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Comparative Analysis of HEC-HMS and Temporal Fusion Transformer for Streamflow Prediction under Climate Change Scenarios in the Swat River Basin

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Abstract: Climate change is expected to significantly alter hydrological regimes in mountainous river basins, increasing uncertainty in future streamflow and flood risk. This study assesses historical and future streamflow dynamics of the Swat River Basin, Pakistan. A comparative framework was adopted using a physically based semi-distributed model (HEC-HMS) and a data-driven deep learning model, the Temporal Fusion Transformer (TFT). Eleven downscaled CMIP6 Global Climate Models (GCMs) were first evaluated using Recursive Feature Elimination coupled with a Random Forest algorithm, resulting in the selection of three top-performing models: INM-CM4-8, MRI-ESM-2-0, and GFDL-ESM4. Historical simulations showed that while HEC-HMS performed satisfactorily in reproducing seasonal flows and runoff volumes, it underestimated extreme flood peaks. In contrast, the TFT model demonstrated very high predictive accuracy and effectively captured extreme events, including the catastrophic 2010 flood. Future projections (2020–2100) under SSP2-4.5 and SSP5-8.5 scenarios indicate a substantial increase in peak flows, particularly under high-emission pathways, with several extreme events projected to occur in the near future. Overall, the results highlight the limitations of conventional hydrological models in simulating non-linear extremes and demonstrate the strong potential of advanced machine-learning models for climate change impact assessment and flood risk management in data-scarce mountainous basins.
Keywords: Climate Change, HEC-HMS, Temporal Fusion Transformer (TFT), CMIP6, Shared Socioeconomic Pathways (SSPs).

I. INTRODUCTION

Climate change has become one of the most pressing global environmental challenges, exerting profound impacts on natural and human systems across the world[1]. Rising global temperatures, altered precipitation patterns, and increased frequency of extreme weather events have significantly modified the hydrological cycle, leading to changes in runoff generation, river flow regimes, and water availability[2] . These climate-driven alterations have intensified the occurrence of floods and droughts, disrupted seasonal flow patterns, and increased uncertainty in hydrological processes, posing serious challenges for water resources planning and management [3]. Consequently, reliable streamflow prediction under current and future climate conditions has become a critical requirement for sustainable water management, disaster risk reduction, and climate change adaptation strategies [4].

Hydrological systems are inherently complex and non-linear, and their response to climate change varies significantly across regions depending on topography, land use, cryosphere influence, and climatic conditions [5]. In particular, river basins fed by snow and glacier melt are highly sensitive to temperature increases, which directly affect melt rates, seasonal runoff distribution, and peak flow magnitudes [6]. Climate projections indicate that future emission scenarios may substantially alter river flow characteristics, including shifts in peak flow timing, increased flood intensity, and reduced low flows during dry seasons [7]. These projected changes underscore the need for robust modeling frameworks capable of capturing both historical hydrological behavior and future climate-induced variability.

Pakistan is among the countries most vulnerable to climate change impacts due to its geographical location, diverse climate zones, and heavy reliance on climate-sensitive water resources [5]. The country has experienced a noticeable increase in the frequency and intensity of extreme hydrological events over recent decades, including devastating floods and prolonged droughts [6]. Pakistan's river systems, particularly those forming the Indus River Basin, are predominantly fed by snow and glacier melt from the Hindu Kush–Karakoram–Himalaya (HKH) region, making them extremely sensitive to temperature rise and changes in precipitation patterns [7]. Climate change projections suggest that increasing temperatures may accelerate glacier retreat in the short term, leading to higher flows and flood risks, followed by long-term reductions in water availability as glacier reserves diminish.

The adverse impacts of climate change on Pakistan's water sector are further exacerbated by rapid population growth, increasing water demand, and limited adaptive capacity. Reliable streamflow prediction is therefore essential for effective flood forecasting, reservoir operation, irrigation planning, and climate-resilient infrastructure development. In this context, assessing the performance of different streamflow prediction approaches under future climate scenarios is of critical importance for informed decision-making and sustainable water resources management in Pakistan.

The Swat River Basin, a major sub-basin of the Upper Indus Basin, holds significant hydrological, ecological, and socio-economic importance in northern Pakistan [8]. Originating from the Hindu Kush mountains, the Swat River is primarily fed by snowmelt, glacier melt, and monsoon rainfall, resulting in pronounced seasonal variability in streamflow [9]. The basin supports agriculture, hydropower generation, domestic water supply, and livelihoods of millions of people, making it highly sensitive to hydrological changes [8]. In recent decades, the Swat River Basin has witnessed several extreme flood events, most notably the catastrophic flood of 2010, which caused widespread damage to infrastructure, agriculture, and settlements [10].

Climate change is expected to further intensify hydrological extremes in the Swat River Basin, with projections indicating increased monsoon rainfall variability, higher peak flows, and enhanced flood risk under future climate scenarios [11]. At the same time, changes in snow accumulation and melt dynamics may significantly affect seasonal flow distribution, potentially reducing water availability during critical dry periods. These challenges highlight the urgent need for accurate and reliable streamflow prediction tools that can support climate change impact assessment and adaptive water management in the Swat River Basin.

Hydrological modeling has long been recognized as a fundamental tool for understanding watershed processes and predicting river flows under varying climatic conditions [12]. Among the widely used hydrological models, the Hydrologic Engineering Center–Hydrologic Modeling System (HEC-HMS) has gained global recognition for its capability to simulate rainfall–runoff processes in both event-based and continuous modeling modes [13]. HEC-HMS employs conceptual and semi-distributed representations of key hydrological processes, including precipitation losses, surface runoff generation, baseflow contribution, and channel routing. Due to its flexibility, computational efficiency, and strong physical basis, HEC-HMS has been extensively applied for flood forecasting, watershed management, and climate change impact studies across diverse hydro-climatic regions [14].

In climate change studies, HEC-HMS is often driven by downscaled climate model outputs to assess future changes in streamflow under different emission scenarios [14]. However, the model's performance is highly dependent on parameter calibration, input data quality, and assumptions regarding the stationarity of hydrological processes. Under changing climate conditions, these assumptions may not always hold, potentially limiting the model's ability to capture complex, non-linear climate–hydrology interactions [15]. As a result, there is growing interest in exploring complementary modeling approaches that can enhance predictive accuracy under non-stationary climate conditions.

In recent years, machine learning and deep learning techniques have emerged as powerful alternatives to traditional hydrological models for streamflow prediction. These data-driven approaches are capable of learning complex, non-linear relationships between climatic inputs and hydrological responses without explicitly representing physical processes [16]. Among advanced deep learning models, the Temporal Fusion Transformer (TFT) has gained increasing attention due to its superior performance in multi-horizon time-series forecasting tasks [17]. TFT integrates recurrent neural networks with attention mechanisms and gating structures, enabling it to effectively capture both short-term dynamics and long-term dependencies in time-series data [18].

A key advantage of TFT lies in its ability to incorporate multiple types of inputs, including static variables (e.g., basin characteristics) and time-varying covariates (e.g., precipitation and temperature), making it particularly suitable for hydrological forecasting under climate change scenarios [18]. Furthermore, TFT provides a degree of interpretability through attention weights, allowing researchers to identify the relative importance of different input variables and time steps in streamflow prediction [19]. Recent studies have demonstrated that TFT outperforms traditional statistical models and several machine learning techniques in streamflow forecasting, particularly in complex and data-rich environments [20].

Despite the proven strengths of both physics-based hydrological models and advanced deep learning techniques, there remains a lack of comprehensive comparative studies evaluating their performance under future climate change scenarios, especially in snow- and glacier-fed river basins such as the Swat River Basin. Most existing studies focus on either hydrological modeling or machine learning approaches in isolation, limiting insights into their relative strengths and limitations under non-stationary climate conditions. A direct comparison between HEC-HMS and Temporal Fusion Transformer can therefore provide valuable understanding of how conceptual hydrological models and deep learning approaches respond to climate-induced hydrological changes.

In this context, the present study aims to conduct a comparative analysis of HEC-HMS and Temporal Fusion Transformer for streamflow prediction under different climate change scenarios in the Swat River Basin. By evaluating the performance of both models under historical and future climate conditions, this research seeks to assess their applicability, robustness, and predictive capability for climate-resilient water resources management. The findings of this study are expected to contribute to improved understanding of the role of physical and data-driven models in streamflow prediction and to support informed decision-making for climate adaptation and flood risk management in Pakistan.

A. Research Objectives

The primary objective of this study is to comparatively evaluate the performance of a physics-based hydrological model (HEC-HMS) and a deep learning model (Temporal Fusion Transformer) for streamflow prediction under different climate change scenarios in the Swat River Basin. Specifically, the study aims to assess the ability of both models to simulate historical streamflow, project future streamflow using climate change scenarios, and capture variations in flow magnitude, seasonality, and extremes. The comparative analysis is intended to identify the strengths and limitations of each modeling approach and to provide insights for climate-resilient water resources management and flood risk mitigation in the Swat River Basin.

II. METHODOLOGY

A. Study Area

The Swat River Basin, located in the northwestern region of Pakistan, serves as the study area for this research. The basin lies between approximately 35.2° to 35.9° North latitude and 72.0° to 72.8° East longitude. Originating from the Hindu Kush mountain range, the Swat River flows southward and joins the Kabul River near Charsadda. The basin is characterized by complex topography, ranging from high-altitude mountainous terrain to relatively flatter downstream areas, and is predominantly influenced by snowmelt, glacier melt, and monsoon rainfall. Due to its climatic sensitivity, hydrological variability, and history of extreme flood events, the Swat River Basin provides a suitable and representative case study for assessing streamflow prediction under different climate change scenarios.

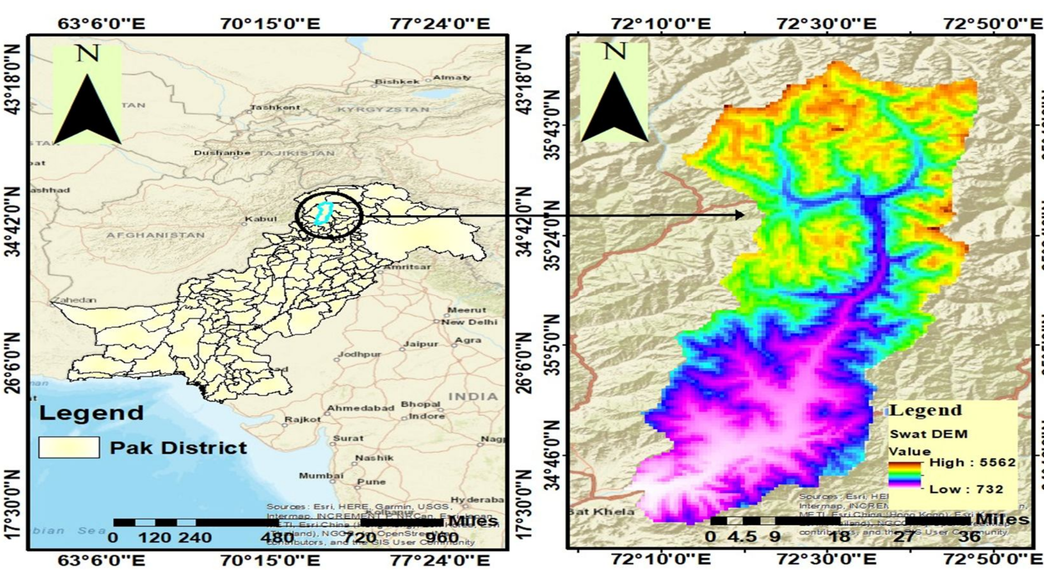

Figure 1 : Study area

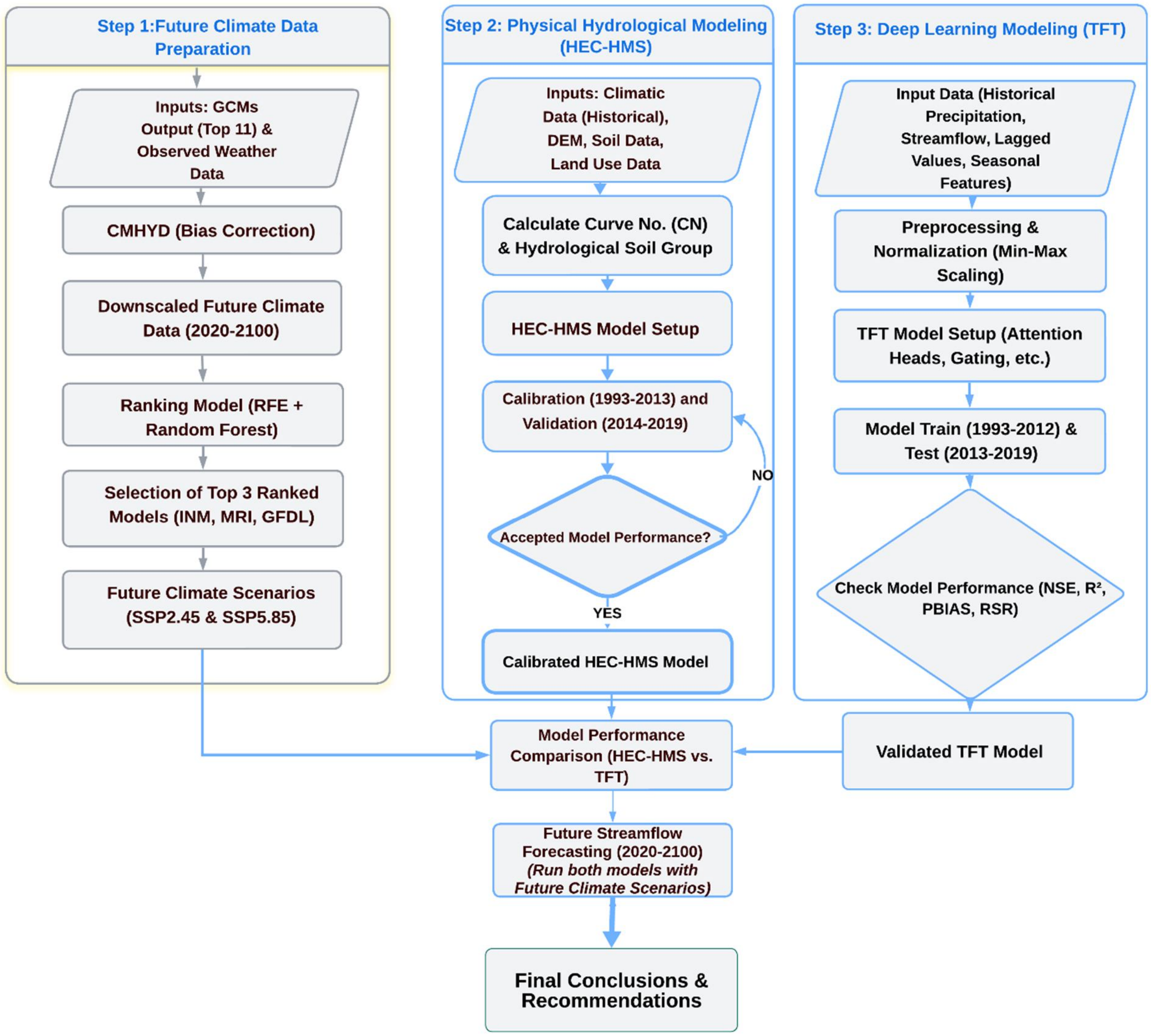

Figure 2: Methodology for streamflow prediction using temporal fusion transformer (TFT) model for the swat river basin

B. Topographic Data

To represent the topographic and physical characteristics of the Swat River Basin**,** a 30 m × 30 m Digital Elevation Model (DEM) was obtained from the USGS Earth Explorer platform. The DEM was utilized for watershed delineation, stream network generation, slope analysis, and flow direction extraction within the HEC-HMS modeling framework. Land use and land cover (LULC) data were derived from MODIS products, while soil characteristics were obtained from the Food and Agriculture Organization (FAO) soil database. These spatial datasets collectively facilitated accurate representation of basin physiography, hydrological response units, and runoff generation processes, enabling reliable simulation of historical and climate change–driven streamflow conditions in the Swat River Basin.

C. Future Climate Data Preparation

Global Climate Model (GCM) outputs were employed to represent future climatic conditions over the Swat River Basin. Historical observed meteorological data were used as a reference to correct systematic biases in raw GCM outputs. Bias correction was performed using the CMHYD tool, which has been widely applied for climate change impact assessments on hydrological systems [21]. The bias-corrected climate projections were then statistically downscaled to generate basin-scale daily precipitation and temperature data for the period 2020–2100.

To reduce uncertainty associated with the use of multiple climate models, a model ranking and selection procedure was implemented using Recursive Feature Elimination (RFE) combined with Random Forest algorithms. This approach enabled objective evaluation of GCM performance against observed climate data [22].

Based on the ranking results, the top three GCMs (INM, MRI, and GFDL) were selected for further analysis. Future climate projections were considered under SSP2–4.5 and SSP5–8.5 scenarios, representing intermediate and high-emission pathways, respectively [23].

D. Physical Hydrological Modeling Using HEC-HMS

The HEC-HMS model was developed to simulate rainfall–runoff processes in the Swat River Basin. Spatial inputs included a 30 m × 30 m Digital Elevation Model (DEM), land use/land cover data, and soil characteristics, which were used for watershed delineation, stream network generation, slope analysis, and hydrological parameter estimation. Hydrological soil groups and Curve Number (CN) values were calculated based on soil and land use data to represent infiltration and runoff generation processes [23].

Historical climatic data were used as inputs to the HEC-HMS model. The model was calibrated for the period 1993–2013 and validated for 2014–2019 using observed streamflow data. Model performance was evaluated using standard hydrological performance indicators, including the Nash–Sutcliffe Efficiency (NSE), coefficient of determination (R^2), percent bias (PBIAS), and root mean square error (RMSE). Calibration was iteratively refined until acceptable performance was achieved. The calibrated HEC-HMS model was then forced with future climate projections under SSP2–4.5 and SSP5–8.5 scenarios to simulate future streamflow for the period 2020–2100.

E. Deep Learning Modeling Using Temporal Fusion Transformer (TFT)

In parallel, a Temporal Fusion Transformer (TFT) model was developed for data-driven streamflow prediction. Historical precipitation, temperature, and streamflow data were used as input features, along with lagged streamflow values and seasonal indicators to capture temporal dependencies. Prior to model training, all input variables were preprocessed and normalized using Min–Max scaling to improve model convergence and stability.

The TFT architecture was configured with attention mechanisms, gating layers, and recurrent components to effectively capture both short-term dynamics and long-term temporal dependencies in hydrological time series [24]. The dataset was divided into training (1993–2012) and testing (2013–2019) periods. Model performance was evaluated using NSE, R^2, PBIAS, and RSR, ensuring consistency with the evaluation metrics used for the HEC-HMS model. The validated TFT model was subsequently driven by future climate inputs to generate streamflow projections under SSP2–4.5 and SSP5–8.5 scenarios for the period 2020–2100.

F. Comparative Analysis and Future Streamflow Projection

A comprehensive comparative analysis was conducted to evaluate the performance of HEC-HMS and TFT under both historical and future climate conditions. The comparison focused on model accuracy, ability to reproduce seasonal variability, peak flows, and low-flow conditions. Both models were finally used to generate future streamflow projections (2020–2100) under selected climate scenarios. The comparative results were analyzed to assess the strengths and limitations of physics-based and deep learning approaches for climate change impact assessment and to support climate-resilient water resources planning in the Swat River Basin [25].

III. RESULTS

A. GCM Ranking Using RFE and Random Forest

To ensure accurate future streamflow projections for the Swat Basin, a rigorous selection of Global Climate Models (GCMs) was performed. Eleven downscaled CMIP6 GCMs were evaluated using Recursive Feature Elimination (RFE) with a Random Forest regressor to assess their predictive performance against historical precipitation. The RFE analysis identified the top three models INM-CM4-8, MRI-ESM-2-0, and GFDL-ESM4 which were then used for hydrological simulations. Focusing on these best-performing models reduces input uncertainty and ensures that the streamflow projections from HEC-HMS and TFT are based on the most reliable climate data.

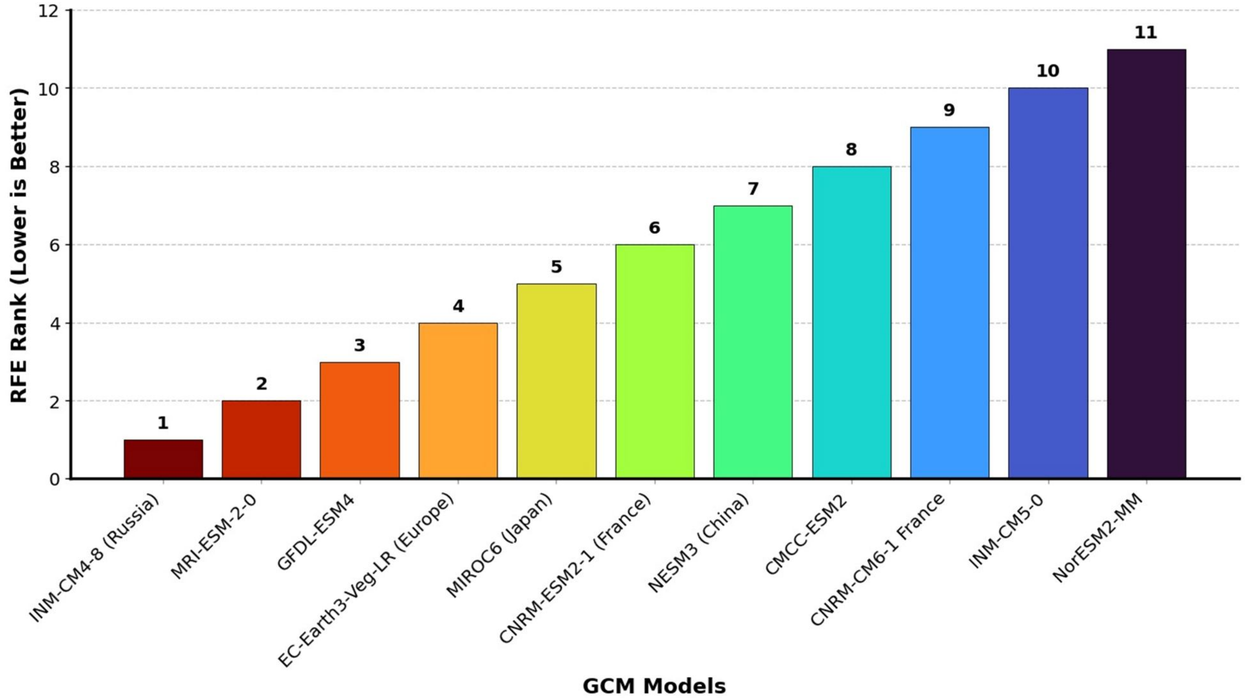

Figure 3 : Ranking of GCMs using RFE and Random Forest

B. Hydrological Model Performance

The semi-distributed, physically-based HEC-HMS model was calibrated and validated for the Swat Basin at the Chakdara outlet to ensure accurate future streamflow projections. A 27-year historical dataset (1993–2019) was split into a calibration period (1993–2013) and a validation period (2014–2019). Model performance was evaluated using Nash-Sutcliffe Efficiency (NSE), Coefficient of Determination (R^2), Percent Bias (PBIAS), and RMSE-Standard Deviation Ratio (RSR), with performance ratings summarized in Table 3.1.

Table 1 : Statistical Performance Ratings for Hydrological Models.

Performance rating	RSR	NSE	PBIAS (%)
Very Good	$0 \leq RSR \leq 0.5$	$0.75 < NSE \leq 1$	$-10 < PBIAS < 10$
Good	$0.5 < RSR \leq 0.6$	$0.65 < NSE \leq 0.75$	$\pm 10 \leq PBIAS < \pm 15$
Satisfactory	$0.6 < RSR \leq 0.7$	$0.5 < NSE \leq 0.65$	$\pm 15 \leq PBIAS < \pm 25$
Unsatisfactory	$RSR > 0.7$	$NSE \leq 0.5$	$PBIAS \geq 25$

1) HEC-HMS

Calibration and validation:

The HEC-HMS model showed satisfactory performance for both calibration (NSE = 0.612, RSR = 0.62) and validation (NSE = 0.609, RSR = 0.63) periods, with PBIAS values of +1.11% and -9.09%, indicating very good simulation of overall water balance and runoff volume. R^2 values of 0.65 and 0.68 further confirm a satisfactory correlation between observed and simulated flows as shown in table 2.

The model successfully reproduced seasonal hydrograph patterns, baseflow, and total water volume as shown in Figures 4. However, it significantly underestimated extreme peak flows, such as the August 2010 flood (observed 7,601.3 m³/s vs. simulated 2,632.7 m³/s) and the 2016 peak (observed 848.5 m³/s vs. simulated 529.6 m³/s), reflecting a common limitation of semi-distributed, physically-based models that prioritize volumetric accuracy over capturing extreme, non-linear flood events. Overall, HEC-HMS provides a reliable baseline despite this peak-flow limitation.

Table 2 : HEC-HMS Model Performance for Calibration and Validation

Summary Statistics Table							
Calibration (1993–2013)				Validation (2014–2019)			
RSR	NSE	PBIAS	R2	RSR	NSE	PBIAS	R2
0.62	0.612	1.11	0.65	0.63	0.609	-9.09	0.68

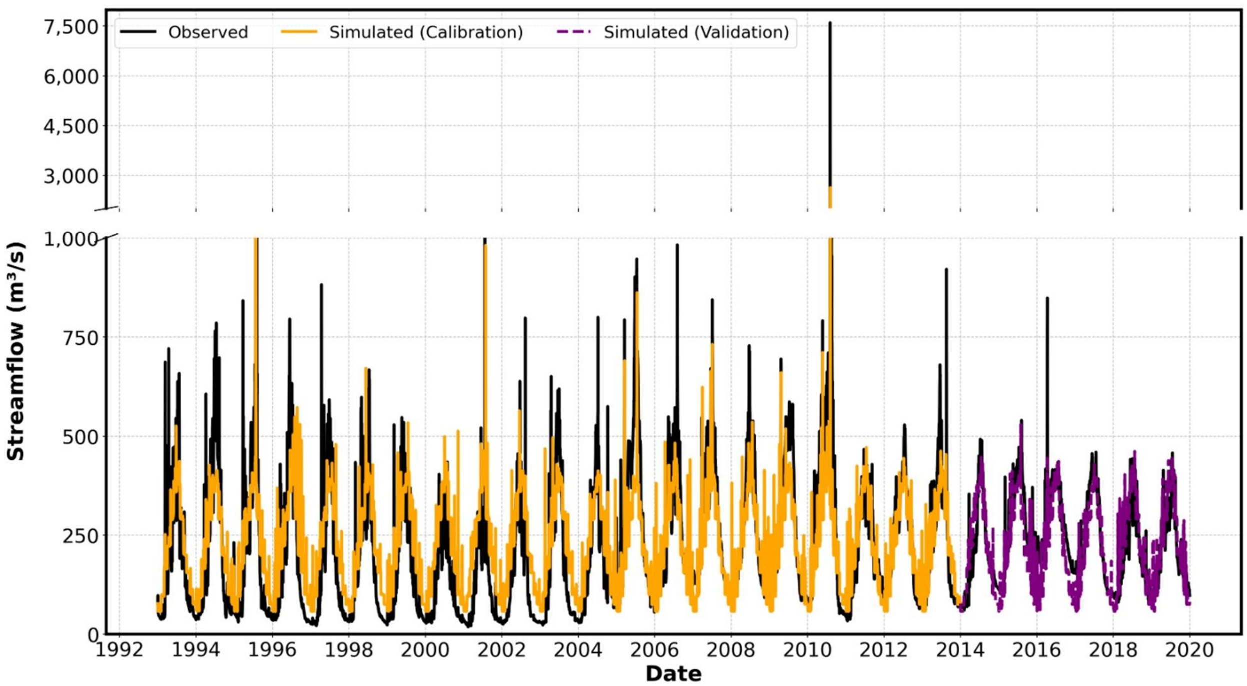

Figure 4 : Observed vs. HEC-HMS simulated daily streamflow during calibration and validation

2) TFT

Training and testing

The historical dataset (1993–2019) was divided into training (1993–2012, 70%) and testing (2013–2019, 30%) periods to develop the TFT model for daily streamflow prediction using precipitation, lagged streamflow, and seasonal features. After Min–Max normalization, the model was trained for 215 epochs using the Adam optimizer (learning rate = 0.0001) and a quantile loss function (τ = 0.9) to enhance high-flow prediction. The TFT model demonstrated exceptional performance, achieving "Very Good" ratings across all evaluation metrics during both training (NSE = 0.960, PBIAS = +2.83%) and testing (NSE = 0.953, RSR = 0.217, PBIAS = +3.19%) phases. Visual analyses further confirmed its robustness, as the model accurately captured seasonal dynamics and extreme events, including the 2010 flood peak, which was simulated at 7,384 m³/s against an observed 7,601 m³/s (97% accuracy). The strong alignment along the 1:1 line in the scatter plot (R^2 = 0.953) highlights the TFT model's superior generalization and reliability for future streamflow and flood forecasting.

Table 3 : TFT Model Performance Statistics

Summary Statistics Table							
Calibration (1993–2012)				Validation			
RSR	NSE	PBIAS	R2	RSR	NSE	PBIAS	R2
0.1993	0.96	2.8322	0.96	0.2539	0.95	3.1880	0.95

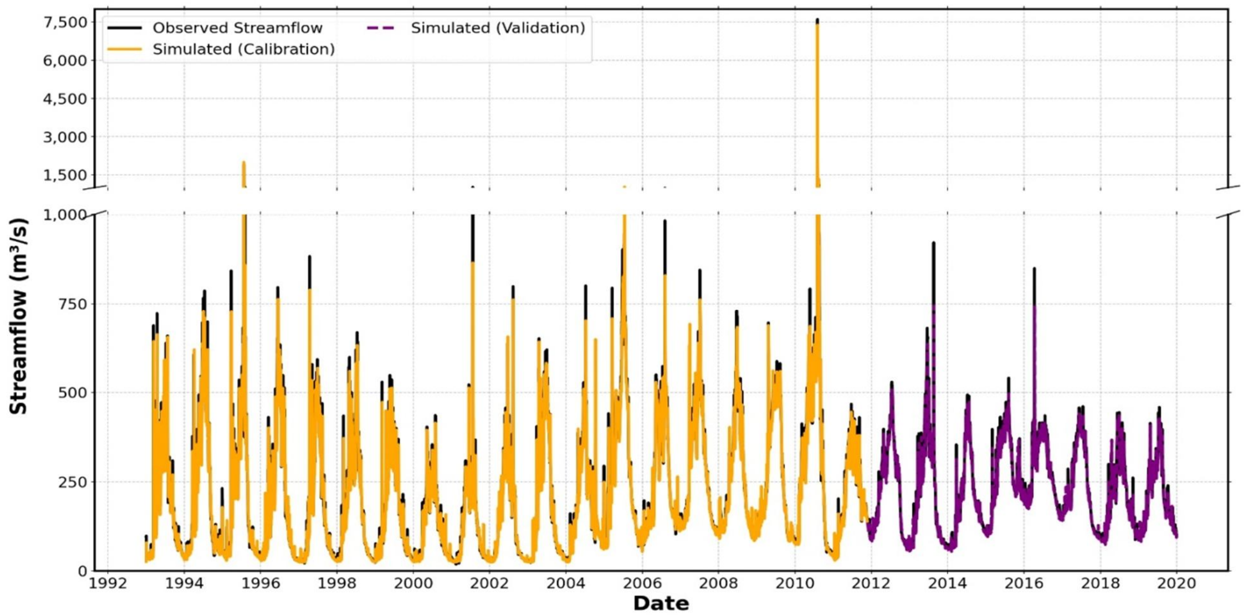

Figure 5: Observed vs. TFT simulated daily streamflow during calibration and validation

3) *Comparative Model Performance and Selection*

Daily streamflow at the proposed intake site of the Mingora Gravity Water Scheme was modeled using both a conventional, process-based approach (HEC-HMS) and an advanced deep-learning approach (Temporal Fusion Transformer, TFT). The HEC-HMS model produced consistent and acceptable results during both calibration (1993–2013) and validation (2014–2019), with NSE values of 0.612 and 0.609 and corresponding R^2 values of 0.65 and 0.68, indicating satisfactory representation of basin-scale hydrological behavior and runoff volumes. However, its ability to reproduce extreme flood peaks was limited. In contrast, the TFT model exhibited substantially higher predictive skill, achieving NSE and R^2 values of 0.960 during training and maintaining similarly strong performance during testing (NSE = 0.953, R^2 = 0.953), along with a low testing PBIAS of +3.19%. The TFT model effectively captured both normal flow conditions and highly non-linear extreme events, including major flood peaks, which were underestimated by HEC-HMS. Overall, while HEC-HMS serves as a dependable traditional reference model, the superior accuracy and robustness of the TFT model make it more suitable for future streamflow projection and climate impact assessment in the Swat Basin.

C. *Future Streamflow Scenarios*

To evaluate the long-term influence of climate change on the Mingora Gravity Water Supply Scheme, streamflow projections were developed for the period 2020–2100. Future simulations were performed using both the calibrated, process-based HEC-HMS model and the data-driven Temporal Fusion Transformer (TFT) model. These projections were forced with downscaled and bias-corrected precipitation outputs from the three best-performing CMIP6 General Circulation Models—INM-CM4-8, MRI-ESM-2-0, and GFDL-ESM4. For each selected GCM, simulations were carried out under two contrasting Shared Socioeconomic Pathways: SSP2-4.5, representing a medium-emissions trajectory, and SSP5-8.5, representing a high-emissions scenario.

The resulting streamflow hydrographs illustrate the possible magnitude, variability, and seasonal evolution of future flows at the Swat River intake, offering critical insight into the range of hydrological conditions that may affect the scheme under changing climatic conditions.

1) Projections based on INM-CM4-8 (HEC-HMS):

The INM-CM4-8 General Circulation Model, which ranked highest in the model selection analysis, generated the most severe peak flow estimates among the three selected GCMs, indicating a heightened level of future flood risk. The HEC-HMS-based projections illustrated in Figures 6 reveal a pronounced sensitivity of the basin's hydrological response to extreme rainfall events. Under the medium-emissions SSP2-4.5 scenario, a peak precipitation event of 68.1 mm resulted in a simulated maximum discharge of 2,515.4 m³/s in 2085. In contrast, under the high-emissions SSP5-8.5 pathway, an exceptionally intense rainfall event of 157.3 mm produced a substantially larger flood peak of 4,688.9 m³/s as early as 2028. This corresponds to an approximate 86% increase in peak discharge, primarily driven by the near-doubling of extreme precipitation intensity, underscoring the amplified flood hazards associated with high-emission climate futures.

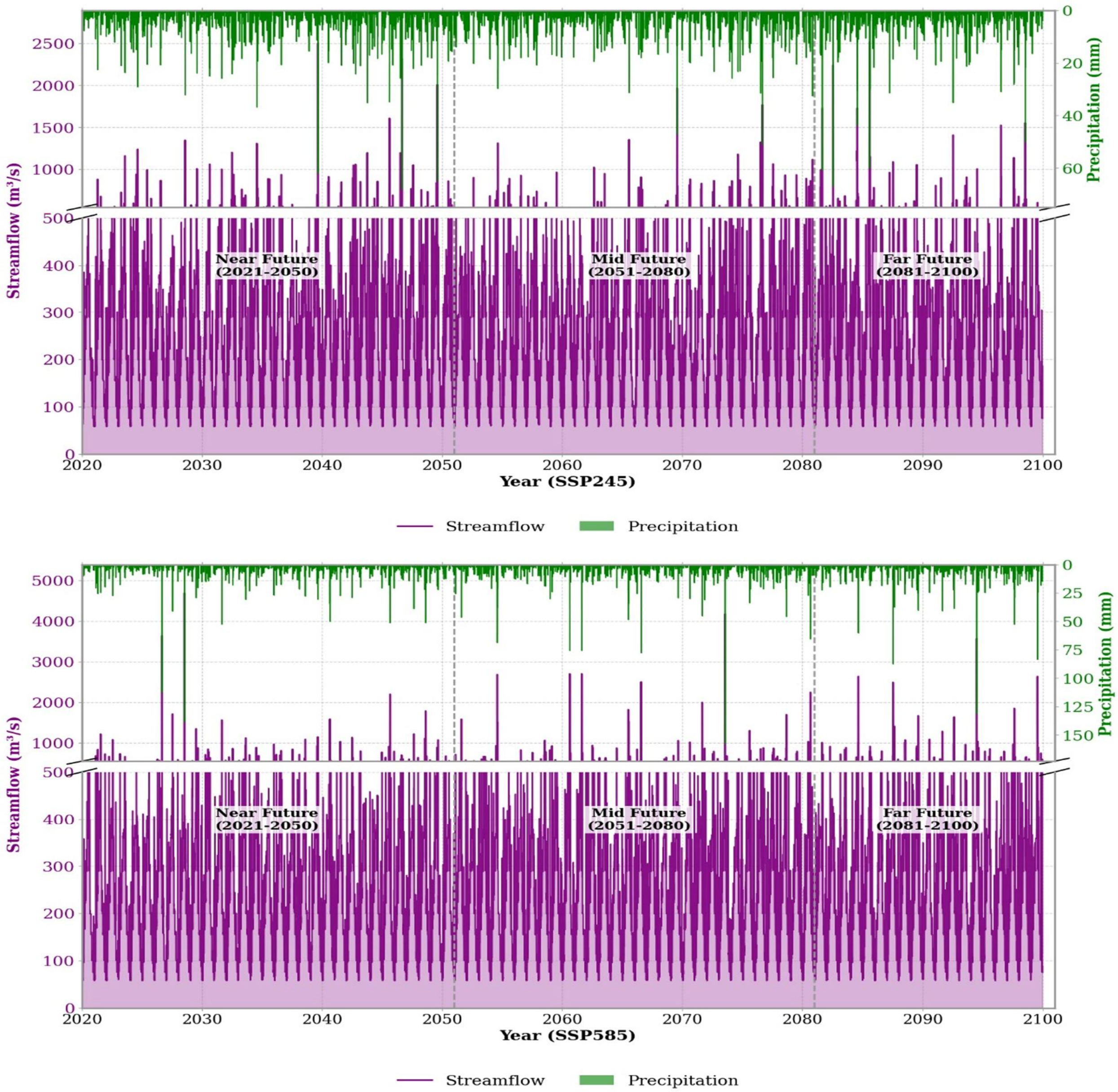

Figure 6 : Projected future daily streamflow (2020-2100) for INM-CM4-8 GCM under SSP2-4.5 and SSP5-8.8 using HEC-HMS.

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2) Projections based on INM-CM4-8 (TFT):

The future projections generated by the TFT model, presented in Figures 7, further reinforce these observations by highlighting the model's strong responsiveness to extreme climatic forcing. Under the moderate-emissions SSP2-4.5 scenario, the projected maximum streamflow attains a peak value of 3,670.0 m³/s in 2046. In contrast, the high-emissions SSP5-8.5 scenario yields an exceptionally severe flood event, with a projected peak discharge of 6,301.9 m³/s occurring in 2026, associated with an extreme precipitation event of 165.2 mm. The occurrence of this magnitude of flooding in the near future underscores the accelerated emergence of hydrological risks under high-emission pathways and highlights the urgent need for early adaptation and risk mitigation measures.

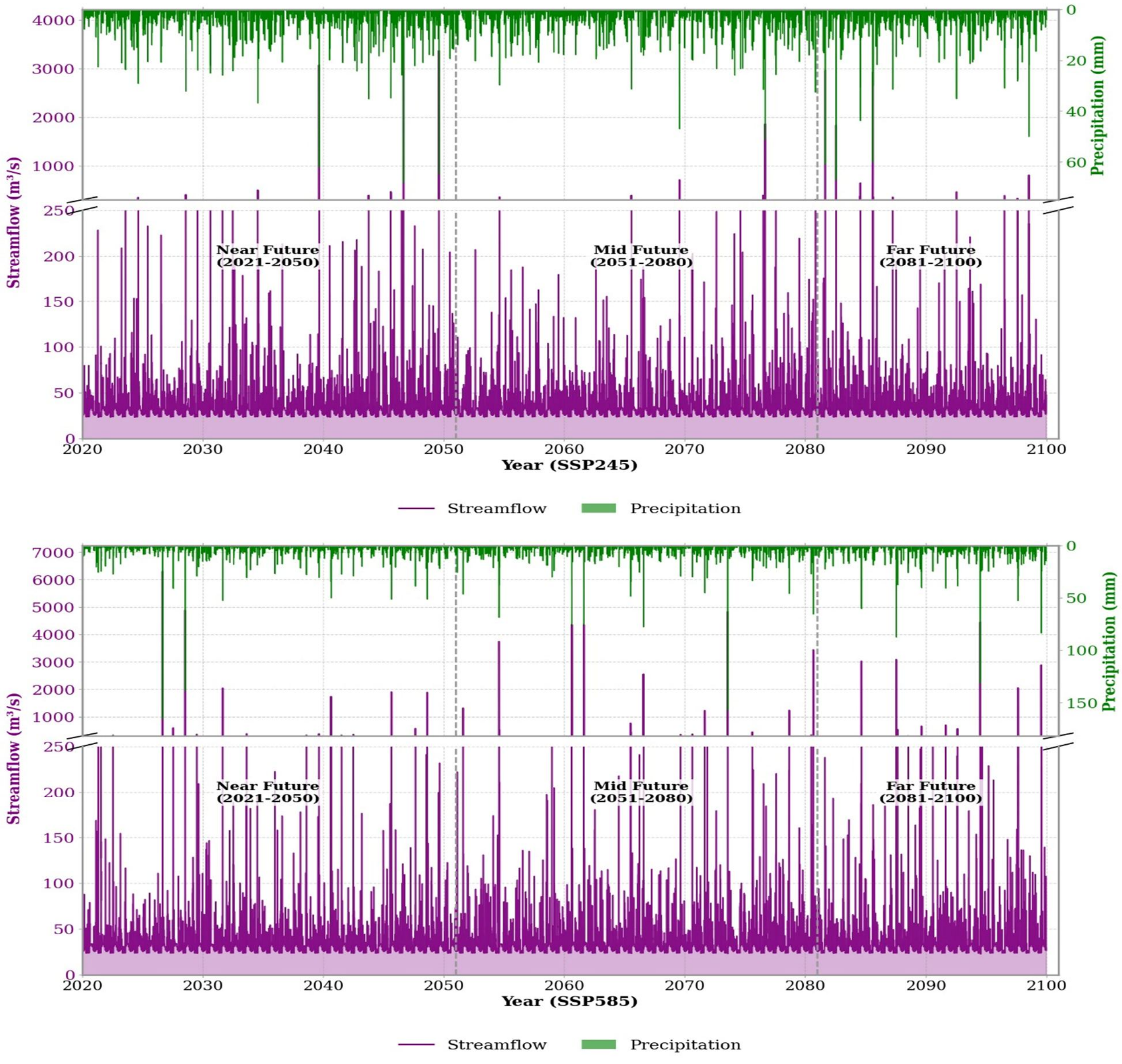

Figure 7 : Projected future daily streamflow (2020-2100) for INM-CM4-8 GCM under SSP2-4.5 and SSP5-8.8 using TFT

3) Projections based on MRI (HEC-HMS)

Figures 8 illustrate that the HEC-HMS model projects notable peak flow events during the Near Future period around 2037. Under the medium-emissions SSP2-4.5 scenario, the simulated maximum discharge reaches 2,064.3 m³/s, corresponding to a precipitation event of 52.1 mm. Under the high-emissions SSP5-8.5 pathway, the projected peak flow increases further to 2,223.9 m³/s, driven by a slightly higher rainfall intensity of 55.9 mm. These results indicate a moderate amplification of flood magnitudes under higher emission conditions during the near-term period.

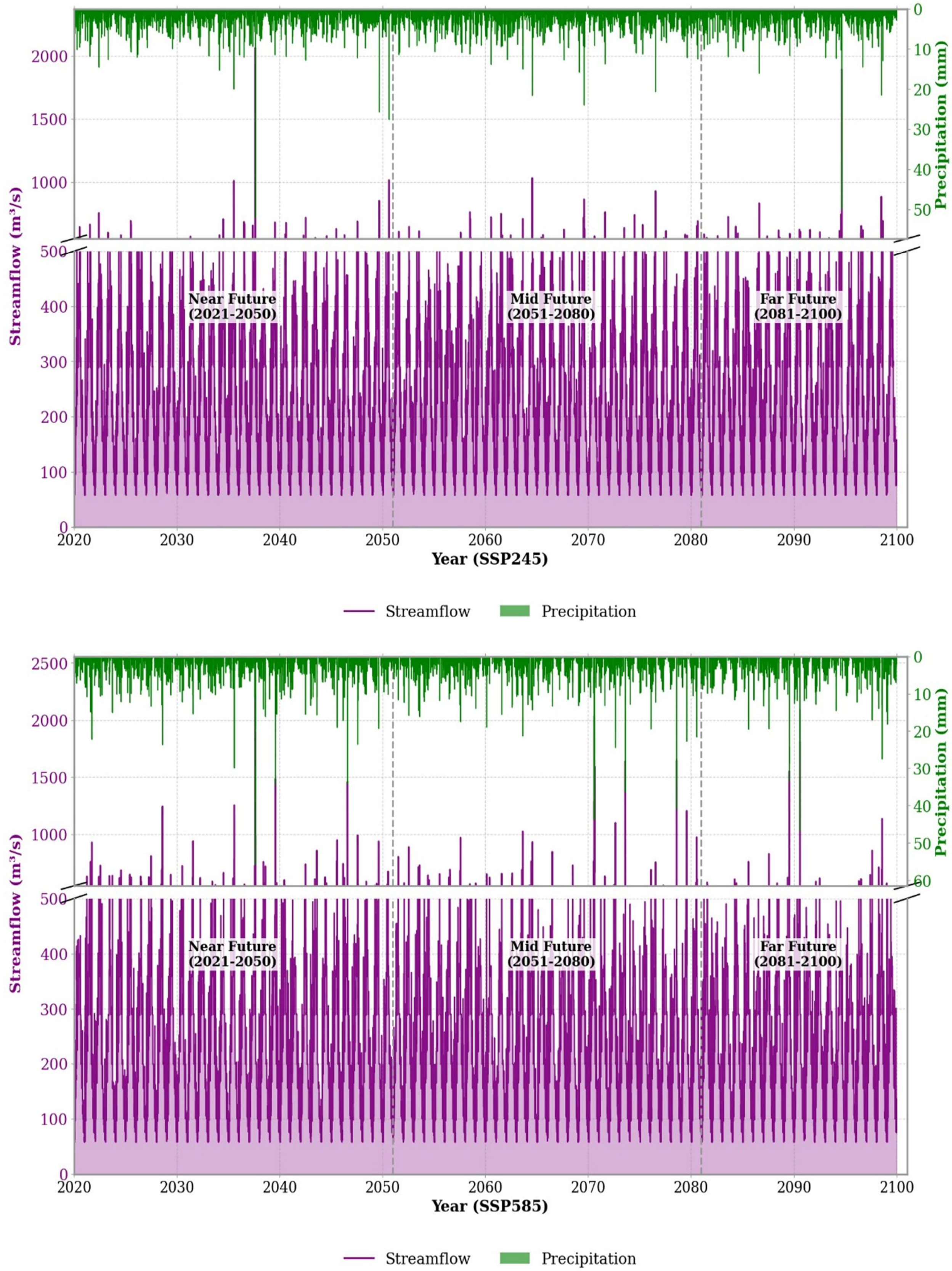

Figure 8 : Projected future daily streamflow (2020-2100) for MRI GCM under SSP2-4.5 and SSP5-8.8 using HEC-HMS

4) Projections Based on MRI (TFT)

The TFT-based projections shown in Figures 9 exhibit close consistency with the physically based HEC-HMS results. Under the SSP2-4.5 scenario, the TFT model simulated a peak discharge of 2,027.9 m³/s occurring in 2037, while under the high-emissions SSP5-8.5 pathway, the projected peak increased to 2,429.2 m³/s. The strong correspondence between the two modeling approaches for the MRI GCM enhances confidence in these projections and indicates a high likelihood of flood events exceeding 2,000 m³/s in the near-future period, particularly around 2037.

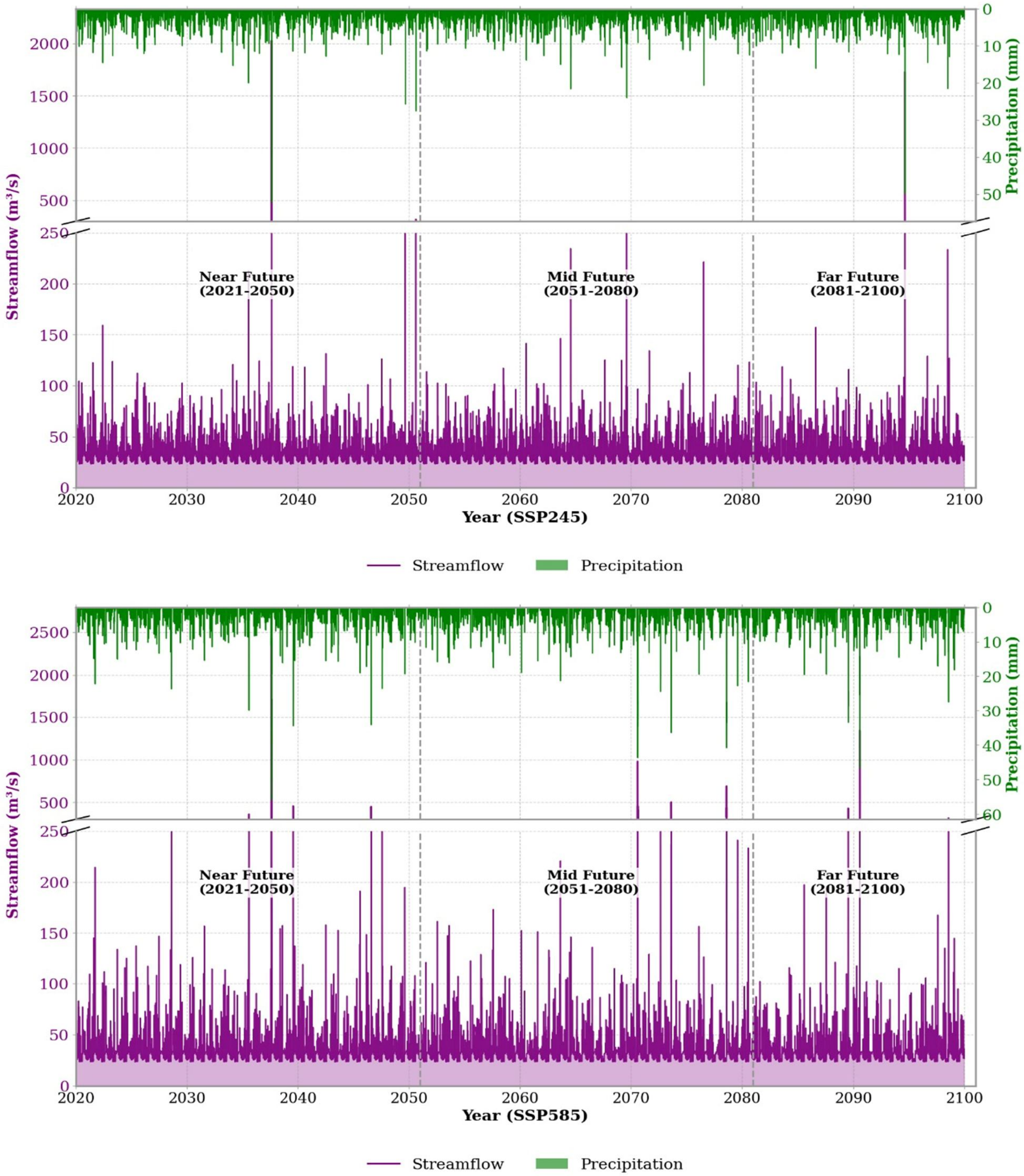

Figure 9 : Projected future daily streamflow (2020-2100) for MRI GCM under SSP2-4.5 and SSP5-8.8 using TFT

5) Projections based on GFDL (HEC-HMS)

Finally, future streamflow projections derived from the GFDL-ESM4 GCM were examined, revealing the largest contrast between the two emission pathways. The HEC-HMS simulations shown in Figures 10 indicate that under the moderate-emissions SSP2-4.5 scenario, the projected maximum peak discharge remains relatively modest and occurs in the far-future period around 2084. In contrast, under the high-emissions SSP5-8.5 scenario, the peak discharge increases substantially to approximately 2,033 m³/s and shifts temporally to the mid-future period around 2060. This pronounced change suggests that higher emission trajectories not only intensify peak streamflow but may also accelerate the occurrence of extreme hydrological events.

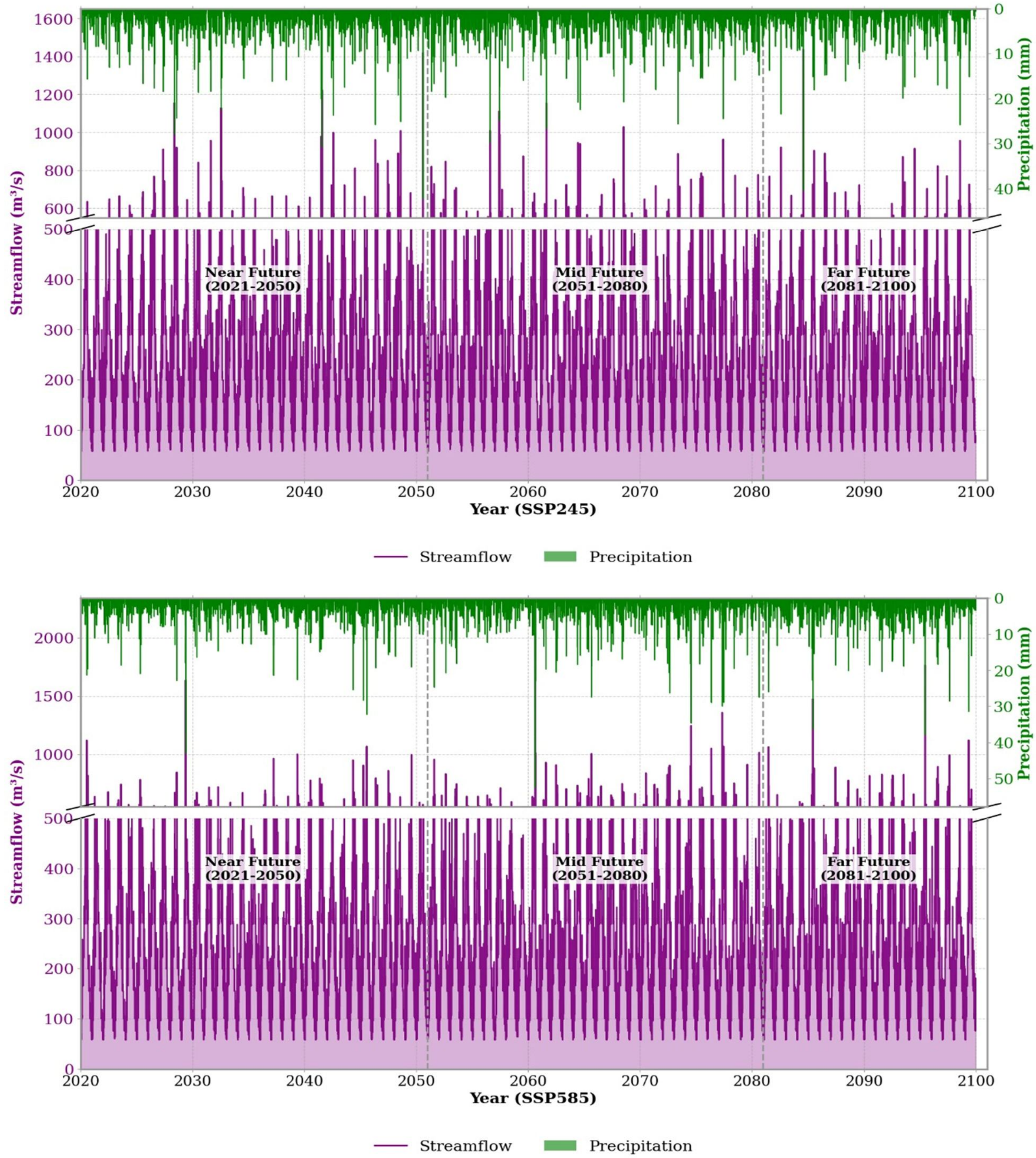

Figure 10 : Projected future daily streamflow (2020-2100) for GFDL GCM under SSP2-4.5 and SSP5-8.8 using HEC-HMS

6) Projections based on GFDL(TFT)

The TFT-based projections presented in Figures 11 reveal a pronounced sensitivity to the selected emission scenario. Under the moderate-emissions SSP2-4.5 pathway, the projected peak discharge is the lowest among all analyzed scenarios, reaching only 833.3 m³/s. In sharp contrast, the high-emissions SSP5-8.5 scenario produces a substantially larger peak flow of 2,062.5 m³/s, corresponding to an increase of approximately 147.5%. This pronounced divergence underscores the TFT model's ability to represent highly non-linear hydrological responses, particularly the amplified translation of extreme precipitation into streamflow under intensified climate forcing.

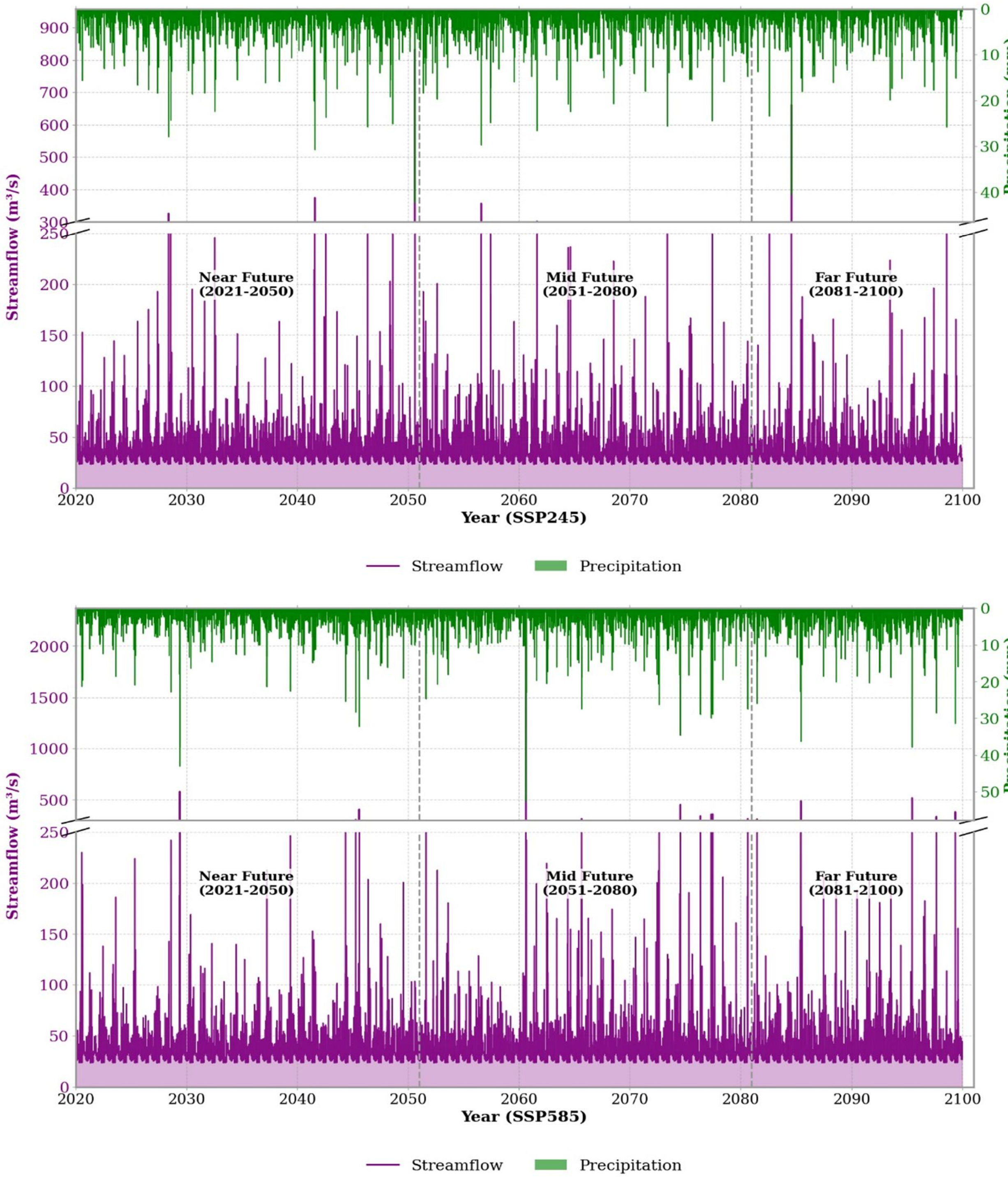

Figure 11 : Projected future daily streamflow (2020-2100) for GFDL GCM under SSP2-4.5 and SSP5-8.8 using TFT

IV. CONCLUSION

This study investigated the impacts of climate change on streamflow in the Swat River Basin, focusing on the proposed intake of the Mingora Gravity Water Supply Scheme. Two modeling approaches were employed: the physically-based, semi-distributed HEC-HMS model and the data-driven Temporal Fusion Transformer (TFT) model. Eleven downscaled CMIP6 GCMs were evaluated using Recursive Feature Elimination with Random Forest to select the top three models (INM-CM4-8, MRI-ESM-2-0, and GFDL-ESM4) for driving future streamflow projections under moderate (SSP2-4.5) and high-emissions (SSP5-8.5) scenarios.

The HEC-HMS model performed satisfactorily in both calibration and validation, reliably simulating seasonal flows and overall water balance, but it significantly underestimated extreme peak events, such as the catastrophic 2010 flood. In contrast, the TFT model demonstrated very high predictive accuracy, capturing both low and high flows effectively, including extreme flood peaks. This highlights the TFT model's superior capability to learn complex, non-linear hydrological responses from historical data and its robustness for future streamflow forecasting.

Future projections indicate substantial increases in peak flows under high-emissions scenarios, particularly for the INM-CM4-8 and TFT simulations, with some extreme events projected to occur in the near future (2020–2040). Comparisons between the two models show that while HEC-HMS provides a reliable baseline, TFT projections capture higher-magnitude floods and greater sensitivity to climate forcing, emphasizing the importance of using advanced machine learning approaches for risk assessment.

Overall, this research demonstrates that climate change is likely to intensify streamflow variability and extreme events in the Swat River Basin. The findings underscore the need for adaptive water resource planning and flood risk management, particularly under high-emission pathways. The integration of machine learning models like TFT with physically-based hydrological models provides a robust framework for improving the accuracy of streamflow projections and informing sustainable water management strategies in the region.

V. DISCUSSION

The results of this study provide a detailed assessment of streamflow dynamics in the Swat River Basin under historical and future climate scenarios, highlighting both the strengths and limitations of physically-based and machine learning modeling approaches. The HEC-HMS model successfully reproduced the general seasonal and annual streamflow patterns, as evidenced by satisfactory NSE and R^2 values during calibration and validation. Its accurate simulation of volumetric flows and baseflow demonstrates that semi-distributed, physically-based models remain reliable for routine hydrological assessments. However, as observed in the extreme flood events of 2010 and 2016, HEC-HMS substantially underestimated peak flows, consistent with the known limitations of such models in capturing highly non-linear hydrological responses under extreme precipitation events.

In contrast, the Temporal Fusion Transformer (TFT) model exhibited outstanding predictive performance, consistently achieving "Very Good" ratings across all statistical metrics, including NSE, R^2, and PBIAS. Importantly, the TFT accurately simulated historical extreme events, including the 2010 catastrophic flood, with near-perfect agreement with observed peak flows. This demonstrates the model's ability to capture complex, non-linear interactions between precipitation, antecedent flows, and seasonal factors, making it particularly suitable for projecting future flood risks under climate change. The strong alignment of observed and simulated hydrographs across both low and high flows further underscores the robustness and generalization capability of TFT models for streamflow prediction in complex basins like Swat.Future projections under SSP2-4.5 and SSP5-8.5 scenarios reveal marked increases in peak flows and overall variability, with higher emissions leading to both larger flood magnitudes and shifts in the timing of extreme events. Among the three selected GCMs, INM-CM4-8 consistently produced the highest peak flows, while the TFT model amplified these trends, capturing substantial non-linear responses to extreme precipitation. Near-future projections (2020–2040) under SSP5-8.5 highlight the potential for early-onset hydrological hazards, emphasizing the importance of proactive risk management and adaptation strategies. The comparison between HEC-HMS and TFT projections illustrates that while physically-based models provide a conventional baseline for water balance and seasonal flows, machine learning models offer enhanced sensitivity to extreme events and climate-driven variability, making them invaluable for future planning under uncertainty.

The findings have significant implications for water resource management in the Swat Basin. First, reliance solely on physically-based models may underestimate flood risk, potentially compromising the design and operation of infrastructure like the Mingora Gravity Water Supply Scheme. Second, the integration of data-driven models like TFT allows for more accurate forecasting of extreme events, enabling targeted interventions and adaptive strategies. Lastly, the use of multiple GCMs and emission scenarios ensures that uncertainties in climate projections are systematically considered, providing a more comprehensive understanding of potential future hydrological conditions.

In summary, this study highlights the complementary strengths of physically-based and machine learning approaches, demonstrating that the combination of HEC-HMS and TFT models provides a robust framework for streamflow prediction under climate change. The results underscore the urgency of incorporating high-emission scenario projections into regional water management planning, particularly for flood mitigation, infrastructure design, and long-term sustainability of water resources in the Swat Basin.

VI. LIMITATIONS

Future studies should enhance streamflow simulations in the Swat River Basin by incorporating temperature related parameters, particularly to better represent snowmelt and evapotranspiration processes that were not considered in this study. While the constant baseflow and lag routing methods provided satisfactory results, alternative baseflow separation and routing techniques available in HEC-HMS should be explored to improve the representation of groundwater contributions and flood wave dynamics. Additionally, the integration of hybrid modeling approaches that combine physically-based models with advanced machine-learning techniques, such as the TFT model, is recommended to further improve the reliability of future streamflow projections and support climate-resilient water resource planning.

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