METHODOLOGY TO ESTIMATE SEASONAL PREDICTIONS OF CAPACITY FACTOR

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Summary

Climate predictions tailored to the wind energy sector represent an innovation to better understand the future variability of wind energy resources. This study describes a simple methodology to develop tailored information for the wind energy users that can be easily integrated in their decision-making processes. The challenge for the translation of the climate variables provided by the seasonal prediction systems into wind energy impact variables has not been previously addressed, because these methodologies have to take into account the systematic errors inherent to the climate predictions.

In this technical report we have developed a simple methodology that translates wind speed and temperature seasonal predictions into capacity factor, a tailored variable for some wind energy user needs. Firstly, the seasonal predictions of wind speed and temperature have been bias-adjusted, a crucial step to produce useful information. Then, adjusted predictions have been used in a transfer model based on impact surfaces. Impact surfaces relate discretized climate variables (wind or temperature) with impact variables (capacity factor). Two impact surfaces, one from past observations and another for the seasonal predictions, are combined to generate seasonal predictions of capacity factor.

Finally, the quality of the probabilistic seasonal predictions of the capacity factor obtained from the transfer model has been explored. In addition, the benefits of these predictions to the wind energy users in terms of wind energy supply or demand have been discussed.

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1. Introduction

The energy sector is the largest greenhouse gases emitting sector, being responsible for 35% of global emissions (Pachauri et al. 2014). Mitigation efforts in several countries are promoting the growth of low-carbon energies. The EU targets at least a 27% share of renewable energy consumption by 2030 and at least a 35% share is expected by 2050 (European Commission 2016). This ever-growing amount of renewable energy sources (RES) in the electricity mix makes production, transmission and distribution of energy increasingly sensitive to weather and climate variability. Hydro power currently provides the largest amounts of renewable energy supply in Europe (57% of RES in 2014), but there is limited opportunity for further development of this technology (Burtin & Silva 2015). Hence, the growth of RES will be mainly based on wind and photovoltaic solar power, which are highly variable and much more sensitive to weather fluctuations, and cannot be directly controlled by plant operators, as hydro does allow.

Wind energy is the second leading renewable energy source worldwide, only exceeded by hydropower in terms of installed capacity (Santos et al. 2015; Pryor & Barthelmie 2010). Due to the rapid growth that this industry is experiencing and its market penetration, the intermittent temporal variability of the wind resource is of great importance. Operational and economic issues related to wind energy (finance, insurance, planning or strategy assessment) require the modelling and forecasting of the wind power generation processes at a wide range of temporal and spatial scales (Fant et al. 2016).

The wind industry has traditionally used wind power forecasts at short (from hours to a few days) time scales (Pinson et al. 2009a). At longer time scales, the need of climate information representative of the next few decades for resource evaluation has raised the interest of the wind energy users in climate projections (Reyers et al. 2014). Hence, between weather forecasting and climate projections, there is a gap of information that could be cover by climate predictions, whose time scale varies from one month up to one decade into the future.

At seasonal time scales, current energy practices employ a simple approach based on a retrospective observed climatology. Instead, probabilistic climate predictions at seasonal time scales can better address a long list of challenges to produce climate information that responds to the expectations of the users (Doblas-Reyes et al. 2013). Moreover, these predictions can be used to make specific decisions that affect energy demand and supply, as well as decisions relative to the planning of maintenance work.

The main limitation for the implementation of the seasonal predictions for decision making is the large amount of information that arises from the seasonal forecasts (e.g. uncertainty, skill and reliability assessments, bias-correction techniques, probabilistic approaches, …), which is hard to understand and in most cases the users are not able to incorporate it in a useful manner for their daily activities. Hence, the main goal of this work is to develop tailored climate information that can be afterwards used as a tool to inform wind energy users with greater accuracy than their current approaches.

Instead of the climate variables, we want to provide more tailored variables to specific wind applications, and capacity factor has been selected for this purpose. Capacity factor (CF) is the average power produced over a period of time, normalized by the maximum power of a wind-turbine. This is a very useful indicator for the wind energy users because it indicates the extent of use of a wind farm and can provide extra information relative to the wind energy production. The state-of-the-art climate prediction systems do not directly simulate this specific variable, therefore a transfer model to compute CF from typical climate variables is required.

For short term time scales accurate forecasts of CF require high temporal and spatial resolution(e.g. Pinson et al. 2009); however, for the seasonal predictions there is not still available in the bibliography any methodology that can be applied for the prediction of CF. This methodology has been developed to address the systematic errors and biases that are inherent to global climate models, with the aim to produce CF predictions with the best accuracy available.

In this report we have illustrated the main steps for the development of a transfer model to estimate seasonal predictions of CF. The transfer model is based on impact surfaces, which are tools to visualize the CF generation in a climatic context. The model takes into account the seasonal forecasts errors, which will be minimized by a bias-adjustment process. However, the accuracy of the CF predictions depends on many factors like the operating limitations of a wind farm which are not in the scope of this analysis. Finally, we have also discussed how the CF predictions could be beneficial for a particular decision-making process, the balance between wind energy supply and demand.

This study is organized as follows. Section 2 describes the data and methodology employed for the estimation of seasonal predictions of CF which consist in three main steps. Section 3 provides an overview of the results for a particular region. Section 4 includes a discussion about the importance of the seasonal predictions of capacity factor for the balance of wind energy supply and demand. Finally Section 5 summarizes the most relevant conclusions and future work.

2. Data and methodology

2.1. Data description

In this study we employ the 10-m wind speed and 2-m temperature forecasts from the ECMWF System 4 (System4) operational seasonal prediction system (Molteni et al. 2011) which is based on a global climate model, with coupled atmospheric and oceanic components. System4 is run in ensemble prediction mode. Ensemble predictions are a way to deal with uncertainties in the climate system, in particular those associated with the imperfections of the initial conditions. For this reason, the operational System4 forecasts are produced at the beginning of each month up to seven months into the future with 51-member ensembles.

The predictions considered here are those issued on the 1st of November, for which three-month statistics for the December-January-February (DJF) are computed. The analysis focuses on the boreal winter as this season has the largest wind speed variability in the Northern Hemisphere (Archer and Jacobson 2013) and it can be more relevant for the wind energy users than other seasons due to the higher variability of wind power supply (Bett and Thornton 2015). This illustrates the potential of seasonal predictions for end users in those places where the inter-annual variability of the wind energy resources is the largest, although other seasons have also been analysed and the conclusions apply equally. Predictions over the period 1981–2014 have been used in the study.

To evaluate the System4 forecast quality, we compare the predicted 10-m wind speed and 2-m temperature with the corresponding variables of the ERA-Interim reanalysis (Dee et al. 2011). Given the sparsity of global wind observations, reanalyses have demonstrated their potential usefulness for large-scale wind energy applications (Cannon et al. 2015) especially for illustrative purposes.

2.2. Methodology

Traditionally, the state-of-the art climate prediction systems do not produce relevant variables for wind energy decision making such CF, therefore a methodology to estimate these user-friendly predictions from climate variables such as wind speed and temperature is needed.

The capacity factor (CF) is a widely used estimate for wind energy users, because it provides information about the extent of use of a power plant. The CF can be expressed as follows:

$$CF(\%) = \frac{WP_{prod}}{WP_{\max}} \times 100$$

CF is the ratio of the average wind power produced over a period of time (WP_{prod}), normalized by the maximum wind power that can be generated by a wind-turbine ($WP_{\max}$). To compute seasonal predictions of CF we have used impact surfaces (MacLeod & Morse 2014), a tool which allows the visualization of the relationship between an impact variable that can be of interest for any societal application (CF in this report) with climate variables (10-m wind speed and 2-m temperature).

The methodology has been applied in one-year-out cross-validation to emulate true operational prediction conditions when no observed information about the future is available. This means that for each season in the period 1981-2014, the seasonal predictions of CF generated for each year have been computed from the seasonal predictions of wind speed and temperature in the same period and the with all the years in observations available except the target one.

2.2.1. Transfer Model

The proposed method to produce CF seasonal predictions has been summarized in Figure 1 and consists of three main steps, which are further explained in the next subsections.

2.2.1 a) Step 1: transformation of ERA-Interim wind speed and temperature into CF

A CF reference dataset that can be used as a reference for the validation of the estimated seasonal predictions of CF is not currently available at global scale. For that reason, the first step of our methodology has been the application of a transfer model (Macleod et al. 2016) which converts wind speed and temperature from the ERA-Interim reanalysis into CF. This transformation takes into account several factors which have an influence in the CF predictions:

- Non-linear relationship between wind speed and wind power generated by a wind turbine (i.e. the power curve).
- The increase of wind speed from 10-m to turbine height.
- Influence of fluctuations in air density due to temperature variability.
- Temporal wind speed variability.
- Losses due to transmission and distribution of electricity (i.e. performance ratio of 0.725).

This model has been applied over daily means of wind speed and temperature from 6-hourly data, in order to produce daily CF (STEP1 in Figure 1). This approach has been applied at daily bases, because it produces the optimal result of the monthly and seasonal CF (Macleod et al. 2016).

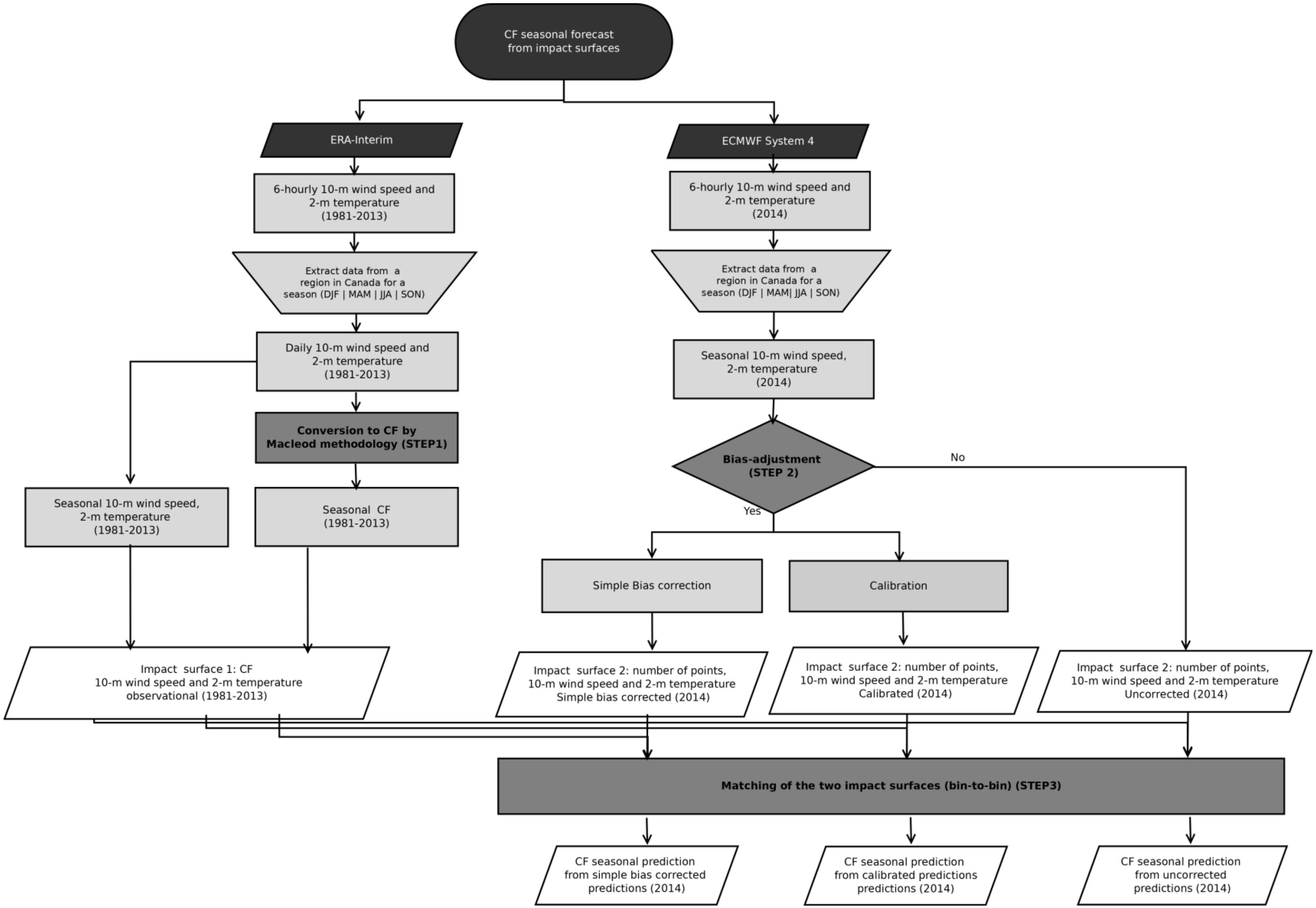

Figure 1. *Flow chart of the main steps used to estimate seasonal predictions of capacity factor based on wind speed and temperature.*

2.2.1. b) Step 2: bias adjustment of seasonal predictions

The variables predicted by a climate forecast system are affected by biases resulting from the inability to perfectly reproduce numerically all the relevant processes responsible of climate variability (Doblas-Reyes et al. 2013). This is the main limitation of predictions to be implemented in decision-making processes. Therefore, to produce seasonal predictions with similar statistical properties to those observed and fulfill usability and acceptable reliability wind energy user requirements, two different bias-adjustments have been applied.

The two methods applied are: a simple bias correction and a calibration method. The former is based on the assumption that the reference and predicted distributions can be shifted to have similar means and variances. The latter is a calibration technique based on inflating the ensemble spread to obtain a reliable outcome. Both methods are linear, parsimonious and robust, which are essential features for the small samples typical of current climate forecast systems, and assume that the distributions are Gaussian.

These methods have been applied in "one-year-out" cross-validation over the System 4 seasonal predictions of wind speed and temperature (STEP 2 in Figure 1) providing forecasts with improved statistical properties. The bias-adjustments have been applied as in Torralba et al. (2016) and the corrected wind speeds and temperatures have been used as inputs to generate seasonal predictions of CF.

2.2.1. c) Step 3: estimation of CF seasonal predictions from impact surfaces

The computation of the CF seasonal predictions requires the information computed in the previous two sub-sections (step 1 and 2, Sections 2.2.1.a and 2.2.1.b, respectively):

1. Wind speed, temperature and CF from ERA-Interim (step 1) have been discretized into 16 bins and visualized in an impact surface (impact surface 1) for a particular season (DJF) in the test period (1981-2013). This impact surface contains the information about the climatological relationship between CF with the wind speeds and temperatures.

2. Bias-adjusted seasonal predictions of wind speed and temperature (step 2) for the same season (DJF), but in the target year (2014), have been also discretized and represented in an impact surface (impact surface 2). The impact variable represented in impact surface 2 is the number of points that corresponds with each pair of the seasonal predictions of wind speed and temperature for that season.

Impact surfaces 1 and 2 have been combined in order to generate seasonal predictions of CF. The bin-to-bin matching between the CF values in impact surface 1 and the number of predicted pairs of wind speed and temperature from impact surface 2 allow the construction of a histogram. The histogram contains the climatological CF values from impact surface 1 as breaks and the counts of the histogram are the predicted frequencies of each wind speed and temperature seasonal forecasts from impact surface 2.

The main caveat of this methodology is that certain bins have a CF value in impact surface 1, but they do not have any correspondence with a value of number of points in impact surface 2, preventing from the matching of the two impact surfaces.

To fulfill the available information in all the bins, we have extended the information in the two impact surfaces:

- Impact Surface 1, the bins without value of CF have been filled with the same capacity factor value of the nearest bin.

- Impact Surface 2 the information has been extended by a two dimensional kernel density estimation (McLean Sloughter et al. 2013)over the squared grid defined by the impact surface defined by bias-adjusted seasonal predictions of wind speed and temperature. As a result we have obtained a bivariate probability density function which provides a density value for each bin.

This two extended impact surfaces which contains information for each bin have been combined to produce capacity factor values and their associated probability. The probability density function of the seasonal predictions of CF has been represented as a boxplot.

2.2.2. Verification

There are several ways to assess the quality of seasonal forecasts, each of which gives information about different aspects of the forecast. To simplify the discussion, results in this technical note will focus on correlation.

Pearson correlation measures the linear correspondence between the observed and predicted values and it is useful to quantify the potential skill, which is the maximum skill that can be achieved for an index in a particular region given a forecast system (Doblas-Reyes et al. 2013). Correlation maps have been computed with the ensemble means of the seasonal forecast and the reference value in a season for the period 1981-2014. A perfect agreement along time between the reference and seasonal predictions would give 1.0. Positive correlation indicates that the forecast are on average better than a naive climatological forecast, while negative values appear where the predictions are worse than the climatology.

3. Results

In this section the steps to compute the seasonal prediction of capacity factor for DJF 2014 are displayed. To illustrate the methodology, we have selected one region in Canada [49.6º-51.7ºN and 246º-248.2º E] (Figure 2 top left corner) This location is interesting from a wind energy user point of view because it has experienced a great development of wind energy in recent years (Vaillancourt et al. 2014). However, more regions should be explored to obtain robust conclusions.

The discretized seasonal average of the CF output computed from ERA-Interim wind speed and temperature for the selected Canadian region are represented as an impact surface in **Error! Reference source not found.**. It shows the climatological relationship between the three variables in that region, where the maximum CF values are associated to high wind speeds and low temperatures. This impact surface evidences that wind speed is the main driver of CF in this region in the boreal winter, because at low (high) wind speeds low (high) CF values are produced.

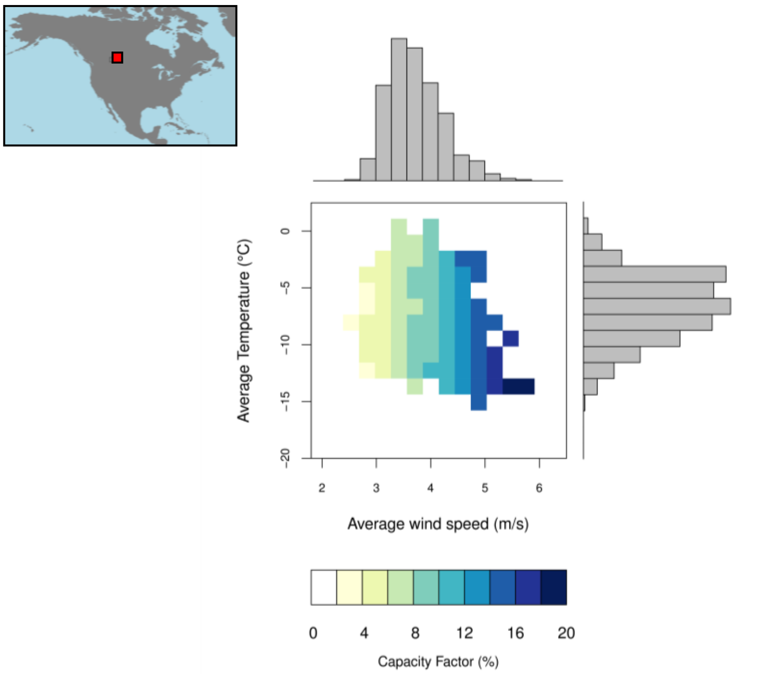

***Figure 2**. Impact surface of the mean capacity factor (%) for a Canadian region in DJF 1981-2013.*

Marginal histograms correspond to 10-m wind speed (m/s) in the x-axis and 2-m temperature (ºC) in the y-axis from ERA-Interim. On the top-left corner the specific location for which the study has been done is included. Year 2014 is not included in the analysis that leads to this figure because, in a forecasting context, when making a forecast for this year the observations will not be available at the time of issuing the forecast.

The number of points with each pair of wind speed and temperature values from the seasonal predictions from ECMWF System 4 is represented in the impact surfaces displayed in Figure 3. The comparison of the marginal histograms included in the impact surfaces from seasonal prediction and reanalysis reveals that uncorrected predictions (**Error! Reference source not found.**a) show a more narrow range of wind speed and temperature values than the climatological ones (**Error! Reference source not found.**), because in that case the minimum wind speeds are over 3m/s and below 5 m/s. The seasonal predicted temperatures take a range of values higher than the climatological ones, with values under -15 ºC. However, such performance changes when the biases are corrected.

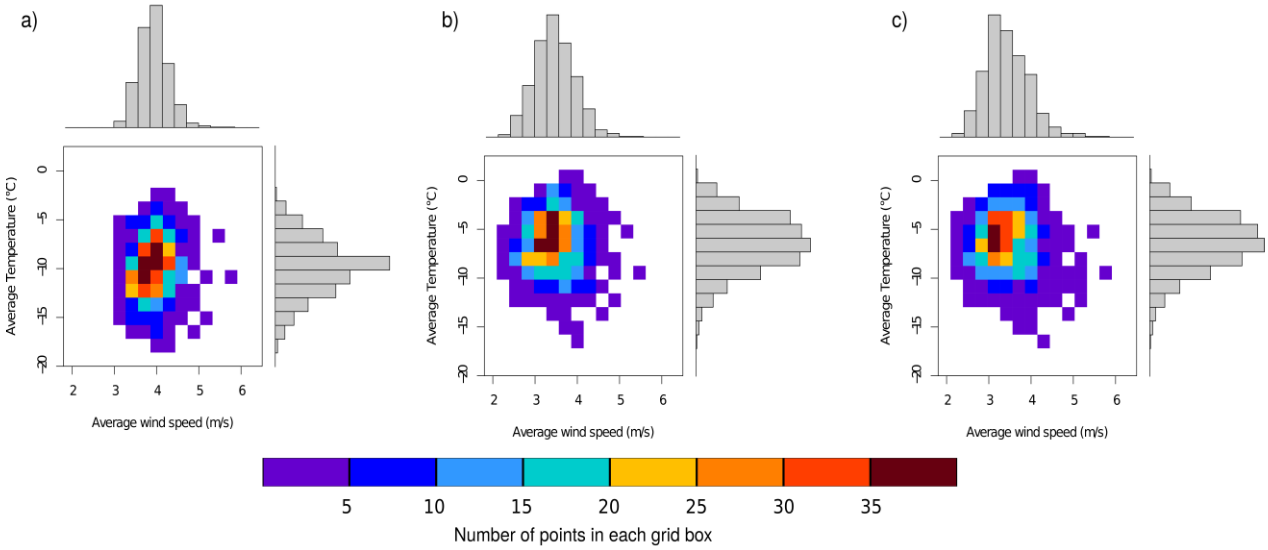

Figure 3. Impact surfaces of the number of pairs in each grid box for a Canadian region in DJF 2014.

Marginal histograms show seasonal averages of 10-m wind speed in the x-axis and 2-m temperature in the y-axis from ECMWF System4 initialized on the 1st of November 2014. a) raw data (uncorrected), b) simple bias correction and c) calibration.

The simple bias corrected wind speed and temperature seasonal predictions (**Error! Reference source not found.** b) display the frequency maximum (dark red colours in Figure 3 b) when the temperatures are close to -5ºC and the wind speeds are above 3.5 m/s. These values are in agreement with the marginal histograms for the climatology (**Error! Reference source not found.**), which indicates similar conditions of predicted wind and temperature for the winter in 2014 in comparison with climatological ones. However, it can also be noticed in Figure 3 that the seasonal predictions of wind speeds and temperature rarely simulate values in those bins corresponding to both wind speeds over 5 m/s and temperatures below -10ºC, differently from climatology.

Calibrated predictions (**Error! Reference source not found.** c) show similar histograms to the simple bias corrected ones, although slight differences are observed, as for example, the maximum of the wind speed histogram which is found for values under 3.5 m/s. Although the two bias adjustment techniques correct the mean and standard deviation of the seasonal predictions, the calibration method corrects the ensemble spread to produce more reliable probabilities, for that reason some differences in the bias-adjusted predictions are expected.

The discrepancies between the wind speed and temperature values of the seasonal predictions (**Error! Reference source not found.**) and ERA-Interim (**Error! Reference source not found.**) prevent the matching of the two impact surfaces to generate the seasonal predictions of CF, because there are some bins in **Error! Reference source not found.** which have a CF value associated but don't have it in the seasonal predictions (**Error! Reference source not found.**). Taking into account this limitation, the information available in the impact surfaces has been extended by using the methods described in Section 2.2.1.c. These extended impact surfaces have been illustrated in Figure 4.

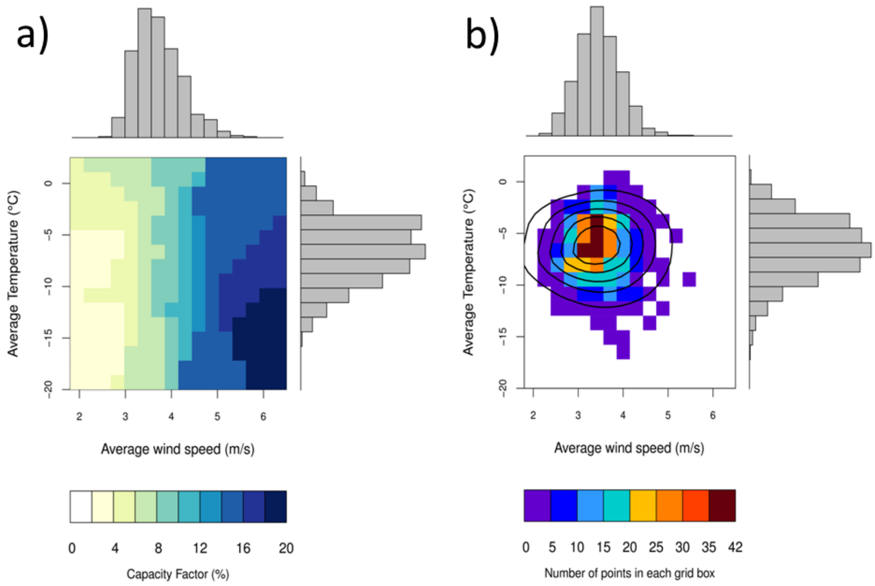

***Figure 4**. Extended impact surfaces for the the Canadian region in DJF (simple bias corrected).*

*a) same as **Error! Reference source not found.**, but the bins without CF values have been replaced by the CF value of the nearest bin; b) same as **Error! Reference source not found.**b but including the contours to illustrate the bivariate density function applied to assign one density value at each particular bin.*

Figure 4a shows that CF variations depends mainly on wind speed, but it can also be appreciated that the maximum CF is produced together with the minimum temperature values. In Figure 4b, contours shows the densities associated with each bin of the predictions of wind speed and temperature. As illustration, the simple bias correction is shown, but the same method has been applied over the uncorrected and calibrated seasonal predictions.

The result of the matching of these two impact surfaces bin-to-bin has been performed for each particular year (1981-2015), in cross-validation. The probability density functions of the CF seasonal predictions have been summarized in Figure 5.

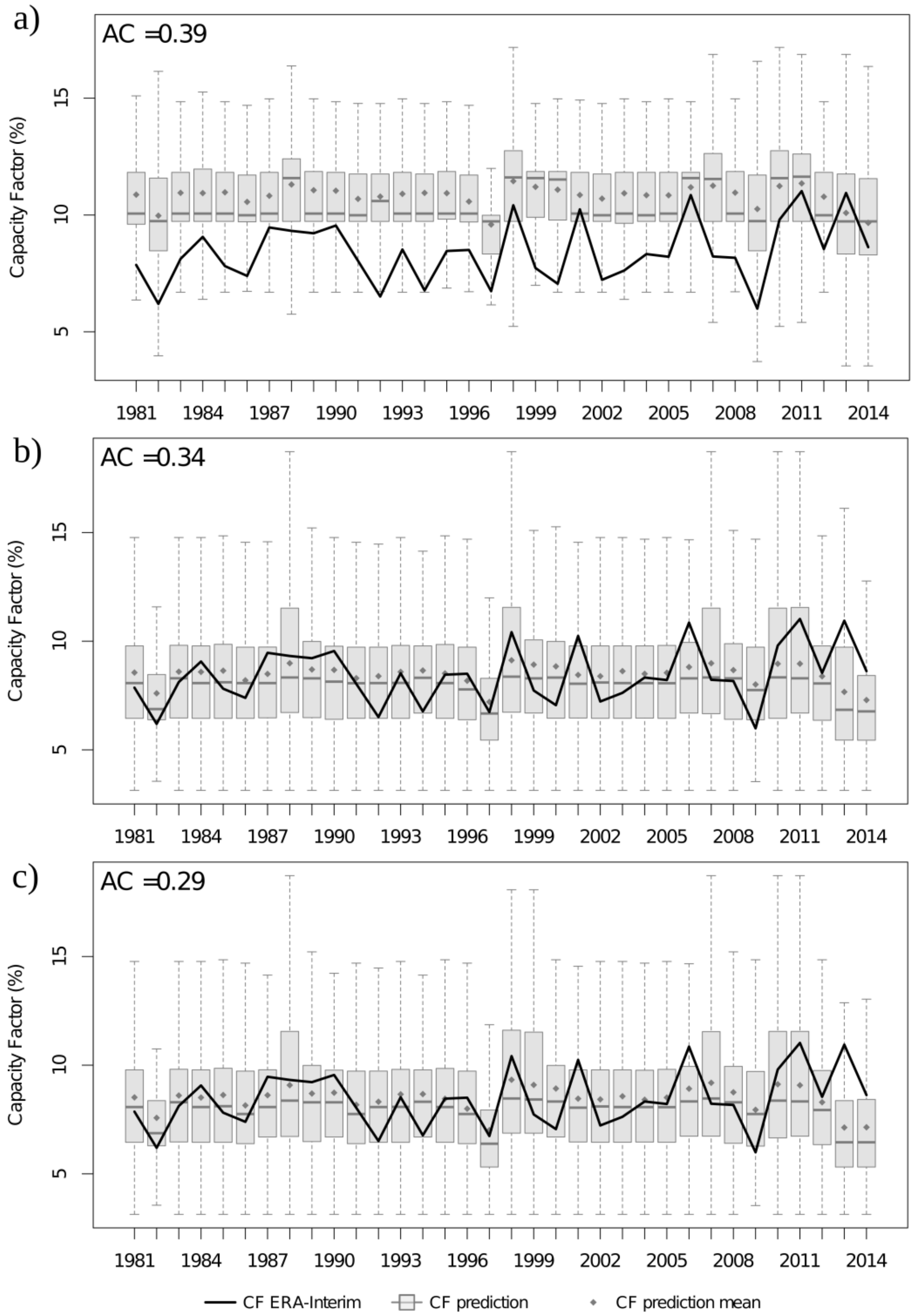

***Figure 5**. Boxplots with seasonal predictions of CF obtained from wind speed and temperature.*

CF obtained from a) raw (uncorrected), b) simple bias corrected and c) calibrated 10-m wind speed and 2-m temperature during 1981-2014 for the chosen Canadian region in DJF. Central box corresponds to the interquartile range of the ensemble, the thick horizontal bar to the median, the whiskers to the 5th and 95th percentiles and the black line denotes the ERA-Interim value. Correlation of the ensemble mean prediction with ERA-Interim is shown in the top left corner.

The probabilistic CF seasonal predictions obtained as output of the transfer model from the three different types of data (raw, bias corrected and calibrated) show some differences between them (Figure 5). CF predictions attained from the uncorrected wind and temperature (Figure 5a) show a bias that is removed when the two bias-adjustments used in this report are applied (Figure 5 b and c). These results show how, if the bias is corrected, the output of the transfer model produce CF predictions with minimized systematic errors.

The correlation values between predictions and ERA-Interim are displayed on the top-left corner of each plot (Figure 5a-c). It can be observed that they change for the three different cases: uncorrected (0.39), simple bias corrected (0.34) and calibrated (0.29) predictions. Although the correlation is invariant to the bias-adjustments, a reduction of correlation is expected when these method are applied in cross-validation. This is due to the estimation of the parameters has associated an uncertainty that is propagated into the predictions. The reduction of the correlation is slightly higher for the calibration than for the simple bias correction because the calibration requires the estimation of more parameters than those for the simple bias correction. However the calibration produces more reliable results (Torralba et al. 2017) In addition, the transformation from the wind speed and temperature into CF also introduces some uncertainty that might produce a reduction of the correlation values. In spite of this reduction of correlation values, these methods generate predictions with positive potential skill and minimized systematic errors, which evidences that predictions can represent an added value relative to predictions based only on climatology or uncorrected forecasts.

4. Discussion: implications of CF seasonal predictions for the balance of wind energy supply and demand

This section aims to explain how the CF seasonal predictions could be an added value for a particular decision-making process: the matching of wind energy supply and demand. In particular wind energy users who can be affected by this issue are Transmission System Operators (TSO), which are responsible for the security and continuity of power supply, and need to maintain a constant balance between generation and demand (Figure 6). A significant discrepancy of power supply and demand would result in blackouts, while small discrepancies can be balanced by changing the speed of alternators which is assumed to be constant at 50Hz in permanent regimes. A specific deviation (which is system dependent) from this value may cause a disconnection of power generators from the system causing chain reactions and consequently blackouts (Dubus & Trotignon 2015).

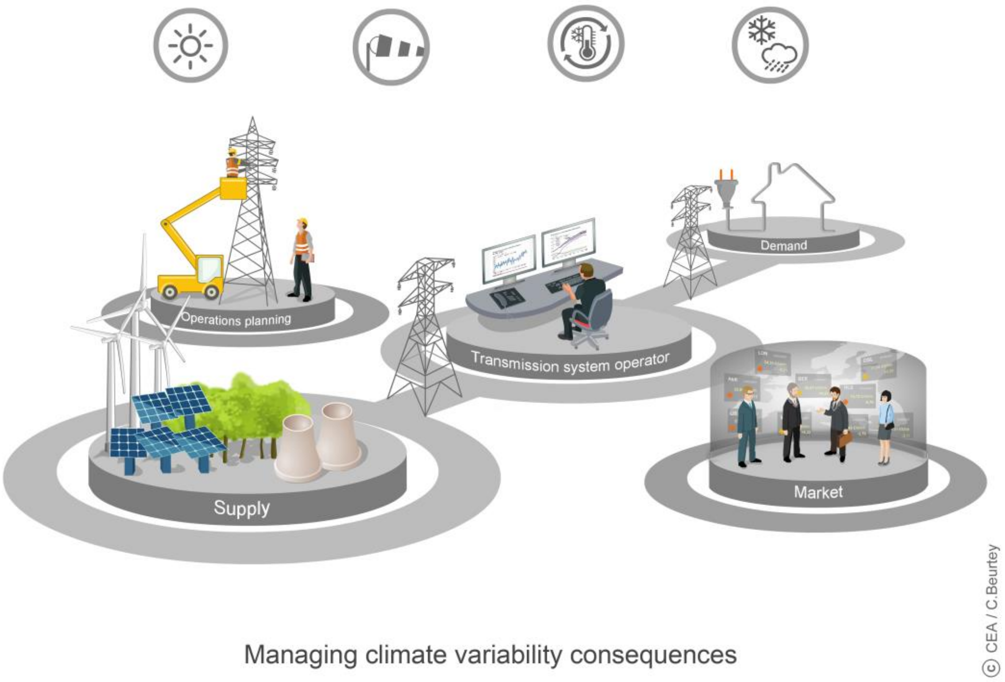

***Figure 6**. The central role of TSO to balance supply and demand.*

Infography from Clim4Energy project (http://clim4energy.climate.copernicus.eu/)

Electricity demand variability is quite well understood and depends on several factors: economy (e.g. strength of industrial activity), human activities (e.g. labour days, festivities or shop opening times), weather and climate (e.g. cold or hot spells that require building air-conditioning) among others. The fact that total demand in a region is aggregated over a very large number of end-users contributes to reduce variability in the demand evolution. Hence, although forecasts of aggregated demand based on historical data and statistical analysis have some limitations, they can provide reasonably good information for the decision making.

Consequently, supply of energy can be scheduled and requested with anticipation to traditional power plants, according to predicted demand needs.

However, wind power production cannot be scheduled as it depends on the chaotic nature of atmospheric variability at several temporal scales. On the short term (seconds to minutes), such variabilities are automatically balanced by primary and secondary reserves, which comprise spinning reserves (power plants in part load operation mode) and standing reserves (rapidly starting plants). Interconnections with neighboring electrical systems are also routinely used for balancing the grids. However, over larger temporal scales (from days to seasons), tertiary reserves need to be scheduled manually to restore primary and secondary sources (Funk 2016). Therefore, subseasonal and seasonal forecasts of CF and methodologies to improve the accuracy of those predictions are both essential to anticipate the need of activating tertiary reserves.

In Europe, the bigger risks concentrate in winter and summer periods, when demand peaks due to heating and cooling happen. Notice that the critical factor in this discussion is not the amount of generation itself, but the ability to forecast its variations. The European countries with highest penetration of wind in their electricity mix, for instance Denmark, Spain, Portugal or Germany, have already faced some of the challenges of balancing supply and demand. They have regulated the energy market with economic penalties in the cases where actual generation deviates too much from forecasts used in daily market auctions, and have increased capacity of transmission lines with neighbor countries allowing higher import/export operations.

A specially critical case is the North Seas Countries' Offshore Grid Initiative, a collaboration between countries bordering the North Sea that provides interconnection and integration of off-shore wind energy with on-shore power plants using especially hydroelectricity as storage for offshore excess wind energy (Funk 2016). In this case, the subseasonal and seasonal predictions of CF (or amplitude of the wind power) variability can be crucial due to big amounts of installed capacity in a relatively small area experiencing similar wind conditions. In case of generalized wind stilling or storminess, the effects in generation would be synchronized in all sites.

5. Conclusions

Seasonal prediction systems do not produce users-friendly variables. For this reason, the development of a methodology which can use climate information to generate indicators that can be more useful for wind energy applications is required. This study describes the methodology employed to develop useful climate information that can be easily integrated in wind energy decision-making processes. The main aim of this work has been to develop a model which translates wind speed and temperature seasonal predictions into CF tailored variable to some wind energy user needs. This model has been applied in a particular region in Canada to illustrate the potential benefit of the information produced for wind energy applications.

Firstly, an impact model that transform observational wind speed and temperature into CF was used as a reference (Macleod et al. 2017). This first step was very important because there is not available any global dataset of capacity factor that can be used for validation purposes. An illustration of the climatological relationship between the three variables used in this study (wind speed, temperature and capacity factor) has been done for a specific region in Canada. In this case, the main driver of CF is the wind speed, but the highest values of CF are produced for the lowest temperatures in that region. This climatological relationship should be further explored over different regions in order to identify weather or not the results are similar, and clarify which is the role of temperature in the wind power production.

The second step of the methodology has been the application of bias-adjustment techniques that can minimise the systematic errors of the seasonal predictions. The two methods considered in this report produce similar results for the wind speed and temperature. Nevertheless, small differences have been identified between them because, although both methods correct the mean of the predictions, the calibration method also corrects the ensemble spread to produce more reliable outcomes.

The bias-corrected predictions and the CF of reference obtained in steps 2 and 3 have been discretized and combined to produce probabilistic seasonal predictions of CF. The transfer model produce CF predictions with minimized systematic errors when bias corrected predictions of wind speed and temperature are used. The positive correlation values of these predictions indicate the added value of the seasonal predictions of CF relative to the climatology.

Finally, the usefulness of the probabilistic seasonal predictions of the capacity factor, obtained from the transfer model, has been discussed particularly their impact on the matching of energy supply and demand, decision for which the accuracy of those predictions is essential to anticipate the need of activating tertiary reserves.

Future work will focus on the application of this methodology to different regions, and on the validation of the transfer model for those specific locations where CF observations will be available and can be used for the validation of these predictions.

6. Acknowledgements

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