Estimation of Groundwater Recharge Using GIS Based Wetspass-M Model: The Case of Dedaba Watershed, Rift Valley Lakes Basin, Ethiopia

MASTERS OF SCIENCE THESIS

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ADVISORS APPROVAL SHEET

This is to certify that the thesis entitled **“Estimation of Groundwater Recharge Using GIS Based Wetspass-M Model: The Case of Dedaba Watershed, Rift Valley Lakes Basin, Ethiopia”** has been submitted in the partial fulfilment of the requirement for the degree of **Master of Science** in **Hydraulic Engineering**, the graduate program of the department of Hydraulic and Water Resources Engineering has been carried out by **Jibril Wakeyo Wario** ID No. **GPHydrW/0010/12,** under our supervision. Therefore we recommend that the student has fulfilled the requirements and hence hereby can submit the thesis to the department.

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We, the undersigned, members of the Board of Examiners of the final open defence by **Jibril Wakeyo Wario** have read and evaluated his thesis entitled '**Estimation of Groundwater Recharge Using GIS Based Wetspass-M Model: The Case of Dedaba Watershed, Rift Valley Lakes Basin, Ethiopia''** and examined the candidate. This is, therefore, to certify that the thesis has been accepted in partial fulfilment of the requirements for the degree.

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LIST OF ABBREVIATIONS AND ACRONYMS

AGRL- Agriculture Land

ASCII- American Standard Code for Information Exchange

BRL- Bare Land

BUA- Built Up Area

CR- Consistency Ratio

DEM- Digital Elevation Model

DMC- Double Mass Curve

ERDAS- Earth Resource Data Analysis System

ETi- Actual evapotranspiration from impervious surface

ETM+- Enhanced Thematic Mapper Plus

ETo- Actual evapotranspiration from open water

ETs- Actual evapotranspiration from bare soil

ETV- Actual evapotranspiration from the vegetation

FAO- Food and Agriculture Organization

FRST- Forest Land

GIS- Geographical Information System

GRL- Grassland

GWD- Groundwater Depth

IDW- Inverse Distance Weight

LULC- Land use/Land Cover

LULCC- Land use/Land Cover change

M.A.S. L- Meters above Sea Level

MER- Main Ethiopian Rift Valley

MoWIE- Ministry of Water Irrigation and Energy

NMA- National Meteorological Agency

OLI- Operation Landsat Imager

OUPI- Oromia Urban Planning Enterprise

PET- Total Potential Evapotranspiration

RS- Remote Sensing

SOE- Survey of Ethiopia

SRTM- Shuttle Radar Topography Mission

SWL- Static Water Level

TBL- Table of Values

TIRS- Thermal Infrared Sensor

TM- Thematic Mapper

USDA- United State Department of Agriculture

USGS- United States Geological Survey

WETSPASS-M- Water and energy transfer between soil, plants, and atmosphere under quasi-steady-state

WTF- Water Table Fluctuation

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ABSTRACT

The Dedaba watershed, located within the Rift Valley Lakes Basin in Oromia, Ethiopia, is experiencing significant changes driven by agricultural expansion, land use and land cover (LULC) changes, and a growing population. These dynamics, combined with insufficient watershed management, have resulted in water resource depletion, pollution, and environmental degradation. The escalating demand for groundwater, driven by the population increase, present a considerable challenge in this region. This study utilized the WetSpass-M (Water and Energy Transfer between Soil, Plants, and Atmosphere under quasi-Steady State – Monthly) model, a spatially-distributed water balance model, to assess seasonal and annual groundwater recharge, actual evapotranspiration, and surface runoff in the Dedaba watershed. The model integrates spatially distributed data on precipitation, potential evapotranspiration, temperature, wind speed, soil types, LULC, and topography. These datasets, processed using GIS techniques, allowed for the generation of detailed spatial water balance components. Calibration and validation of the model were conducted using observed groundwater levels and streamflow data, ensuring accurate simulations. The calibrated WetSpass-M model revealed groundwater recharge estimates ranging from 0.46 to 65.4 mm/year, with an average of 37.47 mm/year, representing 3.4% of the total recharge. To understand the impacts of LULC changes on groundwater recharge, the model was applied using LULC data from 1990 and 2020. Results indicated a continuous decline in recharge rates over this period, underscoring the significant influence of LULC on groundwater resources. Specifically, the model estimated recharge at 3.29 mm in January 1990, peaking at 6.03 mm in September, and dropping to 0.13 mm in December. By 2005, these values had decreased, with January at 2.84 mm, September at 5.2 mm, and December at 0.12 mm. The downward trend persisted into 2020, with recharge starting at 2.61 mm in January, peaking at 4.52 mm in September, and reaching 0.12 mm in December. The study highlights the critical need to consider temporal variability and long-term trends in groundwater recharge for sustainable water management in the Dedaba watershed. The analysis of LULC changes shows a rapid urban expansion, reduction of forests and grasslands, and consequent threats to groundwater recharge. Mitigating these risks requires collaborative efforts, including promoting afforestation, water-conserving urban farming, sustainable agricultural practices, and artificial recharge techniques. Future research should incorporate climate change projections to enhance groundwater recharge predictions and improve water resource management strategies.

Keywords*: GIS, WetSpass model, Groundwater recharge, Dedaba watershed, and LUL*

CHAPTER ONEN: INTRODUCTION

Groundwater recharge is a hydrologic process where water moves downward from surface water to groundwater. Recharge occurs both naturally (through the water cycle) and through anthropogenic processes (i.e., artificial groundwater recharge), where rainwater and /or reclaimed water is routed to the subsurface (Pandian et al., 2014). Ethiopia possesses abundant surface and subsurface water resources, though they exhibit considerable spatial and temporal variability. Nine lakes and 12 river basins are widely distributed in the country. Ethiopia has also groundwater potential, ranging from 2.6 to 2.65 billion m^3, and an estimated 122 billion m^3 of annual runoff water (Awulachew et al., 2007). However, <5% of the surface water potential is currently utilized by the people, and groundwater is a potential, but untouched resource(Tesfamichael et al., 2013).

Recharge is estimated using methods such as the chloride ion mass balance, empirical approaches, the water-balance method, the water budget model, or by multiplying the extent of water-level fluctuations in wells by the specific yield of the aquifer material (Yun et al., 2011). But commonly groundwater recharge is determined to a large extent as an imbalance at the land surface between precipitation and evaporative demand (Gebreryfael, 2008). To manage groundwater efficiently and sustainably, it is essential to understand the seasonal and annual variations in water resources, particularly runoff, evapotranspiration, and recharge (Obuobie et al., 2008). Groundwater resources are highly influenced by climatic factors, geological formations, topography, soil properties, and land-use types (Dragoni & Sukhija, 2013), a detailed understanding of watershed physical and biological characteristics are important.

According to (Batelaan et al.,1996), accurate quantification of groundwater resources involves the identification of hydrological and biophysical characteristics of the watershed. Regional groundwater models used to analyze groundwater systems, particularly infiltration–discharge relationships, are often based on steady-state conditions and therefore require long-term average recharge inputs. However, the spatial variation in recharge due to factors such as diverse land use, soil types, and slope can be significant and should be considered in regional groundwater models. Hence, WetSpass-M was built as a physically-based method for estimation of the long-term average, spatially varying, water balance components: surface runoff, actual evapotranspiration, and groundwater recharge. It was developed based on the foundations of the time-dependent, spatially distributed water balance model WetSpa (Wang et al., 1997).

The rate of water-table recharge varies depending on environmental factors, as well as topographic, meteorological, hydrological, and hydrogeological characteristics. For reliable and accurate analysis, groundwater recharge on a large and complex scale is often assessed using numerical models. These models are valuable for spatial analysis and can be integrated with Geographic Information Systems (GIS), offering a flexible toolset for resource management. (Kornkul & Chotpantarat, 2013).

The Dedaba Watershed experiences a significant portion of its water use being sourced from groundwater. This is primarily due to the seasonal nature of rainfall in the region, which results in ephemeral streams and rivers. (Lammesa, 2017) Hence, this forces the local communities to use subsurface water for domestic uses and in some cases for irrigation purposes. Though this groundwater is recharged from precipitation, utilization of this resource is going on without a basic understanding of the recharge amount and its areal distribution as well as the temporal and spatial variation of the other water balance components which creates a critical problem for its management in the watershed This paper estimates groundwater recharge, surface runoff, and evapotranspiration for the Dedaba watershed using the WetSpass-M modeling method.

1.2 Statement of the Problem

The Dedaba watershed has experienced considerable agricultural practices and land cover changes in recent years due to an increasing population. Inappropriate management of the watershed, depletion of water through pollution, and environmental degradation have become clear challenges. The demand for groundwater resources is increasing day by day due to the ever-increasing population. Despite the high potential groundwater resources in the study area, there are many challenges, including high spatial and temporal variability in rainfall, global climate change, deforestation, land degradation, and a high population growth rate. These challenges put immense pressure on groundwater resources. Quantification of the rate and seasonal changes of groundwater recharge is crucial for efficient groundwater resource management. However, the complex hydrological dynamics and limited data availability in the region make it difficult to accurately estimate groundwater recharge using traditional methods. This study aims to address these challenges by utilizing the GIS-based WetSpass-M model to improve the accuracy and spatial resolution of groundwater recharge estimation in the Dedaba watershed, thereby contributing to more informed and sustainable water resource management practices in the region.

1.3 Objective

1.3.1 General objective

The main objective of this study is to estimate groundwater recharge of the Dedaba watershed using the WetSpass-M model.

1.3.1.1 Specific objectives

- To estimate the distributed actual evapotranspiration and surface runoff of the watershed.
- To estimate the distributed seasonal and annual groundwater recharge of the watershed.
- To assess the impact of changes in land use/land cover on groundwater recharge in the study area using GIS and RS data for 1990, 2005 and 2020.

1.4 Research questions

To attain the objective of the study, the following questions should be answered:

- ✓ What is the contribution of the groundwater recharge to the total water balance of the sub-basin?
- ✓ What is the spatial and temporal variation of recharge rate of Dedaba sub-basin?
- ✓ What is the extent the change in land use/land cover impact groundwater recharge in the study area?

1.5. Scope of the Study

This research investigates groundwater recharge patterns within the Dedaba Watershed, located in the West Arsi Zone, Oromia Region, Ethiopia. The watershed covers an area of approximately 296.17 km². Accurate estimation of groundwater recharge is crucial for understanding the water balance of the Dedaba Watershed and developing sustainable water management strategies. The study employs the WetSpass-M model, a spatially distributed simulation model that simulates water and energy transfer processes between soil, vegetation, and the atmosphere. The model estimates the spatial and temporal variations of groundwater recharge across the watershed. Key water balance components considered include actual evapotranspiration, surface runoff, and groundwater recharge. To ensure model accuracy, a rigorous calibration and validation process conducted using available hydro-meteorological data specific to the Dedaba Watershed. The required data include: Meteorological data, Groundwater depth data, Slope and topography data, Soil data, Land use/land cover (LULC) data. This study focuses on three key objectives within the Dedaba Watershed: Quantify groundwater recharge, evaluate water balance components and assess land use impact.

1.6 Significance of the Study

Groundwater recharge of seasonal and annual levels has been quantified graphically and mathematically in this study. Because water scarcity and surplus during the dry and rainy seasons, respectively, are the major issues impacting sustainable development in the research area, particularly for sustainable agricultural production, estimating the groundwater recharge quantity was useful in managing the water resource.

The research is important for successfully managing water resources, making the best use of available water, improving water sources, and minimizing the effects of drought and water shortage crises.

CHAPTER TWO: LITERATURE REVIEW

2.1 Water resources and hydrologic cycle

Water is transported from land, open water bodies and plants as a water vapor to the atmosphere through evaporation and transpiration and back to the Earth 's surface as precipitation, falling as either rain or snow. Nowadays, the global hydrological cycle has been responding to the observed effects of global warming, which include increasing atmospheric water vapor content and changing precipitation patterns (Chen & Grasby, 2014).

The hydrologic cycle is the conceptual model which states the storage and movements of water between the biosphere, atmosphere, lithosphere and hydrosphere. Water on this planet can be stored in any of the following reservoirs: atmosphere, oceans, lakes, rivers, soils, glaciers, snowfields and groundwater. Water moves from one reservoir to another by way of processes like evaporation, condensation, precipitation, deposition, runoff, infiltration, sublimation, transpiration, melting and groundwater flow (Baychiken, 2018).

The oceans supply most of the evaporated water found in the atmosphere. From this evaporated water, only 91% is returned to the ocean basins by way of precipitation. The remaining 9% is transported to areas over landmass where climatological factors induce the formation of precipitation (Karamouz et al., 2003).

Water is a naturally circulating resource that is continuously recharged. Even if the stocks of water in natural and artificial reservoirs are helpful to increase the available water resources for human society, the flow of water would be the main focus in water resources valuations (Oki, 2005). The hydrological cycle is also defined as a water transfer cycle that occurs continuously in nature; at which the phenomena of evaporation and evapotranspiration, precipitation and runoff take place during the water transfer system (Raghunath, 2006). Precipitation and runoff are only the visible components of this process. Other components such as evaporation, infiltration, transpiration, percolation, groundwater recharge and discharge etc. are other important mechanisms of this cycle. The water exchange between the land surface and the atmosphere is based on the continuous evaporation of water from the Earth, the temporary storage of water in the form of water vapour in the atmosphere and the return of water to the land surface through several forms of precipitation such as rain, snow, sleet or hail. Even if these mechanisms are relatively simple to represent, the interaction between the land surface and underground and in particular groundwater movement is not so easy to visualize (Karamouz et al., 2003).

2.1.1 Groundwater recharge

Groundwater recharge can be defined as the entry of water into the saturated zone of water made available at the water table surface together with the associated flow away from the water table within the saturated zone (Pandian et al., 2014). Most natural groundwater recharge is derived directly from rainfall and snowmelt that infiltrate through the surface and migrate to the water table. To quantify recharge from precipitation, it is critical to understand rainfall-runoff relationships. The first step is to determine the fraction of precipitation available for groundwater recharge, after subtracting what is lost to overland flow (runoff) and evapotranspiration (ET). The vital to the rainfall-runoff relationship is the soil type, the antecedent moisture condition, and the land cover. Well-drained soils generally have high effective porosities and high hydraulic conductivities, whereas soils that are poorly drained have higher total porosities and lower hydraulic conductivities. These physical properties combine with initial moisture content to determine the infiltration capacity of surficial soils. The land cover determines the fraction of precipitation available for infiltration. Impervious, paved surfaces prevent any water from entering the soil column, while open, well-vegetated fields are conducive to infiltration. (Xu, 2002).

Because rainfall is the primary source of recharge for the groundwater system, the groundwater recharge system is variable in both space and time. Recharge techniques differ from place to place, and there is no agreement that a method established and employed in one location would produce consistent results when used in another. Before settling on a recharge method, it is crucial to identify the likely flow mechanisms and important elements impacting the recharge in an area. (Daniel, 2016).

Water enters to ground-water systems in recharge areas and moves through them, as dictated by hydraulic gradients transmissivity and hydraulic conductivities, to discharge areas. The identification of recharge areas is becoming increasingly important because of the expanding use of the land surface for waste disposal. Recharge rates vary from year to year, depending on land cover types of the area, the intensity of precipitation and its seasonal distribution, air temperature, and other factors. Among the other factors are land use. For example, recharge rates are much higher in highly vegetated area than in impermeable cities and asphalt roads (Ralph, 1980).

In humid areas with porous and permeable soils, $1/4^{th}$ of annual rainfall may recharge the aquifer. In contrast, in desert regions recharge is very small 1% of rainfall or less (Johon, 2002).

Aquifers in these areas may contain very old water, which has accumulated over centuries under different climatic conditions.

Groundwater recharge happens when a part of precipitation on the ground surface infiltrates through the soil and reaches the water table. Recharge can be known as water moving from the land surface to the unsaturated zone. When water reaches the water table, it can go out of the groundwater to surface water, which is called discharge.(Shukla & Jaber, 2006).

2.1.2 Estimation of groundwater recharge

Groundwater recharge cannot be measured directly and is difficult to accurately estimate. Groundwater recharge estimation is very significant for the effective and sustainable management of groundwater systems. Groundwater recharge refers to the process through which water infiltrates from the surface into the ground, replenishing the groundwater resources. Groundwater recharge is influenced by several factors such as the type of soil, weather conditions, land use, and terrain (Lerner et al., 1990) .Estimating groundwater recharge is essential in managing groundwater resources sustainably. The estimation of groundwater recharge involves determining the amount of water that infiltrates into the ground and subsequently increasing the water content of an aquifer.

There are various methods to estimate groundwater recharge, including geomorphologic, hydrological, and geochemical methods. The geomorphologic method involves identifying the characteristics of the surface topography and the hydrological regime, measuring the infiltration rate and the soil moisture, and estimating groundwater recharge. The hydrological method involves measuring the water level and the flow rate of groundwater in a well or a borehole, and using these measurements to estimate the groundwater recharge. The geochemical method involves analyzing the chemical properties of groundwater and using these properties to estimate the groundwater recharge.(Rudra et al., 2022)

Estimating groundwater recharge is crucial in evaluating groundwater resources, understanding the sustainable yield of aquifers, and preventing overexploitation and contamination of groundwater. Groundwater recharge is a complex process influenced by various factors, and accurate estimation requires a combination of different methods.(Lammesa, 2017). The development of effective recharge estimation methods that incorporate the changing environmental factors is essential for the sustainable management of groundwater resources.

For estimating groundwater recharge different methods exist. According to (Scanlon et al., 2002) groundwater recharge methods have been classified based on hydrological zones from which the recharge data is obtained as surface water, unsaturated zone and saturated zone. The groundwater recharge estimation methods are further classified into physical techniques, tracers and numerical modelling within each of the hydrologic zones.

2.1.3 Estimation of actual evapotranspiration and runoff

Evapotranspiration (ET)is a sum of evaporation from open water bodies and bare soil, interception loss by vegetation and transpiration through plants (Dereje & Nedaw, 2019). atmospheric humidity, net radiation, wind speed and temperature of the area are the governing factors (Craig et al., 2010). The hydrological basin needs to control groundwater recharge, overland flow and soil moisture. It is expressed by potential evapotranspiration (PET) which is the possible water to evaporate from the watershed through the plant and directly from open water bodies as well as bare soil from the land surface, and actual evapotranspiration (AET) which is the actual water that is evaporated to the atmosphere.

For competing for actual surface runoff, the runoff coefficient is a function of soil texture, slope, and vegetation type inputs (Mustafa & Ali, 2013). It is an estimate of how much water from precipitation flowed onto the ground surface via rivers and streams.

2.1.4 Impacts of land use/land cover on groundwater recharge

Land use and land cover changes are one of the major factors that affect groundwater recharge. Their impacts vary widely based on the type of land use and the soil properties of the area. The impacts of land use/land cover on groundwater recharge reveals that agricultural activities, deforestation, urbanization, and mining are some of the major factors that negatively affect groundwater recharge.

Groundwater is intimately connected with the landscape and land use that it underlies and most of the landscape and is vulnerable to the anthropogenic activities on the land surface above. Land use affects groundwater resources through changes in recharge and by changing water demands. Therefore, the rapid economic development and the accelerated urbanization in recent decades have resulted in the serious degradation of water resources (Su et al., 2015) via urbanization, industrialization, and intensive agriculture that result in rapid landscape change with the loss of ecological capacities (Ricca and Guagliardi, 2015). Human activity is one of the major driving forces leading to changes in land cover characteristics and subsequently hydrologic processes (Bonansea, 2016).

The increased impervious area has been a major factor in contributing to decreased infiltration, which results in increased surface water storage. The large pressure of the growing population increased demands for food, fodder, and fuel combined with industrial activities have essentially led to rapid change in land use patterns in developing countries. Information on the rate and kind of change in the land resources is essential for proper planning, management, and regularizing the use of such resources. The land use information is needed in the analysis of environmental processes and problems(Zarei et al., 2016).

Land use and land cover changes have a profound impact on groundwater recharge. Therefore, sustainable land use management policies and practices are necessary for maintaining groundwater resources.

2.2 Factors affecting groundwater recharge

Groundwater recharge is influenced by a variety of factors, including climate change, land use and land cover (LULC) changes, soil type, vegetation type and cover, elevation, and precipitation patterns. These factors can either increase or decrease groundwater recharge rates, depending on the specific conditions.(Prasad et al.., 2008) Climate change impacts groundwater recharge through changes in precipitation and temperature patterns. Increased temperatures can lead to enhanced evapotranspiration, reducing the amount of water available for recharge. Changes in precipitation patterns can also affect recharge rates, as increased rainfall can lead to increased runoff and reduced infiltration into the soil. This can result in decreased groundwater recharge rates over time.

LULC changes can significantly impact groundwater recharge rates. For example, the conversion of natural vegetation to agricultural land can lead to increased surface runoff and reduced infiltration, resulting in decreased groundwater recharge. Restoration of bare land to more natural vegetation can also lead to increased groundwater recharge rates. (Annesh and Paresh, 2015) Soil type and vegetation cover can also affect groundwater recharge rates. For example, soils with high permeability and vegetation with deep roots can enhance infiltration and increase groundwater recharge. On the other hand, soils with low permeability and vegetation with shallow roots can reduce infiltration and decrease groundwater recharge.

Elevation and precipitation patterns can also influence groundwater recharge rates. Higher elevations typically receive more precipitation, which can lead to increased groundwater recharge rates. Precipitation patterns, such as the frequency and intensity of storms, can also impact recharge rates by affecting the amount of water available for infiltration.

Other factors that can affect groundwater recharge rates include urbanization, which can lead to increased runoff and reduced infiltration due to the presence of impervious surfaces. Additionally, the quality of the recharge water can impact the effectiveness of the recharge process, as contaminated water can lead to decreased water quality and potential health risks.
Groundwater recharge is influenced by a complex interplay of factors, including climate change, LULC changes, soil type, vegetation, elevation, and precipitation patterns. Understanding these factors is crucial for effective management of groundwater resources and ensuring sustainable water supply.

2.3 Hydrological models for groundwater recharge

Groundwater recharge models are essential tools used to assess the rate and quantity of water that infiltrates the subsurface and is stored in aquifers. These models integrate measurements of groundwater supply, and other physical and climatic factors, to determine the recharge rate of aquifers. Recently, these models have been increasingly used to understand the responses of watershed systems to climate change, which has necessitated the comparison between different groundwater recharge models (Moriasi, 2007). This review explores various groundwater recharge models, their structures, and the key factors that influence their selection. Groundwater recharge models are vital for the management and sustainable use of groundwater resources. They enable the monitoring of recharge rates and volumes into aquifers and provide predictions of future trends. Consequently, these models are essential for resource management, particularly in regions with limited freshwater availability.

There are various types of recharge models, including simple, semi-distributed, and distributed models. Simple models are popular due to their ease of use and minimal data requirements. Semi-distributed models build on the simplicity of simple models, offering more detailed insights into groundwater recharge processes. Distributed models, the most complex of the three, provide the most accurate simulation of aquifer behavior and are typically used in large-scale areas. Several factors influence the selection of these models, depending on the specific needs and complexity of the study. (Pistocchi et al., 2008). The selection of an appropriate groundwater recharge model is influenced by several critical factors, including the intended purpose of the model, the prevailing hydrogeological conditions, and the availability of relevant data. Different models are optimized for specific applications, and the unique hydrogeological characteristics of a site can significantly determine the suitability of a particular model. Moreover, the availability of comprehensive data is essential for model accuracy; insufficient data can complicate the selection process, making it challenging to identify the most appropriate model for a given scenario.(Beven, 2001)

This evaluation highlights the strengths and weaknesses of various groundwater recharge models. Simple models are easy to use due to their low complexity, while semi-distributed models offer the advantage of estimating recharge variability across different areas. Distributed models, although more complex, are ideal for large regions and provide greater accuracy compared to other models. However,Be the drawbacks of these complex models include the need for advanced computer systems, extensive data, and significant costs. To ensure a model accurately reflects reality, thorough calibration and validation are essential. A well-calibrated and validated model yields reliable predictions, enhancing confidence in its results. However, achieving this requires high-quality data, and the calibration and validation process can be both time-consuming and expensive. (Batelaan & De Smedt, 2007)

Models for estimating groundwater recharge vary in complexity and requirements. The choice of a model depends on the specific hydrogeological conditions of a region and the purpose of the model. Model selection must be carefully considered, and the process of calibration and validation is crucial. While current models are useful, improvements in data quality, technology, and model sophistication are expected to lead to advances in groundwater recharge modeling in the future.

Hydrological models are simplified systems to compute the processes of the hydrological cycle (Precipitation, Infiltration, Interception, Evaporation, Runoff, etc.) in an entire river basin based on a set of interrelated equations that try to convert the physical laws, which governs the complex natural phenomena (Barbara, 2008).

Hydrological models can be classified into three groups based on their representation of physical processes: conceptual models, physically-based distributed models, and empirical models (Beven, 2001). Physically-based distributed models, often referred to as white-box models, are grounded in the fundamental laws governing natural phenomena. These models mirror the logical structure of real-world systems and are particularly useful under changing conditions. They are designed according to the principles of physical processes, incorporating the conservation of mass, energy, and momentum. These models utilize a variety of parameters to represent the heterogeneities within a catchment, such as in infiltration, evaporation, and SHE models. Recently, there have been significant advances in understanding and modeling hydrological processes, with the development of topography-driven, conceptual, flexible, semi-distributed model structures (Gharari et al., 2013).

Regional groundwater models used for identifying and analyzing groundwater system (infiltration-percolation-discharge relations) are often quasi-steady-state and therefore it needs a long-term average input data. Thus, WetSpass-M, which yields spatially varying groundwater recharge using spatially varying soil, land-use, and meteorological inputs, can be used for the purpose of understanding the characteristics of groundwater recharge (Batelaan & Woldeamlak, 2020). Empirical models (Black box) which mathematical correlations are obtained based on the observed data analysis rather than based on the physical processes in the catchment e.g., Unit hydrograph-based model, Linear regression model. Conceptual models (sometimes called grey-box models) are intermediate between theoretical and empirical models which is consider physical laws in highly simplified form (Dandy & Maier, 2005).

2.3.1 SWAT-MODFLOW

SWAT-MODFLOW is a loosely coupled model that integrates SWAT and MODFLOW to simulate surface and groundwater hydrology. SWAT, developed by the U.S. Department of Agriculture's Agricultural Research Service, is a continuous, daily time-step model designed to simulate surface water flow, sediment, and nutrient transport on a watershed scale (Arnold et al. 2012). SWAT encompasses various components, including climate, hydrology, soil temperature, plant growth, nutrients, pesticides, land management, and bacteria. For a comprehensive overview of SWAT, refer to the detailed documentation provided by Arnold et.al. (2012).

Modular Three-Dimensional Finite-Difference Groundwater Flow (MODFLOW) is a physically-based, distributed finite-difference three-dimensional (3D) groundwater flow simulation model (McDonald & Harbaugh, 1988). Using a gridded spatial discretization, SWAT-MODFLOW can simulate three-dimensional groundwater flow processes at the continuum volume of the saturated zone by taking into consideration hydrogeological properties of the aquifer and feedback fluxes between surface water and groundwater interactions as well as the occurrence and spatial distribution of discharge. SWAT-MODFLOW simultaneously solves the groundwater flow differential equation using the finite difference approach (Kim et al., 2008). In addition, the model can spatially represent groundwater head or groundwater elevation (Bailey et al., 2017).

SWAT represents the groundwater component in two control volumes: the shallow aquifer and the deep aquifer. The groundwater component was developed compatible with the surface components, requiring only the readily available inputs from the field (Arnold et al., 1993). Variation in the shallow and deep aquifer storages is estimated by using a lumped model, and this has been reported as the main drawback of the SWAT groundwater component (Sophocleous et al., 1999). Integration of SWAT with a fully distributed groundwater model MODFLOW was attempted in a few studies to simulate the spatially varying recharge, evaporation from the aquifer and the groundwater table (Sophocleous et al., 1999, Kim et al., 2008). In the SWAT-MODLFOW integration, SWAT model is split before the groundwater module, and the MODFLOW is added to simulate the shallow and deep aquifer components. This increases the model complexity, first, due to the difference in the spatial disaggregation approaches adopted in SWAT and MODFLOW. SWAT uses virtual areas called HRUs, which have unique soil-vegetation-slope combination, but no spatial reference within the sub-basin (Kim et al., 2008). The integration of SWAT-MODFLOW requires transferring HRU information to the corresponding pixels. Additionally, when SWAT is divided before the groundwater module, the interactions between various layers must be carefully represented. Unlike GIS-integrated versions such as ArcSWAT, integrated models like SWAT-MODFLOW do not run as a single unit, preventing the seamless replacement of components like MODFLOW. For this analysis, ArcSWAT—publicly available and running as a single program—was used, with the assumption that its built-in groundwater processes are adequate for the current level of analysis.

2.3.2 HYPE

HYPE, which stands for Hydrological Predictions for the Environment (Lindström et al., 2010) is a hydrological model used to assess water resources at both small and large scales. It is a process-based, semi-distributed, and conceptual model designed to simulate multiple basins with varying soil types, geomorphology, topography, and land use. HYPE integrates landscape elements and hydrological compartments along flow paths, accounting for nutrient turnover and transport. Calculations are performed on a daily time step for coupled sub-basins, with model parameters related to soil type and land use.

Developed by the Swedish Meteorological and Hydrological Institute (SMHI) between 2005 and 2007, HYPE is based on the HBV model (Lindström et al., 1997) and aims to predict the impacts of climate and land use changes on aquatic systems. The model evaluates changes in the water budget and nutrient loads (nitrogen and phosphorus) from the catchment area .(Donnelly et al., 2016).

HYPE is a dynamic model that handles daily water fluxes in catchments, capturing the highly variable nature of hydrological processes over time and space. It generates hydrographs for each sub-basin and separates them into surface runoff and groundwater outflow components, allowing for the calculation of recharge (effective infiltration) values. This capability facilitates the evaluation of groundwater outflow in ungauged basins and comparison with existing observations. The HYPE database can be used, updated, and expanded with new information, providing an additional resource for groundwater data.

2.3.3 PRMS

PRMS, or Precipitation Runoff Modeling System, is a modular, distributed-parameter model designed to assess the effects of various precipitation, climate conditions, and land use on streamflow, sediment yield, and overall basin hydrology (Markstrom et al., 2010). The model simulates snowpack formation and melt, making it particularly useful for basins where snowmelt is a significant component of streamflow. PRMS can function as both a lumped and a distributed-parameter model.

Developed as a deterministic, distributed-parameter system, PRMS evaluates the impacts of precipitation, climate, and land cover/land use on streamflow, sediment yield, and general basin hydrology (Leavesley et al., 1983). Groundwater recharge, which is the amount of water entering the groundwater reservoir, is the sum of groundwater discharge to lakes or streams (base flow) and groundwater sinks. (Cherkauer, 2004) utilized PRMS and GIS to quantify groundwater recharge at multiple scales, presenting a method to define most inputs from GIS and hydrological data, thereby simplifying PRMS calibration by reducing the degrees of freedom. (Vaccaro & Olsen, 2007) applied the model to estimate groundwater recharge for the Yakima River Basin aquifer system in Washington, USA, for both predevelopment and current land use/land cover conditions. Their findings indicated an increase in recharge due to irrigation. (Burns et al., 2012) used PRMS to estimate recharge while evaluating long-term water-level declines in basalt aquifers near Mosier, Oregon, USA, with PRMS serving as the primary tool for estimating recharge across the study area.

2.3.4 MIKE-SHE

The MIKE SHE models (DHI, 2007) is a comprehensive, deterministic, distributed, and physically-based system designed to simulate all key processes in the land phase of the hydrologic cycle. It includes a range of pre- and post-processing tools and employs a combination of simple and advanced techniques for different hydrologic processes. The model accounts for interception, precipitation, infiltration, evapotranspiration, sub-flows in saturated and unsaturated zones, surface flow, and flow in ditches or channels.

Simulations with MIKE SHE (Refsgaard & Storm, 1995), was conducted at sub-hourly intervals using hourly meteorological data from 1995 to 2014, collected both on-site and from nearby stations. The model simulates how rainfall is intercepted by vegetation, leading to evaporation, while the remaining water reaches the surface where it may infiltrate, evaporate, or run off if depression storage is met. Water that infiltrates the subsurface can either be evaporated or percolate to the water table, contributing to groundwater recharge.

Evaporation and transpiration were modeled using the Kristensen and Jensen evapotranspiration model (Kristensen & Jensen, 1975), which incorporates potential evapotranspiration estimated by the FAO 56 Penman–Monteith method soil moisture availability, and crop characteristics in each grid cell. When rainfall exceeds the infiltration capacity, water ponds on the surface and contributes to runoff. The model's dynamic infiltration capacity depends on the unsaturated hydraulic conductivity (Ku) and the water content properties (saturation point, field capacity, and permanent wilting point) of the surface media. The Van Genuchten model (Van Genuchten, 1980) describes the relationship between water content, conductivity, and matric potential.

Runoff is simulated using a 2-D diffusive wave approximation, influenced by topographic slope, surface roughness, and detention storage—the volume of water stored in surface depressions before runoff begins. Unsaturated zone flow is modeled as a 1-D column using the full Richards equations (Richards, 1931) with finite-difference cells that vary in discretization from the ground surface to the unsaturated–saturated zone interface. Due to the variable vadose zone thickness and low water fluxes, the model was run multiple times to establish consistent initial conditions. Analysis began when changes in average recharge values between runs stabilized at about 0.3%, indicating near-steady-state conditions. Recharge was calculated whenever infiltration water reached the water table. Most precipitation events do not result in recharge as infiltration is intercepted and evaporated.

Groundwater flow was represented using the 3-D finite-difference Darcy equation. Fixed head boundaries along the lateral sides and the bottom of the model domain (490 m.a.s.l.) simulated flow to and from the deeper groundwater system, which extends several hundred meters beyond the integrated model. These fixed heads were based on observed groundwater levels and simulations from a detailed 3-D groundwater flow model that includes both the catchment and a larger surrounding domain (Aqua & MWH, 2007). Groundwater contribution to streamflow was minimal and intermittent (approximately 0.1 mm/year from 1995 to 2014), occurring only at the farthest downstream location where the groundwater table is close to the surface.

2.3.5 WetSpass-M

WetSpass-M stands for water and energy transfer between soil, plants and atmosphere under quasi-steady-state conditions (Batelaan & De Smedt, 2001). It is a physically-based model for the estimation of long-term average spatial patterns of groundwater recharge, surface runoff and evapotranspiration employing physical and empirical relationships. WetSpass-M is a quasi-steady-state model developed as a regional groundwater model to simulate infiltration–discharge relations based on long-term average recharge input data. This model simulates water balance components, surface runoff, actual evapotranspiration and groundwater recharge based on distributed data.

The model was developed as a method to estimate long-term average, distributed water balance components (Batelaan & De Smedt, 2001). This model was developed based the time-dependent spatially distributed water balance model WetSpa. The model has been developed and applied to study the influence of long-term effects of land cover changes on the water regime in a basin (De Smedt & Batelaan, 2003). By using long-term average standard hydrometeorological parameters as inputs, the model simulates the temporal average and spatial information of surface runoff, actual evapotranspiration, and groundwater recharge have been simulated.

The model estimates spatial groundwater recharge at seasonal and annual scales. Regional groundwater models used for analyzing recharge-discharge relations are often quasi-steady and need long-term average recharge input that accounts for the spatial variability of the recharge. Thus, they can use the recharge output from WetSpass-M for their computations. WetSpass-M is especially suited for studying long-term effects of land-use changes on the water regime in a watershed and was founded on the time-dependent spatially distributed water balance model, called “WetSpa” (De Smedt & Batelaan, 2003).

Inputs for this model include grids maps of land use, groundwater depth, precipitation, potential evapotranspiration, wind-speed, temperature, soil, and slope and parameters tables such as land use and soil types are connected to the model as attribute tables of their respective grids. The model makes use of grid GIS technology and digital data to partition the precipitation into a surface runoff, evapotranspiration and groundwater recharge.

Parameter tables such as land-use and soil types are connected to the model as attribute tables of land use and soil raster maps, which allow new definitions of climatic as well as land-use and soil types (Batelaan & Woldeamlak, 2003).

WetSpass-M was originally developed for conditions in temperate regions for Europe in particular. WetSpass-M have been developed to be used worldwide (Rwanga, 2013). It has been successfully applied in different areas of the world. The WetSpass-M model has first applied successfully in Belgium (Batelaan & De Smedt, 2001).

In the WetSpass-M model total water balance for a raster, the cell is split into independent water balances for the vegetated, bare soil, open-water, and impervious parts of each cell. This accounts for the non-uniformity of the land-use per cell, which is dependent on the resolution of the raster cell. The processes in each part of a cell are set in a cascading way. This means that an order of occurrence of the processes, after the precipitation event, is assumed. Defining such an order is a prerequisite for the seasonal timescale with which the processes will be quantified.

A mixture of physical and empirical relationships is used to describe the processes. The quantity determined for each process is consequently limited by several constraints (Batelaan & De Smedt, 2007). WetSpass-M is developed as to regional groundwater models are quasi-steady-state used to simulate infiltration–discharge relations based on long-term average recharge input data. This model simulates water balance components, surface runoff, actual evapotranspiration and groundwater recharge based on distributed data. The model estimates spatial groundwater recharge at seasonal and annual scales.

The WetSpass-M model is a sophisticated tool used for simulating water balance components, including groundwater recharge, surface runoff, and actual evapotranspiration. This literature review explores various studies that have utilized the WetSpass-M model, highlighting the methodologies, geographical contexts, results, and differences observed in these studies.

Spatial-Temporal Water Balance Estimation in 2022, a study focused on the Moulouya Basin in Morocco used the WetSpass-M model to evaluate the spatial and temporal distributions of water balance components (Mustapha et al., 2022). This study provided detailed insights into the model's capability to handle different land cover types and its effectiveness in various climatic conditions.

Hydrological processes in Ethiopian river basins another study conducted in 2022 applied the WetSpass-M model to the river basins of Ethiopia, particularly the Bilate river basin (Abera et al., 2022). This study emphasized the model's calibration processes and its ability to predict surface runoff and base flow accurately. The study also discussed the impact of climatic changes on the model's outputs.

Groundwater Recharge and Cross-Validation a study highlighted in 2021 developed the WetSpass model at a 90 m grid resolution to simulate groundwater recharge (Alemu et al., 2021). The spatial recharge map produced by WetSpass was cross-validated with water table fluctuation data, providing a robust method for verifying the model's accuracy.

Water Balance in Iraq's Low Folded Zone in 2023, the WetSpass-M model was used to estimate average monthly recharge, surface runoff, and actual evapotranspiration in Iraq's Low Folded Zone. This study was notable for its detailed performance evaluation and the temporal and spatial distribution of the simulated water balance components.

Differences in geographical application the application of the WetSpass-M model in diverse geographical settings from the floodplains of Europe to the arid regions of Iraq and the varied climates of Morocco and Ethiopia demonstrates its adaptability. However, these studies also highlighted the need for region-specific calibration to account for local environmental and climatic conditions.

2.3.6 Reason for WetSpass-M selection

The WetSpass-M model presents several advantages that enhance its value in hydrological research, particularly in assessing water balance components and groundwater recharge.

Integration of Spatial Data: One of the key strengths of WetSpass-M is its integration of diverse spatial data inputs, including digital elevation models (DEM), land use, soil texture, and groundwater depth distribution. This detailed pixel-scale representation allows for more accurate simulations across varied landscapes (A. Amiri et al., 2024).

Comprehensive Water Balance Calculation: The model is adept at calculating multiple hydrological components, such as evapotranspiration, surface runoff, and groundwater recharge. This comprehensive approach provides a detailed view of the water balance within a catchment area, which is essential for effective water resource management (Zeleke & Merkel, 2009).

Flexibility and Customization: WetSpass-M is noted for its user-friendly and adaptable design, enabling researchers to customize parameters based on specific ecosystems and climatic conditions. This versatility makes the model suitable for a wide range of applications in different geographical contexts (Asrade et al., 2024)

Empirical and Physical Correlations: The model employs a combination of empirical and physical correlations to describe hydrological processes. This dual approach enhances its ability to simulate complex interactions within the hydrological cycle, thereby improving prediction reliability (Klemens & Klemens, 2021)

Temporal and Spatial Analysis: WetSpass-M is capable of analyzing the long-term spatial distribution and variability of groundwater recharge on monthly, seasonal, and annual bases. This feature is particularly useful for understanding the impacts of climate and land use changes over time (A. Amiri et al., 2024).

Compatibility with GIS: The model integrates effectively with Geographic Information Systems (GIS), facilitating the visualization and analysis of hydrological data. This compatibility supports enhanced decision-making in water resource management(M. Amiri et al., 2022)

In summary, the WetSpass-M model stands out due to its detailed spatial analysis, flexibility, and comprehensive approach to hydrological modeling. These attributes make it an excellent choice for research and a valuable tool for hydrology practitioners.

The WetSpass-M model has proven to be a valuable tool in hydrological modeling, capable of providing detailed insights into water balance components across different landscapes and climatic conditions. The studies reviewed here underscore the model's adaptability and the importance of precise calibration and validation to achieve reliable results.

2.4. WetSpass-M models calibration

Model calibration is the process of minimizing differences between observation and model output by tuning model parameters. This process of changing parameter values is used to obtain simulated results that most likely reflect observed values. The general approach to calibration is one of trial-and-error in which various values for each parameter are tried, their effects are noted and appropriate changes are made to improve agreement between simulated and recorded values (Johnson, 1998). The procedure is to manipulate and compare the simulated parameter values against recorded values using both numerical and graphical methods. According to (Johnson, 1998) numerical and graphical methods are used to compare simulated and recorded values over the simulation periods. The calibration process requires a procedure to evaluate the success of a given calibration and another procedure to adjust the parameter estimates for the next validation.

Model verification involves checking the validity of the parameter values for a period not originally simulated. Once the calibration process has been used to estimate the best values for the model parameters, the outcome needs to be evaluated to determine if the results provide adequate information for the intended period. Validation consists of an objective test on how well the model outputs fit the data by using data that were not used for the calibration process. The usual method is to test the performance of the calibrated model on a selected portion of the data that were not used during the calibration processes. Calibration data fit values are used to simulate for the intended portion of time for future periods that were likely yield simulated and verified values (Johnson, 1998). Through calibrating the parameter values over the longer simulation periods, a verification value was immediately be obtained for the next simulation period.

2.5 WetSpass-M models validation

Groundwater recharge estimation plays a vital role in understanding and managing water resources. The WetSpass-M model is a widely used tool for simulating water balance components, including groundwater recharge, surface runoff, and actual evapotranspiration. The model has been validated using various methods, including the water table fluctuation (WTF) method. This method involves calculating the change in groundwater storage and linking it to the resulting water table fluctuations through the storage parameter (specific yield in unconfined aquifer). The WTF method is considered one of the most promising and attractive due to its accuracy, ease of use, and low cost of application. The WetSpass-M model offers a valuable tool for this purpose, but like any model, it requires validation to ensure its accuracy. The Water Table Fluctuation (WTF) method presents a promising approach for validating WetSpass-M's recharge estimates by directly measuring changes in groundwater storage. This review examines the effectiveness of the WTF method in validating the WetSpass-M model across various studies. (Yueqiu et al., 2018) applied the WTF method in a fractured aquifer system in China. They compared recharge estimates from both methods for a three-year period and found a good agreement with an R^2 value of 0.82. The study highlighted the importance of accurate specific yield determination for reliable validation. (Dowlatabadi et al., 2023) employed the WTF method in an alluvial aquifer in India. Their analysis over five years revealed moderate agreement ($R^2 = 0.65$) between WetSpass-M and WTF estimates. The authors attributed discrepancies to potential model limitations in capturing localized recharge processes.

(Zhou et al., 2022) focused on validating WetSpass-M in a heterogeneous karst aquifer in China. They implemented the WTF method at multiple monitoring wells and observed varying levels of agreement (R^2 ranging from 0.52 to 0.87). The study emphasized the influence of spatial heterogeneity on validation results.

The WTF method offers a valuable tool for validating the WetSpass-M model, with studies demonstrating varying levels of agreement depending on specific contexts. While data quality, aquifer characteristics, and spatial scales influence the results, the method provides valuable insights into model performance.

The water fluctuation method, also known as the water table fluctuation method, is a commonly used technique for measuring groundwater recharge. The method is based on the principle that the water table in an unconfined aquifer responds to changes in recharge and can be used to estimate recharge rates.

Several studies have utilized the water fluctuation method to estimate groundwater recharge in different regions with varying hydrogeological conditions. For instance, in a study conducted by (Abustan et al., 2019), the water fluctuation method was used to estimate groundwater recharge rates in a coastal aquifer in Malaysia. The findings showed that the recharge rates varied throughout the year with higher rates during the wet season and lower rates during the dry season.

Another study carried out by (Sharma et al., 2015) used the water fluctuation method to estimate groundwater recharge in a semi-arid region of India. The study indicated that the method was effective in estimating recharge rates in areas where little is known about groundwater recharge processes. The study also suggested that the water fluctuation method could be combined with other methods to improve the accuracy of recharge estimates.

In a different study, (Singh & Mondal, 2014) investigated the influence of anthropogenic activities on groundwater recharge using the water fluctuation method in a mining region of India. The study revealed that mining activities had a significant impact on groundwater recharge rates in the area, leading to severe groundwater depletion.

The WetSpass-M model has been validated using the water table fluctuation method in several studies. The method involves calculating the change in groundwater storage and linking it to the resulting water table fluctuations through the storage parameter (specific yield in unconfined aquifer). The model has been shown to be effective in simulating water balance components and linking these changes to groundwater system responses in various geographical settings.

2.6 WetSpass-M model Performance Evaluations

The WetSpass-M model's performance has been widely evaluated in various studies, and the results demonstrate its effectiveness in accurately estimating hydrological components such as groundwater recharge, surface runoff, and evapotranspiration. Various statistical measures are employed to evaluate the model's performance, including the mean squared error (MSE), coefficient of variation (CV), mean absolute error (MAE), coefficient of determination (R^2), and root mean squared error (RMSE). These metrics provide quantitative estimates of the goodness of fit between observed and simulated values. For example, in one study, the RMSE was used to determine the accuracy of the model's predictions, with lower RMSE values indicating better model performance (Alemu et al., 2021).

Several studies have validated the WetSpass-M model's ability to estimate groundwater recharge accurately. For instance, a study in the Low Folded Zone of Iraq reported a very good performance rating with a Relative Streamflow Residual (RSR) value between 0 and 0.5 for groundwater recharge estimation (Mustapha et al., 2022). Another study in Aceh, Indonesia, found that the model's simulated recharge values closely matched the observed data, with an NSE of 0.82 and a PBIAS of -2.5%. The WetSpass-M model has also demonstrated reliable performance in simulating surface runoff and evapotranspiration. In the Low Folded Zone study, the model achieved a good performance rating (RSR between 0.5 and 0.6) for surface runoff estimation (Al Kuisi & El-Naqa, 2013). Additionally, the model's simulated actual evapotranspiration values showed excellent agreement with validated results, as reported in the same study (Alemu et al., 2021).

The WetSpass-M model is a reliable tool for estimating various hydrological components, with its performance being widely evaluated and validated across different study areas and climatic conditions. The model's accuracy in simulating groundwater recharge, surface runoff, and evapotranspiration has been consistently demonstrated, making it a valuable tool for integrated water resource management and decision-making.

2.7 Role of GIS and remote sensing in groundwater recharge

GIS and remote sensing technologies play a crucial role in groundwater recharge studies. These technologies provide a means to accurately identify and map the hydrological properties of an area including topography, soil properties, land use, and land cover. In the context of groundwater recharge, GIS and remote sensing can be used to identify potential sites for rainwater harvesting and artificial recharge of groundwater which enables the replenishment of dwindling groundwater resources.

One of the primary uses of GIS in groundwater recharge studies is the mapping of the groundwater potential zones. By overlaying maps of soil types, topography, land use and other relevant data, GIS helps identify the areas with high permeability that can facilitate percolation of rainwater into the groundwater table. The result is a map that serves as an important information source for groundwater recharge planning.(Lammesa, 2017)

Remote sensing technology is also used to identify the physical attributes of a study area that might impact groundwater recharge processes. Remote sensing data can be used to map drainage networks, flow directions, and potential recharge zones in a study area. The technology can also be used to monitor changes in groundwater levels, which helps identify over-exploitation of the resource and the areas in which groundwater-level declines are occurring most rapidly. In addition, remote sensing can be used to monitor land use covers, and detect changes in vegetation cover that have an impact on groundwater recharge.

Another crucial role of GIS and remote sensing is in the planning and implementation of groundwater recharge projects. Through the use of spatial analysis functions and overlay operations, GIS is used to identify suitable areas for construction of artificial recharge structures like percolation ponds, recharge trenches, or recharge wells. While remote sensing data allows for monitoring of the efficacy of these recharge structures and predicting areas requiring more intervention.(Jacques, 1999)

GIS and remote sensing technologies offer a comprehensive and integrated approach to groundwater recharge, equipping decision-makers and planners with a wealth of information to effectively manage and protect our groundwater resources.

2.8 Image classification techniques

Image classification is the most important part of digital image analysis. It is very nice to have a "clear picture" or an image, showing a magnitude of colors illustrating various features of the underlying terrain, but it is quite useless unless to know what the colors mean.

Image classification is used to identify and portray, as a unique gray level (or color), the features occurring in an image in terms of the object or type of land cover these features actually represent on the ground. The intent of the image classification process is to categorize all pixels in a digital image into one of several land cover classes, or "themes". This categorized data may then be used to produce thematic maps of the land cover present in an image. Normally, multispectral data are used to perform the classification and, indeed, the spectral pattern present within the data for each pixel is used as the numerical basis for categorization.

Image processing takes a basic understanding of remote sensing and of digital images through the fundamental stages of image processing. It also provides a varied set of cases for application of image processing and introduces a wide range of processing techniques. These form the basis for continued development to advanced level. It is the process of assigning each pixel of an image to a particular group or class.

There are two main classification methods which are supervised classification and unsupervised Classification. Image classification is mostly performed using ERDAS Imagine software. ERDAS Imagine is an image processing software package that allows users to process the geospatial and other imagery as well as vector data. ERDAS can also handle hyper spectral imagery and LiDAR (Light Detection and Ranging) from various sensors. ERDAS also offers a 3D viewing module (Virtual GIS) and a vector module for modeling the native programming language is EML (ERDAS Macro Language). ERDAS is integrated within other GIS and remote sensing applications and the storage format for the imagery can be read in many other applications (*.img files). Leica Geo-systems also purchased ER Mapper to add to their mapping software. Imagine is tightly woven into the GIS fabric more than other image processing software packages and that is the advantage of this package.

2.8.1 Supervised classification

During supervised classification, the classifier/expertise identifies examples of the information classes (i.e., land cover type) of interest in the image which is called "training sites". The image processing software system is then used to develop a statistical characterization of the reflectance for each information class. This stage is often called "signature analysis" and may involve developing a characterization as simple as the mean or the average of reflectance on each band, or as complex as detailed analyses of the mean, variances and covariance over all bands. Once a statistical characterization has been achieved for each information class, the image is then classified by examining the reflectance for each pixel and making a decision about which of the signatures it resembles most.

The objective is to extend, or extrapolate information on land cover types for a known area of the image to the unknown areas of the whole image. The image analyst defines a number of training areas for each land cover category. The computer generates spectral signatures based on this information. Typically, a maximum likelihood descriptor is used to measure the spread of values around the mean of the class. Each pixel of the image is assigned as far as possible to one of the land cover groups, as defined by the signature.

2.8.2 Unsupervised classification

Unsupervised classification is a method which examines a large number of unknown pixels and divides into a number of classed based on natural groupings present in the image values. Unlike supervised classification, unsupervised classification does not require analyst specified training data. The basic premise is that values within a given cover type should be close together in the measurement space (i.e., have similar gray levels), whereas data in different classes should be comparatively well separated (i.e., have very different gray levels) (Lillesand & Kiefer, 1994). Unsupervised classification is the simplest technique. Within the image data for the different wavelengths the computer is asked to determine a user-defined number of clusters. Each cluster represents a land cover class or sub-class. The mean digital value for each input band could be represented as a spectral reflectance profile. The cluster represents the spread of values around the mean for the land cover class. After the classification has been completed each class should be examined and assigned a name. It may also be necessary to merge a number of classes into a single category.

The classes that result from unsupervised classification are spectral classed which is based on natural groupings of the image values, the identification of these spectral classes will not be initially known, must compare classified data to some form of reference data (such as larger scale imagery, maps, or site visits) to determine the identity and informational values of the spectral classes (Lillesand & Kiefer, 1994).

An unsupervised approach is useful where no prior ground information exists; is not biased in defining classes; is relatively rapid to compute; and accounts for all cover types in an image. However the process of identifying and merging classes can be time consuming and the statistical description of the spread of values within the cluster is not as good as the maximum likelihood classifier. Conversely the supervised maximum likelihood approach is time consuming when identifying training areas; relatively slow to compute; and can only produce a class map for which there are training areas (Pembury, 2005).

Unsupervised classification is becoming increasingly popular in agencies involved in long term GIS database maintenance. The reason is that there are now systems that use clustering procedures that are extremely fast and require little in the nature of operational parameters. Thus, it is becoming possible to train GIS analysis with only a general familiarity with remote sensing to undertake classifications that meet typical map accuracy standards. With suitable ground truth accuracy assessment procedures, this tool can provide a remarkably rapid means of producing quality land cover data on a continuing basis.

2.8.3 Accuracy assessment

Accuracy Assessments were performed on classified images to determine how well the classification process accomplished the task. An accuracy assessment compares your classified image to an image, which is assumed correct (such as an aerial photo). This task was accomplished by compiling an error matrix. An error matrix is a table of values that compares the value assigned during the classification process to the actual value from an aerial photo.

These were compared on a point-by-point basis. A random set of points was generated for the region covered by the area. Then using the aerial photos, the value for each point was identified. Then, these same random points were used to identify each point's known value in the classified image. The error matrix table was completed by comparing these two values. An important component of accuracy assessment, Cohen's kappa co-efficient was calculated from the error matrix. Kappa tells us how well the classification process performed as compared to just randomly assigning values, i.e., did we do better than random. (Tammy E., 2013).

CHAPTER THREE: MATERIALS AND METHODS

3.1 Description of the study area

3.1.1 Location and Topography

Dedaba watershed is located in the West Arsi zone of the Oromia Regional State near Kuyera town. The watershed touches five administrative districts: Gadab Hasasa, Qore, Kofale, Arsi Nagele and Shashemane. This watershed is part of the Rift Valley basin. The Dedaba river catchment area is located at a latitude of 7°7' 0" to 7º 19′ 30" N and a longitude of 38° 37' 0" to 39° 05' 30"E. It has a total drainage area of approximately 296.17 Km^2.This watershed plays an essential role in the hydrological cycle of the region, ultimately draining into the nearby Lake Shala.

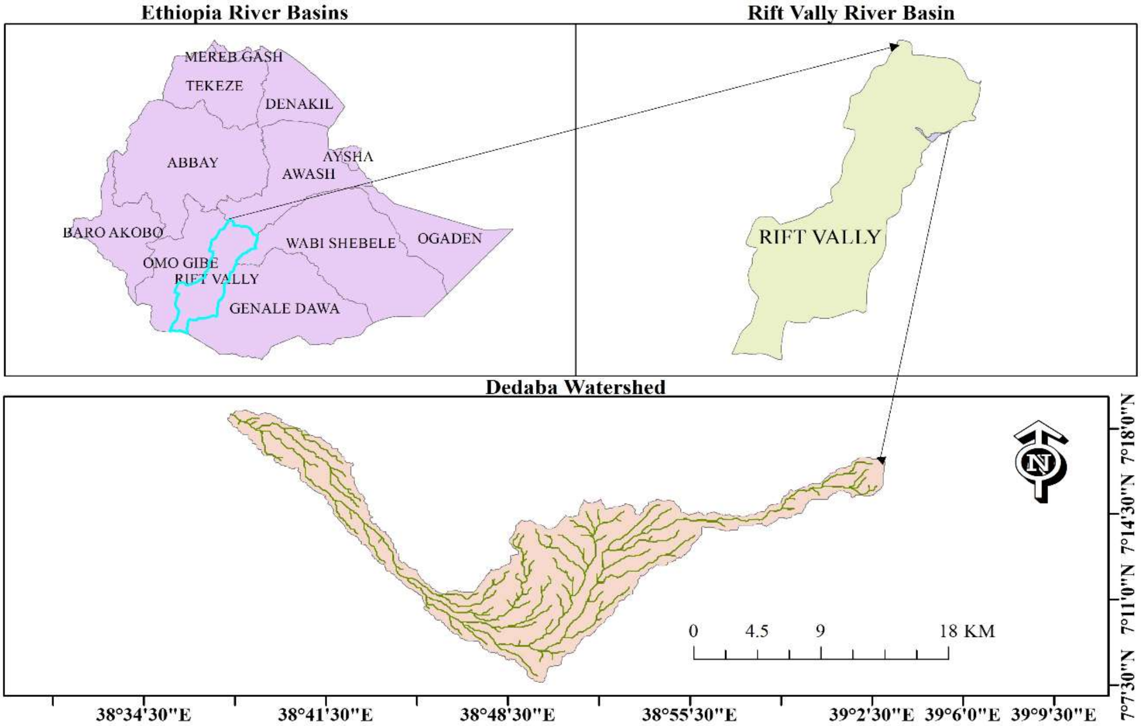
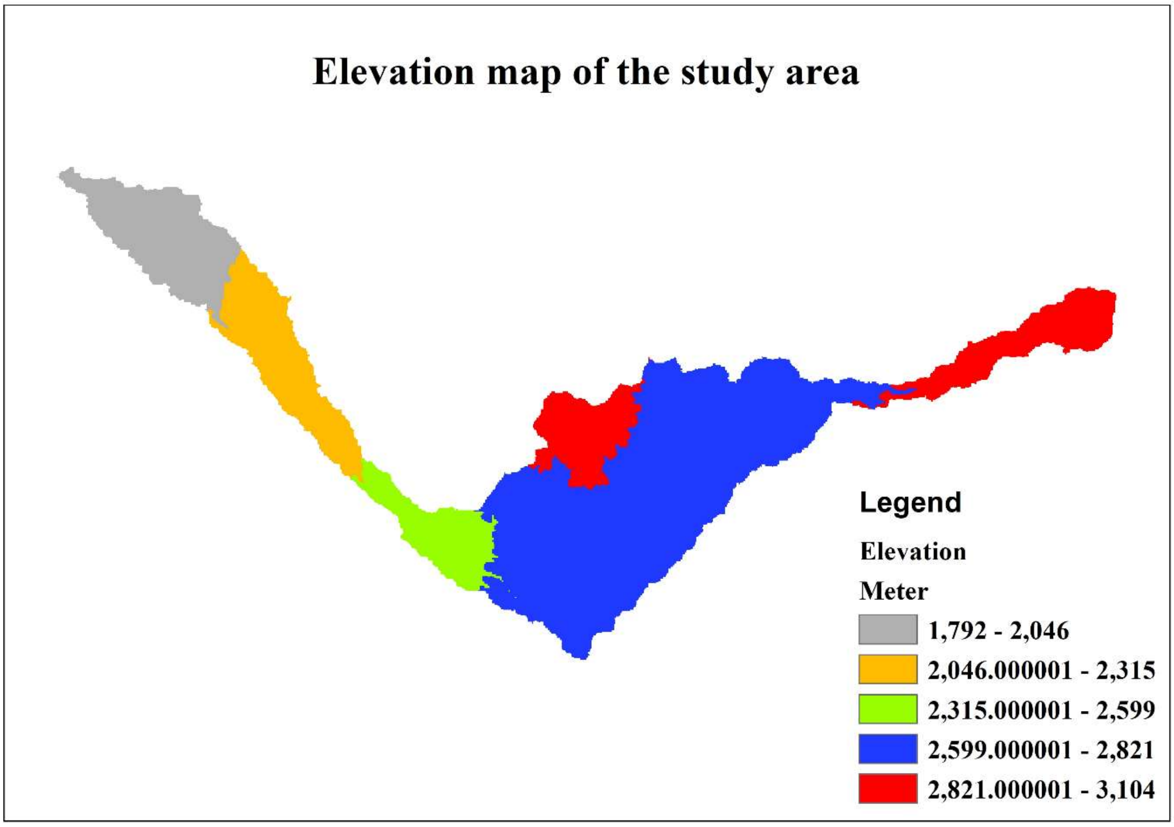


Figure 3.1 Location of Dedaba WaterShed

Estimating groundwater recharge using WetSpass-M models in ArcGIS 10.8 requires an understanding of the topography of the area. Topography plays a significant role in the hydrological cycle by influencing the distribution and movement of precipitation and runoff.

Process DEM data prepare the DEM data using ArcGIS 10.8 tools such as slope analysis, flow direction, and flow accumulation.



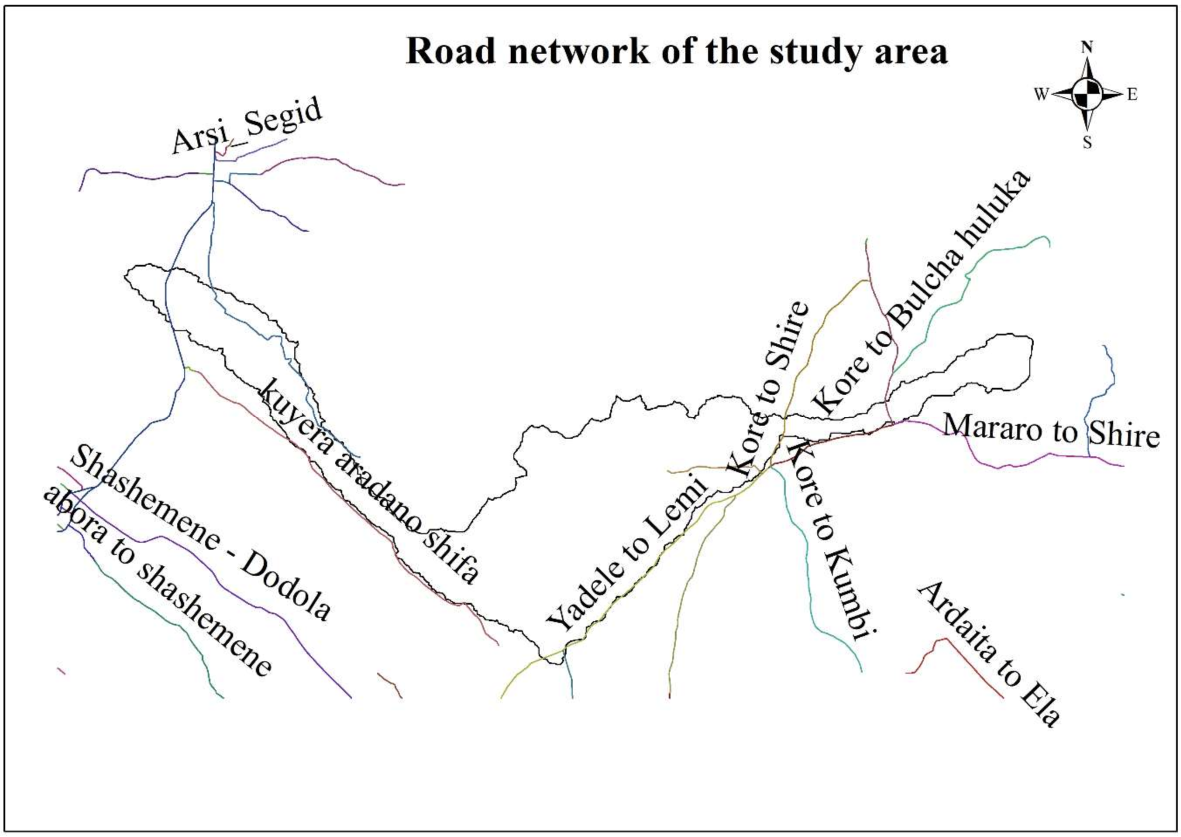


Figure 3.2 DEM and Road network of the study area

The research area sits along the eastern edge of the Main Ethiopian Rift Valley. This area is dominated by flat plains with occasional rolling hills. Particularly, the eastern portion of the study area borders on gently sloping land that gradually descends towards Lake Shalla. On average, the elevation across the watershed is 2540.17 meters above sea level. The highest point is near the Qore ridges, reaching 3364 meters, while the lowest point sits in the flat region at 1765 meters.

3.1.2 Climate of the study area

The study area exhibits a mean elevation of 2,540.17 meters above sea level (asl), ranging from 1,745 meters asl to 3,364 meters asl. This elevational gradient corresponds to a characteristic Woyna Dega and Dega temperature regime, with a mean annual temperature between 13.45°C and 17.27°C. Temperature is a primary climatic factor influencing evapotranspiration, surface runoff, and groundwater recharge. Warmer air has a greater capacity to hold vapor, leading to increased evaporative rates when water temperature is also high (Shaw, 1994).

The region experiences a bimodal precipitation pattern, characterized by distinct wet seasons occurring in March-June and August-September. These wet seasons are noteworthy for the absence of well-defined intervening dry periods. The confluence of high infiltration rates and interconnected surface runoff with the area's porous geologic formations facilitates significant groundwater recharge (Craig et al., 2010).

Climate is also a critical factor when considering the impact of land-use and land-cover modifications on groundwater recharge, as these changes can alter water balance components. The precise assessment of groundwater recharge using hydrological models, such as WetSpass-M within ArcGIS 10.8, necessitates careful data collection, strong model development, calibration, and a comprehensive grasp of the key factors influencing recharge processes in the study area.

Rainfall data

Annual rainfall data of four meteorological stations, which are found in and around the study area (Kofele, Shashemene, kuyera and Bokoj) were collected from the Ethiopia National Meteorology Agency. The data are presented in Appendix 4. The collected data were checked for continuity, homogeneity, and consistency as described below.

Data Cleaning and Quality Control

Missing rainfall data can be estimated by either the arithmetic mean method or the normal ratio method. If the normal (long term mean) annual rainfall at each index station is within 10% of that for the station with the missing record, simple arithmetic mean of rainfall at index stations will provide an approximate value for the missing record, otherwise normal ratio method is applied (Subramanya, 2008). In this study, the normal ration method was used as the variation in the mean annual rainfall values were found to be more than 10%.

The equation of the Normal Ratio Method is given below

$$P_A = \frac{1}{n}\left(\frac{N_A P_B}{N_B} + \frac{N_A P_C}{N_C} + \cdots + \frac{N_A P_N}{N_N}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Eq. 3.1$$

where, N_A, N_B, N_C…N_N=normal annual rainfall values at station A, B, C …N: P_B, P_C… P_N =rainfall records at index stations at the time of missing records and P_A= an estimated value for missing record at station A.

Homogeneity test

Homogeneity analyses are used to identify a change in the statistical properties of the time series. The causes can be either natural or man-made. These include alterations to land use and relocation of the observation station. Therefore, to select the representative meteorological station for the analysis of areal rainfall estimation, checking the homogeneity of group stations is essential and the homogeneity of the selected gauging station's monthly rainfall records was carried out by non-dimensional parametrization.(Li & He, 2019)

$$Pi = \frac{Over\ year\ average\ monthly\ PCP\ for\ mont\ \ i}{the\ over\ years\ average\ yearly\ PCP\ of\ station} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Eq. 3.2$$

where Pi: non-dimensional values of precipitation for a month i, PCP: precipitation of the station

The selected stations were also plotted for comparison with each other in Figure 3.3. They showed the same model and pattern for the selected station. These assure that the selected stations were homogenous.

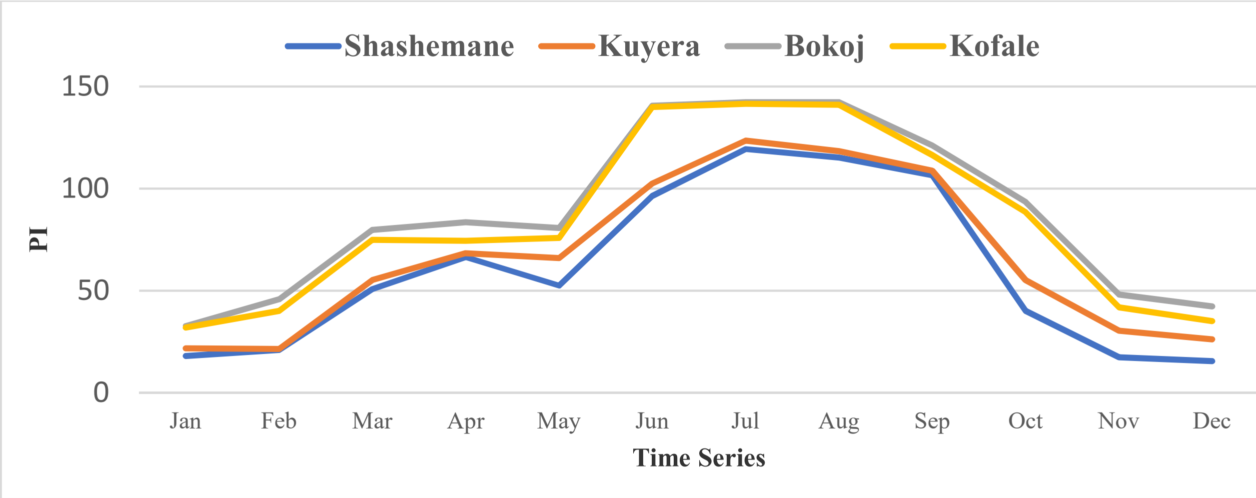


Figure 3.3 Homogeneity test for the stations used

Consistency test

A double mass curve (DMC) was used to check the consistency of rainfall for adjustment of inconsistent data. This technique is based on the principle that when each recorded data comes from the same parent sample, they are consistent. A double-mass curve is a graph of the cumulative catch at the rain gauge of interest versus the cumulative catch of one or more gauges in the region that has been subjected to similar hydro-meteorological occurrences and is known to be consistent. The double-mass curve has a constant slope if a rainfall record of the hydro-meteorological occurrences for the record is consistent. A change in the slope of the double mass curve would suggest that an external factor has caused changes in the character of the measured values.(Nayak & Satyanarayana, 2016) If a change in slope is evident, then either the record needs to be adjusted with either the early or the later period of record which is not disturbed.

$$Pcx = Px * \left(\frac{Mc}{Ma}\right) \qquad \text{Eq. 3.3}$$

Where: Pcx = corrected precipitation at any time t_1 at station X; Px = originally recorded precipitation at time t_1 at station X; Mc = corrected slope of the double-mass curve; Ma = original slope of the double-mass curve.

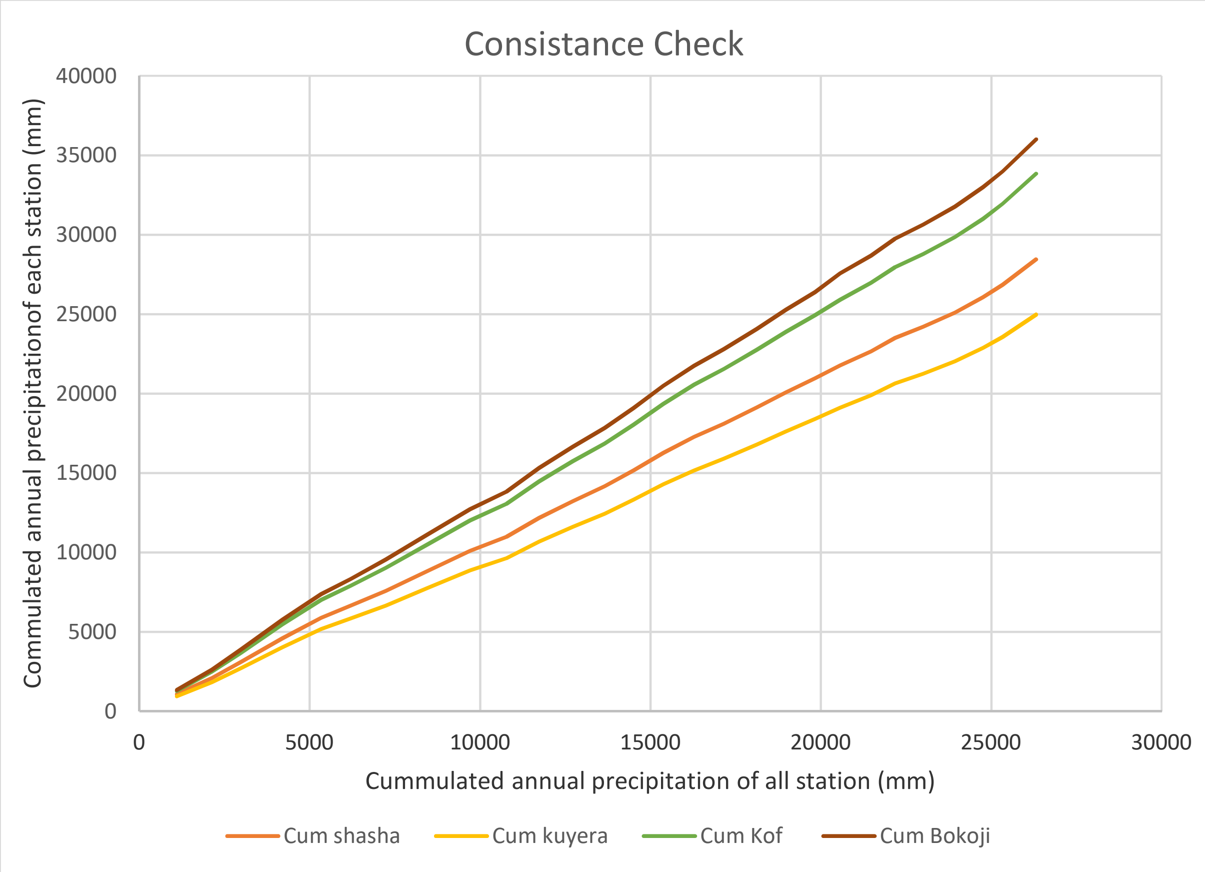


Figure 3.4 plot of double mass curve for four stations in the study area

Development of areal rainfall data

Hydrological modelling for water resource management often necessitates the creation of areal rainfall data. ArcGIS 10.8, a powerful Geographic Information System (GIS) platform, offers a suite of tools for spatial data analysis and visualization, including the development of these crucial datasets. This methodology outlines the process for developing areal rainfall data within ArcGIS 10.8 in the context hydrological modelling.

Monthly or temporally relevant precipitation data should be obtained from the Ethiopian National Meteorological Agency (NMA). Data import and management: The acquired precipitation data is imported into ArcGIS 10.8 and stored in a suitable format for subsequent analysis.

The selection of an appropriate spatial interpolation method is crucial for accurate areal rainfall data development. This methodology details the Inverse Distance Weighted (IDW) approach, a commonly used technique within ArcGIS 10.8. The choice of interpolation method should be guided by the characteristics of the precipitation data and the specific objectives of the study.

Spatial interpolation estimates values at unsampled locations based on the known values of neighboring sample points. IDW is a popular interpolation technique that assigns greater weight to closer data points when estimating values in unsampled areas (Shepard, 1968).

The conceptual simplicity of IDW makes it a widely adopted method across various disciplines (Watson & Philip, 1985). Efficiency for Continuous Phenomena: IDW demonstrates efficiency in predicting continuous spatial phenomena exhibiting spatial autocorrelation, such as temperature or elevation (Hutchinson, 1989).

IDW assumes a smooth and continuous spatial distribution of the data, which may not always reflect reality. Sensitivity to Outliers: Outliers within the data can significantly influence IDW results, requiring careful consideration. Power Parameter Selection: The choice of the power parameter in IDW is critical for optimal results, and researchers should carefully consider its impact (Hutchinson, 1989).

The IDW interpolation method within ArcGIS 10.8 offers a user-friendly and efficient approach for developing areal rainfall data. However, researchers should be aware of the limitations associated with IDW, particularly regarding assumptions about spatial variation and sensitivity to outliers. Careful consideration of data characteristics and study objectives is essential when selecting the most appropriate spatial interpolation technique for hydrological modeling.

The prepared rainfall map is classified into five categories as shown in (Figure 3.5) below.

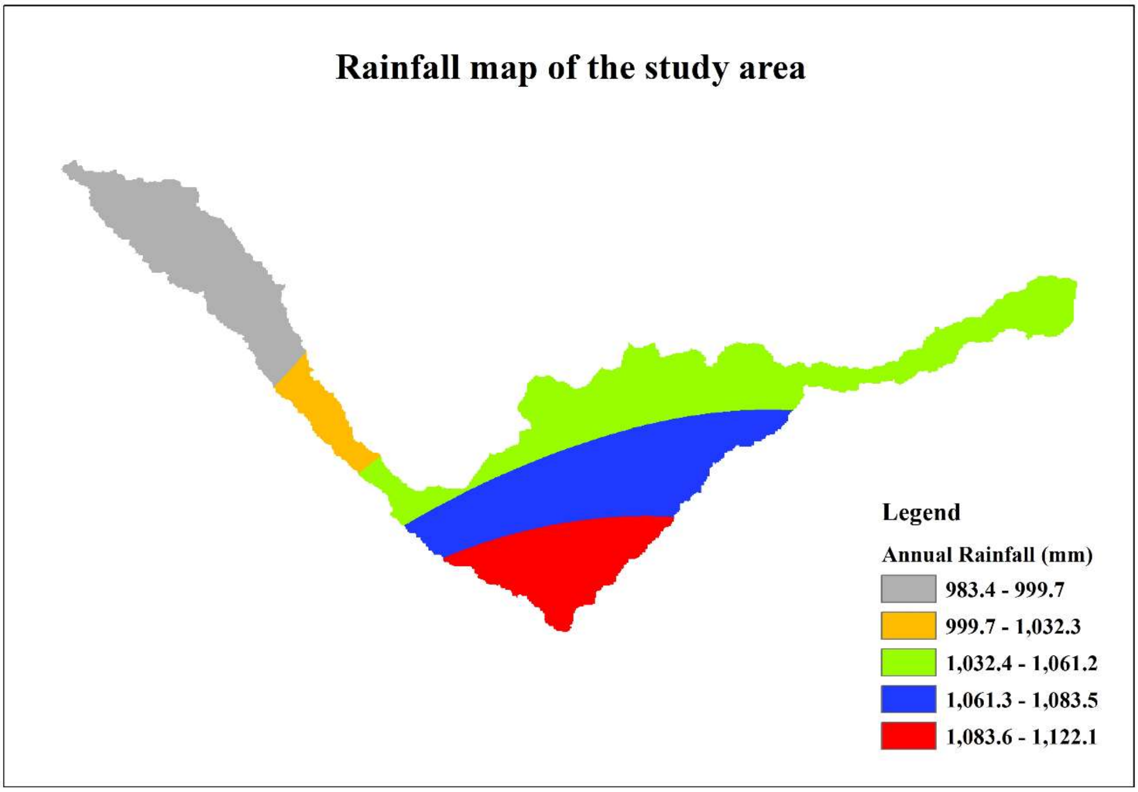


Figure 3.5 Annual rainfall map of the study area

3.1.3 Soil

An investigation into the soil characteristics of the Dedaba watershed was undertaken to assess their impact on groundwater infiltration. Soil data procured from the Ministry of Agriculture was subjected to rigorous analysis using ArcGIS 10.8 software. This analysis identified three primary soil textural classes within the study area: clay, clay loam, and loam, as illustrated in Figure 3.6. These textural variations exert a significant influence on groundwater infiltration and the rate of precipitation percolation through the soil profile. In general, clay soils exhibit the lowest infiltration rates due to their finer particle size and reduced pore spaces. Conversely, loam and clay loam textures offer enhanced permeability, facilitating greater infiltration of water into the subsurface

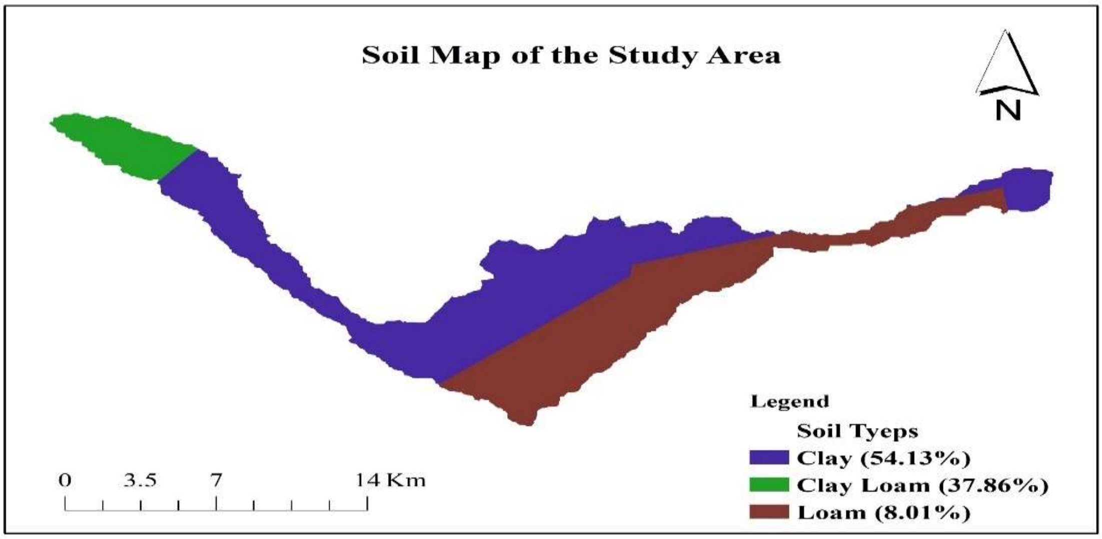


Figure 3.6 Soil map of the study area

3.1.4 Slope

This study looks at how steepness of the land (slope) affects water flow in the Dedaba watershed. We'll create a map showing gentle slopes (flat areas) and steeper slopes using elevation data. Then, we'll compare this map to features like streams and underground rock formations to see how slopes affect where water goes. Steeper slopes might have faster flowing streams, while gentle slopes might have more water soaking into the ground.

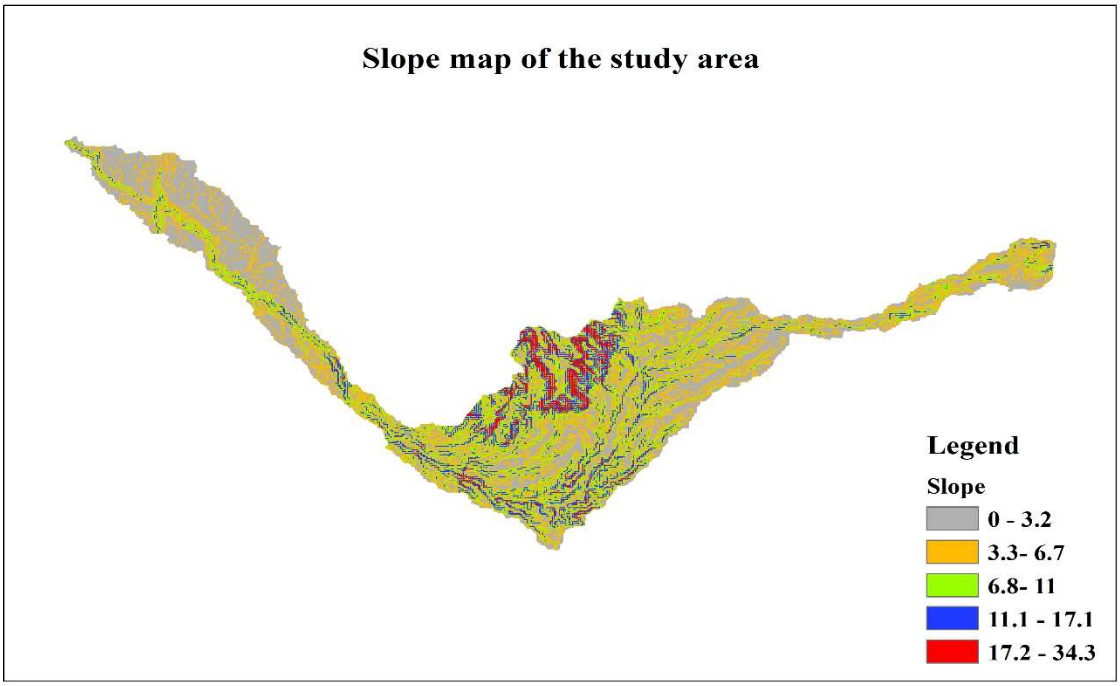


Figure 3.7 Slope map of the study area

3.1.5 Assessment of land use/land cover changes

3.1.5.1 Data from satellite images

The image for LU/LC change has been obtained using three Landsat images; Landsat of 1990,2005 and 2020. These Landsat images selected throughout the study period and with a cloud cover of zero were collected from U.S. Geological Survey (USGS) Center for Earth Resources Observation and Science (EROS) via node of (https://earthexplorer.usgs.gov/). The image data files were downloaded in zipped files from the Global land cover facility (GLCF) website and extracted to Tiff format files. The acquisition dates, sensor, path/row, and resolution of satellite images used in this study were summarized in Table 3.1.

Table 3.1 The acquisition dates, sensor, path/row, and resolution of the satellite image

Satellite name	Sensor	Path/raw	Date of acquisition	Reference data	Pixel size
LANDSAT_5	Landsat TM	168/55	Jan/18/1990	1990	15m*15m
LANDSAT_7	Landsat ETM+	136/47	Dec/26/2005	2005	15m* 15m
LANDSAT_8	Landsat OLI & TIRS	127/26	Nov/19/2020	2020	15m*15m

To adjust the pixel size of LANDSAT_5 imagery from 30m x 30m to 15m x 15m for the WetSpass-M model using ArcMap use the resample tool. This tool allows to change the spatial resolution of raster data to a specified cell size. However, it's important to note that resampling to a finer resolution does not increase the actual resolution of the data; it only interpolates the values to create smaller pixels.(Vivone et al., 2015)

3.1.5.2 Image processing and classification

Image preprocessing each Landsat image was georeferenced to WGS_84 datum and Universal Transverse Mercator (UTM) Zone 37N. Preprocessing was performed, including Layer stacking, Band color combination and Processing using ERDAS IMAGINE 2015 software. The study area was clipped from the stacked images using ERDAS IMAGINE 2015. Color composition was applied to satellite images for better viewing of surface features.

Image classification assigned pixels of raster images to predefined land cover classes. Factors affecting classification included classification methods, algorithms and training site collection. Classification techniques were categorized as Supervised, Unsupervised and Hybrid (unsupervised followed by supervised). Unsupervised classification used ISODATA (Iterative

Self-Organizing Data Analysis Technique) clustering algorithm. Supervised classification used Maximum Likelihood Classification (MLC) algorithm with training areas.(Jensen, 2016)

Supervised classification was used in this study, the most common method. It automatically categorizes pixels with similar spectral values into land cover classes. Supervised classification trusts on prior knowledge of spectral pattern recognition. It requires manual identification of training sites as reference/ground truth to determine spectral signatures. The land cover map was produced by pixel-based supervised classification. Training sites were chosen based on the analyst's expertise and implement by Google Earth. The final land cover map was derived from pixel-based supervised classification, enhanced for precision and class distinction.

3.1.5.3 Land use/Landcover map

To develop the land use/land cover map of the study area, satellite images for the years 1990, 2005, and 2020 were acquired for analysis. Specifically, Landsat 5 TM images were obtained for 1990, Landsat 7 ETM+ images for 2005, and Landsat 8 OLI images for 2020, all of which were downloaded from the USGS website. The satellite images for each respective year were processed using ERDAS IMAGINE 2015. This processing involved layer stacking, sub-setting the study area from the stacked images, and then classifying the images using the supervised classification technique. Once preprocessing was completed, image classification was conducted. The final step involved post-classification of the images. To verify and validate the results, an accuracy assessment of the classified images was performed as described below.

Accuracy assessment

Accuracy assessment is an important step in the image classification process. It is a process used to estimate the accuracy of image classification by comparing the classified map with a reference map (Caetano et al., 2005). Error matrix was used to derive a series of descriptive and analytical statistics for accuracy assessment (Manandhar et al., 2009). The columns of the matrix depict the number of pixels per class for the reference data, and the rows show the number of pixels per class for the classified image. From this error matrix, overall accuracy, user's and producer's accuracy were reported. Based on Google Earth Map, which was not used for classification purposes, the confusion matrix table was produced in Table 3.2. This matrix compares the relation between known reference data (ground truth) and the corresponding results of the classification.

Table 3.2 Confusion Matrix Table for 2020 land use and land cover

	Reference Data					
Classified Data	Bare Land	Agricultural Land	Grass Land	Built-up Area	Forest area	Total LU/LC
BRL	56	4	2	3	2	67
AGRL	3	112	4	2	3	124
GRL	2	4	57	1	3	67
BTUA	3	5	1	67	0	76
FRST	1	3	2	0	64	70
Total Producer	65	128	66	73	72	404
Number of LULC correctly classified=404 Overall Classification Accuracy% = 88.12%						

As shown in Table 3.2 above, the confusion matrix indicates that the overall accuracy assessment is very strong i.e., 88.12% which is greater than the requirement for strongly acceptable classification, i.e., 84% (Anderson et al., 1976). The accuracy assessment of users and producers was also calculated for each land class and revealed satisfactory agreement. The kappa value of 0.854 suggests that the classification occurred from a random sample class classification. Since the kappa value has risen beyond 80%, it indicates significant agreement. User accuracy: As stated in Table 3.3, user accuracy is a measure that indicates the likelihood that a pixel is a Class of the sample after the classifier labels the pixel.

Table 3.3 Users and producers accuracy table

Class Name	Users Accuracy	Producers Accuracy
BRL	83.58%	86.15%
AGRL	90.32%	87.50%
GRL	85.07%	86.36%
BTUA	88.16%	91.78%
FRST	91.43%	88.89%

Producer accuracy: Producer accuracy is a measure indicating the probability that the classifier has labeled an image pixel into the sample area given that the ground truth of the sample area.

Overall accuracy: The overall accuracy is calculated by summing the number of pixels classified correctly and dividing by the total number of pixels sampled. The ground truth image or ground truth training area defines the true class of the pixels. The pixels classified correctly are found along the diagonal of the confusion matrix table which lists the number of pixels that were classified into the correct ground truth class. The total number of pixels is the sum of all the pixels in all the ground truth classes.

The kappa coefficient is calculated by multiplying the total number of pixels in all the ground truth classes by the sum of the confusion matrix diagonals, subtracting the sum of the ground truth pixels in a class times the sum of the classified pixels in that class summed over all classes, and dividing by the total number of pixels squared minus the sum of the ground truth pixels in that class times the sum of the classified pixels in that class summed over all classes as shown in table 3.4. In addition, it is a way to measure the actual agreement and chance agreement between the reference data and the classified data. The Kappa coefficient represents the proportion of agreement obtained after removing the proportion of agreement that could be expected to occur by chance (Foody, 2002). This would be expressed in terms of the percentage of strong, moderate and poor agreement i.e., a value >0.80 (80%) strong agreement; a value between 0.40 and 0.80 (40 to 80%) represents moderate agreement; and a value < 0.40 (40%) represents poor agreement.

Table 3.4 Conditional kappa coefficient for each LULC

Land use land cover types	Conditional kappa for each LULC class	Kappa coefficient in (%)
BRL	0.8779	87.79
AGRL	0.8701	87.01
GRL	0.8779	87.79
BTUA	0.8770	87.70
FRST	0.8774	87.74
Overall kappa statistics =0.8761		87.61

After passing through long processes, the land use/land cover of the study area was classified into four classes as forest land, buildup land, bare land, and agricultural land as shown in Figure 3.8 below. Out of 296.17km^2 of the study area 218.34, 3.64, 24.58, 6.87 and 42.74km^2 have fallen under agriculture, bare land, forest land, grass land and buildup respectively with an overall accuracy percent of 87.61 and kappa that coefficient of 0.854 which has a great agreement with (Congalton & Green, 1999) values.

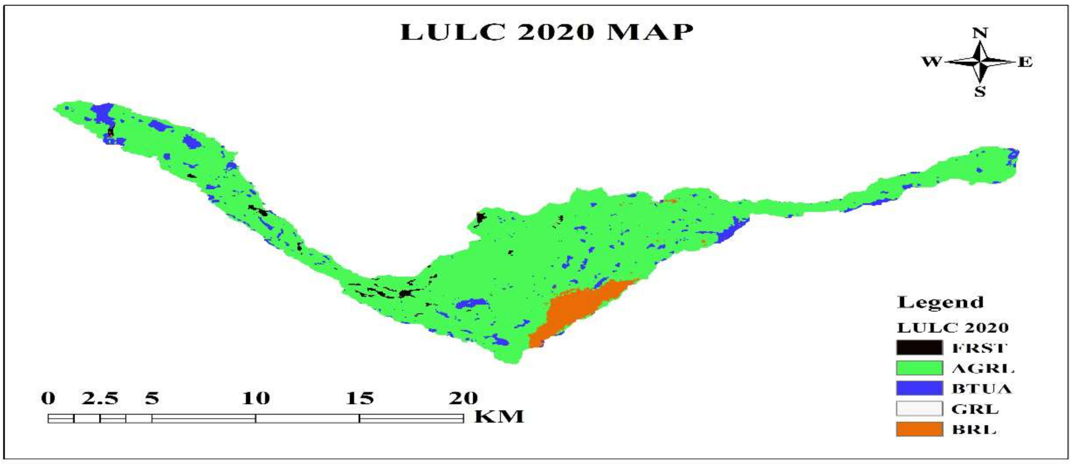


Figure 3.8 Land use/Land cover map of the study area

3.2. Data Sources

To achieve the aim/objectives of this study, both primary and secondary data are used. Some data used in this research generated from different sources. The major data used in this study includes Soil data from Ministry of agriculture of Ethiopia, Rainfall data taken from Ethiopia National Meteorology Agency, Land use land cover, slope, geomorphology and drainage data were generated from downloaded all from USGS earth resource observation system data canter. (https://earthexplorer.usgs.gov). Rainfall Map prepared from Ethiopia National Meteorological Agency. Soil map of the study area prepared from soil data from ministry of agriculture, field observation, reports, and journals. All the above data are collected, manipulated, and analyzed in GIS and RS Environment to use for further analysis on determining groundwater potential zone delineation.

3.2.1. Primary Data

The primary data are use Landsat 8 current land use/land cover of the study area and it is downloaded from U.S. Geological Survey Global Visualization Viewer Website without the presence of cloud cover. SRTM images derive from USGS with spatial resolution of are used to extract Digital Elevation Model (DEM) of Dedaba watershed and it is use to extract slope map, rainfall data taken from National Meteorological Agency to create rainfall map of the study area. Field observation with experts of environmental protection officers and residents who are near to the study are to get more information.

3.2.2. Secondary Data

The secondary data used in this study includes soil map of the study area from ministry of agriculture for mapping soil types in the study area. Additionally, secondary data for the study was gathered from reports, journals and governmental institutions manuals used in the management of water resource.

3.3 Groundwater recharge estimation

Groundwater recharge, the infiltration and subsequent replenishment of aquifers by surface or subsurface water, constitutes a critical component of the hydrological cycle and underpins sustainable water resource management. This methodology presents the approach employed to estimate groundwater recharge within the study area, leveraging the WetSpass-M model integrated within the ArcGIS platform.

A multitude of techniques exist for quantifying groundwater recharge. This study adopts the water balance framework, which meticulously accounts for all water inflows and outflows within a defined spatial domain. The WetSpass-M model, developed by Esayas et al. (2018), is a widely recognized tool within ArcGIS specifically designed to implement the water balance approach for recharge estimation.

To facilitate recharge estimation using WetSpass-M, various gridded datasets were acquired or generated, encompassing: Meteorological Data (Monthly Timescale): Rainfall, temperature, wind speed, and potential evapotranspiration data were either directly obtained (Ethiopia National Meteorological Agency). Static Spatial Data: Soil type, groundwater depth, slope, topographic elevation, and land use/land cover data were procured or prepared. These static datasets were considered to exhibit minimal temporal variation and were assumed to be constant throughout the year for modelling purposes.

Standardization of cell size across all grid layers was paramount to ensure compatibility with WetSpass-M. All datasets were meticulously resampled or adjusted to possess identical row, column, and cell size dimensions. Notably, meteorological data was prepared on a monthly basis to account for seasonal variations in atmospheric conditions.

The selection of these specific gridded datasets aligns with established practices in analogous studies conducted globally (De Smedt & Batelaan, 2003). Subsequent sections will delve into the procedures employed for generating these grid layers and the application of the WetSpass-M model for groundwater recharge estimation.

Accurate quantification of groundwater recharge is an indispensable cornerstone of effective water resource management strategies. A comprehensive understanding of recharge rates and their origin is crucial for informed decision-making related to water allocation and usage. In the context of climate change and ever-increasing water demands, the ability to estimate recharge becomes even more critical for predicting future water availability. The adoption of appropriate recharge estimation methods, coupled with the utilization of reliable data, is paramount for ensuring the sustainable management of vital groundwater resources.

3.3.1 Rainfall

The rainfall data from the Ethiopia National Meteorology Agency was spatially interpolated using the Inverse Distance Weighted (IDW) method to create a gridded rainfall map covering the Dedaba watershed. IDW was chosen as the interpolation technique because it is fast and easy to implement, and each interpolated value is a weighted average of the surrounding sample points.

The interpolated rainfall grid map was prepared in an ArcGIS 10.8-compatible raster format to be used as an input for the WetSpass-M model. The rainfall grid map had the same spatial resolution as the other input parameters, such as land use, soil texture, and topography. Convert the data into a gridded format compatible with the WetSpass-M ASCII raster. Selected period represents the long-term average climatic conditions for 10 and 30 years. The long-term average monthly rainfall distribution in and around the watershed is shown in Figure 3.9.

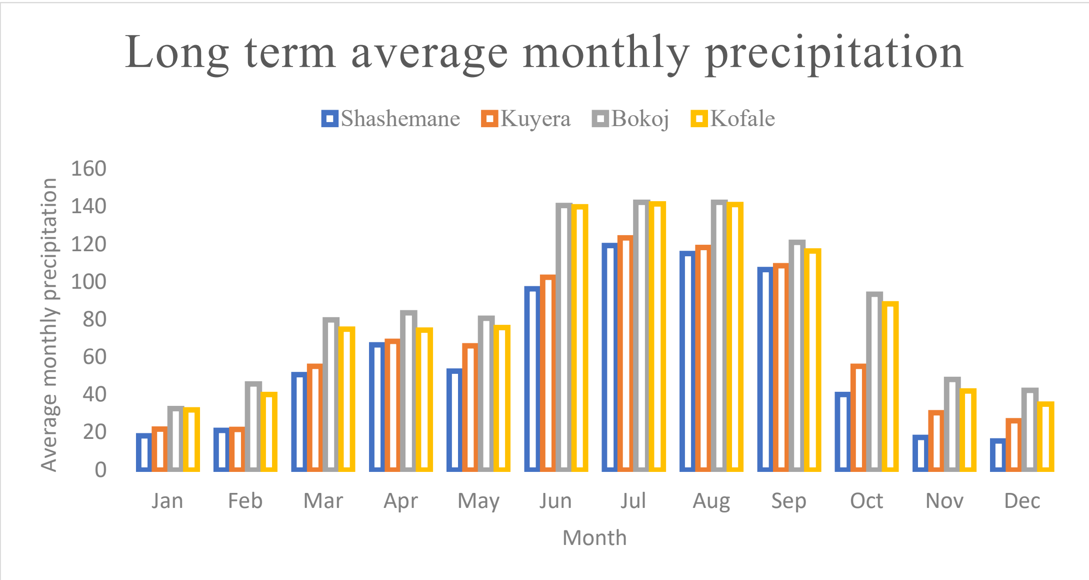


Figure 3.9 Monthly rainfall for stations in and around the study area

Using the IDW interpolation with batch processing the rainfall of the study area is presented as follows and it was converted to ASCII file format to make the map have the same column and row.

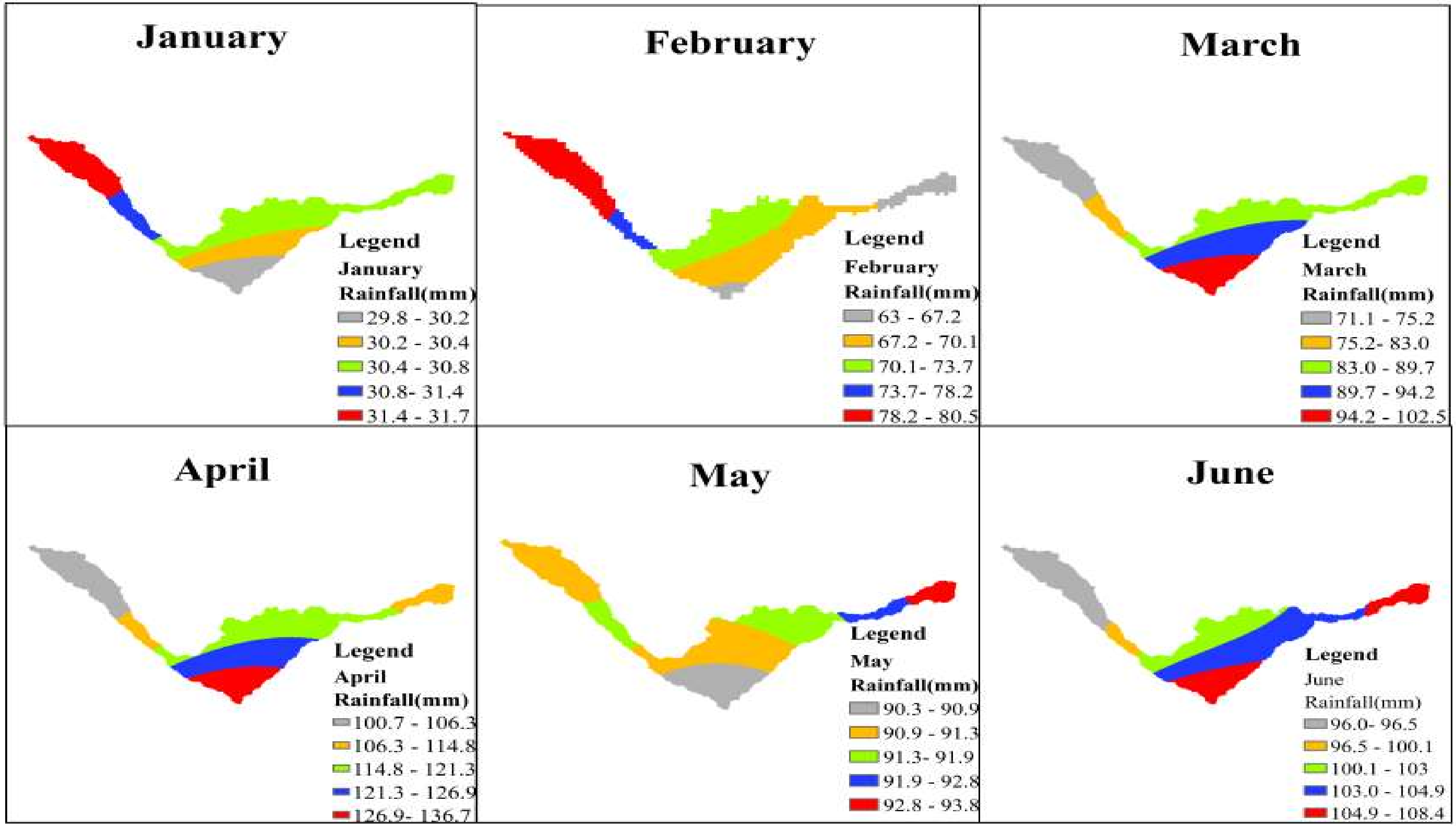


Figure 3.10 (a) Long term monthly rainfall Dedaba Watershed (January to June)

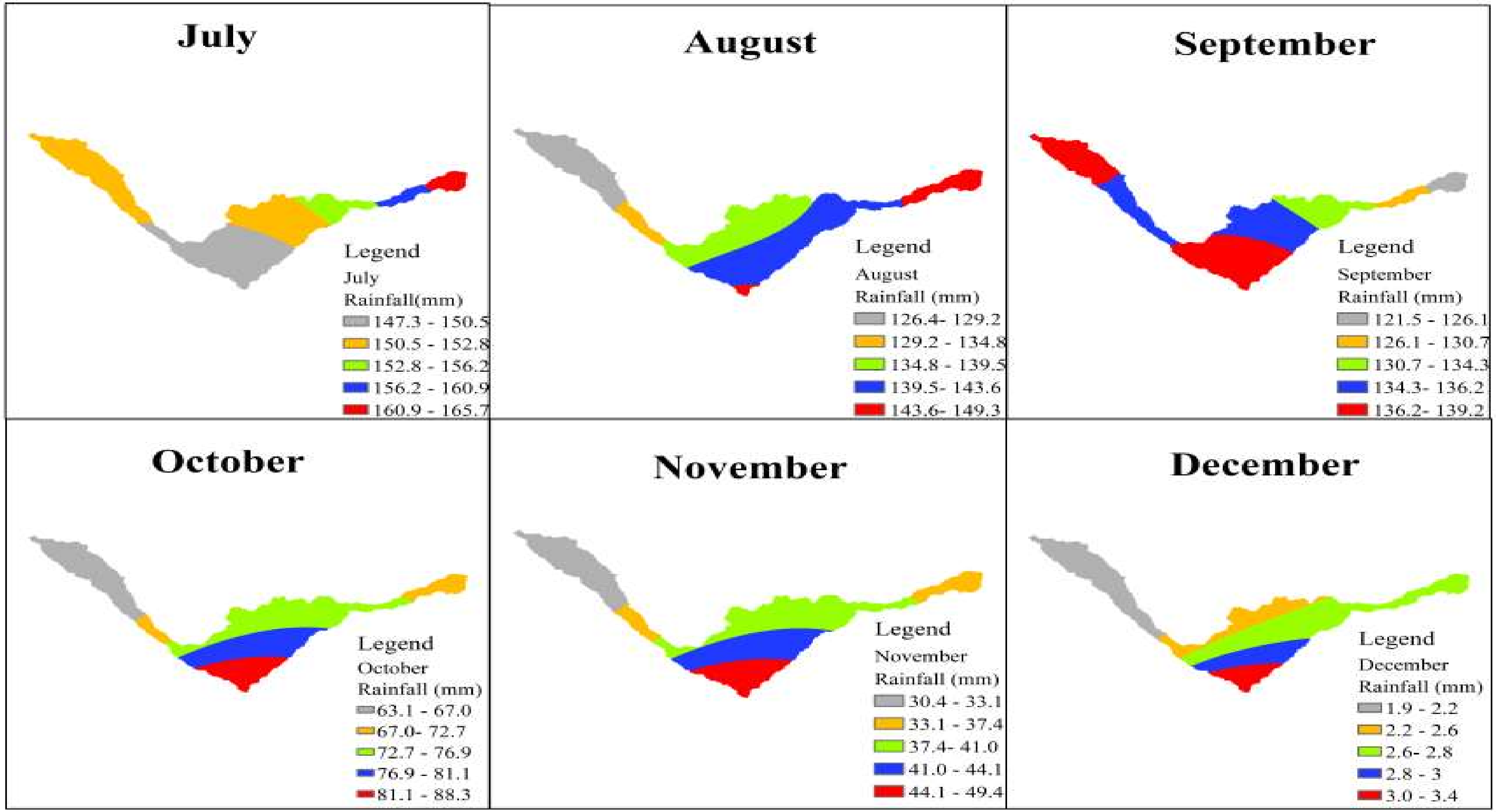


Figure 3.10 (b) Long term monthly rainfall Dedaba Watershed (July to December)

3.3.2 Temperature

To prepare temperature data for groundwater recharge estimation using the WetSpass-M model, gather long-term historical temperature data on average temperature. This data was obtained from the Ethiopian National Meteorology Agency. The spatial interpolation methods are used to create a continuous temperature surface from point data. Inverse Distance Weighting (IDW), which assumes that points closer to each other are more similar than those further apart.(Dile et al., 2016)

To convert the interpolated temperature data into a raster map format that is compatible with ArcGIS-10.8 software. This raster map should have the same spatial resolution as other input parameters for the WetSpass-M model, such as rainfall, land use, and soil texture. If the WetSpass-M model requires temperature data at a specific temporal scale (e.g., monthly or seasonal), the temperature data should be prepared accordingly. The temperature data into the required time intervals. combine the prepared temperature raster maps with other hydrological data inputs required by the WetSpass-M model, such as precipitation, potential evapotranspiration, and land cover data.

The temperature data can be adequately prepared and formatted as input for the WetSpass-M model to estimate groundwater recharge, the model's simulations are based on accurate and spatially representative temperature information.(Abdollahi et al., 2017)

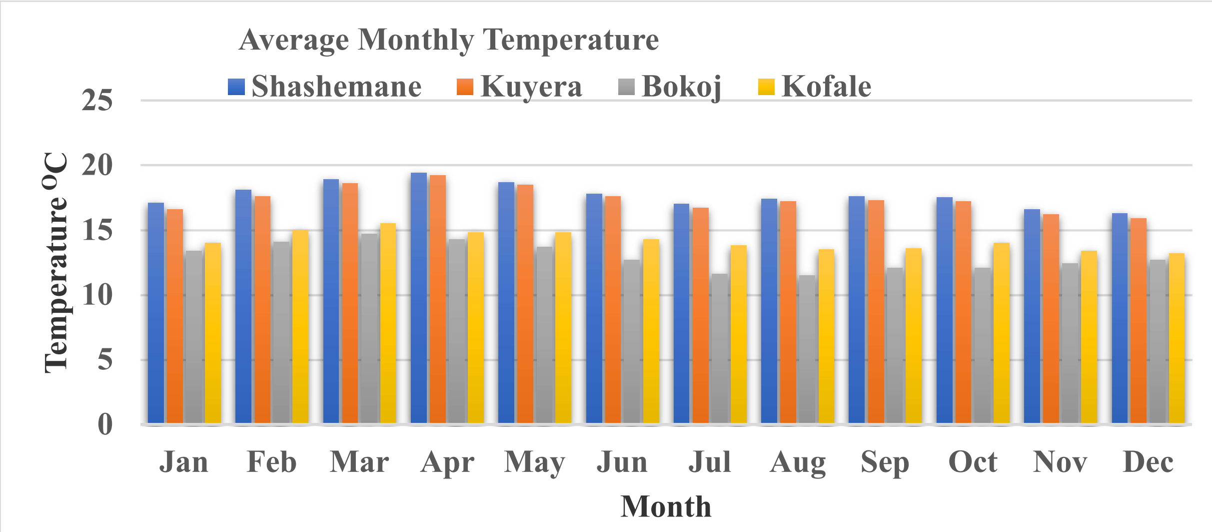


Figure 3.11 Monthly average temperature value of surrounding stations

Using IDW interpolation with batch processing temperature map is also prepared and then it was converted to ASCII file format. The long-term average monthly temperature value ranges between 14.49°c and 17.256°c throughout the year with a mean of 15.997°c.

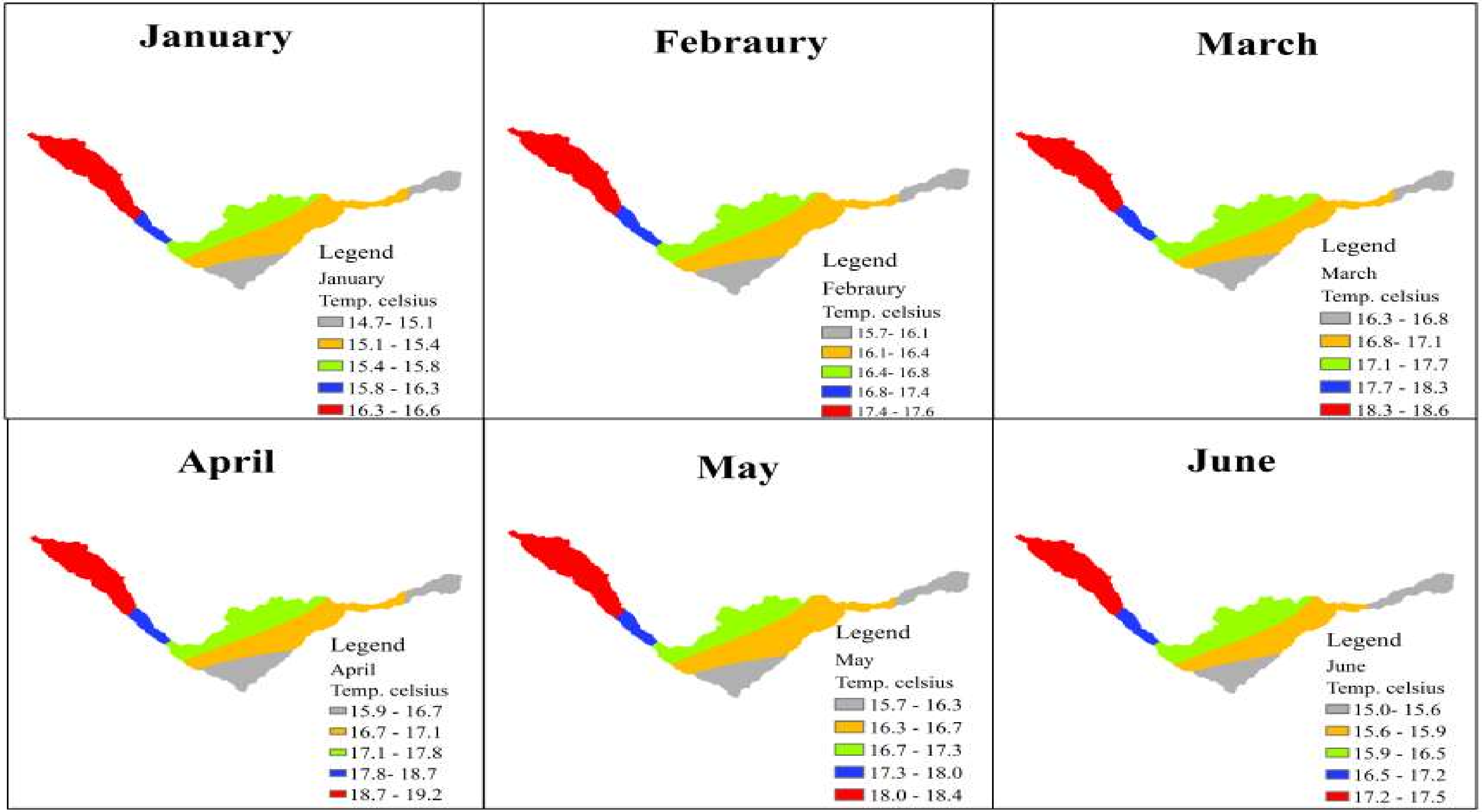


Figure 3.12 (a) Long term monthly temperature Dedaba Watershed (January to June)

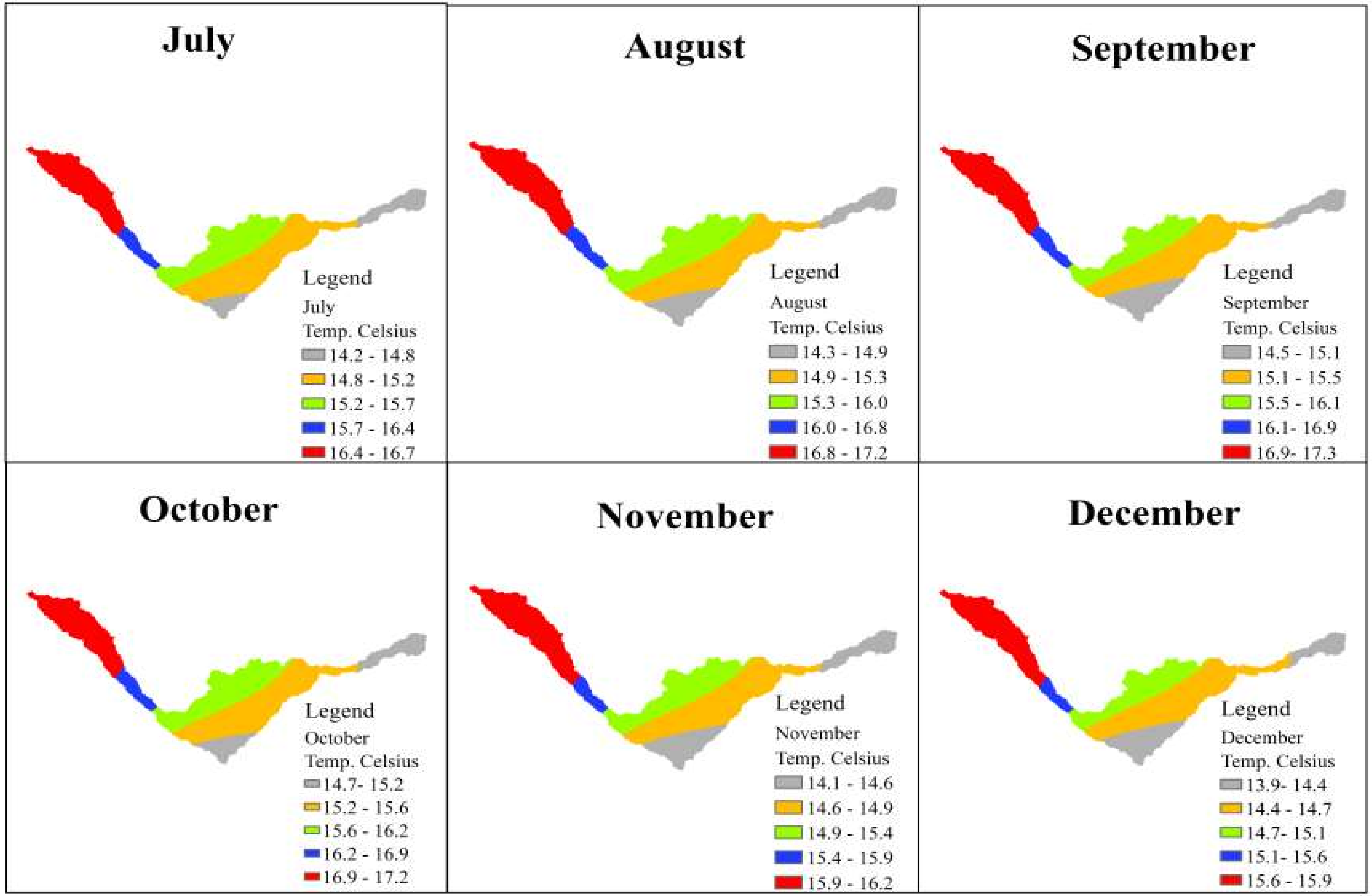


Figure 3.12 (b) Long term monthly temperatur Dedaba Watershed (July to December)

3.3.3 Potential evapotranspiration

To prepare potential evapotranspiration (PET) data for groundwater recharge estimation using the WetSpass-M model, gather historical data from the Ethiopian National Meteorology Agency, including temperature, humidity, wind speed, and solar radiation. These data are essential for calculating PET using the Penman-Monteith equation. Preprocess the collected data to ensure they are in the required format and resolution for input into the WetSpass-M model. This may involve converting the data into raster maps with a resolution based on the digital elevation model (DEM) and a cell size of 15 × 15 m. Use the collected meteorological data to calculate PET using the Penman-Monteith equation method. This equation takes into account the temperature, humidity, wind speed, and solar radiation to estimate the amount of water that would be evaporated from a hypothetical grass reference crop under standard conditions.

Integrate the calculated PET data with other input parameters, such as precipitation, land use, and soil texture, to create a comprehensive dataset for the WetSpass-M model. The PET grid map had the same spatial resolution as the other input parameters, such as rainfall, land use, and soil texture.

To obtain long-term historical PET data, spatially interpolate it using IDW to create a gridded PET map, and ensure the PET data is in the correct format and resolution to match the other input parameters required by the WetSpass-M model for groundwater recharge estimation.

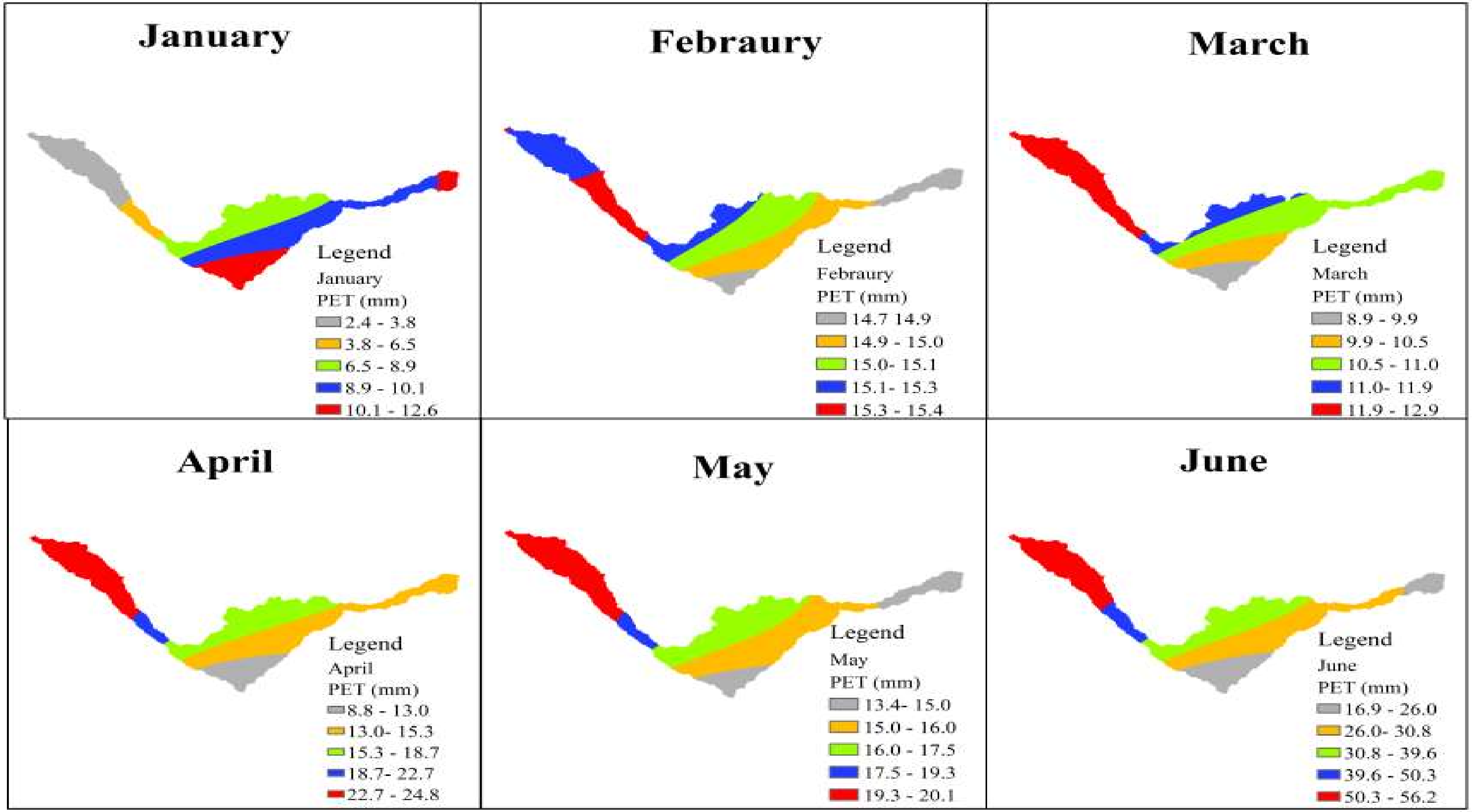


Figure 3.13 (a) Long term monthly PET Dedaba Watershed (January to June)

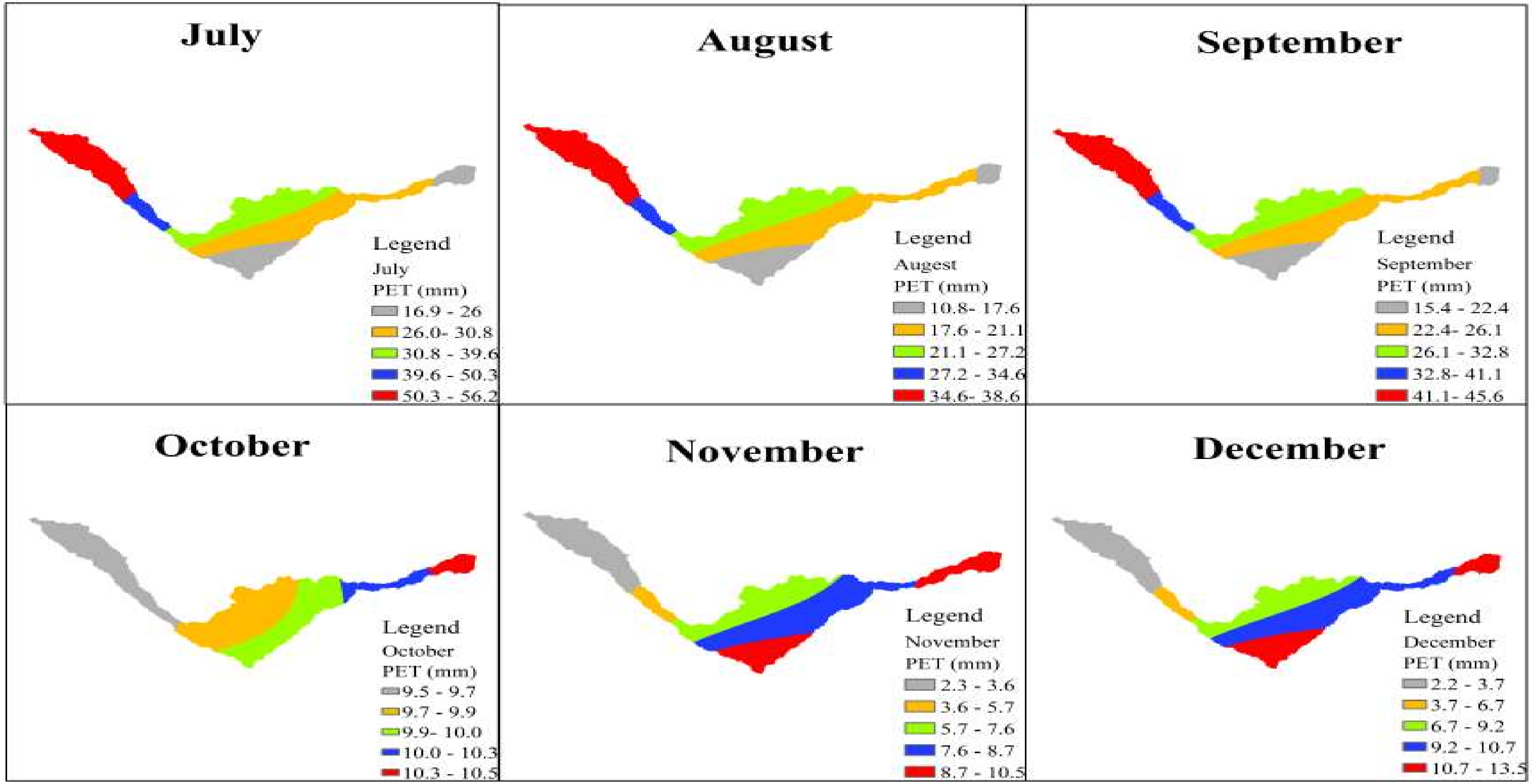


Figure 3.13 (b) Long term monthly PET Dedaba Watershed (July to December)

3.3.4 Wind speed

To prepare wind speed data for groundwater recharge estimation using the WetSpass-M model, gather historical wind speed data from the Ethiopian National Meteorology Agency. This data is essential for estimating groundwater recharge. The collected wind speed data is in the required format and resolution for input into the WetSpass-M model. Converting the data into raster maps with a resolution based on the digital elevation model (DEM) and a cell size of 15 × 15 m. Spatial interpolation methods are used to estimate wind speed values at locations where they are not directly measured. The spatial interpolation methods are used to create a continuous wind speed surface from point data. Inverse Distance Weighting (IDW) is one such method mentioned in the search results, which assumes that points closer to each other are more similar than those further apart.

Integrate the prepared wind speed data with other input parameters, such as precipitation, land use, and soil texture, to create a comprehensive dataset for the WetSpass-M model. The wind speed data is adequately prepared and formatted as input for the WetSpass-M model to estimate groundwater recharge. The model's simulations are based on accurate and spatially representative wind speed information.

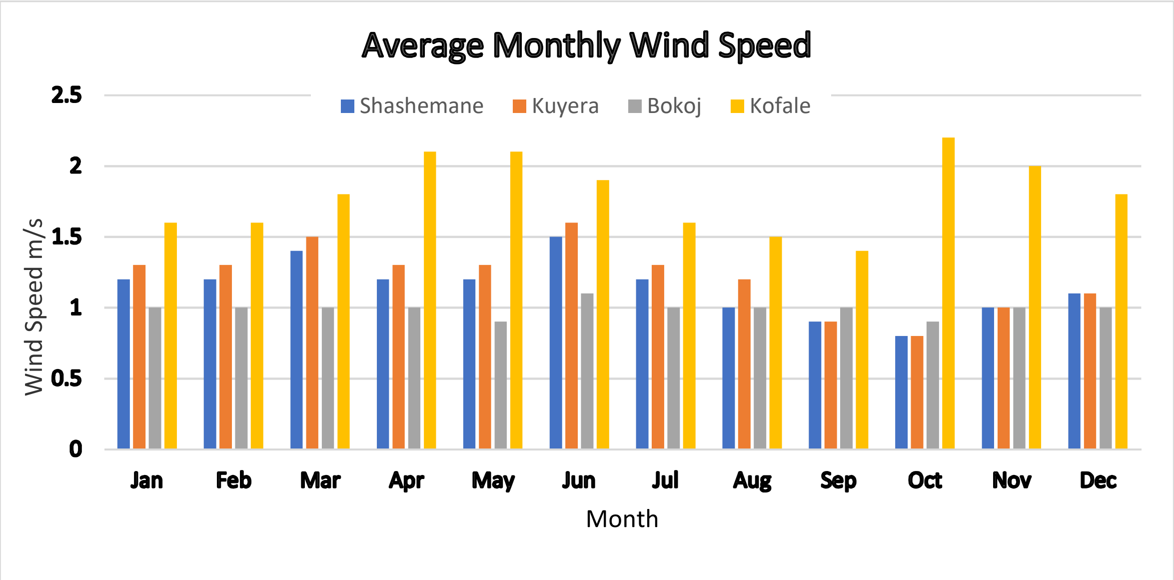


Figure 3.14 Monthly average wind speed value in and around Dedaba Watershed

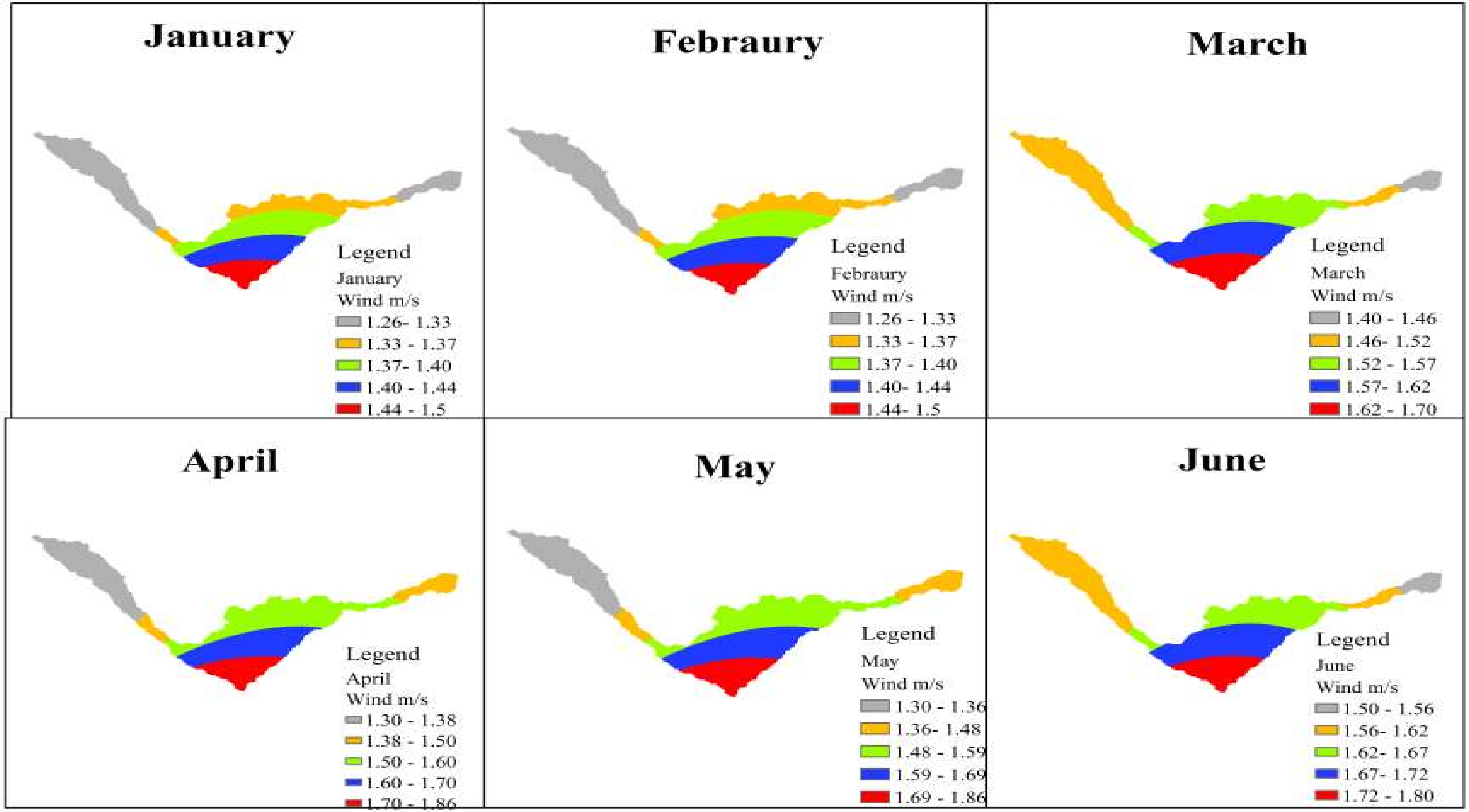


Figure 3.15 (a) Long term monthly wind speed Dedaba Watershed (January to June)

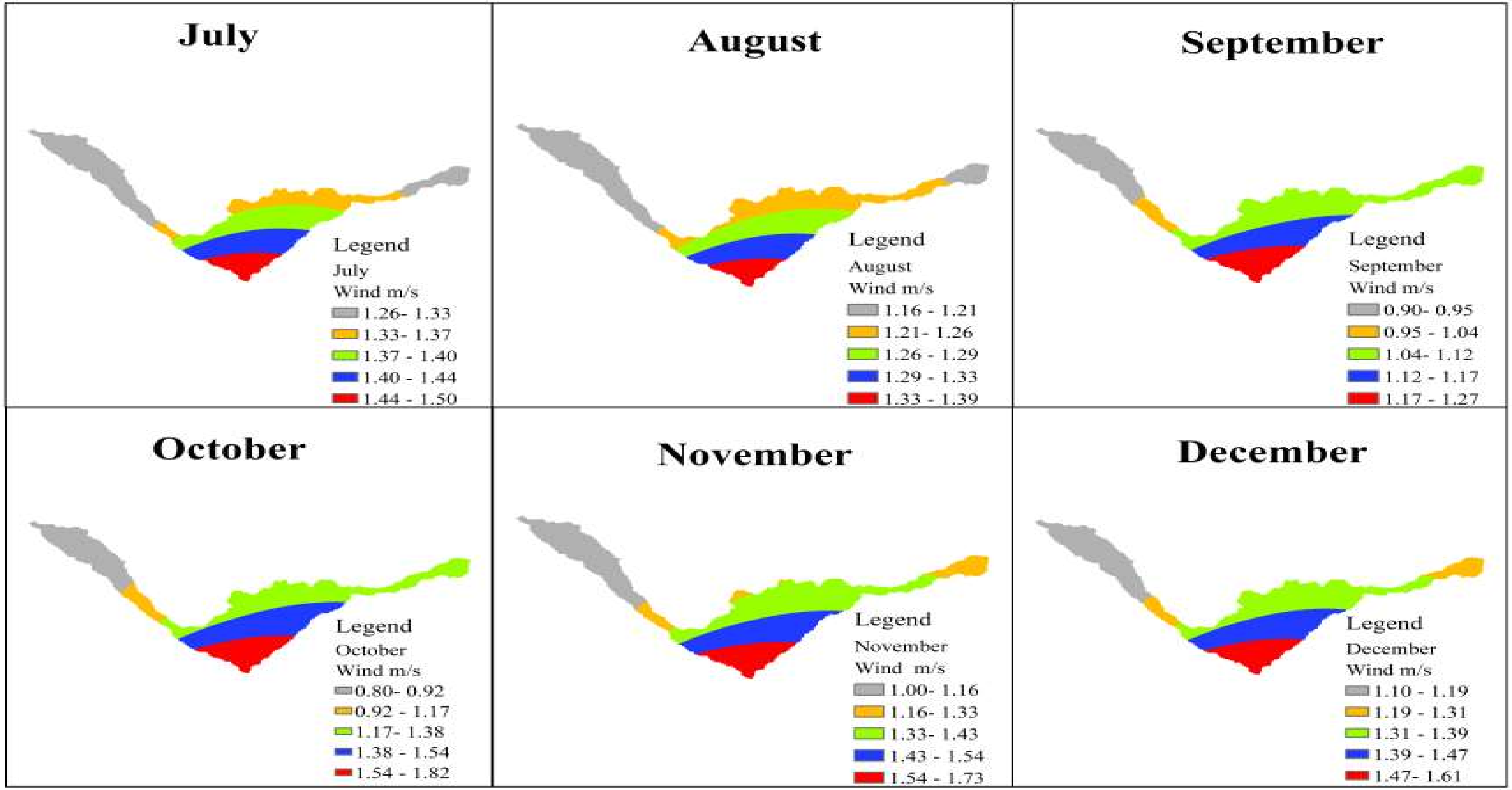


Figure 3.15 (b) Long term monthly wind speed Dedaba Watershed (July to December)

3.3.5 Groundwater depth

To prepare groundwater depth data for groundwater recharge estimation using the WetSpass-M model, Gather groundwater depth data from reliable sources West Arsi Zone Water and Energy Office, borehole records, or groundwater level measurements. The spatial interpolation techniques, Inverse Distance Weighting (IDW), to create a continuous groundwater depth map from the point-based monitoring well data. This will provide a gridded groundwater depth dataset that matches the spatial resolution of the other input parameters. This data is essential for estimating groundwater recharge. the collected groundwater depth data is in the required format and resolution for input into the WetSpass-M model. Converting the data into raster maps with a resolution based on the digital elevation model (DEM) and a cell size of 15× 15m. Model integrate the prepared groundwater depth data with other input parameters, such as precipitation, land use, and soil texture, to create a comprehensive dataset for the WetSpass-M model. Prepared and integrated groundwater depth data into the WetSpass-M model for groundwater recharge estimation.

The groundwater depth has been calculated by deducting static water level from ground surface level and its map was produced. These data were interpolated using ArcGIS 10.8 IDW spatial analyst tool to represent the total area of the watershed and then the grid map is converted to ASCII file format for model simulation.

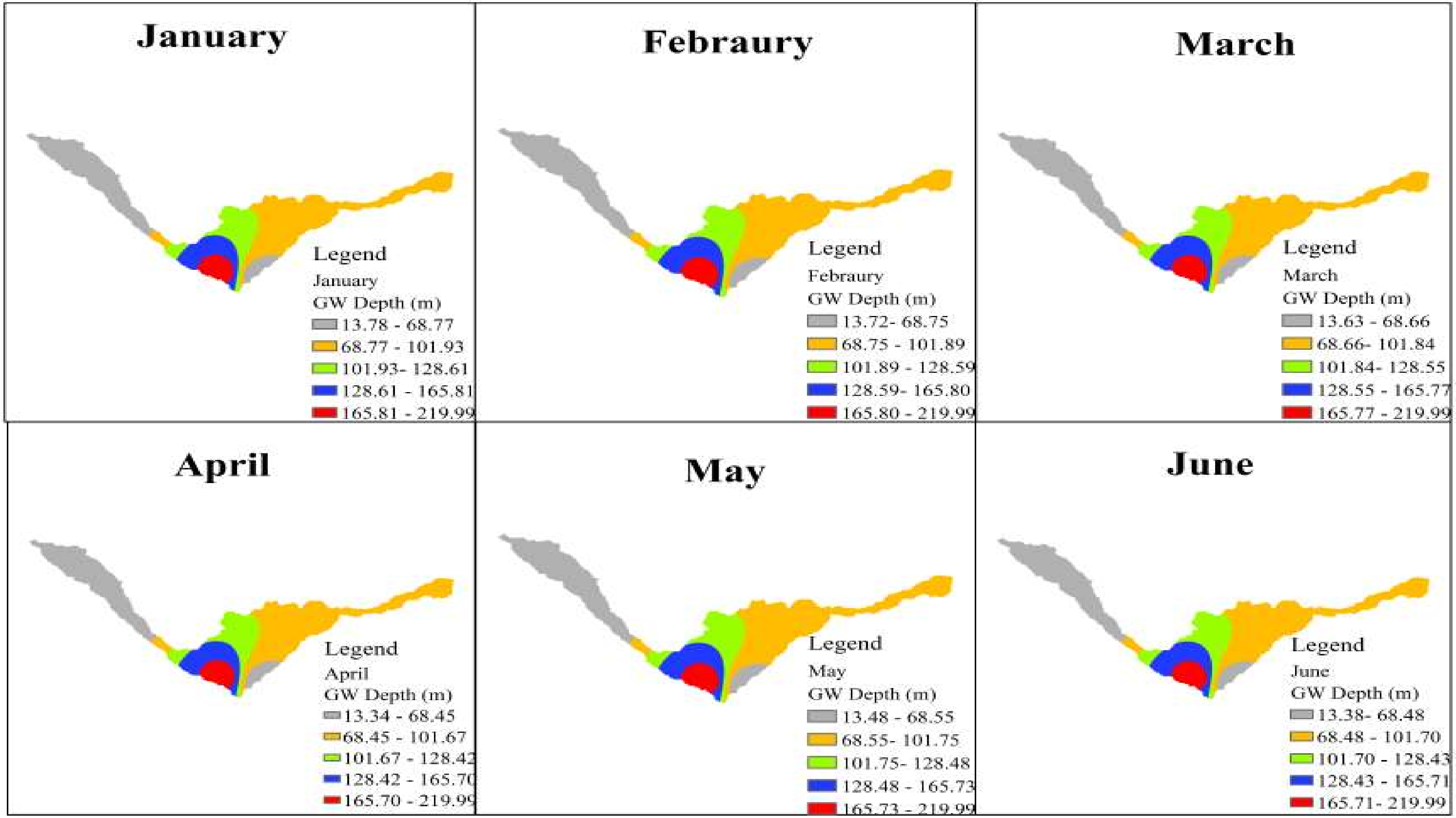


Figure 3.16 (a) Long term monthly groundwater depth Dedaba Watershed (January to June)

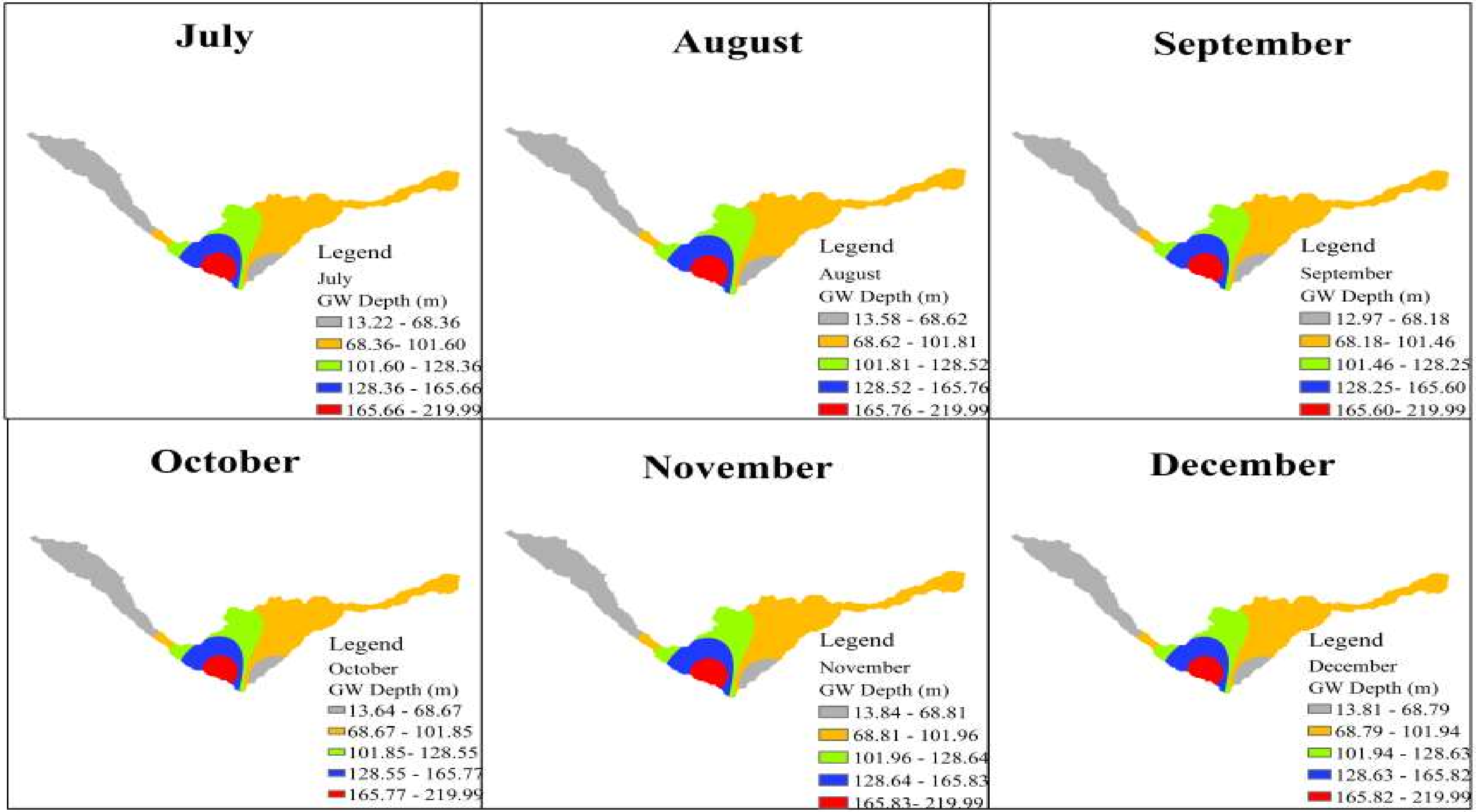


Figure 3.16 (b) Long term monthly groundwater depth Dedaba Watershed (July to December)

3.3.6 Land use/land cover

Land use/land cover (LULC) plays a significant role in groundwater recharge estimation as the type of land use and vegetation cover affects the infiltration rate and the amount of water that can reach the underground aquifer. Infiltration is the process by which water seeps through the ground surface and recharges groundwater. Different types of land cover have different infiltration rates and capacities to hold water, which influence the recharge rate to the groundwater. For example, open grasslands have a higher infiltration rate compared to dense forests where vegetation and leaf litter can slow down the water's penetration. Therefore, the LULC map of an area is a crucial input for estimating groundwater recharge.

The land use map is prepared by interpreting satellite or aerial images, and the land cover classes are defined based on the vegetation, built-up area, or other features. The LULC map is then used to calculate the recharge rate and to understand how different land use practices influence groundwater recharge. For example, agricultural lands with regular plowing may have lower infiltration rates compared to naturally vegetated areas. Urban areas, which have a lot of impervious surfaces like roads and buildings, have reduced infiltration rates, thus decreasing groundwater recharge.

Land use is an important characteristic to govern the surface runoff process that affects infiltration(recharge), evapotranspiration and erosion. Different land-use types have different influencing capacities on recharge, runoff process and evapotranspiration rates, due to their different leaf area indices, root depth and size (Batelaan and DeSmedt, 2001). t is a highly sensitive parameter for estimating recharge using WetSpass-M modeling. Water and Land Resource created Ethiopia's land use/land cover map. This map was used to derive and modify the Dedaba watershed land uses land cover.

Understanding the LULC pattern and its relationship to groundwater recharge is essential for assessing and managing water resources in a sustainable manner. The estimation of groundwater recharge can be improved by incorporating detailed LULC maps that reflect the current land use practices and vegetation cover. Groundwater recharge estimation WetSpass-M model that consider LULC patterns can assist decision-makers in developing appropriate land use management interventions and conservation measures to support sustainable groundwater recharge.

3.3.7 Topography

Groundwater recharge estimation is an essential aspect of water resource management, particularly in arid and semi-arid regions where groundwater is frequently the primary source of freshwater. Topography, defined as the physical features of the earth's surface, plays a critical role in groundwater recharge estimation. Accurate topographic data can be utilized to predict the volume and timing of groundwater recharge, and this information is critical for the sustainable management of groundwater resources.

Topography affects groundwater recharge by influencing the rate and direction of water movement in soil and rock layers. Undulating landscapes with varying elevations tend to have numerous depressions, which function as potential recharge zones for groundwater aquifers. The slope of the topography can also play a role in determining whether water infiltrates into and recharges groundwater or runs off the surface. Therefore, the impact of topography in recharge estimation is significant, and its consideration enhances the accuracy and reliability of recharge prediction models.

The topography (elevation) map of the watershed was obtained from DEM which is downloaded from the Shuttle Radar Topography Mission (SRTM) dataset of the United States of Geological Survey (USGS) and processed in ArcGIS environment finally the map format was changed to ASCII file format for a further model effective run.

Incorporating topography data is critical in groundwater recharge estimation WetSpass-M model as it influences water infiltration, movement, and recharge rates. The advanced technology of remote sensing and GIS tools facilitates accurate mapping and quantification of topographic features in the recharge estimation process. Integrating topographic data into groundwater recharge estimation provides better insights and understanding of the recharge process, and this information can help support sustainable groundwater resource management practices.

3.3.8 Slope

The WetSpass-M model is a prominent tool within the field of hydrology, employed to simulate and quantify water balance components across a landscape. A critical input for the model is slope data, which significantly influences the distribution of vital water resources.

WetSpass-M utilizes Digital Elevation Models (DEMs) to acquire slope information. A DEM is a geospatial representation of terrain elevation, typically structured as a grid with values assigned to each cell. The model calculates slope by analyzing the change in elevation between neighboring cells within the DEM. This change is then divided by the horizontal distance separating the cells, resulting in a comprehensive slope map that depicts the terrain's steepness at each point.

The generated slope map plays a pivotal role in WetSpass-M's simulation of water flow. Steeper slopes facilitate faster surface runoff, the phenomenon occurring when precipitation exceeds the infiltration capacity of the soil. Slope also exerts a significant influence on groundwater recharge by impacting the movement of water through the soil profile and into the underlying aquifer.

For WetSpass-M to utilize the slope data effectively, it requires conversion into a specific format: ASCII. Geographic Information Systems (GIS) software, such as ArcGIS, provides the "Raster to ASCII" tool specifically designed for this purpose. This tool facilitates the conversion of the grid-based slope data (raster) into a text file (ASCII) compatible with the model.

Once the slope data is converted to ASCII format, WetSpass-M can control it for its core function: simulating water flow across the landscape. The model utilizes the slope information to estimate critical water balance components such as groundwater recharge, evapotranspiration, and surface runoff. This comprehensive analysis provides valuable insights into the distribution and behavior of water resources within a specific area. Finally, the raster grid map was transformed to ASCII format for model processing at a resolution of 15m*15m.

3.3.9 Soil

This research method outlines the process of utilizing soil data within the WetSpass-M distributed hydrological model to assess water balance components. Soil properties play a critical role in infiltration capacity, directly affecting the distribution of groundwater recharge, evapotranspiration, and surface runoff.

The WetSpass-M model uses a soil map to generate the soil data. The soil map is a raster map that represents the soil type at each location, typically in the form of a grid. The soil map can be obtained from various sources, such as soil surveys or remote sensing data.

The soil map is then used by the WetSpass-M model to simulate the infiltration capacity of the soil. The model uses the soil type to calculate the rate of infiltration, which is the flow of water into the soil. The soil type also affects the rate of groundwater recharge, as it influences the movement of water through the soil profile and into the underlying aquifer.

To convert the soil data from a raster format to ASCII format, the Raster to ASCII tool in ArcGIS can be used. This tool converts a raster dataset to an ASCII file representing raster data. The input raster dataset can be any valid raster dataset, and the output ASCII raster file can be specified by the user. The tool writes the origin as the lower left corner of the lower left cell, and the end of each row of data from the raster is terminated with a carriage return character in the file.

The ASCII file can be used as input for the WetSpass-M model, which requires the soil data in ASCII format. The model uses the soil data to simulate the infiltration capacity of the soil and estimate groundwater recharge, evapotranspiration, and surface runoff.

The WetSpass-M model uses soil data from a soil map to simulate the infiltration capacity of the soil and estimate groundwater recharge, evapotranspiration, and surface runoff. The soil input is crucial for the model, as it affects the distribution of these water balance components. The Raster to ASCII tool in ArcGIS can be used to convert the soil data from a raster format to ASCII format, which is required by the WetSpass-M model. Finally, the raster grid map was transformed to ASCII format for model processing at a resolution of 15m*15m.

3.3.10 Parameters for WetSpass-M

The WetSpass-M model represents a distributed water balance model operating on a monthly scale. Its primary purpose is to compute key hydrological components such as actual evapotranspiration, surface runoff, and groundwater recharge. The model strictly obeys to the water balance equation, necessitating a various arrangement of input parameters for accurately simulating these hydrological processes. These inputs encompass meteorological conditions, topographical features, land use and cover, soil characteristics, and groundwater levels. These parameters can be efficiently organized into ASCII grid format using Geographic Information System (GIS) tools.

Essentially the model relies on two distinct types of inputs: spatial data presented in an ASCII grid map and parameter data structured in TBL format tables. The ASCII grid map combines spatially-distributed data, including land use or cover, elevation, slope, soil texture, and groundwater depth. Facilitating the model's operation are four specific parameter tables in TBL format, which are indispensable. These tables encompass land use parameters, soil parameters, and the number of rainy days, serving as attribute lookup tables for the model's input. The integration of these developed grid maps and parameter tables empowers the model to engage with the input data effectively, thereby generating average values crucial for the simulation process.

3.3.11 Model calibration

The WetSpass-M model is a widely used tool for simulating the water balance of a catchment area. Calibrating this model is crucial for ensuring its accuracy and reliability in representing the real-world system. The total flow in a stream or river from a watershed is a function of base flow (Q_b) and surface runoff (Q_s), which is equivalent to the long-term monthly average river discharge from the watershed.

The model calibration process involves manually adjusting different parameters within specified ranges to optimize the fit between simulated and observed values. The key calibration parameters are:

Interception parameter (a): Determines the amount of precipitation captured by vegetation

Evapotranspiration coefficient (α): Affects the rate at which soil and vegetation release water vapor into the atmosphere

Surface runoff threshold (LP): Defines the threshold at which runoff begins to occur

Runoff delay factor (x): Determines the timing of surface runoff release

Base flow (β): Represents the contribution of groundwater to streamflow

The parameters are adjusted until an optimal fit is achieved between the simulated and observed stream discharge recorded at a river gauge station.

Streamflow data is crucial for water resource studies. In this case, daily streamflow data for the Dedaba River from 1990 to 2020 was collected from the Ministry of Water, Irrigation, and Electricity of Ethiopia and used for calibration purposes to analyze groundwater recharge estimation.

The total flow in a stream is the sum of base flow and surface runoff:

$Q_{total}=Q_s+Q_b$……………………………………………………………………………Eq.3.4

Where:

Q_{total} (m^3/month): Total streamflow in the river

Q_s (m^3/month): Simulated surface runoff

Q_b (m^3/month): Simulated base flow

3.3.12 Model Validation

Water Table Fluctuation (WTF) Method this method involves calculating the change in groundwater storage and linking it to the resulting water table fluctuations through the storage parameter (specific yield in unconfined aquifer). The WTF method is used to validate the WetSpass-M model by comparing the simulated groundwater recharge with the calculated recharge using the WTF method.(Rudra et al., 2022)

Validation of the WetSpass-M Model using the Water Table Fluctuation Method can be used to validate the WetSpass-M model by comparing the simulated groundwater recharge values with those estimated using the WTF method.

The water table fluctuation (WTF) method uses the following equation to estimate groundwater recharge:

$\mathbf{R(t_j) = Sy * \Delta H(t_j)}$…………………………………………………………………… Eq 3.5

Where:

$R(t_j)$ is the recharge occurring between times t_0 and t_j (in mm)

Sy is the specific yield (dimensionless)

ΔH(t_j) is the peak water level rise attributed to the recharge period (in mm)

The key assumptions of this method are: The observed well hydrograph depicts only natural water-table fluctuations caused by groundwater recharge and discharge. The specific yield (Sy) is known and constant over the time period of the water-table fluctuations. The pre-recharge water-level recession can be extrapolated to determine ΔH(tj).

The WTF method involves two main steps: Identifying the water table rise (ΔH) associated with a recharge event and multiplying the water table rise by the specific yield (Sy) to calculate the recharge amount.

This simple equation allows estimating groundwater recharge based on observed water table fluctuations in observation wells, provided the specific yield is known.

Run the calibrated WetSpass-M model for the same time period and location as the WTF method. Compare the simulated recharge values from WetSpass-M with the recharge estimates obtained using the WTF method. Evaluate the model performance using statistical measures such as the Nash-Sutcliffe efficiency (NSE), coefficient of determination (R^2), or root mean square error (RMSE). Assess the model's ability to accurately simulate groundwater rechargebased on the validation results.

The WTF method offers a straightforward approach to assess the WetSpass-M model's capability to simulate groundwater recharge, presenting both benefits and drawbacks. While it enables direct validation, the precision of this validation hinges on the WTF method's own reliability. This reliability can be influenced by various factors, including evapotranspiration, changes in atmospheric pressure, and groundwater extraction. It's also important to note that the WTF method is exclusively suitable for unconfined aquifers.

3.3.13 Model performance evaluation

To evaluate the model simulation outputs relative to the observed data, model performance evaluation is necessary. There is a various method to evaluate the model performance during calibration and validation periods. For this study coefficient of determination (R2), Nash and Sutcliff simulation efficiency (NSE), and PBIAS were used.

The determination Coefficient describes the linear relationship between simulated and observed data. Its value ranges from zero to one. A higher value close to 1 indicates good co-relation and typically values greater than 0.6 are considered acceptable (Santhi et al., 2001).

$$R^2 = \frac{[\sum(Qo - mean.Qo)(Qs - mean.Qs)]2}{\sum(Qo - mean.Qo)2 \; \sum(Qs - mean.Qs)2} \quad \text{Eq 3.6}$$

The Nash and Sutcliffe simulation efficiency indicates how well the plots of observed versus simulated data fit the 1:1 line. The value ranges from negative infinity to one. Values greater than 0.5, indicate the simulated value predicted better. A value greater than 0.5 is acceptable performance (Santhi et al., 2001).

$$NSE = 1 - [\frac{\sum(Qo - Qs)2}{\sum(Qo - Mean.Qo)2}] \quad \text{Eq 3.7}$$

The proportion of PBIAS describes the tendency of the simulated data to be greater or smaller than the observed data, expressed as a percentage. The optimum PBIAS value is zero and low indicates that the model simulation is satisfactory. Positive values indicate a tendency of the model to underestimate while negative values indicate overestimation (Moriasi, 2007).

$$PBIAS = [\frac{\sum(Qo - Qs)}{\sum Qo}] \quad \text{Eq 3.8}$$

3.4 Impacts of land use/land cover on groundwater recharge

The influence of Land Use and Land Cover (LULC) on groundwater recharge is wide. This impact can be assessed using ArcGIS, a Geographic Information System (GIS) software, and the WetSpass-M model.

ArcGIS offers strong spatial analysis tools that can be utilized to generate and examine various LULC maps. These maps can identify areas that are likely to enhance groundwater recharge, such as forests, wetland and grasslands. Conversely, it can also identify regions that may decrease groundwater recharge, like urban or agricultural lands.(Owuor et al., 2016)

After identifying the potential effects of different LULC types on groundwater recharge through GIS analysis, modeling techniques can offer more comprehensive insights. The WetSpass-M model can be used to simulate water movement through the soil and compute recharge rates in the area of interest, thereby quantifying the impact of LULC on groundwater recharge.

The combined application of ArcGIS 10.8 and the WetSpass-M model aids in understanding the influence of LULC on groundwater recharge. This understanding can guide the development of effective strategies to improvement recharge rates in various areas.

To achieve this goal, the methods and data employed in this section are consistent with those outlined and used. In this scenario, all variables were held constant, with the exception of the land use/land cover for the year 1990.

3.5 General framework of the study

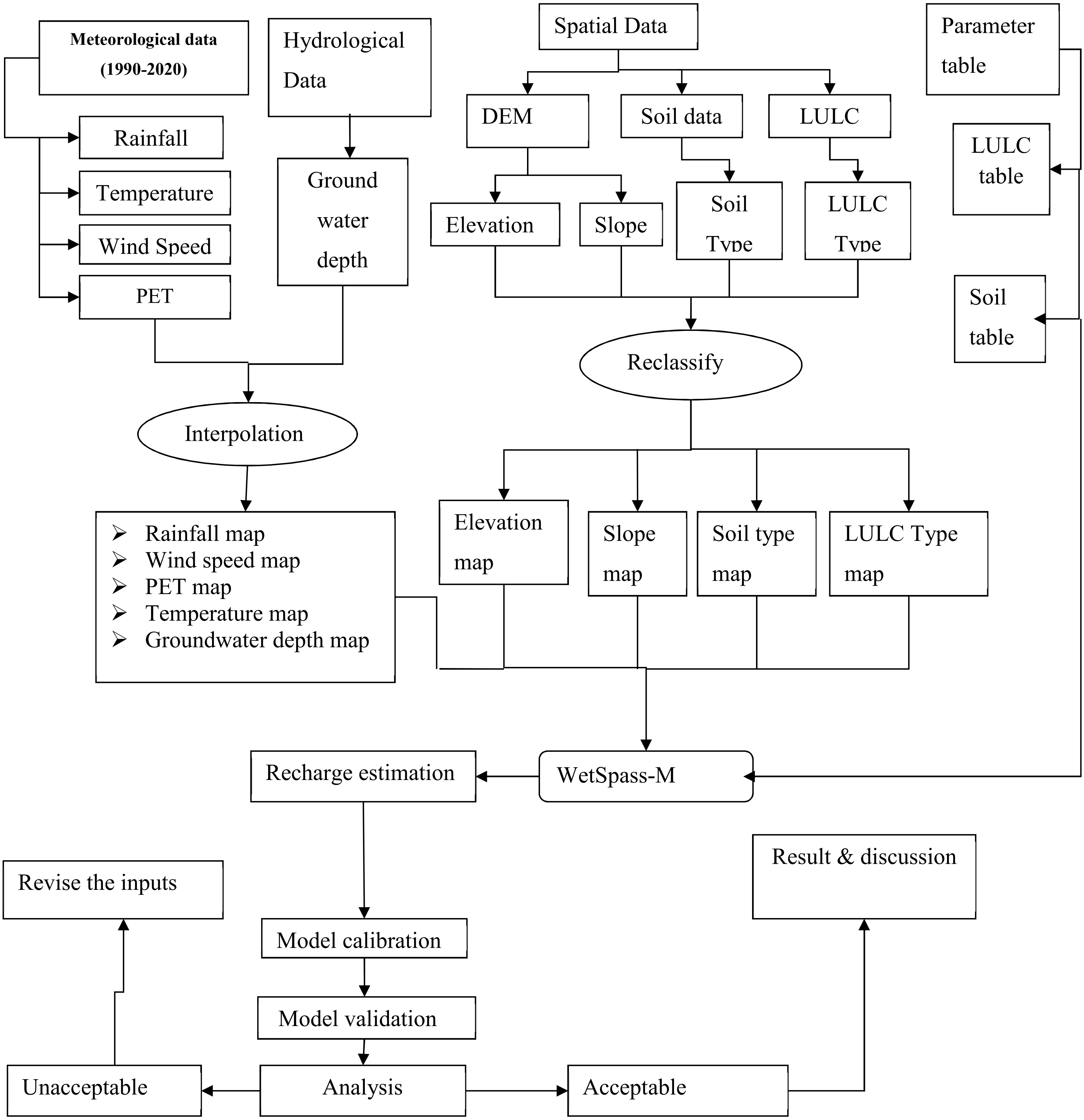


Figure 3.16 Flow chart depicting general work of this research

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Recharge estimation

Groundwater recharge estimation is the act of determining the quantifying of water that seeps through the Earth's surface to reach underground aquifers. This influx of water is essential for replenishing our groundwater supplies which serve as a critical source for drinking water, agricultural irrigation, and industrial activities. Precise estimation of groundwater recharge is a basis of responsible water resource management.

The task of estimating groundwater recharge presents significant challenges due to the complex interplay of factors involved. The rate of recharge can be influenced by variables such as the intensity of precipitation, the type of soil, the extent of vegetative cover, and the environment. A variety of estimation techniques exist, each with its own degree of complexity and precision. The direct methods involve the actual measurement of water percolating through the soil, utilizing tools like lysimeters and tracers. While these methods can provide accurate results they are often costly and require large effort.

The indirect methods techniques infer recharge rates from related measurements, such as changes in the water table, analysis of streamflow records, or monitoring soil moisture levels. These methods tend to be more feasible to implement but may loss some accuracy.

Modeling is computational groundwater flow models offer a way to simulate recharge processes by integrating diverse data inputs, including meteorological conditions, land usage patterns, and characteristics of aquifers. These models are sophisticated and necessitate specialized knowledge for effective application.

4.1.1 Model calibration

The WetSpass-M model, stream base flow cannot be taken as equal to recharge. The WetSpass-M model is designed to simulate various hydrological components separately, including surface runoff, evapotranspiration, and groundwater recharge. Each of these components is calculated based on different parameters and processes.

Stream base flow, which is part of the hydrological output of the model, typically represents the portion of streamflow that is sustained during dry periods and is primarily fed by groundwater discharge. On the other hand, recharge in the WetSpass-M model refers to the process by which water moves downward from surface water to groundwater. This is a separate component and is not directly equated to base flow in the model's calculations.

The calibration and validation processes for the WetSpass-M model, as described in the search results, involve adjusting parameters to match observed data for both surface runoff and base flow, but these are treated as distinct outputs from the model. The model's framework and its application in various studies emphasize the separate treatment and estimation of these hydrological components.

Therefore, while base flow and recharge are both related to groundwater, they represent different aspects of the hydrological cycle in the context of the WetSpass-M model, and one cannot be simply equated to the other.

The WetSpass-M model, surface runoff cannot be taken as equal to runoff. The model calculates surface runoff separately from total runoff.

The WetSpass-M model simulates the water balance components, including surface runoff, groundwater recharge, and actual evapotranspiration, for each raster cell. Surface runoff is calculated based on factors such as rainfall, interception, soil infiltration capacity, land use type, and soil texture.

Total runoff, on the other hand, is not explicitly mentioned in the WetSpass-M model's calculations. The model focuses on estimating surface runoff as one of the main water balance components. The WetSpass-M model calculates surface runoff in mm/month using a rational method based on actual surface runoff and soil parameters. Therefore, it is clear that surface runoff and total runoff are not considered equal in the WetSpass-M model, as the model specifically focuses on estimating surface runoff as a separate water balance component.

The summation of baseflow and surface runoff simulated by the WetSpass model was used to calibrate the model with ground observed streamflow data obtained from the Dedaba watershed as shown in table 12 appendices.

NSE of 0.89, a correlation of coefficient of determination R^2 of 0.97, and 23 percent of bias were obtained with the parameters of the optimal soil moisture alfa coefficient value of “x” = 9.5, LP = 0.95, interception parameter “a” = 9.5, and a runoff delay factor “x” = 0.9.

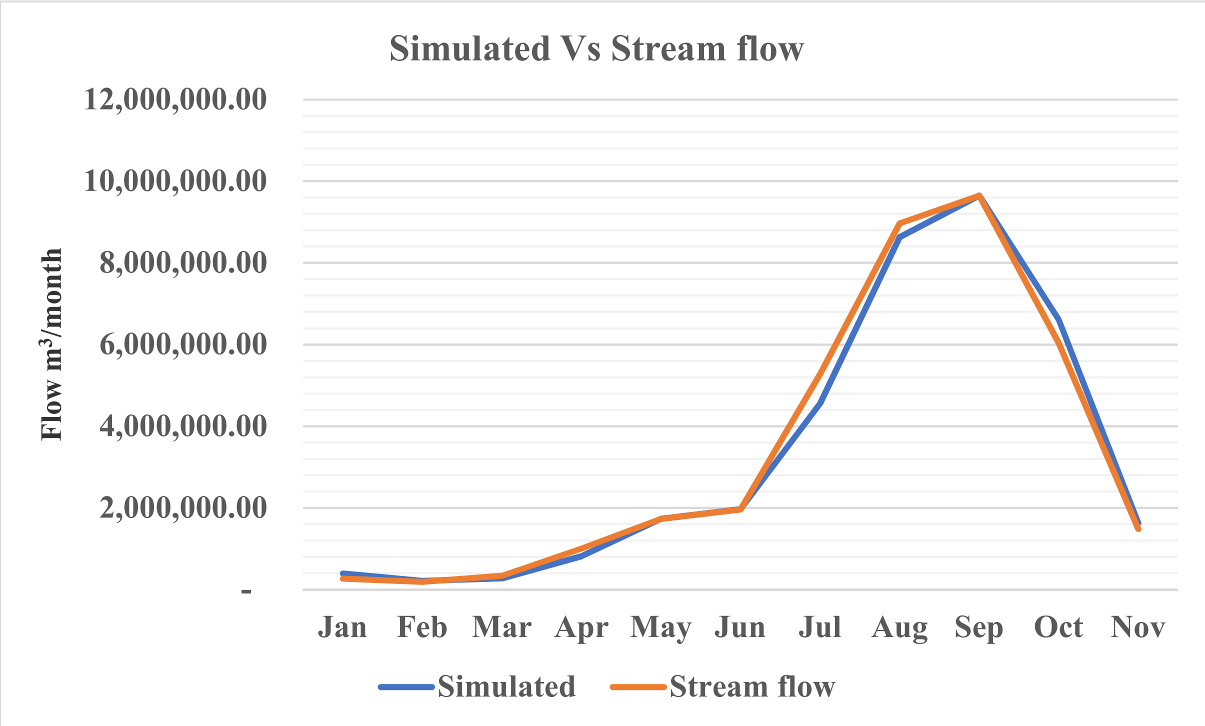


Figure 4.1 Compression between simulated and Stream flow data

4.1.2 Validation model

The observed data were obtained from Qore Woreda, West Arsi Zone Water and Energy Groundwater Level Depertement of water resource management which recorded the detailed yearly groundwater levels from about 3 monitoring points in Qore Woreda. A WetSpass-M modeling approach can be used to simulate groundwater table fluctuations and validate the accuracy of the estimated recharge rate. To validate the results of a model used for groundwater table fluctuation method, criteria can be considered. Comparison of simulated and observed groundwater table fluctuations: The simulated fluctuations must match closely with observed fluctuations to ensure that the model is accurate. Furthermore, the simulated groundwater recharge at corresponding positions in 2012 were extracted by ArcGIS 10.8. The simulated and measured groundwater recharges, which showed a good linear relationship with an R^2 of 0.79. Thus, we assumed that the water balance components simulated by the WetSpass-M model in 2010 and 2020 are still reasonable.

4.2. Model outputs

After running the WetSpass-M model, spatial grid maps of the watershed have been produced monthly. Effective runoff WetSpass-M model produces three main grid maps continuously with one run simulation. Hence, minimum and maximum values of surface runoff, actual evapotranspiration, and recharge were produced for the Dedaba watershed. Expressing surface runoff, actual evapotranspiration, and groundwater recharge in millimeters(mm) within the WetSpass-M model enhances the clarity, consistency, and applicability of hydrological data, making it a valuable tool for researchers and experts in the field of water resource management. The watershed simulated values were unique average values produced from each cell in the watershed as summarized in table 4.1 below. Hence, the following discussions explain the detail of these issues.

Table 4.1: Simulated monthly water balance components (mm)

Months	**Water Balance components (2020)**		
	Recharge	**Runoff**	**AET**
Jan	2.61	2.21	25.84
Feb	1.74	1.47	17.21
Mar	1.46	1.23	14.46
Apr	1.60	1.35	15.83
May	1.49	1.26	14.75
Jun	1.55	1.31	15.36
Jul	2.50	2.12	24.80
Aug	3.61	3.06	35.84
Sep	4.52	3.83	44.82
Oct	3.11	2.63	30.81
Nov	1.06	0.90	10.54
Dec	0.12	0.10	1.14

4.2.1 Actual evapotranspiration (AET)

The WetSpass-M model calculated the actual evapotranspiration as a sum of evaporations from the open water bodies, transpiration through vegetated cover, interception loss by vegetation, and evaporation from bare soil. Actual evapotranspiration is a major component of water balance to determine groundwater recharge of the Dedaba watershed. The result showed that a minimum and maximum value of 1.14mm and 44.82mm respectively with an average of 21.24mm of water was lost through evapotranspiration in a month from the watershed. On average, this accounts for 84.3% of the watershed's average rainfall (86.1mm). This is happened due to the high rate of radiation and the dry wind availability as well as the presence of different land use land covers in the study area. The Dedaba watershed is mostly covered by different vegetation like agriculture, and forest. This facilitates evapotranspiration by reducing surface runoff in the watershed.

The WetSpass model simulated the actual evapotranspiration monthly. To get the annual values for the water balance components of the watershed the monthly results have to be summed up from twelve months.

4.2.2 Surface runoff

A spatial long-term average monthly surface runoff simulated by the WetSpass model was presented in table 4.1 above. The model result shows that the annual value of runoff in the Dedaba watershed varies in the range from 0.1 mm to 3.83 mm as a minimum and maximum values respectively with a mean of 1.81 mm. The mean value accounted for about 7.2 % of the total annual average rainfall of the watershed. The runoff value was highly dependent on runoff coefficients. The runoff coefficient is also highly influenced by the change in soil moisture, infiltration capacity, land use/land cover, and the amount and intensity of rainfall, and also the spatial variation of surface runoff value in the watershed is highly dependent on different biophysical factors such as slope.

4.3.3 Groundwater recharge

The amount of infiltration-percolation into groundwater recharge depends on different factors such as slope, land use, soil texture, and groundwater level (Al Kuisi & El-Naqa, 2013). There were different models used to estimate recharge in a given area depending on actual areal conditions.

In this case, the WetSpass-m model estimates the long-term monthly spatiotemporal distribution of groundwater recharge subtracting surface runoff and evapotranspiration from precipitation. The model determined the average monthly groundwater recharge depending on different input variables. The recharge was estimated as the residual of the water balance components from precipitation. Due to this, it responded to variations with varying in different input variables and model parameters. According to the WetSpass result, the annual recharge of the Dedaba watershed is between 0.12mm and 4.52mm as a minimum and maximum value respectively with a mean of 2.14mm. The mean value accounts for about 8.49% of the total annual average rainfall of the watershed.

Therefore, it could be said that the WetSpass model has worked well in Dedaba watershed and has simulated hydrological water balance components efficiently.

4.3.1 Estimate the distributed seasonal and annual groundwater recharge

The analysis of average seasonal data for climatic variables plays a crucial role in enhancing the understanding of groundwater dynamics. Seasonal fluctuations, particularly in rainfall, directly influence groundwater recharge rates. By accurately capturing these variations, more precise models of groundwater replenishment can be developed. For instance, during the rainy season (Kiremt), which occurs from June to September in the studied watershed, there is a significant increase in precipitation that leads to higher groundwater recharge rates compared to the dry season (Bega). These seasonal differences in rainfall demonstrate the direct relationship between precipitation and recharge rates, highlighting the importance of incorporating seasonal variations in hydrological modelling.

The use of constant values for land use and other environmental parameters, while simplifying the modelling process, underscores their importance in determining recharge rates. Although these factors remain unchanged in the model, they represent critical underlying conditions that can significantly affect recharge dynamics.

The implications of employing seasonal-based modelling for sustainable water resource management are substantial. By understanding the seasonal recharge patterns, water extraction and usage can be better planned, helping to prevent the over-extraction of groundwater resources. This is particularly crucial in regions where water demand is increasing, and groundwater is a primary resource. Moreover, the model can identify areas at risk of groundwater depletion, enabling policymakers to implement conservation efforts where necessary.

The use of the WetSpass-M model with averaged seasonal inputs and constant environmental parameters provided a strong and reliable framework for estimating groundwater recharge.

Table 4.2 Simulated Seasonally water balance components (mm)

Season	**Months**	**Recharge**
Winter (Bega)	December to February	7.6
Spring (Tseday)	March to May	14.1
Summer (Keremt)	June to August	25.4
Autumn (Belg)	September to November	12.1

On an annual scale, the model estimated groundwater recharge across the watershed to range from 0.46 to 65.4 mm/year, averaging 37.47 mm/year.

4.3.4 Impact of land use change on groundwater recharge

Running the WetSpass-M model on three distinct images consistently generates monthly spatial grid maps of the watershed. Groundwater recharge can be significantly affected by changes in land use and land cover (LULC). As previously outlined in the methods, all input parameters for the WetSpaas-M model remain constant, with the exception of LULC changes for 1990, 2005, and 2020. Over these three decades, the recharge component of the water balance, as simulated by the WetSpass-M model, has exhibited notable variations.

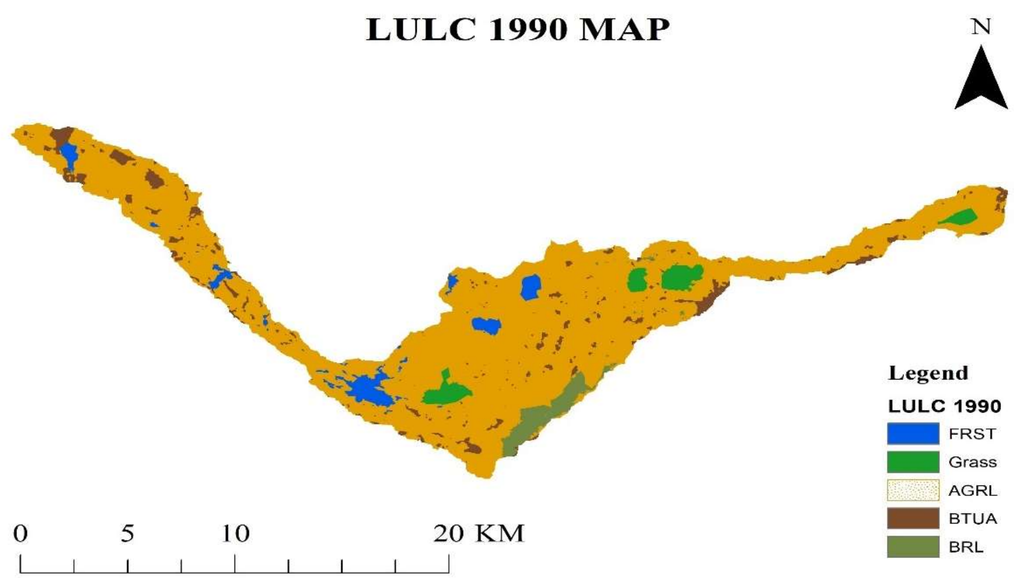


Figure 4.2 Maps of land cover changes in Dedaba watershed in 1990

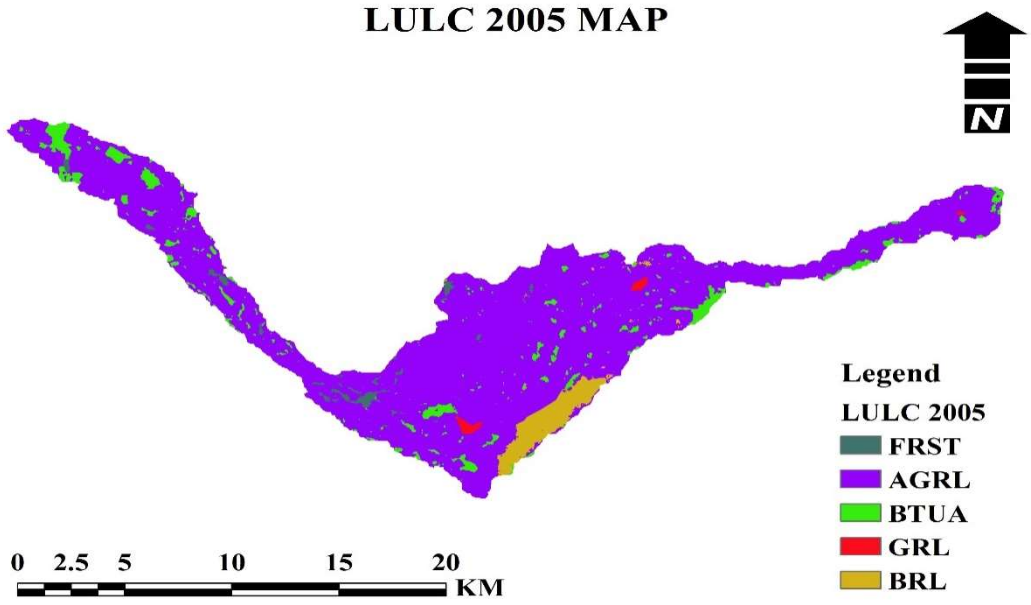


Figure 4.3 Maps of land cover changes in Dedaba watershed in 2005

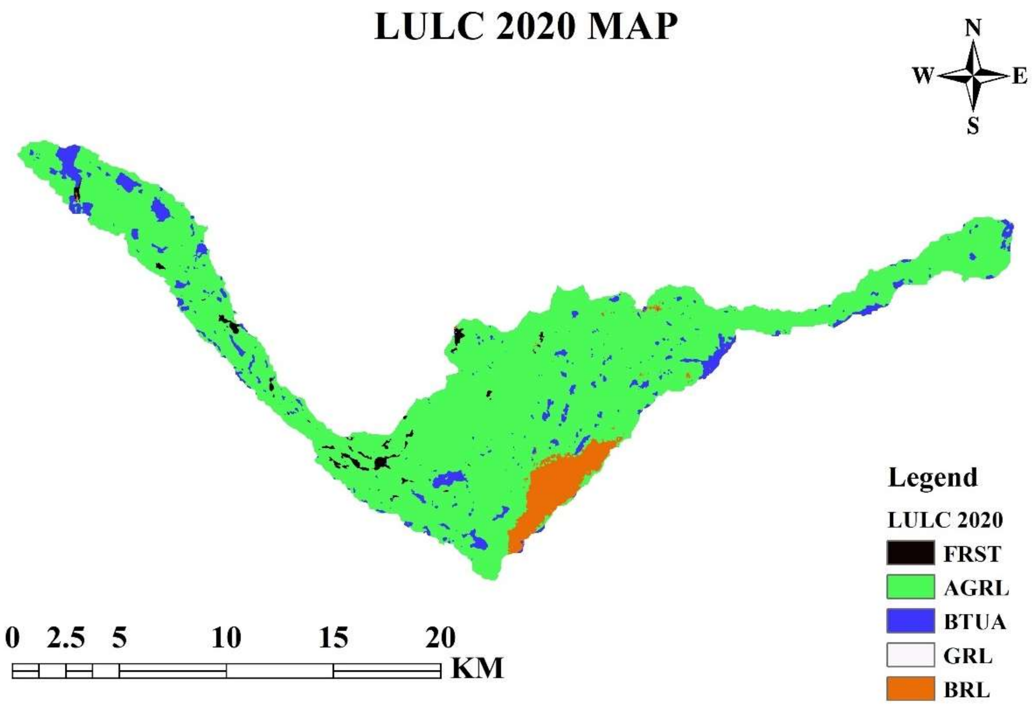


Figure 4.4 Maps of land cover changes in Dedaba watershed in 2020

The LULC analyses showed that the occurrence of LULCC in the Dedaba watershed. The result was shown in the percent of temporal change and rate of change in table 4.2 below.

Table 4.3 Area of LULCC, temporal changes, and rate of change

LULC classes		AGRL	BRL	GRL	FRST	BTUA
Area in Km²	1990	200.63	14.72	22.86	44.25	13.71
	2005	206.4	15.62	19.31	34.65	20.19
	2020	214.13	15.73	10.57	30.21	25.53
Area in percent	1990	67.74	4.97	7.72	14.94	4.63
	2005	69.69	5.27	6.52	11.7	6.82
	2020	72.3	5.31	3.57	10.2	8.62
Temporal change (%)	1990-2005	2.88	6.11	-15.53	-21.69	47.26
	1990-2020	6.73	6.86	-53.76	-31.73	86.21
Rate of Change (% /yr)	1990-2005	0.19	0.41	-1.04	-1.45	3.15
	1990-2020	0.22	0.23	-1.79	-1.06	2.87

The table provided shows the (LULC) classes over three different years: 1990, 2005, and 2020. The area of AGRL increased from 200.63 km² in 1990 to 214.13 km² in 2020, which is a 6.73% increase over 30 years. This translates to an annual growth rate of 0.22%. The area of BRL slightly increased from 14.72 km² in 1990 to 15.73 km² in 2020, a 6.86% increase over 30 years. The annual growth rate is 0.23%. The area of GRL significantly decreased from 22.86 km² in 1990 to 10.57 km² in 2020, a 53.76% decrease over 30 years. The annual decrease rate is 1.79%. The area of FRST decreased from 44.25 km² in 1990 to 30.21 km² in 2020, a 31.73% decrease over 30 years. The annual decrease rate is 1.06%. The area of BTUA increased from 13.71 km² in 1990 to 25.53 km² in 2020, an 86.21% increase over 30 years. This translates to an annual growth rate of 2.87%.

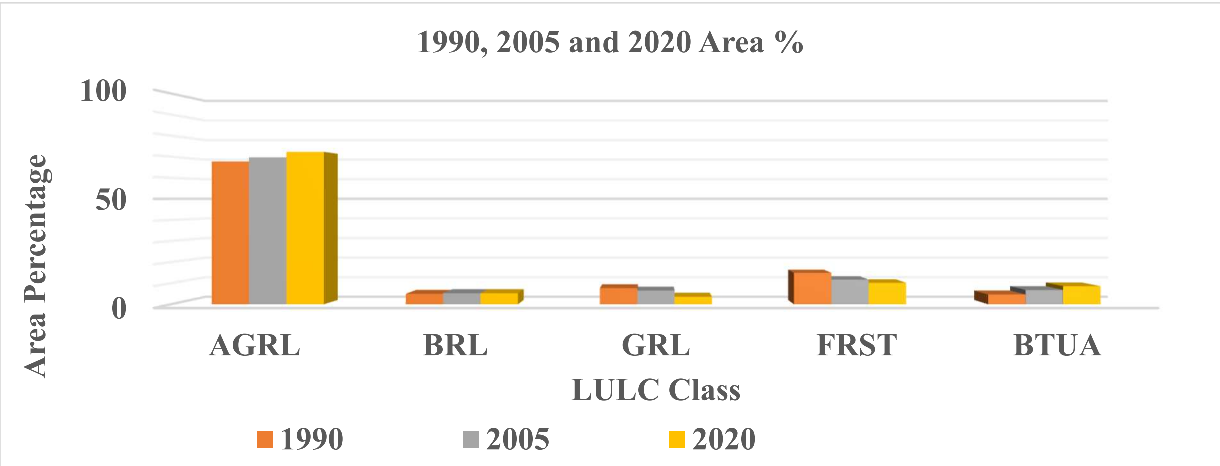


Figure 4.5 Area percentage of different land use types in 1990, 2005 and 2020

Table 4.4 The model result of water balance components in 1990, 2005 and 2020.

Month	Water Balance components (2020)			Water Balance components (2005)			Water Balance components (1990)		
	Recharge	**Runoff**	**AET**	**Recharge**	**Runoff**	**AET**	**Recharge**	**Runoff**	**AET**
Jan	2.61	2.21	25.84	2.84	2.16	25.50	3.29	2.10	26.49
Feb	1.74	1.47	17.21	1.84	1.40	17.38	2.13	1.40	17.64
Mar	1.46	1.23	14.46	1.47	1.21	14.60	1.71	1.17	14.82
Apr	1.60	1.35	15.83	1.66	1.20	15.40	1.93	1.29	16.23
May	1.49	1.26	14.75	1.50	1.23	14.90	1.74	1.21	15.12
Jun	1.55	1.31	15.36	1.59	1.29	15.51	1.85	1.25	14.80
Jul	2.50	2.12	24.80	2.70	2.10	25.05	3.13	2.01	25.42
Aug	3.61	3.06	35.84	4.08	2.93	35.40	4.74	2.91	36.75
Sep	4.52	3.83	44.82	5.20	3.63	45.26	6.03	3.64	45.94
Oct	3.11	2.63	30.81	3.48	2.58	31.12	4.04	2.50	30.03
Nov	1.06	0.90	10.54	1.07	0.70	9.86	1.24	0.86	10.81
Dec	0.12	0.10	1.14	0.12	0.10	1.16	0.13	0.09	1.17

Focusing on the recharge results from 1990, the WetSpass-M model's simulated recharge rates were generally higher than in later years. Recharge commenced at 3.29 mm in January, reached a peak of 6.03 mm in September, and hit a low of 0.13 mm in December.

In 2005, recharge rates across all months showed a minor decrease compared to 1990. The WetSpass-M model's simulated recharge started at 2.84 mm in January, peaked at 5.2 mm in September, and fell to its lowest at 0.12 mm in December.

By 2020, the WetSpass-M model's simulated recharge rates had declined even more. The year began with a recharge rate of 2.61 mm in January, reached a high of 4.52 mm in September, and concluded with the lowest rate of 0.12 mm in December.

The result indicates a general downward trend in recharge rates from 1990 to 2020, as simulated by the WetSpass-M model. This trend could be linked to changes in land use and land cover over these years, which can have a substantial impact on groundwater recharge, thereby affecting the availability and sustainability of water resources.

CHAPTER FIVE: SUMMARY, CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The WetSpass-M model is a powerful tool for estimating groundwater recharge in regions with sparse data. It uses a variety of spatially-gridded parameters, such as precipitation, evapotranspiration, land cover, and soil properties, to simulate the hydrologic cycle at a high resolution. By tracking water fluxes between different surface and subsurface compartments, the model can accurately calculate the amount and timing of recharge under different climatic conditions and land use scenarios.

One major advantage of the WetSpass-M model is its flexibility and adaptability to various geographical settings. The model can be calibrated and validated using monitoring data and field observations, which improves its accuracy and reliability. Furthermore, the model can be used to evaluate the impact of different management practices, such as irrigation, vegetation restoration, and land use change, on groundwater recharge and availability. This can be particularly valuable for decision-makers who need to balance competing demands for water resources.

The catchment's land use, soil type, hydrometeorology, topography, slope, and geology all have been researched in order to assess groundwater recharge. The emphasis was placed on gathering primary field information as well as existing data in order to create complete information pertinent to estimating the areal distribution of recharge and the other water balance component of the watershed.

The water balance components of the vegetated area, bare-soil, open-water bodies, and impervious land surfaces are used to compute the total water balance of a raster cell for a given watershed using the WetSpass-M model and the total evapotranspiration, surface runoff, and groundwater recharge of a raster cell was calculated. For this calculation generally, two types of data such as meteor-hydrological and spatial data were used. Comparing the model result with the results obtained by different researchers in different areas the model showed good agreement with the study area.

The impacts of LULC changes in the study area using this model by taking the three image of different years that means 1990, 2005 and 2020 satellite images. The result shown that three of LULC parameters were decreased and two of LULC were increased including built-up area and the urban land promotes surface runoff and decreases groundwater recharges.

5.2 Recommendation

In light of the key findings from this study and the conclusions drawn, the following recommendations are proposed.

- To improve water resource planning and management, it is recommended that the WetSpass-M model be tested using additional data sources, such as continuous groundwater monitoring from wells and alternative direct recharge estimation methods. Incorporating these data will enhance the model's accuracy and reliability, providing a more comprehensive understanding of the water system, especially in relation to groundwater dynamics and recharge rates. This expanded testing can help identify potential gaps and improve decision-making in water resource management strategies.
- In areas where the slope exceeds 8%, it is crucial to prioritize afforestation and adopt water-conserving farming practices. The steeper slope increases the risk of soil erosion and water runoff, making it difficult for rainwater to naturally infiltrate the ground and recharge aquifers. By planting trees (afforestation), the soil structure is stabilized, reducing erosion and promoting better water retention. Additionally, implementing farming techniques that minimize water usage and enhance soil moisture retention can further improve sustainability in these regions. Together with these practices, artificial recharge methods such as constructing recharge ponds or using trenches to direct water into the soil should be actively encouraged to enhance groundwater recharge, counteract the effects of runoff, and support long-term water availability.
- Future studies on estimating groundwater recharge should place a strong emphasis on incorporating the impacts of climate change. This can be achieved by integrating climate projections into the WetSpass-M models used for groundwater recharge estimation. In this way, researchers will be able to better understand how changing climate conditions such as variations in precipitation patterns, temperature increases, and extreme weather events affect the processes that contribute to groundwater recharge. This integration will enhance the accuracy and reliability of groundwater recharge estimates, allowing for more effective water resource management and planning in the face of ongoing climate change.

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TABLES IN APPENDICES

Table 1: Long-term average monthly wind speed (m/s)

Station Name	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Shashemane	1.2	1.2	1.4	1.2	1.2	1.5	1.2	1	0.9	0.8	1	1.1
Kuyera	1.3	1.3	1.5	1.3	1.3	1.6	1.3	1.2	0.9	0.8	1	1.1
Bokoj	1	1	1	1	0.9	1.1	1	1	1	0.9	1	1
Kofale	1.6	1.6	1.8	2.1	2.1	1.9	1.6	1.5	1.4	2.2	2	1.8

Source: National Meteorological Agency of Ethiopia

Table 2: Long-term average monthly temperature (ºC)

Station Name	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Shashemane	17.1	18.1	18.9	19.4	18.7	17.8	17.0	17.4	17.6	17.5	16.6	16.3
Kuyera	16.6	17.6	18.6	19.2	18.5	17.6	16.7	17.2	17.3	17.2	16.2	15.9
Bokoj	13.4	14.1	14.7	14.3	13.7	12.7	11.6	11.5	12.1	12.1	12.4	12.7
Kofale	14.0	15.0	15.5	14.8	14.8	14.3	13.8	13.5	13.6	14.0	13.4	13.2

Source: National Meteorological Agency of Ethiopia

Table 3: Typical values of specific yield for different soil types.

Soil	Sy	Soil	Sy
Clay	0.02–0.035	Medium sands	0.09–0.13
Loam	0.02–0.05	Medium coarse sand	0.10–0.15
Sandy loam	0.03–0.06	Coarse sand	0.11–0.15
Silty sand	0.06–0.1	Sandstone	0.02–0.03
Fine sand	0.08–0.12	Limestone	0.008–0.10

Source: USGS was released in 1967

Table 4: Long term average monthly rainfall (mm)

Station Name	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Shashemane	31	82	77.3	106.2	92.5	91.3	148.5	126.4	131.6	60.1	31.4	3.5
Kuyera	31.7	80.5	71.1	100.7	91	95	152.5	126.4	137	63.1	30.4	4
Bokoj	30.7	42.8	74.8	81.5	99.7	116.7	200.2	175.3	89.1	53.4	18.5	10.3
Kofale	29.2	61.1	112.9	149.6	89.5	113.4	144.7	150.1	142.4	98.4	56.6	25.6

Source: National Meteorological Agency of Ethiopia

Table 5: Long-term average monthly groundwater depth (m)

Well Name	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Watara Shagule	48.2	48.2	48.1	48.1	48.1	48.1	48.1	48.1	48.0	48.2	48.2	48.2
Harago Lemano	38.5	38.2	38.2	38.1	38.1	38.1	38.1	38.2	38.2	38.2	38.3	38.5
Jengela Wandera	27.5	27.4	27.3	27.0	27.2	27.1	26.9	26.2	27.2	27.3	27.6	27.6
Moke Gurmicho	220.0	220.0	220.0	220.0	220.0	220.0	220.0	220.0	220.0	220.0	220.0	220.0
Gobe health Centre	13.7	13.7	13.6	13.3	13.4	13.3	13.2	13.5	12.9	13.6	13.8	13.8
Gode Kerso	139.5	139.5	139.4	139.3	139.4	139.4	139.3	139.4	139.3	139.5	139.5	139.5

Source: West Arsi Zone water and energy office

Table 6: Long-term average monthly groundwater change in water table height (mm)

Well Name	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Wondo Gode	60.5	58.4	57.1	63.5	66.2	88.6	102.0	103.0	105.0	90.0	59.0	58.2
Sigida	65.3	63.1	61.7	68.6	71.5	95.7	110.2	111.2	113.4	97.2	63.7	62.9
Kachema	66.6	64.2	62.8	69.9	72.8	97.5	112.2	113.3	115.5	99.0	64.9	64.0

Source: Qore Woreda water and energy office

Table 7: Land use/cover lookup parameter table

Code	LUSE_ TYPE	RUNOFF _ VEG	VEG _ AREA	BARE _ AREA	IMP_ AREA	OPEN W_ AREA	ROOT_ DEPTH	LAI	MIN_ STOM	VEG_ HEIGHT	nManing	Land Factor	Aerodyn Resistance
2	build-up	Grass	0.5	0	0.5	0	0.3	2	100	0.12	0.04	0.5	212.01
7	barea land	bare soil	0	1	0	0	0.05	0	110	0.001	0.09	0.222	426.67
21	agriculture	Crop (Maize)	0.8	0.2	0	0	0.4	4	180	0.6	0.037	0.541	115.01
33	forest	Forest	1	0	0	0	2	5	375	16	0.1	0.2	28.10
307	grass land	Grass	1	0	0	0	0.3	2	140	0.12	0.035	0.571	212.01

Table 8: Soil parameter lookup table

ID	SOIL	FIELDCAPAC	WILTINGPNT	PAW	RESIDUAL WC	A1	EVAPODEPTH	TENSIONHHT	P_FRAC_SUM	P_FRAC_WIN	Teta
12	clay	0.46	0.33	0.13	0.09	0.21	0.05	0.37	0.95	0.85	0.852
5	loam	0.25	0.12	0.13	0.027	0.37	0.05	0.11	0.15	0.02	0.333
9	Clay loam	0.33	0.19	0.14	0.075	0.27	0.05	0.26	0.62	0.41	0.493

Soil table attributes

Number = Soil type number; Soil = Soil type (texture); Fieldcapac = Field capacity; Wiltingpnt = Wilting Point; PAW = Plant available water content; Residual = Residual water content; A1 = Calibration parameter dependent on the sand content of the soil; Evapodepth = Bare soil evaporation depth; Tensionsh = Tension saturated height; Pfrac_sum = Fraction of summer precipitation contributing to Hortonian runoff; P_frac_win = Fraction of winter precipitation contributing to Hortonian runoff.

Table 9: Four months rainy days in the Dedaba watershed

Code	**Rainy Days**	**Code**	**Rainy Days**
1	3	25	6
2	2	26	9
3	1	27	8
4	4	28	14
5	5	29	12
6	17	30	4
7	12	31	7
8	14	32	10
9	8	33	9
10	12	34	12
11	4	35	15
12	9	36	18
13	10	37	19
14	11	38	11
15	14	39	2
16	3	40	3
17	4	41	4
18	1	42	1
19	10	43	4
20	6	44	7
21	5	45	5
22	2	46	14
23	3	47	14
24	7	48	19

Table 10: Simulated monthly stream flow data (m^3/month)

Month	Q_{surf}[m^3/month]	Q_b[m^3/month]	Q_{surf}[m^3/month] + Q_b(m^3/month)
Jan	21,728.90	373,342.06	395,070.97
Feb	14,877.49	197,658.14	212,535.64
Mar	17,652.90	253,930.17	271,583.07
Apr	122,212.38	692,536.83	814,749.21
May	519,837.18	1,212,953.41	1,732,790.59
Jun	786,527.85	1,179,791.78	1,966,319.63
Jul	3,877,836.12	684,324.02	4,562,160.14
Aug	7,767,750.59	863,083.40	8,630,833.99
Sep	8,975,868.72	675,603.02	9,651,471.74
Oct	5,878,663.01	726,576.33	6,605,239.34
Nov	324,544.49	1,298,177.95	1,622,722.44
Dec	23,232.68	363,978.67	387,211.35

Table 11: Simulated versus Stream flow monthly stream flow data (m^3/month)

Month	Simulated	Stream flow
Jan	395,070.97	263,380.65
Feb	212,535.64	185,620.65
Mar	271,583.07	335,287.74
Apr	814,749.21	1,005,863.23
May	1,732,790.59	1,729,114.84
Jun	1,966,319.63	1,962,394.84
Jul	4,562,160.14	5,285,171.61
Aug	8,630,833.99	8,970,828.39
Sep	9,651,471.74	9,644,748.39
Oct	6,605,239.34	6,038,523.87
Nov	1,622,722.44	1,483,292.90
Dec	387,211.35	352,010.32

Table 12: Stream flow monthly average (m^3/Sec)

year	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
1990	0.11	0.14	0.16	0.07	0.44	0.17	1.81	3.95	2.78	2.7	0.83	0.09
1991	0.08	0.03	0.08	0.13	0.18	1.55	3.06	2.03	3.03	1.07	0.52	0.09
1992	0.05	0.01	0.05	0.25	1.2	1.33	1.69	1.39	2.66	1.92	0.69	0.15
1993	0.17	0.26	0.1	0.38	1.75	2.13	4.13	4.27	3.91	4.34	1.18	0.23
1994	0.13	0.1	0.14	0.13	0.22	0.31	5.16	4.25	4.19	1.15	0.23	0.13
1995	0.09	0.1	0.22	0.46	0.72	0.39	1.46	4.08	3.1	0.89	0.21	0.15
1996	0.2	0.07	0.19	0.53	1.14	2.5	2.19	4.55	1.9	1.22	0.28	0.13
1997	0.19	0.05	0.06	0.64	0.32	0.97	3.09	4.28	1.88	2.82	1.41	0.36
1998	0.21	0.1	0.24	0.31	1.06	1.36	2.53	2.66	2.22	4.52	0.83	0.15
1999	0.08	0.05	0.14	0.07	0.09	0.61	2.27	3.4	2.15	2.3	0.52	0.15
2000	0.11	0.07	0.05	0.13	0.18	0.35	1.43	4.19	2.78	3.88	0.69	0.2
2001	0.11	0.1	0.38	0.25	0.4	2.12	3.47	4.44	3.03	1.98	0.38	0.18
2002	0.13	0.06	0.16	0.06	0.25	0.28	4.27	1.77	2.66	1.07	0.2	0.17
2003	0.08	0.05	0.08	0.58	0.44	0.21	1.42	2.34	4.47	2.28	0.52	0.15
2004	0.11	0.07	0.05	0.13	0.18	0.16	4.15	2.03	3.06	3.59	0.28	0.09
2005	0.08	0.04	0.13	0.2	1.2	0.43	1.81	2.25	4.72	1.74	0.4	0.09
2006	0.05	0.08	0.2	1.72	2.19	0.88	3.06	4.16	5.15	1.93	0.48	0.15
2007	0.1	0.16	0.1	0.27	0.34	0.51	1.69	3.95	6.58	2.7	0.33	0.15
2008	0.08	0.02	0.01	0.03	0.13	0.16	0.49	2.03	4.29	1.07	3.26	0.1
2009	0.09	0.02	0.03	0.2	1.2	0.17	0.27	1.39	2.3	1.92	0.11	0.09
2010	0.19	0.14	0.34	1.35	3.33	1.55	3.05	3.21	5.67	1.6	0.22	0.08
2011	0.08	0.03	0.05	0.03	0.23	1.33	0.44	4.35	3.94	4.38	0.59	0.12
2012	0.04	0.01	0	0.14	0.21	0.09	0.11	2.64	5.81	1.42	0.09	0.03
2013	0.01	0	0.09	0.1	0.41	0.21	1.72	7.96	5.64	3.76	0.29	0.06
2014	0.03	0.12	0.07	0.28	0.82	0.2	0.99	7.29	6.49	5.01	0.26	0.09
2015	0.04	0.02	0.08	0.02	0.07	0.23	1.51	4.65	5.78	2.7	0.63	0.15
2016	0.08	0.1	0.14	0.2	1.06	0.88	1.69	2.25	2.22	1.74	0.52	0.18
2017	0.11	0.06	0.05	1.72	0.09	0.51	0.49	4.16	4.47	1.93	0.69	0.17
2018	0.11	0.05	0.38	0.27	0.18	0.16	0.27	3.95	2.78	1.6	0.38	0.15
2019	0.13	0.07	0.16	0.03	0.4	0.17	3.05	2.03	3.03	1.07	0.2	0.09
2020	0.08	0.04	0.08	1.35	0.25	1.55	0.44	1.39	2.66	1.92	0.52	0.09

Source: Ministry of water, Irrigation and Energy