

ASSESSING LONG-TERM CLIMATE VARIABILITY IMPACTS ON STREAMFLOW AND DROUGHT TO PROMOTE SUSTAINABLE WATER RESOURCES AND AGRICULTURAL MANAGEMENT IN BORKENA WATERSHED, AWASH BASIN, ETHIOPIA

ÉVALUATION DES IMPACTS DE LA VARIABILITÉ CLIMATIQUE À LONG TERME SUR LE DÉBIT DES COURS D'EAU ET LA SÉCHERESSE AFIN D'ENCOURAGER UNE GESTION DURABLE DES RESSOURCES EN EAU ET DE L'AGRICULTURE DANS LE BASSIN VERSANT DE BORKENA, DANS LE BASSIN DE L'AWASH, EN ÉTHIOPIE

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Abstract

Climate variability and change pose significant challenges to water resources and agriculture, particularly in the Borkena Watershed, part of Ethiopia's Awash Basin. The region is prone to recurring droughts that disrupt agricultural productivity and water availability, exacerbating socio-economic vulnerabilities. Despite the critical need to understand long-term climate impacts, research specifically targeting the Borkena Watershed is limited. This study investigates how climate variability influences water availability and drought patterns in the watershed. The objectives were to assess the performance of CMIP6 climate models under two Shared Socioeconomic Pathways (SSP2-4.5 and SSP5-8.5) and evaluate projected changes in precipitation, temperature, and streamflow. Using observed data (1985–2014) and projections (2041–2100), three models GFDL-CM3, MPI-ESM2-MR, and HADGEM2-AO were identified as best performing for the study area. The SWAT model simulated streamflow, while drought patterns were analyzed using the Reconnaissance Drought Index (RDI), Streamflow Drought Index (SDI), and Agricultural Standardized Precipitation Index (aSPI). Results indicate that maximum rainfall is projected to increase by 11.37% and 13.89%, while maximum temperatures may rise by 4.14°C and 5.23°C under SSP2-4.5 and SSP5-8.5, respectively. Despite higher rainfall and temperature, streamflow is predicted to decline by 36.29% and 32.04%, indicating reduced water availability. Hazardous drought events are expected to be most frequent at Kombolcha, Kemisse, and Cheffa stations, with agricultural droughts posing the greatest threat. The findings highlight the urgent need for integrated watershed management, sustainable water resource utilization, climate-smart agriculture, early warning systems, and community-based adaptation strategies to enhance resilience. Implementing these measures can mitigate the impacts of long-term climate variability on streamflow and future drought patterns, ensuring more secure water resources and sustainable agriculture in the Borkena Watershed.

Keywords: Borkena watershed, climate change; drought pattern, Mitigation Measures.

RESUME

La variabilité et le changement climatiques posent des défis majeurs pour les ressources en eau et l'agriculture, en particulier dans le bassin versant de Borkena, qui fait partie du bassin de l'Awash en Éthiopie. La région est exposée à des sécheresses récurrentes qui affectent la productivité agricole et la disponibilité en eau, aggravant ainsi les vulnérabilités socio-économiques. Malgré la nécessité

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cruciale de comprendre les impacts climatiques à long terme, il existe peu de recherches dirigées particulièrement vers le bassin versant de Borkena. Cette étude examine la manière dont la variabilité climatique influence la disponibilité en eau et les tendances de sécheresse dans le bassin versant. Il s'agissait d'évaluer les performances des modèles climatiques CMIP6 selon deux scénarios socio-économiques communs (SSP2-4,5 et SSP5-8,5) et d'analyser les changements prévus en matière de précipitations, de température et de débit fluvial. À partir de données d'observation (1985–2014) et de projections (2041–2100), trois modèles — GFDL-CM3, MPI-ESM2-MR et HADGEM2-AO — ont été identifiés comme étant bien performants pour la zone d'étude. Le modèle SWAT a permis de simuler le débit fluvial, tandis que les tendances de sécheresse ont été analysés à l'aide de l'Indice de reconnaissance de la sécheresse (RDI), de l'indice de sécheresse d'écoulement fluvial (SDI) et de l'indice de précipitations standardisé pour l'agriculture (aSPI). Les résultats indiquent que les précipitations maximales devraient augmenter de 11,37% et 13,89%, tandis que les températures maximales pourraient augmenter de 4,14 °C et 5,23 °C respectivement dans le cadre des scénarios SSP2-4,5 et SSP5-8,5. Malgré une augmentation des précipitations et des températures, les débits fluviaux sont destinés à diminuer de 36,29% et 32,04%, signalant ainsi une réduction de la disponibilité en eau. Les événements de sécheresse dangereux devraient être les plus fréquents aux stations de Kombolcha, de Kemisse et de Cheffa, les sécheresses agricoles constituant la menace la plus grave. Les résultats soulignent la nécessité d'avoir une gestion intégrée du bassin versant, une utilisation durable des ressources en eau, une agriculture adaptée au climat, des systèmes d'alerte précoce et des stratégies d'adaptation communautaires pour renforcer la résistance. La mise en œuvre de ces mesures peut atténuer les impacts de la variabilité climatique à long terme sur le débit fluvial et les tendances futures de sécheresse, garantissant ainsi une meilleure sécurité des ressources en eau et une agriculture durable dans le bassin versant de Borkena

Mots-clés : Bassin versant de Borkena; Changement climatique; Tendances de sécheresse, Mesures d'atténuation.

1. Introduction

Climate change has a profound impact on hydrological systems, especially in regions sensitive to fluctuations in temperature and precipitation. Research indicates that shifts in rainfall patterns and rising temperatures contribute to increased evapotranspiration rates, which, in turn, reduce water availability and heighten the severity of drought conditions. These changes significantly affect the water cycle, posing challenges for both water resources management and agricultural productivity (Ficklin et al., 2019).

Such impacts are particularly pronounced in arid and semi-arid regions, where even slight climatic changes significantly affect water resource dynamics (Bastola et al., 2011). This underscores the necessity of utilizing advanced climate models to predict future trends in water balance and assess their potential impacts. Climate change has become a major global concern, profoundly influencing water resources, evapotranspiration rates, and drought patterns. Projections derived from future climate scenarios, such as those created under the Coupled Model Inter-comparison Project Phase 6 (CMIP-6), are crucial for understanding regional effects and informing sustainable water resource management strategies (Eyring et al., 2016).

The Borkena Sub-Basin in Ethiopia, an area highly dependent on agriculture and vulnerable to climate variability, is experiencing growing challenges as a result of shifting rainfall patterns, rising temperatures, and more frequent drought events (Gebrechorkos et al., 2020). Understanding the impacts of climate projections on hydrological processes, such as evapotranspiration, is essential for developing effective adaptive strategies in vulnerable regions.

The Coupled Model Inter-comparison Project Phase 6 (CMIP-6) offers more advanced projections for climate impact studies, featuring improved spatial resolution and a more accurate representation of physical processes compared to CMIP-5 (Eyring et al., 2016). CMIP-6 models incorporate a broader range of Shared Socioeconomic Pathways (SSPs), enabling more comprehensive simulations of future

climate scenarios. These models have been utilized by researchers to assess regional impacts on water systems, showcasing their capacity to deliver valuable insights for developing effective adaptation strategies (Hausfather & Peters, 2020).

Climate change refers to long-term shifts in the average weather conditions of a region, influenced by factors such as rainfall, temperature, wind, and humidity. It is driven by both natural causes, including variations in Earth's orbit, tilt, volcanic eruptions, and processes like desertification and forest fires, as well as human activities such as burning fossil fuels, deforestation, and urbanization. Changes in mean temperature and precipitation patterns can have significant impacts on both natural ecosystems and human systems (IPCC, 2014).

Freshwater resources are vital to all sectors and regions and are prone to direct effects. However, vulnerabilities to climate change vary regionally (Falloon & Betts, 2010). Future climate change projections are far from forecasts. Rather they are different probable scenarios constructed based on population and world development assumptions, these scenarios were run by diverse institutions using climate or circulation models. Studies by (Gebrechorkos et al., 2020) reveal that climate variability in Ethiopia has led to erratic rainfall patterns and prolonged droughts and is further projected to intensify under future climate scenarios. This highlights the importance of conducting localized assessments, such as those focusing on the Borkena Sub-Basin, to inform sustainable water management strategies.

The climate change results provide valuable insights for making informed decisions on water resource management, agriculture, transportation, and urban development at the national, regional, and municipal levels. The novelty of this study lies in the following key aspects: 1) Localized Analysis of Climate Variability, 2) Integration of CMIP-6 Models and Drought Indices, 3) Streamflow Simulation Using SWAT, and 4) Station-Specific Drought Hazard Identification. The study not only predicts future hydrological changes but also translates these projections into actionable strategies for climate adaptation.

2. Material and Methods

2.1.1 Material

2.1.1 Study Area Description

The Borkena Sub-Basin, covering an area of 1,658.2 km² in the Awash Basin of northeastern Ethiopia, has elevations ranging from 1,200 to 3,000 meters, leading to varied climatic conditions. The region experiences with a bimodal rainfall pattern, receiving between 700 and 1,200 mm of annual precipitation (see Figure 1).

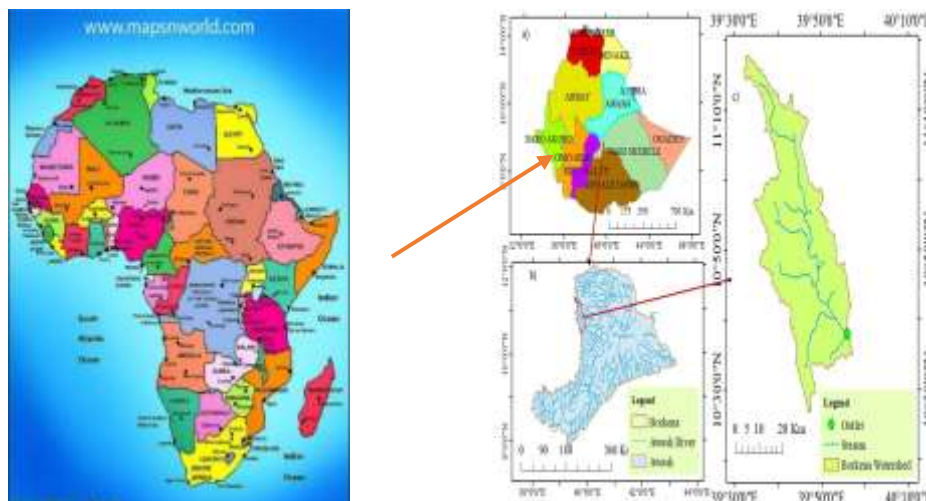


Figure 1: Location Map a) Africa Map; b) Ethiopia River basins; c) Awash River Basin; and d) Borkena Sub – Basin

2.1.2 Data Collection and Quality Check

Daily meteorological data, including precipitation, temperature, radiation, relative humidity, and wind speed, were sourced from the Ethiopian National Meteorological Agency (ENMA). The Digital Elevation Model (DEM) was obtained from the United States Geological Survey (USGS) website (<http://earthexplorer.usgs.gov>). Additionally, daily hydrological data were provided by the Ethiopian Ministry of Water and Energy (MoWE). The tools utilized in this study are listed in Table 1.

Table 1: Data type, sources, and purpose

Data type	Source	Purpose
Meteorological data	Ethiopian National Meteorological Agency (ENMA)	Input for SWAT model
Hydrological data	Ministry of Water and Energy	SWAT model calibration and Validation
DEM (20m*20m)	USGS (http://earthexplorer.usgs.gov)	SWAT Sub - Basin Delineation
Soil (1: 250,000)	Ministry of Water and Energy	SWAT - HRU definition for soil
Land use (1: 250,000)	Ministry of Water and Energy	SWAT - HRU definition for land

2.2 Global climate model (GCM) data)

Future data on precipitation and temperature are essential for assessing the impacts of climate change on these variables, as well as for forecasting streamflow over future time frames. The future climate data for this study were obtained from the Earth System Grid Federation (ESGF) website, which hosts the Coupled Model Inter-comparison Project Phase 6 (CMIP-6) scenarios (<https://esgf-node.llnl.gov/projects/cmip6/>), those data are listed in Table 2.

Table 2: Different Models and Sources of Data

S. No	Model institution	Developed by
1	GFDL-CM3	Australia
2	MPI-ESM2-MR	China
3	HadGEM2-AO	China
4	MPI-ESM2-MR-ESM2-0	USA
5	E3SM-1-0	USA
6	CAS_FGOALS	Japan
7	BCC-CSM2-MR	Germany
8	INM-CM5-0	Japan
9	GFDL-CM3	UK
10	ACCESS-ESM1-5	Japan
11	NorESM2-LM	USA
12	CESM2	USA
13	NESM3	Japan
14	CIESM	China
15	CanESM5	Australia
16	CESM2-FV2	Chain

2.1 Methods

2.1.1 Observed data quality testing

To make sure that the model receives exact and correct data and to produce a simulated result that can be believed in, a data quality test needs to be performed out. The missing hydro-meteorological data were filled in, followed by homogeneity and consistency tests, and then a trend analysis was conducted.

2.1.2 GCMs data bias correction

The fundamental concept of bias correction is to identify and adjust for potential discrepancies between simulated and observed climatic variables. Several bias correction methods exist, particularly for precipitation and temperature. In this study, linear scaling was employed as the chosen method for bias correction (Fang et al., 2015, M'Po et al., 2016) and variance scaling methods (Vithlani & Rank, 2016) were used for precipitation and temperature correction of climate data respectively, by Utilizing the CMhyd tool (<https://swat.tamu.edu/software/cmhyd/>).

2.1.3 Evaluations of CMIP-6 climate model outputs

The best-fit models for this study were chosen by assessing the outputs of sixteen GCM models after bias adjustment. Model performance was evaluated using graphical methods and statistical indicators, including RMSE, PBAIS, and correlation coefficients (r).

2.1.4 Trend analysis of future temperatures and precipitation

The Mann-Kendall test does not assume anything about the distribution of the data, is robust against outliers, and does not require the removal of outliers prior to trend identification (Takele et al., 2022). If a later data value is higher than an earlier one, S increases by 1. If an earlier value is higher, S decreases by 1. The final S value is the net result of these changes.

2.1.5 Soil and Water Assessment Tool (SWAT) modeling

The SWAT model, developed by the Agricultural Research Service of the United States Department of Agriculture, is a semi-distributed, physically based, and time-continuous hydrological model. Streamflow in SWAT is simulated using the following water balance equation (Arnold et al., 1998)

$$SW_t = SW_0 + \sum_{j=1}^t (R_{day} - Q_{surf} - Ea - W_{seep} - Q_{gw}) \quad (1)$$

2.1.6 Model performance Evaluation

Coefficient of determination (R^2) (Krause et al., 2005), Nash-Sutcliffe efficiency (NSE) (Nash, 1970), and percent of bias (Gupta et al., 1999) statistical parameters have been used to evaluate the SWAT model's performance evaluation described in table3.

Table 3:the SWAT performance rate

No.	Performance rating	NSE	R^2	PBIAS
1	Excellent	$0.75 < NSE \leq 1.00$	$0.7 < R^2 \leq 1.00$	$PBIAS \leq \pm 10$
2	Good	$0.65 < NSE \leq 0.75$	$0.6 < R^2 \leq 0.7$	$\pm 10 \leq PBIAS < \pm 15$
3	Satisfactory	$0.50 < NSE \leq 0.65$	$0.50 < R^2 \leq 0.6$	$\pm 15 \leq PBIAS < \pm 25$
4	Unsatisfactory	$NSE \leq 0.50$	$R^2 \leq 0.50$	$PBIAS \geq 25$

(Source: Moriasi et al., 2007)

2.2. Drought Index

The Drought Indices Calculator (DrinC) software was developed (Tigkas et al., 2022; Surendran et al., 2017) and addressed the drought characterization (**Hydrological, Meteorological and Agricultural drought**) based on indices, providing means for drought analysis based on drought indices for research and operational purposes (Tigkas et al., 2016). DrinC is a stand-alone software, freely available online (<https://drought-software.com> accessed on 29 April 2022).

2.2.1 Reconnaissance Drought Index (RDI)

RDI is a recent drought analysis indicator which considers the effect of temperature in drought monitoring (Jain et al., 2015), RDI uses both precipitation and temperature as input data to overcome the limitation of SPI to understand the effect of temperature on water balance (Asadi Zarch et al., 2011). The computation of RDI (Equation 2) is based on the ratio of total precipitation (P) to potential evapotranspiration (PET) accumulated over the selected time scale (k) on the annual basis (k=12).

$$\alpha = \frac{\sum_{j=1}^{12} P_{ij}}{\sum_{j=1}^{12} PET_{ij}} \quad (2)$$

With P_{ij} and PET_{ij} the precipitation and potential evapotranspiration of the jth month of the ith year.

2.2.2 Agricultural Standardized Precipitation Indices (aSPI)

The characterization of agricultural drought is focusing on the conditions affecting the development of vegetation, which is linked to the specific system under study (Tigkas et al., 2022). The aSPI follows SPI's standardization by fitting the effective precipitation series to a statistical distribution, then transforming it into a normal distribution (Equation 3). The cumulative probability distribution is converted using the following approximation (Abramowitz, 1964):

$$aSPI = -\left(t - \frac{c0+c1t+c2t^2}{1+d1t+d2t^2+d3t^3}\right), 0 < H(x) < 0.5 \text{ In which } t = \sqrt{\ln(1/H(x)^2)}$$

$aSPI = \left(t - \frac{c0+c1t+c2t^2}{1+d1t+d2t^2+d3t^3}\right), 0.5 < H(x) < 1.0 \text{ In which } t = \sqrt{\ln(1/(1-H(x))^2)}$ with the following constant values:

$$C0 = 2.515517, C1 = 0.802853, C2 = 0.010328, d1 = 1.43278, d2 = 0.189269, d3 = 0.001308 \quad (3)$$

2.2.3 Streamflow Drought Index (SDI)

In this study, we computed the Streamflow Drought Index (SDI) for gauging stations during both the historical period and future projections. The SDI is determined based on cumulative streamflow volumes $V_{i,k}$ for each reference period k of the ith hydrological year, as defined in Equation 4.

$$SDI_{i,k} = \frac{V_{i,k} - V_k^-}{\sigma_k} \quad i = 1,2 \quad K = 1,2,3,4 \quad (4)$$

Where V_k and S_k are, respectively, the mean and the standard deviation of cumulative streamflow volumes of the reference period k as these are estimated over a long period.

2.2.4 Drought Identification and Characterizations

This study defines drought events by frequency, duration, and magnitude. A drought begins when the index exceeds -0.99 and ends when it drops below -2.

Table 4: Classification of Drought Index according to RDI, SDI, and aSPI values (McKee et al., 1993).

RDI, SDI and aSPI	Drought level
> 2.00	Extremely wet
1.50 to 1.99	Very wet
1.00 to 1.49	Moderately wet
-0.99 to 0.99	Near Normal
-1.00 to -1.49	Moderate Drought
-1.50 to -1.99	Severe Drought
< -2	Extreme drought

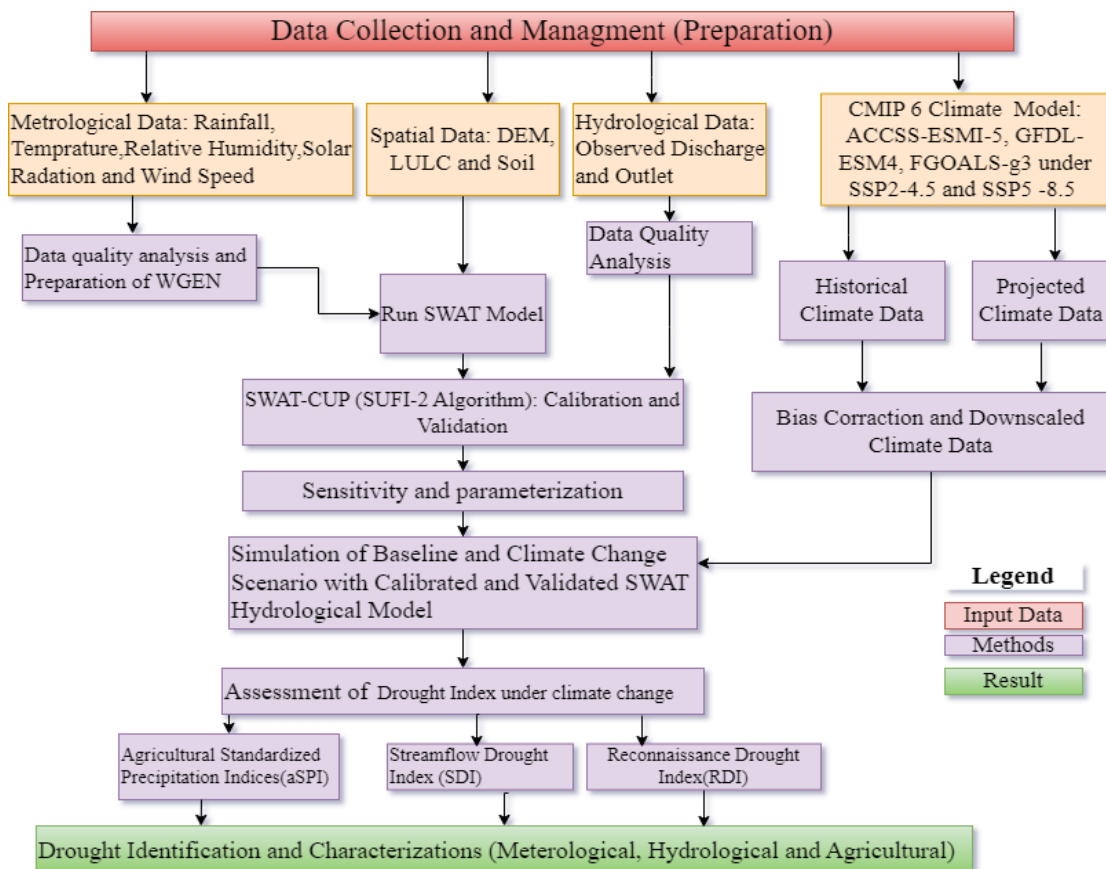


Figure 2:Flow chart of the study.

3. Results

3.1 Observed data quality test

Data quality tests were conducted to assess homogeneity and consistency using the double mass curve and non-dimensional plot analysis. The results are presented in Figure 3 (a & b).

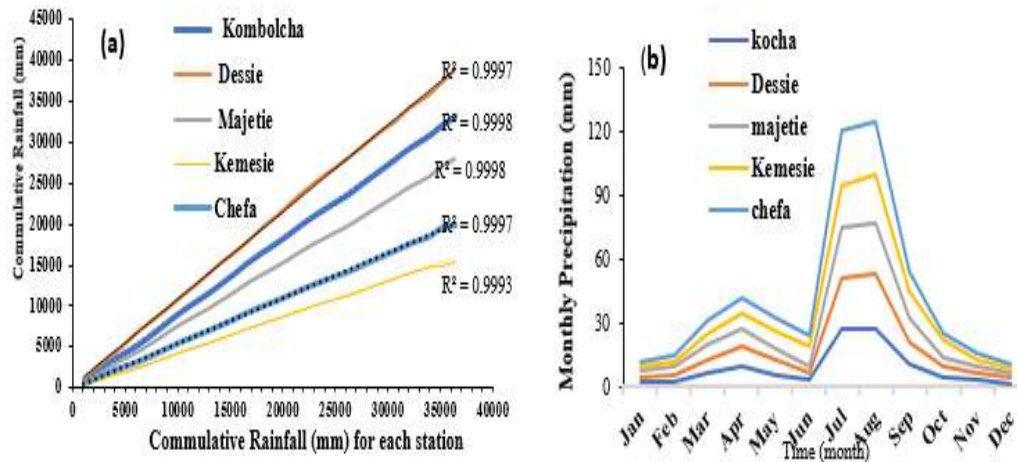


Figure 3: Consistency (a) and Homogeneity Test (b) in the study area

3.2 Climate Change Impact Assessment

3.2.1 Evaluation of best Fit Climate Models in the study area

Sixteen global climate models were available for the Borkena Sub-Basin. Three models were selected under SMHI based on graphical methods and statistical indicators. The selected models are shown in Table 5

Table 5: Statistical indicators for selecting GCM:

no	Model type	RMSE (PCP(m m/day))	Correlation coefficient	PBIAS
1	GFDL-CM3	2.18	0.83	-0.35
2	MPI-ESM2-MR	5.10	0.52	-0.89
3	HadGEM2-AO	5.9	0.38	-0.06
4	MPI-ESM2-MR-E	7.28	0.31	-0.016
5	E3SM-1-0	9.3	0.30	-0.06
6	CAS_FGOALS	10.11	0.39	-0.14
7	BCC-CSM2-MR	9.67	0.49	-0.18
8	INM-CM5-0	10.19	0.19	-0.09
9	MIROC-6	10.29	0.12	-0.95
10	ACCESS-ESM1-5	16.10	0.34	-0.002
11	NorESM2-LM	10.31	0.26	-0.39
12	CESM2	12.34	0.98	-1.25
13	NESM3	13.73	0.24	-0.09
14	CIESM	14.05	0.21	-0.12
15	CanESM5	13.09	0.45	-0.95
16	CESM2-FV2	13.22	0.98	-0.78

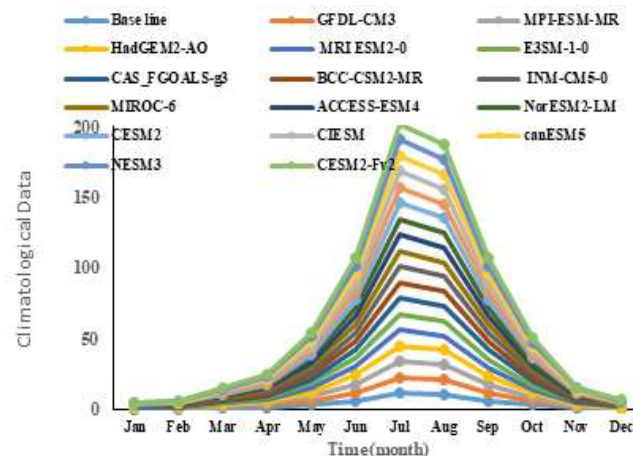


Figure 4: Graphical analysis of selecting GCMS

3.2.2 Trend test of projected climate data

The Mann-Kendall statistic was used to evaluate rainfall trends from 2041 to 2100 at meteorological stations. The p-value exceeded the significance level ($\alpha = 0.05$), meaning the null hypothesis was not rejected. After bias correction, projected rainfall for the 2050s and 2080s was analyzed. Results showed an increasing trend in annual rainfall under both SSP2-4.5 and SSP5-8.5 scenarios, indicating higher precipitation in future periods (Figures 5, 6, and 7).

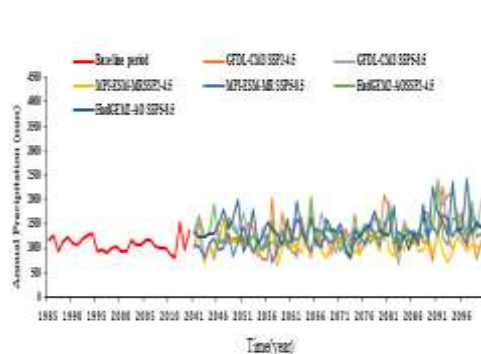


Figure 5: Mann-Kendall trend Test analysis Precipitation for both Baseline and Future Scenario data

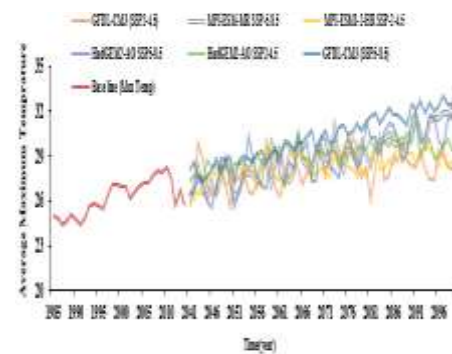


Figure 6: Mann-Kendall Trend test analysis of Maximum temp for both Baseline and Future Scenario data

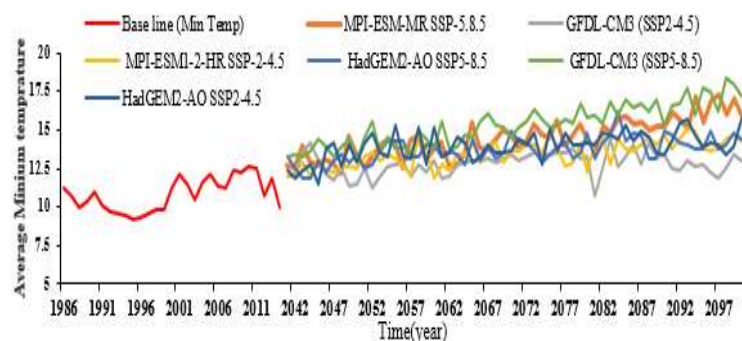


Figure 7: Mann-Kendall Trend test for Projected minimum Temperature in Borkena Sub - Basin for the future

3.3 Future Climate Change

3.3.1 Future Precipitation Change

The expected changes in mean annual, seasonal, and monthly rainfall compared to the baseline period are as follows: Annual precipitation is projected to increase by up to 27% in the 2050s and 41.17% in the 2080s. Additionally, monthly precipitation may rise by 87% in December and 98% in January respectively (see Figure 8).

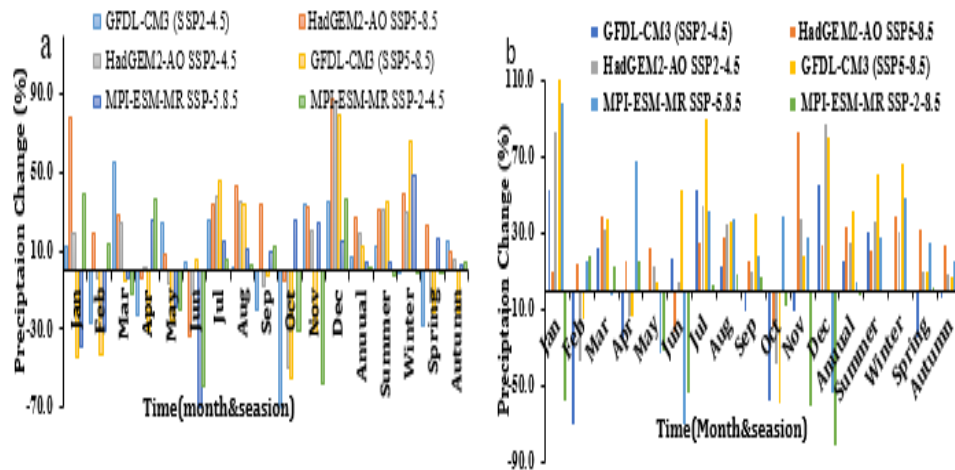


Figure 8: climate change impact on future precipitation under the 2050s (a) and 2080s (b)

3.3.2 Climate Change in Projected Temperature

Changes in projected Maximum Temperature: The analysis examined changes in maximum temperature across time horizons using three GCMs under different SSPs. Compared to the baseline, the maximum annual temperature is projected to increase by up to 20.65% in the 2050s and 10.4% in the 2080s (see Figure 9).

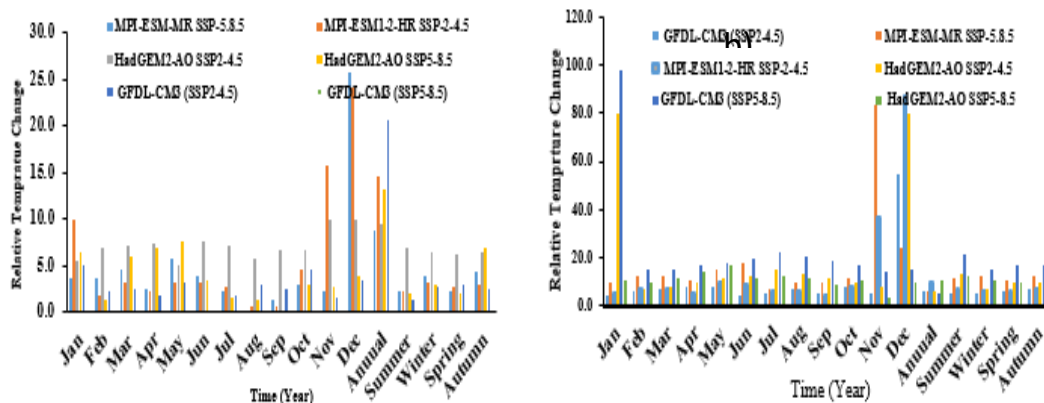


Figure 9: Climate change impact on future Maximum Temperature under 2050s (a) and 2080s (b)

Changes in projected Minimum Temperature: Projected changes in mean annual minimum temperature for the Borkena Sub-Basin vary across time horizons and GCMs under different SSPs. The maximum increase is expected to reach 31.2% by the 2050s and 51.1% by the 2080s, compared to the baseline (see Figure 10).

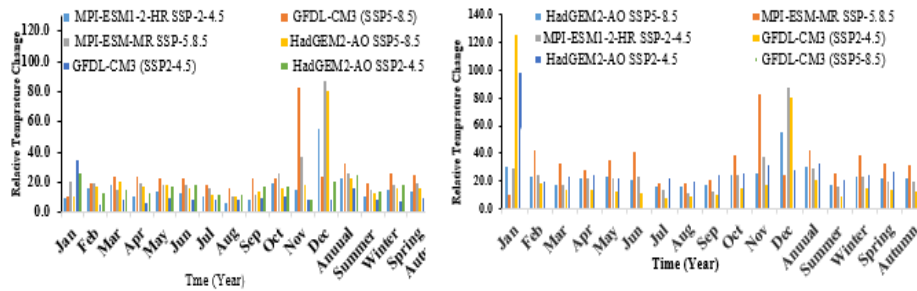


Figure 10::Annual, seasonal, and monthly minimum temperature change a) the 2050s and b) the 2080s

3.4 Hydrological modeling results

3.4.1 Calibration and Validation

Table 6: Selected Parameters Sensitivity Analysis in the SWAT Model

No	Parameters	Description	Fitted-value	Min_V	Max_V	p-value	t-stat value
1	R_CN2.mgt	Initial SCS curve number for moisture condition I	-0.3	-0.3	1.25	0	-13
2	V_ESCO.hru	Soil evaporation compensation factor	0.5	0	1	0	-4.333
3	R_SOL_Z (...)...sol	Soil depth [mm]	0.175	-0.25	0.25	0.002	2.512
4	V_LAT_TTIME.hru	Lateral flow travel time	114.012	0.25	120.3	0.046	2.24
5	R_CANMX.hru	Maximum canopy storage	2.17	0	10	0.12	1.736
6	V_GWQMN.gw	Shallow aquifer requires for return flow'	1.3	0	500	0.125	-1.71
7	V_ALPHA_BF.gw	Base flow alpha factor for bank storage	0.583	0	1	0.15	1.61
8	R_EPCO.hru	Plant uptake compensation factor	0.35	0	1	0.15	1.62
9	V_GW_DELAY.gw	Groundwater recap coefficient	175	0	500	0.2	-1.41
10	R_CH_N2.rte	Manning's "n" value for the main channel	0.3833	0	1	0.28	-1.31
11	R_SOL_AWC	Soil available water capacity (mm Water/mm)	0.05833	-0.25	0.25	0.48	-1.21
12	R_REVAPMN.gw	percolation to the deep aquifer	1.571	0	500	0.58	0.721
13	V_ALPHA_BNK.rte	Base flow alpha factor for bank storage	0.293	0	1	0.66	-0.45
14	R_SOL_K (...)...sol	Saturated Hydraulic conductivity	0.125	-0.25	0.25	0.7	0.45

Note i) R- Sensitive parameter indicates multiply by 1+ given fitted value, V-sensitive parameter replace the value by the given fitted value

Calibration and validation analysis was conducted using daily flow data from 2000 to 2010 for calibration and from 2011 to 2014 for validation. Additionally, data from 1998 to 1999 were used as a warm-up period during calibration. A sensitivity analysis was performed to determine the influence of input

parameters on streamflow, running 500 simulations with SUFI-2. The global sensitivity analysis yielded favorable results (Figures 11a & b), identifying fourteen key parameters that significantly impact hydrological processes in the study area see (table 6). For the Borkena Sub-Basin, the soil evaporation compensation factor (ESCO), soil depth, and curve number (CN) were found to be the most influential. Among these, the SCS Curve Number II (CN2) was the most sensitive, as it depends on soil texture, soil type, permeability, and land use/land cover. The SWAT model's performance was evaluated with an RMSE of 0.8063 and R^2 of 0.861 for calibration, and an RMSE of 0.8188 and R^2 of 0.8432 for validation, demonstrating strong model reliability.

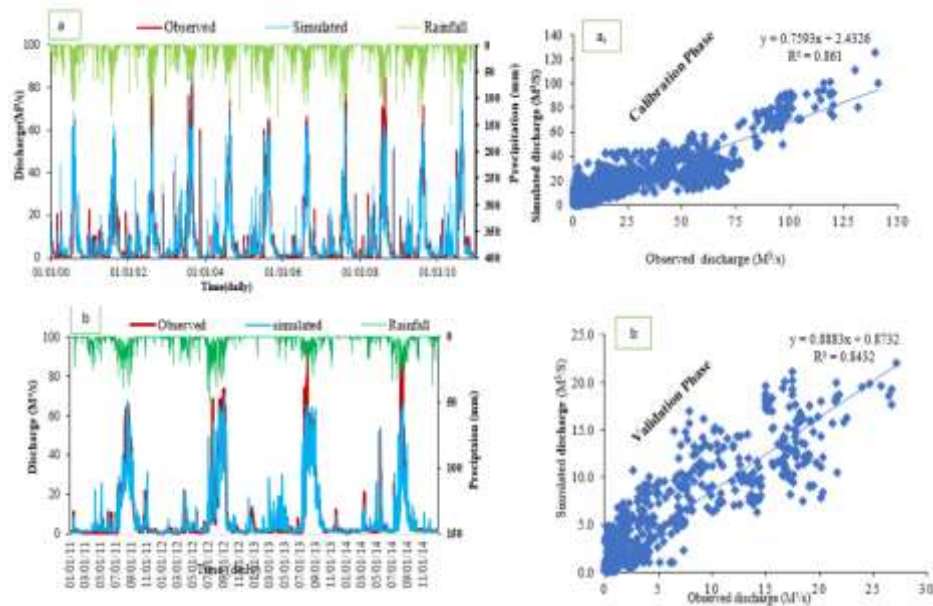


Figure 11: Hydrograph of daily simulated and observed flow for calibration (a) and validation (b)

3.5 Future Climate Change Impact on Water Availability

The hydrological modeling analysis using SWAT revealed significant variations in streamflow under different climate change scenarios. The maximum increase in monthly streamflow ranged from 42.12% to 82.51%, while the maximum decrease varied between 34.42% and 61.22% under SSP4.5 and SSP8.5 for different time horizons. Overall, seasonal streamflow increased in winter, autumn, and spring but showed a declining trend in summer. Annual streamflow also decreased across all GCMs and SSPs, as shown in Figures 12a and 12b

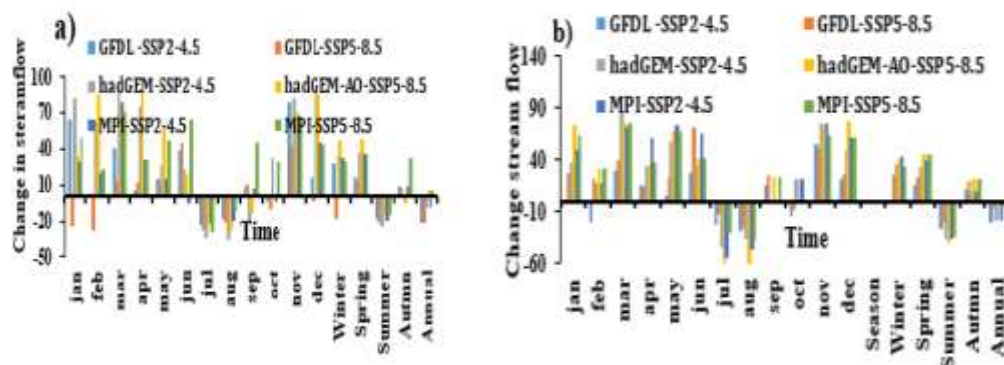


Figure 12: Percentage change in seasonal and annual flow volume a) the 2050s and b) 2080s

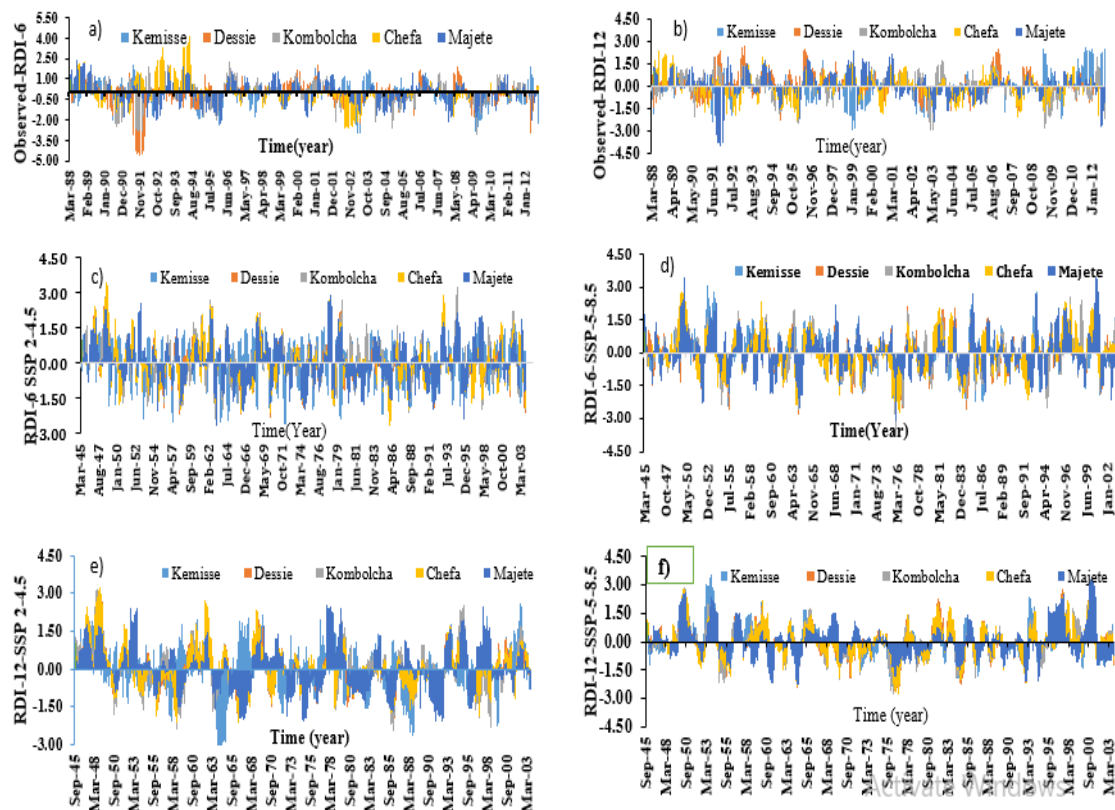
3.6 Future Drought Patterns

3.6.1 Meteorological Drought Pattern

A meteorological drought analysis was carried out in the Borkena Sub-Basin using RDI data from six meteorological stations. The study considered climate change and utilized both historical climate data (1985–2014) and future climate data (2041–2100) from three ensemble GCMs (GFDL-CM3, MPI-ESM2-MR, and HADGEM2-AO) under SSP2-4.5 and SSP5-8.5 scenarios. An analysis of RDI indices at multiple time scales (6 and 12 months) was conducted, as shown in Figure 13. The 6-month scale was used to assess medium-term drought, while the 12-month scale was used to evaluate long-term drought. Based on the analysis, it is evident that the decades with the highest magnitude and frequency of drought hazards at the Kombolcha, Kemisse, and Cheffa stations were as follows: 2066 (-1.8, 3.20%), 2063 (-1.52, 7.65%), and 2066s (-1.50, 5.64%). In terms of spatial distribution, drought occurrence was more frequent at the Kemisse station (7.65% in 2063) compared to the other stations.

3.6.2 Agricultural Drought Pattern

An analysis of agricultural drought was conducted using the aSPI method. Six meteorological stations were considered, and climate change was accounted for by utilizing both historical data (1985–2014) and future projections (2041–2100) from three different ensemble GCMs (GFDL-CM3, MPI-ESM2-MR, and HADGEM2-AO) under SSP2-4.5 and SSP5-8.5 scenarios. Similar to the RDI analysis, the aSPI was calculated for two different time scales: aSPI-6 and aSPI-12. The results, as depicted in Figure 13, indicate that the Borkena Sub-Basin was frequently impacted by severe and extreme agricultural droughts. The most perilous decades under SSP2-4.5 (aSPI-12) for Kombolcha, Cheffa, and Kemisse were identified as: 2067 (-1.9, 4.76%), 2095 (-1.57, 7.46%), and 2087 (-1.8, 5.64%). In terms of location, the Kemisse and Kombolcha stations experienced agricultural drought more frequently compared to the other stations.



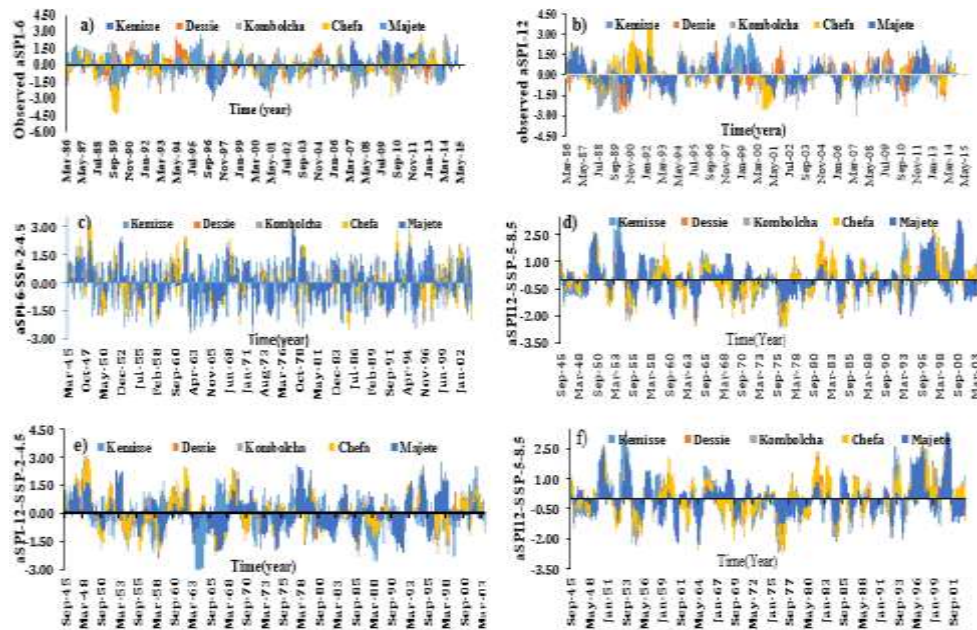


Figure 13: Meteorological and Agricultural drought (RDI-6 & RDI-12) for both base line period (a & b), future SSP 2-4.5 (c & d) and future SSP 5-8.5 (e & f)

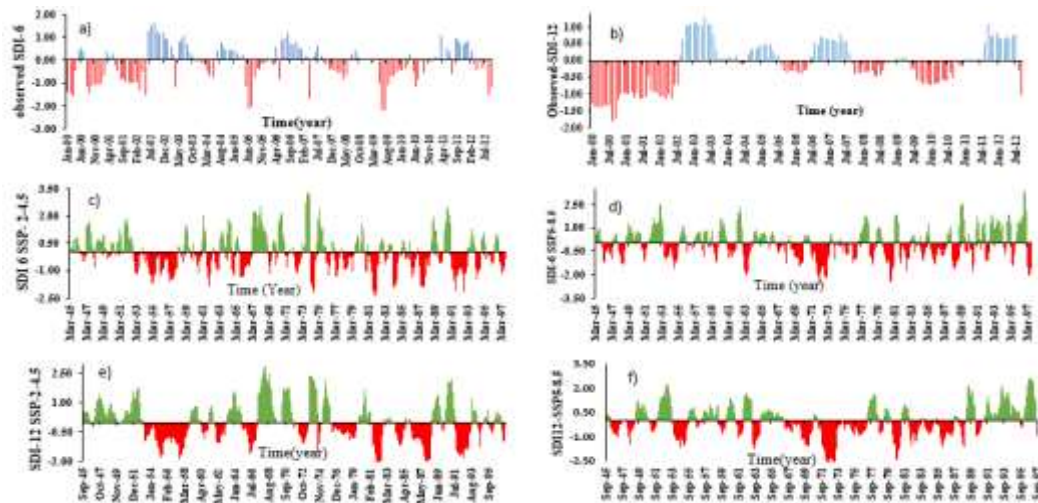


Figure 14: Hydrological drought index (SDI-6 & SDI-12) for both base period (a & b), future SSP 2-4.5 (c & d) and future SSP 5-8.5 (e & f)

3.6.3 Hydrological Drought Pattern

The pattern of both historical and future hydrologic droughts was analyzed using the Standardized Drought Index (SDI) at 6-month and 12-month time scales. This analysis focused on assessing drought years, drought magnitude, drought frequency, and drought level, as shown in Figure 14.

4. Conclusion

This study aimed to assess the performance of the latest CMIP-6 climate models, focusing on two representative Shared Socioeconomic Pathways (SSP2-4.5 and SSP5-8.5). The study also examined the impact of climate change on drought characteristics in the Borkena Sub-Basin, located in the Awash

Basin of Ethiopia. Among the sixteen climate models evaluated, three—GFDL-CM3, MPI-ESM2-MR, and HADGEM2-AO—were identified as the most suitable based on their alignment with observed data. The baseline period (1985–2014) served as a reference, while projections for 2041–2100 represented future climate scenarios.

Trend analysis revealed a slight decrease in precipitation and an increase in temperature compared to the baseline. Projections indicate that annual maximum rainfall is expected to increase by 11.37% and 13.89% under SSP4.5 and SSP8.5, respectively, for the 2050s and 2080s. Maximum average temperatures are projected to rise by 4.14°C and 5.23°C under the HadGEM2-AO-SSP8.5 scenario for the same periods. Despite the increase in precipitation and temperature, the SWAT model predicts a significant decline in maximum streamflow, with reductions of 36.29% and 32.04% under SSP4.5 and SSP8.5, respectively. These reductions suggest a greater likelihood of drought occurrence at various time scales (1-month, 3-month, 6-month, and 12-month intervals). On the annual (RDI-12) scale, severe agricultural drought events were observed in stations such as Kombolcha, Kemisse, and Cheffa. Spatial analysis revealed the highest drought magnitudes in Kombolcha (-1.8, 3.20% in 2066), Kemisse (-1.52, 7.65% in 2063), and Cheffa (-1.50, 5.64% in 2066). Meteorological droughts were most frequent in Kemisse, especially in 2063 (7.65%), while agricultural droughts posed the greatest risk in Kombolcha, Cheffa, and Kemisse during periods such as 2067 (-1.9, 4.76%), 2095 (-1.51, 7.46%), and 2087 (-1.8, 5.64%).

Agricultural droughts were observed to be more frequent in Kemisse and Kombolcha compared to other locations. In terms of seasonal patterns, projections suggest a decrease in precipitation and streamflow during the wet seasons and an increase during the dry seasons. These findings underscore the importance of preparedness strategies, such as effective monitoring systems and early detection of drought events. The study also highlights key drivers of water resource challenges, including the increased frequency of droughts and rising temperatures. By employing consistent methodologies, such as climate models and drought indices, the reliability of the findings is enhanced, while station-specific analyses in the Borkena Sub-Basin provide valuable localized insights.

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