EGU24-1225: A Long-term Spatial Runoff and Flood Prediction Method in Higher Accuracy

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Abstract

When estimating future runoff and flood events using a global hydrological model (GHM), the large uncertainties associated with general circulation models (GCMs) and bias in GHM model structure pose significant challenges. In the meantime, most future runoff projections and flood estimations are conducted only at specific gauge stations due to limited data availability, and unable to support basin-wide water resources planning and management. To address these issues, this paper proposes a spatiotemporal-pattern-based machine learning method, DSGPR-EOF, which is a combination of Dual-stage Sparse Gaussian Process Regression (DSGPR) and Empirical Orthogonal Function (EOF). DSGPR-EOF is developed to improve the accuracy of basin-wide runoff projections ,especially for flood estimations, including flood discharge, flood peak time, and flood volume. We apply the proposed method to the Brahmaputra River basin (BRB) known for topographical and climatic diversity to evaluate its effectiveness and efficiency. The DSGPR-EOF method is shown to have higher accuracy in flood peak and runoff projection than the widely used multi-GCMs ensemble mean method. After correction by using the method, the estimation errors of 10-year flood and 100-year flood peak discharge are reduced by 68.6% and 54.5%, respectively. The estimation accuracy of flood peak and volume is highly consistent spatially. Additionally, it shows that this method can apply station-wise observed discharge information to enhancing flood estimations of the entire basin. These findings underscore the practical significance of the DSGPR-EOF method for basin-wide flood estimation.

I. Scientific Questions

Effective water resources management and protection in a river basin requires basin-wide accurate future runoff and flood projections. However, the availability of accurate runoff and flood projections in regions of interest faces substantial challenges due to large uncertainties associated with general circulation models (GCMs) and bias in GHM model structure pose significant challenges. This research proposes a spatiotemporal-pattern-based machine learning method, with the primary objective of accomplishing two key goals:
(1) Enhancing the accuracy of runoff projection and flood estimation at each grid within a given basin with low computational cost;
(2) Integrating different forms of historical runoff and flood information (i.e. time series data, spatial distribution data) to re-optimize basin-wide estimations in the future.

II. Study Site: Brahmaputra River Basin

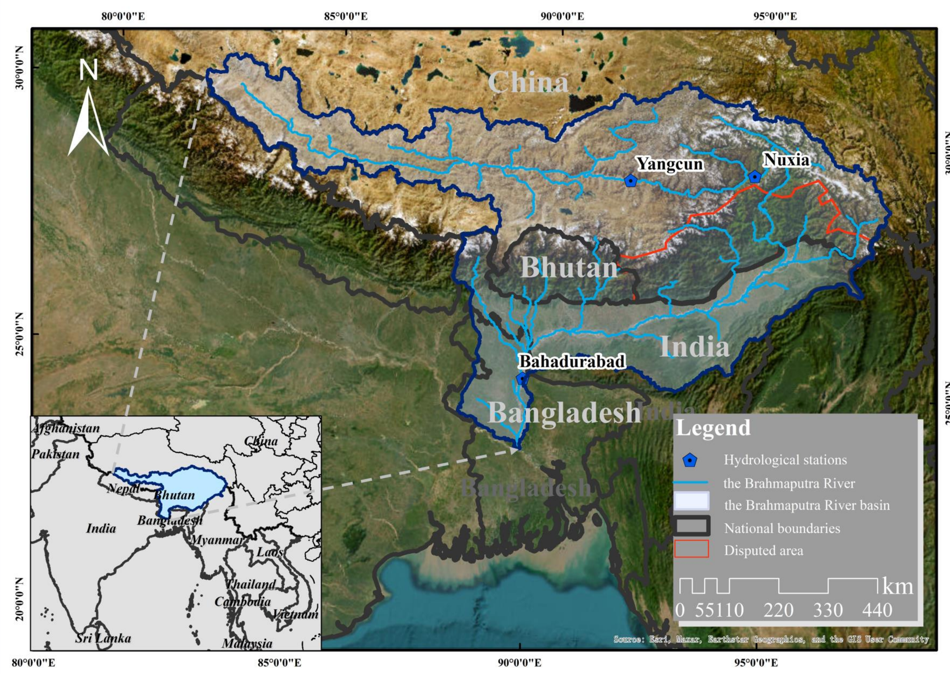

Fig. 1: Overview of the Brahmaputra River basin (BRB) and the four hydrological gauge stations (Yangcun, Nuxia, and Bahadurabad) used in the study.

The basin is suitable for evaluating the proposed method:

- Large intra-annual variation in runoff: The average annual discharge of the Brahmaputra River is 19,824 m^3 s^{-1}, with the flood discharge reaching up to 10 times the dry season discharge.
- Significant heterogeneity in meteorological and terrain conditions: There are diverse landforms, including icy plateaus, rain-rich mountain ranges, floodplains, and deltaic lowlands. The upper reaches consist of a complex mountain system with an average slope of 16.8 m/km, while the lower reaches have a gentle slope of 0.079 m/km.

III. Methodology

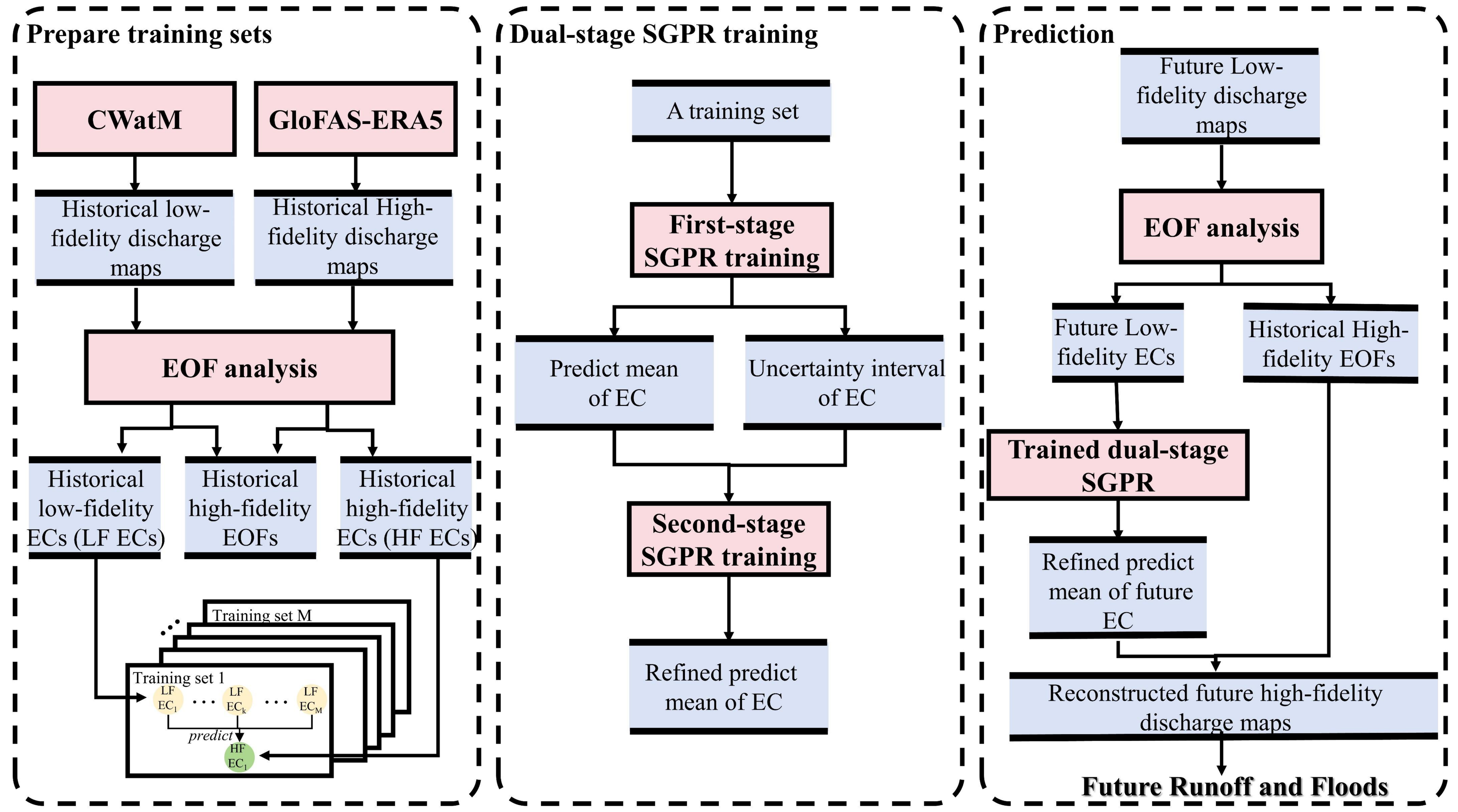

Fig. 2: We developed a spatiotemporal-pattern-based machine learning method, DSGPR-EOF, which is a combination of Dual-stage Sparse Gaussian Process Regression (DSGPR) and Empirical Orthogonal Function (EOF).

◆Improve Computational Efficiency

Reduce dimension: $H = \sum_{k=1}^{K} U_h(k,:)\cdot V_h(:,k)$

Recognize crucial modes: $R_K = \frac{\sum_{k=1}^{K}\lambda_k}{trace\ \Lambda}$

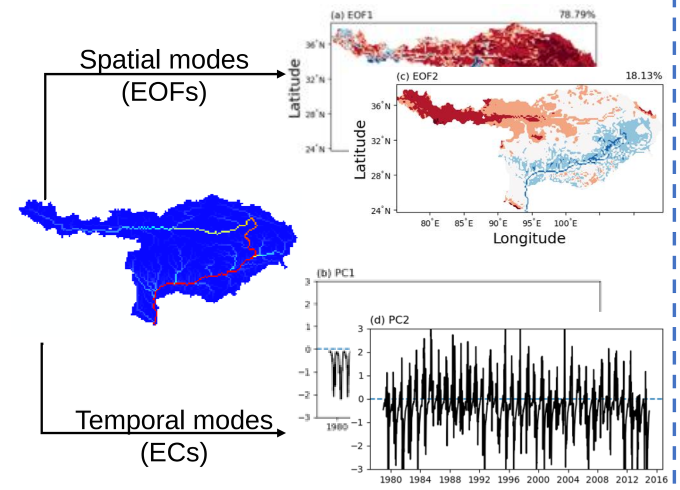

Fig. 3: The illustration of EOF analysis.

◆Enhance Accuracy

- Sparse Gaussian Process Regression (SGPR)

$$GP(x) \sim \mathcal{N}(\mu(x), k(x,x'))$$

$$k(x,x') = \sigma_f^{\,2}\cdot \exp\left\{\frac{-\left(\|x-x'\|_2\right)}{2\eta^2}\right\}$$

- Utilize the information of uncertainty intervals

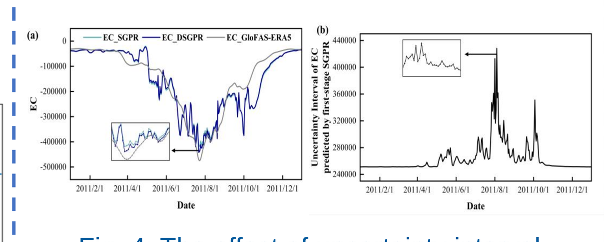

Fig. 4: The effect of uncertainty interval information in EC prediction.

◆Validation

- Cross Validation

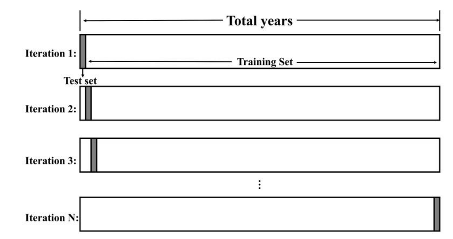

Fig. 5: The diagram of cross validation.

- Evaluation Indicators

Runoff

$CC = \frac{\sum_{t=1}^{T}(Q_{PHF,t}-\overline{Q_{PHF,t}})(Q_{HF,t}-\overline{Q_{HF,t}})}{\sigma_{Q_{PHF}}\sigma_{Q_{HF}}}$

$RMSE = \sqrt{\frac{\sum_{t=1}^{T}(Q_{PHF,t}-Q_{HF,t})^2}{T}}$

$Bias = \frac{Q_{PHF,t}-Q_{HF,t}}{T}$

$NSE_{i,j} = 1 - \frac{\sum_{t=1}^{T}(Q_{HF,i,j,t}-Q_{PHF,i,j,t})^2}{\sum_{t=1}^{T}(Q_{HF,i,j,t}-\overline{Q_{HF,i,j,t}})^2}$

$KGE_{i,j} = 1 - \sqrt{(CC_{i,j}-1)^2 + Bias_{i,j}^{\,2} + \left(\frac{\sigma_{Q_{PHF,i,j,t}}}{\sigma_{Q_{HF,i,j,t}}}-1\right)^2}$

Floods

- Extreme flood peak (EFP)
- Annual maximum flood peak (AMFP)
- Annual maximum three-day flood volume (AM3DV)

IV. Results: Station-wise Validation

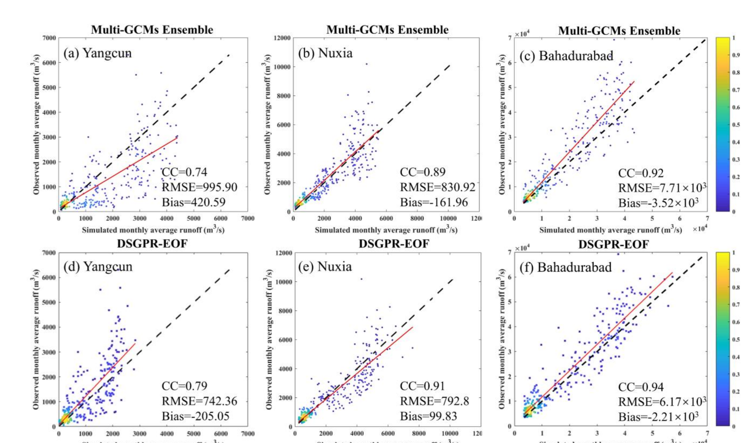

Fig. 6: Evaluation of the monthly runoff corrected by multi-GCMs ensemble average method and DSGPR-EOF method.

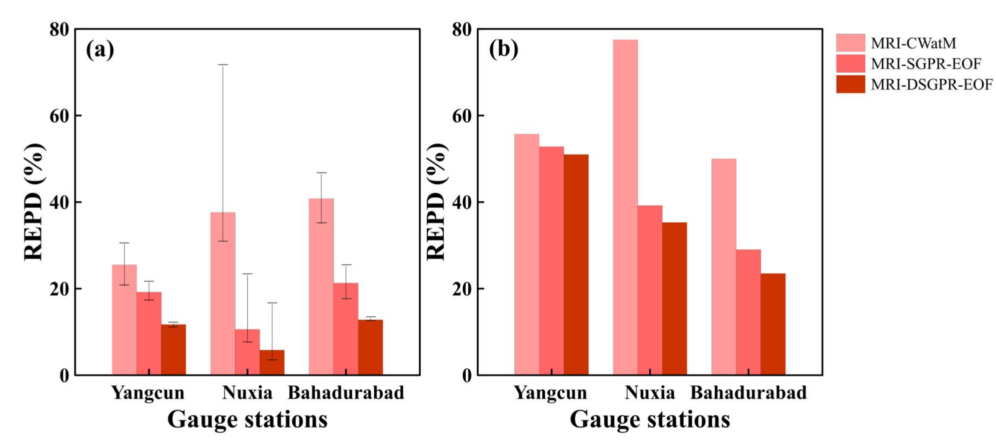

Fig. 7: Relative error of peak discharge (REPD) ranges and means of estimated extreme flood peak (EFP) of (a) 10-year flood and (b) 100-year flood events by the calibrated CWatM, SGPR-EOF method and DSGPR-EOF method.

✓DSGPR-EOF method outperforms multi-GCMs ensemble mean method in runoff projection.
✓Incorporating uncertainty interval information can significantly enhance the accuracy and narrow the bias intervals of extreme value estimations.

V. Results: Spatial Validation

✓ DSGPR-EOF method performs higher overall accuracy and demonstrates high spatial consistency in accuracy for the runoff projections compared to the multi-GCMs ensemble average method.

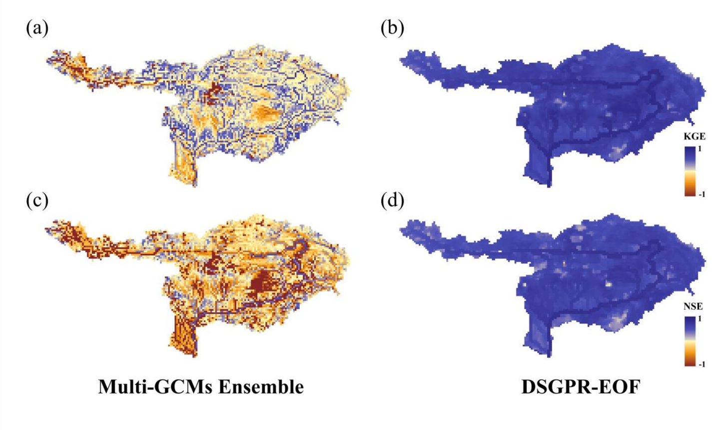

Fig. 8: KGE (a-b) and NSE (c-d) of corrected basin-wide daily runoff during historical period (1979-2014).

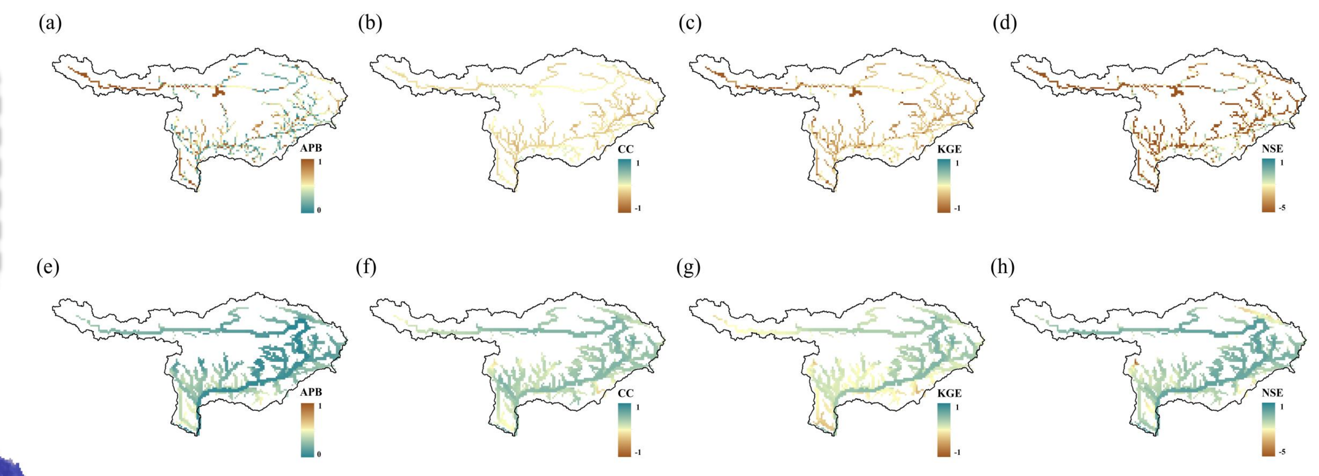

Fig. 9: Spatial performance (APB, CC, KGE, NSE) of AMFP estimation using the calibrated CWatM (a-d) and the DSGPR-EOF method (e-f).

✓ DSGPR-EOF method can enhance the estimation of peak flow time series, not just for certain extreme flood events.
✓ DSGPR-EOF method enhances the accuracy of AMFP estimation throughout the basin and makes the accuracy gap between upstream and downstream smaller, being minimally affected by complex climate and terrain in the BRB.

VI. Results: Application Potential of the Method

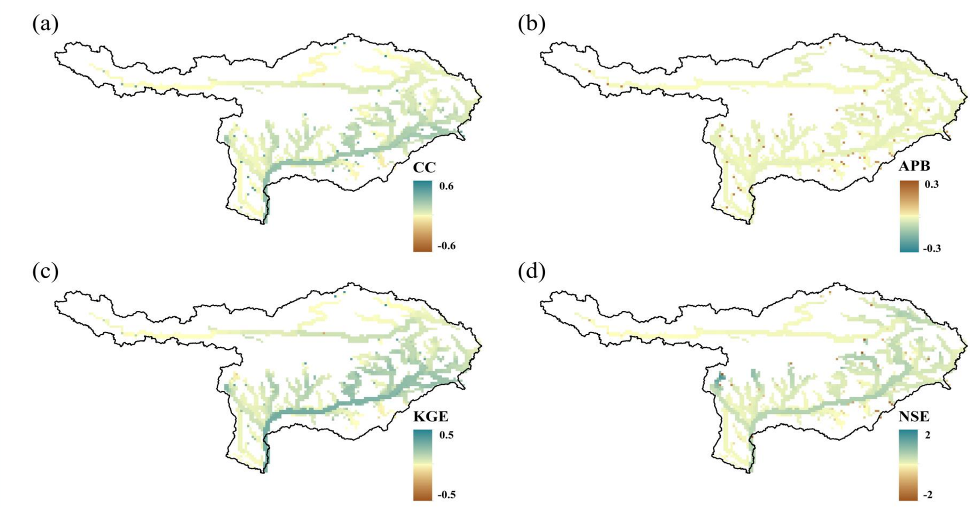

Fig. 10: The change in validation indicators in AMFP estimated by the DSGPR-EOF method after replacing high-fidelity discharge data for observed data at Yangcun, Nuxia and Bahadurabad gauge stations.

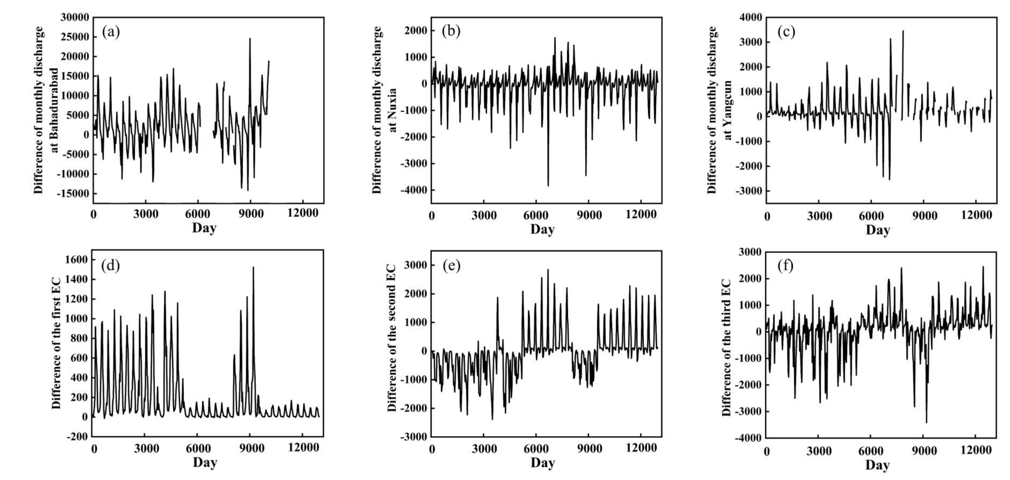

Fig. 11: The difference between observed discharge and high-fidelity discharge at (a) Bahadurabad, (b) Nuxia, and (c) Yangcun gauge stations, and the difference of the first three ECs (d-f).

✓DSGPR-EOF method can apply station-wise observed discharge information (i.e. gauges, satellite altimeter data) to enhancing flood estimations of the entire basin.

✓ DSGPR-EOF method can leverage temporal modes (ECs) to learn error characteristics at gauge stations and subsequently correcting the flood estimations of the entire basin through multiplication with the spatial modes (EOFs).

VII. Conclusion

◆ DSGPR-EOF method outperforms multi-GCMs ensemble mean method in the station-wise accuracy and basin-wide accuracy consistency of runoff projections and flood estimations with low computational costs.
◆ The uncertainty intervals can serve not only as the confidence of estimation, but also as a new source of input to enhance model estimation accuracy.
◆EOF analysis exhibits great potential in integrating multi-form observations to enhance the runoff and flood estimations.

References

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Acknowledgement

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