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Sub-seasonal to seasonal climate predictions for wind energy forecasting

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Abstract. Both renewable energy supply and electricity demand are strongly influenced by meteorological conditions and their evolution over time in terms of climate variability and climate change. However, knowledge of power output and demand forecasting beyond a few days remains poor. Current methodologies assume that long-term resource availability is constant, ignoring the fact that future wind resources could be significantly different from the past wind energy conditions. Such uncertainties create risks that affect investment in wind energy projects at the operational stage where energy yields affect cash flow and the balance of the grid. Here we assess whether sub-seasonal to seasonal climate predictions (S2S) can skilfully predict wind speed in Europe. To illustrate S2S potential applications, two periods with an unusual climate behaviour affecting the energy market will be presented. We find that wind speed forecasted using S2S exhibits predictability some weeks and months in advance in important regions for the energy sector such as the North Sea. If S2S are incorporated into planning activities for energy traders, energy producers, plant operators, plant investors, they could help improve management climate variability related risks.

1. Introduction

Understanding and quantifying climatic conditions from several weeks to months can improve the decision making of renewable energy generation and electricity demand (Figure 1). Climate predictions including both sub-seasonal (up to one month) and seasonal predictions (forthcoming months) have witnessed considerable improvements in the last decade demonstrating that probabilistic forecasting can inform better decision making for some forecast windows and regions [1]. However, despite this improvement, climate predictions come with new set of challenges for users: information is often un-tailored and knowledge of power output forecasting beyond a few days remains poor. This requires the development of robust methodologies to address decision-making needs.

The aim of this work is to assess the skill in forecasting the meteorological-driven component of wind energy production using sub-seasonal to seasonal climate predictions (S2S) and to illustrate their applications by using two different case studies. Within this context, the work done in two European projects: S2S4E (s2s4e.eu/) and NEWA (neweuropeanwindatlas.eu/) will be presented in this contribution.

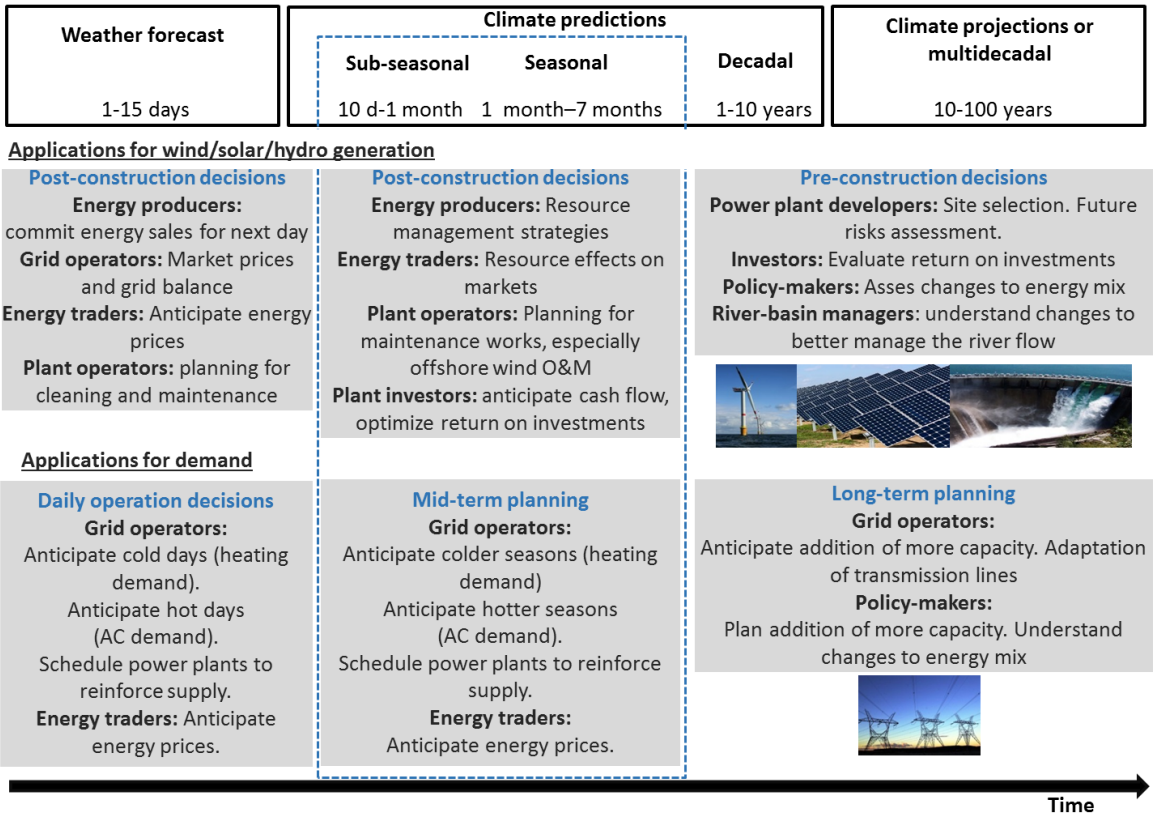

Figure 1. Forecast systems from weather forecast to climate projections including also climate predictions and their potential applications to the energy sector depending on the forecast window. Dotted line highlights the potential applications by using sub-seasonal to seasonal climate predictions.

2. Approach

In sub-seasonal to seasonal climate predictions (S2S), the atmospheric system has lost most of its memory from the initial conditions. Even if the chaotic behavior of the atmosphere does not allow predicting with accuracy the hourly changing weather beyond a few days, climate predictions are feasible because atmospheric variability on monthly/seasonal time-scales is modulated by slowly-varying boundary conditions and can retain memory from internal processes with very slow damping [2]. For a specific variable, e.g. wind speed, predictability will depend on the region, the season, lead time, forecast window and its teleconnections with the main modes of variability (e.g. North Atlantic Oscillation or El Niño-Southern Oscillation).

The forecast quality assessment was set based on two different systems, the ECMWF Extended Range [3], also known as Monthly Prediction System, and the ECMWF SEAS5 for the sub-seasonal and seasonal predictions, respectively. The Monthly Prediction System was obtained from S2S Project database (available at 1.5 degrees) and the SEAS5 from the Copernicus Data Store (available at 1 degree). The period of re-forecast data availability varies between the two systems: 1996-2015 for the Monthly Prediction System launched during the year 2016, while for SEAS5 the period 1993-2015 was used as hindcast.

The main shortcoming of climate predictions is the systematic errors that result from the inability of global circulation models to reproduce all the relevant processes responsible for climate variability and the uncertainty affecting the initial conditions [4]. Hence, climate predictions require bias adjustments in order to minimize forecast errors and produce useful information. Bias adjustment methods produce climate predictions whose statistical properties are similar to those in the underlying observational references [5], allowing the energy business to integrate bias-adjusted climate

predictions in their decision making processes. The predicted ten-meter wind speed and temperature forecast have been calibrated and evaluated with ERA-Interim reanalysis, which has been used as the observational reference [6]. The variance inflation bias-adjusted method, which was used in this study, produces predictions that will have inter annual variance that is equivalent to that of the reference dataset. The method is described in [4] and tested against a simple bias correction for the case of wind in [5]. The inflation of the ensemble spread ensures that predictions have reliable probabilities.

S2S forecasts have been compared with observations to assess wind predictability at different time scales in terms of the Fair Ranked Probability Skill Score (FairRPSS) [7]. FairRPSS is a measure of the predictive skill for the probabilistic forecasts for categorical events. Scores below zero indicate that the predictions are unskillful, those equal to zero are equal to the climatology forecasts, and anything above zero is an improvement upon climatology, up to 1, which indicates a 'perfect' forecast. Fair RPSS has been computed with one of many possible samples from a population, therefore the sampling uncertainty affecting this metric need to be taken into account (significant test at 95% level) to avoid over interpretations of the skill values [8].

Then, two different case studies have been analyzed to illustrate the potential application of S2S. Case studies may be understood as historical periods pointed as relevant by industrial stakeholders, periods with an unusual climate behavior affecting wind energy production. These two case studies represent different contexts and circumstances in terms of: regions, seasons and duration of the event.

3. Results

Skill estimates based on the performance of the systems in the past (20 years), may guide users about the expected performance of the future forecast. Figure 2a illustrates the skill of the Monthly Prediction System of January, two weeks before the target week in January (12-18 days). The positive values of FairRPSS indicate that there is skill in the region, and the wind speeds could be predicted two weeks in advance in many regions of interest for the wind energy sector such as the North Sea and Spain. Figure 2b characterizes the forecast skill in the Fino 1 research platform in the North Sea. Wind speed exhibits high skill (>0.3) in July and from December to March for forecast time of 5-12 days. Skill drops below 0.2 for subsequent forecast times, even though values above 0.2 are observed for forecast time of 1 month in December and of 2 months in July. Negative skill (white boxes) appears starting from forecast time of 19-25 days onward. The skill estimates shown in Figure 2 are the first insights of the skill assessment included in the NEWA wind atlas (neweuropeanwindatlas.eu/) where a comprehensive assessment will be included.

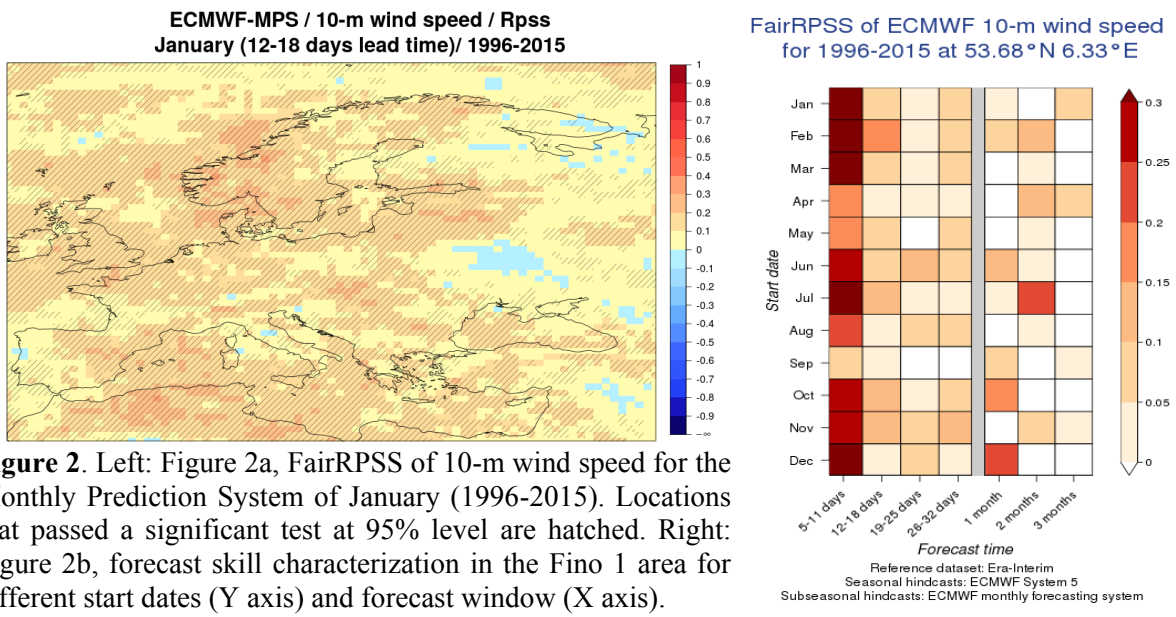

Figure 2. Left: Figure 2a, FairRPSS of 10-m wind speed for the Monthly Prediction System of January (1996-2015). Locations that passed a significant test at 95% level are hatched. Right: Figure 2b, forecast skill characterization in the Fino 1 area for different start dates (Y axis) and forecast window (X axis).

3.1. Case study 1: Cold wave over Europe and lower than usual wind power generation

During the week 17/01/2017-23/01/2017 a cold wave over Europe created a large increase in electricity demand. During this period, there were also low wind speeds over Europe and therefore lower than normal renewable energy supply. In France, under the national regulation authority request, utilities had to stop several nuclear reactors to carefully check some components. This created a situation of high risk that could have been better managed with accurate forecasts.

This case study shows that sub-seasonal predictions of temperature and wind speed (Figure 3 and Table 1) can provide added value to the current practice of using climatological forecasts. The skill increases considerably at shorter lead times and is greater for temperature than for wind speed. There is therefore confidence in anticipating episodes of high electricity demand a few weeks in advance (cold spells), although less confidence in ensuring that wind energy supply can meet the demand.

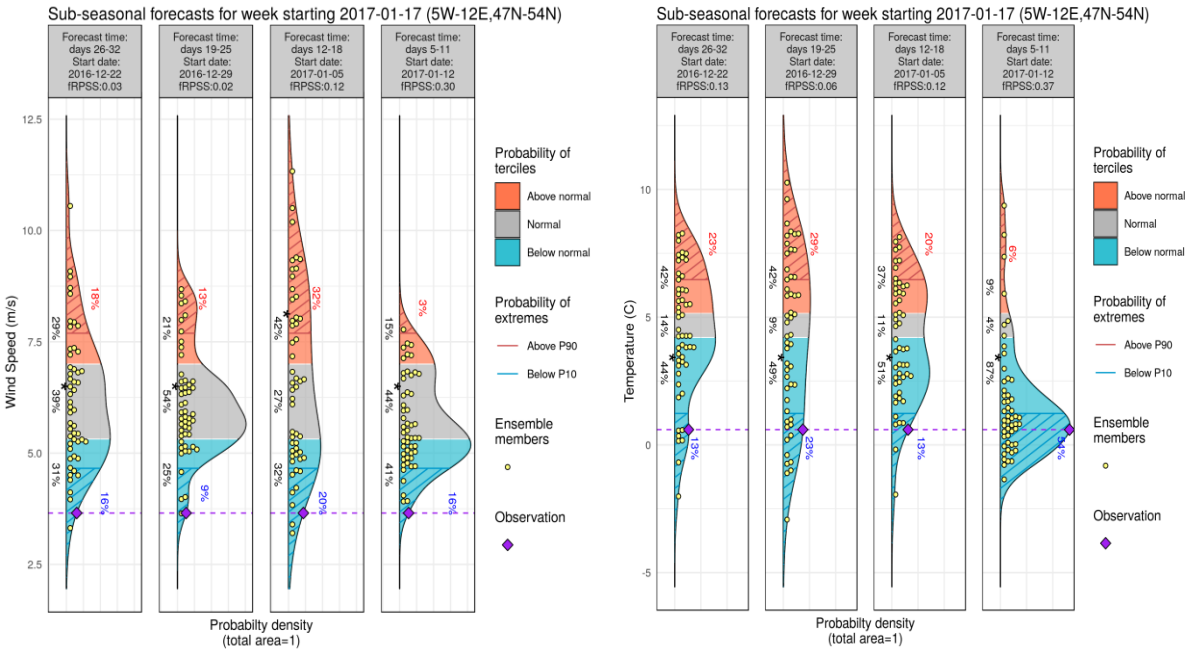

Figure 3. Sub-seasonal forecasts for wind speed (left) and temperature (right) for the week 17/01/2017-23/01/2017. Lead time ranges from 4 to 1 week in advance. Area of study: 5W-12W, 47N-54N). Yellow dots represent the members of the forecasts organized into three categories of equal size (terciles; above normal, normal and below normal) defined according to the climatology. Black percentages represent the forecast probabilities of each tercile, the most likely tercile is highlighted with a black star and the blue and red percentages represent the probabilities for p10 and p90 (hatched areas), respectively. Purple diamonds represent the observations for the target period.

Table 1. Associated probability skill (FairRPSS and Fair Brier Skill Score for percentile 10 and 90) scores are shown for wind speed and temperature for the area of study (5W-12E, 47N-54N).

Skill	Weeks before January 17-23. Wind speed				Weeks before January 17-23. Temperature			
	4	3	2	1	4	3	2	1
FairRPSS	0.03	0.02	0.12	0.30	0.13	0.06	0.12	0.37
BS P10	0.07	-0.02	0.00	0.21	-0.03	-0.04	0.26	0.59
BS P90	0.02	0.01	-0.01	0.19	-0.12	0.05	-0.15	0.29

3.2. Case study 2: Wind drought in North America

During the first quarter of 2015 the United States experienced a widespread and extended episode of low wind speeds [9]. This episode had a strong impact on wind power generation. Some wind farms did not generate enough cash for their steady payments, and the value of wind farm assets decreased.

Forecasts available for January to March 2015 did predict a lower than usual wind speeds situation over the area under study three months in advance. However, predictions were increasingly ambiguous as time passed by, reaching an almost equal probability for each tercile one month ahead of the target period (Figure 3). Despite being the weakest forecast, December's prediction showed ensemble members pointing at really low values for wind speed, not completely forecasting the actual values (purple diamond), but close to the extremely low observations of the variable. The skill associated with the forecasts was fair for all three lead times, meaning the predictions were better than plain climatology and could be taken into account (Table 2).

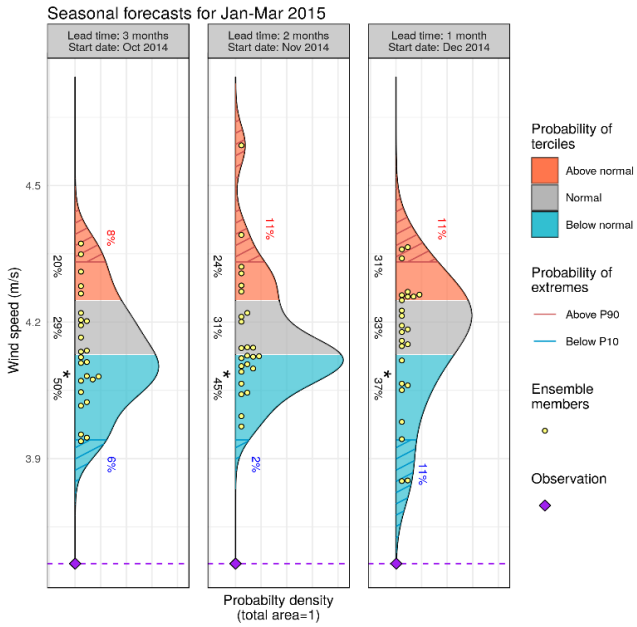

Figure 4. As Figure 3. Wind-speed seasonal forecasts for January to March 2015. Lead time ranges from 3 to 1 months in advance. Area of study: (124W-95W, 26N-44N).

Table 2. As table 1. January to March 2015. Area of study: (124W-95W, 26N-44N).

SKILL Wind	Forecast lead time		
	3-months (October)	2-months (November)	1-month (December)
FairRPSS	0.35	0.39	0.35
BS P10	-0.07	-0.27	-0.16
BS P90	0.10	0.04	0.07

4. Conclusions

Recent advances in global climate models, which simulate the physics of the whole climate system, demonstrate that probabilistic forecasting approaches can produce improved information upon retrospective climatology at certain spatial and temporal scales. Hence, energy decision makers now have a new set of tools to strengthen their decision making. Sub-seasonal to seasonal climate predictions (S2S) could be an important planning tool for energy traders, producers, plant operators, plant investors that can lead to better and timely management climate variability related risks.

The main conclusions of this work are two. First, the wind speed forecasted by S2S exhibits predictability some weeks and months in advance in important regions for the energy sector such as the North Sea. Second, current methodologies assume that future conditions will be like those of the past; an approach that makes impossible to anticipate extreme events that have never happened before.

This work aims at assessing the merits and caveats of climate prediction systems in predicting wind energy resources. To foster the uptake of S2S predictions in decision making processes, two complementary works are being performed during the preparation of this contribution. One is an economic analysis of relevant case studies (including the two presented in this contribution), understood as an evaluation of S2S predictions from the decision making point of view. The other will be an assessment of the use of S2S predictions in a real-time operational context. Both works will be public reports available through the S2S4E project website (www.s2s4e.eu).

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References

[1] Alessandrini S., Sperati S., and Pinson P., 2013. A comparison between the ECMWF and COSMO Ensemble Prediction Systems applied to short-term wind power forecasting on real data. *Applied energy*, 107, 271-280.

[2] Doblas-Reyes F. J., García-Serrano J., Lienert F., Biescas A.P. and Rodrigues L. R., 2013. Seasonal climate predictability and forecasting: status and prospects *Wiley Interdis. Rev.: Clim. Change* 4 245–68

[3] Vitart F., 2004. Monthly Forecasting at ECMWF. *Monthly Weather Review*, 132(12), pp.2761–2779.

[4] Doblas-Reyes F J, Hagedorn R, and Palmer TN, 2005. The rationale behind the success of multi-model ensembles in seasonal forecasting - II. Calibration and combination. *Tellus A*, 57 (3), 234–252

[5] Torralba V., Doblas-Reyes F. J., MacLeod D, Christel I. and Davis M. 2017. Seasonal Climate Prediction: A New Source of Information for the Management of Wind Energy Resources. *Journal of Applied Meteorology and Climatology*, 56(5), 1231-1247. doi: 10.1175/JAMC-D-16-0204.1

[6] Dee DP, Uppala SM, Simmons AJ, Berrisford P, Poli P, Kobayashi S, Andrae U, Balmaseda MA, Balsamo G, Bauer P, Bechtold P, Beljaars ACM, van de Berg L, Bidlot J, Bormann N, Delsol C, Dragani R, Fuentes M, Geer AJ, Haimberger L, Healy SB, Hersbach H, Hólm EV, Isaksen L, Köllberg P, Köhler M, Matricardi M, Mcnally AP, Monge-Sanz BM, Morcrette JJ, Park BK, Peubey C, de Rosnay P, Tavolato C, Thépaut JN, Vitart F, 2011 The ERA-Interim reanalysis: configuration and performance of the data assimilation system. *Q J R Meteorol Soc* 137(656):553–597

[7] Ferro, 2014. Fair scores for ensemble forecasts. *Quarterly Journal of the Royal Meteorological Society*, 140 (683), 1917–1923.

[8] Bradley, A. A., Schwartz, S. S., & Hashino, T., 2008. Sampling uncertainty and confidence intervals for the Brier score and Brier skill score. *Weather and Forecasting*, 23(5), 992-1006.

[9] Lledó Ll., Bellprat O., Doblas-Reyes F.J. and Soret A., 2018. Investigating the effects of Pacific sea surface temperatures on the wind drought of 2015 over the United States. *Journal of Geophysical Research Atmospheres*, doi: 10.1029/2017JD028019.