

Integrated Assessment of Climate and Land Use/Land Cover Change Effects on Hydrological Responses in the Hare River Watershed, Southern Ethiopia

Elias Mone Chumpudhe ^{1,*} and Yoseph Arba Orke ²

¹ Department of Meteorology and Hydrology, Faculty of Natural and Environmental Science, Wollega University, Nekemte 2510, Ethiopia

² Faculty of Meteorology and Hydrology, Arba Minch Water Technology Institute, Arba Minch University, Arba Minch 4400, Ethiopia

* Correspondence author: eliasmon@wollegauniversity.edu.et

Abstract: This study assesses the integrated impacts of land use/land cover (LULC) change and climate change on hydrological responses in the Hare watershed, Southern Ethiopia, using the SWAT model. Historical climate trends, LULC dynamics, and future climate projections based on CMIP6 scenarios were analyzed. The model was calibrated and validated using observed stream flow data. Results indicate that LULC change and climate variability significantly influence surface runoff, evapotranspiration, base flow, and water yield. Combined scenarios showed stronger hydrological responses compared to individual impacts. The findings provide useful insights for sustainable watershed management under changing climate and land-use conditions.

Keywords: Climate change; Land use land cover; SWAT; Hydrological response; CMIP6; Hare watershed

1. Introduction

The two most well-known worldwide environmental changes are land use/cover and climate changes, which have varying consequences on natural eco-systems and hydrological behaviors of the watersheds ([Mengistu et al., 2023](#)) and produce a strong influence on the hydrological processes of the watersheds. Human intervention results in space and time variation on water resources. This intervention pushes climate and land use/cover (LULC) changes to modify the amount of surface runoff, aquifer recharge, and river flows, which in turn impacts the availability of water resources ([Dibaba et al., 2020](#)).

In Ethiopia, water resources face threats from land use cover and climate change ([Mengistu et al., 2023](#)). The climate change study across the country indicates the hydrological pattern of the watershed was affected strong and the land use study across the country shows a massive increase in agricultural area ([Bekele et al., 2019](#)). Therefore understanding and studying the individual and combined impact of land use/cover and climate change on the future hydrology of the watershed is important to manage the water resource sustainably. This is also crucial for the hare watershed to understand temporal variability due to climate and LULC change in hydrology.

In general, the effects of climate change have been overlooked in the majority of LULC studies, and vice versa. Due to their strong interdependence and a lack of information on scales that are important to local stakeholders, farmers, and decision-makers regarding the impact of LULC and climate change, their interaction is not well understood. To achieve a healthy ecosystem, land use, and climate change mitigation, one must have a thorough understanding of the values and impacts of land, water, and climate management, as well as how and where to target interventions. Besides, past studies in the watershed did not use the most recent climate change scenarios. Therefore, to manage the water resource and



environment in the face of future changes, scientific research is needed to understand the combined effect of LULC and climate change on the watershed.

This thesis seeks to quantify the effects of land use land cover and climate change on these hydrological components. This information is essential for creating well-informed and practical plans to deal with the region's water resources sustainably and adjust to the changing climate.

The general objective of the study is to assess hydrological responses to climate and land use land cover alterations in the Hare watershed using SWAT model. The specific objectives of this study:

To assess the historical and future trends and patterns of climate variables especially temperature and precipitation in the Hare watershed. In addition the study investigate the impacts of climate change and land use/land cover changes on hydrological processes.

2. Materials and Methods

2.1. Description of the study area

The Hare River watershed, is situated in the southern Ethiopian Rift Valley's Abaya-Chamo sub basin and drains into Lake Abaya, which has an enclosed area of roughly 183 km². The Hare watershed's general geographic boundaries are found between 6°4'00" and 6°17'30" N latitudes and between 37°27'00" and 37°45'00" E longitudes. The study area's topography is well characterized by steep slopes, generally increases in elevation above mean sea level from the downstream (1220 m) to the upstream (3493 m) as shown in [Figure 1](#).

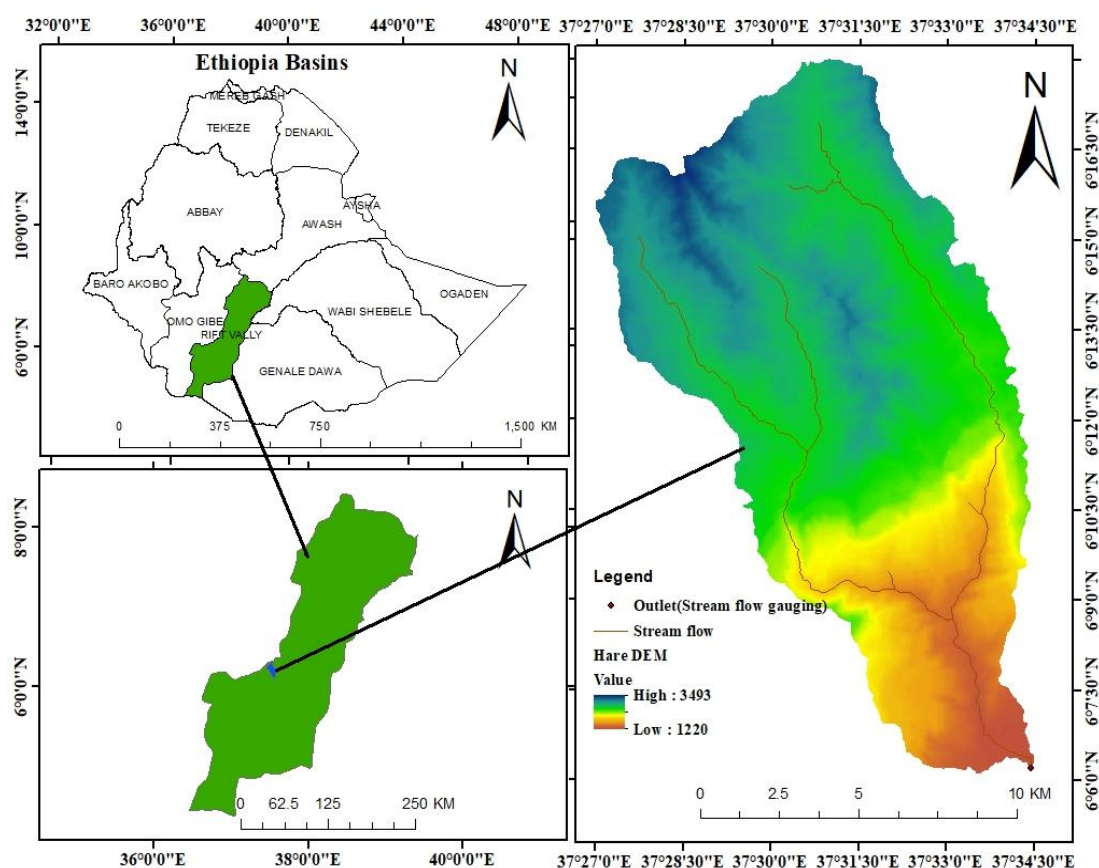


Figure 1. Location of study area map

2.2. Climate

Ethiopia's climate is classified in a variety of ways namely Throthwaite's Rainfall regimes, Traditional, Koppen's, and Agro-climatic zone classifications. Based on the altitude and temperature of the areas, traditional classification system identifies five climatic zones: Wurch (cold climate at altitudes above 3000 meters), Dega (temperate climate in the highlands at altitudes between 2500 and 3000 meters), Woina Dega (warm climate at altitudes between 1500 and 2500 meters), Kola (hot and arid type), and Berha (hot and hyper-arid type, less than 500 meters) ([Gonfa, 1996](#)).

2.3. Land Use/Cover Data

Rain-fed agriculture is the most commonly used traditional farming method in Ethiopia. Erosion of sediment on the land surface can be significantly influenced by land use and land cover. Soil erosion caused by precipitation can be lessened by vegetation cover. Land cover changes have increased sediment output at catchment outlets and accelerated erosion, such as the conversion of dense forest to agricultural land (Arnell et al., 2019). The majority of the Hare watershed is covered in lightly farmed area, with some higher-elevation forestland. There is shrub vegetation and extensively farmed land in the lower half of the catchment. There is also a lot of wetlands vegetation in the study area. Regions that are shrubby and moderately cultivated make up the majority of the study area (Ayalew, 2023). The digital land use land cover (LULC) map was downloaded from the USGS dataset (<http://www.earthexplorer.usgs.gov> Landsat). LULC data are fed into the SWAT model to determine the spatial distribution of various land use and land cover classes.

2.4. Satellite data

The primary tool used for mapping the comprehensive LULC map of the Hare watershed was a Landsat image. For this study, satellite images are required to create a LULC map of the study area. The overall description of the sensor is shown in Table 1. All images were taken from Google Earth Engine (GEE), which provides access to a wide range of satellite imagery from various sources, including Landsat, Sentinel , MODIS, and more (Kumar & Mutanga, 2018). All satellite data acquisition is considered cloud-free. So the data Acquired with cloud cover is less than 5% which helps to gain atmospherically corrected data. Additionally, level two satellite data are acquired, which are geometrically and radio metrically corrected.

Table 1. Description of Landsat imagery

No	Sensors	Acquisition date	Cloud cover (%)
1	Landsat 7ETM	Feb 20, 2003	3
2	Landsat 8(OLI)	Dec 13, 2013	0
3	Landsat 8(OLI)	Feb 23, 2023	0.05

All Landsat data has a spatial resolution of 30m x 30m with paths 169 and rows 56. The temporal resolution was 16 days. The climate and hydrological data were generally described in Table 2.

Table 2. General Description of the climate and hydrological data source

Data type	Data source	Spatial resolution	Temporal resolution	Time period	Description
Observed Climate data	Ethiopian Meteorological Institute (EMI)	Point	Daily	1992 - 2021	Precipitation, minimum& maximum temperature etc.
Hydrology	Ethiopian Ministry of water and Energy	Point	Daily	1998 - 2014	Stream Flow data
DEM	https://www.earthexplorer.usgs.gov/	30m X 30m			Digital elevation model
Soil data	FAO/UNESCO				Soil type
Land use/cover data	https://www.earthexplorer.usgs.gov Landsat/	30m X 30m		2003, 2013, 2023	Land cover/use data
Modeled Climate RCM/ GCM data	Earth System Grid Federation (ESGF) (https://esgf-data.dkrz.de/search/cmip6-dkrz)	Point	daily	1985- 2100	Future precipitation &temperature

2.5. Methods of Data Analysis

2.5.1. Data quality control

Quality control of data prior to its use in modeling is crucial because the outcome of a model is dependent upon the caliber of its input data. The homogeneity and consistency methods were used in this study to test the data quality control, and the normal ratio and arithmetic averaging methods was used to fill in any missing data.

Detecting homogeneity is crucial for understanding data variability. The homogeneity of rainfall data is crucial for accurately assessing trends and patterns. When data is deemed homogeneous, it indicates that the measurements were taken under consistent conditions, using the same instruments, and in a similar environment (Ho Ming Kang and Fadhilah Yusof, 2012). Data from an observation station is considered homogeneous if it exhibits a similar pattern to data from nearby stations (Che Ros et al., 2016). When data is considered homogeneous, it indicates that measurements have consistently been conducted using identical techniques equipment, location timing, and environmental conditions. In this study, non-dimensional rainfall records are used to check the homogeneity of selected stations in the watershed. The assessment of non-dimensional homogeneity indicates that if the non-dimensional precipitation plot of stations demonstrates a consistent rainfall pattern, as depicted in Figure 2 the rainfall is considered homogeneous.

The Non-dimensional value (P_i) for each station has been defined as:

$$P_i^* = \left(\frac{P_i}{P_{av}} \right) * 100 \quad (1)$$

P_i^* is the Non-dimensional value of rainfall (month), P_i is over year averaged monthly rainfall at station i (ARF), and P_{av} is over year average yearly rainfall of station i .

Homogeneity testing of rainfall data involves plotting the percentage of rainfall for each station on the y-axis and the months on the x-axis. When the pattern of rainfall is consistent across the area, it is considered homogeneous. The graphs presented below depict a nearly identical pattern between all the points, indicating that the rainfall pattern is homogeneous across all stations. This consistency is reflected by a bimodal rainfall pattern. Overall, these findings demonstrate that all stations exhibit acceptable homogeneity and display uniform trends in rainfall.

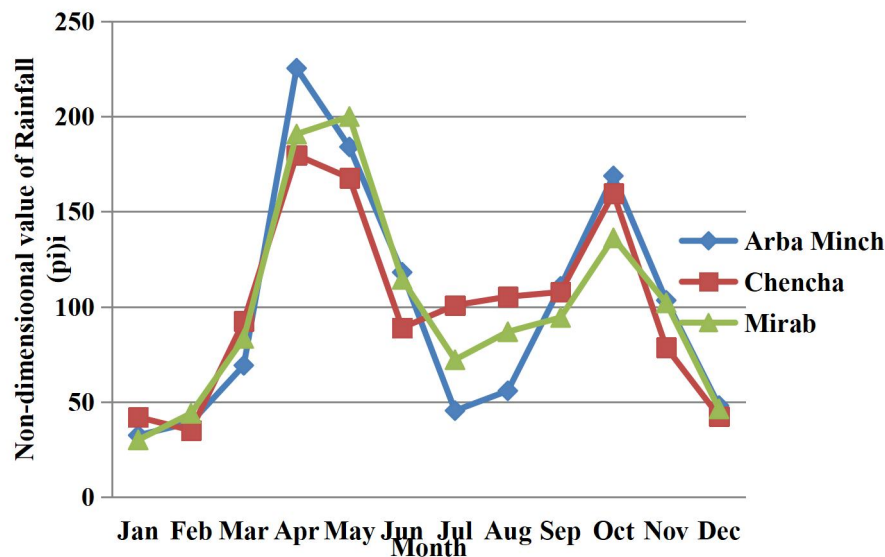


Figure 2. Non-dimensional homogeneity tests

2.5.2. Classified image accuracy assessment

There are different methods available to check the accuracy of classified Land use-land Cover (LULC) data. One such method is the ground truth test, which involves physically visiting and observing the actual land use and land cover classes on the ground. This can be done through field surveys, site visits, and photo interpretation. Another method is the error matrix, which is a table that compares the observed and classified LULC classes for each pixel in the image. It helps in evaluating the accuracy of the classified land use-land cover map.

Furthermore, the kappa statistic is calculated using below equation, it measures the agreement between the observed and classified LULC classes and can be used to assess the accuracy of the classified land use-land cover map.

The formula used to calculate the kappa coefficient is:-

$$K = \frac{Po - Pe}{1 - Pe} \quad (2)$$

where, Po the proportion of observed agreements, Pe an agreement expected by Chance. In this study, the accuracy assessment of classified maps was carried out using GEE. The GEE code editor helped to calculate the kappa coefficient, overall accuracy, and produces confusion matrix of the classified map.

The SWAT model with ArcGIS was used in combination with Arc SWAT to preprocess GIS data. This program uses a simple graphic user interface to make formatting GIS data for SWAT model simulations easier. Watershed delineation, hydrological response unit, weather production, and SWAT simulation are the pre-processing tasks in Arc SWAT.

Setting up the Soil and Water Assessment Tool (SWAT) model requires five primary steps: data preparation, watershed delineation, Hydrologic Response Unit (HRU) analysis, weather data definition, and model execution. Required Input Data, Digital Elevation Model (DEM): Defines topography, slope, and stream networks. Land Use / Land Cover (LULC) Map: Classifies vegetation and surface cover. Soil Map: Identifies soil types and physical properties. Weather Data: Includes daily precipitation, temperature, wind, humidity, and solar radiation

2.5.3. Watershed Delineation and Hydrologic Response Unit (HRU)

As previously mentioned, ARC SWAT 2012 was used to do the watershed analysis. The processes included projecting, clipping, and converting vector to raster data. A digital elevation model (DEM) with a resolution of 30 m by 30 m was used to delineate the watershed. The sub-basin outputs and stream network were identified. The catchment area's sub-basins were identified in Figure 3. Stream definition, land cover, soil, and slope data were combined to construct hydrologic response units (HRUs). The Arc-SWAT program was developed using the FAO's soil classifications in order to connect the data to the SWAT database. In addition, the LULC contributed to the establishment of HRU by using Google Earth Engine's (GEE) 2013 classified land. To comprehend the model, the land use type was combined with the SWAT database. The watershed was divided into 125 HRU and 19 sub-basins,

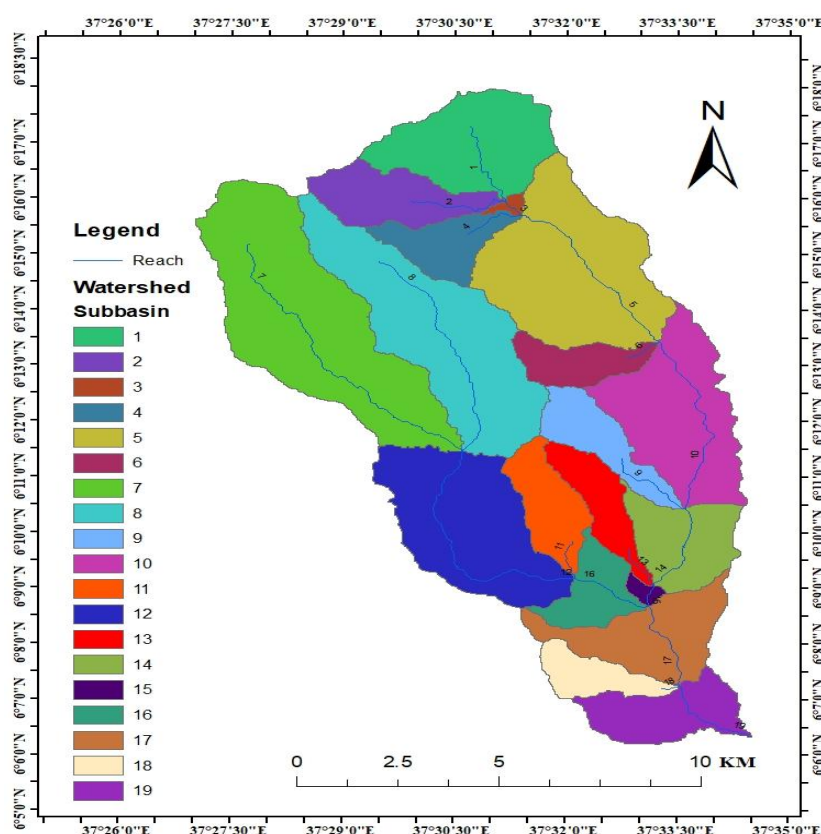


Figure 3. Sub-basin of Hare Watershed.

2.6. Arc SWAT Calibration and Validation

2.6.1. Sensitivity analysis

Sensitivity analysis is a reliable method for assessing the ability to adapt of various components used in hydrological process simulation and figuring out how parameters affect the prediction of flow, sediment, and other model output (Refsgaard & Storm, 1990). It is essential to ensure that SWAT input parameters are within a realistic uncertainty range as shown in below table. Approximately 16 parameters were used to find more sensitive parameters, and nine of them were chosen in Table 3. Therefore, it is essential for the calibration and validation procedure to determine which parameters are most sensitive to a watershed or sub-basin. The final sensitivity analysis parameters chosen based on the study area literature are displayed in Table 3.

Table 3. Calibration parameters

Parameters	Description	Range
ALPHA_BNK.rte	Base-flow alpha factor (Days)	0-1
EPCO.hru	Plant uptake compensation factor	0-1
CN2.mgt	SCS runoff curve number relative	± 0.2
SOL_K.sol	Saturated hydraulic conductivity(mm/hr)	0-0.25
SURLAG.bsn	Surface runoff lag time	0-10
HRU_SLP.hru	Slope relative	0-1
ALPHA_BF.gw	Base-flow alpha factor (days)	0-1
CH_K2.rte	Effective hydraulic conductivity (mm/hr)	0-150
RCHRG_DP.GW	Deep aquifer percolation fraction	0-1

The sensitivity analysis was conducted over 11 years, encompassing the calibration phase from January 1st, 1998, to December 31st, 2008. T-test or stat and p-values to assess the sensitivity of each parameter. The t-statistic serves as an indicator of sensitivity, with larger absolute values indicating higher sensitivity. Meanwhile, p-values assess the significance of this sensitivity. A p-value approaching zero signifies greater significance (K. C. Abbaspour, 2012).

2.6.2. SWAT Calibration and Validation

In order to achieve the greatest possible fit between simulated and actual flow data, calibration involves adjusting model parameters. Contrarily, validation is the process of making sure that, without altering the parameter values, the calibrated model can correctly predict flow patterns after the calibration phase has ended. In this study, the model was validated between 2009 and 2014 after being calibrated between 1998 and 2008.

2.6.3. SWAT Model performance evaluation

Comparisons of simulated and observed variables are routinely used to evaluate and report hydrologic model behavior and performance. In various modeling studies, visual inspection, different statistical techniques and objective functions will be applied to assess the model's performance and the goodness-of-fit between the simulated and observed hydrograph during the calibration and validation periods. In this investigation, the Nash and Sutcliffe simulation (NSE), coefficient of determination (R^2) and Percent bias (PBIAS) were employed. The below table 4 indicates the model performance evaluation criteria. (Moriassi et al., 2007).

Table 4. Model performance evaluation

Rating	R ²	NSE	PBIAS (%)
Very Good	0.75-1	0.75-1	< 10
Good	0.65-0.75	0.65-0.75	10-15
Satisfactory	0.5-0.65	0.5-0.65	15-25
Unsatisfactory	< 0.50	≤ 0.50	>25

2.7. A Framework of the study

In the below, [Figure 4](#) presents a technique summary for the current investigation. This study was focused on Hare River Watershed in the Rift Valley Basin of Ethiopia to evaluate hydrological response for land use land cover and climate change using the integrated ArcGIS, CMhyd, CMIP6, and SWAT models.

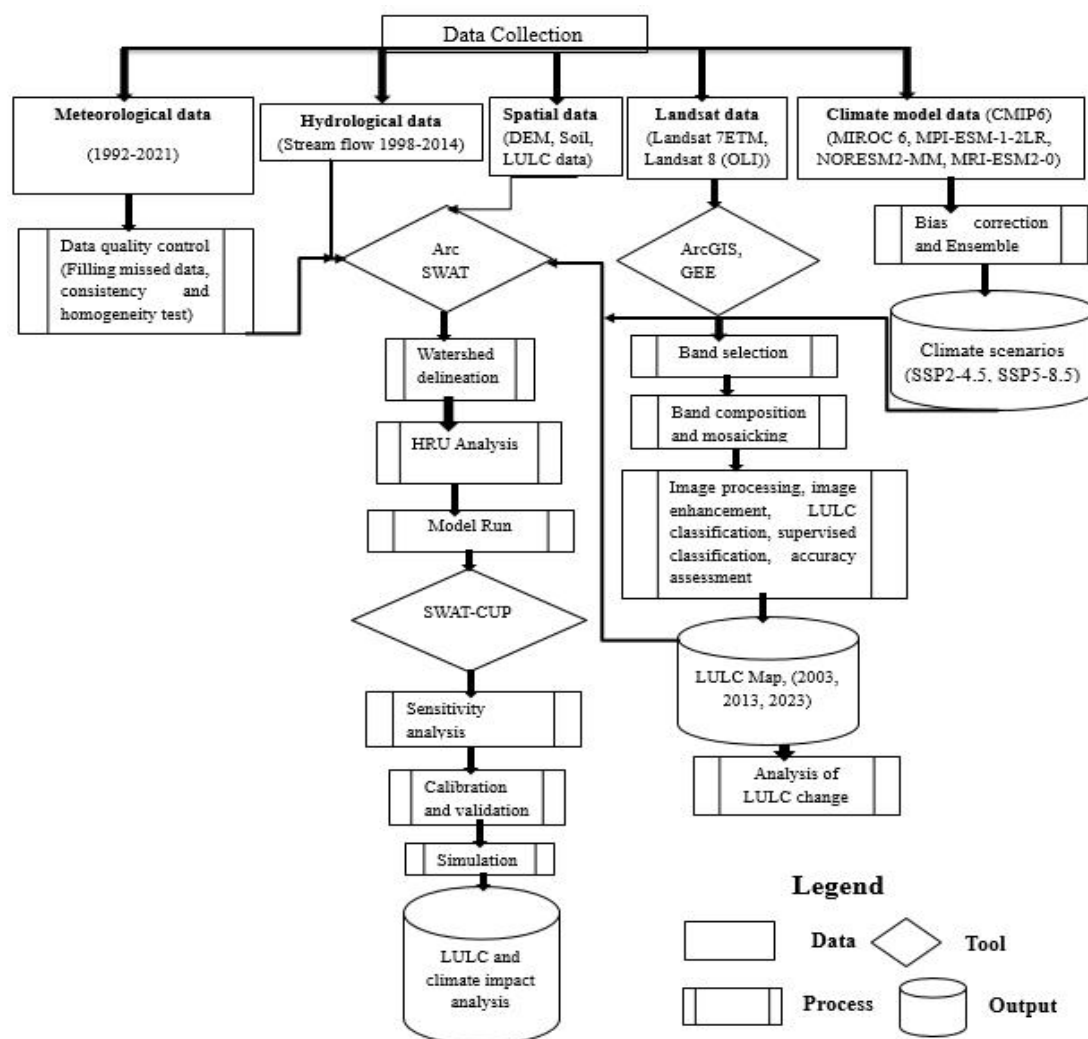


Figure 4. Conceptual flow chart of the study

3. Results and Discussion

The Google Earth Engine code editor was used in this study to build three land cover maps of the Hare Watershed. These maps' correctness was evaluated using the platform's pertinent accuracy indices. Predicting the future pattern of land use is made easier by the labeled map. The two anticipated land uses and land cover of the watershed, as well as the related effects, are also covered in detail in this chapter. The land use land cover accuracy assessment is shown in [Table 5](#).

Table 5. Result of LULC map Accuracy Assessment

Year	Kappa Coefficient, K (%)	Overall Accuracy (%)
2003	78	84
2013	84.16	90.48
2023	87	91.67

The overall accuracy of the land cover map generated using the 2003, 2013, and 2023 satellite images is 0.84, 0.90, and 0.91, with kappa values of 0.78, 0.84, and 0.87, respectively. The Kappa statistic ranges from -1 to 1, with 1 indicating perfect agreement and 0 indicating agreement that is no better than chance, with classifications of poor for values less than 0.40, fair to good for values between 0.40 and 0.75, and excellent for values greater than 0.75 (Roy et al., 2014).

3.1. Land use and land cover map

The LULC change of the Hare Watershed, have significantly detected over the study periods. In this study, three land use land cover classified maps of the Hare Watershed, The land use/cover major classes identified were agricultural land (intensively cultivated and moderately cultivated), Forest and shrub land. Generally, the significant increase or decrease of each land use class is shown in the Figure 5.

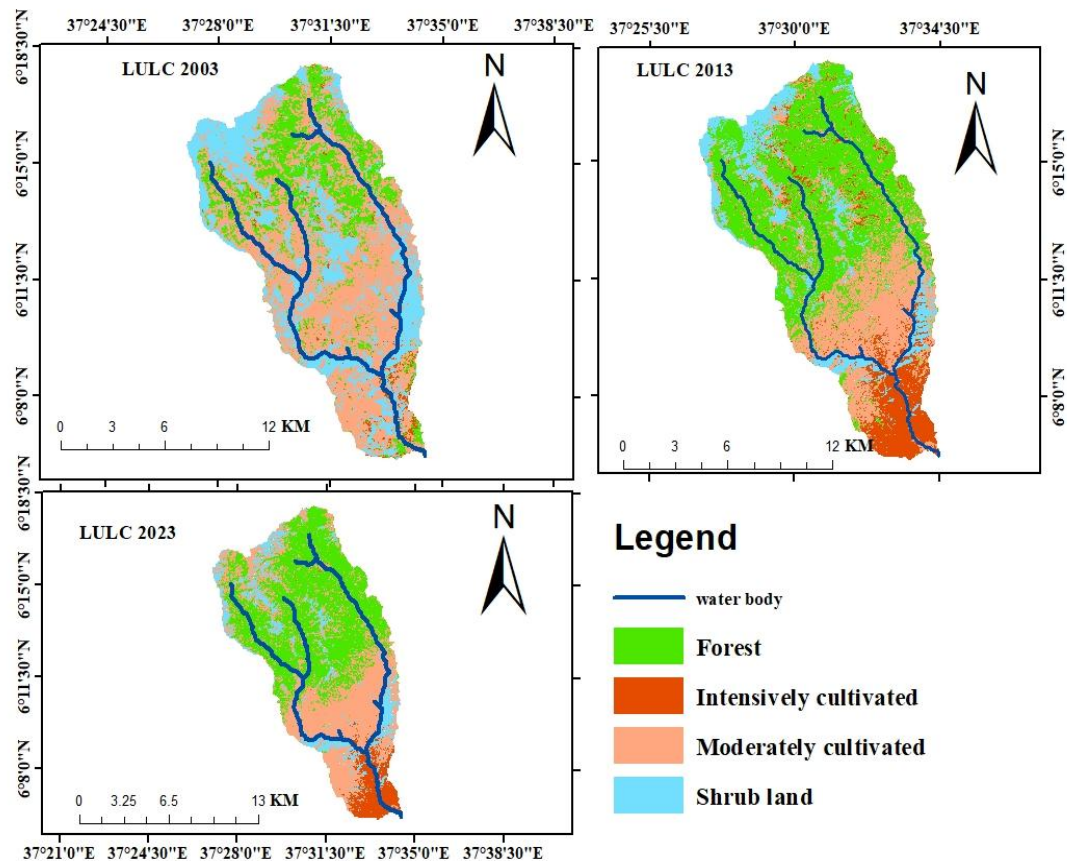


Figure 5. Land use land cover map of 2003, 2013 and 2023

Figure 5 represents, the land uses Land cover of the watershed in 2003 was distributed as follows: 19.08% Forest land, 1.64% intensively cultivated land, 50.87% moderately cultivated land, and 28.42% Shrub land. In the year 2013, the land use in the watershed was distributed as follows: 44.99% Forest land, 12.44% intensively cultivated land, 29.33% moderately cultivated land, and 13.24% Shrub land. In the year 2023, the land use in the watershed was distributed as follows: 44.58% Forest land, 6.85% intensively cultivated land, 37.74% moderately cultivated land, and 10.83% Shrub land.

3.2. Land Use Land Cover Change

According to LULC classification obtained from three time periods (2003, 2013, and 2023), the change detection was assessed and analysis was done based on the persistence and transformation of

LULC of one type to another. This rate of change of land use land cover in the Hare watershed fluctuated over some time.

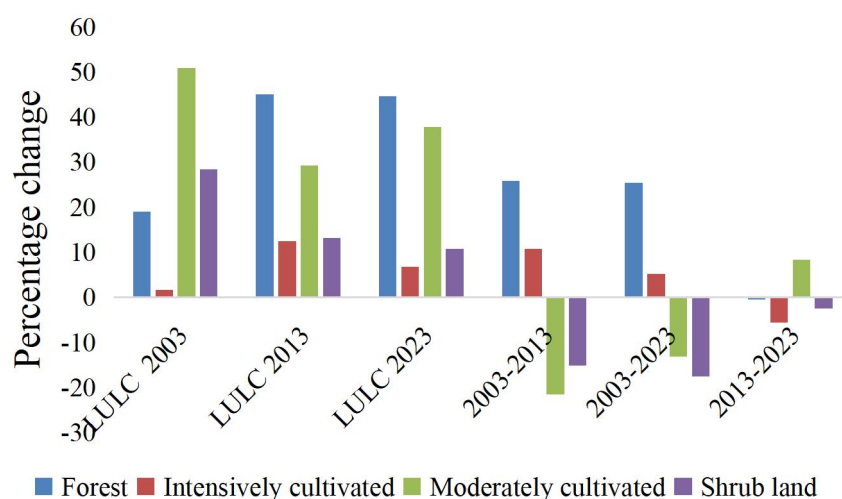


Figure 6. Area percentage of Hare Watershed, which is covered by specific LULC classes and the Corresponding changes in percentage in terms of total area (2003–2023)

Figure 6 demonstrates that moderately cultivated was the major occupied LULC type in 2003, accounting for approximately 50.87% of the total area, followed by shrub land at 28.42%. Forest land and intensively cultivated covered approximately 19.08% and 1.64% of the area, respectively. The intensively cultivated land occupied area increased to 6.85% in 2023 from 1.64% in 2003.

Studies suggest land use and land cover change in the basins of Ethiopia have been influenced by various factors such as population pressure, resettlement programs, climate change, and anthropogenic activity (Regasa Shiferaw, 2021).

3.3. Projected land use and land cover

Below Figure shows the projected business-as-usual scenarios. When comparing the simulated and real land use maps of 2023, MOLUSCE's validation result yielded a 90.5 percent accuracy rate and an overall acceptable kappa score of 0.78. It is important to remember that kappa values fall into one of three categories: poor (less than 0.40), fair to good (between 0.40 and 0.75), and outstanding (more than 0.75) (Roy et al., 2014). Figure 7a shows the anticipated business-us-usual (BAU) LULC map. Compared to the gradually displayed agricultural area, the map shows a significantly reduced forest area in the upper portion of the catchment. In most areas of the watershed, the plant cover was superb, but it will begin to dwindle in 2053. Agricultural practices predominate in the watershed's middle region, while the shrub land surrounding the outlet has diminished and transformed into a scatter type. Conservation scenarios (CON) (Figure 7b) were idealized scenarios with significant increases in forest cover, in contrast to BAU. The majority of the space is covered by vegetation.

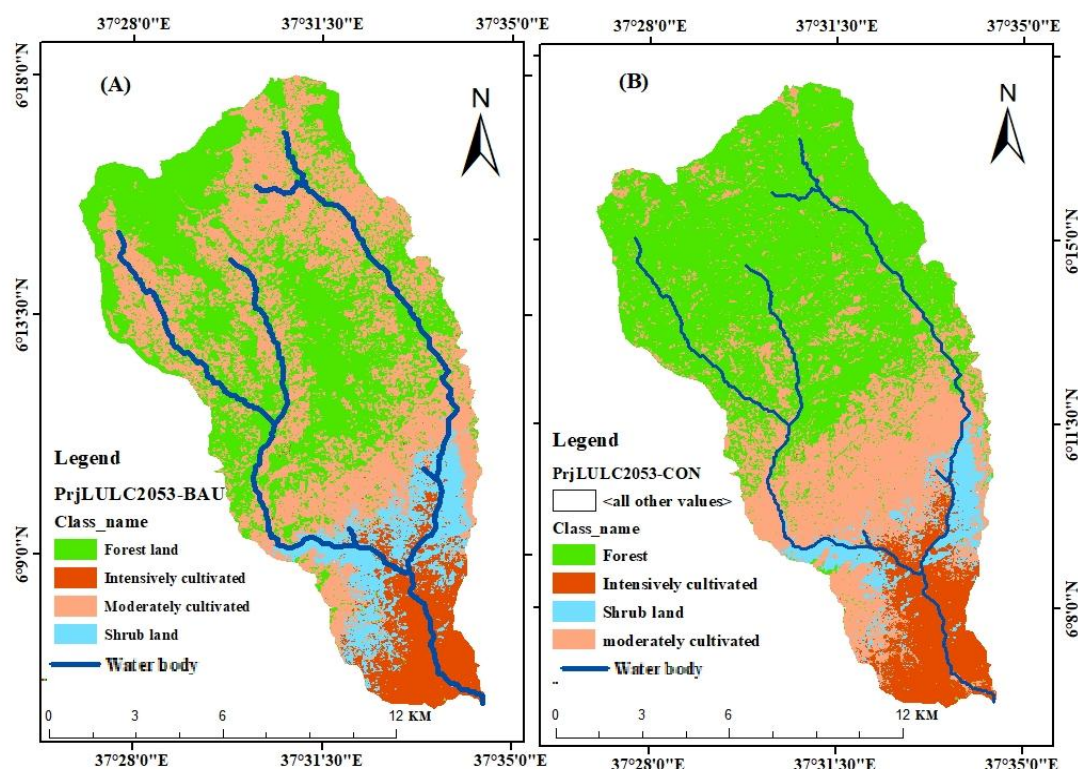


Figure 7. (A) business-us-usual of 2053 and (B) conservation of 2053

3.4. Land use land cover change detection

It shows the region where LULC changes from one type to another over time. Table shows the percentage changes between the Hare Watershed's BAS, BAU, and CON.

Table 6. Percentage change of land use land cover

LULC class	Baseline (%)	BAU (%)		CON (%)	
	BAS	2053	Change	2053	Change
Forest land	76.13	71.65	-4.48	88.65	12.52
Intensively cultivated	21.05	26.6	5.55	22.67	1.62
Moderately cultivated	49.61	60.69	11.08	48.46	-1.15
Shrub land	22.40	10.25	-12.15	9.22	-13.18

Table 6 makes it abundantly evident that, while using the present road (BAU), forest land and shrub land are expected to decrease by 4.48% and 12.15 in 2053, respectively whereas intensively and moderately cultivated land are expected to increase by 5.55% and 11.08%, respectively, over the research period. The outcomes of the BAU scenario's agricultural land expansion are consistent with research conducted in Ethiopia's Lake Tana area by (Teklay et al., 2021). In the CON scenario, moderately cultivated and shrub land are reduced by 13.18% and 1.15 resulting in a 12.52% increase in forest land within the watershed.

3.5. Climate variables trend analysis

3.5.1. Maximum and Minimum temperature trend

The initial data analysis was conducted to determine the statistical characteristics (mean, standard deviation) of the annual maximum and minimum temperature series for the period 1992-2021. The mean annual maximum and minimum temperature is 30.67oC and 17.35oC with standard deviation of 0.45oC and 0.52oC, respectively. The results of the Mann-Kendall test of annual Maximum temperature during the period 1992-2021 was shows statistically significant positive trend as the computed p-value (two-tailed) 0.022 is lower than the significance level alpha at 5% significant level in the Figure 8. The annual minimum temperature shows the Significant upward trend as the computed p-value 0.007 is lower than the significance $\alpha=0.05$ significant level.

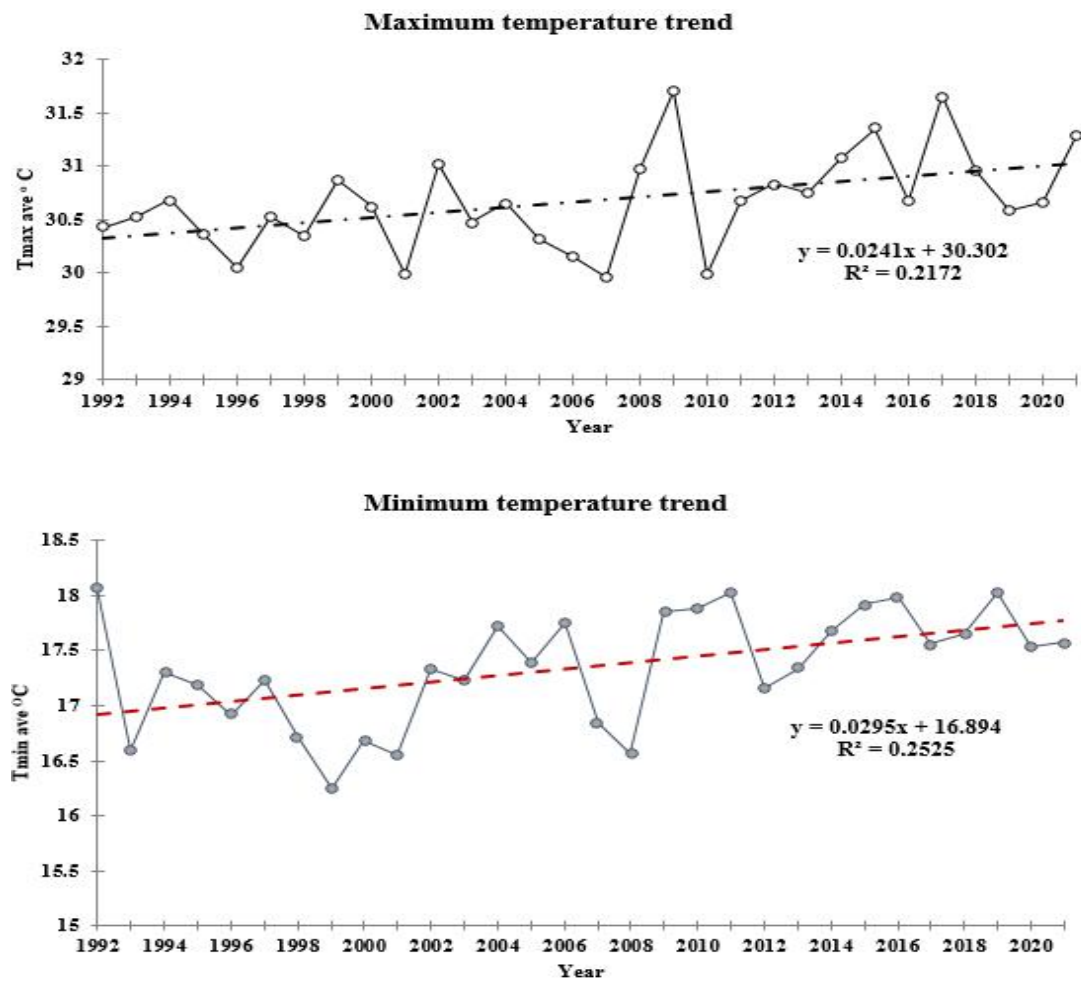


Figure 8. Annual Maximum and Minimum temperature trend for the period of 1992-2021

3.5.2. Precipitation trend

Based on [Figure 9](#), the fluctuations in the mean annual precipitation data throughout the entire study period are evident. The area's precipitation shows a statistically insignificant downward trend as the computed p-value 0.432 is greater than the significance $\alpha=0.05$ significant level. Based on a Mann-Kendall trend test, if there is "no trend" in the series, it means that the observations in the time series are considered independent and identically distributed, meaning there's no statistically significant monotonic (either increasing or decreasing) trend over time.

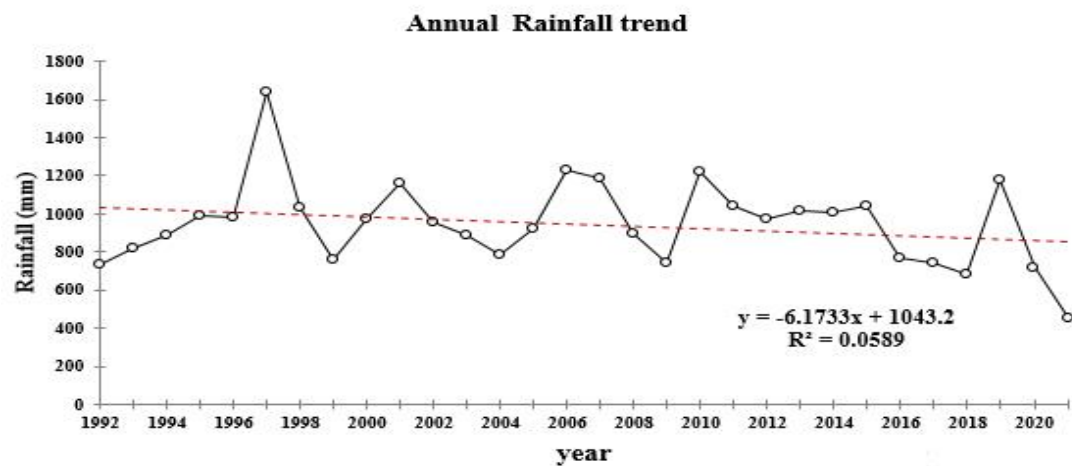


Figure 9. Annual precipitation trend for the period 1991-2021

3.5.3 Climate data comparison with observed

The comparison of four CMIP6 GCMs and their ensemble are shown in Table 7 below. The correlation coefficient of the ensemble is 0.72, which is a greater value compared to others. According to the research's correlation approach to 1, it is more correlated to the observed one. On the other hand, the smaller coefficient variation on the data shown in the ensemble of climate models is 9.3%. A smaller CV value indicates a more reliable (consistent) measurement (Shechtman, 2013). A lower RMSE value indicates a better fit between the model's predictions and the actual data, while a higher RMSE value indicates a poorer fit. Additionally, the systematic error was less on the ensemble of the model.

Table 7. Comparison of GCMs and their Ensemble

Climate models	Annual Rainfall(mm)	Correlation	CV (%)	RMSE	Bias (%)
Observed	1200	-	0.22	-	-
NOREESM2-MM	1140	0.3	10.23	176.3	3.5
MIROC-6	1030	0.4	11.27	180.54	3.67
MPI-ESM-1-2LR	1146.4	0.32	15.44	278.8	7.2
MRI-ESM-0	1237	0.22	16.32	243.7	8.17
Ensembles	1224.5	0.72	9.3	150.4	1.78

The four GCM models were selected due to their correction with acceptable value. The ensemble climate model better represents the watershed climate pattern based on the statistical analysis. This study aligns with the finding in Northern Europe which analyzed the performance of 12 different CMIP6 models in predicting precipitation data in Northern Europe by (Moradian et al., 2023). The results revealed that the accuracy of the CMIP6 models varied across the research area, but the ensemble method was beneficial in enhancing the projection accuracy. Therefore this study used ensemble climate data for the impact assessment.

Ensemble model (average of individual models) performs best overall, with rainfall (1224.5 mm) close to observe. Highest correlation (0.72), lowest RMSE (150.4), and lowest bias (1.78%). CV (9.3%) is lower than all individual models, suggesting more stable predictions. While individual models vary in performance, the ensemble output provides the most accurate and reliable estimation compared to observed rainfall data.

The comparison of the selected ensemble of GCMs before and after correction with witnesses for the period 1992–2021 is shown in Figure 10. The climate pattern before correction is overestimated precipitation data of the watershed with the largest overestimation being in June but correction enhanced the reliability of the climate data.

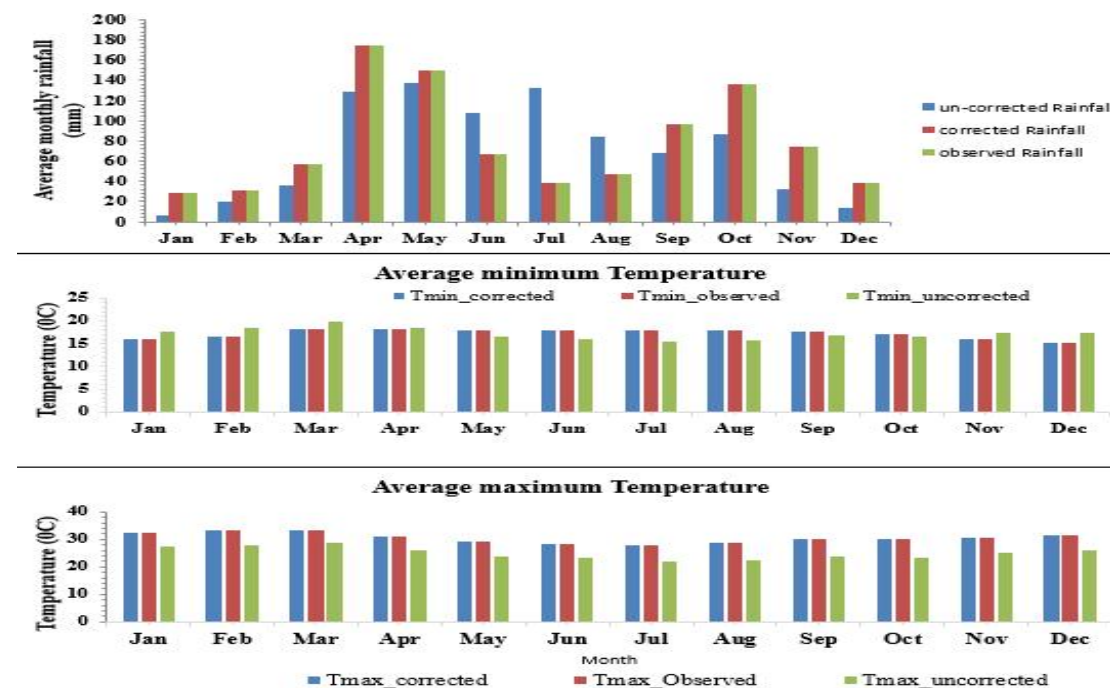


Figure 10. Comparison of observed, corrected and uncorrected rainfall, minimum temperature and maximum temperature

3.5.4. Climate change of the future

The projected monthly rainfall patterns show varying changes in direction and magnitude between the SSP2-4.5 and SSP5-8.5 scenarios. [Figure 11](#) shows that the average monthly rainfall may drop in February and December while increasing in January, March, April, July, August, and November under both SSP2-4.5 and SSP5-8.5 scenarios. The annual mean rainfall is anticipated to increase by 40.32 mm (3.66%) and 80.29 mm (6.69%) for SSP2-4.5 and SSP5-8.5, respectively. Overall, the research reveals that the two scenarios (SSP2-4.5 and SSP5-8.5) exhibit diverse patterns of rainfall change, with varying implications for different.

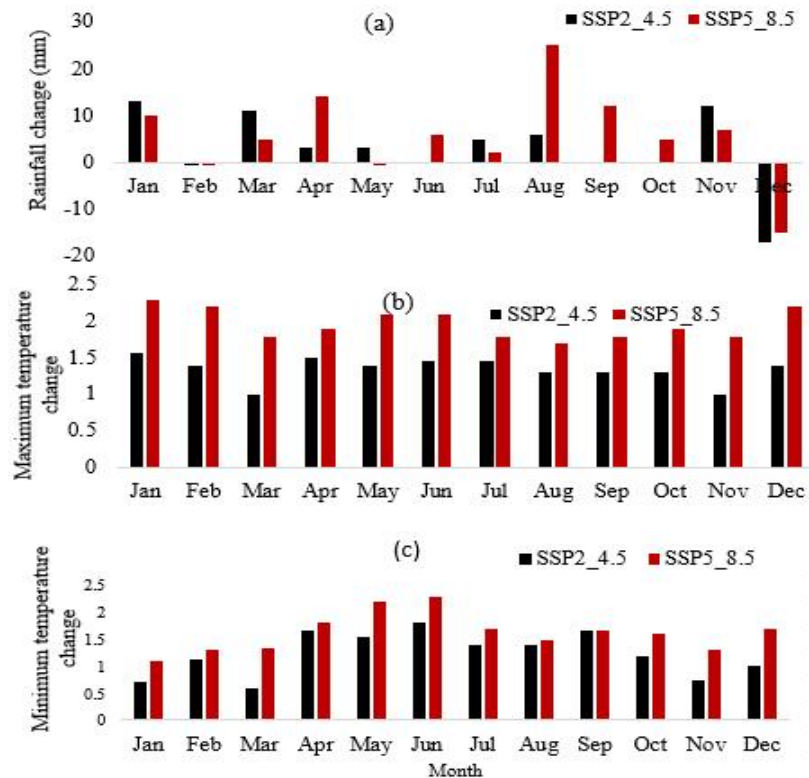


Figure 11. Projected change of monthly (a) Rainfall, (b) Maximum Temperature and (c) Minimum Temperature

The temperature maximum and minimum change increase under both SSP2-4.5 and SSP5- 8.5 scenarios. The mean annual temperature maximum is projected to increase by 1.4oC (5.13%) and 1.9oC (7.42%) under SSP2-4.5 and SSP5-8.5, respectively. For temperature minimum, the annual minimum temperature change is 1.2oC (7.45%) under SSP2-4.5 and 1.42oC (9.92%) under SSP5-8.5. As shown in Figure above, the maximum change occurred in June for temperature max with 2.1oC under SSP5-8.5 and 1.45oC under SSP2-4.5. In contrast, a minimum change in maximum temperature was exhibited in March for both scenarios.

The maximum change in minimum temperature seen in June was 1.8oC and 2.3oC under SSP2-4.5 and SSP5-8.5, respectively. Under SSP2-4.5, the magnitude of the temperature maximum increment varies from 1.050oC to 1.46oC. Under SSP5-8.5, the monthly temperature maximum varies from 1.8 to 2.1oC. It was noted that the maximum temperature change is higher than the minimum temperature. These findings line with the study in the upper Awash sub-basin of Ethiopia for the CMPI6 model ([Balcha et al., 2022](#)).

3.5.5. Model calibration and validation

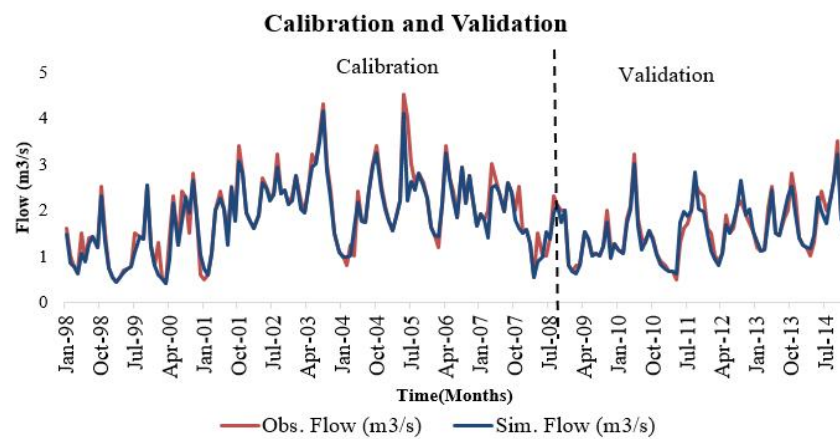
The results obtained from the Uniform Latin Hypercube Sampling (LHS) approach in RSWAT, during the calibration period, the following fitted value of the parameter obtained to which used to simulate the scenarios as shown in [Table 8](#).

Table 8. Parameters and their ranges with fitted value

Parameters	Change	Fitted value	Range
ALPHA_BF.gw	replace	0.043	0-1
CN2.mgt	relative	0.137	±0.2
SURLAG.bsn	relative	5.0366	0-10
SOL_K.sol	relative	0.169	0-0.25
HRU_SLP.hru	relative	0.2739	0-1
EPCO.hru	replace	0.5882	0-1
ALPHA_BNK.rte	replace	0.0887	0-1
RCHRG_DP.gw	replace	0.5207	0-1
CH_K2.rte	replace	113.38	0-150

According to the results obtained from the sensitivity analysis using the Uniform Latin Hypercube Sampling (LHS) approach in R-SWAT, the parameters were ranked based on the t-statistic and p-value. The t-statistic provides a measure of the parameter sensitivity, while the p-value indicates the significance of the sensitivity of the parameters (K. C. Abbaspour, 2012).

The validation process continues simultaneously in the RSWAT background with parameters obtained during the calibration process. The calibration for period of 1998-2008 and validation of the model utilized 2009–2014 data sets. Figure 12 clarify the graphical representation for calibration and validation.

**Figure 12.** Calibration and validation of average monthly observed and simulated flow (1998-2014)

The summary results of the model performance during calibration and validation are presented in Table 9.

Table 9. Summary of model performance evaluation for calibration and validation period on monthly time steps

Period	R ²	NSE	PBIAS(%)
Calibration	0.86	0.84	4.2
Validation	0.82	0.74	9.7

3.6. The Impact of Climate and LULC Change on hydrological response

3.6.1. Hydrologic Response to Land-Use and Land-Cover Change

Changes in land use and land cover affect river flows by changing how watersheds respond hydrologically. This has led to a need for knowledge of the extent of these changes in watershed hydrology for various water resources project planning and implementation (Mango et al., 2011). To analyze land use/cover change on the watershed hydrology, calibrated SWAT models were used under three land use scenarios (BAS, BAU, and CON) with the baseline climate data. To understand the individual effects of land use and land cover changes, a simulation was conducted in the two scenarios (S2 and S3) in Table 10. The changes in annual and monthly surface runoff (Qsur), evapotranspiration (ET), base flow (BF), and water yield (Wyd) are listed in Tables 10 and Figure 13, respectively. Comparing the simulated value with the REF, BAU has increased surface runoff by 5.34% and water yield by 0.397%, but ET and BF decreased by 0.41% and 2.04%, respectively.

Table 10. Land use change impact on the hydrological process under BAU and CON

Hydrological process	statistics	REF	BAU	CON
Qsur	Mean (mm)	153.82	162.03	127.44
	Change (%)	-	5.34	17.15
ET	Mean (mm)	585.6	583.22	594
	Change (%)	-	-0.41	1.43
BF	Mean (mm)	231.59	226.87	243.31
	Change (%)	-	-2.04	5.06
Wyld	Mean (mm)	526.01	528.1	517.5
	Change (%)	-	0.397	-1.62

The Business-as-usual (BAU) scenario has increased Qsur (5.34%), because of the significant expansion of agricultural land by 8.08% compared to the baseline map (BAS) (Table 10), leading to a reduction in plant cover. This reduction in plant cover has decreased canopy interception and plant transpiration, limiting the potential increase in evapotranspiration. Additionally, the conversion of forest land to agricultural land has altered the properties of the topsoil, decreasing permeability and infiltration. Consequently, more rainfall now turns into surface runoff (Marhaento et al., 2017).

In contrast, the CON scenarios demonstrate a reduction in agricultural land, which in turn leads to a decrease in Qsur by 17.15%. The positive correlation between agricultural land expansion and surface runoff has been elucidated in studies by (Gebremicael et al., 2019; Gebresamuel et al., 2010). Furthermore, the increase in plant cover under CON scenarios results in lower Qsur and an increase in ET. The study has highlighted the close connection between evapotranspiration and forest expansion, suggesting that an increase in forest cover can lead to a decrease in surface runoff and water yield by (Ning et al., 2020). Under the conservation (CON) scenarios, the watershed BF increases by 5.06%. Vegetated land, such as evergreen forests, can improve soil water storage capacity by encouraging deeper root penetration and enhancing biotic activity in the topsoil. This finding aligns with the research conducted in the Geba watershed in northern Ethiopia by (Gebremicael et al., 2019). On the other hand, the decrease in Wyld under CON scenarios results from the increment of the ET and reduction of Qsur.

In the period of 12 months, the wettest months typically exhibit high surface runoff, with maximum surface runoff (Qsur) seen in April. Conversely, the driest seasons, spanning from December to February, showcase the lowest Qsur levels, with February recording values lower than other months under business-as-usual (BAU) conditions. In contrast, under the Conservation (CON) scenario, a maximum decrease in Qsur was shown in April, with a higher magnitude reduction, around 3.92 mm compared to REF. Interestingly, evapotranspiration (ET) demonstrated higher values in March compared to other months under both scenarios. This elevation in ET levels could be attributed to the crop growth stage during this period. Studies have shown that evapotranspiration values are closely related to crop growth, with higher values observed during the cropping season when vegetation cover is dense (Roy et al., 2014). The base flow (BF) of the catchment attained its peak in November under both conditions, while February exhibited the lowest BF flow. During the driest months of December and January, the base flow supply to the Wyld of the catchment is more than other parameters. The Wyld is maximum in May due to the high surface and base flow relative to other seasons.

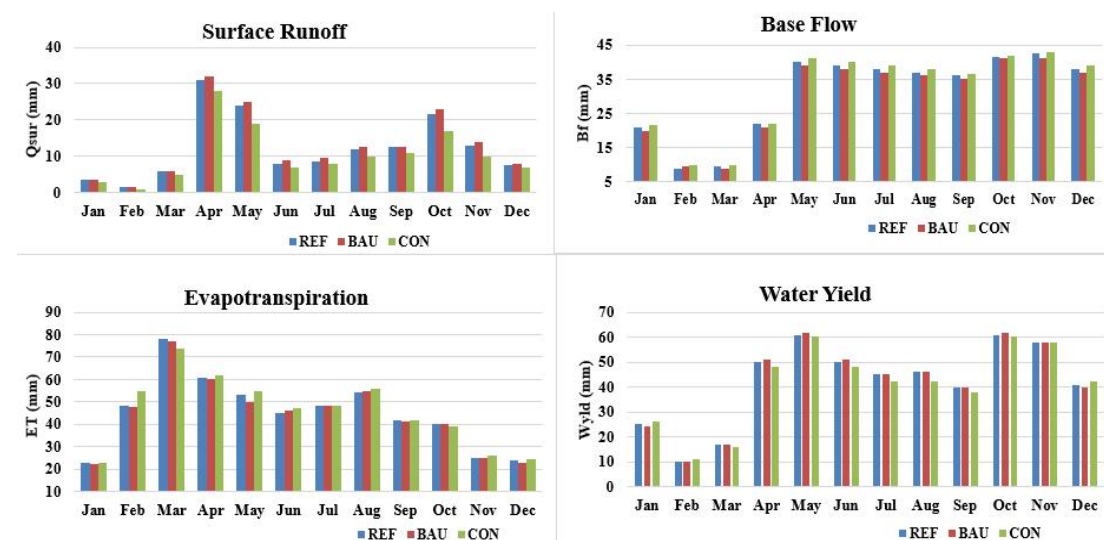


Figure 13. Simulated mean monthly hydrological variables under REF, BAU, and CON

3.6.2. Climate change impact on hydrology

The impacts of climate change on hydrological processes were evaluated by running simulations with the calibrated SWAT model under three climate scenarios (baseline, SSP2-4.5, and SSP5-8.5) with BAS land map.

Table 11. Simulated mean annual water yield (Wyld), surface runoff (Qsur), base flow (BF), and evapotranspiration (ET) for the reference period (1992-2014) and climate change scenarios (2050-2070)

Hydrological process	statistics	REF	SSP2-4.5	SSP5-8.5
Qsur	Mean (mm)	153.82	91.07	88.07
	Change (%)	-	-40.79	-42.74
ET	Mean (mm)	585.6	610.6	630.4
	Change (%)	-	4.27	7.65
BF	Mean (mm)	231.59	283.6	290.2
	Change (%)	-	22.46	25.30
Wyld	Mean (mm)	526.01	543.21	548.5
	Change (%)	-	3.3	4.3

Table 11 clearly shows that SSP2-4.5 and SSP5-8.5 climate scenarios show a dramatic decrease in Qsur, around 40.79% for SSP2-4.5 and 42.74% for SSP5-8.5, respectively. Despite this decrease in Qsur, other hydrological processes have shown an increase.

The temperature change increases the annual BF of the watershed under both climate scenarios by 22.46% and 25.3% under SSP2-4.5 and SSP5-8.5, respectively. As result of the temperature is anticipated to increase under both scenarios, for example, SSP5-8.5 with a 5.13% incremental on maximum temperature and 9.92% in minimum temperature. This temperature increase can cause soil drying, cracking, and the formation of more macro pores, which increase the soil conductivity to water and consequently increase the infiltration rate of the catchment. More water infiltrated into the ground storage, resulting in a high water to stream in the form of BF. On the other hand, one of the factors that have contributed to an increase in evapotranspiration (ET) within the watershed is the anticipation of increased temperature. The maximum and minimum temperature change records show an upward trend, especially in the rainy seasons. For instance, the maximum temperature increase will be exhibited in June, which is the rainy month in the watershed. Additionally, the increase of ET and BF partitioned the precipitation more, which results to decreased surface runoff. This finding agrees with a study in the Ponnaiyar basin in India using the CMIP6 climate model, who found that maximum ET and Wyld are expected to increase at the end of 2070, while Qsur shows a decrease for the climate model called MPI-ESM1-2-LR by 6.18 % at the end of 2070 by (Balu et al., 2023). Other studies in Ethiopia have also indicated a decrease in Qsur due to climate change, for example (Mengistu et al., 2023).

Figure 14 indicates that in the driest months (January, February, and March), the base flow was at its minimum due to reduced rainfall. For instance, February exhibited the lowest base flow, possibly influenced by decreased rainfall, which in turn reduce the infiltrated water into ground storage. In monthly, an increase ET in February and March led to a reduction in the Wyld of the watershed in the same month under both climate scenarios. This observation aligns with research conducted in the northeast region of the Tibetan mountains by (Chien et al., 2013). The Wyld is maximum under SSP5-8.5 in October, this shows the BF and the Qsur of contribution are high in similar months. The Wyld of December was more contributed from the BF of the watershed, the Qsur was minimal because of the less rain and higher temperature in the driest months

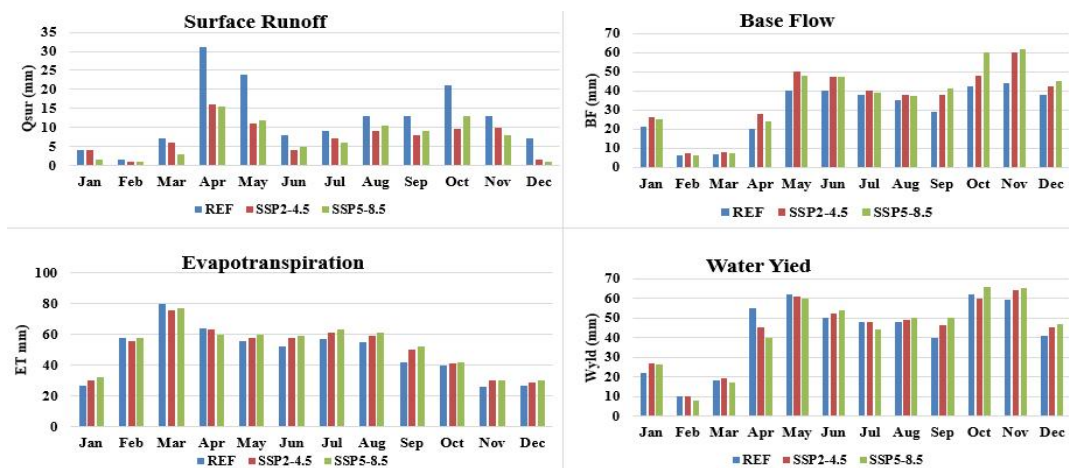


Figure 14. Simulated mean monthly hydrological variables under REF, SSP2-4.5 and SSP5-8.5

3.6.3. The combined impact of Land use land cover and climate change

The combined impact of climate and land use change was evaluated by simulating scenarios using the calibrated SWAT hydrological model. Four simulations (S6, S7, S8, and S9) were conducted.

The result in [Table 12](#) shows that, a mean annual decrease in surface runoff by 37.2% under the BAU4.5 scenario and 54.69% under the CON4.5 scenario. The difference in the decline between BAU4.5 and BAU8.5 scenarios was minimum, as was the same case for CON4.5 and CON8.5 scenarios.

Table 12. Simulated mean annual water yield (Wyld), surface runoff (Qsur), base flow (BF), and evapotranspiration (ET) for the combined scenarios

Hydrological process	statistics	REF	BAU4.5	BAU8.5	CON4.5	CON8.5
Qsur	Mean (mm)	153.82	96.62	94.4	69.69	68
	Change (%)	-	-37.2	-38.63	-54.69	-55.79
ET	Mean (mm)	585.6	616.7	634.3	621.3	638.5
	Change (%)	-	5.31	8.28	6.1	9.03
BF	Mean (mm)	231.59	289.6	291.7	301.8	305.9
	Change (%)	-	25.05	25.95	30.3	32.09
Wyld	Mean (mm)	526.01	540	542.5	535.3	541.6
	Change (%)	-	2.66	3.13	1.76	2.96

Compared to the individual effect of land use/land cover (LULC) with combined scenarios on surface runoff, the combined scenarios exhibited lower Qsur. In contrast to LULC, climate change had a greater impact than BAU4.5 and BAU8.5 on surface runoff. The ET effect was more pronounced in the combined scenarios than in the individuals with a higher magnitude under CON8.5 in the [Figure 15](#).

The base flow (BF) of the watershed increased in both combined simulations compared to the REF by 25.05%, 25.95%, 30.3%, and 32.9% under BAU4.5, BAU8.5, CON4.5, and CON8.5, respectively. The individual impacts of LULC and climate change are less base flow (BF) than in the combined scenarios. The highest BF shown in CON8.5 was around a 32.9% increase compared to REF, but the individual impact of climate and LULC was a 25.3% increase under SSP5-8.5 and 5.06% incremental under CON scenarios, respectively. This finding has an agreement with research on Baro Basin, Ethiopia, despite the magnitude of the water balance components ([Mengistu et al., 2023](#)). The CON4.5 and CON8.5 results show that planting trees on steep slopes is advised to decrease soil runoff, which is a significant factor contributing to soil erosion and flooding.

The water yield (Wyld) was higher in some combined scenarios than in the individual scenarios, For example in BAU4.5 the wyld was 2.66% incremental but, in BAU and SSP2- 4.5 it was 0.397% and 3.3% incremental, respectively.

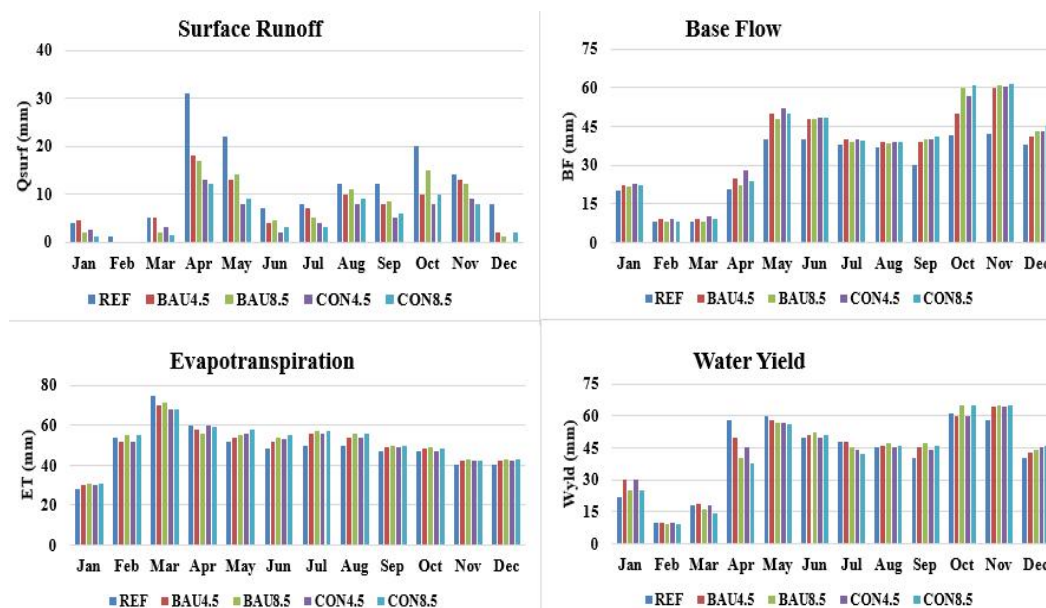


Figure 15. Combined LULC and climate change impact on the hydrology of Hare Watershed

4. Conclusion

The Hare Watershed was assessed in order to examine the impact of both LULC and climate change separately and in combination on hydrology, which includes surface runoff, evapotranspiration, base flow, and water yield for future use. Quantifying the future water supply is essential to reducing the recent anthropogenic alterations.

The baseline hydrological parameter availability was determined by analyzing the observed climatic data from three meteorological stations. For the analysis, an ensemble mean of four recently published CMIP6 climate model findings with lower error was used. The performance of the climate model was assessed using statistical measures like coefficient of variation, bias mean absolute error (MAE), and root mean square error (RMSE). Before analyzing climate ensemble outputs, bias correction adjustments were done.

Projected land-use/cover scenarios were created using the Module of Land-use Change Evaluation (MOLUSCE) and involved into SWAT, a process-based watershed hydrology model. Three periods' worthwhile of land use changes were examined, and the expected BAU scenarios reveal a notable increase in agricultural area while a decrease in plant covering. The catchment's afforestation was idealized in order to produce a conservation land use map (CON). By 2053, there will be more agricultural activity in the Hare Watershed, according to the projected land use/cover change under the deforestation (BAU) scenario.

The objective functions Nash-Sutcliffe Efficiency (NSE), coefficient of determination (R^2), and percentage of bias (Pbias) were used to objectively assess the SWAT hydrological model. The most suitable parameters were chosen, and the recently used R-SWAT was used to calibrate and validate the model. Using stream flow at the catchment outlet for both calibration and validation, the model performed as follows: $R^2 = 0.86$, $NSE = 0.84$, and $PBIAS = 4.2\%$ for calibration, and $R^2 = 0.82$, $NSE = 0.74$, and $PBIAS = 9.7\%$ for validation.

The results show that the combined scenarios significantly affect base flow, surface runoff, and watershed water yield. When compared to all other scenarios, the BAU8.5 scenario has the catchment's highest water yield. In the watershed, surface runoff rises greater under the BAU (deforestation scenarios) than under the Conservation (CON) afforestation scenarios. However, compared to the individual scenarios, the combined climate and land use scenarios exhibit a more noticeable decrease in surface runoff. Under combined LULC and climate scenarios, increases in plant cover increase evapotranspiration. Similar to this, climate change scenarios largely dictate the magnitude and direction of monthly increases in evapotranspiration, with the afforestation effect having greatest effects from March to April, while controlling for other factors. The study's results can offer important insights into how land cover and use contribute to hydrological components and how climate change affects the dynamics of hydrological variables.

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Data Availability

The climate projection data used in this study were obtained from the Coupled Model Inter-comparison Project Phase 6 (CMIP6), which is publicly available through the Earth System Grid Federation (ESGF) data portal. Land use/land cover, hydrological, and other supporting datasets were obtained from publicly accessible sources as described in the Materials and Methods section. The processed datasets, model input files, calibration data, and simulation outputs generated during this study are available from the corresponding author upon reasonable request to support the reproducibility of the research.

Competing Interests

The authors declare that they have no competing interests. The authors have no known financial or personal relationships that could have influenced the work reported in this manuscript.

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