Seasonal streamflow forecasting – Which are the drivers controlling the forecast quality?

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EGU 2020

Frameworks of sensitivity analyses

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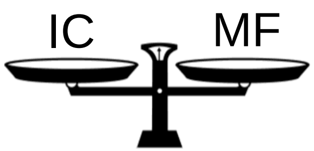
Skill

January – LT2
against simulation

What causes
this skill pattern?

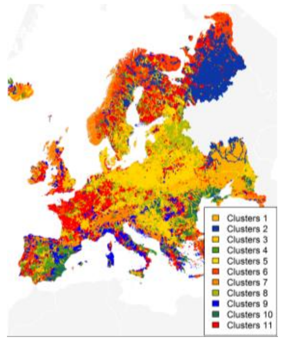
Skill sensitivity

Where does the predictability comes from?
or
How to improve these forecasts?



Skill vs Catchment characteristics

What catchment characteristics can explain
this pattern ?



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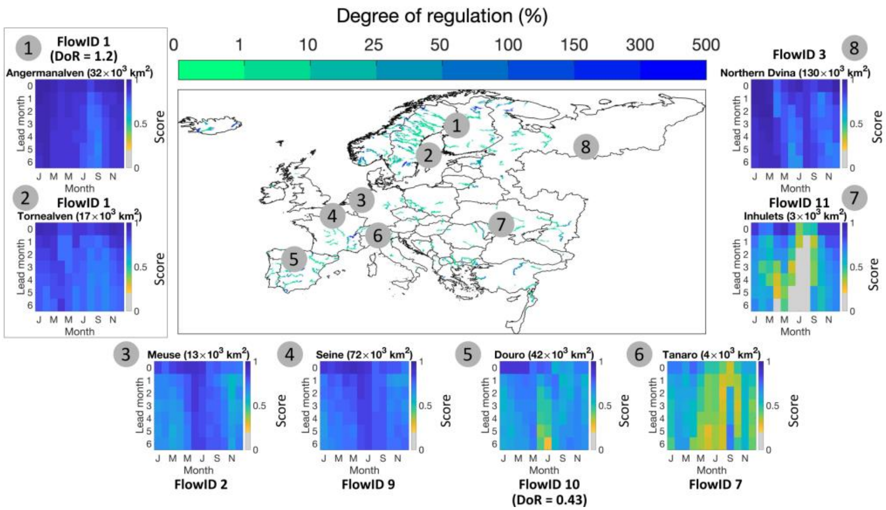
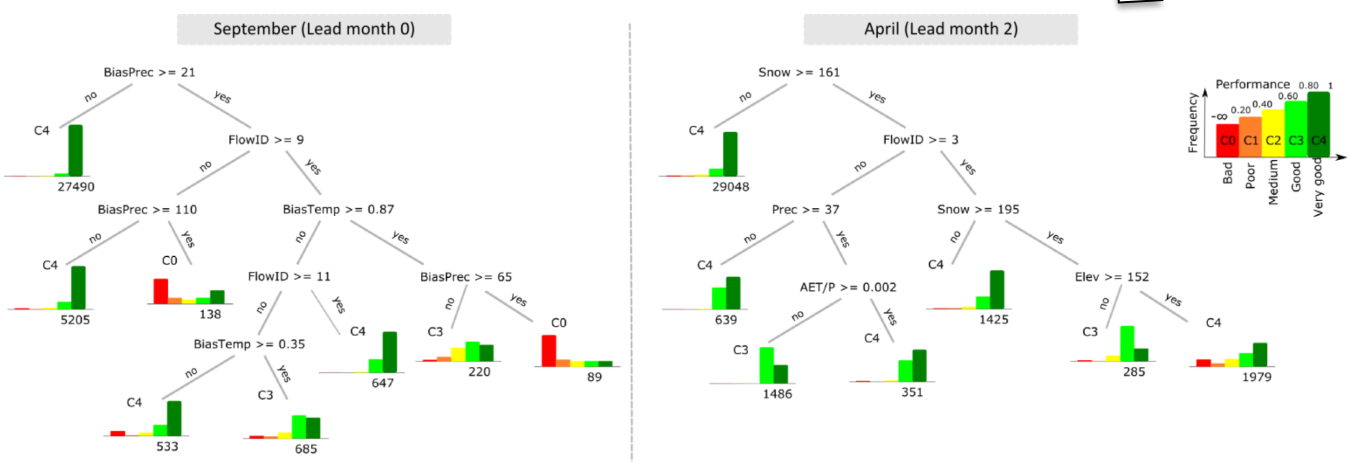
Use of Machine Learning (ML) for performance attribution

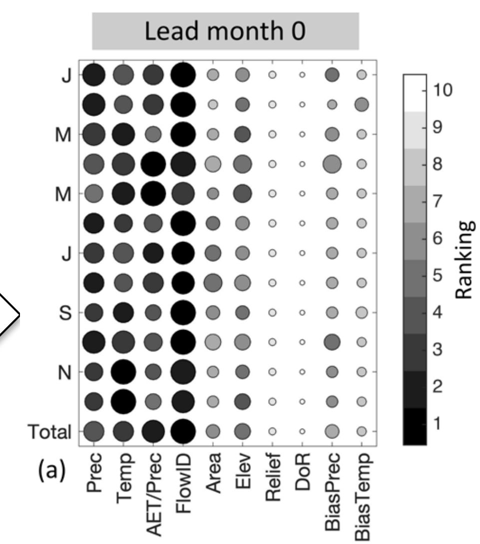


Climatology / Forcing biases (9)	Topography (4)	Human impact (1)
Precipitation (mm/month)	Area (km²)	Degree of regulation (%)
Temperature (ºC)	Elevation (m)	
Snow depth (cm/month)	Relief ratio (-)	
Actual evaporation (mm/month)	Slope (%)	
Potential evaporation (mm/month)		
Dryness index (-)		
Evaporative index (-)		
Bias in precipitation (%)		
Bias in temperature (%)		

+ Flow characteristic regions

Classification and Regression Trees





Bias-adjustment of SEAS5 forecasts

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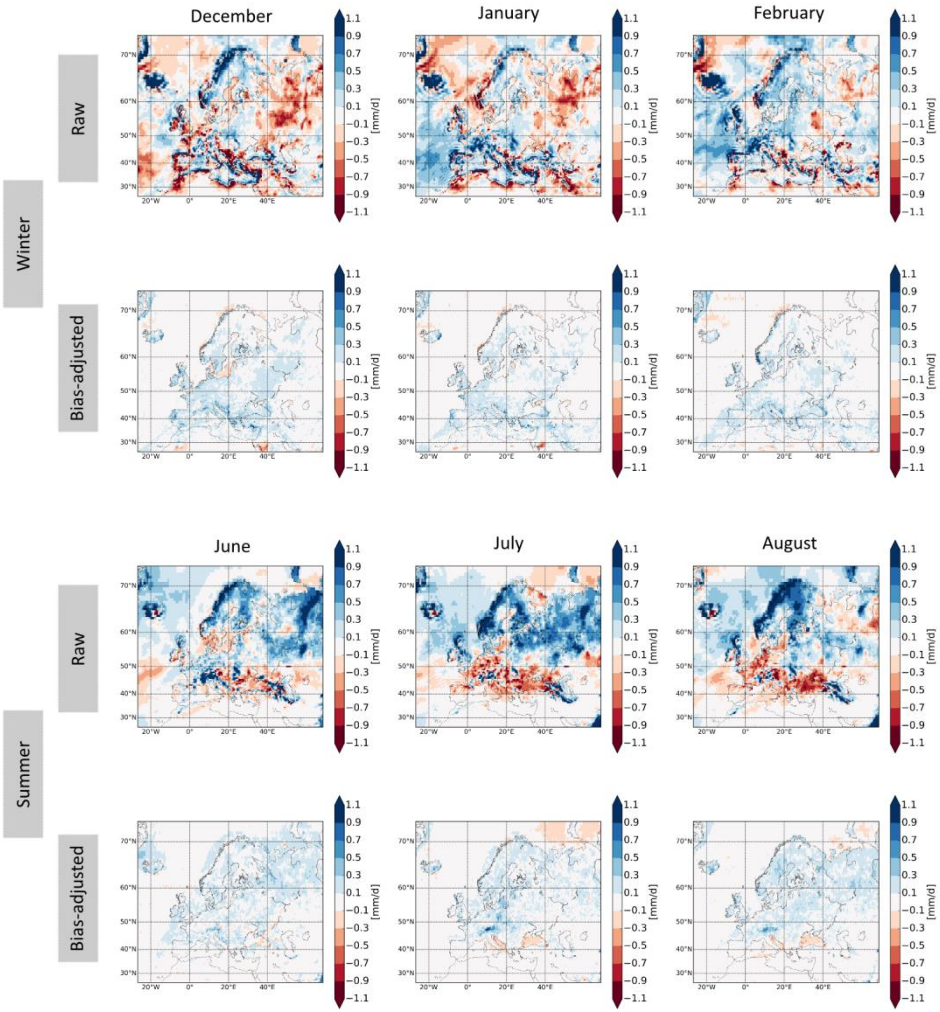


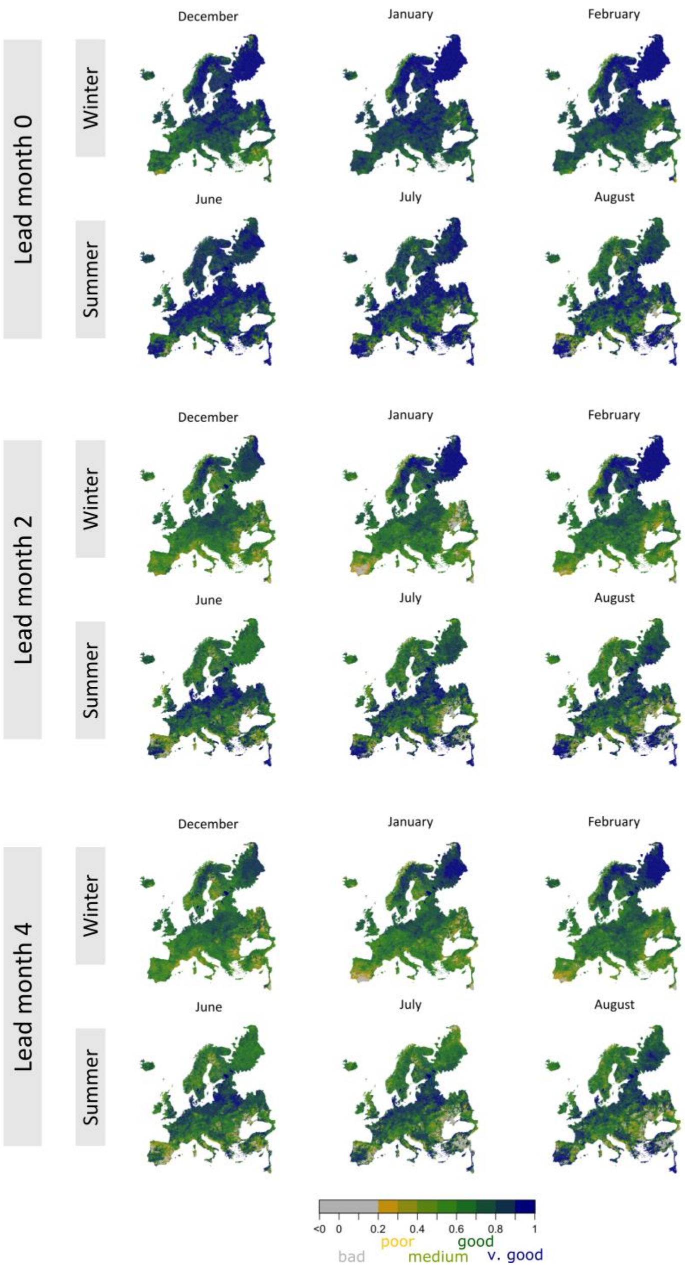
Biases in raw and bias-adjusted precipitation forecasts for the winter and summer months and lead month 0.

Distribution-Based Scaling (DBS; Yang et al., 2010) is a tool for bias-adjustment of forecasts in order to make them suitable for hydrological impact assessment. The approach of DBS is to match the observed and simulated frequency distributions by assuming variable-dependent theoretical distributions.

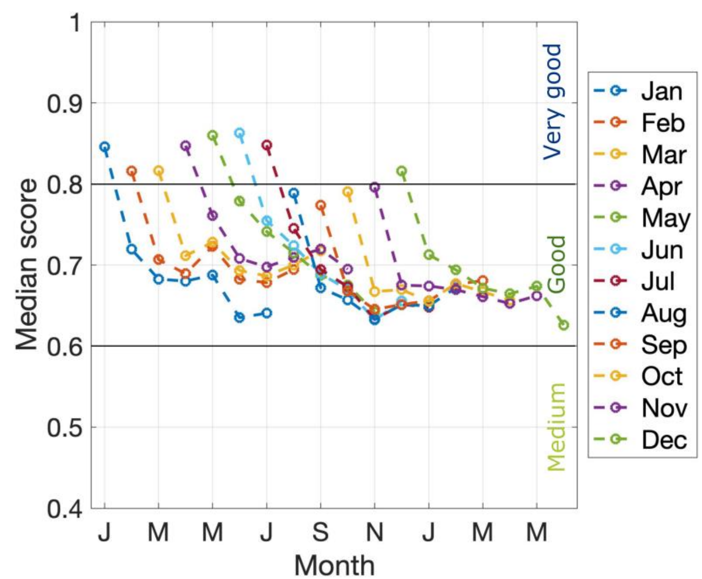
Despite the effectiveness of the DBS method, some biases unavoidably remain in the meteorological forecasts (particularly in precipitation).

Remaining biases are propagated in the forecasting production chain, and hence potentially affecting the hydrological forecast quality.

Hydrological forecast quality



Standardized the *CRPS* score (*CRPS´*) by dividing it by the monthly mean of the “pseudo-observations” (*MQ*):
CRPS´ = 1 – *CRPS* / *MQ*

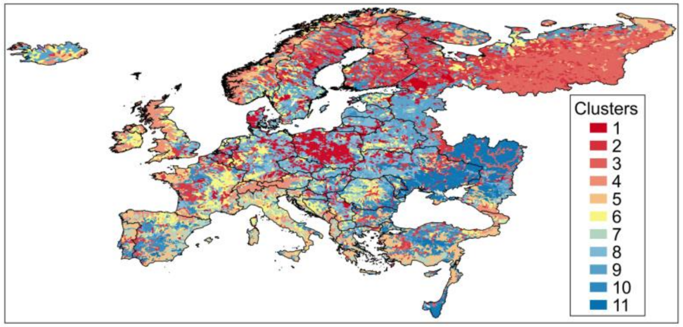


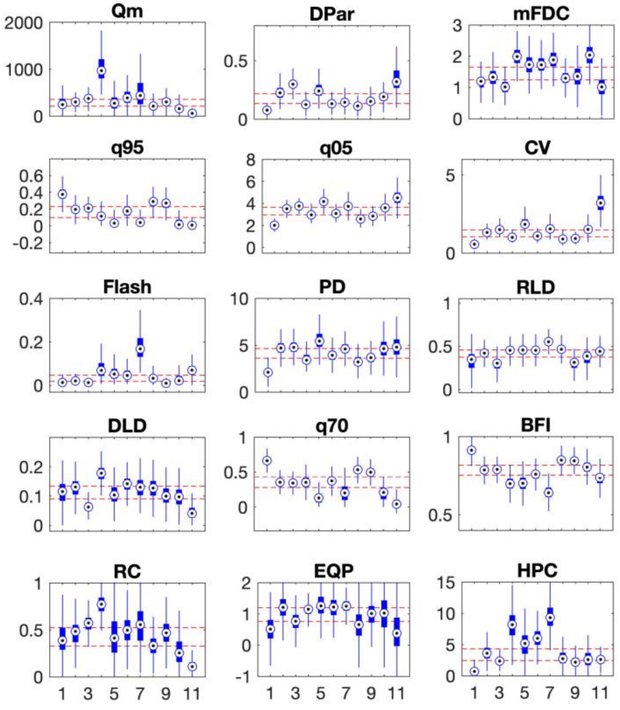
Median forecasting quality (in terms of the *CRPS´* score) as a function of lead time and initialisation month over the entire European domain

Clustering of European catchments

15 flow signatures → 11 clusters → Cluster characteristics

- Mean annual specific runoff (Qm)
- Normalised high flow (q05)
- Normalised low flow (q95)
- Normalised relatively low flow (q70)
- Slope of flow duration curve (mFDC)
- Range of Parde coefficient (DPar)
- Coefficient of variation (CV)
- Flashiness (Flash)
- Normalised peak distribution (PD)
- Rising limb density (RLD)
- Declining limb density (DLD)
- Baseflow index (BFI)
- Runoff coefficient (RC)
- Streamflow elasticity (EQP)
- High pulse count (HPC)

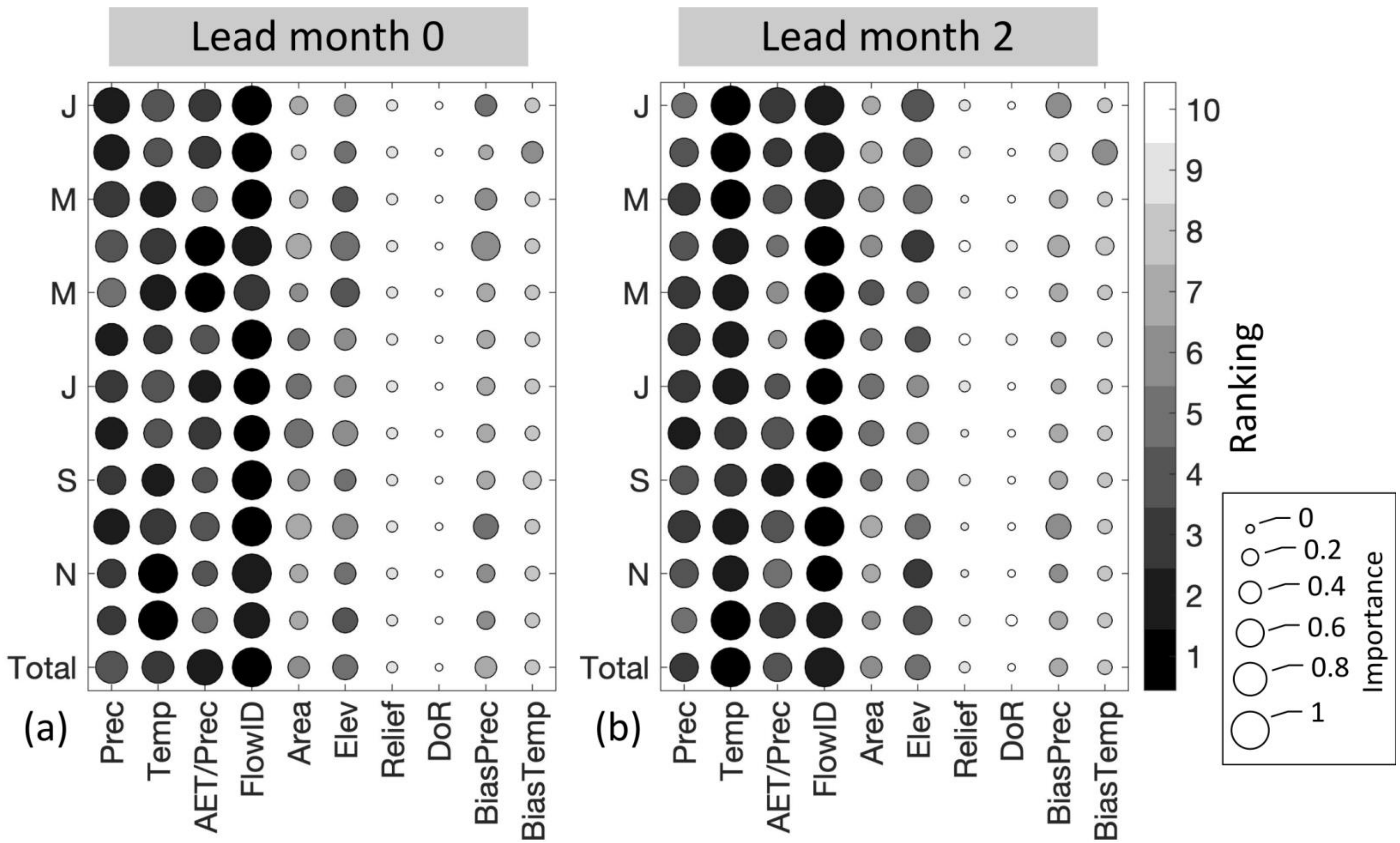




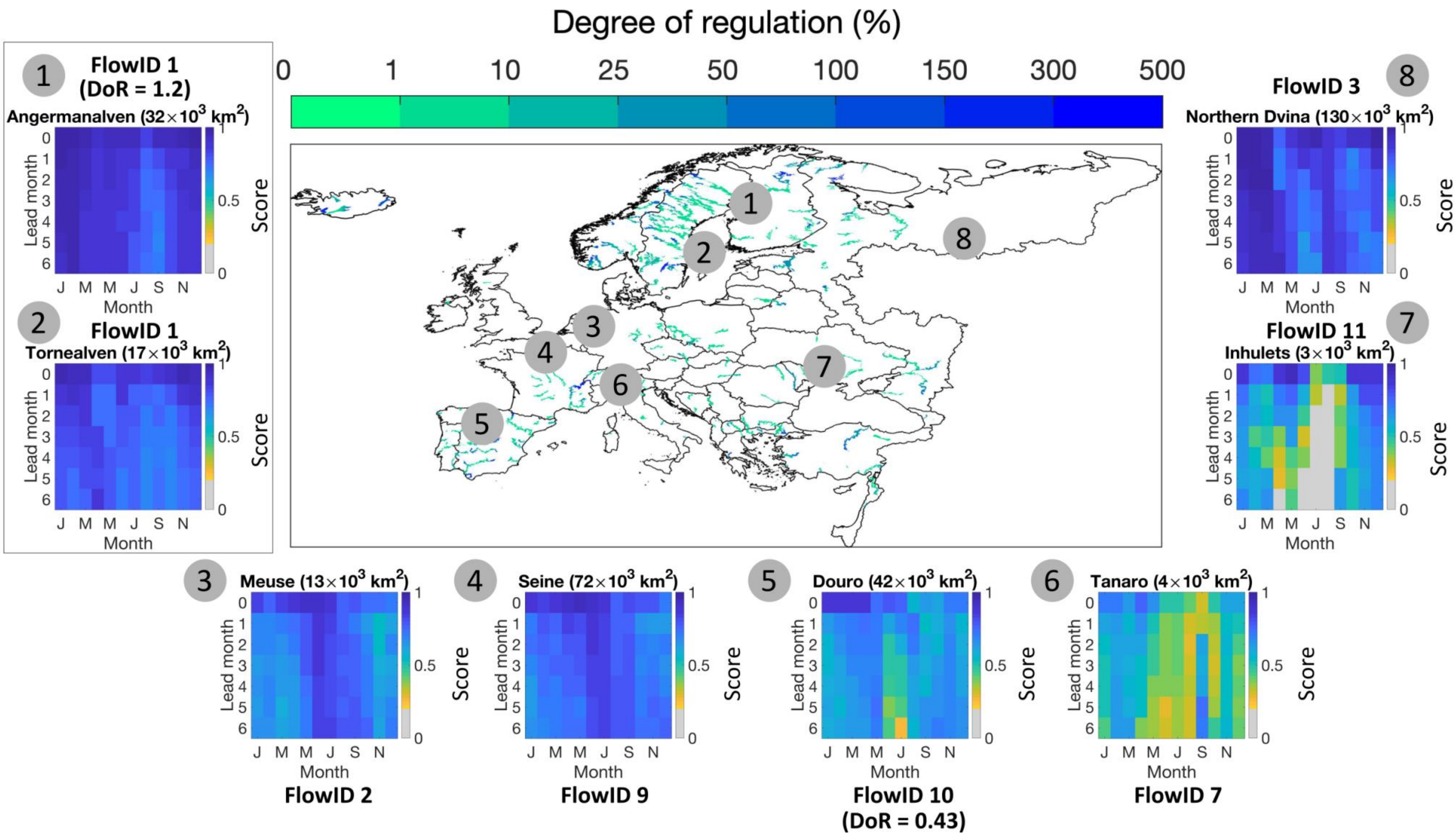
Pechlivanidis et al., 2020 WRR

Machine Learning analysis

Ranking the descriptors based on their importance (with 1 being the most important)

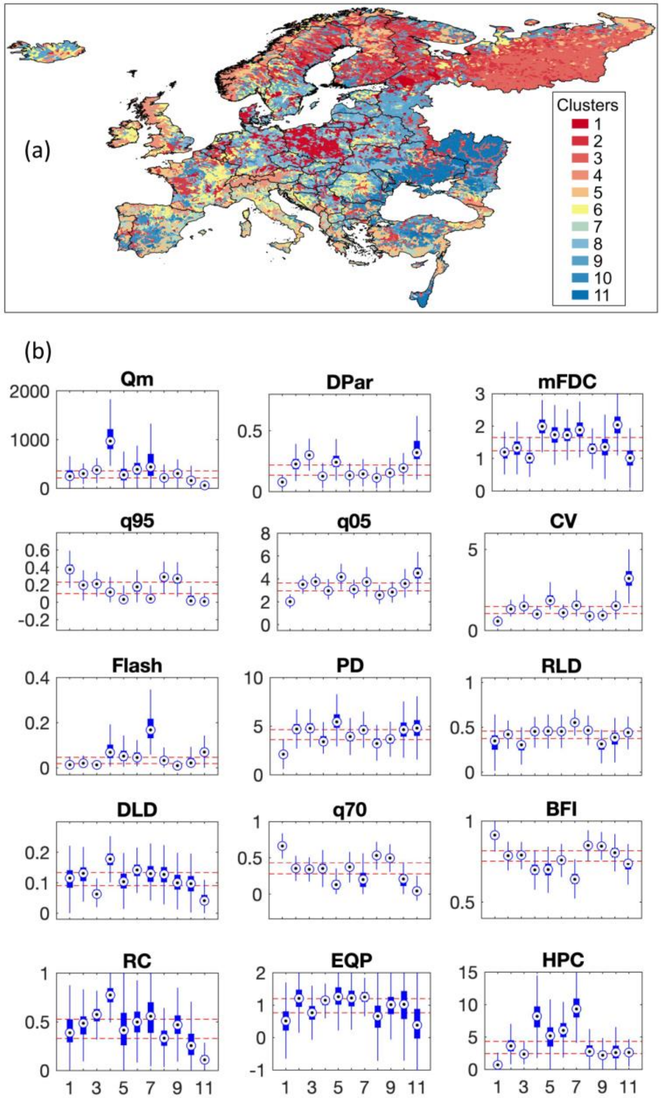


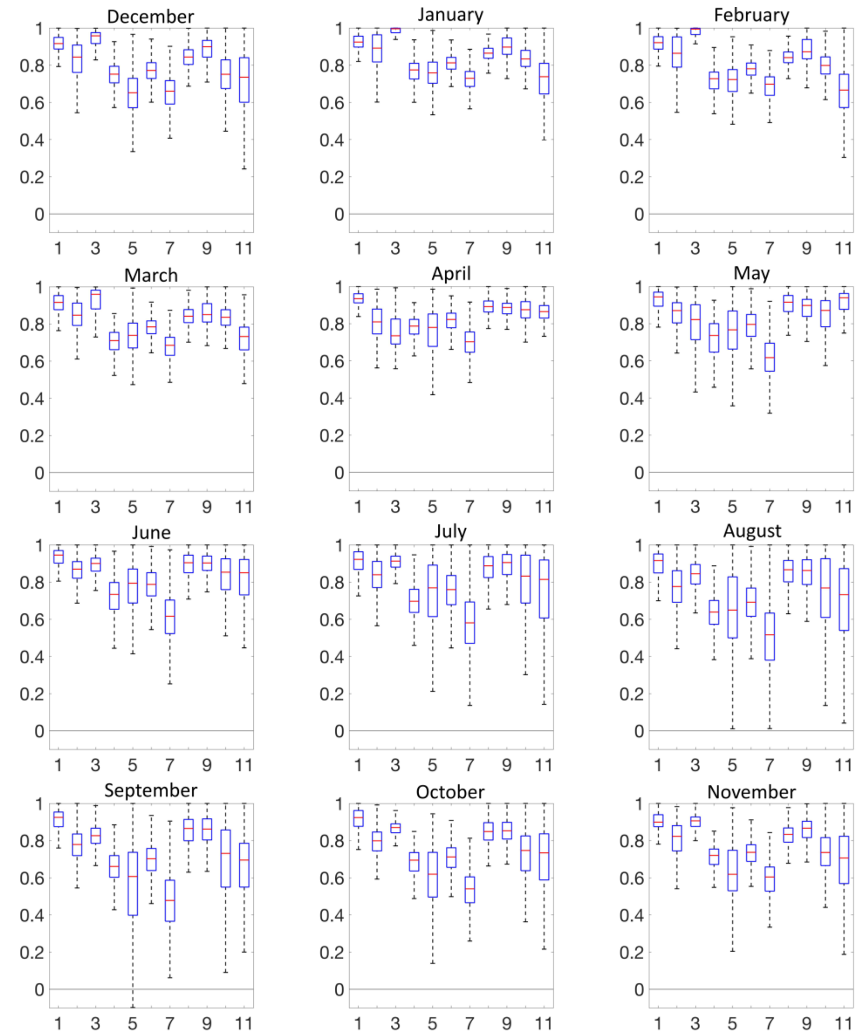
Relating forecast quality to hydrological processes (1)



Relating forecast quality to hydrological processes (2)

Closer look on the flow regimes





Conclusions

- SEAS5 meteorological forecasts have biases that need to be adjusted prior to their use in an impact (hydrological) model. These biases are not similar in terms of magnitude and spatial variability; large positive and negative biases in precipitation forecasts with sharp gradients between regions. Even when a bias-adjustment methodology is applied remaining biases still exist and their magnitude depends on the variable of interest.

- The European basins can be categorized into 11 clusters based on similarities in streamflow signatures revealing dominating hydrological processes. Overall, dominant streamflow generation processes, including baseflow, dampening, human alterations and climate, could explain the hydrological clustering across Europe.

- The quality of the seasonal streamflow forecasts varies both geographically and seasonally, depends on the initialization month and deteriorates with increased lead months. The highest predictability over Europe overall is shown from April to August, and the predictability decreases in autumn and winter. High forecast quality is shown in central and northern Europe in winter in the short lead months, and in central and western Europe in summer.

- The quality of the seasonal streamflow forecasts is linked to physiographic and hydro-climatic descriptors, whilst the descriptors' importance varies with initialization month and lead month. The hydrological similarity, temperature, precipitation, evaporative index and precipitation forecast biases are strongly linked to the streamflow forecast quality. Seasonal streamflows can be well predicted in river systems of generally long memory (due to snow-related processes, dampening from lakes/wetlands, aquifer contribution, long recessions); however the predictability is poor in cold and semi-arid climates with the river systems immediately responding to the precipitation signal (short river memory systems).

The SMHI Hydrology R&D unit

You are always welcome to share your views!

Acknowledgements

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