ASSESSING SPATIAL AND TEMPORAL VARIATION OF GROUNDWATER RECHARGE; CASE STUDY NAIROBI AQUIFER SUITE.

by

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Department of Geomatic Engineering and Geospatial Information Systems (GEGIS)

DECLARATION

I declare that this project is my own work and has not been submitted by anybody else in any other university for the award of any degree to the best of my knowledge.

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CERTIFICATION

This project has been submitted for examination with my approval as the candidate's supervisor.

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Abstract

Groundwater recharge refers to the quantity of water that seeps into the subsurface and is essential for managing groundwater resources and setting budgets of its hydrogeological nature. The assessment of spatial and temporal distribution of groundwater recharge is a required input to groundwater modeling of the Nairobi aquifer system (NAS) at different management scenarios. It is acknowledged that climate change and variability was cause for concern in the management of the resource. Moreover it has been identified that insufficient scientific information and limited understanding of groundwater due to inadequate monitoring, are major challenges plaguing the resource. WetSpass-M, a GIS-based spatially distributed water balance model, was implemented to assess monthly and annual averages of groundwater recharge in the upper Athi basin for the period between 2008 and 2020. Trend analysis of the simulated recharge maps was performed for the period between 2008 and 2020 using the Mann Kendall test. The simulation of groundwater recharge for the year 2024 was done using a random forest model. The basic relevant input-data for the model was prepared using the ArcGIS software. The datasets comprise of monthly climate records (e.g., rainfall, temperature, windspeed), land cover, soil map, groundwater depth and slope.

Recharge values between for the year 2008 ranged from 162mm to -609mm. The year 2012 values ranged from 323mm and -672mm. The recharge values for the year 2016 ranged from 307mm to -627mm. For the year 2020, recharge values ranged from 496mm to -515mm. Groundwater recharge represented 8% of the total precipitation. The average recharge trend was -0.03/month for the area at a level of significance of 54.4% which suggests a lack of monotonic trend. The predicted recharge for the year 2024 ranged from 386mm and -367mm. The study further showed that recharge mostly occurs in the wet months of April, May and November. The observations made

in 2008 showed that the drought occurrence in that period affected groundwater recharge as precipitation was low contributing only 1%. Significant amounts of precipitation, as observed in the research, was distributed to surface runoff (75%) during wet seasons while only 8% is recharged. The sub basin also lost significant amounts of groundwater to evapotranspiration (60%) during the dry seasons.

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Acronyms and abbreviations

W.R.A. Water Resources Authority

N.A.S. Nairobi Aquifer Suite

WETSPASS Water and Energy Transfer between Soil, Plants and Atmosphere under quasi-Steady State

G.I.S Geographical Information Systems

TBL Table of values

PET Potential Evapotranspiration

ET Evapotranspiration

DEM Digital Elevation Model

ASCII American Standard Code for Information Exchange

USDA United States Department of Agriculture

HWSD Harmonized World Soil Database

RS Remote Sensing

RF Random Forest

CART Classification and Regression Tree

KNN K-Nearest Neighbour

RMSE Root Mean Square

MAE Mean Absolute Error

NSE Nesh Sutcliffe Efficiency

LULC Land use / Land Cover

LST Land Surface Temperature

1. INTRODUCTION

1.1 Background of the study

Water is crucial in sustaining life on earth. In addition, it is considered to be at the center of every development (Ochungo et al., 2019). Water can be sourced from rivers, streams, reservoirs, springs, and groundwater.

Groundwater is described as the amount of water stored beneath the Earth's crust through wells, tunnels, or drainage systems or by pumping. Furthermore, it can be defined as the water present in the zone of saturation below the ground. Groundwater occurrence is governed by Landforms, structural features and topography (Ahirwar, 2020). It accounts for 22% of the world's total fresh water and is considered to be drought buffer for many cities (Ochungo et al., 2019). Studies have shown that groundwater is the most extracted raw material with the global withdrawal estimated to be between 600 and 700 km^3 / year. It is considered as the world's largest fresh water resource essential in the sustainability of diverse ecosystems, that is important in providing water security and critical to food security (Roy et al., 2020). In addition, groundwater is an important source for water supply in various capacities (Ravijar, 2017).

According to the World Bank, it is estimated that a third of the world's population depends on groundwater for consumption. According to the Africa water vision 2025 report, 75% of the population depends on groundwater as a main source for drinking water as well as for agricultural and industrial use. Due to deficiencies in available water resources in Kenya, groundwater has increasingly been used as an alternative to meet the water demands of the population in both urban and rural areas. A significant population within the Greater Nairobi region depends on it for consumption. It is estimated that it supports 60% of the water needs within the region (Mumma et al. 2011). Groundwater dependence is expected to increase due to an increasing population and climate variability that leads to the decline in reliability of alternative water resources (Oiro et al. 2020). Therefore, it is crucial to understand groundwater dynamics which is necessary for groundwater management and sustainability. In order to achieve sustainability, it is considered good practice to study both abstraction and recharge. Groundwater abstraction is described as the act of withdrawing water from resources that are beneath the earth's surface for consumption.

Groundwater recharge is described as the result of flow of water underneath reaching the saturated zone (Ahirwar, 2020). It is an important component of the hydrological cycles that is significant in maintaining water balance at local, regional and global scale (Fauzia et al. 2021). Factors that govern groundwater flow are rock types and their structural properties, topography, drainage network, landform pattern, Land use and land cover patterns as well as meteorological conditions (Ahirwar, 2020).

Groundwater abstraction is important to meeting fundamental human requirements on both short and long time periods. Estimating groundwater recharge is critical in water resource management, especially in places where groundwater is critical for local water supply. Exact calculation of regional groundwater recharge necessitates a thorough understanding of the area's hydrological processes, which may be significantly affected by global change and human activities (Oiro et al., 2020).

Several methods have been developed with the intention of assessing and quantifying groundwater recharge. To simulate and quantify spatial variation in groundwater recharge, a set of hydrological models has been created. In ungauged basins, physically dispersed models such as MIKE SHE (System Hydrological European) have done well. TOPMODEL (Topographic Hydrologic Model) is useful for estimating runoff zones in hilly locations. The SWAT (Soil and Water Assessment Tool) has been widely used to forecast the impacts of various soil textures, plant covers, and land-use on water production, sediment yield, and non-point source pollution, which requires a huge number of complex factors (Zhang et al., 2017). The WetSpass model takes multiple influencing elements into consideration, including land-use type, terrain, temperature, precipitation, and wind speed, and can assess the long-term consequences of urbanization on the water regime in a watershed. More significantly, it is highly configurable and responds to new parameter definitions (Abdollahi et al., 2016).

Evaluating seasonal and yearly changes in water resources, particularly runoff, evapotranspiration, and recharge, is required for effective and sustainable groundwater management. Thorough understanding of watershed physical and biological features is essential since groundwater resources are susceptible to climatic variables, geological formation, topography, soil qualities and land-use types.

Identification of a watershed's hydrological and biophysical features is required for accurate estimation of groundwater resources. Regional groundwater models used to analyze groundwater systems (infiltration–discharge relationships) are frequently steady state and, as a result, require long-term average recharge input. The geographical variation in recharge, on the other hand, might be substantial owing to dispersed land-use, soil type, slope, and so on, and should be accounted for in regional groundwater models (Mathenge et al., 2020).

The rate of groundwater recharge varies based on environmental parameters such as topographic, meteorological, hydrological, and hydrogeological features, among others. Groundwater recharge study on a large and complicated scale is utilized for dependability and accuracy by numerical models that are beneficial for spatial analysis and conjunction with Geographic

Information System (GIS) in terms of offering a versatile toolset for resource management (Rwanga et al., 2013).

The modified WetSpass-M model is a raster-based water balance model that divides precipitation into interception, surface runoff, evapotranspiration, and recharge for each grid cell. The fundamental input includes distributed land use, soil texture, groundwater depth, slope, and climatic data (rainfall, potential evapotranspiration, number of wet days, wind, and temperature). To handle land-use variability inside the cell, four sub-cell fractions for each land-use class are specified per grid cell: vegetative cover, bare soil, open water, and impervious surface (Abdollahi et al., 2017).

Because the catchment's rainfall is seasonal, the tributaries and the main river are mostly ephemeral. As a result, groundwater is used not just for drinking but also for household and, in certain circumstances, agricultural purposes. Despite the fact that this groundwater is recharged by precipitation, it is being used without a fundamental understanding of the recharge quantity and its area distribution, as well as the spatial and temporal variation of the other water balance components, which creates a major challenge for groundwater resource management (Baychiken et al., 2018).

Large aquifer characteristics, like transmissivities, storage coefficients, and comparable quantities, are difficult to estimate with adequate precision. Large aquifer modeling appears to be a virtually impossible undertaking. However, the information on fluxes into and out of the storage is critical for water availability. Fortunately, several forms of remote sensing data are now accessible for evaluating the water balance of an underground reservoir. Precipitation, surface runoff, evapotranspiration, and anthropogenic abstractions all contribute to the water balance of an underground storage reservoir (Meresa and Taye, 2018).

Groundwater recharge assessment is heavily impacted by the availability of data in space and time, which is especially problematic in the case of ungauged catchments. Fortunately, all of these hydrological components, whether directly or indirectly linked, are available in reasonably high spatial resolution remote sensing products (Salem et al., 2019).

Therefore, the aim of the study was to deploy the model in conjunction with instruments of geographic information system/science (GIS) for estimating groundwater recharge of the Nairobi Aquifer System (NAS). The WetSpass-M model has been applied in previous studies to assess groundwater recharge over large spatial regions at different conditions (Zhang et al., 2017; Zarei et., al 2016; Olarinoye et al., 2020). This can be used to later develop an accurate hydrological model for the NAS. The model can then be used to evaluate sustainable consumption of water and local water resource management alternatives.

1.2 Problem Statement

The Nairobi aquifer system (NAS) occurs underneath the Nairobi Metropolitan Area and spans an area of 6 759 km2. The NAS underpins regions such as Ongata Rongai, Ngong, Isinya, Kitengela, Mavoko, Mlolongo, Ruiru, Juja, and Kikuyu, as well as several satellite towns around Nairobi (WRA, 2020). Groundwater abstracted from the Nairobi Aquifer Suite constitutes approximately 25% of the water needs across the Greater Nairobi region (Oiro et al., 2020). Groundwater studies entail the consideration of two main factors which are recharge and abstraction. Ideally recharge should be more or equal to groundwater abstraction amounts to be considered as being sustainable, which is not the case for the Nairobi aquifer suite (Mumma et al 2011).

Groundwater recharge occurs only in the aquifer's western and northwestern regions (Oiro et al., 2018). According to the WRA strategic plan report, this areas have been affected by Land use changes that physically disturb aquifers and impede groundwater flow. Furthermore, they also acknowledged that Climate change and variability was cause for concern in the management of the resource. Weak surveillance and a lack of monitoring of the water resource has attributed largely to the mismanagement of the resource. Moreover it has been identified that insufficient scientific information and limited understanding of groundwater due to inadequate monitoring, are major challenges plaguing the resource (Oiro et al., 2018).

Nairobi aquifer suite studies have been conducted exhaustively on groundwater abstraction while limited studies have been conducted to understand groundwater recharge dynamics within the aquifer (Simiyu et al 2015). This is a cause for concern as the demand for the resource is expected to increase due to an increasing population. In addition, the existing alternative resources are deemed to be unreliable hence causing a dependency on the resource.

In order to ensure the sustainability of the resource, it is important to ensure that aquifer recharge areas are properly managed by setting up appropriate policies. Furthermore, recommendations have been made on the importance of modelling catchment areas to develop a water balance on recharge & abstraction that will elucidate the sustainability of prevailing practices (Simiyu et al., 2015). Therefore, in order to make informed decisions on aquifer recharge management, it is important to understand how it has been affected in the past and how it will be affected in the future based on current practices, which is what this study aims to solve.

1.3 Objectives

1.3.1 Main Objective

- To conduct spatial and temporal analysis of groundwater recharge within the aquifer recharge zones of the Nairobi Aquifer suite between the years 2008 and 2020.

1.3.2 Specific Objectives

- To quantify groundwater recharge for the years 2008, 2012, 2016 and 2020 using the Modified WetSpass Model
- To analyze the recharge trends between the years 2008 and 2020 using the Mann Kendall test
- To explore future trends in groundwater recharge for the year 2024 using a random forest model.

1.4 Significance and Justification

This research will entail the quantification of seasonal and annual groundwater recharge amounts. Water scarcity and surplus during the dry and rainy seasons, respectively, are the primary challenges influencing sustainable development in the research region, particularly for sustainable agricultural output; measuring the groundwater recharge quantity will help to manage the water resource. The Water Resources Authority (WRA) has identified that acquiring data on water resources and managing them is key to ensuring sustainable use of the resource.

Furthermore, more baseline information on factors influencing groundwater recharge is crucial for experts and policy makers tasked with the mandate of ensuring the resource is appropriately used.

2. LITERATURE REVIEW

2.1 Water resources and hydrological cycle

Land, open water and plants give out water vapor that is carried to the sky through evaporation and transpiration, before returning as precipitation, either rain or snow, to the Earth's surface. The global hydrological cycle is already responding to the documented impacts of global warming, including an increase in atmospheric water vapor concentration and changes in precipitation patterns (Ayele, 2020)

It is estimated that 1.36 billion km^3 of water is accessible globally, with 97.2 percent being salty water, primarily in oceans, and 2.8 percent being freshwater (Raghunath, 2006). Despite the fact that large quantities of water, such as the ocean and vast lakes, contain a large volume of water, it is not immediately beneficial to humans. The water that is kept as groundwater and the remaining water found on land surfaces, in lakes, and in streams is the water that is immediately used by humans (Baychiken, 2018).

According to the Water resources Authority (WRA), Kenya is classified as a country with scarcity of water. It has 6 basins with the natural resource of renewable freshwater estimated to be around 21 BCM (billion cubic meters), or 650 m3 per capita per year. If a country's renewable freshwater potential is less than 1,000 m3 per capita per year, it is classified as "water-scarce." Kenya is expected to have a renewable freshwater supply of only 235 m3 per capita per year by 2025.

In order to evaluate and identify the occurrence of water, as well as to create and manage water supplies, it is essential to understand the hydrologic cycle. It's easier to explain the hydrologic cycle's main aspects by starting with evaporation from plants, exposed surfaces, such as the land surface, and from the ocean, even though it has no beginning or finish (Ayele, 2020). Water vapour is trapped in the atmosphere and condenses into clouds that, given suitable conditions, return water to land or seas in the form of rain. Vegetation and other surface materials are wetted and subsequently soaked by rain, which infiltrates into the ground. Infiltration rates depend on land use, topographic slope, soil type, and precipitation intensity. In addition overland flow occurs when precipitation surpasses infiltration.

Precipitation and runoff are the only parts that are visible. Evaporation, infiltration, transpiration, percolation, groundwater recharge and discharge, etc., are additional significant phenomena in this cycle that must be considered. Rain, snow, ice, sleet, and hail all contribute to the land surface-atmosphere-water exchange. The Earth's surface continuously evaporates water and the atmosphere temporarily stores it as water vapour, which returns to the land surface in the form of precipitation. When it comes to groundwater flow and interaction between land surface and subsurface, it's not as easy to depict.

2.1.1 Groundwater resources

Groundwater occurs in two distinct zones. The first zone is found directly under the ground surface. It is referred to as the unsaturated zone since it includes both water and air. The second zone, which occurs below the unsaturated zone, is full of water and is referred to as the saturated zone. It is the only subterranean water accessible to supply wells and springs (Manna et al., 2019)

Percolation of water from the land surface into the saturated zone replenishes the saturated zone. Aquifers can store groundwater in two ways. If an aquifer is partially filled with water, the top of the saturated zone can rise and fall as it pleases. This type of aquifer has unconfined water, and the aquifers are known as unconfined aquifers. When a confining bed fully covers an aquifer, the water is said to be contained in the aquifer. Contained aquifers are those that fall within this category (Mair et al., 2013).

2.1.2 Rainfall-Recharge

Understanding the connection between rainfall and runoff is essential for calculating recharging of the groundwater table. Because precipitation is the primary means of natural groundwater replenishment. The land cover, soil type, and prior moisture state are the most important determinants of rainfall-runoff relationships. Effective porosity and hydraulic conductivity are both high in well-drained soils; total porosity is higher and hydraulic conductivity is lower in poorly drained soils. Dry, well-drained soils recharge groundwater faster than wet, poorly-drained soils. The connection between rainfall and runoff is also influenced by land use and land cover. In order to calculate the quantity of ground water recharge, you must first deduct from rainfall what is lost to overland flow (runoff) and evapotranspiration (ET) (Armanous et al., 2016).

2.1.3 Groundwater Recharge

The term "recharge" refers to the quantity of water that seeps into the subsurface before becoming a member of the saturated zone or aquifer (Healy, 2012). Groundwater recharge is essential for managing groundwater resources and setting budgets because of its hydrogeological nature. The quantity of rainfall and geological factors influence how much groundwater recharges (Tesfaldet et al., 2019).

A catchment area's recharge system is a complicated aggregation that may be characterized by a variety of diagnostic indicators. Quantitative and qualitative spatial connections between chosen variables indicate the status of the active surface in a specific catchment region in terms of rainfall distribution and shallow groundwater recharge infiltration. Due to the fact that this is a process that changes over time and space, infiltration is dependent on climatic factors, water circulation aspects, and quasi-stationary and variable environmental features of a specific area, which are frequently difficult to determine through direct measurements or observations (Graf et al., 2018).

Research on groundwater recharge by infiltration emphasizes the challenge of estimating its magnitude with uncertainty when complete data are unavailable and point data cannot be converted into a recharge field.

2.1.4 Estimation of Groundwater Recharge.

Groundwater recharge is difficult to correctly predict since it cannot be monitored directly. Estimating groundwater recharge is critical for successful and long-term groundwater system management. Recharge can be represented as a percentage of yearly rainfall or as an average annual water rate in millimeters. By multiplying the recharge rate by the land area under consideration, the volume of recharge, given in cubic meters per year, may be determined.

There are several ways for estimating ground water recharge based on the actual physical processes of the recharge. The three hydrological zones of study are surface water, unsaturated zones, and saturated zones. Among the methodologies are physical modeling, numerical modeling, and tracer techniques. Physical methods, such as channel-water budgets, seepage meters, and base flow discharge; tracer methods, such as stable isotopes of oxygen and hydrogen; and numerical modeling methods, such as groundwater flow numerical models, are all included in groundwater study methods.

Several approaches, including experimental methods, hydrological budget (HB), empirical methods, distributed hydrological budget (DHB), and water table fluctuation (WTF), are used to estimate groundwater recharge amounts (Salem et al., 2019).

2.2 Groundwater Recharge Models.

Hydrological models are simplified systems that quantify the hydrological cycle operations in a whole river basin or sections of it. They are based on a collection of interconnected equations that attempt to transform physical principles that control very complicated natural events. Furthermore, several types of models may be employed, based on the desired result, the current database, input factors, and the needed analysis. The representation of physical processes represented by rainfall-runoff models might be based on a simple mathematical connection between input and output variables of the basin, or it can contain a description of basic processes involved in runoff formation (Gebremeskel et al., 2017).

Distributed models have been developed in the last few years to conduct groundwater recharge studies. Several of these models have been classified "physically-based," implying that they have been parameterized in terms of quantities that are physically measurable, at least in principle. Has claimed that such models are purely conceptual in nature, because the physically-based values are oversimplifications of reality that are not quantifiable using existing point scale methodologies. Despite this, the current generation of hydrological models' distributed design allows them to take use of new data processing techniques capable of managing precise variability of catchment features, even if just for a subset of model parameters (Rwanga et al., 2013).

A study conducted in Thepkasattri sub-district, Thailand, investigated the geographical and temporal variation of groundwater recharge through the integration of chloride mass balance (CMB) and water table fluctuation (WTF) techniques. The chloride concentration of typical rainfall and groundwater samples was determined. Furthermore, the WTF technique was applied to groundwater level data from 2012 to 2015 (Tesfaldet et al., 2020). (Henrique et al., 2019) performed the calibration and validation of a hydrological model in a karst region of Minas Gerais (the Jequitiba River basin), using the JAMS J2000 framework for the interpretation of the results from a water resources management perspective. The model was seen to be fit for hydrological studies for Karst areas and larger water basins that exceed 1000 km^2. The

HEC-GeoHMS model was used to estimate annual recharge of Groundwater table in Shinile sub- basin that entailed rainfall runoff modeling and estimation of the total runoff, estimating potential evapotranspiration over the entire sub-catchments, estimating groundwater recharge using water balance approach and Modeling well fields in the basin and assessing the impact of abstraction on Water supply of cities and the Shinile basin groundwater table (Ahmed et al., 2018).

The SHE model was developed as a result of a belief that conventional rainfall/runoff models are inadequate for addressing many urgent hydrological issues, particularly those relating to the influence of human activities on land-use change and water quality. These issues can only be addressed by using models that have a physical basis and allow for geographical changes within a watershed. The results of the model were that the physical foundation and flexible operational structure of the SHE allow the model to use as much or as little data as is available, as well as to integrate data on topography, vegetation, and soil qualities that are not typically included in catchment models. It does not require a lengthy hydro meteorological record for calibration, and its dispersed nature allows for the simulation of geographic heterogeneity in catchment inputs and outputs. However, because the model requires a huge quantity of data, new operational techniques must be developed. Thus, geographical scale effects or simply a lack of data can cause substantial uncertainty in the values of catchment parameters employed in simulations (Ayele et al., 2020).

Regional groundwater models used for detecting and evaluating groundwater systems (infiltration-percolation-discharge relationships) are frequently quasi-steady state, requiring long-term average input data. Thus, WetSpass, which generates geographically variable groundwater recharge from spatially different soil, land-use, and meteorological inputs, may be utilized to better understand groundwater recharge features (Armaneous and Negm, 2016).

2.2.1 WetSpass-M Model

The modified water and energy transfer among soil, plants, and atmosphere (WetSpass-M) model is a raster-based water balance model that separates precipitation into interception, surface runoff, evapotranspiration, and recharge for each grid cell. The main inputs include distributed land use, soil texture, groundwater depth, slope, and climatic data (rainfall, potential evapotranspiration, number of wet days, wind, and temperature). To handle land-use variability inside the cell, each grid cell has four sub-cell fractions for each land-use class: vegetative cover, bare soil, open water, and impermeable surface (Batelaan and De Smedt 2001, 2007; Ampe et al. 2012).

On a seasonal timeframe, the original WetSpass model simulates all hydrological parameters. Reading the data is the first step in the processing process, which is considered a separate internal operation (process 0). For each time step (monthly), the grid cell water balance comprises interception, surface runoff, evapotranspiration, and recharge. For the computation of the water balance at the grid cell level, land-use/land-cover fractions are employed as weighting factors (Abdollahi et al., 2016).

2.2.2 Applications of WetSpass-M model.

The WetSpass-M model was used in a study conducted in Beijing, China, to evaluate spatial groundwater recharge at seasonal and yearly scales based on several connections. The model was used to assess the impacts of urbanization on water balance on a regional scale. The interactions between impervious surfaces, landscape pattern indices, and water balance components were measured as well. The WetSpass model findings revealed substantial seasonal variations in surface runoff, groundwater recharge, and evapotranspiration (Zhang et al., 2017).

The study of the spatial and temporal distribution of groundwater recharge was required as an input to the development of the regional groundwater model in the Drava flood plain, Hungary, for more realistic simulations of different management scenarios. The examination of simulation data revealed that the WetSpass-M model accurately represented the hydrological water budget components in the Drava basin. Furthermore, a better knowledge of the simulated long-term average geographical distribution of water balance components proved beneficial for managing and planning the Drava basin's available water resources (Salem et al., 2019).

Groundwater resources in the Werii watershed, Ethiopia, were estimated based on spatial variations of land use, soil texture, topography, slope, groundwater level, and hydro-meteorological conditions. To meet irrigation water deficiencies, a safe yield groundwater abstraction rate up was found that could be utilized without jeopardizing groundwater sustainability. The researchers concluded that the WetSpass model may be used to predict water balance components in semi-arid locations if the model input parameters were tailored to local conditions. The study concluded that the WetSpass model may be used to simulate water balance components in semi-arid locations if the model input parameters were tailored to local circumstances (Gebremeskel et al., 2017).

A study conducted in Arusha, Tanzania, combined satellite imagery, urban growth modelling and hydrogeological field expeditions to estimate the potential impacts of urbanization and climate change on groundwater. The WetSpass-M model was used to compute water balance components (Evapotranspiration, surface run-off and groundwater recharge) that were used for development of a groundwater model (Olarinoye et al., 2020). The model was used to analyze groundwater recharge, surface runoff, and evapotranspiration in the Mashhad basin using a spatially distributed water balance model (WetSpass-M) under different land-use types. The simulated results show that the WetSpass-M model is adequate for simulating the components of water balance in the Mashhad basin (Zarei et al., 2016).

The seasonal and yearly water balance components of the Jewha watershed have successfully been simulated using the WetSpass-M model. The sensitivity analysis of the various input factors was performed, and the majority of the variables in the Jewha watershed were found to be very sensitive. According to the findings of the study, rainfall, potential evapotranspiration, and slope are the most important hydrologic processes in the study region in terms of influencing the amount and rate of the various water balance components. The parametric coefficients of alpha coefficients, interception coefficients, and the Lp coefficient also were relatively sensitive (Ayele et al., 2020).

2.3 Trend Analysis

Groundwater recharge is influenced by several factors that vary in space and time. Spatiotemporal analysis refers to the study of data containing time characteristics as well absolute and relative locations in three-dimensional space, as well as the process and methodology for evaluating this data (Dong et al., 2020). Trend analysis is an effective technique in hydrological analysis for analyzing the features of hydrological data such as rainfall, dry periods, and stream flow processes (Woo et al., 2021).

Several methods have been suggested to perform trend analysis on spatiotemporal data. The majority of spatio-temporal data analysis approaches focus on spatio-temporal data mining and clustering algorithms. The Mann Kendall test is the preferred technique to conduct trend analysis on phenomena that vary on a seasonal basis in a non-linear pattern. The application of the technique is observed in space time mining models that look at variations in trends on a spatial and temporal scale (Dong et al., 2021).

2.4 Groundwater recharge Forecasting

Sensible water management decision making need fast, trustworthy, and actionable information. Improving techniques for accurate seasonal forecasting of changing groundwater levels is an approach for better groundwater resource management**.** The advancements in computer modelling as well as machine learning methods are relevant to groundwater studies based on scientific research (Kombo et al., 2020).

Various machine learning techniques have been suggested to perform spatial and temporal predictions. Spatiotemporal predictions entail the prediction of the occurrence, amount, and/or condition of geographical events, often based on training data (Hengl et al., 2018). The models suggested including Boosted Regression Tree (BRT), Regression Kriging and Random Forest models.

In the sense that sampling sites and general sampling patterns are neglected during the estimate of MLA model parameters, Random Forest (RF) is essentially a non-spatial method to spatial prediction. In order to avoid sub-optimal predictions several factors are considered while using the model for spatial predictions. Spatial proximity and spatial relationships between observations are accounted for through covariates. The buffer distance between the observed location and the total number of training points, as well as process-based variables, are considered. Geographic covariates are generally smooth and reflect the geometric composition of locations, but process-based covariates need specialist knowledge and a rethinking of how processes should be represented. To make RF relevant to spatial statistics issues, it is also necessary to prepare geographical measures of proximity and connectivity between observations, to account for spatial autocorrelation Hengl et al., 2018).

K nearest neighbor (KNN) and Random Forest model was used to make short term predictions of seasonal variation of groundwater levels for aquifers situated within the Eastern parts of Rwanda using hydroclimatic data. The conclusion was that the model was seen to be fit based on the high performance in terms of root mean square (RMSE), Mean Absolute error (MAE), Nash-Sutcliffe (NSE), and coefficient of determination (R^2).

3. DATA AND METHODOLOGY

3.1 Study area

3.1.1 Description of the study area.

The NAS is located in the Kenyan highlands on the Eastern flank of the Great Rift Valley, East Africa. It occupies the Upper Athi Basin, covering parts of the Ngong and Mbagathi sub basin, which form part of the five major basin areas of Kenya (Fig 1). The region's elevation is at a range from 1400 m on the eastern floodplains to 2700 m in the Northwestern part of the NAS, located within latitude 0°37′58″–1°59′23″ south and longitude 36°34′27″–37°28′17″ east.

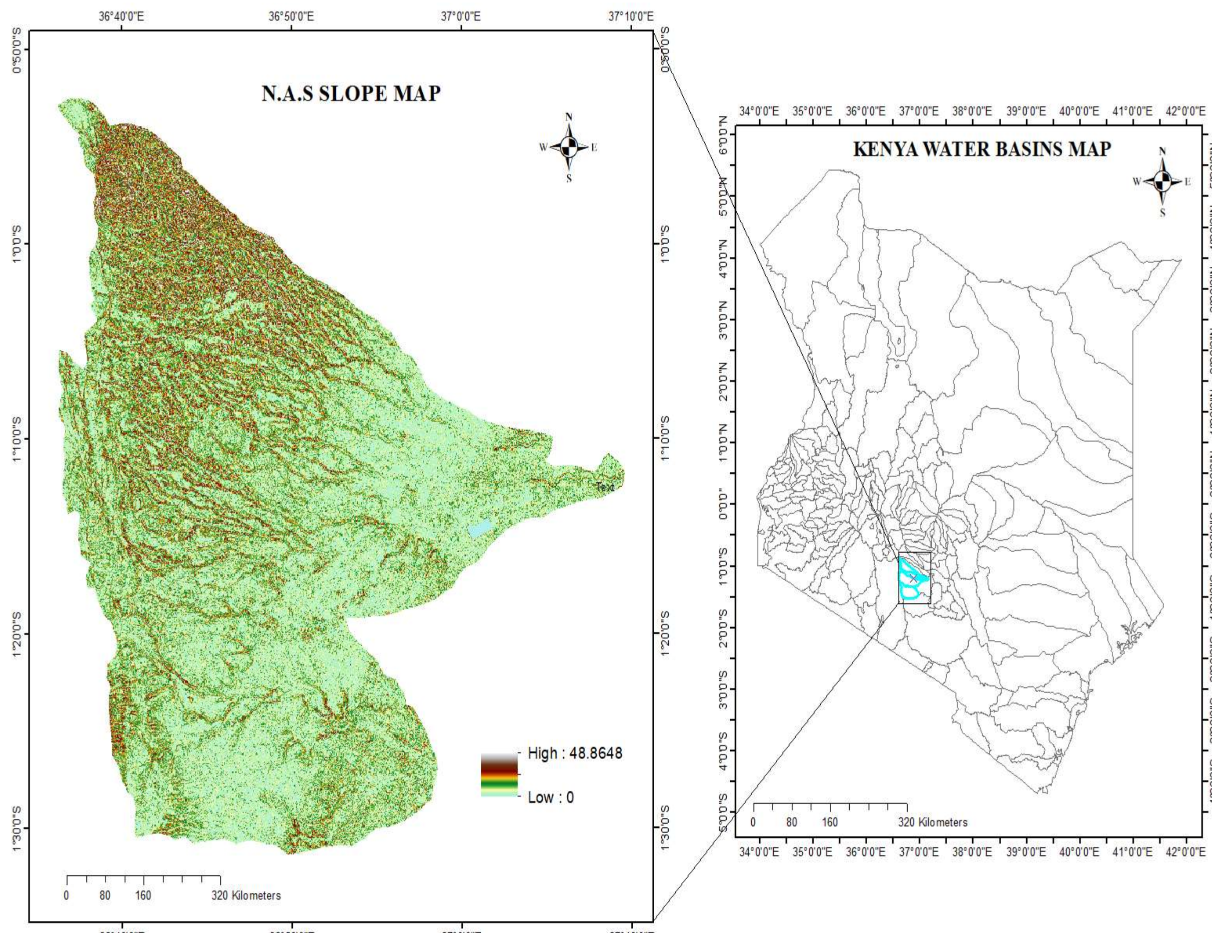

Figure 1: Upper Athi Basin Map

3.1.2 Nairobi Aquifer System (N.A.S) Recharge zones.

The Nairobi aquifer system (NAS) underpins the Nairobi metropolitan region as well as a number of outlying settlements. It cover an area size of 6 648 km^2 with the depth of the Upper Aquifer system (UAS) depth being 200 m while the lower aquifer depth is estimated to be 400 m deep. The NAS yield potential is estimated to be 860 m^3/day for the UAS while that of the Lower Aquifer system (LAS) being 240 m^3/day. The dominant flow type of the NAS is characterized to intergranular and fracture. The areas that has been identified to be high potential recharge areas for the aquifer lie within the 3AA to 3CB sub basins (WRA, 2020).

3.1.3 Climate of the study area

A subtropical montane climate characterizes the NAS region. Temperatures range from 22 to 25 degrees Celsius on an annual basis. In the coldest months (June/July), however, low temperatures can exceed 10 °C. With an average temperature of 24 °C, the months of January to mid-March are the sunniest and hottest, preceding the months of March to May, which are characterized by significant rains. The yearly average humidity varies between 60 and 84 percent, depending on the precipitation pattern. Yearly precipitation in the study area ranges from 700 mm in the southeastern lowlands and floodplains to over 1,400 mm in the northern highlands with an average annual precipitation of 1,050 mm. For the months of March to May, heavy rains are observed, with a second peak in November, resulting in an annual bi-modal distribution, with floods occurring in lowland areas and within built-up areas during the hardest storms.

Wind speed conditions within the N.A.S area range between 2m/s to 5 m/s. The highest values are observed within the months of November and March and the lowest wind speed values observed during the months of May and August (W.R.A 2020)

3.1.4 Soil Types and geological formation

Nairobi Aquifer Suite (NAS) is a multilayer volcanic aquifer made up of aquifer units that consist of volcanic flows of varying ages. Trachytic lavas are classified into three units: the Upper Trachyte Division, the Middle Trachyte Division, and the Lower Trachyte Division. Tigoni, Karura, Kabete, and Ruiru Dam Trachytes, as well as the Kerichwa Valley Tuffs, make up the Middle Trachyte Division, with the tuffs serving as the primary aquifer. Nairobi Trachyte, Nairobi Phonolite, Mbagathi Phonolitic Trachyte, Athi Tuffs and Lake Beds sediments, and Kapiti Phonolite are all rocks in the Lower Trachyte Division.

3.2 Data

Table 1 is a summary of the data required and their respective sources.

Table 1: Data sources

Data	**Source**	**Used for**
Landsat 7&8 Satellite Imagery (30m)	https://earthexplorer.usgs.gov/	Land use / Land cover (LULC) classification maps; Land surface Temperature (LST)
Depth to Groundwater	Water Resource Authority (W.R.A)	To generate Groundwater level map
Digital Elevation Model (D.E.M) (12.5m)	https://asf.alaska.edu/data-sets/derived-data-sets/alos-palsar-rtc/alos-palsar-radiometric-terrain-correction/	To generate slope map

Precipitation (Monthly) (0.05^0 arc)	https://developers.google.com/earth-engine/datasets/catalog/UCSB-CHG_CHIRPS_PENTAD	To generate rainfall map
Wind Speed (250m)	https://globalwindatlas.info/	To generate windspeed map
Potential Evapotranspiration (P.E.T)	https://lpdaac.usgs.gov/products/myd16a2v006/	To generate Potential evapotranspiration map
Leaf Area Index (LAI)	https://lpdaac.usgs.gov/products/mcd15a2hv006/	To generate wind speed map.
Soil Type	https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/	To generate soil type classification map (U.S.D.A)

3.2.1 Climate data

WetSpass-M requires daily precipitation, maximum and lowest temperatures, potential evapotranspiration, daily relative humidity, and wind speed as climatic input data for hydrological modeling. Because of the lack of meteorological data and inadequate recordkeeping for the study region, satellite data is used.

The CHIRPS system will be utilized to collect daily precipitation data. CHIRPS is a worldwide gridded precipitation dataset with a spatial resolution of 0.5°. It is based on data from satellites and a worldwide network of rain gauges. CHIRPS datasets may be utilized to provide precise hydrological modeling findings (Grusson, Anctil, Sauvage, & Pérez, 2017). The R programming language is used to extract precipitation quantities from CHIRPS raster datasets. The results is a rainfall map of the study area as shown by figure 2.

LAI is defined as one-half of total needle surface area per unit ground area in broadleaf canopies while in coniferous canopies, it is defined as one-half of total needle surface area per unit ground area. The MCD15A2H Version 6.1 Moderate Resolution Imaging Spectroradiometer (MODIS) Level 4, Combined Fraction of Photosynthetically Active Radiation (FPAR), and Leaf Area Index (LAI) product is an 8-day composite dataset with 500-meter pixel size (Fig 3).

Wind speed data is retrieved from the Global Wind Atlas database. This data has a spatial resolution of 250m. Land surface temperature (L.S.T.) (Fig 4) data will be calculated and utilized to derive maximum and lowest temperature values (Pepin et al., 2016). According to research, LST can be used as a temperature replacement. Furthermore, in regions with a substantial urban footprint, LST values must be considered for climate-related research (Mason, 2020).

Potential Evapotranspiration (PET) is defined as the quantity of water vapour that a plant or soil surface might generate per unit area and unit time in the absence of a water supply restriction. The WetSpass model requires the measured PET in the watershed. MOD16A2 MYD16A2, a MODIS PET product with a spatial resolution of 500m, is used to generate PET. The data is be available on the NASA Earth data website. Because the data is in sinusoidal grid, it must be transformed to WGS84 (Fig 5).

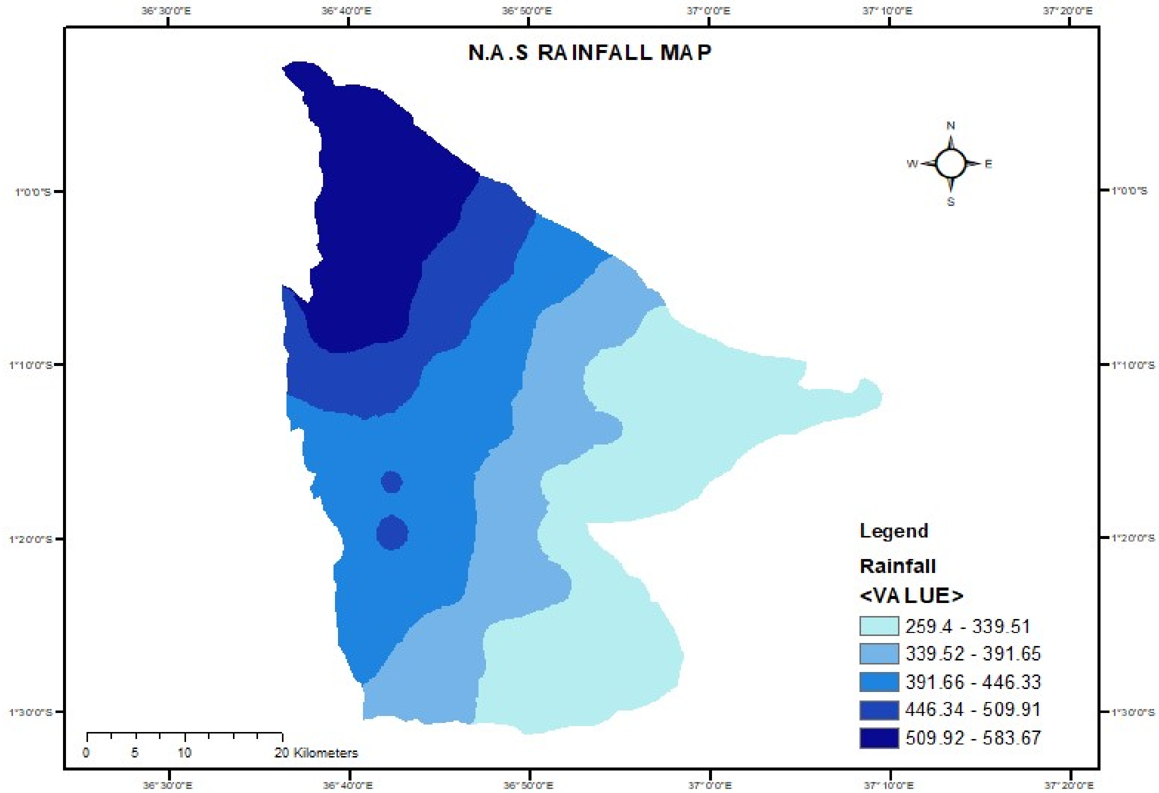

Figure 2: N.A.S rainfall map

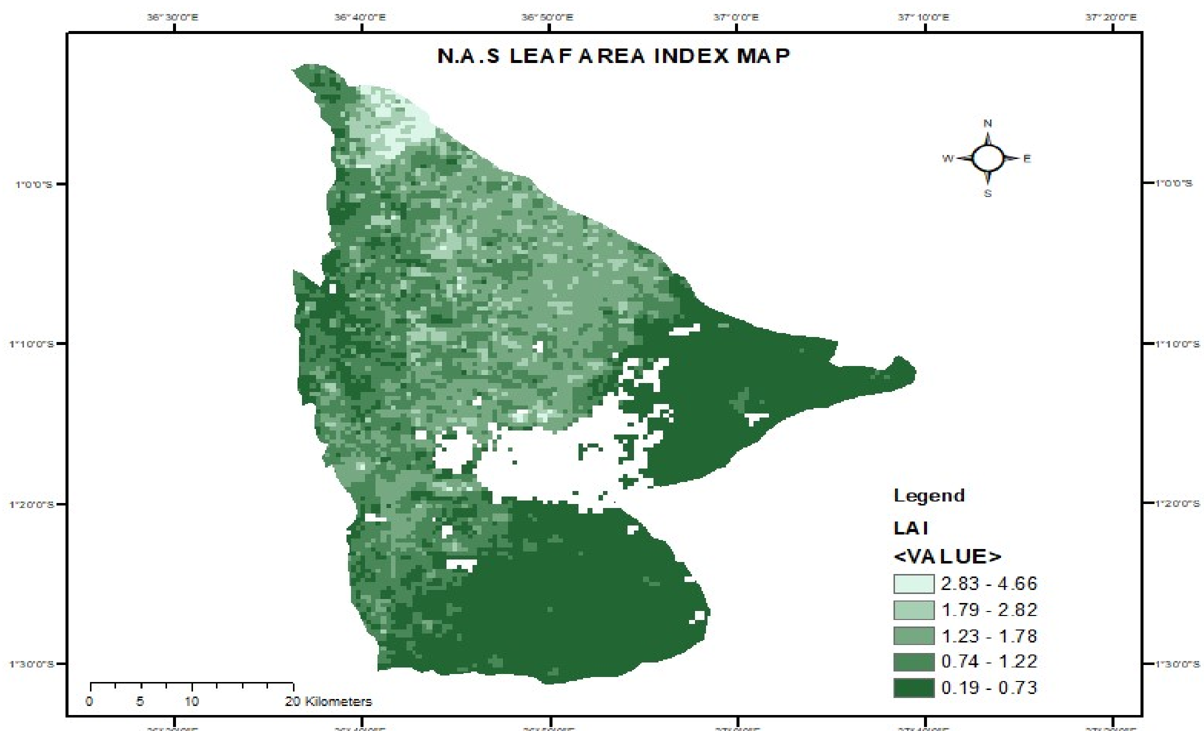

Figure 3: N.A.S leaf area index map

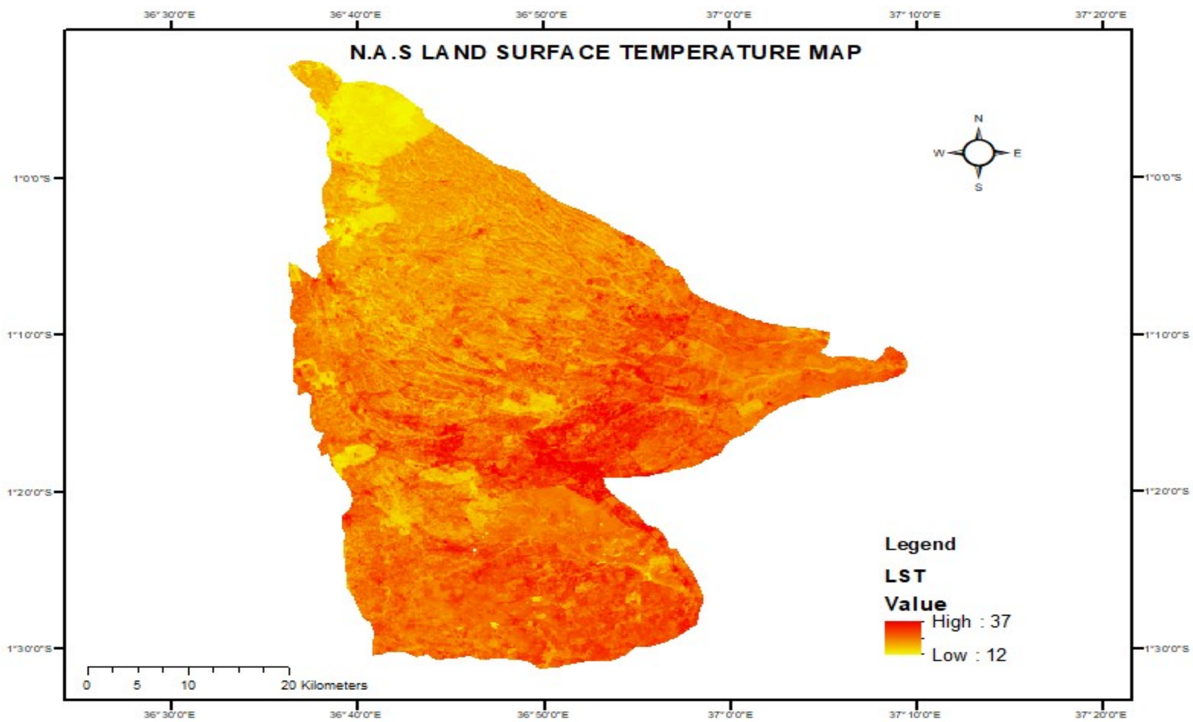

Figure 4: N.A.S land surface temperature map

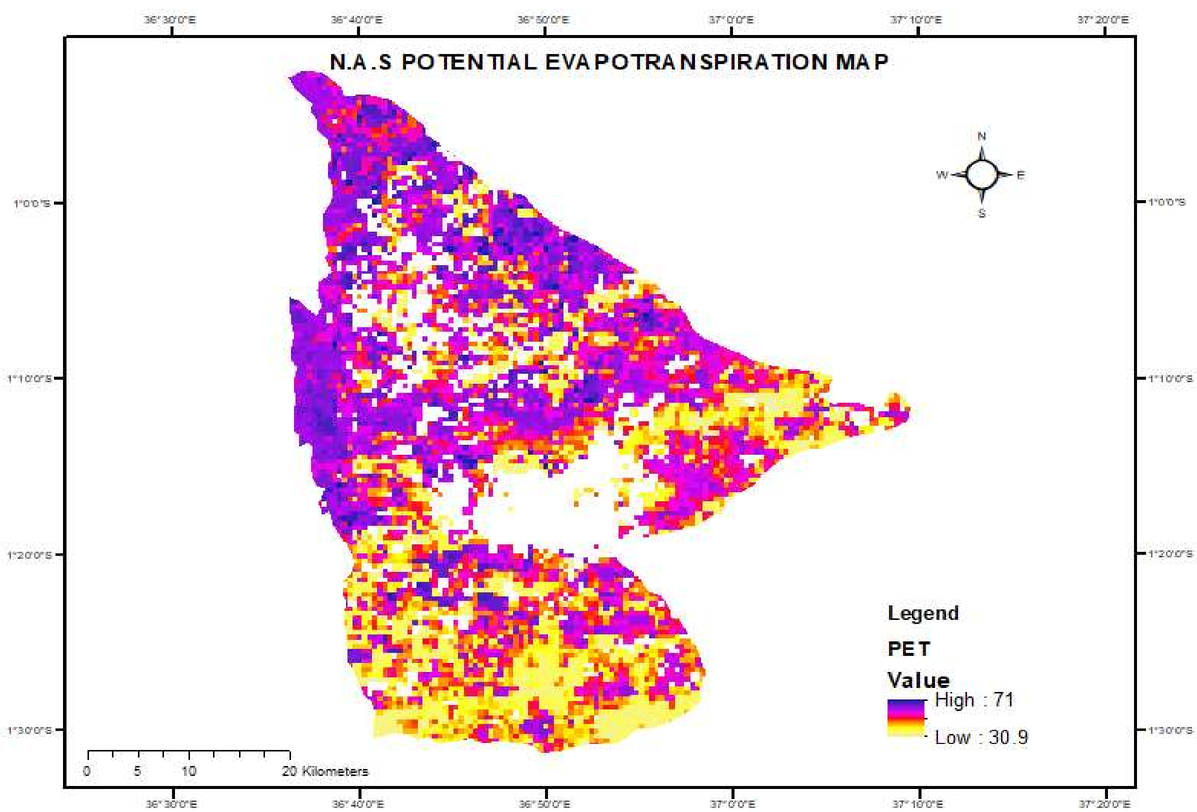

Figure 5: N.A.S potential evapotranspiration map

3.2.2 Land use and Land cover.

Land use is a significant regulating element for the hydrological processes of a specific watershed, which include recharge, evapotranspiration, interception, and runoff (Salem et al., 2019). This study's land use and land cover map is created using cloud-free Landsat ETM+ and Landsat OLI data. The imagery is being gathered for the research period of 2008 to 2020.The Land use map will be classified using supervised classification, particularly a Classification and regression (CART) classifier. Ground truth data acquired from Google Earth images will be used to test the accuracy of the land use and land cover categorization. The Land cover classification resulted into seven classes namely Agricultural areas, Bareland, Built-up areas, Forested areas, Grassland and water bodies (Fig 6). The Land cover map was then reclassified into classes that are required for WetSpass-M model simulation

of groundwater recharge (Fig 7).

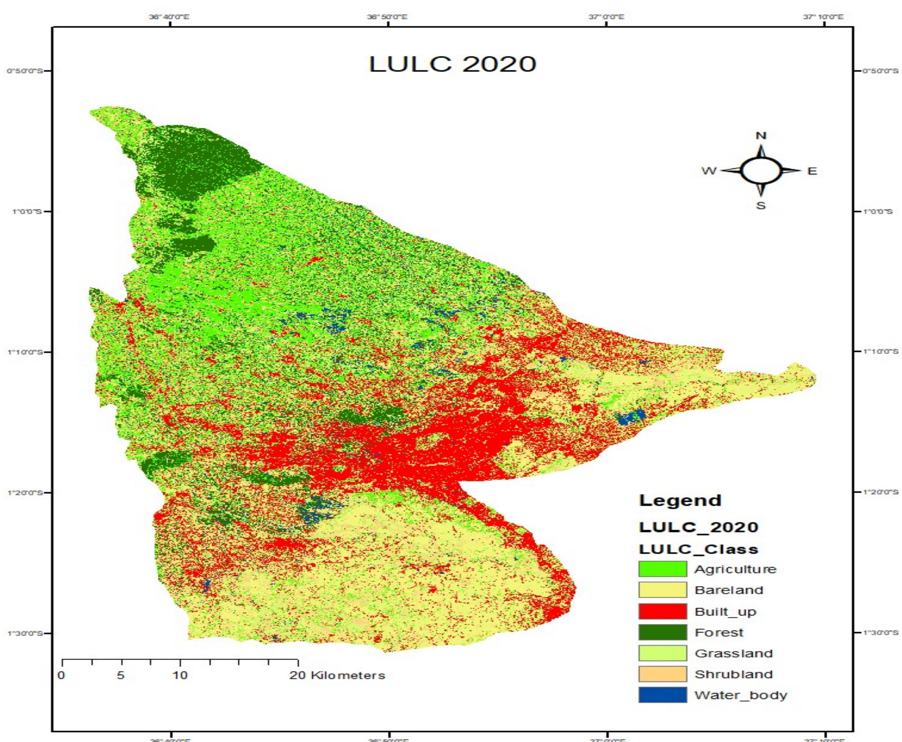

Figure 6: Land use / Land cover map

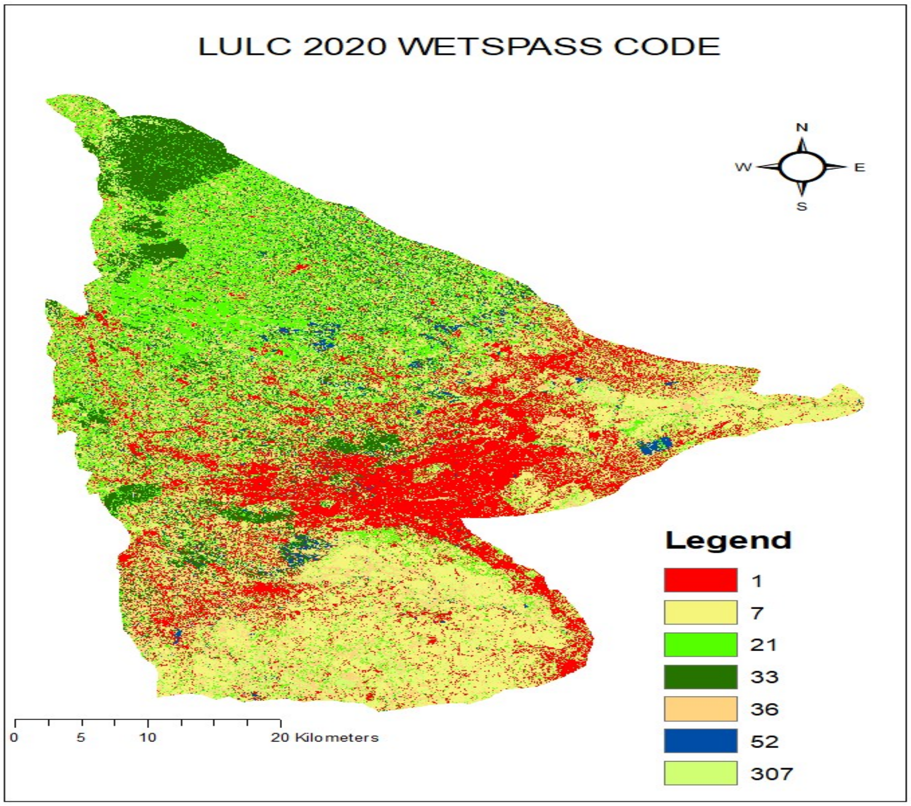

Figure 7: Land use land cover 2020

3.2.3 Soil Data

The soil map of the N.A.S region is obtained from ICPAC geoportal. Using the United States Department of Agriculture (USDA) textural classification methods, soils in the study area are classified into five textural classes based on grain size: loamy sand, clay loam, silty clay loam, and clay loam. The results of the soil type classification within the NAS recharge areas were clay, loam and sandy clay loam (Fig 8).

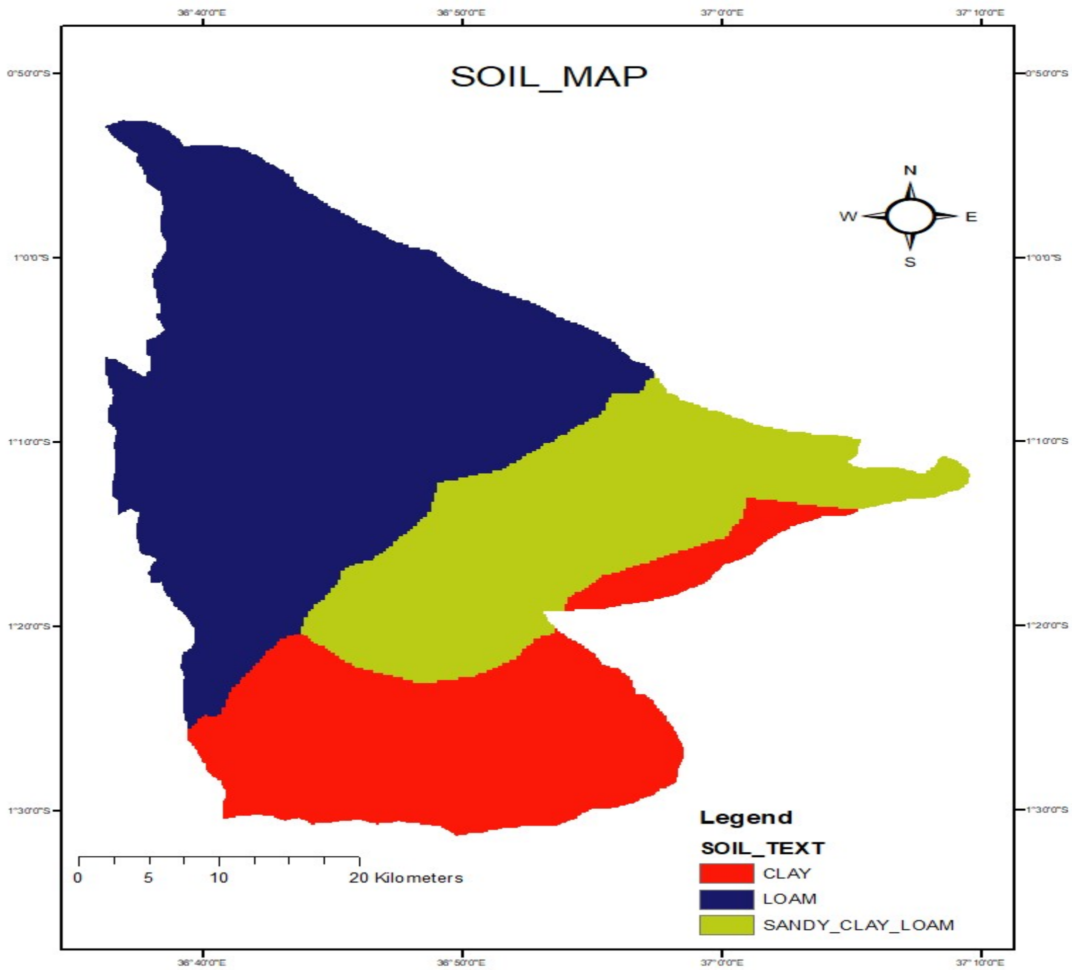

Figure 8: Soil map

3.2.4 Topographical parameters.

The digital elevation model (DEM) is preprocessed before being used to estimate any parameters (all sinks, and peaks were filled to ensure the continuity of flow to the research area's watershed). The NAS (elevation and slope) map is created using an ALOS DEM obtained from the NASA Earth data ASF website. The slope values for the study area ranged between 0 and 49 (Fig 9).

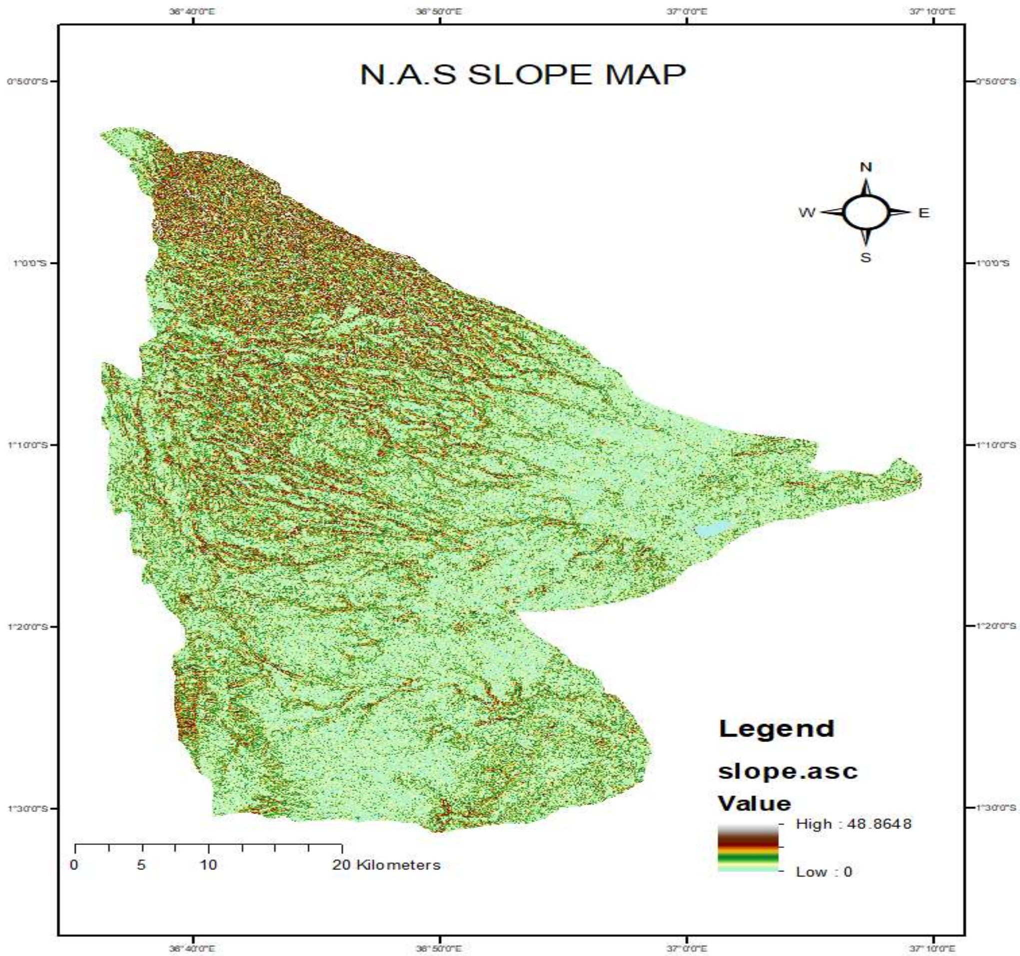

Figure 9: N.A.S slope map

3.2.5 Groundwater level mapping

The data obtained by the Water Resources Authority will be used to create groundwater level maps (WRA). Interpolation is necessary to create a groundwater level map since the data is in comma delimited format (csv) and the model wants the data to be in the form of gridded maps. Kriging method was utilized for interpolation. The groundwater level values were within in the range of 15 metres and -160 metres (Fig 10).

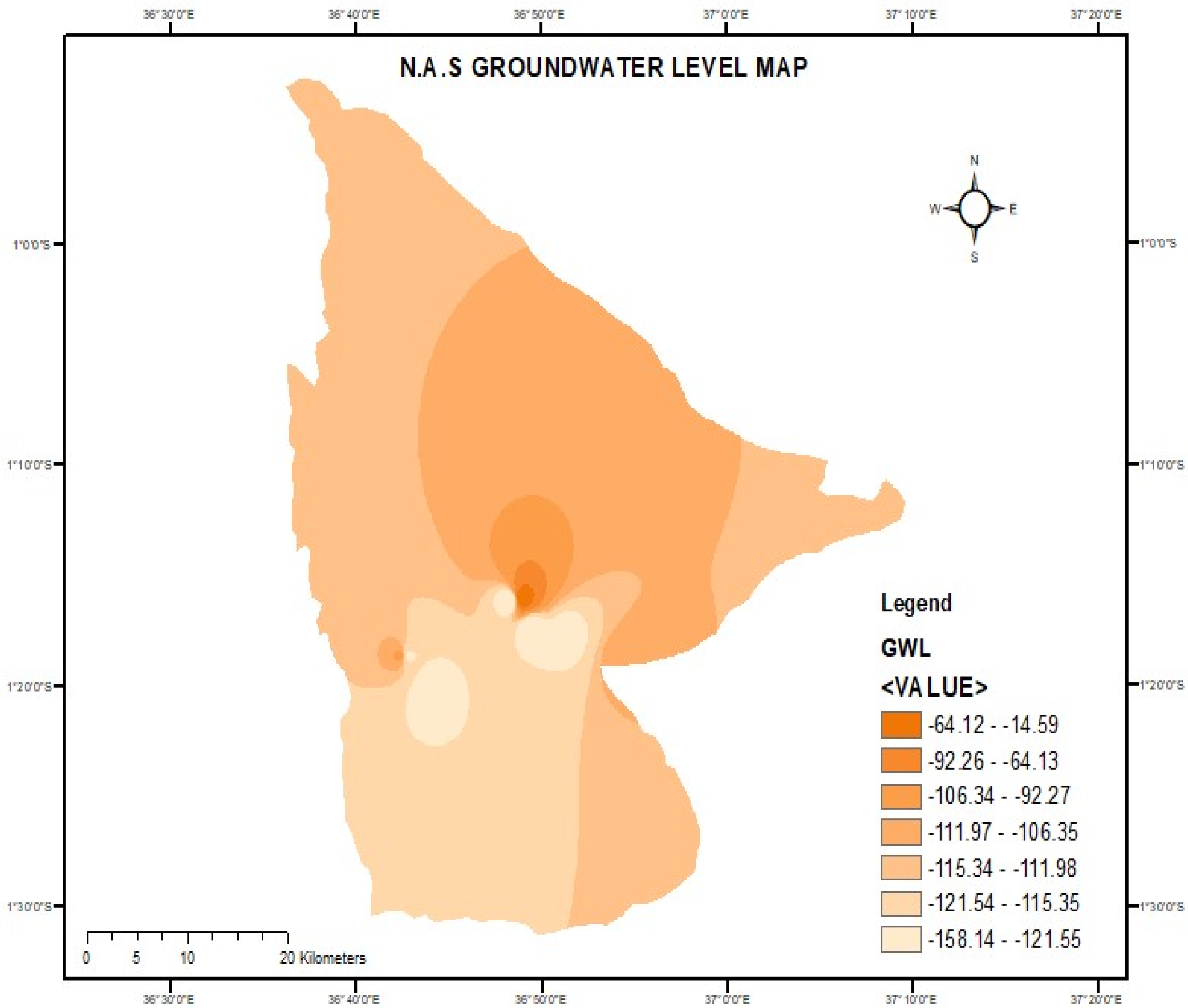

Figure 10: N.A.S ground water level map

3.3 Methodology

Figure 10 shows the workflow used in the achievement of both the overall and specific objectives of this research project:

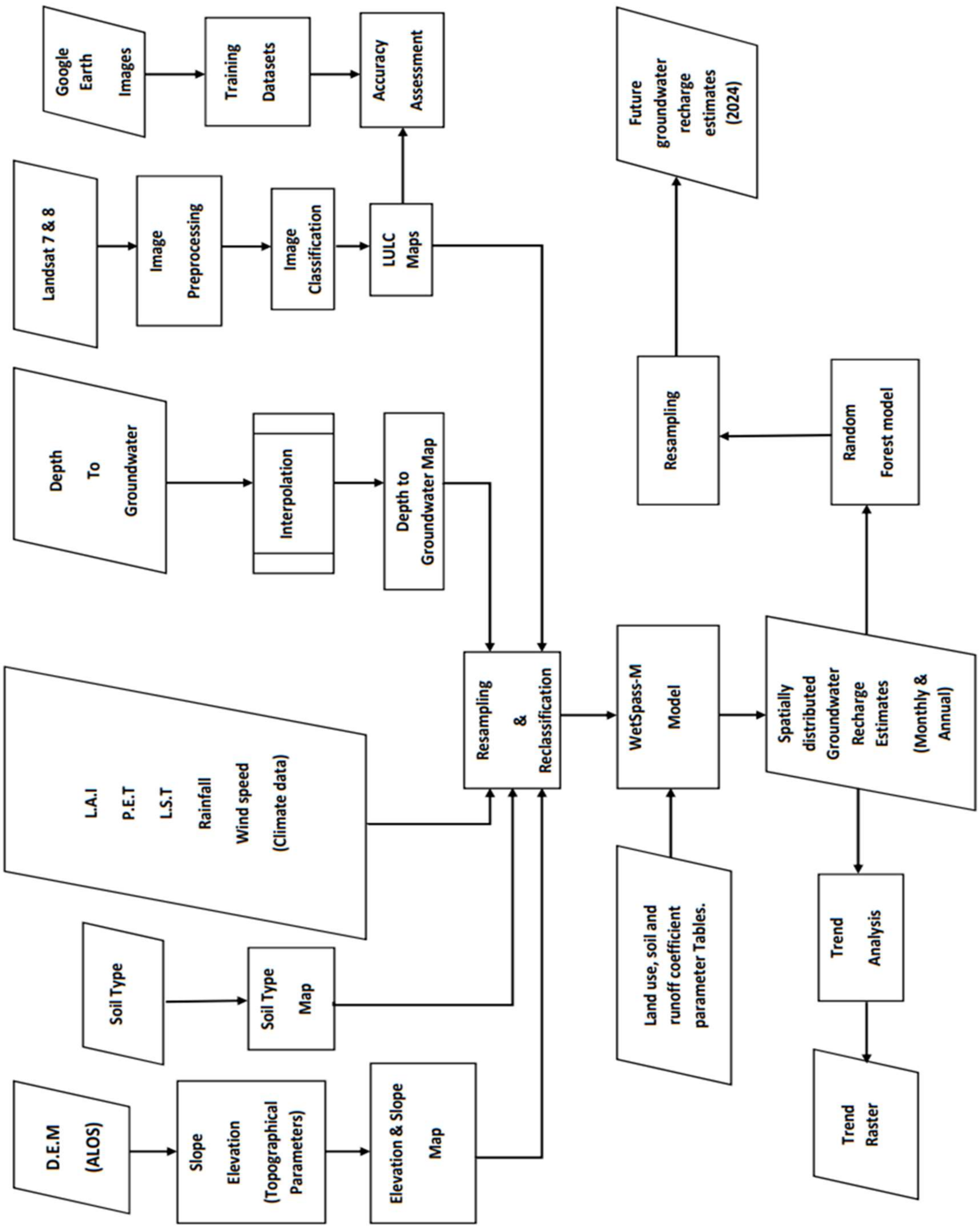

Figure 11: Methodology Flowchart

3.3.1 Hydrological model

Depending on the result to be examined, the database already in place, and the input variables, several alternative models can be used. A basic mathematical relationship between a basin's input and output variables can be utilized to depict physical processes represented by rainfall-runoff models, or fundamental processes involved in runoff formation. Throughout the last few decades, numerous models have been developed in various regions of the world. Physical distributed models, conceptual models, and data-driven models are the three sorts of models (Abdollahi et al., 2016).

The physically based distributed hydrological model WetSpass-M will be used in the study estimation of groundwater recharge and water balance components of the watershed. The model employs groundwater parameters such as land use type, soil textural type, precipitation, interception, surface runoff, and infiltration, evapotranspiration, and groundwater levels.

The descriptions of the WetSpass-M model are discussed in the sections that follow.

a) WetSpass-M Model

The modified WetSpass-M model is a raster-based water balance model that divides precipitation into interception, surface runoff, evapotranspiration, and recharge for each grid cell. The fundamental input includes distributed land use, soil texture, groundwater depth, slope, and climatic data (rainfall, potential evapotranspiration, number of wet days, wind, and temperature).

To handle land-use variability inside the cell, four sub-cell fractions for each land-use class are specified per grid cell: vegetative cover, bare soil, open water, and impervious surface (Batelaan and De Smedt 2001, 2007; Ampe et al. 2012).

On a seasonal timeframe, the original WetSpass model replicates all hydrological processes. Reading the data is the first step in the processing process, which is considered a separate internal operation (process 0). For each time step (monthly), the grid cell water balance comprises interception (process 1), surface runoff (process 2), evapotranspiration (process 3) and recharge (process 4). The model calculates monthly surface runoff in (mm/month) using a rationale method using an actual surface runoff and soil moisture coefficient. Groundwater recharge spatial distribution is estimated on a monthly basis as a residual term of the water budget components, by subtracting the monthly surface runoff and actual Evapotranspiration from the monthly rainfall. The spatial distribution of groundwater recharge relies on topography, slope, soil type, land cover/land use and climatological conditions (Salem et al., 2019)

For the computation of the water balance at the grid cell level, land-use/land-cover fractions are employed as weighting factors.

Model concept

Because the model is distributed, the water balance computation is done at the raster cell level. Individual raster water balance is calculated by adding independent water balances for each raster. A raster cell's vegetated, bare soil, open water, and impervious fraction and the total amount of water. The total water balance of a given area is thus calculated as the sum of the water balances of each raster cell.

Calculation of the water balance for each raster cell.

The water balance components of vegetated, bare-soil, open-water, and impervious surfaces are all considered as briefly mentioned earlier, used to calculate the total water balance of a raster cell.

$$ET_{raster} = a_v ET_v + a_s E_s + a_0 E_0 + a_i E_i \quad \text{(eqn 1)}$$

$$S_{raster} = a_v S_v + a_s S_s + a_0 S_0 + a_i S_i \quad \text{(eqn 2)}$$

$$R_{raster} = a_v R_V + a_s R_s + a_0 R_0 + a_i R_i \quad \text{(eqn 3)}$$

Where ET_{raster}, S_{raster}, and R_{raster} are the total evapotranspiration, surface runoff, and groundwater recharge of a raster cell, respectively, with a_v, a_s, a_o, and a_i denoting the vegetated, bare-soil, open-water, and impermeable area components.

The next sections go over how to calculate each component's water balance. The water balance of each of the above-mentioned components of a raster cell is computed using precipitation as a starting point, with the rest of the processes (interception, runoff, Evapotranspiration and recharging) occur in a sequential order. This order is required for the seasonal time scale that will be used to quantify the processes. Following is a discussion of the water balance for the various components.

Vegetated area.

A vegetated area's water balance is determined by the average seasonal precipitation (P), interception fraction (I), surface runoff (S_v), real transpiration (T_v), and groundwater recharge (R_v). The equation below demonstrates the relationship between the components.

$$P = I + S_v + T_v + R_v \quad \text{(eqn 4)}$$

Interception

The interception fraction is a constant percentage of the yearly precipitation value, depending on the kind of plant. As a result, as the annual total rainfall amount increases, the fraction drops (because the vegetation cover is assumed to stay constant during the simulation period).

Surface runoff

The amount of precipitation, precipitation intensity, interception, and soil infiltration capacity are all used to compute surface runoff.

$$\boldsymbol{S_{v-pot} = C_{sv}(P - I)} \quad \text{(eqn 5)}$$

Where Csv is a surface runoff coefficient for vegetated infiltration regions, and is a function of vegetation, soil type, and slope, the potential surface runoff (Sv-pot) is computed first. In groundwater discharge zones, saturated surface runoff occurs, resulting in an extremely high surface runoff coefficient. Because of the lessened dependence on soil, vegetation type, and proximity to the river, the coefficient is typically considered to be constant in this case.

The actual surface runoff from the Sv-pot is estimated in the second phase by taking into account variations in precipitation intensities in relation to soil infiltration capabilities.

$$\boldsymbol{S_v = C_{Hor}\, S_{v-pot}} \quad \text{(eqn 6)}$$

Where C_{Hor} is a parameter for parameterizing the portion of seasonal precipitation that contributes to the Hortonian overland flow. Because all intensities of precipitation contribute to surface runoff, C_{Hor} for groundwater discharge regions is equal to 1.0. Surface runoff in infiltration regions can only be generated by high-intensity storms.

Evapotranspiration

A reference value of transpiration is acquired from open-water evaporation and a vegetation coefficient is used to calculate seasonal evapotranspiration:

$$\boldsymbol{T_{rv} = cE_o} \quad \text{(eqn 7)}$$

T_{rv} = reference transpiration of a vegetated surface.

E_o = potential evaporation of open water.

c = coefficient of vegetation [−].

This vegetation coefficient may be determined by dividing the Penman-Monteith equation's reference vegetation transpiration by the Penman equation's potential open-water evaporation:

$$\boldsymbol{C} = \frac{\mathbf{1} + {}^{\boldsymbol{\gamma}}/_{\Delta}}{\mathbf{1} + {}^{\boldsymbol{\gamma}}/_{\Delta}\left(\mathbf{1} + \frac{\boldsymbol{r_c}}{\boldsymbol{r_a}}\right)} \qquad \text{(eqn 8)}$$

γ = psychrometric constant [ML-1T -2C -1];

Δ = slope of the first derivative of the saturated vapor pressure curve (slope of saturation vapor pressure at the prevailing air temperature) [ML-1T -2C - 1];

r_c = canopy resistance

r_a = aerodynamic resistance given by

$$\boldsymbol{r_a} = \frac{\mathbf{1}}{\boldsymbol{k^2 u^a}}(\mathbf{ln}\left(\frac{\boldsymbol{z_a - d}}{\boldsymbol{z_o}}\right))^2 \qquad \text{(eqn 9)}$$

k is the Von Karman constant (0.4).

u_a is the wind speed at measurement level za = 2m.

d is the zero-plane displacement length.

z_o is the roughness length for the vegetation or soil.

The Penman coefficient (Ÿ/Δ) changes with temperature and may be found in table 2.

Table 2: Variation of Penman coefficient $\frac{\gamma}{\Delta}$ with temperature

$T(°C)$	-20	-10	0	5	10	15	20	25	30	35	40
$\frac{\gamma}{\Delta}$	5.86	2.83	1.46	1.07	0.76	0.59	0.45	0.35	0.27	0.25	0.17

Because there is no constraint on soil or water availability in vegetated groundwater discharge regions, real transpiration (T_v) equals reference transpiration:

$$\boldsymbol{T_v = T_{rv} \quad if \quad (G_d - h_t) \leq R_d} \qquad \text{(eqn 10)}$$

G_d, is groundwater depth.

h_t is the tension saturated height

R_d is the rooting depth [L]. For vegetated areas where the groundwater level is below the root zone the actual transpiration is given by:

$$\boldsymbol{f(\theta) = 1 - a_1^{\frac{w}{T_{rv}}}} \qquad \text{(eqn 11)}$$

given,

$$\boldsymbol{w = P + \left(\theta_{fc} - \theta_{pwp}\right)R_d} \qquad \text{(eqn 12)}$$

a_1 is a calibrated parameter related to the sand content of a soil type;

w is the available water for transpiration and

$\theta fc - \theta pwp$ is the plant available water content per time step, stated as the difference in water content at field capacity and at permanent wilting point.

Recharge

A residual term of the water balance is then used to determine the final component, groundwater recharge

$$R_v = P - S_v - ET_v - I \qquad \text{(eqn 13)}$$

When you add together transpiration T_v and E_s (the evaporation from bare soil located in between the plants), you get E_{Tv} [LT^{-1}], which is the real evapotranspiration.

Estimation of regionally dispersed recharge, plant type and soil types are used along with slope and groundwater depth as well as precipitation and evapotranspiration variables such as temperature and wind speed to determine the recharge rate. In addition, discharge regions will experience some recharge since there is a small unsaturated zone that exists even in discharge areas Vegetation increases transpiration during the wet months, causing a decrease in recharge values in discharge regions throughout the dry months.

On a seasonal basis, there are two approaches to include changes in storage into the model. When it comes to wet season, for example, the plant-available soil moisture reservoir is considered to be full, whereas in the dry season it can be reduced in the model; and when it comes to dry season, for example, a different groundwater depth can be utilized in the model.

Bare-soil, Open-water and Impervious surfaces.

Calculation of the water balance for bare soil, open water, and impermeable surfaces, the same technique is used. The main distinction is that there is no vegetation in these circumstances, therefore there is no word for interception and transpiration to speak of in these situations. As a result, the E_{Tv} becomes E_s.

b) Model Input Data

Meteorological data (precipitation, air temperature and wind speed) as well as soil types, topography and land use/land cover of the examined region are required to run the WetSpass-M model.

With the use of Geographic Information Systems (ArcGIS), these input data are produced as grid maps. The input model maps will be resampled to a raster's cell size is 90m x 90m.

3.3.2 Trend analysis

The Mann Kendall tests is the most applied technique in space-time mining models. Assuming the total number of datasets is indicated by N, the statistic S can be computed as (Fung et al., 2020);

$$\boldsymbol{s} = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \boldsymbol{sgn}(\gamma_j - \gamma_i) \qquad \text{(eqn 14)}$$

$Y_{j\ \text{indicates}}$ the value j^{th} data, while n indicates the number of data.

$$\boldsymbol{sgn}(\boldsymbol{\theta}) = \begin{cases} +1 & \text{if } \theta = \gamma_j - \gamma_i > 0 \\ 0 & \text{if } \theta = \gamma_j - \gamma_i = 0 \\ -1 & \text{if } \theta = \gamma_j - \gamma_i < 0 \end{cases} \qquad \text{(eqn 15)}$$

S's positive (negative) value indicates an upward (downward) trend. The S is considered to represent the data's value, whereas N represents the quantity of data points.

$$\boldsymbol{E}[\boldsymbol{S}] = \boldsymbol{0} \qquad \text{(eqn 16)}$$

$$\boldsymbol{var}(\boldsymbol{S}) = \frac{[N(N-1)(2N+5) - \sum_{i=1}^{n} t_i i(i-1)(2i+5)]}{18} \qquad \text{(eqn 17)}$$

where t_i denotes the number of data points in the i_{th} linked group Finally, the standardized test statistics Z may be calculated using the following formula:

$$z = \begin{Bmatrix} (S-1)/\sqrt{Var(S)} & S > 0 \\ 0 & \\ (S+1)/\sqrt{Var(S)} & S < 0 \end{Bmatrix} \qquad \text{(eqn 18)}$$

A positive Z value indicates a rising trend, whereas a negative one indicates a falling trend. Trends were assessed with a significance threshold of = 0.05 in this study. If the absolute value of Z is larger than 1.96, the null hypothesis of no trend is rejected.

3.3.3 Random Forest model

The WetSpass-M estimated groundwater will be utilized to forecast water recharge for sites not measured in the basin, using the Random Forests model the monthly groundwater recharge maps can be extrapolated.

The annual groundwater recharge maps were aggregated to 900 meters resolution, taking the maximum values at each pixel. The maps were then stacked to form one raster image of the annual recharge maps.

The first step involved converting the raster stack to a data frame and then to a matrix. Two similar matrices were then created, one containing the time points for each element in the matrix and the other matrix containing the cell numbers. The next procedure was the creation of a full data frame with one row per measurement. Since the cell number isn't numeric data, it is converted to a factor by adding "c" to the cell number. In order to maintain enough zeroes to keep the sort order, a "sprint f" function was used.

I then fit 5529 models by splitting the data frame and using "lapply" function to get a list of 5529 models. The "sapply" function is used to predict over the 5529 models for the year 2024 with the result being a vector. The vector is then plugged to a new raster object resulting to spatial map.

4. RESULTS

4.1 Model Validation

The validation of the model was performed using stream flow data obtained from Water Resources Authority (W.R.A). The stream flow simulation process requires both surface run off values and baseflow values.

Surface runoff values, which are an output of the model were obtained at each river node. The base flow values were separated from the Observed stream flow values using the WETSPRO software from the observed stream flow values. The expression that describes the relationship between stream flow, surface runoff and base flow is as below.

Stream flow = Surface Runoff +Base flow.

The co-efficient of determination of the observed and simulated stream flow values was determined to be a value of 0.79 indicating a high correlation (Fig 12).

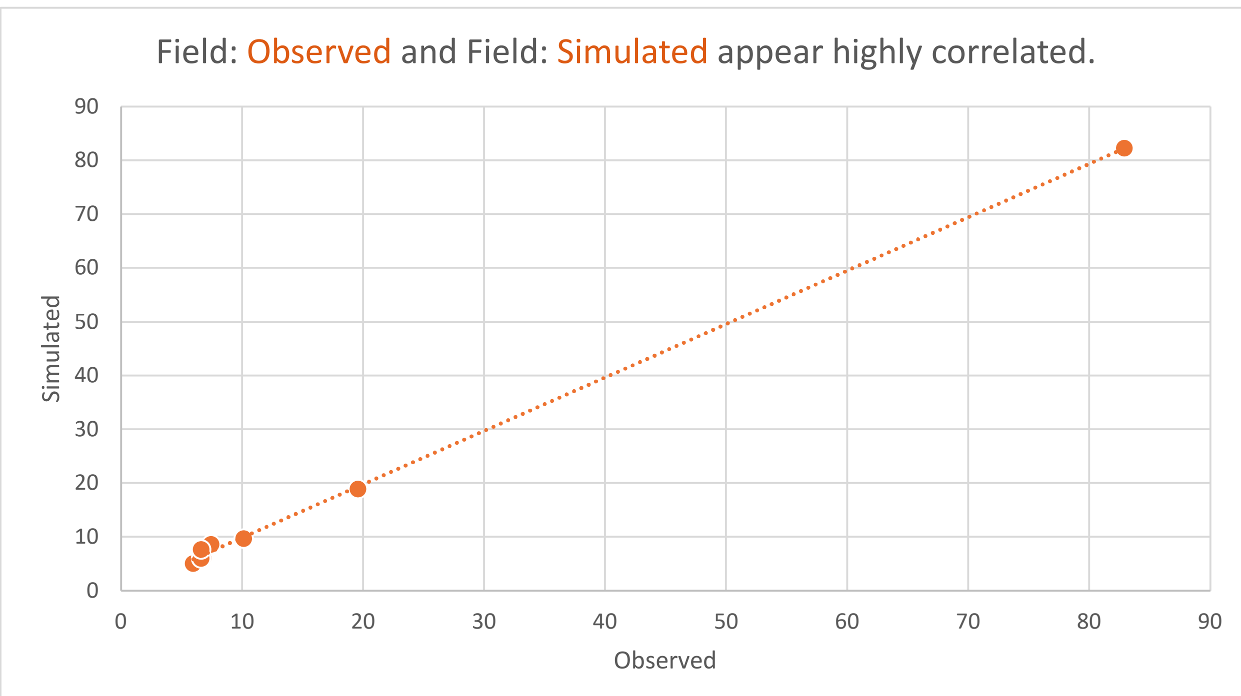

Figure 12: Stream flow co-efficient of determination chart between the Months of May and December 2008.

4.2 Groundwater Recharge Maps.

The first objective was to quantify groundwater recharge for the years 2008, 2012, 2016 and 2020. The simulation of groundwater recharge was done on a monthly basis using the WetSpass-M model.

For the year 2008, the highest positive recharge of 60mm was observed in the month of April. In general months that were observed to have experienced a positive recharge trend were March, April, May, November. There was an observation of negative recharge trends during the months of January, February, June, July, August, September, October and December (Fig. 13).

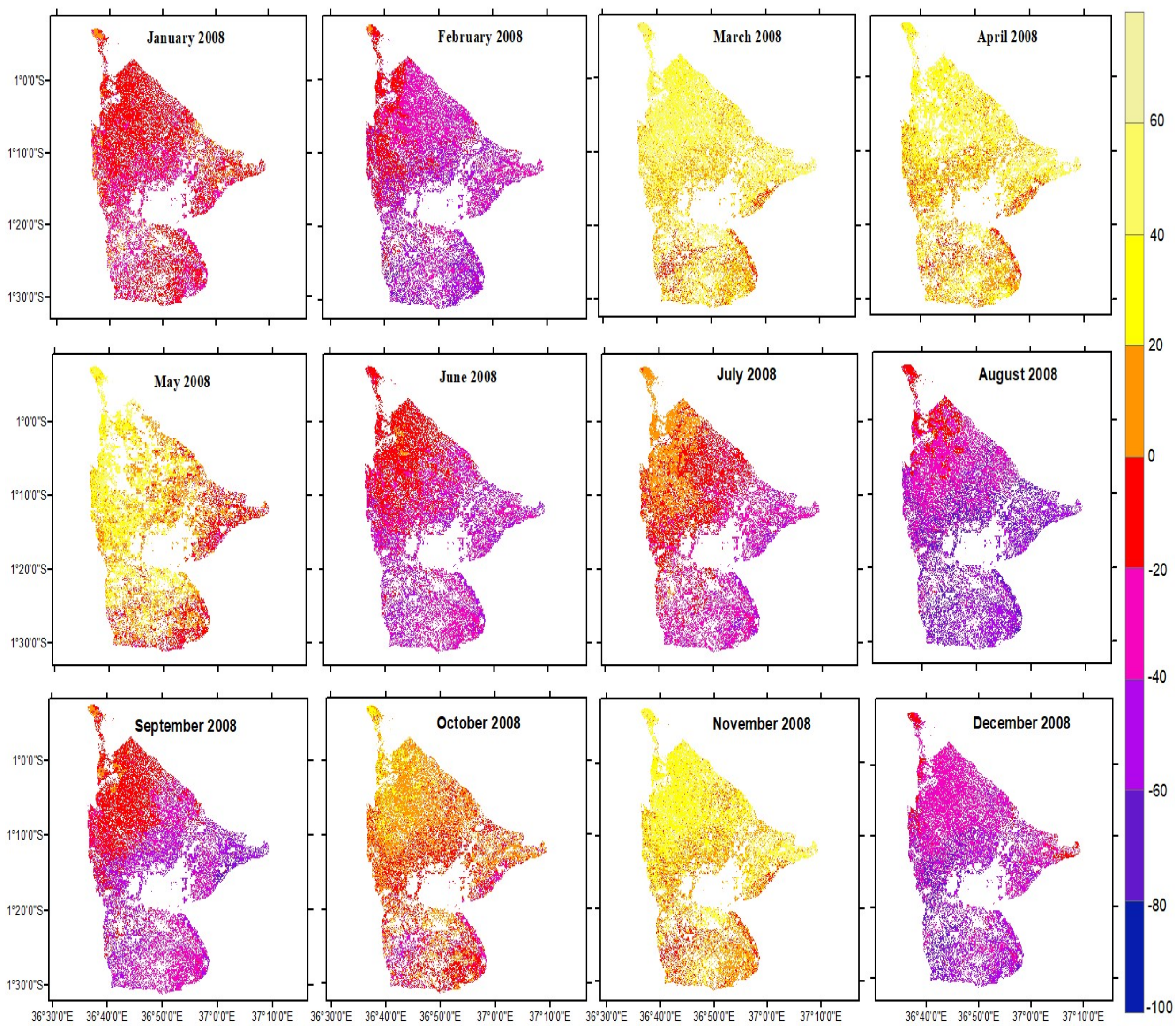

Figure 13: Monthly Groundwater recharge year 2008.

The simulation of groundwater recharge for the year 2012 showed the following results. The highest positive recharge (100mm) was observed in the month of April. The results show that the months in which positive recharge was observed were April, May and November. There was an observation of negative recharge trends during the months of January, February, March, June, July, August, September, October and December (Fig 14).

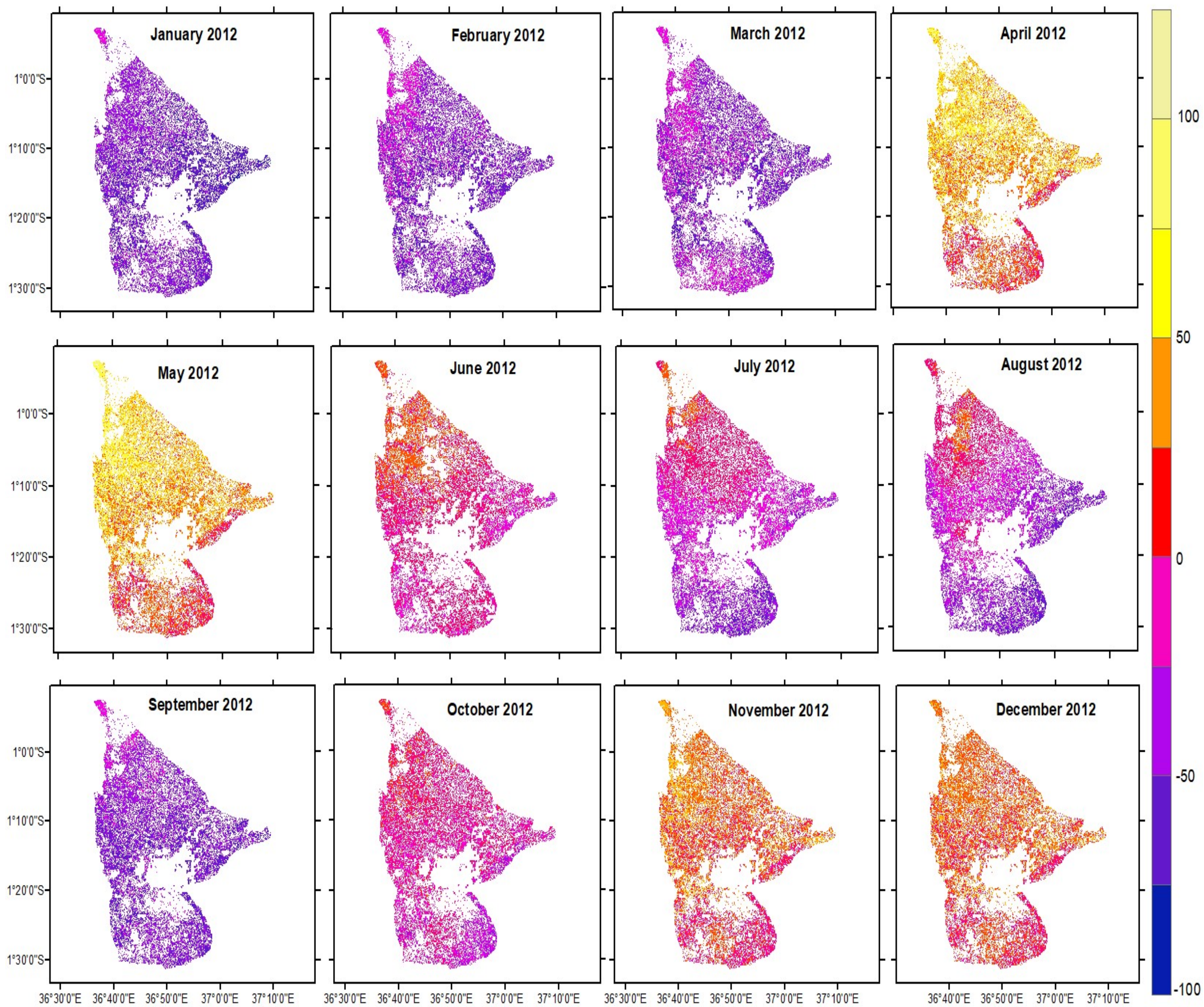

Figure 14: Monthly groundwater recharge year 2012

The monthly results for the year 2016 are as follows. The highest positive recharge (122mm) was observed in the month of May. In general months that were observed to have experienced a positive recharge trend were January, March, July, and August. There was an observation of negative recharge trends during the months of February, April, May, June, September, October, November, and December (Fig 15).

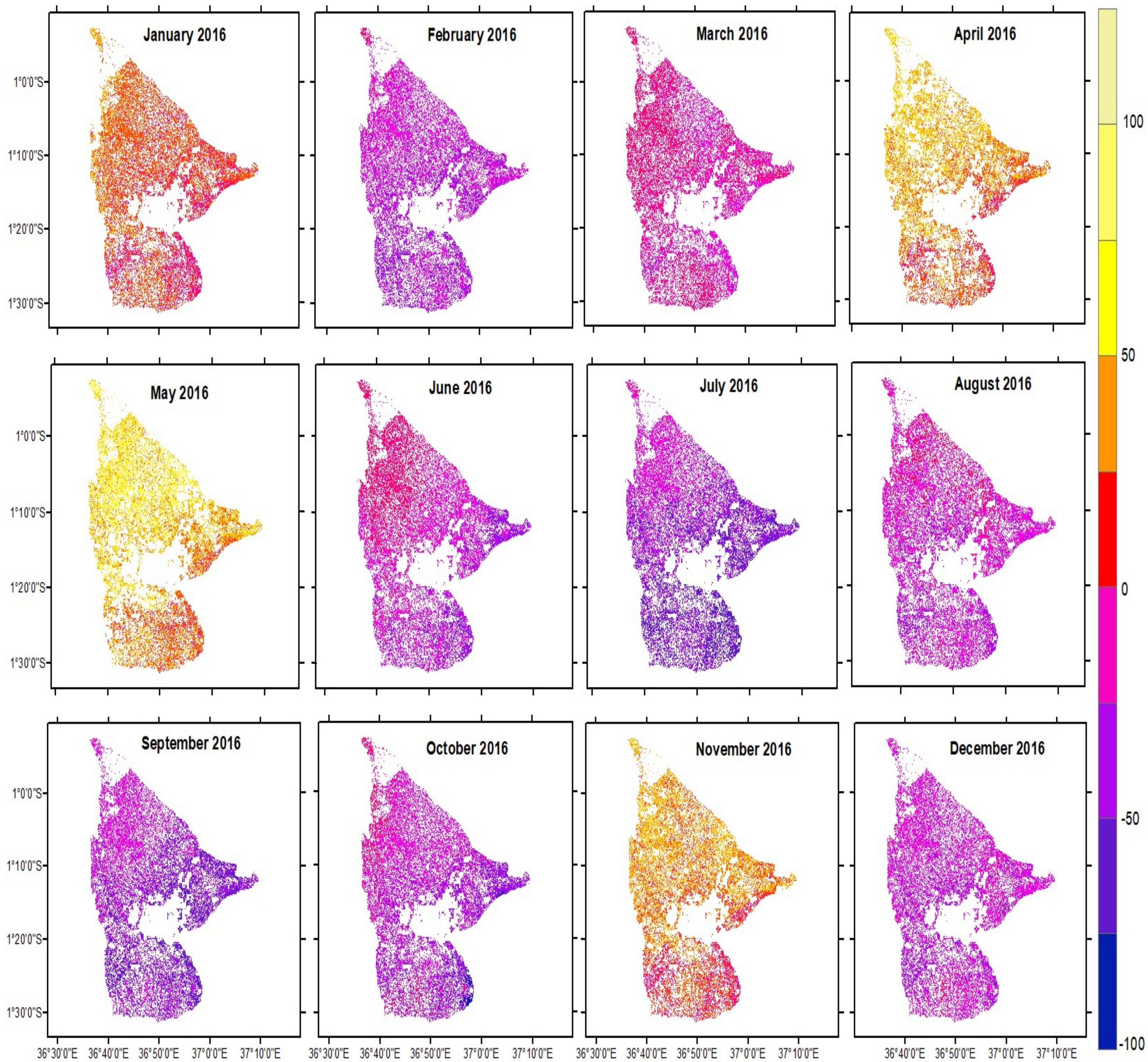

Figure 15: Monthly Groundwater recharge 2016.

For the year 2020, the monthly simulation results are as follows. The highest positive recharge (142mm) was observed in the month of April. In general months that were observed to have experienced a positive recharge trend were March, April, May and November. There was an observation of negative recharge trends during the months of February, June, July, August, September and October (Fig 16).

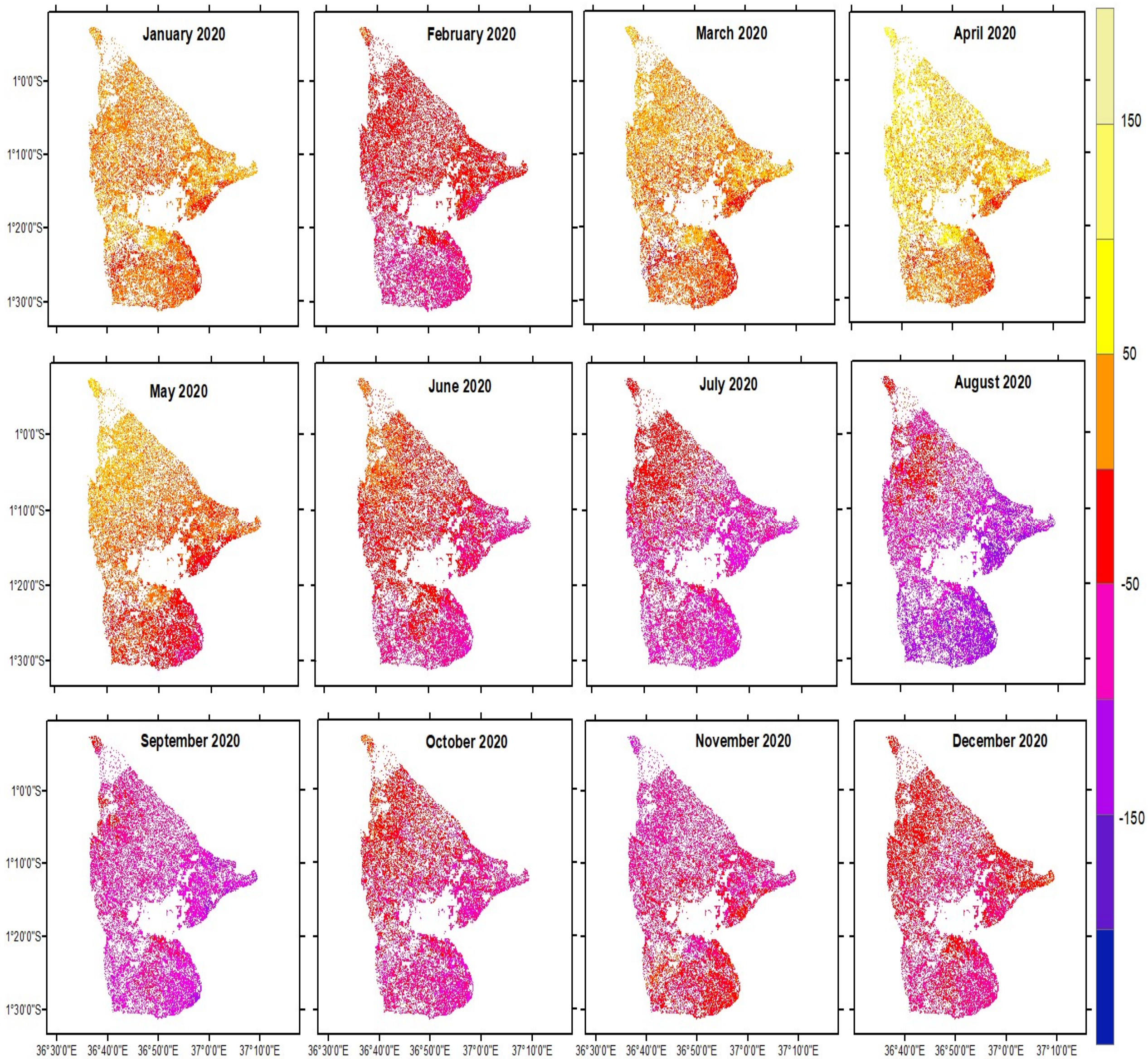

Figure 16: Monthly Groundwater recharge 2020.

The Annual groundwater recharge maps were obtained by summing the monthly raster outputs of the model for each epoch. The net maximum recharge values for the year 2008, 2012, 2016 and 2020 annual recharge rates were observed to be 37mm, 182mm, 220mm, 497mm respectively (Fig 17).

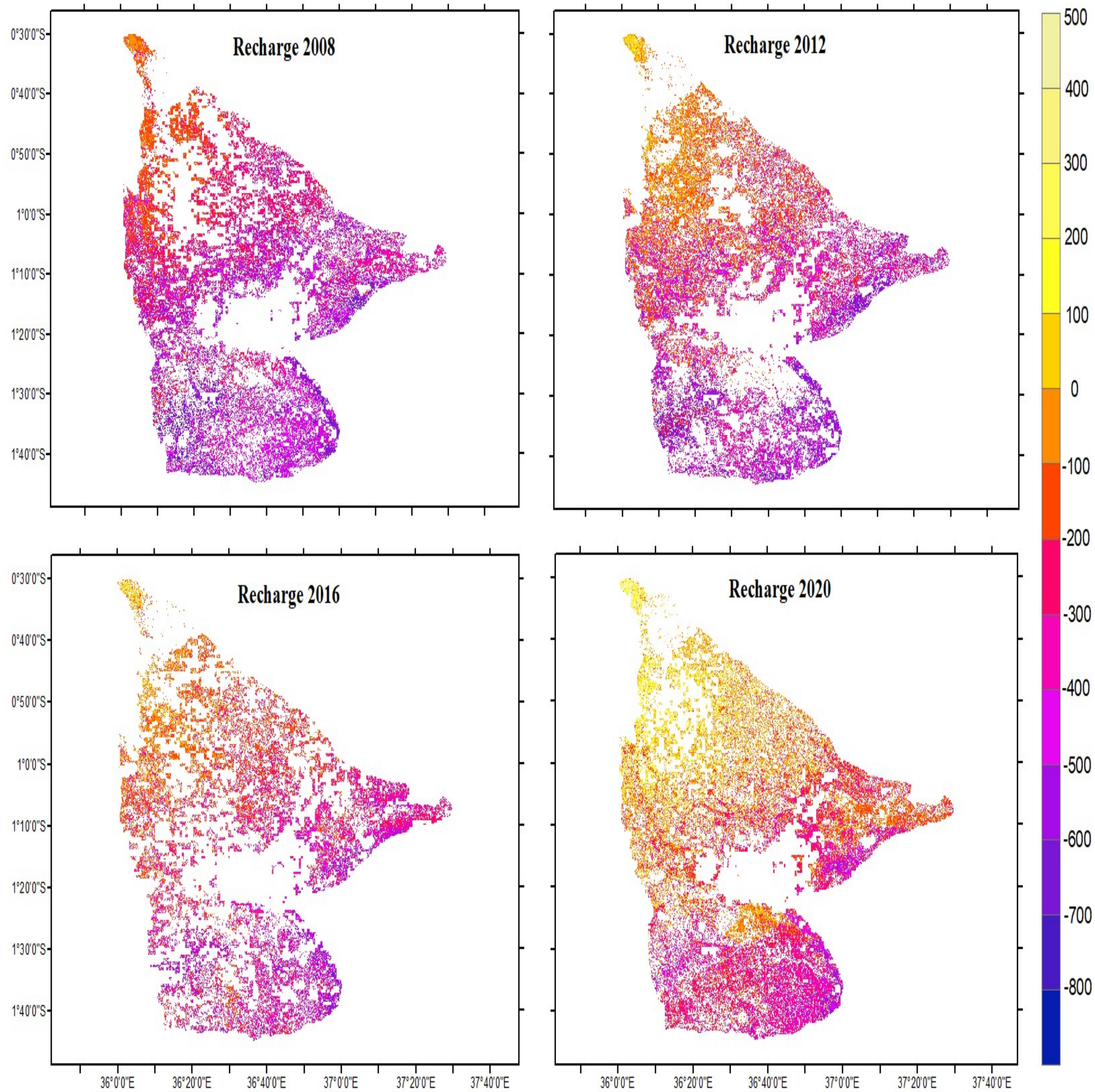

Figure 17: Annual Groundwater recharge Maps (1) 2008; (2) 2012; (3) 2016; (4) 2020.

4.3 Trend Analysis

The monthly groundwater recharge trend values were in the range between 0.6 mm and -0.67 mm (Fig 18). The average trend for the entire study area was -0.03 mm at a P value of 0.544 which indicates that the trends are insignificant for the entire study area as shown by figure 19.

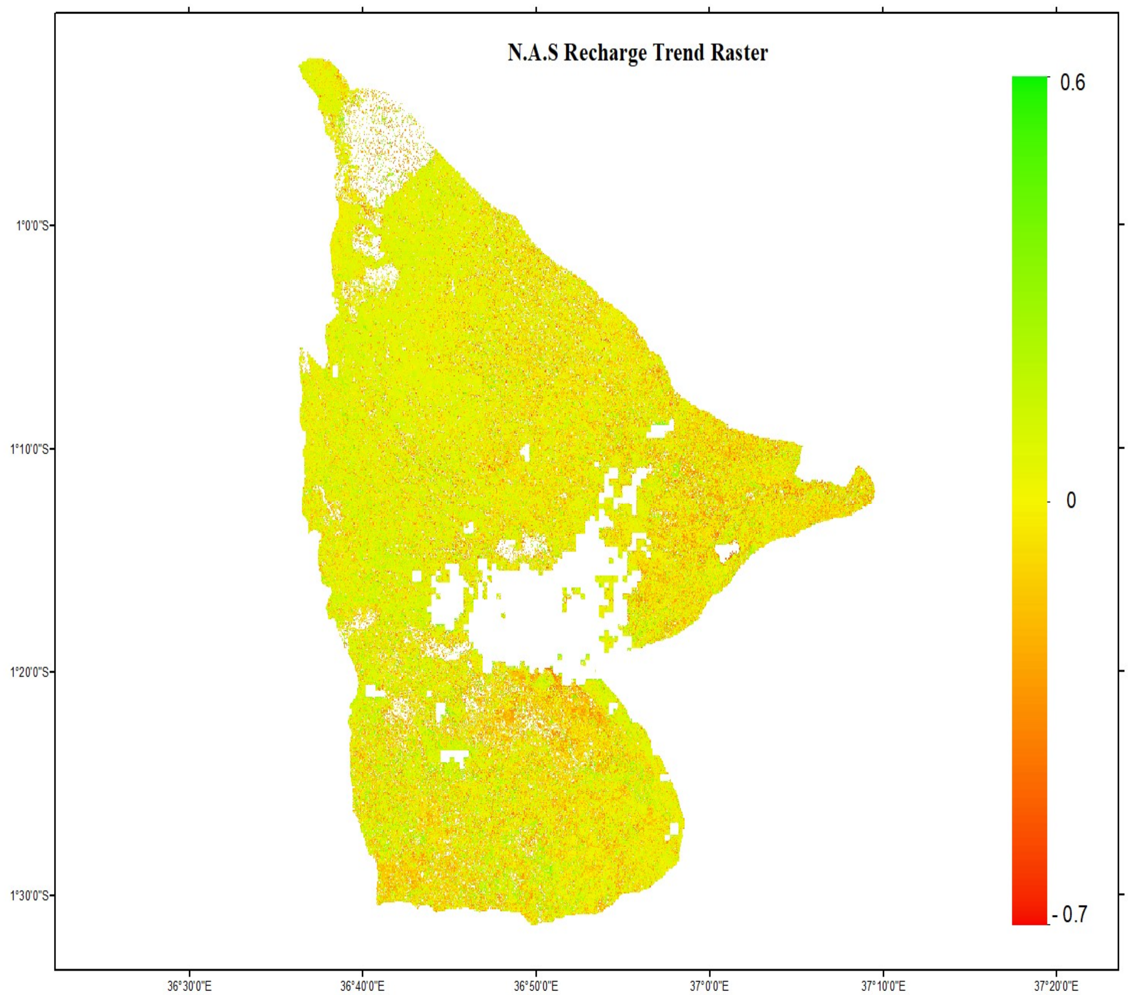

Figure 18: Trend Raster.

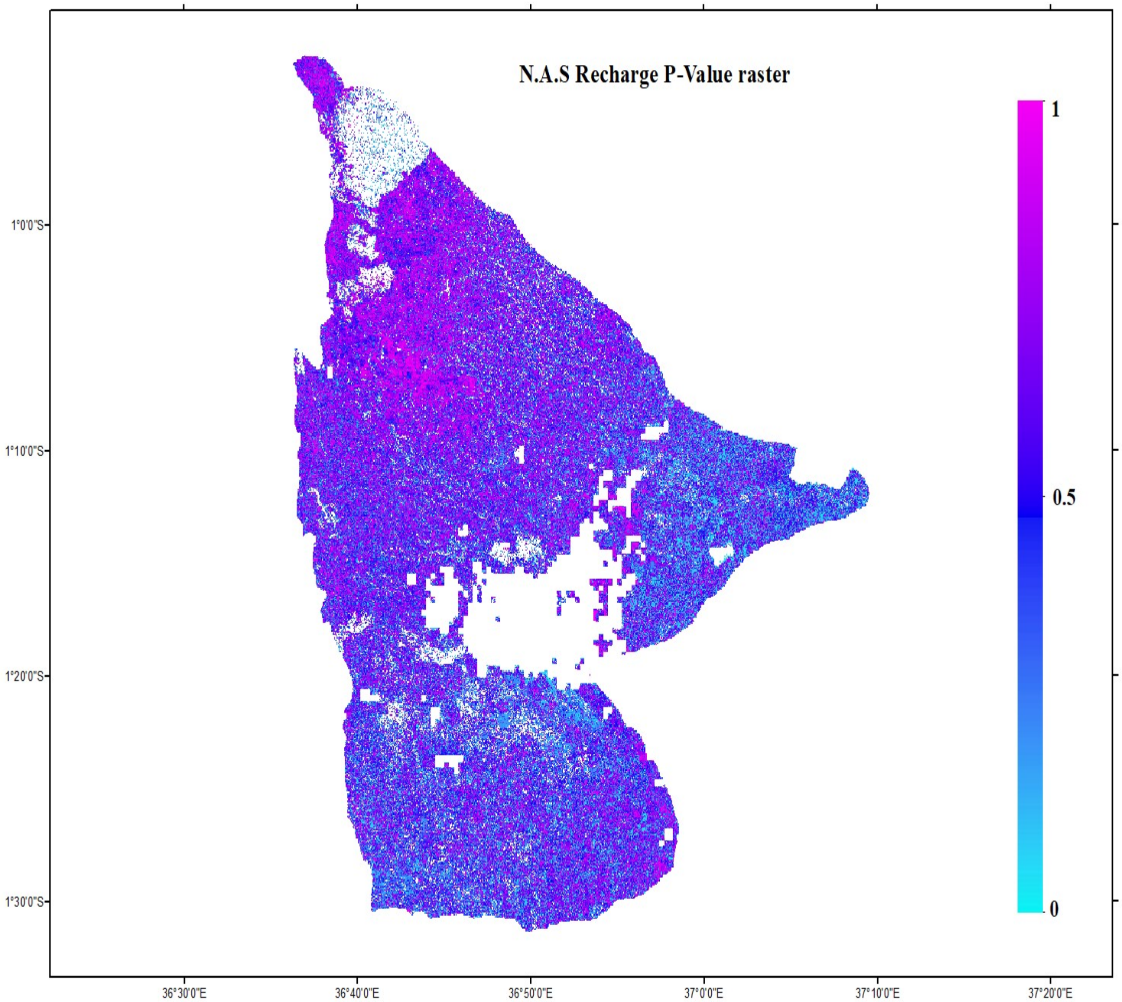

Figure 19: Spatially distributed P-value.

4.4 Groundwater Recharge Forecasting.

The results of forecasting groundwater recharge to the year 2024 using the random forest model was a net maximum groundwater recharge value of 386mm.

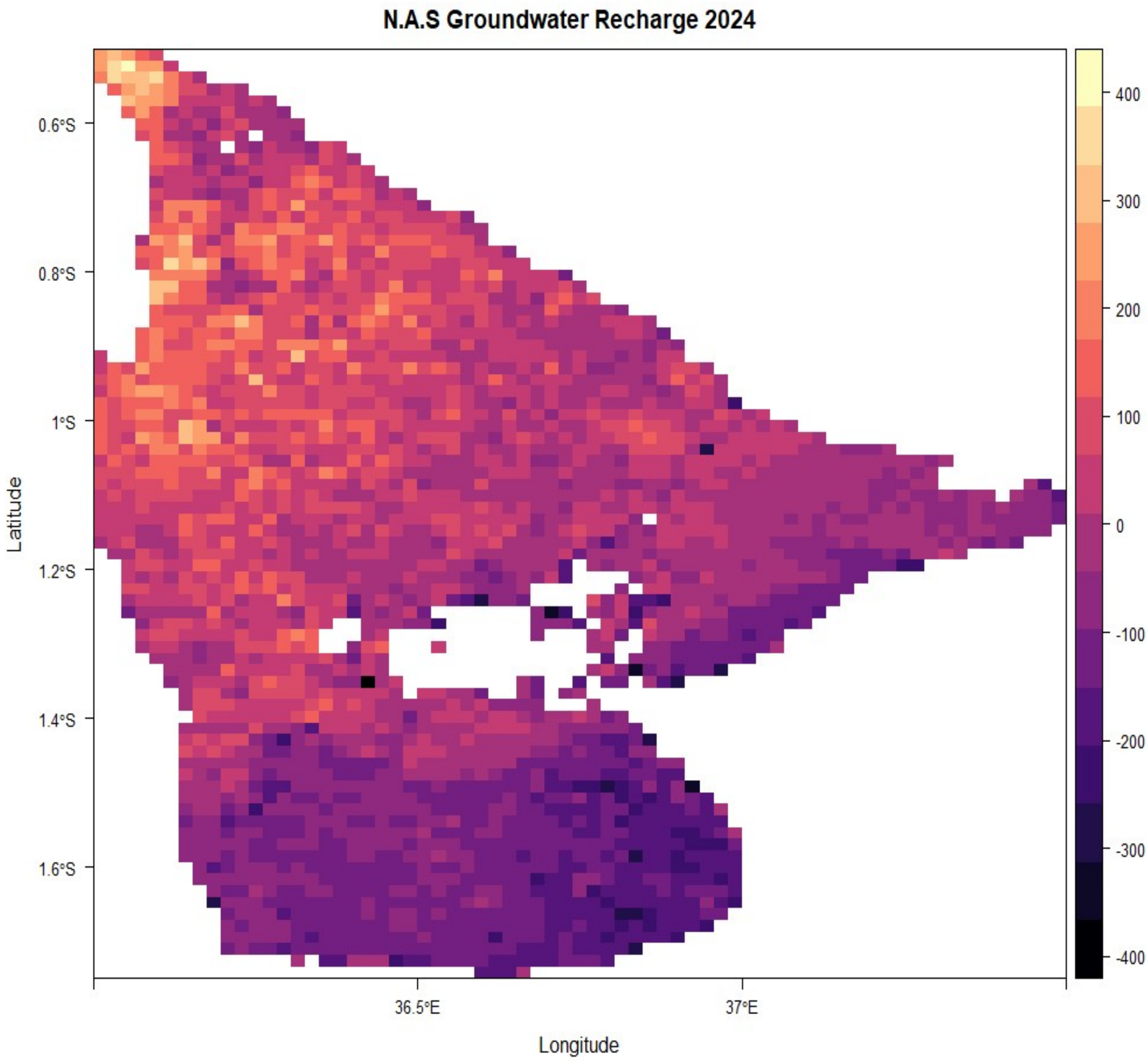

Figure 20: Annual groundwater recharge 2024.

4.5 Regression Analysis Results.

In order to determine the level of influence that each of the input variables has to groundwater recharge, regression analysis was performed. The results of the regression analysis (Table 3) indicate that the input variables with significant positive influence to groundwater recharge within the study area were Land use, Interception and surface run-off.

Table 3:Regression analysis results.

Variable	**Level of significance (R^2)**
Cell evapotranspiration	0.0321
Wind	0.0002
Slope	0.0036
Leaf area index	0.0002
Potential Evapotranspiration	0.0283
Soil	0.0124
Land use	0.1100
Surface Run-off	0.2047
Groundwater Levels	0.0007
Interception	0.1407
Rainfall	0.0210

5. DISCUSSION

The spatial and temporal variation in several climatological and biophysical input parameters, primarily rainfall, causes variations in groundwater recharge. The wet months have long duration, intensity, and amount of precipitation, as well as high soil moisture, which increases groundwater recharge. The variation in several climatological and biophysical input parameters, primarily rainfall, alters groundwater recharge rates. Various models can be applied to estimate recharge in different areas depending on their conditions. In this case the WetSpass-M model monthly and annual spatial distribution of groundwater recharge of the NAS region by subtracting the monthly surface runoff and evapotranspiration from the monthly precipitation.

The principal outputs of the WetSpass-M model are raster maps of monthly groundwater recharge, surface run-off, interception, and actual evapotranspiration for the years 2008, 2012, 2016 and 2020 (48-time steps). The pixels in these maps each represent the magnitude of the water budget of evaporation from open water, impervious surface area, bare soil, interception, and transpiration of vegetation cover.

Spatial monthly, seasonal and annual groundwater recharge simulated by the WetSpass model are presented by (Fig 13-17) for the years 2008, 2012, 2016 and 2020 respectively. The simulated groundwater recharge values of the upper Athi Basin for the year 2008 (Fig 13) ranged from 162 mm and -201mm for the wet months while the dry months recharge values ranged from -101 mm and -609 mm. The mean groundwater recharge value (5mm) in the wet months (March, April, May, and November) of 2008 represented 1% of the average rainfall(458mm). The mean groundwater recharge value during the dry months of 2008 was -363 mm with an average rainfall of 245mm which suggests that the rainfall was totally distributed to other water balance components (Evapotranspiration and surface runoff). The average evapotranspiration value for the dry months in 2008 was 529 mm while the average surface runoff was 83 mm which represented 34% of the precipitation in that period. The evapotranspiration rates were therefore exceeded precipitation by 69% during the dry months of 2008.

The simulated groundwater recharge for the year 2012 (Fig 14) ranged from 323 mm and – 101 mm during the wet months while the groundwater recharge values for the dry months ranged from -51 mm and -672mm. The mean groundwater recharge value for the wet months (64mm) represented 8% of the average rainfall (817mm). The mean groundwater recharge for the dry months was -367mm with an average rainfall of 456mm suggesting the water budget was distributed to evapotranspiration and surface runoff. The mean evapotranspiration (144mm) for the wet months represented 17% of the average rainfall while the mean surface runoff (614mm) represented 75% of the average rainfall. The dry months' mean evapotranspiration was 581 mm while the mean surface runoff (241mm) represented 52% of the average rainfall (456mm). The evapotranspiration rates were therefore exceeded precipitation by 63% during the dry months of 2012.

The simulated groundwater recharge for the year 2016 (Fig 15) ranged from 307 mm and –84 mm during the wet months while the groundwater recharge values for the dry months ranged from -54 mm and -627mm. The mean groundwater recharge value for the wet months (80mm) represented 13% of the average rainfall (596mm). The mean groundwater recharge for the dry months was -349mm with an average rainfall of 341mm suggesting the water budget was distributed to evapotranspiration and surface runoff. The mean evapotranspiration (111mm) for the wet months represented 18% of the average rainfall while the mean surface runoff (394mm) represented 66% of the average rainfall. The dry months' mean evapotranspiration was 574mm while the mean surface runoff (113mm) represented 33% of the average rainfall (341mm). The evapotranspiration rates were therefore exceeded precipitation by 60% during the dry months of 2016.

The simulated groundwater recharge for the year 2020 (Fig 16) ranged from 364mm and – 150mm during the wet months while the groundwater recharge values for the dry months ranged from 133mm and -515mm. The mean groundwater recharge value for the wet months (58mm) represented 7% of the average rainfall (800mm). The mean groundwater recharge for the dry months was -215mm with an average rainfall of 436mm suggesting the water budget was distributed to evapotranspiration and surface runoff. The mean evapotranspiration (182mm) for the wet months represented 22% of the average rainfall while the mean surface runoff (525mm) represented 65% of the average rainfall. The dry months' mean evapotranspiration was 464mm while the mean surface runoff (176mm) represented 40% of the average rainfall (436mm). The evapotranspiration rates were therefore exceeded precipitation by 44% during the dry months of 2020.

The groundwater recharge distribution in the upper Athi basin varies spatially. The Northwestern part of the basin receives more recharge than other areas. This can be attributed to loam soils which are highly permeable (Fig 8), agricultural and grassland land use types that reduces runoff rates hence encouraging recharge (Fig 6). Furthermore, this area is located in the highlands that are normally recharge zones in any basin (Ayele, 2020). It is also important to note that the area does experience the highest rainfall distribution which is an important water balance component to groundwater recharge.

The geological characteristics of the area also affects the rate and amount of recharge in the area. The permeability of the rock is a major factor that affects groundwater recharge. Different rock types are available in the upper Athi basin as addressed in section 3.1.4. The highlands have highly weathered and fractured aphanitic soils that encourage recharge. In the lowland areas of the basin, phonolites are the main geological unit which encourage occurrence of shallow groundwater systems (Saggerson, 1991).

Negative and extremely low recharge rates were observed in the south part of the basin. The extremely low recharge rates can be attributed to low rainfall distribution, clay soils which are highly impermeable (Fig 8), bare soil and shrubland land use types that increases evapotranspiration and runoff rates (Fig 6). Furthermore, this area is topographically low which are mostly discharge areas than recharge areas. Negative recharge values are associated with higher evapotranspiration rates than surface runoff rates and recharge rates. This is because of the occurrence of shallow groundwater system in the south that is absorbed by the surrounding vegetation. The plants thereafter release the water to the atmosphere through evapotranspiration which exceeded rainfall distribution.

The results of the trend analysis performed on the monthly groundwater recharge values was a trend raster for the study area ranging from 0.6 mm to -0.6mm (Fig 18) and a spatial p-value raster ranging from 0 to 1 (Fig 19).

The mean recharge trend was -0.03mm/month and the average p value was 0.544. This means that since the p-value is above 0.05, the research fails to reject the hypothesis. The conclusion therefore is that there is no sufficient evidence to suggest that there is a monotonic trend. This can be attributed to the seasonal and long-term variation of climatic variables i.e., precipitation.

The predicted annual groundwater recharge for the year 2024 ranged from 320mm and -329 mm. The maximum recharge value was observed as having decreased from 429 mm in the year 2020.

In summary, the highest rainfall percentage (13%) was distributed to recharge was the year 2016. The recharge distributed in the year 2008 was significantly low due to the meteorological drought experienced in that period.

The Nairobi aquifer suite (NAS) is mostly recharged in the northwestern part of the sub-basin (Fig 13-17) which is consistent with the previous studies (Mumma et al., 2011). The study also showed that recharge mostly occurs in the wet months of April, May and November which is consistent with the findings of a research conducted on recharge within the stony Athi subcachment (3AA) (Fig 1) for the years 1984, 1995, 2005 and 2017 (Mathenge et al., 2020). However, there was an apparent disagreement between the computed percentage of rainfall distributed to recharge from their study (14%) and the computations of this study (8%). The disparity can be attributed to the employment of different datasets. The use of remotely sensed datasets especially for potential evapotranspiration (MOD16A2 MYD16A2) in this study allowed for the quantification of negative net recharge rates. Since this would be accounted for in the water budget computation, the expectation therefore is that the net recharge distributed from rainfall would be slightly lower.

6. CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

The study aimed at performing spatial and temporal analysis of groundwater recharge within the aquifer recharge zones of the Nairobi aquifer suite for the years between 2008 and 2020. This was achieved by quantifying recharge for the years 2008, 2012, 2016 and 2020 using the WetSpass-M model. Trend analysis was performed to determine the groundwater recharge rates for the years between 2008 and 2020 using the Mann Kendall test. The generated spatially distributed recharge maps were used to predict annual groundwater recharge trends for the year 2024 using a random forest model.

The results of this study were as follows:

- Recharge values for the year 2008 ranged from 162mm and -609mm.
- Recharge values for the year 2012 ranged from 323mm and -672mm.
- Recharge values for the year 2016 ranged from 307mm and -627mm.
- Recharge values for the year 2020 ranged from 496mm to -515mm.
- The average recharge trend for the area was -0.03mm/month between 2008 and 2020 at 54.4% level of significance.
- Recharge values for the year 2024 ranged from 320mm and -329mm.
- The study further showed that recharge occurs mostly during the wet months specifically April, May and November.
- The observations made in 2008 showed that the drought occurrence in that period affected groundwater recharge as precipitation was low contributing only 1%.
- Significant amounts of precipitation, as observed in the research, was distributed to surface runoff (75%) during wet seasons while only 8% is recharged.
- The sub basin also lost significant amounts of groundwater to evapotranspiration (60%) during the dry seasons.

- The findings of this research can be used for groundwater modeling of the Nairobi aquifer system.

6.2 Recommendation

Recommendations for future studies are as follows:

- Future studies should conduct groundwater recharge studies at reduced epoch intervals to give a more accurate depiction of the water balance.
- Groundwater levels should be collected monthly to generate groundwater maps monthly rather than on a seasonal basis. Furthermore, groundwater observation wells should be established across the entire sub basin to generate more accurate depth to groundwater maps.
- The use of more than one method for recharge estimation is crucial to check for accuracy of results.
- The spatial resolution of the datasets can be improved in order to improve on spatial variation of the recharge simulations.

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