Enhancing SWAT Streamflow Simulations Using Remote Sensing and Physics-Guided Machine Learning in a Himalayan Sub-Basin.

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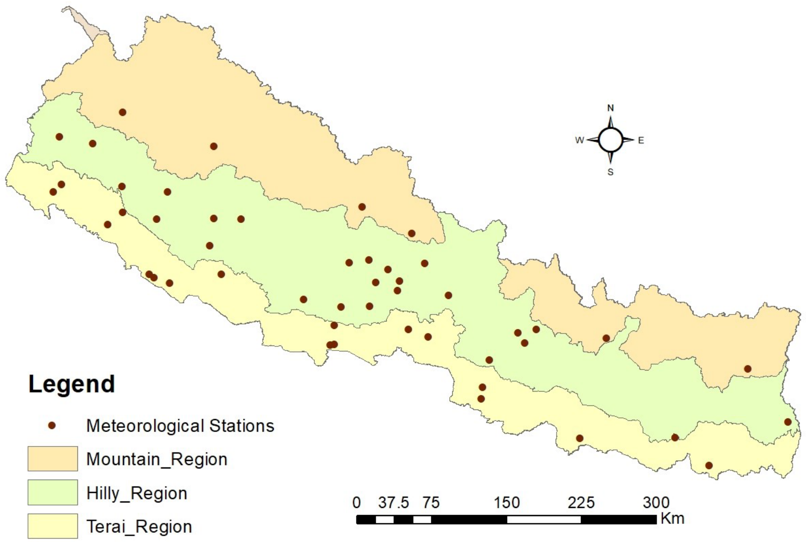
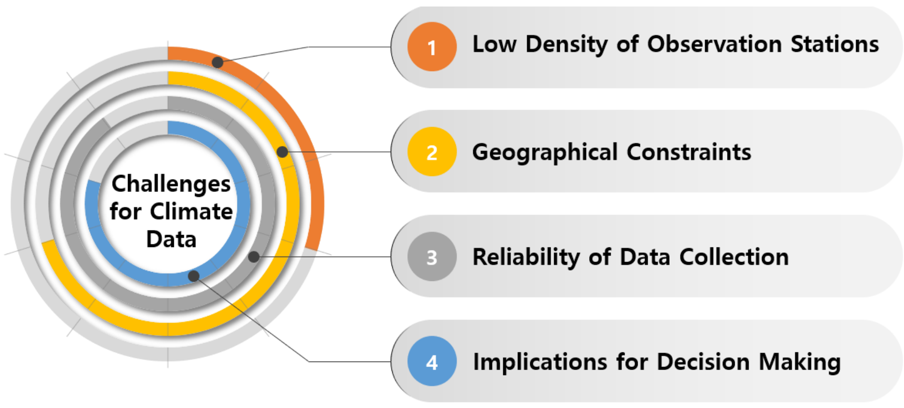
1.1 Background of the study





Low Density of Stations:

- characterized by a low density of stations, resulting in limited data coverage across the country.
- Uneven distribution of stations, with fewer stations in higher Himalayan regions, poses challenges in capturing comprehensive climate data.

Geographical Constraints:

- The majority of meteorological stations are situated on foothills, leading to data inconsistencies and limited representation of higher elevation climate patterns.
- Difficulties in operating and maintaining stations, particularly in remote and inaccessible areas, contribute to gaps and poor data quality.

Gaps in Data Collection:

- Meteorological stations in higher regions often experience data gaps and discontinuities, primarily due to challenging terrain and adverse weather conditions.
- Inadequate infrastructure and technical constraints further contribute to the intermittent and incomplete nature of data collection in these regions.

Implications for Decision-Making:

- Insufficient and uneven meteorological data coverage hinders accurate climate assessments.

1.2 Problem Statement

Hydrological models like SWAT often underperform in mountainous basins due to sparse ground data, complex terrain, and difficulty capturing low-flow and peak-flow events.

Pure machine learning models improve accuracy but lack physical interpretability, making them unreliable for hydrological decision-making and transferability.

There is a critical need for a hybrid modeling approach that combines the strengths of physics-based models and remote sensing-driven machine learning to improve both prediction accuracy and interpretability.

1.3 Objectives of the Work

Enhance

Enhance SWAT streamflow simulations by integrating a residual correction layer using machine learning models (RF, XGBoost, LSTM, PG-LSTM).

Leverage

Leverage remote sensing products (GPM, MODIS NDVI, LST) to improve spatial and temporal representation of hydrological drivers in data-scarce basins.

Ensure

Ensure model interpretability and transferability by applying SHAP to quantify the contribution of each input and enable transparent decision-making in complex mountainous terrain.

2.1 Framework of the Research

Step 1: Calibrate SWAT using ground-based rainfall, ET, temperature, and observed streamflow at outlet

Step 2: Extract satellite-derived products (GPM, MODIS NDVI, LST)

Step 3: Compute residuals = observed – SWAT simulated streamflow

Step 4: Train ML models (RF, XGBoost, LSTM, PG-LSTM) to predict residuals using RS inputs

Step 5: Correct SWAT output using ML predictions

Step 6: Evaluate models using NSE, KGE, RMSE,PBIAS

Step 7: Apply SHAP for interpretability (only for RF/XGBoost)

2.2 Description- SWAT model

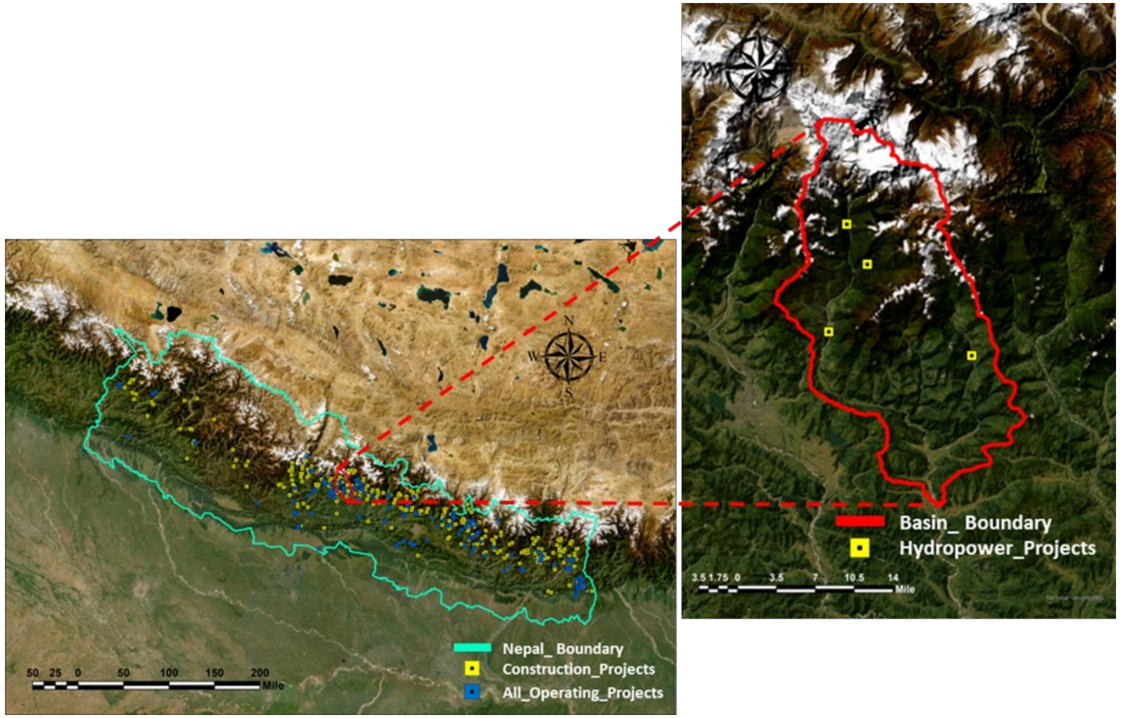
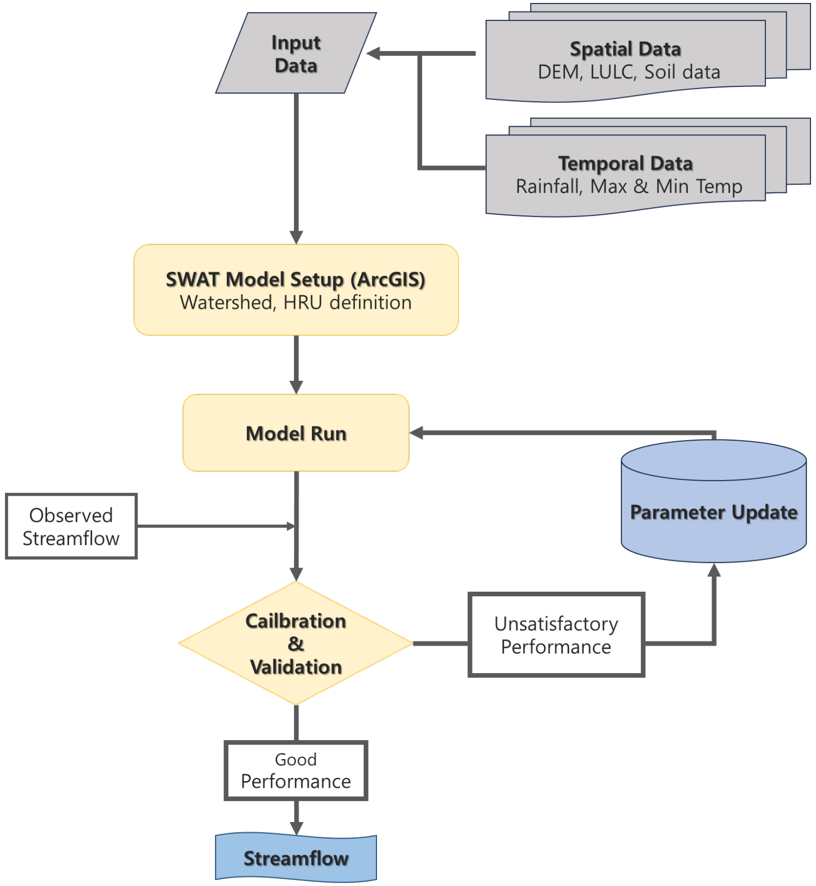


Figure. Location of Study Area

SWAT Model



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

SW_0= Initial Water content (mm)

R_{day}= Amount of rainfall on day i. (mm)

Q_{surf}= Surface runoff on day i(mm)

Ea= Amount of Evapotranspiration on day i(mm) –Hargreaves

Wseep= Amount of water percolating on day i. (mm)

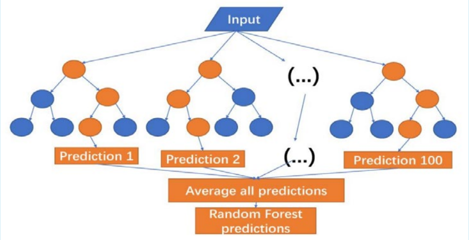
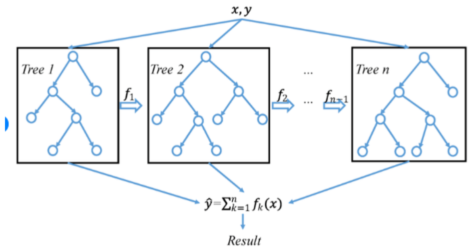
Qgw= Amount of return flow on day i. (mm)

T= time (days)

1. **Model Setup**
   - Precipitation data from 5 stations
   - Temperature data from 3 stations
2. **Calibration Period (2002-2011)**
   - Warm-up period (2000-2001)
   - SWAT-CUP - initial parameter calibration

3. Validation Period (2012-2019)

2.2 Description- Machine Learning Models for SWAT Residual Correction

Model	Description	Purpose	Key Input Features
Random Forest (RF) 	➢ Ensemble of decision trees trained on random subsets of data and features ➢ Reduces overfitting through averaging ➢ Handles complex nonlinear relationships well.	❑ Learns the residuals (Observed – SWAT) to correct SWAT bias ❑ Provides robust post-processing across all flow regimes.	○ SWAT-simulated streamflow ○ Observed precipitation ○ Satellite precipitation (GPM) ○ Vegetation index(MODISNDVI) ○ Evapotranspiration
XGBoost (Extreme Gradient Boosting) 	➢ Boosting-based model that builds trees sequentially to reduce residuals ➢ Incorporates regularization to prevent overfitting. ➢ Efficient and highly accurate on structured/tabular data.	❑ Refines SWAT predictions with strong emphasis on low- and high-flow events. ❑ Learns complex correction patterns from remote sensing and observational data	○ SWAT-simulated streamflow ○ Observed precipitation ○ Satellite precipitation (GPM) ○ Vegetation index(MODISNDVI) ○ Evapotranspiration

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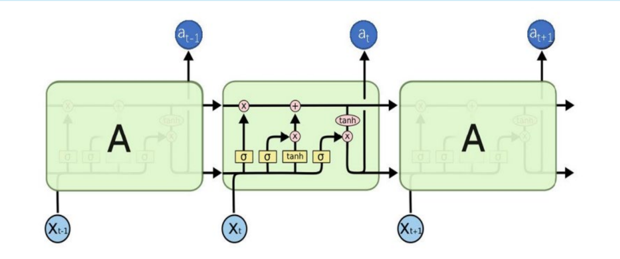
2.2 Description- Machine Learning Models for SWAT Residual Correction

Model	Description	Purpose	Key Input Features
LSTM (Bidirectional Long Short-Term Memory) 	✅ Uses two stacked bidirectional LSTM layers to capture both forward and backward temporal dependencies. ✅ Learns directly from observed streamflow sequences without applying physical constraints. ✅ Final dense layer outputs streamflow predictions from remote sensing and climate inputs.	✅ Predicts full streamflow directly from remote sensing and observational datasets. ✅ Useful in data-driven forecasting where physical simulations are absent or unreliable..	◆ Observed precipitation (PCP) ◆ Satellite precipitation (GPM) ◆ Vegetation index (MODIS NDVI) ◆ Evapotranspiration
PG-LSTM (Physics-Guided Long Short-Term Memory)	✅ LSTM network optimized with dropout, batch normalization, and hyperparameter tuning. ✅ Learns log-residuals between observed and SWAT-simulated flows. ✅ Combines physical consistency (SWAT) with data-driven correction using residual learning.	✅ Post-processes SWAT output by learning model errors. ✅ Preserves hydrological realism and improves predictions in both low and high flow periods. ✅ Emphasizes monsoon and high-flow periods using a weighted loss function.	◆ SWAT-simulated streamflow ◆ Observed precipitation (PCP) ◆ Satellite precipitation (GPM) ◆ Vegetation index (MODIS NDVI) ◆ Evapotranspiration

SWAT Modelling -- Calibration

Observed Rainfall-Runoff Pattern

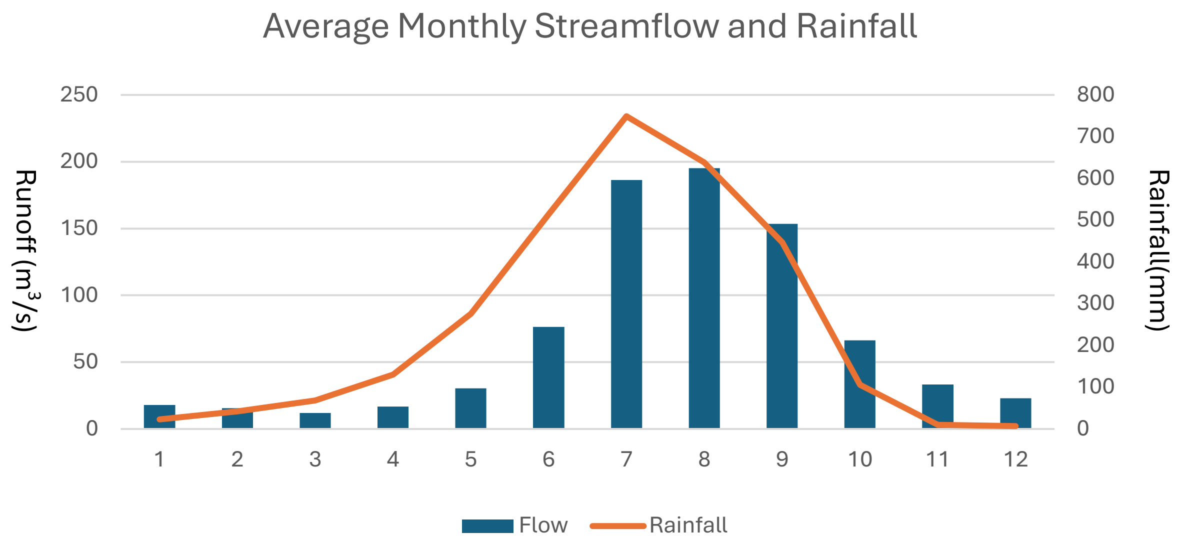


Table : List of Parameters selected for calibration

Parameter_Name	Fitted_Value	Min_value	Max_value
1:R__CN2.mgt	-0.198	-0.349	-0.184
2:R__CN2.mgt	-0.216	-0.256	-0.156
3:V__ALPHA_BF.gw	0.626	0.435	0.837
4:V__GW_DELAY.gw	206.941	132.410	261.580
5: V__GWQMN.gw	2294.074	1804.000	3390.000
6:R__CH_N1.sub	-0.012	-0.169	0.022
7:R__CH_N2.rte	-0.011	-0.054	0.149
8:V__TLAPS.sub	-9.031	-10.000	-6.500
9:V__SURLAG.bsn	12.878	8.217	14.717
10:R__SOL_BD(..).sol	0.155	-0.009	0.161
11:R__GW_SPYLD.gw	-0.001	-0.043	0.042
12:R__OV_N.hru	0.036	0.000	0.230
13:V__SNOCOVMX.bsn	165.542	135.040	205.160
14:V__GDRAIN_BSN.bsn	66.698	60.405	76.178
15:R__SOL_K(..).sol	-0.018	-0.111	0.091
16:R__SOL_AWC(..).sol	0.009	0.006	0.020
17:V__LAT_TTIME.hru	22.704	21.297	63.918
18:V__GW_REVAP.gw	0.098	0.070	0.118
19:V__REVAPMN.gw	356.354	310.480	436.856
20:V__SFTMP.bsn	1.5	-0.166	3.500
21:V__SMTMP.bsn	-0.950	-2.218	0.594
22:V__TIMP.bsn	0.602	0.444	0.749
23:V__SMFMX.bsn	3.451	2.537	4.537
24:V__SMFMN.bsn	3.627	2.713	4.537
25:V__RCHRG_DP.gw	0.505	0.378	0.611
26:V__ESCO.bsn	0.275	0.097	0.349
27:V__EPCO.bsn	0.247	0.116	0.324
28:V__SNO50COV.bsn	0.646	0.620	0.807
29:V__CANMX.hru	7.069	0.000	53.150
30:R__SOL_Z(..).sol	0.245	-0.041	0.279

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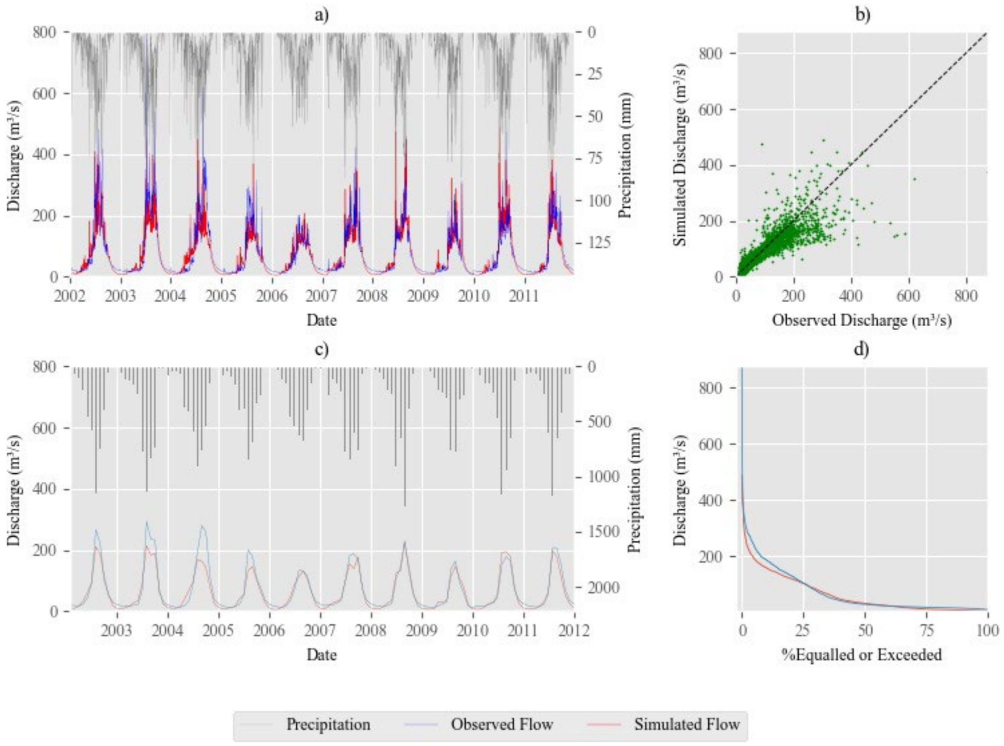
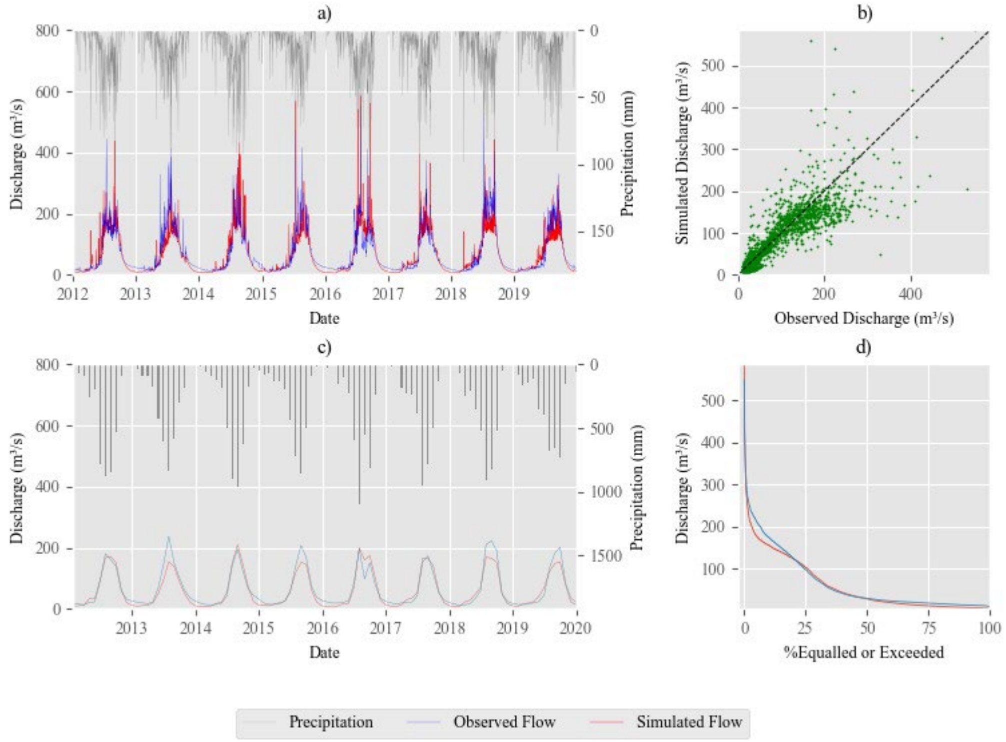
1. SWAT Modelling: Calibration



Statistic	Mean Flows(m³/s)		Standard Deviation (m³/s)		Performance Indicators			
	Observed	Simulated	Observed	Simulated	NSE	PBIAS	RSR	KGE
Calibration (2002-2011)	70.04	62.74	80.39	68.25	0.77	10.41%	0.48	0.78

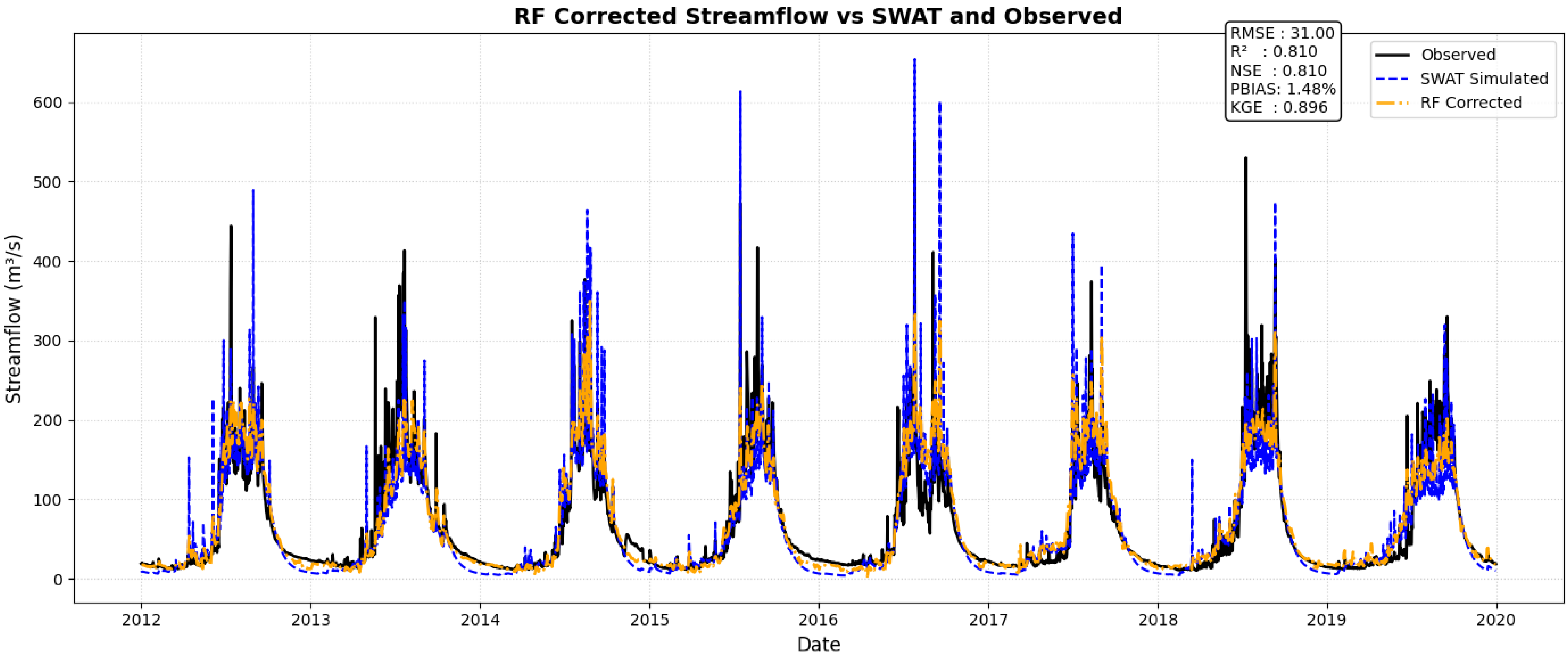
2. SWAT Modelling: Validation

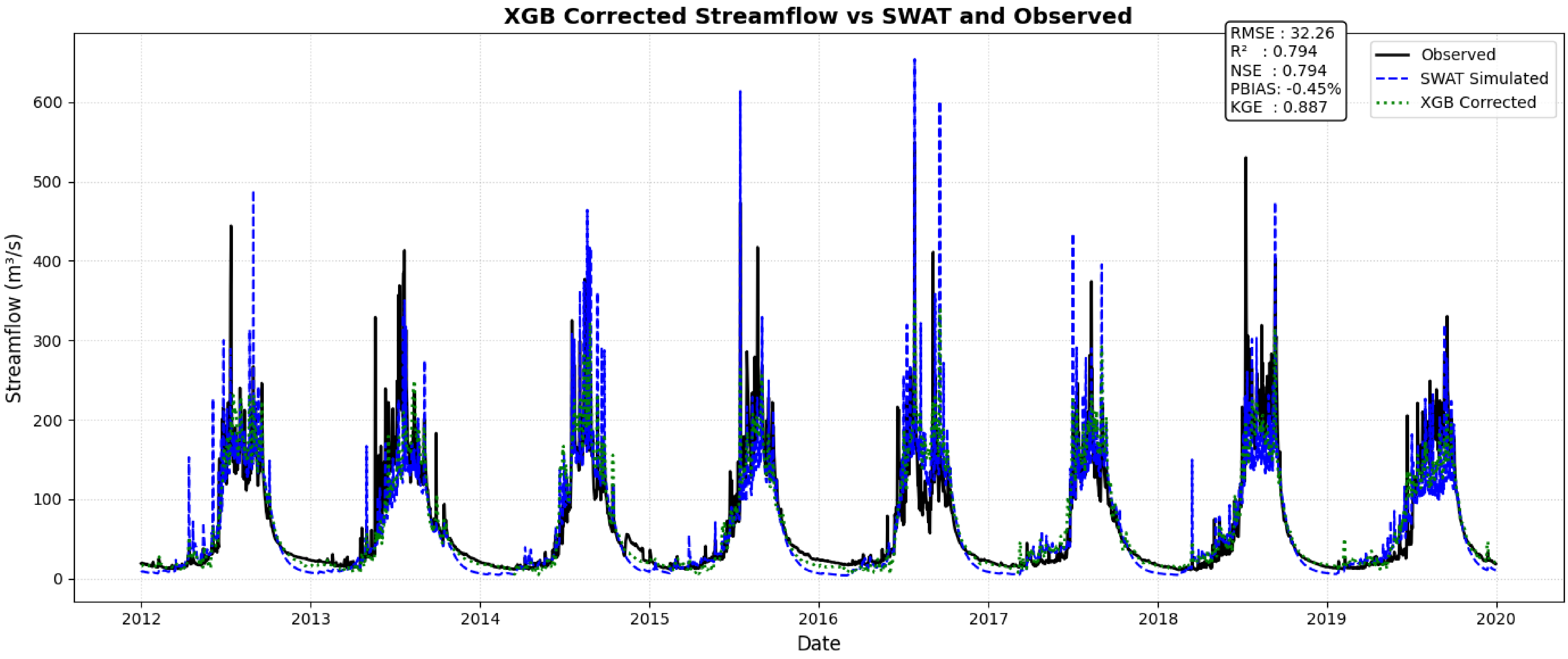


Statistic	Mean Flows(m³/s)		Standard Deviation (m³/s)		Performance Indicators			
	Observed	Simulated	Observed	Simulated	NSE	PBIAS	RSR	KGE
Validation (2012-2019)	66.28	60.78	71.07	66.77	0.77	8.29%	0.48	0.85

Figure 1 (a)Daily Simulated and observed hydrograph for calibration (2002-2011) period. (b) Scatter plot of simulated and observed discharge. (C) Monthly Simulated and observed hydrograph for calibration (2002-2011) period. (d) FDC of observed and simulated flow.

Figure 2 (a)Daily Simulated and observed hydrograph for validation (2012-2019) period. (b) Scatter plot of simulated and observed discharge. (C) Monthly Simulated and observed hydrograph for validation (2002-2011) period. (d) FDC of observed and simulated flow.


RF Corrected Streamflow vs SWAT and Observed
RMSE : 31.00
R² : 0.810
NSE : 0.810
PBIAS: 1.48%
KGE : 0.896
Observed
SWAT Simulated
RF Corrected
Streamflow (m³/s)
0
100
200
300
400
500
600
2012
2013
2014
2015
2016
2017
2018
2019
2020
Date



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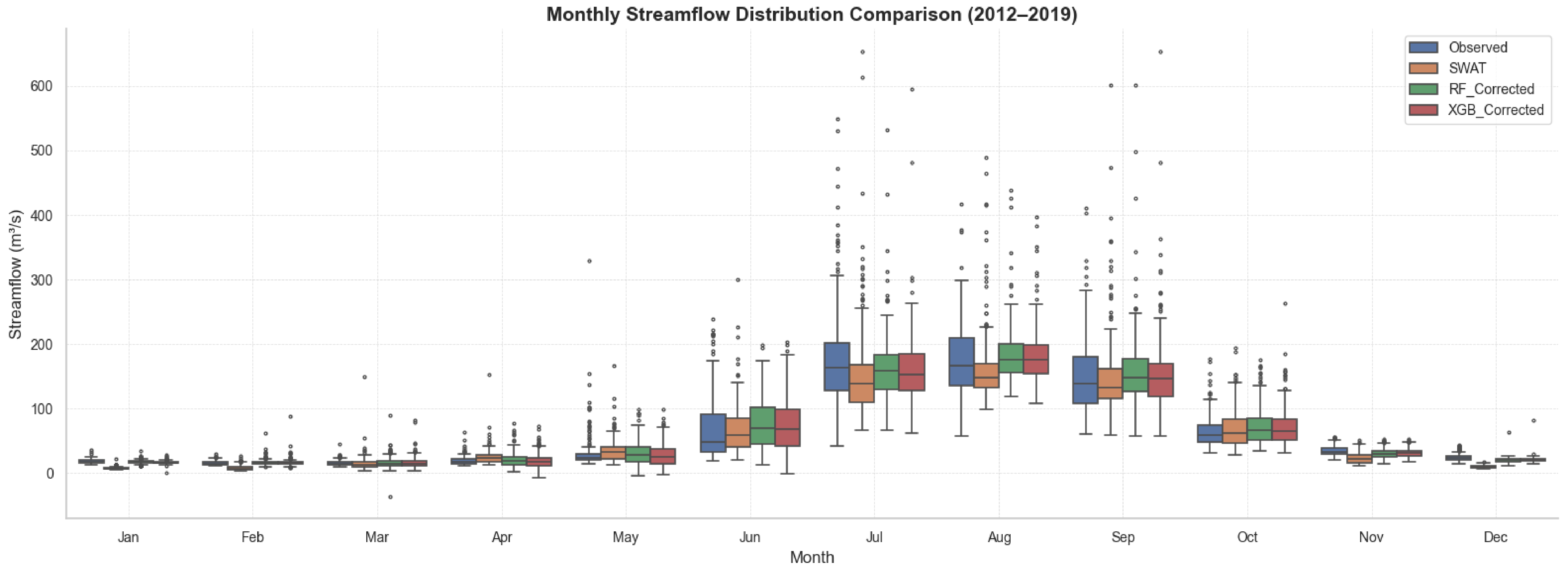

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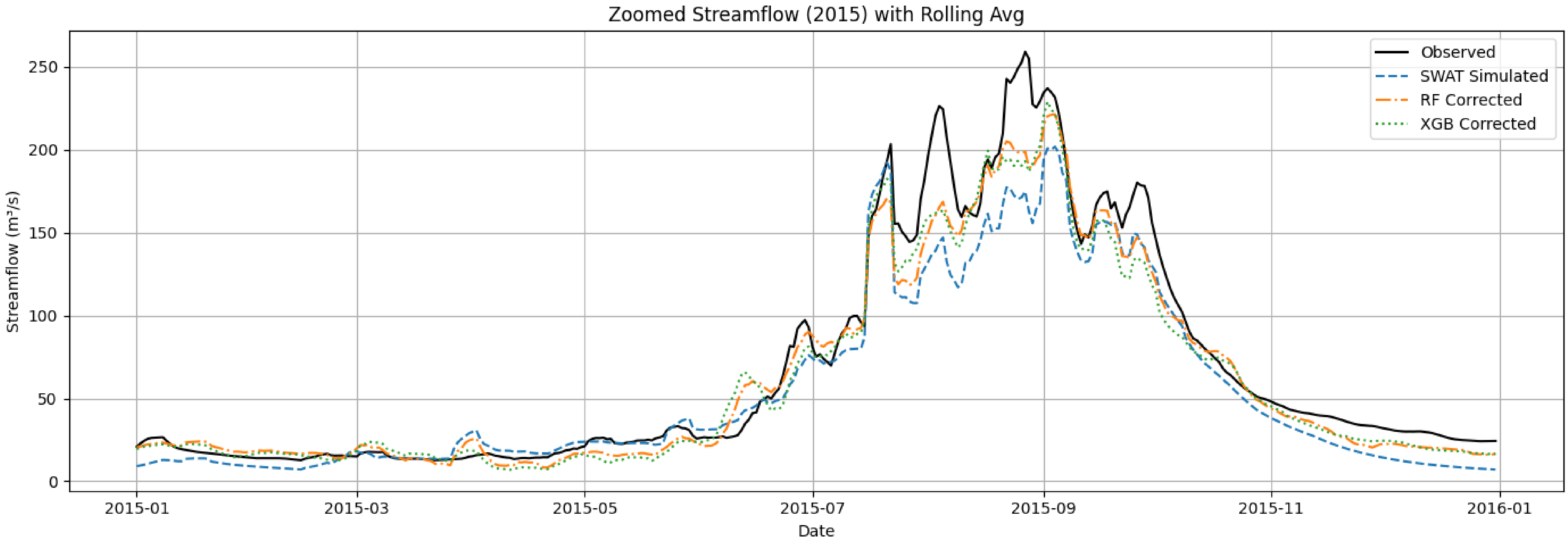
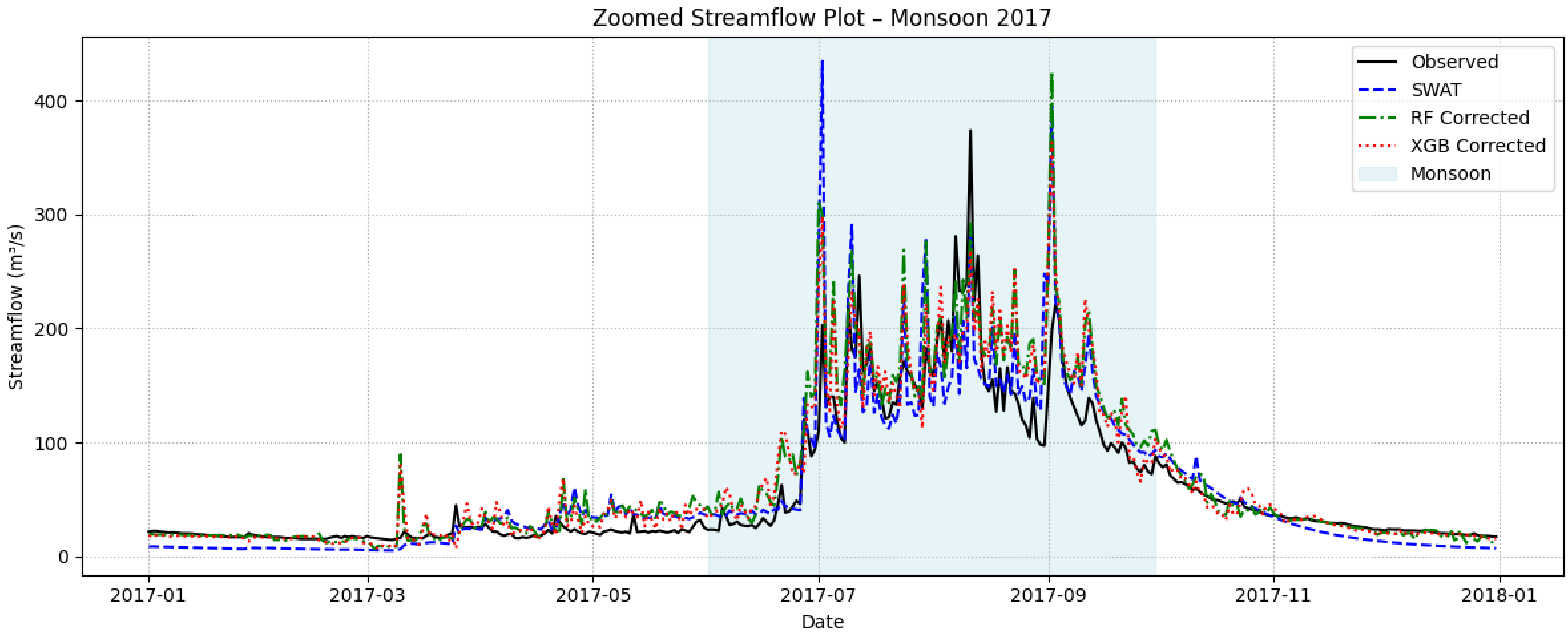
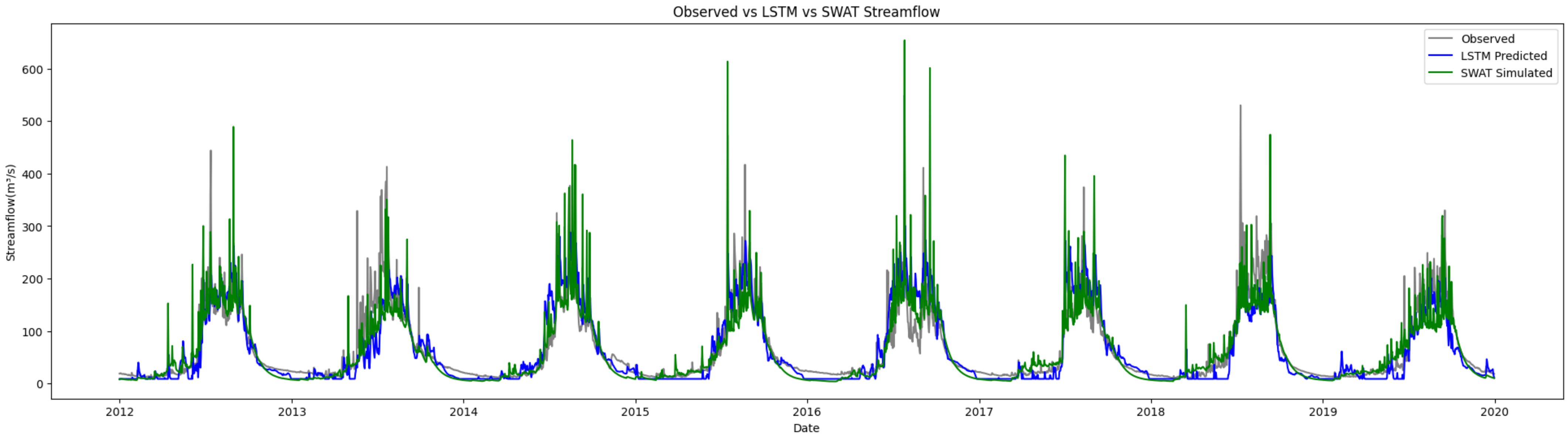
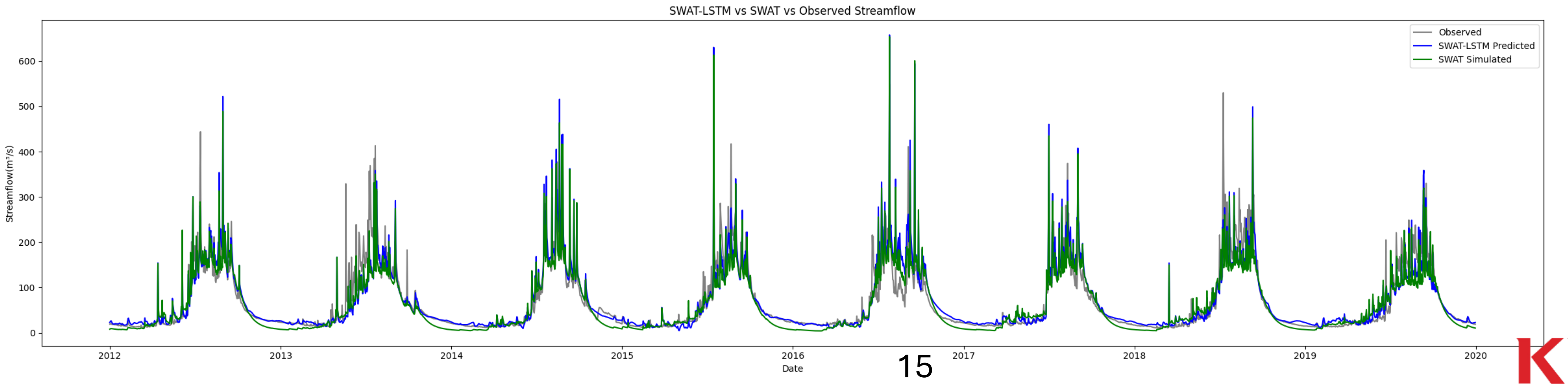

Zoomed Streamflow (2015) with Rolling Avg
Observed
SWAT Simulated
RF Corrected
XGB Corrected
Streamflow (m³/s)
0
50
100
150
200
250
2015-01
2015-03
2015-05
2015-07
2015-09
2015-11
2016-01
Date


Zoomed Streamflow Plot – Monsoon 2017
Streamflow (m³/s)
400
300
200
100
0
2017-01
2017-03
2017-05
2017-07
2017-09
2017-11
2018-01
Date
Observed
SWAT
RF Corrected
XGB Corrected
Monsoon



LSTM
RMSE: 36.721
R^2: 0.733
NSE: 0.733
PBIAS: 8.24%
KGE: 0.835



SWAT-LSTM
RMSE: 33.190
R^2: 0.782
NSE: 0.782
PBIAS: -3.31%
KGE: 0.887

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Preliminary Conclusion

🔷 Hybrid Modeling Advantage

→ Successfully integrated **process-based (SWAT)** and **data-driven models (ML/DL)** to enhance streamflow prediction in a Himalayan basin.

🌐 Power of Remote Sensing

→ Leveraged multi-source RS data—**GPM precipitation**, **MODIS NDVI** to enrich input features and compensate for sparse ground observations.

🔹 SWAT Baseline Insights

→ Captured seasonal variability but **underestimated peak flows** and lagged in timing—especially during monsoon periods.

📊 ML Residual Correction Performance

→ **Random Forest** showed the best **overall statistical metrics** (e.g., RMSE, NSE, KGE).
→ **XGBoost** excelled in **monsoon dynamics**, better aligning with peak flow timing and magnitude.

📊 Strength of PG-LSTM (Physics-Guided LSTM)

→ Trained on **log-residuals between observed and SWAT flows**, PG-LSTM retained **physical consistency** while improving predictive accuracy.
→ Outperformed standalone LSTM, with **lower bias** and **higher NSE/KGE**.

🌱 Key Takeaway

→ The study highlights the value of **hybrid, remote sensing-informed models** for improving streamflow predictions—critical for **climate resilience, water planning, and hydropower development** in data-scarce regions.

Future Directions

🧩 Explainable AI for Hydrology

→ Apply SHAP (SHapley Additive Explanations) to interpret feature importance and understand the role of remote sensing inputs in streamflow correction across ML models.

🌐 Model Transferability to Ungauged Basins

→ Test model robustness in ungauged or sparsely monitored catchments, exploring generalization across diverse topographic and climatic conditions.

📈 Integration with Climate Projections

→ Incorporate bias-corrected CMIP6 GCM outputs into the PG-LSTM framework to enable future streamflow prediction and support climate adaptation planning.

🚧 Operationalization for Water Infrastructure

→ Translate model outputs into real-time or scenario-based decision support tools for hydropower design, reservoir operation, and flood forecasting in data-scarce Himalayan regions

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Thank you for your attention

Question & Answer

Feedbacks and further queries are appreciated @
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LSTM MODEL:

- To develop a Long Short-Term Memory (LSTM) network capable of directly predicting observed streamflow, with a specific focus on improving the accuracy of flow predictions by utilizing a specialized loss calculation during model training.

Section	Details
1. Data Preparation & Preprocessing	**Inputs**: Observed streamflow, meteorological variables (rainfall, temperature) **Target Variable**: Observed streamflow **Scaling**: MinMaxScaler (0–1) **Sequence Creation**: 30 day rolling window for LSTM input format
2. Train-Test Split	**Training Set**: 2002- 2011 **Testing Set**: 2012-2019 **Preservation**: SWAT and observed streamflow retained for evaluation
3. LSTM Model Development	**Architecture**: 1 LSTM layer, dropout (0.0–0.4), final Dense layer for residual output **Optimization**: RandomSearch (10 trials), learning rates [1e-2, 1e-3, 5e-4, 1e-4] **Training Strategy**: MSE loss, Adam optimizer, EarlyStopping.
4. Prediction & Hybridization	**Best Model Selection**: Based on lowest validation loss **Prediction**: Inverse-transform and clip negative values **Post-processing**: Ensure physically realistic (non-negative) flow values
5. Model Evaluation	**Test Metrics**: RMSE, R^2, NSE, PBIAS, KGE:

Hybrid SWAT-LSTM MODEL:

- To improve the accuracy of streamflow simulations by synergistically combining a physically-based hydrological model (SWAT) with a data-driven Long Short-Term Memory (LSTM) network.
- The LSTM component aims to learn and correct the systematic errors or residuals present in the initial SWAT model outputs, leading to a more robust and precise final prediction

Section	Details
1. Data Preparation & Preprocessing	**Inputs**: Observed streamflow, SWAT output, meteorological variables (Rainfall, temperature, ET) **Target Variable**: Residual = Observed − SWAT Simulated **Scaling**: MinMaxScaler (0–1) **Sequence Creation**: 30-day rolling window (lookback) for LSTM input format
2. Train-Test Split	**Training Set**: 2002- 2011 **Testing Set**: 2012-2019 **Preservation**: SWAT and observed streamflow retained for evaluation
3. LSTM Model Development	**Architecture**: 2 LSTM layers, dropout (0.0–0.4), final Dense layer for residual output **Optimization**: RandomSearch (10 trials), learning rates [1e-2, 1e-3, 5e-4, 1e-4] **Training Strategy**: MSE loss, Adam optimizer, EarlyStopping.
4. Prediction & Hybridization	**Best Model Selection**: Based on lowest validation loss **Residual Forecasting**: Applied on test set, inverse transformed **Final Output**: Predicted Flow = SWAT Simulated + LSTM Predicted Residual
5. Model Evaluation	**Test Metrics**: RMSE, R^2, NSE, PBIAS, KGE: