Stay Report

To: Zentralanstalt für Meteorologie und Geodynamik — ZAMG, Vienna, Austria
Period: November 22nd – December 17th, 2021
Topic: Work on analog-based post-processing method
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The analog-based method application to gridded data post-processing

1 Introduction

I stayed at the Zentralanstalt für Meteorologie und Geodynamik (ZAMG) for four weeks during which I was working on the analog-based post-processing method applied to an NWP model output for gridded forecasts. This is the continuation of previous work carried out during several previous stays.
Analogies between, for example, similar past forecasts, measurements, or analyses are a potentially useful tool when the training dataset is long enough, thus enabling an adequate identification of true analogs. Thus, reducing the number of degrees of freedom in the matching procedure makes this method an excellent candidate for point-based post-processing, where NWP input can be deterministic or ensemble forecast. Previously, the point-based analog approach was thoroughly tested as a deterministic approach (Odak Plenkovic et al., 2018) and applied to calibrate the A-LAEF ensemble (Odak Plenkovic et al, 2020).
However, accurate forecasts at remote locations are used to drive many user-specific applications (e.g., road temperature forecasts along an entire roadway, soil temperature forecasts for agriculture, wind speed for windfarms). For that reason, besides the point-based post-processing for the measuring sites, there is also an increasing demand for gridded products.
The latter is a direct motivation for the development of tools needed for using an analog-based method to produce gridded output based on an analysis. The purpose of this report is to present recent developments achieved during the ACCORD stay at ZAMG, which took place November 22nd – December 17th, 2021, including some practical details. During this stay, the algorithms for two analog-based experiments that produce gridded products are developed and followed by preliminary results. The progress is also described in a form of an article for the ACCORD Newsletter.

2 Data and algorithms

Previously used algorithms were not developed for large datasets, so optimization was the first necessary step. The scripts are adjusted to work in Python3 and were parallelized. Using the .h5 format in I/O in the `read_hdf` function accelerated the process. Due to the time constraints, datasets prepared during the previous stays are used. As input to the analog methods, the control member of the ECMWF ensemble forecast is used as a raw forecast. The gridded INCA analysis fields (Haiden et al., 2011) is used as a "ground truth", similar to the observations in the point-based analog approach. For testing the novel gridded analog algorithm within a decent amount of time, the INCA wind speed analyses are bilinearly interpolated onto the ECMWF forecast grid. This will be changed once the algorithms are properly tested and validated.
After the algorithms optimizations, several experiments were performed, including two distinctive approaches, Point-by-Point and Field-wise, that will be explained in more detail afterward. All

experiments mentioned in this report use wind speed and direction variables as predictors, normalized by standard deviation but no additional predictor-weighting strategy is currently applied.
The analog ensemble (AnEn) consists of 10 INCA wind speed values corresponding to 10 best-matching analogs for the ECMWF control member. The analyzed INCA wind speed values are also used as observed values in the verification procedure. Since the years used for training and a year as indented validation data set in the following experiments sometimes differ, they will be explicitly stated for each experiment further on.

Point-by-Point approach

The first approach is the simplest transfer from point-based to gridded products: treating every grid point as an independent location. The quality of the analog is thus evaluated by the following metric:

$$\|F_t A_{t'}\| = \sum_{i=1}^{N_A} \frac{w_i}{\sigma_{fi}} \sqrt{\sum_{j=-\tilde{t}}^{\tilde{t}} \left(F_{i,t+j} - A_{i,t'+j}\right)^2}, \tag{1}$$

where F_t is the current NWP deterministic forecast at a given grid point, valid at the future time t, whereas $A_{t'}$ is an analog at a given point with the same forecast lead time, but valid at a past time t'. The N_A is the number of predictors used in the search for analogs, w_i are the weights corresponding to a particular predictor, normalized with the standard deviation of the time series of past forecasts of a given variable at the same grid point is σ_{fi}. The $\tilde{t}$ is equal to half the number of additional times over which the metric is computed (the half of the time window of any specified width), therefore $F_{i,t+j}$ and $A_{i,t'+j}$ are the values of the forecast and the analog in the time window for a given variable, respectively. Analogs are found independently for every forecast time and grid point, narrowing the search around the particular time of a day by a time window. The example of probabilistic forecast produced by this approach is shown in Figure 1. To emphasize the fact that grid points are treated independently, only the markers at the exact grid point locations are used here. The latter also provides better insight into the domain size and horizontal resolution for all the experiments provided in this work. The standard practice, however, would be using contour function for displaying such forecasts. It can be noted that, even though the Point-by-Point approach is a good starting point, it might produce noisy forecasts (as in Frediani et al., 2017). Additionally, since every grid point is treated separately, the method itself is still computationally slow.

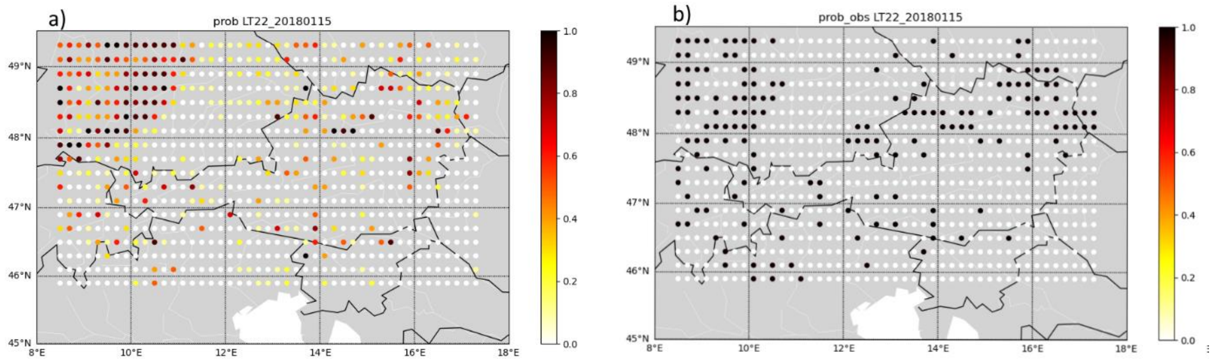

Figure 1. The example of probabilistic forecast that wind speed will exceed 5 m/s predicted by Point-by-Point analog-based approach for January 15th, 2018 (lead time 22 h) and the domain used for all the experiments (a) and the corresponding observations derived from INCA analysis and bilinearly interpolated to ECMWF grid (b).

Field-wise approach

Similarly, to the previous approach, the distance metric (1) is calculated independently for every forecast time and grid point using ECMWF forecasts, narrowing the search around the particular time of a day by a time window. However, in order to determine the best match (i.e., best analog), the calculated metric is averaged over an entire field, instead of each grid point separately. In other words, one can compare an average error on the entire field and use the mean value to choose the most similar fields,

selecting the 10 lowest values. The gridded INCA wind speed analyses corresponding to those historical timestamps are used and they include all grid points.
For these experiments, for fairer comparison with the Point-by-Point approach, only the INCA wind speed values bilinearly interpolated to ECMWF grid are used as members of analog ensemble forecast (as in Figure 1). However, such a constraint is not generally required. Moreover, the potential benefit of this approach is the possibility of using different grid setups, e.g., differing in horizontal resolution and/or exact location of grid points. Additionally, since the Field-wise approach is much more computationally quicker, several experiments are executed.

3 Results

As already mentioned, several different analog-based experiments are executed and compared, using INCA wind speed analysis as observed values. The experiments are for one winter (January) and one summer month (July), producing consistent results. For that reason, only the results for January are shown in this work.
The main aim of any kind of NWP model post-processing is to improve the results of the raw model. All analog-based experiments show an improvement compared to the raw ECMWF forecasts. The latter can be noticed if, for example, the lead-time performance measured by RMSE for raw ECMWF (Figure 2) is compared to AnEn RMSE values for the ensemble mean in Figures 3b and 5.

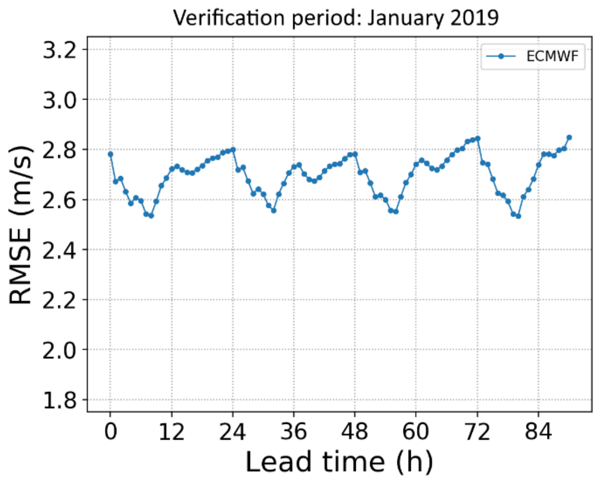

Figure 2. The RMSE values for ECMWF control ensemble member forecast at different lead times during January 2019. The forecasts are verified using INCA analysis wind speed values on the entire domain.

The Point-by-Point and Field-wise analog approaches are compared, taking into consideration the simplicity and effectiveness of execution (e.g., computational speed) as well as success in overall performance (e.g., better verification scores). Even though the Point-by-Point approach is much more similar to point-based application and thus was much easier to implement, the algorithm is still relatively slow, whereas the Field-wise approach is much faster. For example, for a month-long Point-by-Point algorithm that uses a 1-year-long training dataset, the execution lasted ~5 h. On the other hand, to produce month-long Field-wise-approach-based forecasts that use a 2-years-long dataset for training needed only ~40 min to finish using the same machine. The difference in execution is probably due to averaging the distance metric, reducing the number of times that the Field-wise approach needs to open/close INCA files, etc. For these practical reasons, it made sense to compare the Field-wise approach with longer training to the Point-by-Point approach with shorter training (Figure 3). The results for January 2019 are comparable for these two approaches, measured by CRPS and RMSE-spread plot (Figure 3). One can notice that differences among approaches slightly increase with the lead time. Also, the Field-wise approach seems to be less prone to underdispersiveness.

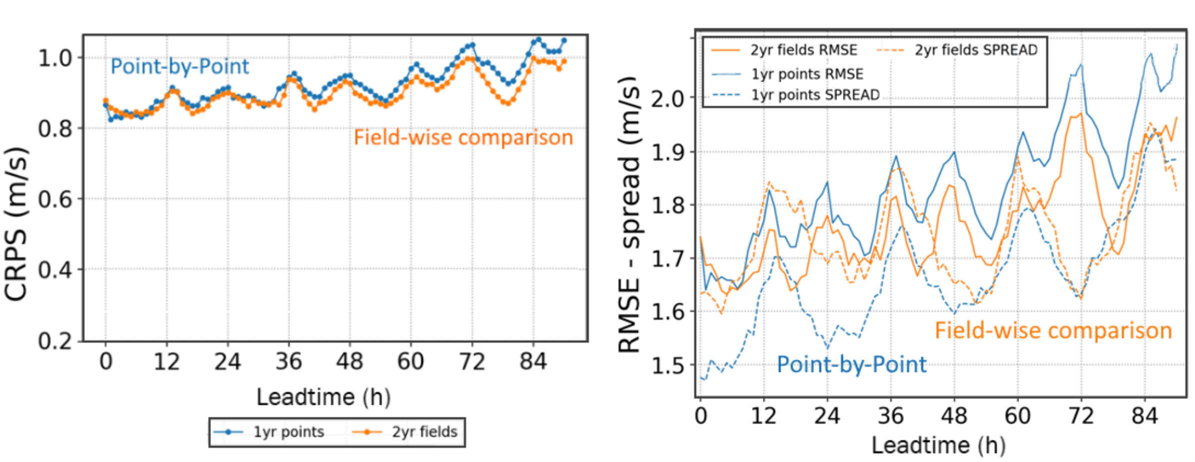

Figure 3. The CRPS (a) and RMSE-spread (b) for the Point-by-Point analog-based approach (using a 1-year-long training dataset) is compared to the Field-wise approach (using a 2-years-long training dataset) during January 2019. All forecasts are verified using INCA analysis wind speed values on the entire domain.

Since the Field-wise approach with 2-years-long training is used for inter-comparison with the Point-by-Point approach, the sensitivity to training length is also examined. The results show that error measured by AnEn mean RMSE is smaller for the longer training, as expected, whereas the spread remains similar (Figure 4).

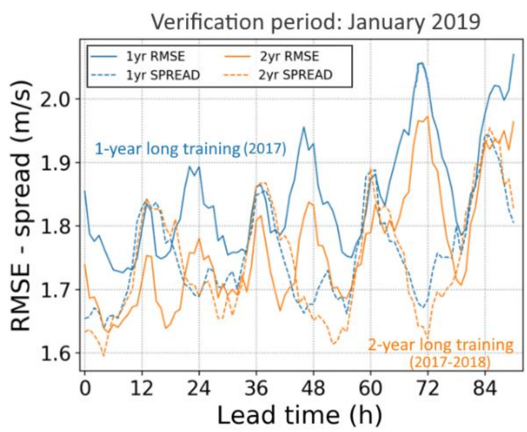

Figure 4. The intercomparison of the Field-wise analog-based method approach that uses a 1-year-long training dataset (2017) and the one that uses a 2-years-long training dataset (2017-2018) using the RMSE-spread plot. The results are calculated for January 2019. All forecasts are verified using INCA analysis wind speed values on the entire domain.

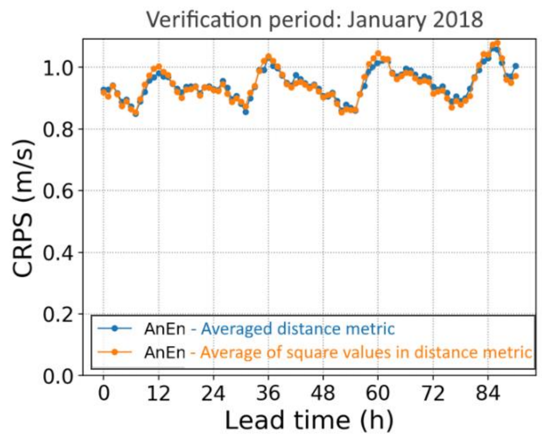

Figure 5. The Field-wise analog-based experiment for which the average distance metric on the entire field is used to define best matching analogs is compared to the experiment for which the squares of distance metric are averaged, weighing the larger values at the grid points more. The comparison is made using the CRPS measure and shown for January 2018. All forecasts are verified using INCA analysis wind speed values on the entire domain.

While implementing the Field-wise approach the question arose if it would be better to weigh the larger distance metric (at a particular grid point) values more, before averaging the values for the entire field and using it for choosing the best analogs. To answer if such modification could improve the result further, the distance metric values at grid points are squared and then averaged. The difference metric across the field would thus be treated more like "root-mean-square-difference" than like "mean bias".

The results however show very few differences among these two experiments (Figure 5). For that reason, the more simplified approach that uses only averaging is adopted.

4 Current progress, discussion and future work

To summarize, the tools needed for using an analog-based method to produce gridded output are successfully developed. Two distinctive approaches are tested, Point-by-Point and Field-wise approach, generating comparable results when using training datasets of the same length. The preliminary results also show that the Field-wise experiment with 2-years-long training seems to produce the best result, gets very close to the Point-by-Point experiment with 1-year-long training, and is computationally less demanding.

In addition to these experiments, future work might include an additional method for choosing the best analogs in order to simplify the information. For instance, one can identify objects (also in Frediani et al., 2017), use principal components (PC, as in Xavier and Goswami, 2007) or empirical orthogonal functions (EOF; similarly as a point-based application in Barnett and Preisendorfer, 1978; also Zorita and Storch, 1998). Moreover, first steps to develop approach that uses EOFs are already made during this stay. The training data is used to calculate EOFs, and training is thus saved as EOFs and principal components (PCs) timeseries. Preliminary results show that using only 4 or 5 EOFs might capture majority of the variance in the training (e.g., for the 2017.-2018. training period in Figure 7), for both wind speed and direction.

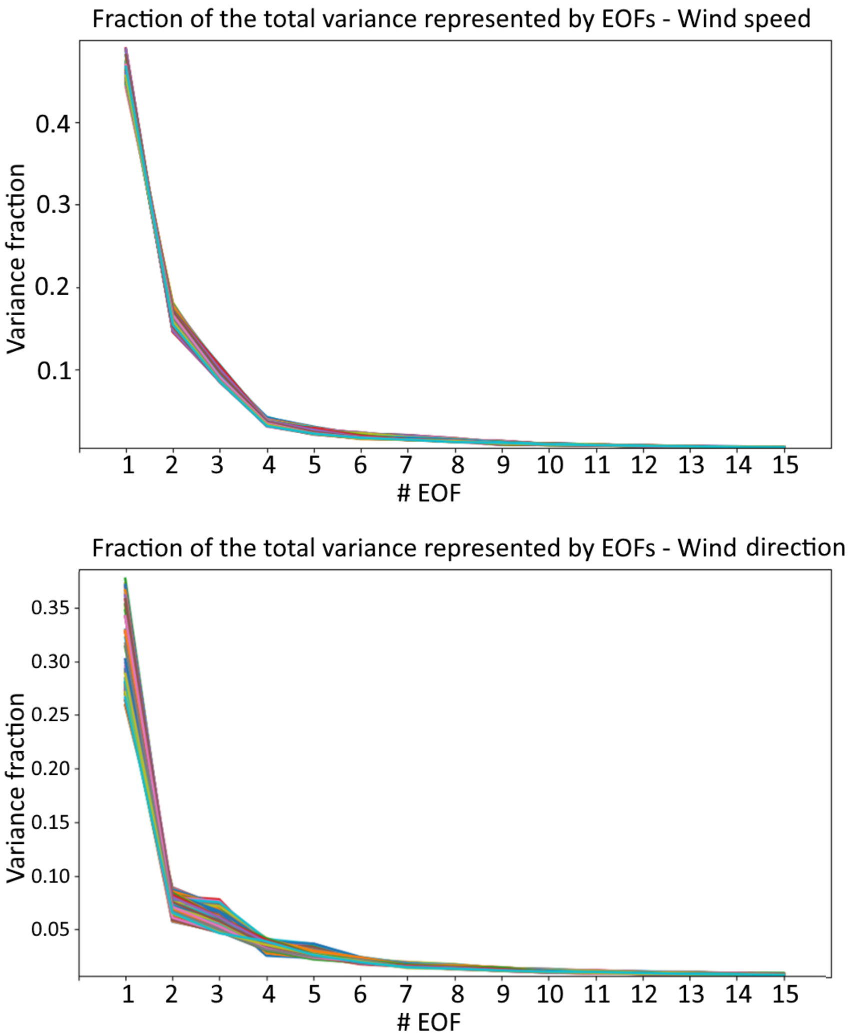

Figure 7. The fraction of the total variance in the training period (2017.-2018.) represented by EOFs for wind speed and direction predictors.

The raw NWP that needs to be post-processed by analog-based algorithm should then be translated into "current" PCs using pre-calculated EOFs. The "similarity" between different analogs can then be calculated using PCs as different predictors in the algorithm. This procedure might also include different weights, e.g., depending on the variable and/or variance fraction described by each EOF. It needs to be mentioned that the algorithms for such procedure are partially developed, but since the results are suspicious they need further inspection.
Finally, several other ideas are mentioned as a possible continuation of this work. For instance, additional calibration might also be done using ensemble model output statistics (EMOS) or EMOS can even be blended in the analog-searching procedure. Also, methods such as quantile mapping and rank-weighted best-member dressing (Hamill and Scheuerer, 2018) or Schaake shuffle (as in Scheuerer and Hamill, 2018) can also be considered.

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5 References

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