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*Article*

# Evaluation of the Streamflow Response to Agricultural Land Expansion in the Thiba River Watershed in Kenya

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**Abstract:** The increasing global population necessitates increased agricultural production, driving the expansion of agricultural lands and advancement of irrigation farming to supplement the inconsistent and insufficient rainfall patterns prevalent in many regions. This study aimed to evaluate the potential impacts of the expansion of agricultural lands on the streamflow regime of the Thiba River and its impact on the downstream users. The study involved comparing the 2004 and 2014 land uses and using the Hydrologic Engineering Centre's Hydrologic Modelling Systems (HEC-GeoHMS and HEC-HMS) for long-term impact simulations. The results showed a considerable decline in the streamflow in the dry months compared to the wet months, with increasing water abstraction trends from 2007 to 2014. The long-term impact assessment showed an average decline in streamflow in the near (2030) and far (2060) future due to land use and population changes with minimal impact from the increasing precipitation. Based on these findings, there is a need for proper water management and adaptation mechanisms to be put in place to maintain the future water supply from the Thiba River. This study's findings could assist policy and decision-makers in making informed water resource management decisions.

**Keywords:** agricultural land; irrigation; land use change; streamflow; Thiba River watershed; water abstraction

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## 1. Introduction

Agricultural production has continuously been increasing all over the world, mainly due to increased food demand due to the growing population (Food and Agriculture Organization of the United Nations [FAO], 2017b; Mateo-Sagasta et al., 2018). This has prompted the expansion of agricultural lands and the development of irrigation farming to supplement most areas' unreliable and low rainfall capacities. Agriculture, by far, consumes the highest amount of global world water resources, with irrigation accounting for the maximum share of global freshwater withdrawals (Siebert et al., 2010). According to Zeng and Cai (2014), approximately 70% of the global freshwater withdrawal is used to meet irrigation water requirements.

In Kenya, just like the rest of the world, agriculture is the leading water consumer accounting for over 80% of the available water (Muema et al., 2018). The Kenyan government has initiated and promoted various agricultural projects, especially irrigation projects, to increase agricultural productivity and enhance food security. Despite the many advantages of irrigation, some adverse effects are experienced in irrigated areas. These negative effects include influences on the hydrological regime such as the decline of the base flow and reduction in discharge of the stream caused by over-exploitation of water resources or disruption of the natural hydrological regime through manmade structures. Additionally, irrigation could result in water erosion caused by inappropriate irrigation methods on sloping fields, as well as affect surface and groundwater quality (Fernández-Cirelli et al., 2009).

The Mwea Irrigation Scheme (MIS) in the Thiba River watershed, one of Kenya's largest irrigation schemes, has tremendously expanded since 2003, after Kenya's Vision 2030 plan establishment. The Kenyan government has substantially invested in expanding irrigation to bridge the over one million hectares gap required by 2030 to sustain food production (Muema et al., 2018). The MIS was established in 1954, with currently over 30,000 acres of gazetted land, of which 22,000 acres are utilized for paddy rice production and the remainder for settlement, public utilities, and subsistence crop cultivation (National Irrigation Authority, 2023). Paddy rice farming has resulted in the expansion of the area surrounding the scheme by approximately 8,600 acres. This new area was not planned for and has worsened the situation in terms of water availability for the scheme (National Irrigation Authority, 2023). However, there is limited information on actual water abstracted from the river and the potential impacts on streamflow associated with increased commercial agricultural activities.

The continuous expansion of agricultural land in the study area by the government and individual farmers has substantially increased the demand for water from the Thiba River. This demand is further exacerbated by the high population growth in the area, putting extra pressure on the already diminishing water resources. As agricultural productivity rises to meet the growing food demand, the expansion of agricultural lands becomes inevitable, resulting in increased agricultural water demand and more strain on the Thiba River. The escalating agricultural water demand, combined with domestic and industrial needs, has resulted in increased water abstractions from the river, mainly in the upstream areas with higher population densities and agricultural activities, consequently affecting the downstream water availability (Akoko et al., 2020). Furthermore, water pollution by fertilizers, agrochemicals, and sedimentation exported from the cultivated fields affects the river's water quality, compounding the problem.

Despite these challenges, there is a lack of studies examining the impact of continuous agricultural land expansion and increased water abstraction on the Thiba River's flow regime. This knowledge gap hinders the development of effective water and land management strategies for sustainability and appropriate water resource utilization in the watershed. This study aimed to evaluate the streamflow response to agricultural water abstraction and its variability with rainfall for the Thiba River watershed. The relationship between streamflow and water abstraction and the land use change from 2004 to 2014 was examined. The Hydrologic Engineering Centre's Hydrologic Modelling Systems (HEC-HMS) and its Geospatial extension (HEC-GeoHMS) models were used to predict future scenarios based on a practical approach to obtaining long-term land use and climate changes in the near future (2030) and in the far future (2060).

## 2. Materials and Methods

### *2.1. Study Area*

Thiba River watershed (Figure 1a) is located in Kirinyaga and Embu Counties of Kenya at latitudes 0° 5' S and 0° 47' S, and longitudes 37° 12'E and 37° 32'E and it's approximately 100 km North-East of Kenya's capital city, Nairobi. It covers an estimated area of 1648 km$^2$. The watershed is located in the upper region of the Tana River basin that is drained by rivers Thiba, Nyamindi, Rupigazi, and several other smaller streams. Thiba River receives its waters from a higher elevation region in Mount Kenya. The watershed has several agricultural activities upstream and downstream, including the MIS, which is well known for paddy rice production in Kenya. The MIS covers over 15% of this watershed and consumes the highest irrigation water in the area. Other agricultural practices in the watershed that depend on irrigation include cultivating maize and other subsistence crops. Thiba River drains its water to the Kaburu hydroelectric dam, one of the seven hydro-power stations in the Upper Tana Basin.

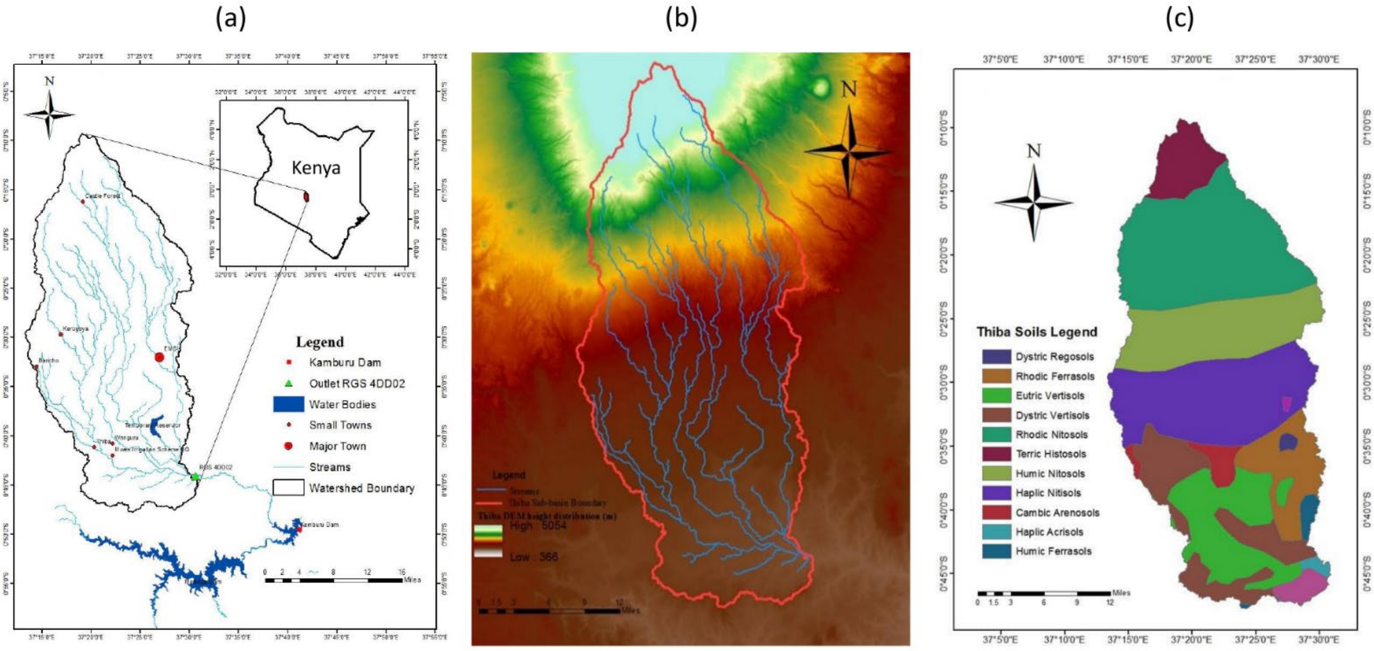


**Figure 1.** The Thiba River watershed (a) location (b) topography and (c) soil type maps.

The climate in the study area ranges from tropical to semi-arid in the upstream to downstream, having annual precipitation ranging from 400 mm in the lowland areas to about 2000 mm in the highland areas of Mount Kenya. The average annual precipitation in the watershed is 944 mm (Akoko et al., 2020). However, lower rainfall patterns are mostly experienced in January, February, June, July, and August. The temperatures in the watershed range from 13 °C in the highlands to around 30 °C in the lowlands. The hottest months are between January and February, whereas the coolest months are between June and July. The mean temperature for the watershed is about 23 °C. The elevation of the watershed (Figure 1b) varies spatially, ranging from as high as 5000 m in the highland region of Mount Kenya to less than 1000 m in the lowland region. The watershed's soil type (Figure 1c) is mainly black cotton and volcanic soils. The high-elevated regions around Mount Kenya are characterized by histosols and nitisols, which are majorly formed from volcanic ash deposits. These soils are more productive (agriculturally) than most soils in this watershed despite undergoing a series of weathering (FAO et al., 2012).

The watershed's predominant land-use activity is commercial flood irrigation of paddy rice in the MIS. Some farmers in this watershed also practice horticultural farming, whereas others only focus on subsistence farming, such as growing maize and beans (Nyamai et al., 2012). The MIS accounted for 88% of rice produced in Kenya between 2005 and 2010 (National Irrigation Authority, 2023). The scheme receives over 80% of its water supply from Nyamindi and Thiba Rivers, which have a link canal joining them to transfer water from the Nyamidi River to the Thiba River. Irrigation water is abstracted from the rivers by gravity action through fixed intake weirs and then conveyed and distributed in the scheme via unlined open channel systems.

### *2.2. Data Acquisition*

The topography data used a 30 m resolution Digital Elevation Map (DEM) for the Thiba River watershed (Figure 1b) obtained from the Shuttle Radar Topography Mission (SRTM) elevation data was downloaded from the USGS website (United States Geological Survey, 2017). The soil data map for the Thiba River watershed (Figure 1c) was downloaded from the Soil and Terrain (SOTER) database for the Upper Tana catchment, of which the study area is located at the scale of 1:250,000 (Batjes, 2011; Dijkshoorn et al., 2011). The classified land use maps for 2004 and 2014 were downloaded from the FAO's Africover project database (FAO, 2017a). These land use maps are produced from visual interpretation of digitally enhanced Landsat TM images (Bands 4,3,2) (Di Gregorio & Latham, 2003; Jansen & Di Gregorio, 2003). The 2009 Kenyan population grid map obtained from the International Livestock Research Institute (ILRI) website was used to extract the study area's population density grid to project the future population in 2030 and 2060 for future analysis.

The daily observed rainfall data from 2000 to 2009 obtained from the Kenya Meteorological Department (KMD) for three meteorological stations (Embu, Kerugoya, and Castle Forest) within the Thiba River watershed was used for the study. Satellite rainfall data for the study period obtained from the global cleaning weather data was used to fill in the missing gaps. The daily observed streamflow data for Thiba River from 2000 to 2009 was obtained from the Water Resources Management Authority (WRMA) in Embu, Kenya, and National Irrigation Authority (NIA) in MIS, Kirinyaga County, Kenya. The statistical method of data filling was adopted to fill in the missing data. Due to a lack of consistent discharge data from several gauging stations within the watershed, only one gauging station at the watershed outlet, River Gauging Station (RGS) 4DD02 (0° 25' 48' 'S 37° 30' 22''E), was used. Past agricultural water abstraction data from MIS was obtained from the NIB located at the scheme and the WRMA in Embu. The data from the NIB was compared to that from the WRMA to validate it. The available water abstraction data obtained was from 2007 to 2014. This data was used to establish the abstraction trend due to agricultural activities within the watershed. The average monthly potential evapotranspiration data for the Thiba River watershed was obtained using the FAO's Climate and Water balance (CLIMWAT) and Crop Water Requirement (CROPWAT) models for the Embu, Mwea, and Kerugoya stations (FAO, 2015). Then the average value for the three stations was used to represent the whole catchment. This potential evapotranspiration data was calculated using the Penman-Monteith equation in CROPWAT. The potential evapotranspiration ranges from a mean of 1700 mm in the low elevation savannah zone to less than 500 mm annually in the summit region with an overall average of 1000 mm (Notter et al., 2007).

### *2.3. Model Description*

The future impacts of agricultural land expansion on streamflow were analyzed using the HEC-GeoHMS coupled with the HEC-HMS model. The model choice was due to the simplicity and straightforward approach in its application. It analyzes watershed hydrology in both lumped and quasi-distributed forms. HEC-GeoHMS has well-developed data management and visualization functions. It also performs spatial analysis when developing distributed hydrologic parameters, which saves time and costs and helps in accuracy enhancement (United States Army Corps of Engineers [USACE], 2010).

The HEC-GeoHMS is a free public-domain hydrological modeling software that was designed by the United States Army Corps of Engineering (USACE) Hydrologic Engineering Centre (HEC) to help and assist engineers, hydrologists, or those with limited GIS experience to be able to visualize spatial information, perform spatial analysis functions, delineate catchments boundaries and streams, document watershed characteristics, and prepare hydrological model inputs (USACE, 2013). It is a physically based, lumped, semi-distributed, and geospatial hydrological tool that was developed to process geospatial data and create their input files in GIS. HEC-GeoHMS is used to translate GIS spatial data into model files for HEC-HMS. ArcGIS is used for data formatting, processing, and coordinate transformation. HEC-GeoHMS uses DEM for catchment delineation and preparation of various hydrologic inputs. The interconnection between GIS, HEC-GeoHMS, and HEC-HMS is illustrated in Figure 2.

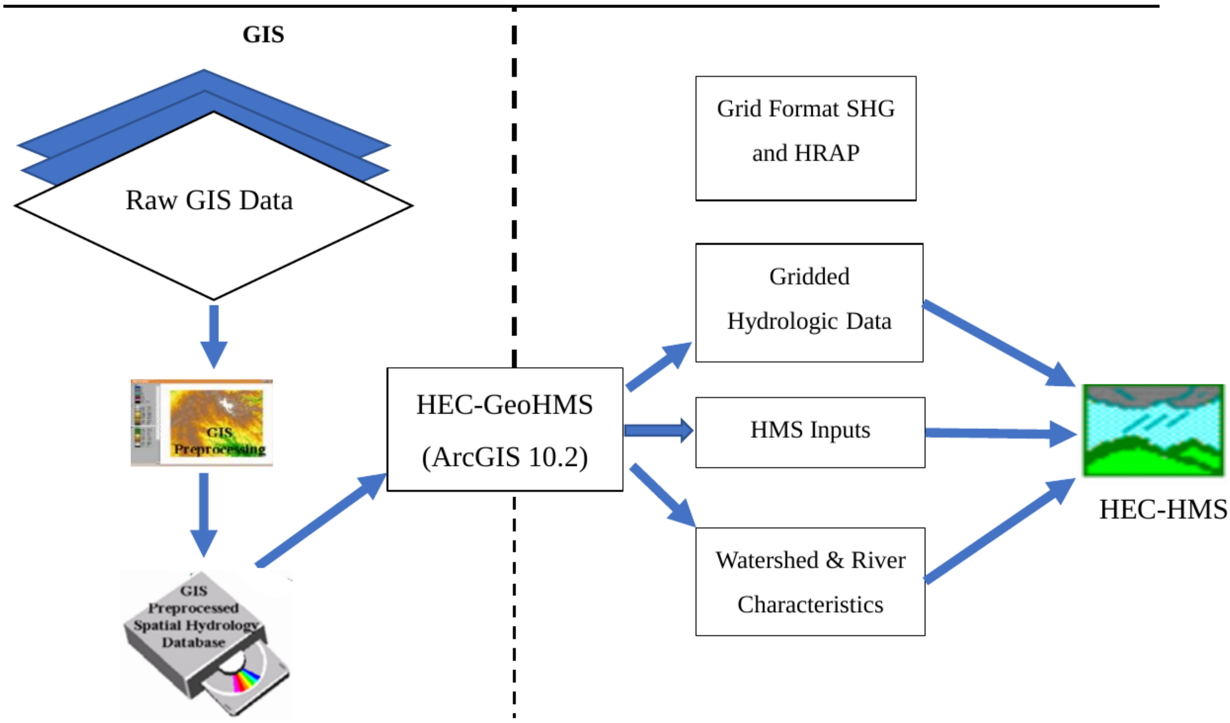


**Figure 2.** Schematic diagram of the relationship between GIS, HEC-GeoHMS, and HEC-HMS.

The HEC-HMS model divides the watershed into smaller subbasins to simulate the hydrologic cycle's energy and mass flux balances (USACE, 2010). The model runoff simulation components include (i) the precipitation specification option, describing the observed (historical) rainfall at a given location; (ii) the loss models to estimate the runoff volume based on the precipitation and the watershed's characteristics;(iii) the direct runoff models accounting for the overland flow, storage, and energy losses; (iv) the hydrologic routing models accounting for storage and energy flux during water movement through the stream channels; (v) models of naturally occurring confluences and bifurcations; and (vi) models of water control measures such as diversions and storage facilities. The model also contains a distributed runoff model for radar-based precipitation data and a continuous soil moisture accounting model for simulating the watershed's long-term response to wetting and drying

*2.4. Model Set-up and Run*

HEC-GeoHMS 10.2, which is the ArcGIS 10.2 geo-processing extension, and Arc Hydro tools were used to generate and process geospatial information of the watershed, such as streamflow paths, sub-basins, catchment boundary, elevations, and soil type. The three main data sets that were used in this research to model the agricultural expansion impacts on streamflow included the DEM, which gave the topographic information of the watershed, land use data, and hydrological data (precipitation, streamflow, and evapotranspiration data). These data were then processed and computed using HEC-GeoHMS in ArcGIS 10.2 to generate the parameters required for the HEC-HMS model input to generate runoff simulations.

The HEC-GeoHMS delineated the watershed into 24 subbasins based on their slope characteristics, length of the stream, and number of tributaries joining the main channel. Each of these 24 subbasins had their parameters, but for this study, their averages were used in the simulation process to simplify the processing. The precipitation data from the three rain gauge stations were assigned to each of the 24 subbasin depending on the station's proximity to the centroid of the subbasin. The discharge data at the outlet watershed was used to calibrate and validate the model.

The Soil Conservation Service Curve Number (SCS-CN) method (United States Department of Agriculture, 2016) was used to simulate the watershed hydrology so that when estimating the future land cover changes due to agricultural expansion, the curve number change would be used to represent the changes. The initial abstraction was assumed to be equivalent to 0.2S, where S represented the potential maximum retention capacity for the normal antecedent moisture conditions. This retention was adjusted on a 5-day antecedent rainfall (Chow et al., 1988). Once all the parameters were set, 1000 simulation runs were made from 1998 to 2009, with the first two years set for the model warm-up.

### 2.5. Model Evaluation

The HEC-HMS model was calibrated (2000–2004) and validated (2005–2009) using the observed daily streamflow data at the watershed outlet. The SCS-CN loss parameters, which included the initial abstraction, the percent imperviousness, and the curve number for each subbasin, were calculated in HEC-GeoHMS as initial values. The time of concentration, $T_c$, was calculated by obtaining the longest flow path in HEC-GeoHMS (Hoblit & Curtis, 2003). The model calibration was done using the model optimization feature, which automatically adjusts various parameters to obtain a minimum objective function value that matches the observed values (USACE, 2013). The observed actual river flow discharges were input into the time series data manager, after which the simulated flows were compared to these actual flows. Several iterations were made, each with 1000 runs, until the best set of parameter values with the highest efficiency were obtained. The calibrated parameters included the runoff loss functions, such as the initial abstractions and CN, transform functions, such as the lag time, and routing functions, such as the Muskingum routing parameters. The lag time and the Muskingum K value were the most sensitive calibration parameters. The curve number values based on the land use data for 2004 and 2014 were kept as initially estimated in HEC-GeoHMS. The best model parameters obtained after calibration were used to run the model for the land use scenarios in the study area. The model performance was evaluated using the hydrologic goodness of fit based on the Nash-Sutcliff Efficiency (NSE), the coefficient of determination ($R^2$), and the percent bias (PBIAS). Moriasi et al. (2007) recommended NSE > 0.5, R2 > 0.5, and PBIAS ±25% for a satisfactory streamflow model performance.

### 2.6. Variation in Agricultural Water Abstraction and Streamflow

The relationship between agricultural water abstraction and streamflow was determined using Spearman's Rank Correlation Test. Correlation methods such as Spearman's Rank, Kendall Rank, and Pearson are commonly used in hydrological studies due to their relative simplicity and high validity (Fowler et al., 2007). The correlation analysis was used to complement regression models in this study by measuring the strength of the relationship between the dependent and the independent variables. It, therefore, provided a test of the statistical significance of the data by showing the degree to which the two variables changed. The Spearman Rank correlation was chosen since it is a non-parametric test that does not make distributional assumptions about the population under investigation. The Spearman's rank coefficient, ρ, was used to measure the linear relationship between two sets of ranked data (Zar, 1972). The coefficient was calculated using Equation (1):

$$\varrho = 1 - \frac{6\sum_{i=1}^{n}\left(x_i - y_i\right)^2}{n\left(n^2 - 1\right)} \tag{1}$$

Where n is the number of values in each dataset, and $x_i$ and $y_i$ represents the two sets of variables under consideration in the $i^{th}$ observation.

### 2.7. Land Use Change Detection

Land use data for the Thiba River watershed were obtained for 2004 and 2014 to compare the changes in land use within this watershed. The period chosen was ten years apart to show the notable changes in land use in the basin due to increased agricultural area. These land uses were classified into eight classes: irrigated agriculture, rain-fed agriculture, bare land, forests, urban area, shrubs, herbaceous plants, and water. Change detection between the 2004 and 2014 land use maps was determined using comparison statistics whereby each land use area percentage was obtained.

### 2.8. Long-Term Streamflow Response to Land Use and Climate Changes

The long-term impacts of agricultural land expansion on streamflow were estimated using projected changes in precipitation, land use, and their combinations. The HEC-HMS model has a forecasting manager used to input the projected data. The 2014 land use and population data were used to project the future land use and water demand, while the projected precipitation estimated the future water input.

Future land use scenarios of in 2030 representing the near future and 2060 representing the far future were used to predict future streamflow. A simple but practical approach was adopted to develop the future land use data in ArcGIS by overlaying the 2014 land use shapefile with the projected population density shapefiles for 2030 and 2060. The population density maps for 2030 and 2060 were obtained by applying a constant 1.7% population growth rate per annum to the existing population density map of 2009, obtained from the current census data available for Kenya at that time (Kenya National Bureau of Statistics, 2010). The new population densities were used to predict the future land uses with the assumption that the future land use will be highly dependent on the population growth. Assumption was also made that as the population increased, the existing forest land would be converted to agriculture land. In that way, the land use maps for 2030 and 2060 were thus created. It's important to note that the relationship between population growth and land use changes is complex and depends on many other factors, including urbanization and the region's transition stage (Acharya & Nangia, 2004). The HEC-HMS model parameters for processing runoff, such as the curve numbers, lag times, and the Muskingum parameters, were then recalculated based on the developed future land use scenarios.

The future precipitation was estimated using the moderate representative concentration pathway (RCP4.5) with an ensemble of three statistically downscaled and bias-corrected Global Climate Models (GFDL-ESM2M, HadGEM2-ES, NorESM1-M) for the region (Bentsen et al., 2013; Dunne et al., 2012; Jones et al., 2011). The climate data used in this study was downloaded from the Water Weather Energy Ecosystem website (www.2w2e.com) at a 0.5º spatial resolution for the coordinates range of latitude −1º to 0º south, and longitude 37º to 38º east. Global climate data are generally more reliable for temperature than precipitation prediction; however, ensemble approaches could reduce these uncertainties (Kawasaki et al., 2010). The ensemble of the climate model projections shows an average annual temperature rise of 0.4 °C in 2030 and 1.4 °C in 2060; and a projected average annual precipitation increase of 2.2% by 2030 and 5.7% by 2060 with higher increases in March (4.1% and 12.5%) and October (9.4% and 18.2%) in the two periods. These estimations align with the Intergovernmental Panel on Climate Change (IPCC) reports projections in East Africa for precipitation that predict no change to 2.5% in the next decade and between 6% to 10% increase by 2100 (Kiem et al., 2008; Meehl et al., 2007).

## 3. Results and Discussions

### *3.1. Model Sensitivity Analysis, Calibration, and Validation*

The model evaluation was preceded by the sensitivity analysis of the most influential parameters in the watershed. A global sensitivity test was conducted on streamflow parameters obtained from the HEC-GeoHMS and the best parameters used in the HEC-HMS for the model simulation. The HEC-HMS model has an automatic calibration package that can estimate specific model parameters based on their initial conditions. The sensitive parameters were then used to calibrate the model. The SCS-CN and the Muskingum routing parameters were the most sensitive parameters. The curve number is an essential hydrology parameter as it directly affects the rates of surface runoff and infiltration in the watershed. The SCS-CN value is influenced by the watershed's land use, soil characteristics, and the initial soil moisture conditions (Mishra et al., 2012; Rallison & Miller, 1982). A higher SCS-CN value results in higher surface runoff than infiltration, while a lower value results in more infiltration than surface runoff. The Muskingum K value determines the average routing time of runoff from each reach. It is based on a simple finite difference approximation of the continuity equation and considers the storage characteristics of the channel reach (USACE, 2010). The Muskingum parameter also has a dimensionless weight parameter, X, which determines the relative weighting of the inflow and outflow in the storage calculation. The value of X ranged from 0 to 0.5, with 0.2 being the best value used to adjust the behavior of the runoff movement through each reach. If X is set to 0, the model represents a linear reservoir with storage solely determined by the outflow rate and K value. If X is set to 0.5, equal weight is given to inflow and outflow, resulting in a uniformly progressive wave that does not attenuate as it moves through the reach (USACE, 2010).

The model adequately captured the monthly streamflow simulations' magnitude and temporal dynamics, replicating most high and low flows during calibration and validation, as shown in Figure 3. The model produced good performance evaluation results with NSE and $R^2$ values of 0.66 and 0.68, respectively, during calibration, and 0.61 and 0.65, during validation. The simulations generally underestimated the observations with PBIAS values of 0.18 and 0.14 during calibration and validation, respectively, which is considered acceptable considering the numerous uncertainties associated with modeling. The model's uncertainty could be due to errors in the input data (e.g., meteorological data), measured data errors (e.g., streamflow observations), and model simplifications (Meaurio et al., 2015; Rostamian et al., 2008; Tolson & Shoemaker, 2007). The findings from this study were comparable to those obtained by Yasin et al. (2015), in which they modeled hill torrents in Pakistan using HEC-GeoHMS and HEC-HMS and found an acceptable NSE value of 0.54. From these findings, the model was considered suitable for adoption in the watershed.

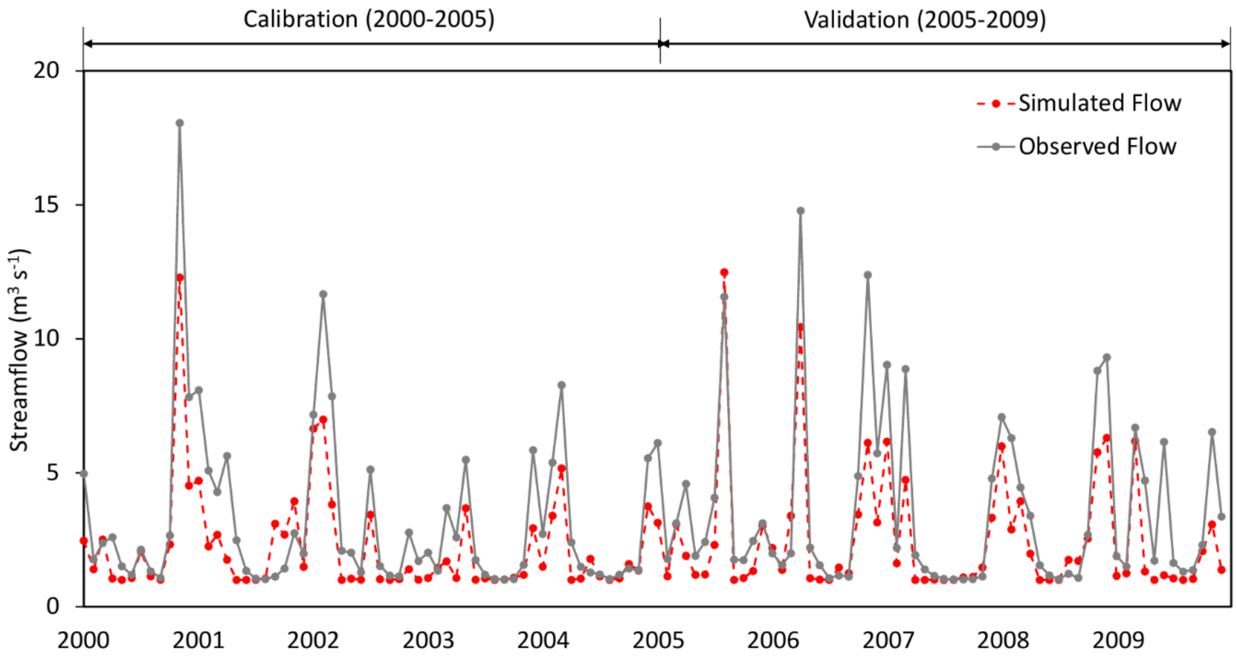


**Figure 3.** Comparison of monthly observed and simulated streamflow hydrographs during calibration (2000 to 2004) and validation (2005—2009) at the outlet of the Thiba River watershed.

### *3.2. Agricultural Water Abstraction and Streamflow Analysis*

The analysis of the data provided by NIB and WRMA showed an increasing trajectory of water abstraction from the Thiba River between 2007 and 2014, as shown in Figure 4. The highest abstraction of about 9.3 million $m^3$ happened in 2014, whereas the lowest of about 7.2 million $m^3$ occurred in 2009. This increase in abstraction in 2014 could be attributed to reduced rainfall due to the drought experienced in Eastern Africa that year. Conversely, water abstraction in 2009 was lower due to high rainfall in that year, thus reducing the dependency on the river water. The seasonal distribution of water abstraction pattern indicated higher abstractions in the dry months of January to February and June to October, coinciding with high irrigation water demand. The changes in the flow regime of Thiba River could be attributed to various factors, with water abstraction considered one of the primary drivers. The largest proportion of water abstraction was due to increased requirements for irrigation, occasioned by the increased land area under irrigation, especially within the MIS. These findings are consistent with previous studies by Ngigi et al. (2007), who observed similar agricultural water abstraction patterns in the Ewaso Ng'iro River.

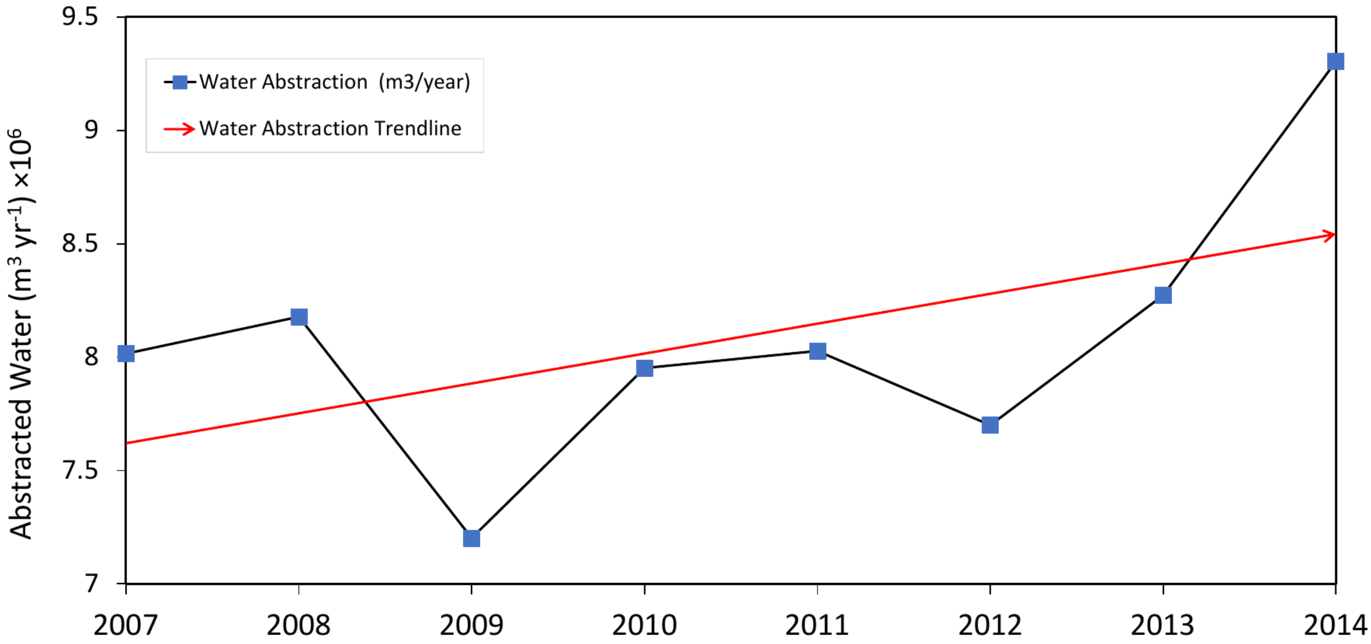


**Figure 4.** Annual water abstraction trend from the Thiba River between 2007 to 2014.

The correlation between streamflow and agricultural water abstraction from 2007 to 2014 gave a highly significant and strong inverse relationship with a decreasing trend, as shown in Figure 5a. Water abstraction analysis revealed that about 0.23 $m^3$ $s^{-1}$ (approximately 20000 $m^3$ $day^{-1}$) was abstracted during the dry seasons, whereas 0.06 $m^3$ $s^{-1}$ (approximately 5000 $m^3$ $day^{-1}$) of the river's flow was abstracted during the wet seasons, as demonstrated in Figure 5b. This implies that about 35% of the river's flow during dry season and only 3% of the flow during wet season flow were abstracted from the Thiba River. These findings compare to Ngigi et al. (2007) findings that irrigation water abstraction is a key contributor to streamflow reduction in dry spells, exacerbated by unregulated and illegal water abstraction practices.

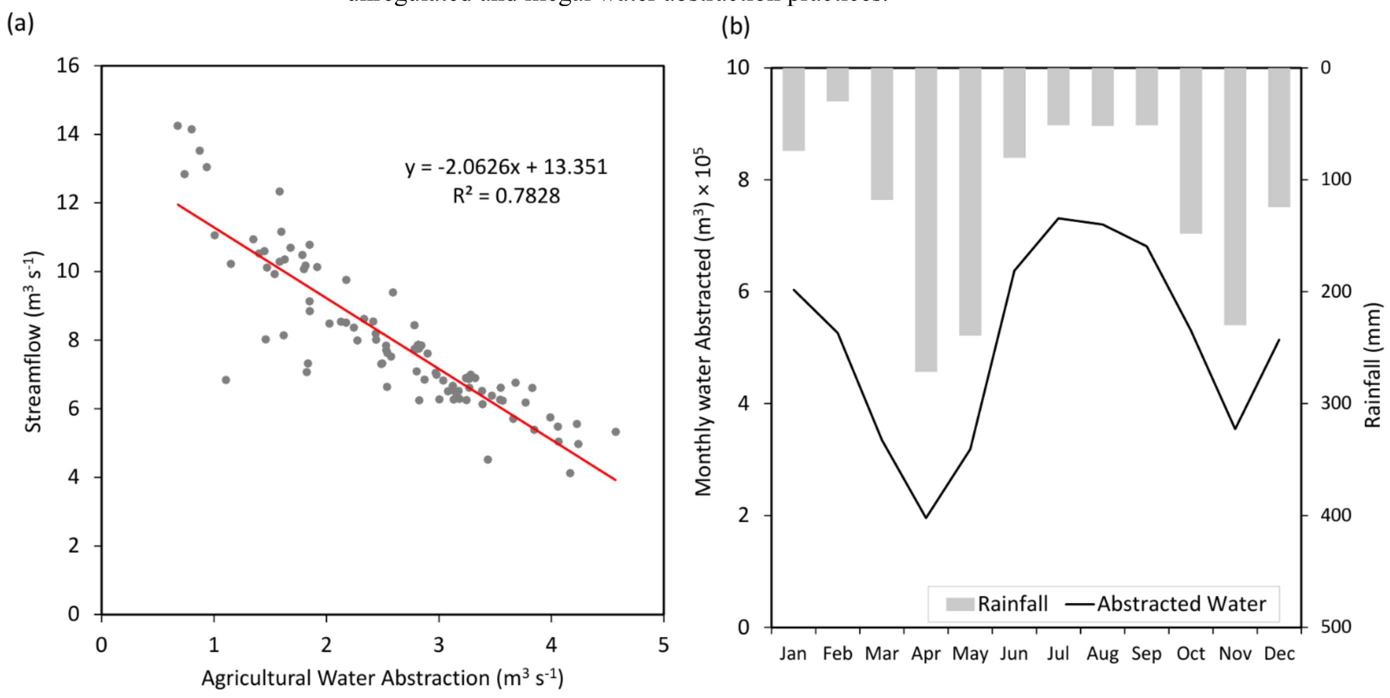


**Figure 5.** (a) Correlation between agricultural water abstraction and streamflow (b) comparison of monthly average water abstraction and rainfall trends from 2007 to 2014.

The findings from the Thiba River are consistent with previous research across geographical contexts. For instance, in the Ewaso Ng'iro River, Ngigi et al. (2007) observed similar agricultural water abstraction patterns with about 62% of dry season flow and 43% of wet season flow being abstracted from the river. Similarly, in the Naro Moru River, Aeschbacher et al. (2005) reported a 30% streamflow decline between 1960 and 2005 attributed to water abstraction, thus demonstrating the long-term and cumulative nature of water abstraction's influence on river regime. The consistency and reliability of the relationship between irrigation water abstraction and streamflow fluctuations in the Thiba River is further validated by the similarities between our findings and those of other studies. These findings emphasize the need to strike a balance between human activities like agriculture and adopting more sustainable measures to manage our water supplies.

### *3.3. Land Use Change Analysis*

The Thiba River watershed experienced substantial spatial land use changes, within the course of a decade, from 2004 to 2014. The major land use activities include agriculture (> 60%) and forest (>30%) accounting for almost 95% of the watershed area. Land uses in the watershed were classified into eight categories, as illustrated in Figure 6. In the 2014 land use map (Figure 6b), the major land use activity was rainfed agricultural farming (50.5%), which included crops such as maize, coffee, and tea. Approximately 15% of the watershed was used for irrigated agriculture, with paddy rice farming in MIS being predominant. Horticultural crops also form part of the irrigated crops. The forested region around Mount Kenya, which covers almost a third of the watershed, witnessed a decrease in coverage by 6.2% from 2004 to 2014 (Figure 7). This decline in the forested area could be attributed to multiple factors, including deforestation to create room for agricultural activities, residential areas expansion to accommodate more people, and to a lesser extent, population growth driving the demand for timber and fuel. Additionally, the conversion of forest land to agricultural use may have also been influenced by the expansion of rainfed and irrigated agricultural land. Within the same period, the rainfed agricultural land increased by almost 5%, whereas the irrigated agricultural increased by only 1%.

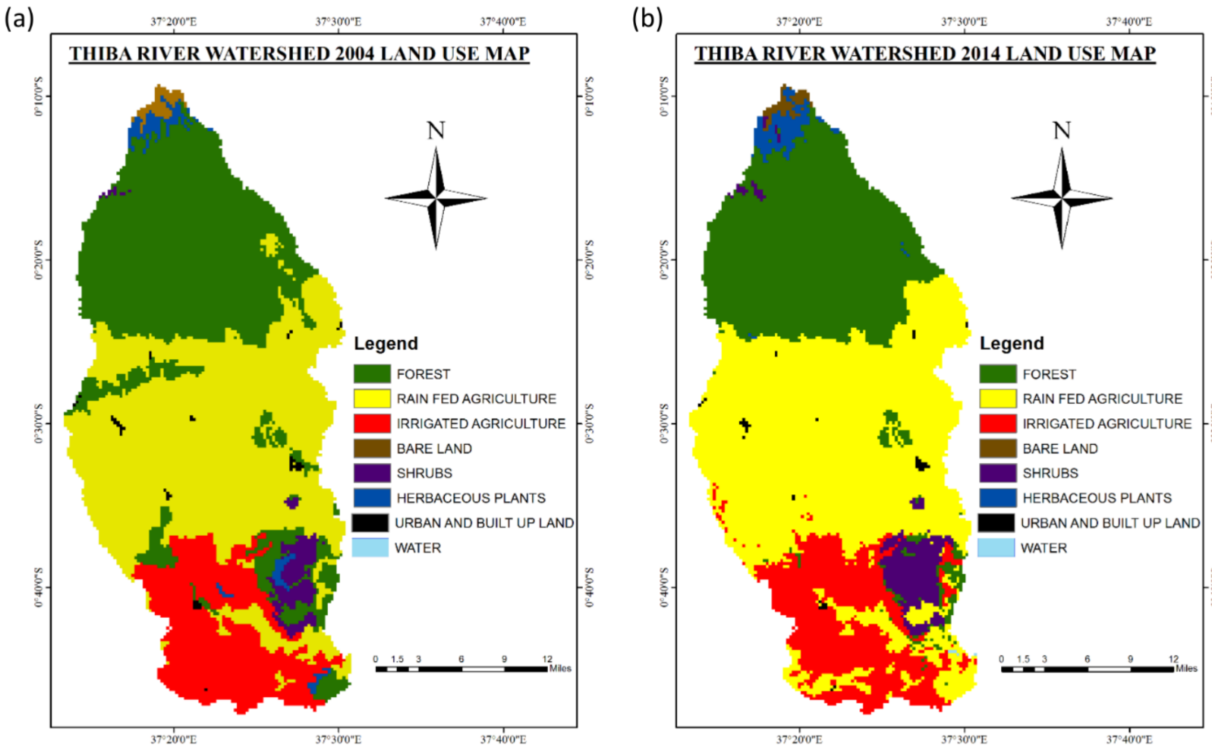


**Figure 6.** Thiba River watershed spatial distribution of land use maps for (a) 2004 and (b) 2014.

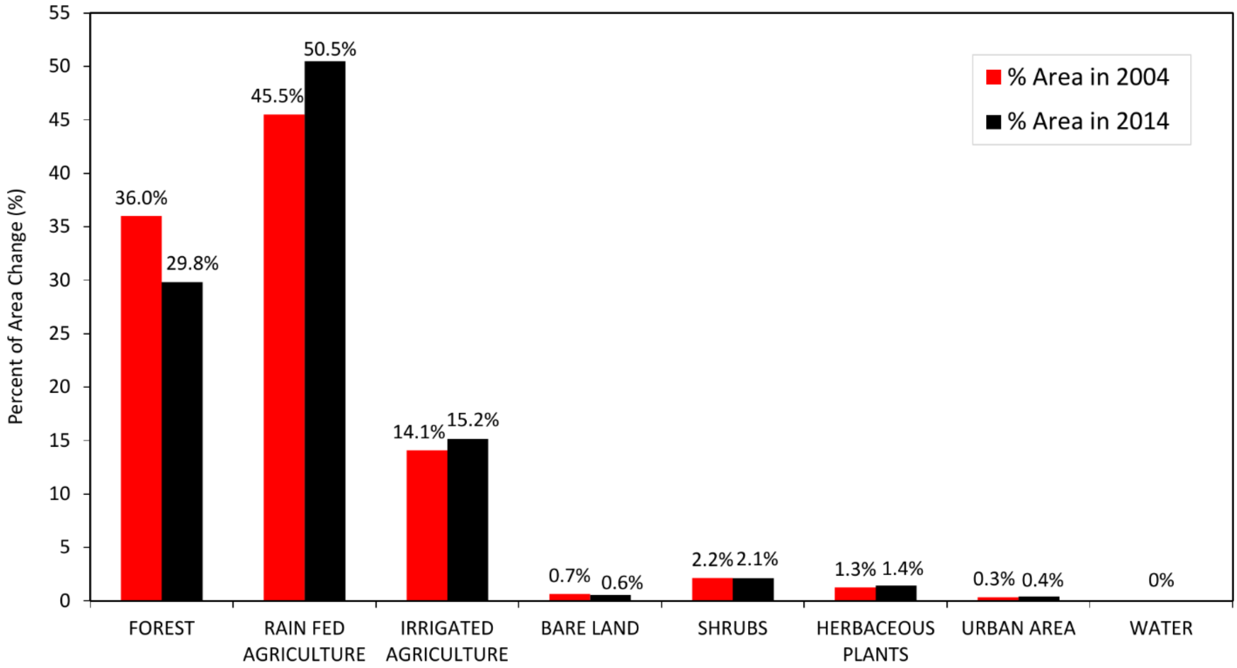


**Figure 7.** Land use change analysis from 2004 to 2014 in the Thiba River watershed.

The conversion of forests to give way to agricultural land since 2004 could be attributed to the increased population growth within the Upper Tana catchment's rural areas, which encompasses the Thiba River watershed. This population surge has increased the demand for agricultural lands, particularly because most of these communities heavily rely on agriculture for sustenance. Therefore, some of the forested areas could have been converted to small-scale agricultural plots, that predominantly depend on rainfall for food production.

It is worth noting that the adoption of unsustainable agricultural practices in many of these areas has exacerbated environmental challenges such as erosion and sedimentation of the rivers and streams. According to Kitheka and Ongwenyi (2002), some of these unstainable practices, such as continuous tillage, create large bare land, potentially contributing to increased runoff volume. In a related study by Ngigi et al. (2007) in the Ewaso Ng'iro river basin, it was observed that agricultural intensification had increased to unprecedented levels due to high population growth in the basin. The study also pointed out that land use changes resulting from population pressures had adverse effects on river flows, environmental degradation, and decreased agricultural production.

To further emphasize the relevance of these findings, it is noteworthy that similar patterns have been observed in other regions. For instance, a study by Kirui (2008) in the Upper Molo catchment found that the area covered by forested land reduced by 48% between 1986 to 2001 due to encroachment by the local farmers in search of more agricultural land. This study likewise concluded that the high demand for agricultural land in the area resulted from increased population, mirroring the situation in the Thiba River watershed.

Based on these findings and the consistency with previous studies, it is apparent that the land use changes observed in the Thiba River watershed are part of a larger trend influenced by population growth and the subsequent demand for more agricultural land to produce more food. However, the adoption of unsustainable agricultural practices exposes the need for targeted interventions to address environmental concerns and promote sustainable land use practices in these areas.

### *3.4. Long-Term Impact Scenario Analysis*

In generating the land use scenario, the 2014 land use map was reclassified into four categories of agricultural land, forest, residential area, and water and overlaid with the projected population density maps to result in new land use areas, as shown in Figure 8. This categorization provided a foundation for assessing the future impacts of land use changes and population growth on water resources in the Thiba River basin. The population change analysis showed that the agricultural water demand would increase from 9.3 million $m^3$ in 2014 (baseline scenario) to 11.6 million $m^3$ in 2030 (near future) and 16 million $m^3$ in 2060 (far future), representing a 24% and 72% increase in 2030 and 2060 agricultural water demand, respectively. These findings highlight the urgent need for adoption of efficient irrigation practices and alternative water sources to meet this projected increase in agricultural water demand. Furthermore, it would be expected that the water demand for other uses would also increase as the population increased, and this would exert more pressure on the Thiba River if no new water sources were developed. In this scenario, projected land use was assumed to be only affected by population change, which would affect the future agricultural water demand. However, it is imperative to recognize that other factors beyond population growth, such as future economic growth, climate change trends, and inter-seasonal variability, would greatly influence the amount of agricultural water required, especially during the dry seasons. As the region's economy and living standards continue to improve, higher water consumption would be for various purposes.

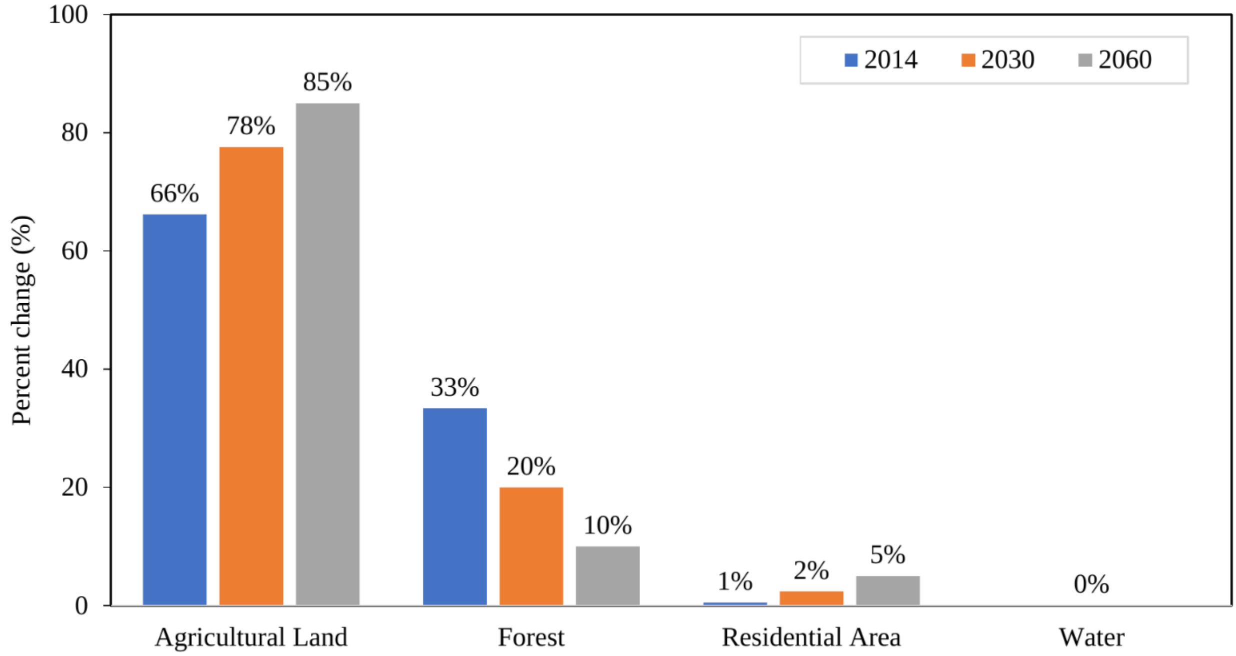


**Figure 8.** The projected percent land use change in 2030 and 2060 compared to 2014 (baseline).

The land use change scenario findings showed that streamflow was reduced by 18% in 2030 and 52% in 2060 compared to the baseline. This streamflow decrease could be attributed to increased water demand due to land use changes and population increase. The increase in residential area would increase the SCS-CN value, thus increasing the surface runoff, which could have also led to the increased streamflow. However, the increase in residential areas was negligible compared to the increase in agricultural water demand. Reduction of the forest land could have also contributed to an increase in streamflow since there was an increase in the bare land created for agricultural purposes, thus increasing runoff. However, this was also outdone by the high levels of water abstraction from the river.

The precipitation change scenario showed an annual streamflow increase of 3% and 6% in 2030 and 2060, respectively, resulting from climate change. This could be attributed to increased 2.2% and 5.7% precipitation in 2030 and 2060, respectively. According to previous IPCC reports (Meehl et al., 2007), the East African region is projected to experience increased precipitation and temperature; however, the impact on streamflow would be negligible due to the high evapotranspiration rates due to the temperature increase compared to the slight precipitation increase. Similar increasing streamflow patterns caused by climate change have also been observed in other parts of Kenya. For instance, Githui et al. (2009) reported a 2.4% to 23.2% increase in streamflow as a result of a 6% to 11.5% rise in precipitation in the 2020s and 2050s in the Nzoia catchment of the Lake Victoria basin in western Kenya. Similarly, Musau et al. (2015) observed an average annual streamflow increase of up to 4.8% in the 2020s and 17.2% in the 2050s in the Mount Elgon watershed using the B1 scenario, albeit reporting high uncertainties.

The final scenario combined land use and precipitation change had a comparable trend to the land use change scenario. Streamflow declined by 15% and 48% in 2030 and 2060, respectively, under this scenario. This could be attributed to the increased water demand in the land use scenario compared to the slight precipitation increase. Despite increasing precipitation, an increase in water demand, mainly agricultural water demand due to population increase, has a higher effect on the stream flow since there would be increased abstractions from the river. The findings were consistent with those obtained by Kawasaki et al. (2010), who reported that population growth and land development had a greater impact on streamflow change than precipitation in the 50 years studied.

The results of the streamflow response in each of the scenarios discussed above are as shown in Figure 9.

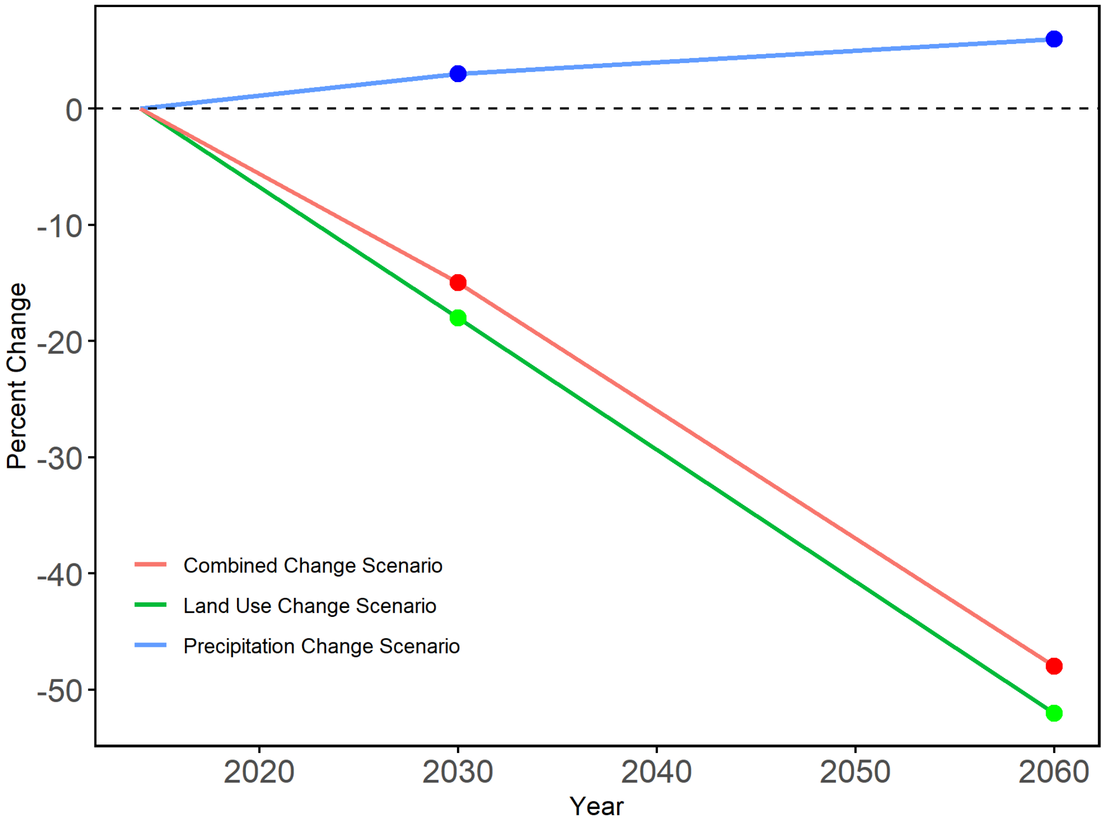


**Figure 9.** Projected annual streamflow change in the Thiba River watershed for changes in land use, precipitation, and their combination in 2030 and 2060 compared to the baseline (2014).

The projected changes in streamflow and agricultural water demand demonstrate the need for adaptive water resource management. To effectively address these challenges, a multifaceted approach is needed, focusing on optimizing water allocation, investing in efficient irrigation methods, and exploring alternative water sources (Pulighe et al., 2021; Rodrigues et al., 2023). This requires collaborative initiatives involving a diverse group of stakeholders, including practitioners, experts, researchers, policy-, and decision-makers.

The substantial increase in agricultural water demand necessitates prompt action. Implementing sustainable agricultural practices, promoting crop diversification, and embracing water-efficient irrigation methods like drip irrigation and precision farming, are vital to mitigating the potential impacts on crop yields and food security (Oduor et al., 2023). Conducting a comprehensive assessment of vulnerable crops in the study area can help guide targeted interventions, ultimately enhancing resilience and sustainability in the face of evolving environmental conditions.

It is important to recognize that reduced agricultural productivity due to water scarcity may have far-reaching socioeconomic consequences. Therefore, policymakers need to take proactive steps to address the potential economic consequences, such as reduced livelihood opportunities, increased migration, and increased dependence on external food sources. Diversifying income sources and promoting alternative livelihoods can enhance resilience. Furthermore, it is imperative to build climate resilience by ensuring that communities and agriculture adapt to water scarcity and climate variability. To facilitate this adaptation, outreach programs such as education and awareness campaigns could be instrumental in fostering sustainable water use practices among local stakeholders.

## 4. Conclusions

This study evaluated the long-term streamflow response to changes in agricultural land in the Thiba River watershed. The decrease in streamflow during dry months and the strong correlation with agricultural water abstraction highlight the need for long-term, sustainable water resource management strategies. The results emphasize the urgent need for proactive policies and adaptive measures that balance agricultural needs with ecosystem conservation to ensure consistent and reliable water supply in the future. The projected decline in future streamflow, exacerbated by population growth and agricultural expansion, requires a paradigm shift in water management practices.

Despite the model simulations providing valuable insights, it is important to acknowledge the inherent uncertainties associated with any modeling approach. The scope of this study was primarily on streamflow dynamics, leaving avenues for future research to explore water quality, ecological impacts, and alternative land management scenarios.

Based on the findings, it would be prudent to implement sustainable water resource management measures such as efficient irrigation techniques, crop selection optimization, and enforcement of water use regulations to mitigate excessive water abstraction. Investing in water-related infrastructure and promoting public awareness regarding responsible water consumption could also contribute to long-term water security.

This research contributes to the state-of-the-art of the complex relationship between land use, hydrology, and water availability. The findings could be useful to water professionals and managers in developing a robust integrated water and land management system, as well as guiding policies and decisions on river water resource management. The methodology and outcomes of this study can be extended to other regions facing similar agricultural and land use management challenges.

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