A Beginners Introduction to the Analog Ensemble Technique

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Sections

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1. Introduction

The Analog Ensemble (AnEn) technique was developed to generate a probability distribution function (PDF) of an expected outcome from a current deterministic forecast and corresponding sets of historical forecasts and verifying observations. A current short-term deterministic forecast is compared to a history of past forecasts. The most similar past forecasts are selected, and the corresponding observations are used to generate a bias adjusted and well-calibrated short-term probabilistic forecast. The AnEn improves short-term weather prediction accuracy, decreases real-time computational costs, and provides spatial and temporal uncertainty estimation (Delle Monache et al. 2011; Delle Monache et al. 2013; Alessasndrini et al. 2015; Zhang et al. 2015). The main requirement to build a skillful AnEn is the availability of an historical set of past observations and predictions from a "frozen" system, for at least several months spanning the seasons relevant for the prediction of interest. However, the best performance is obtained with two years of data, or more.

The technique has implications in physical science subject areas where: 1) single deterministic predictions, past predictions, and their corresponding observations are available; 2) it is necessary to have quantifiable and justifiable measures of uncertainty; and 3) computational resources are precious. Currently in meteorology, this task is accomplished by running a computationally expensive ensemble of simulations generated using a numerical weather prediction (NWP) model. The AnEn technique provides an alternative option for generating probabilistic forecasts without requiring the computational expense of a NWP ensemble thus allowing scientists to choose between the tradeoff of higher resolution modeling or ensemble modeling at a more coarse resolution. Applications of the technique include but are not limited to: a range of weather parameters (e.g., 10-m and 80-m wind speed, 2-m temperature, relative humidity), solar power forecasting, wind power forecasting, air quality forecasting, tropical cyclone predictions, and downscaling of parameters such as wind speed and precipitation.

2. Weather Analogs

What is an analog?

Analog-based methods are techniques in which a current state of the atmosphere is compared with a repository of other states of the atmosphere to determine the most similar scenario in the past (an analog) (Van den Dool, 1989; Hamill and Whitaker, 2006; Delle Monache et al., 2011; Delle Monache et al., 2013). Lorenz (1969) stated that analogues refer to "two states of the atmosphere which resemble each other rather closely" and continued on to say, "Each state may then be looked upon as equivalent to the other state plus a reasonably small 'error'." Traditionally, in meteorology, analogs have been used primarily for pre- and post- processing of NWP forecasts (Hamill and Whitaker, 2006).

<u>A Brief History of Analogs Related Research in the Weather Community</u>

The concept of using analogs, similar past occurrences to current events, has been a part of the meteorological community since the 1960's. The following are a few key highlights of analogs related research from core papers published over the years.

- Lorenz (1969) studied very large maps covering the Northern Hemisphere (200mb, 500mb, and 850mb surfaces at a 1003-point grid, twice per day, for a 5-year dataset) in order to determine if analogs could provide insight into questions regarding error growth in modeling the atmosphere. Lorenz obtained insight into the growth of moderately small errors and extrapolated this information to the growth of small errors. He did conclude that there were too many degrees of freedom to obtain an accurate assessment because the study was able to find mediocre analogs but lacked good, close analog examples. Lorenz (1969) estimated that 140-year worth of upper-level data would be needed to find good analogs and to truly understand the growth of small errors through the use of analogs.

- In 1994, van den Dool (1994) presented research on the length of a training dataset required to produce skillful analog forecasts. In studying 500mb over the Northern Hemisphere, he concluded that a significant size dataset of approximately 10^{30} years would be needed in order to find analogs that could match within current observational error. The exception to this would be if researchers decreased the size of the area over which analogs are sought. Searching for analogs over smaller areas would decrease the size of the dataset size needed.
- Hamill and Whitaker (2006) presented the use of analogs as a tool for precipitation calibration. This study focused on using one predictor at one specific time over a specified tile (grid/raster). Hamill and Whitaker (2006) experimented with a series of analog techniques using a 25-year reforecast dataset with a 15-member ensemble in order to statistically correct precipitation forecasts.
- In relation to the previous concepts, the AnEn technique generates analogs in an extremely localized sense compared to the previous concepts. Continue to Section 3 for further details.
- Panziera et al. (2011), Liechti et al. (2013), and Foresti et al. (2015) studied the use of analogues-based techniques to predict the occurrence of terrain induced (orographic) precipitation. The studies utilized historical mesoscale situations and rainfall fields to determine analogues. For ensuing hydrological runoff predictions, Liechti et al. (2013) showed that discharge forecasts performed better with the use of the analog based system than with the use of deterministic radar data. Panziera et al. (2011) show that the use of historical analogues with a lead time of at least 1-h is better than persistence and is better than the ensemble forecast model used up until a lead time of 4-h is reached.

The above are several examples of different ways the concept of analogs has been implemented or evolved over the years. There is a host of additional reading and information available on this topic.

3. Analog Ensemble Technique Overview

What is the analog ensemble technique and how does it work?

Researchers at the National Center for Atmospheric Research (NCAR) pioneered initial development and investigations of the point-based AnEn technique in 2010 (Delle Monache et al., 2011; Delle Monache et al., 2013). The AnEn estimates the probability distribution of a future value of the predictand variable, y, given a model prediction, f, and the repository of past forecast and the observed real values x. This is represented as a probability, $P(y|xf)$. Figure 1 provides a pictorial representation of the method. At a given time and location, y is the ensemble of observed values (orange squares), which are associated with the most similar forecasts (blue squares) to the current deterministic forecast (black square). Each forecast (black and blue squares) is composed of a multivariate vector of geophysical variables, whereas the observations (green squares) are the geophysical variable to be predicted (Delle Monache et al., 2013). The process

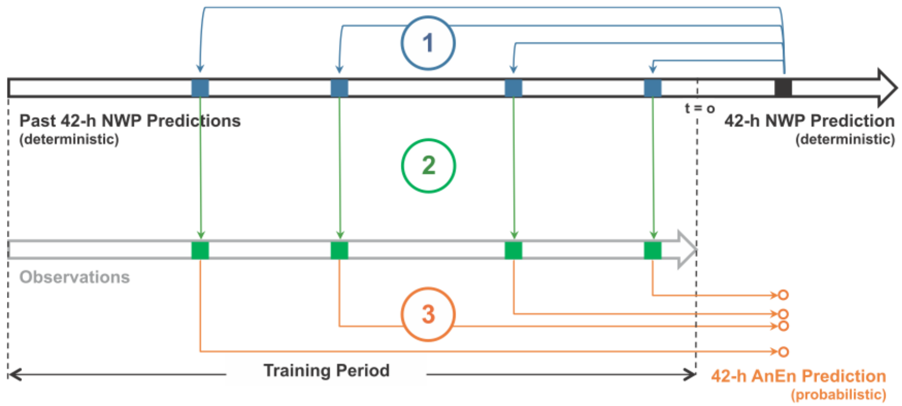


Figure 1: From Delle Monache et al. (2013), this figure provides a pictorial representation of the AnEn technique. The black box indicates the current deterministic NWP. The blue boxes indicate the best matching (i.e. most similar) historical forecasts (analogs) for the current prediction. The best match is determined by the similarity metric described in Equation 1. Corresponding observations (green boxes) are gathered from the data record (search space) and collectively, make up the ensemble of analogs (orange circles). Line numbers 1, 2, and 3 indicate the flow of the process from the current deterministic forecast to the discovery of the most similar past set ups (1), to obtaining the corresponding observations (2), to gathering the observations to generate the ensemble of analogs (3). In summary, using a single deterministic forecast from a NWP model, a set of past predictions and corresponding observations, the AnEn generates a probabilistic distribution of the potential future states of the atmosphere.

is repeated independently for each location in time and space. AnEn members consist of verifying observations for each matching analog in a deterministic NWP output, which have the benefit of being bias corrected and calibrated. The similarity metric shown in Equation 1 determines the best match between the current prediction and past predictions, where F_t is the forecast to be corrected at a given time t and specific location in space.

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

In Equation 1, F_t is the forecast to be corrected at a given time t and specific station location; A_t is an analog forecast at time t' before F_t is issued and at the same location. N_v and w_i are the number of predictors and their weights, respectively; σ_{f_i} is the standard deviation of the time series of past forecasts of a given variable at the same location and $\tilde{t}$ is an integer equal to half the width of the time window over which the metric is computed. $F_{i,t+j}$ and $A_{i,t'+j}$ are values of the prediction and the analog in the time window for a given variable. This metric describes the quality of the analog chosen and is based upon the similarity of the current forecast window to the past forecast time windows available in the historical dataset. E.g., for a three-hour forecast the window would consist of three points, t-3hr, t, and t+3hr.

4. How the AnEn Technique Developed and How it Differs from Previous Analog Related Meteorological Research

How the AnEn Technique Developed

The AnEn technique was developed through a challenge Dr. Delle Monache faced in air quality forecasting. Dr. Delle Monache had data from several air quality forecast models and was trying to combine the Kalman filter correction with an ensemble of models in order to see if he could improve the forecast skill of the short-term (1-2 day) ozone forecasts. The Kalman filter was applied to each of the models available. The ensemble output from before and after the correction was compared. Results showed that the Kalman filter improved the ozone forecasts up to a certain threshold and then the improvement would halt. The improvement would not continue for more rare events and, in these cases, use of the Kalman filter would potentially even degrade the results. Dr. Delle Monache identified that the issue lay in the fact that the Kalman filter gives higher weight to more recent days. In other words, what occurs more recently is very important to the Kalman filter. However, for the specific air quality parameter he was interested in forecasting, the most recent days were not the best for ozone forecasting, particularly when episodic high-concentration were measured, events that typically occur only for one to three days in his data set. Dr. Delle Monache decided he needed to make a correction using a day (any day) in the past that is most similar, where the model is making the same mistake. And the AnEn technique was born!

How the AnEn Technique Differs from Previous Analog Related Meteorological Research

The AnEn differs from traditional analogs tested in the meteorological community in several ways. Rather than a post-processing tool based on the mean of a NWP ensemble, the point-based AnEn is generated using dynamics-based model predictions that are sought independently at each location over a 3-point time window using a multivariate metric (Lorenz, 1969; Delle Monache et al., 2013; Vanvyve et al., 2015). With the AnEn technique, an ensemble is generated from a current deterministic forecast and historical repository of deterministic forecasts. Previously, analogs typically focused on using analogs as a calibration tool for modeling. With the AnEn technique, the entirety of the available historical repository is utilized in the search for most similar past occurrences (Hamill and Whitaker, 2006; Delle Monache et al., 2013).

5. Overview of Current State of the Art with the AnEn Technique

Grid Based Implementation of the Analog Ensemble technique

Note: This work has been submitted and accepted but not yet published so references and full descriptions are limited. Material for this description is extracted from a presentation given by Mr. Simone Sperati at the National Center for Atmospheric Research (NCAR) in Summer 2016 and conversations with Mr. Sperati and his collaborators.

Researchers at the National Center for Atmospheric Research (NCAR) have applied the aforementioned point-based AnEn technique described in Delle Monache et al. (2013) directly to a gridded forecast product in order to use the AnEn to generate two-dimensional (2D) forecast fields. Research results produced a choppy, disjointed field that failed to improve via interpolation. Spatial and temporal consistency was not maintained therefore scientists needed to determine a means of restoring spatio-temporal consistency. This led researchers to the Schaake Shuffle (SS).

What is the Schaake Shuffle?

The SS was developed to reconstruct spatial and temporal variability in forecast variables (Clark et al., 2004; Schefzik et al., 2013). Specifically, Clark et al. (2004), focused on reconstructing downscaled precipitation and temperature fields for four river basins in the United States (U.S.). The method is a post-processing step for forecast model output. In Clark et al. (2004), ensemble members from a forecast model for a specific day are ranked, data values for the parameters of interest (precipitation and temperature) from same dates in the historical record are ranked, the ensemble members are matched to the ranked historical data, and the ensemble members are reordered to match the ordering of the historical data.

Figure 2 provides a clear demonstration of the difference in the output obtained by direct use of the AnEn (top two panels) versus the combination of the AnEn + Schaake Shuffle (AnEn + SS). Application of the SS to the field improved the spatial and temporal consistency of the field. An analysis of forecast improvement compared output from the calibrated Ensemble Prediction System (EPS), the AnEn + SS, and the AnEn + Schaake Shuffle Control Run (CR). The calibrated EPS is output from the calibrated European Centre for Medium-Range Weather Forecasting (ECMWF) EPS, ECMWF deterministic run is used to generate the AnEn, and the AnEn CR is generated from the ECMWF EPS control run. Deterministic and probabilistic metrics such as bias, centered root mean squared error (CRMSE), continuous ranked probability score (CRPS), and rank histograms were used to verify performance. In general, results showed that AnEn + SS performed better than the calibrated EPS and AnEn CR until 36-48 hours out (Sperati, 2016).

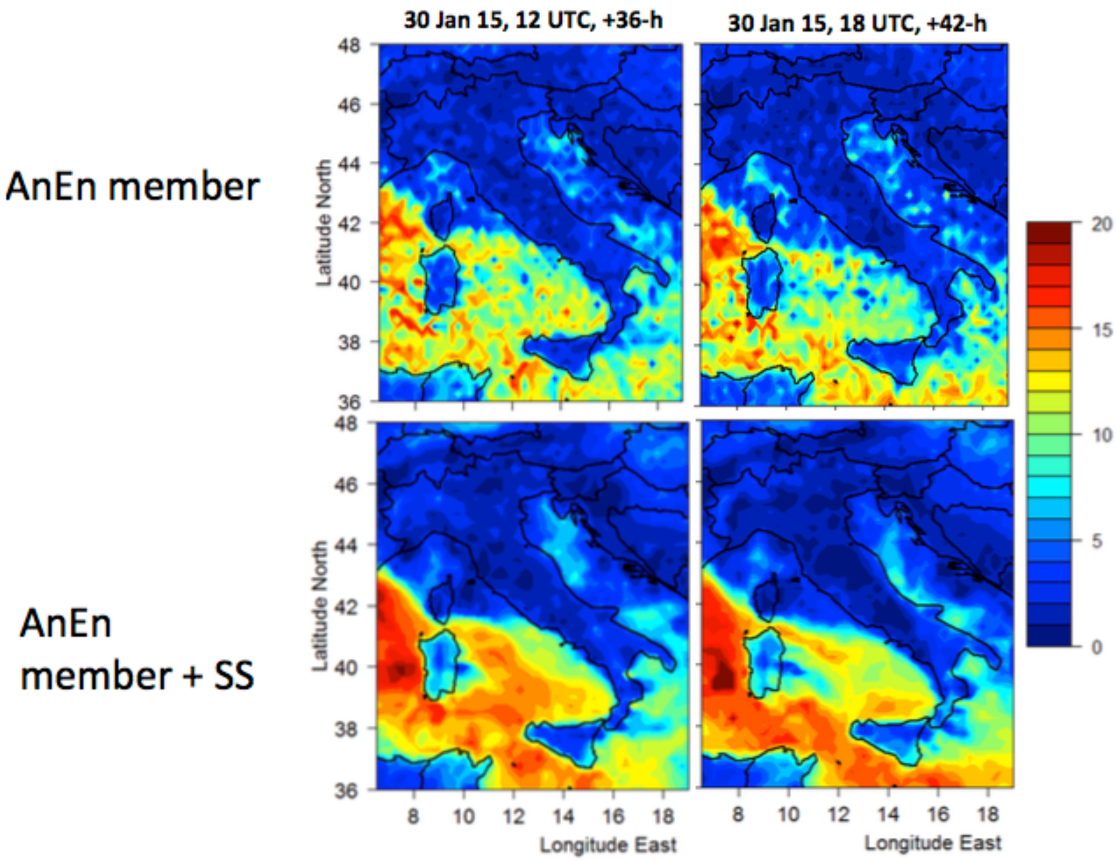


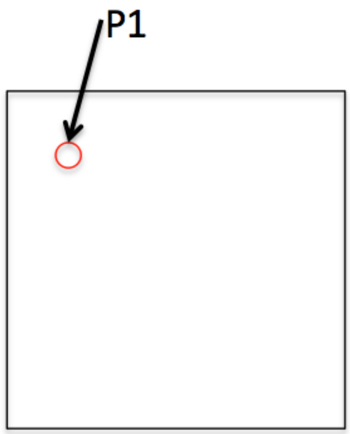
Figure 2: Depicts forecast fields generated using the AnEn (top two figures) and the AnEn + SS (bottom two figures). This presents 10-m wind speed forecasts from each method and shows a distinct difference in the spatial consistency of the combined AnEn + SS. (Source: Slide deck from the presentation by Mr. Sperati on 8 Apr 2016 at NCAR).

How does the AnEn + SS function?

The AnEn chooses the most similar past forecast and selects the corresponding verifying observation. The Schaake Shuffle is applied to the ensemble of analogs where it reorders the members resulting in an improvement of the spatial and temporal grid. The process is stationary. The process generates a different realization of the same stochastic process. The activity below provides a pictorial description of the combination of the AnEn and Schaake Shuffle with a mock map, points, and data values.

<u>Schaake Shuffle Activity</u>
A pictorial description of the AnEn + SS with a mock map, points, and data 'points/values.' Description for three points:

- Time = 00 UTC, lead time = 0
- Number of ensemble members = 4 ensemble members



Point 1 (P1):

- Determine the most similar past forecasts based on the similarity metric defined in Delle Monache et al. (2013):

  4 ensemble members = (5, 2, 1, 10)
- Take the corresponding observation for each chosen forecast and identify the dates each observation came from:
  - Corresponding observations

    Obsv = (4,2,9,10)
  - Dates

    Dates = (00Z 12 Dec, 00Z 1 Dec, 00Z 10 Jan, 00Z 10 Mar)

- Rank the past similar forecasts and the observations

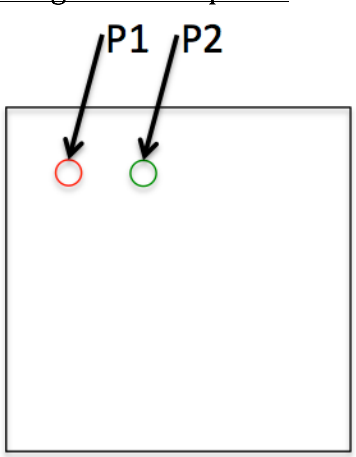
  Ranked past forecasts = (1,2,5,10)

  Ranked (sorted) observations = (2,4,9,10)
- Determine the B function (Copula function)
  - The B function is the connection between the ranked and unranked. This is what is used to shuffle the positions.

    $$B\left(P_{sorted\ obsv} = (1,2,3,4)\right) = (2,1,4,3)$$
  - The B function changes for every lead-time and every station.
- Now using this B function that links the position of the observation before sorting and the position after sorting, re-sort the ensemble forecast members. The result becomes:

  (2, 1, 10, 5)
  - Position one (1) corresponds to the second (2nd) position. Position two (2) corresponds to the first (1st) position. Position three (3) corresponds to the fourth (4th) position in the vector. Position four (4) corresponds to the third (3rd) position in the vector.
- This is executed at lead-time = 0 (analysis). Next, the same process will be executed for lead-time = 1 and so on. However, the same dates (e.g. 12 Dec, 1 Dec, 10 Jan, 10 Mar) must not be used.

Moving to the 2nd point:



Note: (1) the selected dates have to remain the same for ensuing lead times and (2) the same dates have to be the same across multiple locations.

- Dates

  Dates = (00Z 12 Dec, 00Z 1 Dec, 00Z 10 Jan, 00Z 10 Mar)
- Same past forecast dates (could also call this members) but different forecast values and different observations because this is a different location

  4 ensemble members = (6,1,2,9)

  Corresponding Observations = (5,3,8,11)

4 ensemble members$_{sorted}$ = (1,2,6,9)
Sorted: Observations$_{sorted}$ = (3,5,8,11)

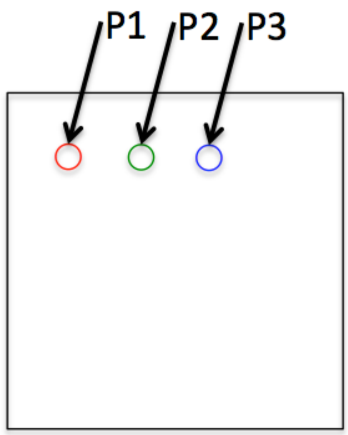
Establish Copula function (B):

$$B(P_{sorted\ obsv} = (1,2,3,4)) = (2,1,4,3)$$

- Use the B function to re-sort ensemble of past forecasts. The result becomes:
  (1,2,6,9)

- This would continue for ensuing lead times

<u>Moving to the 3rd point:</u>



- The same method continues. Try it out for yourself!

<u>Pros and cons of the Schaake Shuffle include:</u>

Pros:

- Improve spatial and temporal consistency
- Generic approach: Generalizability across different domains. Clark et al. (2004) presents the material in the context of precipitation and temperature forecasts but this has applications other fields as well (i.e., stream flow modeling within watersheds, data assimilation of snow)
- The method can be performed across multiple variables
- The SS post processing method is very fast computationally because the Schaake Shuffle executes a series of vector manipulations which can be executed rapidly by computers

Cons:

- Assumption of stationarity. Within the context of using the AnEn + Schaake Shuffle, the stationarity assumption means that dates selected in the historical forecast period must remain the same for (a) subsequent lead times and (b) across multiple locations.
- The AnEn + SS adds a post processing step to the AnEn technique in order to use the AnEn to generate gridded fields. (However, note the previously mentioned positive

with respect to the computational speed of the SS. Therefore, for completeness, we acknowledge that the SS adds a post-processing step however the computational cost is very small and this is simply mentioned here for completeness)

In summary, the implementation of the SS has improved the spatial and temporal consistency for a direct application of the point-based similarity metric described in Delle Monache et al. (2013) to a grid based forecast.

6. References

Alessasndrini S., L. Delle Monache, L. Sperati and G. Cervone, "An analog ensemble for short-term probabilistic solar power forecast," *Applied Energy,* vol. 157, pp. 95-110, 2015.

Berner, J., Shutts, G., Leutbecher, M., Palmer, T., 2009. A spectral stochastic kinetic energy backscatter scheme and its impact on flow-dependent predictability in the ecmwf ensemble prediction system. *Journal of the Atmospheric Sciences* 66 (3), 603–626.

Berner, J., Ha, S.-Y., Hacker, J., Fournier, A., Snyder, C., 2011. Model uncertainty in a mesoscale ensemble prediction system: Stochastic versus multiphysics representations. *Monthly Weather Review* 139 (6), 1972–1995.

Cervone, G., Clemente-Harding, L., Alessandrini, S. and Delle Monache, L., 2017. Short-term photovoltaic power forecasting using Artificial Neural Networks and an Analog Ensemble. *Renewable Energy*, *108*, pp.274-286.

Clark, M., Gangopadhyay, S., Hay, L., Rajagopalan, B., & Wilby, R. (2004). The Schaake shuffle: A method for reconstructing space–time variability in forecasted precipitation and temperature fields. *Journal of Hydrometeorology*, *5*(1), 243-262.

Delle Monache L., T. Nipen, Y. Liu, G. Roux and R. Stull, "Kalman filter and analog schemes to post-process numerical weather predictions," *Monthly Weather Review,* vol. 139, p. 35543570, 2011.

Delle Monache L., T. Eckel, D. Rife, B. Nagarajan and K. Searight, "Probabilistic weather predictions with an analog ensemble," *Monthly Weather Review,* vol. 131, pp. 3498-3516, 2013.

Foresti, L., Panziera, L., Mandapaka, P.V., Germann, U. and Seed, A., 2015. Retrieval of analogue radar images for ensemble nowcasting of orographic rainfall. *Meteorological Applications*, *22*(2), pp.141-155.

Hamill, T.M. and Whitaker, J.S., 2006. Probabilistic quantitative precipitation forecasts based on reforecast analogs: Theory and application. *Monthly Weather Review*, *134*(11), pp. 3209-3229.

Jolliffe, I. T., Stephenson, D. B., 2012. Forecast verification: a practitioner's guide in atmospheric science, 2nd Edition. John Wiley and Sons.

Junk, C., Delle Monache, L., Alessandrini, S., Cervone, G. and von Bremen, L., 2015. Predictor-weighting strategies for probabilistic wind power forecasting with an analog ensemble. *Meteorologische Zeitschrift*, *24*(4), pp.361-379.

Liechti, K., Panziera, L., Germann, U. and Zappa, M., 2013. The potential of radar-based ensemble forecasts for flash-flood early warning in the southern Swiss Alps. *Hydrology and Earth System Sciences*, *17*(10), pp.3853-3869.

Lorenz, E. N., 1963: Deterministic nonperiodic flow. *J. Atmos. Sci.*, **20,** 130–141.

Lorenz, E.N., 1969. Atmospheric predictability as revealed by naturally occurring analogues. *Journal of the Atmospheric sciences*, *26*(4), pp.636-646.

Messner, J. W., Mayr, G. J., 2011. Probabilistic forecasts using analogs in the idealized lorenz96 setting. *Monthly Weather Review* 139 (6), 1960–1971.

Murphy, A. H., Winkler, R. L., 1987. A general framework for forecast verification. *Monthly Weather Review* 115 (7), 1330–1338.

Panziera, L., Germann, U., Gabella, M., Mandapaka, P., 2011. NORA–Nowcasting of orographic rainfall by means of analogues. *Quarterly Journal of the Royal Meteorological Society* 137 (661), 2106–2123.

Van den Dool, H. M., 1989: A new look at weather forecasting through analogues. *Mon. Wea. Rev.*, **117,**2230–2247.

van den Dool, H. M., 1994: Searching for analogues, how long must we wait? *Tellus*, **46A,** 314–324.

Vanvyve, E., Delle Monache, L., Monaghan, A.J. and Pinto, J.O., 2015. Wind resource estimates with an analog ensemble approach. *Renewable Energy*, *74*, pp.761-773.

Wilks, D. S., 1995: *Statistical Methods in the Atmospheric Sciences*. Academic Press, 467 pp.

Zhang J., C. Draxl, T. Hopson, L. Delle Monache, E. Vanvyve and B. M. Hodge, "Comparison of numerical weather prediction based deterministic and probabilistic wind resource assessment methods," *Applied Energy,* vol. 156, pp. 528-541, 2015.

APPENDIX

1. Acronyms

1D	one-dimensional
2D	two-dimensional
AnEn	Analog Ensemble
ANN	Artificial Neural Network
CR	Control Run
CRMSE	Centered Root Mean Square Error
CRPS	Continuous Ranked Probability Score
ECMWF	European Centre for Medium-Range Weather Forecasts
NCAR	National Center for Atmospheric Research
NWP	Numerical Weather Prediction
SS	Schaake Shuffle

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