INDIAN INSTITUTE OF TECHNOLOGY PALAKKAD

Prediction of Streamflow using Machine Learning

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Overview

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Introduction

Overview and Problem Statement

- Predicting streamflow accurately is critical for flood forecasting, reservoir operations, and water management.
- Traditional physically-based models are complex and data-intensive.
- Need for data-driven models that can learn directly from historical data.

Objectives and Motivation

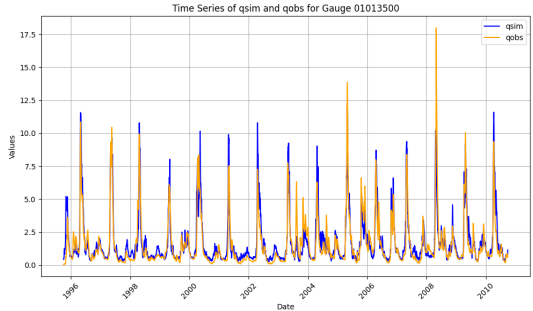
- Develop LSTM-based model for gauged basin streamflow prediction.
- Application of LSTM for unguaged basin prediction.
- Apply **SHAP** to understand how **climate and land use** affect streamflow over time.

Expected Impact

- **Knowledge Transfer:** Learn from data-rich basins and apply to data-scarce ones.
- **Hydrological Insight:** Understand hydrological dynamics using interpretable ML tools.

Recap of previous work

- Initial model (last semester) gave R square of 0.71.
- Added more temporal and static inputs + tuned dropout.
- Final model achieved R square of 0.90 and NSE = 0.8993 on gauged Basin **1013500**.
- Cosine similarity used to find a hydrologically similar ungauged Basin **1030500**.
- Validation on this basin gave NSE = 0.6946 **without using its streamflow data**.
- Confirms model's transferability to ungauged basins.



Feature Inputs for LSTM and SHAP Models

Basins used: 1013500, 1030500, 8029500, 7197000, 5525500

LSTM Model

- **Temporal Features (Daily)**
  - Precipitation
  - Tmax (Daily Maximum Temperature)
  - Tmin (Daily Minimum Temperature)
- **Static / Non-Temporal Features**
  - Elevation, Slope, Area
  - Soil Depth, Soil Type
  - NDVI, Land Cover Class
  - Baseflow Index, Runoff Ratio, Aridity Index
  - Drainage Density, Forest Fraction, Urban Fraction

SHAP Analysis Model

- **Yearly Aggregated Features (1953–2018)**
  - Precipitation (Annual)
  - AET (Actual Evapotranspiration)
  - Tmin, Tmax (Annual Averages)
  - Urban and Agricultural Area Fractions
- **Monthly Aggregated Features (Seasonal SHAP)**
  - Precipitation, AET, Urban
  - Tmin, Tmax (per season)
  - Seasons: Winter, Spring, Summer, Autumn

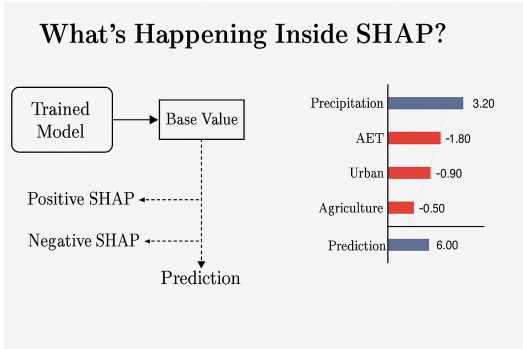
Overview and Motivation

- Investigate the impact of climate variables and land use changes on streamflow and hydrological dynamics over time.
- Apply interpretable machine learning (SHAP) to understand feature contributions and capture hydrological behavior.
- Analyze one representative basin in detail (8029500) and summarize results for others.

What is SHAP and Why Use It?

SHAP (SHapley Additive exPlanations) is a method based on game theory that explains how much each feature (like rainfall, temperature, or urban area) contributed to a prediction.

- SHAP assigns each feature a value that shows:
  - **Magnitude**: How much the feature influenced the prediction.
  - **Direction**: Whether it pushed the prediction higher or lower.
- It provides consistent, local explanations.



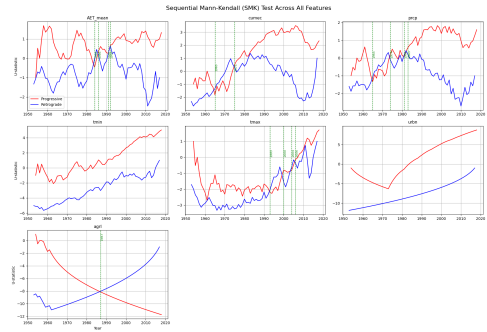
SHAP values visualize feature impact on model predictions, not just average importance.

Why Boosting + SHAP Instead of LSTM?

- LSTM effectively captures temporal patterns but operates as a black box, making interpretation challenging.
- Gradient boosting (e.g., XGBoost) is well-suited for tabular data and provides clearer insights.
- SHAP with XGBoost allows for transparent, feature-level explanations of streamflow dynamics.
- This combination enables understanding of how climate and land features impact hydrological behavior.

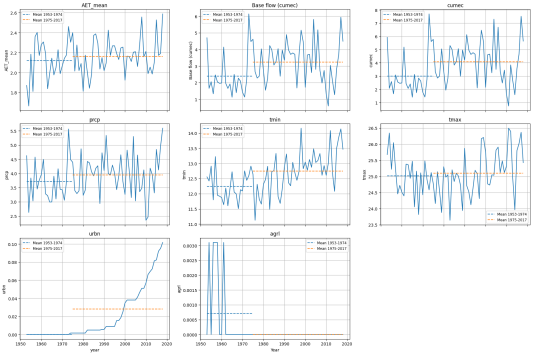
Sequential Mann-Kendall Test for Change Detection

- In hydrology, we often need to test whether a time series (e.g., rainfall, streamflow) is **stationary** or has changed over time.
- The Sequential Mann-Kendall (SMK) test helps detect the **year of change (change point)**.
- It plots:
  - **Progressive (UF)** and **Retrograde (UB)** trend lines
  - Their intersection = **significant shift**



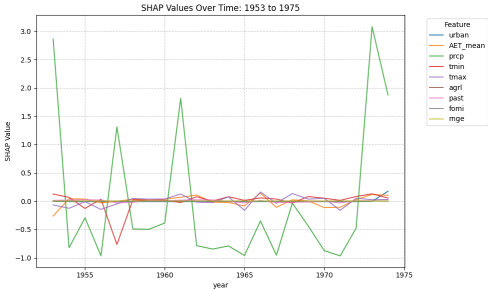
SMK plot showing UF and UB lines across features. Change point identified around 1975.

Mean Comparison Before and After 1975

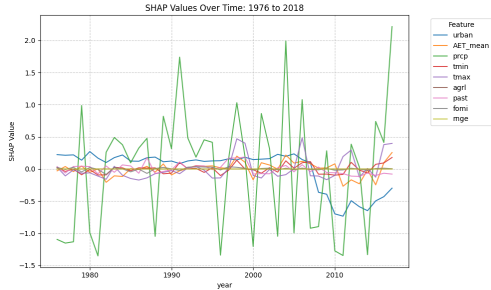


- Increase in Tmin, Tmax, and precipitation.
- Urbanization impact observed post-1975.
- Agricultural land area decreased.
- Higher runoff patterns detected.

SHAP Feature Contributions Over Time



1953–1975

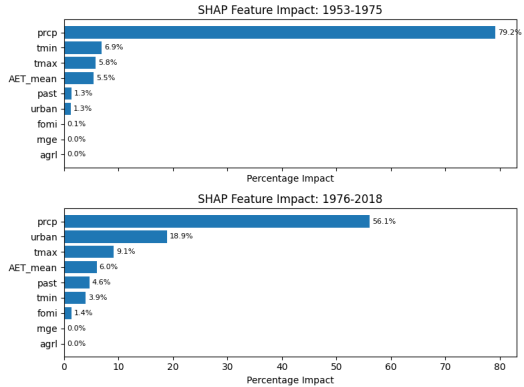


1976–2018

- Precipitation consistently dominant.
- Urbanization influence rises post-1975.

Percentage contributions of key features

- Precipitation remained the most influential driver.
- Urbanization gained significant impact after 1975.
- Climate + Land Use jointly influence streamflow in recent decades.
- Clear shift in dominant features before and after change point.



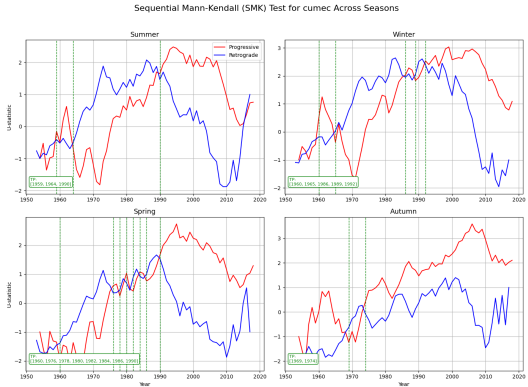
SHAP based feature impact across time

Why Seasonal Analysis?

- Streamflow dynamics vary significantly across seasons.
- Seasonal drivers like **snowmelt, monsoon, evapotranspiration** affect different months differently.
- Aggregating SHAP by season improves:
  - Interpretability of model outputs.
  - Detection of seasonal trends in climate/LULC impact.
- Enables climate-adaptive water resource planning by understanding:
  - What dominates in **Winter** vs. **Summer**, etc.

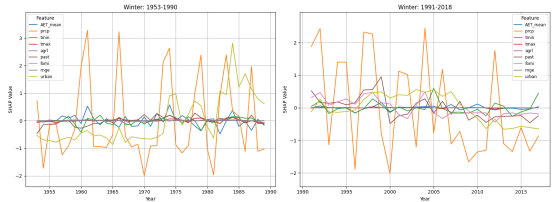
Seasonal Analysis and SMK

- Performed SMK test separately for each season.
- Detected season-specific change points:
  - **Winter:** 1975
  - **Spring:** 1972
  - **Summer:** 1980
  - **Autumn:** 1979
- SHAP was then applied pre/post change point for each season.

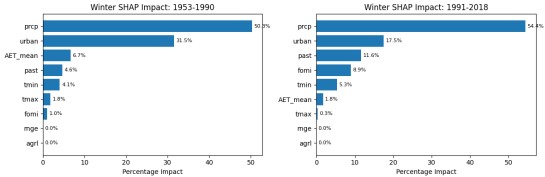


SMK plots for seasonal data (Winter, Spring, Summer, Autumn)

SHAP Seasonal Feature Impact – Winter



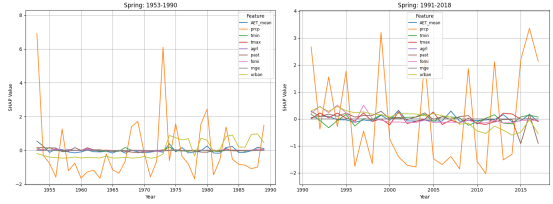
Impact of features on stream flow for winter



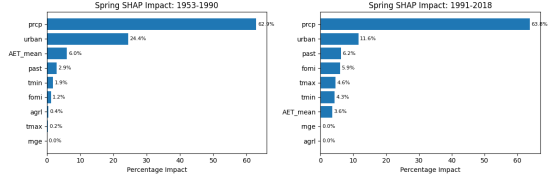
Winter: SHAP feature contributions (before and after the change point)

- **Precipitation** remained the dominant driver, increasing after 1990.
- **Urban influence** dropped significantly, indicating reduced urban impact on winter runoff.
- Soil-related features like **past** and **fomi** gained importance post-change, highlighting stronger soil-driven responses.
- Suggests a shift towards more natural hydrological control during winter flows after 1990.

SHAP Seasonal Feature Impact – Spring



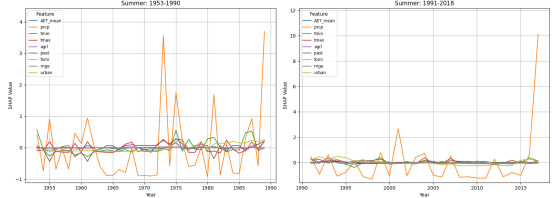
Impact of features on stream flow for Spring



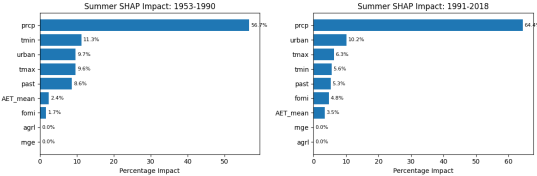
Spring: SHAP feature contributions (before and after the change point)

- Precipitation remained the dominant driver across both periods.
- Post-1975: Urban impact decreased, while contributions from **past** and **fomi** significantly increased.
- This shift indicates a stronger influence of historical land characteristics (past) and soil moisture (fomi) on streamflow during spring.

SHAP Seasonal Feature Impact – Summer



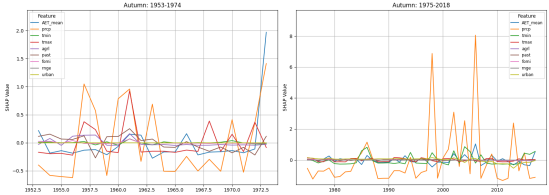
Impact of features on stream flow for Summer



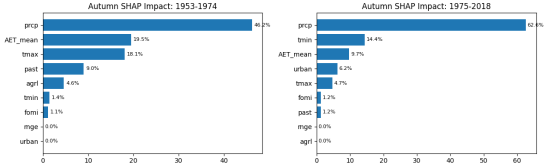
Summer: SHAP feature contributions (before and after the change point)

- Urban land use showed clear monotonic increase in SMK and was among top SHAP contributors.
- Tmax and precipitation continued to dominate, with urban runoff becoming critical post-2000.
- The changes suggest summer runoff became more sensitive to temperature drivers after 1990.

SHAP Seasonal Feature Impact – Autumn



Impact of features on stream flow for Autumn



Autumn: SHAP feature contributions (before and after the change point)

- AET and precipitation displayed trend shifts in SMK plots.
- SHAP values were more evenly distributed among features.
- Weak urban influence but detectable agricultural impact due to harvest-related land changes.
- Reflects increased stormwater sensitivity post-land use change.

SHAP Summary for Other Basins

- **Basin 7197000 (Mixed Humid):**
  - Dominant features: Precipitation, Urban fraction, and Tmax post-1991.
  - Urban SHAP values increased in winter, suggesting runoff influence.
- **Basin 5525500 (Cold Region):**
  - Temperature (Tmax) was most influential, especially in spring and summer.
  - Agriculture influence low and declined after 1990.
- **Observation:**
  - SHAP analysis captured basin-specific patterns in feature importance.
  - Urbanization and temperature emerged as growing contributors post change point.

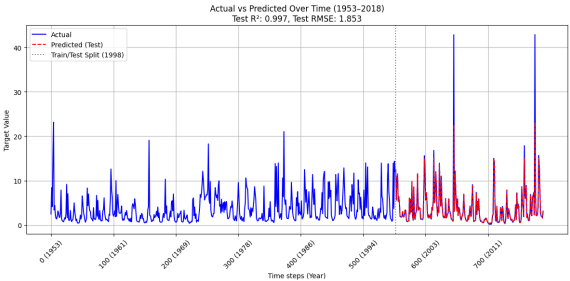
Model Performance Across Basins

- XGBoost models trained using 70% of data and tested on remaining 30%.
- Evaluated on test data (2002–2018) using metrics like R squared, RMSE, Bias.
- Three representative basins tested: Hot Humid, Mixed Humid, and Cold Region.

Basin ID	Climate Zone	Change Point	Top Features After	R squared	RMSE
8029500	Hot Humid	1975	Precip, Urban, AET	0.997	0.86
7197000	Mixed Humid	1991	Precip, Urban, Tmax	0.925	0.965
5525500	Cold Region	1990	Tmax, Precipitation	0.99	0.995

Table: Summary of model performance across three basins

Prediction vs Observed - Basin 8029500 (Hot Humid)



- Model trained with 70% of data, tested on 30% (2002–2018).
- Achieved the best performance among all basins.
- **R squared: 0.997**, **NSE: 0.861**, **RMSE: 0.860**

Insights from Model Results

- **Precipitation** remained the most dominant predictor across all basins and seasons.
- **Urbanization** emerged as a significant contributor post change points - reflecting LULC impact.
- **Seasonal SHAP** analysis highlighted temperature's influence in spring/winter and urban impact in summer.
- **Non-stationarity** detected via SMK helped isolate the impact of changing land/climate patterns.
- Slightly higher RMSE values in Mixed and Cold regions may reflect snowmelt and delayed hydrological responses not fully captured by the model.

Conclusion

- Developed an interpretable streamflow prediction framework using **XGBoost + SHAP**.
- Addressed **non-stationarity** by applying the Sequential Mann-Kendall (SMK) test to identify change points.
- SHAP revealed evolving contributions of features like **precipitation, urbanization, and temperature**.
- Seasonal SHAP analysis showed intra-annual variability - e.g., urban influence in summer, temperature in spring/winter.
- Results validated across diverse climate zones with **R squared ranging from 0.9 to 0.99**.
- The approach provides both **accurate predictions** and **explanations**, aiding future water resource planning.

Thank You!