State-of-the-Art Climate Predictions for Energy Climate Services

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Abstract*- Seasonal predictions of 10-m wind speed can be used by the wind energy sector in a number of decision making processes. Two different techniques of post-processing are applied in order to correct the unavoidable systematic errors present in all forecast systems. Besides an assessment of the impact of these corrections on the quality of the probabilistic forecast system is provided.*

Key words: wind energy, seasonal forecasts, bias-correction, forecast verification

A. Introduction

The need of accurate forecasts becomes increasingly important in the wind energy sector due to the intermittent nature of wind power generation, and the need to match supply with demand at all times [1].

Climate predictions of time scales from a month to decades in the future, and that are tailored to the wind energy sector represent the cutting edge in climate sciences to forecast wind power generation. The seasonal prediction addresses a long list of challenges to produce climate information that responds to the expectations of the users [2]. At these time scales, current energy practices use a deterministic approach based on retrospective climatology, but seasonal predictions have recently been shown to provide additional value.

In particular probabilistic climate predictions of near surface winds can allow end users to take calculated, precautionary action with a potential cost savings to their operations. Electricity system operators can use these predictions to adapt energy supply availability from wind farms, and allow the electric network to conveniently adapt demand and resources [3].

For this reason our main goal is to inform users, with greater accuracy than their current approach, what will be the most likely range of wind speed of the upcoming years. This study analyses the ECMWF S4 seasonal forecast system for wind speed to assess the quality of these predictions and its properties.

B. Data and Methods

The forecasts of 10-m wind speed from the ECMWF S4 model on winter (December, January and February) with a start date of the 1st of November are used, because in this season the wind speed variability is higher. The 10-m wind speed data from ERA-Interim have been also used as reference dataset.

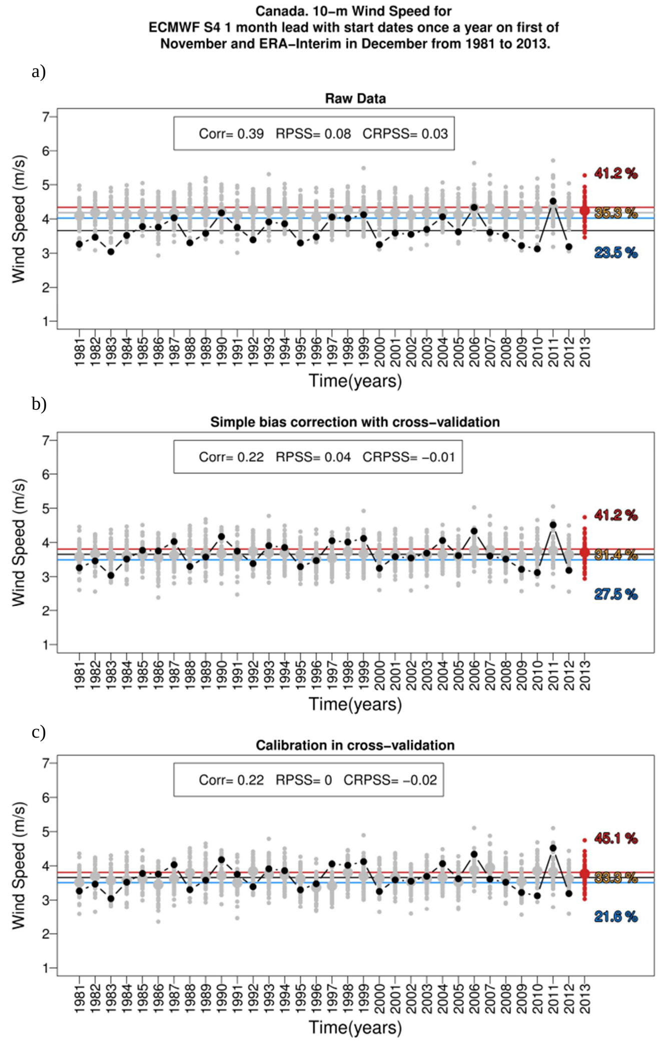

Figure 1. Time series of 10-m wind speed i: a) Raw data, b) Simple Bias corrected and c) Calibrated, in the period 1981-2013. The ensemble members of the hindcasts are represented as small grey dots and the ensemble mean is represented with a large grey dot for each start date. The grey horizontal line shows the mean of the hindcast in whole period. The black dots represent the 10-m wind speed values of ERA-Interim. The black horizontal line shows the mean of the reference in whole period. The blue and red horizontal lines show the lower and upper terciles, respectively. The ensemble members of the forecast year are represented as small red dots and the ensemble mean is represented with a large red dot. The percentages indicates the number of members in each category, which are limited by the terciles.

As with every variable predicted in a coupled model forecast system, the prediction of wind speed is affected by biases. For probabilistic forecasts, this defect consists of their lack of sufficient (probabilistic) reliability: they generally are under-dispersive [4]. To overcome this, two different techniques for the post-processing of ensemble forecasts are considered: a simple bias correction and a calibration method. Both methods use the “one-year out” cross-validated mode, and they provide corrected forecasts with improved statistical properties.

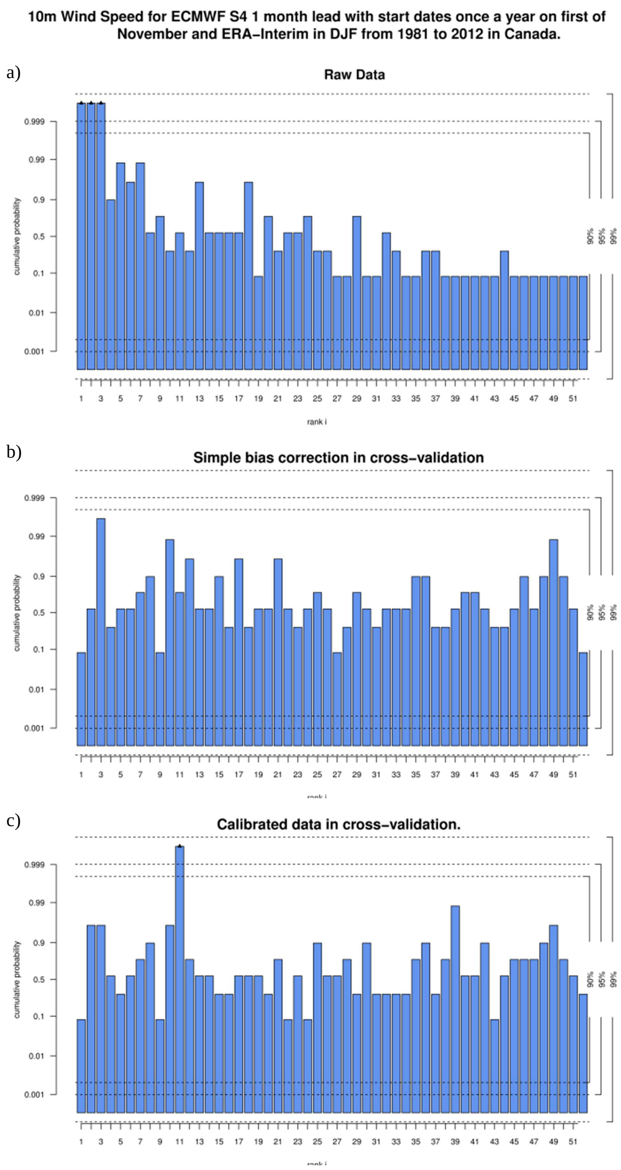

Figure 2. Rank histograms of 10-m wind speeds forecasts a) Raw data, b) Simple Bias corrected and c) Calibrated, in the period 1981-2012. The x-axis represents the rank and the y-axis the cumulative probabilities, which shows if the deviations from the reliable behaviour are systematic or random. The intervals on the right of the plot indicate central 90, 95 and 99 % simultaneous confidence intervals.

C. RESULTS

The impact of these bias corrections on the quality of the ECMWF S4 predictions of near surface wind speed during winter is explored. To offer a comprehensive picture of the post-processing effect on the forecast quality of the system, it is necessary to use different scoring measures as skill scores (Figure 1) or rank histograms (Figure 2). As illustrated, a key region for the wind energy sector in Canada has been analysed.

Figure 1 shows that the skill scores decrease when post-processing techniques are applied. All operations performed on a forecast will increase its uncertainty. Even correcting the bias in the mean implies estimating the mean from the hindcasts, which is an estimate with its own uncertainty and is thus propagated into the forecasts

The rank histograms show if the ensemble members and the verifying observation come from the same probability distribution, in which case the forecasts are statistically consistent and the rank histogram should be flat or uniform. These histograms display the cumulative frequency in the y-axis, which provides quantitative information as to whether the deviations from reliable behavior are systematic or merely random. For the raw data (Figure 2a) a bias seems to be present as the rank histogram shows overpopulated lower ranks. The bias corrected and the calibrated rank histograms (Figures 2b and 2c, respectively) are more homogeneously populated, therefore the reliability of the ensemble improves when post-processing is applied

D. CONCLUSIONS

This study reveals that the different techniques to correct climate predictions produce a statistically consistent ensemble. However, the operations performed decrease their skill, which would correspond to an increase in the uncertainty. Therefore, even though the bias correction is fundamental for climate services, this comes at a price in terms of forecast quality.

REFERENCES

[1] Füss, R., Mahringer, S., & Prokopczuk, M. (2013). Electricity derivatives pricing with forward-looking information. University of St. Gallen, School of Finance Research Paper, (2013/17).

[2] Doblas-Reyes, F. J., García-Serrano, J., Lienert, F., Biescas, A. P., & Rodrigues, L. R. (2013). Seasonal climate predictability and forecasting: status and prospects. Wiley Interdisciplinary Reviews: Climate Change, 4(4), 245-268.

[3] Weisser, D., & Foxon, T. J. (2003). Implications of seasonal and diurnal variations of wind velocity for power output estimation of a turbine: a case study of Grenada. International Journal of Energy Research, 27(13), 1165-1179.

[4] Pinson, P. (2012). Adaptive calibration of (u, v) wind ensemble forecasts. Quarterly Journal of the Royal Meteorological Society, 138(666), 1273-1284.