Update: Downscaling of the SEAS5 to the Greater Region of Luxembourg

Verification

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Outcome of meeting August

Outcome of meeting

Reference dataset

E-OBS dataset is insufficient, as there are not enough observations and therefore the interpolated results are lacking.

ERA5 would be a reasonable choice for substitution, as it is a well described and verified reanalysis. The data can be retrieved from the Copernicus[1] server. Details of dataset on later slides.

Verification metrics

Equations should be clearly stated.

As there were problems in description of the used RMSE in the metrics it is very important to explain and document way of using different verification measures.

[1] https://cds.climate.copernicus.eu/

Outcome of meeting August

Forecast dataset

Temporal range of operational forecast not big enough, re-forecast for a bigger range would be more valuable.

The re-forecast of the SEAS5 dataset is also available on the Copernicus[2] server. It has a set of 25 ensemble members and a resolution of 1° x 1°. More details of dataset on later slides.

Literature reference

Identification of papers with similar problem of verification.

I go forward mainly but not only with the paper by Johnson et al. [13] on the verification of specifically the SEAS5 as I use the re-forecast dataset now.

[2] https://cds.climate.copernicus.eu/

Progress since meeting

Re-forecast download script

- Loops over months from initialization month (03/04/05/06) for 24 years as available through copernicus.eu (1993-2016)
- 25 ensemble members
- 6 hourly temporal resolution
- 1° spatial resolution

Progress since meeting

ERA5 download script

- Loops over months June, July and August for 24 years (1993-2016)
- Reanalysis without members (HRES reference data)
- Using 6-hourly temporal resolution
- 0.25° spatial resolution

Tasks of matching

- Split SEAS5 re-forecast into ensemble members, as they are not treated as a 4th dimension in raw dataset but integrated into "timeline"
- As the ERA5 is downloaded for each month, the files are merged into seasonal files = the files for June, July and August are concatenated
- Both are also downloaded in GRIB format and have to be transformed
- Reducing SEAS5 to JJA only (ERA5 was already downloaded matching only these months)
- For the SEAS5 there is an ensemble mean created

Tasks of matching

- The SEAS5 files with no leadtime = from June to January have the problem that there is no data for the first 6 hours, so the first timestep (01.06.yyyy 00:00 to 06:00) is excluded for all files
- The remapping is here reduced to a resizing as the re-forecast dataset is very course (1°) and interpolating it to the resolution of the before used gridfile would increase the file size without gaining new information
- The 6-hourly data for ERA5 and SEAS5 is each concatenated into a file with all years per file so that these files are the base for further calculations
  - all_years_refc_03/04/05/06_season.nc
  - all_years_era5_season.nc

Tasks of matching

- These files are split up for the individual months and conclude with these files:
  - all_years_refc_03/04/05/06_06/07/08.nc
  - all_years_era5_06/07/08.nc

Verification metrics

Mainly after Johnson et al. (2019) [13], Jolliffe (2012) [14] and Wilks (2011) [33]

- Deterministic measures (ensemble mean)
  - RMSE
  - MAE
  - ME
- Probabilistic measures (ensemble members)
  - Reliability diagrams (not done yet)
  - ACC (not done yet)
  - CRPS
  - Brier score (not done yet)

Equations after which deterministic metrics is calculated:

- Root Mean Squared Error (RMSE)[14]

$$RMSE = \sqrt{\frac{1}{M}\sum_{t=1}^{M}(f_{i,t} - o_{i,t})^2}$$

where M is the number of points in the grid, f/$o_{i,t}$ the value at time t and location i and demonstrates variations in performance across a spatial domain

Equations after which determinitsic metrics is calculated:

- Mean Absolute Error (MAE)[14]

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|f_{i,t} - o_{i,t}\right|$$

- Mean Error (ME) - Bias

$$ME = \frac{1}{N}\sum_{t=1}^{N}(f_{i,t} - o_{i,t})$$

Equations after which probabilistic metrics is calculated:

- Reliability diagram
  - Visualization of probabilities of event
- Anomaly correlation coefficient (ACC) [14]

$$ACC_t = \frac{\sum_{i=1}^{M}(f_i' - \bar{f}_i')(o_i' - \bar{o}_i')}{M s_{f'} s_{o'}}$$

Equations after which probabilistic metrics is calculated:

- Continuous Ranked Probability Score
  - Used within the SpecsVerification package in R[3]
  - Equation within the package is taken from Hersbach (2000) [12] Following data was used:
    - seasonal average at each grid point for each year
    - CRPS map estimated over 24 independent events
    - CRPS averaged over the region for each lead time
    - ERA5 as reference data

[3] https://www.rdocumentation.org/packages/SpecsVerification

Equations after which probabilistic metrics is calculated:

- Brier Score
  - Will also be used within the SpecsVerification package in R[4]

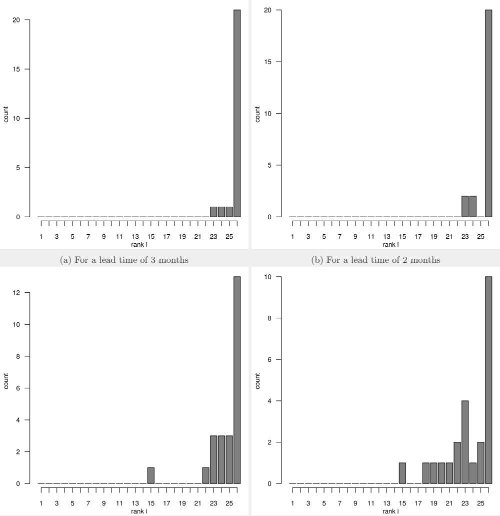
[4] https://www.rdocumentation.org/packages/SpecsVerification

Results

Rank histograms

- Taking a look at general quality of ensemble
- Visualization of reliability
- Therefor the data was:
  - averaged over the respective domain and each year
  - organized in a matrix with
    rows = years and
    columns = ensemble members

Results - first check of data



(a) For a lead time of 3 months

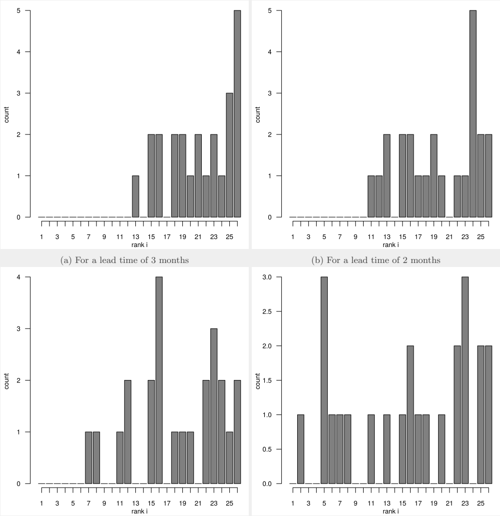
(b) For a lead time of 2 months

(c) For a lead time of 1 month

(d) For no lead time

Figure 9: Rank histograms for the different lead times of the European domain. Calculated over the years of 1993-2016.

Results - first check of data



(a) For a lead time of 3 months

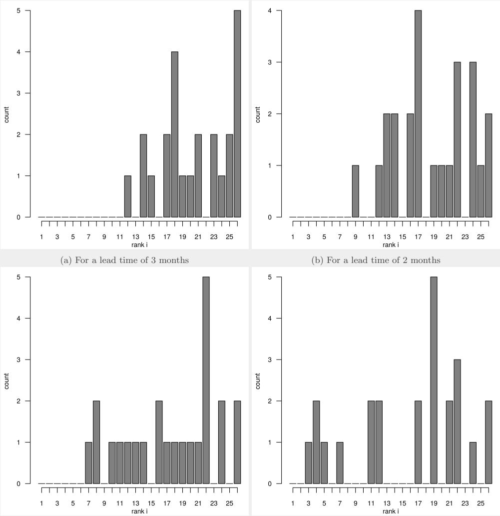
(b) For a lead time of 2 months

(c) For a lead time of 1 month

(d) For no lead time

Figure 9: Rank histograms for the different lead times of the Mid-European domain (PRUDENCE).
Calculated over the years of 1993-2016.

Results - first check of data



(a) For a lead time of 3 months

(b) For a lead time of 2 months

(c) For a lead time of 1 month

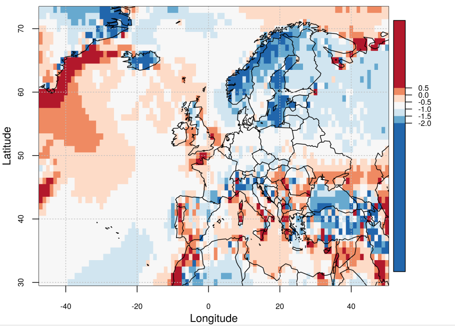
(d) For no lead time

Figure 9: Rank histograms for the different lead times of the Greater Region domain
Calculated over the years of 1993-2016.

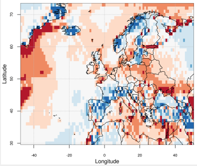
Rank histograms - Analysis

- Show tendency of a higher ensemble reliability with decreasing lead time
- Seem to indicate a cold bias -> Re-forecast is too cold
- Reliability is better with a mean over smaller regions

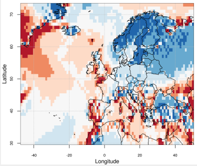
Results - Europe - 3 months leadtime - Bias



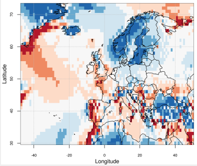
(a) For the seasonal mean over JJA



(b) For a monthly mean over June



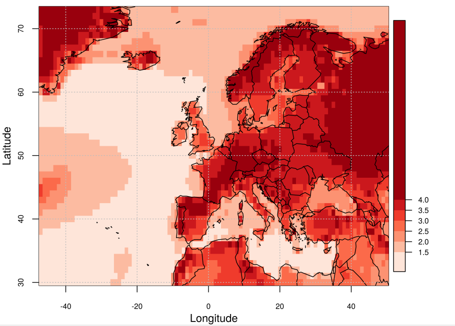
(c) For a monthly mean over July



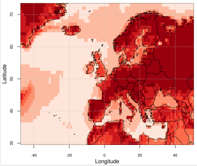
(d) For a monthly mean over August

Figure 6: Bias for a lead time of 3 months for different mean periods.
Calculated over the years of 1993-2016.

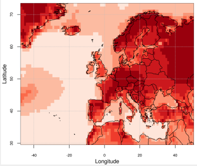
Results - Europe - 3 months leadtime - MAE



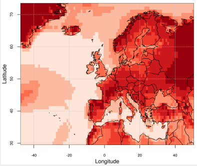
(a) For the seasonal mean over JJA



(b) For a monthly mean over June



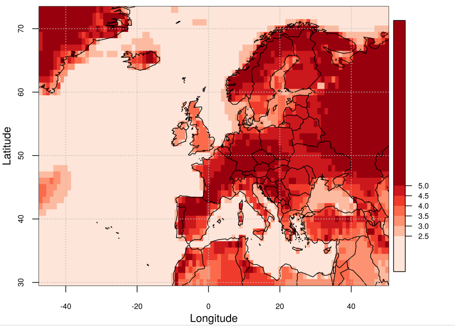
(c) For a monthly mean over July



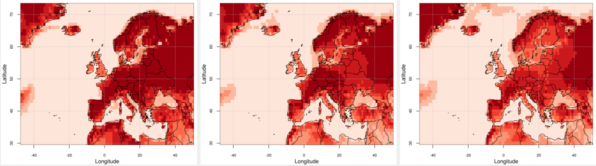
(d) For a monthly mean over August

Figure 7: Mean absolute error for a lead time of 3 months for different mean periods.
Calculated over the years of 1993-2016.

Results - Europe - 3 months leadtime - RMSE



(a) For the seasonal mean over JJA



(b) For a monthly mean over June (c) For a monthly mean over July (d) For a monthly mean over August

Figure 8: Root mean square error for a lead time of 3 months for different mean periods. Calculated over the years of 1993-2016.

Spatial distribution of metrics - Analysis

- Example results for only the lead time of 3 months
- Bias:
  - Cold bias can be seen especially over elevated regions like the Scandinavian mountain range, Greenland's mountain range, Iceland and the Alps
  - Warm bias for the east coast of Greenland for all lead times
  - The values for the bias seem to be in an acceptable range in general
- MAE:
  - The elevated regions seem to be also the source of biggest frequent errors
- RMSE:
  - It seems that the MAE already accounts for the biggest infrequent errors, as the RMSE marks the biggest values in the same regions as the MAE

Mean of metrics over the domain of Europe

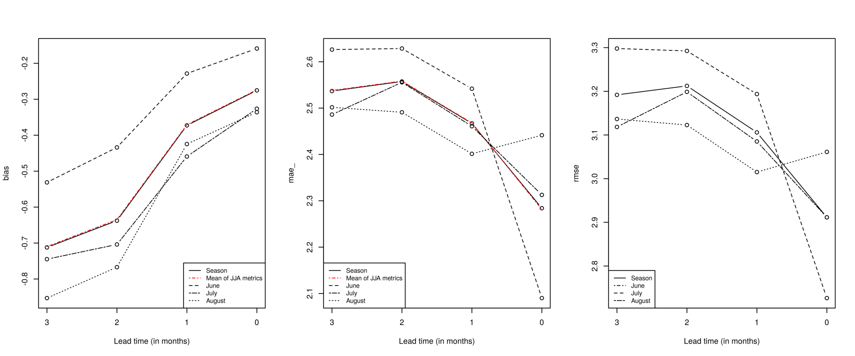


Figure: Spatial mean over the respective metrics for the different lead times.

Mean of metrics over the domain of Europe - Analysis

- Bias:
  - The cold bias can also be seen in a spatial average
  - Bias in general decreasing with decreasing lead time
- MAE:
  - June, July and the seasonal mean of the MAE show decreasing values with no lead time, but an overall stagnation/increase for the 1/2 months lead times
- RMSE:
  - The RMSE is behaving like the MAE

Mean of metrics over the domain of the Greater region

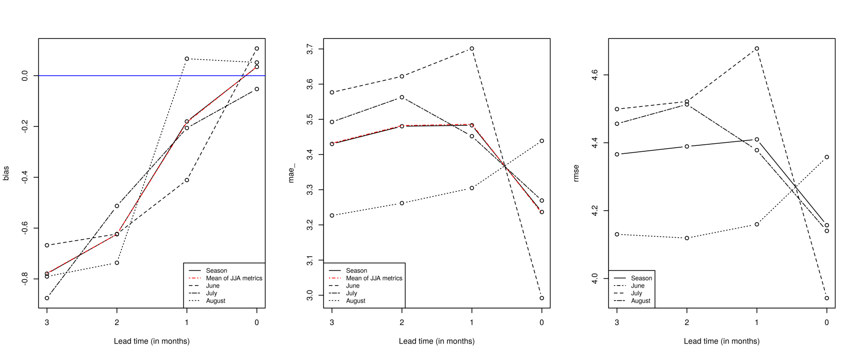


Figure: Spatial mean over the respective metrics for the different lead times.

Results - Greater Region - CRPS

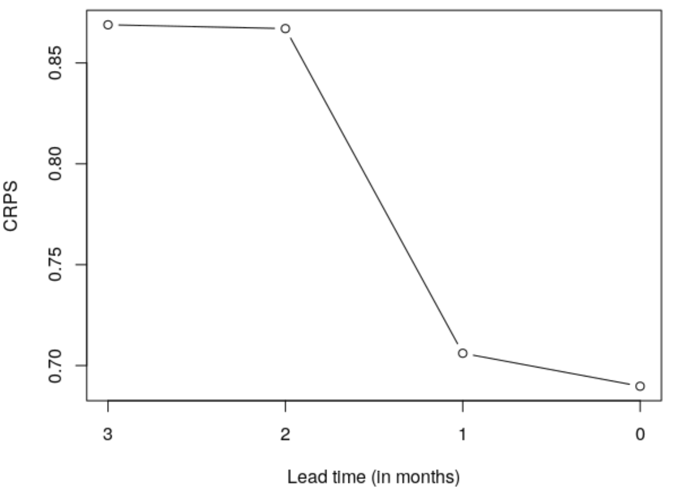


Figure: Spatial mean over CRPS for different lead times.

Results - Greater Region - CRPS

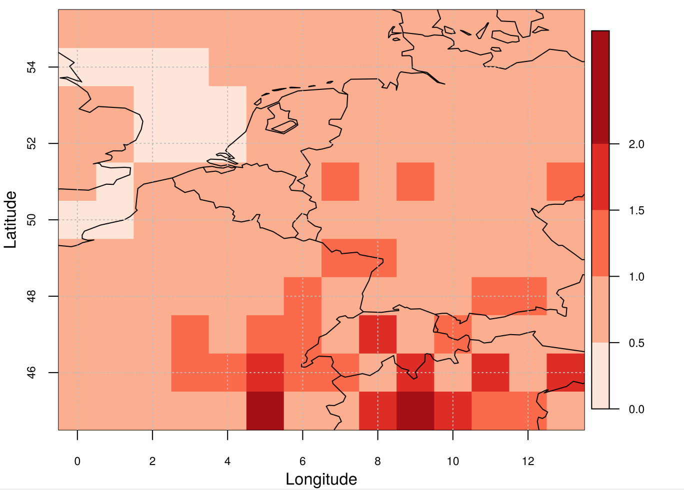


Figure: CRPS map for a lead time of 3 months.

Results - Greater Region - CRPS

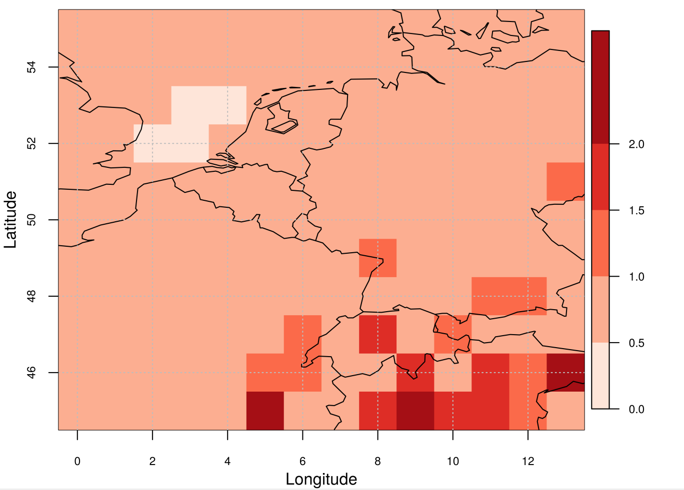


Figure: CRPS map for a lead time of 2 months.

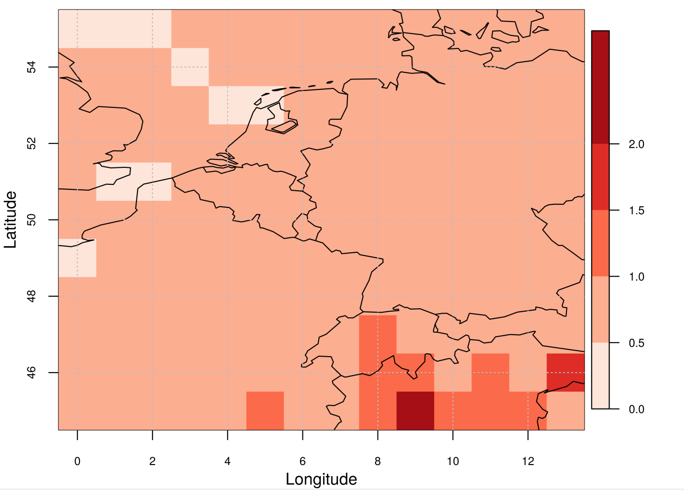


Figure: CRPS map for a lead time of 1 month.

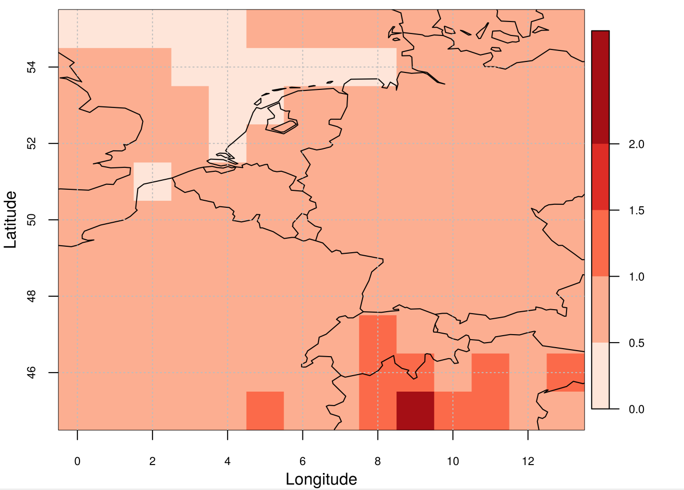


Figure: CRPS map for a lead time of 0 months.

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