Update: Verification of a Seasonal Forecast System

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Overarching Goal

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Verification of a seasonal forecast product over Europe, Mid-Europe and the Greater Region

- Determination of the global forecast system's skill, using a valid reference dataset
- Determination of a dynamically downscaled seasonal forecast product's skill, using the verification metrics defined for the first step

Introduction

Brief introduction to seasonal forecasting

- Long-range outlook of changes in Earth system
- Averaging variables over months or seasons, instead of using high-frequency data
- Using slow-varying components of the system (e.g. seas surface temperature)
- Coupled numerical models are used (model consisting of atmospheric model, ocean model, sea ice model, etc.)
- The ensemble-approach is used to estimate uncertainties

Working Tools

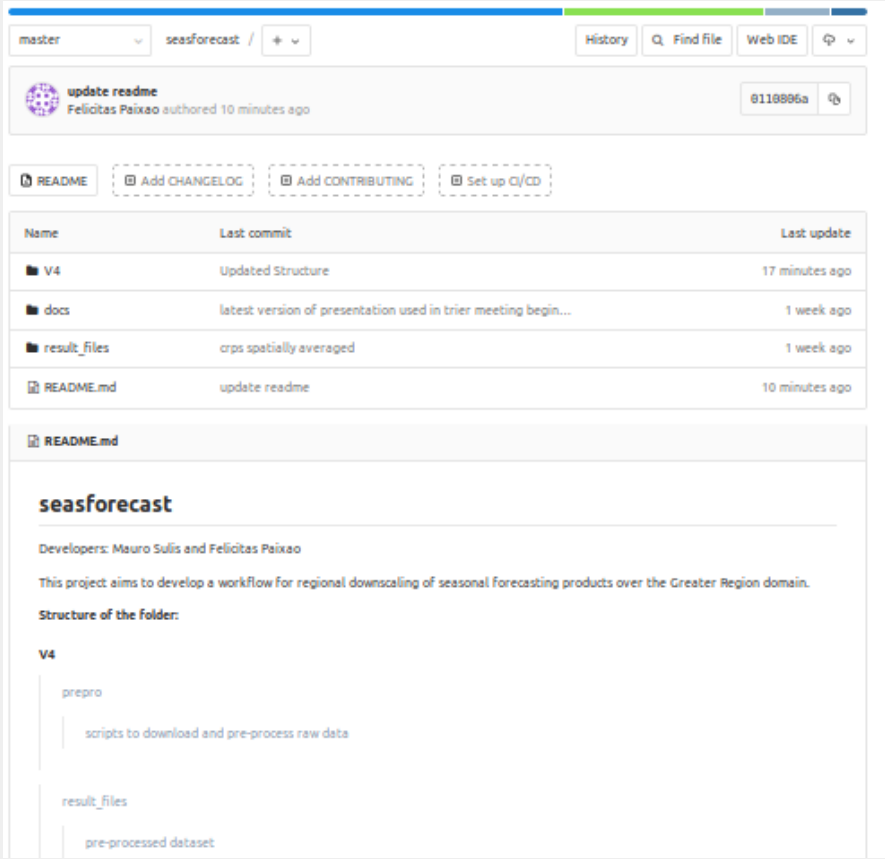
Working Tools

Programming Languages

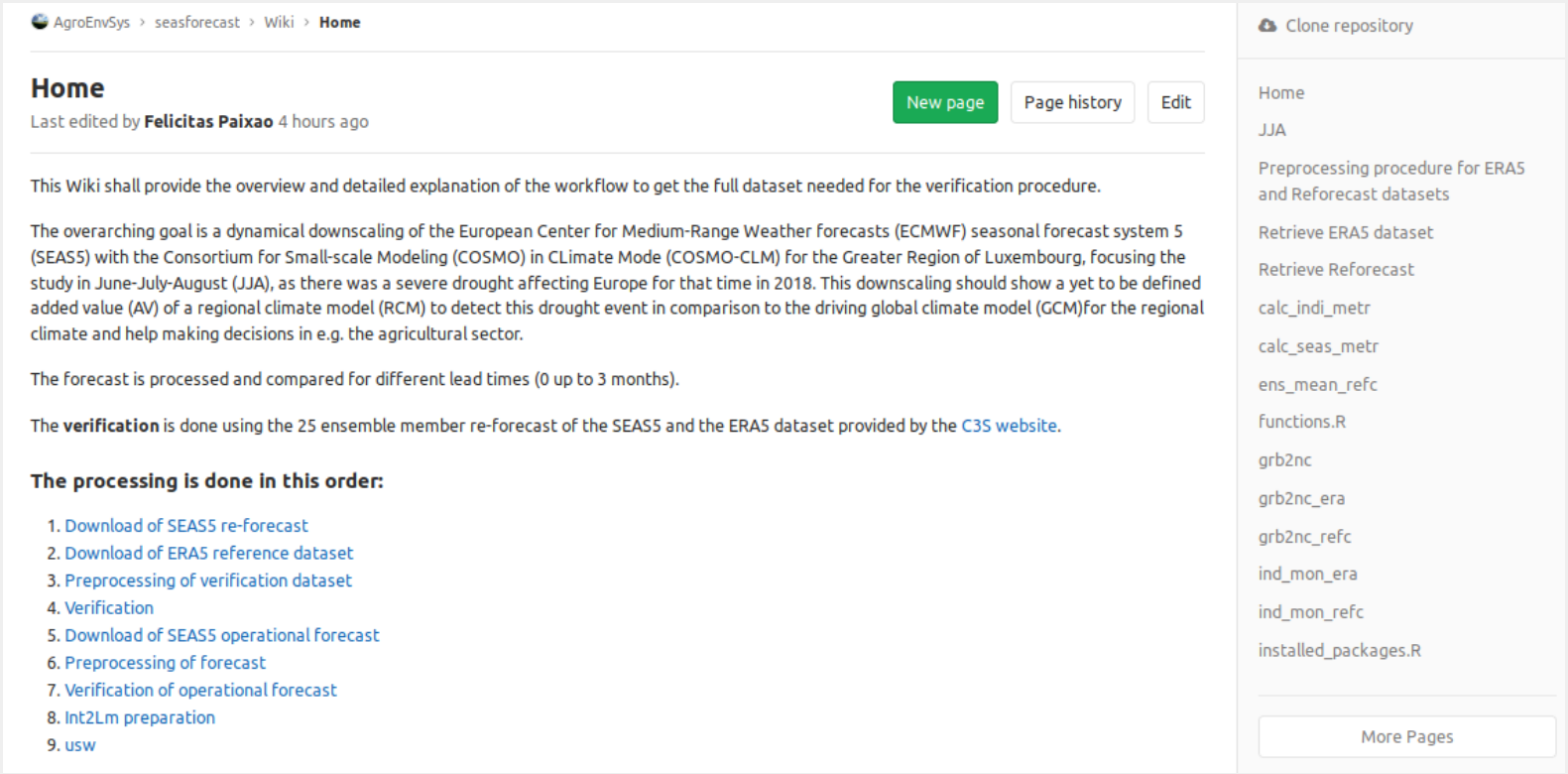
- R
- Bash
  - CDO
  - NCO
- Python
- LaTex

GitLab

- Access to scripts, literature, part of the dataset, the WIKI and more



GitLab



High performance computing (HPC) server

- To handle the dataset(-size) the computing is done on the LIST HPC server

Dataset description

Dataset description - Raw Dataset

ERA5 - reference dataset

- ERA5_yyyy_mm.grib
- 1993 - 2016 (yyyy)
- for June, July and August (mm)
- for variables 2 meter temperature (t2m) and total precipitation (tp) (v)
- 6 hourly temporal resolution
- 0.25° spatial resolution
- Reanalysis without members (HRES reference data)

Seasonal forecast

- refc_yyyy_lt_v.grib
- 1993 - 2016 (yyyy)
- for initialization months March, April, May and June (lt)
- for variables t2m, tmax and tp (v)
- t2m : 6 hourly temporal resolution
- tp;tmax : 24 hourly temporal resolution
- 1° spatial resolution
- 25 ensemble members

Dataset description - Preprocessed Dataset

EU/GR/ME

- **06/07/08/season**
  - ERA5
    - all_years_era5_range_v.nc
    - range: June/July/August/Season
    - v : t2m or tp
  - Seasonal forecast
    - all_years_refc_lt_range_v.nc
    - for initialization months March, April, May and June (lt)

```
[paixao@login01 season]$ ls
all_years_era5_season_p.nc     all_years_refc_04_season_t.nc
all_years_era5_season_t.nc     all_years_refc_05_season_p.nc
all_years_refc_03_season_p.nc  all_years_refc_05_season_t.nc
all_years_refc_03_season_t.nc  all_years_refc_06_season_p.nc
all_years_refc_04_season_p.nc  all_years_refc_06_season_t.nc
```

Figure: Example for the files in the folder EU/season/

Verification Metrics

Verification metrics

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

- Deterministic measures (ensemble mean)
  - RMSE
  - MAE
  - ME (Bias)
- Probabilistic measures (ensemble members)
  - Reliability diagrams
  - CRPS
  - Brier score

Specifications - Deterministic metrics:

- 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

Specifications - Deterministic metrics:

- Mean Absolute Error (MAE)[14]

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

- Mean Error (ME) - Bias

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

Specifications - Probabilistic metrics:

- Reliability diagram
  - Visualization of probabilities of event
- Continuous Ranked Probability Score
  - Used within the SpecsVerification package in R[1]
  - 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
- Brier Score
  - Will also be used within the SpecsVerification package in R

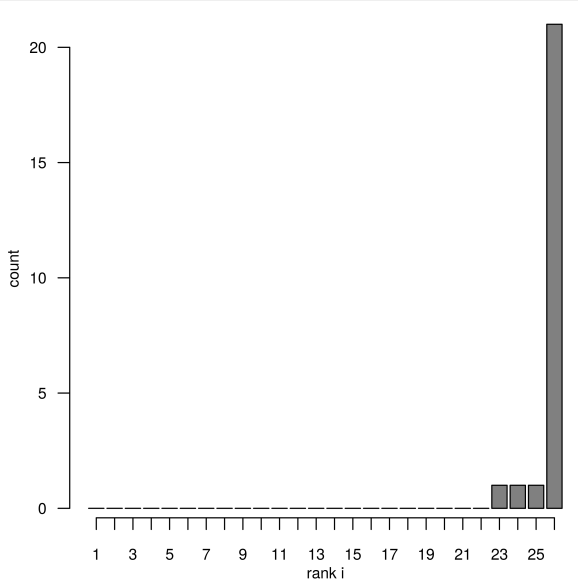
[1] https://www.rdocumentation.org/packages/SpecsVerification

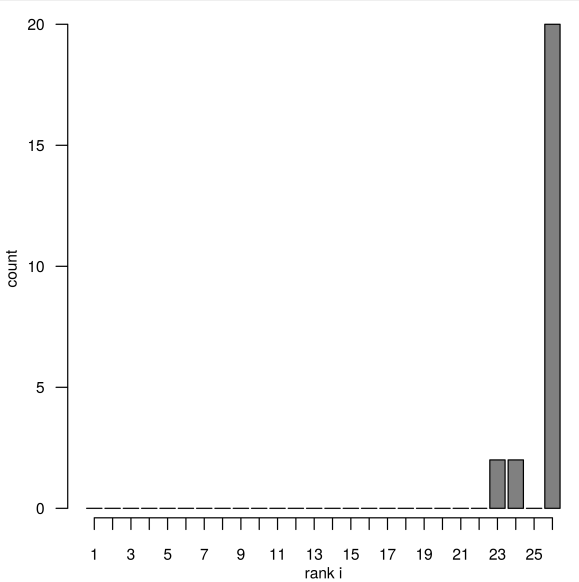
Results

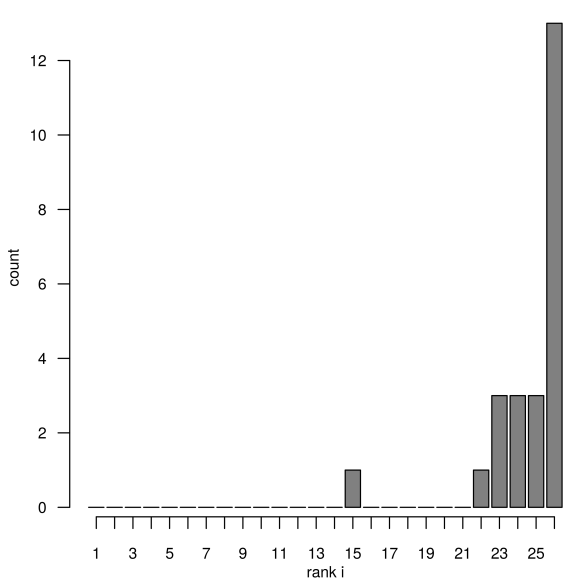
Rank histograms

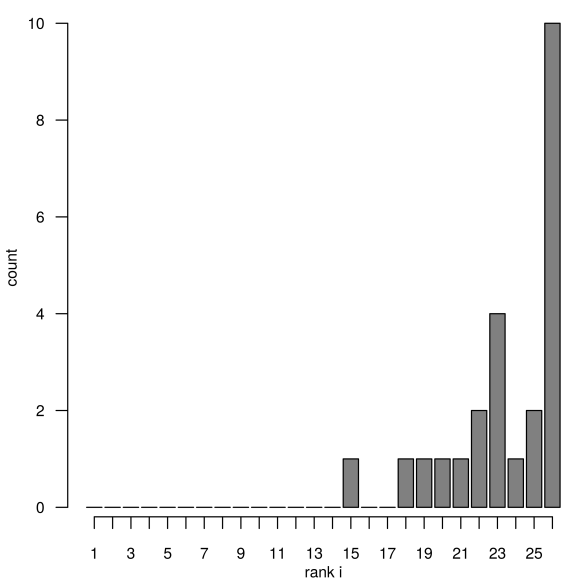
- Taking a look at general quality of ensemble
- Visualization of reliability
- Therefor the data was:
  - averaged over the respective domain and each year
  - organized in a matrix with
    rows = years and
    columns = ensemble members

Results - first check of data (EU)

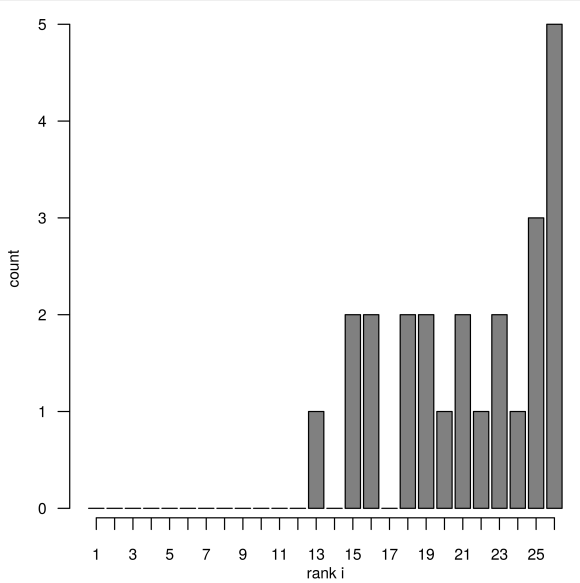


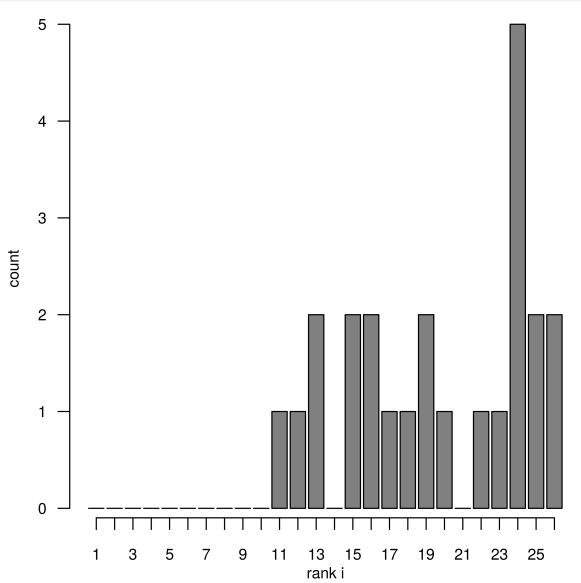


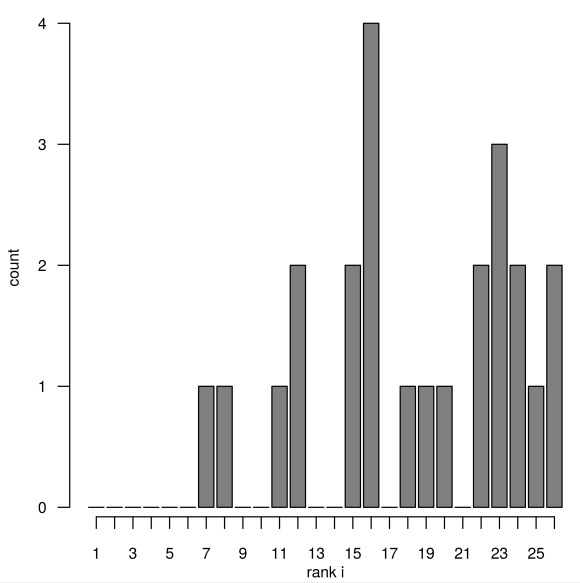


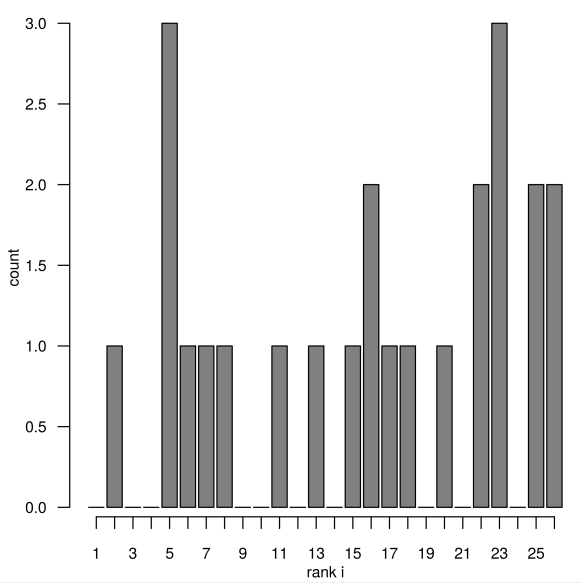


Results - first check of data (ME)

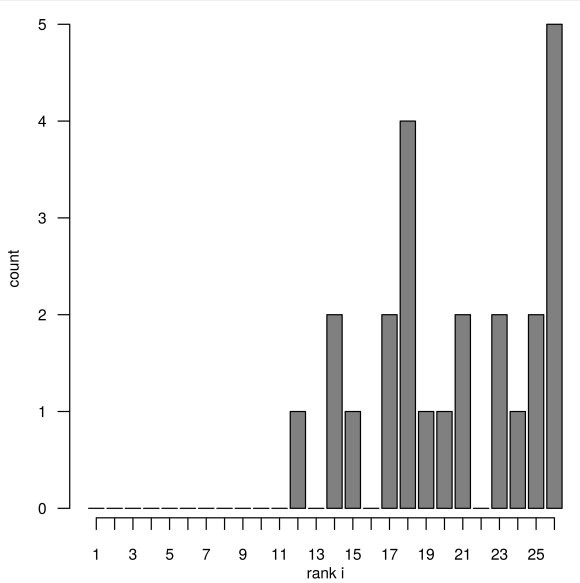


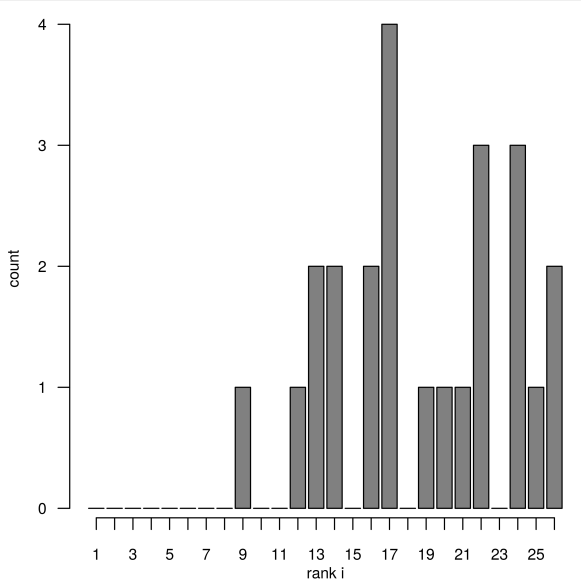


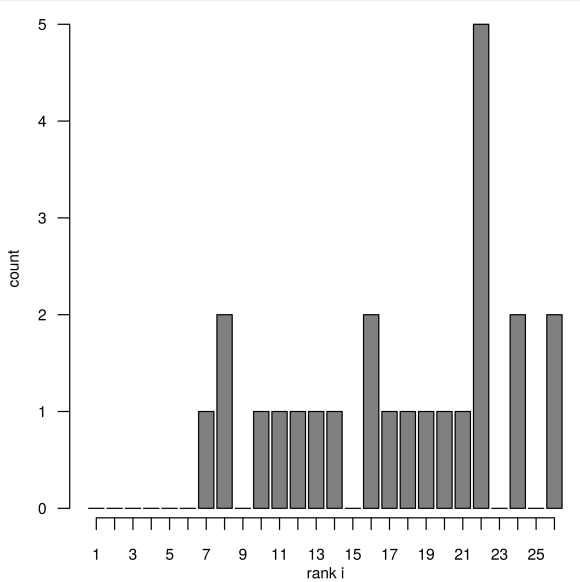


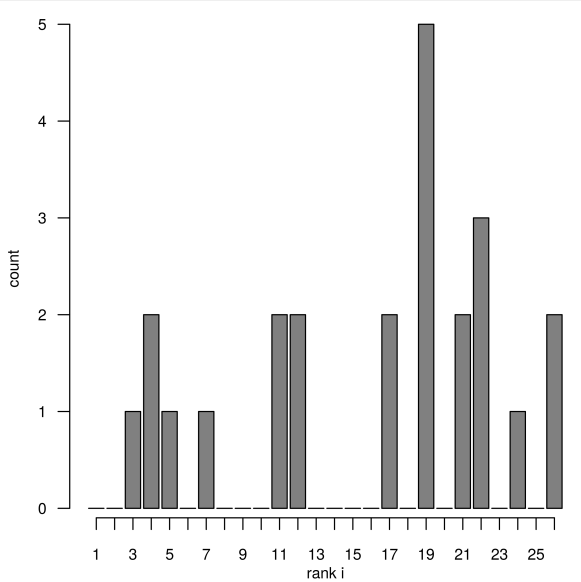


Results - first check of data (GR)





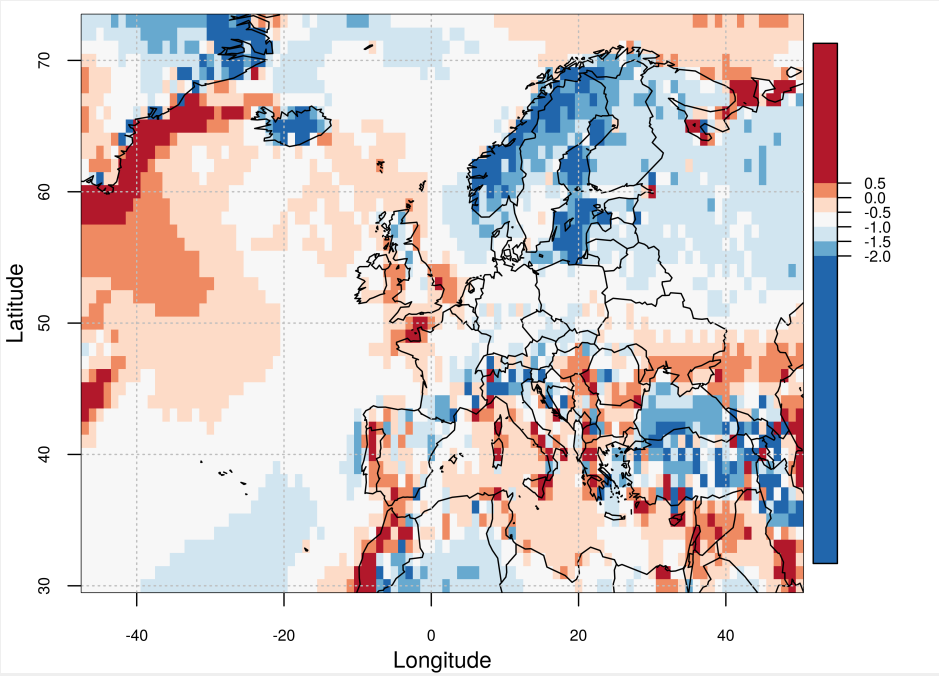




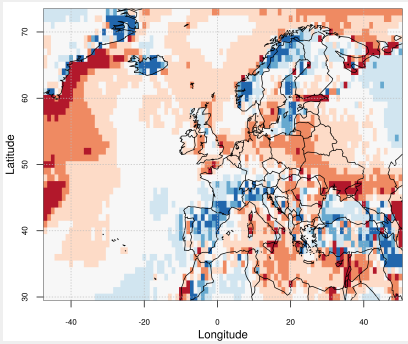
Rank histograms - Analysis

- 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

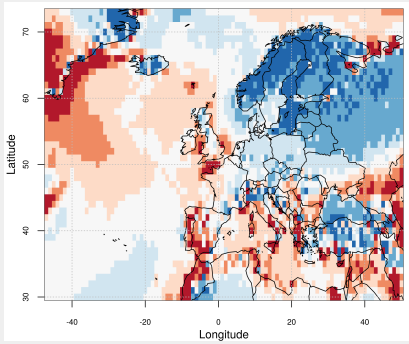
Results - Europe - 3 months leadtime - Bias



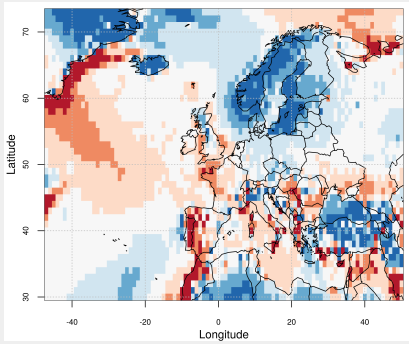
(a) For the seasonal mean over JJA



(b) For a monthly mean over June



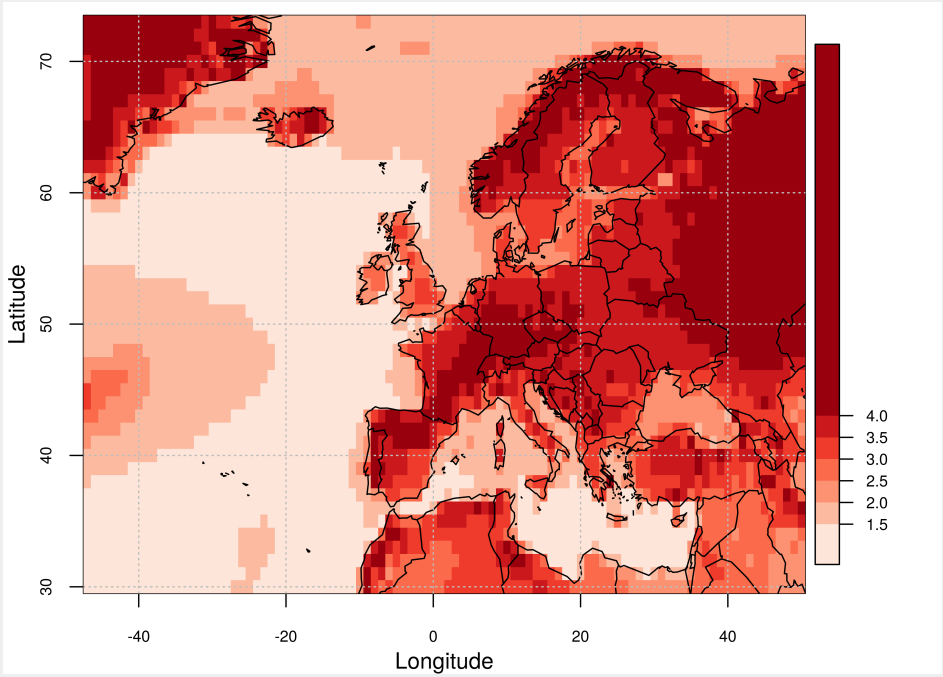
(c) For a monthly mean over July



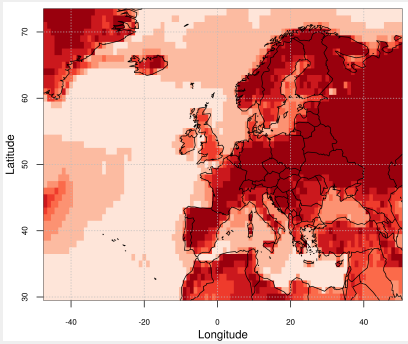
(d) For a monthly mean over August

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

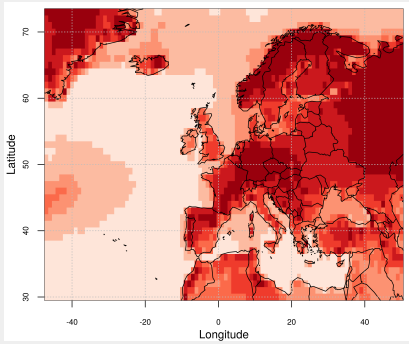
Results - Europe - 3 months leadtime - MAE



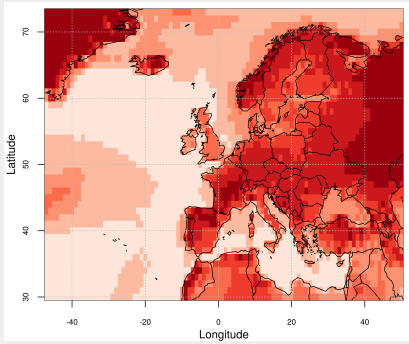
(a) For the seasonal mean over JJA



(b) For a monthly mean over June



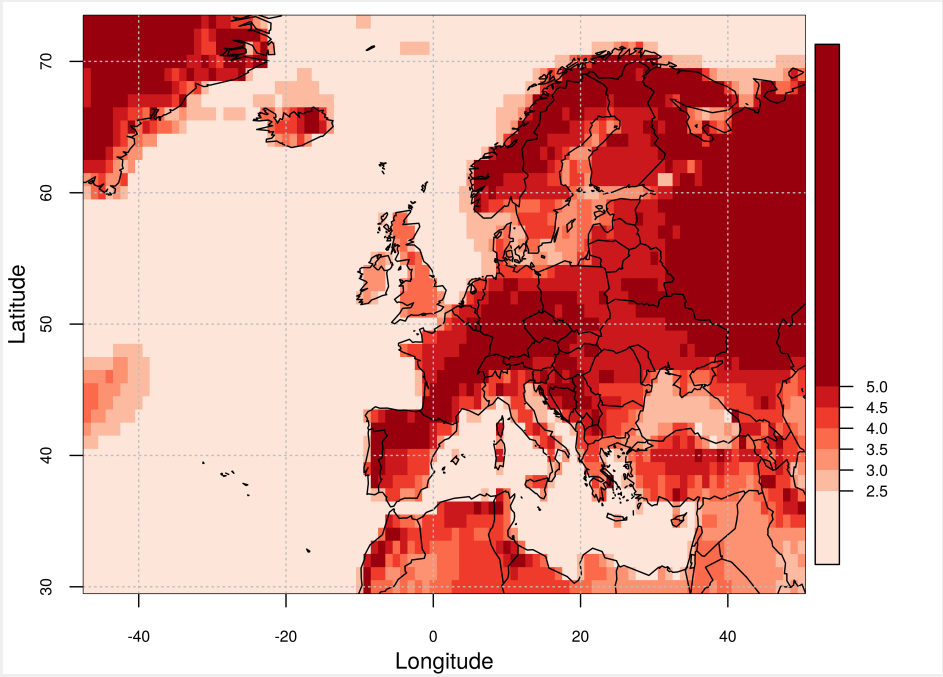
(c) For a monthly mean over July



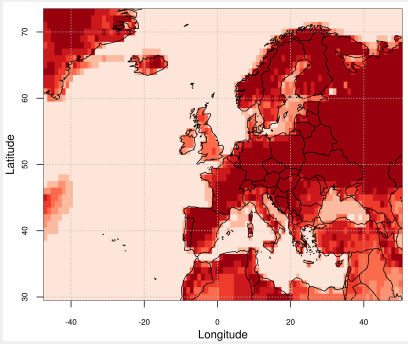
(d) For a monthly mean over August

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

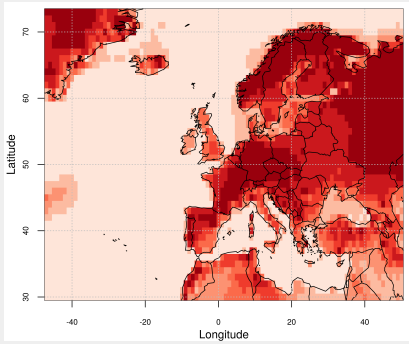
Results - Europe - 3 months leadtime - RMSE



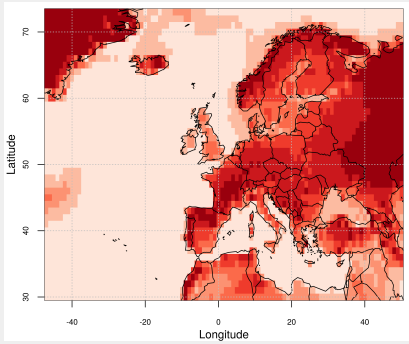
(a) For the seasonal mean over JJA



(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

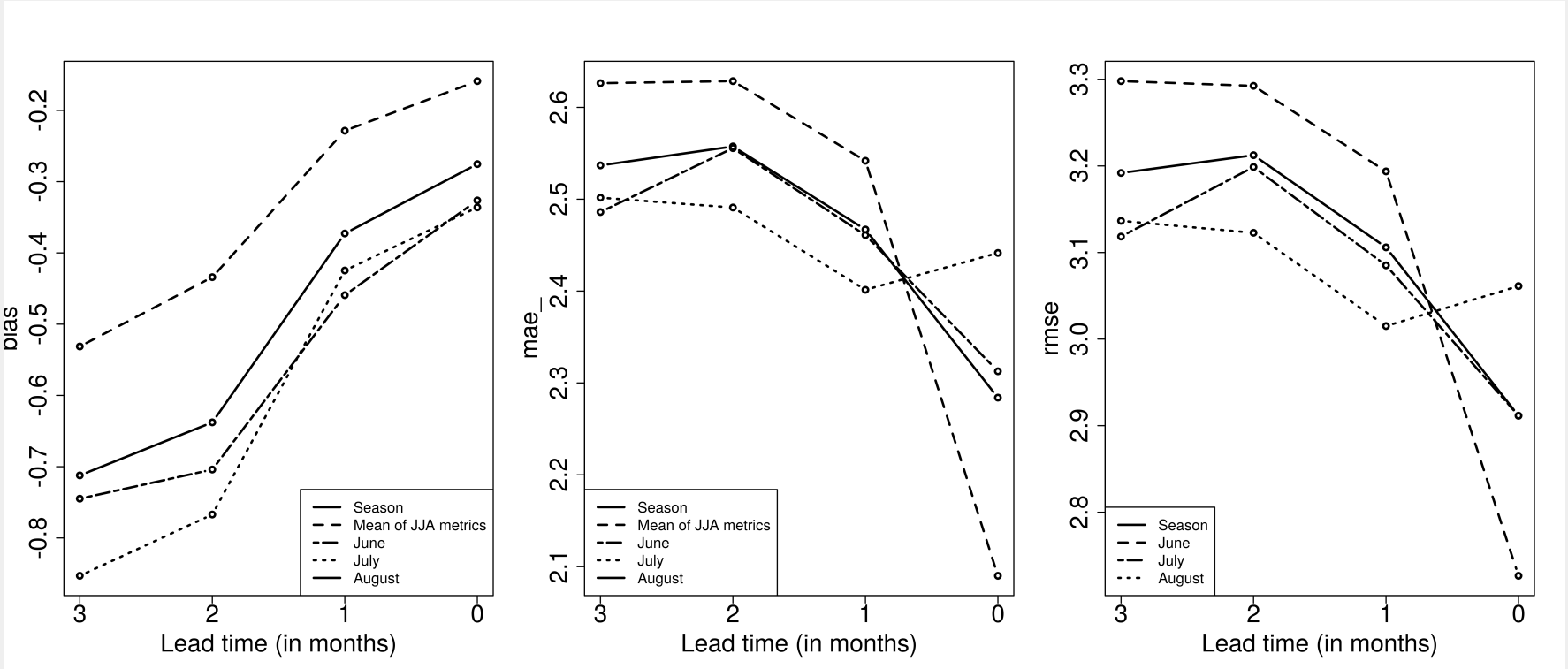


Figure: Spatial mean over the respective metrics for the different lead times.

Results - Europe

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

Results - Greater Region

Mean of metrics over the domain of the Greater region

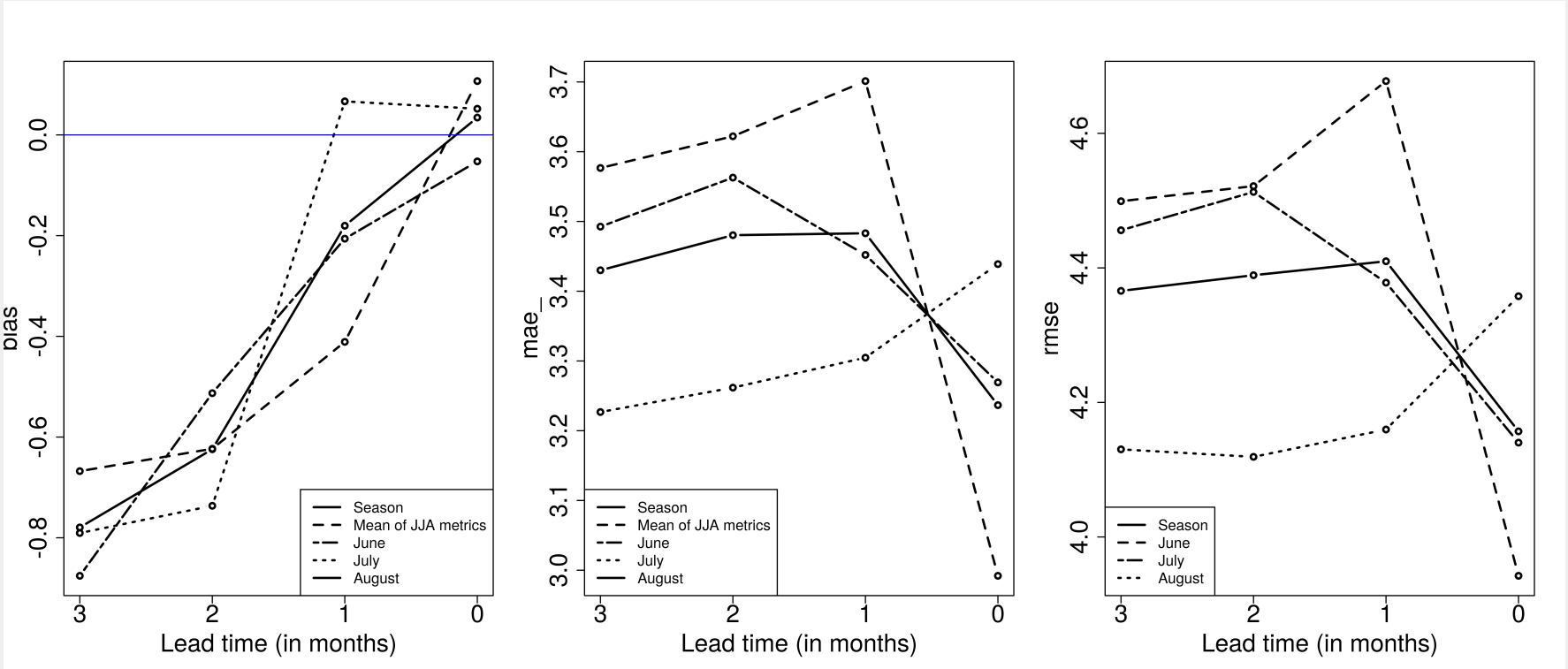


Figure: Spatial mean over the respective metrics for the different lead times.

Results - Greater Region - CRPS

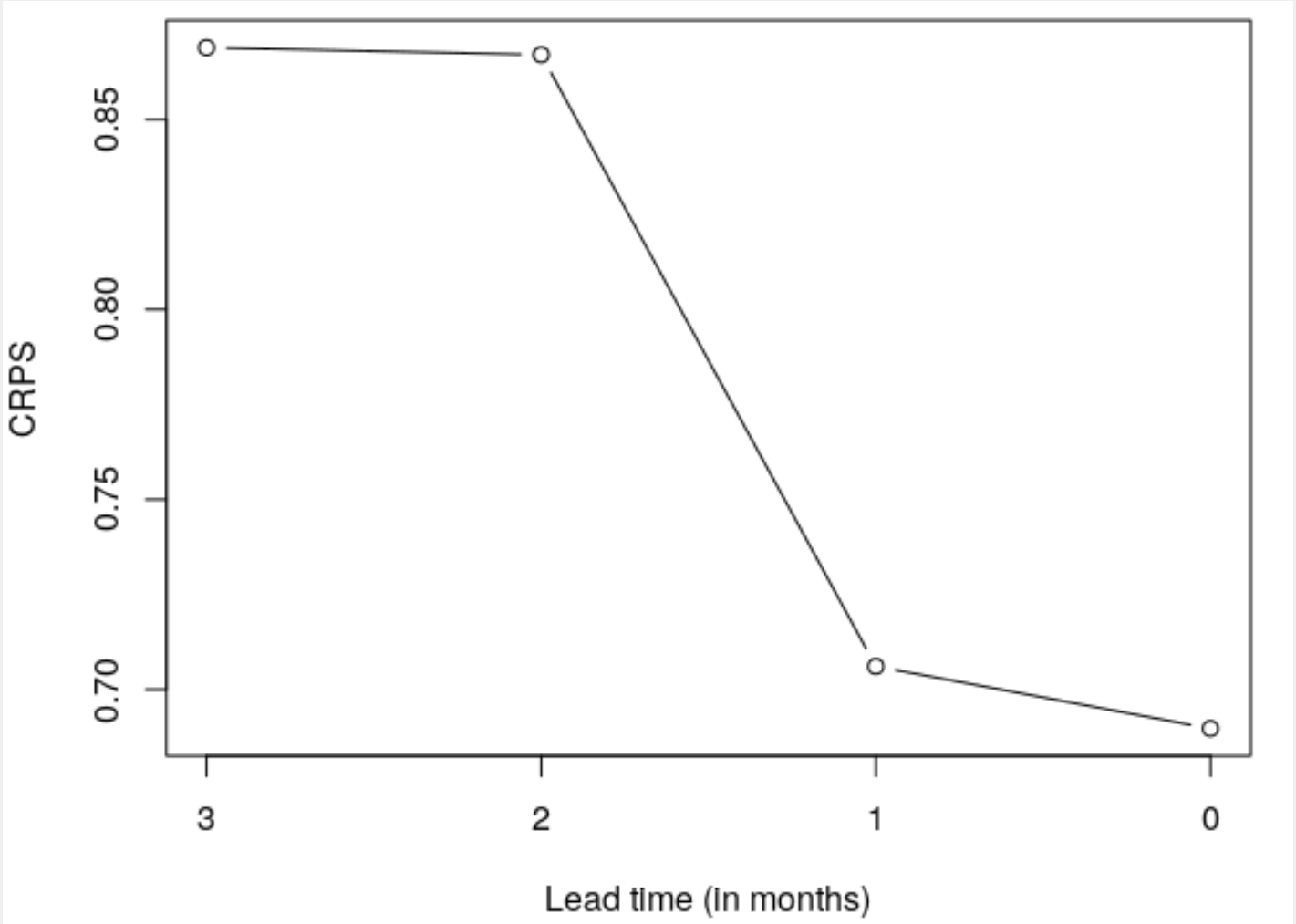


Figure: Spatial mean over CRPS for different lead times.

Results - Greater Region - CRPS

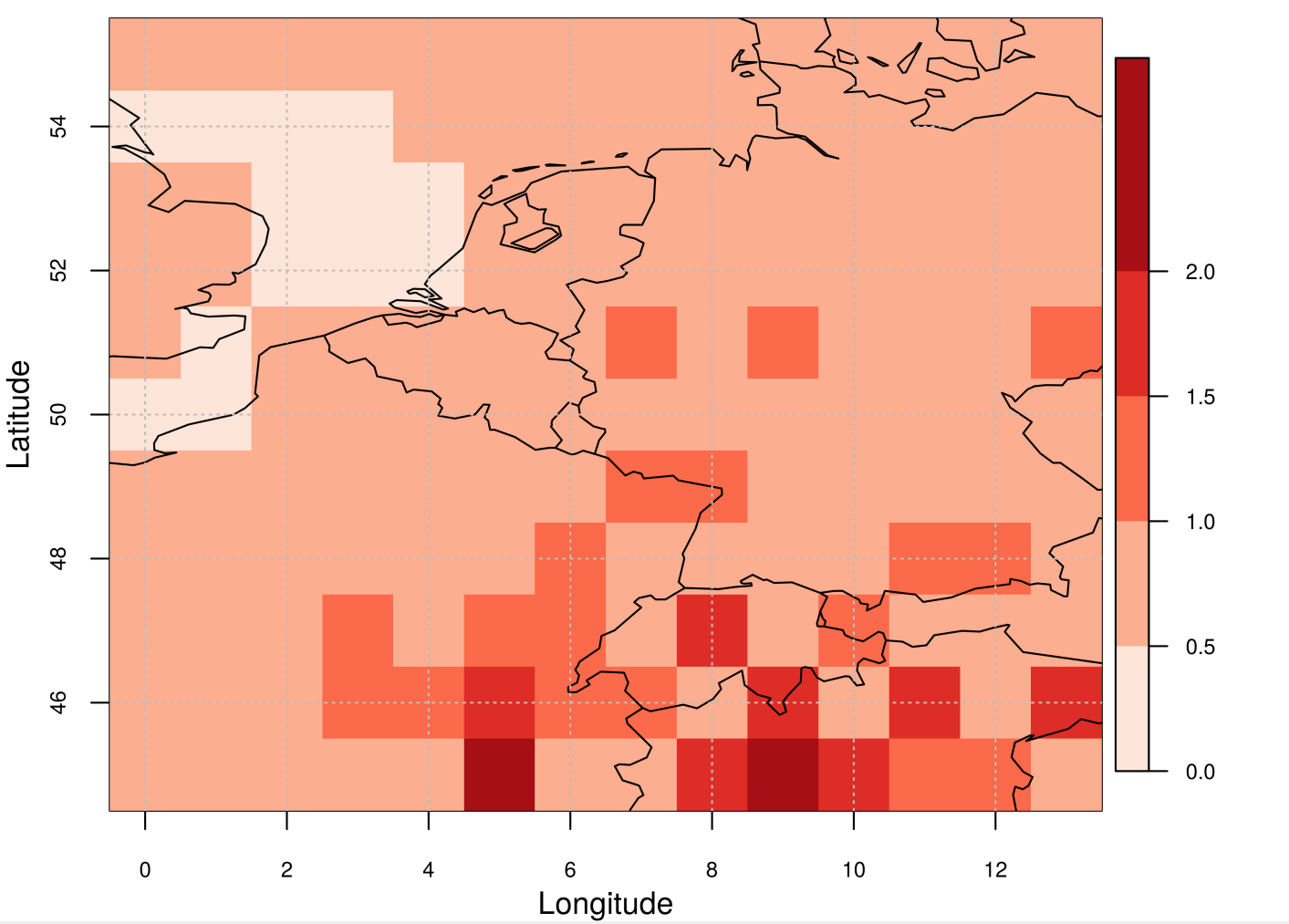


Figure: CRPS map for a lead time of 3 months.

Results - Greater Region - CRPS

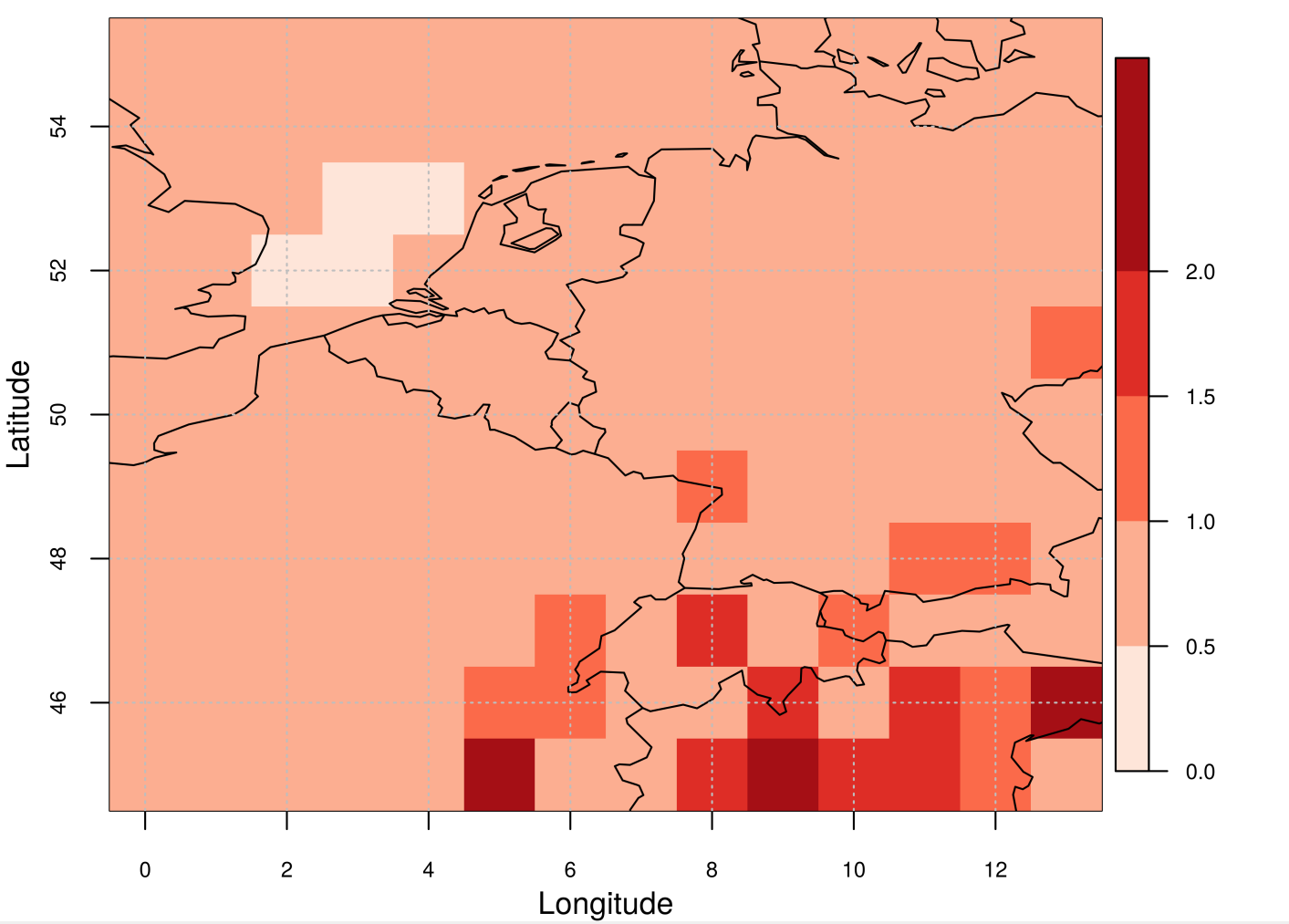


Figure: CRPS map for a lead time of 2 months.

Results - Greater Region - CRPS

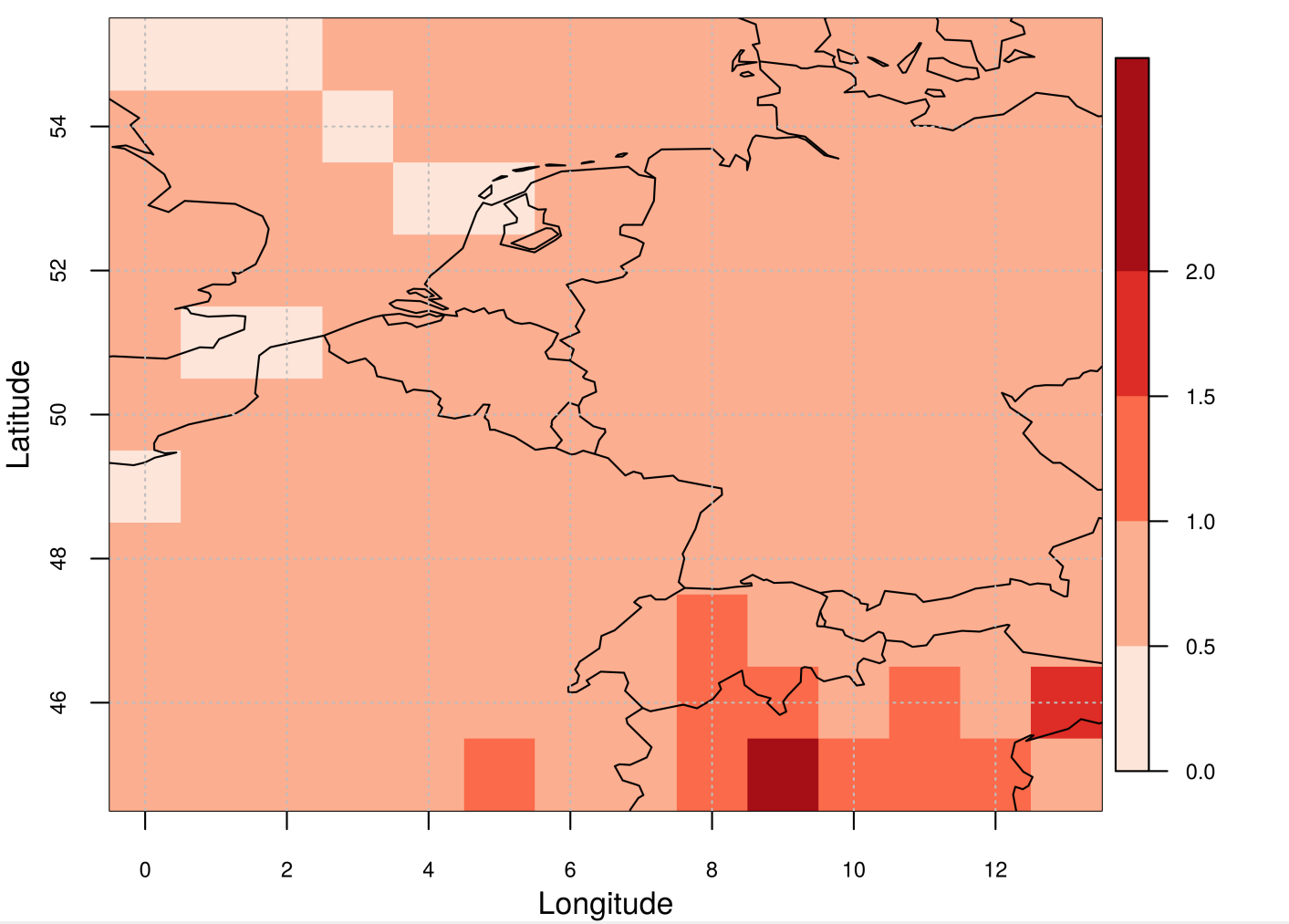


Figure: CRPS map for a lead time of 1 month.

Results - Greater Region - CRPS

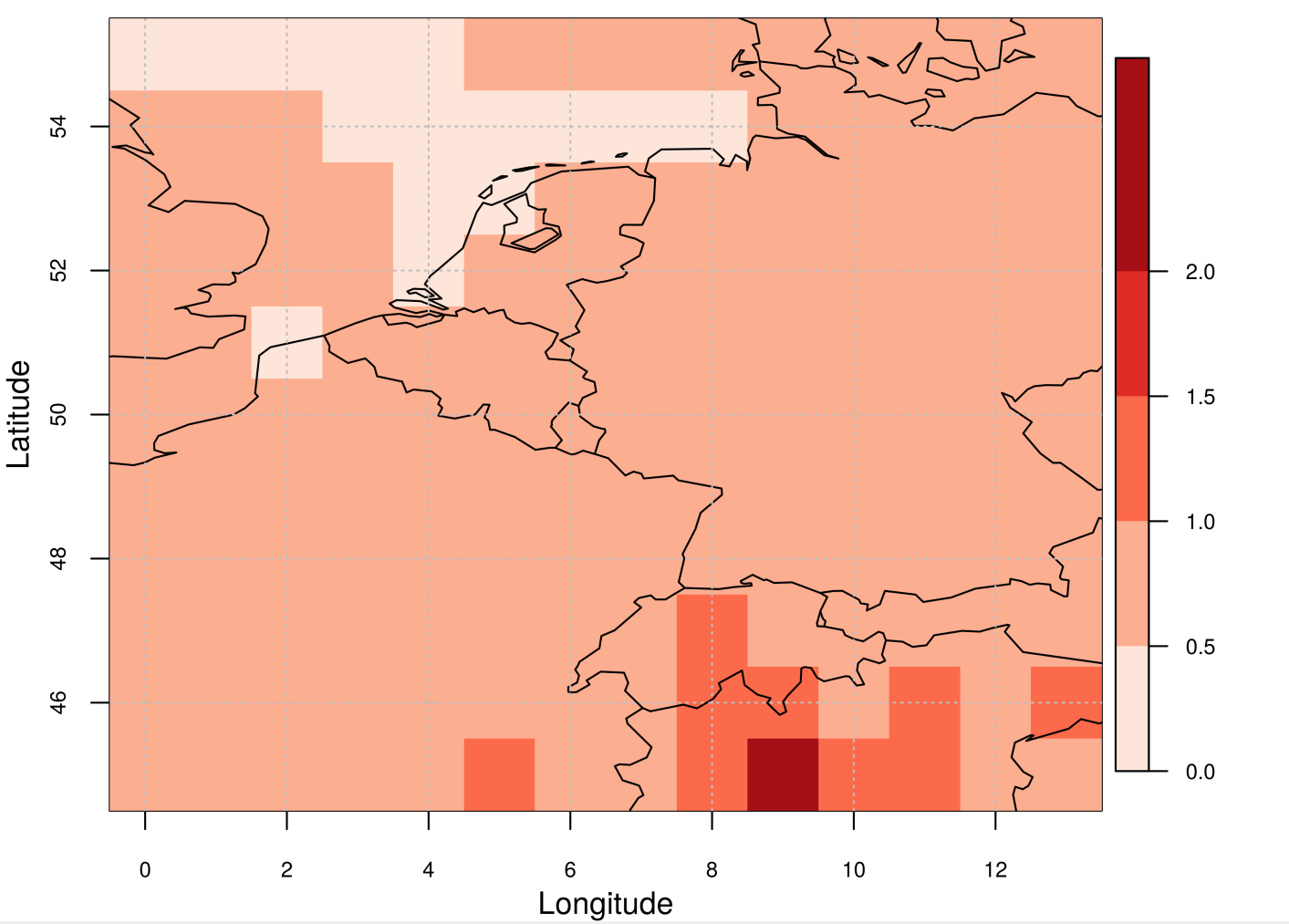


Figure: CRPS map for a lead time of 0 months.

Outlook

Outlook

- Working on
  - Verification Metrics:
    - Skill Score
    - CRPSS
    - Brier Score
    - Reliability diagrams
  - Variables
    - Daily maximum temperature
    - Total Precipitation
- Further tasks
  - Downscaling procedure
  - Determination of added value

A further collaboration with Dr. Mauro Sulis is highly appreciated.

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