A Space-Time Modeling Framework for Projection of Seasonal Streamflow Extremes

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Source: https://www.weather.gov/safety/flood-states-co

University of Colorado Boulder

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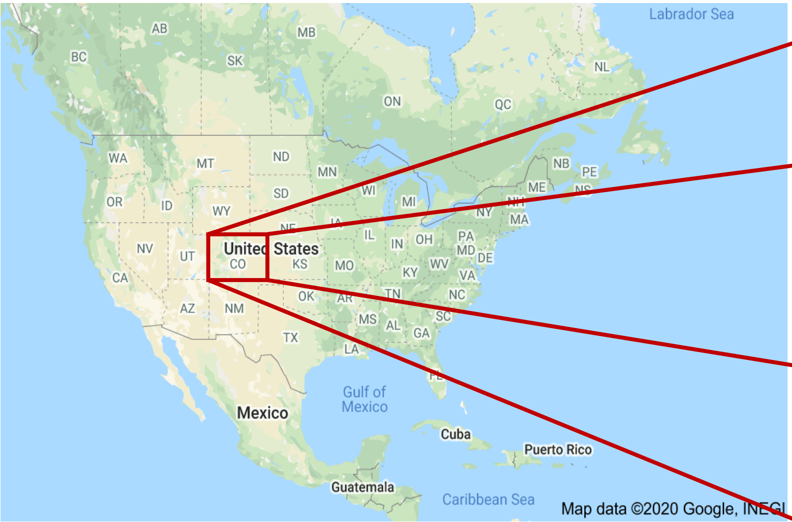
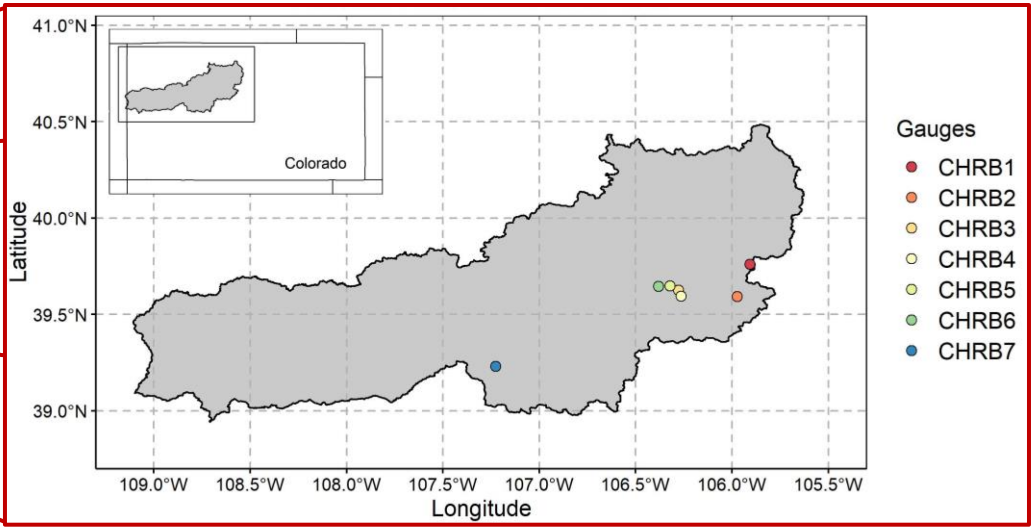
Study Region



Colorado Headwaters River Basin



Source:
RJ Sangosti, The Denver Post

Data

Streamflow

- Daily observed streamflow – U.S. Geological Survey (USGS)
- Years: 1965-2018 (54 years), no. of sites 7
- 3-day maximum (May-Jun) seasonal streamflow

Covariates (1965-2018)

- Climate indices: ENSO, PDO, AMO (https://www.esrl.noaa.gov/psd/data/climateindices/list/)
- April Mean Temperature (AMT) – Global Historical Climatology Network (GHCN) dataset (https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/)
- Snow Water Equivalent (SWE) – Natural Resources Conservation Service (NRCS) (https://wcc.sc.egov.usda.gov/reportGenerator/)

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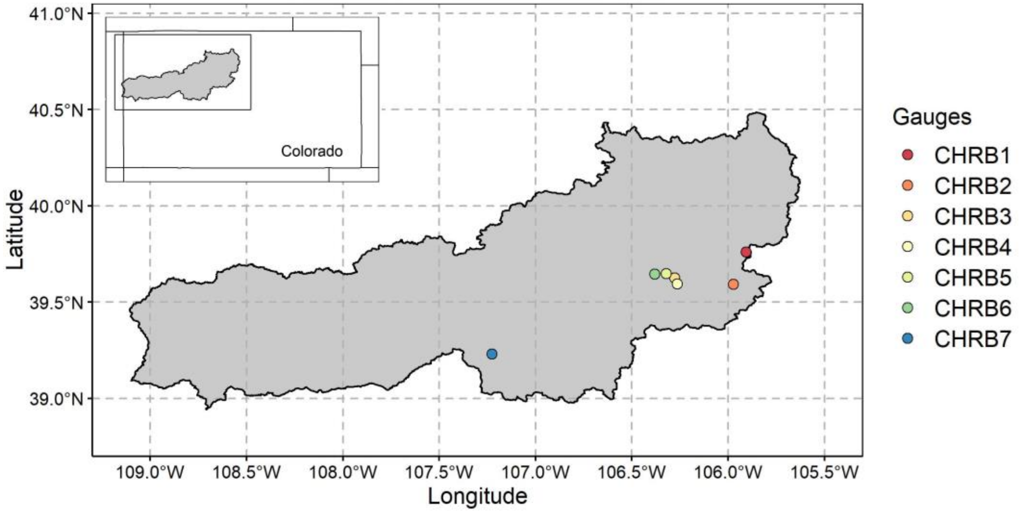
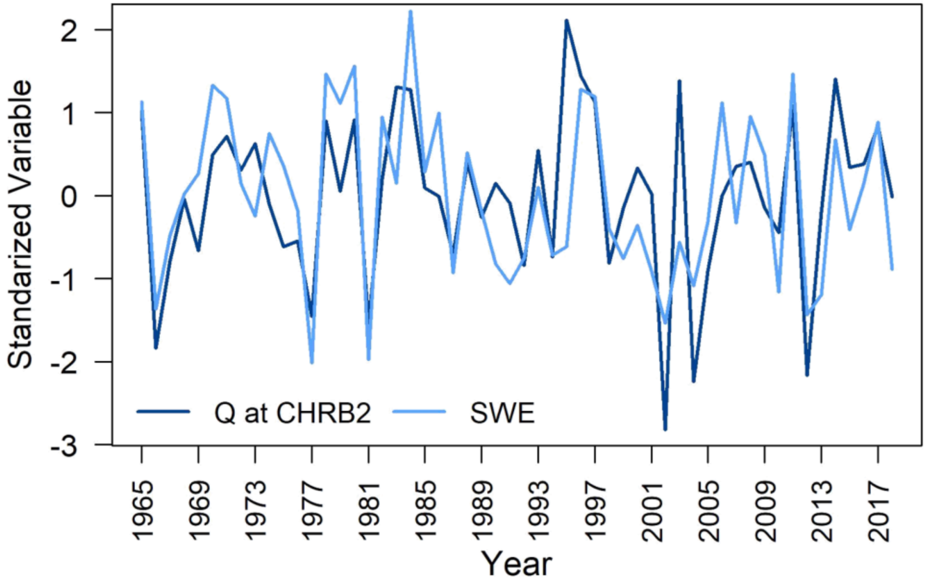
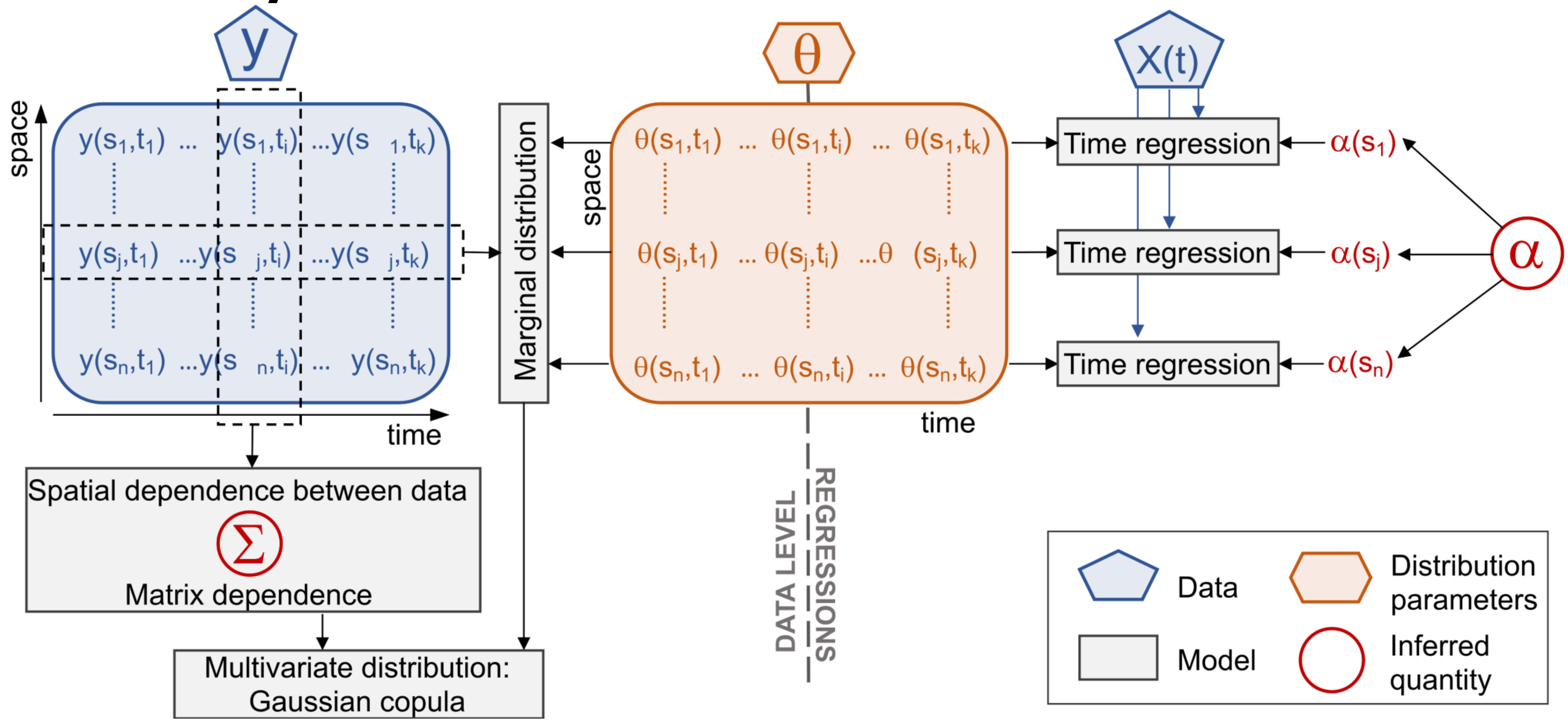




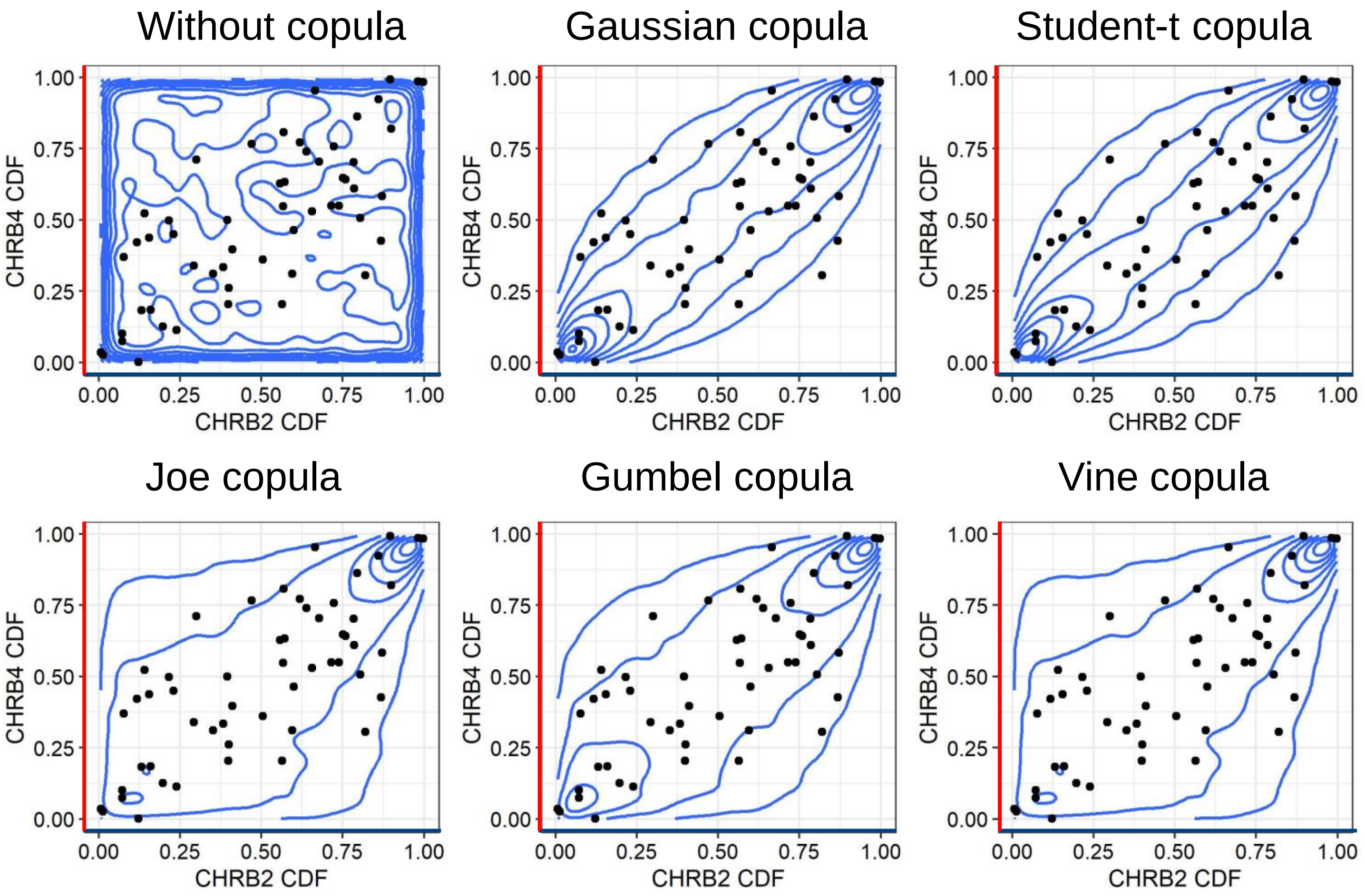
General Bayesian Model Structure



For each time and location

$$y(s_j, t_i) \sim GEV\left(\mu(s_j, t_i), \sigma(s_j, t_i), \xi(s_j, t_i)\right) \qquad \boldsymbol{\theta}(s_j, t_i) = [\mu(s_j, t_i), \log\sigma\,(s_j, t_i), \xi(s_j, t_i)]$$

Gaussian copula can replicate the dependence structure of the observed data



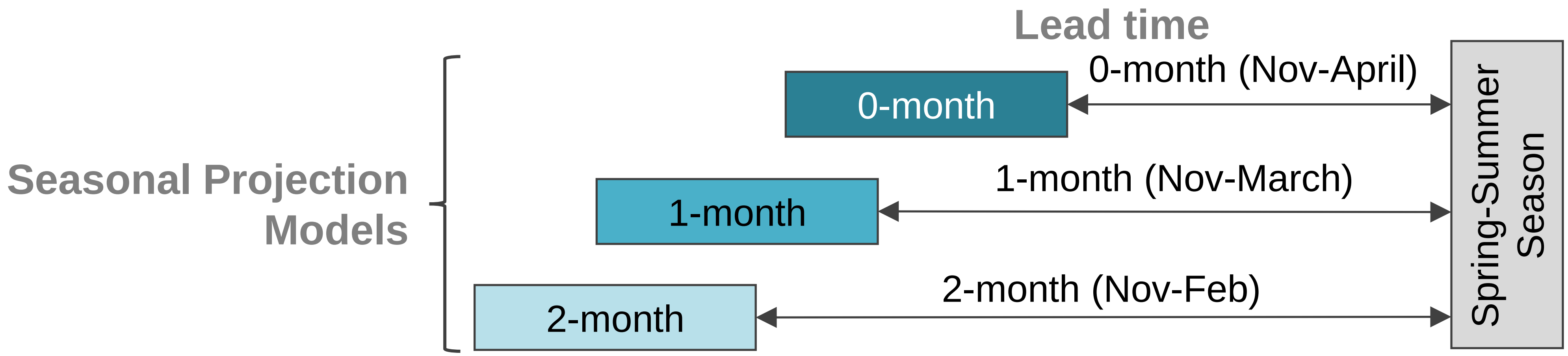
• Observed — Simulated contour lines

Models Considered

We considered 4 models for 0-month lead time (Nov-April)

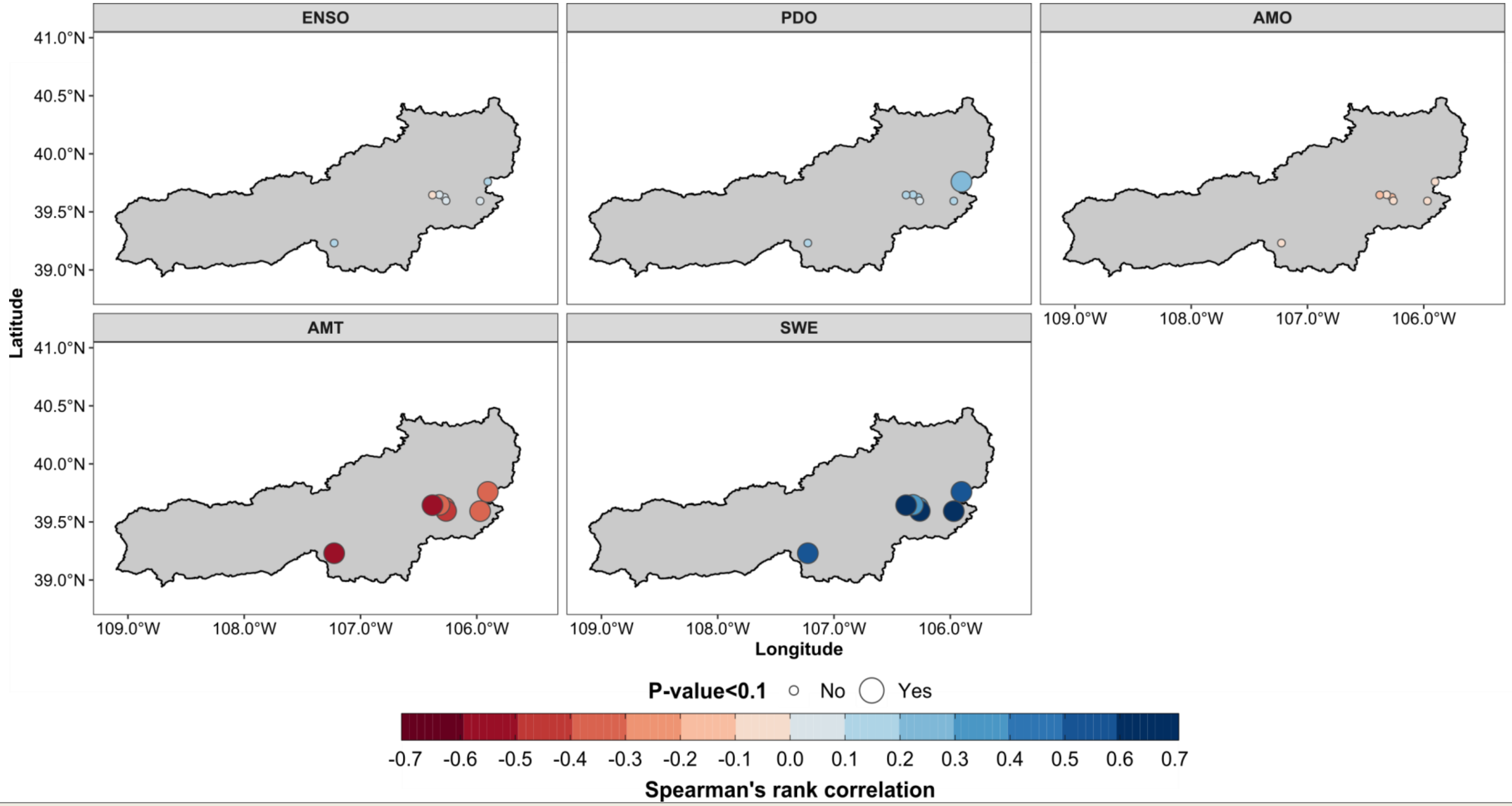
Stationary → Nonstationary SWE → Nonstationary SWE+Climate predictors → Nonstationary SWE+Climate predictors + Gaussian copula

And three different lead times for the last model



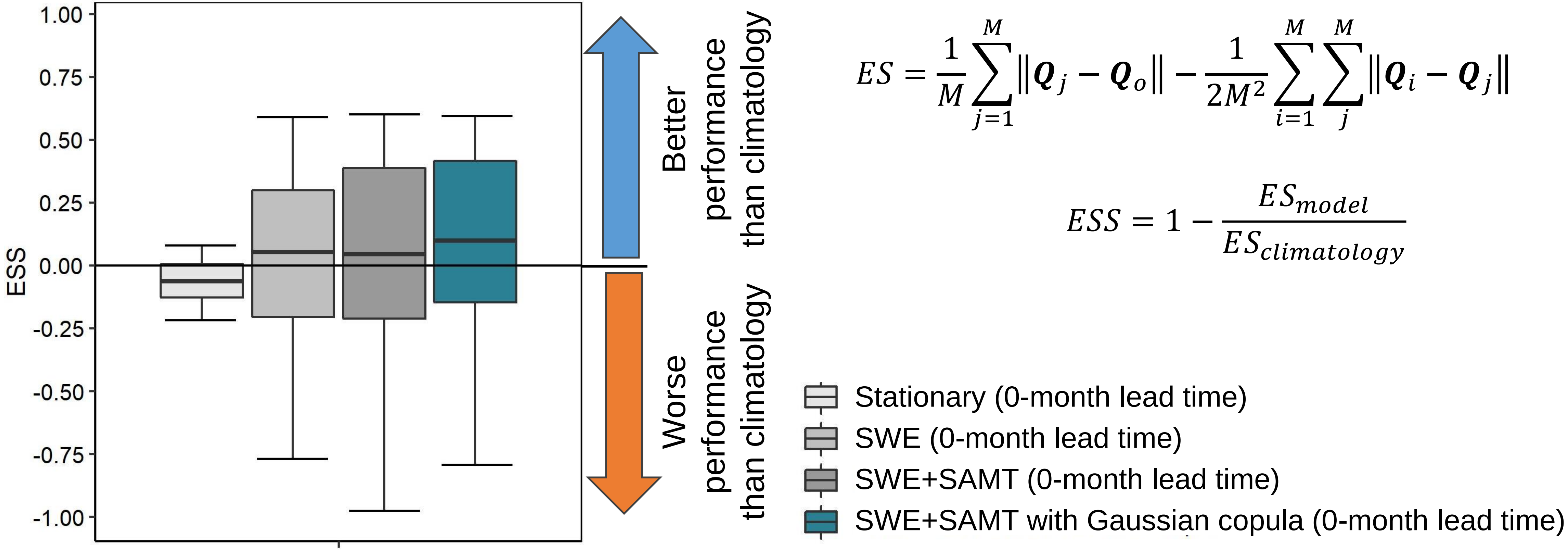
Two covariates show a strong correlation with Seasonal maximum streamflow

Exploratory analysis: 0-month lead time (Nov-April)



Predictors and copula allow to capture the spatial-temporal dependence

Energy Skill Score (ESS)

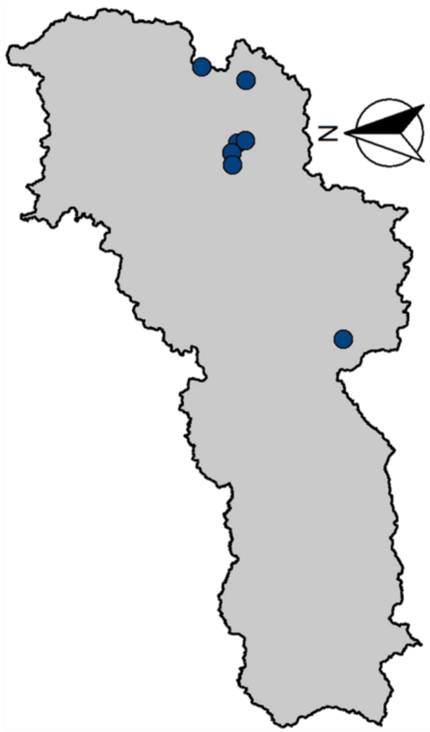


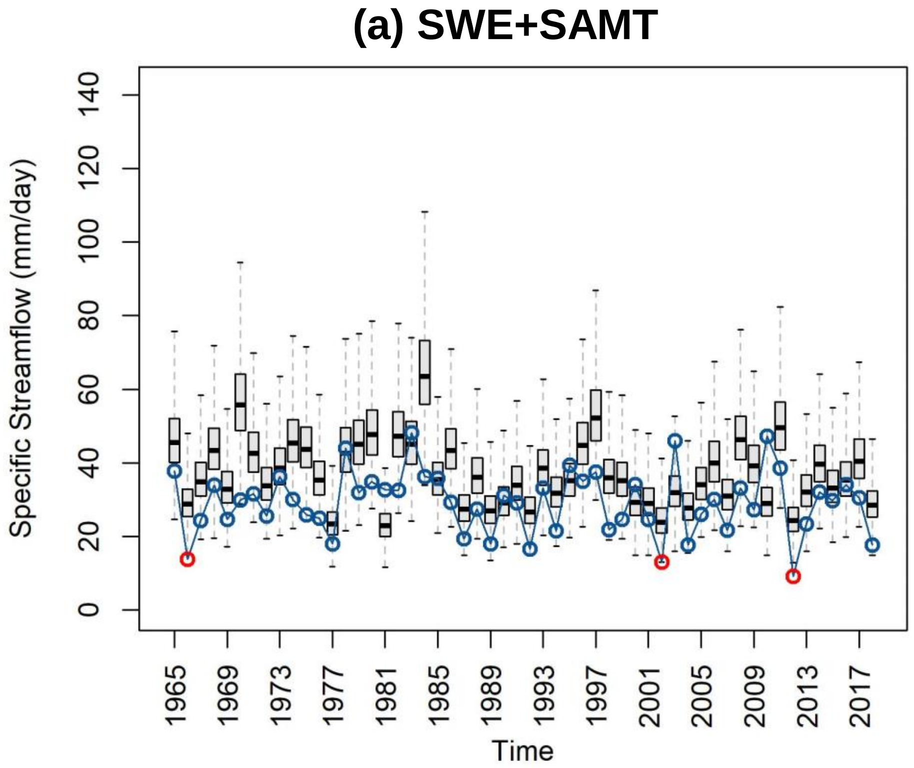
$$ES = \frac{1}{M}\sum_{j=1}^{M}\|\boldsymbol{Q}_j - \boldsymbol{Q}_o\| - \frac{1}{2M^2}\sum_{i=1}^{M}\sum_{j}^{M}\|\boldsymbol{Q}_i - \boldsymbol{Q}_j\|$$

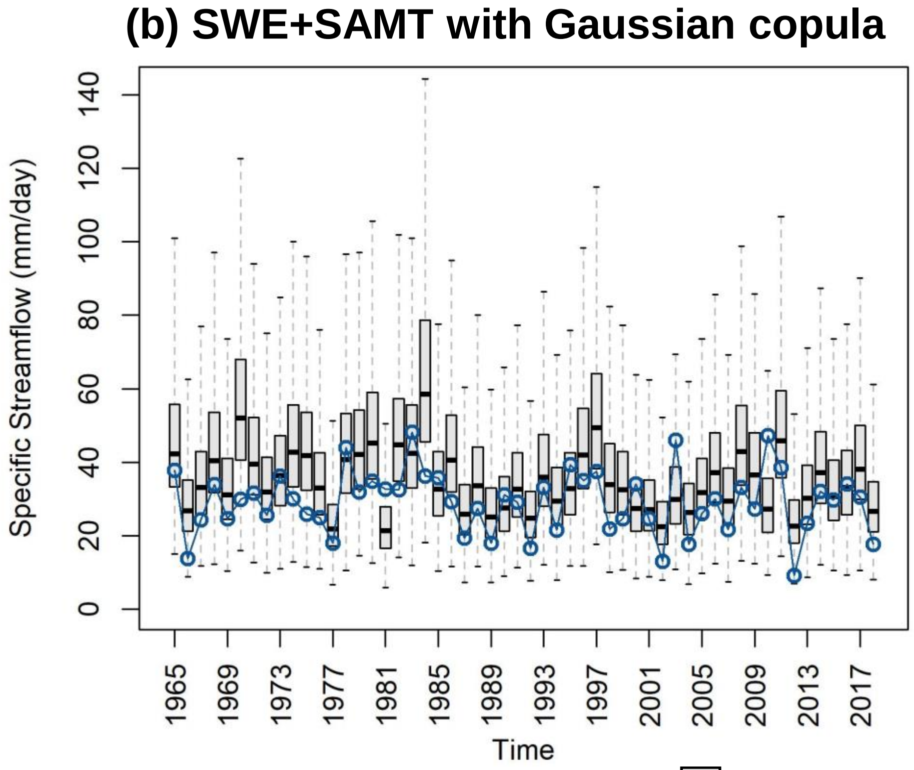
$$ESS = 1 - \frac{ES_{model}}{ES_{climatology}}$$

By adding a copula, the model can capture the observed values

Average of seasonal maximum flow over all gauges, models with SWE+ SAMT (0-month lead time)



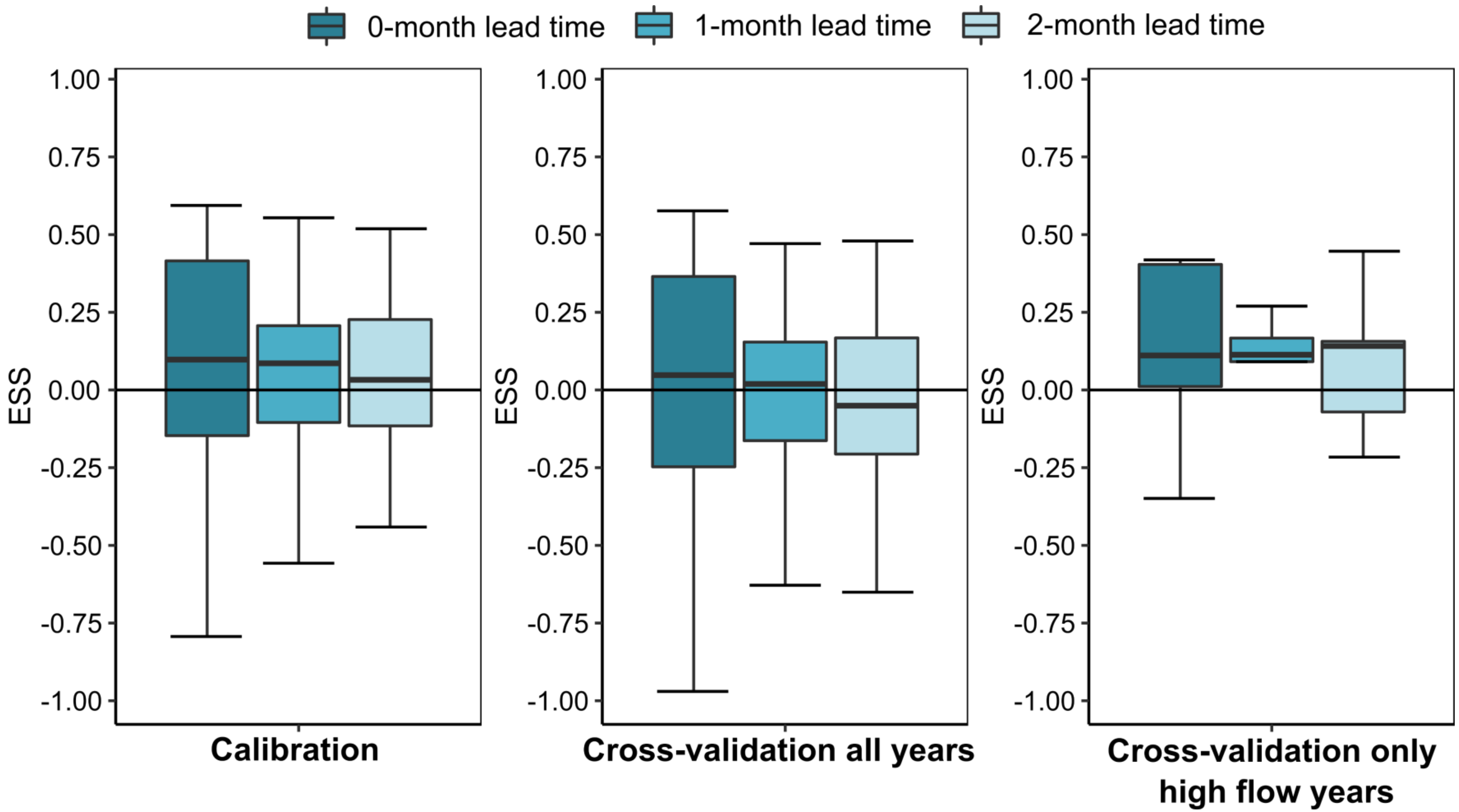




Observation non captured by ensembles Observation captured by ensembles Ensembles

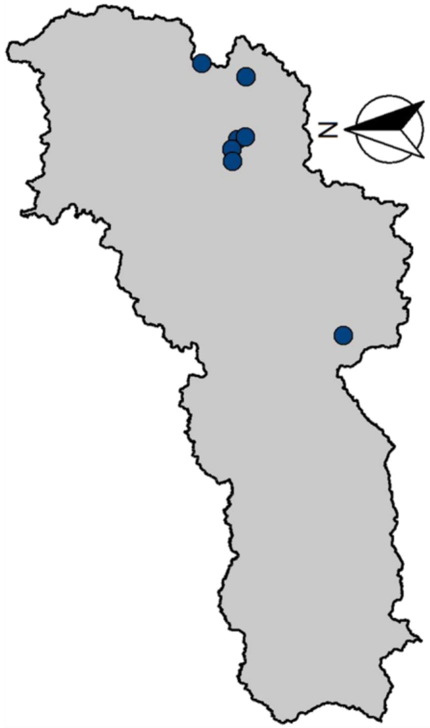
Three models has a better performance than climatology for predict high flows years

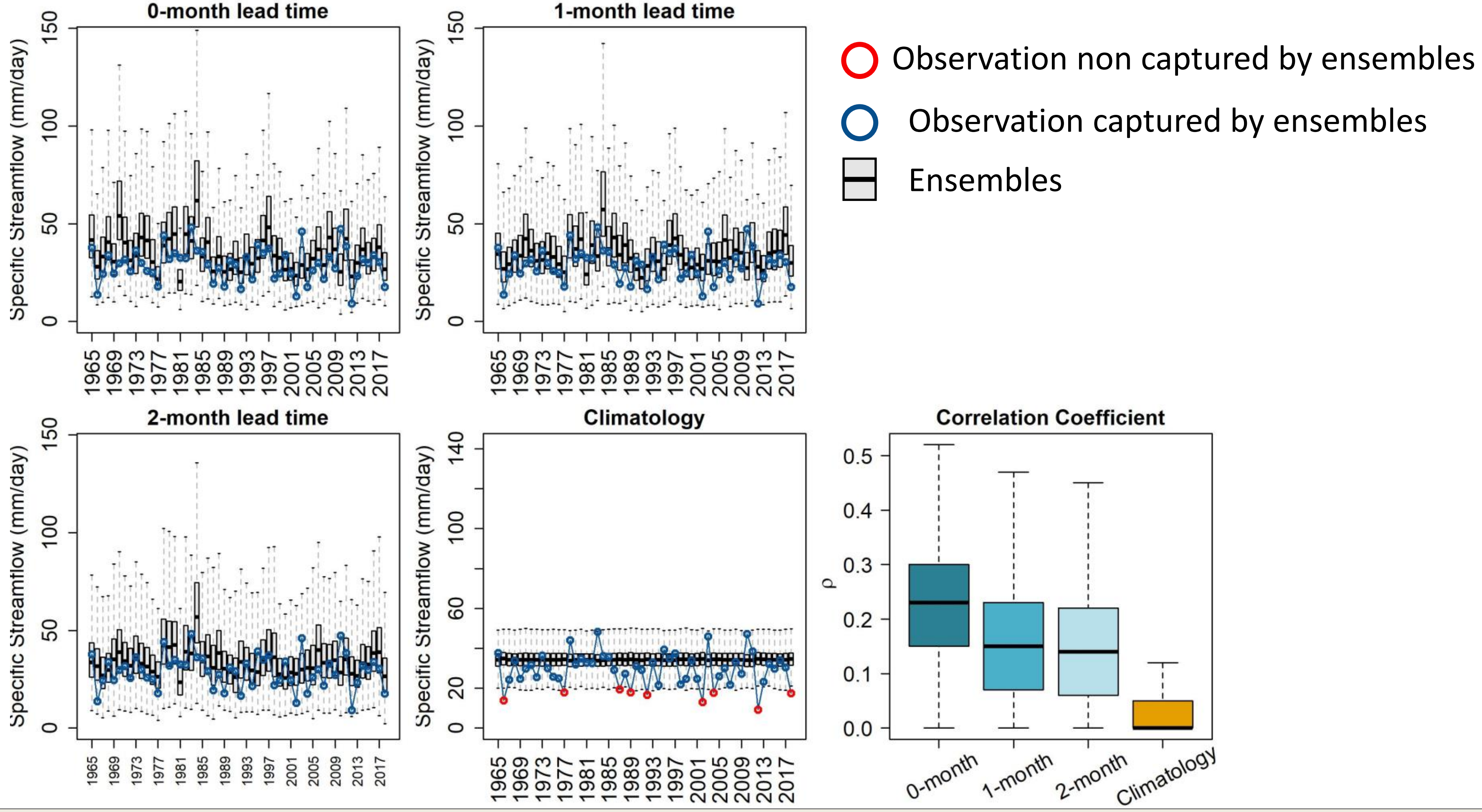
Energy Skill Score (ESS) for different cases



The performance is not so difference between different lead times

average of seasonal maximum flow over all gauges, Case 2 (cross-validation all years)





Deliver interpretable seasonal projections

Proposed Spring Seasonal Projection

- Provide 3 percentiles along with some past streamflow as reference
- Reference values can help to make decision about risk mitigation in advance
- Example: Forecast 2018 for 0-month lead time

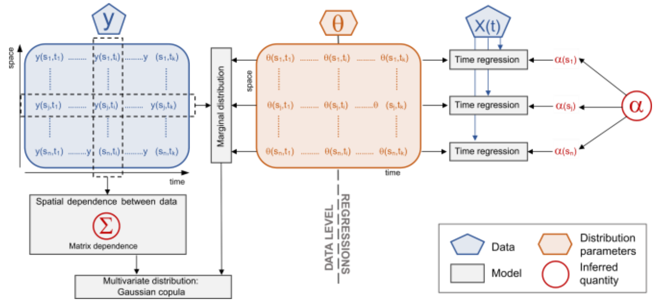
Max streamflow with a xx% of chance of being exceeded

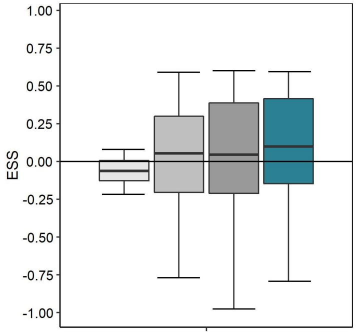
Reference values

Description	Average Seasonal Streamflow (mm/day)
Max streamflow 75% (2018)	21.0
Max streamflow 50% (2018)	26.8
Max streamflow 25% (2018)	35.3
Max streamflow (high flow event)	48.2
Max median streamflow (normal year)	29.2

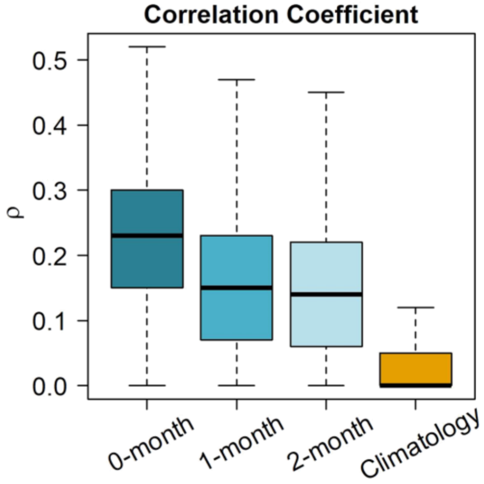
Conclusions

Skillful seasonal projections by considering no stationarity, spatial dependence, and parameter uncertainties





Seasonal projections up to 2 months in advance without reduce the model skill significantly



The framework can be easily applied to another region or adjusted to represents future climate conditions

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