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Spatial Ensemble Post-Processing with Standardized Anomalies

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Abstract

To post-process ensemble predictions to a particular location, often statistical methods are used, especially in complex terrain such as the Alps. When expanded to several stations, the post-processing has to be repeated at every station individually thus losing information about spatial coherence and increasing computational cost. Therefore, we transform observations and predictions to standardized anomalies. Site- and season-specific characteristics are eliminated by subtracting a climatological mean and dividing by the climatological standard deviation from both observations and numerical forecasts. Then ensemble post-processing can be applied simultaneously at multiple locations. Furthermore, this method allows to forecast even at locations where no observations are available. The skill of these forecasts is comparable to forecasts post-processed individually at every station, and even better on average.

Keywords: Statistical post-processing, ensemble post-processing, spatial, temperature, standardized anomalies, climatology, generalized additive model.

1. Introduction

Numerical weather prediction (NWP) models provide spatial forecasts of different meteorological parameters. Due to limited computational power the grid of NWP models is too coarse to sufficiently resolve some small-scale processes, especially in complex terrain, such as the Alps. Therefore, parameterizations together with uncertainties in the initial state and the chaotic nature of the atmosphere lead to errors. Statistical post-processing introduced by Glahn and Lowry (1972) is one way to correct these systematical errors.

To capture forecast uncertainties, many weather centers provide an ensemble of numerical forecasts (Lorenz 1982; Leutbecher and Palmer 2008), with slightly different initial conditions or parameterizations. Since ensemble forecasts usually do not capture all error sources they should also be post-processed with statistical models as in Gneiting, Raftery, Westveld, and Golfman (2005) or Raftery and Gneiting (2005).

However, these statistical models are usually fit separately for separate locations for which a set of historical observations and NWP forecasts is available. Several techniques exist to overcome this limitation and to produce statistical forecasts for an arbitrary point in a re-

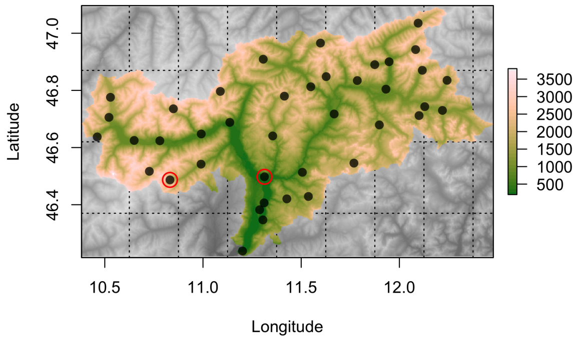

Figure 1: Location of 40 stations in South Tyrol superimposed on topography from the Shuttle Radar Topography Mission (SRTM) and the grid of the ECMWF ensemble forecasts (dotted lines).

gion. Statistical forecasts from the observation sites can be interpolated to arbitrary locations (Hacker and Rife 2007; Glahn, Gilbert, Cosgrove, Ruth, and Sheets 2009), observations can be interpolated onto the NWP grid to post-process every grid point (Schefzik, Thorarinsdottir, and Gneiting 2013) or statistical forecasts representative for a whole region (Scheuerer and Büermann 2014; Scheuerer and König 2014) can be produced. The latter forecasts several stations simultaneously by using anomalies. By subtracting a climatological mean from observations and NWP forecasts site-specific characteristics are removed so that multiple stations can be forecasted with a single model. Additionally, if a spatial climatology of the observations exists, even points in between stations can be predicted.

We modify this method slightly and standardize these anomalies by dividing the difference to a mean value by the standard deviation (Wilks 2011). Thus, also different variabilities of different stations are considered. Furthermore, we fit full seasonal climatologies instead of monthly means to also remove season-specific characteristics. Therefore, all data can be used for training so that the post-processing model does not have to be refitted every day.

The rest of the article is structured as follows: The data are described in the next section, followed by the method. Afterwards the different post-processing models are described and compared. At the end is the conclusion and discussion.

All work has been performed with the statistical software R (R Core Team 2016).

2. Data

Statistical models will be applied to the province of South Tyrol in northern Italy. South Tyrol is an alpine region with a large variation in altitude. 40 stations distributed over altitudes from 208 to 1900 meters amsl provide temporal observations (Figure 1). The numerical ensemble forecasts are produced by the European Centre for Medium-Range Weather Forecasts (ECMWF).

The forecast variable is the temperature at 2 meter above ground (T2m) and the input variables for the statistical models are T2m ensemble mean (m) and standard deviation (s) of the 51 members linearly interpolated to the station locations. We use a lead time of 18 hours of an ensemble forecast initialized at 00 UTC. The period used is from 1 February 2010 to 30 June 2015.

To calculate spatial climatologies, a digital elevation model with a spatial resolution of 90 m from the Shuttle Radar Topography Mission (SRTM, Reuter, Nelson, and Jarvis 2007) is used.

3. Method

3.1. Nonhomogeneous Gaussian regression

To post-process ensemble forecasts, Gneiting *et al.* (2005) introduced nonhomogeneous Gaussian regression (NGR). In NGR, a variable y is assumed to follow a normal distribution with mean μ and standard deviation σ. However, σ is no longer constant as in the seminal work of Glahn and Lowry (1972) but depends on the ensemble spread:

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

$$\mu = b_0 + \ b_1 m, \tag{2}$$

$$\log(\sigma) = c_0 + c_1 \log(s) \tag{3}$$

with b_0, b_1, c_0, c_1 as regression coefficients. In this case μ depends on the ensemble mean and $\log(\sigma)$ on the logarithm of the ensemble standard deviation. The logarithmic link function in Equation 3 is used to ensure positive values for σ. The coefficients b_0, b_1, c_0 and c_1 are estimated with maximum likelihood estimation as implement in the R-package *crch* of Messner, Mayr, and Zeileis (2015).

3.2. Standardized anomalies

Usually NGR has to be repeated at every station and season individually since different measurement sites have different temperature ranges varying over the year, as shown in the top panel of Figure 2. To overcome this problem we use standardized anomalies which remove site- and season-specific characteristics. Additionally, to subtracting the climatological mean, as in Scheuerer and Büermann (2014), we also divide by the climatological standard deviation to account for differences in the climatological variance:

$$\widetilde{y} = \frac{y - \mu_y}{\sigma_y} \tag{4}$$

where μ_y is the mean value of the observations (in Figure 2) and σ_y is its standard deviation (thin lines in Figure 2). Standardized anomalies of ensemble mean and ensemble standard deviation are computed similarly with m and $\log(s)$ respectively ($\widetilde{m} = (m - \mu_m)/\sigma_m$ and $\log(\widetilde{s}) = (\log(s) - \mu_{\log(s)})/\sigma_{\log(s)}$), instead of y.

The central idea behind these standardized anomalies is presented in the bottom panel of Figure 2. The standardized anomalies have no annual cycle and are centered around 0 for both stations which enables to forecasts several stations simultaneously.

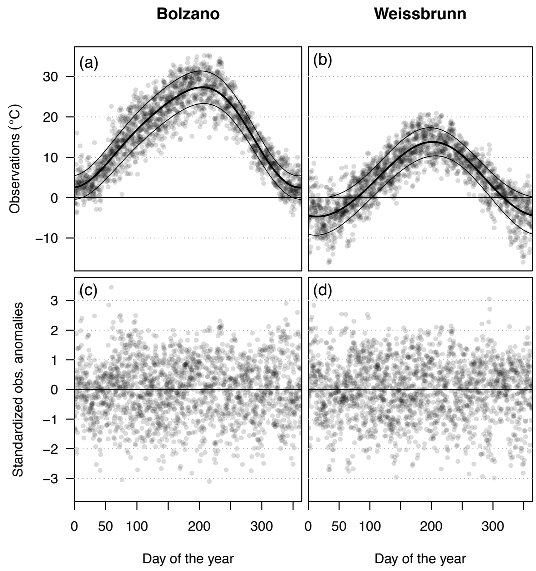

Figure 2: (a) Annual cycle of the observations for the valley station Bolzano (red circle in Figure 1) with the climatology (mean, thick line) and the standard deviation of the climatology (thin lines). (b) and for the mountain station Weissbrunn (red circle in Figure 1). (c) Annual cycle of the standardized observation anomalies for the station Bolzano (d) and for Weissbrunn.

3.3. Standardized anomaly model output statistics (SAMOS)

When NGR is reformulated with standardized anomalies site- and season-specific characteristics are largely removed and only a single model needs to be fit for all stations and seasons instead of fitting models for each location and date individually. We call this SAMOS. Therefore y, m, and s in Equation 1–3 are replaced by $\widetilde{y}$, $\widetilde{m}$ and $\widetilde{s}$.

To obtain temperature forecasts ($\hat{\mu}$) and the corresponding standard deviation ($\hat{\sigma}$), Equations 2 and 3 have to be restructured with Equation 4 to,

$$\hat{\mu} = (b_0 + \; b_1 \widetilde{m}) \cdot \sigma_y + \mu_y \tag{5}$$

and

$$\hat{\sigma} = \exp(c_0 + c_1 \log(\widetilde{s})) \cdot \sigma_y. \tag{6}$$

To produce forecasts for arbitrary locations where no observations are available only climatologies (μ_y and σ_y) of the observations are needed because the coefficients from Equation 1 (b_0, b_1, c_0, c_1), which are fitted on all stations simultaneously, are representative for the whole region. Thus the spatial resolution of these forecasts only depends on the spatial resolution of the climatology.

3.4. Climatology

There are several ways to calculate a spatial climatology. It could be produced at every observation site and then distributed onto the grid with kriging (Aalto, Pirinen, Heikkinen, and Venäläinen 2013), a climatology with non-Euclidean distances as in Frei (2014) could be computed, the 30 days mean at every station individually could be calculated as in Scheuerer and Büermann (2014) or a spatial climatology for all stations could be fitted at once with a generalized additive model (GAM, Aalto *et al.* 2013). The approach in this paper is to work with an extension of the latter (generalized additive models for location, scale and shape (GAMLSS), Rigby and Stasinopoulos 2005; Stasinopoulos and Rigby 2007).

The advantage of a GAMLSS is that a climatological mean (μ) and a variable standard deviation (σ) can be fitted simultaneously very similar to NGR but with the possibility of nonlinear effects. With GAMLSS, the climatology and the standard deviation can be fitted for all stations with

$$\xi \sim N(\mu_\xi, \sigma_\xi), \tag{7}$$

where ξ can be y, m or $\log(s)$. The nonlinear model for μ_ξ is then,

$$\mu_\xi = \beta_0 + \beta_1 \text{alt} + f_1(\text{lat}, \text{lon}) + f_2(\text{yd}) + f_3(\text{yd}) \cdot \text{alt}, \tag{8}$$

with f_1 as spatial smoothing functions of the horizontal coordinates and f_2 and f_3 as smooth, cyclic functions over the day of the year (yd). The influence of the altitude (alt) on the climatology is captured as linear effect and in its interaction with the seasonality. Therefore, it is possible that the altitude effect can vary over the year and the seasonal effect can vary with altitude. A similar equation as for μ_ξ is also used for $\log(\sigma_\xi)$ with the same terms as in Equation 8.

For the observation climatology, station observations are used as input data while the climatologies of the ensemble forecasts uses past forecasts on the ECMWF forecast grid. Thin plate splines are used as spatial smoothing function with a degree of freedom of 30 for y and 20 for m and $\log(s)$. For m and $\log(s)$ the degree of freedom is smaller due to the coarse model grid of the ensemble forecasts (e.g. Figure 1). Analyses of climatologies showed that the degree of freedom does not have a huge impact on the forecasts especially for stations not contained in the training data as long as the degrees of freedom are not close to the maximum possible, which is either the number of stations or number of grid points. Therefore, the degrees of freedom are a tradeoff between forecast performance and computation cost and approximately three-fourths of the maximum. The seasonal smooth functions have harmonic terms at annual and bi-annual frequencies (i.e. four basis functions $\sin(2\pi\ \text{yd}/365)$, $\cos(2\pi\ \text{yd}/365)$, $\sin(4\pi\ \text{yd}/365)$ and $\cos(4\pi\ \text{yd}/365)$).

The different effects for μ_y are illustrated in Figure 3. Where the seasonal effect on the left shows that μ_y has higher values in the summer than in the winter. Additionally, the different colors illustrate that the seasonal effect in valleys (brighter colors) has a higher amplitude than at higher located stations (darker colors). The altitude effect in the middle shows that valley stations have a higher mean temperature than mountain stations. The lines indicate that the difference between stations in the valleys and on the mountains is smaller in the winter (bright colors) than in spring (darker colors). On the right, the spatial effect is plotted where the mean temperature in the south-west is warmer than in the north-east. With all these effects, the climatology of any day and location inside the region of South Tyrol can be provided. These three effects are combined in Figure 4(b). The effects for the ensemble mean and ensemble standard deviation (not shown) are much smoother due to the smooth model topography.

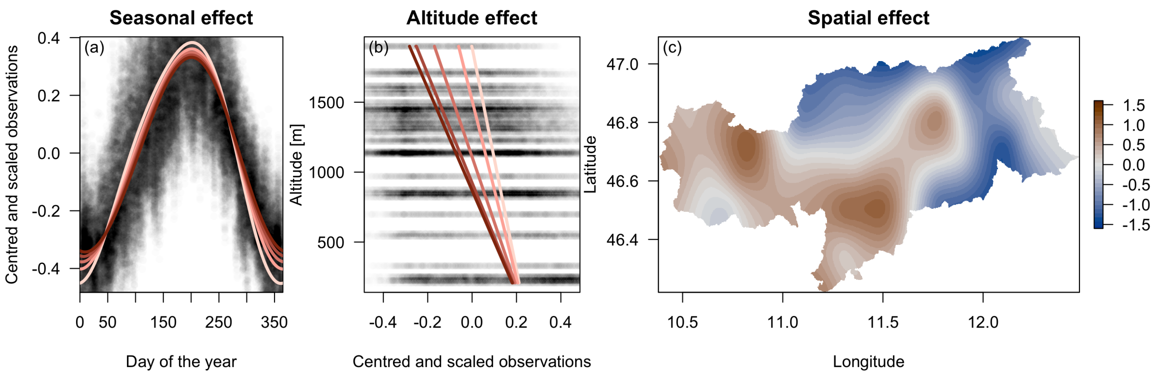

Figure 3: (a) Seasonal effect of μ_y with an interaction with altitude indicated by the colors. The brighter the color, the lower the station. (b) Altitude effect of μ_y with a seasonal interaction. The colors indicate the seasonal effect for 15 December, 15 January, 15 February, 15 March and 15 April (from bright to dark). (c) Spatial effect for μ_y for the region of South Tyrol. The sum of all these effects is visualized in Figure 4(b).

3.5. Forecast example

Spatial forecasts can be produced with these climatologies and Equations 5 and 6. Figure 4 shows an example for 1 July 2015. The difference between the climatologies of ensemble mean and observations is large (top panel). Whereas the observation mean (μ_y) is strongly influenced by the altitude, with mapped valleys and ridges, the model mean (μ_m) only shows a smooth temperature gradient since there are no valleys in the ECMWF model topography. The same result is shown by the climatological standard deviation (middle panel). Whereas σ_y maps valleys with an additional slightly higher standard deviation in the north-east, σ_m only illustrates a smooth increase of standard deviation from south to north. The bottom panel in Figure 4 exemplifies that a raw ensemble forecast does not produce realistic temperature forecasts in complex terrain whereas the SAMOS forecast captures spatial and altitude effects.

4. Different models

To evaluate the performance of SAMOS, several models are compared. The features of the different models are listed in Table 1. They differ in the treatment of anomalies, climatologies and uncertainties. The climatologies can either be a mean value over the last 30 days at every station individually, over the full time series with GAMLSS at every station individually, or at all stations simultaneously. Furthermore, 2-step models to capture the local forecast uncertainty (Scheuerer and Büermann 2014) are tested or the calculation of the NGR differs in the length of the training data and if the NGR is calculated at every station individually or for all stations together simultaneously.

4.1. Ensemble model output statistics (EMOS)

As a reference model an NGR is calculated on the direct observations and ensemble forecasts at every station individually which is known as "ensemble model output statistics" (EMOS, Gneiting *et al.* 2005). 30 days prior to the forecast day are used to fit the model. A forecast for

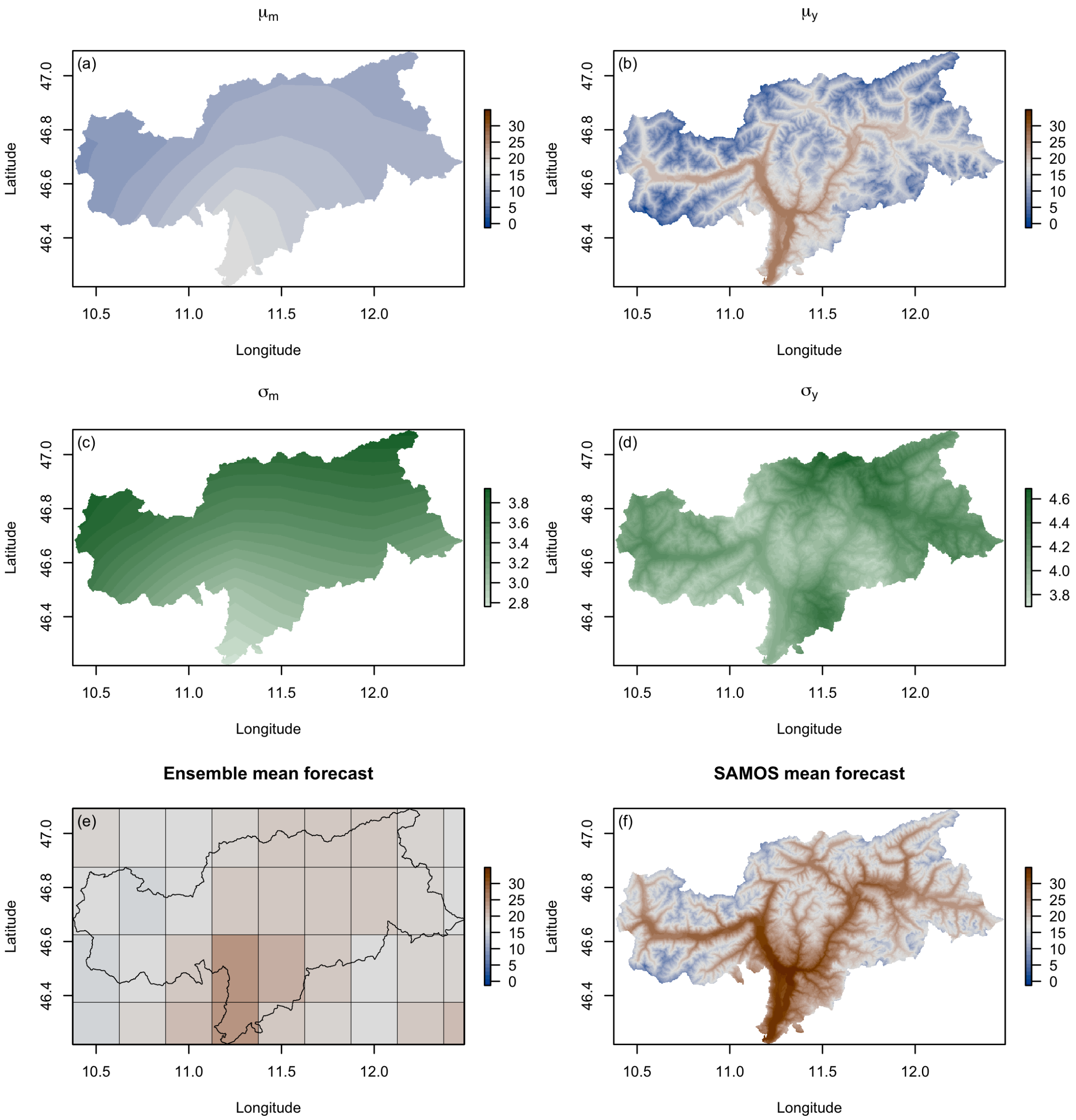

Figure 4: 2-meter temperature climatology of (a) the NWP ensemble mean, (b) of the observations. Standard deviation (c) of the ensemble mean climatology and (d) of the observation climatology (different coloring for both standard deviations). (e) Ensemble mean forecasts at original grid resolution. (f) SAMOS mean forecast for the region of South Tyrol. All figures are for 1 July 2015 and use topography from SRTM data (colors in °C).

Table 1: Features of the different models.

Model	Anomalies	Climatology	Uncertainty	NGR
EMOS	None	—	1-step	Individual
AMOS	Differences	GAMLSS stationwise	1-step	Simultaneous
AMOS 2-step	Differences	GAMLSS stationwise	2-step	Simultaneous
SAMOS 30days	Standardized diff.	30 days stationwise	1-step	Simultaneous
SAMOS stationwise	Standardized diff.	GAMLSS stationwise	1-step	Individual
SAMOS stationwise-simultaneous	Standardized diff.	GAMLSS stationwise	1-step	Simultaneous
SAMOS stationwise-simultaneous 2-step	Standardized diff.	GAMLSS stationwise	2-step	Simultaneous
SAMOS	Standardized diff.	GAMLSS spatial	1-step	Simultaneous

the next day is then produced with the fitted coefficients. Consequently, to get forecasts for every day of the time series, a new model has to be fitted for each day. While this approach requires high computational effort it has the advantage that almost no historical data are needed.

4.2. Ensemble model output statistics with anomalies (AMOS)

Next, difference-anomalies ($\widetilde{y} = y - \mu_y$) replace direct values in the NGR (AMOS). Therefore, a GAMLSS climatology is calculated for every station individually similar to Equation 8 but without spatial and altitude effect (2nd, 3rd and 5th term). Different to EMOS all stations are forecasted with one single model and local forecast uncertainties are not considered. To capture different local forecast uncertainties a 2-step (AMOS 2-step) model approach is used. Therefore, first an ordinary linear regression is fitted and the site-specific mean of the squared residuals are used as additional predictor variable for σ (i.e., add its logarithm to right side of Equation 3). This 2-step model is similar to the 2-step model in Scheuerer and Büermann (2014).

4.3. SAMOS 30days

SAMOS 30days has standardized anomalies and one NGR at all stations simultaneously but with a climatology over the previous 30 days instead of the full time series. As climatology, an average of the last 30 days preceding the forecast day for every station individually is calculated. Afterwards one NGR is applied at all stations simultaneously with the last 30 days as training data. This model is similar to the method in Scheuerer and Büermann (2014) but with standardized anomalies.

4.4. SAMOS stationwise

The second SAMOS uses a stationwise climatology as in AMOS but with standardized anomalies. Additionally, separate NGR models are fitted for each station but with the full time series as training data.

4.5. SAMOS stationwise-simultaneous

SAMOS stationwise-simultaneous has the same climatologies as *SAMOS stationwise* for every station individually and the full time series but the NGR is calculated at all stations simultaneously. Additionally, a 2-step (SAMOS stationwise-simultaneous 2-step) model to capture the local uncertainty is tested similar to Scheuerer and Büermann (2014). This model shows if these standardized anomalies capture all the local uncertainty information that is captured by a 2-step model in Scheuerer and Büermann (2014).

4.6. SAMOS

For this model the climatologies and the NGR are fitted on all stations simultaneously. Compared to the stationwise models the advantage of this model is that in between station points can be forecasted directly without any additional interpolation. Errors can be calculated at station points ("same-station") and in between ("new-station"). For the same-station error, all available stations are used to fit the climatologies and the NGR. Afterwards forecasts for the same stations are made with these fits. For the new-station forecasts a leave-one-out error is calculated. The climatology and the NGR model are fitted on 39 stations and then the forecast is made for the 40th station with these fits. This simulates forecasts for new stations where no historical data are available or for points in between stations. To receive a new-station error for all stations, each station has to be left out once and is then verified.

5. Results

The time series is separated into training and test data to evaluate the forecasts. Therefore, 10-fold cross-validation is applied to all models that use the full time series as training data. For the methods with the 30 day training data, the previous 30 days are used for fitting the model for the following day. As a result, all forecasts are tested on data not contained in the training data.

To verify the performance of the proposed probabilistic forecasts the mean absolute error (MAE) is computed as a deterministic measure and the continuous ranked probability score (CRPS) as a probabilistic measure for each station and model. To see the relative change to a reference model, a skill score (SS) for the MAE and the CRPS is produced:

$$\mathrm{SS} = 1 - \frac{\mathrm{score}}{\mathrm{score}_{ref}}. \tag{9}$$

5.1. Difference- vs. standardized-difference-anomalies

The first results evaluate the benefit of using standardized differences instead of differences as anomalies. AMOS is the reference for the skill score.

Figure 5 demonstrates that the standardized anomalies improve the forecasts by about 4 percent compared to the simple differences for both, the MAE and the CRPS. However, the improvements of the forecasts is only observed for the anomalies with the full climatology. For the method with the 30 days mean as climatology almost no differences occur (not shown). Both anomalies do not benefit from using a 2-step model for the uncertainty.

In review of these results, all following comparisons are for SAMOS variants with standardized anomalies and without the 2-step model for the local uncertainty.

5.2. Different models

To compare the different methods from Table 1, the forecast error at every station is calculated. Figure 6 shows that SAMOS-stationwise performs best. It is on average about 4 percent

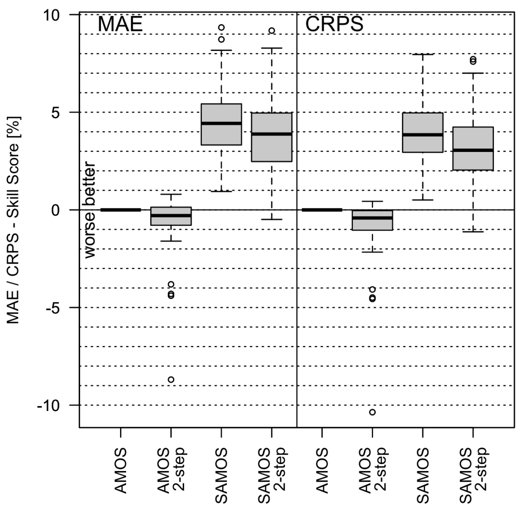

Figure 5: Comparison of different anomalies and additional uncertainty information with SAMOS stationwise-simultaneous method. Every box contains 40 points with one MAE/CRPS per station. The AMOS forecasts are the reference for the skill score.

better than forecasts with a conventional EMOS. If all stations are fitted and forecasted simultaneously with SAMOS stationwise-simultaneously the results are not significantly different.

The *SAMOS 30days* performs similarly as EMOS. Using all available data and a full climatology (SAMOS stationwise-simultaneously) instead of a 30 days mean (SAMOS 30days) does not only save computation time but also clearly improves the forecasts.

The proposed SAMOS (same-stations) method performs on average slightly better than EMOS but worse than SAMOS stationwise or SAMOS stationwise-simultaneously. The only difference between SAMOS stationwise-simultaneously and SAMOS is the climatology. Calculating a spatial climatology instead of separate station climatologies allows directly to forecast in between stations at the expense of a somewhat reduced skill.

When SAMOS is tested on new stations the forecast performance only slightly decreases. The outliers are all locations close to the borders of South Tyrol, a typical problem of spatial methods.

6. Discussion and conclusion

To produce spatial forecasts, a statistical model is fitted on *standardized anomalies*, which remove site- and season-specific characteristics of the data. These standardized anomalies are the difference to a climatological mean and then divided by the climatological standard deviation for the observations and NWP forecasts, respectively.

Without the *season-specific* characteristics longer training data can be used and the fits do not have to be updated every day as in Scheuerer and Büermann (2014) or Gneiting *et al.* (2005). Using longer training data improves the forecasts significantly. A large practical advantage is also that the coefficients from the forecast model need not be recomputed every day. The only time-consuming part is the calculation of the climatologies. However, since the

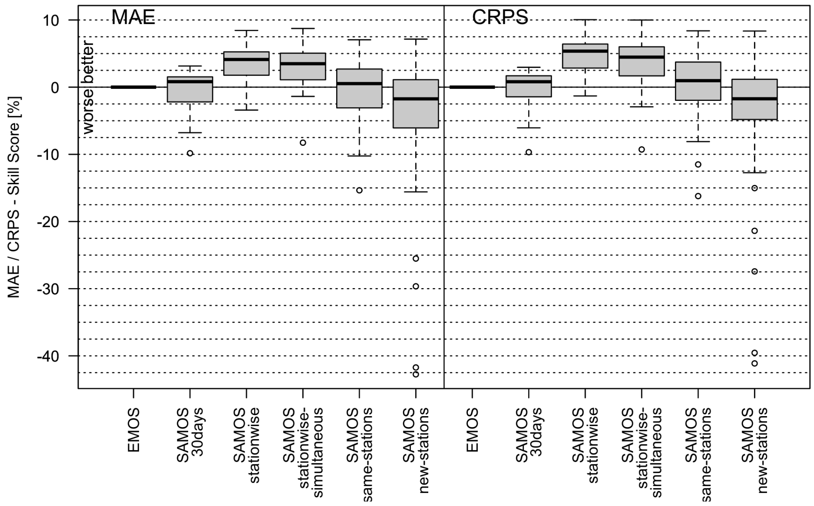

Figure 6: Skill score with EMOS as reference of forecasts computed with different methods listed in Table 1. Each box contains 40 points with one MAE/CRPS per station.

climatology changes slowly it has to be updated only infrequently, e.g. annually.

Without *site-specific* characteristics all stations can be forecasted simultaneously. Furthermore, the fitted coefficients are valid for the whole region and with a spatial climatology of the observations even points in between stations can then be forecasted. Combining all stations with SAMOS does not always improve the forecasts but the method provides forecasts even where no observations are available. The spatial resolution of these forecasts is determined by the spatial resolution of the climatology.

Spatial calibration such as ensemble copula coupling (Schefzik *et al.* 2013) or with Gaussian random fields (Feldmann, Scheuerer, and Thorarinsdottir 2015) could be used to capture dependency structures but have not been applied in this study. Further adjustment of the climatology could also improve the forecast performance. Additionally, an advantage of the proposed method is to use longer training data which would make it a suitable method to use reforecasts (Hagedorn, Hamill, and Whitaker 2008).

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2016-08

Markus Dabernig, Georg J. Mayr, Jakob W. Messner, Achim Zeileis

Spatial ensemble post-processing with standardized anomalies

Abstract
To post-process ensemble predictions to a particular location, often statistical methods are used, especially in complex terrain such as the Alps. When expanded to several stations, the post-processing has to be repeated at every station individually thus losing information about spatial coherence and increasing computational cost. Therefore, we transform observations and predictions to standardized anomalies. Site- and season-specific characteristics are eliminated by subtracting a climatological mean and dividing by the climatological standard deviation from both observations and numerical forecasts. Then ensemble post-processing can be applied simultaneously at multiple locations. Furthermore, this method allows to forecast even at locations where no observations are available. The skill of these forecasts is comparable to forecasts post-processed individually at every station, and even better on average.

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