A novel model independence methodology to improve multi-model seasonal forecasts combination

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SECLI FIRM

S2S4E Climate Services for Clean Energy

CRESCENDO

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Outline

Motivations

- Maximization of skill by using multi-model seasonal forecasts
- MME potential benefit amplifies with increasing independence of the contributing systems

Process-based model inter-comparison

-importance of the diversity of land-surface processes representation

Probabilistic scores and model independence

New metrics:

- Brier Score Covariance
- Signal Covariance

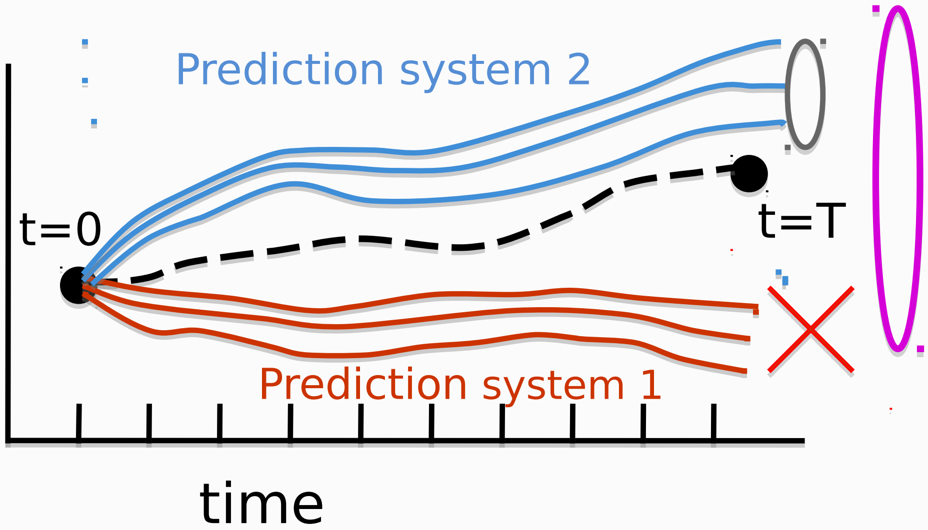
Model combination

-independence of the contributing models and skill improvement in the Grand-MME

-Two case studies: East-EU and Colombia

Conclusions

The rationale behind use of Multi-Models



MME can improve by:

- *Combining the skill from the single models*
- *Improve ensembles dispersion and uncertainty consideration*

➢ *Degree of over-confidence*

➢ *Independence of the contributing Prediction Systems*

Alessandri A., De Felice M., Catalano F., Lee J.-Y., Wang B., Lee D. Y., Yoo J.-H., Weisheimer A., 2018: Grand European and Asian-Pacific multi-model seasonal forecasts: maximization of skill and of potential economical value to end-users. Clim. Dyn., 50, 2719-2738, doi:10.1007/s00382-017-3766-y

The Grand C3S-NMME-JMA Multi Model

11 Prediction Systems:

- **5** from EU **Copernicus C3S**
- **6** from North American **NMME** plus the Japan Meteorological Agency **JMA**

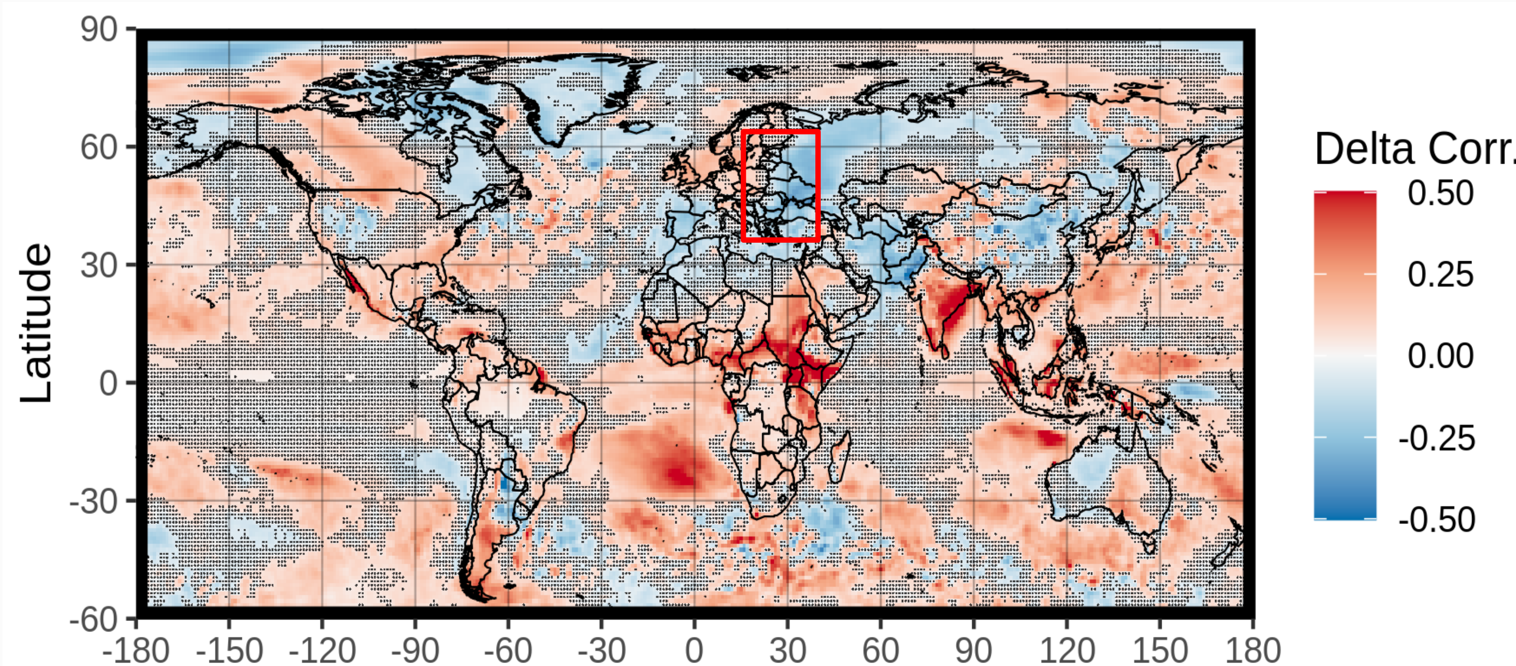
Copernicus C3S
ECMWF, European Centre for Medium-Range Weather Forecasts, UK
MF, Meteo France, France
DWD, Germany National Meteorological Service, Germany
UKMO, UK Met Office, UK
CMCC, Centro Euro-Mediterraneo per i Cambiamenti Climatici, Italy

NMME
NCEP, National Center for Environmental Prediction, USA
GFDL, Geophysical Fluid Dynamics Laboratory, USA
CCSM, Community Climate System Model, USA
GEM, Canada National Meteorological Service, Canada
CAN, Canada National Meteorological Service, Canada
JMA, Japan Meteorological Agency, Japan

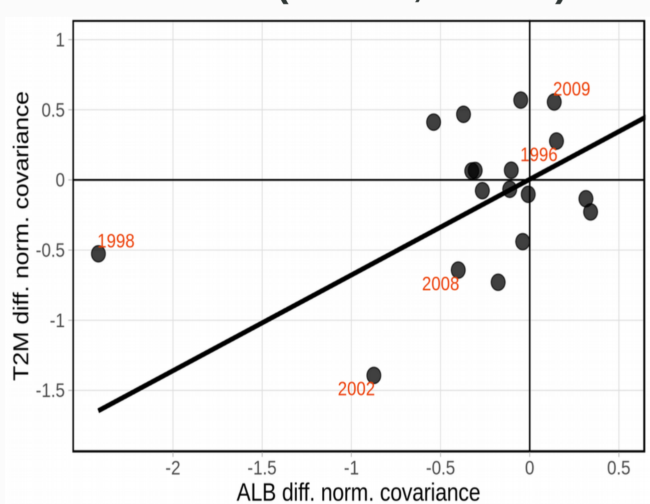
common hindcast period: 1993-2016
start dates: 1 May and 1 Nov

Seasonal hindcasts - 1st Nov start date - 2m Temperature Correlation differences (MODIF minus CTRL) vs. ERA-5

ECMWF minus DWD



East-EU (35-70N; 15-40E)



• $$\Delta \frac{\left(X^{i}_{mod} - \overline{X}_{mod}\right)\left(X^{i}_{obs} - \overline{X}_{obs}\right)}{\sigma^{X}_{mod} \times \sigma^{X}_{obs}}$$

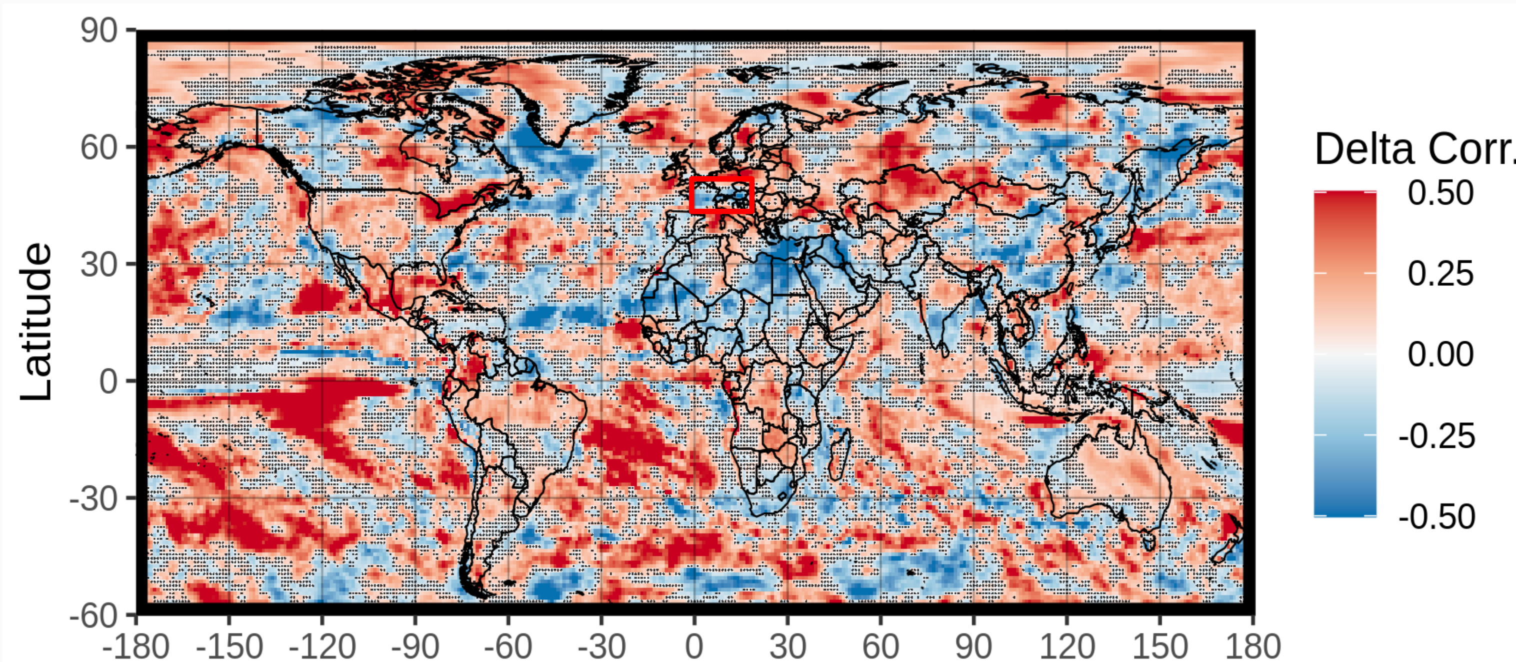
Δ MODIF minus CTRL

i = each single year

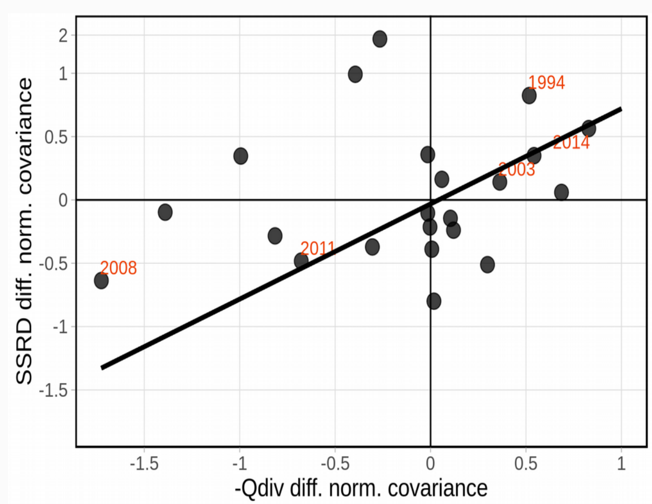
Regression line (coefficient significant at 5% level)

Seasonal hindcasts - 1st May start date - Surf. solar rad. Correlation differences (MODIF minus CTRL) vs. ERA-5

ECMWF minus MeteoFrance



Central-EU (45-50N; 0-16E)



- $\Delta \frac{\left(X^{i}_{\mathrm{mod}} - \overline{X}_{\mathrm{mod}}\right)\left(X^{i}_{obs} - \overline{X}_{obs}\right)}{\sigma^{X}_{\mathrm{mod}} \times \sigma^{X}_{obs}}$

Δ MODIF minus CTRL

i = each single year

Regression line (coefficient significant at 5% level)

Brier Score covariance

The Brier score covariance (BScov) estimates the relative independence of prediction systems 1 and 2:

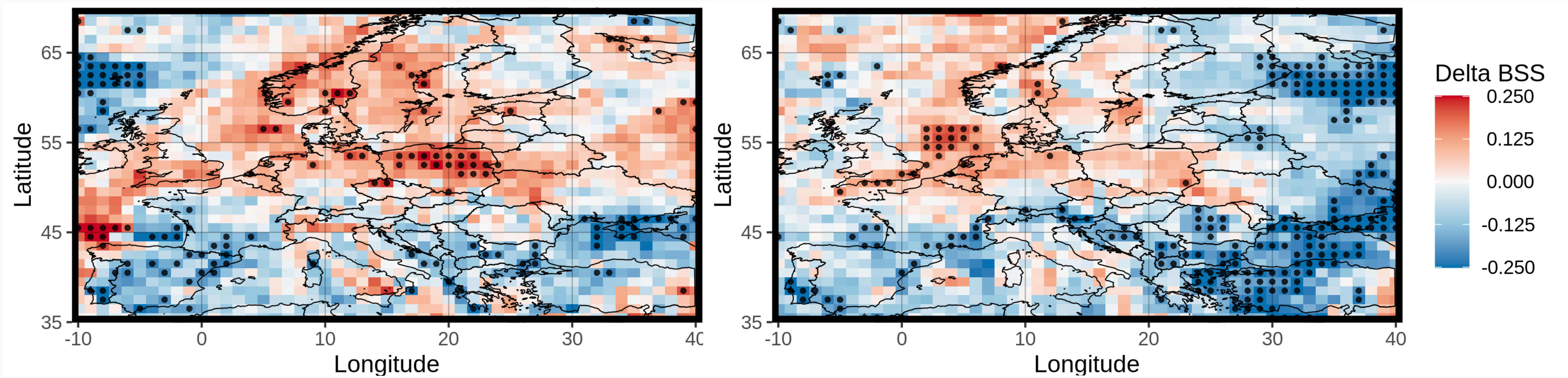
$$BScov = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(y_i^1 - o_i\right)\left(y_i^2 - o_i\right)}{\sqrt{BS^1 \cdot BS^2}}$$

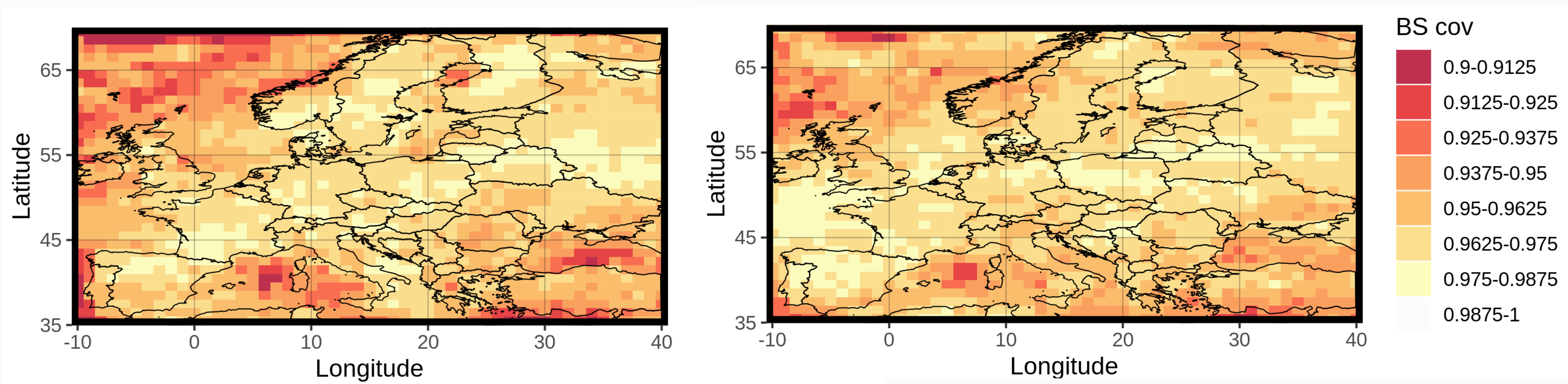
i indicates each hindcast year and n total number of years; y is forecast probability and o is for the observed [0, 1] dichotomous event under consideration.

Seasonal hindcasts - 1st Nov start date - 2m Temperature
BSS lower tercile vs. ERA-5

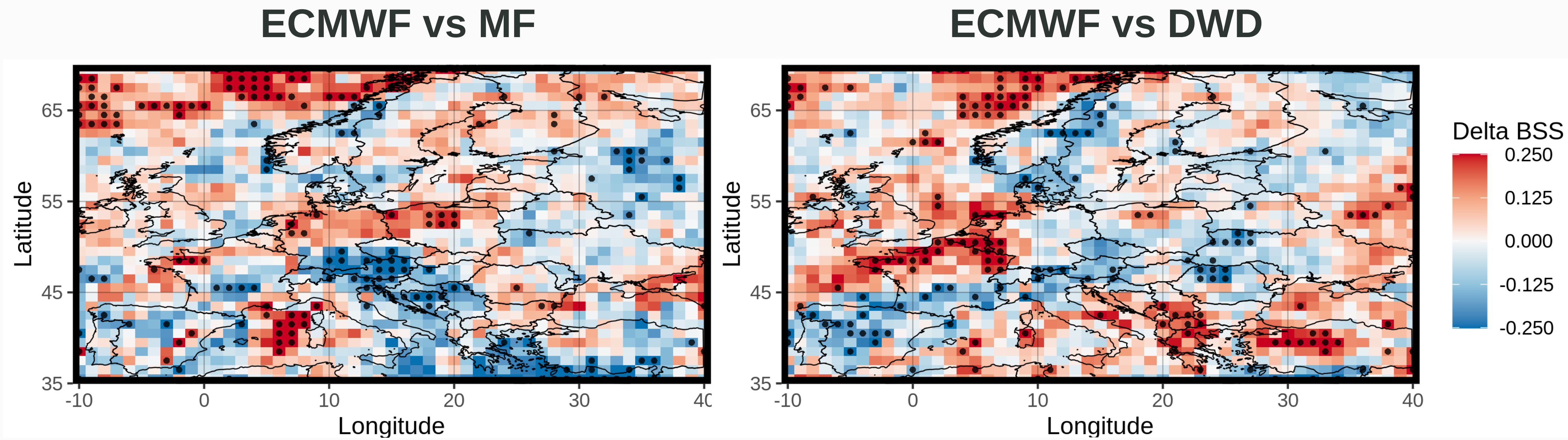
ECMWF vs MF

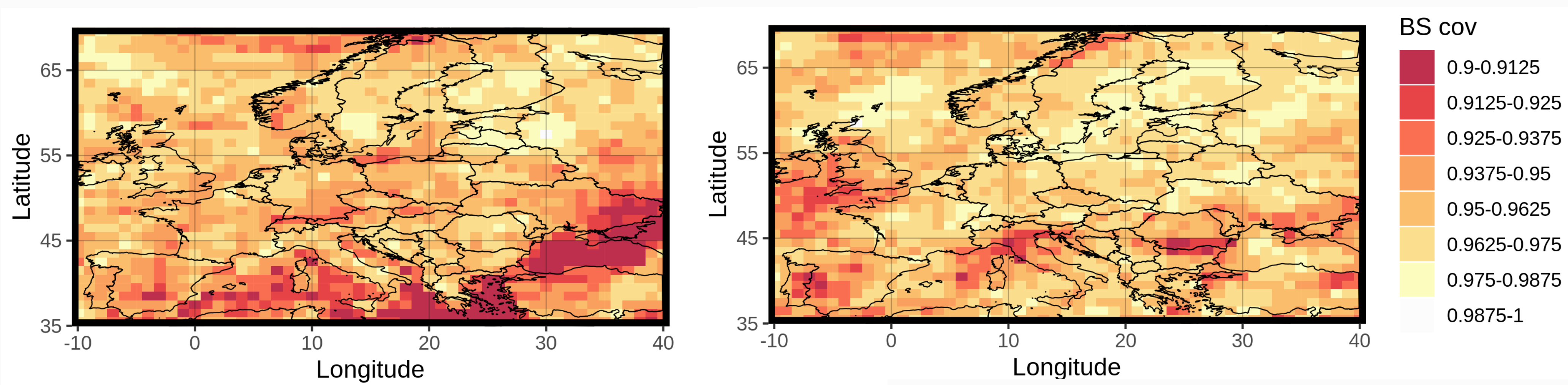
ECMWF vs DWD





Seasonal hindcasts - 1st May start date - Surf. solar rad.
BSS lower tercile vs. ERA-5





Signal covariance

The Signal covariance (Scov) estimates the relative independence of prediction systems 1 and 2:

$$Scov = \frac{\left| \frac{1}{n} \sum_{i=1}^{n} \left(y_i^1 - \bar{y} \right) \left(y_i^2 - \bar{y} \right) \right|}{\sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_i^1 - \bar{y} \right)^2} \cdot \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(y_i^2 - \bar{y} \right)^2}}$$

i indicates each hindcast year, n is the total number of years, y is the rank of the forecast probability and N is the number of times each forecast probability is issued.

Scov estimates how the signal in the two prediction systems is correlated, irrespective of the distance of the two systems from observations.

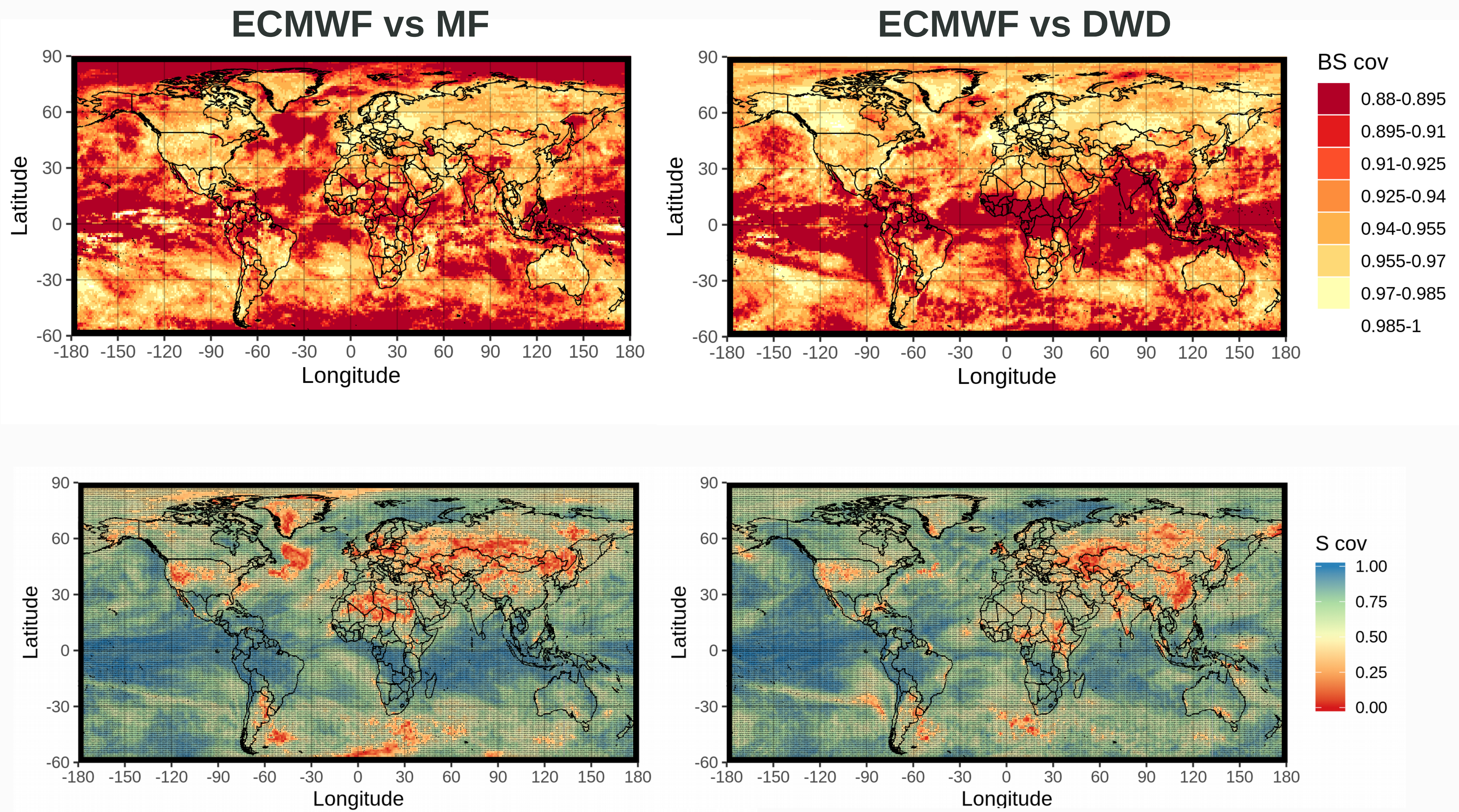
- Scov can be defined positively oriented by:

Scov = 1 → system1 = system2

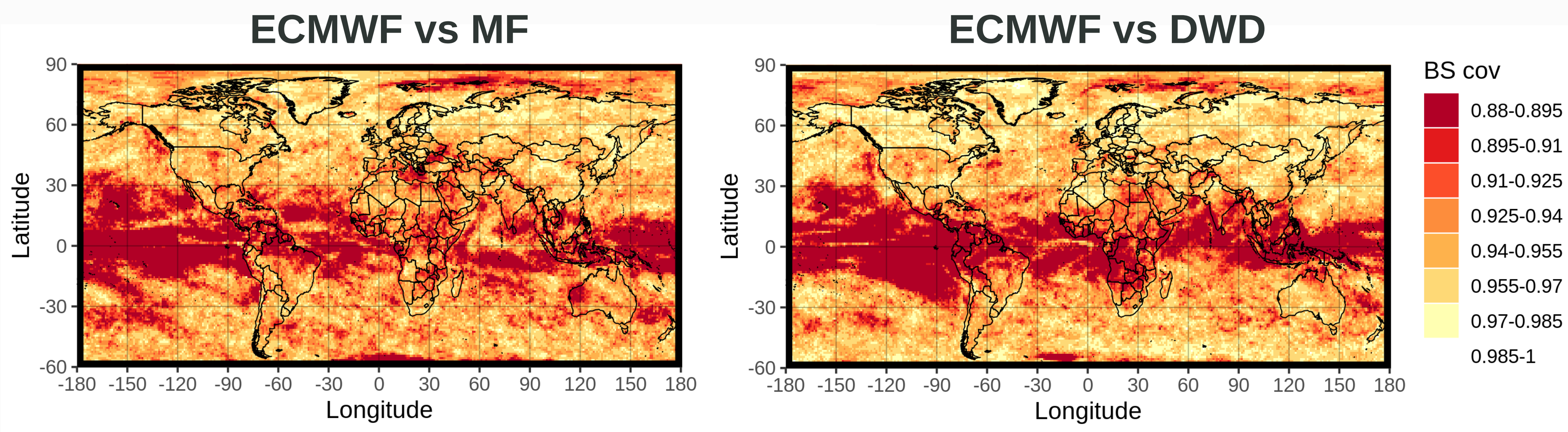
Scov = 0 → system1 and system2 completely independent

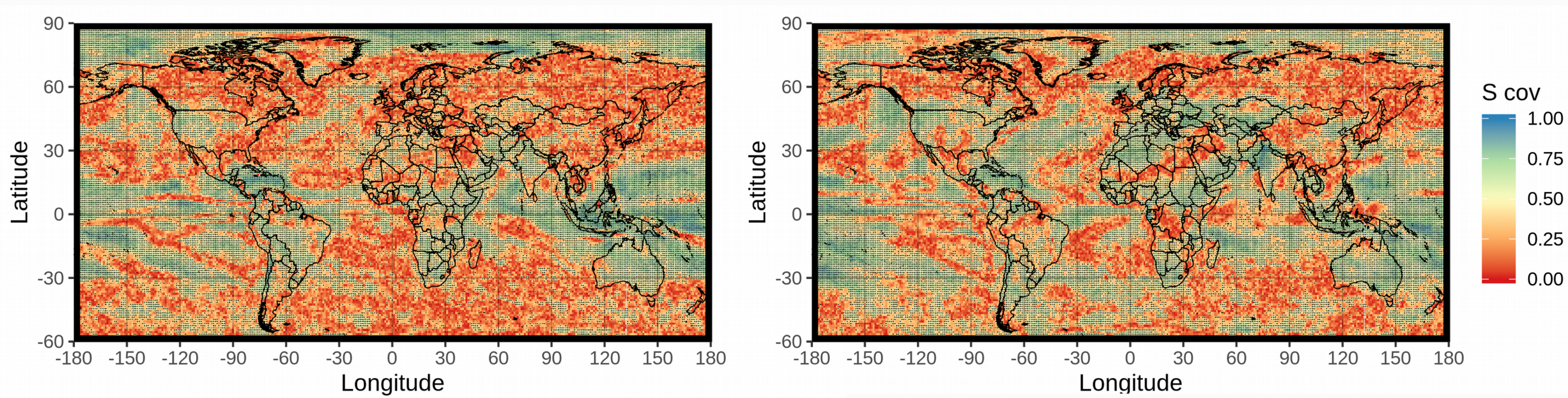
The Scov is used to assess the relative independence of the models from the MME in the probabilistic information they provide.

Seasonal hindcasts - 1st Nov start date - 2m Temperature lower tercile vs. ERA-5

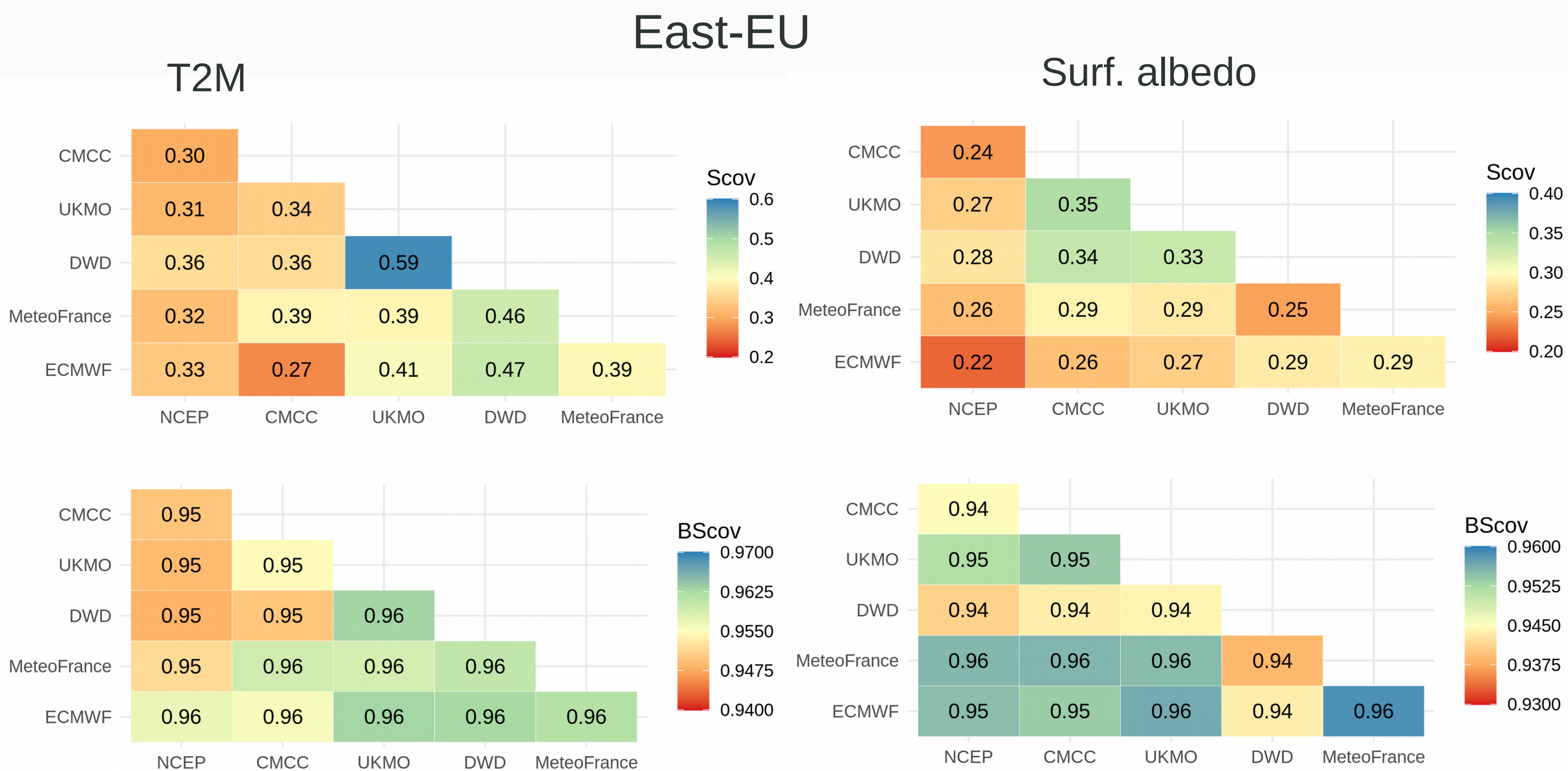


Seasonal hindcasts - 1st May start date - Surf. solar rad. lower tercile vs. ERA5





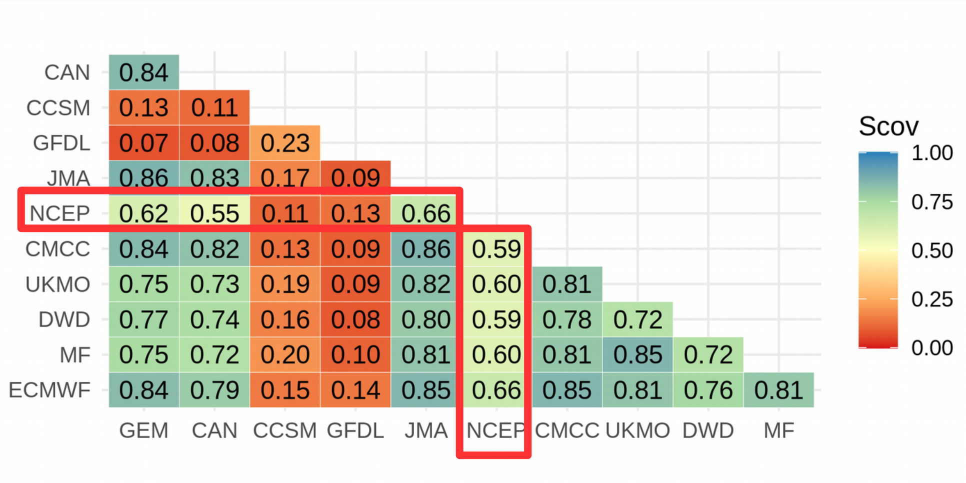
Seasonal hindcasts - 1st Nov start date
lower tercile vs. ERA-5 (T2M) and observational GLCF (albedo)

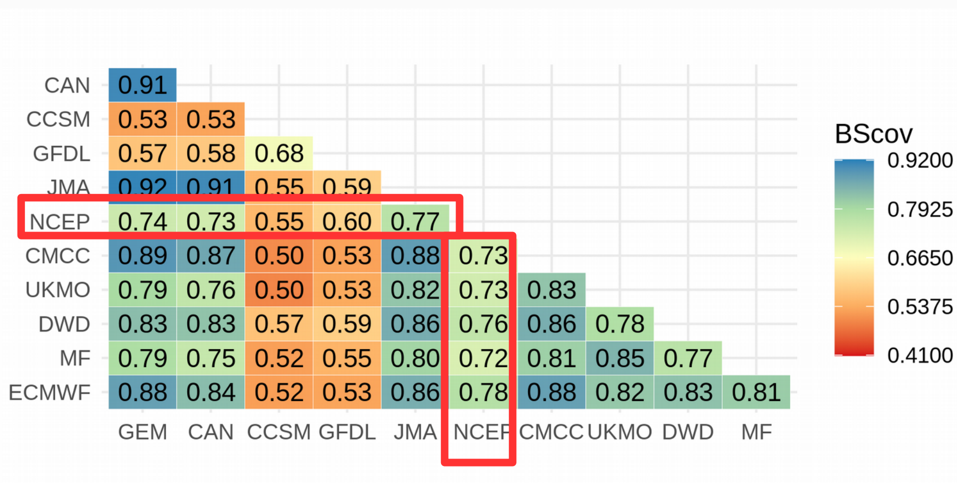


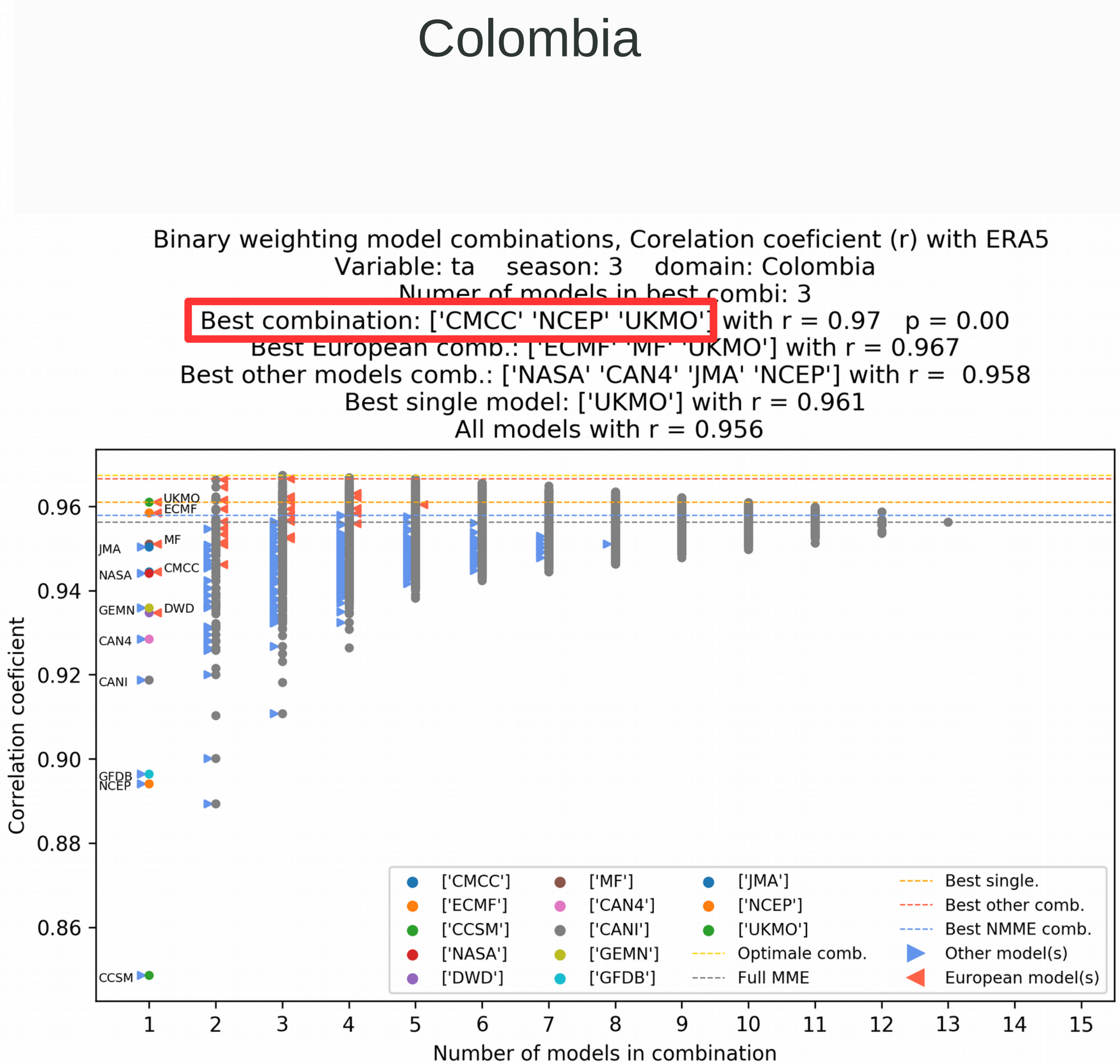
→models with large independence in the driver (albedo) also display large independence in the target (2m temperature)

→adding a model from the NMME (NCEP) to C3S has a large contribution in terms of model independence because of differences in land-surface process representation

Seasonal hindcasts - 1st Nov start date - 2m Temperature lower tercile vs. ERA-5







→NCEP model is not the one with the best skill but appears in the best combination of the MME because of its large degree of independence

Conclusions

- ✓ A novel methodology has been developed to assess the relative independence of the prediction systems in the probabilistic information they provide
  - The degree of independence of the different seasonal prediction systems depends on how the different models reproduce the signal coming from local and remote processes: snow-albedo processes are important for temperature prediction in DJF while atmospheric dynamics through moisture convergence is a key driver of precipitation and surface solar radiation in JJA
  - Two complementary metrics are proposed to quantify model indepence: (1) Brier Score covariance (BScov) considers the models' skill covariance with respect to observations; (2) Signal covariance (Scov) measures the similarity of the signal reproduced by two models irrespectively of the models' distance from the observations
  - Both the independence metrics provide valuable information for MME model selection even over regions where skill differences between two models are small
  - Overall independence is larger when mixing models from NMME and EU C3S and this results in improved skill in the Grand-MME