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Hybrid Data-driven and Process-based Modeling for Streamflow Forecasting Under Climate Change in the Upper Genale River Basin of Ethiopia

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Abstract

This study evaluates streamflow forecasting in Ethiopia's Upper Genale River Basin, focusing on the challenges posed by climate change, regional environmental shifts, and the need for highly accurate data. The research developed a hybrid hydrological framework that integrates the process-based QSWAT+ model with Random Forest, XGBoost, LightGBM, and Long Short-Term Memory (LSTM) algorithms to improve streamflow prediction in the Upper Genale River Basin. Historical climate and hydrological data (1985–2014) were combined with CMIP6 climate projections under SSP2-4.5 and SSP5-8.5 scenarios to assess future hydrological responses. The findings reveal that QSWAT+ achieved satisfactory calibration and validation performance (NSE = 0.74 and 0.71; R^2 = 0.77 and 0.85, respectively), indicating reliable representation of watershed processes. The hybrid framework substantially improved predictive accuracy, with the stacking ensemble model achieving NSE and R^2 values of 0.98. Projections under the SSP2-4.5 and SSP5-8.5 scenarios indicate a clear upward trend in streamflow. Evapotranspiration increased under all scenarios, suggesting growing pressure on water resources. These findings demonstrate that hybrid process-based and machine-learning approaches enhance streamflow forecasting and provide valuable information for climate adaptation, irrigation planning, and sustainable water-resources management in Ethiopian river basins

1 Introduction

Climate change, increasing water demand, and environmental degradation are intensifying pressure on water resources worldwide, making accurate streamflow forecasting essential for sustainable water-resources management. Reliable streamflow predictions support flood-risk reduction, irrigation planning, hydropower generation, drought preparedness, and ecosystem conservation (Shemer et al., 2023). These challenges are particularly pronounced in Sub-Saharan Africa, where climate variability interacts with rapid population growth, limited water-management infrastructure, and high dependence on rain-fed agriculture (Gashaw et al., 2023; Gashu et al., 2019).

Ethiopia is among the countries most vulnerable to climate variability despite possessing considerable surface and groundwater resources. Rising temperatures, shifting rainfall patterns, and increasing hydrological extremes have significant implications for water availability, agricultural productivity, and food security (Bayable et al., 2021; Gebul, 2021). Recent studies have reported increasing temperature trends and substantial spatial variability in precipitation across Ethiopian river basins, suggesting that climate change may alter future hydrological regimes and increase uncertainty in water-resources planning (Assamnew & Tsidu, 2025a; Bedada et al., 2025; Gashaw et al., 2023).

The Upper Genale River Basin (UGRB), located in southeastern Ethiopia, is a strategically important watershed that supports irrigation development, agricultural production, domestic water supply, and planned hydropower investments (Markos, 2020). However, the basin is highly sensitive to climate variability because streamflow generation depends strongly on seasonal rainfall and watershed storage processes. Recent investigations have shown that changes in climate and land use may significantly

affect runoff generation, water yield, and groundwater recharge within the basin (Shigute et al., 2022, 2024a). Consequently, accurate prediction of future streamflow dynamics is critical for supporting climate-resilient development and sustainable water management.

Physically based hydrological models such as the Soil and Water Assessment Tool (SWAT) and SWAT+ have been widely used to simulate watershed processes and evaluate hydrological responses to climate change (Negewo, 2020; Shigute et al., 2024). These models explicitly represent processes such as infiltration, evapotranspiration, groundwater recharge, and channel routing, allowing physically meaningful assessment of watershed behavior. Nevertheless, process-based models often experience difficulties in representing highly nonlinear hydrological interactions and extreme events, especially under non-stationary climate conditions and in data-scarce environments (Krysanova et al., 2018; Sabale et al., 2024).

Machine-learning approaches have emerged as powerful alternatives because they can learn complex nonlinear relationships directly from hydro-climatic observations. Models such as Random Forest (RF), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), and Long Short-Term Memory (LSTM) networks have demonstrated excellent predictive performance in recent hydrological applications (Lu et al., 2023). However, purely data-driven methods often lack physical interpretability and may perform poorly when future climatic conditions differ substantially from historical observations used during model training (Shortridge et al., 2016).

To overcome these limitations, hybrid modelling approaches that combine physically based and data-driven methods have gained increasing attention. Such frameworks integrate hydrological process understanding with the predictive capabilities of modern machine-learning algorithms, resulting in improved forecasting performance and reduced uncertainty (Cao & Ying, 2025; R. Yang et al., 2024). Recent studies in Ethiopia have also demonstrated the potential of hybrid modelling frameworks for improving streamflow prediction and hydro-climatic forecasting (Alemu & Zimale, 2025; Belina et al., 2025b). Nevertheless, no previous study has integrated QSWAT+, advanced machine-learning algorithms, stacking ensemble learning, Bayesian model averaging, and CMIP6 climate projections to assess future streamflow dynamics in the Upper Genale River Basin.

Therefore, this study develops a hybrid hydrological forecasting framework that combines QSWAT+, RF, XGBoost, LightGBM, and LSTM models with ensemble techniques to improve streamflow forecasting. Using CMIP6 climate projections under SSP2-4.5 and SSP5-8.5 scenarios, the study evaluates future climate-change impacts on streamflow and water resources while providing insights for climate-resilient water management in Ethiopia.

2 Methodology

2.1 Description of the Study Area

According to MoWIE(2016), the Genale River originates from the southern slopes of the Bale Mountains massif in the northeast and the Sidamo Mountains in the northwest. The upper Genale Sub-River Basin (study area) is located between 60 52' and 50 20' North latitude and 380 30' and 390 45' East longitude in the upper central region of the Genale Basin. The basin area is approximately 9127.86 km2 (Fig. 1). The study area has three wet seasons: March-May, June-September, and September-November, with two in the lowland and southeastern parts. The average annual rainfall is 1170 mm, and the maximum and minimum temperatures are 18.9-27.74°C and 6.9-11.42°C, respectively.

2.2 Data Collection and Preprocessing

Daily precipitation and temperature data (1985–2014) from five meteorological stations were obtained from the Ethiopian National Meteorological Institute. Missing observations were filled using multiple imputation and the normal-ratio method. To improve spatial coverage, CHIRPS precipitation and CHIRTS temperature datasets were incorporated. Daily streamflow observations from the Chenemsa gauging station (1988–2011) were obtained from the Ministry of Water and Energy (Table 1).

Topographic data were derived from the Shuttle Radar Topography Mission (SRTM) digital elevation model. Land-use and land-cover data were obtained from Copernicus Global Land Cover products and processed in Google Earth Engine. Soil data were derived from the Harmonized World Soil Database as indicated in Table 1.

Table 1
Datasets and model inputs used in this study

Category	Variable	Resolution / Period	Source
Climate	Rainfall	Daily (1985–2014)	ENMI
Climate	Temperature	Daily (1985–2014)	ENMI, CHIRTS
Hydrology	Streamflow	Daily (1988–2011)	MoWE
Topography	DEM	30 m	SRTM
Land Use	LULC	2009	Copernicus
Soil	Soil Map	Basin scale	HWSD
Climate Change	CMIP6 Projections	SSP2-4.5, SSP5-8.5	NASA NEX-GDDP
Modeling	QSWAT+	Hydrological simulation	SWAT+
Machine Learning	RF, XGB, LGBM, LSTM	Streamflow forecasting	Python

Table 1 summarizes the hydro-meteorological, spatial, climate-projection, and modelling datasets used in this study. The integration of ground-based observations with remotely sensed products and climate-model projections provided a comprehensive dataset for hydrological simulation and future climate-impact assessment. Daily rainfall and temperature records from ENMI, supplemented by CHIRPS and

CHIRTS datasets, enhanced spatial and temporal coverage, while streamflow data from the Chenemsa gauging station enabled robust calibration and validation of the QSWAT+ model. The combination of topographic, land-use, and soil datasets facilitated detailed watershed characterization and hydrological response unit (HRU) delineation. Furthermore, CMIP6 climate projections and advanced machine-learning algorithms enabled the development of a hybrid forecasting framework capable of evaluating future streamflow responses under different climate scenarios. Overall, the integrated dataset provided a reliable basis for assessing climate-driven changes in water resources within the Upper Genale River Basin.

Detailed descriptions of meteorological station characteristics, land-use classes, soil distributions, and climate-model evaluation results are provided in Supplementary methodology part.

2.3 Climate Model Selection and Downscaling

Twenty-two CMIP6 global climate models were evaluated against CHIRPS and CHIRTS observations using a Comprehensive Ranking Index based on correlation, bias, and RMSE. CanESM5 was selected for temperature projections, whereas a six-model ensemble was adopted for precipitation projections. Bias correction and statistical downscaling were performed using SD-GCM software. Future climate projections were analyzed for two emission scenarios (SSP2-4.5 and SSP5-8.5) and two future periods: near term (2015–2044) and mid-term (2045–2074).

2.4 Hydrological Modeling

Streamflow simulation was conducted using QSWAT+, the QGIS interface for SWAT+. The watershed was delineated into 13 sub-basins and 731 Hydrologic Response Units (HRUs) using land-use, soil, and slope information. Streamflow simulation was based on the SCS Curve Number approach and watershed water-balance principles.

2.5 Sensitivity Analysis, Calibration, and Validation

Global sensitivity analysis was performed using the Sobol method implemented in the SWAT+ Toolbox. The most influential parameters were subsequently calibrated using the Calibration by Latin Hypercube Sampling Iterations (CALSI) algorithm.

The model was calibrated for 1988–2002 and validated for 2003–2011 following a three-year warm-up period. Model performance was evaluated using the coefficient of determination (R^2), Nash–Sutcliffe efficiency (NSE), root mean square error (RMSE), and percent bias (PBIAS).

2.6 Machine Learning and Hybrid Modeling

Four machine-learning algorithms were implemented: Random Forest, XGBoost, LightGBM, and Long Short-Term Memory (LSTM). Predictor variables included meteorological observations, engineered temporal features, and QSWAT+ outputs.

Hybrid models were constructed by integrating QSWAT+ simulations with machine-learning predictions. A stacking ensemble framework using Ridge Regression as a meta-learner and Bayesian Model Averaging (BMA) were applied to improve forecasting robustness and reduce prediction uncertainty.

2.7 Trend and Climate Impact Analysis

Historical and projected hydro-climatic trends were analyzed using the Mann–Kendall test and Sen's slope estimator. Future changes in precipitation, temperature, streamflow, and water-balance components were quantified relative to the baseline period. Climate-change impacts were evaluated under SSP2-4.5 and SSP5-8.5 scenarios for near-term and mid-term periods.

2.8 Statistical Evaluation

Model performance and future streamflow projections were assessed using R^2, NSE, RMSE, PBIAS, and Rescaled Adjusted Partial Sums (RAPS) analysis. These metrics were used to evaluate forecasting accuracy, temporal consistency, and long-term variability in observed and simulated streamflow.

The detail of the methodology was attached in supplementary methodology part.

2.9 Overall Conceptual Framework of the study

The overall conceptual framework of the study showed that enhanced QSWAT+ remote sensing and ML used data that was used by QSWAT + and remote sensing data to be used by ML, as shown in Fig. 2.

3 Results

3.1 Sensitivity Analysis, Calibration, and Validation

Sensitivity analysis identified cn3_swf, perco, and CN2 as the three most influential parameters controlling streamflow simulation (Table 2). The sensitivity of CN2 highlights the importance of rainfall-runoff partitioning and land-surface conditions, while the sensitivity of perco indicates the critical role of groundwater recharge and subsurface water movement in sustaining basin hydrology. Similar parameter sensitivity patterns have been reported in Ethiopian watersheds including the Upper Genale, Tekeze, and Awash basins (Dile et al., 2016a; Gebremeskel & Kebede, 2017, Shigute et al., 2024).

Table 2
Sensitive parameters, calibrated values, and model performance of QSWAT+

Category	Parameter	Description	Final Value
Sensitive Parameter	CN3_SWF	Pothole evaporation coefficient	0.906
Sensitive Parameter	PERCO	Percolation coefficient	0.928
Sensitive Parameter	CN2	SCS Curve Number	−12.39%
Sensitive Parameter	CANMX	Maximum canopy storage	1.00
Sensitive Parameter	REVAP_MIN	Threshold depth for revap	20.95
Sensitive Parameter	REVAP_CO	Groundwater revap coefficient	0.106
Calibration	R^2	Calibration period	0.77
Calibration	NSE	Calibration period	0.74
Calibration	RMSE ($m^3\ s^{-1}$)	Calibration period	39.76
Calibration	PBIAS (%)	Calibration period	0.51
Validation	R^2	Validation period	0.85
Validation	NSE	Validation period	0.71
Validation	RMSE ($m^3\ s^{-1}$)	Validation period	41.83
Validation	PBIAS (%)	Validation period	−0.10

Most influential parameters identified through Sobol sensitivity analysis, optimized calibration values, and QSWAT+ performance statistics at the Chenemsa gauging station are indicated in Table 2. Only parameters with the highest sensitivity are presented here; complete calibration results are provided in Supplementary result parts of Table S1&S2.

The calibrated QSWAT+ model overestimated peak streamflow in 1988, 1991, 1994, 1999, 2000, and 2001, while most simulated streamflow was underestimated in the validation period. Despite this, monthly streamflow measurements and simulated results were in good agreement (Fig. 3). The model's validation period showed slight underestimation, with PBIAS = -0.096 percent. RMSE = 41.8, MAE = 32.1, NSE = 0.71, and R^2 = 0.85.

Overall, the model generalizes well but has slightly lower efficiency, suggesting it accurately captures flow patterns while increasing magnitude deviations outside the calibration range. The SWAT/QSWAT+ studies typically report calibration NSE values of 0.65–0.80 and slightly lower validation values, highlighting the difficulty of generalizing across different climatic and land-use conditions (Abbaspour et al., 2015). Ethiopian case studies in the Awash, Blue Nile, and Omo-Ghibe basins show calibration NSE values of 0.70–0.80 and validation NSE values of 0.60–0.75 are considered robust (Gebremeskel &

Kebede, 2017; Shawul et al., 2016). The QSWAT+ model is suitable for analyzing streamflow and quantifying climate change's potential impacts on water resources in the study area.

3.2 Hybrid Streamflow Forecasting Performance

Machine-learning models significantly improved prediction accuracy relative to the standalone QSWAT+ model. Among individual models, XGBoost achieved the highest performance, followed by Random Forest and LightGBM. LSTM also performed well but showed slightly lower accuracy than the boosting-based approaches.

Hybrid models further enhanced predictive skill. Hybrid-QSWAT+-XGBoost achieved the best overall performance, indicating that machine-learning algorithms effectively captured residual nonlinear relationships that remained unrepresented by the physical model. Stacking Ensemble and Bayesian Model Averaging approaches produced similarly high performance while reducing model bias and improving prediction stability as indicated in Table 3.

Table 3
Daily Performance matrix of QSWAT+, Machine learning stand-alone, overall hybrid model, BMA model, and hybrid of QSWAT+ with all four other ML models

Model	R^2	RMSE	NSE	PBIAS
QSWAT+	0.77	53.042	0.686	3.733
Random Forest	0.990	9.666	0.990	-0.004
XGBoost	0.999	2.300	0.999	0.001
LightGBM	0.990	9.686	0.990	0.000
LSTM	0.929	25.315	0.929	-1.350
Overall Hybrid Model	0.980	13.513	0.980	-2.394
BMA Model	0.978	14.167	0.978	0.275
Hybrid_QSWAT+_RF	0.985	11.496	0.985	-1.454
Hybrid_QSWAT+_XGB	0.990	9.243	0.990	1.055
Hybrid_QSWAT+_LGBM	0.981	12.920	0.981	-2.346
Hybrid_QSWAT+_LSTM	0.915	27.558	0.915	-5.073

The study analyzed historical and simulated data on streamflow temporal variability, finding high variability in both observed and simulated data, with simulated data showing slightly higher variability compared to observed data. Accordingly, the CV for the observed streamflow is 93.09%, and for the simulated streamflow, it is 95.68% (Table 4).

Table 4
Daily streamflow statistical summary and CV result for historically observed and simulated streamflow data

Metric	Observed	Simulated
Mean (m^3/s)	95.45	101.58
Standard Deviation (m^3/s)	88.85	97.19
Coefficient of Variation (%)	93.09	95.68

RAPS analysis showed that the hybrid framework successfully reproduced both short-term and long-term streamflow variability, including declining and increasing phases observed in the historical record (Supplementary Fig. 7). These results confirm the ability of hybrid models to improve streamflow forecasting while retaining hydrological consistency.

3.3 Climate Change Projections

Future climate projections indicate consistent warming under both SSP2-4.5 and SSP5-8.5 scenarios. Temperature increases become more pronounced during the mid-century period, with minimum temperatures generally increasing faster than maximum temperatures. Summer exhibited the strongest warming signal across all scenarios.

Compared with SSP2-4.5 for the Mid Term, the predicted warming is significantly higher. Thus, the highest maximum and minimum annual temperatures under SSP5-8.5 in the Mid Term, respectively, indicate increases of 0.3°C and 0.331°C per decade, suggesting that the future will be warmer than the base year (Table 5).

Table 5
Mean annual and Seasonal temperature change in °C under different scenarios

Scenario	**SSP2-4.5**				**SSP5-8.5**			
Timeframe	*Near term*		*Midterm*		*Near term*		*Mid term*	
Variables	*Tmax*	*Tminx*	*Tmax*	*Tmin*	*Tmax*	*Tmin*	*Tmax*	*Tmin*
Annual	*0.514*	*0.201*	*0.796*	*1.049*	*0.218*	*0.193*	*1.049*	*2.055*
Autumn	0.190	-0.392	0.633	0.439	0.063	-0.423	1.406	1.624
Winter	0.002	-0.128	-0.484	0.545	-0.283	-0.060	-0.239	1.88
Spring	0.603	-0.240	1.462	0.808	0.370	-0.192	1.319	1.461
Summer	1.363	0.553	1.782	1.311	0.732	0.364	2.227	2.209

In contrast, precipitation projections showed considerable variability among CMIP6 models. Ensemble means indicated moderate reductions in rainfall under SSP2-4.5 and increases under SSP5-8.5,

particularly during the mid-term period (Table 6). This divergence highlights the continuing uncertainty associated with future East African rainfall patterns.

Table 6
Annual Climate Change Comparison among the CMIP6 Models with respect to the base period

Scenario	**SSP2-4.5**		**SSP5-8.5**	
Timeframe	Near term	Midterm	Near term	Mid term
CanESM5	-6.07	15.42	5.49	45.82
FGOALS-g3	-8.09	-18.23	-5.70	-9.86
GISS-E2-1-G	-5.09	-20.94	-5.62	-5.03
INM-CM4-8	6.22	2.74	20.31	31.36
INM-CM5-0	-0.04	0.23	3.99	29.01
KACE-1-0-G	-7.77	-15.24	-7.91	-0.88
Ensembles	-3.47	-6.00	1.76	15.07

The detail of temperature and precipitation change and trend are attached in Supplementary.

3.4 Hydrological Responses to Climate Change

Climate change significantly altered simulated hydrological components. Under SSP2-4.5, decreases in precipitation resulted in reductions in runoff, water yield, groundwater recharge, and lateral flow. Groundwater recharge exhibited some of the largest reductions, suggesting increasing vulnerability of groundwater-supported water supplies.

During the SSP5-8.5 mid-term period, surface runoff increases by 21.65% (Table 7). The Evapotranspiration results show that the future is warming, with the percentage change in ET showing a steady incremental trend. Under SSP5-8.5, increased precipitation led to higher runoff and water yield, particularly during the mid-century period. However, rising temperatures substantially increased evapotranspiration under all scenarios. Consequently, increased rainfall did not necessarily translate into proportional gains in water availability

Table 7
The Annual Projected Water Balance and Percentage Change from the Base Period

Scenarios		**SSP2-4.5SSP245**		**SSP5-8.5SSP585**	
Period	Base period	Near Term	Mid Term	Near Term	Mid Term
Rainfall(mm)	1150	1110	1080	1170	1340
% Change		-3.478	-6.087	1.786	15.517
Surq_gen(mm)	159	155	118	150	191
% Change		-1.274	-24.848	-4.459	21.656
Latq(mm)	18.3	15.4	13.1	15.7	18.1
% Change		-0.25	-0.448	-0.224	-0.017
Wateryld(mm)	187	170	131	166	209
% Change		-1.734	-24.277	-4.046	20.809
perc(mm)	386	225	205	252	287
% Change		-23.469	-30.272	-14.286	-2.381
et(mm)	583	713	743	748	842
%Change		2.59	6.906	7.626	21.151

Future streamflow projections revealed contrasting responses. Near-term simulations indicated slight reductions in annual streamflow under some scenarios, whereas mid-century projections suggested substantial increases, particularly under SSP5-8.5. Monthly and seasonal analyses showed amplified hydrological variability, with some months experiencing large increases in flow while others exhibited significant declines.

Precipitation change in mean monthly aspects showed that under SSP2 4.5 near-term, there is a moderate increase compared to baseline, with seasonal peaks still centered in April–May and September–October, as indicated in Fig. 4a. Similarly, in SP2 4.5 Mid Term, the result of the finding as indicated in Fig. 4b showed stronger amplification of wet season rainfall, especially in October, where precipitation nearly doubles relative to baseline. Similarly, SSP5 8.5, both near and mid-term, shows an increase in rainfall. The SSP5 8.5 Mid Term result indicated a pronounced rise in precipitation, with extreme peaks in April and October, suggesting intensified rainfall events. This showed that monthly and seasonal variability is more observed in the area than annual precipitation distribution. All other variables of water balance components follow the precipitation peaks and high surface runoff in both midterm cases in October and April, which indicate heightened flood potentials. Similarly, water yield increments also align with extreme precipitation months, whereas evapotranspiration across all scenarios increases aspects as indicated in Figs. 4a,b,c, and 4d,

From the result of the study, both SSP pathways show stronger hydrological responses in the mid-term compared to the near term. SSP5 8.5 mid-term is the most extreme, with precipitation and runoff values far exceeding baseline, pointing to greater flood risk and soil erosion potential. The seasonal cycle remains intact (wet peaks in April–May and September–October), but the magnitude of rainfall and runoff is amplified. This means existing water management strategies must adapt to more intense wet seasons. Increased percolation and water yield under mid-term scenarios suggest improved recharge opportunities. However, the concentration of recharge in fewer months could stress aquifers during prolonged dry periods.

Analysis of monthly streamflow percentage change for the near-term and mid-term is presented in Table 8. The monthly average streamflow percentage change for the 'Near-term' period under both 'ssp245' and 'ssp585' scenarios, compared to the historical monthly average baseline (1988–2011), shows the maximum decrease in August for both scenarios in the near-term and mid-term. Under the SSP5-8.5 scenario, the projected ensemble mean flow is expected to increase by 115.4% (April), 82% (July), 47.7% (February), 26.5% (March), 29.5% (November), 34.1% (December), 18.5% (October), 29.3% (January), and 11.3% (May) compared to the simulated baseline flow. Under the SSP2-4.5 scenario, the projected ensemble mean flow is expected to increase by 88.9% (January), 45.8% (February), 21.2% (March), 68.2% (April), 15% (May), 24% (October), 67.6% (November), and 98.7% (December) compared to the simulated baseline flow. However, for other months, the flow is likely to decrease by up to 40.2% with the simulation of QSWATPLUS alone.

Regarding Hybrid simulation results, Under the SSP5-8.5 scenario, the projected ensemble mean flow is expected to increase by 115.4% (April), 82% (July), 47.7% (February), 26.5% (March), 29.5% (November), 34.1% (December), 18.5% (October), 29.3%(January), and 11.3% (May) compared to the simulated baseline flow. Under the SSP2-4.5 scenario, the projected ensemble mean flow is expected to increase by 88.9% (January), 45.8% (February), 21.2% (March), 68.2% (April), 15% (May), 24% (October), 67.6% (November), and 98.7% (December) compared to the simulated baseline flow. However, for other months, the flow is likely to decrease by up to 40.2% with the simulation of QSWATPLUS alone.

Table 8
Monthly Stream flow values in m3/s and forecasted percentage changes from the simulated base period

Scenario	**Projected SSP2-4.5**		**Projected SSP5-8.5**		**SSP2-4.5% change**		**SSP5-8.5% change**	
Timeframe	Near term	Midterm	Near term	Mid term	Near term	Midterm	Near term	Mid term
Jan	87.2	99.0	31.9	95.4	77.0	100.9	-35.1	93.7
Feb	21.4	30.9	16.9	33.1	26.1	65.4	-0.2	95.5
Mar	12.2	19.7	11.0	22.4	-7.5	49.8	-16.7	69.8
Apr	74.3	59.6	30.8	140.6	86.7	49.7	-22.6	253.4
May	164.0	154.3	97.6	210.5	18.5	11.5	-29.5	52.1
Jun	141.0	126.3	63.8	153.6	-30.3	-37.6	-68.5	-24.1
Jul	91.0	94.8	36.8	119.6	-49.7	4.2	-61.2	225.2
Aug	66.4	118.1	93.0	150.2	-67.4	-128.6	-54.3	-26.2
Sep	76.2	135.6	107.5	191.2	-66.5	-40.4	-52.8	-15.9
Oct	280.4	331.4	277.3	307.6	13.7	34.3	12.4	24.7
Nov	284.8	384.0	189.2	327.6	42.7	92.4	-5.2	64.2
Dec	191.6	226.0	81.0	201.0	82.3	115.0	-23.0	91.3

The projected increase and decrease in streamflow during the dry and wet seasons under RCP4.5 and RCP8.5 are attributed to the likely increase and decrease in rainfall amounts during these respective periods. A study by Worqlul et al. (2018) supports this finding, suggesting potential increases in dry season streamflow of up to 64% and decreases in wet season streamflow of up to 19% for future periods.

Regarding peak streamflow forecasting, hybrid captures the msrch April May peak but underestimates the September-October and November peak streamflows, whereas the QSWATPLUS forecast underestimates the March-April-May peak streamflows and captures the September-October and November peaks as indicated in Fig. 5.

Regarding future stream trends, Mann-Kendall tests on future streamflow projections indicated significant downward trends under both SSP245 and SSP585 scenarios across daily, monthly, annual, and seasonal scales when ML models were used for projection, whereas using QSWATPLUS, the increase was particularly pronounced in the high-emission SSP585 scenario. This highlights the anticipated impact of climate change on the Upper Genale Basin's hydrology. The result of the finding is compared with that of QSWATPlus stand-alone, and the BMA models generally provided a more robust and ensemble-averaged projection of these future changes (Fig. 5). Hybrid approaches that combine

process-based hydrological models with machine learning are increasingly used to improve streamflow forecasting accuracy, robustness, and climate-change projections.

Overall, the results suggest that climate change will modify both the magnitude and seasonality of water availability in the basin, creating future challenges related to drought management, groundwater sustainability, and flood control.

4 Discussion

The results demonstrate that integrating process-based hydrological modelling with machine-learning approaches substantially improves streamflow forecasting in the Upper Genale River Basin. While QSWAT+ successfully represented the dominant hydrological processes controlling runoff generation and watershed response, machine-learning algorithms captured complex nonlinear relationships that remained difficult to represent within a physically based framework. Similar improvements have been reported in recent hybrid modelling studies, where coupling hydrological models with boosting algorithms significantly enhanced predictive skill (Yang et al., 2023; Belina et al., 2025a; Cao & Ying, 2025).

The sensitivity analysis revealed the importance of both surface runoff and groundwater processes in controlling streamflow generation. The dominance of CN2 and percolation-related parameters indicates that future changes in rainfall, land use, and soil conditions may substantially affect watershed hydrology. Previous investigations in the Upper Genale Basin and other Ethiopian watersheds have similarly identified curve number and groundwater parameters as major controls on streamflow variability (Dile et al., 2016; Shigute et al., 2024).

The projected warming under all future scenarios is consistent with regional climate projections for Ethiopia and East Africa. Increasing temperatures enhance atmospheric evaporative demand, resulting in greater evapotranspiration losses and reduced effective water availability (Gebrechorkos et al., 2019; Bedada et al., 2025). The stronger increase in minimum temperature relative to maximum temperature observed in this study reflects asymmetric warming patterns that have been reported throughout eastern Africa (IPCC, 2021). Such warming may increase agricultural water demand, reduce soil moisture availability, and intensify pressure on already stressed water-resources systems.

Rainfall projections remain more uncertain than temperature projections. While some CMIP6 models indicate drying tendencies, others suggest increasing precipitation. Similar divergence has been reported in recent East African climate assessments, highlighting the challenges of precipitation forecasting in regions influenced by multiple atmospheric circulation systems (Assamnew & Tsidu, 2025b). Consequently, future hydrological projections should be interpreted as plausible pathways rather than deterministic forecasts.

The contrasting hydrological responses under SSP2-4.5 and SSP5-8.5 have important management implications. Under SSP2-4.5, reductions in groundwater recharge, runoff, and water yield suggest

growing risks of water scarcity and reduced dry-season water availability. Comparable findings have been reported for the Upper Genale Basin, Awash Basin, and other Ethiopian watersheds under moderate-emission scenarios (Shigute et al., 2024; Legass et al., 2026). Conversely, increased runoff and streamflow under SSP5-8.5 indicate greater flood potential and increasing hydrological extremes. These findings suggest that future water management must simultaneously address drought and flood risks.

Several uncertainties should be acknowledged. Hydro-meteorological observations remain sparse and may not fully capture localized climate variability. Although CHIRPS and CHIRTS datasets improved spatial coverage, measurement uncertainty remains unavoidable. Additional uncertainty originates from model structure and parameterization because hydrological models necessarily simplify complex watershed processes (Abbaspour et al., 2015; Krysanova et al., 2018).

Machine-learning algorithms introduce a further source of uncertainty. Their predictive capability depends on the assumption that relationships learned from historical data remain valid under future climate conditions. Under strong climatic shifts, these statistical relationships may change, potentially reducing forecasting reliability (Shortridge et al., 2016). Furthermore, uncertainty among CMIP6 precipitation projections remains substantial and propagates through hydrological simulations (Assamnew & Tsidu, 2025).

Despite these limitations, the hybrid framework provides a valuable decision-support tool for climate adaptation and water-resources management. Future studies should evaluate land-use change impacts, incorporate larger climate-model ensembles, and explore explainable artificial intelligence approaches to improve transparency and robustness.

5 Conclusion

Using observational data from five stations and the CMIP6 GCM, this study assessed the impact of climate change on surface water availability. To select a climate model, the Comprehensive Ranking Index (CRI) was used to evaluate the performance of 22 global climate models from the NASA/GDDP-CMIP6 Earth Engine Image collection against the CHIRPS and CHIRTS observational datasets. The study utilized the CanESM5 for temperature inputs and the ensemble of the six models (CanESM5, FGOALS-g3, GISS-E2-1-G, INM-CM4-8, INM-CM5-0, and KACE-10-G) for precipitation inputs to evaluate the probable effects of climate change on the hydrological components and water resource potential of the upper Genale River basin during the near-term and mid-term periods under SSP2-4.5 and SSP5-8.5.

This study developed a hybrid hydrological forecasting framework integrating QSWAT+ with machine-learning algorithms and CMIP6 climate projections to evaluate future streamflow dynamics in the Upper Genale River Basin. The QSWAT+ model successfully reproduced observed streamflow, while hybrid approaches significantly improved predictive accuracy, with the stacking ensemble and XGBoost-based models outperforming standalone hydrological simulations.

Climate projections consistently indicated increasing temperatures under both SSP2-4.5 and SSP5-8.5 scenarios, whereas precipitation projections remained uncertain. Hydrological simulations suggested reductions in groundwater recharge, runoff, and water yield under SSP2-4.5, while SSP5-8.5 projected increased runoff and higher flood potential, particularly during the mid-century period. Evapotranspiration increased under all scenarios, indicating growing pressure on future water availability.

The findings highlight the importance of integrating physically based and data-driven modelling approaches for climate-change impact assessment and streamflow forecasting. The hybrid framework improves prediction reliability while maintaining hydrological realism, making it particularly valuable for data-scarce regions.

The outcome demonstrates that, under both SSPs, the predicted climate exhibits an increase in temperature in all future periods (in the near-term and midterm). Regarding rainfall, the model exhibits variable phenomena. CanESM5 showed decreasing trends in the near and midterm for SSP2-4.5 and increasing trends under both near and midterm for SSP5-8.5, whereas INM-CM4-8 and INM-CM5-0 showed increasing trends, and the remaining three models (FGOALS-g3, GISS-E2-1-G, and KACE-1-0-G showed decreasing trends in both near-term and mid-term under both SSPs. The change in future temperature and rainfall in comparison with the baseline period could significantly affect the streamflow and water balance components. Under both SSPs, rising temperatures and variability of precipitation during the near-term and midterm are projected to impact the annual hydrological components of the entire study basin. Total water yield, runoff, groundwater flow, and lateral flow are all expected to decline within a range of 1.73% to 2.89%, 1.596% to 2.87%, 16.33% to 18.78%, and 0.23% to 0.24%, respectively. However, evapotranspiration is projected to increase significantly in these future scenarios from 5% to 14% in the near and mid terms. The observed change in hydrological parameters, such as reduction of water yield, runoff, lateral flow, groundwater flow, as well as a rise in evapotranspiration in the study watershed evidently associated with the future change in temperature and rainfall.

Similarly, for streamflow forecasting, the result of the study indicated that the Hybrid Model (Stacking Ensemble) achieved the best performance ($R^2 \approx 0.968$, NSE ≈ 0.968) compared to individual models. Regarding the result of the Mann-Kendall tests, the result revealed a significant increasing trend in daily and seasonal flow for most models. With respect to the robustness of ML models, using ML models significantly improved the robustness over the baseline physically based model by capturing non-linear hydrological dynamics. The Hybrid Model significantly outperformed the standalone QSWATPLUS (NSE ≈ 0.600) and slightly improved upon individual ML models (RF NSE ≈ 0.962). Using these methods reduced Uncertainty since stacking effectively corrected systematic biases, as evidenced by a PBIAS near zero and residuals that are more centered and less skewed compared to individual components. Similarly, the model checked for temporary consistency, and Mann-Kendall tests confirmed that while observed flows showed an increasing trend, the hybrid model residuals maintained 'no trend' (p-value > 0.05), indicating consistent performance across the entire validation timeframe.

The result of the finding is compared with that of QSWATPlus stand-alone, and the hybrid models generally provided a more robust and ensemble-averaged projection of these future changes. Hybrid approaches that combine process-based hydrological models with machine learning are increasingly used to improve streamflow forecasting accuracy, robustness, and climate-change projections.

The streamflow percentages under both scenarios in the near and mid-term future indicate the varied results showed a decreasing trend in the near term under both SSP245 and SSP585, with 7.73 and 35.81%, respectively. However, in the mid-term, the stream flow showed an increasing trend, which implies climate change is significantly impacting the upper Genale River basin's water resources. This could significantly reduce the annual hydrological components of the basin, including total water yield, runoff, groundwater flow, streamflow, and lateral flow. However, evapotranspiration is projected to increase significantly that create a reduction in available water resources. This can have extensive impacts on agriculture and ecosystem services. Designing and implementing water resource management strategies is crucial to minimizing climate change's potential impact on water resources.

Overall, future water-resources planning in the Upper Genale River Basin should prepare for both increasing water scarcity and heightened flood risk. Climate-resilient irrigation systems, groundwater conservation measures, flood-management infrastructure, and climate-informed forecasting systems will be essential for sustainable basin management under future climate conditions.

Key Policy Implications:-

1. Climate-resilient irrigation planning is needed to offset increasing evapotranspiration and future dry-season water shortages.
2. Groundwater monitoring and recharge protection should be prioritized because projected reductions in recharge threaten long-term water security.
3. Flood-risk management infrastructure should be strengthened under high-emission scenarios due to projected increases in runoff and peak flows.
4. Watershed restoration and soil-water conservation programs can reduce erosion, improve infiltration, and increase resilience to climate variability.
5. Climate-informed forecasting systems using hybrid hydrological–machine learning models should be integrated into reservoir operation, drought early warning, and basin-scale water-allocation planning.

Declarations

Conflicts of Interest:

The authors declare no conflicts of interest.

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Author Contribution

All authors whose names appear on the submission made substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data; or the creation of new software used in the work;drafted the work or revised it critically for important intellectual content;approved the version to be published; and agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

All authors contributed to the paper's development and writing, and approved the final manuscript.

All authors have read and agreed to the published version of the manuscript

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Data Availability

Ali, E. A. (2026). Evaluation of the performance of multiple CMIP6 climate models against observational datasets (CHIRPS for precipitation and CHIRTS for temperature) over a specific region (Ganale sub-basin) (Version 1) [Figure]. Zenodo. https://doi.org/10.5281/zenodo.19712765ALI, E. A. (2026). HYBRID DATA-DRIVEN AND PROCESS-BASED MODELING FOR STREAMFLOW FORECASTING UNDER CLIMATE CHANGE IN THE UPPER GENALE BASIN OF ETHIOPIA (Version 1) [Figure]. Zenodo. https://doi.org/10.5281/zenodo.20007686

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Figures

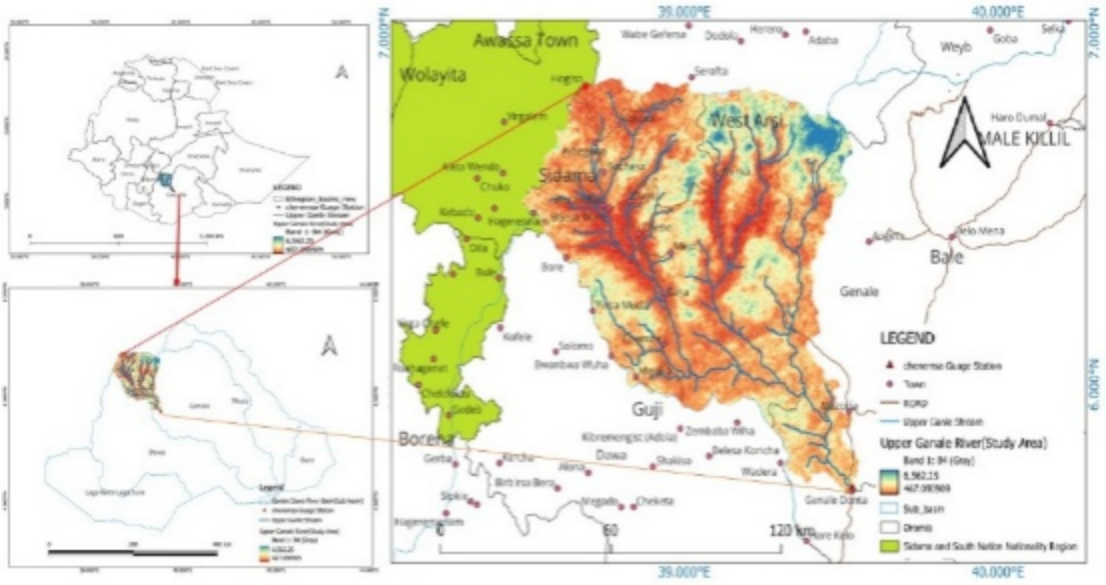


Figure 1

Location Map of the study area

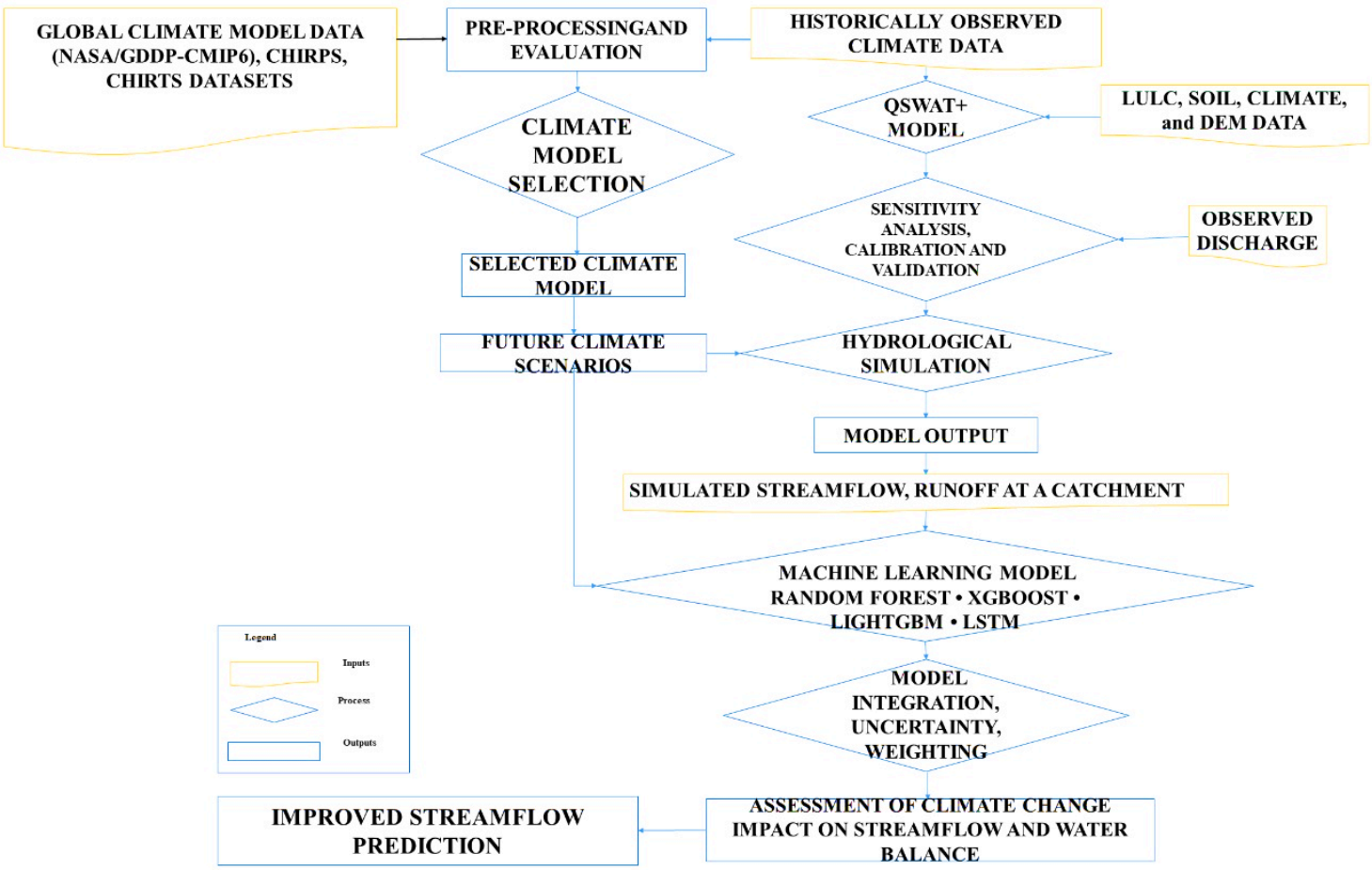


Figure 2

The overall conceptual framework of the study

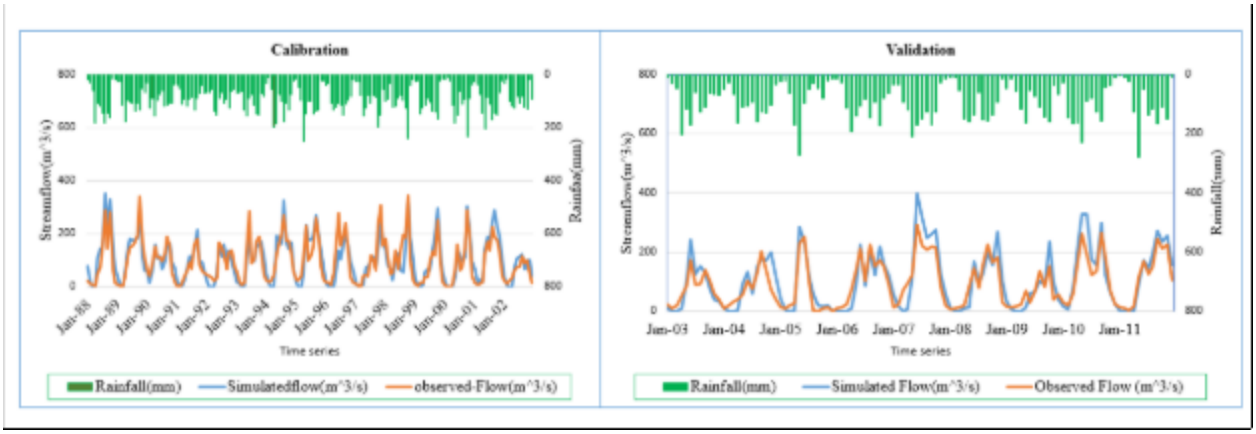


Figure 3

Monthly Average Streamflow Calibration and Validation in a graph with basin monthly average areal rainfall

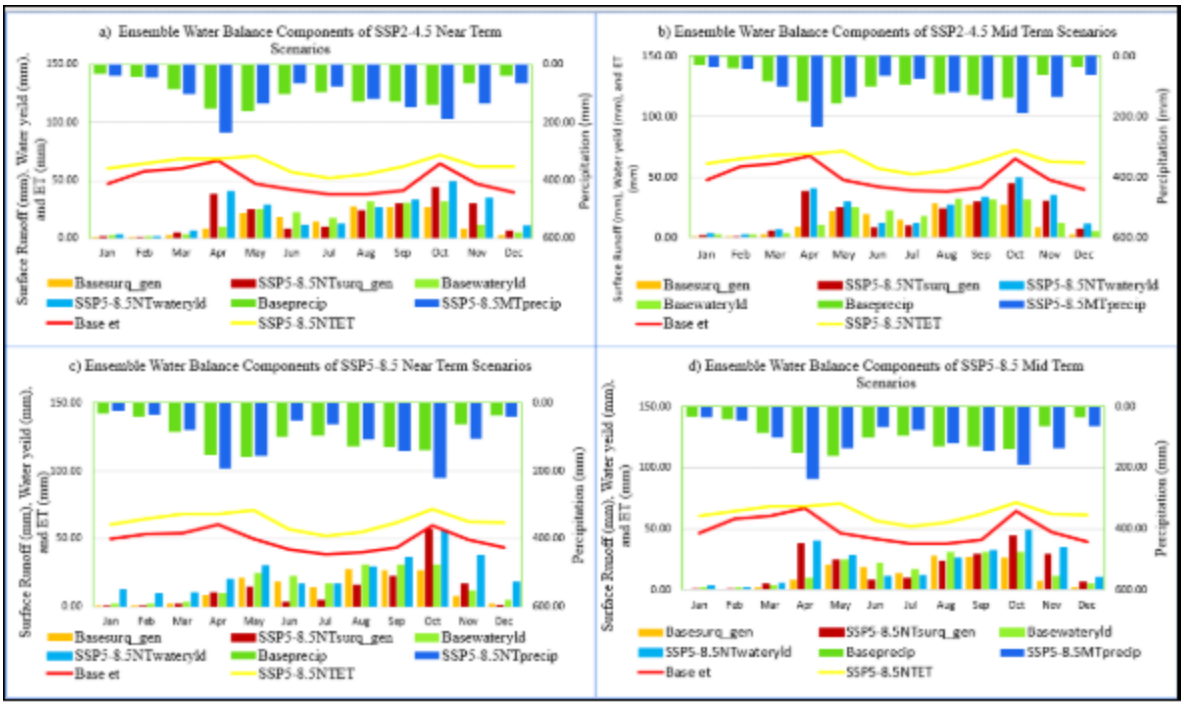


Figure 4

Climate model ensemble mean monthly water balance components percentage changes from the base period under future climate change projection for both SSP2-4.5 and SSP5-8.5 scenarios under both near and midterm periods

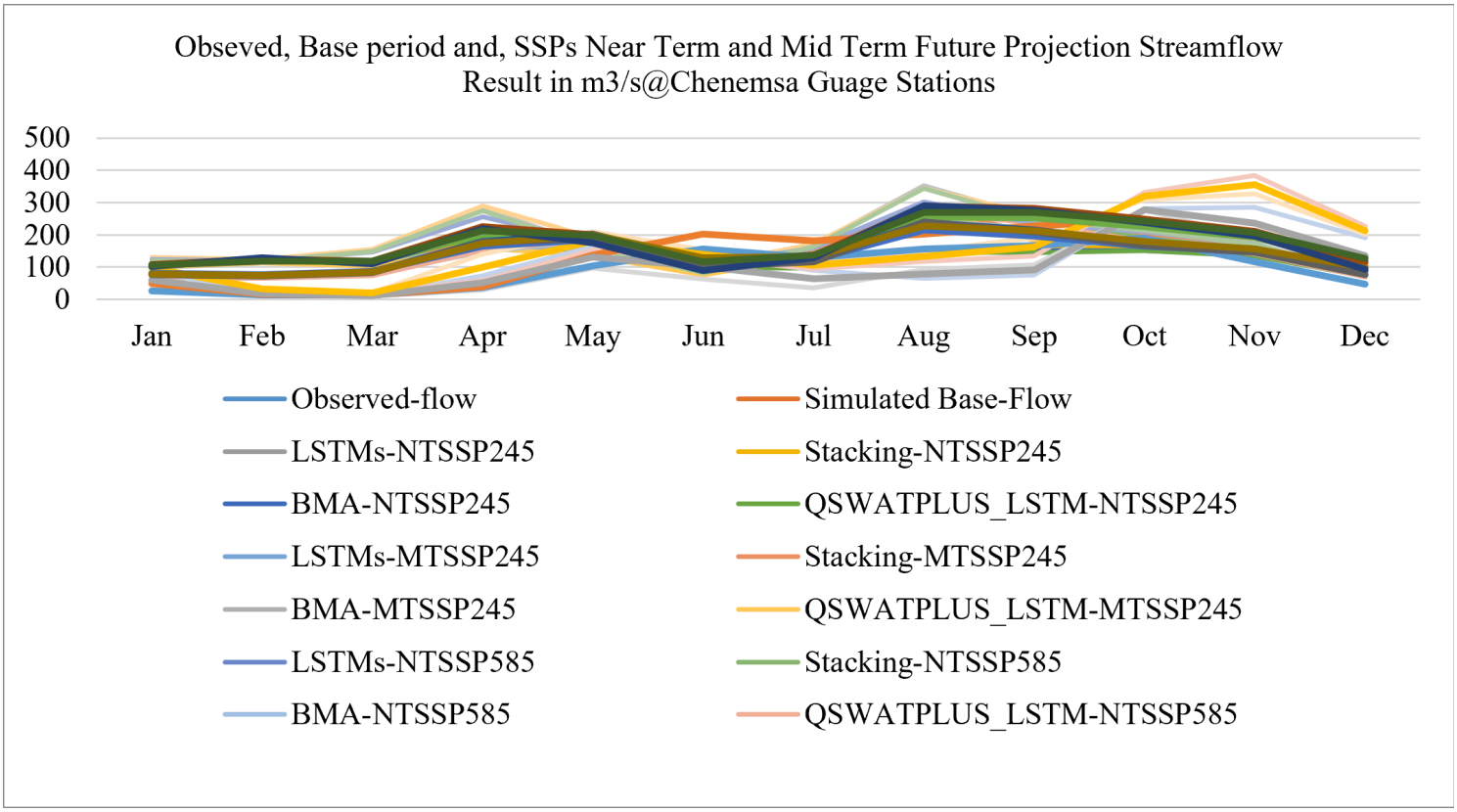


Figure 5

Observed, Base period and SSPs Near Term and Mid Term Future Projection Streamflow Result in m3/s@Chenemsa Gauge Stations

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryPart.pdf