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Assessment of seasonal forecast performance of hydrological extremes over Europe

2022-June-16, EDORA

Objectives:

1. Evaluate bias adjustment of seasonal meteo-forecasts
2. Evaluate predictability of seasonal hydro-forecasts, in terms of lead weeks
3. Investigate drivers of the predictability (ongoing)

Model:	E-HYPE v.3.1.3 (35408 subbasins)
Reference forcing:	HydroGFD product v2.0 (SMHI)
Period:	1993-2015

Meteo forcing:	ECMWF SEAS5 forecasts
Bias-adjust:	Distribution Based Scaling (DBS)
Max lead time:	30 lead weeks
Ensemble:	25 members
Initialization:	Every month

Meteo forcing:	CMCC forecasts
Bias-adjust:	(DBS)
Max lead time:	26 lead weeks
Ensemble:	40 members
Initialization:	Every month

EHYPE: Hundecha et al., 2016
HydroGFD: Berg et al., 2018
DBS: Yang et al., 2010

Bias Adjustment of Seasonal Meteorological Forecasts

ECMWF SEAS5 forecasts

CMCC forecasts

Biases: average difference between the forecast ensemble and the reference
Reference: HydroGFD

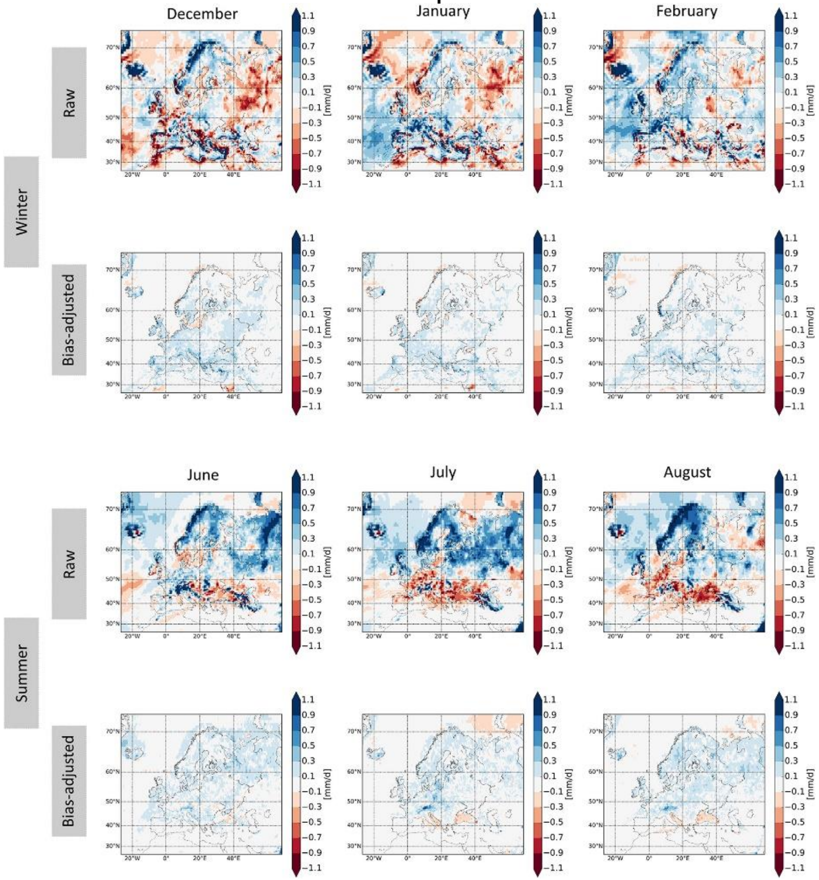
Continuous Ranked Probability Skill Score (CRPSS; Wilks, 2006)

Benchmark: Simulated climatology from HydroGFD
CRPS: Continuous Ranked Probability Score

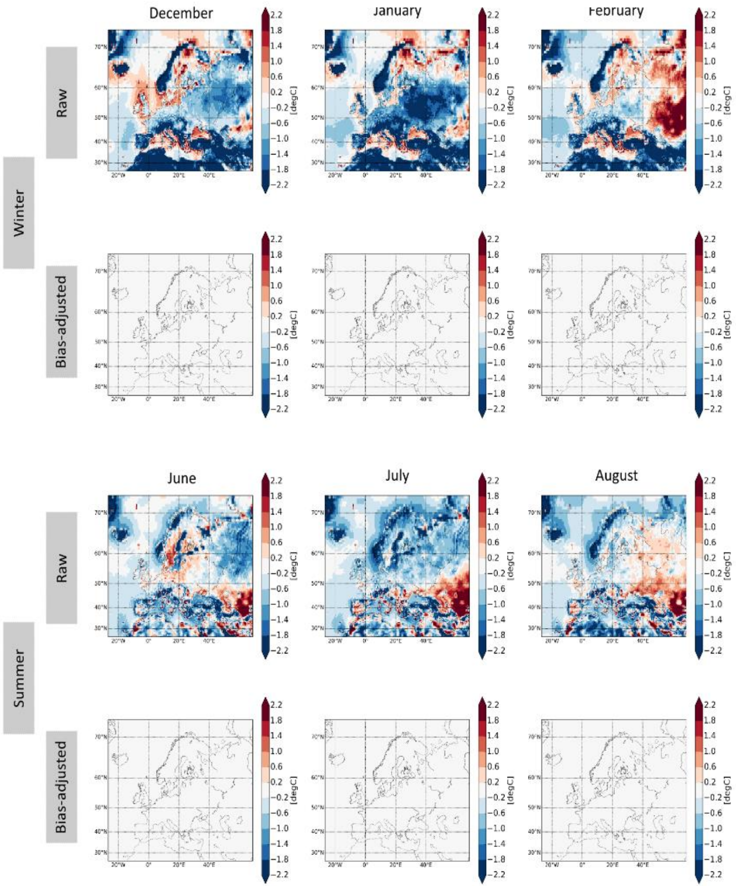
CRPSS: $1 - CRPS/CRPS_{benchmark}$

Quality Control in Bias Adjustment: bias in SEAS5

Precipitation

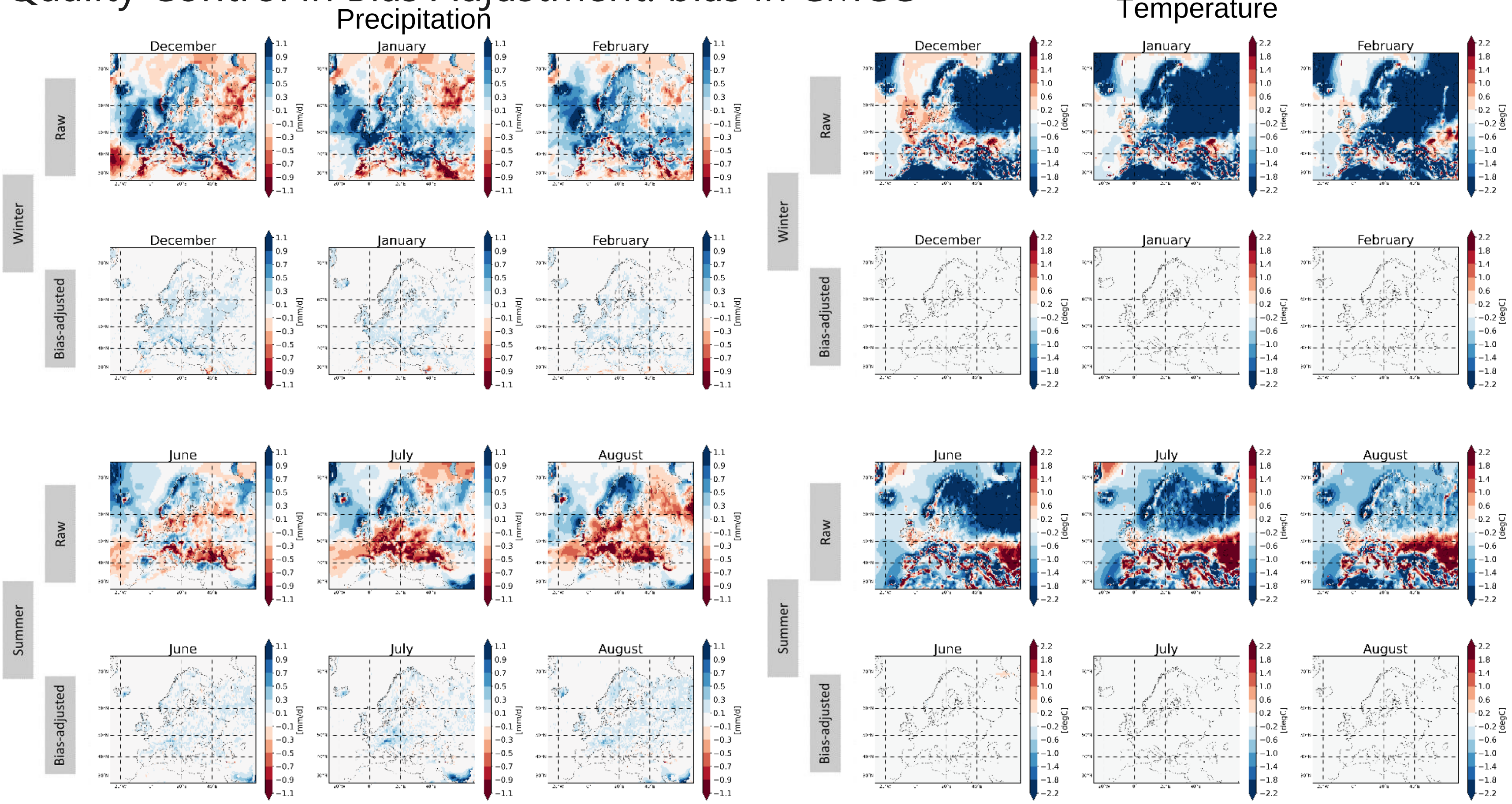


Temperature



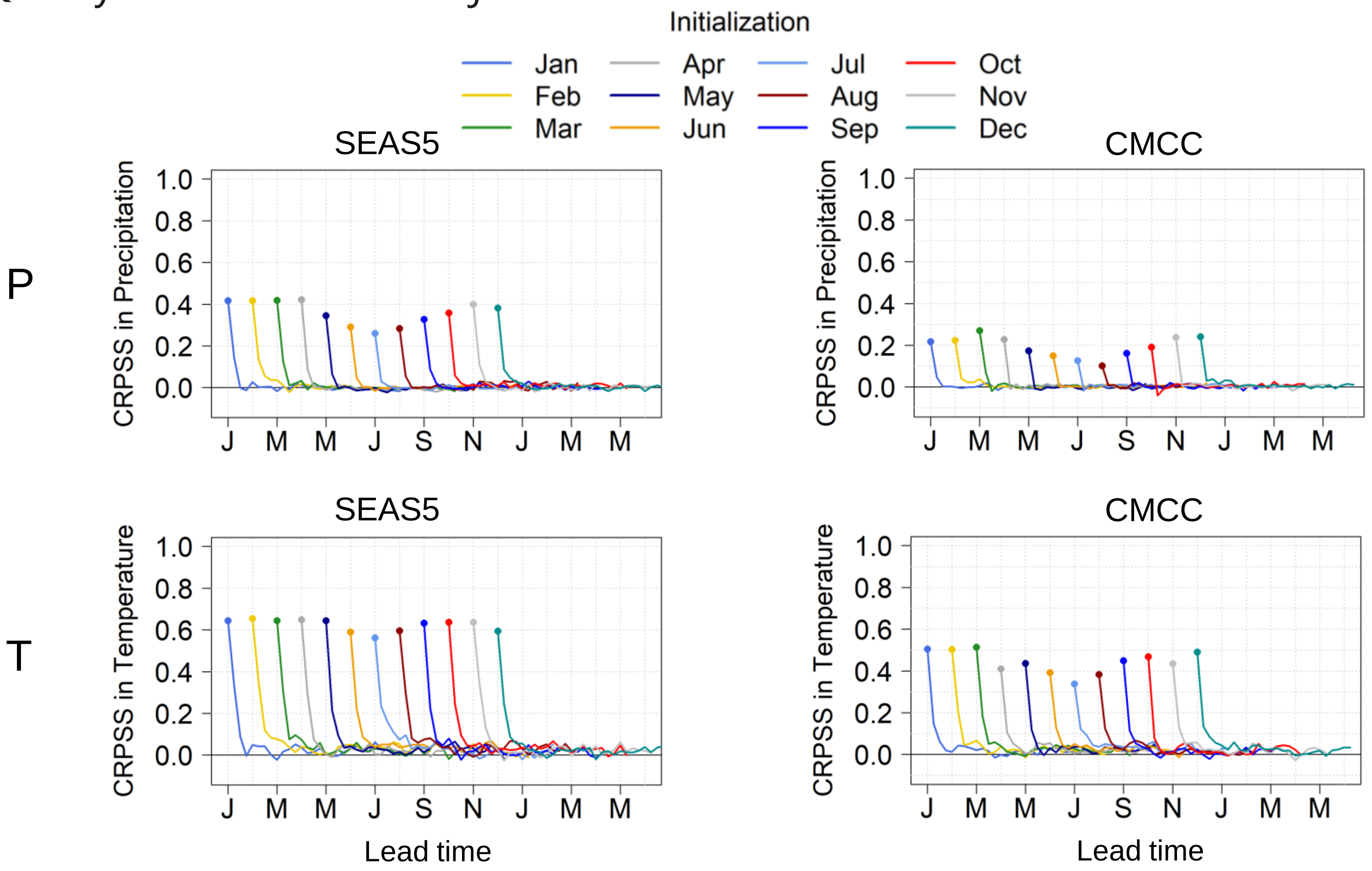
Pechlivanidis, I. G. et al. (2020).

Quality Control in Bias Adjustment: bias in CMCC



By Thomas Bosshard

Quality Control in Bias Adjustment: CRPSS



Seasonal Hydrological Forecasts—Evaluation

SMHI

CRPS
CRPSS

Continuous Ranked Probability Score (CRPS)
Pseudo-observation: Simulation

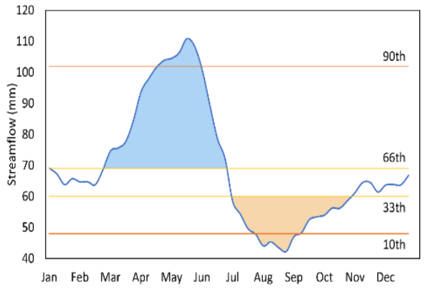
Benchmark: Simulated climatology
$CRPSS = 1 - CRPS/CRPS_{benchmark}$

BS10
BSS10

Brier Score (BS) of low flow (10th) weekly average runoff

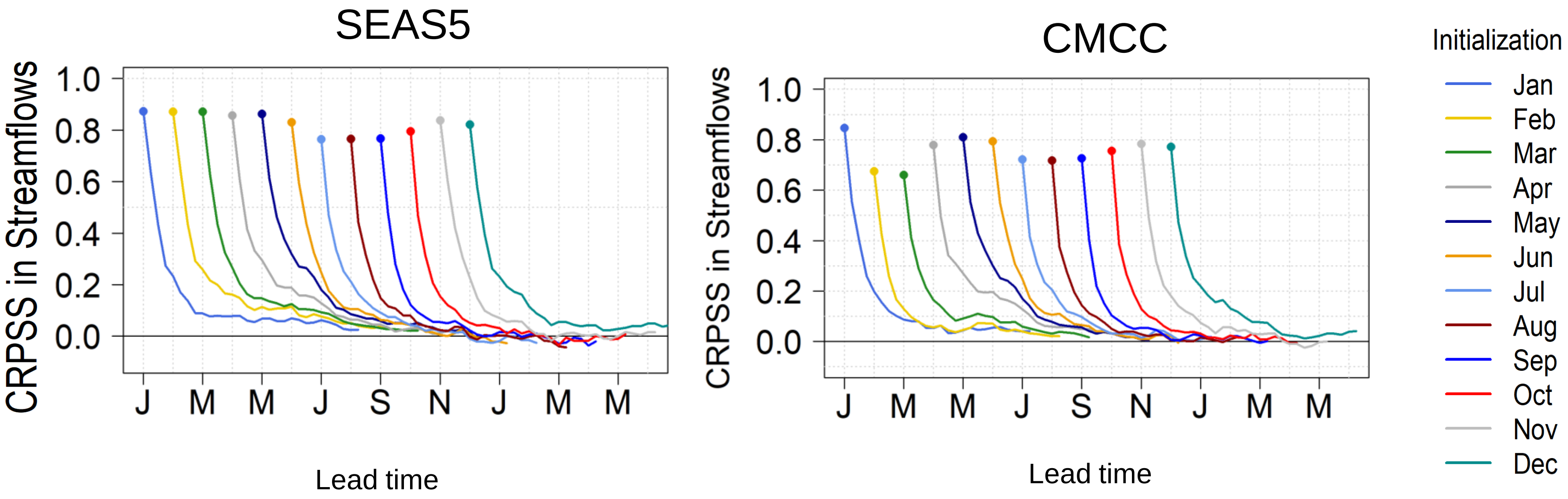
$$BS = \frac{1}{T}\sum_{t=1}^{T}\left(P\left(X(t)\right) - \mathrm{sgn}(obs)\right)^2$$

Benchmark: Simulated climatology
Brier Skill Score: $BSS = 1 - BS/BS_{benchmark}$ ($-\infty$ to 1)
Evaluation periods: Low flow periods (33rd)



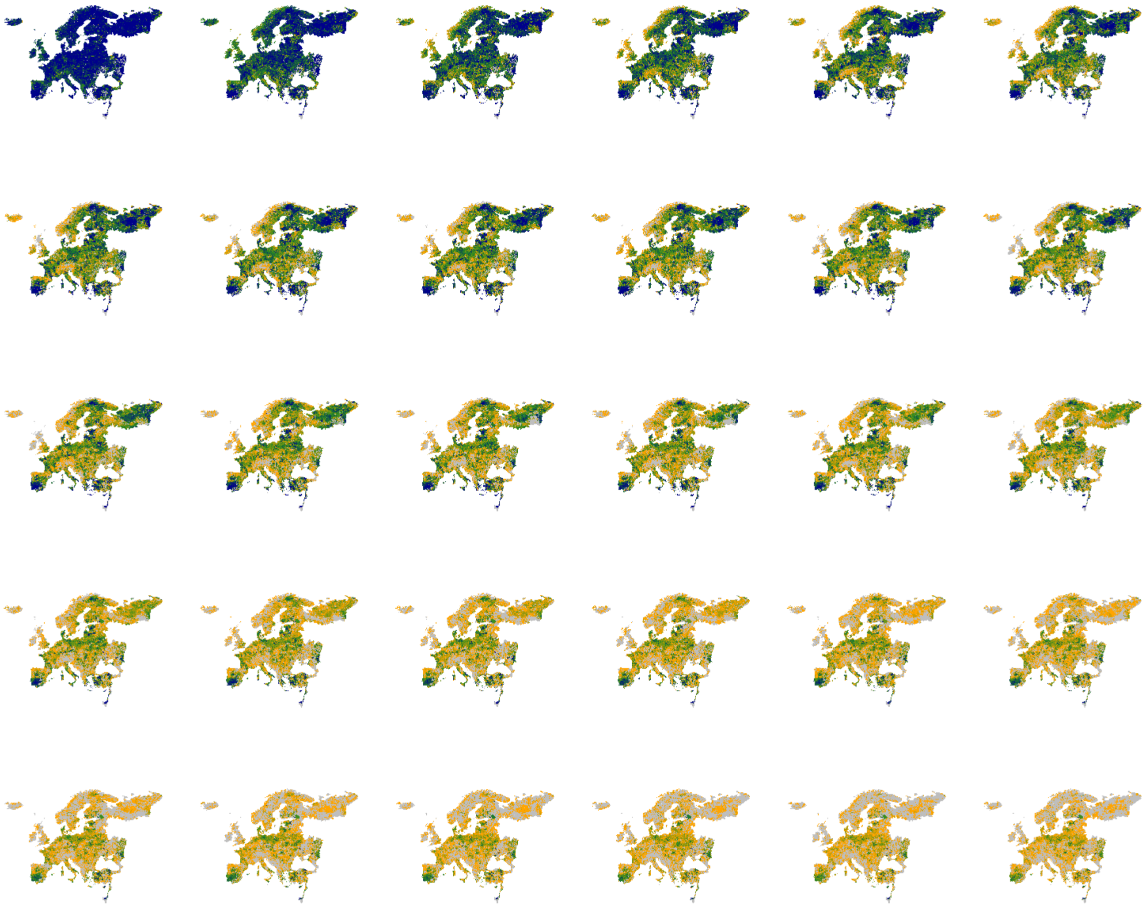
Seasonal Hydrological Forecasts Evaluation: CRPSS

SMHI



Seasonal Hydrological Forecasts Evaluation: BSS10

SMHI



SEAS5

Lead week 0 to 29

Seasonal Hydrological Forecasts Evaluation: BSS10

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CMCC
Lead week 0 to 25

Seasonal Hydrological Forecasts—Identifying Drivers

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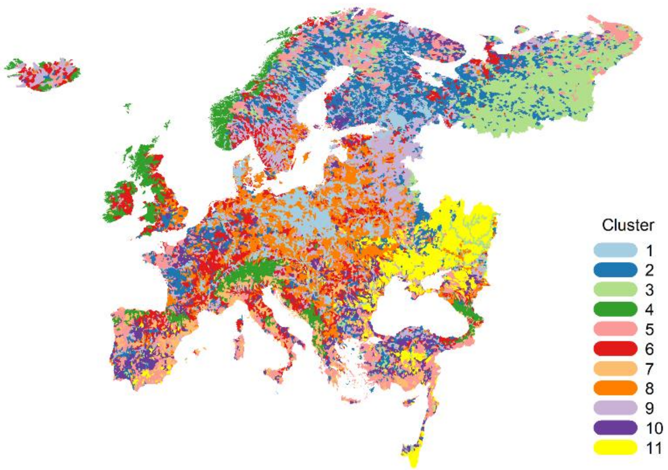


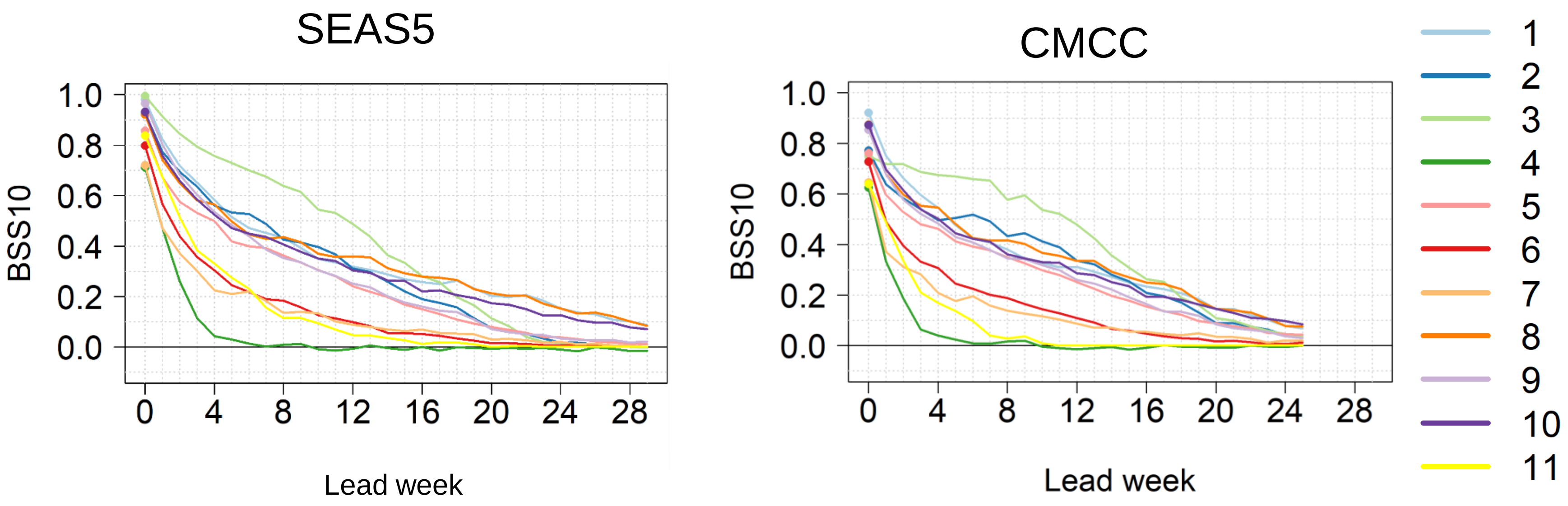
Hydrological similar regions from model simulation

Hydrological signatures		
Qm	Mean annual specific runoff	mm/year
q05	Normalized high streamflow	--
q95	Normalized low streamflow	--
q70	Normalized relatively low streamflow	--
mFDC	Slope of streamflow duration curve	%/%
Dpar	Range of Pardé coefficient	--
CV	Coefficient of variation	--
Flash	Flashiness	--
PD	Normalized peak distribution	--
RLD	Rising limb density	--
DLD	Declining limb density	--
BFI	Baseflow index	--
RC	Runoff coefficient	--
EQP	Streamflow elasticity	--
HPC	High pulse count	--

(Pechlivanidis, I. G. et al. (2020). Water Resources Research https://doi.org/10.1029/2019WR026987)

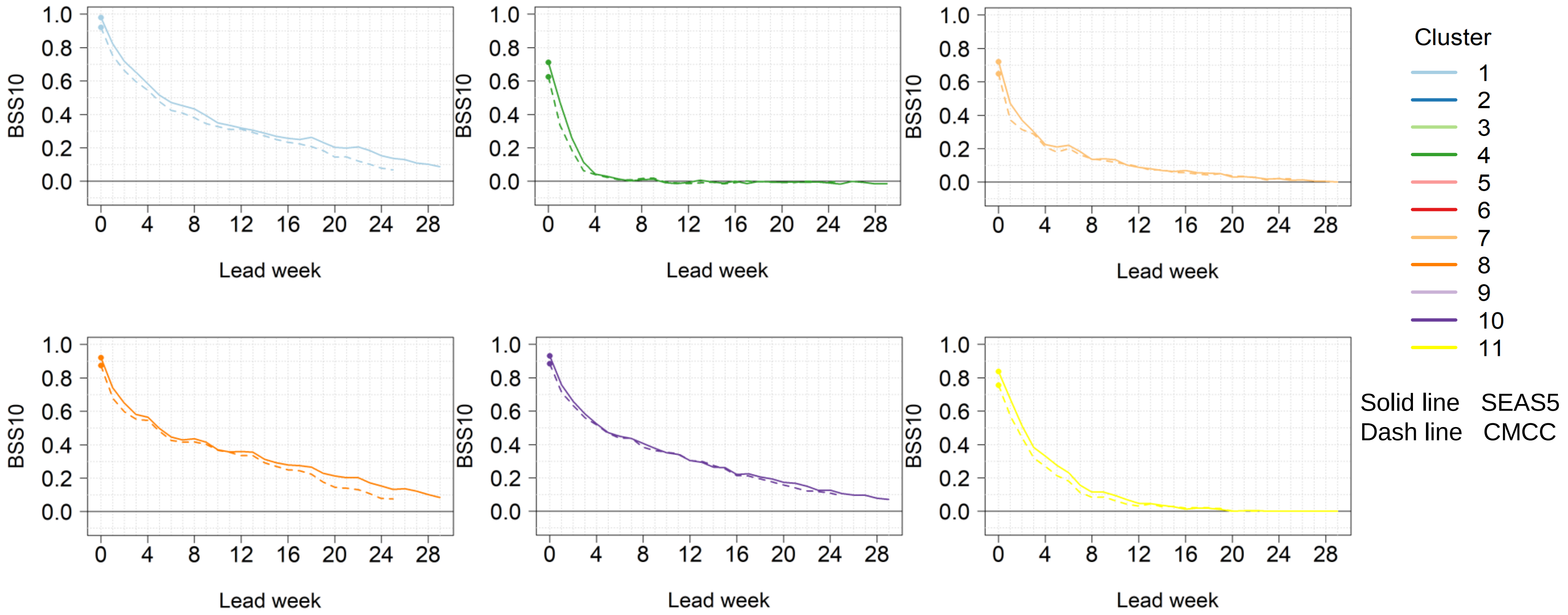
Seasonal Hydrological Forecasts—Identifying Drivers

Predictability of low flow extremes in each hydro-cluster



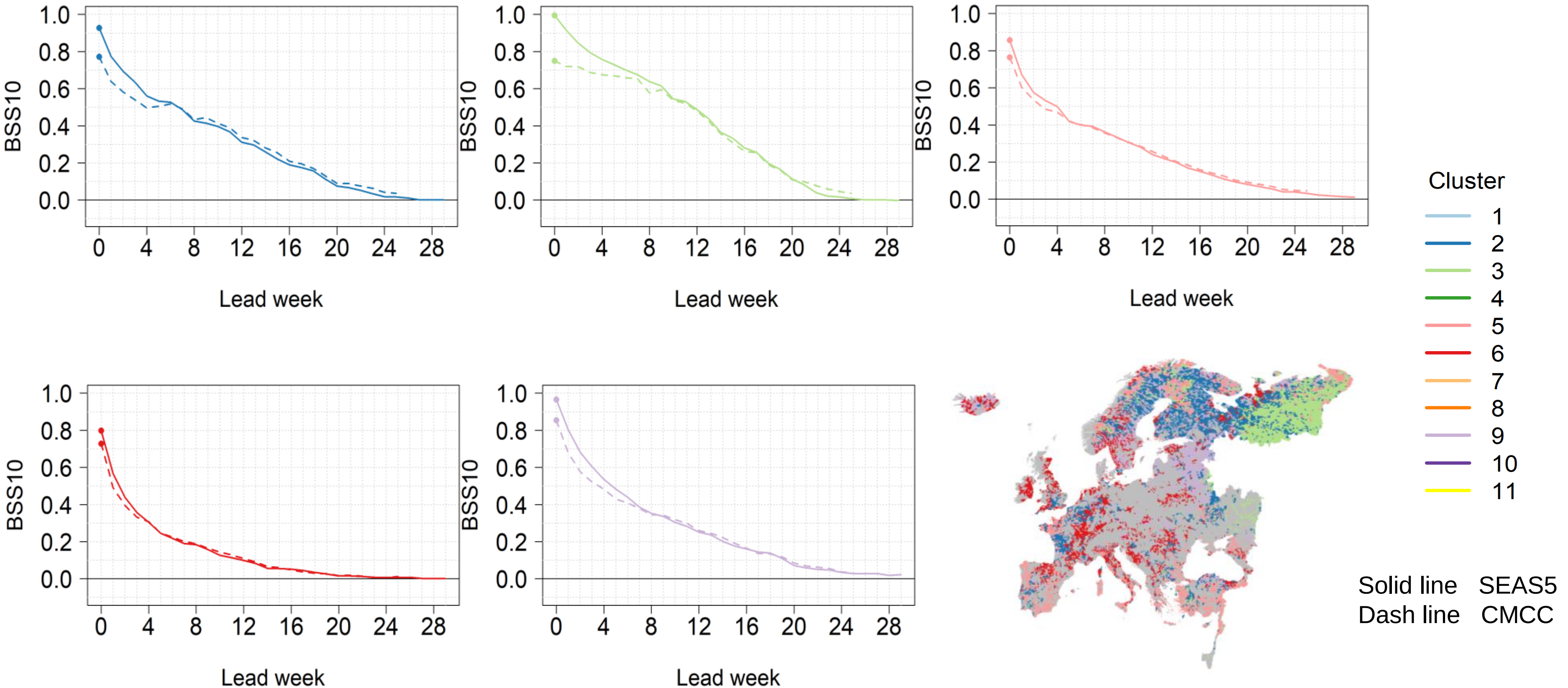
Seasonal Hydrological Forecasts—Identifying Drivers

SMHI



Seasonal Hydrological Forecasts—Identifying Drivers

SMHI



Precipitation driven/snow melt driven, high variability

Conclusions:

The predictability of the seasonal streamflow forecasts on low streamflow extremes

1. achieve high skills in the first several lead weeks (4-6 weeks).
2. varies geographically, deteriorates with increased lead weeks.
3. can be regionalized, based on a priori knowledge of the local hydrological conditions.

Next Step:

1. Explore links between predictabilities and hydrological similarity/climatic characteristics (machine learning)

Thanks for sharing your insights with us!

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