed lower accuracy for midstream regions, indicative of localized parameter improvement, improved handling of recharge uncertainty, and data enrichment from additional field data toward more effective calibration.

To address the spatial and temporal mismatch between GCM outputs and local-scale hydrological applications, ML-based downscaling approach was carried out using the RF technique. A few of the key findings are:

- The future precipitation downscaled data (2030–2049) show a significant decrease in monthly and seasonal rainfall compared to the historical baseline period (1989–2011).
- The Second Inter-Monsoon and Southwest Monsoon, the conventionally wettest months, suffer a sharp fall in forecast rainfall, suggesting possible derangements of conventional wet-season water supply.
- The Northeast Monsoon and First Inter-Monsoon seasons also show a gradual but consistent decrease in rainfall, reflecting a general drying trend for all monsoon seasons.
- Median values of seasonal rainfall are reduced in future conditions that imply drier wet seasons and the potential to impact hydrological regimes and groundwater recharge.
- Future rainfall will be more evenly distributed, though at generally lower levels, which implies reduced variability but prolonged low levels of precipitation.

These findings highlight the compound impact of climate change on rainfall amounts and spatial distribution, and it may result in reduced GWLs, prolonged dry seasons, and increased reliance on adaptive water management practices.

GWL fluctuation estimation under the compound impacts of climate change and LULC change indicates a generally moderate hydrological response in the catchment. Despite the reduction in all the phases of rainfall in the seasons and extensive land transformation, the varying GWLs were nearly within a narrow range. Overall, the mean average GWL decreased by approximately 0.65 m and the maximum GWL by approximately 0.43 m across the catchment. These reductions are hydrologically consistent with decreased infiltration caused by increased impervious surfaces and loss of vegetation cover, and greater groundwater pumping for irrigation. Lower monsoonal rains also contribute to the decreased opportunity for recharge, further diminishing the demand on groundwater resources.

However, the combined magnitude of GWL decline suggests that the catchment is sufficiently resilient to these compound stressors. This may be because there are deeper aquifers, larger storage capacity in the aquifers, and spatially heterogeneous areas of recharge that buffer the effects of declining rainfall and increasing land use intensity.

Additionally, the low degree of change is an indicator that the system can still be below critical groundwater stress levels. However, while aquifer response has so far been steady, accelerating land use intensification and long-term climate variability can push the system beyond its buffering capacity. Therefore, ongoing monitoring and adaptive management of groundwater are required to maintain long-term sustainability.

Results of this study benefit the efficient management of Sri Lanka's dry zone groundwater resources, in the case of the Kumbukkan Oya catchment. The study provides a scientific basis for better planning and water allocation. An understanding of how GWLs can reduce, especially during droughts, empowers governments to formulate effective water use plans, allocate priority uses such as drinking and irrigation, and implement recharge enhancement practices such as artificial recharge and soil conservation. Moreover, an understanding of how deforestation and urbanization affect groundwater recharge guides land use zoning and policy guidelines. These results also justify the construction of early warning systems by establishing thresholds for initiating water conservation actions at key times.

The immediate beneficiaries of such information are farmers and communities that depend on groundwater for irrigation and drinking purposes. They can prepare themselves in advance by implementing water-saving measures and cropping pattern modifications in anticipation of possible groundwater decline. Decision makers, e.g., at the Department of Irrigation, Central Environmental Authority, and Water Resources Board, can utilize such information to formulate long-term plans for groundwater management. Disaster risk managers can use the predictions to formulate drought mitigation strategies, whereas researchers and academic institutions can benefit from this combined modeling for such research. Environmental organizations and NGOs also benefit since the results can be used in supporting conservation activities, awareness raising, and advocating for sustainable land use practices.

5.2 Recommendations

To improve the performance and reliability of future groundwater research, it is necessary to mitigate the significant shortcomings of this study. These are mainly data deficiencies, simplifications in model assumptions, and environmental and human influences are not accounted. The following are suggested to reduce such limitations and enhance the performance of future groundwater models.

- Future research should include the effects of socio-economic factors, e.g., population growth and land demand, on groundwater use.
- It is recommended to investigate the use of coupled climate-hydrology-socioeconomic models for more integrated impact analysis.

- More comprehensive soil and geological information in models can be utilized to refine model accuracy, especially in mid-catchment regions.
- Also, the use of multiple GCMs and several SSP scenarios can also be recommended.

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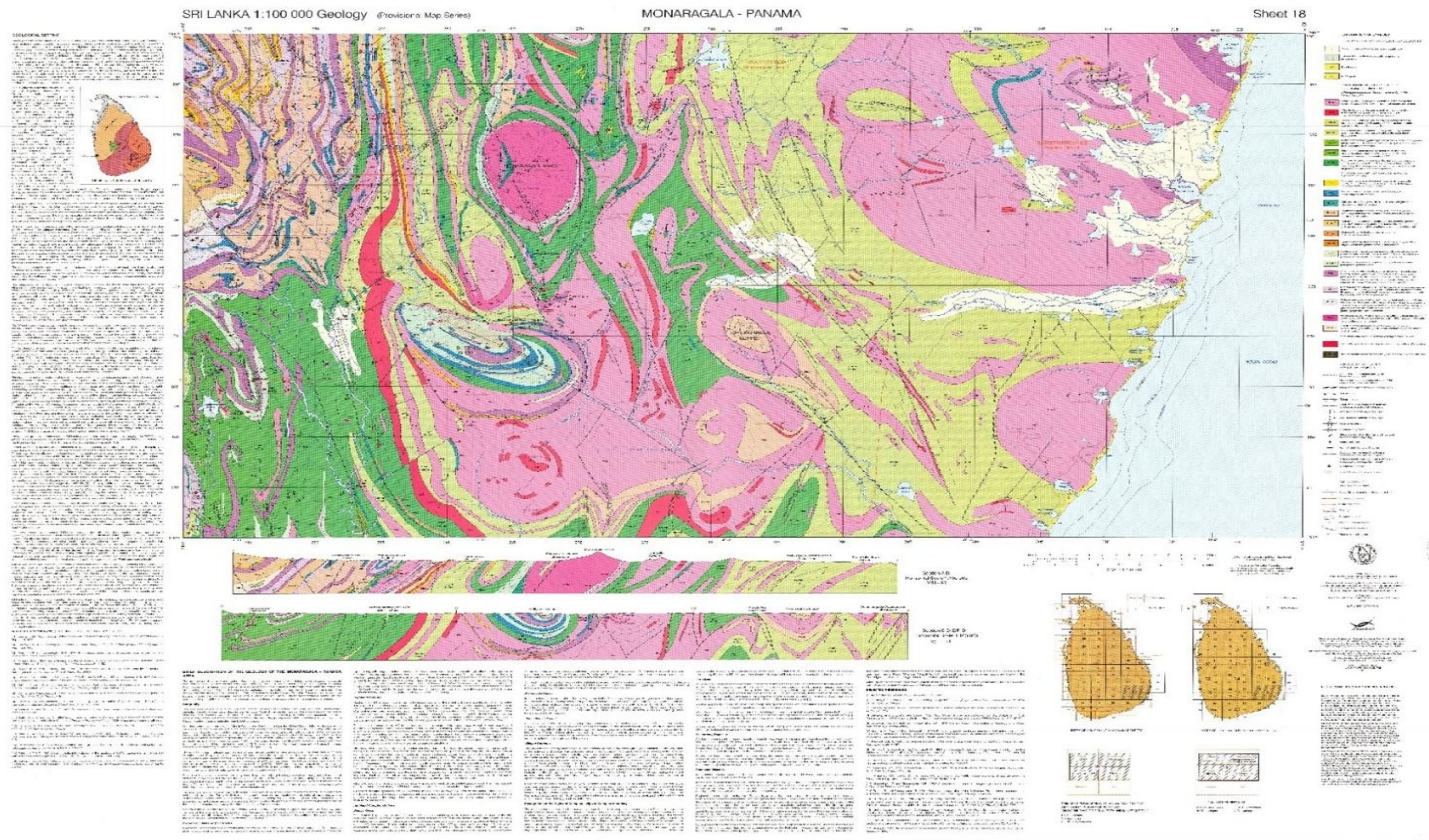
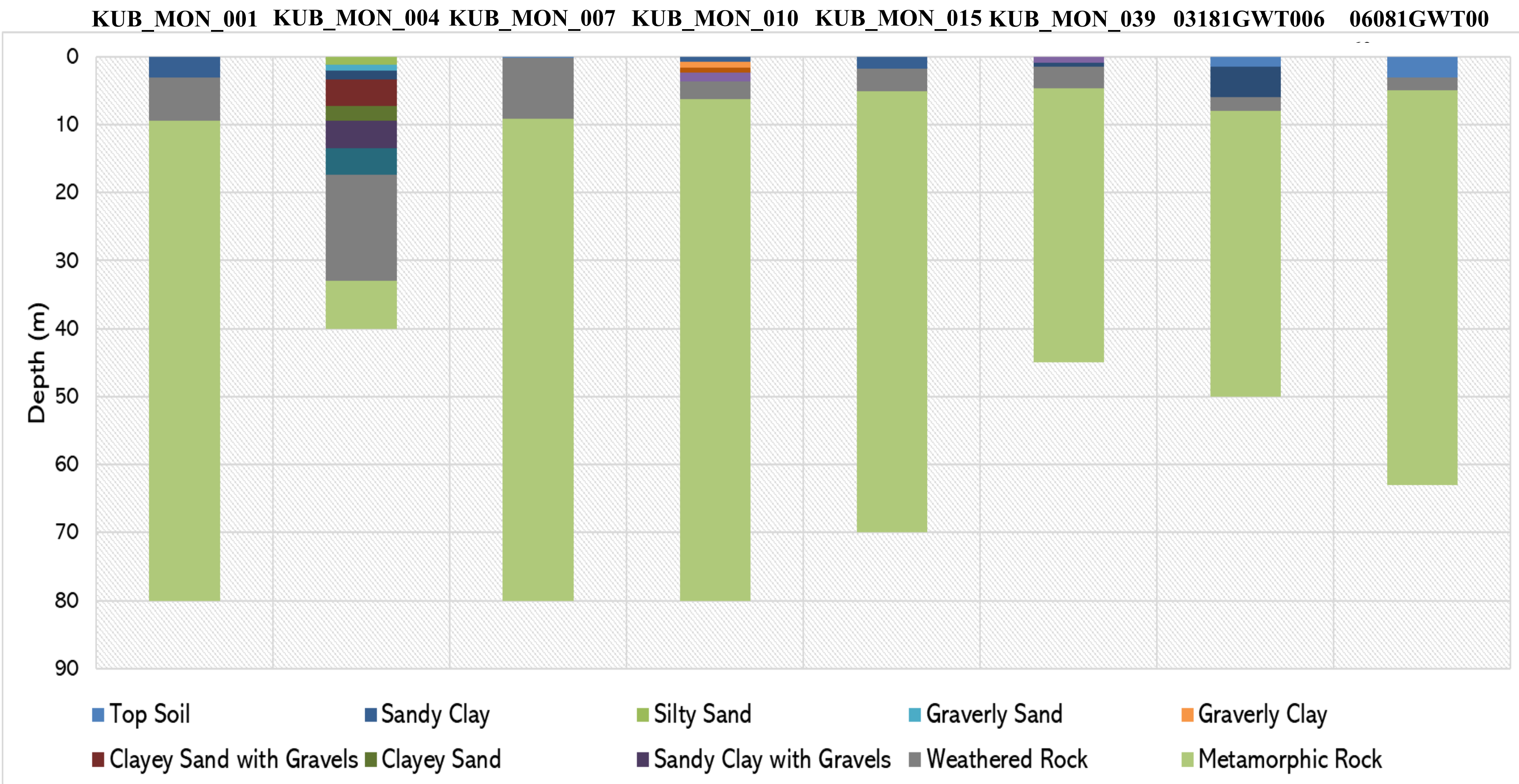
APPENDIX A



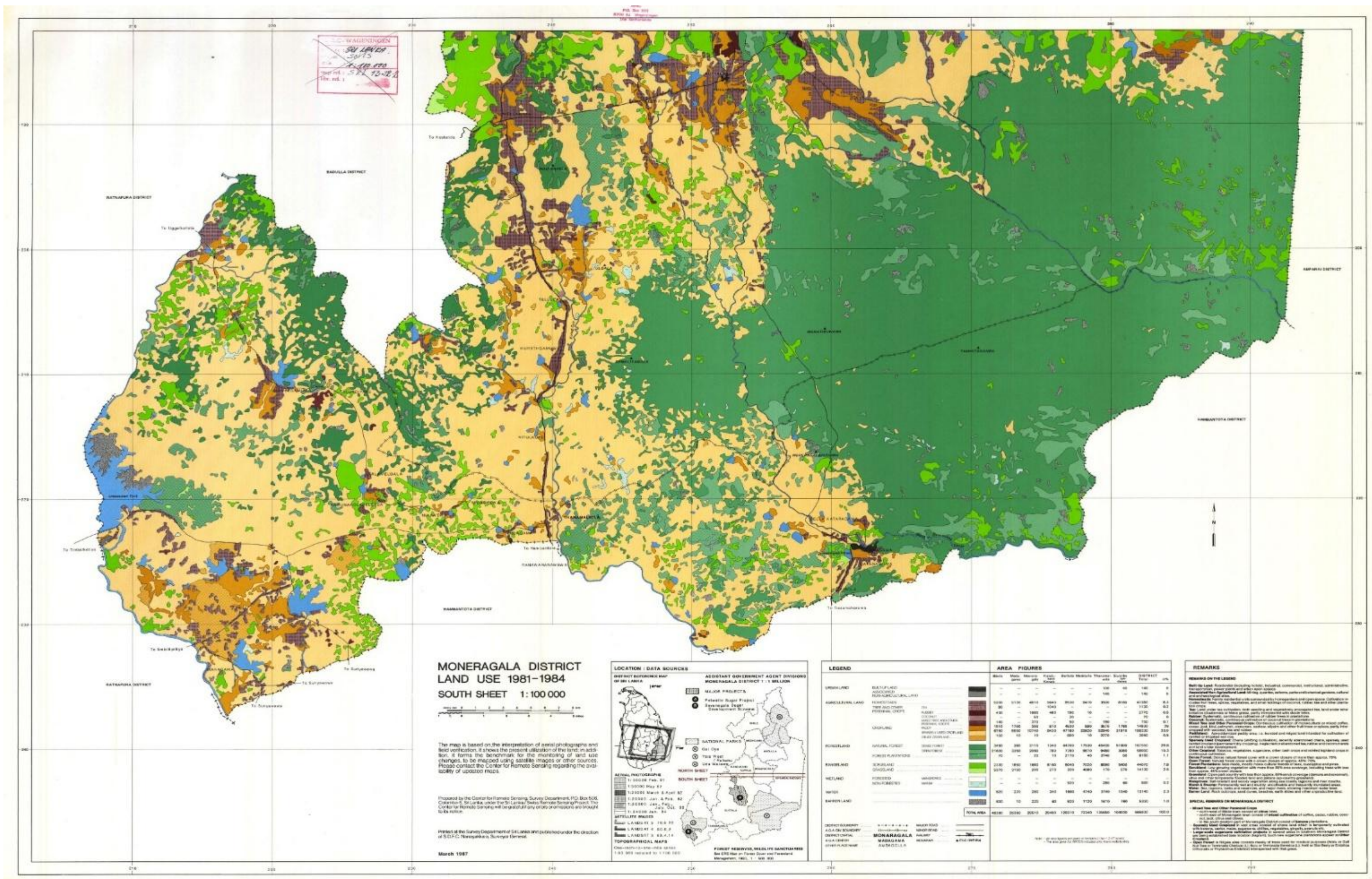
Appendix A: Geological Formation Map of the Monaragala District, Illustrating the Spatial Distribution of Major Rock Types and Structural Features Relevant to Hydrogeological Assessment

APPENDIX B



Appendix B: Borehole Logs of Selected Observation Wells in The Kumbukkan Oya River Basin, Detailing Lithological Variations and Stratigraphic Profiles

APPENDIX C



Appendix C: Land Use Map of the Monaragala District, Showing the Spatial Distribution of Key Land Cover Types Relevant to Hydrological and Environmental Assessment