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Supplement of

Remember the past: a comparison of time-adaptive training schemes for non-homogeneous regression

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Supplement A: Post-processing of daily precipitation sums

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Abstract

The study presented in the manuscript "Remember the past: A comparison of time-adaptive training schemes for non-homogeneous regression" compares three widely-used training approaches with the classical sliding-window model for the application of post-processing near-surface air temperature forecasts across Central Europe. While the normal distribution is typically employed for post-processing air temperatures, this supplement extends the study by post-processing daily precipitation sums using a zero left-censored Gaussian distribution. Despite the different characteristics of daily precipitation sums and the alternative response distribution, the results are very similar to the ones for 2 m temperature forecasts and, hence, nicely support the conclusions given in the paper.

Keywords: Non-homogeneous regression, training data, sliding training window, post-processing, regression splines, ensemble forecasts, daily precipitation sums.

1. Introduction

This supplement extends the comparison study presented in the main manuscript by performing the same evaluation for daily precipitation sums employing an alternative response distribution.

As in the main manuscript the temporal evolution of the estimated coefficients is shown for two stations with different site characteristics followed by the analysis of the predictive performance. The results of all training schemes is evaluated in terms of the continuous ranked probability score (CRPS) conditional on the three data sets with and without the change in the horizontal resolution of the ensemble prediction system (EPS) on March, 8, 2016, as well as grouped for stations classified as topographically plain, mountain foreland, and alpine site. As a reminder, the different training-schemes are briefly summarized as follows:

- *Sliding-window:* The classical *sliding-window* approach as introduced by Gneiting, Raftery, Westveld III, and Goldman (2005) uses solely the n most recent days prior to the day of interest as training data to estimate the statistical models.
- *Regularized sliding-window:* The regularized adaption of the classical *sliding-window*

approach stabilizes the estimation based on early stopping in statistical learning. In this study, it is applied in its original version where the coefficients of the previous day are used as starting values and the optimizer is stopped after a single iteration (Scheuerer 2014).

- *Sliding-window plus:* In order to stabilize the coefficient estimates and to address seasonal effects, data from previous years are additionally included in the training data set. In contrast to the classical *sliding-window* approach, the most recent n days prior to estimation and a respective $(2n + 1)$ days interval centered around the day of interest over the previous years available are used to estimate the coefficients (Vogel, Knippertz, Fink, Schlueter, and Gneiting 2018; Möller, Spazzini, Kraus, Nagler, and Czado 2018).
- *Smooth model:* Rather than adapting the training data set, the *smooth model* makes use of all historical data in combination with cyclic regression splines which allows the coefficients to smoothly evolve over the year.

In comparison to the main manuscript, to account for potentially long periods without precipitation at a specific site, we use a training length of $n = 80$ days in the sliding-window approaches for post-processing daily precipitation sums. This is in the order of common choices in the literature (e.g., Baran and Nemoda 2016) and exactly two times the length employed for post-processing 2 m temperature forecasts as presented in the main manuscript.

2. Methodology and data

To account for non-negative values, the large fraction of zero observations, and the heavy-tailed distribution of precipitation, we proceed as proposed by Stauffer, Mayr, Messner, Umlauf, and Zeileis (2017a): We power-transform observed and modeled daily precipitation sums (member-by-member) with an ad-hoc chosen power parameter of 2. This transformed precipitation y can be assumed to follow a zero left-censored Gaussian distribution $\mathcal{N}_0$,

$$y \sim \mathcal{N}_0(\mu, \sigma). \tag{1}$$

As in the manuscript, the two distribution parameters location μ and scale σ are expressed by the ensemble mean m and ensemble variance or standard deviation s, respectively:

$$\mu = \eta_\mu = \beta_0 + \beta_1 \cdot m, \tag{2}$$
$$\log(\sigma) = \eta_\sigma = \gamma_0 + \gamma_1 \cdot s, \tag{3}$$

with $\beta_\bullet$ and $\gamma_\bullet$ being the corresponding intercept and slope coefficients.

As covariates, we employ the ensemble mean m and the ensemble standard deviation s of bilinearly interpolated power-transformed daily precipitation sum forecasts issued by the global 50-member EPS of the European Centre for Medium-Range Weather Forecasts (ECMWF). Ensemble forecasts and corresponding observations are considered at 15 measurement sites located across Austria, Germany, and Switzerland. The data comprises three groups of five stations located either in plains, mountain foreland, and within mountainous terrain. An overview of the study area is provided in the main manuscript in Fig. 1. For training and validation, we assess forecast steps from +24 h to +72 h ahead on a 24 hourly temporal resolution for the EPS run initialized at 0000 UTC and use the same data period employed in the manuscript, from March 8, 2010 to March 7, 2019.

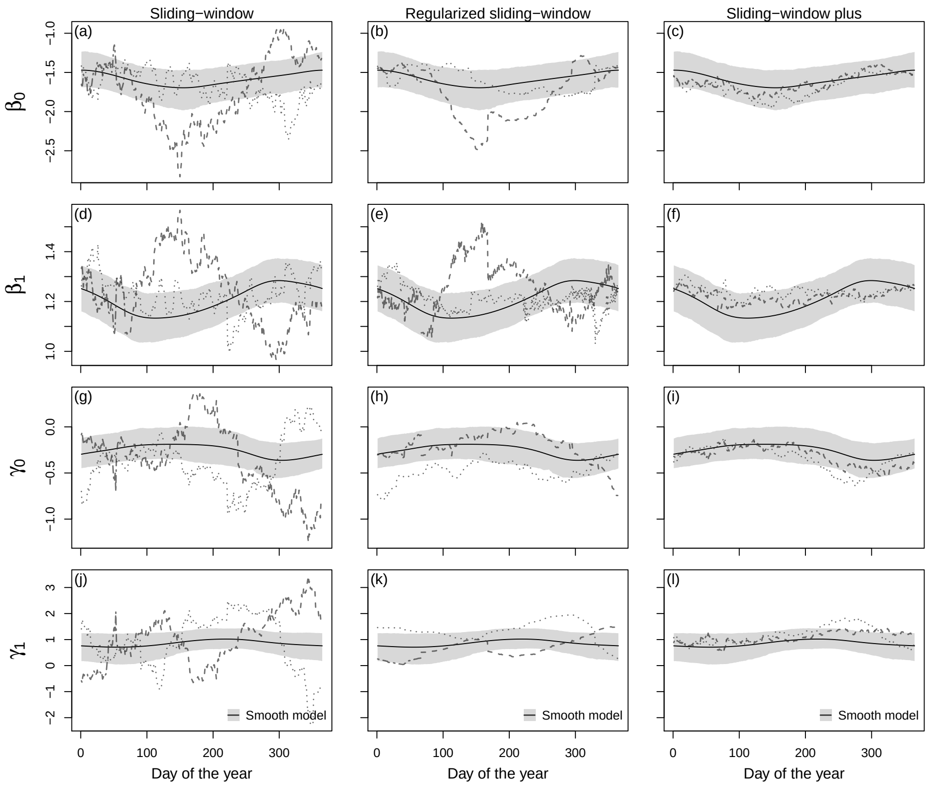

Figure 1: Temporal evolution of regression coefficients for the validation period in data set A, cf. Fig. 2 in the main manuscript, for Innsbruck at forecast step +24 h (valid at 0000 UTC). The coefficient paths are shown for the coefficients β_0 (a–c) and β_1 (d–f) in the location parameter μ, and for the coefficients γ_0 (g–i) and γ_1 (j–l) in the scale parameter σ based on the *sliding-window*, *regularized sliding-window*, and *sliding-window plus* approach (dashed, from left to right) compared to the *smooth model* approach (solid line). The coefficient paths are plotted for the consecutive calendar years 2014, 2015, and 2016 as dashed, dotted, and two-dashed line, respectively. The grey shading represents the 95% credible intervals of the coefficients in the *smooth model* based on MCMC sampling.

3. Results

In comparison to the main manuscript, the presented results compare the performance of the different time-adaptive training schemes for post-processing daily precipitation sums. Figure 1 and Fig. 2 illustrate the temporal evolution of the estimated coefficients shown for two stations representative for one measurement site in the plains (Hamburg) and one in mountainous terrains (Innsbruck). Figure 3 shows the predictive performance of the training schemes evaluated for three groups of stations with different site characteristics and in terms of the CRPS conditional on the three data sets with and without the change in the horizontal resolution of the EPS, as defined in Sect. 2.3.2 of the main manuscript. Due to the employed power-transformation, CRPS values are computed by quantile sampling with $n = 1000$; for a more detailed description compare Stauffer, Umlauf, Messner, Mayr, and Zeileis (2017b).

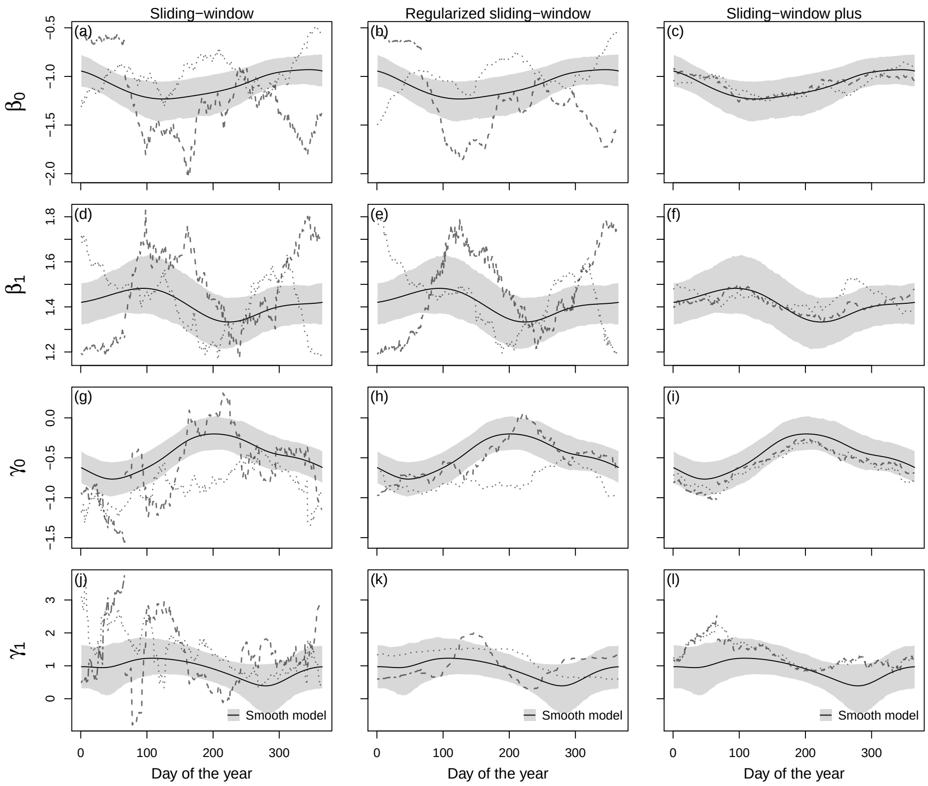

Figure 2: As Fig. 1, but for Hamburg at forecast step +24 h (valid at 0000 UTC).

The results for post-processing daily precipitation sums, depicted in Fig. 1–3, can be summarized as followed:

- For both Innsbruck and Hamburg, the *sliding-window* and *regularized sliding-window* approaches show very strong fluctuations in the evolution of the regression coefficient without a clear seasonal pattern comparing the consecutive years with each other (Fig. 1 and 2).
- The coefficient paths for the *sliding-window plus* approach and the *smooth model* look comparable with quite low seasonal variation in all coefficient paths. For Hamburg, the seasonal variability in the scale parameter is slightly larger than for Innsbruck (Fig. 1 and 2).
- The *sliding-window plus* and the *smooth model* approaches show the highest improvements over the classical *sliding-window* approach with a slightly better performance of the *sliding-window plus* approach for data set C in comparison to data sets A and B (Fig. 3).

4. Conclusion

This supplement provides a comparison evaluating the different time-adaptive training schemes for post-processing daily precipitation sums. To account for non-negative values, the large

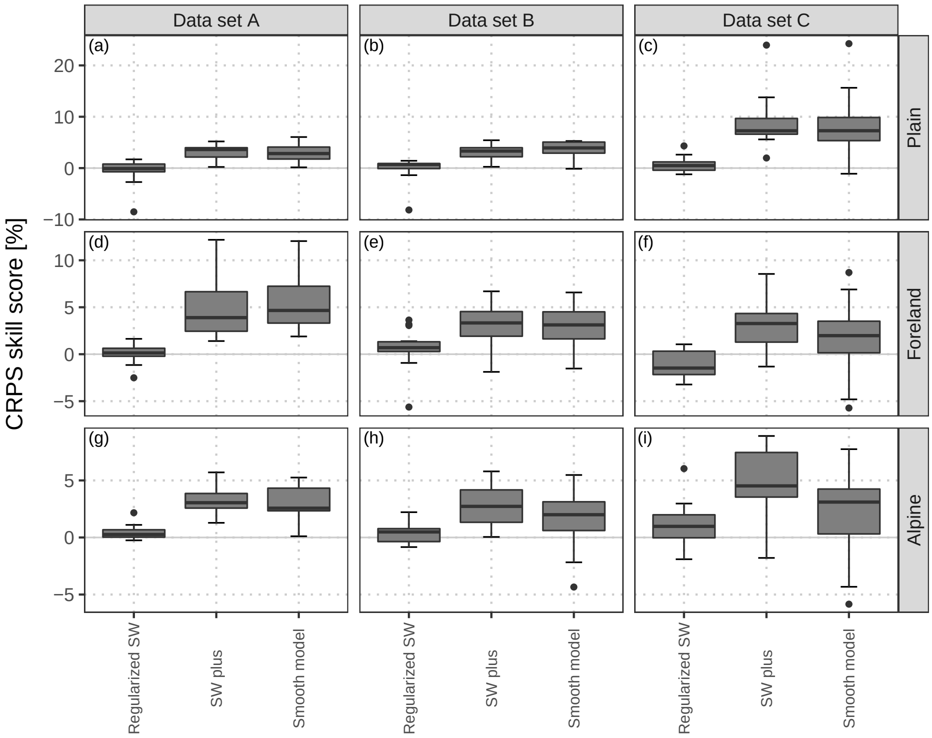

Figure 3: CRPS skill scores clustered into groups of stations located in the plain, in the mountain foreland near the Alps, and within mountainous terrain and for the out-of-sample validation periods according to the different data sets: Data set A without the change in the horizontal resolution of the EPS, data set B with the EPS change in between the training and the validation data sets, and data set C with the EPS change withing training data (cf. Fig. 2 in the main manuscript). Compared are the different time-adaptive training schemes specified in Sect. 2 with the classical *sliding-window* approach as a reference; note that 'sliding-window' is abbreviated as SW in the figure. Each box-whisker contains aggregated skill scores over the forecast steps from +24 h to +72 h on a 24 hourly temporal resolution and over five respective weather stations (cf. Fig. 1 in the main manuscript). Skill scores are in percent, positive values indicate improvements over the reference.

fraction of zero observations, and the strongly positively skewed characteristics of daily precipitation sums, we employ a power-transformation to both the observations and to each ensemble member, and use the zero left-censored Gaussian distribution in the framework of non-homogeneous regression (Stauffer *et al.* 2017a).

Despite the different characteristics of daily precipitation sums and the alternative response distribution, the results are very similar to the ones for 2 m temperature forecasts presented in the main manuscript. This shows that the findings for 2 m temperature can also be transferred to other quantities using different model assumptions and, hence, nicely support the conclusions given in the paper.

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