Summer drought predictability in the Mediterranean region in seasonal forecasts

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1. Introduction, scope and Data

Mediterranean droughts have become more frequent and intense in recent years and are expected to become more widespread in many regions. In this context, **seasonal forecasts produced by global numerical models have emerged as promising tools for seasonal climate risk assessment.** Yet, all seasonal probabilistic forecasts are not equally accurate, and metrics are needed to quantitatively assess their quality.

A rigorous evaluation process is needed to:

- Determine the extent to which seasonal forecasts provide a fruitful advantage over much simpler forecasting systems, such as those based on climatology. [1]
- Help an informed use of seasonal forecasts of droughts and the development of related climate services.

The **Copernicus Climate Change Service (C3S) provides forecast data from several state-of-the-art seasonal prediction systems at 1° x 1° resolution and daily frequency**. [2] Here we use:

- The fifth version of the seasonal forecasting system provided by the ECMWF (**SEAS5**).
- **ERA5** reanalysis.

Region in analysis: [11W - 43°, 28N – 59N], years 1981 through 2020.

2. Methods

Summer droughts detection: **Standardized Precipitation Evapotranspiration Index aggregated over three months (SPEI3)** calculated in August.

- SPEI3: **data initialised on the 1st of June** and aggregated over June, July and August (**0-months lead time**)
- SPEI3: **data initialised on the 1st of May** and aggregated over June, July and August (**1-month lead time**)

Our evaluation process includes several **evaluation metrics**, that test different features describing the quality of the forecast system [3].

Forecast skills are presented as skill scores (SS), which are interpreted as the improvement over a reference forecast.

$$SS = \frac{S - S_{ref}}{S_{perf} - S_{ref}}$$

- S is the score of the forecasting system
- S_{ref} is the score of the reference forecast
- S_{perf} is the perfect score

We calculate from the ERA5 reanalysis all the historical August SPEI3 values. For each year, we use all the historical SPEI3 values except for the one corresponding to that year, in order to form an ensemble of 39 members (one less than the number of forecasted years). This is an **elementary forecast system** based on the observed climatology.

3. Quality evaluation

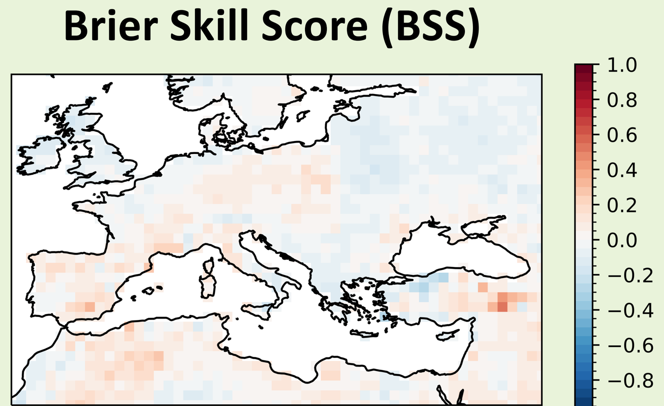
Skill Scores

Based on *categorical observations* (binary outcomes: SPEI3 < -1)

Considering the *probability distribution* of forecasted values

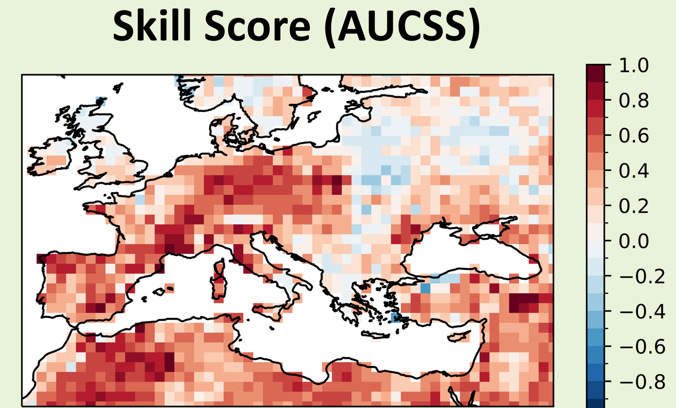
Initialisation: June 1st 0-months lead time

Brier Skill Score (BSS)



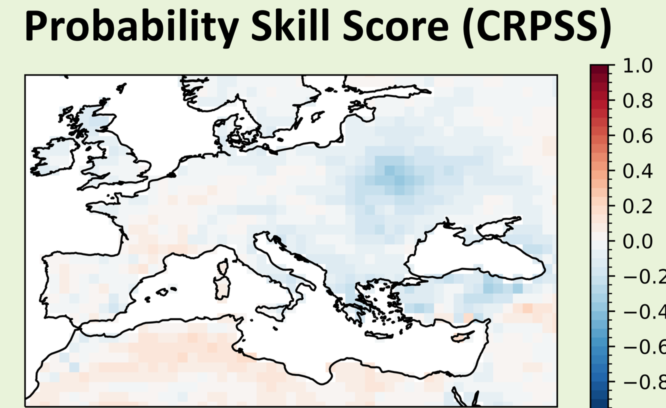
BSS (SPEI3 < -1), lead time 0

Area Under the ROC Curve Skill Score (AUCSS)



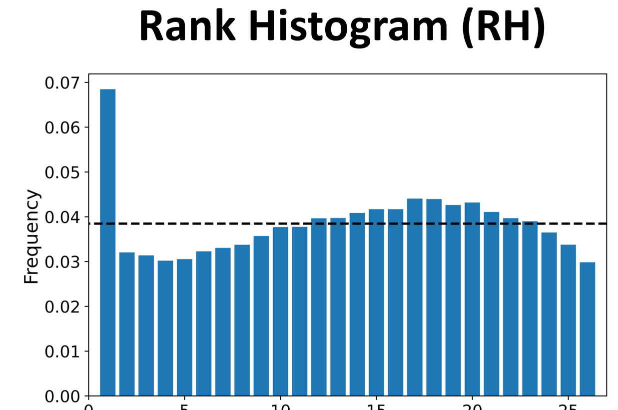
AUCSS (SPEI3 < -1), lead time 0

Continuous Ranked Probability Skill Score (CRPSS)



CRPSS, lead time 0

Rank Histogram (RH)



Mediterranean RH, lead time 0

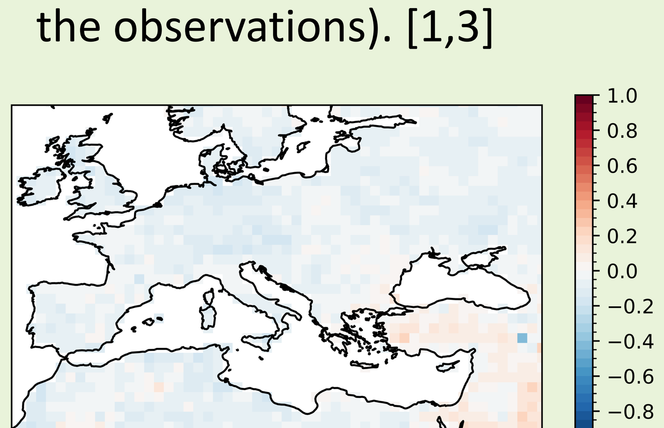
- Averages the squared differences between pairs of forecast probability and subsequent binary observations.
- It measures the overall **accuracy** of the forecast (intended as average correspondence between individual forecasts and the observations). [1,3]

- Measures the area under the Receiver Operating Characteristic curve.
- It measures **discrimination** (If the forecast assigns higher probabilities to events when they occur compared to when they don't, it has discriminatory ability. [1, 3]

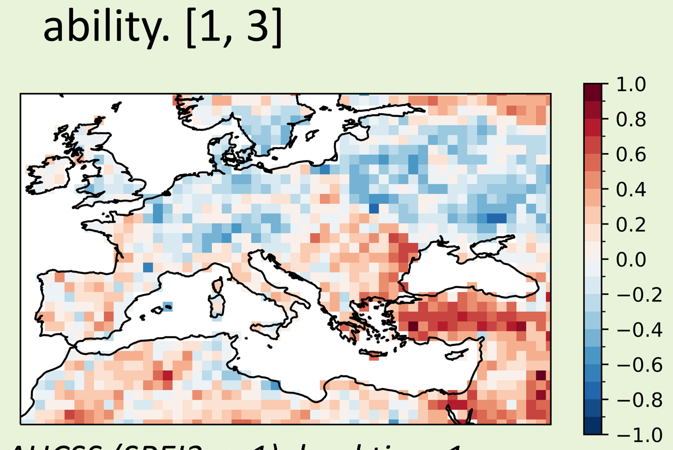
- Averages the difference between the cumulative distribution function (CDF) of the forecast system and the respective observation (represented by a Heaviside step function). [1, 3]
- It measures accuracy and **sharpness** (a sharp forecast exhibits a small spread).

- Compares the ranks of forecasts with the rank of observation.
- It measures whether the probability distribution of observations is well represented by the ensemble. Any deviation from the ideal flat histogram indicates a potential **bias.** [1,3]

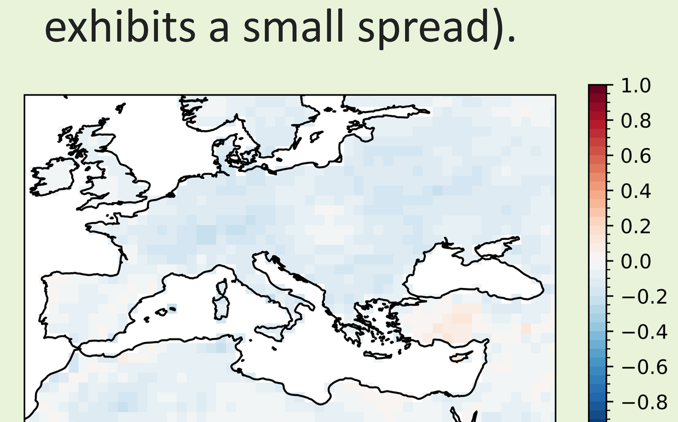
Initialisation: May 1st 1-months lead time



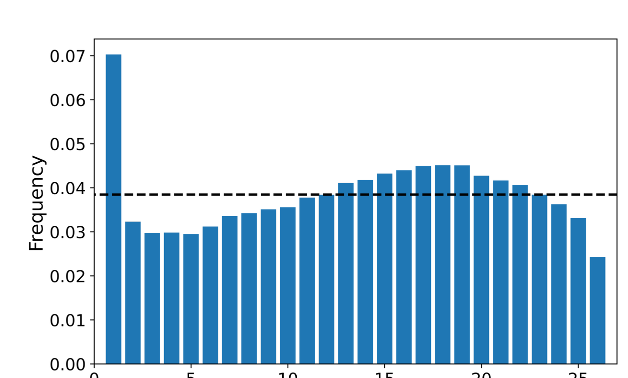
BSS (SPEI3 < -1), lead time 1



AUCSS (SPEI3 < -1), lead time 1

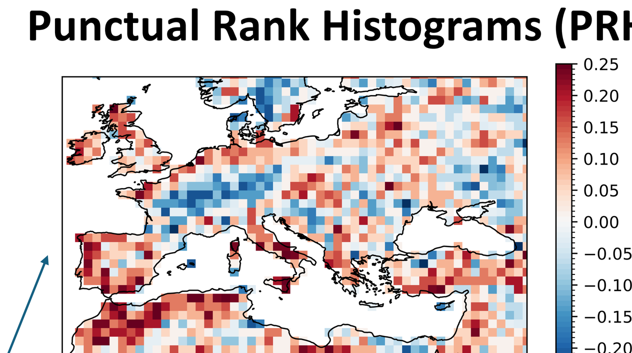


CRPSS, lead time 1

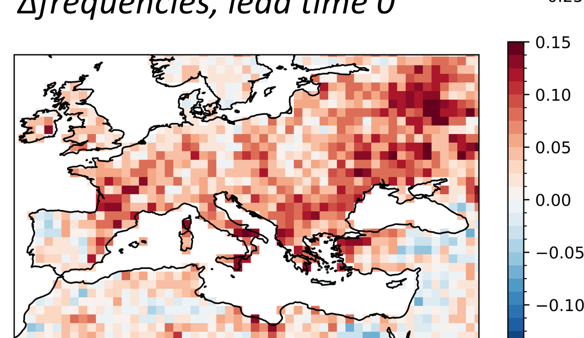


Mediterranean RH, lead time 1

Punctual Rank Histograms (PRH)

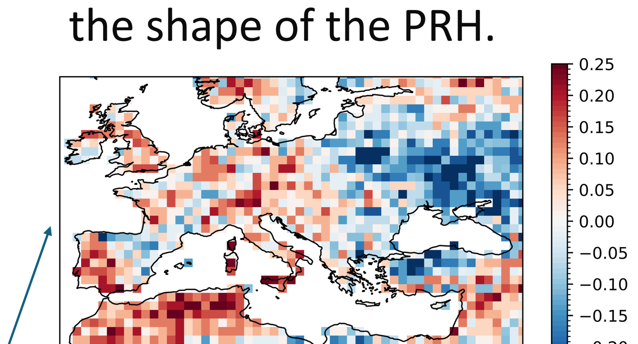


Δfrequencies, lead time 0

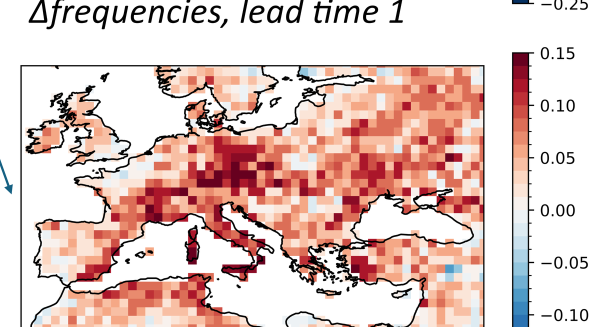


Bin slopes, lead time 0

We replicate one RH for each grid point (three bins only**!**) and produce two maps that together help understanding the shape of the PRH.



Δfrequencies, lead time 1



Bin slopes, lead time 1

The difference between the mean of the frequencies of the side bins and the frequency of the central bin (***Δfrequencies***):

- Positive values: under-dispersion
- Negative values: over-dispersion
- Around zero values: the RH can either be flat (perfect) or the height of the bins is linearly increasing or decreasing.

The slope given by the linear interpolation of the height of the bins in order (***bin slopes***).

- Positive slope: under-forecasting bias
- Negative slope: over-forecasting bias
- Around zero slope: perfect histogram or strongly under-dispersion or over- dispersion biases.

4. Conclusions

- Accuracy and sharpness are limited for all lead times. Improvements/worsenings with respect to the elementary forecast are small.
- Discrimination is good when lead time is 0, and decreases for lead time 1, except over Turkey and North Africa.
- The shape of the rank histograms is similar for the different lead times. A strong under-forecasting bias is present for both lead times.

Next.. Repeat the same procedute with other state-of-the-art seasonal forecasting systems.

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References:

[1] Calì Quaglia et al (2021). Temperature and precipitation seasonal forecasts over the Mediterranean region: added value compared to simple forecasting methods. *Clim. Dyn.* **58**, 2167–2191.

[2] The Copernicus Climate Change Service (C3S) seasonal forecast service: https://www.ecmwf.int/en/forecasts/dataset/c3s-seasonal-forecasts

[3] Wilks DS (2011) Statistical methods in the atmospheric sciences. Academic Press Inc, London