ADVANCING SEASONAL HYDROLOGICAL PREDICTION IN THE UPPER TAGUS BASIN (CENTRAL SPAIN) THROUGH GLOBAL CLIMATE MODEL INTEGRATION AND MACHINE LEARNING TECHNIQUES

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National School of Water and Environmental Engineering, Strasbourg University, France.

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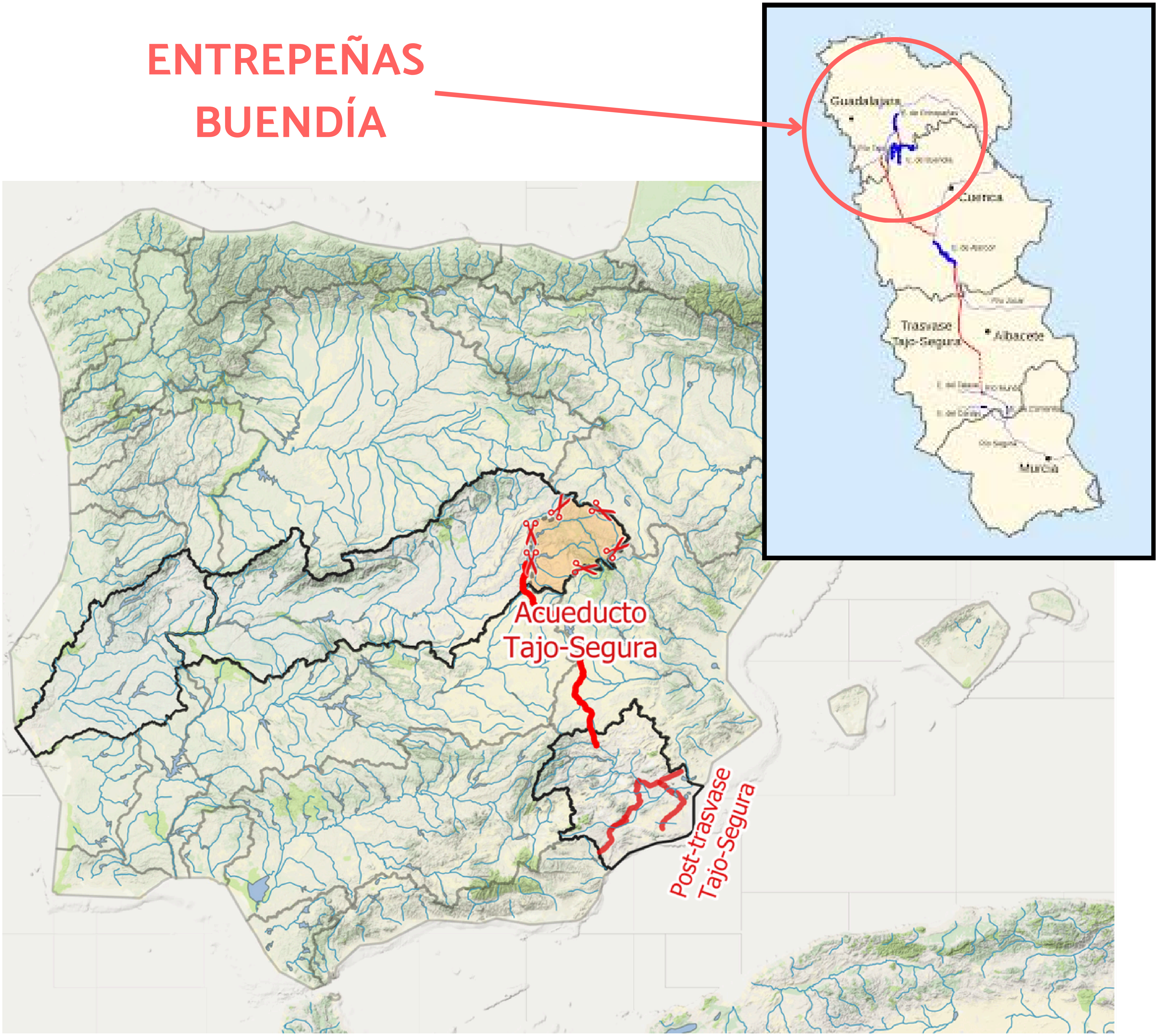
BACKGROUND

- Water Scarcity
- Tagus-Segura Water Transfer (TSWT)
- Need for reliable forecasts:



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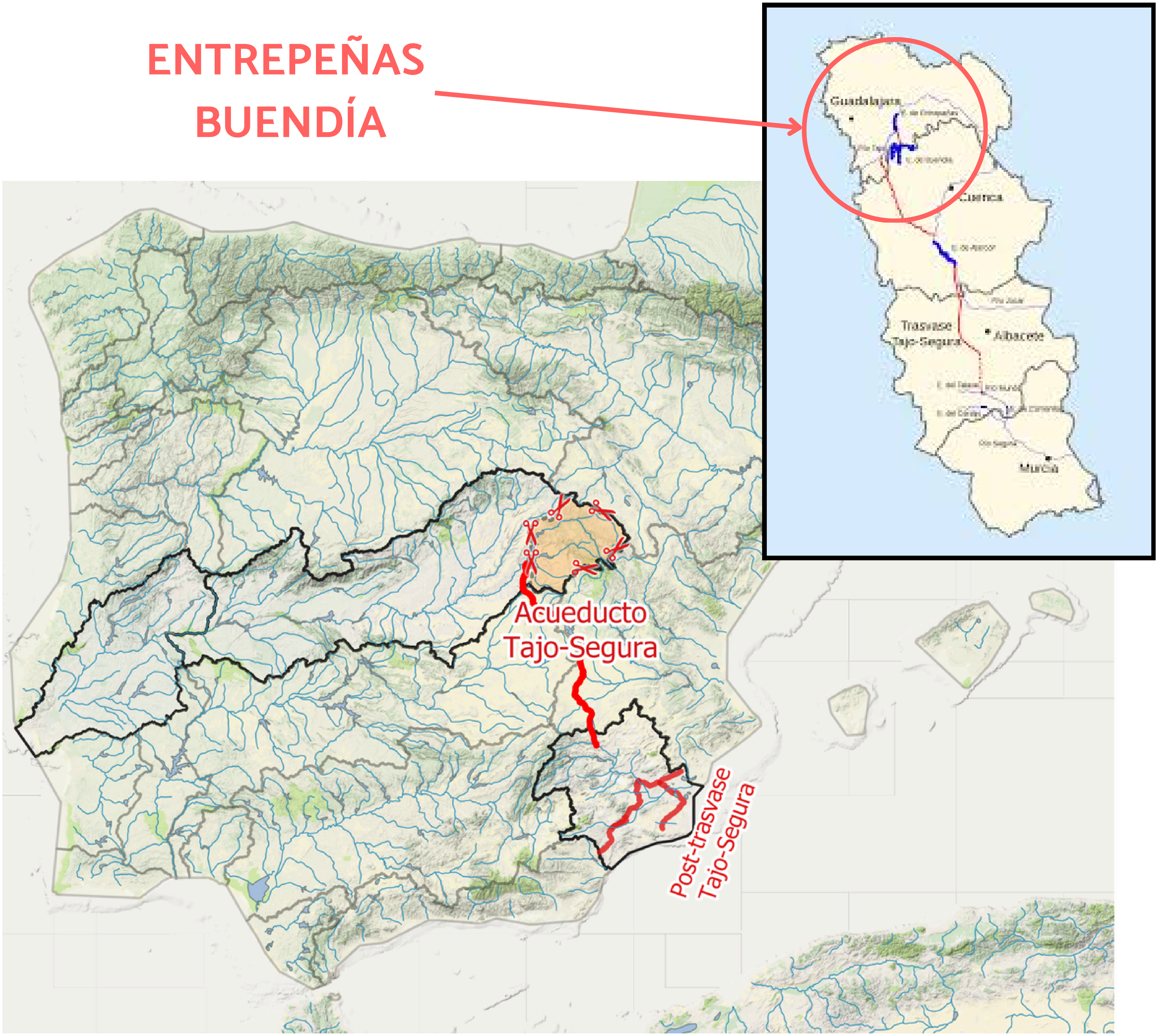
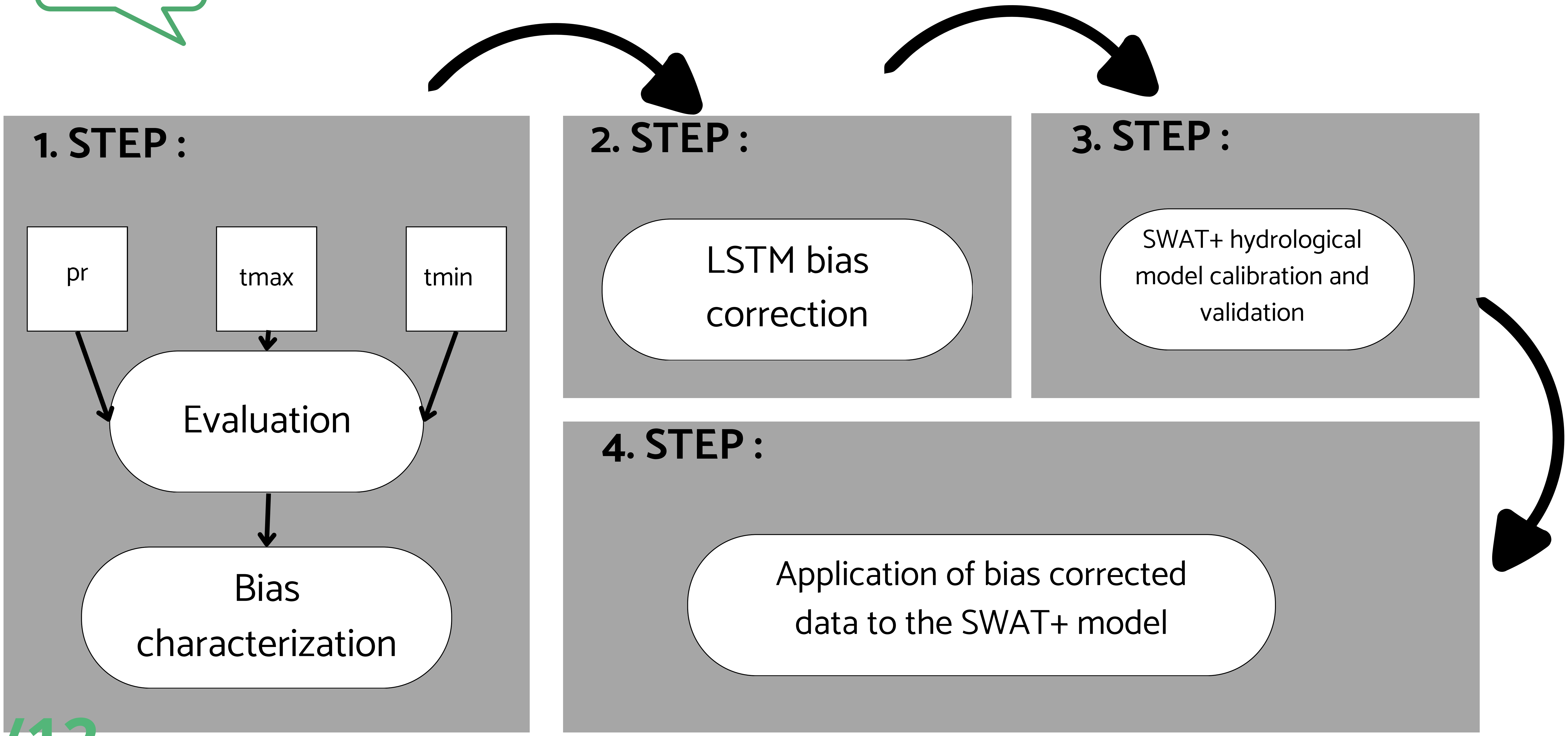
Seasonal Forecasts + ML correction techniques



MATERIALS AND METHODS



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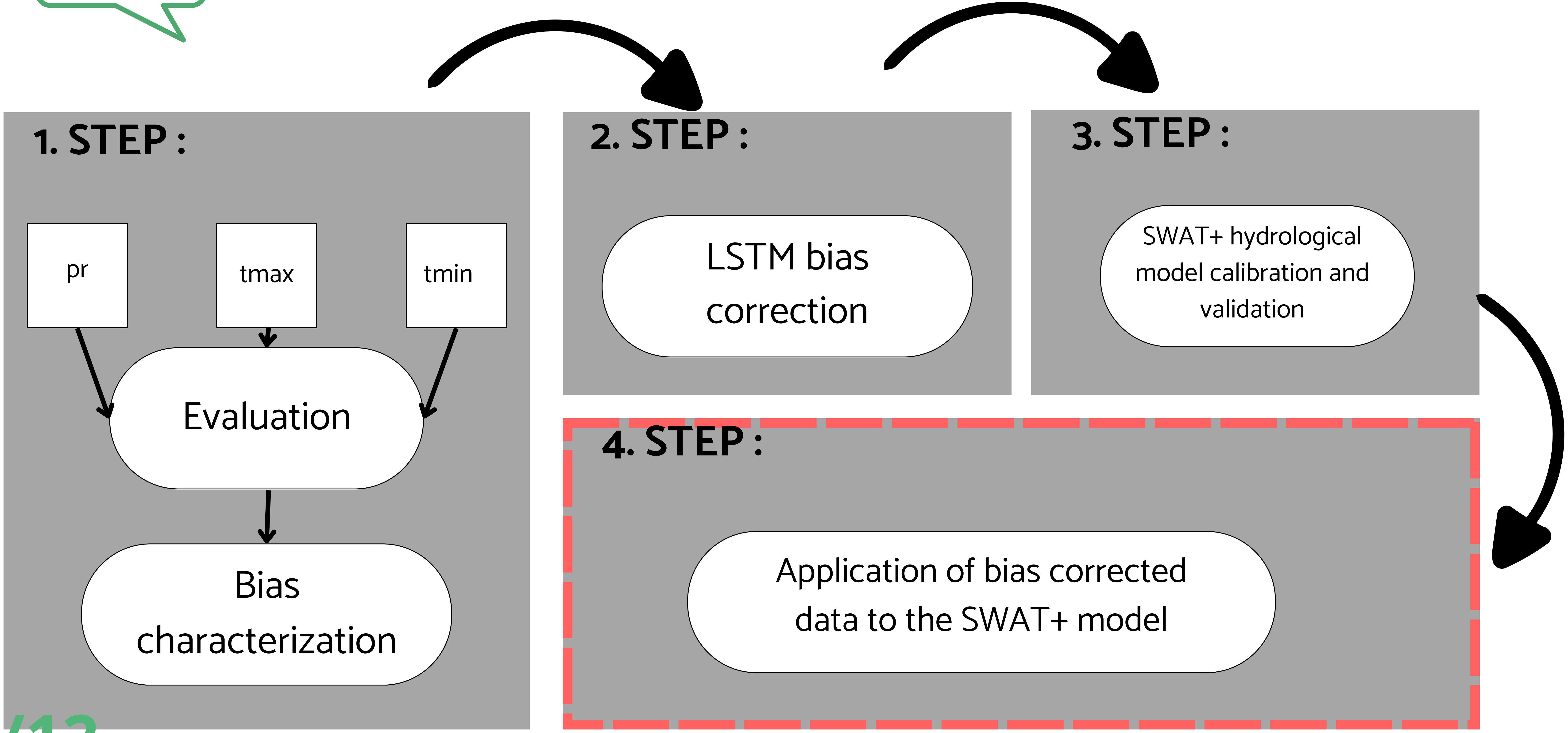

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- Observational data
- Seasonal forecast

Climate data

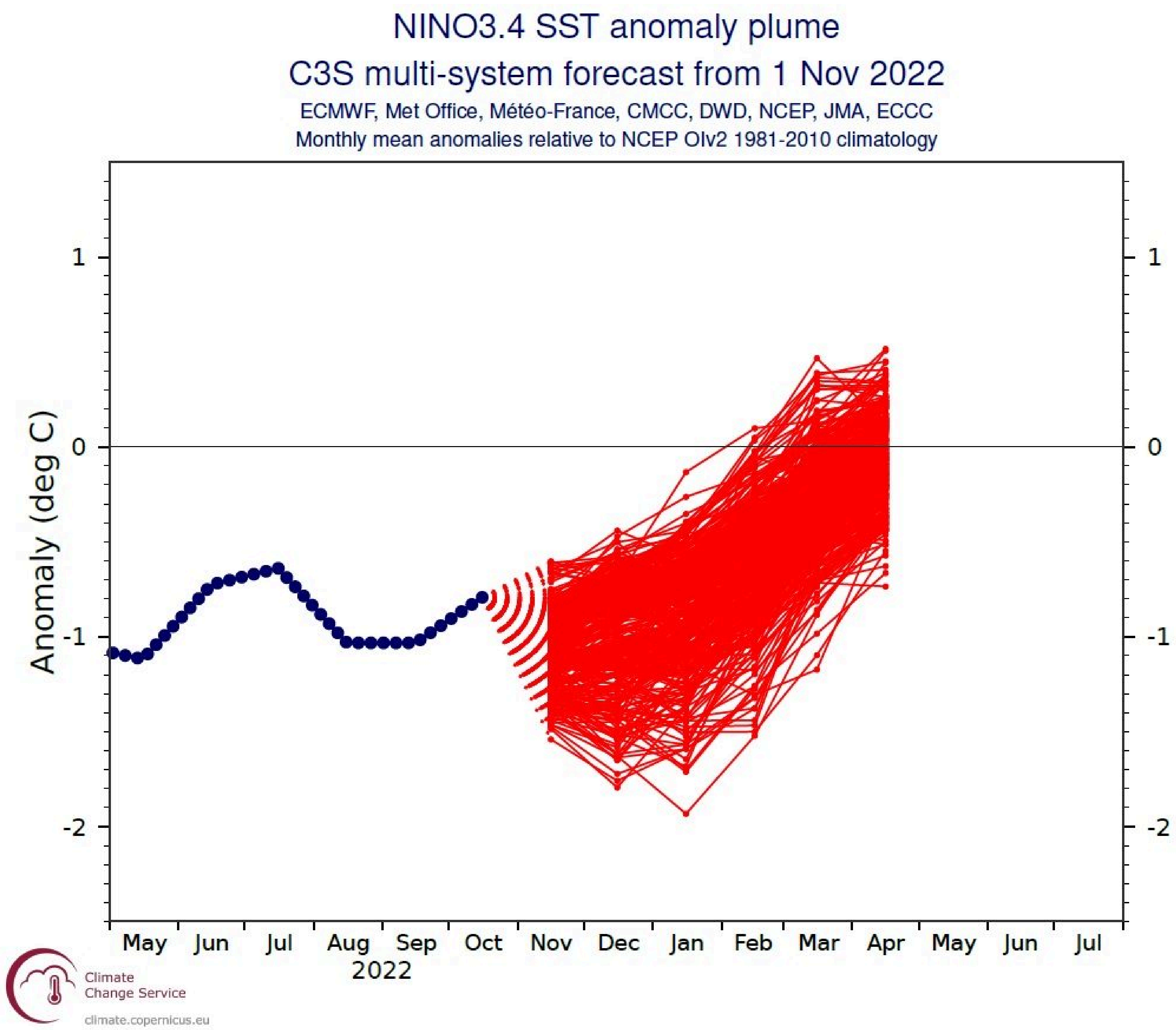
Runoff data

ECMWF SEAS5 (C3WV.5.1)

1981-2016 --> 25 ensemble members

2016- --> 51 members

7 month horizon --> Lead time



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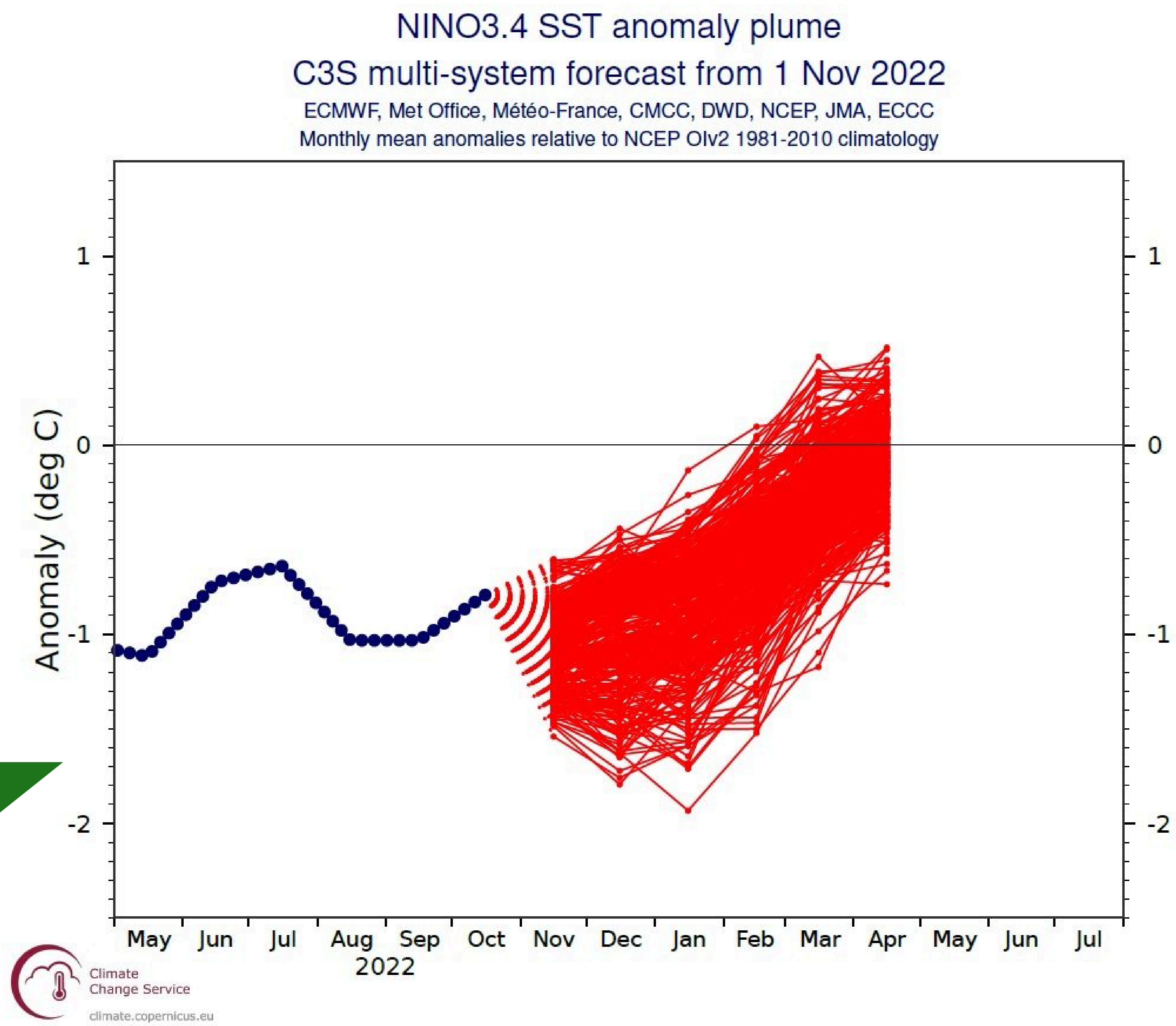

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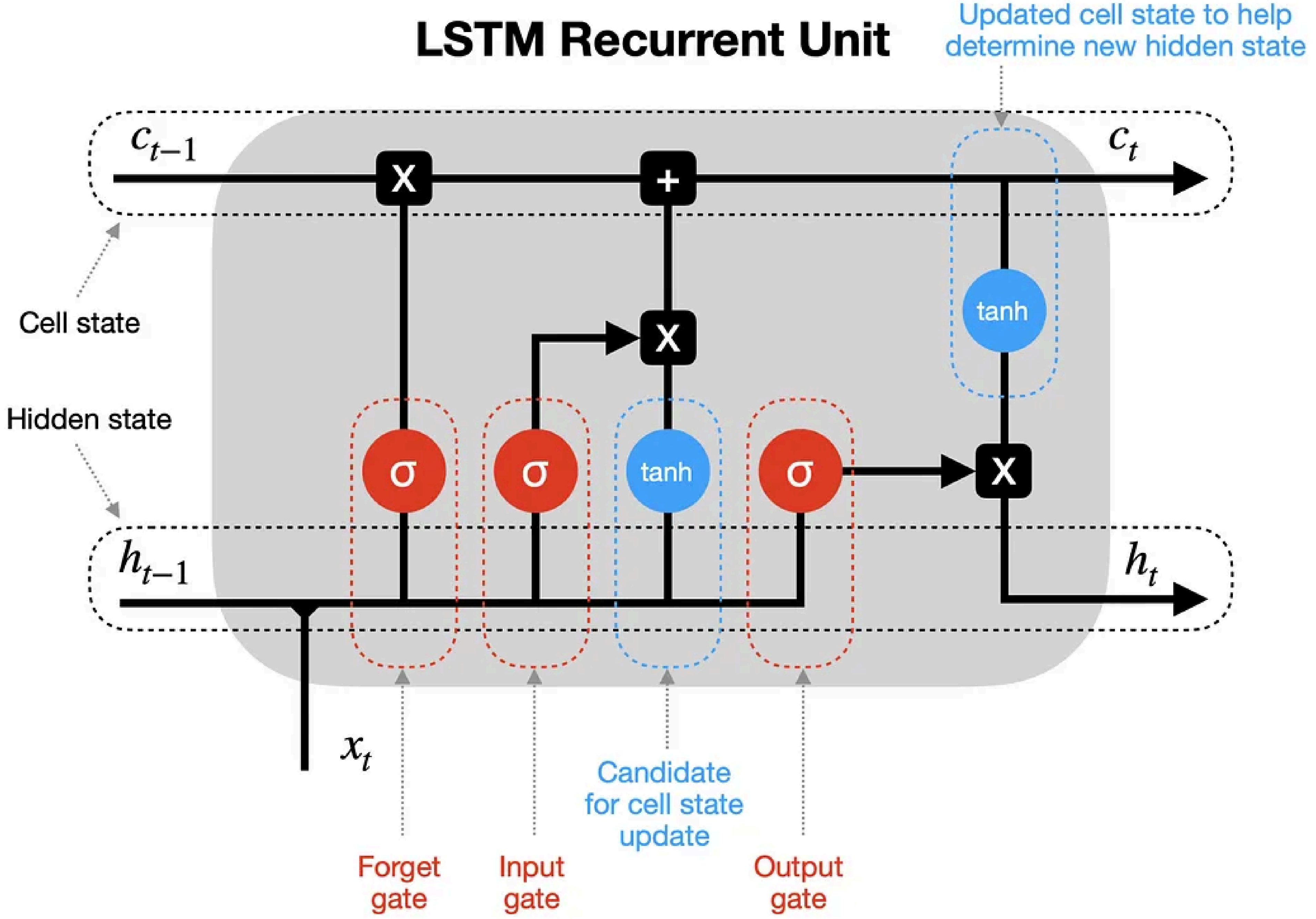
BIAS CORRECTION



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BIAS CORRECTION

HYDROLOGICAL MODEL (SWAT+)

2000-2010 and 2010-2020

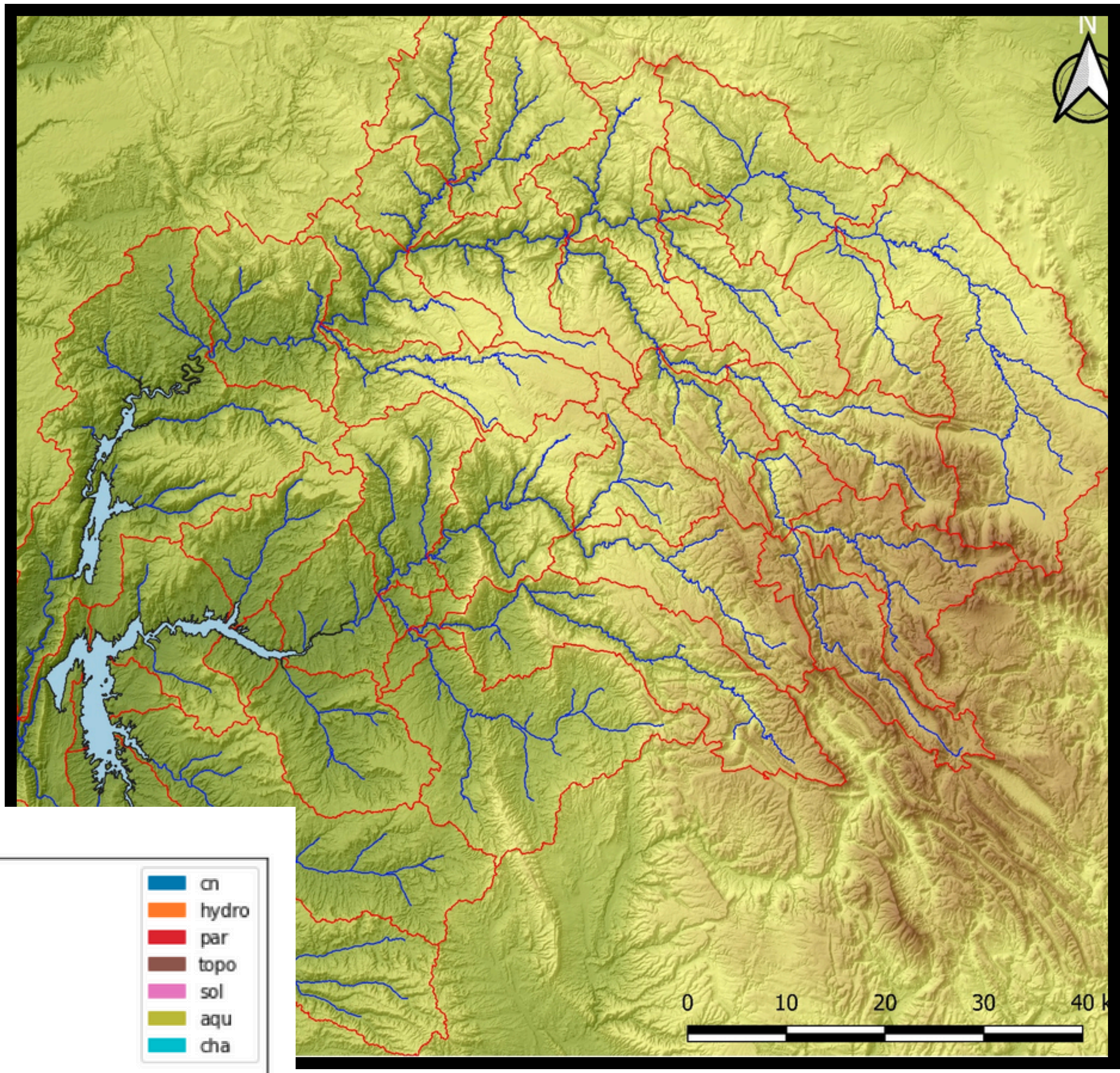
<u>Calibration and validation</u>

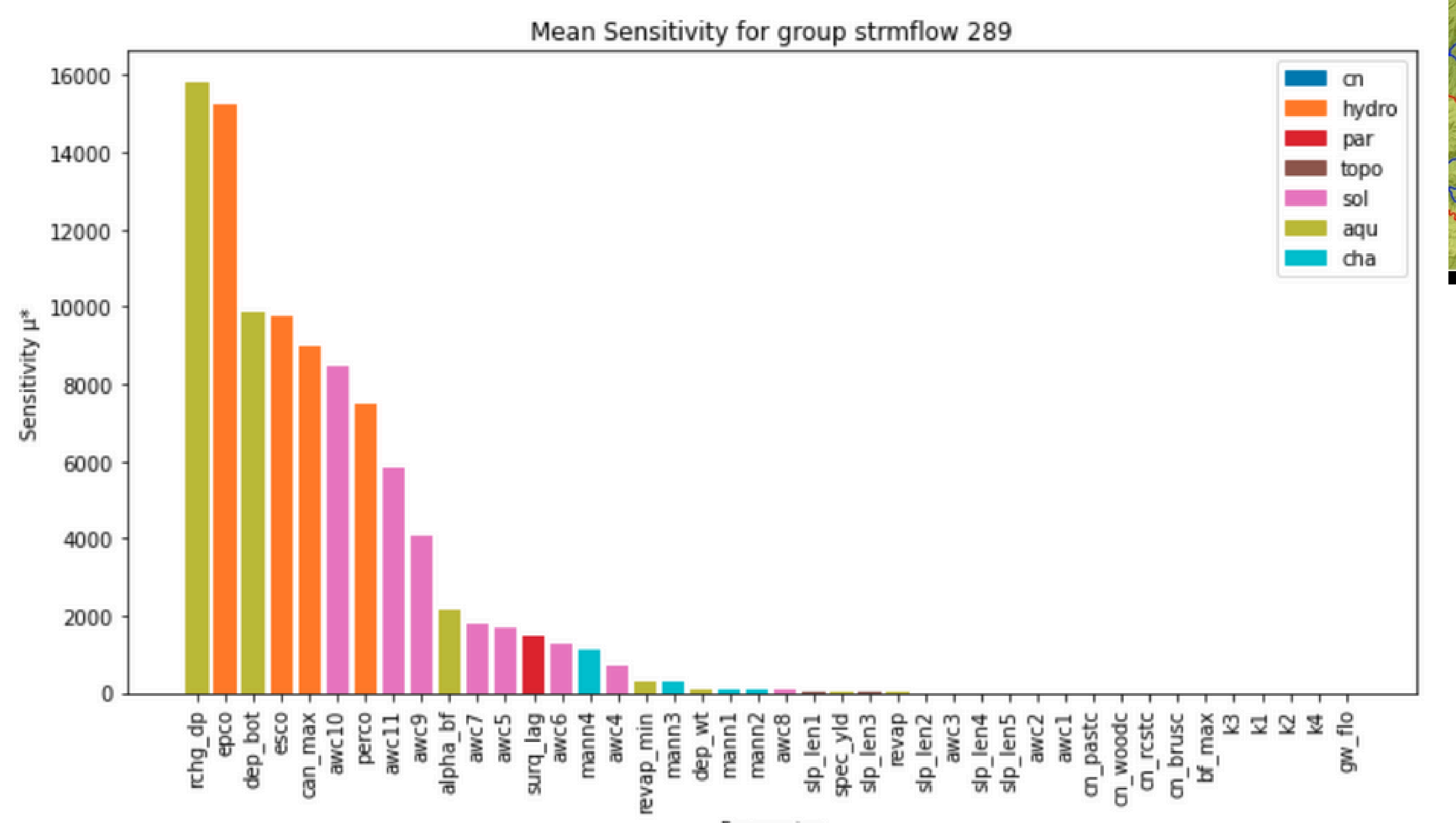
SWAT-CUP SUFI-2 algorithm

Sensitivity analysis (500 iterations)

Objetive function: KGE

1,000 iterations: 500 + 500





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BIAS CORRECTION

HYDROLOGICAL MODEL (SWAT+)

PERFORMANCE INDICATORS

$$\mathrm{Bias}_{\mathrm{Add}} = \frac{1}{N}\sum_{k=1}^{N}(\overline{x}(k) - y(k)),$$

$$\mathrm{Bias}_{\mathrm{mult}} = \frac{\frac{1}{N}\sum_{k=1}^{N}\overline{x}(k)}{\frac{1}{N}\sum_{k=1}^{N}y(k)},$$

$$\mathrm{CRPS}(p(x), y) = \int (p(x) - H(x < y))^2 \mathrm{d}x,$$

OBS

PRED

$$\mathrm{CRPSS} = 1 - \frac{\mathrm{CRPS}_{\mathrm{for}}}{\mathrm{CRPS}_{\mathrm{ref}}},$$

Continuous Ranked Probability Skill Score

RESULTS

- Due to the complexity and amount of data
- Present the results divided in seasons: JFM, AMJ, JAS, OND
- Considering the evolution with lead times
- Considering the spatial variability on the basin
- Each variable

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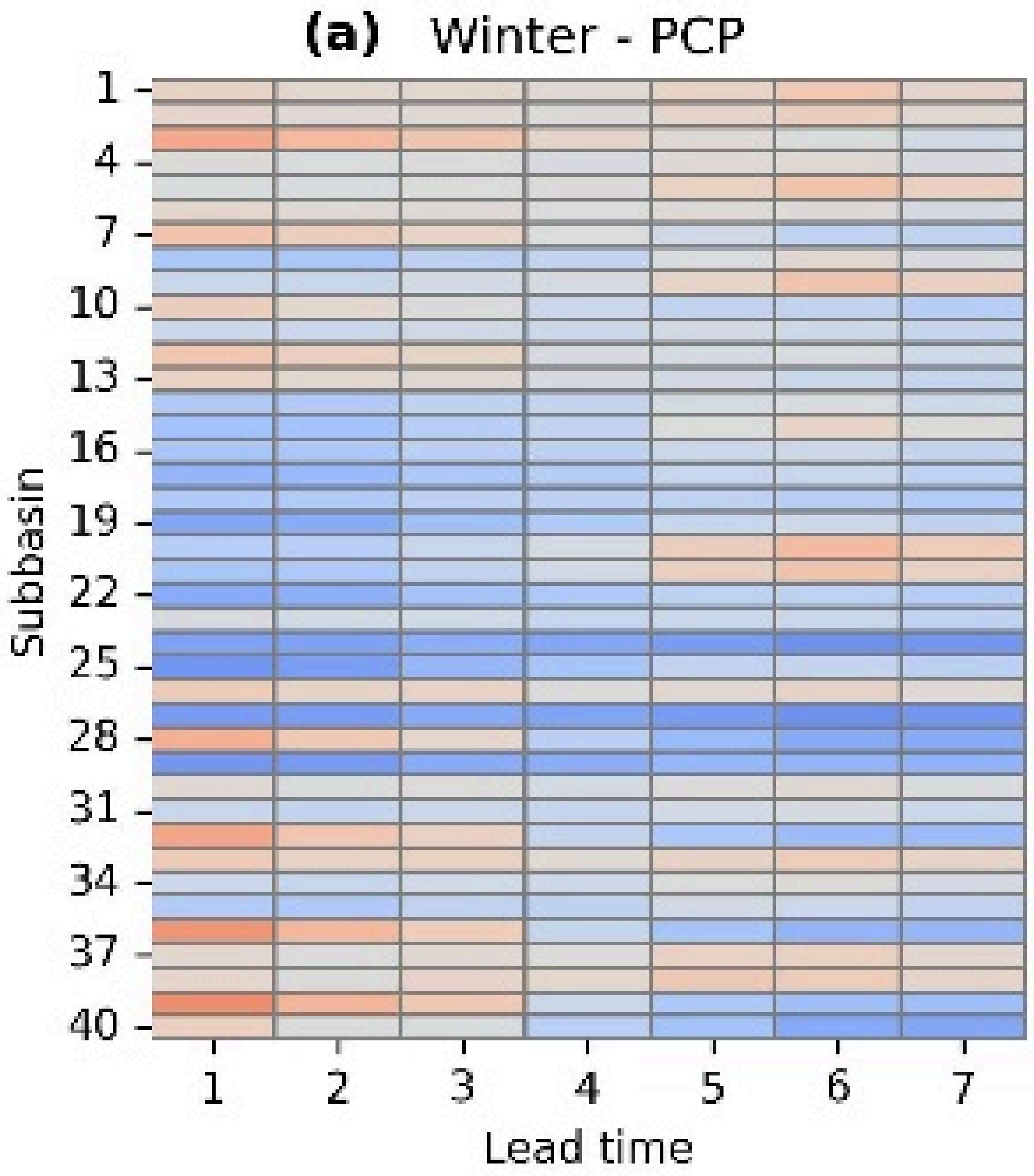
7 month forecast

JAN →

FEB →

MAR →



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Bias of Forecasts

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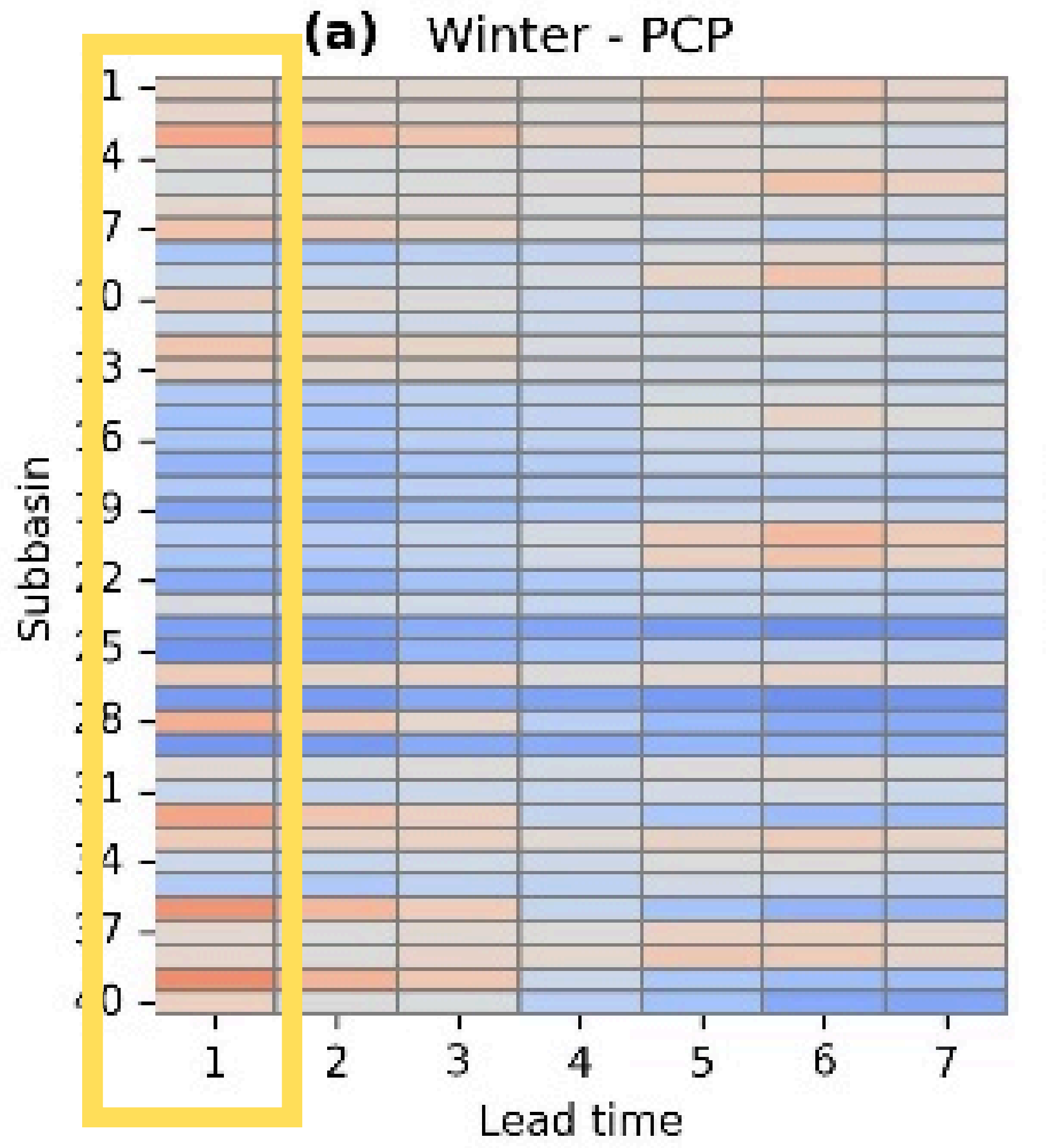
Mean



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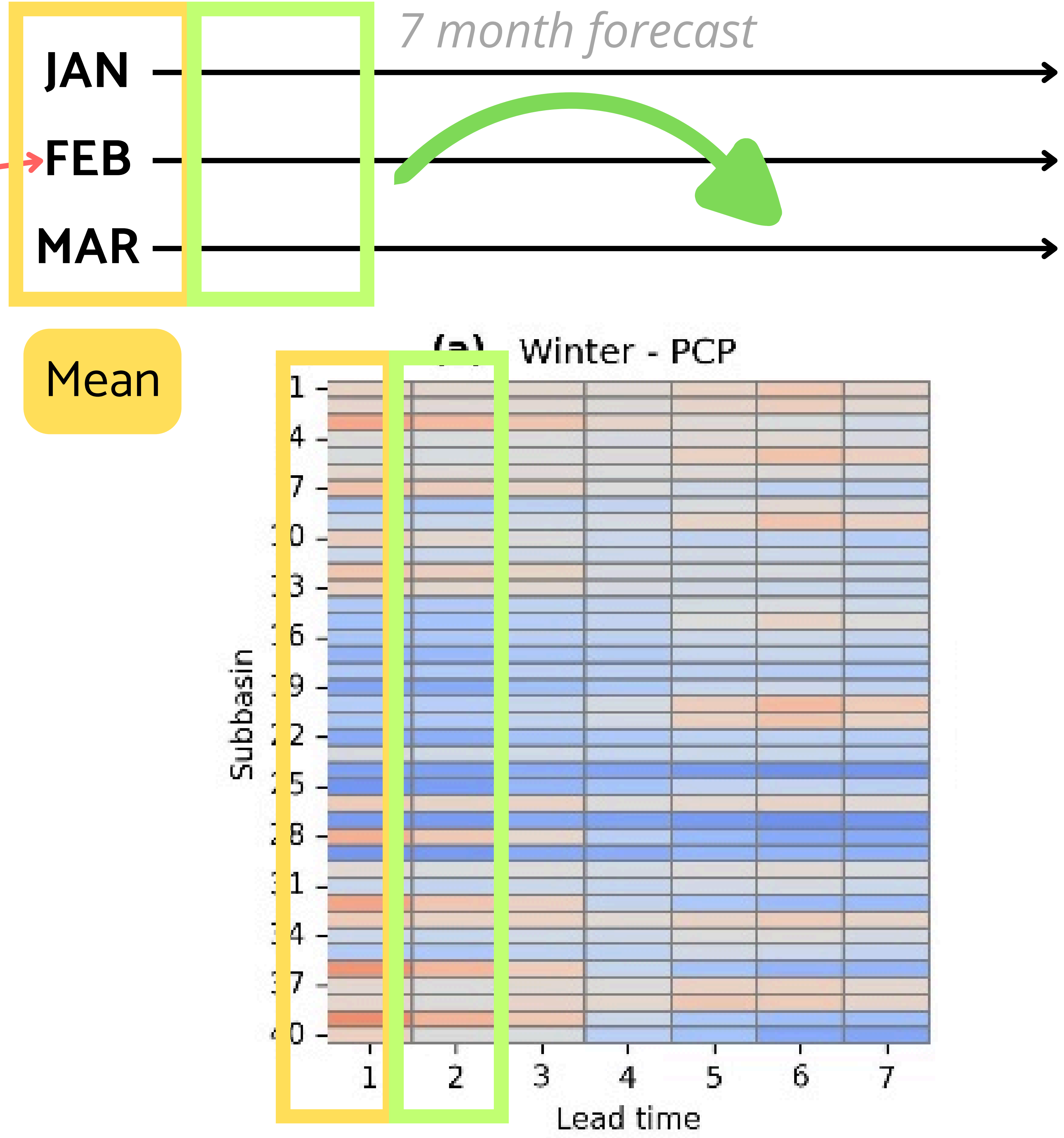
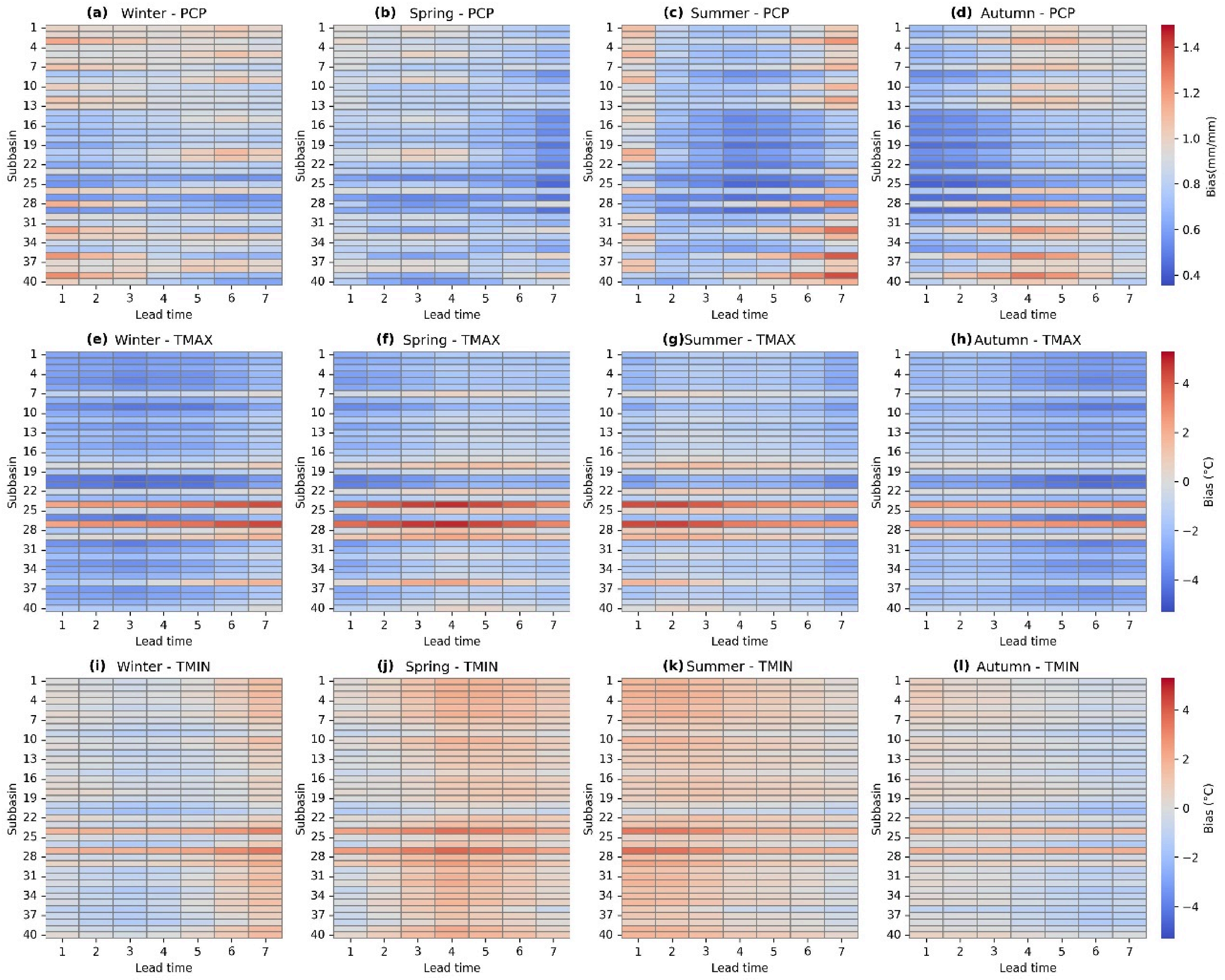


RESULTS

Bias of Forecasts

- Precipitation bias: Generally, the maps show more blue tones, indicating an **underestimation of precipitation**.
- **Temperature** Bias: (Tmax) was generally **underestimated**. The bias is less pronounced for minimum temperature (Tmin), as shown by the softer colors on the heatmap.

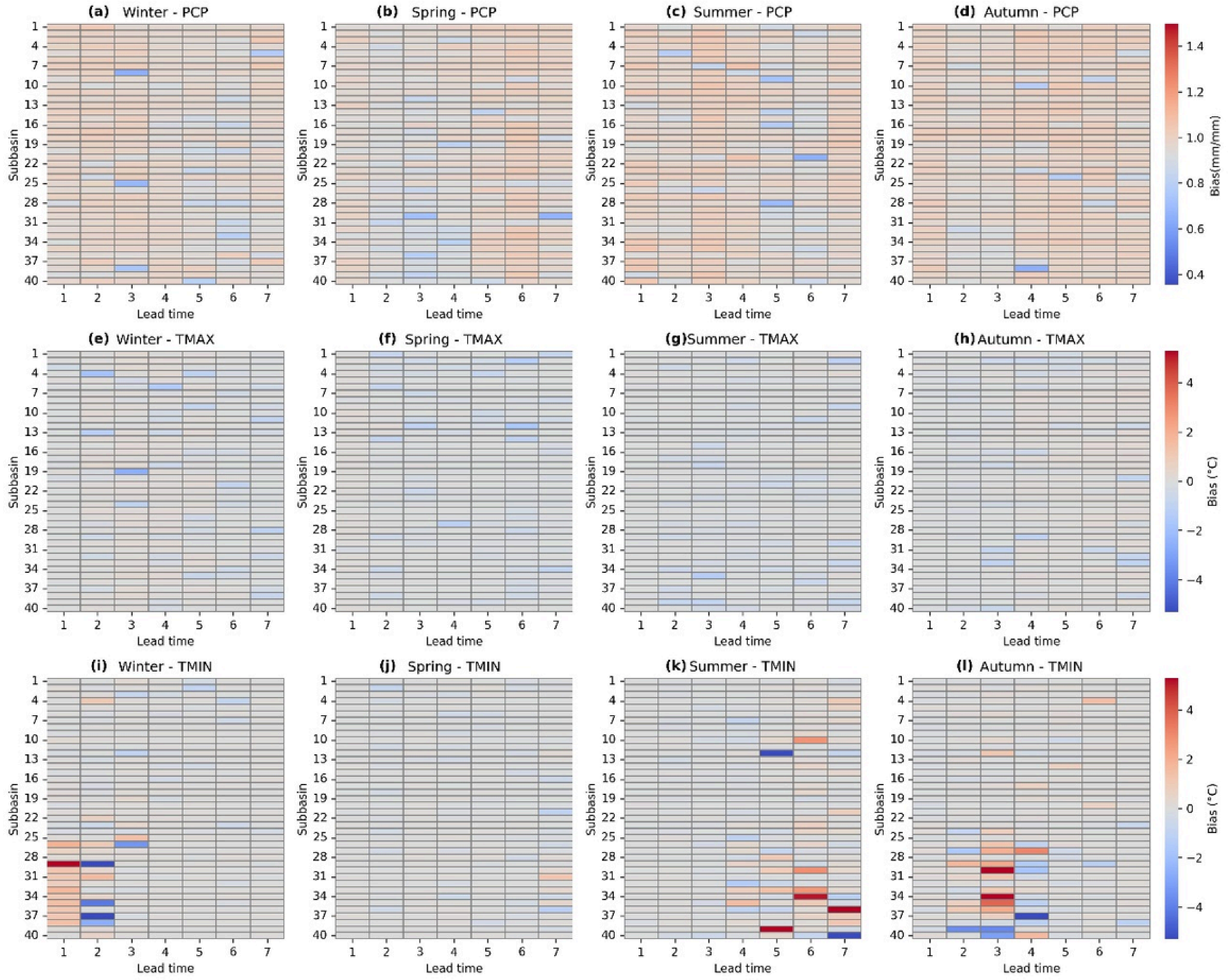


RAW FORECASTS NEED BIAS CORRECTION

RESULTS

Bias of corrected

- **LSTM Training:**
  - Leave-one-out cross validation
  - For each month and each of the 40 sub-basins, we trained an LSTM network. 480 LSTM models for each variable = **1440 LSTM models**
- Monthly correction factor of the bias was calculated and applied to monthly data
  - Precipitation: The bias correction brought values closer to 1 in most cases, indicating **improved accuracy.**
  - Temperature: The correction reduced the bias, bringing values **closer to zero**. However, **Tmin showed less improvement,** with some sub-basins and lead times still having notable bias.



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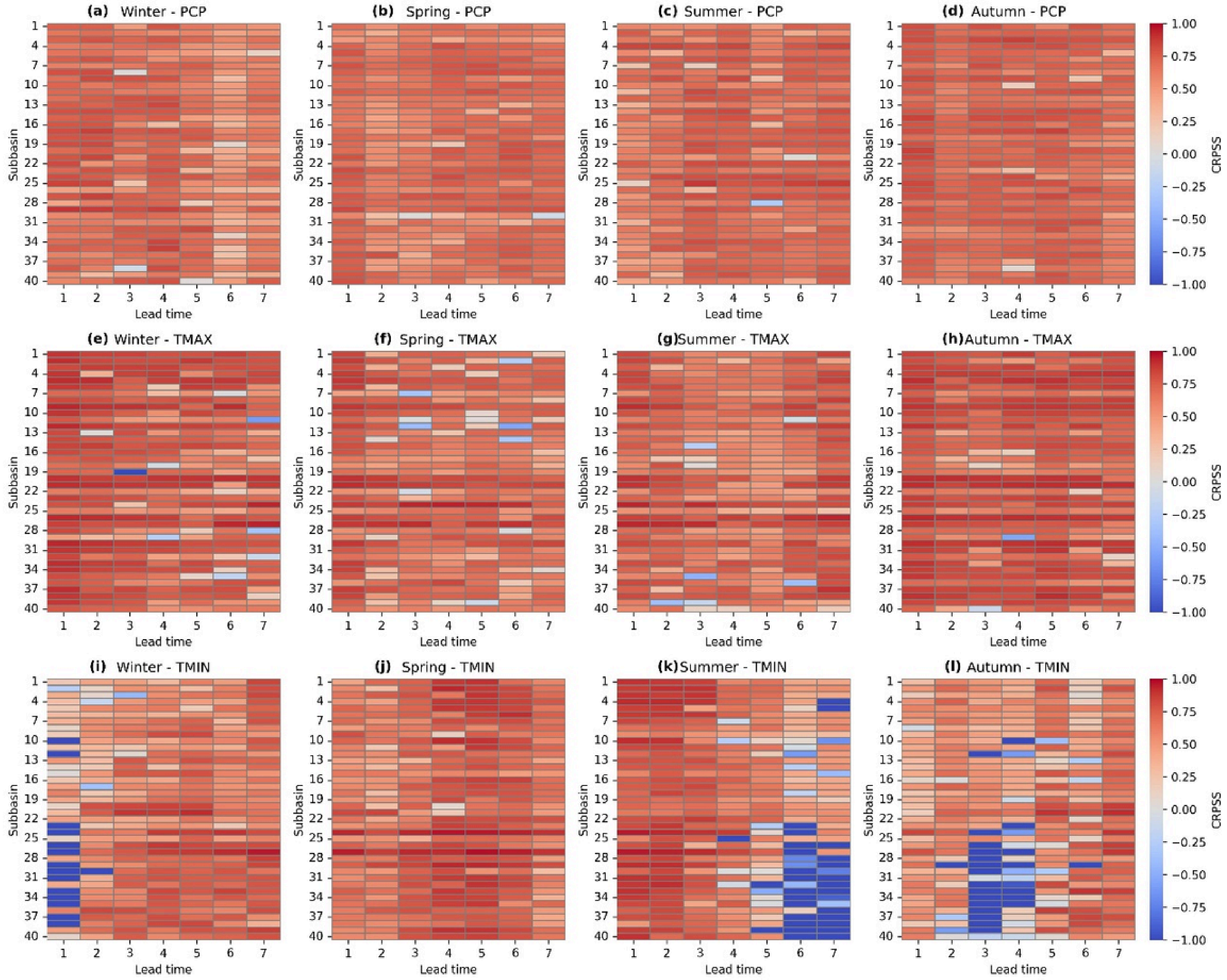
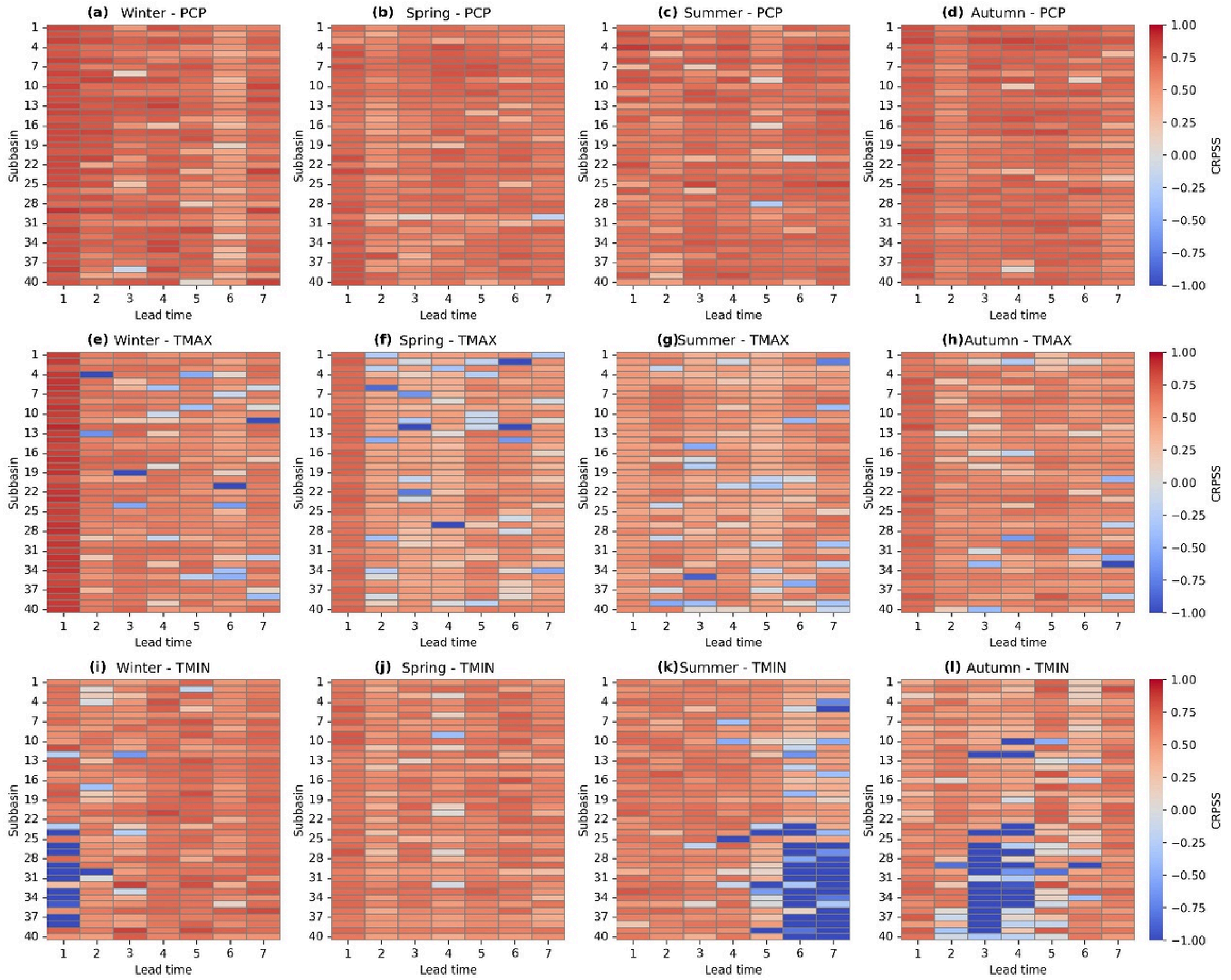


- Bias correction proved **effective**, as evidenced by positive CRPSS values, indicating an enhancement in meteorological forecast accuracy following bias correction.

Performance obs-clim vs. corr

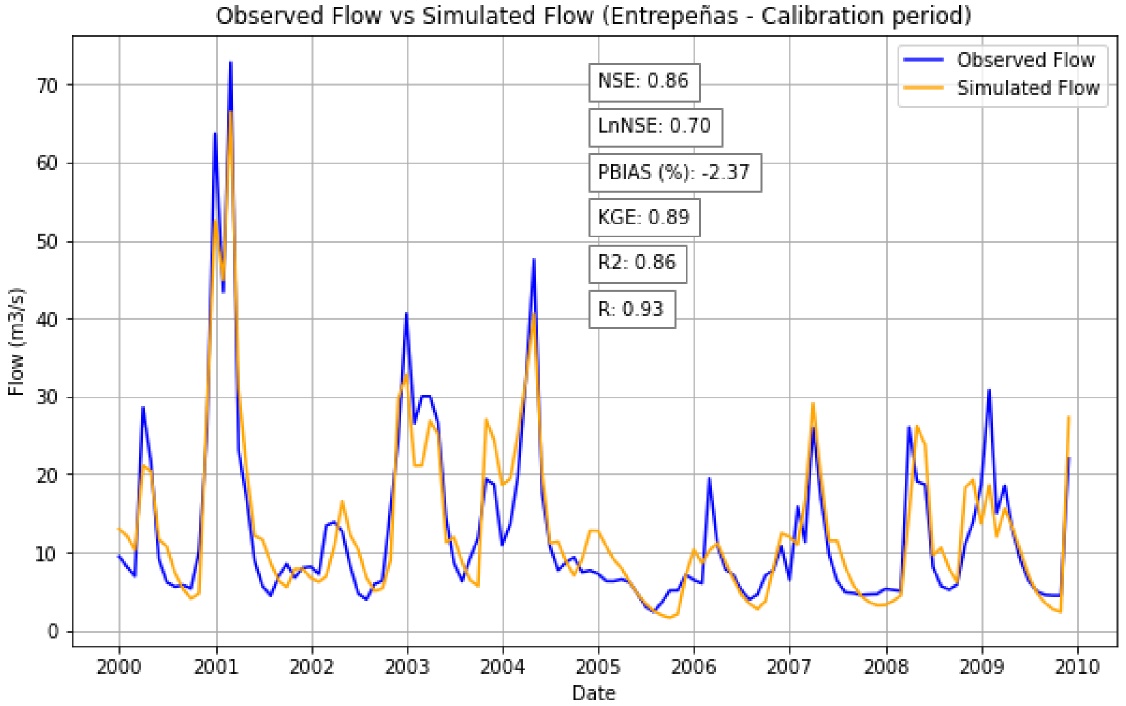
RESULTS

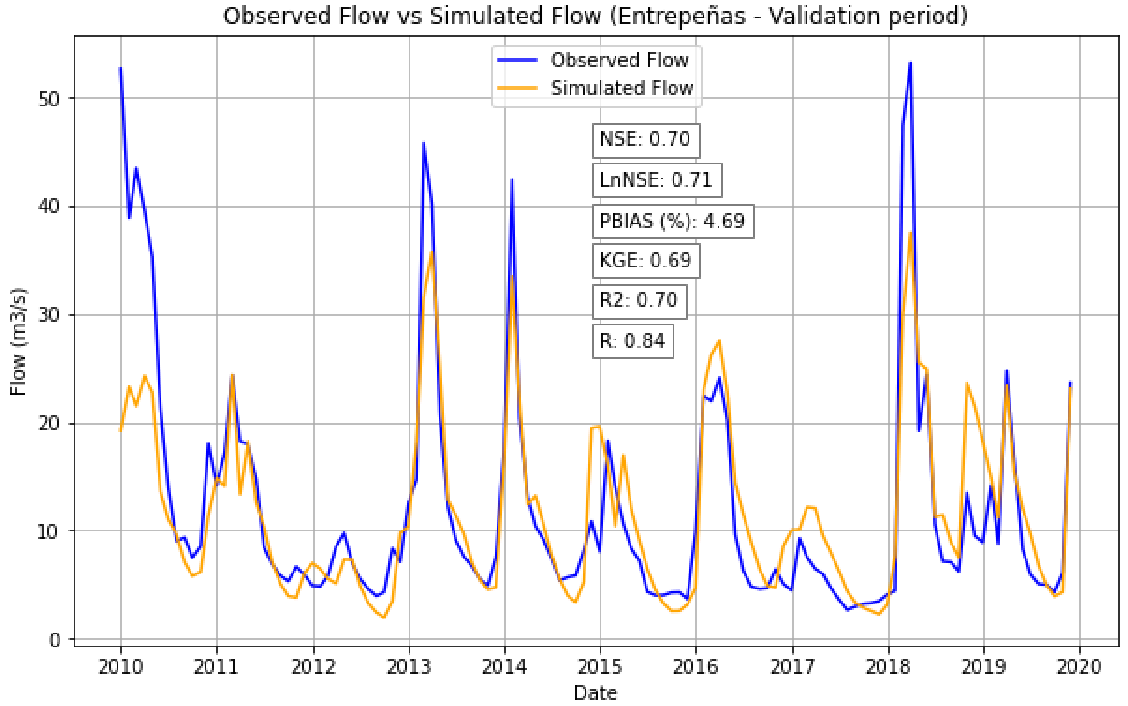
- precipitation being less predictable, machine learning-based correction achieved **significant improvements** over climatology.
- Challenges in Minimum Temperature Forecasting: Minimum temperature forecasts exhibited the **poorest correction** in specific sub-basins during the first month of winter, yet performance was adequate for early lead times in other seasons.



RESULTS

Entrepeñas





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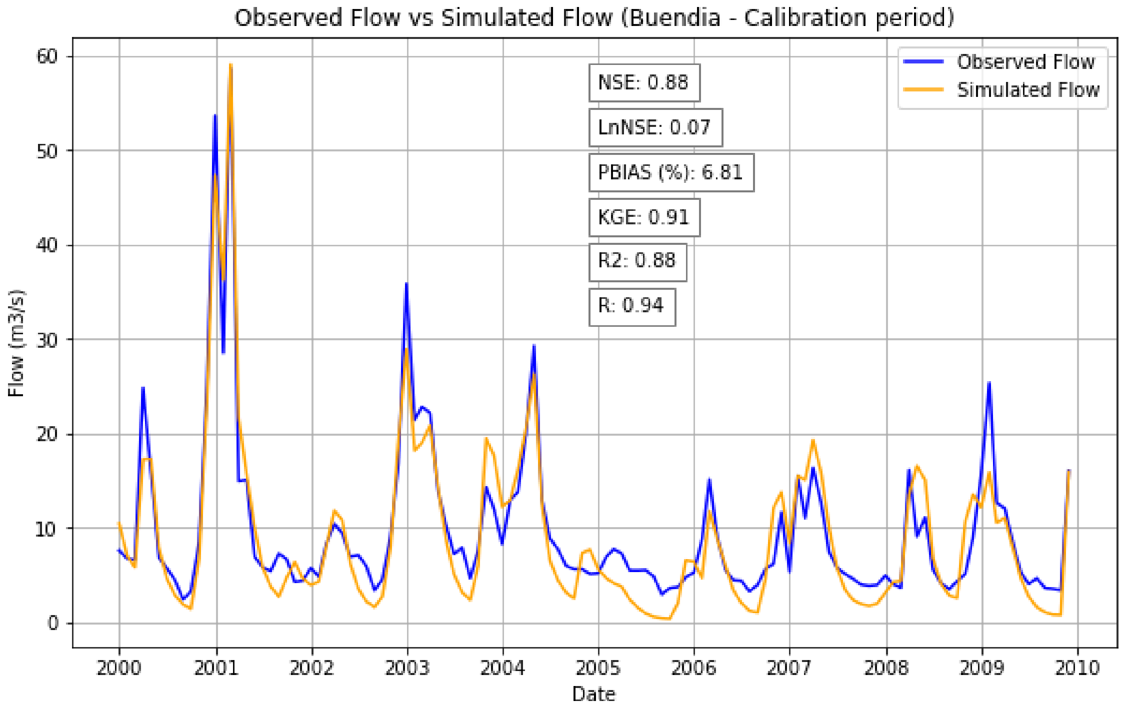

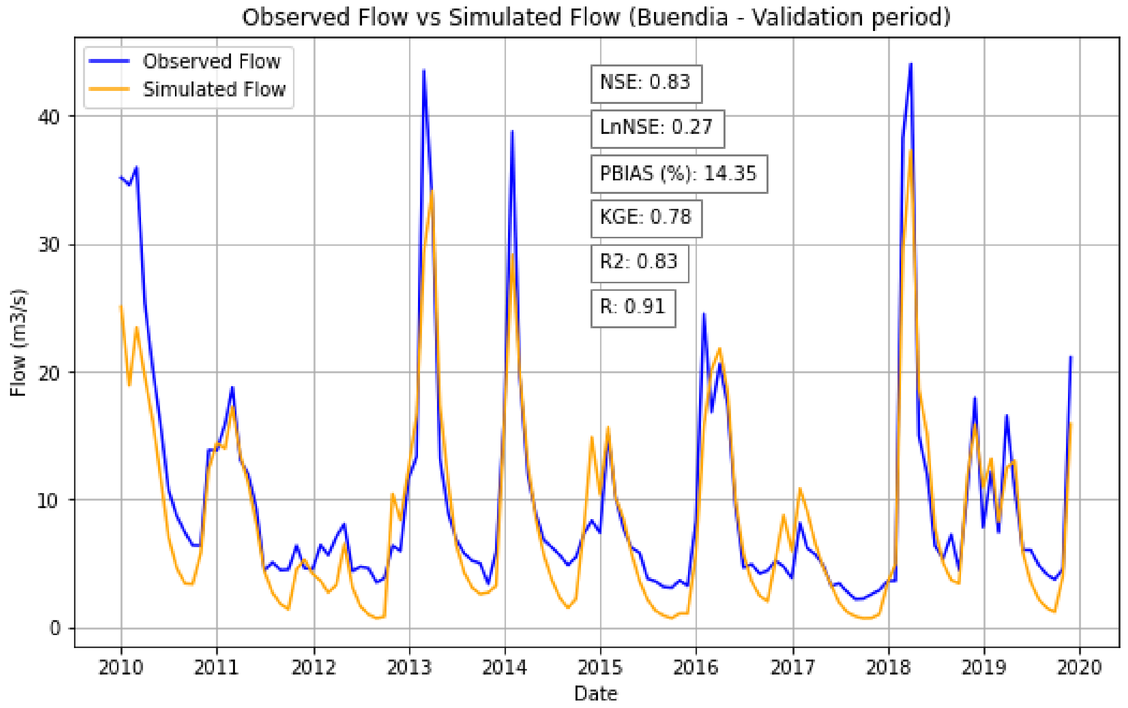

Satisfactory Results

RESULTS

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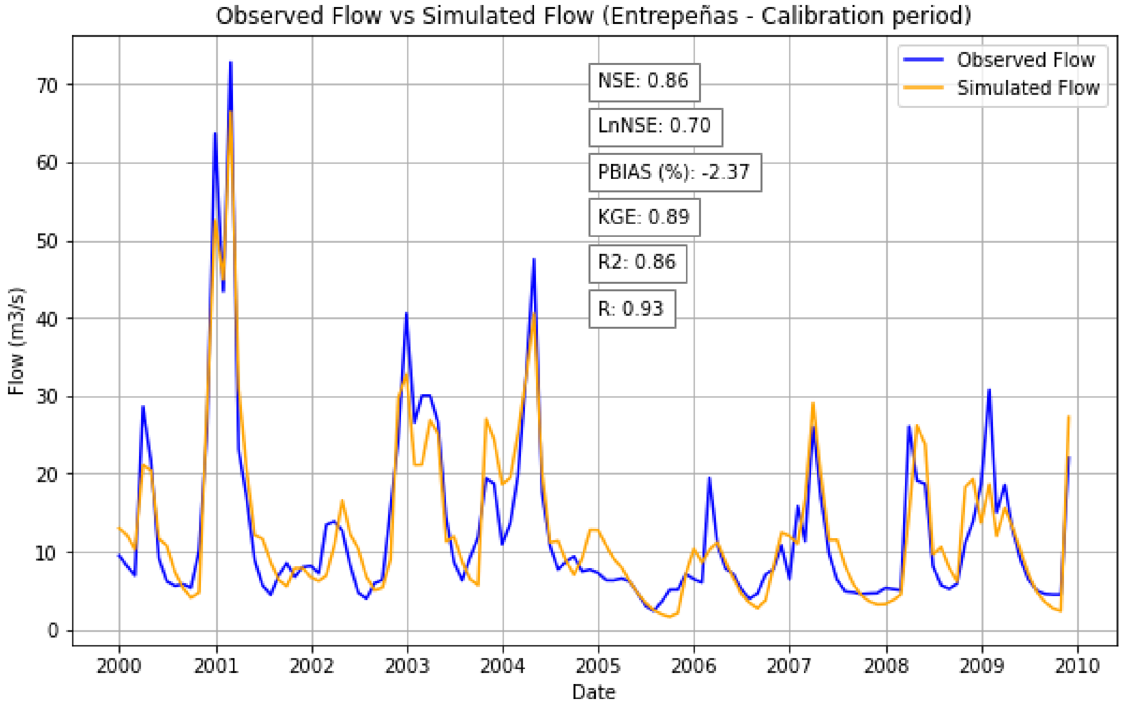

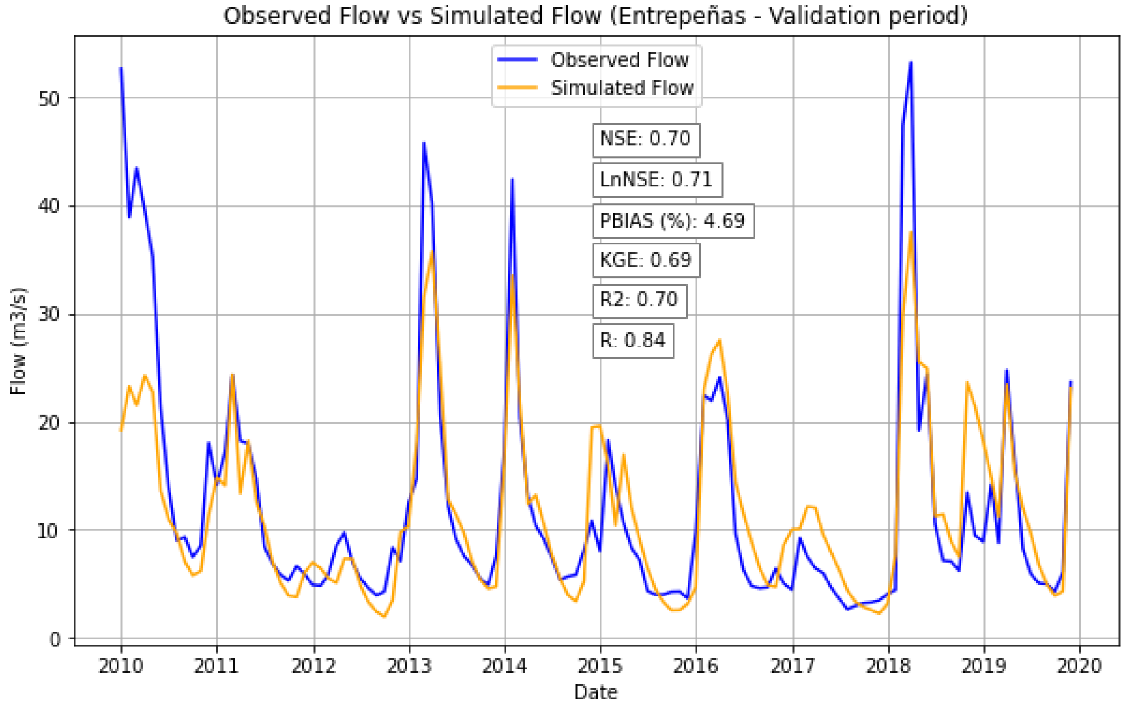

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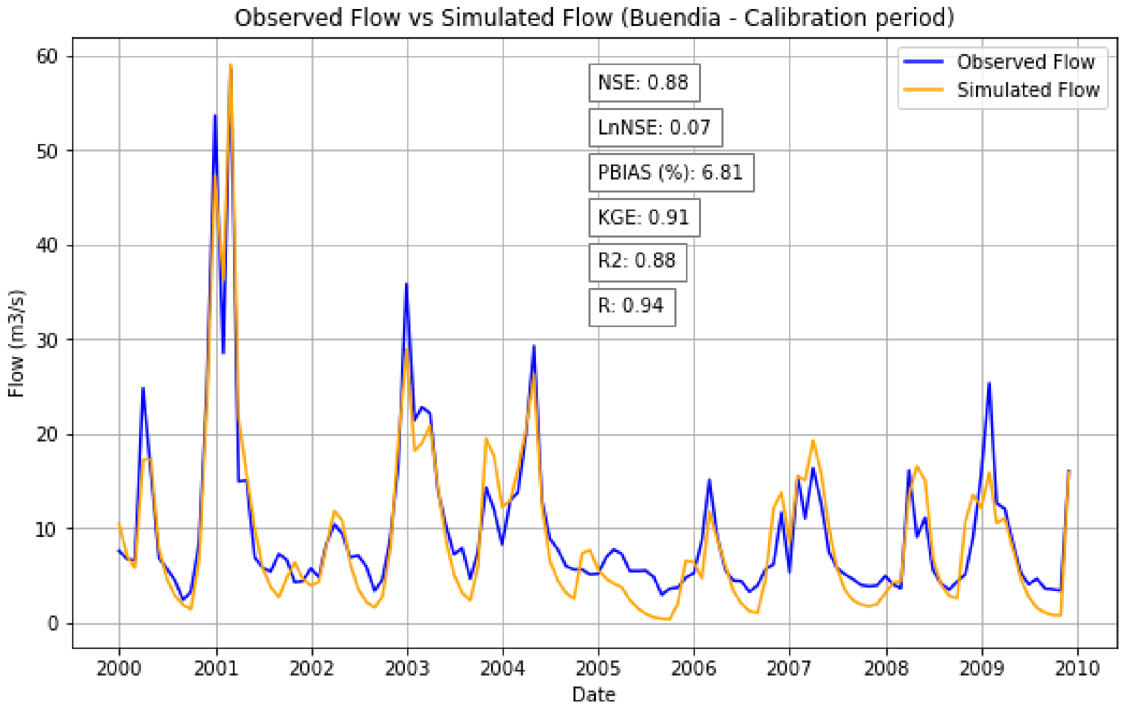

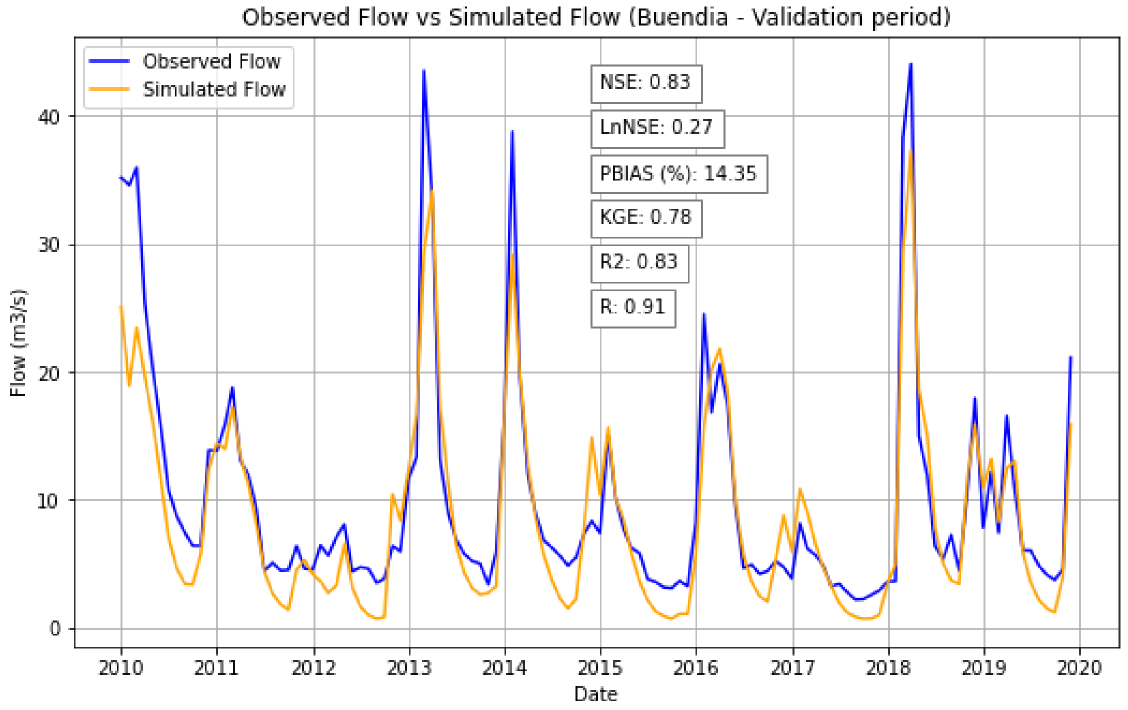

Satisfactory Results

Ready to force SWAT+ with corrected seasonal forecasts

CONCLUSIONS

- Need of a more robust forecasting method
- Seasonal forecast represent a promising option --> Bias Correction
- LSTM models demonstrate to effectively reduce bias
- The developed SWAT model of the Upper Tagus River Basin shows satisactory results for its application
- Next steps: Validate the proposed methodology forcing the SWAT model with corrected seasonal forecast data

THANK YOU

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