Relationship between wind power production and North Atlantic atmospheric circulation over the northeastern Iberian Peninsula

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Abstract The wind power generated during winter months 1999–2003 at several wind farms in the northeastern Iberian Peninsula is investigated through the application of a statistical downscaling. This allows for an improved understanding of the wind power variability and its relationship to the large scale atmospheric circulation. It is found that 97 % of the variability of this non-climatic variable is connected to changes in the atmospheric circulation. The methodological uncertainty associated with multiple configurations of the statistical downscaling method replicates well the observed variability of the wind power, an indication of the robustness of the methodology to changes in the model set up. In addition, the use of the statistical model is extended out of the observational period providing an estimation of the long-term variability of wind power throughout the twentieth century. The extended wind power reconstruction shows large inter-annual and multidecadal variability. Alternative approaches to calibrate the empirical downscaling model using actual wind power observations have also been investigated. They involve the estimation of wind power changes from downscaled wind values and make use of several transfer functions based on the linearity between wind and wind energy. The performance of the latter approaches is similar to the direct downscaling of wind power and may allow wind power production estimations even in the absence of historical wind turbine records. These results can be of great interest for deriving medium/long term impact-oriented energy assessments, especially when wind power observations are missing as well as in the context of climate change scenarios.

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1 Introduction

The impacts of the climate change on a wide range of natural (physical and biological) and human managed systems have experienced a significant growing attention during the last decades (Nicholls et al. 2001; Parry et al. 2007; Munslow and O′Dempsey 2010; Adnan and Atkinson 2011).

Climate impact models are valuable tools to explore the connections between climatic forcings and impacts on ecosystems. There is an extensive variety of impact-oriented applications that calls for methodologies providing climatic information at the spatial scales not resolved by General Circulation Models (GCMs). Examples of the last are river flows and runoff studies (Tisseul et al. 2010; Chiew et al. 2010), agriculture (Zhang 2005), health (van Lieshout et al. 2004) and air quality assessments (Nolte et al. 2008). Extreme events analyses such as strong precipitation episodes (Toreti et al. 2010), heatwaves

(Kuglitsch et al. 2010) or hurricanes intensity and frequency assessments, often required by insurance companies (Bender et al. 2010) also pertain to the context of impact studies. Statistical downscaling methodologies are frequently applied as they can provide reliable estimations of the climatic variables required by impact models at the regional/local scale (Chu and Yu 2010). Alternatively, Regional Circulation Models (RCMs) render estimates with suitable spatial resolution that could serve as inputs to the impact models (Pryor et al. 2005a).

One key aspect of relevance for society that can be subject to the impact of a potential climate change in the future, is the accessibility to energy resources. Further, the conflict between the availability and the increasing energy demand steers a controversial debate between policy makers, ecologists and society in general (Agarwal et al. 2010). The dispute stresses the search of *ad hoc* solutions to fulfill the energy requirements of an increasing global population and comfort-demanding societies (DTI 2006; Dermibas 2009). Considerable effort in the search for new and cleaner energy supplies as substitute to the fossil-fuel reserves, has been made (Hohmeyer and Trittin 2008) with wind energy being one of the resources that has received most attention during last decades. As a consequence, the evaluation of its variability and predictability together with an improved understanding of the inherent relation with its primary agent, the wind, is of great relevance in the frame of renewable energy resource (Mathew et al. 2002; Pryor et al. 2005a; Edenhofer et al. 2011).

A limitation to the understanding of the relation between wind speed and wind power is usually imposed by the insufficient availability of historical power production records. Therefore, a classic handling of the wind power resource evaluation is based on the use of a theoretical probability distribution function (PDF) (Li and Li 2005; Pryor et al. 2005b). Wind turbine outputs have only recently become available. This favours the treatment of the power production as an independent variable alternatively to the classical procedures that obtain wind energy density as a wind related variable (Akpinar and Akpinar 2005; Jamil et al. 1995; Weisser and Foxon 2003; Pryor and Schoof 2005). Thus, the analysis of this non-atmospheric variable as a response to the large scale circulation constitutes a new opportunity to the topic. This is therefore aligned with impact-oriented studies where the understanding of the relationship between the power generation and its main driver, the wind, and eventually the atmospheric circulation becomes of relevance.

In this line, García-Bustamante et al. (2009; GBea09 hereafter) showed the existence of a linear relation between wind and wind power using wind power records from several wind farms in the northeastern Iberian Peninsula (IP). The linear association was found at the monthly

timescale despite the fact that at shorter timescales the expected relation is cubic (Palutikof et al. 1987). In addition, García-Bustamante et al. (2012; GBea11 hereafter) described the connection between the large scale atmospheric circulation and the wind field over the same region applying a statistical downscaling method based on a combination of Principal Component Analysis (PCA) and Canonical Correlation Analysis (CCA). This method assumes linearity between the predictor and predictand simultaneous variations. GBea11 found that the variability of the regional wind (predictand), although modulated by orography, is governed to a great extent by the large scale circulation (predictor). Therefore, considering the transfer of linearity between variables, the question arises whether a linear relationship can also be identified between the large scale atmospheric circulation and the wind power production at monthly timescales. To test this a downscaling procedure as in GBea11 is applied here to monthly wind power production in the role of the predictand.

The analysis that follows illustrates an impact-like case study in order to provide direct wind power downscaled estimations. This topic has not yet been documented in the literature. In addition, optional strategies can be proposed based first on the estimation of the wind field (GBea11) and subsequently the conversion of the downscaled wind into wind power estimations using the observed linear relation between monthly wind and wind power (GBea09). Therefore, the linearity, either between wind power and wind speed or as an inherent feature of the downscaling methodology, that searches for linear associations between the predictand and predictor fields, underlies the arguments for all methodological variants explored within this work. Moreover, the validity of a regional linear association between wind speed and wind power, that is suitable for all wind farms in this study will be discussed. This last method offers advantages as wind power could then be estimated at locations without available records of energy production.

The long-term variability of the wind power production is of interest in diverse applications. For example, the wind resource evaluation for companies and investors requires an analysis of the interannual and decadal fluctuations of the wind energy. An interesting question in this long-term context is whether independent wind speed and power production past estimates maintain the linear relation (see Fig. 1 in GBea09). It allows for estimating wind power from wind prior the instrumental period. In addition, the long-term trends of wind power production or the presence of periods with high/low anomal variations of power generation are of relevance for the wind resource sustainability as well as the wind power production system (Thomas et al. 2009).

The present analysis includes an evaluation of the methodological variance that accounts for the impact on

estimations due to changes in the downscaling model configuration and provides thus insight into the uncertainty associated with wind power estimates. The methodological variance can be considered as one source of the whole cascade of uncertainties that affects the regional climate estimations and propagates from large to regional and local scales (Mitchell and Hulme 1999; Schwierz et al. 2006). At the regional scale, estimates of climatic variables may be affected by the selection of the methodology. The use of a particular methodology also involves a degree of uncertainty that relates to the selection of a certain configuration of the model. For instance, changes in the choice of physical parametrizations (Zhang and Zheng 2004) in the case of dynamical downscaling models or the choice of parameters that are relevant in the design of the statistical downscaling method may also introduce some variability within the regional estimates. This particular source of uncertainty is not usually explored in the case of statistical downscaling models (Huth 2000, 2004) and novel for a wind power variable. We present a sensitivity analysis of wind power downscaled estimates conceptually similar to that in GBea11, where the methodological variance associated with downscaled wind estimates was explored by allowing variations in the parameters of the downscaling model set up.

The following section describes the study region and the datasets used. Section 3 briefly presents the downscaling methodology and its application to wind power and large scale atmospheric circulation predictors. In this section we also evaluate the methodological uncertainties associated with wind power estimations. The wind power long-term variability based on past estimates back to 1850 is further explored and its implications in the context of wind energy resource assessment are discussed. Section 4 investigates several variants to estimate wind power production and compares their ability to reproduce the observations to results from Sect. 3. Moreover, the application of the latter approaches is presented in Sect. 4 as an inference exercise. Potential benefits for the assessment of wind energy availability and sustainability in the absence of wind power historical records are discussed therein. Finally, in Sect. 5 the conclusions are provided.

2 Data and region under study

The Comunidad Foral de Navarra (CFN, Fig. 1) is a region of intricate orography where testing the ability of downscaling methods represents a challenge. Moreover, the spatial focus over the CFN is attractive as the region has gone through a notable development in the use of renewable energies during the last decades, in combination with a compatible energy policy showing significant contributions to the regional energy generation capacities (Faulin et al. 2006). The reader is referred to (Jiménez et al. 2008, 2009; GBea11) for further descriptions of the region.

The analysis is based on the wind speed and wind power production data recorded at three wind farms at the CFN (Aritz, El Perdón and Alaiz, blue squares in Fig. 1, top right). A wind power production time series from each wind farm was obtained by calculating the spatial average of the power outputs from every wind turbine at each wind farm (García-Bustamante et al. 2008; GBea08 hereafter). Wind data series were also collected from anemometers located at the hub height of wind farm turbines, between 30 and 45 m. Wind and wind power records span throughout the period June 1999 to May 2003. Ideally the observational series would cover a period long enough to allow for an accurate representation, not only of the intra-annual, but also of the long-term variability of the wind power. However, the length of the calibration period is imposed by the availability of observed records. Nevertheless, statistical models have successfully been applied in cases with observational periods no longer than a decade (Huth 2002, 2004; Orlowsky et al. 2008).

Monthly values were calculated from the original hourly records. The monthly temporal resolution allows for filtering short term fluctuations of the power production that relate to more local effects and technical aspects (such as manipulation or shading between turbines) that distort the wind speed-wind power linear relationship. An example of time series at El Perdón, is shown in Fig. 1. Standardized monthly wind (green) and wind power production (blue) show large intra- and interannual variability and evidence the linear connection between changes in time of both variables for the whole period of observations (GBea09). Correlations between monthly wind and wind power at Aritz, El Perdón and Alaiz reach 0.76, 0.94 and 0.96, respectively.

In addition, an extended wind dataset with observations from January 1992 to September 2005 is employed in the last part of the study to illustrate the relative performance of alternative methods to obtain wind power estimates. The geographical distribution of the 29 meteorological stations within this dataset and the observed mean wind field (vectors) are shown in Fig. 1 (top). The channeling effect of the Ebro Valley is obvious. Drier and colder winds with a dominant NW-SE orientation are known as *Cierzo*; the wind from the opposite direction (*Bochorno*) is milder and moister (de Pedraza 1985; Garcí a and Reija 1994). Some stations in the central and northern parts of the region show a slightly different orientation of the mean flow. These sites correspond to a good degree to locations with more complex orographical features and to more windy sites like the wind farms. This can also be identified in Fig. 1 (top)

Fig. 1 The region under study.
Top left panel shows the Iberian
Peninsula and the main
geographical features
surrounding the Comunidad
Foral de Navarra. The *right
panel* amplifies the region of the
CFN and its orography
(*shading*). *Blue squares*
correspond to the wind farm
locations: Aritz, El Perdón and
Alaiz (see Table 1 in GBea08).
Circles stand for the location of
the wind stations (*orange
circles* represent those stations
with anemometers at 2 m while
the *white* ones are located at 10
m height; labels at each location
correspond to those in Jiménez
et al. 2008, see Table 1 therein
for wind sites description). The
mean wind field is also
represented (vectors) together
with the mean wind speed (*solid
red contours*) and the
corresponding standard
deviation (*dashed grey
contours*). *Bottom* standardized
monthly wind (*green*) and wind
power (*blue*) observed time
series at El Perdón. Monthly
values between 2002/03 and
2002/05 were removed for the
analysis as they showed
questionable quality due to
errors in the data recording
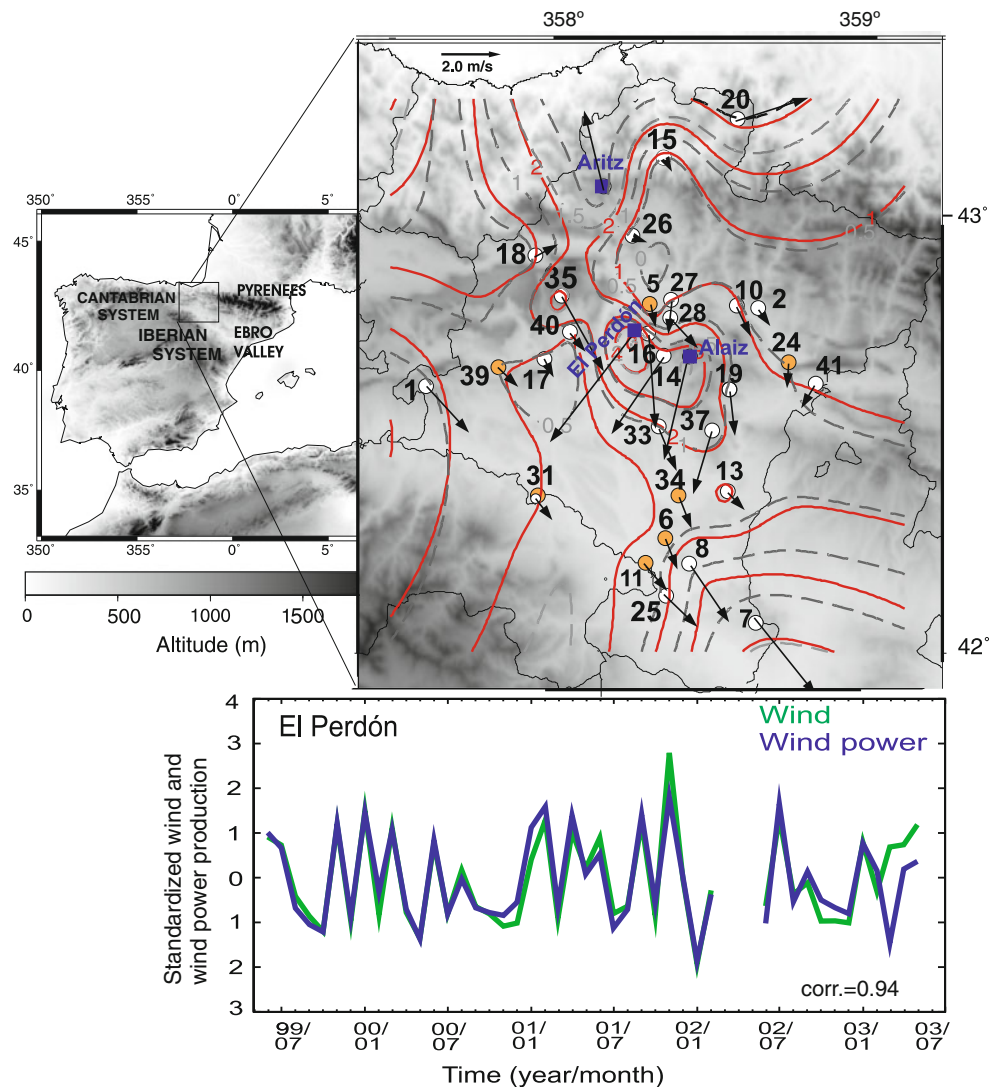
examining the solid red (dashed grey) contours that represent the mean (standard deviation) wind velocity.

Both datasets have been already used in other studies that explored the variability of the wind field in the region (Jiménez et al. 2008, 2009; GBea11) and the relation between wind and wind power production at the wind farm locations (GBea08; GBea09). The datasets were subject to respective quality control procedures, more exhaustive in the case of the wind stations over the CFN (Jiménez et al. 2010).

Several gridded (2.5°lat. × 2.5°lon.) variables over the North Atlantic region and Europe are used as predictor fields in the downscaling experiments: the sea level pressure (SLP), 850 and 500 hPa geopotential heights (ϕ_{850} and ϕ_{500}), 10-m height zonal (U10) and meridional (V10) wind components and 500–850 hPa thickness data ($Z_{500-850}$). These fields are taken from the ERA-40 reanalysis of the European Center for Medium-Range Weather Forecast (ECMWF; Uppala et al. 2005) from

1992 to 2002. Analyses from the ECMWF global model outputs (Jakob et al. 2000) are also used to complete the whole period of observations (2002–2005); for the sake of simplicity this dataset will be referred to as the ECMWF fields henceforth. We use the ERA-40 reanalysis in order to allow for comparisons with a previous study (GBea11).

In order to provide an extension of power estimates to the past (Sect. 3.4), only one variable, the SLP, but with longer temporal coverage is used. Additional datasets are considered in this part of the study: (a) monthly SLP observations from 1899 to 2005 from the National Center for Atmospheric Research (NCAR; Trenberth and Paolino 1980, updated) and (b) an observational dataset provided by the Hadley Centre consisting of historical gridded monthly mean SLPs (HadSLP2) for the period 1850–2004 (Allan and Ansell 2006).

The present study is focused on the most windy months September–March, when the link between the atmospheric circulation and the regional wind field is strongest.

3 Statistical downscaling of wind power production

3.1 Downscaling methodology

The CCA is a multivariate statistical technique that identifies linear associations between sets of predictor and predictand variables that are optimally correlated (Hotelling 1936; Glahn 1968). The original matrix of time-space dependent data is projected onto their Empirical Orthogonal Functions (EOFs) to reduce noise and the number of degrees of freedom. The methodology is fully described in von Storch and Zwiers (1999). Before the calibration of the statistical method the annual cycle is removed in such a way that anomalies are obtained by subtracting the monthly climatological mean. To ensure long-term stationarity, time series are detrended applying a linear least square fit (Xoplaki et al. 2003). Anomalies from the large scale fields are weighted considering the decreasing size of grid boxes with latitude (North et al. 1982). Additionally the time series are normalized, with respect to the whole observational period, to present unit variance. The resulting patterns are re-scaled by the standard deviation at each site after applying the CCA so that they present actual physical units of the field.

The performance of the downscaling model is evaluated by applying a crossvalidation technique that allows for avoiding a possible overfitting of data by the model (Michaelsen 1987). The estimations obtained in every time step of the crossvalidation procedure involve the recalculation of anomalies, EOFs and CCAs. Here the crossvalidation subset consists of a single monthly value, however, variations on the size of the sampling subsets are discussed later in the manuscript. The ability of the method is explored in terms of the correlation coefficient and the Brier Skill Score (ρ and β, respectively; Barnett and Preisendorfer 1987).

A certain combination of the model parameters was selected in a first step, prior to the sensitivity analysis. Such a selection (thereafter called the *reference case*) does not correspond necessarily to the optimal configuration, although it generates wind power estimates that reasonably agree with the observations. This serves to illustrate the potential of the methodology and allows for the understanding of the associations between predictors and predictand. To enable comparisons, the choice of parameters for this reference case is similar to that in GBea11, i.e., the predictor fields employed are the ϕ_{850} and the $Z_{500-850}$ from the ECMWF fields as they can provide a comprehensive description of dynamical and thermal forcings from the atmosphere; the geographical window spans from $35°N$ to $65°N$ and $40°W$ to $10°E$; 4 predictor EOFs, that account for a 81 % of the total variance, are retained for the analysis. Only 2 EOFs of the wind power predictand are considered in the reference case due to the short period of observations and the limited spatial coverage (three locations). They retain however a 97 % of the total observed variance. The two canonical modes are then kept for the regression step in the downscaling model.

3.2 Coupled modes of variability

The two canonical pairs of patterns ($CCA1_{pow}$ and $CCA2_{pow}$) and their respective amplitude time series, that describe temporal changes of sign and intensity of the corresponding patterns, are shown in Fig. 2. The first large scale canonical pattern (Fig. 2a) consists of a negative (positive) anomaly centre located westward of the British Isles. This configuration is connected with anomalous southwesterly (northeasterly) flow in the region (Jiménez et al. 2009). In its positive phase the corresponding local pattern (Fig. 2c) shows a dipole with positive anomalies of wind power production to the north and negative ones to the centre of the region. This pattern is coherent with that obtained if a comparable CCA is applied to the wind velocity as predictand. The resulting canonical pattern of the wind (not shown) shows identically windy conditions, equivalent to positive wind power anomalies, in the northern areas and a decelerated flow, equivalent to negative wind power anomalies, to the centre of the region, in its positive phase. Thus, this CCA mode shows an out-of-phase flow over the northern areas with respect to circulations over the central mountains and the Ebro Valley (Jiménez et al. 2008). The variance explained by the first canonical mode is 25 % in the case of the large scale predictors and 63 % for the wind power. The corresponding canonical time series present a strong correlation (0.89, Fig. 2e). The coherent coupling in the variations of both predictor and predictand patterns suggests that this mode is responsible for the wind power monthly variability at the wind farm locations. This can also be concluded from the correlations between the wind power monthly observations and the two canonical time series (Table 1). Correlation values are indicative of consistency in the monthly variations of observed wind power at the three wind farms and the time component of CCA1 mode. It is interesting to note that the out-of-phase wind power variations at El Perdón and Alaiz with respect to that in Aritz is observable in the reverse of sign of the correlation values.

It is worth noting that the large scale $CCA1_{pow}$ pattern resembles the second pattern obtained by GBea11 for the wind field. This pattern was found to be responsible for anomalous eastward geostrophic flow over the region. The corresponding canonical pattern of the wind therein showed a more zonal orientation of the circulation at the windiest locations over northern and central parts of the CFN, thus, at the wind farm locations. As stated in GBea11

Fig. 2 **a** and **b** canonical patterns of the predictor fields (ϕ_{850} hPa, *shaded*, and $Z_{500-850}$ hPa in *contours*); **c** and **d** canonical patterns of the regional wind power (predictand) and **e** and **f** amplitude time series of the $CCA1_{pow}$ (*left*) and $CCA2_{pow}$ (*right*) modes
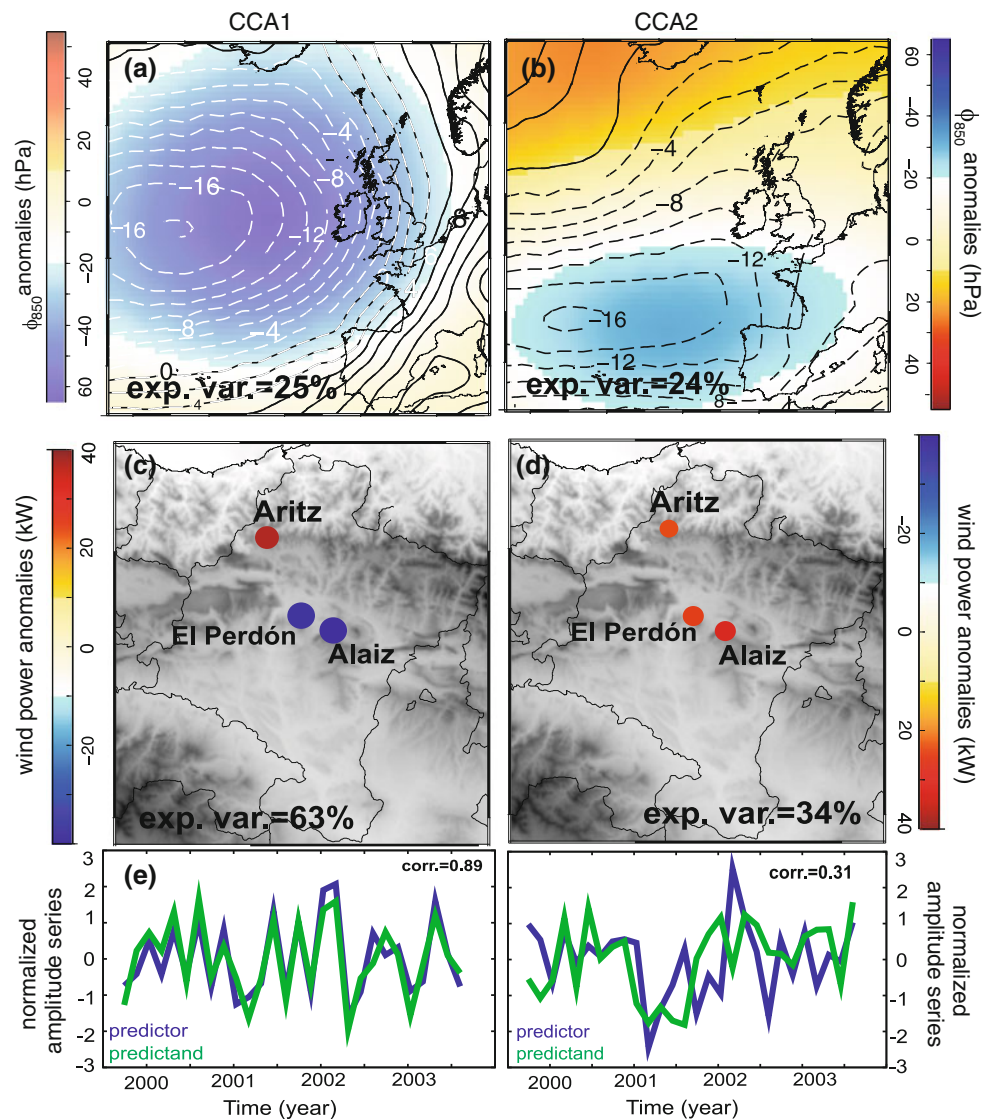

Table 1 Correlation values between the two first canonical series and the observed monthly values of the wind power production at each one of the wind farms

	Aritz	El Perdón	Alaiz
CCA1	−0.66	0.73	0.66
CCA2	0.34	0.52	0.65

the sites located at higher altitudes, exhibited a large influence of quasi-geostrophic circulations and are therefore hardly affected by smaller scale effects. Hence, the variability of both the wind and the wind power at these specific locations is dominated by the same large scale patterns (Fig. 2a). This idea further provides a sense of validation of the results from the application of the downscaling model to the wind power predictand.

The second CCA circulation pattern (Fig. 2b) shows a monopole structure with negative wind power anomalies

in its positive phase, less intense but with a broader penetration into the peninsula compared to that of $CCA1_{pow}$. This implies a similar influence of the large scale flow over the northern and central parts of the region and thus, it favours the appearance of positive wind power anomalies at the three wind farms (Fig. 2d). The second CCA mode accounts for 24 % (34 %) of the large scale predictor fields (wind power predictand) variance. The amplitude time series of $CCA2_{pow}$ shows somewhat lower temporal concordance (canonical correlation is 0.31, Fig. 2f). However, the second mode is also kept for the subsequent analyses for consistency with the reference CCA model configuration in GBea11 and because at least in one of the locations (Alaiz), it contributes to improve the predictability of the wind power estimation (see correlation values in Table 1). The canonical series of both first and second CCA modes indicate considerable intra-annual variability.

3.3 Model validation and methodological uncertainty analysis

After the calibration, the downscaling model outputs are subject to a crossvalidation process. The correlation (Beta Brier skill score) values, i.e., ρ (β), are represented in Fig. 3d. ρ is a measure of the temporal concordance between the observations and estimations. β provides a measure of the variance of observations that is accounted for by the model. This coefficient is defined as $\beta = 1 - \left[S_{ES}^2 / S_{OB}^2 \right]$, where S_{ES}^2 represents the variance of the estimations error and S_{OB}^2 is the observations variance, provided that the climatology is selected as a reference to evaluate the error. In such conditions $\beta = 0$ represents a prediction not better than climatology. If the estimations error variance is similar to that of the observations a positive β is obtained (the better the prediction, the closer to 1). These scores evidence the presence of some predictability for the wind farms Aritz and El Perdón, where ρ/β are 0.71/0.40 and 0.54/0.15, respectively. The performance is poorer at Alaiz ($\rho/\beta = 0.35/0.01$). Nevertheless, the main hypothesis is substantiated at two of the locations which is indicative of a linear relationship between the large scale circulation and the variability of the wind power generated at the wind farms. The lower scores in Alaiz will be further discussed in the following paragraphs.

The downscaling model based on the reference configuration yields validated wind power estimations at the three locations (Fig. 3a, b, c). The observed (black line) and reference estimated (dash-dotted grey line) series show good agreement through most part of the observational period, especially at Aritz (Fig. 3a). Nonetheless, the agreement between observed and estimated wind power series is also noticeable at El Perdón, particularly for the periods 1999 to about mid 2000 (correlation 0.88) and from 2001 to 2002 (correlation 0.98). Interestingly, and in spite of the difference in the global correlation scores at El Perdón and Alaiz (see Fig. 3d), at the latter site the agreement between observations and estimates is also apparent. In fact, the correlation value for the period September 1999 to March 2000 (February and December 2001) is 0.89 (0.72, Fig. 3c). In view of this agreement between observed and estimated values it can be argued that in some periods the downscaling method performs reasonably well, while other time intervals (i.e., 09/2000–01/2001 and 10/2002–03/2003) the skill of the method decreases, particularly at Alaiz. Those periods, that to a great extent are coincident at El Perdón and Alaiz (Fig. 3b and c), will show an important contribution to the methodological uncertainty in all wind farms.

In this part of the analysis and following GBea11, the sensitivity of the wind power estimates to changes in the model configuration is explored. Different sizes of the large scale domain are examined: nine different spatial windows that cover from larger domains over the northern Atlantic and Mediterranean areas to smaller windows over the target region, that may still show some predictability potential, are analyzed here as in GBea11 (see Fig. 8 therein for details on the extension of the spatial windows). Several dynamical and thermal large scale predictor fields, that were already detailed in Sect. 2, and combinations of two or three of them are explored, yielding a total of 25 options. In addition, a varying number of EOF and CCA modes for the analysis are evaluated: the number of retained EOFs fluctuates between 2 and 6 for the large scale predictor and between 2 and 3 for the predictand. The maximum values were determined by calculating the statistically significant correlations between predictor and predictand principal components (PCs). The minimum number of EOFs was selected by determining the breakpoint in the curves describing the explained variance versus the number of EOFs/CCAs (as in GBea11). This represents an indicator of the EOFs that should be included as they retain the larger amount of the original variance. The maximum number of CCA modes retained is imposed by the minimum number of EOFs (3). Considering the previous requirements about maximum/minimum number of patterns, 13 combinations of this model parameter are possible. Finally, the size of the crossvalidation subsets was also evaluated although its selection does not impact the connection between the large scale circulation and the regional predictand. By doing so it can be verified whether the skill of the downscaling model depends on the specific choice of the crossvalidation subset size. This was done by exploring nine different possibilities from one month to four years ($4 \times 7 = 28$ months). For further details on the number of options for all parameters the reader is referred to Table 4 in GBea11.

The spread of estimates (26,325 different combinations) provides a measure of the methodological uncertainty obtained by allowing, within the ranges described above, systematic variations in the model parameter values. The uncertainty is represented by the frequency distribution (deciles with respect to the median, blue area) in Fig. 3a, b and c for Aritz, El Perdón and Alaiz, respectively, together with the observations (red line) and the maximum and minimum estimates (dotted blue line) for illustration. Aritz (Fig. 3a) shows the narrowest uncertainty distribution. For the other two sites the distribution replicates reasonably well the variability of the observations. Therefore, it can be concluded that the methodology is robust to multiple changes in the model configuration. All figures evidence a wider distribution, and thus larger uncertainty in estimations, during the periods where the concordance between observed and estimated series decreases (between the middle and the end of 2001 and from the end of 2002

Fig. 3 Deciles distribution (wrt the median) of the uncertainty associated with the wind power estimates (degraded *blue* area); observations are given in *red* at Aritz (**a**), El Perdón (**b**) and Alaiz (**c**) wind farms; the reference case estimate (*dash-dotted grey line*) and the maximum and minimum values (*dashed blue line*) are also represented. The observations that fall out of the range of values defined by the uncertainty distribution are tagged in the horizontal axis for illustration. **d** Correlation and Brier skill scores calculated between the wind power observations and estimations at the three wind farms within the CFN region
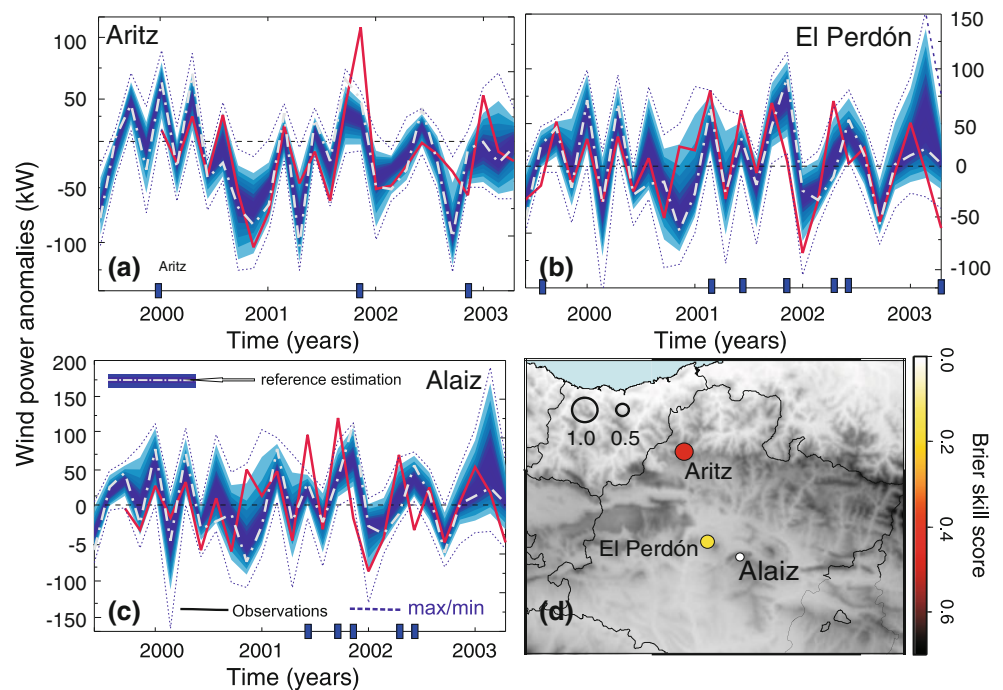
onwards). The latter supports the relevance of assessing the methodological sensitivity to changes in model parameters, especially for those time steps that reveal a reduced predictability. Nonetheless, the observations within those periods fall well within the range of the uncertainty intervals produced by the ensemble of downscaled estimates. The observations that fall out of the range of values defined by the uncertainty distribution at Aritz, El Perdón and Alaiz, respectively are tagged in the horizontal axis of Fig. 3a, b and c for illustration. It is worth noting that more observed values are confined in the uncertainty area in the case of Alaiz with respect to El Perdón (Fig. 3b and c). Thus, it can be argued that, in spite of the lower skill scores obtained in Alaiz, the performance at this site and at El Perdón is comparable. However, the less agreement between observations and estimations at certain time steps might be associated not only with a reduced predictability of the model but also with the quality of the measurements (GBea08). At this respect it is also important to note that the limited length of wind power records allows to capture only a certain portion of the spectral variability.

The reference estimations (dash-dotted lines in Fig. 3a, b and c) fall well within the envelope of the uncertainty distribution and thus the reference selected configuration can be considered as representative of the whole ensemble of estimations.

3.4 Long-term wind power variability

In order to shed light on the long term variations of the wind power, past estimates of power production are

obtained. The statistical downscaling method allows to obtain estimations out of the observational period by using the relation found between the wind power and the large scale circulation predictors during the calibration period (1999–2003). Using this relation the statistical downscaling methodology allows for extending estimations in the absence of predictand records. This can be accomplished within a regression scheme using the available historical information from large scale predictor fields. This examination can help clarifying some aspects related to the long term variations of wind power including the plausible linear relation with the wind at interannual and decadal timescales.

Past estimates of wind power using the reference CCA configuration (identical to that of Sect. 3.1) at El Perdón as an example are represented in Fig. 4 (the conclusions drawn here for El Perdón are also valid for Alaiz and Aritz). Wind power estimation is extended back to the mid 19th century using SLP information. As mentioned in Sect. 2, several SLP predictor datasets are used to reconstruct the past variability of the wind power: ECMWF SLP (light blue line in Fig. 4a, $R_{Pow-ecmwf}$), NCAR SLP (green line, $R_{Pow-ncar}$) and HadSLP2 database (violet line, $R_{Pow-had2}$). A good agreement between the three reference reconstructions can be seen in Fig. 4a. Additionally, we obtain an independent reconstruction for the wind speed (dashed lines) with an analogous procedure. Independence between wind and wind power reconstructions implies that a CCA is applied separately to wind observations in order to obtain the wind field reconstructions shown in Fig. 4a. All series are standardized to allow for a better comparison and they
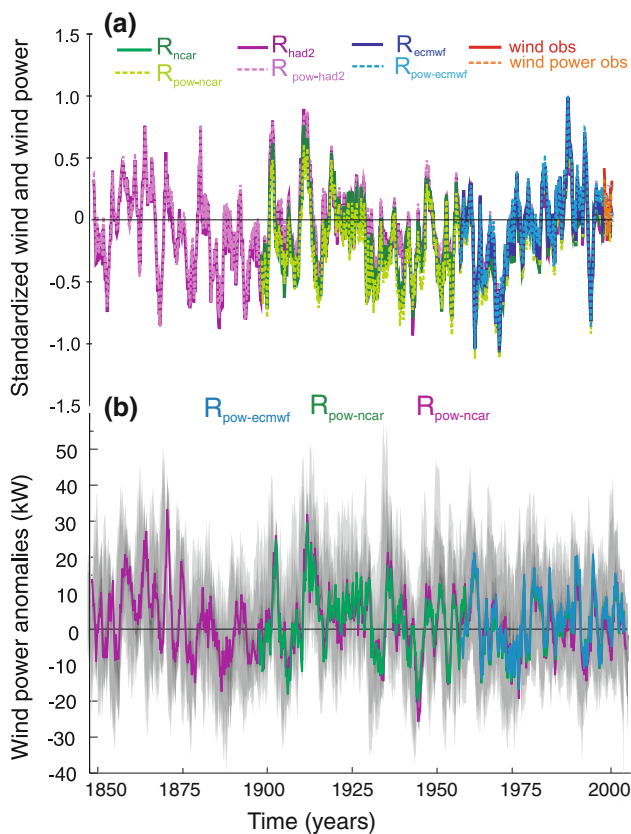
Fig. 4 **a** Reconstructed monthly wind and wind power standardized series at El Perdón. The estimations are calculated using the reference configuration of the downscaling method (Sect. 3.1). See legend for *color* and *line* type assignment. All series are 2 year moving average filter outputs. **b** Reconstructed monthly wind power at El Perdón obtained with the reference configuration of the downscaling method. The deciles distribution (wrt the median) of the methodological uncertainty, calculated by sistematically varying the parameters of the statistical downscaling model set up, is also represented (*grey shading*). Note that wind power in *panel* **a** is standardized to allow for a better comparison with the wind speed estimates, while in panel **b** the anomalies of the estimated wind power are represented

are represented with a 2-year moving-average filter. It is evident that both variables preserve their linear relation throughout the whole reconstruction period (correlation values are 0.98 in the three cases). Therefore, linearity between wind and wind power is an inherent feature of the relation between the two variables that holds from monthly to annual and also longer timescales. As mentioned earlier, the linear relation is an interesting property that will show relevant implications from the perspective of using alternative conceptual approaches to obtain wind power estimates. This will be explored in the last subsection.

Further, it is worth noting that the independent reconstructions of wind speed and wind power are consistent with each other, providing robustness to the estimation of both variables. This is specially interesting if we recall the short length of the calibration period. It would be

reasonable to expect that inter-decadal or even longer term large scale variability could contribute to changes in the regional wind field not accounted for by the statistical downscaling model built using only 5 years of data. This could be the case, for instance, if a mode having a relevant contribution to the low frequency variability, would however not show a significant contribution to the explained variance during the calibration period. Nonetheless, even if this problem can arguably be mitigated using longer instrumental datasets, it is inherent to this type of exercises for any given length of the calibration period. Therefore, there may always exist relevant variability at lower frequency that is not captured due to the length of the available instrumental series.

The reference reconstructions reveal no overall trends for the whole reconstruction period, although a marked tendency to increase power production is found between 1960 and 1990. This is in agreement with GBea11. Previous studies have found links between an increase of the 10 m wind in the North Sea and the intensification of a NAO-like SLP pattern from 1960s to mid-1990s (Suselj et al. 1999; Brayshaw et al. 2011). Further, considerable intra- and interannual variability can be seen in Fig. 4a.

The assumption of stationarity between predictor and predictand relationship deserves some attention. The main drawback of the statistical methodologies that provide past estimates of any climatic variable relates to the fact that the strength of the cross-scales connection might change depending on the time period considered. In such a situation the long-term past estimates could be affected and in principle there is no robust way of assessing this potential effect even in the case of long calibration periods. Therefore, an approach to overcome this uncertainty consists of estimating the methodological variance as similar to GBea11. There, the impact of the selection of a specific model configuration on the long-term estimates of wind, that was negligible during the calibration period, was shown. The methodological variance of the regional wind power reconstructions related to variations in the parameters of the model configuration (see also Sect. 3.3) has also been calculated (Fig. 4b). The three wind power reference reconstructions (based on the three SLP datasets) are also shown (the colors of the different reference reconstructions are identical to those in Fig. 4a). Series are given with a 2-year moving average filter. The area defined by the frequency distribution (grey), that accounts for the dispersion of estimates due to the multiple model configurations explored, preserves to a great extent the variability of the reference configuration estimates. Thus, the methodological variance at longer timescales also shows a robust response of the model to changes in its relevant parameters. Nonetheless, the uncertainty estimation is significant since anomalies of some tens of kW implies a large gap between

the real generation and the estimation of power production that could be of great importance for manufacturers, promotors or electricity markets.

4 Alternative methods for the estimation of wind power production

The approach presented in the previous section for the direct estimation of wind power production is based on evidences of linearity between the wind variability and atmospheric circulation in previous works (GBea11). We have shown that this linear assumption can be transferred to the case of the wind power due to an empirical linear association between wind and wind power at monthly timescales that was observed in GBea09. It has been also tested that the linearity between the two variables holds for longer (interannual to decadal) timescales. In this section, such empirical linear relationship serves as the rationale to explore alternative strategies providing wind power estimates at sites without available observations. In doing so, the regional character of the wind-wind power relationship will also be assessed.

The estimation of wind power is undertaken with simple variants as substitutes of the direct downscaling of wind power explored above. This will provide independent wind power estimates that can be compared with those from Sect. 3 The alternative technique consists in the downscaling of the wind field followed by the translation of the wind estimates into wind power using a transfer function based on their linear association. In this line, two variants have been explored in order to obtain comparable estimations of wind power. These variants could present advantages and different implications depending on the specific situation, for instance, in the absence of wind power data at several locations over the CFN.

The first alternative approach, hereafter $CCA_{Pow-mod}$, where *mod* stands for wind speed, consists in obtaining downscaled wind speed estimates and their subsequent conversion into wind power values. The latter step is carried out by applying a linear regression between the standardized observed wind and wind power during the calibration period at the corresponding wind farm. Only those months entering the CCA (September–March) in both, wind speed and wind power cases, are considered in the calculation of the regression parameters. In order to make estimations independent from the fitted model, a single regression is calculated for each time step by excluding the target month and estimating it from the independent regression over the remaining monthly values within the dataset. The procedure is repeated for every month and also independently for each wind farm. The linear regressions (one per month) are represented in
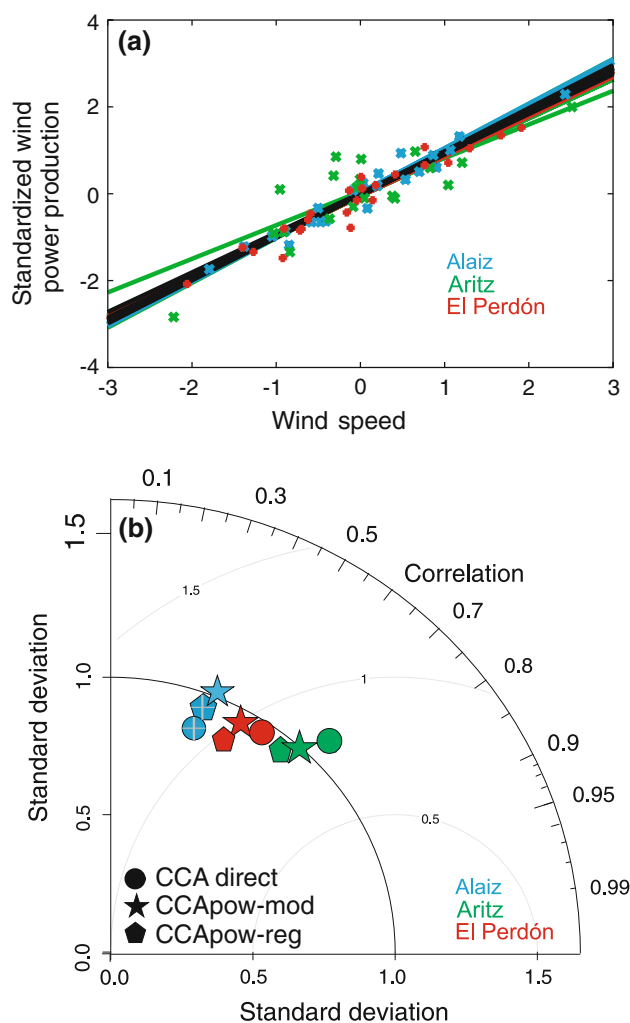

Fig. 5 a Monthly standardized wind speed versus wind power observations. *Colors* represent each wind farm (see legend). Their corresponding linear fits (one per month) are also shown. *Black lines* depict the regional fits (one per month). **b** Taylor diagram for the wind power production estimations. *Circles* stand for the direct downscaling of the wind power, stars for $CCA_{Pow-mod}$, and pentagons for $CCA_{Pow-reg}$

Fig. 5a where blue corresponds to Alaiz, green to Aritz and red to El Perdón. The standardized monthly wind and wind power observations are represented by crosses with the corresponding color. Interestingly, the weakest linear relationship corresponds to the wind farm in which the best scores are achieved during the validation of the downscaling method (Aritz, green in Fig. 5a). Notwithstanding, correlations in the case of Aritz (0.85 on average considering all independent regressions), although lower than in the other sites (0.95 in El Perdón and 0.98 in Alaiz), are still indicative of a robust linearity between wind speed and wind power. It can be argued that this behavior is related to potential deficiencies in the quality of observations or aspects connected to the manipulation of wind turbines.

The second variant, $CCA_{Pow-reg}$, involves a *regional* linear regression as transfer function between downscaled wind and wind power estimates. This implies that, instead of fitting the standardized wind power and wind speed observations individually at each site, a unique regression valid for the three locations is calculated. Additionally, as in the previous cases regressions are calculated for each time step to keep independence between observations and estimations. In standardized conditions (zero mean and unit variance) the linear relation between wind power and wind speed can be expressed as $P = \rho \cdot w$, where P and w are the monthly standardized wind power and wind speed, respectively and ρ represents the correlation coefficient. Thus, the relation between both variables becomes independent of the particular features of each location as for instance, the type of wind turbines installed, that can provide different levels of wind power output according to their dimensions. The assumption involves the use of a single regression model that can be considered valid to describe the linear relationship between wind power and wind speed at the three locations, and therefore it is denoted as the *regional* linear transfer function. The basis for this hypothesis is the degree of agreement (Fig. 5a) between the linear fits at the different sites (blue at Alaiz, red at El Perdón and green at Aritz) and the *regional* regressions (black, also one per month). In view of the small dispersion of wind speed-wind power pairs at each wind farm and that of the regional case, it can be said that a regional regression model is a reasonable approach to estimate the wind power production at the three sites. Then, this $CCA_{Pow-reg}$ case is comparable to the $CCA_{Pow-mod}$ variant except for using a regional linear model to translate wind into wind power instead of using a local linear regression (one per site).

In all variants the downscaled wind speed is obtained by making use of reference configurations identical to that of Sect. 3. All estimations of wind power are in the last step re-scaled with the standard deviations of the observed power at the corresponding wind farm. A Taylor diagram (Taylor 2001) in Fig. 5b compares the performance of all methodological variants. A different color (as in Fig. 5a) is assigned to each one of the three wind farms within the dataset. In addition, symbols are representative of the corresponding approach followed to obtain the wind power estimations. Correlations are within the range 0.26–0.75 (values not significant at the 0.05 level are distinguished by a cross). The standard deviation ratios between observations and estimations are comprised in the interval (0.5, 1.1). The variance is generally underestimated in all cases except for $CCA_{Pow-reg}$ at Aritz. In view of Fig. 5b it is apparent that the direct downscaling of the wind power production (red circles, see Sect. 3.1) performs somewhat better than the other three more elaborated approaches

although the three approaches show comparable skill in reproducing the observed wind power. The scores of each variant are grouped, at every site, around similar values of correlation and a slightly larger degree of scattering for the deviation ratios. Thus, the variants employed do not produce a large impact on the resulting variance of estimations nor do they distort the linear relation between wind speed and wind power. In contrast, the differences in the scores observed in Fig. 5b depend mostly on the specific location. This suggests that the better the results from the downscaling step, the better the wind power estimations from all the variant approaches. One of the winds farms (Aritz) shows better results than the other two. The difference in the ability of the statistical model to reproduce the observed wind power depending on the site could be indicative of some spatial variability, as discussed in the previous paragraphs and illustrated in Fig. 3. Therein, a better predictability in northern than in central areas of the CFN, both for wind and wind power, was found. This is consistent with results in GBea11, where it was shown that the Ebro Valley and the northern areas indicate better predictability than other locations in the central part of the region. This represents an additional argument that provides consistency to the conclusions met in this section regarding the application of the CCA to obtain wind power estimates.

4.1 Applications: estimating wind power in the absence of observations

This section aims at illustrating a potential use of the predictability of the wind power production based on the downscaling of the wind field and the subsequent use of the regional linear relation between the wind speed and the turbine outputs. This application allows for obtaining wind energy estimations at locations with no availability of observed wind power records.

As it has been shown, $CCA_{Pow-reg}$ can be assumed as a sound approach to obtain wind energy estimates at monthly timescales. This can be also understood if it is recalled that the extent to which the wind power estimations reproduce the observations has proven to depend mainly on the skill of the downscaling step. Thus, an interesting application of the latter would be the estimation of the wind power production also in those sites with no wind power production records but for which wind speed measurements are available. Wind power production estimates in the following case study are obtained by first applying a CCA to wind observations. In this case the CCA is calculated using wind components as predictands to illustrate the orientation of circulations over the region. The performance of this variant that makes use of zonal and meridional wind components (that could be denoted CCA_{Pow-uv}) was also
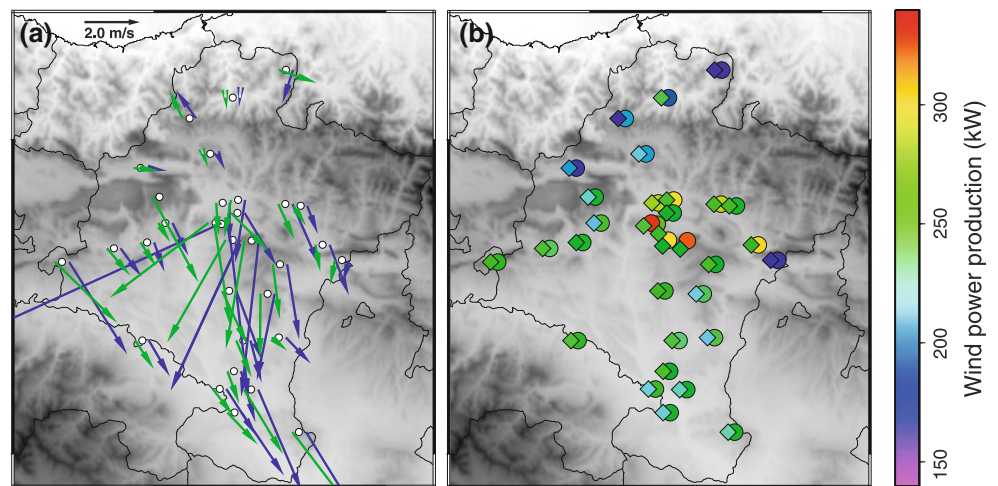
tested (not shown). It yields comparable results to those
from the approaches explored in the previous paragraphs
using wind speed as predictand. Wind speed values are
calculated from the wind components (observed, blue and
downscaled, green in Fig. 6a) and finally, wind power
estimations are obtained via the regional linear transfer
function. An example of this is represented in Fig. 6b.
September 2001 has been randomly selected to illustrate
windy conditions over the CFN. The spatial distribution of
the wind field for the selected month is plotted in Fig. 6a.
For this month high mean wind velocities are recorded in
most of the locations within the dataset, except for those
sites at the north of the region, where lower winds can be
noticed. This month stand as representative for the out-of-
phase wind variations in northern areas with respect to the
rest of the CFN (Jiménez et al. 2008). Additionally, there is
a reasonable agreement between observations and estima-
tions, not only in the direction but also in the length of
vectors, representative of the intensity of the wind. As
mentioned above, if it is assumed that a regional linear fit
conveniently represents the relationship between wind
speed and wind power at all locations, then it seems per-
tinent to obtain local wind power estimates by applying the
regional linear transfer function to both observed and
downscaled wind fields. The wind power estimations are
re-scaled (multiplying by the average standard deviation
and adding the mean of the observed wind power). This is
represented in Fig. 6b, where circles stand for power pro-
duction calculated from the observed wind and diamonds
represent the production obtained from the downscaled
wind. As expected, there is a good agreement between both
wind power estimates in most of the sites (recall that wind
power at the wind farms is observed while in the rest of
sites it is estimated from wind values). Some locations in
central CFN evidence poorer concordance between obser-
vations and estimations related to a poorer performance of
the downscaling approach as it was discussed before. A

final comment is worth concerning Fig. 6b. Estimations of
wind power in this inference exercise are obtained for wind
speed values at the hub heights (around 30–45 m in this
case study). The wind was extrapolated in height by using
the power law (Pryor and Schoof 2005). A more elaborated
approach for the extrapolation of wind values with height
as, for instance, the application of the logarithmic wind
profile (Stull 1990; Arya 2000), would require information
about the surface roughness at each location. However the
purpose here is to illustrate potential applications of the
wind-wind power regional linear relation within a down-
scaling context in a simple fashion, rather than presenting
more refined approaches for the estimation of wind power
production. Thus, this can be considered a straightforward
application of the estimation of wind power based on a
downscaling frame even in the absence of power produc-
tion records. This approach may help in estimating the
potential availability of wind energy over a wider region,
provided that a regional linear transfer function can be
assumed and that the variability of the wind field at
monthly timescales is dominated by the large scale
circulation.

5 Conclusions

This work has provided some insight into the relationship
of the wind power generated (between 1999 and 2003) at
three wind farms over the northeastern Iberian Peninsula,
and the large scale atmospheric circulation over the North
Atlantic area. This study can be placed in the context of the
impact-oriented analyses as the target variable is non-cli-
matic but depends on variations of the wind field and
ultimately, of the large scale atmospheric circulation.
Different approaches that render wind power estimations
have been tested. First, a direct downscaling of the wind
power production as predictand variable was explored at

those sites with historical wind turbine outputs. This exercise showed the existence of wind power predictability at the wind farms through the application of a statistical downscaling method (CCA). The methodological variance associated to multiple changes in the configuration of the downscaling model was also explored. It has been shown that the method is robust to variations of the parameters in the model set up. Hints on enlarged methodological uncertainty during periods with lower predictability have been also provided.

Additionally, an estimation of the long-term past variability of the wind power outside of the observational period allowed for an insight into the low frequency changes of the power production at the wind farms. It was shown that the wind power past estimates share coherent variability with an independent wind speed reconstruction at longer than those timescales of the instrumental period. The latter suggests robustness in the estimation of past variations of wind power in spite of the shortness of the calibration period. In this work it has been shown that the generation of wind energy presents considerable variability at interannual and interdecadal timescales. This type of exercise allows for an insight into the potential variability of local wind power production at interannual and decadal timescales. Typically, for the evaluation of a specific location on its suitability as a wind energy facility, a single year of observations is considered sufficient to assess the range of variability of the wind (Barbour and Walker 2008). However, as shown, the natural variability of the wind power resource can be considerably large from year to year and consequently the power production could be significantly different to the expected if a single year is considered to evaluate the suitability of a certain location for wind energy generation purposes. Analogously, regarding the uncertainty associated to estimations, it can be said that a single estimation does not provide a robust level of confidence. For instance, providing a suitable estimation of the uncertainty in estimations is desirable in order to take part in the electricity market in order to maintain reasonable margins of the risk associated with the goodness of wind power production predictions (Zeineldin et al. 2009).

Other alternatives to the direct downscaling of wind power were also tested based on the downscaling of the wind field followed by a linear transfer function to obtain final wind power values. The different methodologies evidenced a local dependence on the ability of the downscaling model to provide reasonable estimations of wind/wind power. The locations with poorer performance at some periods or time steps in the downscaling of the wind power coincide to a good degree with those where the downscaling of the wind field suffers also a decrease in the ability to reproduce the observed variability.

One inference analysis is presented as an example of potential applications of the wind power production estimations. Downscaled wind at every location was used to obtain power production estimates over the whole CFN through the use of a regional linear relation between wind and wind power. The added value of this approach lies in the possibility of estimating wind power at sites with no availability of wind power series, providing thus an idea of the wind power generation that would be feasible over the region.

The application of this kind of methodologies to non-meteorological variables shape a framework for climate related impact analyses. Underlying arguments are based on evidences of the large scale circulation governing monthly variations of the wind power production in the region. This allows for the application of simple strategies to assess the spatial and temporal variability of the wind power together with its associated uncertainty over the region under study. Such evaluations could be of relevance to assess the impact on wind energy resources of potential changes in wind and wind power variability due to the expected evolution of the climate in the future.

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