

Higher-Order Internal Modes of Variability Imprinted in Year-to-Year California Streamflow Changes

A science-centric machine learning study

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Self Introduction



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Motivation and General Framework

- Streamflow is a key component in hydroclimate system.
 - It is influenced by anthropogenic climate change and internal variability.
 - What is the most important factor that influences streamflow in California?
 - Previous studies:
 - Large-scale climate variability (teleconnections).
 - Composite-based analysis.
 - Linear-based correlation.
 - Patterns in local domain.
 - Lack connection between global and local-scale.
 - Independent testing set missing.
 - Build a regression model
 - Use internal variability indices and anthropogenic forcings to predict streamflow in California.
 - The explained variance can be used to quantify the predictability.
 - The feature importance can be used to rank the variables.
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- ```
graph TD; A[Modes of Variability, External Forcings] --> B[Regression Model]; B --> C[Streamflow]
```

# Inputs and Outputs Datasets

- Available datasets/methods
  - **CMIP6 simulations: augment training samples.**
    - 6 models, each with 10 ensembles.
  - **Modes of variability indices:**
    - PCMDI Metrics Package (PMP): derive modes of variability indices from climate simulations and observations using Empirical Orthogonal Function (EOF) and Common Basis Function (CBF).
  - **Streamflow:**
    - USGS observations, independent testing set.
    - CMIP-forced simulations.
      - Inter-Sectoral Impact Model Intercomparison Project (ISIMIP): bias-corrected and downscaled temperature and precipitation to force regional hydrology models. **Quarter degree, do not tune for all basins.**
      - Long-Short Term Memory (LSTM) model: takes daily time series of basin-mean precipitation, temperature. Trained towards USGS observations. Forced by BCSD-CMIP6 for historical projections.

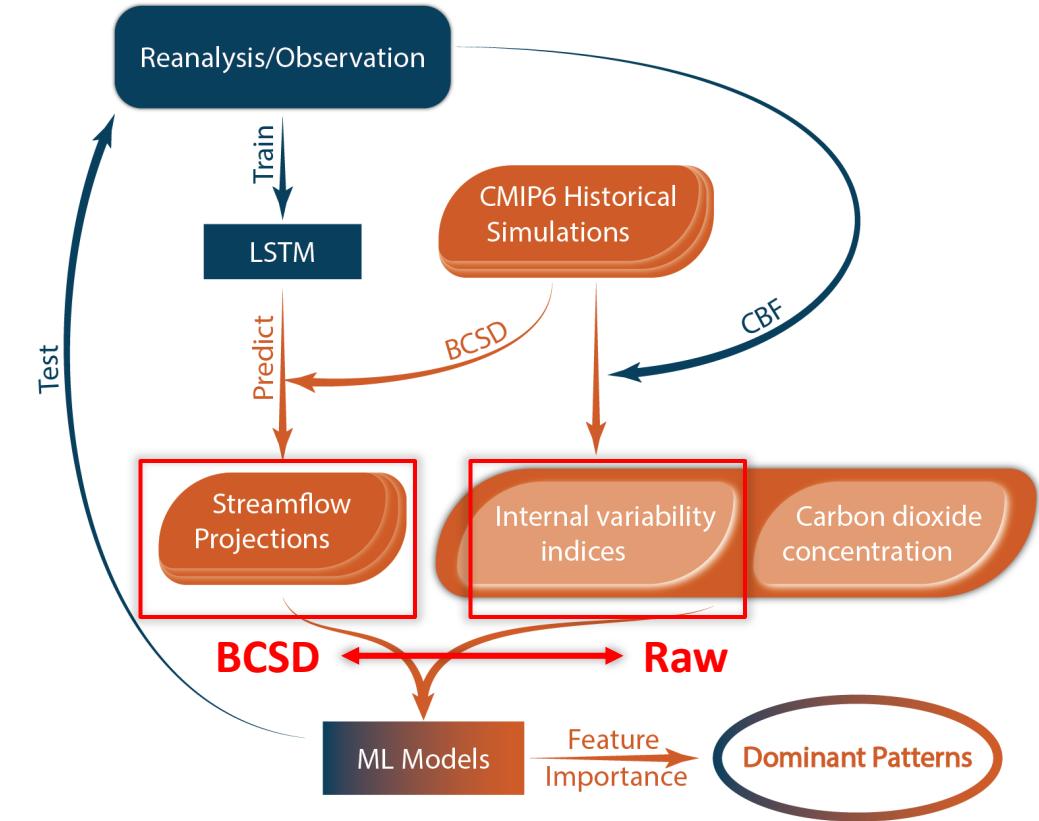


Figure. Schematic work flow. Blue for reanalysis and red for climate simulations.

# Validation of EOF/CBF and BCSD

- Validate whether BCSD would change the variability
  - IPSL-CM6A-LR (GCM)
  - BCSD (with NOAA OISST as reference)
- CBF (right) shows BCSD would not change variability
- EOF (left) shows swapping of EOFs is needed for higher-order EOFs
  - PC-6 from BCSD matches well with PC-5 from GCM
  - Further discussion in Lee et al., 2021

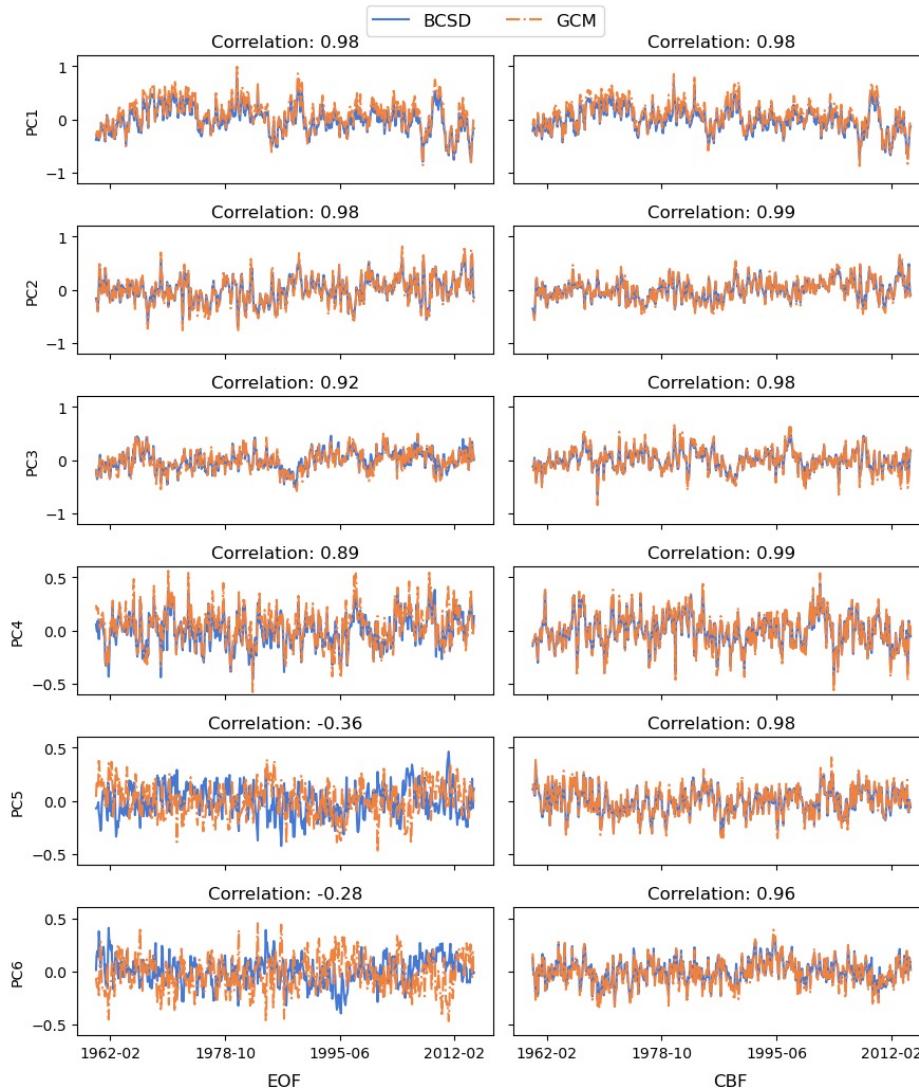


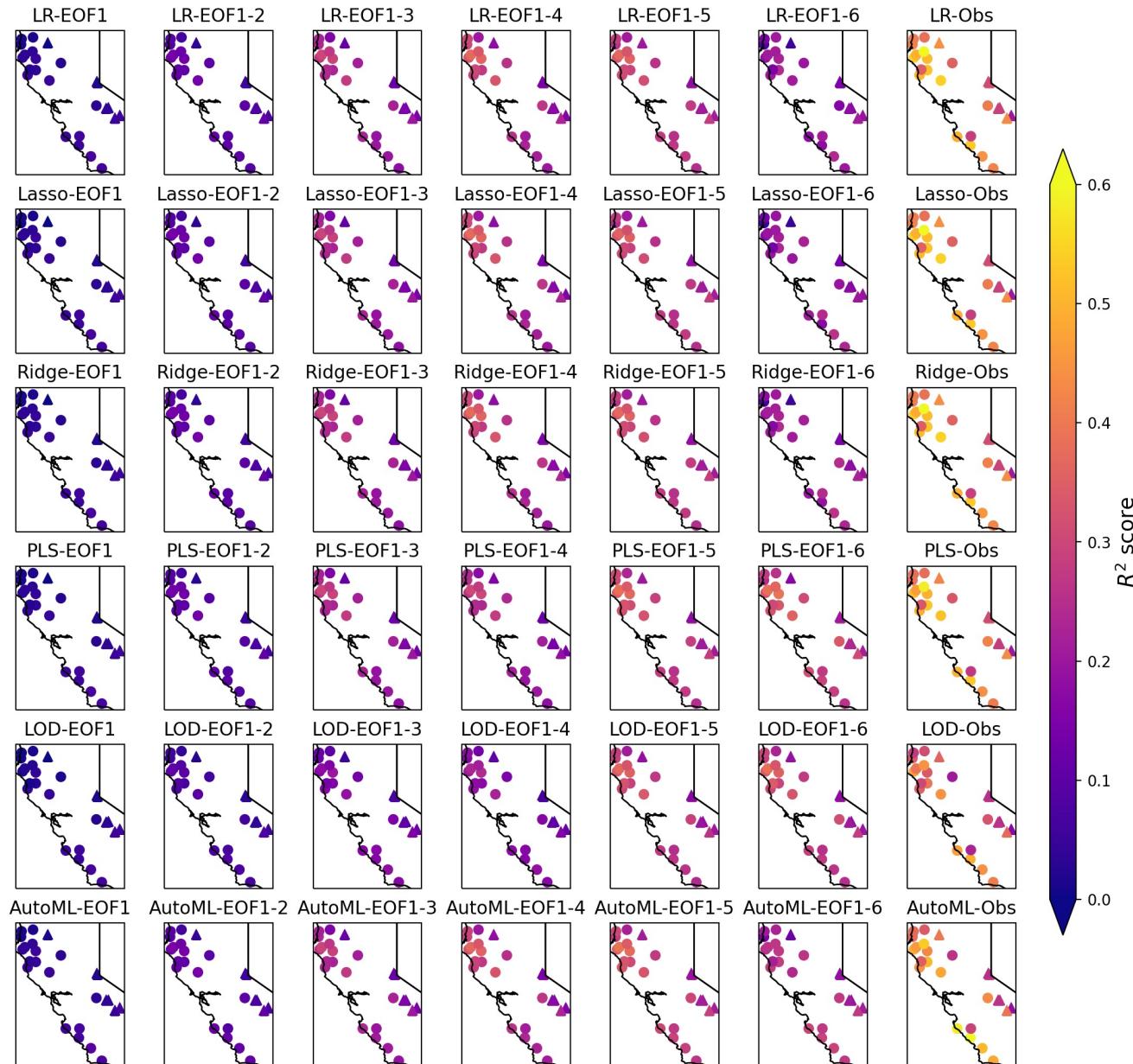
Figure. PC time series of the PDO domain from BCSD data (blue lines) and raw IPSL-CM6A-LR simulation. (PC: Principal Components)

# ML Model Performance

- ML models:
  - Linear Regression (LR)
  - Lasso
  - Ridge
  - Linear Orthogonal Decomposition (LOD)
  - Partial Least Squares Regression (PLS)
  - Automated Machine Learning (AutoGluon)
- Output:
  - *Seasonal peak streamflow: peak month, month prior and after*
  - *Standardized anomalies*
- Input:
  - *Concurrent or previous season variability indices*

Figure. Cross-validation results from ML models (left 6 cols) and performance on observations (rightmost col).

Triangles for basins with peaks in summer time and squares for basins with winter time peaks.



# ML Model Performance

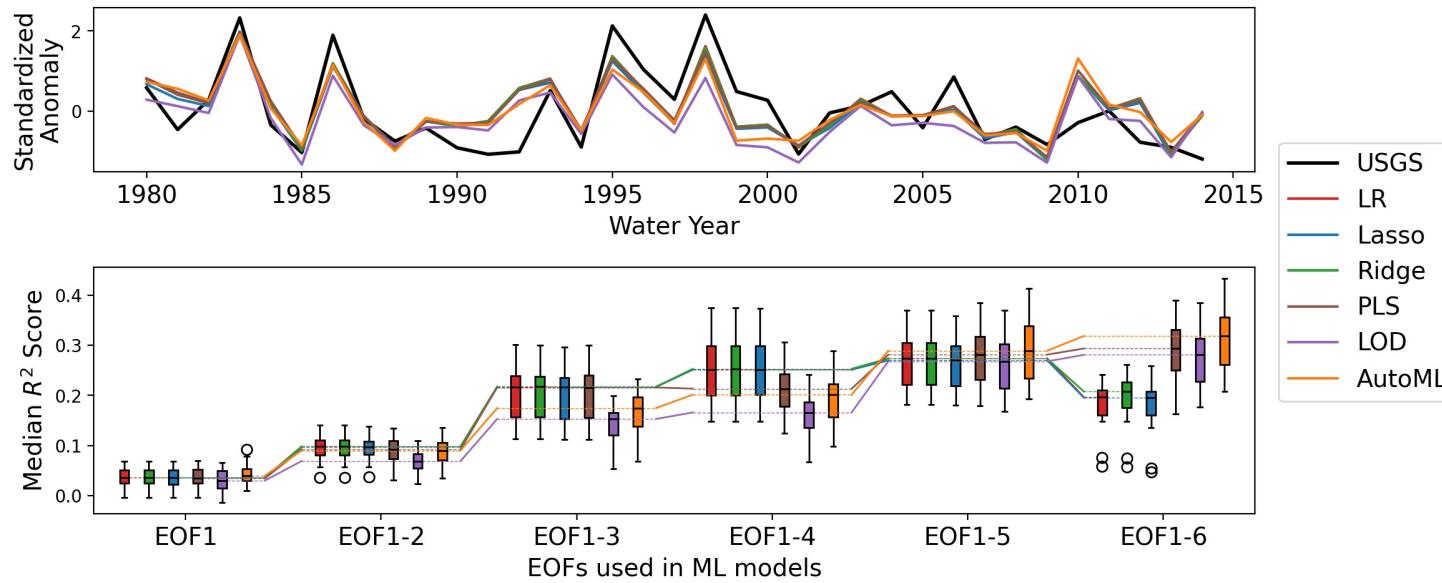


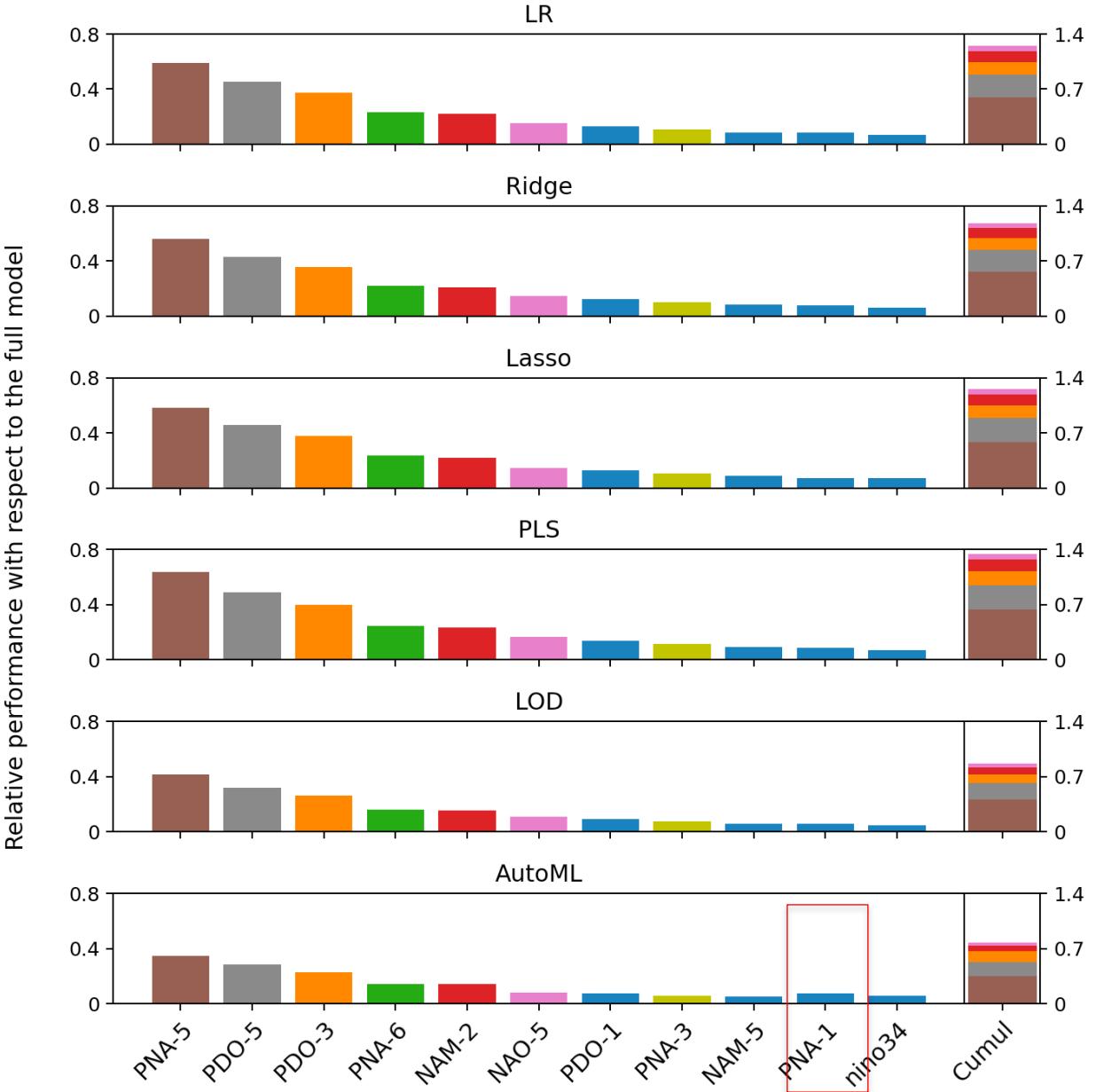
Figure. ML predictions of standardized peak flow anomalies vs observation for a selected basin (top); Cross-validation median performance with respect to the number of EOFs (bottom).

- ML models can generalize to reanalysis/observation
- Prediction skill increases with the number of EOFs
- AutoML, PLS and LOD have better regularization skills

# Feature Importance

- Diagnose the feature importance by adding variables into ML models (isolate the predictability)
  - Compare the predictability from each variable separately
  - Cumulatively add variables to account the correlations among variables (“forward pass”)
  - Feature importance for California in general (median R<sup>2</sup>)
- Retrain all the models with the cross-validation setting

Figure. Feature importance ranked by predictability. Left columns for models with individual predictor. Rightmost column for models with variables added cumulatively.



# Feature Importance

Focus on the common agreements from different ML models: **PNA-5** and **PDO-5**

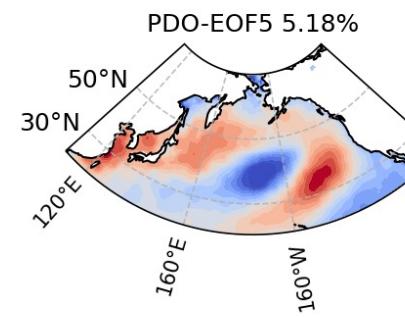
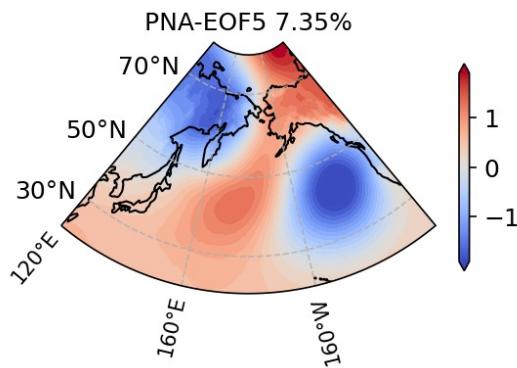


Figure. PNA-5 SLP pattern and PDO-5 SST pattern.

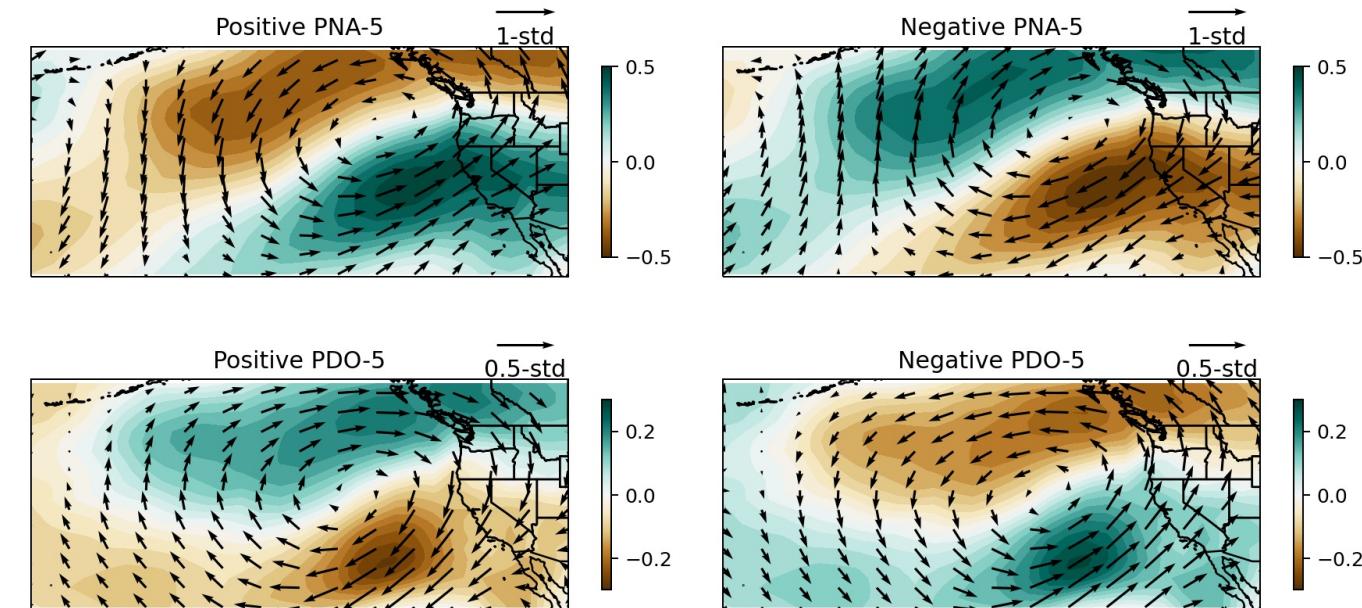
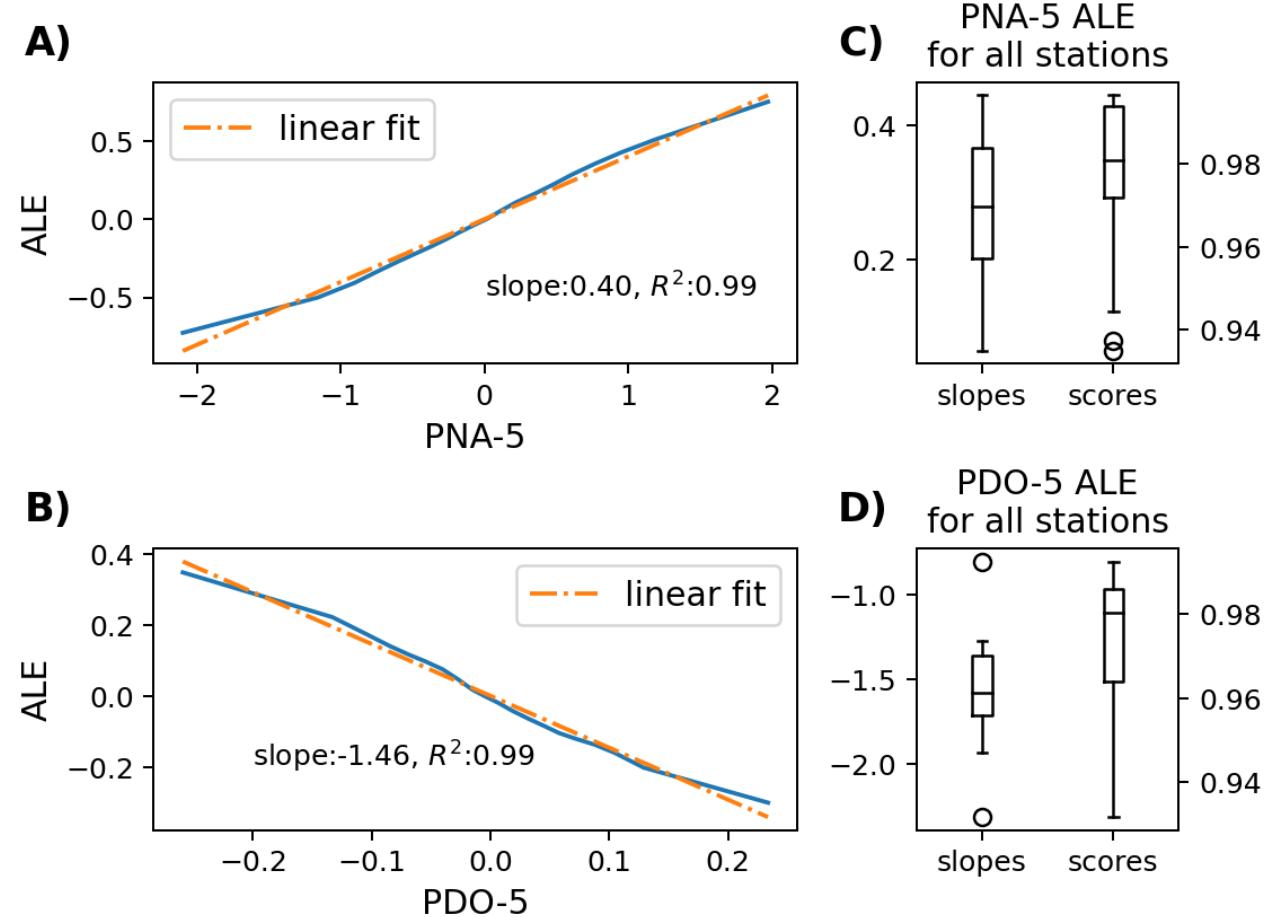


Figure. Composites of standardized anomaly of integrated water vapor transport from IPSL-CM6A-LR with respect to PNA-5 (top) and PDO-5 (bottom).

# Feature Sensitivity

- How does PNA-5/PDO-5 affect streamflow? Is it linear or nonlinear?
  - Use **AutoML** as a testbed since it considers potential nonlinear relationship and has the highest overall skill score.
  - Use **accumulated local effect (ALE)** to account for correlations among features.
- The response shows “quasi-”linear.

Figure. Accumulated Local Effect (ALE) for PNA-5 (A) and PDO-5 (B) at a selected basin. Distribution of ALE slope and linear fit score over California for PNA-5 (C) and PDO-5 (D)



# Conclusions

- Higher-order modes of variability show better predictability for basin-scale streamflow changes than well-known variability indices;
- By taking the higher-order of EOFs from well-known variability domains, we can connect between local features and larger-scale patterns.
- ML models agree on the feature importance, and PNA-5 and PDO-5 are the two most dominant features.
- The relationship is quasi-linear.
- BCSD preserves variability. Useful for variability-related studies.



# Future Work

- Western US snowpack detection: since BCSD can preserve internal variability, similar framework can be used to generate snowpack projections (CMIP6->BCSD->DL/process-based models) and applications.

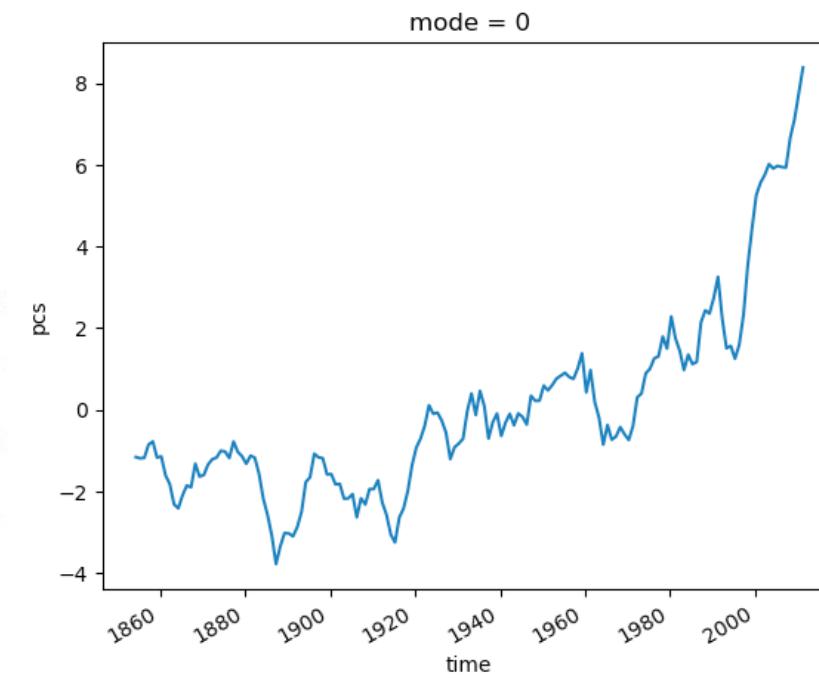
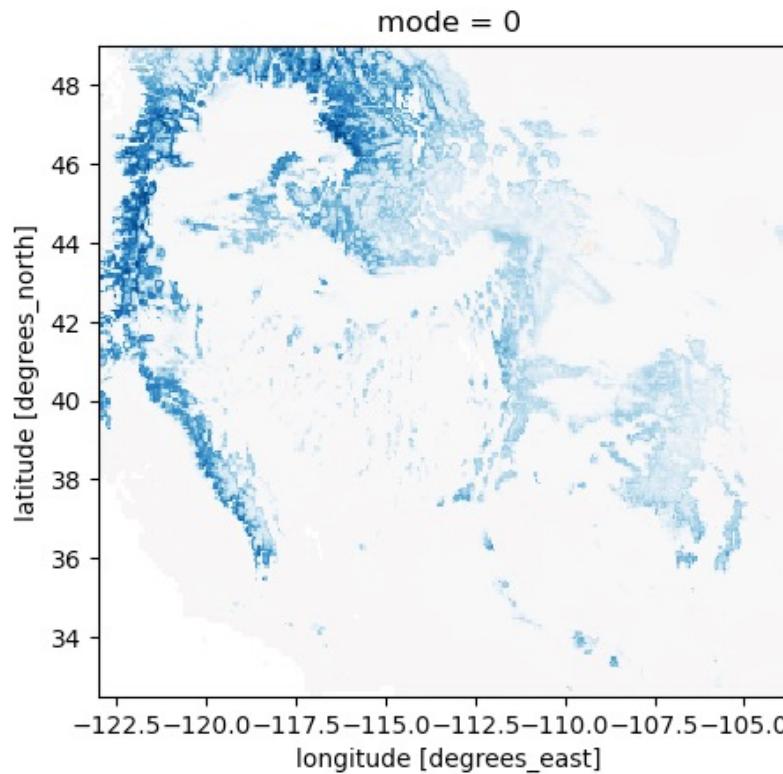


Figure. Multi-model ensemble mean fingerprint and PC of normalized snow water equivalent.



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# Internal Variability Domains

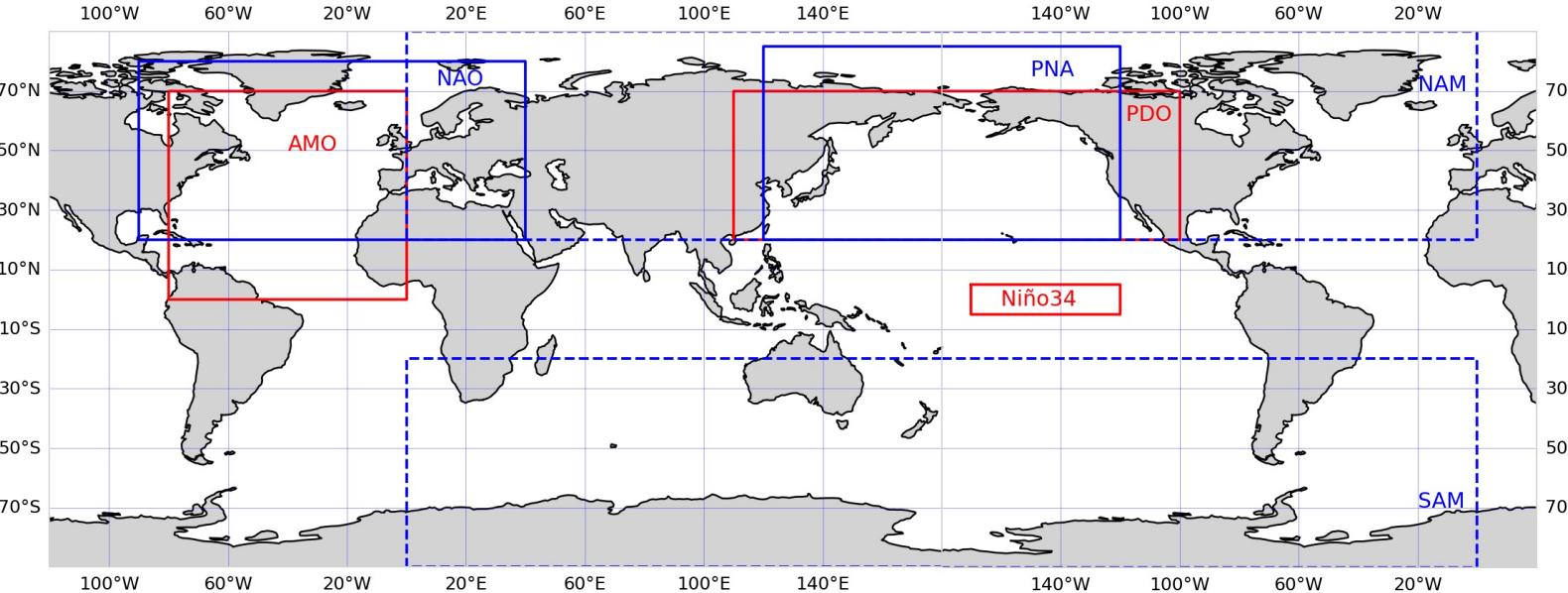
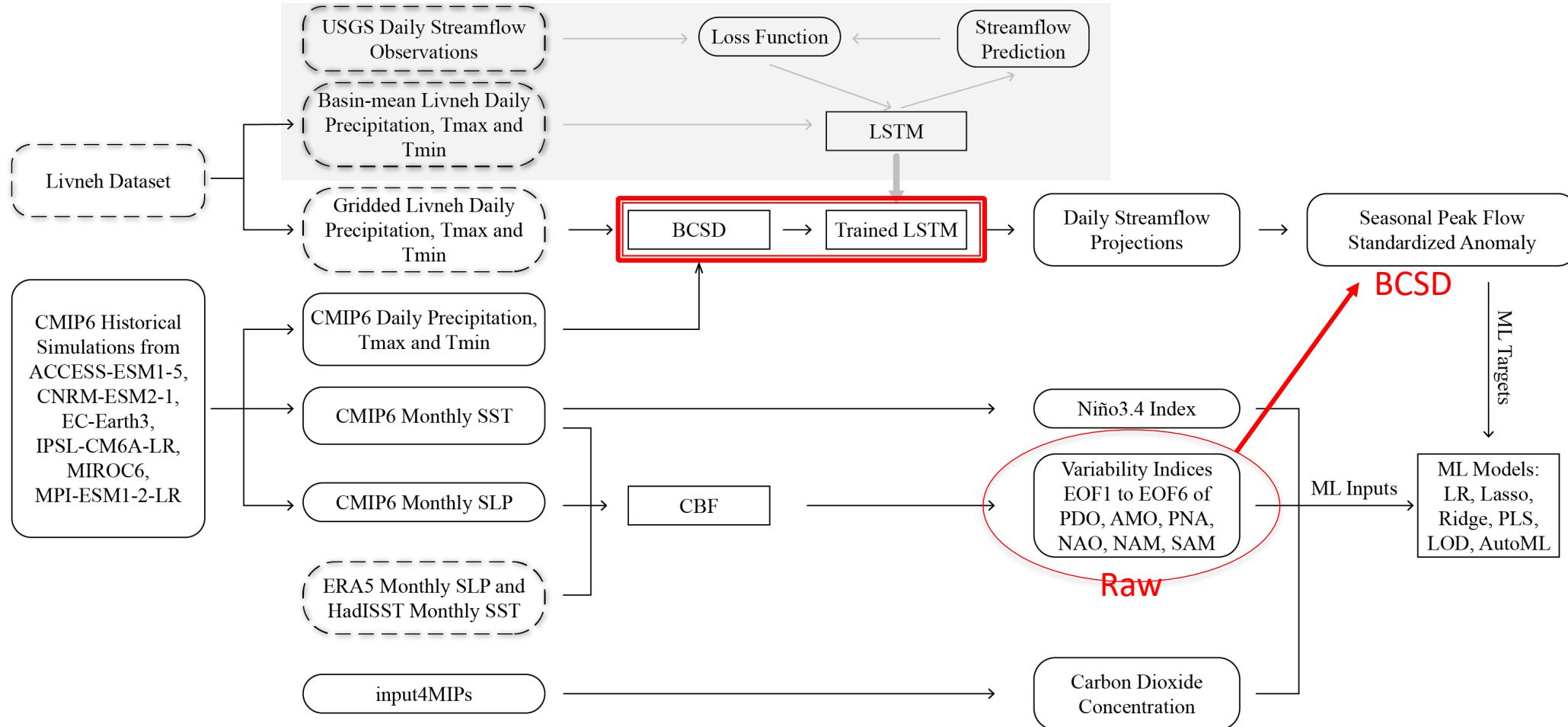


Figure. Internal variability domains. Dashed lines for NAM and SAM.

# Technical Workflow



# LSTM Performance

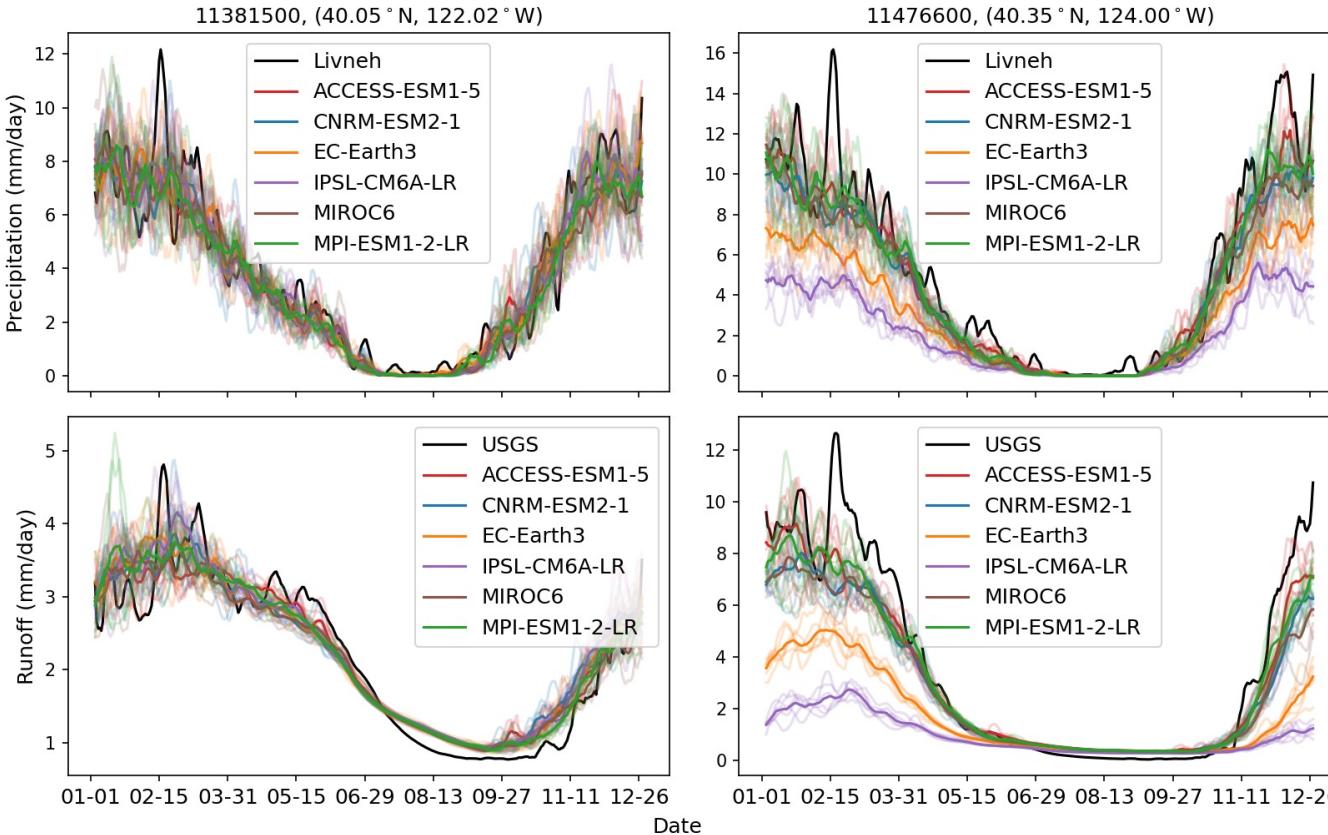
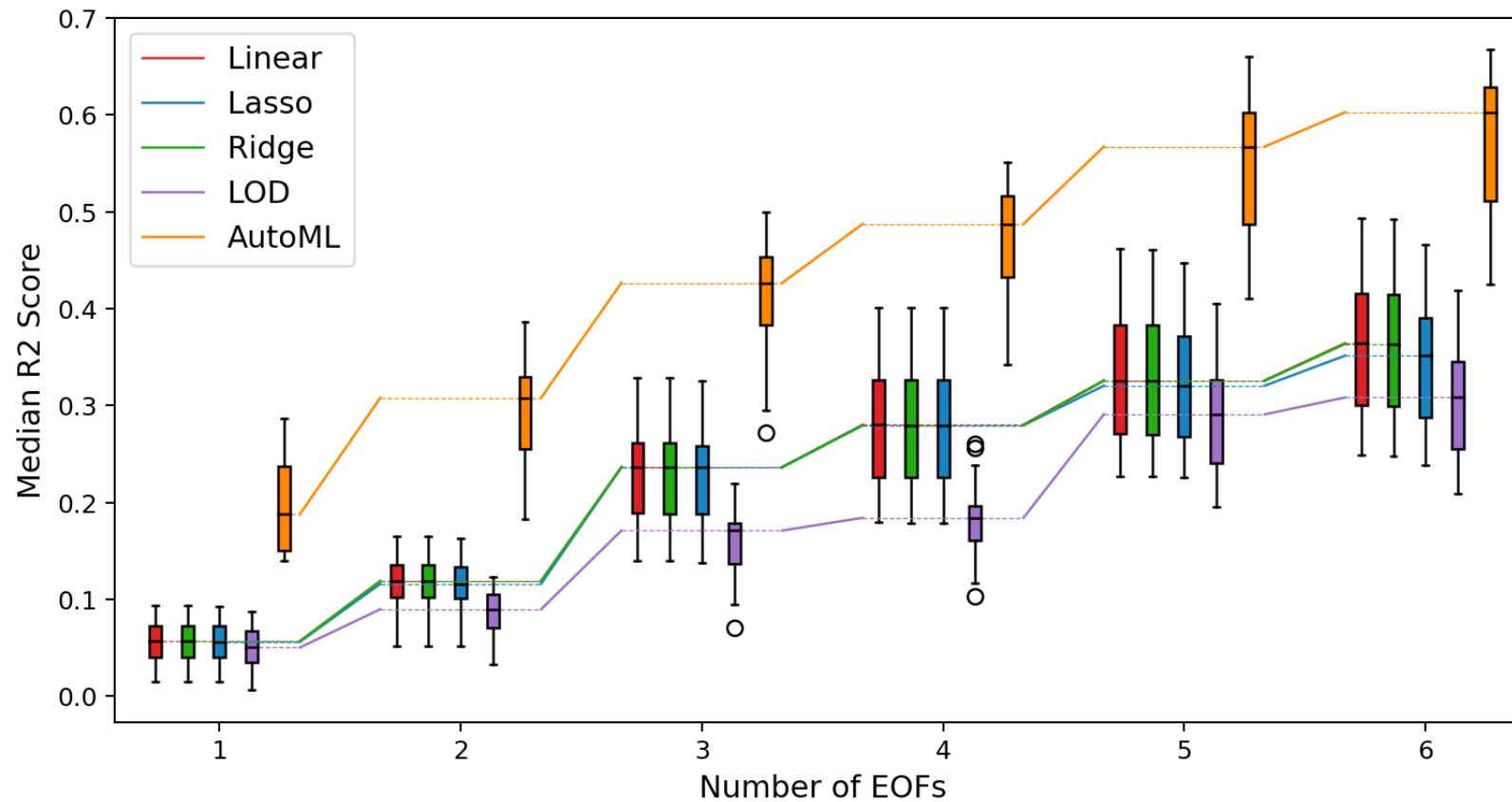


Figure. Daily precipitation climatology (top) and streamflow climatology (bottom) from two selected basins (left and right columns).

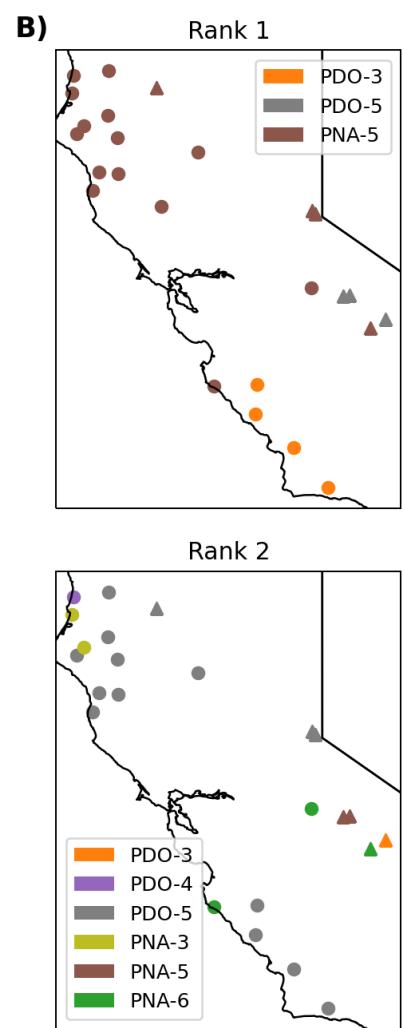
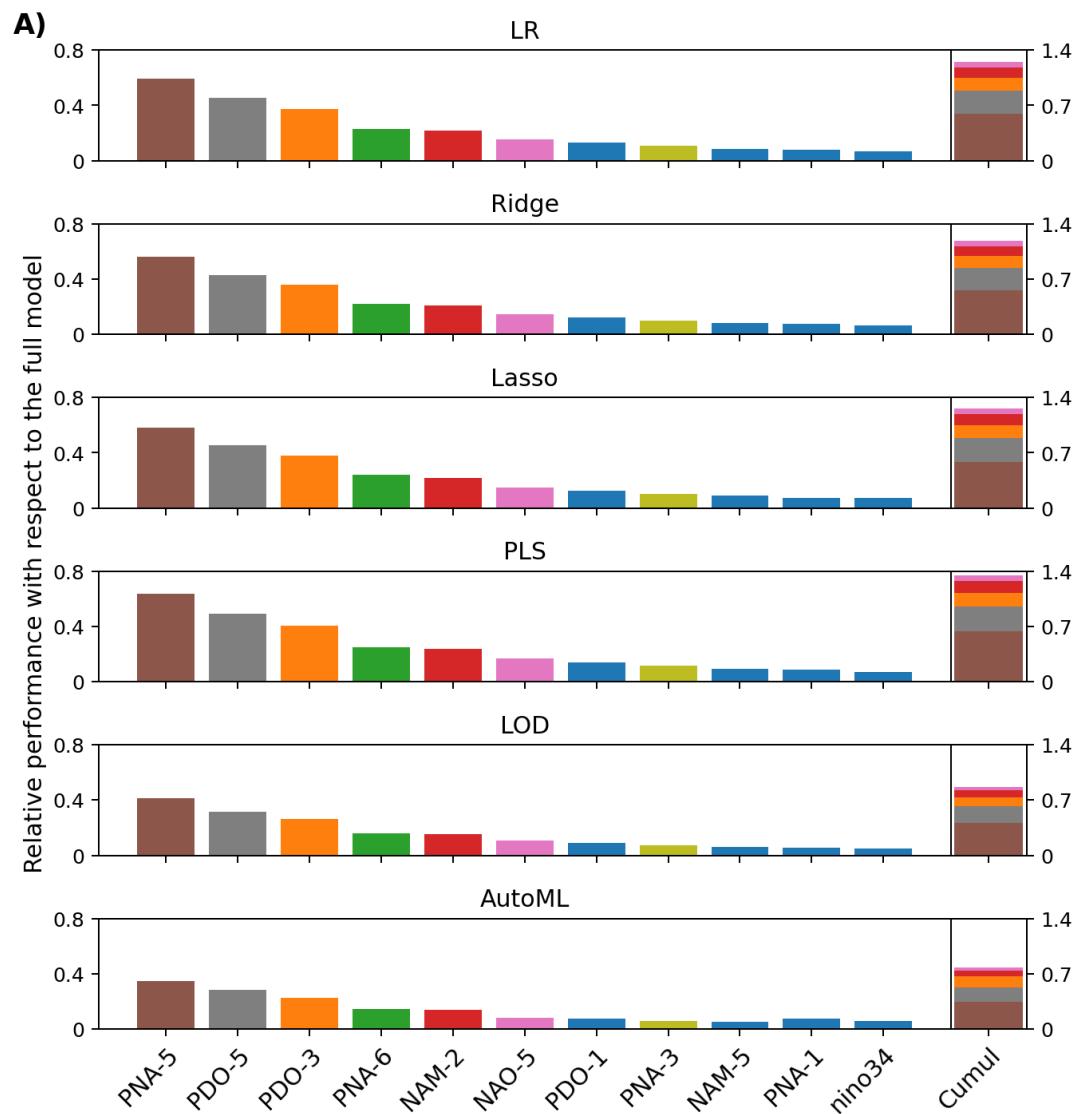
- LSTM accuracy of daily streamflow prediction has been proved
- For historical projection, the bottleneck is the biases in precipitation
- To mitigate the biases, use standardized streamflow anomalies
- Output/Target: LSTM-projected seasonal peak streamflow
  - Peak month, month prior and after
  - Standardized anomalies
- Input: seasonal variability indices
  - Concurrent season or previous season

# Training cross-validation R2



Training R2 with respect to number of EOFs.

# Feature Importance



# Cross validation

