Exploring the relation of temperature forecast performance to climate, circulation, soil and vegetation variables

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International Earth Surface Seminar
October 21, 2021

International Max Planck Research School for Global Biogeochemical Cycles

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Motivation

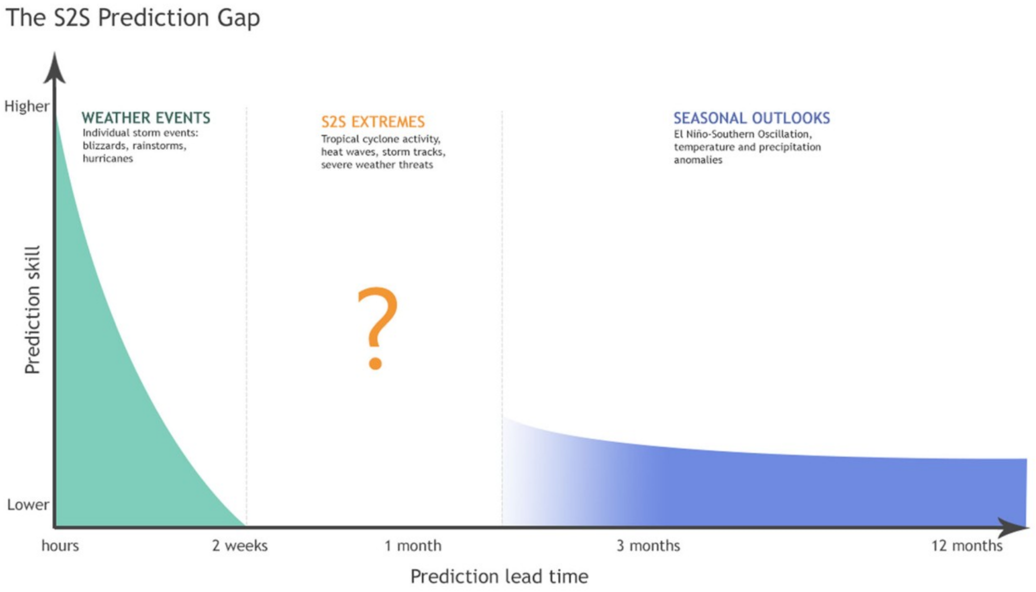


Fig 1. A schematic illustrating the S2S or weather–climate prediction gap.

(From Mariotti et al., 2018)

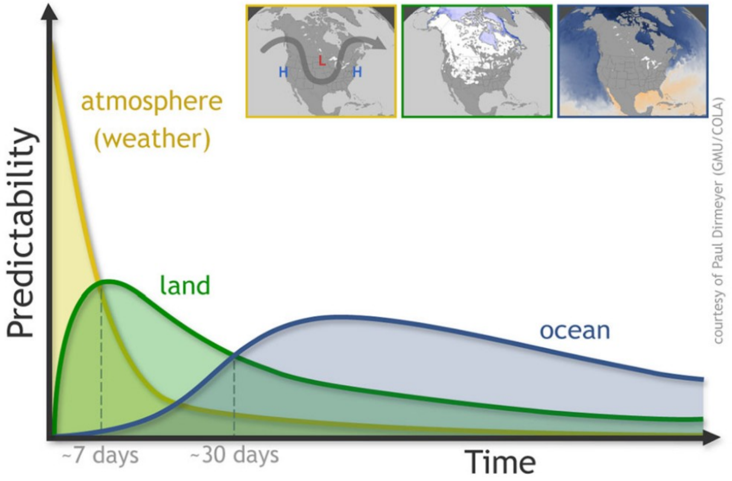
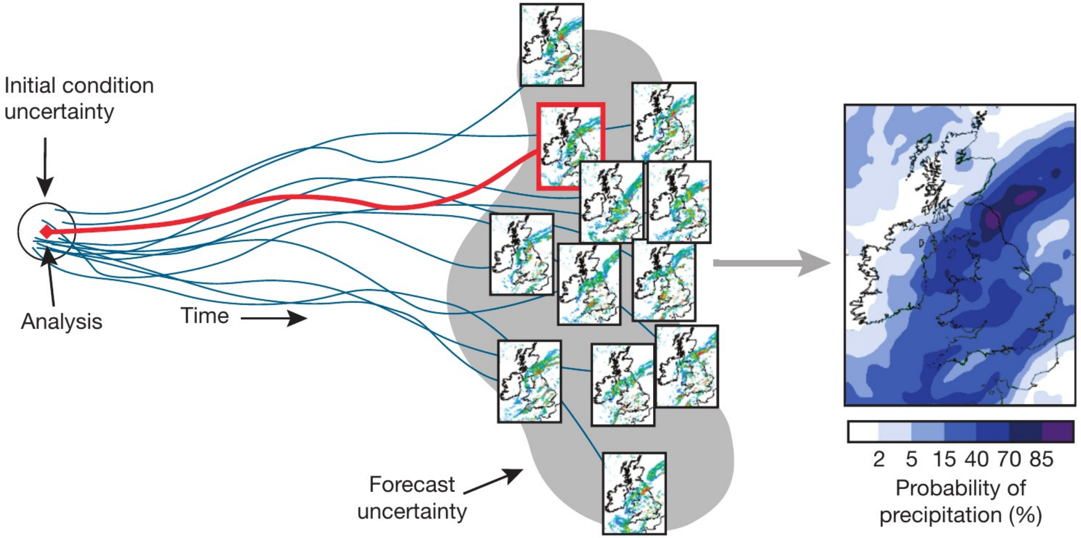


Fig 2. A schematic illustrating the role of different parts of the Earth's climate system (atmosphere, purple; land surface, green; ocean, blue) as sources of S2S predictability (vertical axis).

(From Mariotti et al., 2018)

Motivation



- Scientific and technological developments have led to the improvement of weather forecast performance.

- Non-linearity of the modeled system limit forecast skill.

Fig. 3 Schematic diagram of ensemble forecasts used to estimate the probability of precipitation over the UK (From Bauer et al., 2015)

Motivation

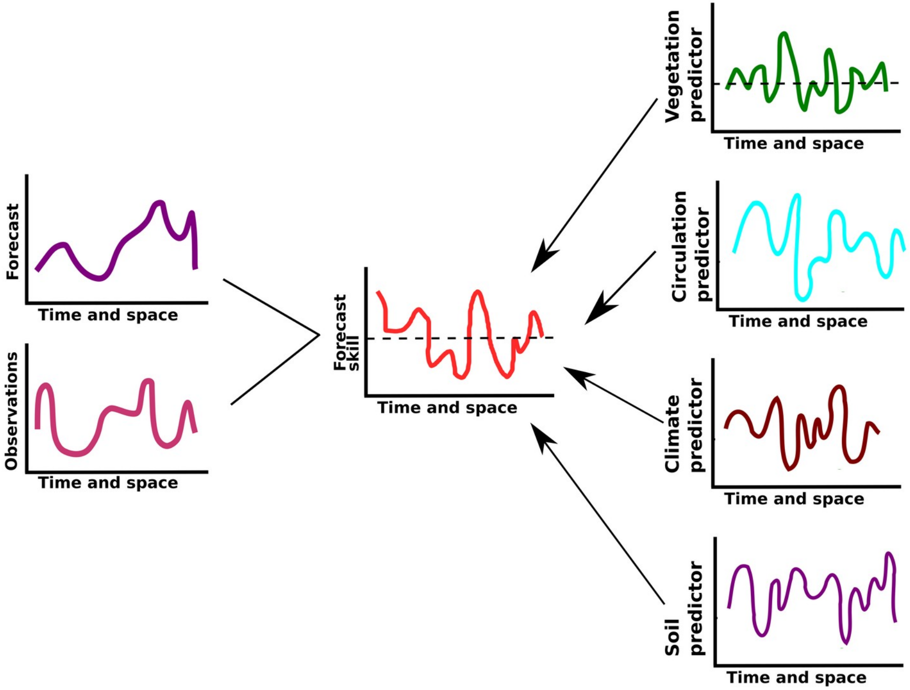


Fig. 4 Schematic diagram of the motivation of the study

- Numerical weather prediction models still err in their estimations.
- Forecast error varies in time and space.
- Can we link forecast error to land-surface related variables?
- Which of these variables explain most of the spatial (regions) and temporal (seasons) variability of the forecast error?

Data

Table 1 Groups of predictors of forecast error

Predictor	Abbrev.	Source	Reference
Precipitation	tp	ERA5	Hersbach et al. (2020)
Incoming solar radiation	ssrd		
Sea surface temperature	sst		
Sensible heat flux fraction	hf	FLUXCOM	Jung et al. (2019)
Wind	wind	ERA5	Hersbach et al. (2020)
Surface pressure	sp		
Madden Julian Oscillation index	mjo	NOAA	Wheeler and Hendon (2004)
El Niño Southern Oscillation	enso		Trenberth (1997)
North Atlantic Oscillation index	nao		Van Den Dool et al. (2000)
Leaf area index	lai	MODIS	Mynemi et al. (2015)
Enhanced vegetation index	evi		Didan (2015)
Normalized difference water index	ndwi		Schaaf and Wang (2015)
Vegetation optical depth	vod	VODCA	Moesinger et al. (2020)
Gross primary productivity	gpp	FLUXCOM	Jung et al. (2019)
Evaporative fraction	ef		
Soil moisture 0-50 cm	sm50	SoMo.ml	O and Orth (2021)
Soil moisture 0-10 cm	sm1		
Soil moisture 10-30 cm	sm2		
Soil moisture 30-50 cm	sm3		

Table 2 Variables to compute forecast skill

Variable	Abbrev.	Source	Reference
Temperature at 2 m	t2m	ECMWF S2S	Vitart et al. (2017)
Temperature at 2 m	t2m	MERRA-2	Gelaro et al. (2017)

Data specifications:

- Period of analysis: 01-01-2001 to 31-12-2018
- Weekly averages from daily values
- 0.5 degree spatial resolution
- Global domain

Methodology

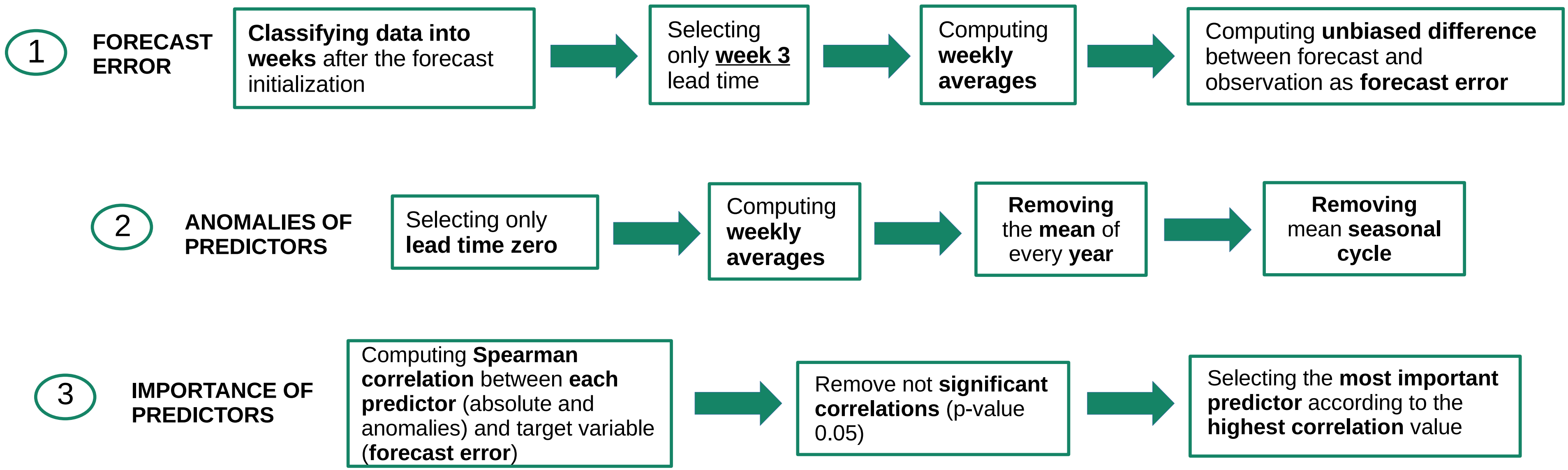


Fig. 5 Schematic diagram of the methodology

Results

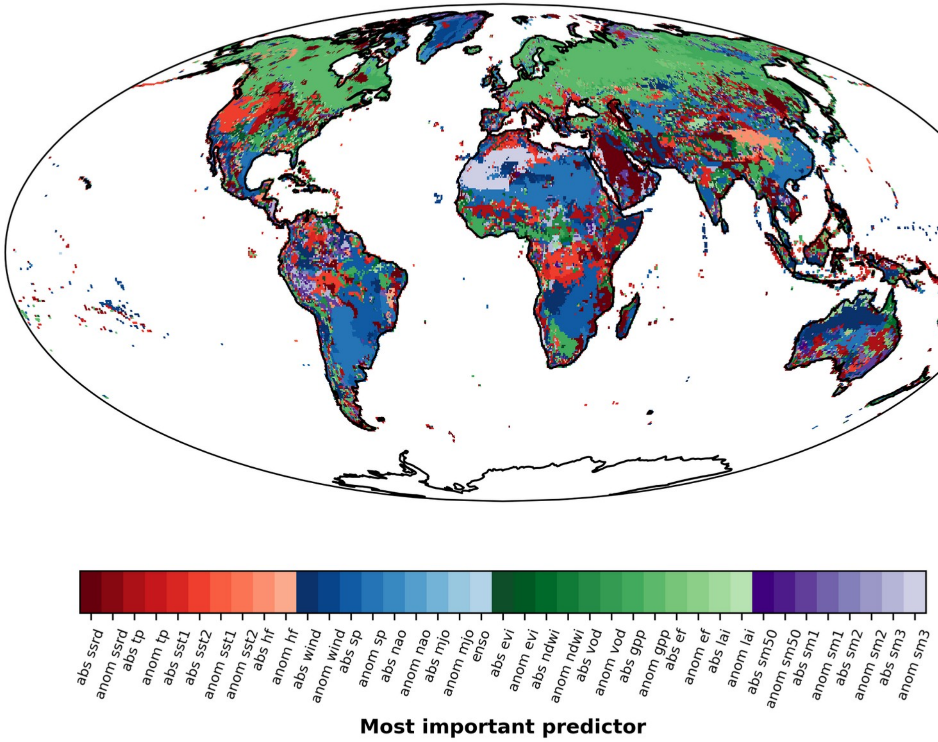


Fig. 6 Most important predictor of forecast error

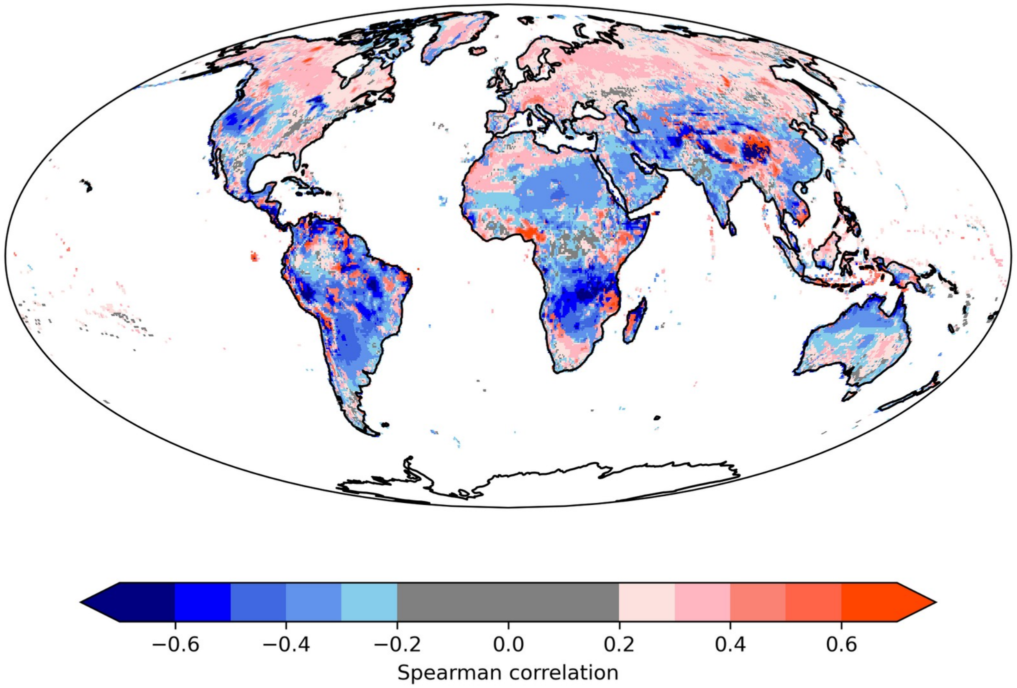


Fig. 7 Highest correlation value between predictors and forecast error

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Results

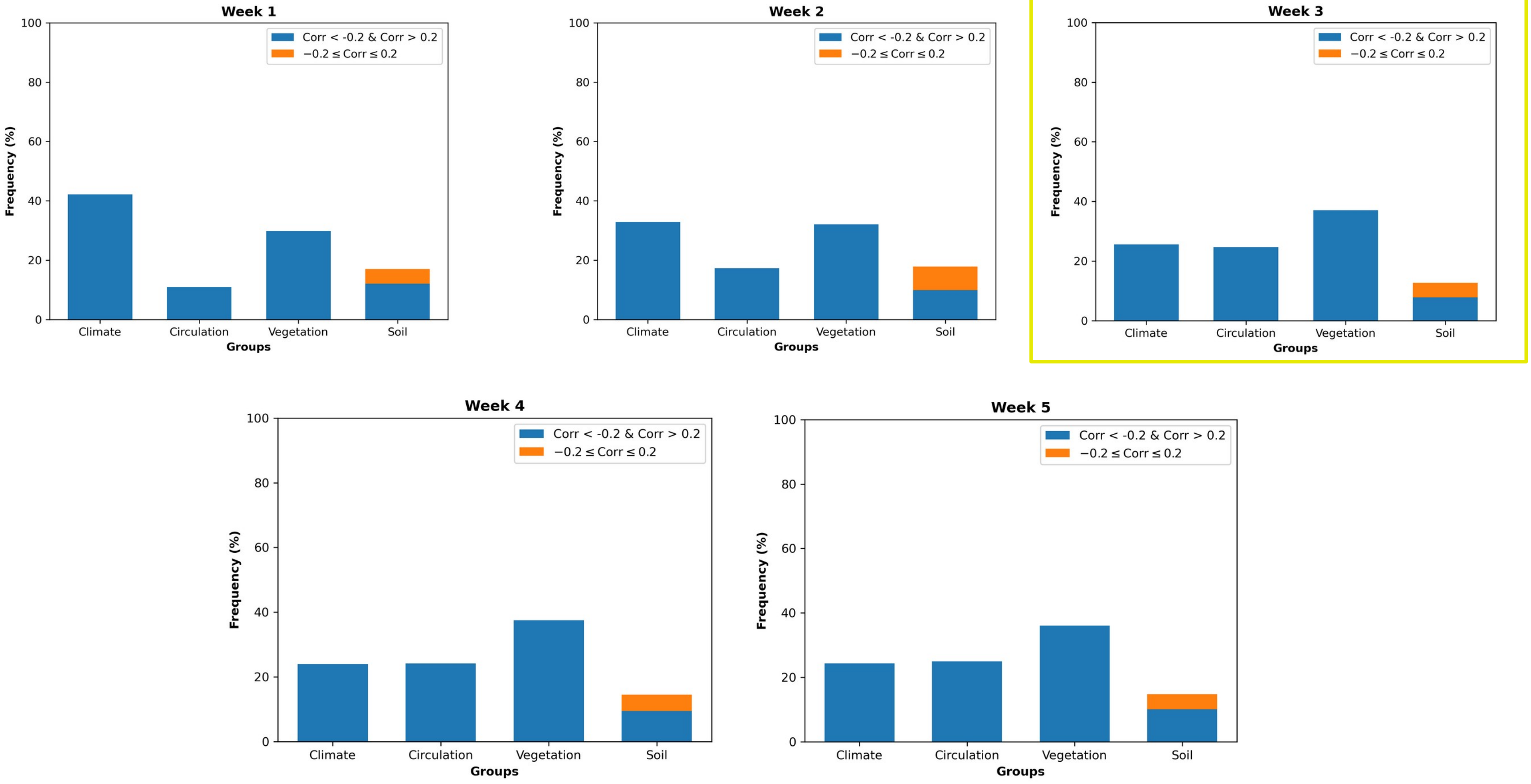


Fig. 8 Importance of groups of predictors of forecast error for different weeks after the forecast initialization

Results

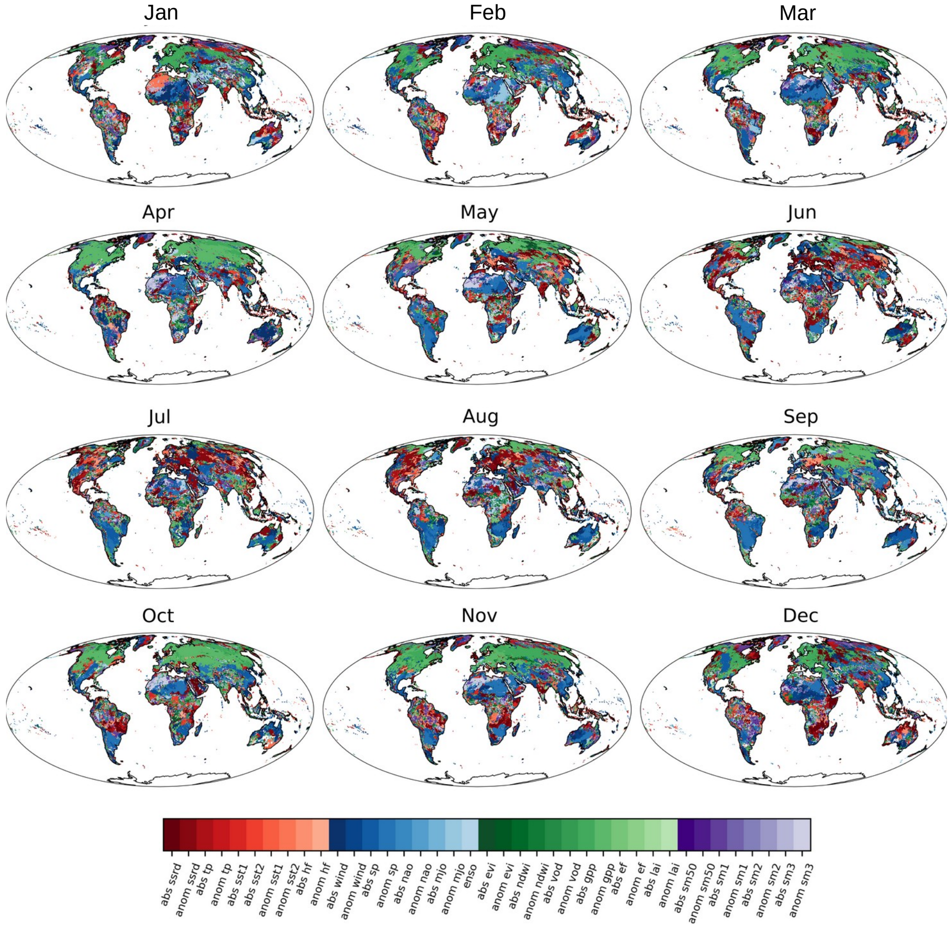


Fig. 9 Seasonal cycle of most important predictor of forecast error

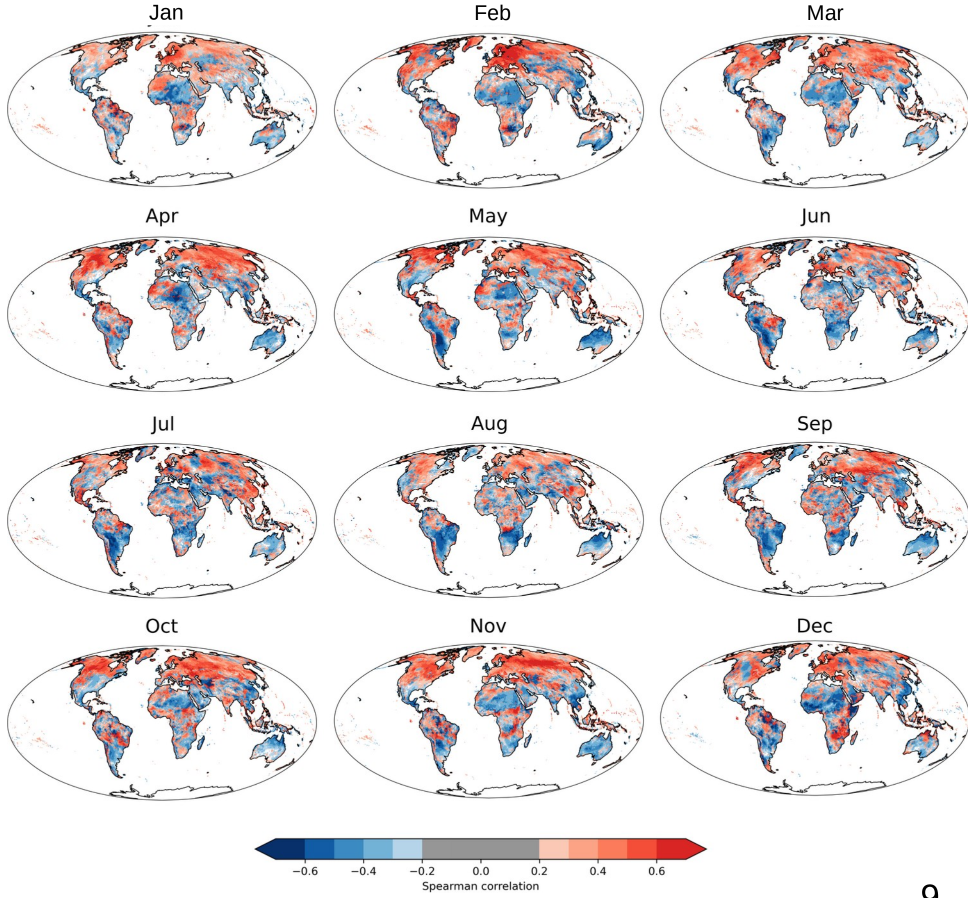


Fig. 10 Seasonal cycle of correlation values

Results

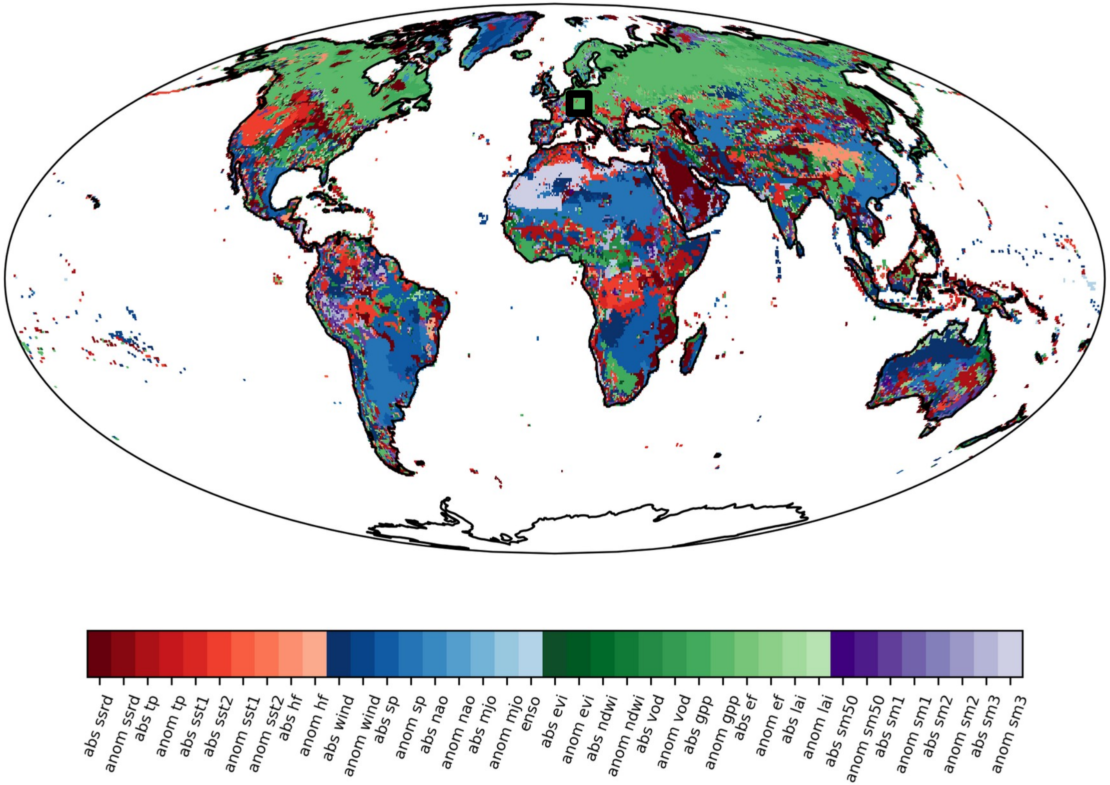
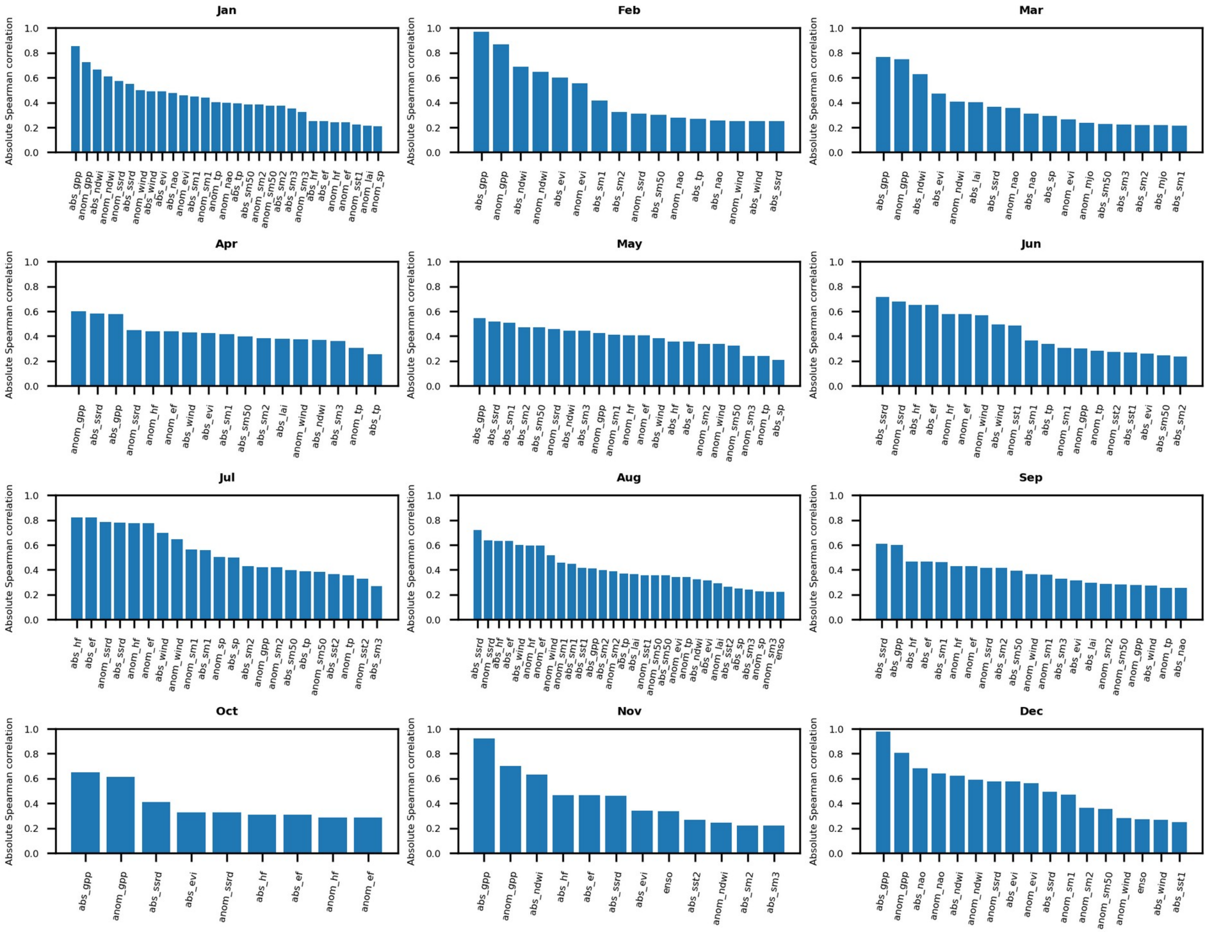


Fig. 6 Most important predictor of forecast error

Results



- GPP (absoulte and anomalies) are in the first positions of the rankings during january-april and october-december.

- Solar radiation and heat fluxes are in the first positions of the rankings during may-september.

Fig. 11 Seasonal cycle of the ranking of most important predictor in Central Europe

Results

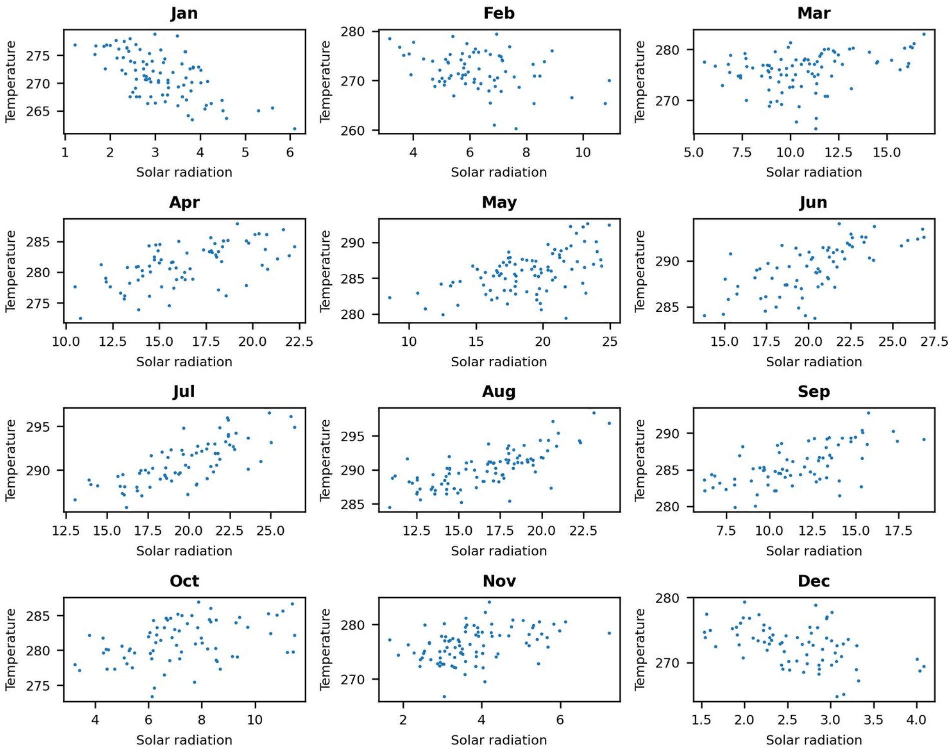


Fig. 12 Seasonal cycle of the scatterplots between ssrd and t2m

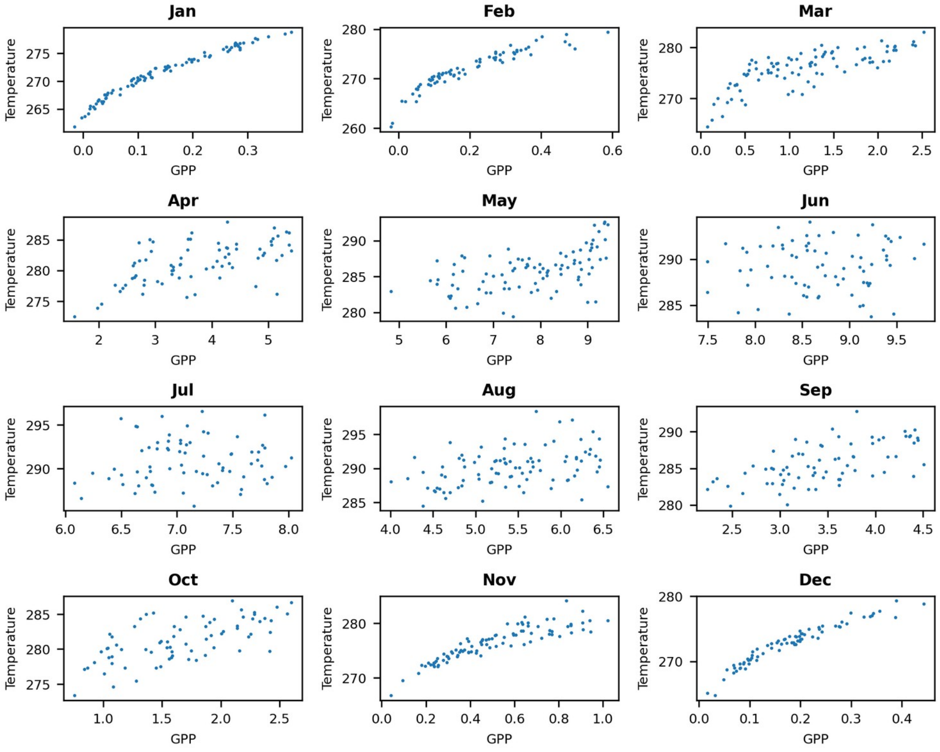


Fig. 13 Seasonal cycle of the scatterplots between GPP and t2m

Methodology

Ecosystem Limitation Index (ELI)
from Denissen et al. (2020)

$$\mathrm{ELI} = \mathrm{corr}(A_{SM}, A_{ET}) - \mathrm{corr}(A_{t2m}, A_{ET})$$

ELI > 0 Water control
ELI ≈ 0 Transitional
ELI < 0 Energy control

Table 3 Variables to compute ELI

Variable	**Abbrev.**	**Source**	**Reference**
Temperature at 2 m	t2m	ERA5	Hersbach et al. (2020)
Latent heat flux	ET		
Soil moisture 0-50 cm	SM		

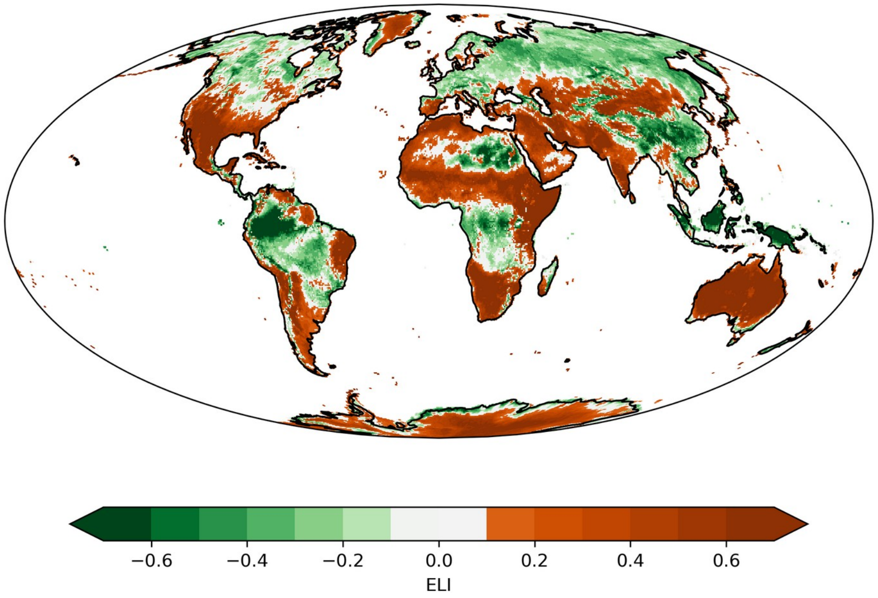


Fig. 14 Long term mean of ELI

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Results

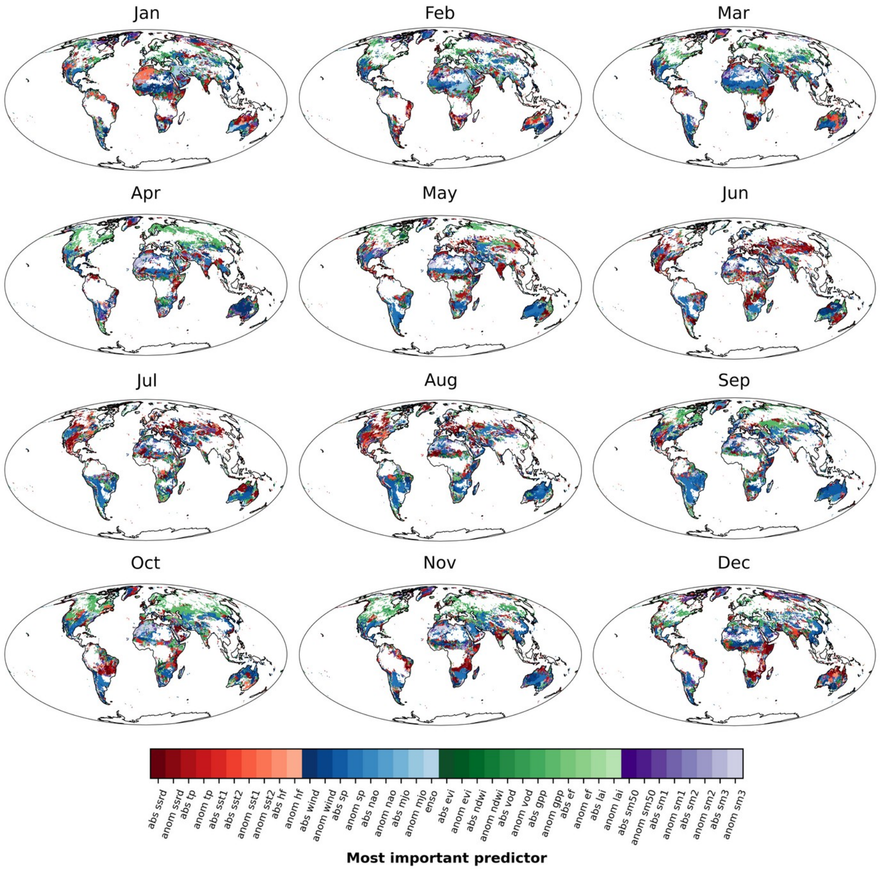

Fig. 15 Seasonal cycle of most important predictor of forecast error for water limited conditions

Results

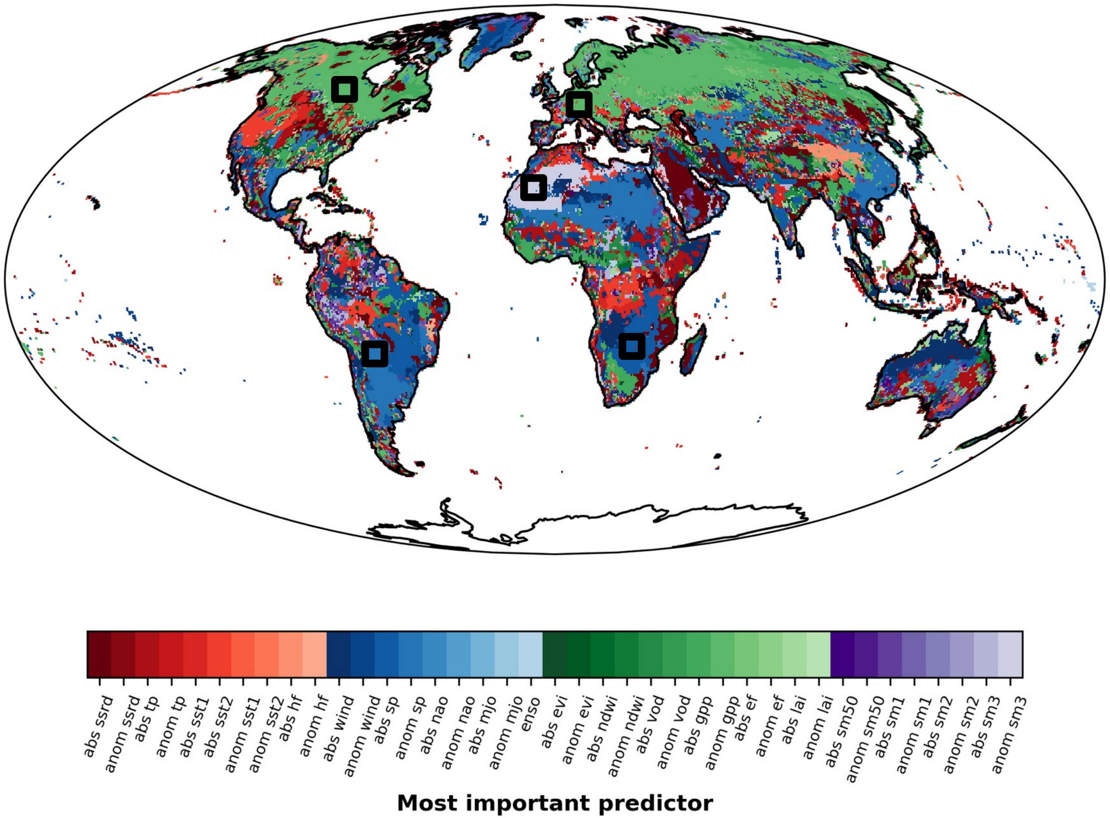

Fig. 6 Most important predictor of forecast error

Results

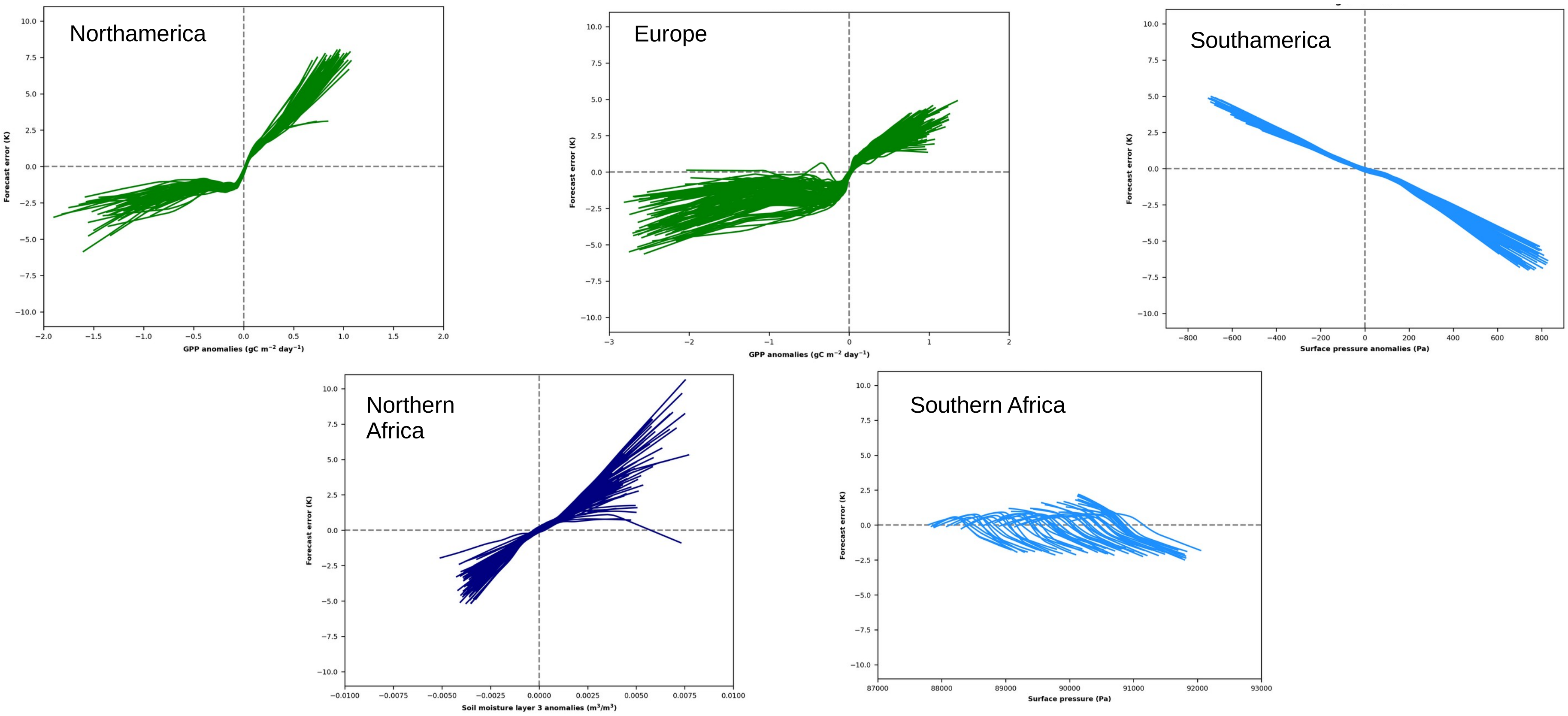

Fig. 16 Smoothing lines of the scatterplots between forecast error and most important predictor in each region

Main messages

- Circulation predictors are important in Southern hemisphere (Amazon basin, La Plata basin, Australia)
- Vegetation predictors are important in Central Africa
- Climate predictors are important in Northern hemisphere during summer months
- Soil moisture predictors are important in arid regions (Northern Africa)
- In selected regions, we found forecast errors close to zero when anomalies of predictors close to zero

Outlook

- Include differences in surface pressure (as other circulation index).
- ALE plots (Accumulated Local Effects plots).
- Extension of temporal analysis and focus on extreme events (droughts and heat waves).
- Include a Random forest analysis with Shap values to quantify the importance of each predictor in forecast error.
- Evaluate the representation of water and energy limited regions in the forecasting system.

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