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**Barcelona
Supercomputing
Center**

Centro Nacional de Supercomputación

Forecast quality assessment of multi-annual predictions of mean and extreme temperature and precipitation: multi-model evaluation and impact of model initialisation

Carlos Delgado-Torres, Markus G. Donat, Panos J. Athanasiadis, Pierre-Antoine Bretonnière, Louis-Philippe Caron, Nick J. Dunstone, Nube Gonzalez-Reviriego, An-Chi Ho, Dario Nicoli, Klaus Pankatz, Andreas Paxian, Núria Pérez-Zanón, Margarida Samsó-Cabré, Balakrishnan Solaraju-Murali, Albert Soret, and Francisco J. Doblas-Reyes

15IMSC
Toulouse, June 2024

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Objectives

- Evaluate the **forecast quality** of the decadal predictions contributing to CMIP6/DCPP in predicting near-surface air **temperature, precipitation**, the **AMV** index and the **GSAT** anomalies.

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- Estimate the **impact of model initialisation** by comparing the skill of the decadal predictions and historical forcing simulations multi-model ensembles.
- Estimate how much skill is lost for not having all the predictions available in real-time by comparing a **research multi-model ensemble (13 forecast systems)** against an **operational multi-model ensemble (4 forecast systems)**.

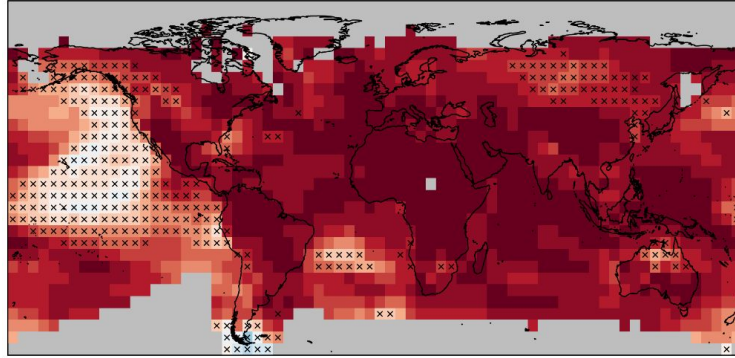
Data and methods

- **Forecast period:** forecast years 1-5
- **Evaluation period:** 1961-2014
- **Variables:** temperature and precipitation
- **Indices:** AMV index and GSAT anomalies
- **Reference forecasts:**
 - Climatological forecast
 - Individual forecast systems
 - Historical simulations
 - Operational multi-model

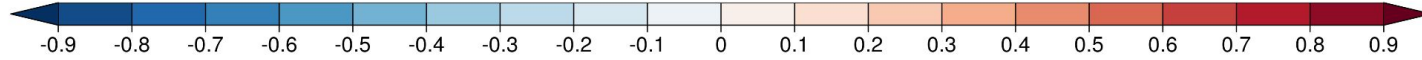
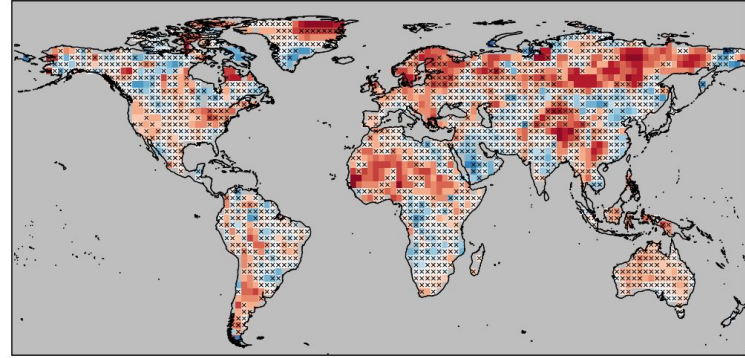
Forecast system	DCPP members	HIST members	Initialisation month
BCC-CSM2-MR	8	3	January
CanESM5	20	40	January
CESM1-1-CAM5-CMIP5	40	40	November
CMCC-CM2-SR5	10	1	November
EC-Earth3-i1	10	10	November
EC-Earth3-i2	5	-	November
HadGEM3-GC3.1-MM	10	4	November
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MIROC6	10	10	November
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MPI-ESM1.2-LR	16	10	November
MRI-ESM2-0	10	5	November
NorCPM1	10	30	October
	169 members	195 members	

DCPP multi-model skill

Temperature



Precipitation

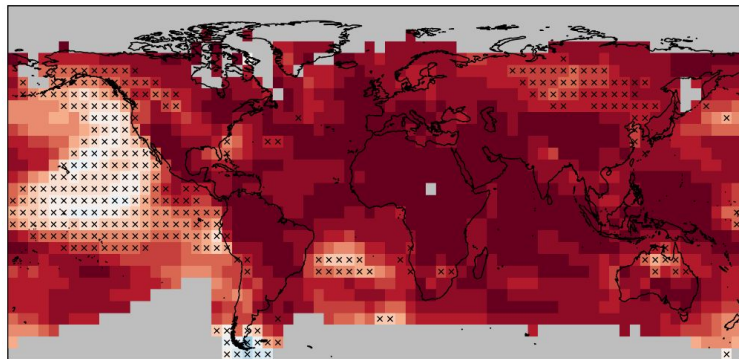


ACC for forecast years 1-5

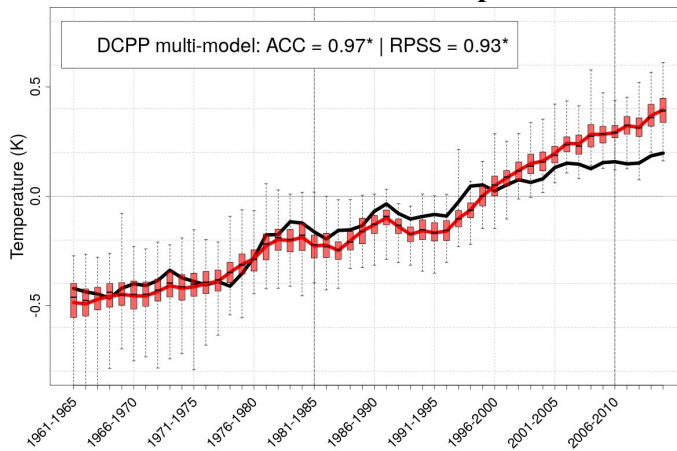
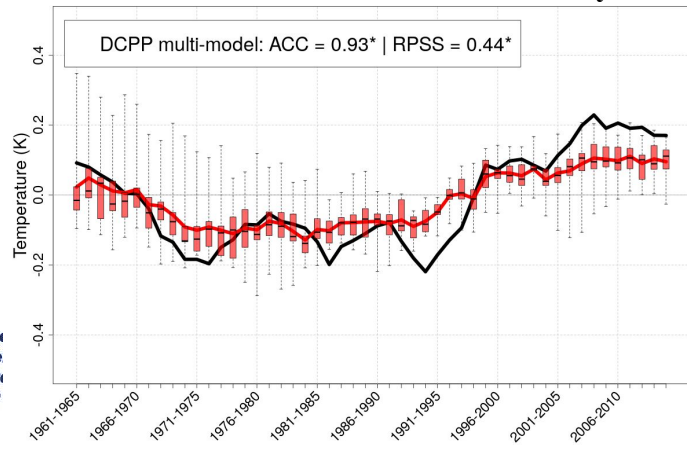
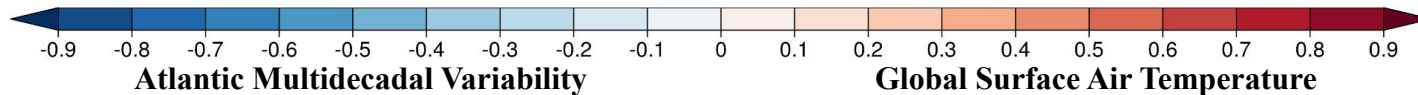
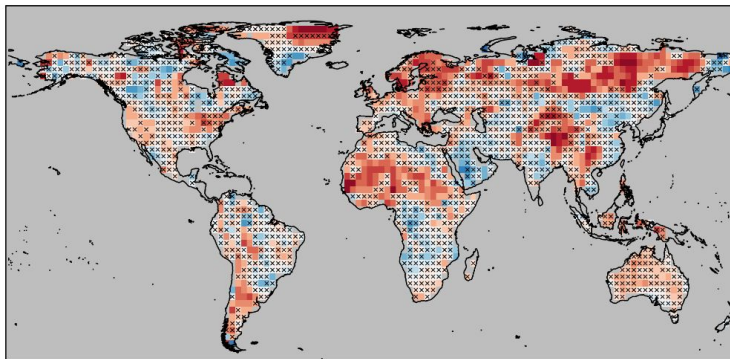
DCPP multi-model ensemble: **169 members** from **13 forecast systems**

DCPP multi-model skill

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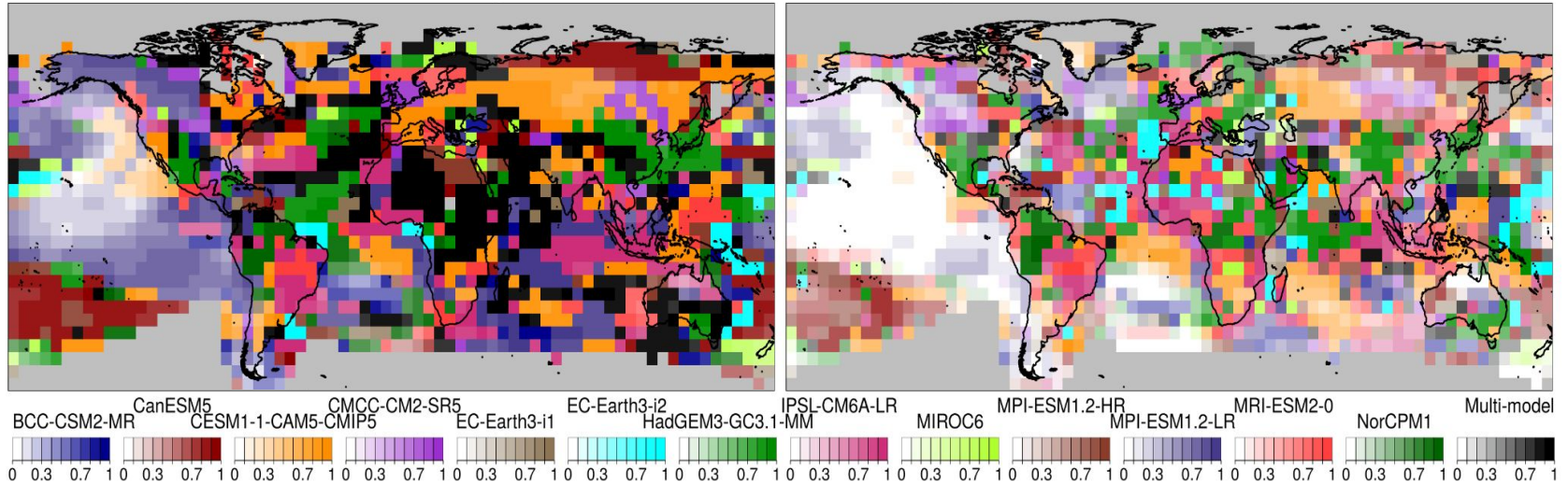
Precipitation



Multi-model vs individual forecast systems

Highest ACC

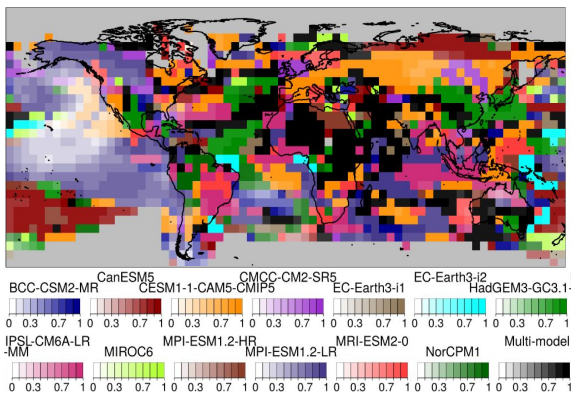
Highest RPSS



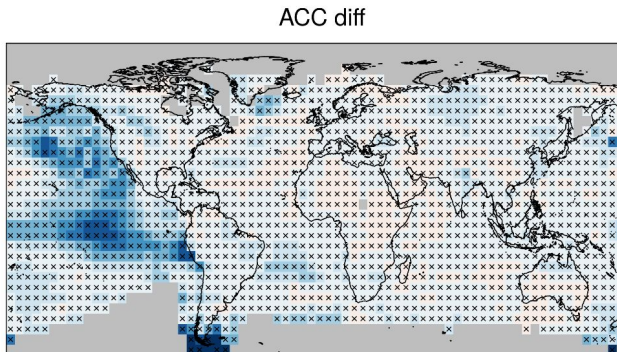
Forecast system or multi-model with the **highest skill** in predicting temperature for the **forecast years 1-5**

Multi-model vs individual forecast systems

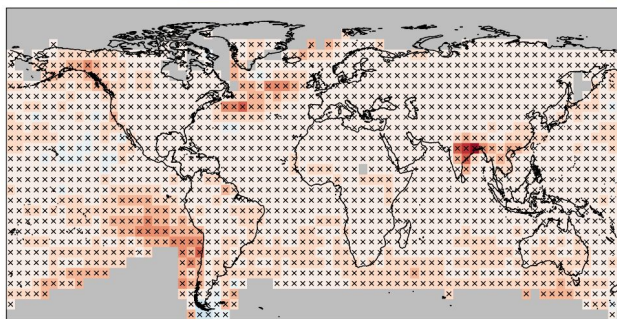
Highest ACC - Temperature



Multi-model vs Max-model

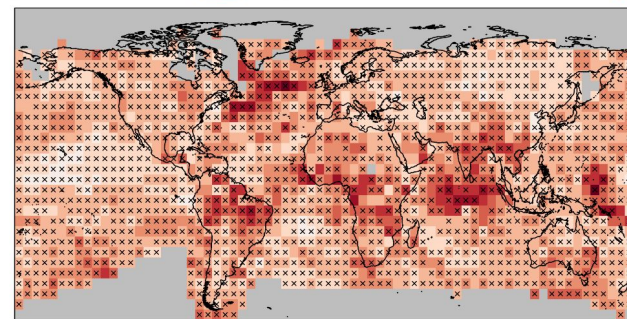
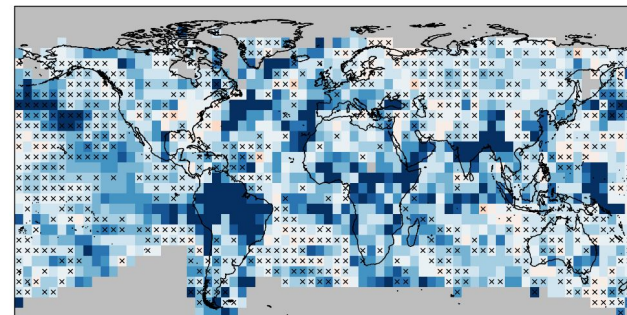


Multi-model vs Median-model



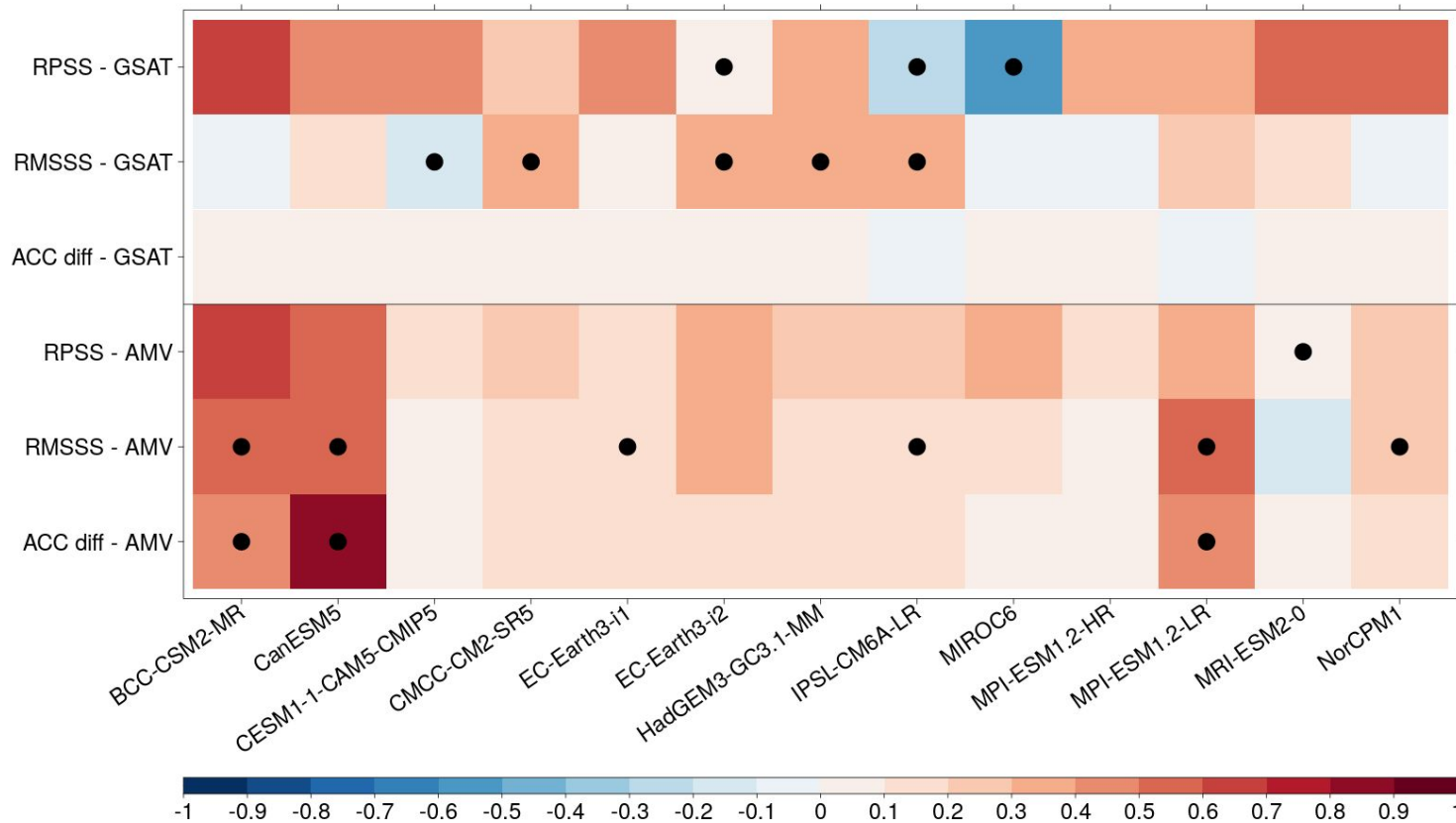
ACC diff

RPSS



- Multi-model generally **worse** than the best forecast system.
- Multi-model generally **better** than the 50% of the forecast systems.

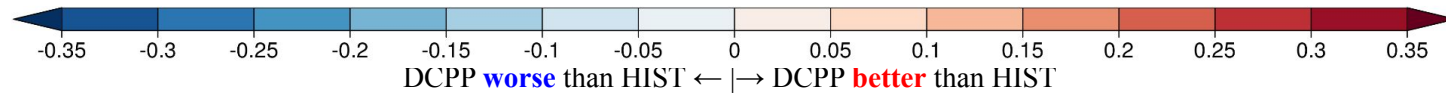
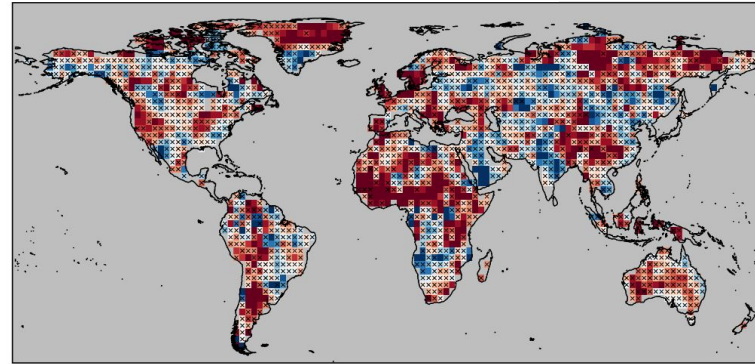
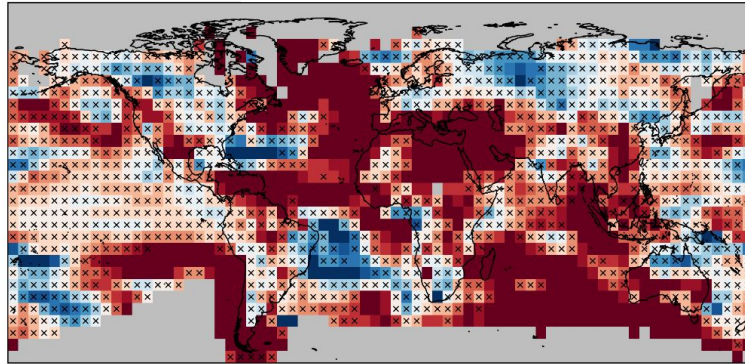
Multi-model vs individual forecast systems



Impact of initialisation

Temperature

Precipitation



Residual correlation for **forecast years 1-5**

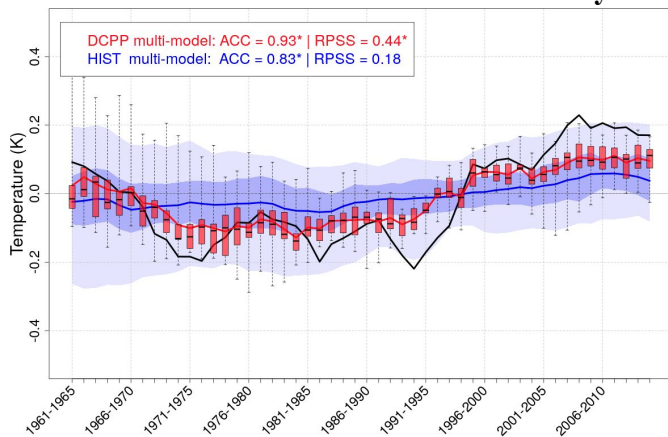
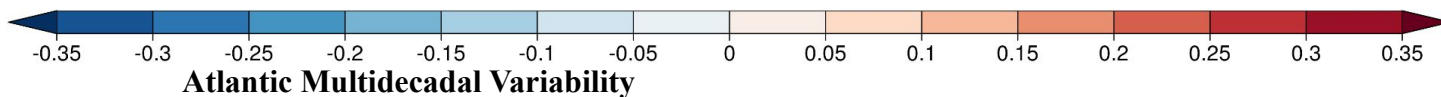
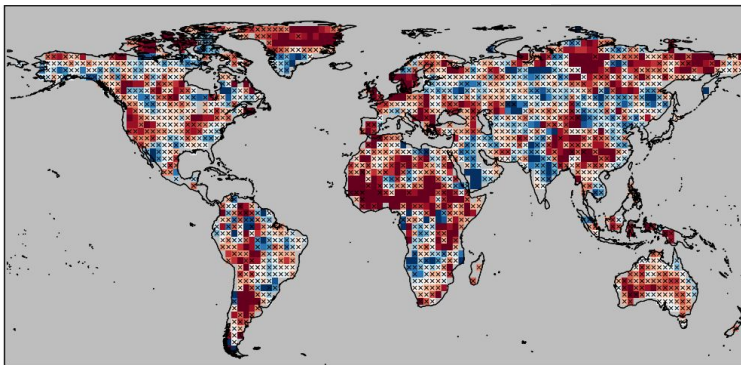
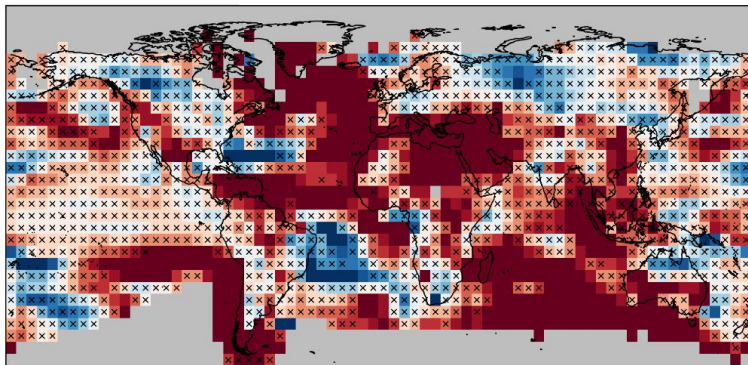
DCPP multi-model ensemble: **169 members** from **13 forecast systems**

HIST multi-model ensemble: **195 members** from the same forecast systems

Impact of initialisation

Temperature

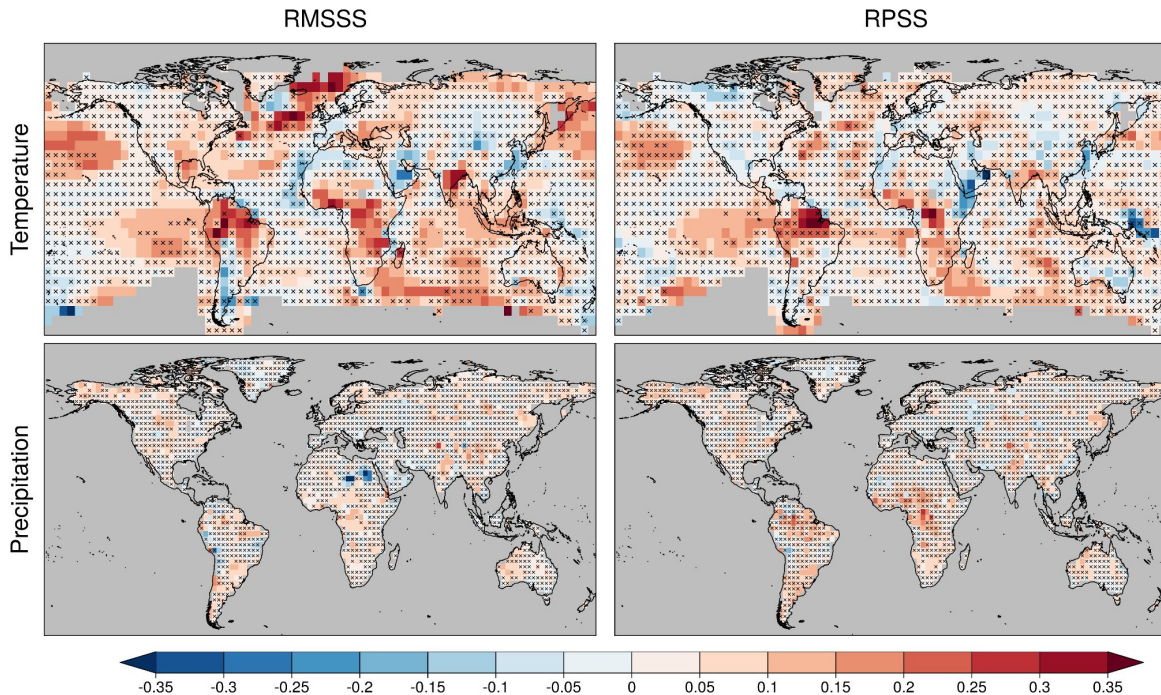
Precipitation



Index	Residual ACC	RPSS
AMV	0.75*	0.32*
GSAT	0.45*	-0.06

- **DCPP** multi-model ensemble: **169** members
- **HIST** multi-model ensemble: **195** members

DCPP vs C3S_34c multi-model (13 vs 4 systems)



DCPP multi-model **worse** than C3S_34c multi-model ← | → DCPP multi-model **better** than C3S_34c multi-model

- DCPP multi-model: **169 members** from **13 forecast systems**.
- C3S_34c multi-model: **40 members** from **4 forecast systems** (CMCC-CM2-SR5, EC-Earth3-i1, HadGEM3-GC3.1-MM and MPI-ESM1.2-HR).

Main findings

- **DCPP multi-model skill:**
 - Generally high for temperature, particularly over land regions.
 - Lower for precipitation (limited to regions over Central Africa, Europe, and Asia).

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 - The best system generally provides the highest skill for a particular location, variable and forecast period.
 - Highest forecast quality for a particular climate service.
 - The multi-model provides higher skill than, at least, the 50% of the systems.
 - More straightforward operational forecast generation.
 - More real-time predictions would allow selecting the best forecast system or multi-model (sub)ensemble for each specific region, variable and forecast period.

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 - More straightforward operational forecast generation.
 - More real-time predictions would allow selecting the best forecast system or multi-model (sub)ensemble for each specific region, variable and forecast period.
- **DCPP vs HIST multi-models:**
 - Added value of initialisation over some ocean and land regions for temperature and precipitation.
 - Added value for AMV and GSAT.



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Thank you!

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Toulouse, June 2024

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- Assess the **multi-model forecast quality** for **extreme indices** based on daily minimum and maximum temperature and precipitation at multi-annual time scales.

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Data and methods

- **Forecast period:** forecast years 1-5
- **Evaluation period:** 1961-2014 (start dates 1960-2009)
- **Variables:** monthly temperature (TAS) and precipitation (PR)
- **Extreme indices (ETCCDI)**
 - Daily maximum temperature: TXx and TX90p
 - Daily minimum temperature: TNn and TN10p
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EC-Earth3-i4	10	-	November
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MPI-ESM1.2-HR	10	10	November
MRI-ESM2-0	10	6	November
NorCPM1-i1	10	30	October
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	133 members	134 members	

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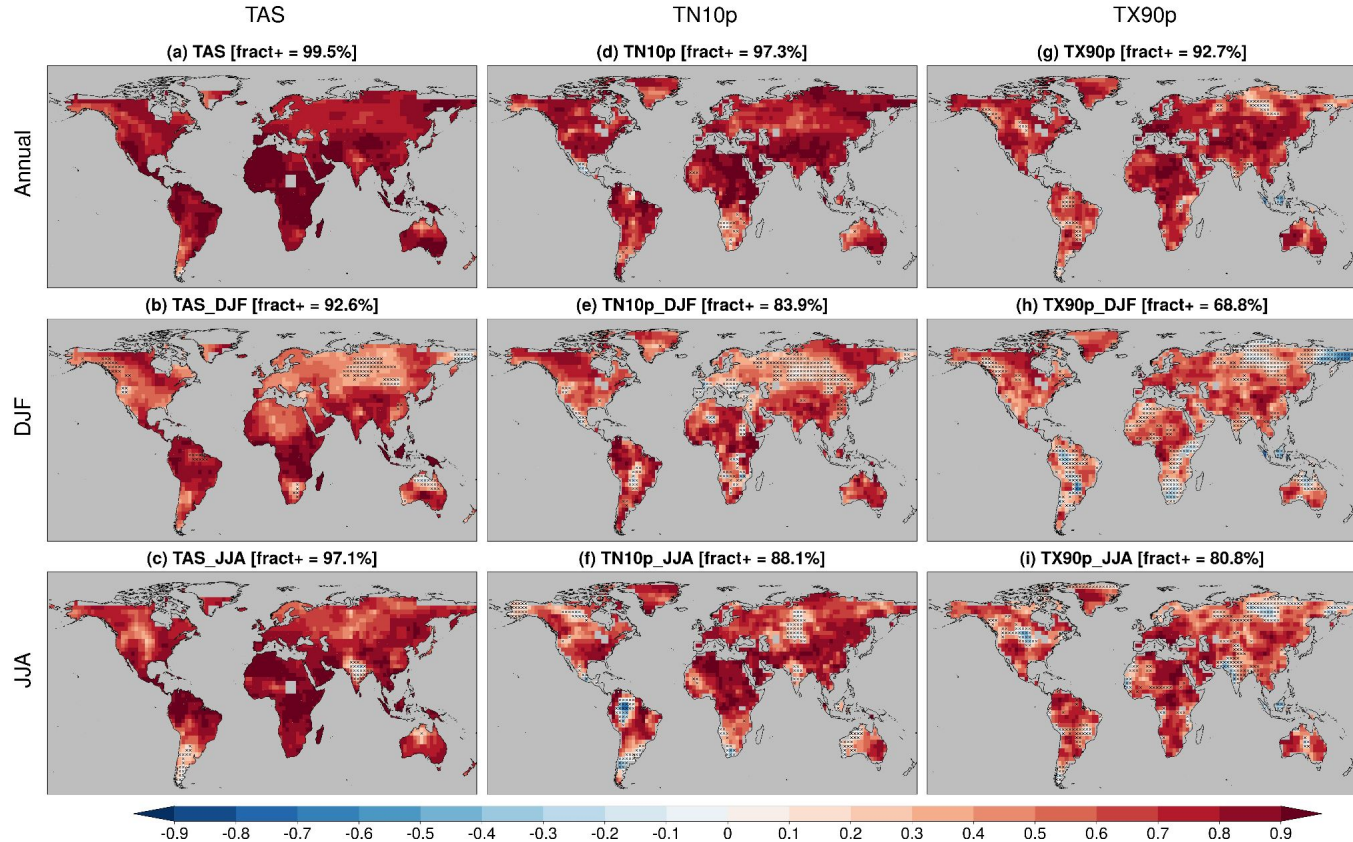
Related to **frequency**

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Multi-model skill - Temperature extremes

The DCPP multi-model ensemble **skillfully predicts** variations in the **temperature extremes** over most land regions.

The **extreme indices** are predicted with **lower skill** than the mean quantities.



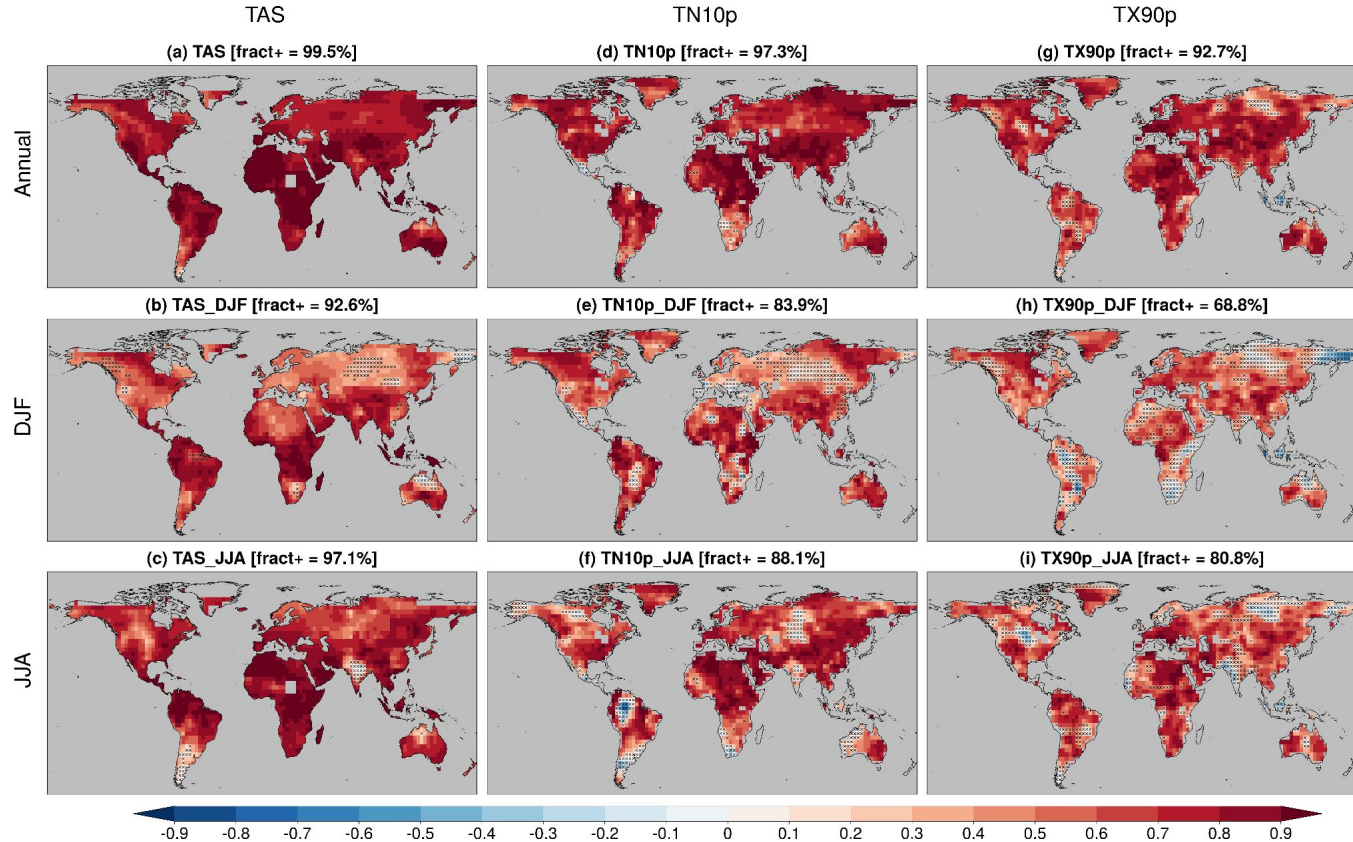
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Higher skill for indices based on minimum temperature than those based on maximum temperature.

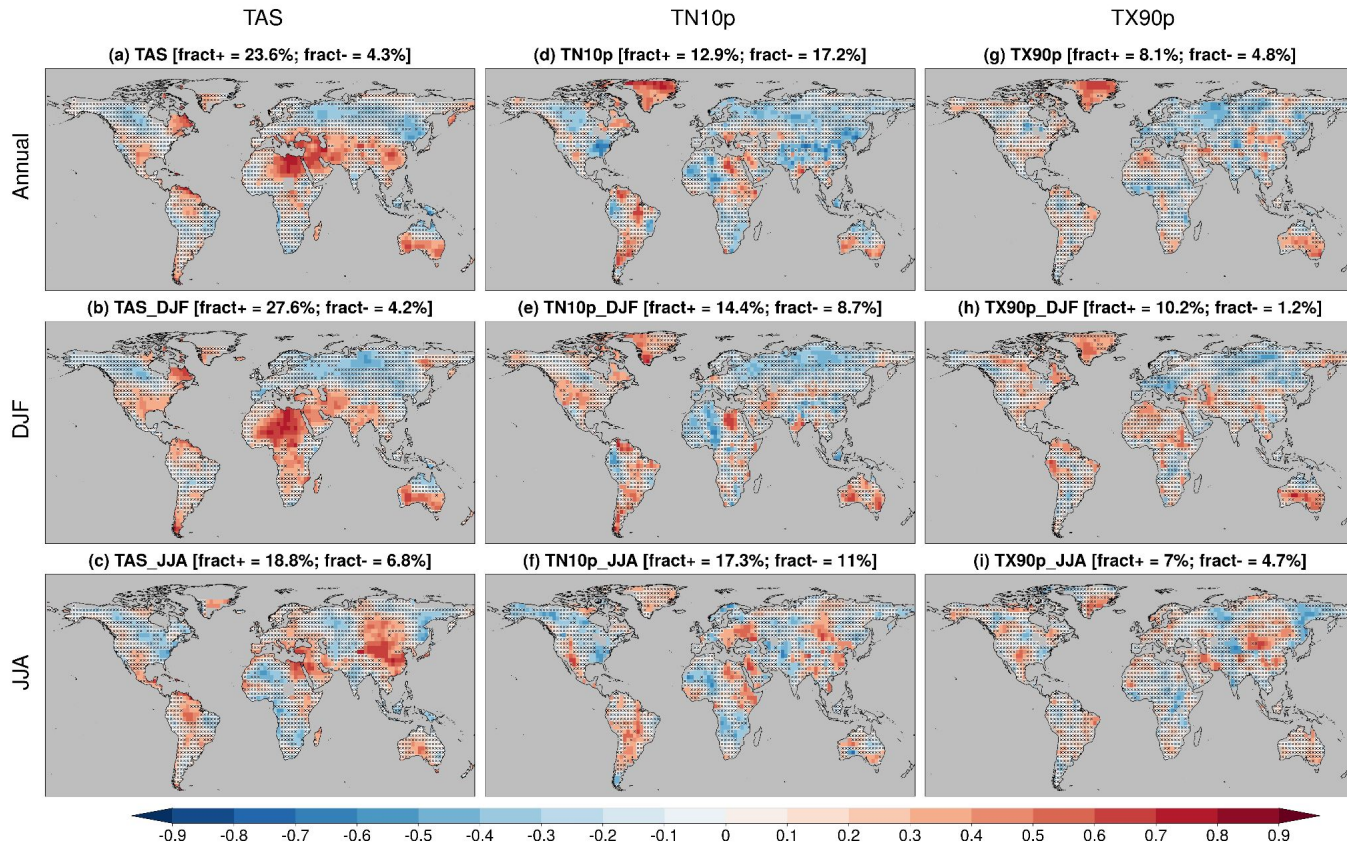
Generally higher prediction skill in **summer** than in winter.



Impact of initialisation - Temperature extremes

Different impact of model initialisation depending on the season.

Some regions show **added value** for predictions of **mean temperature**.

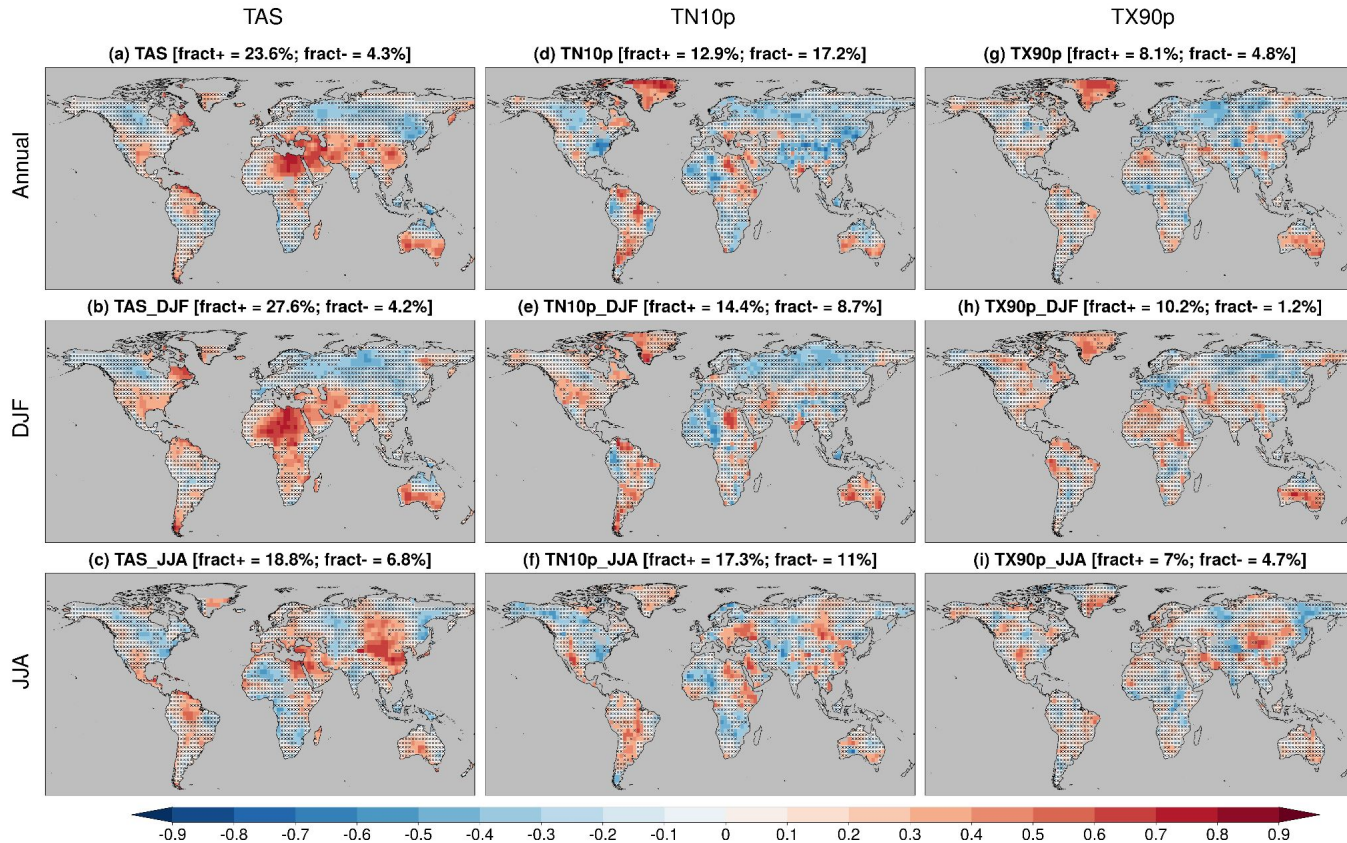


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For **extreme temperature**, the impact of initialisation is **generally low** and highly **region-dependent**.

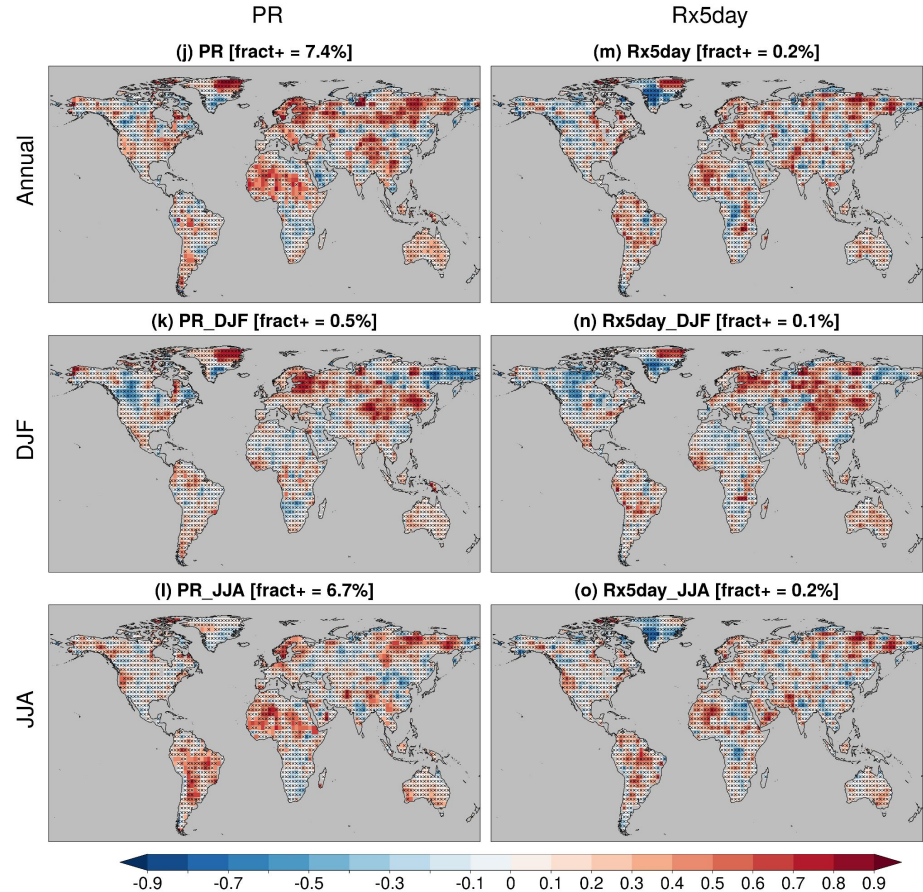


Multi-model skill - Precipitation extremes

The prediction skill for **precipitation extremes** is much **more limited** than for temperature extremes.

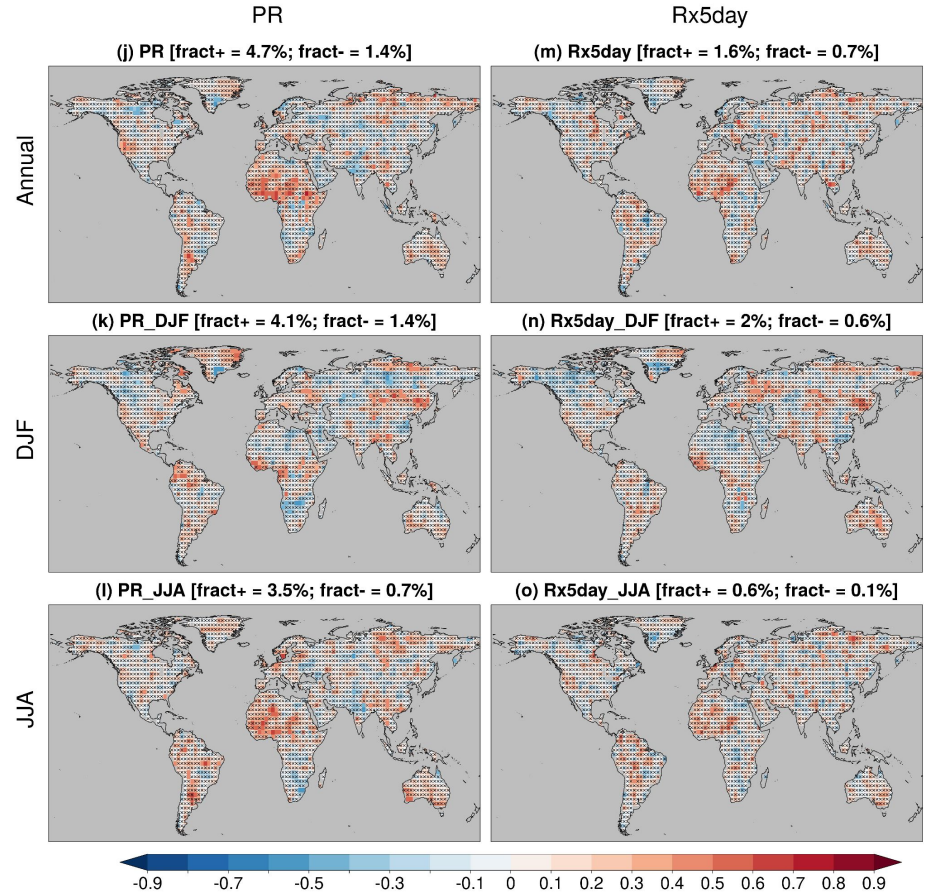
Different regions where the multi-model is skillful for **summer and winter**.

Generally **similar patterns** for mean and extreme precipitation.



Impact of initialisation - Precipitation extremes

Low added value from model initialisation for prediction of mean and extreme precipitation.



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- **Higher prediction skill in summer** than in winter.
- The **added value from model initialisation** for predictions of extremes is generally **low and highly region-dependent**.