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Sub-seasonal predictability of extreme European weather events

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The predictability of 2m-temperatures in Europe changes with the desired level of detail and the extremity and type of situation. A benchmark is set by evaluating ECMWF extended range forecasts, both raw and statistically post-processed, against predictands derived from the gridded E-OBS dataset. Statistical post-processing extends forecast horizons in winter with multiple days, depending on the location. Aggregation in space can make temperatures more predictable, whereas time aggregation only helps for moderate events.

Introduction

The forecast horizon of European surface weather variables is generally short and can conditionally be extended by sources of predictability. The horizon furthermore depends on the definition of the response variable and constitutes a trade-off between the threshold or extremity of the anomaly one wants to predict, the level of spatial and temporal resolution and the desired lead-time (Fig. 1).

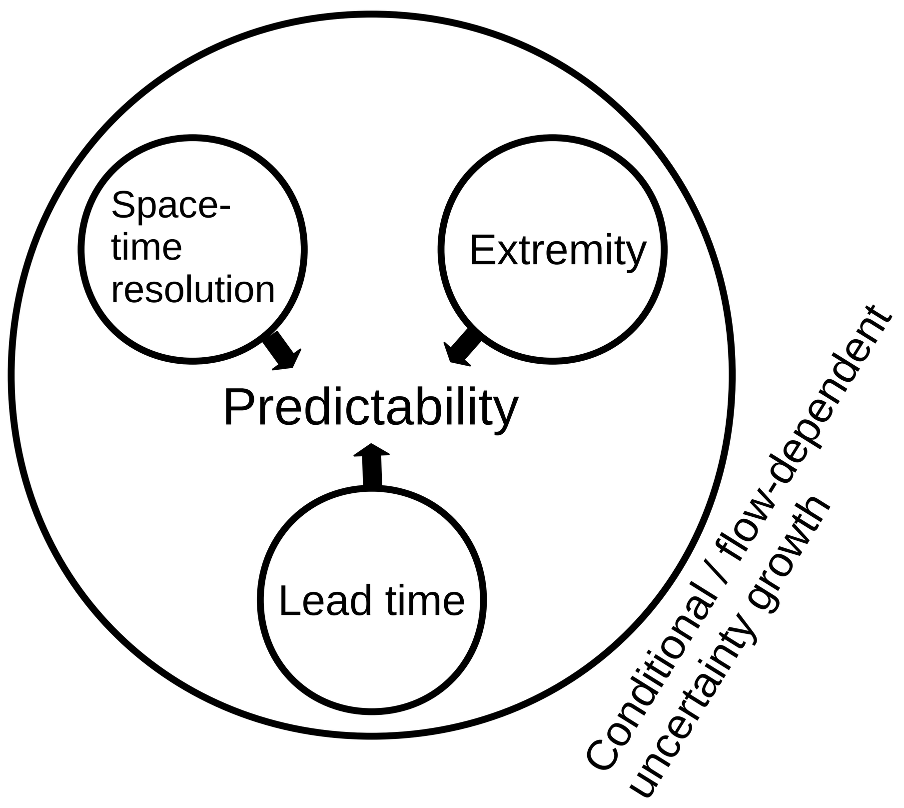

Figure 1: *Predictability trade-off in probabilistic forecasting of weather variables.*

Taking predictand definition as the starting point, this research aims to set a benchmark for predictability under different levels of detail, to find if there exists a general optimum, and to find if there is a special class of events which, for Europe, enjoys conditional extended predictability.

Constructed predictands

Daily mean 2m temperatures in DJF were obtained from the E-OBS dataset and were averaged in time and space according to Table 1. The same was done for the 20 year extended range re-forecasts of IFS cycle 41r1. Their overlapping period is 1995 till 2015.

Table 1: *Spatial and temporal resolutions of the predictand. Extremity in terms of local climatological quantiles.*

factor	unit	steps
time	[days]	1, 2, 3, 4, 5, 6, 7
space	[degrees]	0.25, 0.75, 1.25, 2, 3
extremity	[quantile]	0.1, 0.15, 0.25, 0.33, 0.66

To control the influence of extremity on predictability, we define various events based on the non-exceedence of the local climatological quantiles in Table 1. These climatologies were built from daily E-OBS in the period 1980 till 2015, and were also subject to aggregation (Fig. 2).

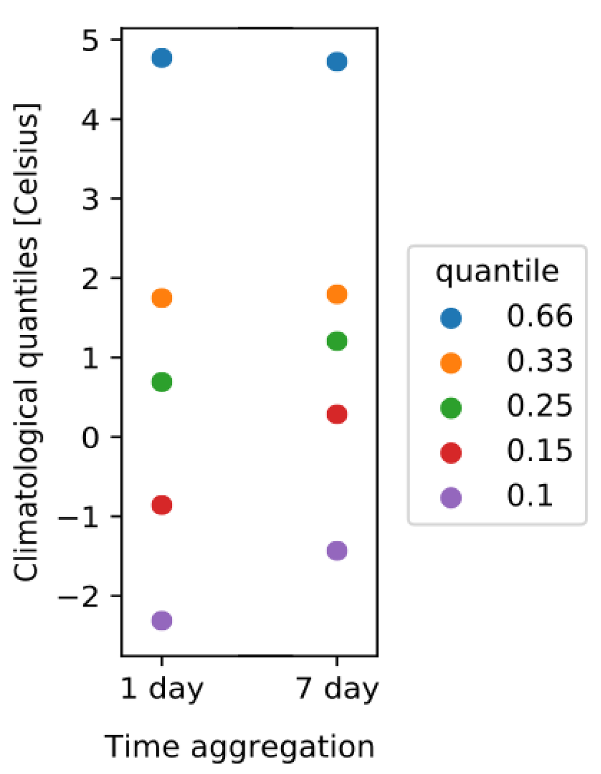

Figure 2: *Influence of temporal aggregation on the local climatological quantiles. Temperatures are for the twentieth day of the year, in the 0.75 degree gridbox closest to De Bilt, Netherlands.*

Post-processing and scoring

We investigate the predictability as forecast by the IFS. So to obtain a fairer estimate of the forecast horizon we correct biases and under- and over-dispersion with a Non-homogeneous Gaussian Regression (NGR)[1]. The normal distribution is assumed to have a location parameter μ_i and scale parameter σ_i that respectively vary with ensemble mean m_i and standard deviation s_i.

$$\mu_i = \alpha_1 + \alpha_2 \cdot m_i \quad (1)$$

$$\ln(\sigma_i) = \beta_1 + \beta_2 \cdot s_i \quad (2)$$

It is trained by minimization of its closed form continuous ranked probability score in a 3-fold cross-validation, where the model is trained on 2/3 and scored on the other 1/3 of the dataset. We score with the Brier score, which measures the MSE of probabilistic forecasts p_j [0 to 1] for binary events o_j [0 or 1] in the verification set of size n:

$$BS = \frac{1}{n}\sum_{j=1}^{n}(p_j - o_j)^2, \quad (3)$$

where the events are the non-exceedance of the local climatological quantiles for that day in the year. This score is then transformed to the Brier skill score with local climatology as reference forecast.

Forecast horizon

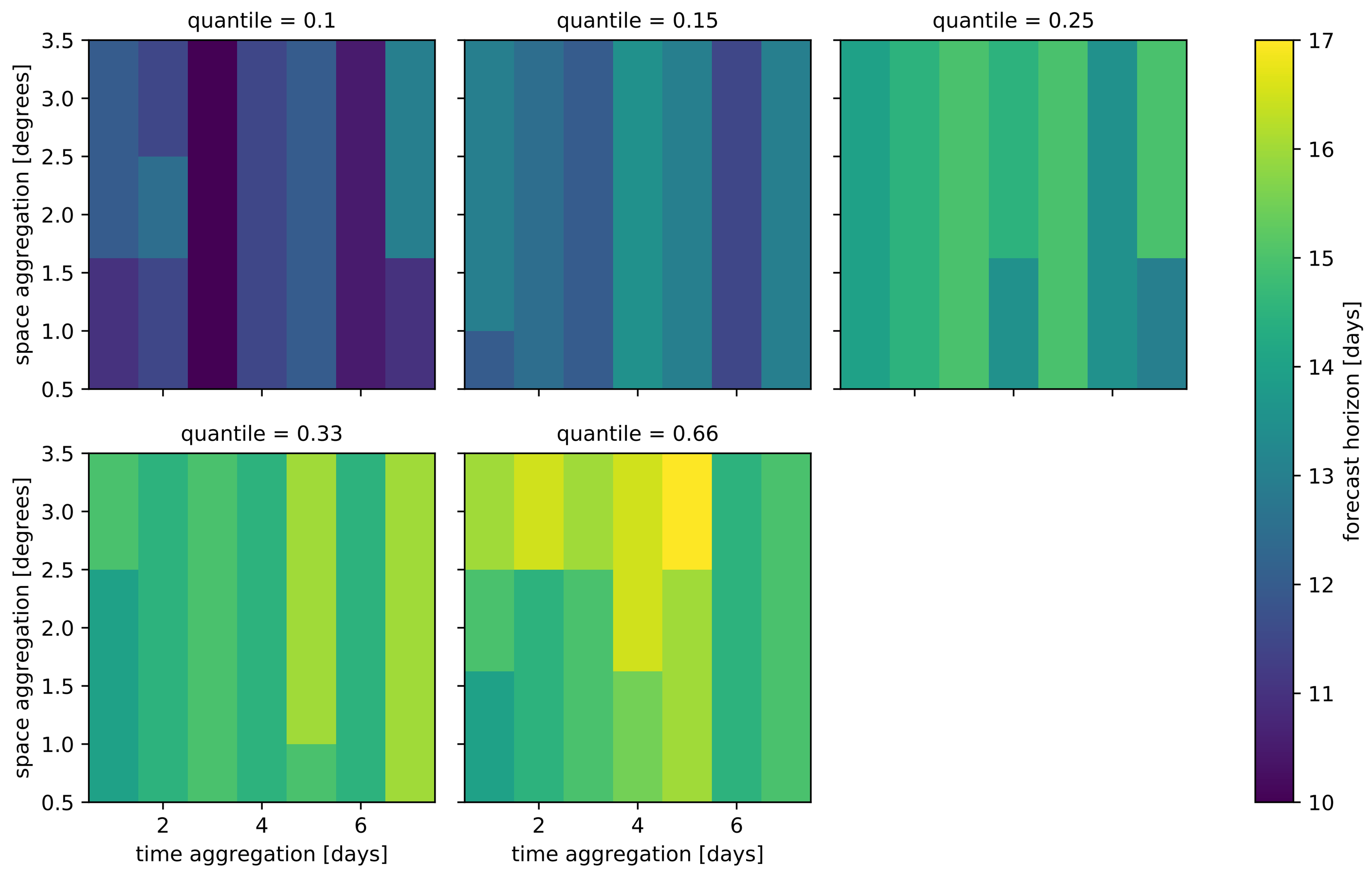

Figure 4: *Europe wide forecast horizons of the post-processed forecasts as influenced by time aggregation (x-axis), space aggregation (y-axis) and extremity. Each panel displays the horizons for a different quantile. The forecast horizon*[2] *is defined as the (mid-point) lead time before the spatial mean Brier Skill Score drops below 0.05.*

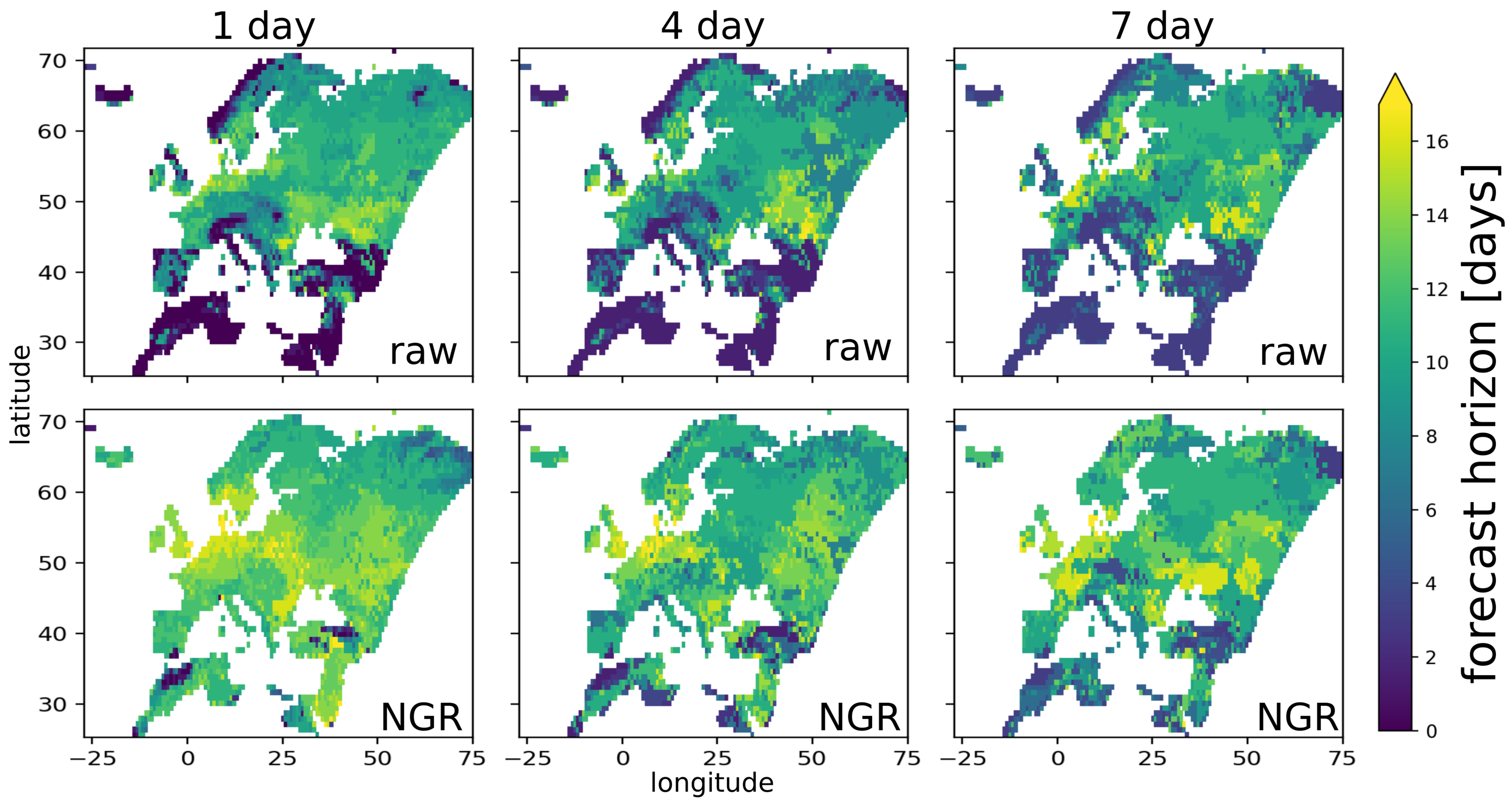

Figure 5: *Local forecast horizons for the 0.15 quantile on a 0.75 degree grid as influenced by post-processing and temporal aggregation. The upper row displays raw ECMWF forecasts and the lower row the post-processed forecasts. The forecast horizon*[2] *is defined as the (mid-point) lead time before the local Brier Skill Score drops below 0.05.*

Forecast skill

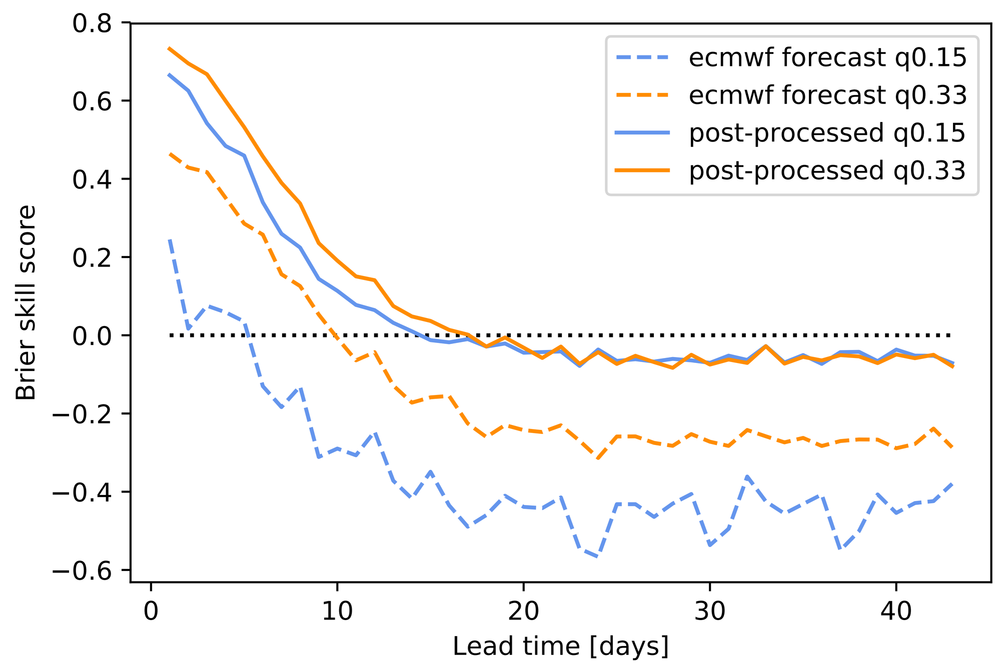

Figure 3: *Europe wide skill of the ECMWF and post-processed forecasts for two quantiles on a 2 degree spatial aggregation and 4 day temporal aggregation.*

Outlook

In this general benchmark no clear temporal aggregation optimimum was found. We therefore will extend the analysis to summer temperatures, with time-space-maxima instead of means. We will also investigate heatwave classifications at varying resolutions, to see if such events have conditionally extended forecast horizons.

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[1] *Gneiting et al. 2005, Monthly Weather Review.* [2] *Buizza and Leutbecher. 2015, Quarterly Journal of the Royal Meteorological Society.*