

Project Course CE:299

Coupling SWAT and LSTM for
Improving Daily Streamflow
Simulation in Mahanadi Basin

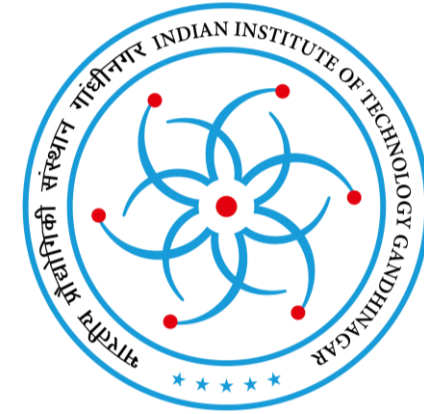
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Introduction

Importance of streamflow simulation in hydrology

SWAT: Robust but limited by assumptions and biases

LSTM: Learns patterns from historical data

Hybrid SWAT-LSTM model aims to improve prediction accuracy





Objective

To improve streamflow simulation accuracy by coupling the SWAT model with an LSTM-based post-processing approach that reduces errors and bias, particularly during high and low flow periods.

Study Area and Data

This study primarily focuses on the Tikarpara station, a key location within the Mahanadi basin that lies downstream of most tributaries. Tikarpara is strategically important due to its proximity to the Hirakud Dam and its relevance in flood monitoring and water resource management.

Data Used for Study



Daily precipitation data was collected. Data ranges from 1951 to 2019.

Daily temperature data was collected. Data ranges from 1951 to 2019.

Temperature 



Observed Streamflow

Daily streamflow observations were collected. Data ranges from 1973 to 2013.

DEM covering the Mahanadi River Basin.

Digital Elevation Model 



Land Use Data

Land Use and Land Cover (LULC) data used.

Soil data was collected for the study area.

Soil Data 

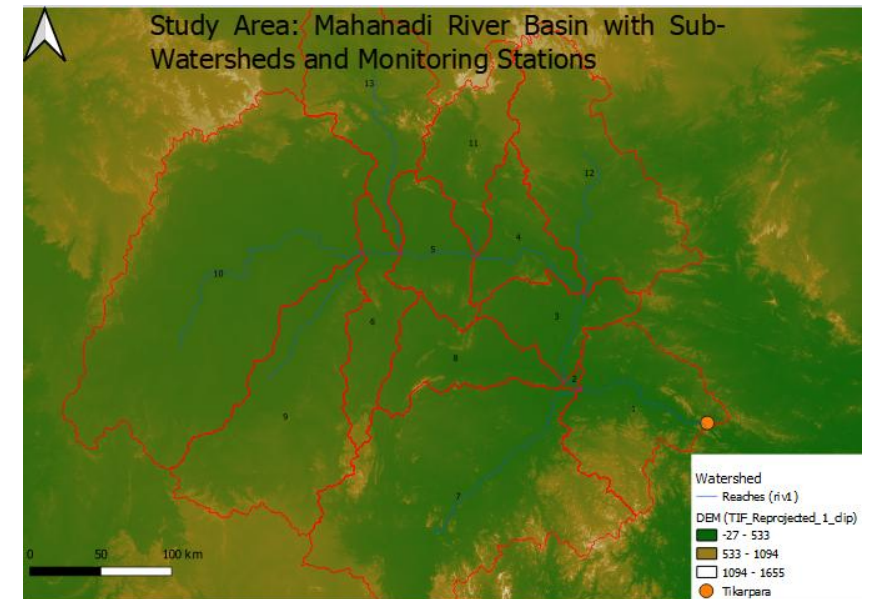
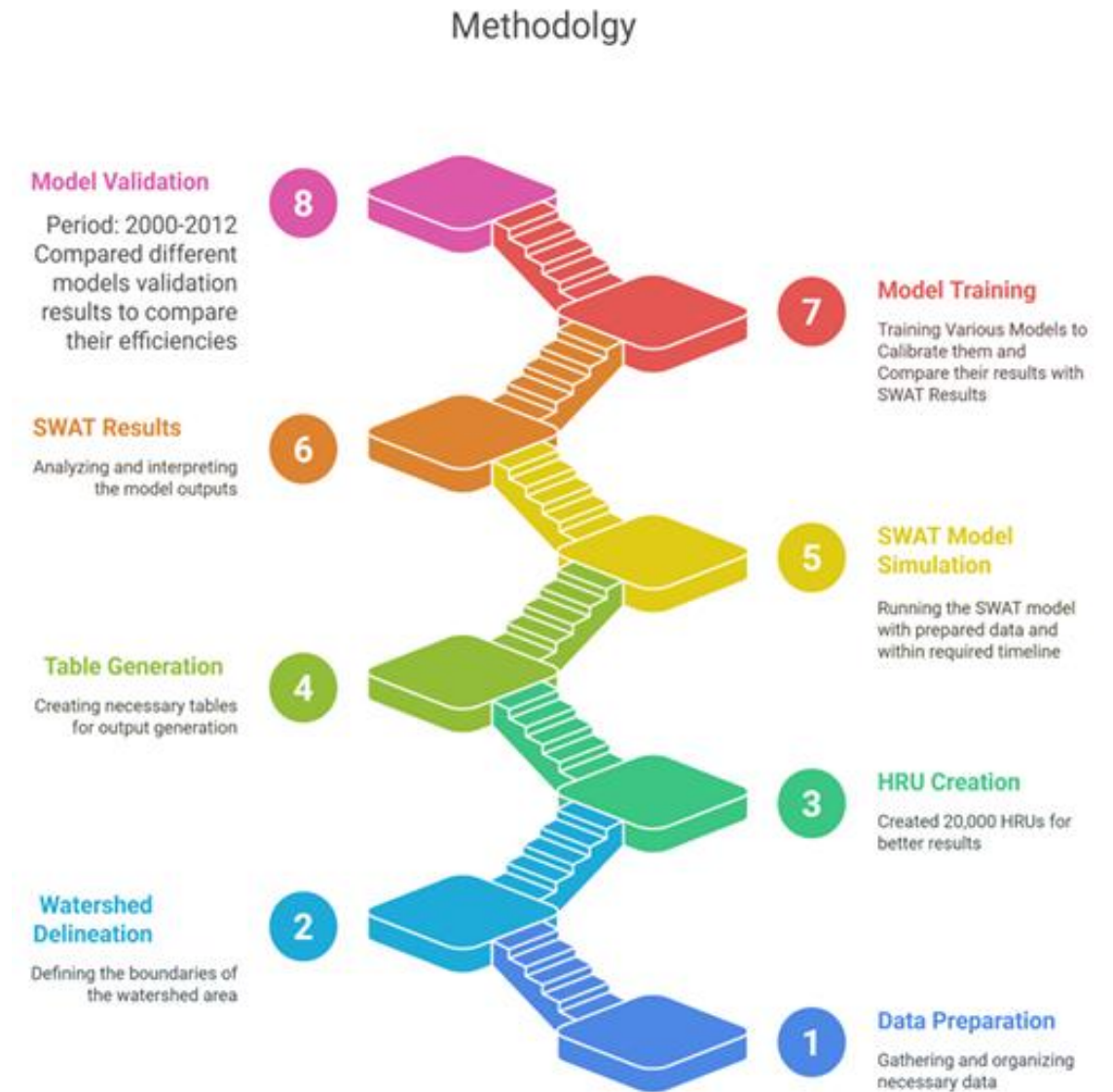


Fig.1 Area of Study

Methodolgy



Results

SWAT Model Performance (1951–2013):

NSE : -0.5447

R^2 : -0.5447

RMSE : 3885.93 m³/s

PBIAS : 94.67 %

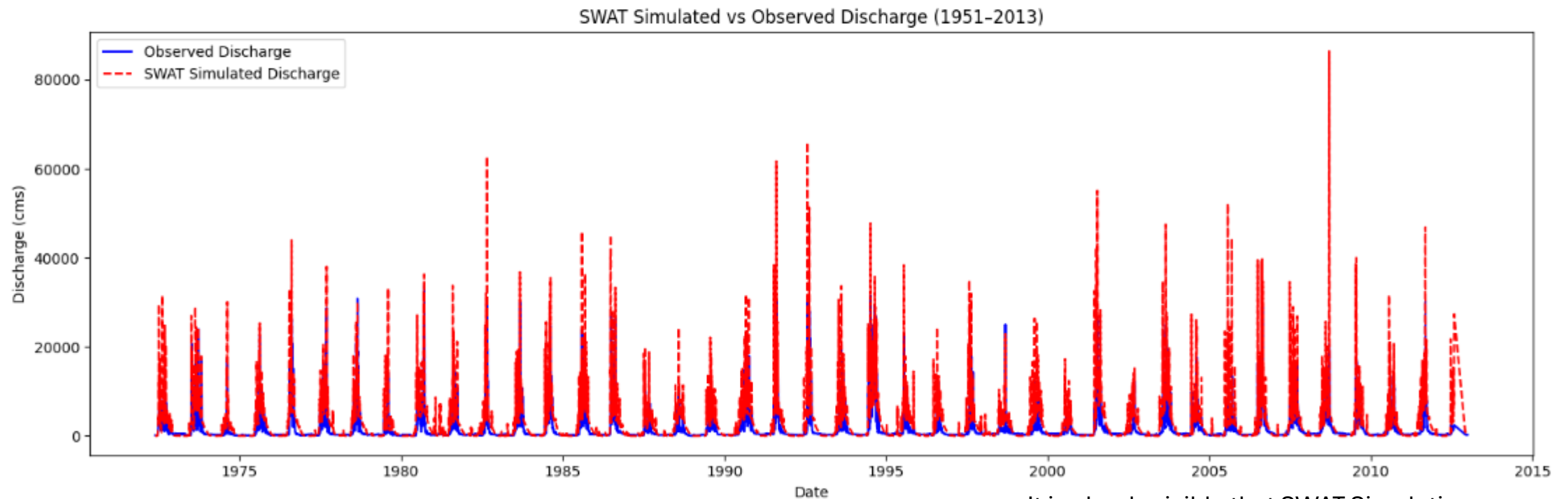


Fig.2 SWAT simulations vs Observed Values

It is clearly visible that SWAT Simulations are capturing variations well but there is huge difference in values.

Results

Calibration(1973-2000) and Validation(2001-2012)

LSTM RMSE: 1322.83

LSTM NSE: 0.7811

LSTM R^2 : 0.7811

LSTM Discharge Prediction vs Observed (2001-2012)

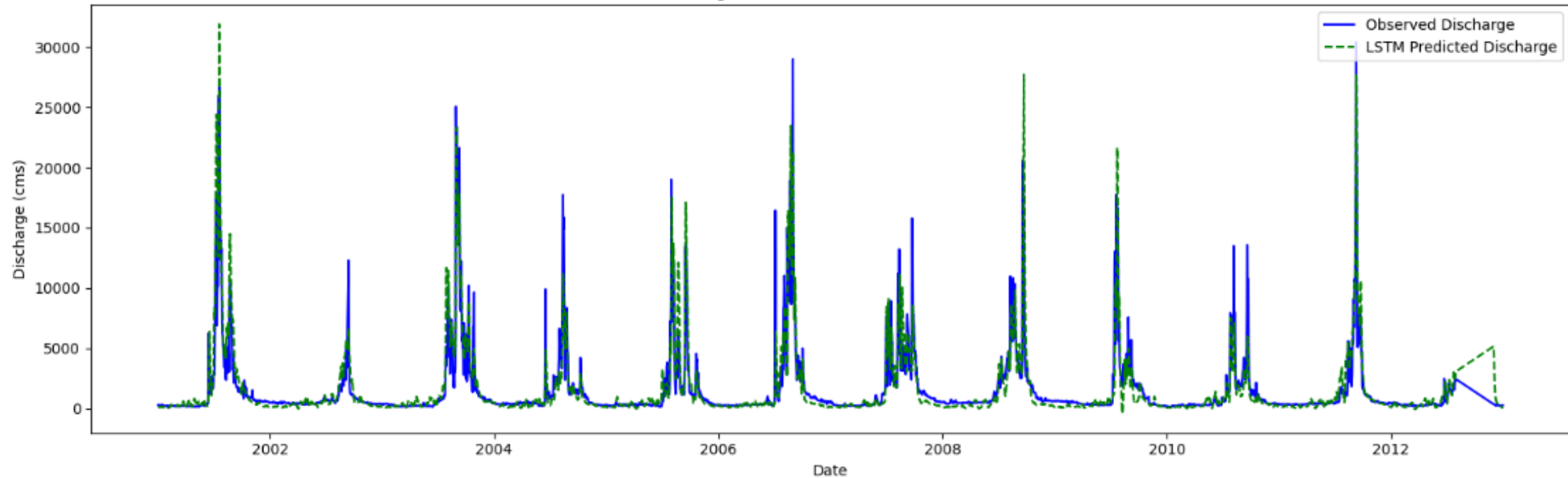


Fig.3 LSTM Predictions vs Observed (2001-2012)

We can see this model is capturing trends and values both a lot better than SWAT simulations.

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Results

Calibration(1973-2000) and Validation(2001-2012)

Random Forest RMSE: 1374.55

Random Forest NSE: 0.7636

Random Forest R^2 : 0.7636

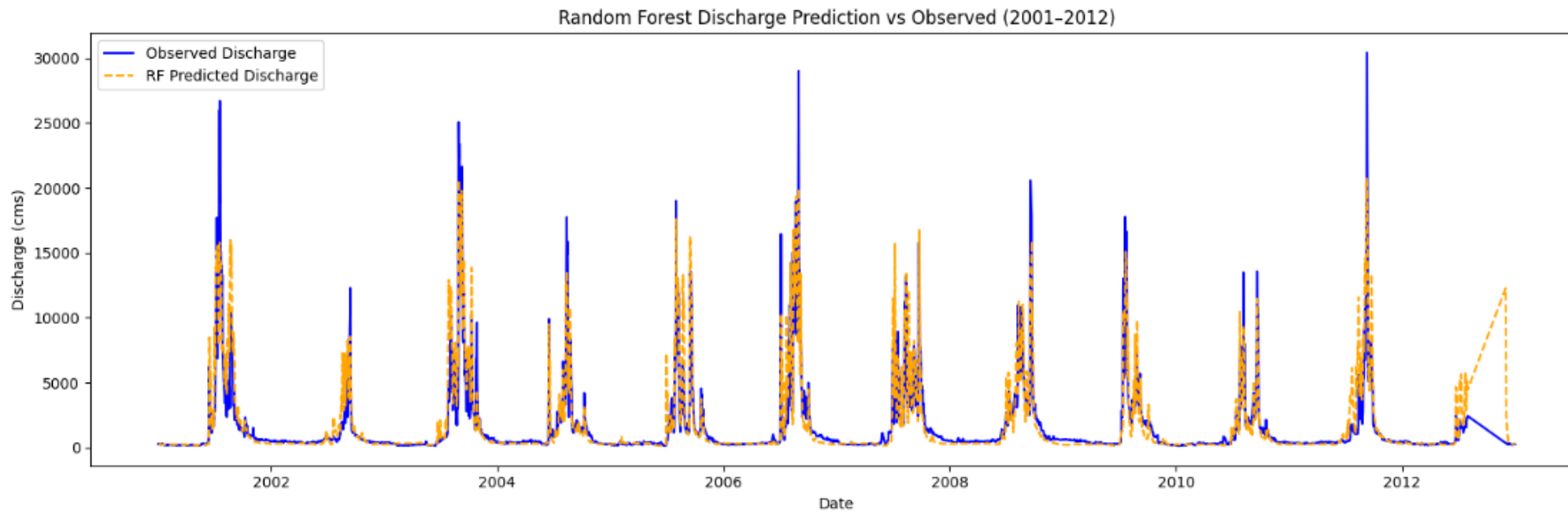


Fig.4 Random Forest Predictions vs Observed (2001-2012)

We can see the RF model performs poorer than the SWAT-LSTM model. This happens because RF does not capture the temporal dependencies and sequence patterns effectively, especially during high peak flow events. RF tends to underpredict peak discharges and overpredict baseflows, which results in less accurate discharge simulation compared to the LSTM model

Conclusion

- Standalone SWAT needs calibration which depends on tuning different Parameters which takes time and is a difficult process.
NSE = -0.54 and PBIAS = $+95\%$ over 1951–2013 indicates severe overestimation of both flood peaks and low flows.
- We can improve calibration of SWAT by coupling it with Machine Learning.
- Data-driven ML models deliver major gains
LSTM: NSE = 0.78 , $R^2 = 0.78$, RMSE = $1323 \text{ m}^3/\text{s}$, PBIAS = 5%
Random Forest: NSE = 0.76 , $R^2 = 0.76$, RMSE = $1375 \text{ m}^3/\text{s}$, PBIAS = 7%
- LSTM edges out RF in capturing both high-flow peaks and baseflows during 2001–2012

Key takeaway:
Pure process-based models struggle with complex nonlinearity, whereas ML (especially LSTM) can effectively learn residual errors and reduce bias

Implication:
Coupling SWAT with an LSTM error-corrector harnesses physical realism and data flexibility for more reliable streamflow forecasts.

References

Mei, Z., Peng, T., Chen, L. et al. Coupling SWAT and LSTM for Improving Daily Streamflow Simulation in a Humid and Semi-humid River Basin. Water Resource Manage 39, 397–418 (2025).

<https://doi.org/10.1007/s11269-024-03975-w>

https://github.com/coconutgrapefruit/SWAT-LSTM_ver4

Thank You

