Gli eventi della Rete Rurale

TAVOLO NAZIONALE DI COORDINAMENTO NEL SETTORE DELL'AGROMETEOROLOGIA

Incontro tematico
13 gennaio 2023
Web Conference

RRN – Scheda 5.3 Agrometeore

Le previsioni stagionali del Centro Euro-Mediterraneo sui Cambiamenti Climatici: uno sguardo al futuro e al passato

Come sfruttare al meglio le informazioni prodotte dalle previsioni stagionali per migliorare la gestione delle pratiche agricole e limitare le ripercussioni dei cambiamenti climatici in agricoltura?

L'incontro sarà l'occasione per approfondire il tema e presentare le previsioni stagionali per i prossimi mesi, prodotte dal CMCC. Verrà, inoltre, illustrato un confronto tra il segnale rilevato dalle previsioni stagionali per la stagione estiva dello scorso anno e i dati osservati a diverse scale spaziali.

RETERURALE NAZIONALE 20142020 · mipaaf · crea

Progetto realizzato con il contributo del FEASR (Fondo Europeo Agricolo per lo Sviluppo Rurale) nell'ambito delle attività previste dal Programma Rete Rurale Nazionale 2014-2020

Previsioni stagionali CMCC: primavera/estate 2022 e inverno/primavera 2023

Silvio Gualdi, Andrea Borrelli, Marianna Benassi, Antonella Sanna, Stefano Tibaldi, Zhiqi Yang, Panos Athanasiadis + contribution from CMCC colleagues

cmcc
Centro Euro-Mediterraneo sui Cambiamenti Climatici

Outline

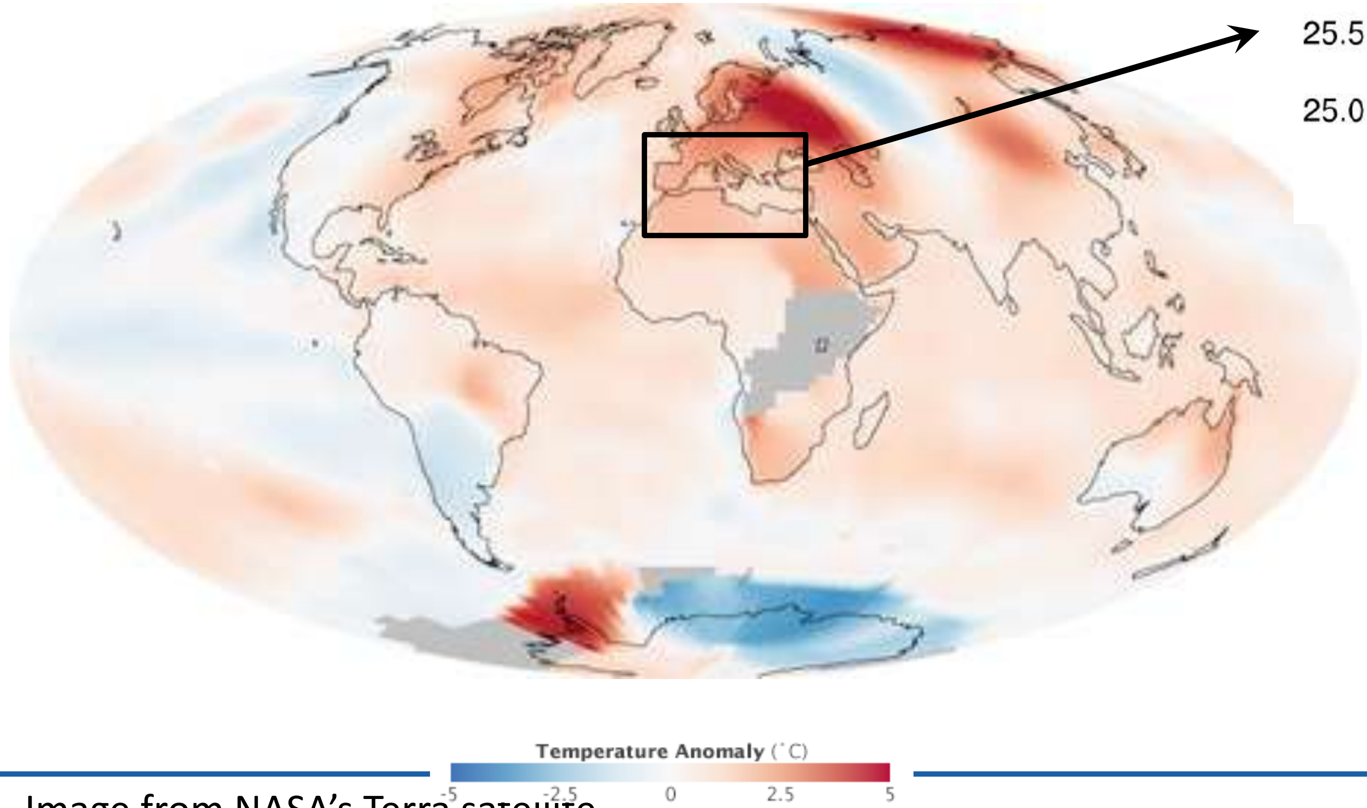
The main objective of this talk is to provide a (quick) overview of the past seasonal forecasts (spring/summer 2022) and of the coming seasons (winter/spring 2023).

1. **Recap of what seasonal predictions are.**
2. **The CMCC seasonal prediction system.**
3. **The CMCC seasonal predictions of the drought period during past spring and summer (2022).**
4. **The CMCC seasonal predictions of the coming seasons (winter/spring 2023).**

Recap

Recap

Regional Variability



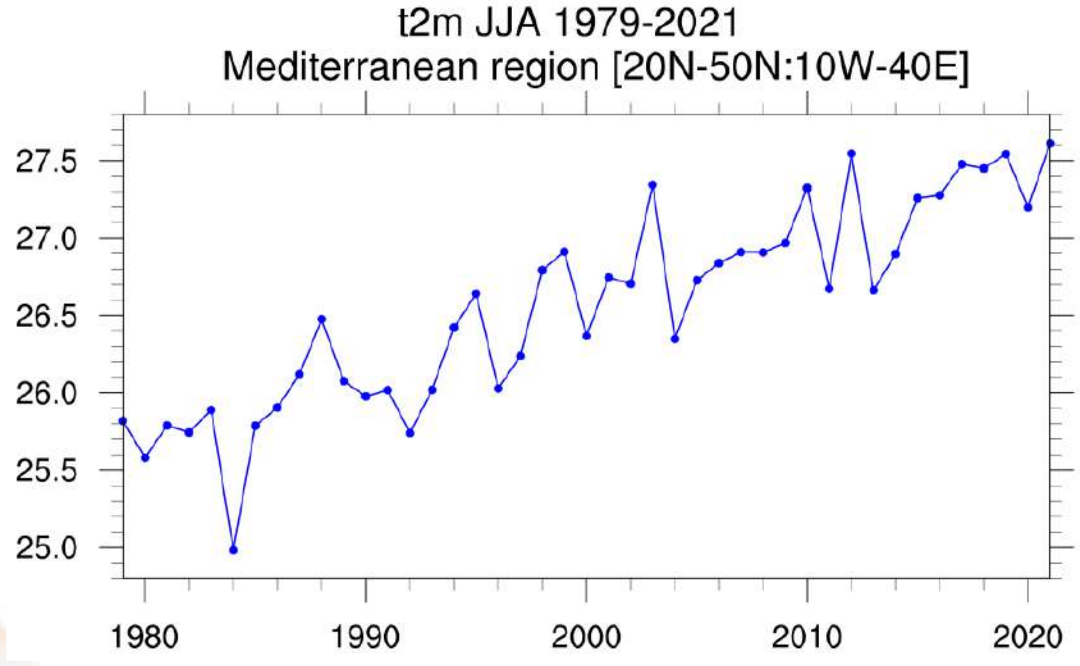
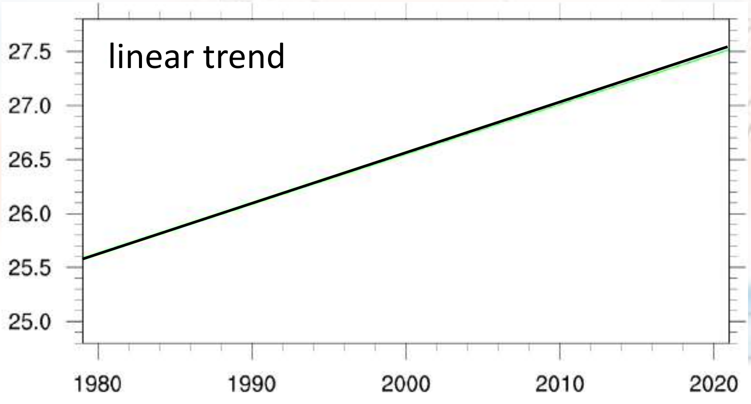


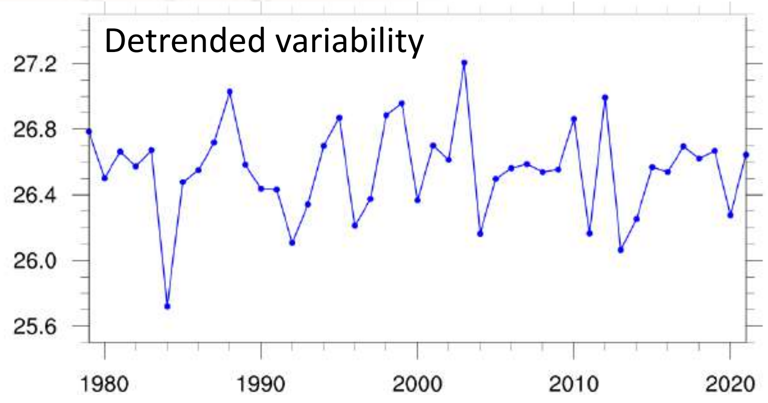
Image from NASA's Terra satellite

Recap

Time Scales of Variability

Are these climatic fluctuations at interannual and decadal time scales predictable?





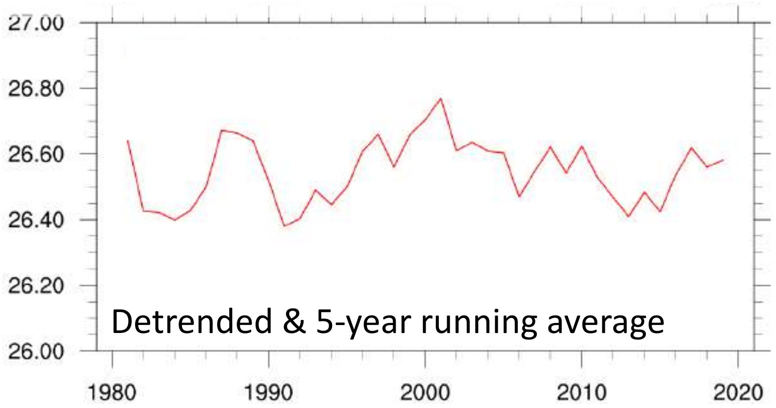
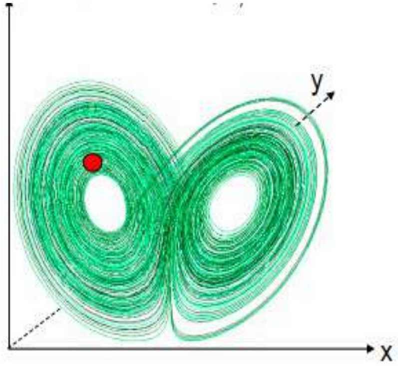


Image from NASA's Terra satellite

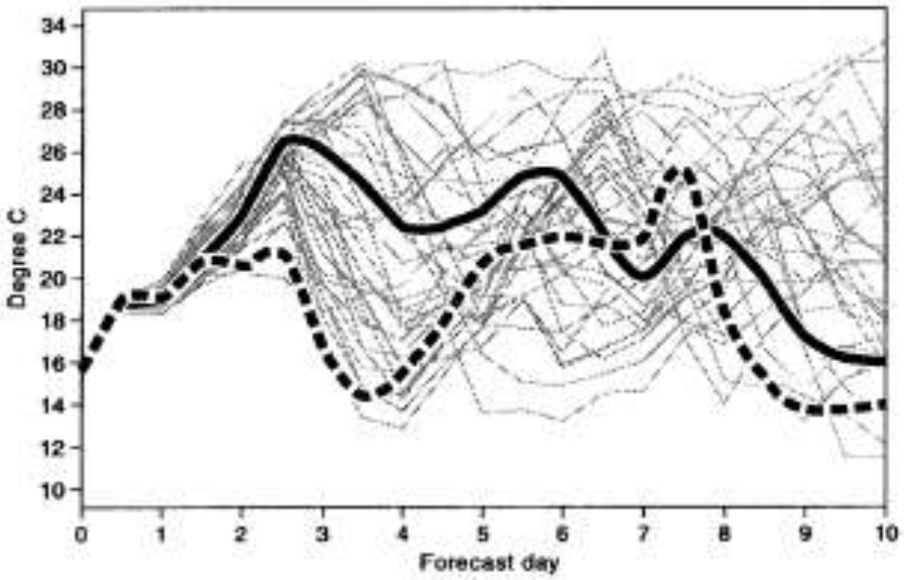
Recap

How is it possible to make climate predictions considered that weather is a chaotic system?

Edward N. Lorenz (1917–2008)



The atmosphere is a **chaotic system**: due to the strong non–linearity of the atmospheric dynamics, simulations (predictions) of the evolution of the atmosphere are very sensitive to (small) changes in their initial conditions.



Limit of deterministic predictability: given by the growth rate of the (inevitable) errors in the initial state → the atmosphere loses memory of its initial conditions after a **few days** (limit of about 10–15 days).

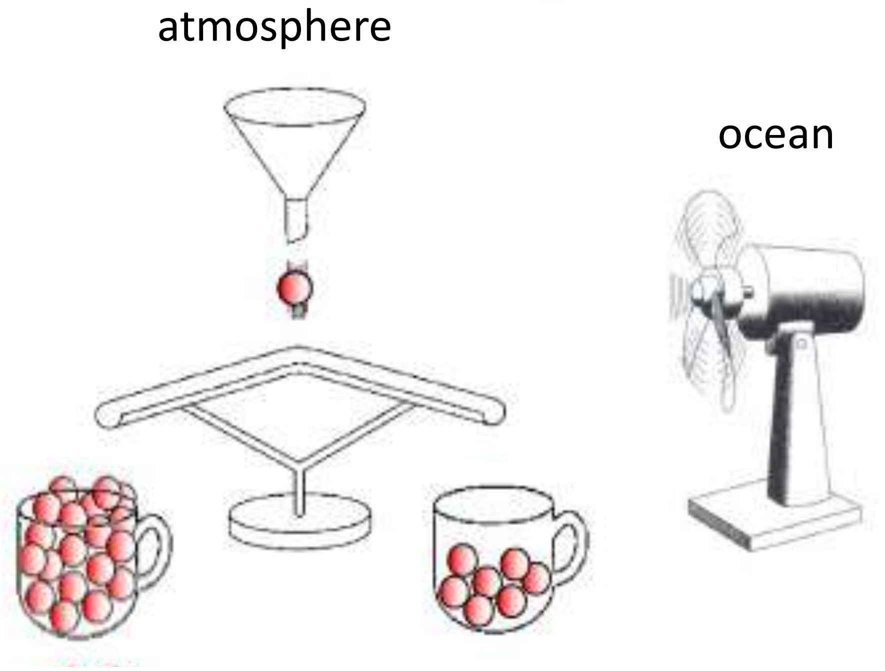
Predictability of the first kind (or initial value problem)

The memory of the **land–surface** (snow, soil moisture, vegetation) to initial conditions can extend **to several months**

The memory of the **ocean** to initial conditions can range **from months to (many) years**.

Recap

<u>**Ocean, land surface and sea–ice**</u> are characterised by slower dynamical processes, providing a <u>**long–term memory**</u> which leads to <u>**skill in predicting climate evolution.**</u>



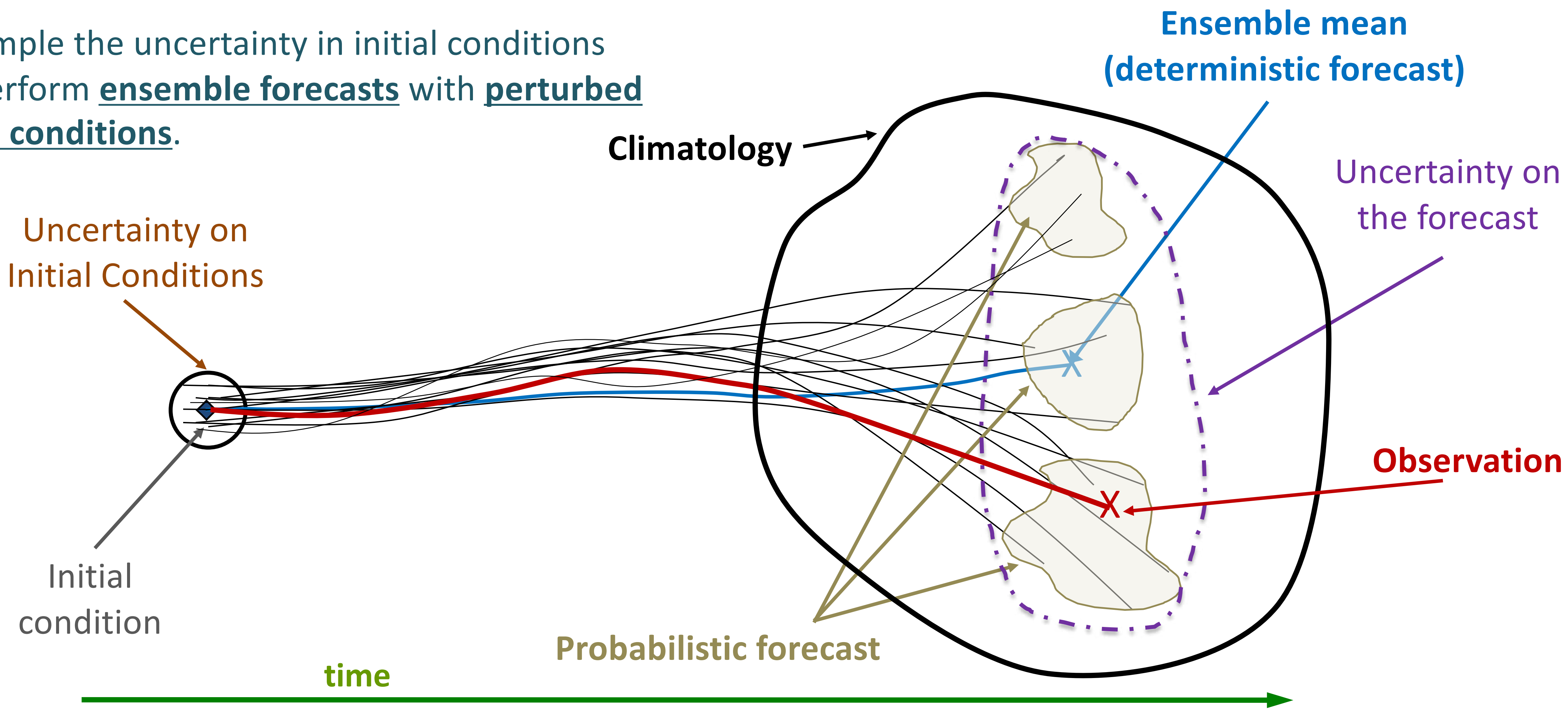
(Palmer, 1998)

Even though **individual weather events** are not predictable beyond 10 days, the ***average weather behaviour*** (climate) may be **influenced by predictable boundary conditions** (e.g. land–surface, ocean, …) for **several months or longer**.

Predictability of the <u>second</u> kind (or boundary conditions problem)

Recap

To sample the uncertainty in initial conditions we perform **ensemble forecasts** with **perturbed initial conditions**.



Readapted from Trzaska (http://portal.iri.columbia.edu)

The external forcing makes some state more probable than others

Recap

Climate Change

C3S multi-system seasonal forecast

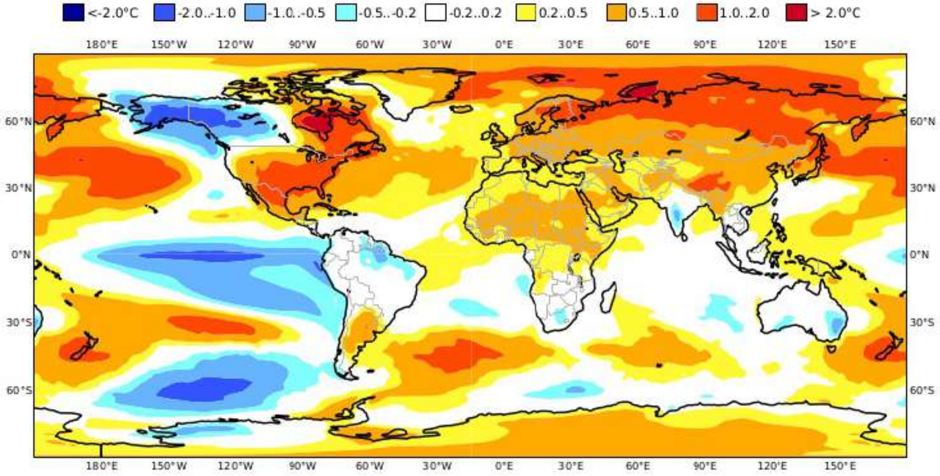
DJF 2021-2022 Prediction – Start date: 2021 November 1st

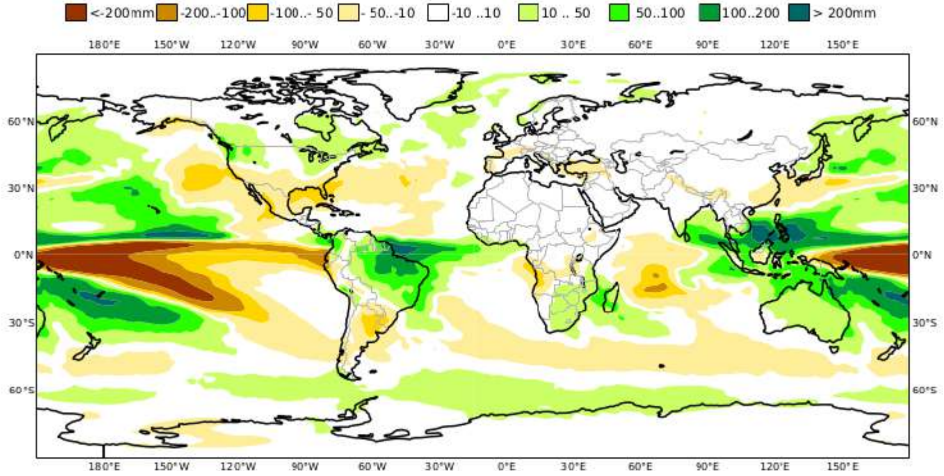
(reference period 1993–2016)

T2m

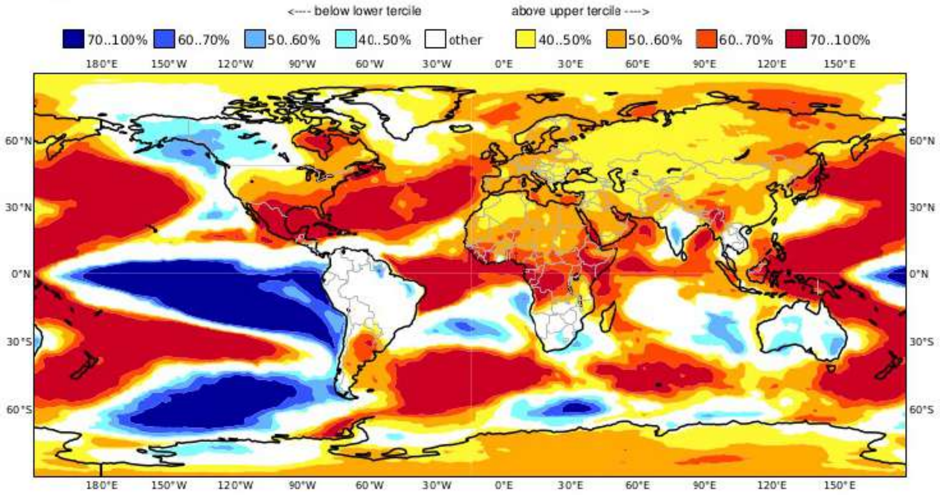
Precipitation

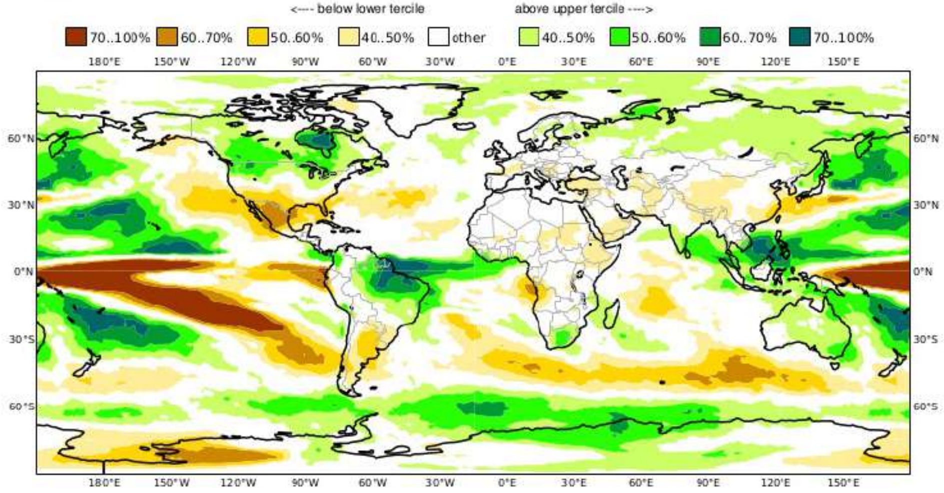
DJF mean anomaly





DJF probabilistic forecast





The CMCC seasonal prediction system

CMCC in the seasonal prediction system

CMCC in the seasonal forecasting field

➢ CMCC has been actively **involved in experimental seasonal forecasting over the past 20 years** (e.g., EU Projects DEMETER 1999-2003; MERSEA 2003-2007; ENSEMBLES 2004-2009; CLIMAFRICA 2010-2014).

➢ Since January 2013, CMCC produces **seasonal forecasts operationally**: every month a seasonal forecast of the next 6 months is issued.

➢ Since June 2013, CMCC contributes to the **Mediterranean Outlook Forum** (MedCOF, member of the Governing Board).

➢ Since April 2014, CMCC contributes to the **APCC multi-model ensemble seasonal forecasting** (**www.apcc21.org/eng/index.jsp**).

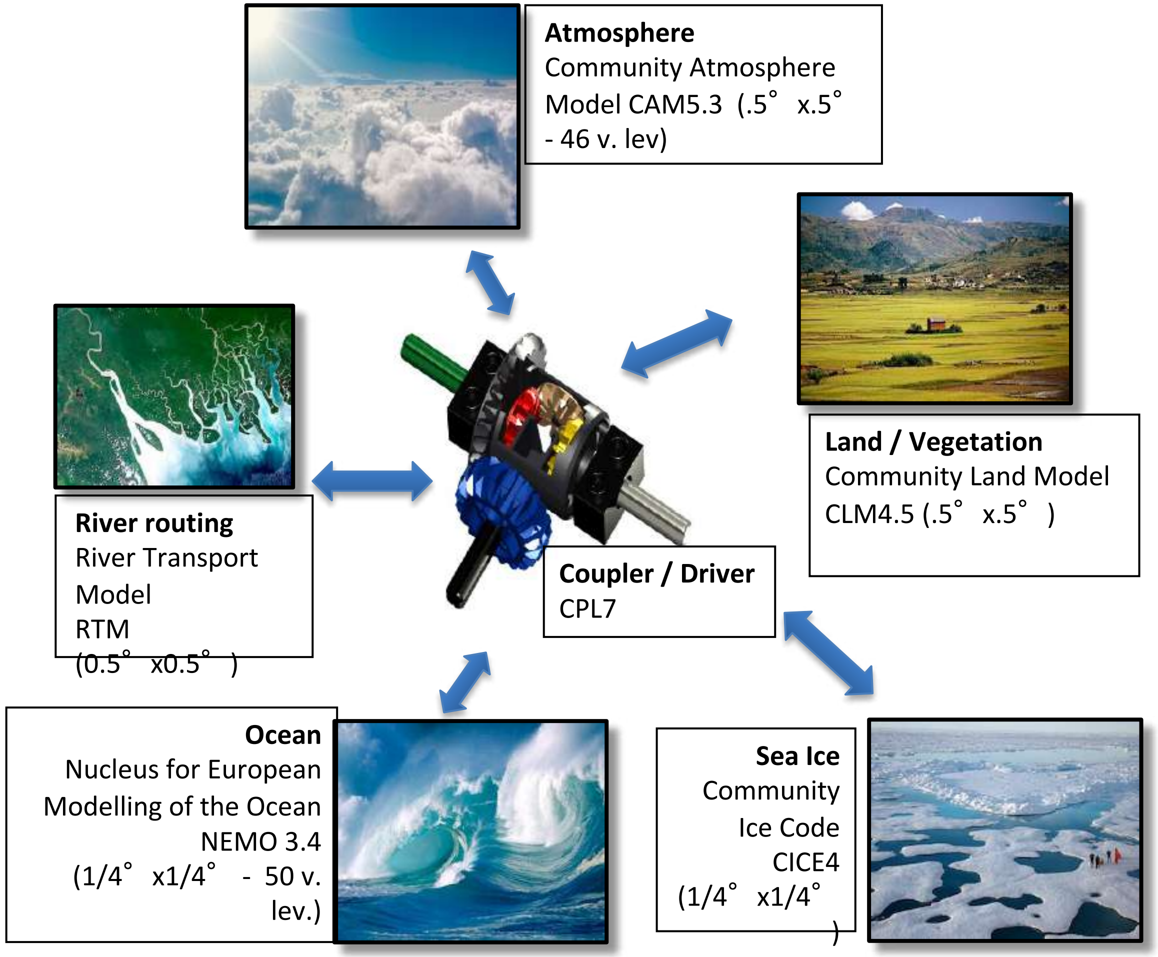
➢ Since January 2016, CMCC contributes to the **Pre–Operational Phase of the Copernicus C3S multi–model ensemble seasonal forecast system.**

➢ Since April 2018, CMCC contributes to the **Operational Phase of the Copernicus C3S multi–model ensemble seasonal forecast system** (**climate.copernicus.eu/seasonal-forecasts**).

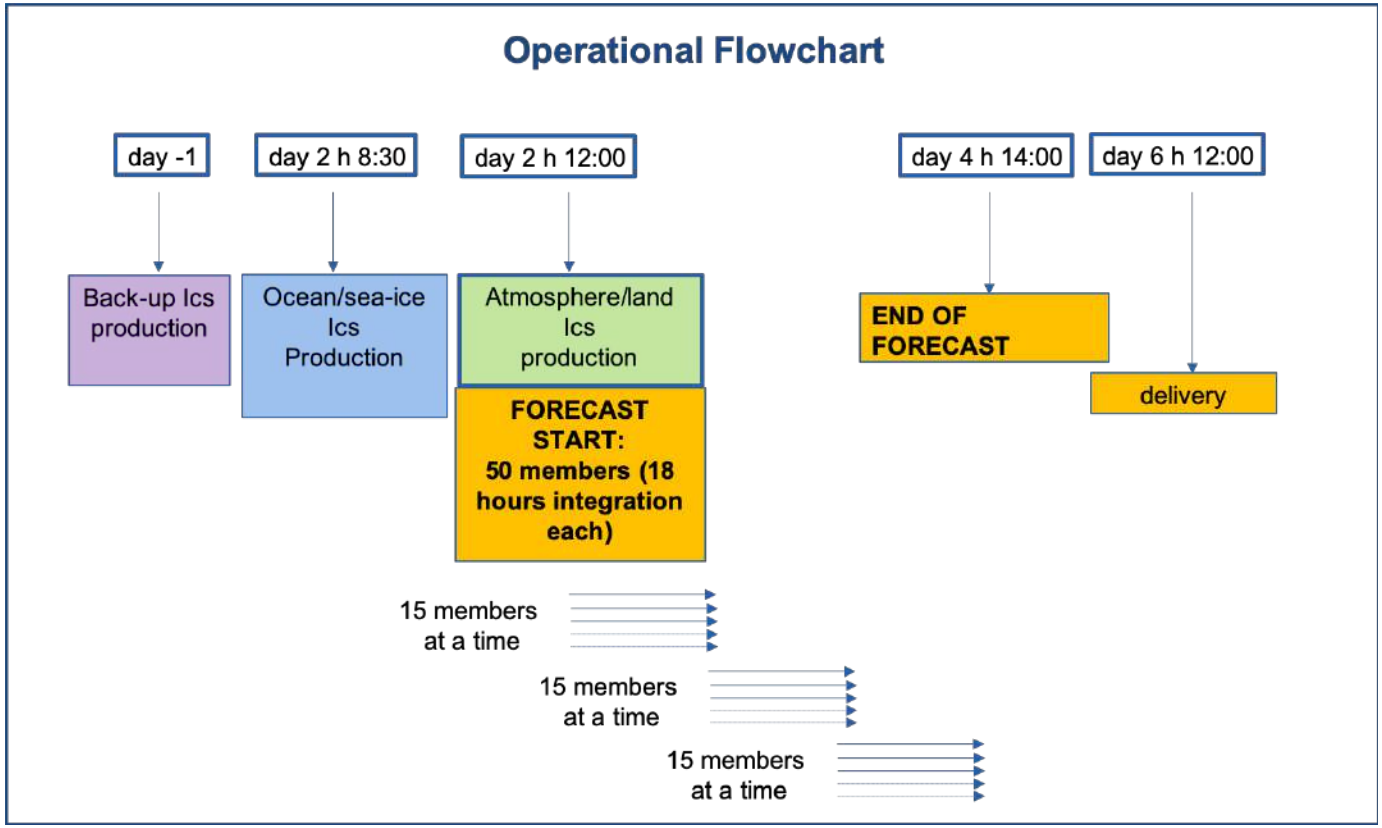
➢ Since June 2021, CMCC contributes to the **WMO Lead Centre for Long–Range Forecasts Multi–Model Ensembe** (**www.wmolc.org**).

CMCC in the seasonal prediction system

The model



The workflow



CMCC in the seasonal prediction system: the initial conditions

Initial Condition Perturbations → Ensemble Forecasts

- The initial condition (I.C.) for the forecasts are created from a **larger set of initial conditions obtained by combining different ocean, atmosphere and land states**.

- **Ten (10) atmospheric I.C.s** are prepared starting from 1-day back lagged in time atmospheric states provided by ECMWF (10 EDA analyses), interpolated to the CAM grid and integrated in time in the SPS3.5 system up to the actual forecast start-date (1rst of the month, h: 00:00).

- **Three (3) land state I.C.s** are obtained from the land analyses performed with CLM forced with atmospheric fields from different analyses (ECMWF, NCEP, F(ECMWF,NCEP))

- **Perturbed ocean I.C.s are created by generating nine (9) reanalyses** through perturbation of the ocean observations (in the analysis step), perturbation of atmospheric forcing and introduction of stochastic physics, in the forecast step.

10 atmospheric ICs (1-day back lagged in time each + SPS3.5 forecast)

3 CLM4.5 forced with ECMWF and NCEP atmospheric forcing to Land Surface

9 OCEAN ANALYSIS resulting from data assimilation

270 ICs

50 forecast members

CMCC in the seasonal prediction system: the skill

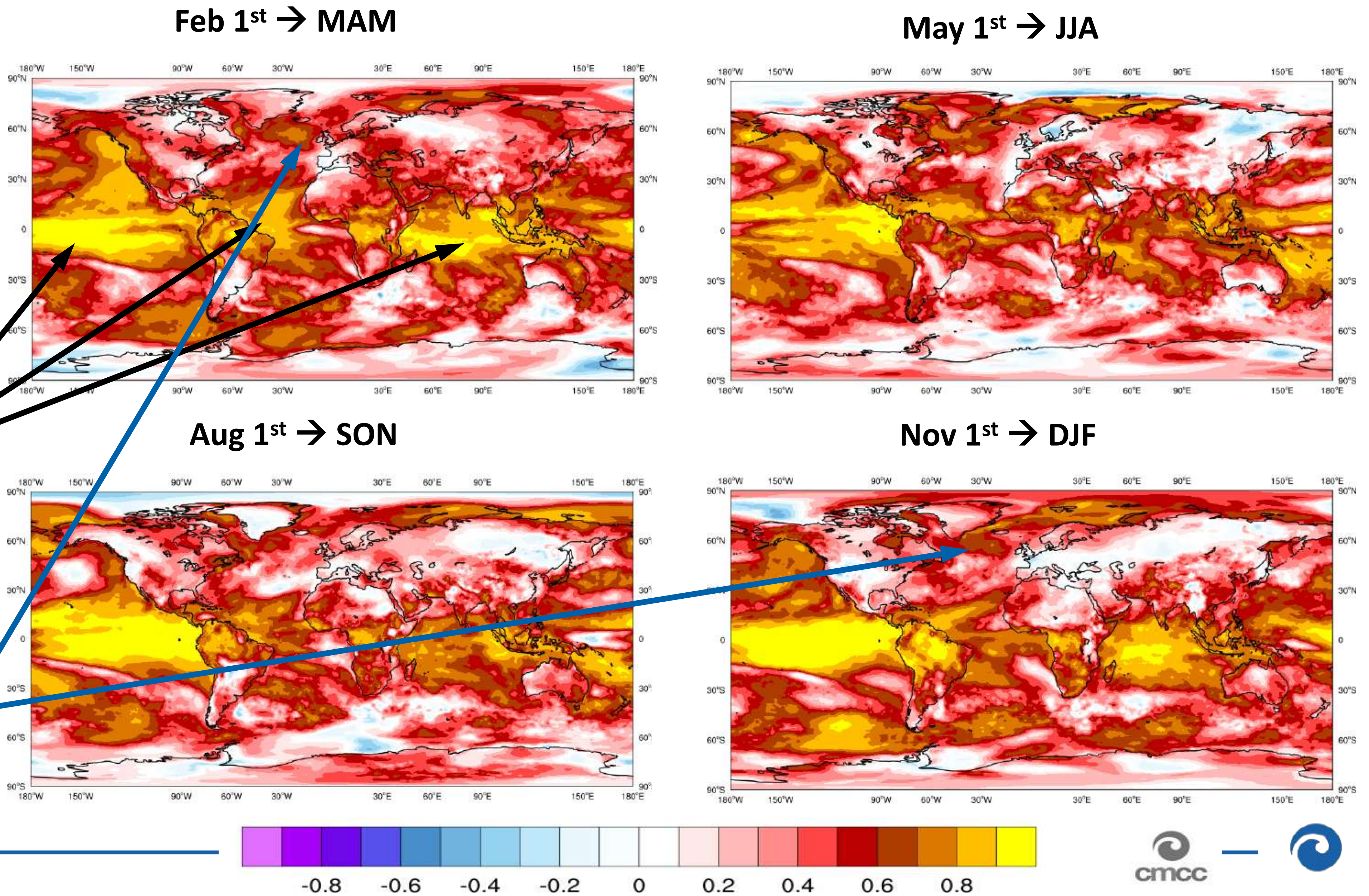
T2m ACC

(reference period 1993 – 2016)

Lead season 1

Lead time 1 refers to the season starting one month after the start date (e.g. Feb lead 1 = MAM)

- Skill is higher in the Tropical oceans (ENSO and teleconnections) and extra-trop. Pacific
- Good skill in the northern Atlantic region, particularly in the winter and the spring



CMCC SPS3.5 (Gualdi et al. 2020)

CMCC in the seasonal prediction system: the skill

Precip ACC

(reference period 1993 – 2016)

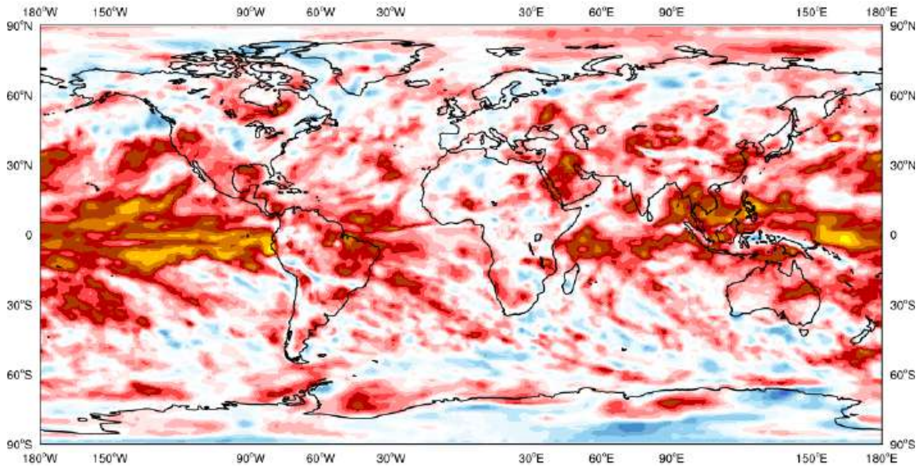
Lead season 1

Lead time 1 refers to the season starting one month after the start date (e.g. Feb lead 1 = MAM)

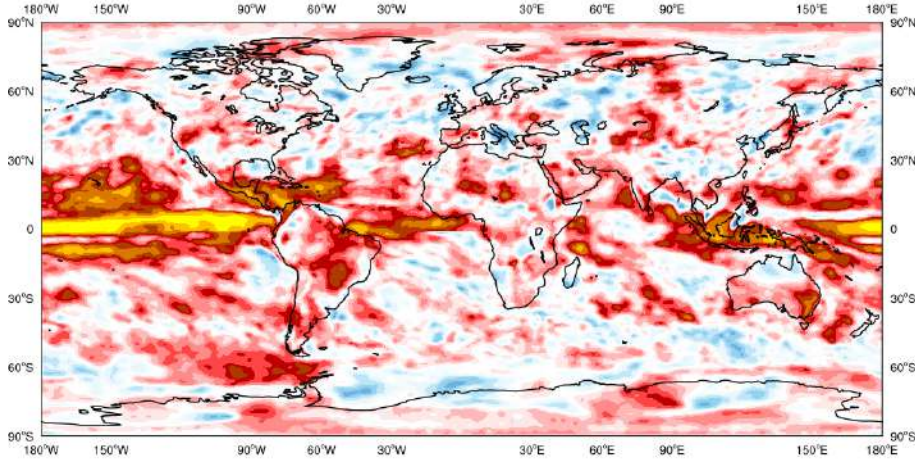
- Skill is higher in the Tropical oceans (ENSO and teleconnections) and extra-trop. Pacific

- Good skill in the northern Atlantic region, particularly in the winter and the spring

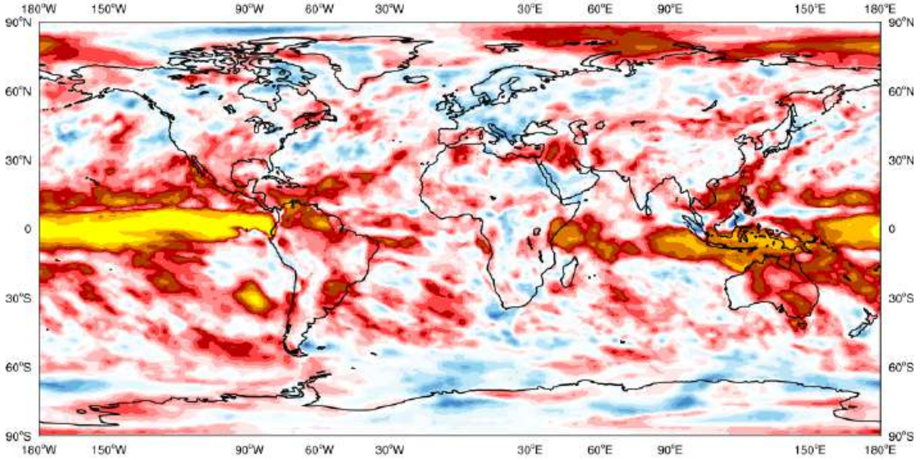
Feb 1st → MAM



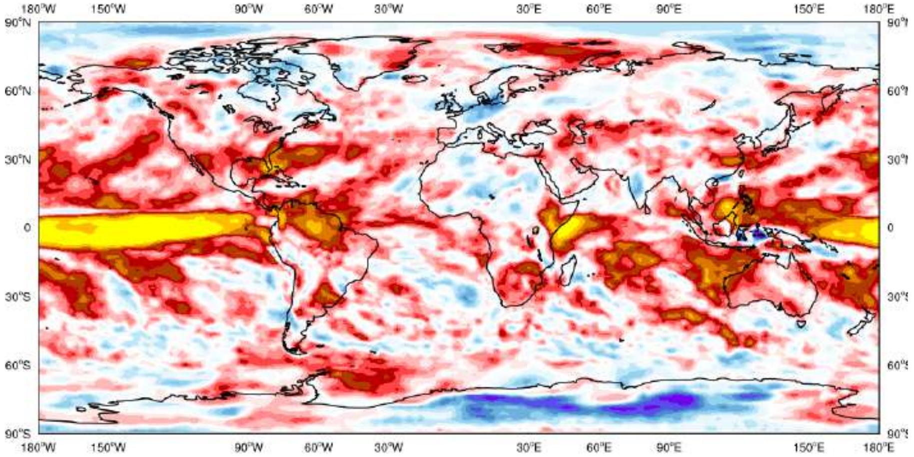
May 1st → JJA

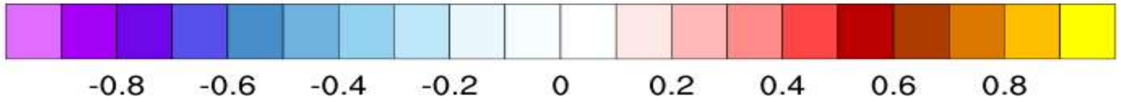


Aug 1st → SON



Nov 1st → DJF





CMCC SPS3.5 (Gualdi et al. 2020)

CMCC in the seasonal prediction system: the skill

DJF Forecasts
initialised on
<u>November 1st</u>

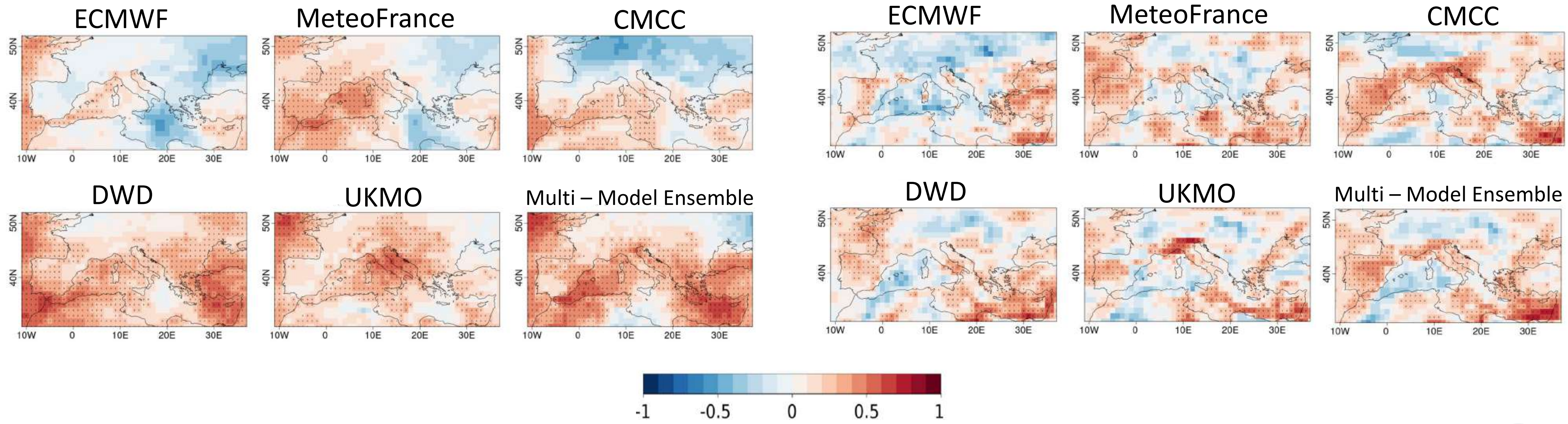
C3S multi–system
(5 prediction systems)

Climate Change

Anomaly Correlation Coefficients
with respect to ERA5, 1993 – 2014

2m-Temperature

Precipitation



Stippling = significant correlations (95% confidence level).

Modified from Calì Quaglia et al. 2021

CMCC in the seasonal prediction system: the skill

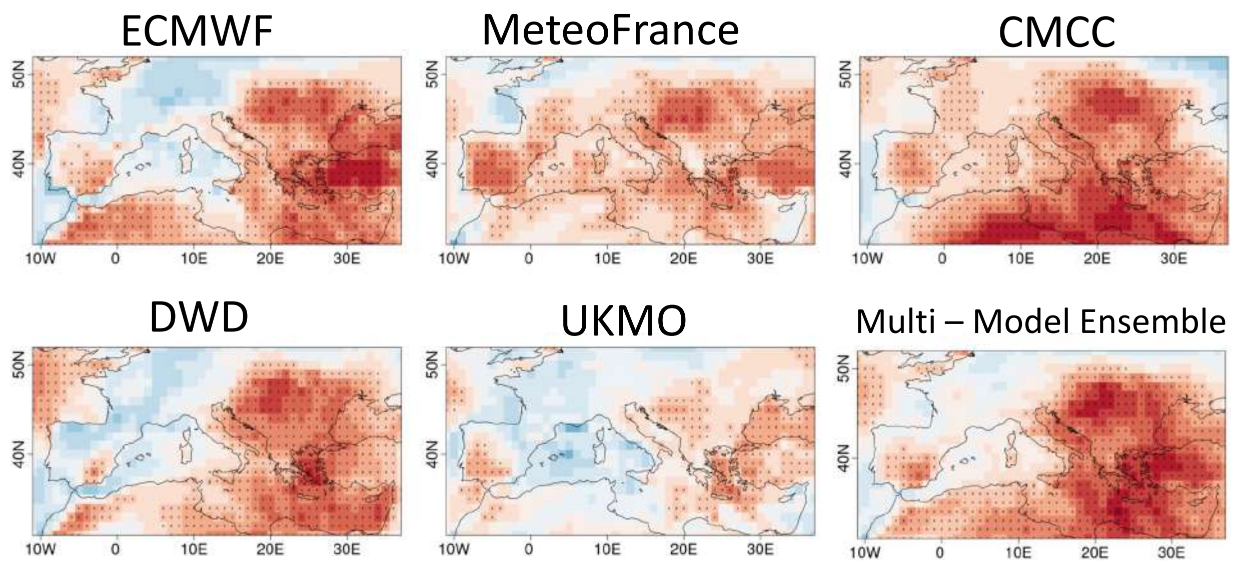
JJA Forecasts
initialised on
May 1st

C3S multi–system
(5 prediction systems)

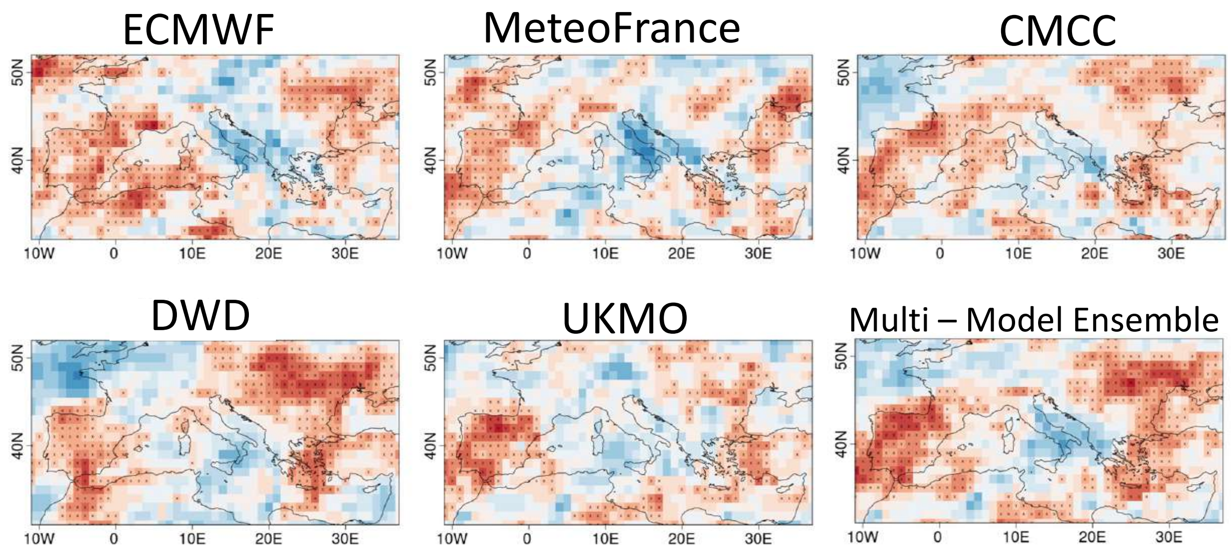
Anomaly Correlation Coefficients

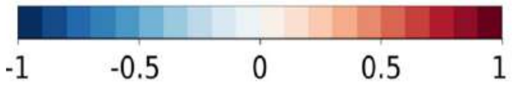
with respect to ERA5, 1993 – 2014

2m-Temperature



Precipitation





Stippling = significant correlations (95% confidence level).

Modified from Calì Quaglia et al. 2021

CMCC in the seasonal prediction system: the skill

NDJ Forecasts **initialised on Nov 1st**

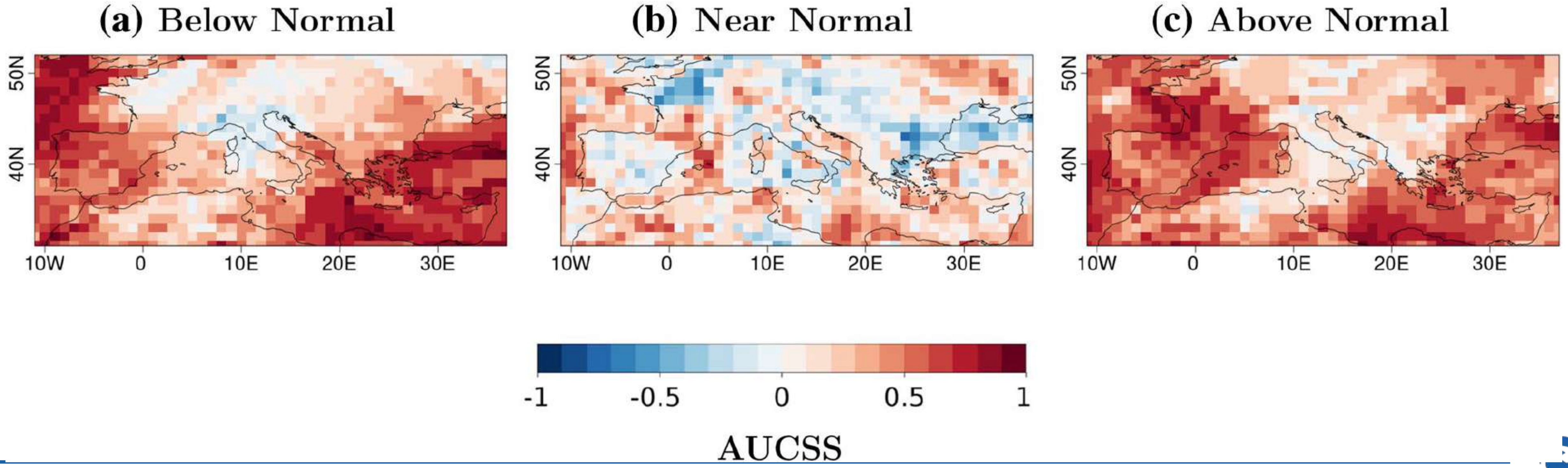
Relative Operating Characteristic (ROC)
with respect to ERA5, 1993 – 2014

C3S multi–system
(5 prediction systems)

Climate Change

ROC area maps for the Multi–Model Ensemble T2m anomaly winter forecasts at lead time 0, starting date November 1st and for the three terciles: below normal, near normal, above normal.

2m-Temperature



Stippling = significant correlations (95% confidence level).

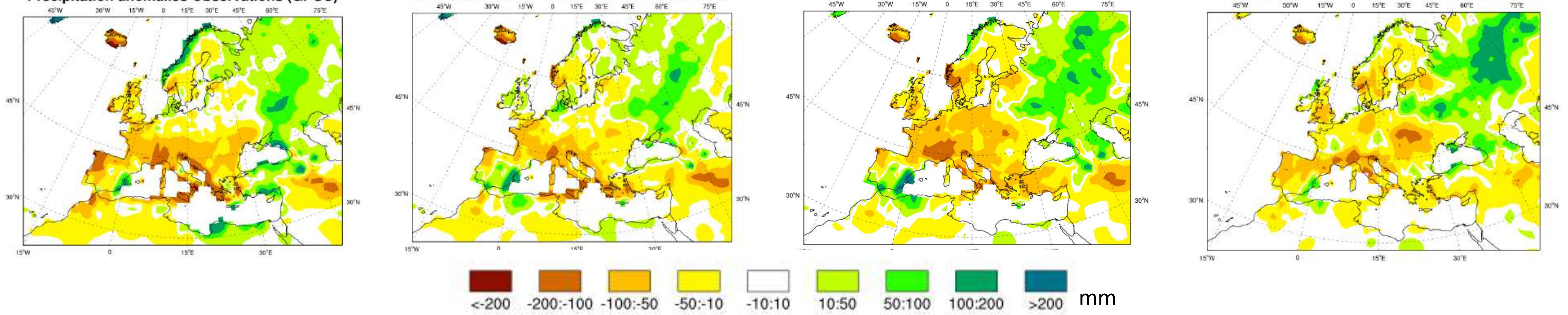
Calì Quaglia et al. 2021

spring/summer 2022

Drought spring/summer 2022

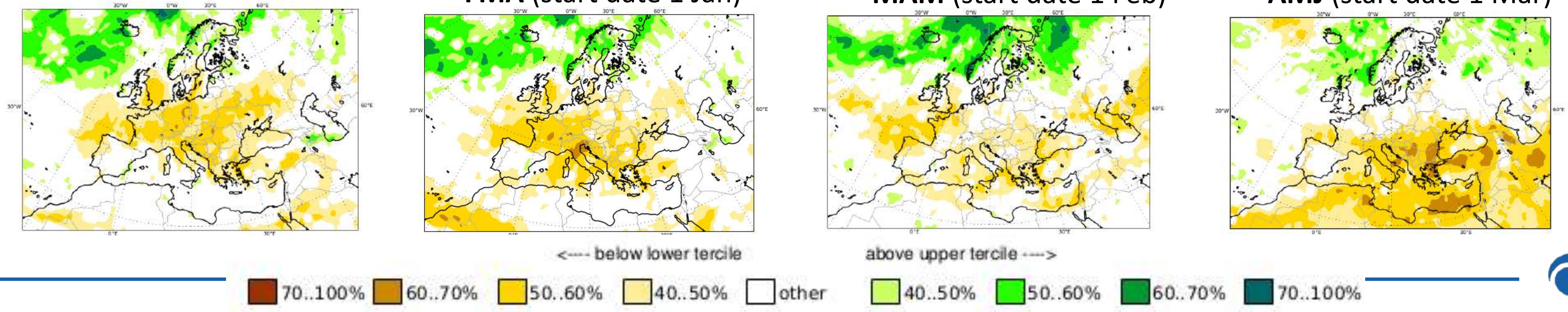
Reference period: 1993 - 2016

2022 JFM Precipitation anomalies Observations (GPCC) | 2022 FMA Precipitation anomalies Observations (GPCC) | 2022 MAM Precipitation anomalies Observations (GPCC) | 2022 AMJ Precipitation anomalies Observations (GPCC)



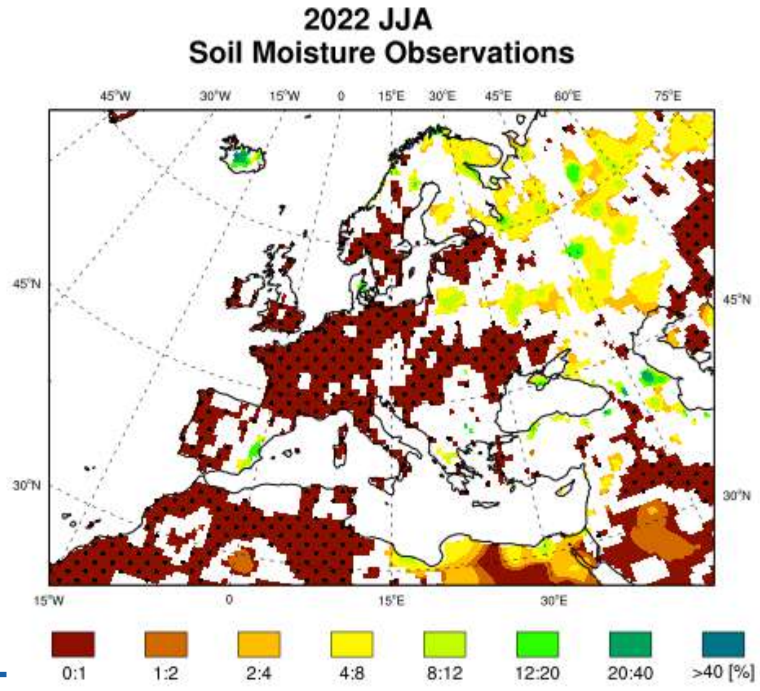
Precipitation forecast: Probability (most likely category of precipitation)

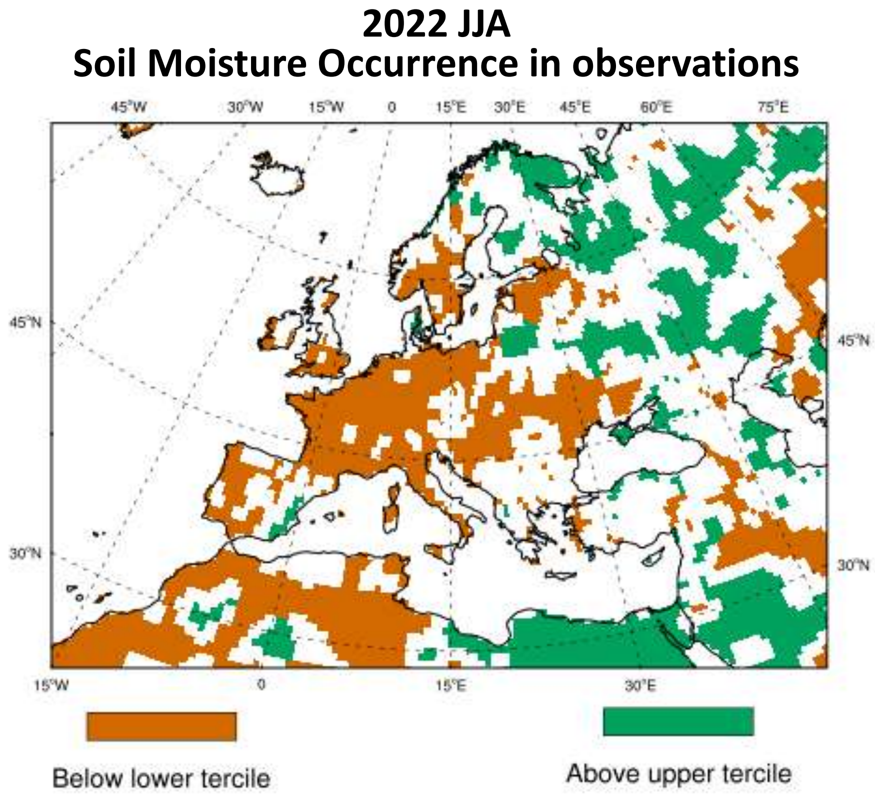
JFM (start date 1 Dec) | **FMA** (start date 1 Jan) | **MAM** (start date 1 Feb) | **AMJ** (start date 1 Mar)

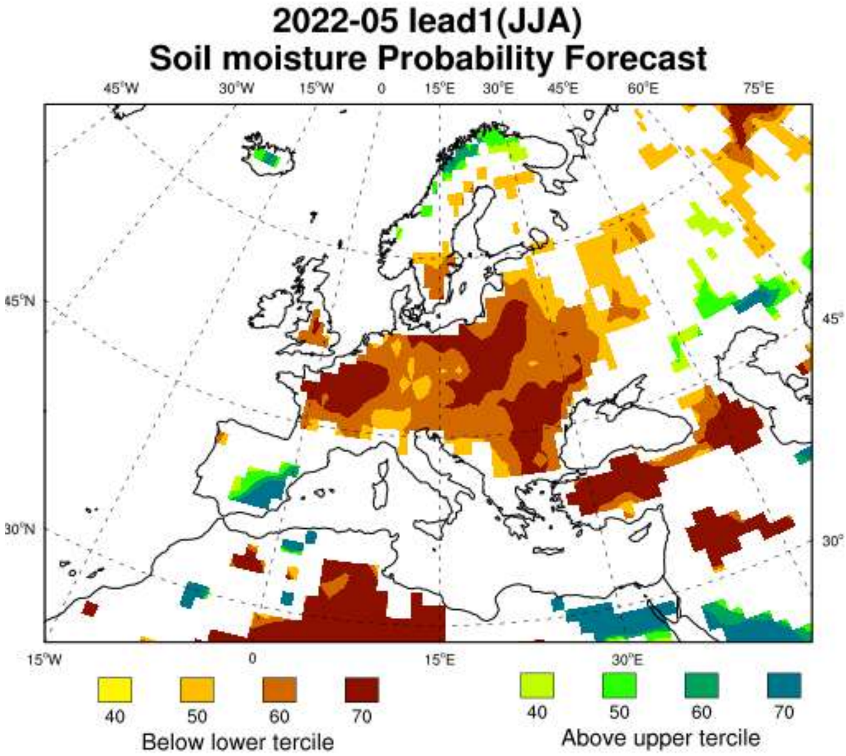


Reference period: 1993 - 2016

Soil moisture evaluation 2022 JJA





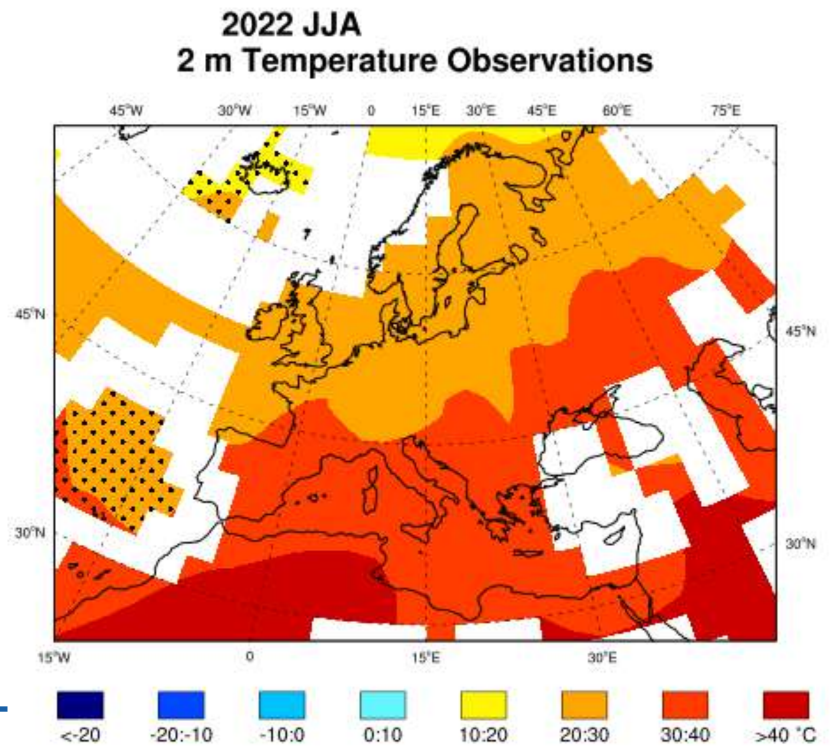


Probability: most likely category

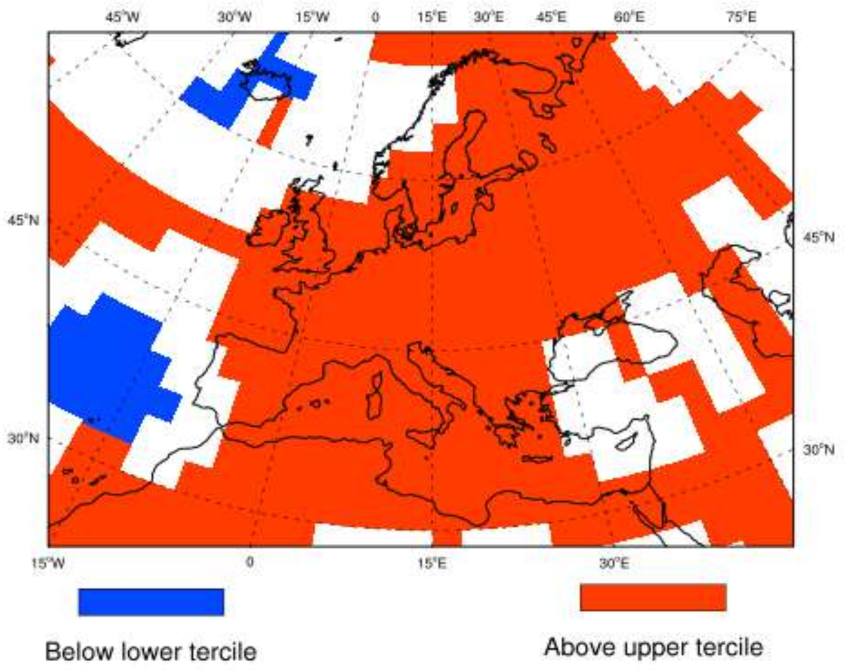
Hot & dry summer 2022

Reference period: 1993 - 2016

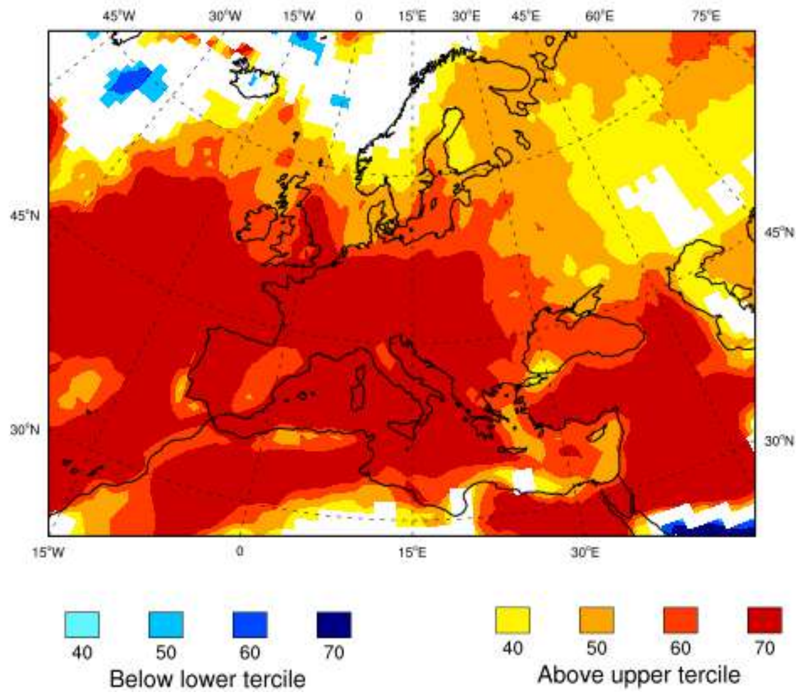
2m Temp. evaluation 2022 JJA



2022 JJA 2m Temperature occurrence in observations



2022-05 lead (JJA) 2m Temperature probability forecast

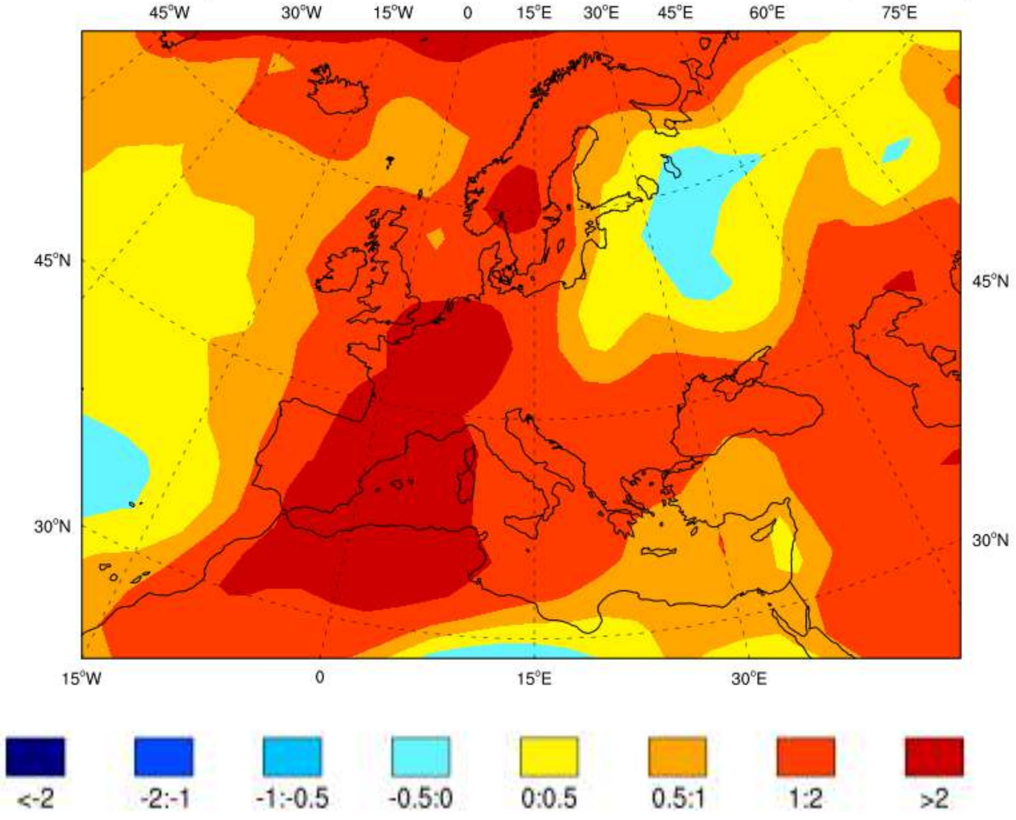


Probability: most likely category

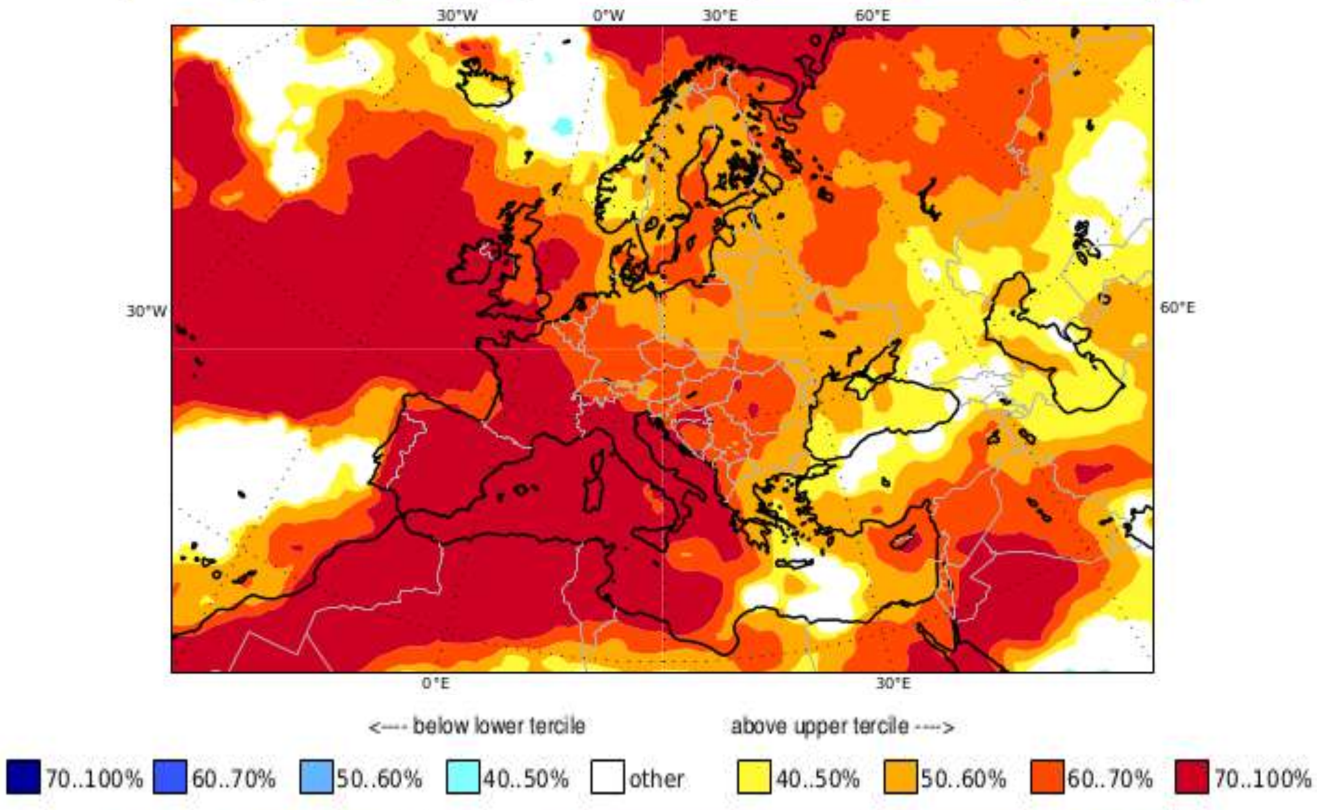
Hot autumn 2022

Reference period: 1993 - 2016

2022 SON
2m temperature anomalies Observations (NCEP)



2022 SON
2m temperature Forecast (start date 1 Aug)

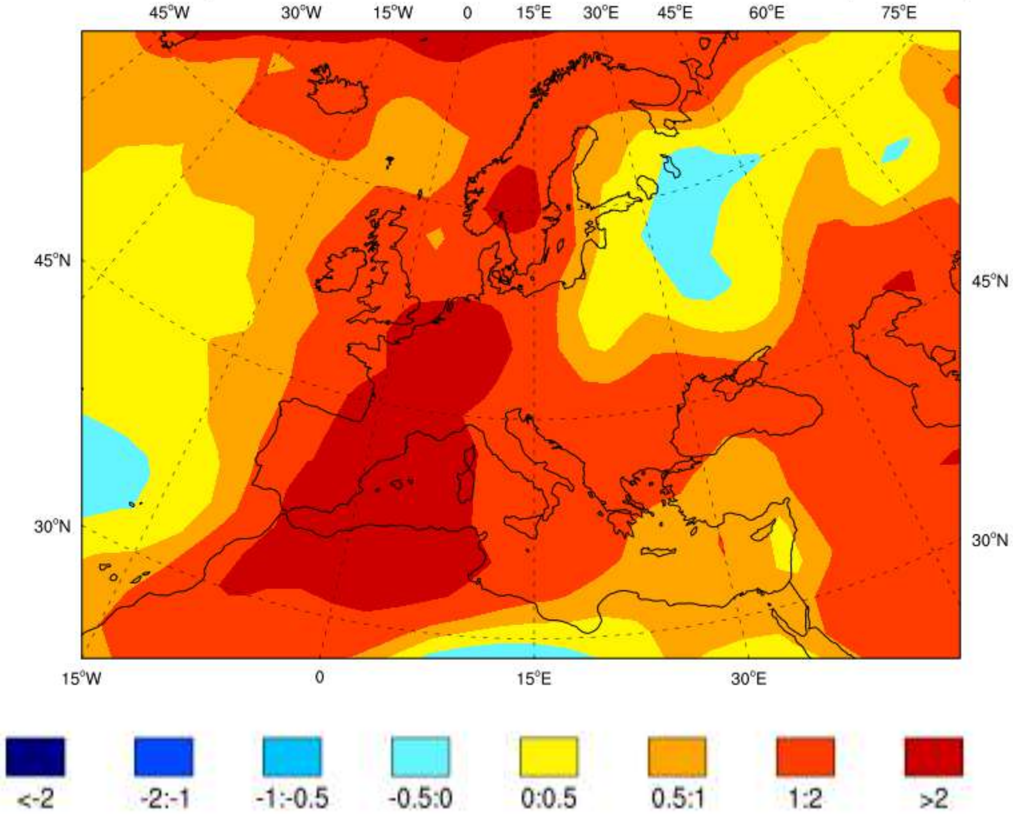


Probability: most likely category of 2mT

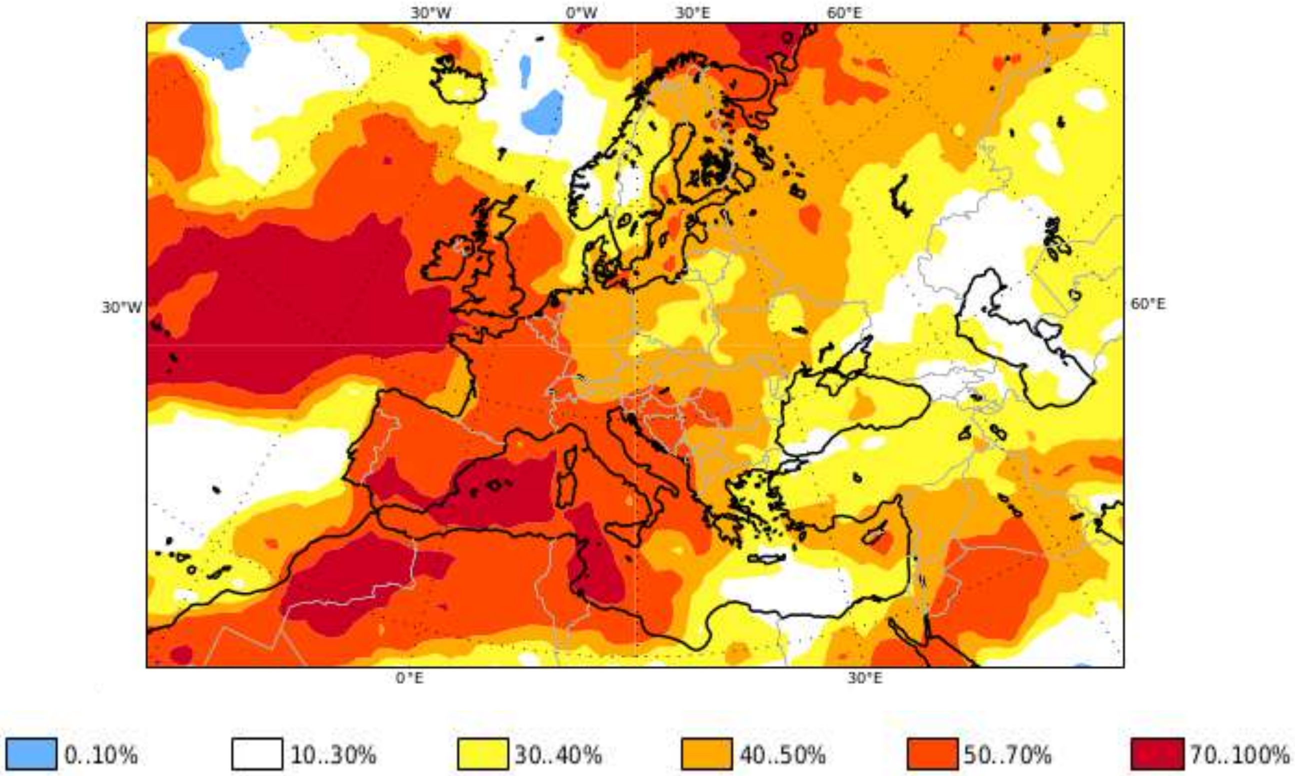
Hot autumn 2022

Reference period: 1993 - 2016

2022 SON
2m temperature anomalies Observations (NCEP)



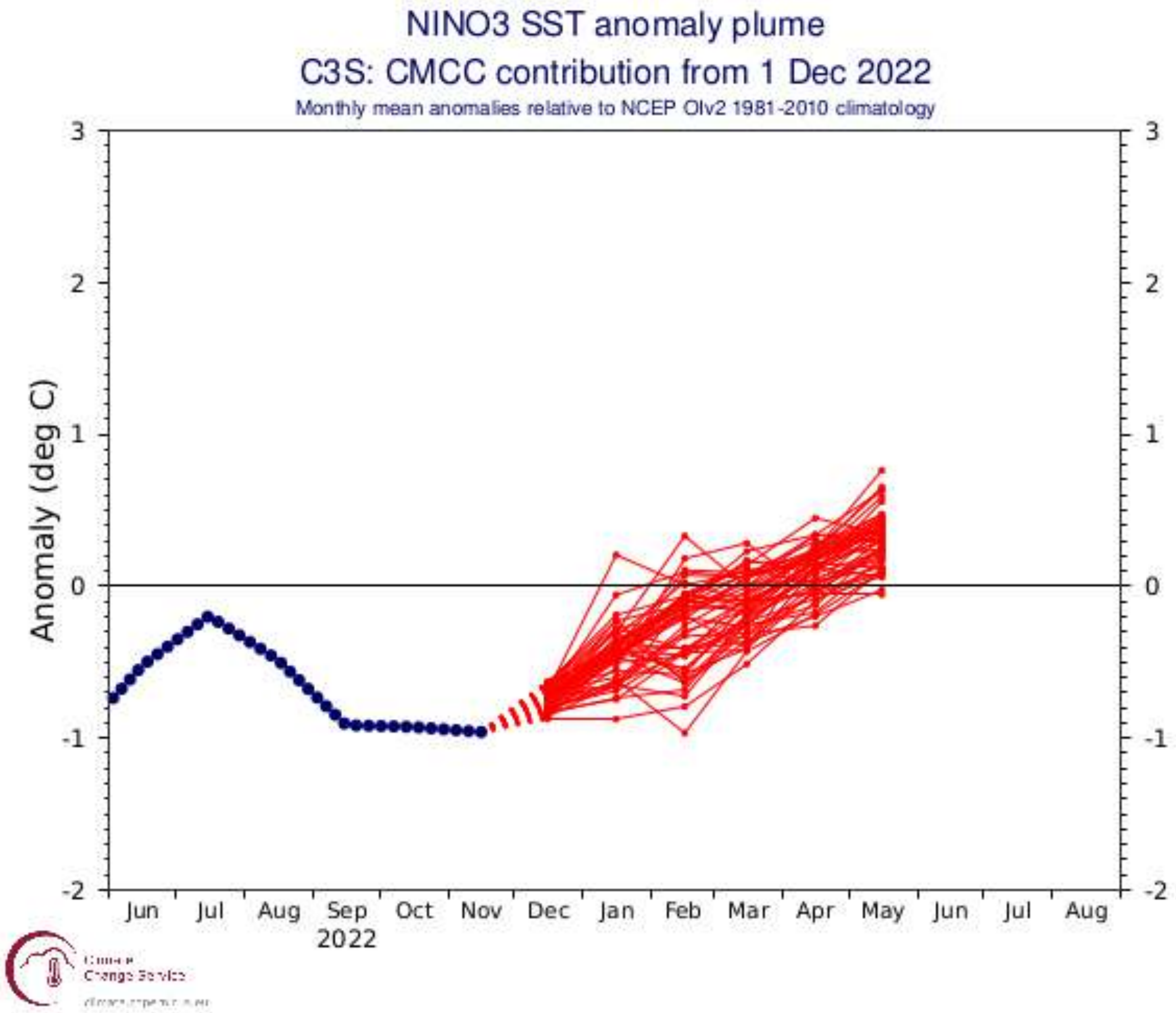
2022 SON
2m temperature Forecast (start date 1 Aug)



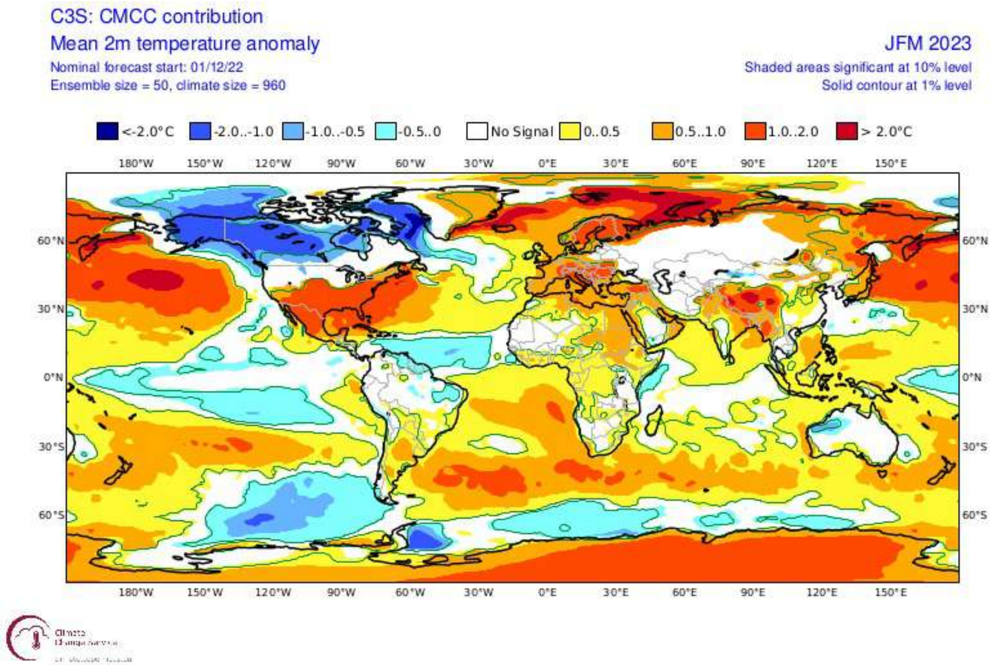
Probability: highest 20% of climatology of 2mT

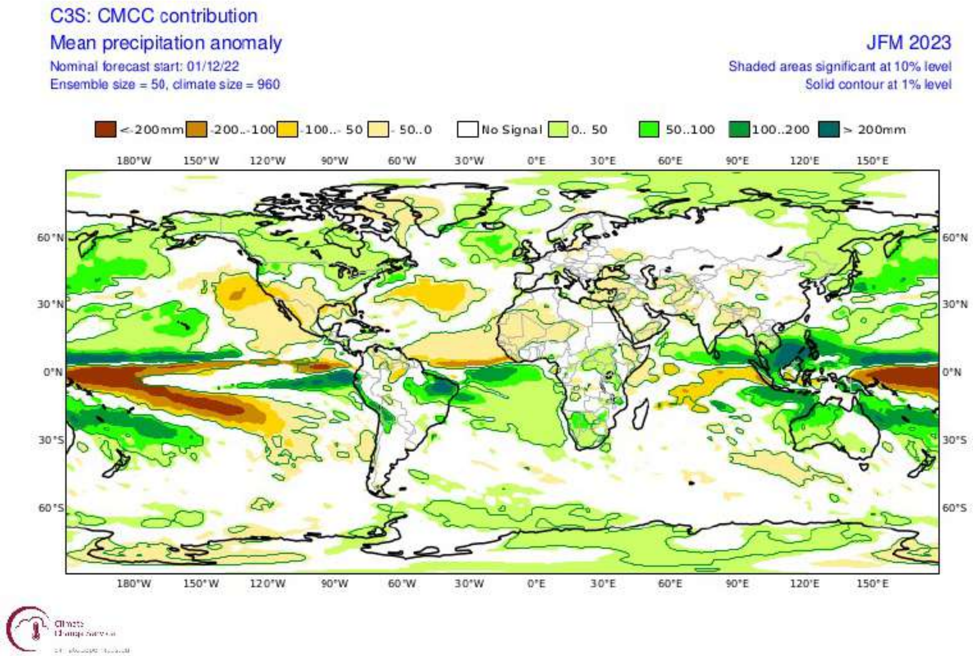
winter/spring 2023

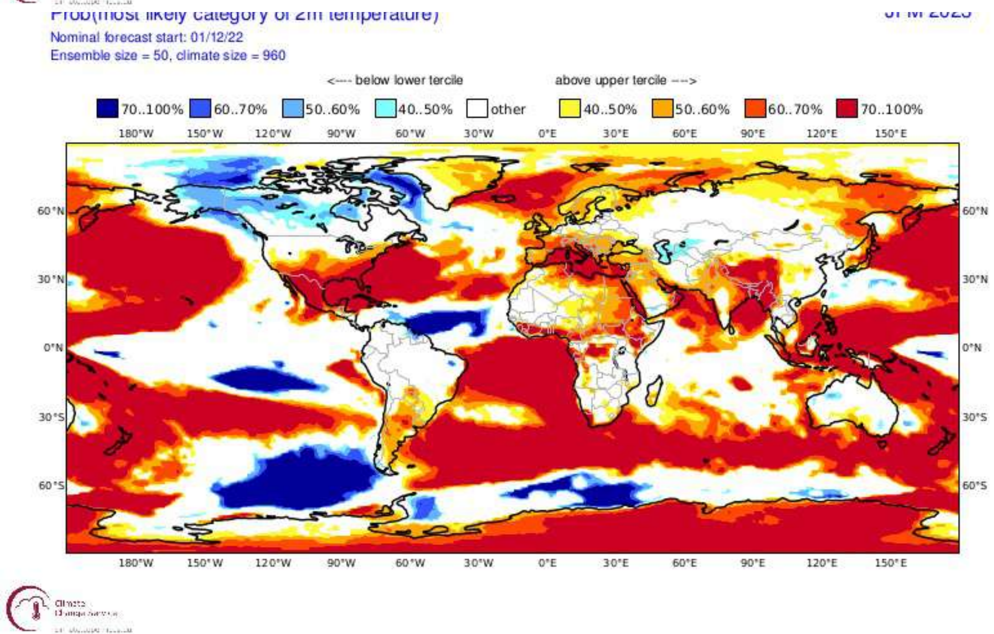
Forecast winter/spring 2023 – start date 01 Dec 2022

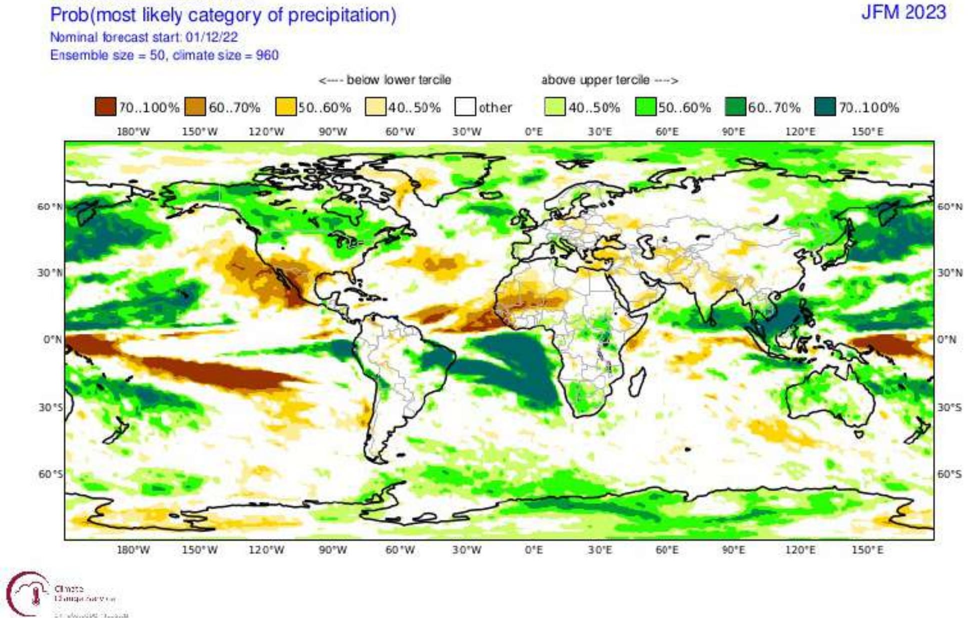


Forecast winter/spring 2023 – start date 01 Dec 2022





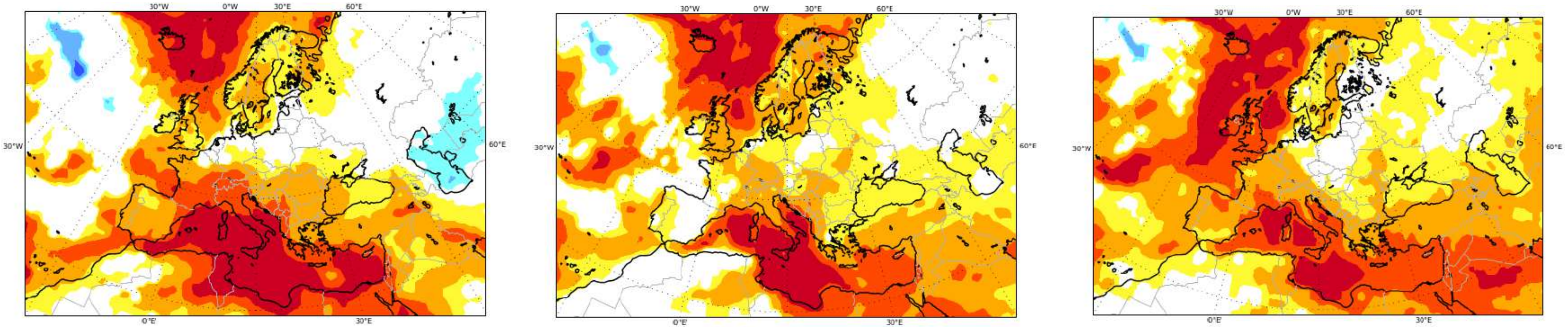




Forecast winter/spring 2023 – start date 01 Dec 2022

	JFM	FMA	MAM

T2m

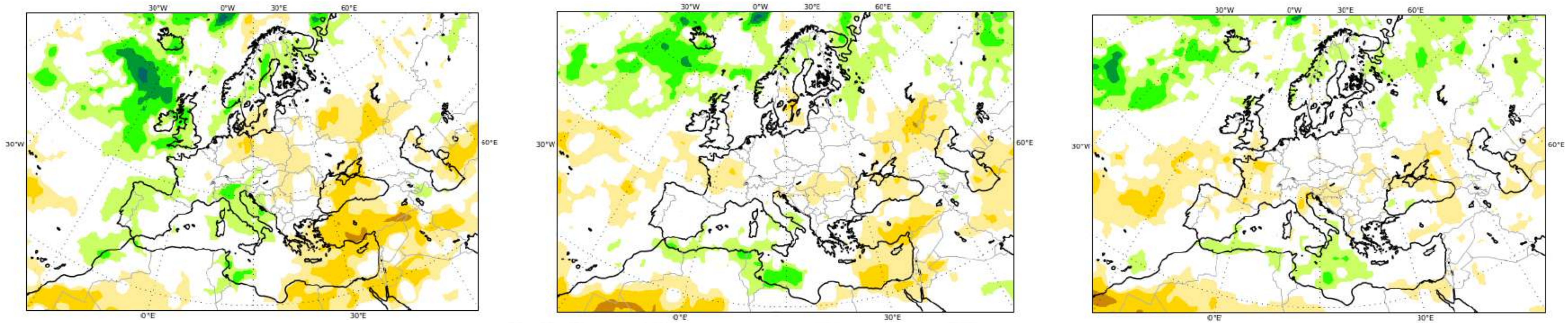


Probability: most likely category of 2mT

<---- below lower tercile | above upper tercile ---->

70..100% | 60..70% | 50..60% | 40..50% | other | 40..50% | 50..60% | 60..70% | 70..100%

Prec



<---- below lower tercile | above upper tercile ---->

70..100% | 60..70% | 50..60% | 40..50% | other | 40..50% | 50..60% | 60..70% | 70..100%

Current developments

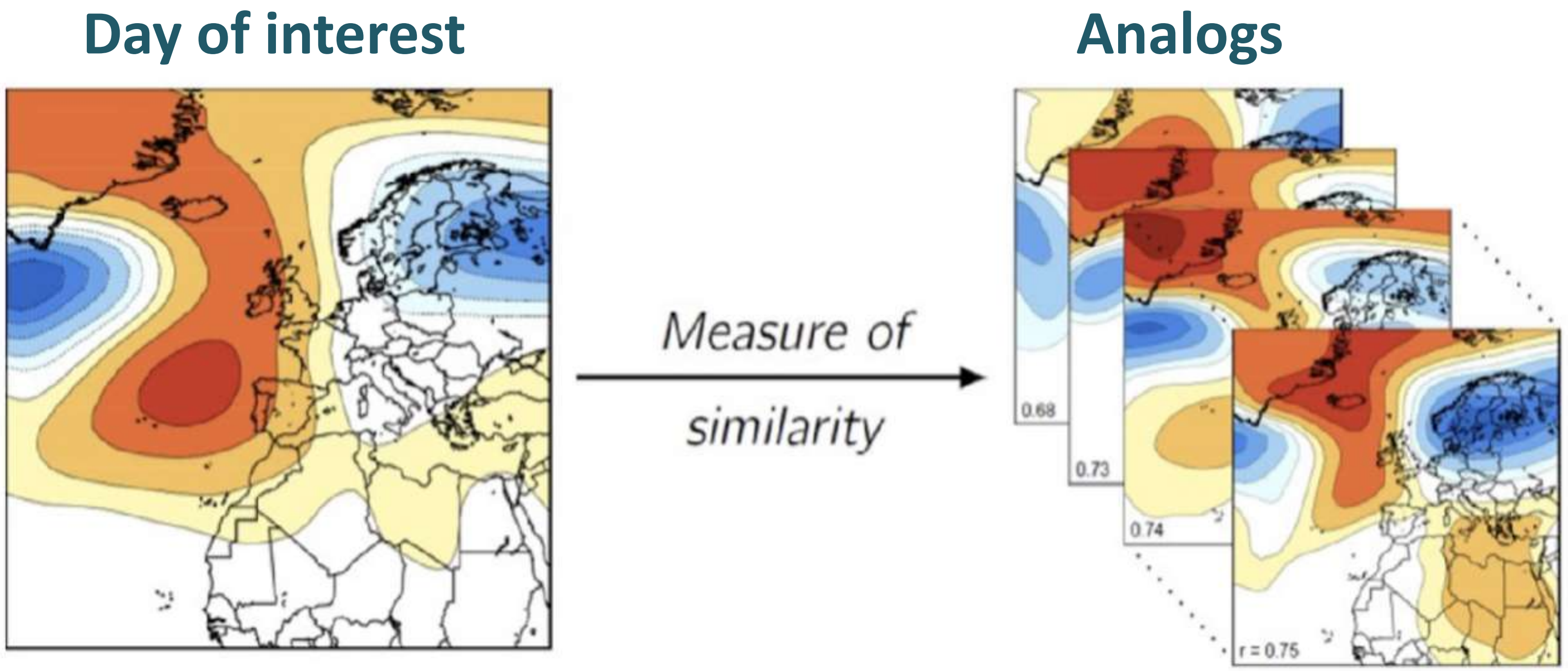
Searching for Analogs: Method

Analogs: days within the database which have a similar large scale pattern to the day of interest (Yiou et al, 2013).

The **downscaled field** is obtained by selecting the field of interest (i.e. precipitation, temperature) in the best analog day (e.g. 1986/05/07) to the target day (e.g. 2021/05/01). The best analog is defined as the day with minimum distance from the target day at (1) large scale, (2) large scale and local scale, (3) large scale, local scale and maxima correlation (CST_Analogs and Analogs functions by Alvarez-Castro et al within Perez-Zanon et al, 2022 and CSTools, CRAN).

Predictors: SLP and/or SST at Large Scale

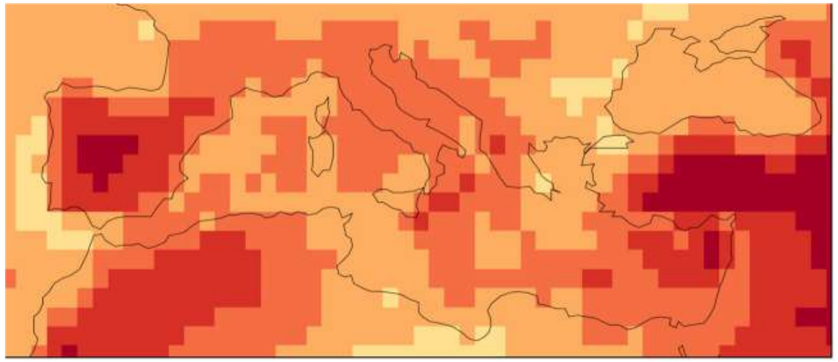
Predictands: Precipitation, Temperature at local scale



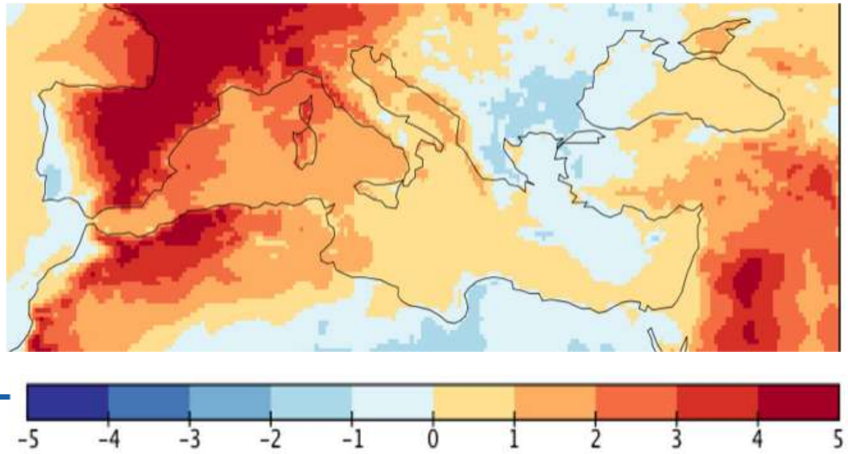
Downscaling of T2m using Analogs for JJA 2022

- Example of downscaling of seasonal forecast temperature **from 1º to 0.25º of horizontal resolution**.
- Using the method of Analogs we can **downscale and bias correct** the data of seasonal forecast models since is based on observations/reanalyses.
- Although there is a limitation of a gridded dataset for observation, using **Analogs** we can downscale different variables and regions.
- Since is a downscaling based on the dynamics, a **large scale region** should be selected in advance. In the case of this example, the Mediterranean region, we have selected the North Atlantic region (based on a previous study of correlation not shown here)

2-metre Temperature



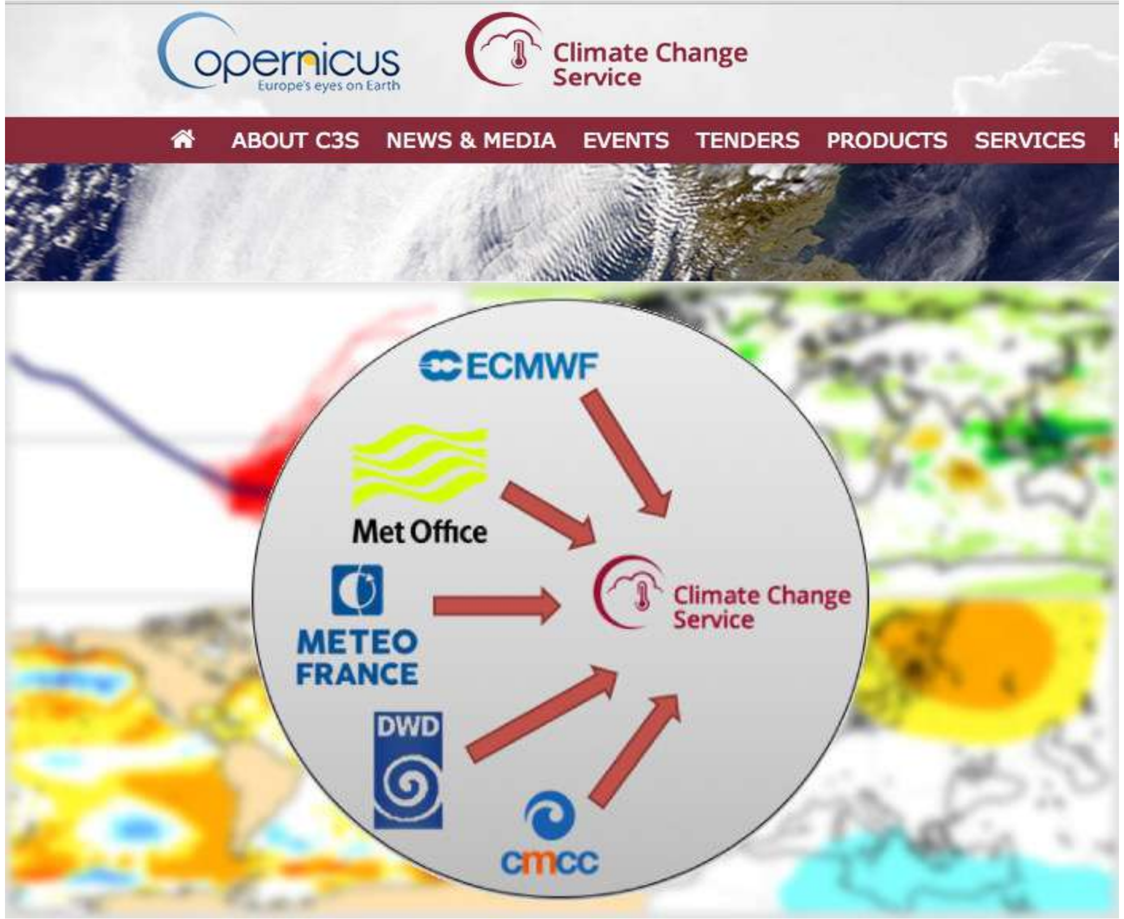
Forecast



OBS

(anom C)

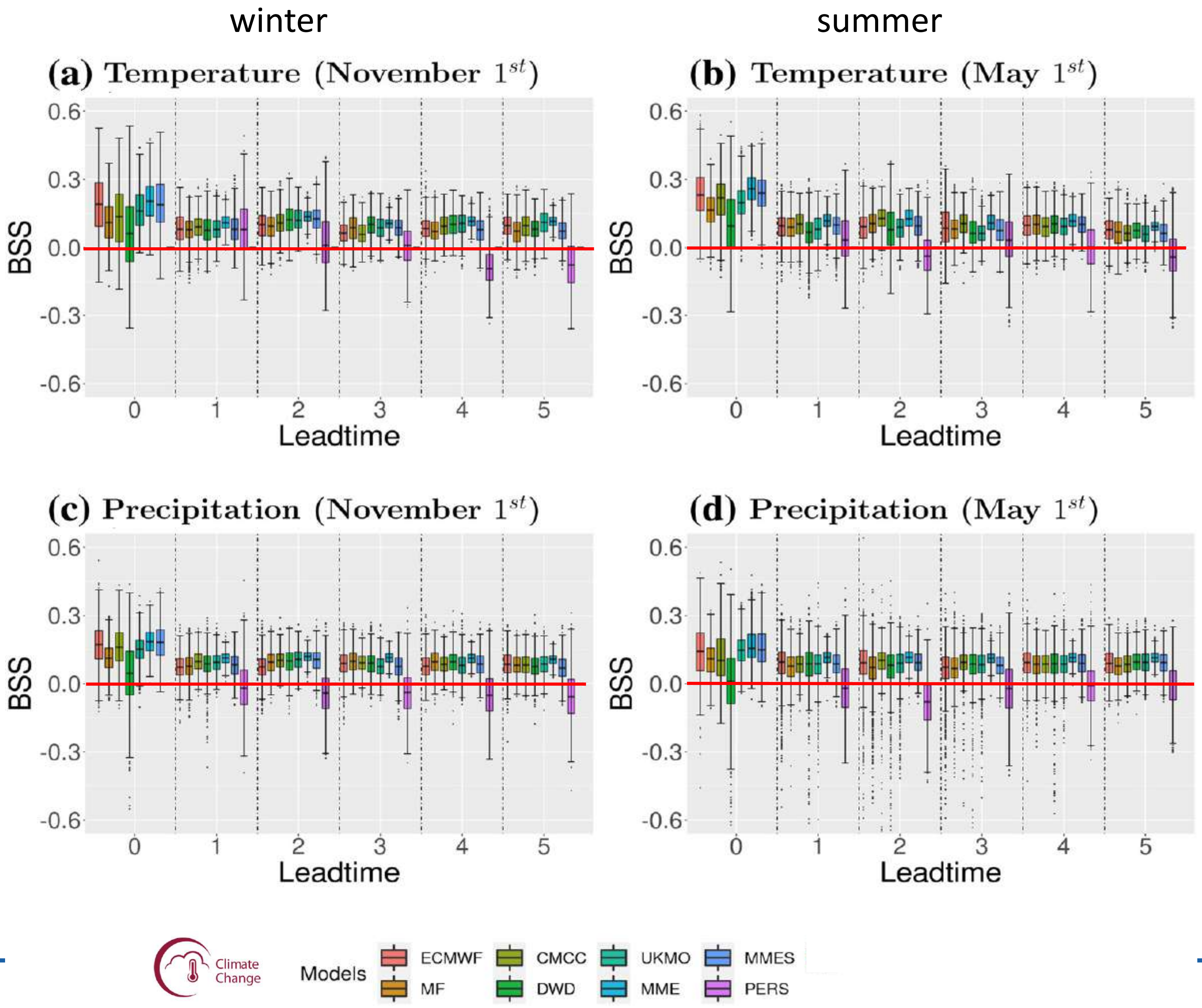
Thank you



https://climate.copernicus.eu/seasonal-forecasts

https://www.wmolc.org/

CMCC in the seasonal prediction system: the skill



Brier skill score (BSS) of **winter** and **summer temperature and precipitation anomaly** forecasts, for all models and lead times.

Brier score (BS)

$$BS = \frac{1}{N}\sum_{t=1}^{N}(f_t - o_t)^2$$

$\mathbf{f_t}$ is the probability of the forecast, $\mathbf{o_t}$ the actual outcome of the event at instance t (0 if it does not happen and 1 if it does happen) and N is the number of forecasting instances

$$BSS = 1 - \frac{BS_{fcst}}{BS_{clim}}$$

Boxplots summarise the statistics of the distribution of the **BSS** over the **Mediterranean domain.**

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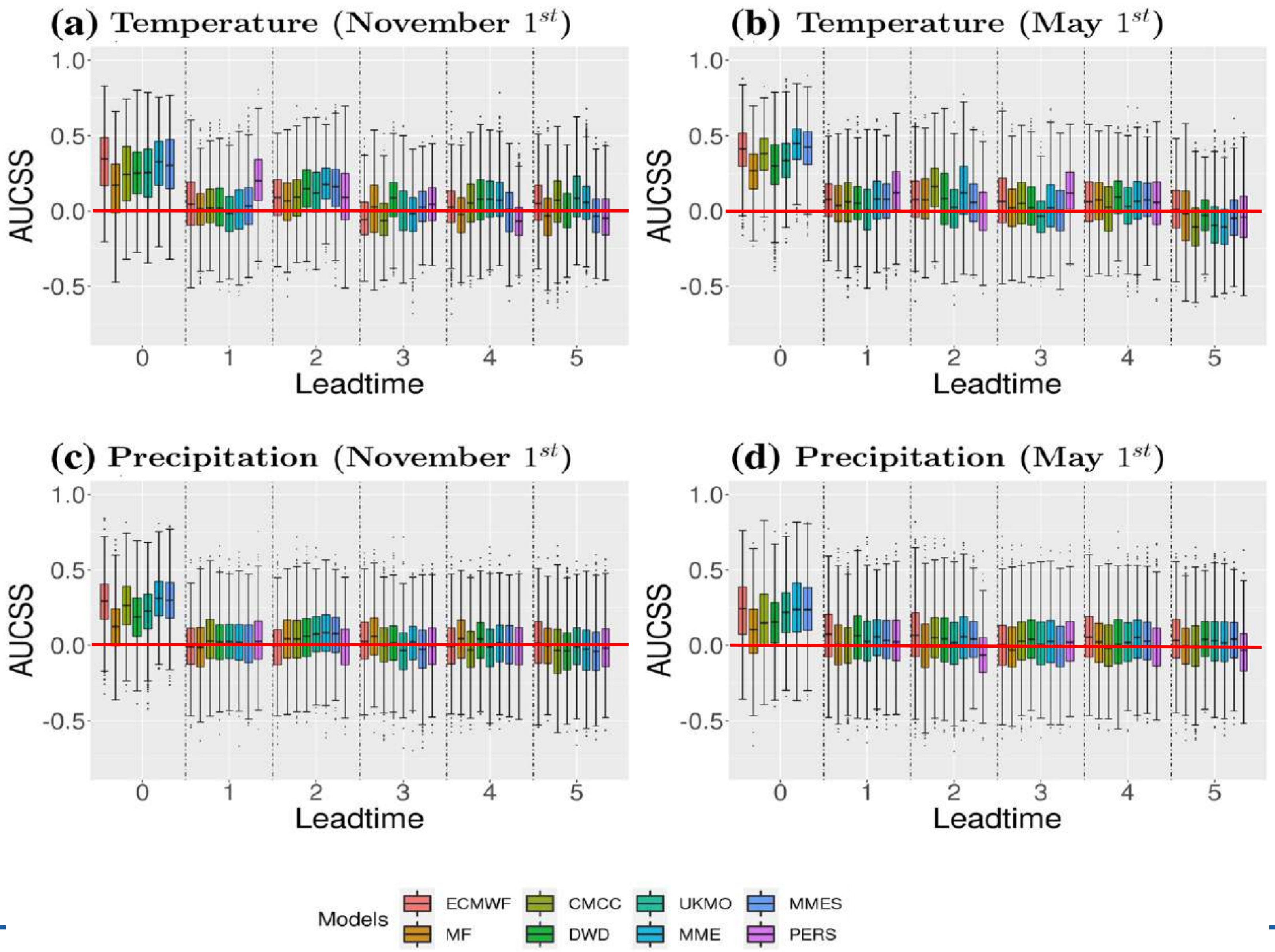
CMCC in the seasonal prediction system: the skill

winter summer



ROC curve skill score (**Area under the curve skill score, AUCSS**) of winter and summer, temperature and precipitation anomaly forecast for all models and lead times, averaged over the three terciles.

	Predicted	
Observed	Hit event	False alarm
	Missed event	Correct negative

Boxplots summarise the statistics of the distribution of the **AUCSS** over the **Mediterranean domain.**

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