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

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Abstract

We developed a space-time model to project seasonal streamflow extremes on a river network for at several lead times. In this, the extremes – 3-day maximum streamflow - at each gauge location on the network are assumed to be realized from a Generalized Extreme Value (GEV) distribution with temporal non-stationary parameters. The parameters are modeled as a linear function of suitable covariates. In addition, the spatial dependence of the extremes across the network is modeled via a Gaussian copula. The parameters of the non-stationary GEV at each location are estimated via maximum likelihood, whereas those of the Copula are estimated via maximum pseudo-likelihood. Best subset of covariates are selected using AIC. Ensembles of streamflow in time, which are based on the varying temporal covariates and from the Copula, are generated, consequently, capturing the spatial and temporal variability and the attendant uncertainty. We applied this framework to project spring (May-Jun) season 3-day maximum flow at seven gauges in the Upper Colorado River Basin (UCRB) network, at 0 ˜ 3 months lead time. In this basin, almost all of the annual flow and extremes that cause severe flooding, arrives during the spring season as a result of melting of snow accumulated during the preceding winter season. As potential covariates, we used indices of large scale climate teleconnection – ENSO, AMO, and PDO, regional mean snow water equivalent and temperature from the preceding winter season. The skill of the probabilistic projections of flow extremes is assessed by rank histograms and skill scores such as CRPSS and ES for marginal and spatial performance. We also evaluate the utility of Gaussian Copula by computing spatial threshold exceedance probabilities compared to a model without the Copula – i.e. independent model at each gauge. The validation indicates that the model is able to capture the space-time variability of flow extremes very well, and the skills increase with decreasing lead time. Also the use of climate variables enhances skill relative to using just the snow information. The median projections and their uncertainties are highly consistent with the observations with a Gaussian copula than without it, indicating the role of spatial dependence. This framework will be of use in long leading planning of flood risk mitigation strategies.

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

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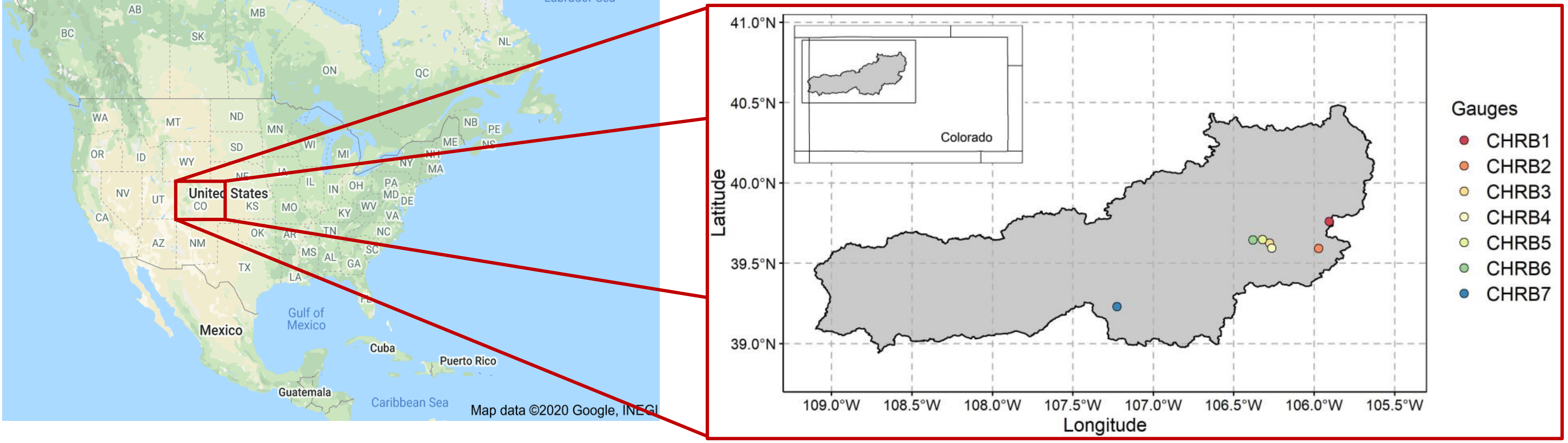
CIRES
NSF
FULBRIGHT

Study Region

Colorado Headwaters River Basin



Source:
RJ Sangosti, The Denver Post

Data

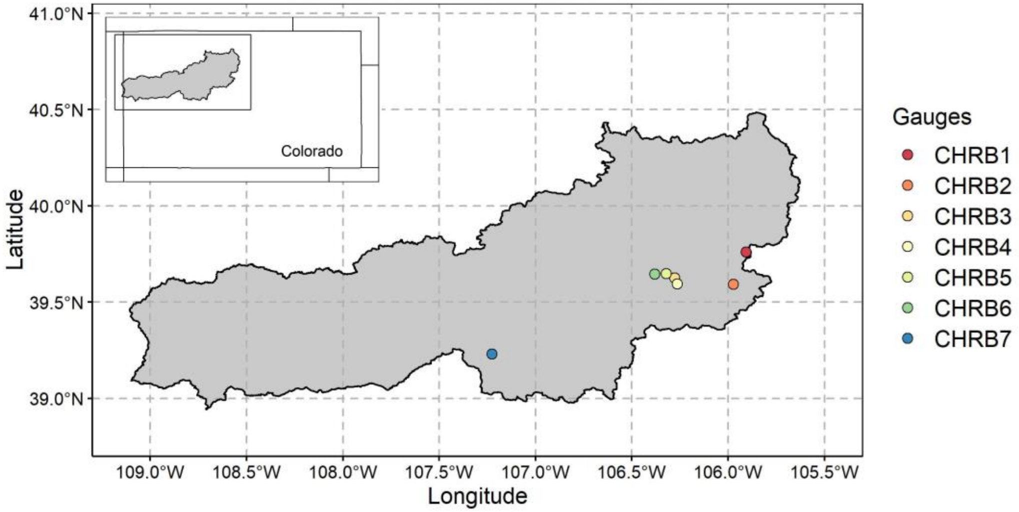
Streamflow

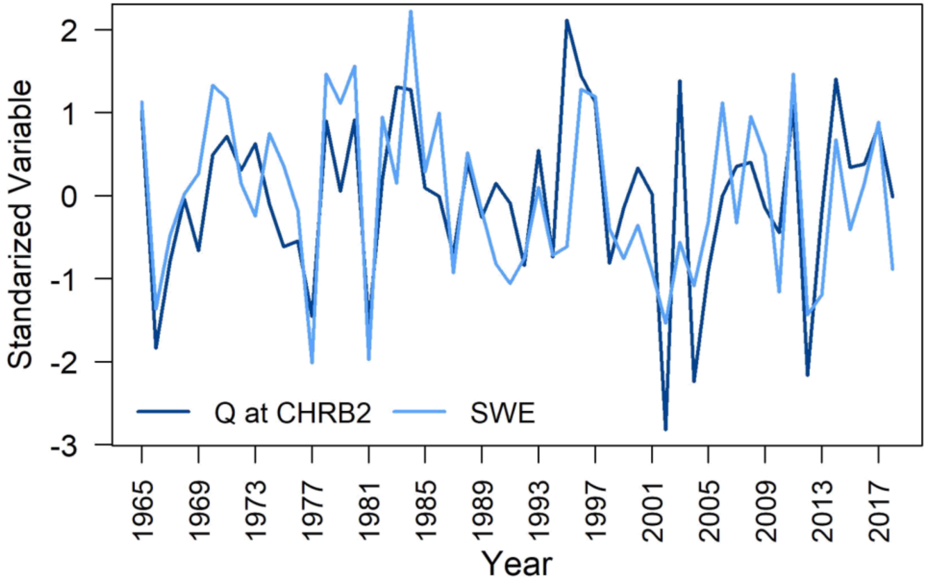
- Daily observed streamflow – U.S. Geological Survey (USGS)
- Years: 1965-2018 (54 years), no. of sites 7
- 3-day maximum (May-Jun) seasonal streamflow

Covariates (1965-2018)

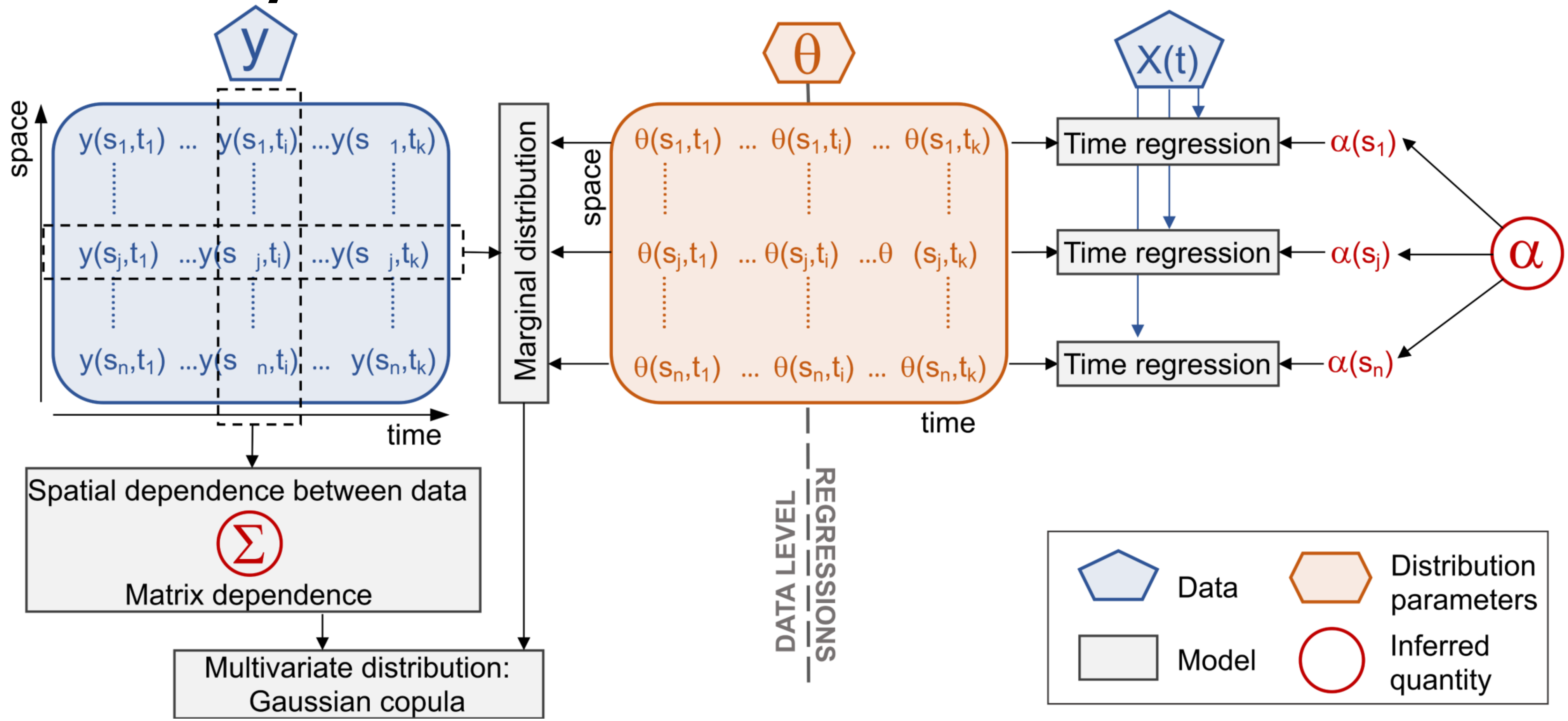
- Climate indices: ENSO, PDO, AMO (https://www.esrl.noaa.gov/psd/data/climateindices/list/)
- April Mean Temperature (AMT) – Global Historical Climatology Network (GHCN) dataset (https://www1.ncdc.noaa.gov/pub/data/ghcn/daily/)
- Snow Water Equivalent (SWE) – Natural Resources Conservation Service (NRCS)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

Colorado Headwaters River Basin





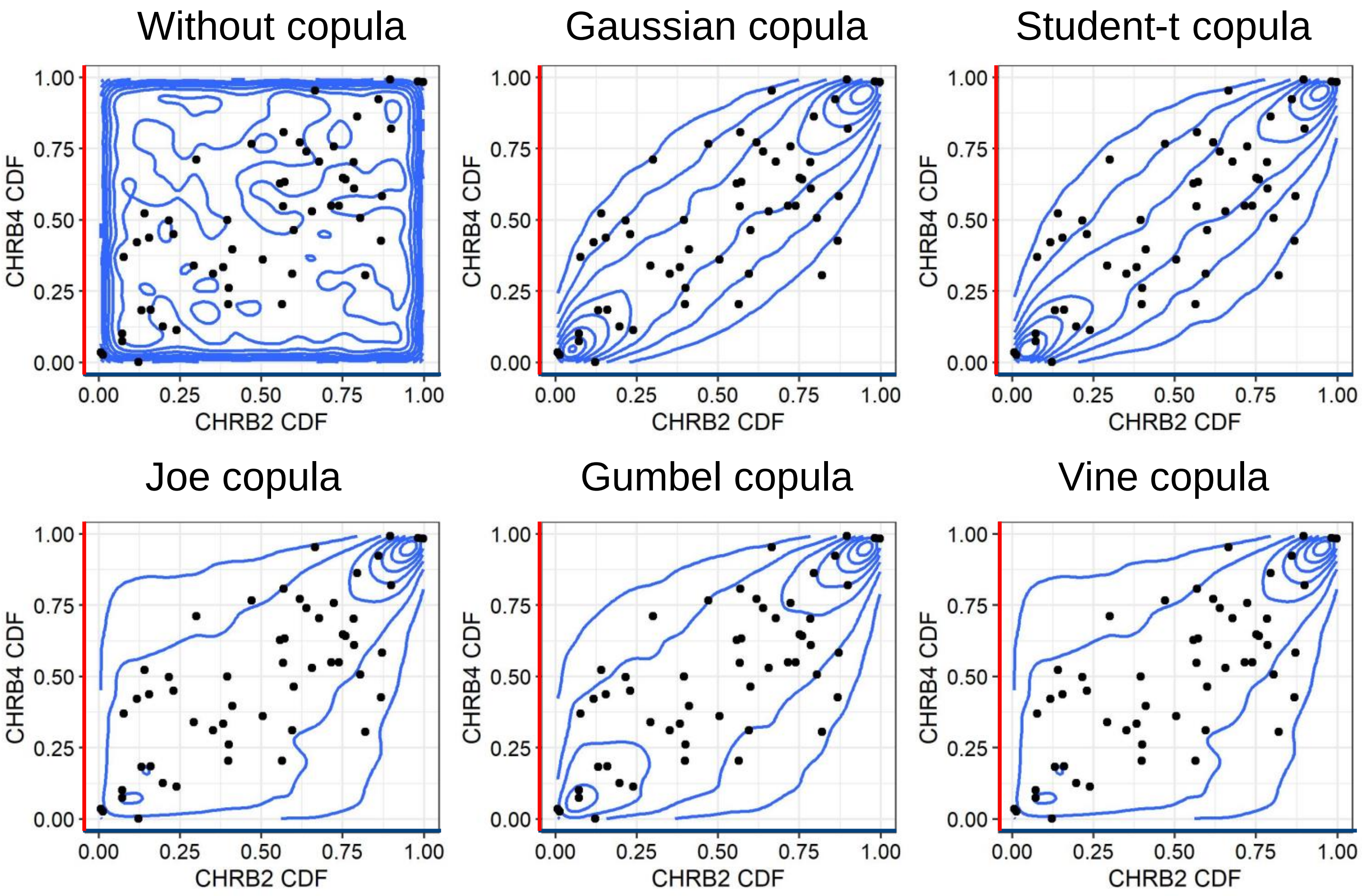
General Bayesian Model Structure



For each time and location

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

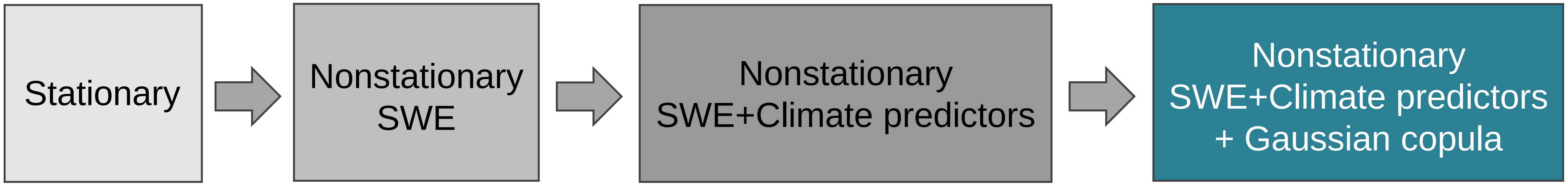
Gaussian copula can replicate the dependence structure of the observed data



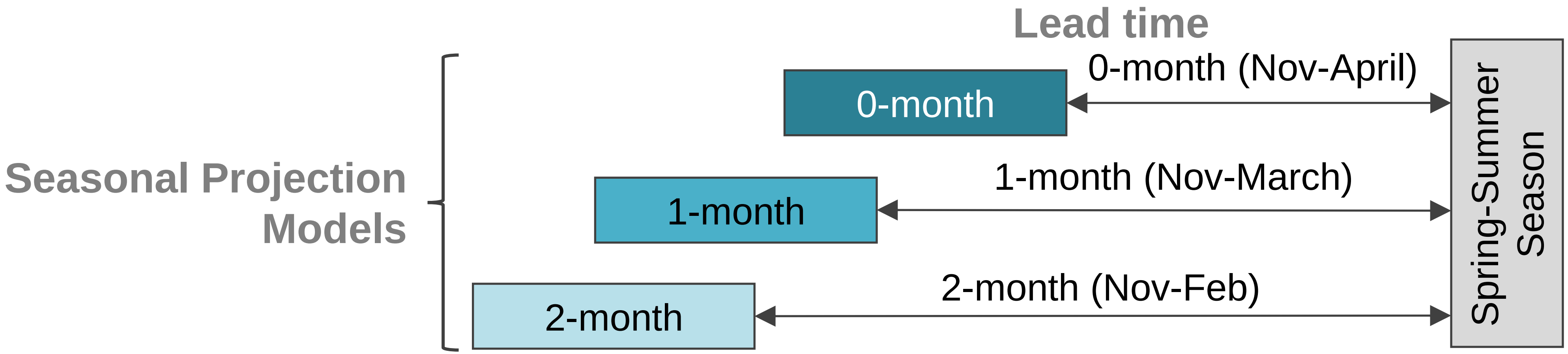
• Observed — Simulated contour lines

Models Considered

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

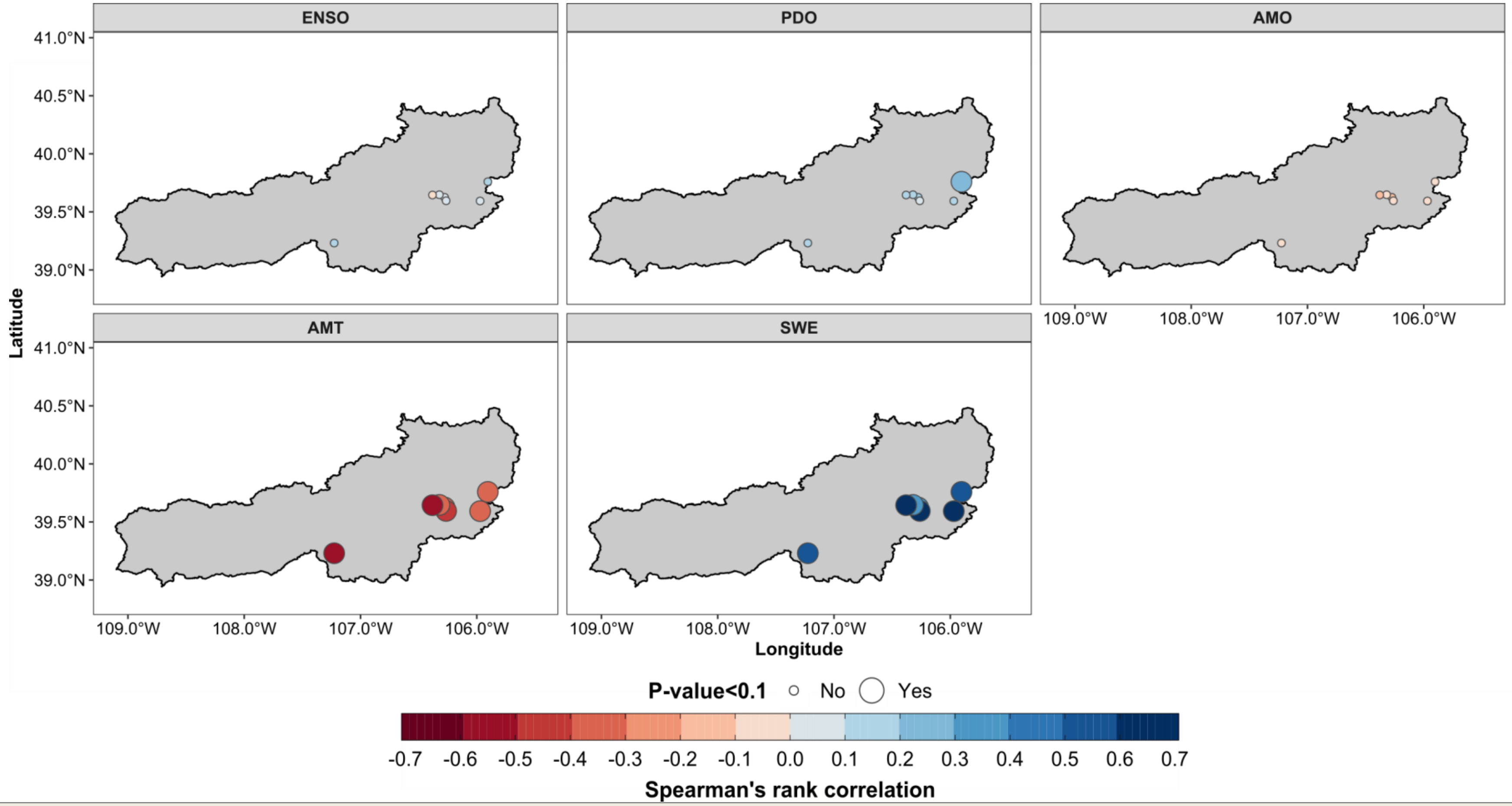


And three different lead times for the last model



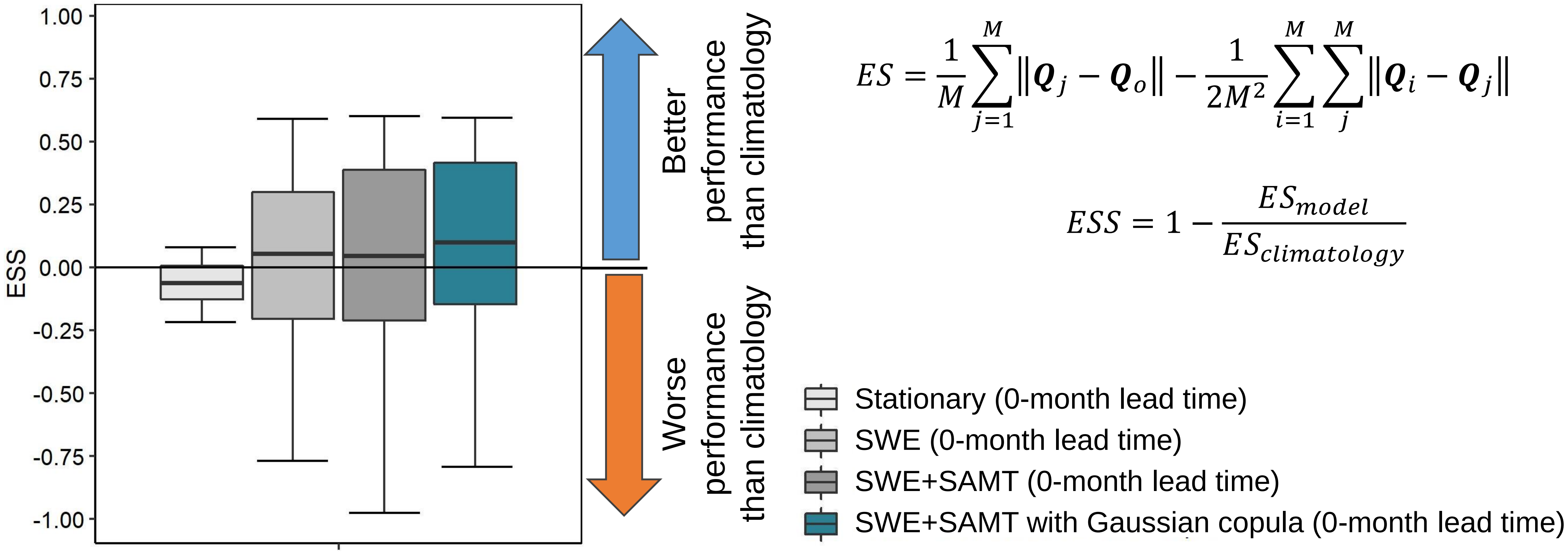
Two covariates show a strong correlation with Seasonal maximum streamflow

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



Predictors and copula allow to capture the spatial-temporal dependence

Energy Skill Score (ESS)

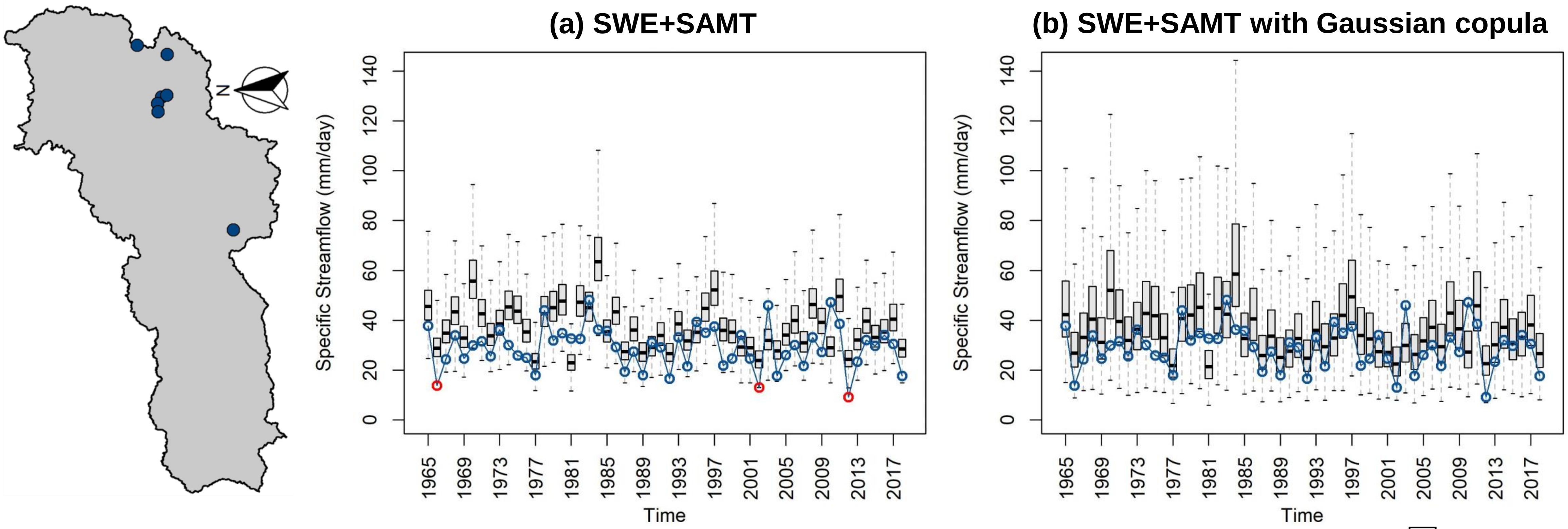


$$ES = \frac{1}{M}\sum_{j=1}^{M}\|\boldsymbol{Q}_j - \boldsymbol{Q}_o\| - \frac{1}{2M^2}\sum_{i=1}^{M}\sum_{j}^{M}\|\boldsymbol{Q}_i - \boldsymbol{Q}_j\|$$

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

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

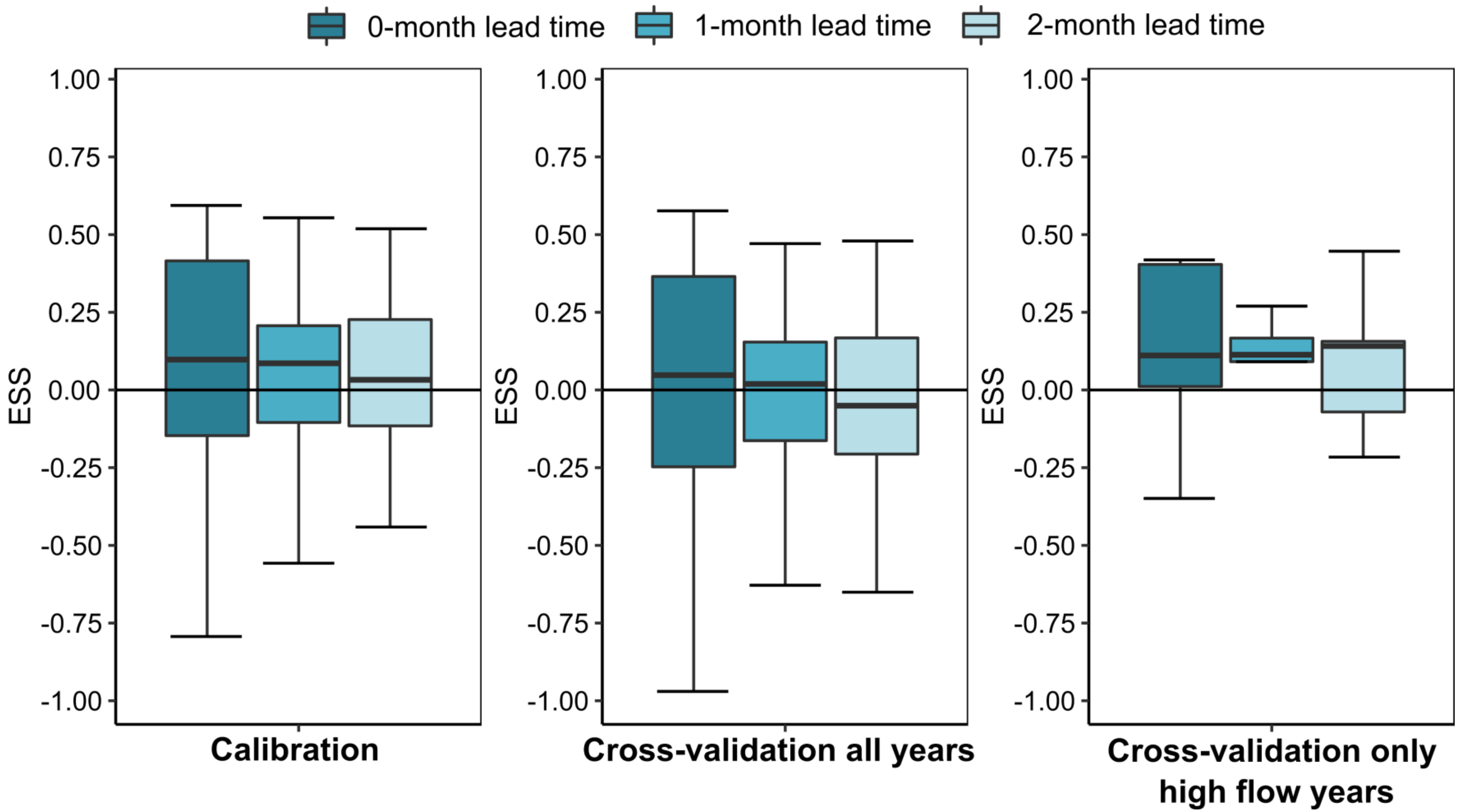
Average of seasonal maximum flow over all gauges, models with SWE+ SAMT (0-month lead time)



Observation non captured by ensembles   Observation captured by ensembles   Ensembles

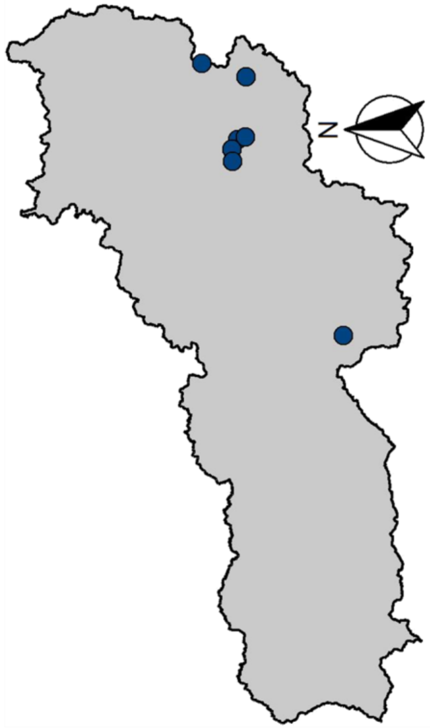
Three models has a better performance than climatology for predict high flows years

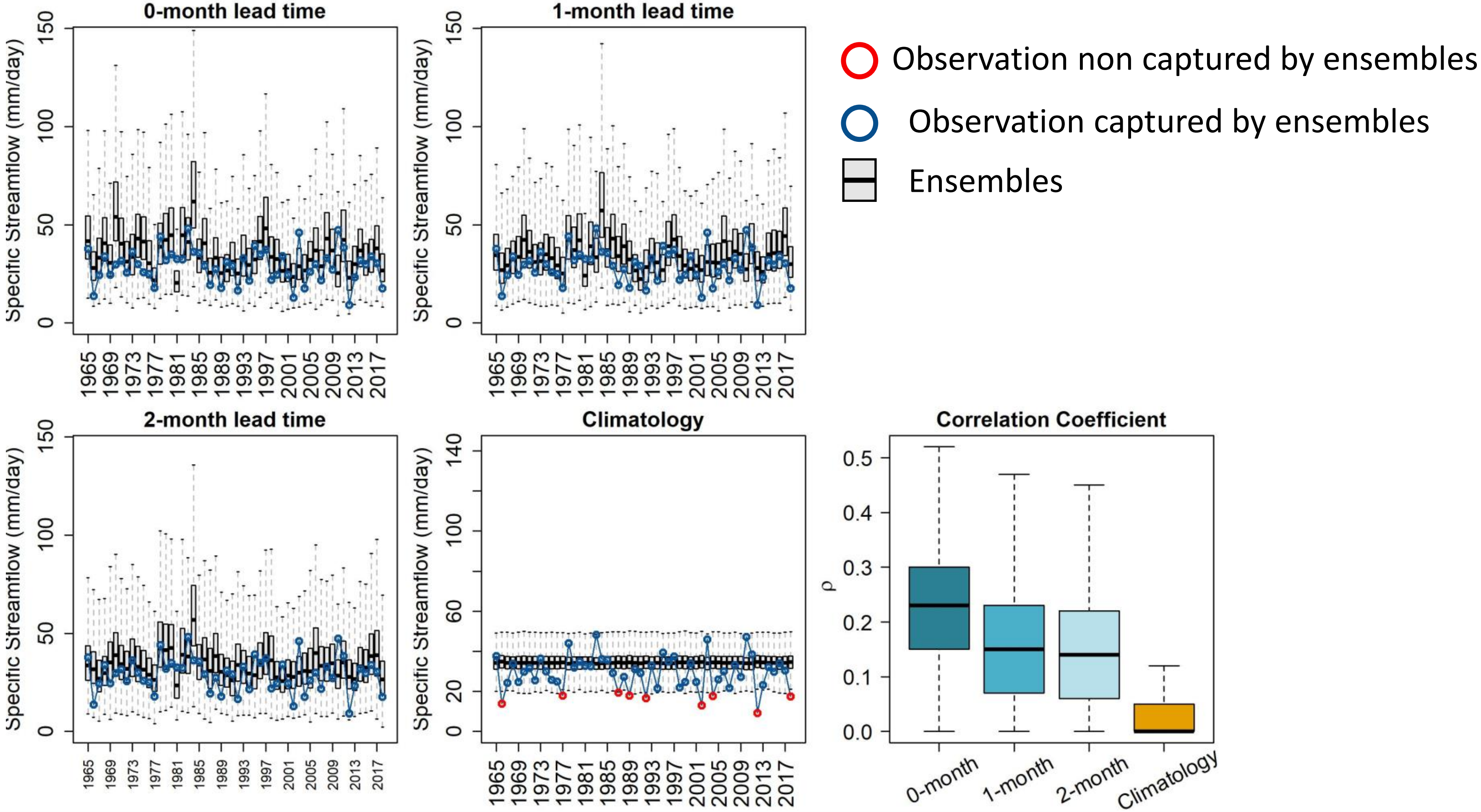
Energy Skill Score (ESS) for different cases



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

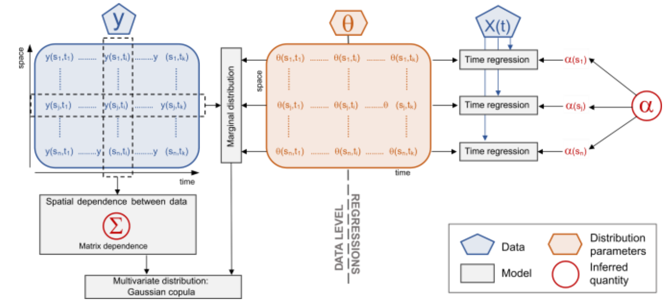
Max streamflow with a xx% of chance of being exceeded

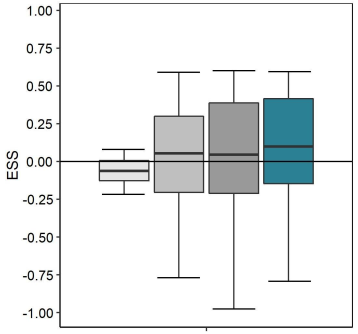
Reference values

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

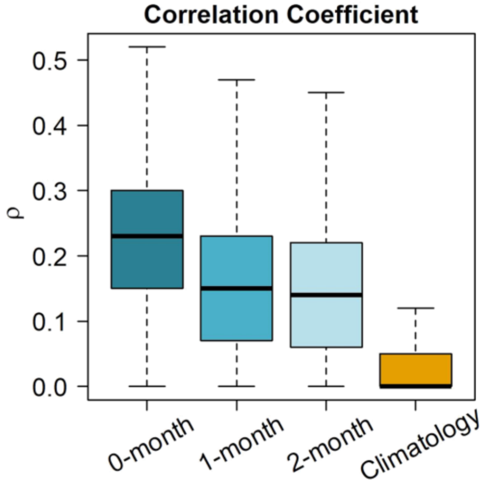
Conclusions

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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