State-of-the-art in climate Predictions for Energy Climate Services

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References

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1. Introduction

Climate predictions of time scales from one month to decades in the future 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 [1]. 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.

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

2. Data

The seasonal analysis is based on the ensemble forecasts of 10-m wind speed from the ECMWF S4 model for winter (December-January-February) with a start date of the 1st of November. We use the 51 members of the wind speed data available on the regular latitude-longitude grid of cell-size 0.75° over a period spanning 1981 to 2013. The surface wind speed data from ERA-Interim have been used for validation.

3. Methodology

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 are generally under-dispersive [2].

To overcome this, two different techniques for the post-processing of ensemble forecasts are considered: a simple bias correction and a calibration method. The former is based on the assumption that the reference and predicted distributions are well approximated by a normal distribution. The latter is a calibration technique which inflates the model variance, and the inflation of the ensemble is required in order to obtain a reliable outcome.

Both methods use the "one-year out" cross-validated mode, and they provide corrected forecasts with improved statistical properties.

4. Results

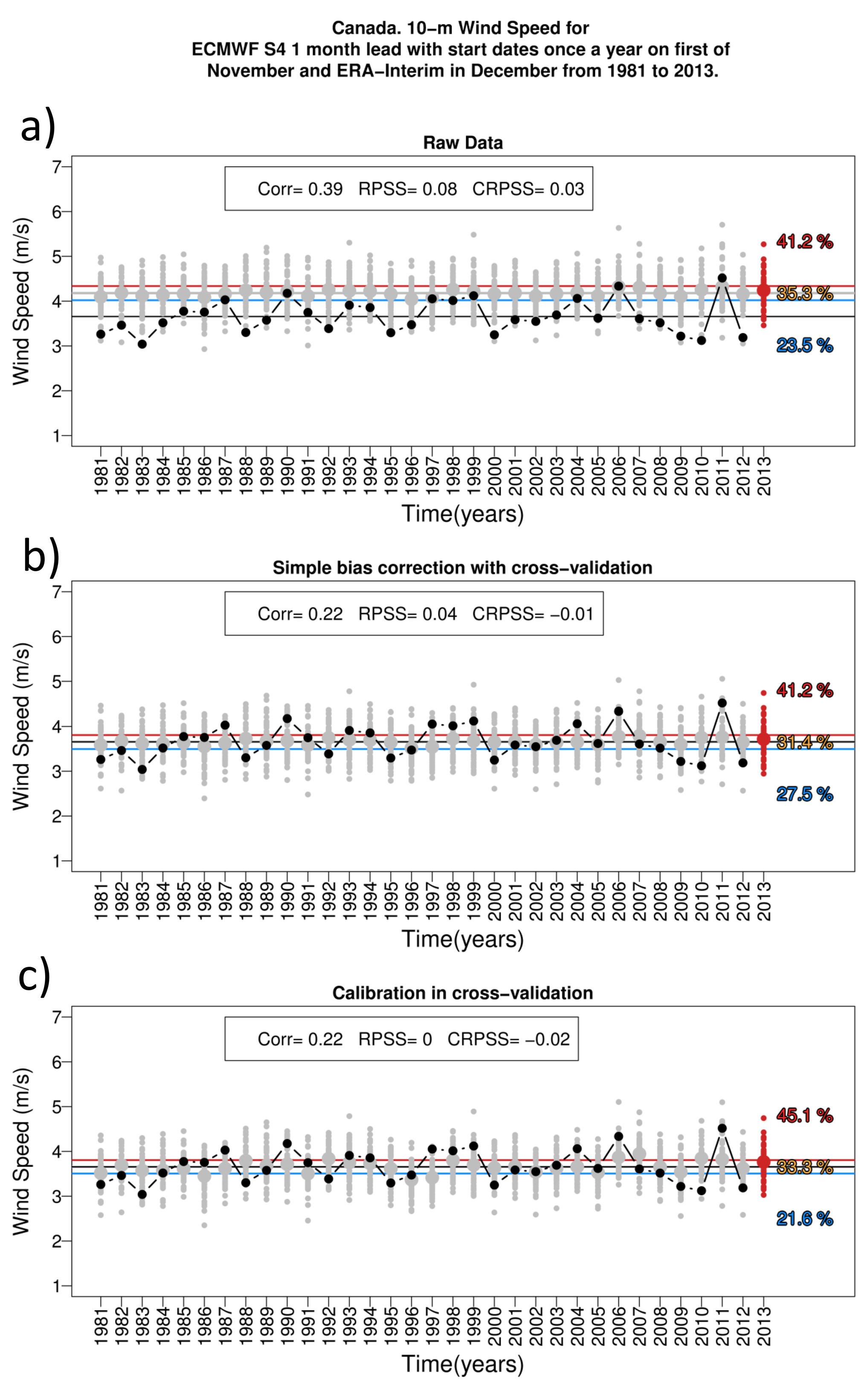

Figure 1. Time series of 10-m wind speed i: a) Raw data, b) Simple Bias corrected and c) Calibrated, in the period 1981-2013. The ensemble members of the hindcasts (small grey dots) and the ensemble mean (large grey dots) are represented with a for each start date. The grey horizontal line shows the mean of the hindcast in whole period and blue and red horizontal lines show its 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 The black dots represent the 10-m wind speed values of ERA-Interim (reference). The black horizontal line shows the mean of the reference in whole period.

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 with 4 grid-points for the wind energy sector in Canada has been analysed.

Figure 1 displays the time-series for the spatial average of the selected grid-points in the Canadian region. The probabilities of wind speeds in each category differ when post-processing is applied because the average statistical properties of the hindcast have been modified to be similar to those of the reference dataset, thus the terciles and their linked probabilities change. The skill scores (Figure 1) 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. In addition, the calibrated forecasts (Figure 1c) have slightly lower skill than the raw (Figure 1a) and the simple bias corrected data (Figure 1b), but the gain in forecast quality for these predictions comes through the correction of the underestimation and overestimation of the ensemble spread and provides more reliable forecasts.

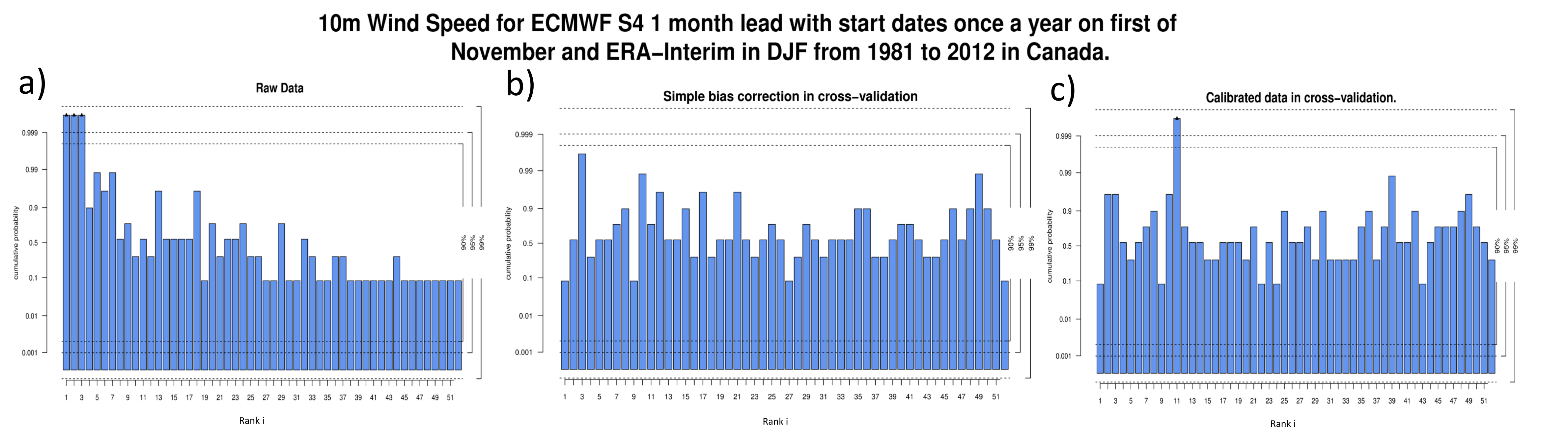

Figure 2. Rank histograms of 10-m wind speeds forecasts a) Raw data, b) Simple Bias corrected and c) Calibrated, in the period 1981-2012. The x-axis represents the rank and the y-axis the cumulative probabilities, which shows if the deviations from the reliable behavior are systematic or random. The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

The rank histograms (Figure 2) 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, but because of sampling variations the histograms are almost never exactly flat [3]. 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 seems to improve when post-processing is applied.

	Raw data			Simple bias correction			Calibration		
	Pearson χ^2	JP slope	JP convex	Pearson χ^2	JP slope	JP convex	Pearson χ^2	JP slope	JP convex
Test statistic	462.69	167.26	83.64	54	0.15	0.62	62.94	0.62	2.15
p-value	0	0	0	0.36	0.70	0.43	0.12	0.97	0.14

Table1. Statistical tests. Pearson χ^2 statistic, the Jolliffe-Primo test statistic for slope (JP slope), and the Jolliffe-Primo test statistic for convexity (JP convex) for the Raw Data, Simple bias Correction and Calibration cases .Their p-values under the null hypothesis of an asymptotically flat rank histogram are included.

To validate this visual result and assess if the deviations from the flatness of the rank histograms are attributed to chance or deficiencies in the forecasts, goodness-of-fit test statistics are computed and included in the Table 1. They indicate that departures from the flatness exist for the Raw Data, in particular the JP slope test statistic points out that there is a bias. The results are significant, because the p-values are zero. The statistics, linked to the simple bias corrected and the calibrated data, decrease indicating that the deviation of the flatness is low. The higher p-values confirm that there is no evidence against the null hypothesis of uniformity.

5. 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.