A simplified seasonal forecasting strategy, applied to wind and solar power in Europe

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Abstract

We demonstrate the current levels of skill for seasonal forecasts of wind and irradiance in Europe, using forecast systems available from the Copernicus Climate Change Service (C3S). While skill is patchy, there is potential for the development of climate services for the energy sector. Following previous studies, we show that a simple linear regression-based method, using the hindcast and forecast ensemble means, provides a straightforward approach to produce reliable probabilistic seasonal forecasts in the cases where there is skill. This method extends naturally to using a larger-scale feature of the climate, such as the North Atlantic Oscillation, as the climate model predictor, providing opportunities to improve the skill in some cases.

We further demonstrate that taking a seasonal average and a regional (e.g. national) average means that wind and solar power generation are highly correlated with single climate variables (wind speed and irradiance): the detailed non-linear transformations from meteorological variables to energy variables, which can be essential for precision on weather forecasting timescales and for climatological studies, are usually not necessary when producing seasonal forecasts of these average quantities.

Together, our results demonstrate that, in the cases where there is skill in seasonal forecasts of wind speed and irradiance, or a correlated larger-scale climate predictor, it can be very straightforward to forecast seasonal mean wind and solar power generation based on those climate variables, without requiring complex transformations. This greatly simplifies the process of developing a useful seasonal climate service.

Keywords: Seasonal forecasting, Renewable energy, Wind, Solar, Climate services

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Practical Implications

There is an increasing demand for seasonal climate prediction services for the energy sector, in order to improve financial planning or reduce financial risks. Potential users include owners/operators of generation facilities (e.g. wind/solar farms), transmission/distribution networks, system operators, regulators, policy makers and financial traders.

Greater availability of seasonal forecast and hindcast data, through projects like the Copernicus Climate Change Service (C3S), is enabling many organisations – private companies, national meteorological services, energy companies – to start to develop seasonal climate services for their customers' needs.

We show that seasonal forecast skill for wind speed and solar irradiance in Europe is very patchy: Although it is high enough to be useful in some cases, this is far from universal across all regions and seasons. Services should be developed for specific, select cases, rather than generally.

We demonstrate that a simple methodology, based on linear regression between a climate model predictor variable and the observed energy/climate variable of interest to the users, can greatly simplify the production of a probabilistic seasonal climate forecast.

We also show that the process of taking a seasonal average and a regional average (e.g. over a European country) means that the resulting average wind and solar power generation are highly correlated with the average wind speed and solar irradiance, respectively. Together with the modest levels of forecast skill, this removes the need for complex transformations performed at high temporal/spatial resolution, such as wind turbine power curves, scaling to turbine hub height, or including the temperature-dependence of solar power. The seasonal mean, regional mean values are much more strongly correlated (mostly > 0.9) than the skill of the forecasting system itself.

This methodology is dependent on the availability of multi-decadal time series of the quantity of interest from the energy-sector user of the climate service. The development of the service will therefore benefit strongly from close collaboration

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with the prospective users. A service could be further improved in some cases through direct engagement with climate forecast data providers, to utilise the latest models, data sets and research into how to optimise the use of the seasonal forecasts.

1. Introduction

Seasonal climate prediction, forecasting statistics of the weather over a period of several months, with a lead time of several weeks, has long been an area of interest to the energy sector (e.g. Weiss, 1982; Troccoli et al., 2008; Troccoli, 2010; Doblas-Reyes et al., 2013). Recent improvements in the levels of skill in seasonal forecast systems, particularly at mid-latitudes (e.g. Scaife et al., 2014; Smith et al., 2016), has meant that seasonal forecasting climate services are now starting to be developed in earnest (e.g. Prudhomme et al., 2017; Palin et al., 2016; Viel et al., 2016; Clark et al., 2017; Buontempo, 2018). At the same time, the introduction of increasingly important levels of weather-dependent renewable electricity generation means that demand for skillful and reliable seasonal forecasting services, tailored to the requirements of users in the energy sector, is only likely to increase in the coming years.

The energy sector is itself very diverse, especially when considering the different arrangements across European countries: owners and operators of electricity generation facilities, operators of the transmission or distribution networks, energy traders, system regulators and policy makers all have different needs and aims. Indeed, such organisations often employ specialist meteorologists: they help to translate the weather and climate conditions in the forecasts, and their uncertainties, into the energy quantities required by their colleagues for decision-making. They therefore act as internal climate service providers.

Increasing amounts of observational and forecast data are now being made more easily available to users, through initiatives such as the European Commission's *Copernicus Climate Change Service* (C3S), in partnership with national meteorological services and other organisations across Europe. However, there is often a gulf between developers of these data sets, and the needs of the climate service providers and users within energy sector organisations. It is this gap that we consider in this paper, by demonstrating how seasonal forecast data, made available through programmes like C3S, could be used to provide useful information for the energy sector.

The C3S programme is providing data, tools and guidance to allow seasonal forecasting climate services to be developed, using the latest climate prediction systems. The *European Climatic Energy Mixes* (ECEM) proof-of-concept service, a C3S Sectoral Information System, has developed new observation-based data sets that are relevant for studying the impacts of climate variability on the European energy sector. It has also examined the skill of seasonal forecasts provided through the C3S Climate Data Store (Troccoli et al., 2018).

In this paper, we use data produced in the ECEM project to demonstrate how seasonal forecasts for the European wind and solar energy sectors can be produced in a relatively straightforward way, without compromising on the need to provide probabilistic forecasts. In section 2, we describe the seasonal hindcast and observation-based data sets we use to assess the forecast systems. We then consider the skill of the seasonal forecasting systems in section 3, and demonstrate a simple approach to producing reliable probabilistic forecasts. Section 4 describes how we might translate the skill found in forecasting climate variables into skillful energy forecasts. We discuss the benefits of more detailed co-design of forecasting services in section 5. Finally, we summarise our conclusions in section 6.

2. Data sets

To assess the performance of different seasonal forecast systems, we use their hindcast data sets, obtained from the C3S Climate Data Store. We compare the hindcasts against observation-based data sets produced through the ECEM project. We describe these in the following subsections.

2.1. Seasonal hindcasts

Three hindcast data sets were obtained from ECMWF during the pre-operational phase of the C3S Climate Data Store (Raoult et al., 2017)[1] in late 2017, from three different production centres: ECMWF (Molteni et al., 2011), Mto-France (Mto-France, 2015) and the Met Office (MacLachlan et al., 2015; Williams et al., 2015). Table 1 describes some key details of these three forecast systems, relevant for the present study. The forecast systems differ not only in the formulation of their underlying climate models, but also in the way the forecasts are initialised, and in how the forecast and hindcast data sets are compiled from those initialised runs. We refer the reader to the references above for more comprehensive descriptions of each particular system.

Each hindcast comprises climate model simulations that are ran forward for several months after initialisation. A new, independently initialised set of runs is available for every month of each 20–30-year data set. This allows the behaviour of each forecast system to be examined by providing a series of retrospective climate predictions. Although these large data sets provide the freedom to examine forecasts of many different periods over a range of different lead times, seasonal forecasts typically focus on forecasting for 3-month seasons, with a lead time of one month. Here, we focus on forecasts of the average conditions in winter (December–January–February, DJF) and summer (June–July–August, JJA), initialised in early November and May respectively.

2.2. Observation-based data

We use the ERA-Interim reanalysis data (Dee et al., 2011) as a proxy for observations, as well as the climate data set that was developed as part of the ECEM project (Jones et al., 2017). This is also based on ERA-Interim, but is then ias-adjusted using various station-based and satellite-based observational data

[1]The C3S Climate Data Store can be accessed at `https://cds.climate.copernicus.eu`

Table 1: Summary details for seasonal prediction systems used here. The years in the hindcast period column refer to those of the initialisation dates (May and November).

Production centre	Forecast System	Model	Spatial resolution	Hindcast period	Hindcast ensemble
ECMWF	System 4	IFS Cyc36r4	T255 L91 (~ 80 km)	1981–2010 (30 years)	51 members
Mto-France	System 5	Arpege-IFS Cyc37	T255 L91 (~ 80 km)	1993–2014 (22 years)	15 members
Met Office	GloSea5-GC2	HadGEM3-GC2	N216 L85 (~ 60 km)	1993–2015 (23 years)	28 members

sets. The ECEM climate data is data is available at a 0.5 grid resolution and covers the period 1979–2016.

We also use national-scale electricity supply data from the energy data set developed in ECEM (Dubus et al. 2017a,b; Saint-Drenan et al. 2018; see also Troccoli et al. 2018). While this data is based on actual, observed generation data from across Europe, it is in fact modelled (as are reanalyses of course). The capacity factor (the amount of power generation at a given moment as a fraction of the installed generation capacity) for a given generation source, such as wind, is modelled and calibrated against measured data over a recent period with a known installed capacity. This model is then applied to the weather of the historical period, while imagining the same installed capacity as in the present. This allows the production of long time series that accurately describe the meteorological dependence of electricity generation in different regions. Without this, the data would be dominated by the varying technological, economic, political or social factors that strongly affect the actual levels of installed capacity, which varies markedly over time. Although the data is provided in terms of total generation (i.e. energy) and mean generation rate (i.e. power) as well as capacity factors, we simply use the capacity factor data here as it is not necessary to convert further for our analysis.

The national-scale ECEM data sets cover 33 European countries. Offshore areas belonging to countries are excluded, as much of the ECEM climate data was bias adjusted using measurements from land stations, and the energy data was derived from that.

This is an important restriction:[2] offshore wind power generation has much higher capacity factors than onshore, and some countries have significant amounts of offshore wind power installed. Our results therefore shouldn't be seen as reflecting the "national" capacity, but the land-based capacity. Our main points will nevertheless hold in either case.

We use the ECEM wind power data that is based on a statistical model using a support vector regression technique. A lack of adequate training data in some cases means that it only covers 23 countries, although it tends to perform slightly better than the ECEM data produced using a physically-based wind turbine model (see Dubus et al. 2017a for details). In practice, they are both well correlated and the choice does not affect our results (Bett et al., 2018a).

[2]To be addressed in future versions of the data set.

The solar photovoltaic (PV) generation data from ECEM is based on the mixed physical and statistical method of Saint-Drenan et al. (2017). It takes into account the tilt and orientation of the solar panels, and includes a dependence on air temperature as well as irradiance to estimate power output for a reference PV system (solar PV panels operate more efficiently at lower temperatures).

The detailed formulation of the models for wind and solar power is not the focus of this study, and indeed many model variations were tested as part of the ECEM project. The strength of the resulting data sets lies in them covering the same multi-decadal period, having been calibrated against a comprehensive set of national electricity production data gathered from a range of sources. We shall be treating them as the observational "truth" for the purposes of this study.

3. Reliable probabilistic forecasts of climate variables

In this section we describe the skill of the three systems in forecasting wind speed and irradiance, and demonstrate how the ensemble means can be used to provide reliable probabilistic forecasts of these quantities.

3.1. Skill of directly forecasting climate variables

One of the simplest ways of measuring the forecast skill of a given variable is through the interannual Pearson correlations between the observed values of that variable, and the ensemble-mean values from the hindcasts (recall that we are considering predictions of 3-month averages with a 1-month lead time). The correlation skill for wind speeds and irradiance, for the three forecast systems in both summer and winter, is mapped in Figure 1. (Figure B.8 in Appendix B shows the skill of the same hindcasts measured against the ECEM observational data. There is no significant difference in the results, other than the ECEM-based data lacking sea points for wind speed.)

The skill is clearly patchy, and varies between the different models, seasons and variables: one cannot make broad statements like "model X has skill in forecasting variable Y". This is typical of seasonal forecasting in extratropical regions, and is important for informing expectations about seasonal forecasts, such as when communicating with users: seasonal forecasts perform at a very different level of predictability than traditional weather forecasts, or even medium-range subseasonal ensemble forecasts. They must be used selectively, choosing

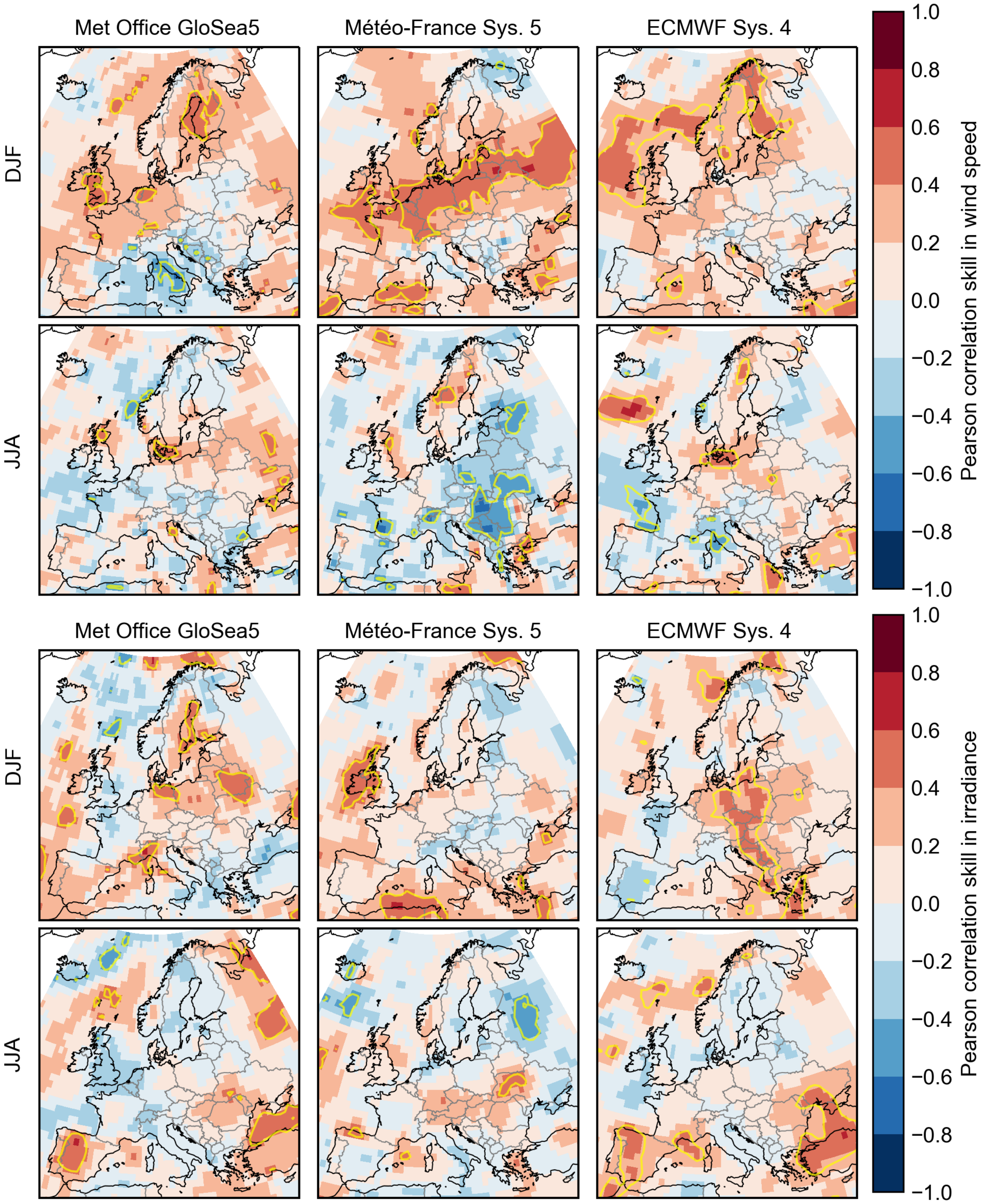

Figure 1: Skill, as measured by the correlation coefficient, of seasonal forecasts of wind (upper rows) and irradiance (lower rows), from the three hindcasts we use here (columns, as labelled), against ERA-Interim data. (Similar plots using the correlation against the ECEM observational data are available in Figure B.8.) Forecasts are for the 3-month averages of winter (DJF) and summer (JJA) as labelled, at a lead time of one month (i.e. November and May initialisation respectively). The yellow contour marks a notional threshold for significance, using the Fisher z-test at the 5% level.

only the cases (regions, seasons, models, variables) where we can be confident that there is skill.

Furthermore, since the correlation is based on the very limited number of years in the hindcast data sets, it is itself rather uncertain. A confidence interval on the correlations can be calculated using a Fisher z-transformation. This is a simple analytic estimate, which assumes that the hindcast and observational data follow a bivariate normal distribution. While this is clearly not true for wind speed and irradiance in general (e.g. winds are often considered to follow a Weibull distribution: Hennessey 1977; Carta et al. 2009; Harris and Cook 2014), it is a reasonable assumption in this case because of the Central Limit Theorem: after averaging to get seasonal means, country means and ensemble means, the remaining 20–30 pairs of data points are usually indistinguishable from being normally distributed (this is due in part to the small data sample). The correlation values for the confidence interval are given by

$$r_{\mathrm{CI}\pm} = \tanh\left(\operatorname{artanh}(r) \pm \frac{z}{\sqrt{N-3}}\right), \tag{1}$$

where r is the correlation whose confidence intervals we are estimating, and z is the value at the 2.5th percentile of a standardised normal distribution, such that the confidence interval on the correlation is at the 95% level. Note that this confidence interval depends only on the number of years N in the data sets, and the value of the correlation itself. This means that we can write down the critical correlation thresholds for significance by this measure (the smallest correlation r_{crit} such that $|r_{\mathrm{CI}\pm}| > 0$), which for the hindcasts we use here are:

- $r_{\mathrm{crit}}(N = 30) = \pm 0.360$ (ECMWF)
- $r_{\mathrm{crit}}(N = 23) = \pm 0.412$ (Met Office)
- $r_{\mathrm{crit}}(N = 22) = \pm 0.422$ (Mto-France)

Contours marking the notional 5% significance thresholds on the correlations according to this test are marked on the skill maps in Figures 1 and B.8.

There is also uncertainty due to the finite ensemble size. However, due in part to the signal-to-noise problem (discussed in the next subsection), the skill increases systematically with ensemble size (e.g. Dunstone et al., 2016), following a clear theoretical relationship (Murphy, 1990). Furthermore, since the forecast ensemble sizes are the same size or larger than the hindcast ensembles, it is safe to treat the skill we find here as a lower limit on the actual forecast skill, and do not consider the impact of ensemble size further.

Area-weighted averaging over relatively large regions can enhance the forecast skill by reducing the gridpoint-scale noise. In Europe, individual countries can represent sufficiently large areas to achieve this, and often represent relevant administrative boundaries for users, making it a convenient choice for aggregating the forecasts. Time series of observations and hindcast for each country are available on the ECEM Demonstrator[3]. As this study focuses on methodology, we give an illustrative example in Figure 2, showing hindcasts of winter wind speed in Finland from the three systems, together with observations. The hindcast ensemble means are shown after applying a simple linear bias and variance correction, which leaves the correlation skill unchanged:

$$U'_{\mathrm{hc}}(t) = \overline{U_{\mathrm{ob}}} + \left(U_{\mathrm{hc}}(t) - \overline{U_{\mathrm{hc}}}\right)\frac{\sigma(U_{\mathrm{ob}})}{\sigma(U_{\mathrm{hc}})}, \tag{2}$$

for wind speed data U, where the prime indicates the corrected data, the overbar indicates the long-term mean, σ is the interannual standard deviation, 'hc' indicates the hindcast ensemble means and 'ob' indicates the observational time series.

We take the approach that some degree of bias and/or variance correction will always be necessary when producing a forecast. While it is important to understand the biases in the mean state or variability of the climate model, in order to improve the model and its forecasts, that is not our goal here: the important quantity in this case, in terms of skill, is the standardised co-variability of the initialised model with respect to the observations, i.e. the correlation.

3.2. Reliable probabilistic forecasts using the ensemble means

The uncertainty of seasonal forecasts means that, in order to provide useful and robust information for decision-making, they should be used probabilistically. However, we have focused so far on showing the skill of the ensemble mean and its correlation, which would traditionally imply deterministic forecasts. We could of course use the distribution of ensemble members as an indication of the forecast probability distribution, and use one of a wide range of probabilistic skill scores instead. If the ensemble members in each grid cell are pooled over a large region, then the results can be reasonably robust. This is typically done over areas roughly the size of Europe (e.g. MacLachlan et al. 2015). For the ECEM project, the probabilistic Brier and ROC skill scores were calculated for each European country individually. These results are available on the ECEM Demonstrator, and summarised in Bett et al. (2018b). However, the skill in such small regions is relatively low and usually not statistically significant, as it is limited by sampling noise. One approach to circumvent this is to use a large moving window of grid cells to assess the probabilistic skill or reliability in the surrounding region (e.g. Clark et al., 2017). However, while this provides useful model diagnostic information, it limits the generality and immediate applicability of the skill information for users.

There are many other methods of deriving probabilistic forecasts from the ensemble member distribution, known in general as Ensemble Model Output Statistics (EMOS, e.g. Wilks 2011). A simple approach would be to apply the Central Limit Theorem again, and assume that the "true" forecast probability distribution is just a normal distribution with the mean and variance well estimated by those of the empirical distribution of the ensemble members. Other more precise techniques include forms of kernel dressing (e.g. Bröcker and Smith, 2008; Suckling and Smith, 2013; Smith et al., 2015), and various recalibration techniques incorporating bias and variance corrections

[3] http://ecem.wemcouncil.org

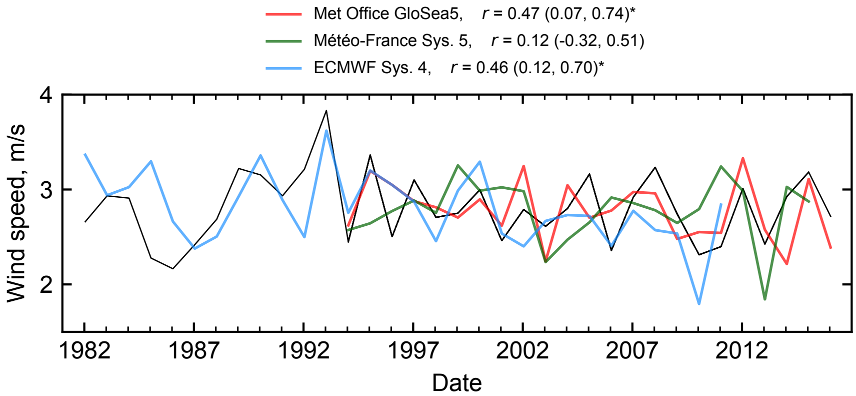

Figure 2: Time series of winter wind speed in Finland, showing observations (black/grey) and hindcast ensemble mean data (colours, as labelled), after bias and variance correcting (see text). Points are plotted at the January of the DJF period they cover. The correlations r between observations and hindcast are shown in the legend, including their 95% confidence intervals. They are marked with a * where the correlation is significantly different to zero.

(e.g. Gneiting et al., 2005; Sansom et al., 2016; Torralba et al., 2017, and references therein).

A key requirement is that the probabilities generated by the forecast system are *reliable*, meaning that, of the times when an event is forecast with a given probability, it is observed to occur with the same frequency as that probability. If the events are observed to occur more frequently than that forecast probability, then the forecasts are underconfident; and if the event occurs less often, then the forecasts are overconfident. Just as forecasts will, in general, need some form of bias and variance correction, they will also need some degree of recalibration to ensure they produce reliable probabilities.

Although climate predictions have historically been regarded as being overconfident (i.e. ensemble members agree with each other better than they agree with the observations), it has recently been discovered (Eade et al., 2014; Scaife and Smith, 2018) that many climate models also produce *underconfident* forecasts in some cases. Of particular relevance here is that this particularly affects the North Atlantic sector, including dynamical features such as the North Atlantic Oscillation (NAO) and Arctic Oscillation (AO), which have a direct influence on European winter climate. As discussed in the recent review of Scaife and Smith (2018), this underconfidence stems from the ensemble members exhibiting less predictability than the observed world, such that they cannot be regarded as being fair realisations of the real world. This means that we should be wary of using the ensemble members directly, and put more trust in the ensemble mean as a quantity that maximises the skill available from the climate model, minimising the noise in the ensemble members. (This also means that ensemble size is critical to getting good levels of skill.) These recent findings emphasize the need for calibration of forecast probabilities, and the problems of using the ensemble members directly. We will describe here a much simpler method of producing calibrated probabilistic forecasts, without using the ensemble member distribution at all.

Rather than considering the observations and hindcast ensemble mean data as a time series, we can instead examine their joint distribution, shown as a scatter plot, which directly illustrates their correlation. A simple linear regression can be performed, describing the linear relationship between the two as well as its uncertainty. We can then use that linear regression with a new forecast of a climate model predictor to transform it into a forecast of a future observation; the probabilities of any given value being observed are provided by the prediction interval on the regression.

We illustrate this procedure in Figure 3, for the Met Office hindcasts of winter mean wind speed in Finland (as already shown in Figure 2). In the scatter plot, the hindcast data are shown without bias and variance correction, for illustration, as this is taken care of by the linear regression. An imagined forecast is included, shown in blue, in which the climate model produced an ensemble mean forecast of $3.6\,\mathrm{m\,s^{-1}}$. The central estimate of the predicted future observation can be seen at approximately $3.0\,\mathrm{m\,s^{-1}}$. We can also see the probability of the new observation being above average: it is the fraction of the prediction interval that is above the dotted horizontal mean line. Since linear regressions are obviously monotonic, this is the *only* point along the horizontal axis where the wind speeds are forecast to be above average with this probability. As long as it is reasonable to describe the relationship between forecast and observations with a linear regression, then the forecast probabilities are necessarily well-calibrated, within the constraints of sampling uncertainty: the probabilities are given by the prediction interval, and the prediction interval *is* the conditional distribution of the observations given a forecast with that probability, taking into account the sampling error. The forecast probabilities must match the observed frequencies, within the limitations of sampling uncertainty. (Appendix A gives a more mathematical description of this point.) Just as the linear regression bias-corrects and variance-corrects the hindcast data to match the observations, it also calibrates the probabilities, such that they match the observed frequencies.

It is important to emphasise that this only applies because the system has some skill in this case, and the Central Limit Theorem (from averaging over a season, region, and ensemble)

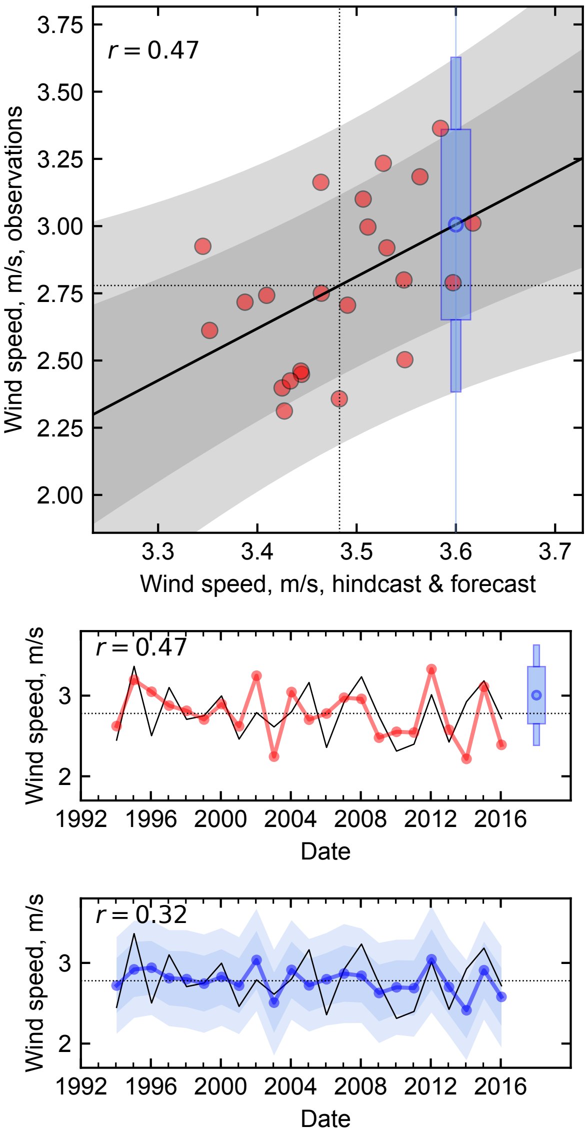

Figure 3: Winter wind speed in Finland, showing hindcast data from the Met Office system, and observations. Top panel: Scatter plot showing the relationship between hindcast ensemble means and observations (red dots, one per year, shown without bias or variance correction). The linear regression is shown as a black line, with the the inner 75% and 95% of the prediction interval shown as grey shading. The mean observed and hindcast values are shown as horizontal and vertical dotted lines respectively. A hypothetical forecast is shown in blue at 3.6 m s^{-1}, with boxes highlighting the prediction interval at that point. Middle panel: The same data, but shown as a time series. The hindcast points (red) are plotted after bias and variance correction, with the observations in black, and the hypothetical forecast shown again in blue. Bottom panel: Time series showing the same observations, but with leave-one-out forecasts (blue): Each forecast point is derived from the hindcast ensemble mean for that year, and the linear regression between the observations and hindcast ensemble-means in the remaining 22 years. The blue shading indicates the inner 75% and 95% of the prediction interval for each forecast.

pushes the data towards being linearly-related and normally distributed, albeit with relatively few data points. Having no skill means the points in the scatter plot are uncorrelated, so it is not sensible to relate them using a linear fit. The method we present might also not apply if we were not considering an average quantity, e.g. when counting the occurrence of some event per season. In that case, the data might not follow a linear relationship, and a different approach would be necessary.

It is also expected that, if orders of magnitude more data were available, such as centuries of points instead of decades, and if the skill was significantly higher, then there would be justification for using much more precise techniques to refine the probabilistic distribution (e.g. more detailed EMOS techniques, machine learning, etc.). However, as we have seen, seasonal forecast skill for wind and irradiance in Europe tends to be not much above the threshold for statistical significance at best, and there can only be limited benefit in more detailed statistical techniques – making precise fits to noise is unhelpful.

In the top and middle panels of Figure 3 we have shown the result of adding a new forecast point after the existing 23-year hindcast period. This reflects the procedure that would be used in a real-time forecast, but it can also be helpful to understand the behaviour using the same method to “forecast” any of those 23 historical years. The bottom panel of Figure 3 demonstrates this, where we treat each hindcast year in turn as a forecast, predicted using its ensemble mean applied to the linear regression based on the remaining 22 years. The resulting skill – the correlation between the observations and these 23 “leave-one-out” predictions – is lower, as is expected from using one fewer year in the training data set each time. The size of the change, from 0.47 down to 0.32, might seem large, but recall that, with only 23 data points a correlation of 0.47 is only just significantly different to zero: the 95% confidence interval is 0.07–0.74. A correlation of 0.32 is easily within the range of possible ‘true’ values, even *without* leave-one-out testing.

3.3. *Indirect forecasting of climate variables*

So far, we have only considered ‘direct’ forecasting, in the sense of using one quantity output from a forecast model to predict the same quantity in observations. However, a useful feature of the linear regression method described above is that it offers a straightforward approach for producing ‘indirect’ forecasts: using one climate variable, measured in one location, to predict another variable and/or location.

For example, in the scatter plot shown in Fig. 3, we could replace the variable on the horizontal axis with any other predictor from the forecast models. This could be the same meteorological variable, but measured over a larger area, to increase the skill: for example using the mean wind speed over an area covering the whole British Isles region, land and sea, to forecast the UK mean wind speed. This could be particularly important when forecasting for smaller regions or countries in Europe, as low levels of skill can often be improved by averaging over a larger area, if the wind speeds are sufficiently spatially correlated, by reducing the gridpoint-scale noise. The method then functions as a simple statistical downscaling technique.

Another alternative is to use a larger-scale dynamical feature of the climate, such as the NAO, to forecast a local meteorological variable. The NAO is well-correlated with many features of the northern and southern European winter climate, and we demonstrate the observed correlation of a simple NAO index[4] with wind speed and irradiance in Figure 4. If it can be skilfully predicted, then using the NAO index as the predictor can lead to more skillful forecasts of the target variable in many cases. Recent advances in seasonal climate prediction systems have demonstrated significant skill in forecasting the NAO (e.g. Scaife et al., 2014; Butler et al., 2016; Athanasiadis et al., 2017; Baker et al., 2018b), leading in turn to demonstrations of improved skill in other variables across Europe (e.g. Karpechko et al., 2015; Svensson et al., 2015; Clark et al., 2017; Baker et al., 2018a)

Going further, the variable on the *vertical* axis of the scatter plot, the predictand, could instead be a quantity of more direct relevance to the user; it need not be restricted to meteorological parameters. Palin et al. (2016) demonstrated how the NAO can be used to forecast various impact metrics for the UK transport sector, such as the need for aircraft de-icing at Heathrow Airport. This strategy could clearly be applied to the energy sector.

This also means that we are not restricted to forecasting the mean value: a user might be more interested in the risk of some event (such as an extreme) occurring within the season (the details of which would be highly user-specific). Calculating this kind of counting statistic directly from the forecast model data is likely to be noisier, and hence less skillful, than a quantity based on averaging. Following the above discussion, it might be possible in some situations to use the seasonal mean from the forecast system to predict the seasonal frequency of the event of interest, using observations of those frequencies in the regression. Thornton et al. (2019), in their study of seasonal forecasts of gas demand, provide an example of this situation. They found that the observed seasonal mean gas demand can be linearly related to atmospheric circulation indices from the forecast model. However, the number of high gas demand days per winter showed a non-linear relationship, with many seasons having no high-demand days. In cases like these other approaches would be necessary to produce a regression-based forecast, such as transforming the count-variable first to linearize the relationship.

4. Forecasting wind and solar power generation

There is a clear need in many applications for detailed transformation models between meteorological and energy variables. Short term (daily, hourly or less) forecasts of wind or solar power, based on weather forecasts, need to be highly accurate to allow the output of individual sites to be carefully managed (e.g. Giebel et al., 2011; De Felice et al., 2015; Haupt, 2018). Similarly, climatological risk studies, for example to allow financing for individual site development, or for planning

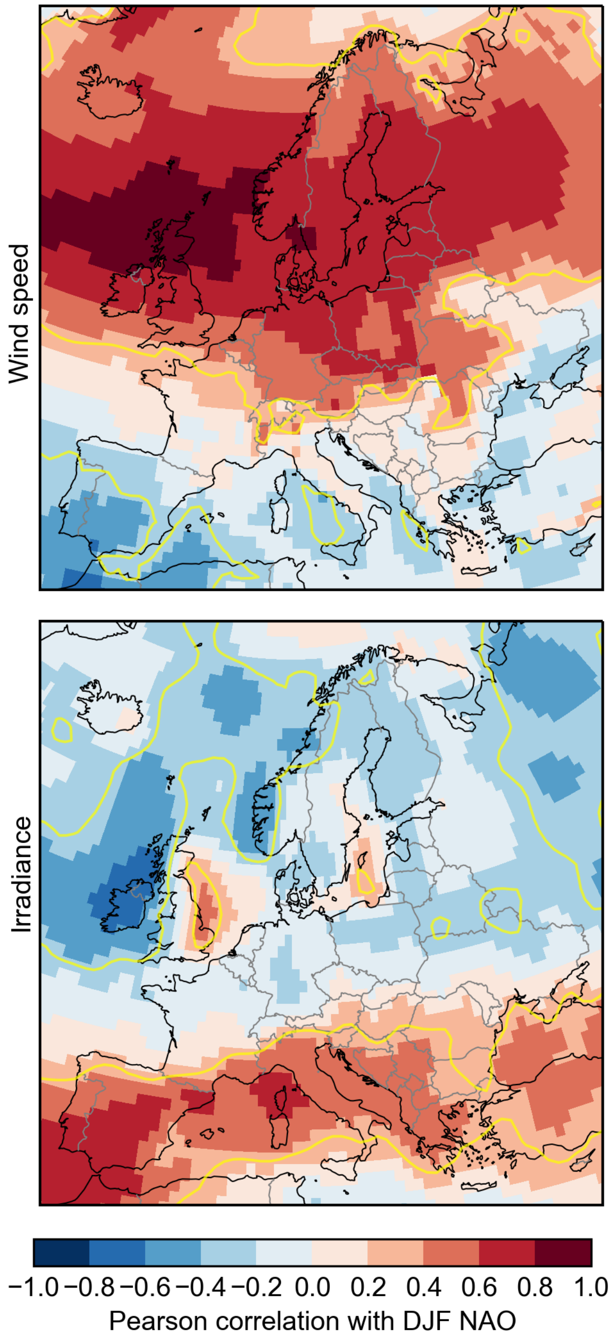

Figure 4: Maps of the correlation between the DJF NAO index and wind speed (top) and irradiance (bottom), using ERA-Interim data (winters 1979/1980 to 2015/2016 inclusive). Contours are included in yellow at $r = \pm 0.325$, the notional threshold for significance over 37 years at the 5% level.

[4] We use the simple difference between the mean sea level pressure in a southern box (−28° E to −20° E, 36° N to 40° N) and a northern box (−21° E to −16° E, 63° N to 70° N).

future transmission/distribution grid requirements, can also require accurate transformations across timescales (e.g. Cannon et al., 2015; Bett and Thornton, 2016; MacLeod et al., 2018). Indeed, the ECEM national-scale wind and solar PV data, which we use as 'observations' here, are constructed on that basis.

However, the spatial and temporal scales used in seasonal forecasts allow us to take a different approach. Figure 5 shows the correlations between the climate and energy variables, at the seasonal-average, country-average scale. In the case of wind power, the correlations with mean wind speeds for most countries is over 0.9, and apart from Romania (and in summer, Bulgaria) they all have $r > 0.8$. In the case of solar power, all countries show correlations with irradiance more closely than 0.97 (note the different colour scale).

The strength of these correlations means that, where there is skill in the underlying climate variable C, we can again use a simple linear transformation to make a forecast of the energy generation E, similarly to equation (2):

$$E'(t) = \overline{E_{\rm ob}} + \left(C(t) - \overline{C_{\rm hc}}\right) \frac{\sigma(E_{\rm ob})}{\sigma(C_{\rm hc})}. \tag{3}$$

It is worth emphasising some consequences of this, as it might be seen as going against common practice and understanding in energy meteorology:

- It is not necessary to include the temperature dependence of solar PV generation: the correlation simply between solar capacity factor and irradiance alone is far greater than the seasonal forecast skill.
- Scaling the wind speeds from the meteorological standard 10 m to a more typical wind turbine hub height like 100 m is also not necessary: Standard scaling procedures such as using a power law, whereby $U_{100\rm m} = (100/10)^{\alpha} U_{10\rm m}$, do not affect the correlation, and are effectively already accounted for by linear corrections like in equations (2) and (3).
- It is not necessary to use instantaneous wind speeds (or irradiance) at high temporal resolution and transform them through a power curve to obtain the wind power (or solar power), before seasonally averaging: there would be negligible benefit over simply using the seasonal mean wind speed and linearly correcting.

This last point is demonstrated explicitly in Bett et al. (2018a). As we have seen, the direct skill in wind speed is almost never above 0.6 (Figure 1), and the 95% confidence interval on that correlation is roughly 0.25–0.8. We have also seen that the relationship between mean wind speed and mean wind power is almost always > 0.9 already (Figure 5). So, although that relationship might be improved slightly by transforming instantaneous wind speeds through a power curve before taking the seasonal and country averages, that improvement will make negligible improvements to the seasonal forecast skill. It might reduce the overall bias, but again, that will be taken care of in any case through a bias correction.

So, we can see that it is the relatively low (and uncertain) levels of skill in seasonal forecasts of the climate variables, together with the very high correlations between the climate and energy variables at the scale of seasonal and country averages, which allows a simple linear transformation. This also determines the caveats on our findings: For example, these high climate–energy correlations do not apply universally. Bett et al. (2018a) and De Felice et al. (2018) demonstrated that electricity demand and hydroelectricity generation can both exhibit more complex relationships with the climate across Europe than wind and solar, showing strong correlations in some cases, and much weaker in others. They could therefore benefit from more careful modelling than a simple linear regression, or at least a more cautious case-by-case approach. Similarly, if quantities other than a seasonal mean are required, such as the frequency of extreme events, then other approaches might also be required, as already discussed. Finally, there could be cases, with existing or future forecast systems, where much higher levels of skill could be obtained, perhaps based on indirect forecasting of the impacts for a particular stakeholder, or improved climate models or initialisation. In that case, a more sophisticated transformation of the climate variable, to reach a good linear relationship with the impact variable, might be beneficial.

5. Optimisation from co-design

In this paper, we have focused on how developers of climate services can use freely-available data (e.g. from C3S) to provide seasonal forecasts in a relatively straightforward way. However, it is important to note that it is usually the case that more optimal forecast services can be produced through a close co-design process: the climate service developer bringing in domain-specific expertise from both the energy ('service user') and climate ('data producer') sides.

The benefits of co-design on making forecasts more useful, and usable, by focusing them more on the practical needs of stakeholders, are well documented (e.g. Bruno Soares and Dessai, 2015, 2016; Bruno Soares, 2017; Buontempo et al., 2017; Golding et al., 2017). It might be the case that the prospective user of the service needs forecasts issued at particular times of the year, or covering particular periods – where we have looked at forecasting DJF from November for example, a user might need longer lead times, or forecasts for financial quarters rather than meteorological seasons. An important precondition of the linear regression approach we have described here is the availability of multi-decadal time series of the user's quantity of interest. Although projects like ECEM provide general energy-sector time series data that can be applied to many cases, particular users might require other specific quantities. This data is unlikely to be publicly available, and is often commercially sensitive, so close engagement with the users becomes essential to develop a service optimised for the users.

More optimal use of seasonal forecasting data can also be achieved though direct engagement with the providers of that data, who might be able to provide newer versions of models, or different configurations or lead times, which might not yet be available through online portals like C3S.

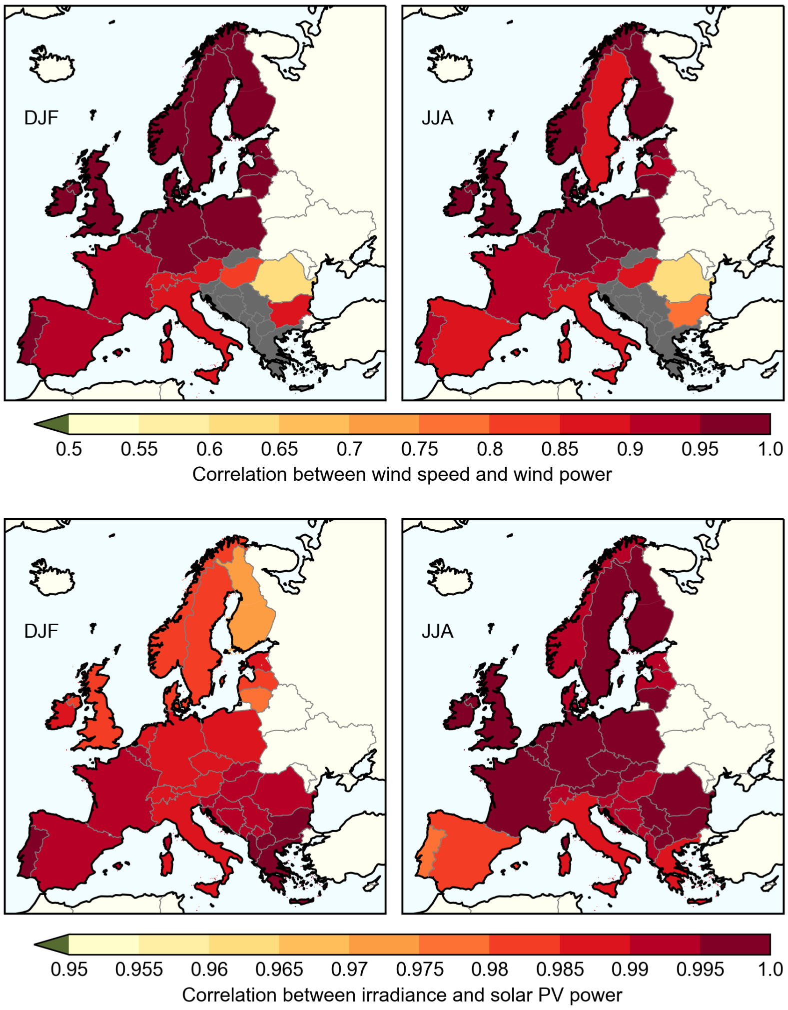

Figure 5: Maps of the correlation between the observed country-average climate variable and energy variable data, for DJF and JJA as labelled. Top: wind speed and wind power capacity factor. Bottom: irradiance and solar PV capacity factor.

As an illustrative example, we show in Figure 6 the correlation skill achieved from the Met Office GloSea5 system using a different set of initialisation dates to the data available from the C3S CDS. As described in MacLachlan et al. (2015) and subsequent updates[5], the GloSea5 hindcast model runs comprise 7 members initialised on the 1st, 9th, 17th, and 25th of each month. The CDS GloSea5 data for 'November' initialisation (for DJF forecasts) comprises a 28-member ensemble, built on the 7 members from each of the 9th, 17th, 25th October, and 1st November (with a similar sequence in April/May for JJA forecasts). In contrast, MacLachlan et al. (2015) suggests that for skill assessment the 3 *nearest* weeks to 1st November should be used, i.e. the 7 members from the 25th October and 1st and 9th November, yielding a 21-member ensemble (the hindcasts are typically run ahead of their initialisation dates, so this data would be available on 1st November). This reduces the effective lead time for the forecasts, which can improve the skill. Furthermore, as of 2019, the same model version had been running operationally for over two years, doubling the number of hindcast members available, potentially further improving the skill. Figure 6 demonstrates the skill in forecasting wind speed using the resulting 42-member hindcast. Some improvements in skill are clearly visible (compare with the top-left panel in Figure 1). It is important however to note that most differences between the maps are simply noise, and reflect the uncertainty in the skill assessments generally.

Another benefit of climate service developers engaging directly with climate data providers is that the service could benefit from research into more optimal post-processing of the model data. For example, Baker et al. (2018a) and Thornton et al. (2019) both demonstrate improvements in forecast skill from selecting appropriate large-scale predictors for their specific impact metrics, as discussed in section 3.3. De Felice et al. (2018) and Stringer et al. (2019) demonstrate more complex post-processing used to derive the daily data needed for hydrological applications, while retaining the skillful signals from the larger-scale predictors.

[5] https://www.metoffice.gov.uk/research/climate/seasonal-to-decadal/gpc-outlooks/notice

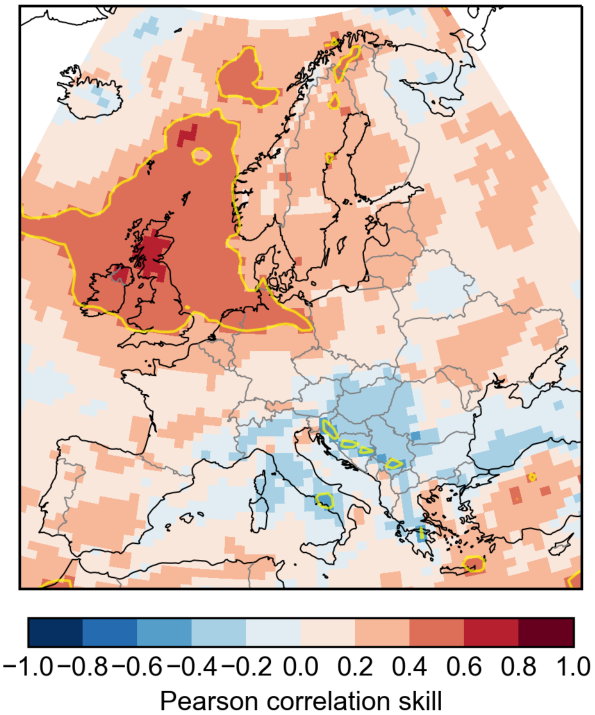

Figure 6: Correlation skill of seasonal forecasts of DJF wind speed from the Met Office GloSea5 system. Here we use a different hindcast configuration to the results from the CDS version shown in Figure 1, using a 42-member ensemble with a shorter effective lead time centred on 1st November. As in previous plots, the yellow contour marks a notional threshold for significance, using the Fisher z-test at the 5% level.

6. Conclusions and summary

We have demonstrated the baseline levels of skill of seasonal forecasting systems available from C3S for wind speeds and solar irradiance across Europe, showing that the skill is patchy. Seasonal forecasts must therefore be used selectively and carefully.

We have described a simple method for producing well-calibrated probabilistic seasonal forecasts for the cases where there is significant skill, based on the linear regression of the observational timeseries on the corresponding hindcast ensemble means. The hindcast data need not be the same climate variable as is being forecast, and indeed skill might be improved in some cases by using a larger-scale climate predictor such as the NAO. Going further, the variable being forecast need not be a meteorological observable, but could be the energy metric required directly by the climate service recipient – thus providing a simple way of producing well-calibrated probabilistic forecasts of wind and solar power generation.

The application of this approach to the European energy sector follows the work of Palin et al. (2016) in producing skillful seasonal forecasts for the UK transport sector, and has been used in the development of a prototype climate service for Yangtze River basin rainfall (Bett et al., 2018c), as well as various studies demonstrating the use of the NAO to forecast other climate variables across Europe (e.g. Svensson et al., 2015; Karpechko et al., 2015).

Forecasts on "weather" timescales (hours to weeks), and detailed climatological studies such as for site selection or assessing network resilience, need a high degree of precision and accuracy, such that detailed transformations are required from wind speed and irradiance (and temperature) to the final wind and solar power generation metrics. However, our results make it clear that, when averaged over seasonal time scales, and over the spatial scales of European countries, such complex transformations are not usually necessary. Simple linear regression between the climate variable produced from the forecast model, and the energy variable required, can be sufficient. Furthermore, by performing the linear regression on the ensemble means of the hindcast data sets, the forecasts are automatically bias- and variance-corrected, with calibrated probabilities.

It is the country, seasonal and ensemble averaging that allows this to work, by reducing noise and pushing variables towards being normally distributed and linearly related. This also means that this approach will not be appropriate in all cases. For example, the number of extreme events per season is unlikely to be linearly related to a climate driver (Thornton et al., 2019), and in some use cases more sophisticated downscaling techniques might need to be developed if higher spatial or temporal resolution is required (e.g. De Felice et al., 2018; Stringer et al., 2019).

For many cases however – and together with the increased availability of seasonal forecasting data through initiatives like the C3S Climate Data Store and the ECEM Demonstrator tool – our results show how the process of developing useful seasonal forecasting climate services for wind and solar power can be greatly simplified. Further optimisation of the forecasts could also be possible, by drawing on the domain expertise of both the climate model data providers and the energy sector stakeholders, tailoring the service by balancing model capabilities and user needs. In all cases however, there is scope for much greater use of seasonal forecasts, aiming to reduce financial risks for the renewable energy sector.

Acknowledgements

The authors would like to acknowledge funding for the European Climatic Energy Mixes (ECEM) project by the Copernicus Climate Change Service (C3S), a programme being implemented by the European Centre for Medium-Range Weather Forecasts (ECMWF) on behalf of the European Commission (grant number: 2015/C3S_441_Lot2_UEA), and funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 776868 (SECLI-FIRM project), and grant agreement No. 776787 (S2S4E project).

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Appendix A. The reliability of probabilistic forecasts produced by linear regression

Here we demonstrate that the linear regression method described in the text, using the hindcast ensemble means, necessarily produces forecasts with well-calibrated probabilities, if the hindcast is skillful. The description is based on Wilks (2011), and we refer the reader there for further details.

The hindcast data (ensemble means from an initialised climate model) and observation-based data are samples from an underlying population joint distribution, which describes the relationship between the climate model and the real world in terms of the variables of interest. The hindcast is sampled from a predictor variable X, and the observations are sampled from a predictand variable Y. (We use these names to correspond to the x and y axes of a scatter plot such as in Fig. 3.) We assume that the population distribution is a bivariate normal distribution, with marginal normal distributions

$$X \sim \mathcal{N}\left(\mu_X, \sigma_X^2\right), \tag{A.1}$$

$$Y \sim \mathcal{N}\left(\mu_Y, \sigma_Y^2\right), \tag{A.2}$$

where μ and σ represent the population means and standard deviations respectively. The conditional distribution of Y given a 'forecast' $X = x_{\mathrm{fc}}$ is also a normal distribution:

$$\begin{aligned} Y|x_{\mathrm{fc}} &\sim \mathcal{N}\left(\mu_{Y|x_{\mathrm{fc}}},\ \sigma^2_{Y|x_{\mathrm{fc}}}\right) && \text{(A.3)} \\ &\sim \mathcal{N}\left(\mu_Y + \frac{\sigma_Y}{\sigma_X}\rho\left(x_{\mathrm{fc}} - \mu_X\right),\ \left(1-\rho^2\right)\sigma_Y^2\right), && \text{(A.4)} \end{aligned}$$

where ρ is the correlation between X and Y. The mean of that conditional distribution is given by the linear regression of Y on X,

$$\mu_{Y|x_{\mathrm{fc}}} \equiv \hat{Y}(x_{\mathrm{fc}}) = \alpha + \beta x_{\mathrm{fc}}, \tag{A.5}$$

where

$$\alpha = \mu_Y - \beta\mu_X, \tag{A.6}$$
$$\beta = \rho\frac{\sigma_Y}{\sigma_X}. \tag{A.7}$$

The conditional distribution in equation (A.4) is the sampling distribution for the observation that occurs when the climate model (the ensemble mean forecast) produces the value $X = x_{\mathrm{fc}}$. If a forecast system is reliable, then of the times when an event is forecast with a given probability, it is observed to occur with a frequency equal to that probability. If we knew the population parameters, then the result of forecasting using linear regression would be exactly reliable: if our forecast system issued a value x_{fc}, then the probability of observing a value of Y *is* simply the conditional distribution that describes the observed frequency, $Y|x_{\mathrm{fc}}$.

In reality however, we have a limited sample of n points (years) in both observations y_i, and hindcast x_i, for $i = 1 \ldots n$. This adds uncertainty due to sampling variation, which we need to take into account. The linear regression derived from the n pairs of sample points is

$$\hat{y} = a + bx, \tag{A.8}$$

such that the central prediction of an observation from the predictor point x_i is $\hat{y}_i = a + bx_i$. That regression model point $\hat{y}_i$ differs from the actual observations y_i by an error e_i, such that $y_i = \hat{y}_i + e_i$. The model parameters are given by

$$a = \bar{y} - b\bar{x} \tag{A.9}$$
$$b = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sum_i (x_i - \bar{x})^2} \equiv r\frac{s_y}{s_x}. \tag{A.10}$$

where the overbar represents the sample mean, s represents the sample standard deviation, and r is the sample correlation from the n points.

So, the actual conditional probability distribution that we could measure, for the observation that will occur after the climate model has produced the forecast point $x = x_{\mathrm{fc}}$ – i.e. the prediction interval – can be written as

$$y_{\mathrm{fc}} \sim \mathcal{N}\left(\hat{y}_{\mathrm{fc}},\ s^2_{\mathrm{fc}}\right). \tag{A.11}$$

For the probabilistic forecasts made using this method to be reliable, then this has to match the conditional distribution from the underlying population, equation (A.4).

Just as in equation (A.5), the mean is given by the linear regression, $\hat{y}_{\mathrm{fc}} = a + bx_{\mathrm{fc}}$. The sample variance corresponding to $\sigma^2_{Y|x_{\mathrm{fc}}}$ is the variance of observational points around the regression line, $s^2_{y|x}$, i.e. simply the variance of the errors,

$$s^2_{y|x} \equiv s^2_e = \frac{1}{n-2}\sum_i (y_i - \hat{y}_i)^2 . \tag{A.12}$$

However, because we have estimated the regression line itself, the prediction variance s^2_{fc} is bigger than this: we need to add a term for the sample variation in the estimate $\bar{y}$ of the observational mean μ_Y (equivalent to the error on the intercept estimate a); and a term that accounts for the error in the regression gradient b. Together, these terms give the required variance,

$$s^2_{\mathrm{fc}} = s^2_e\left(1 + \frac{1}{n} + \frac{(x_{\mathrm{fc}} - \bar{x})^2}{\sum_i (x_i - \bar{x})^2}\right). \tag{A.13}$$

If the linear regression represents a very good fit, then s^2_e will be small. Furthermore, if there is a large number of data points, then the second term ($1/n$, from estimating the regression intercept) will be small, and the third term will also be small (assuming $x_{\mathrm{fc}} - \bar{x}$ is a similar size to the other $x_i - \bar{x}$, then it is reduced by there being n such terms in the denominator): s^2_{fc} will therefore tend towards $\sigma^2_{Y|x_{\mathrm{fc}}}$ for large n.

Therefore, if the forecast system is significantly skillful and there is a genuine linear relationship between the observations and the climate model output, then the prediction interval will provide the best estimate of the conditional distribution of observations given a forecast value from the climate model – i.e., it will provide probabilistic forecasts that are well calibrated given the sampling uncertainty.

Recently, Yang et al. (2016, 2018) have investigated the relationship between correlation and the reliability and resolution components of the Brier skill score, both empirically and theoretically. They found a clear relationship between the correlation and the resolution score (the ability of a forecast system to resolve events into groups with different observed frequencies). However, they demonstrated that there is no clear relationship between the correlation and the reliability. This is not inconsistent with out reasoning here: Although we are relating correlation and reliability in some sense, it is the linear regression, rather than the correlation, which allows us to produce calibrated probabilities.

Figure A.7 shows reliability/attributes diagrams (Wilks, 2011; Hsu and Murphy, 1986), which demonstrate our linear regression technique calibrating an underconfident forecast system, through Monte Carlo simulation. We first sample 100 “hindcast ensemble mean” and “observation” points from a bivariate normal distribution, with a population correlation (skill) $\rho = 0.6$. The linear regression is then performed on the joint distribution of those sample points. We then produce 1000 new “forecast ensemble mean” points, and the corresponding new “observations” that would occur afterwards, by again sampling from that original bivariate normal distribution.

For the first reliability diagram, we produce a 1000-member overdispersive ensemble for each of the 1000 forecast ensemble means. The reliability diagram from these forecast ensembles therefore shows the forecast system is underconfident: the line is too steep.

We then apply the linear regression to each forecast ensemble mean to give central estimates and prediction intervals. The second reliability diagram is produced by sampling the prediction intervals 1000 times (like the forecast ensembles in the first diagram). Now, the reliability diagram shows well-calibrated probabilities: the line is close to the 1:1 diagonal.

Appendix B. Skill maps using ECEM observational data

The ECEM project produced bias-adjusted climate data sets (Jones et al., 2017). Although we mostly use ERA-Interim reanalysis as our observational data in the rest of this paper, the results hold for the ECEM observational data too. We show in Figure B.8 the correlation skill maps of wind speed and irradiance, for the three forecast systems, using the ECEM data rather than ERA-Interim (cf. Figure 1).

The bias adjustments used to produce the data amount to more than a simple linear bias removal (which would not affect the correlation), and the ECEM climate data was used when producing the corresponding energy supply/demand data, so it is an important comparison to make. In practice however, the differences are very small, although for the wind speeds it does emphasize that only onshore regions were considered when producing the wind power data sets.

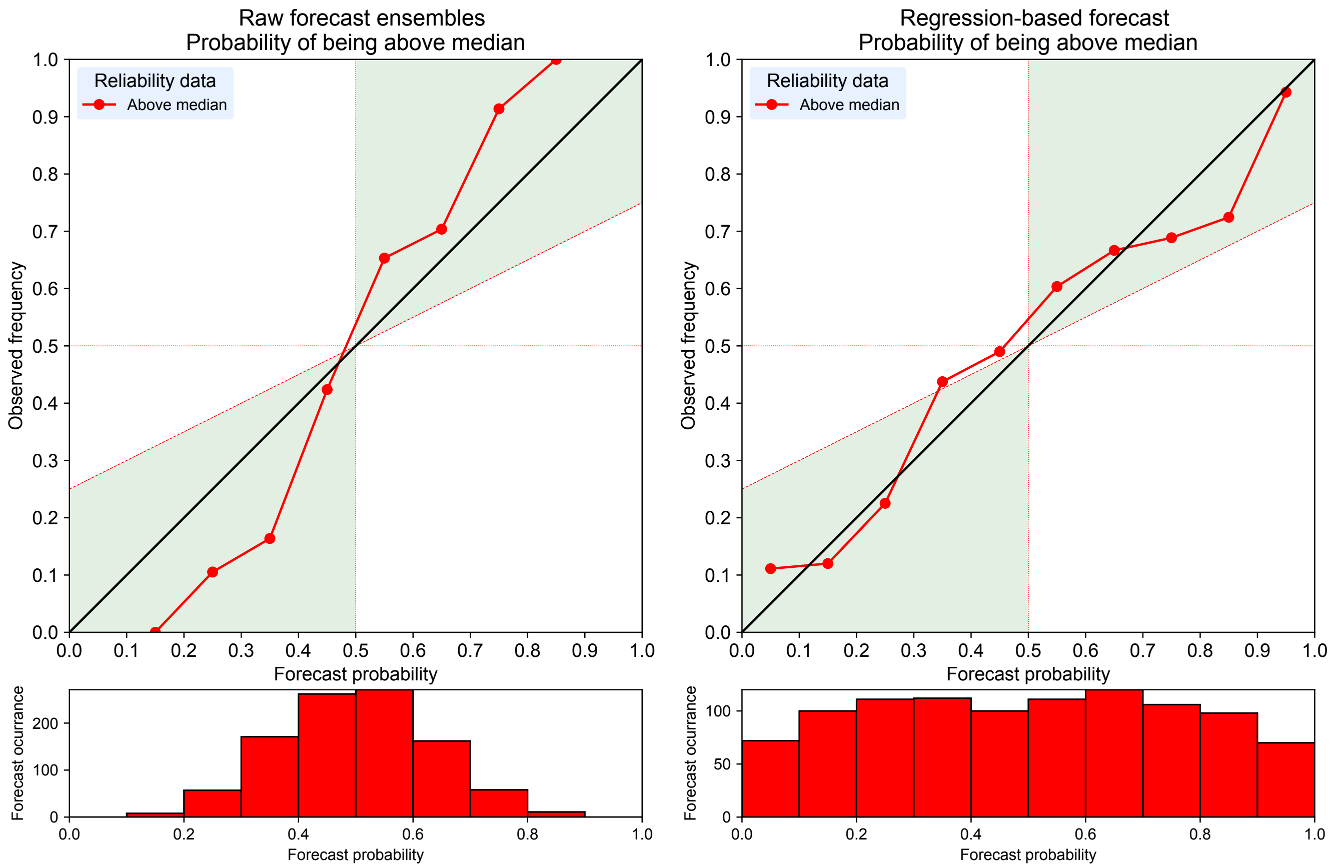

Figure A.7: Reliability and sharpness diagrams for forecasting probabilities of an observation being above the climatological median. The region of positive Brier skill score is shaded in green, and the perfect reliability line (1:1) is shown in black. Left: The results from an overdispersive (underconfident) forecast ensemble. Right: Results from the well-calibrated forecasts produced using the linear regression method based on the same forecast ensemble means.

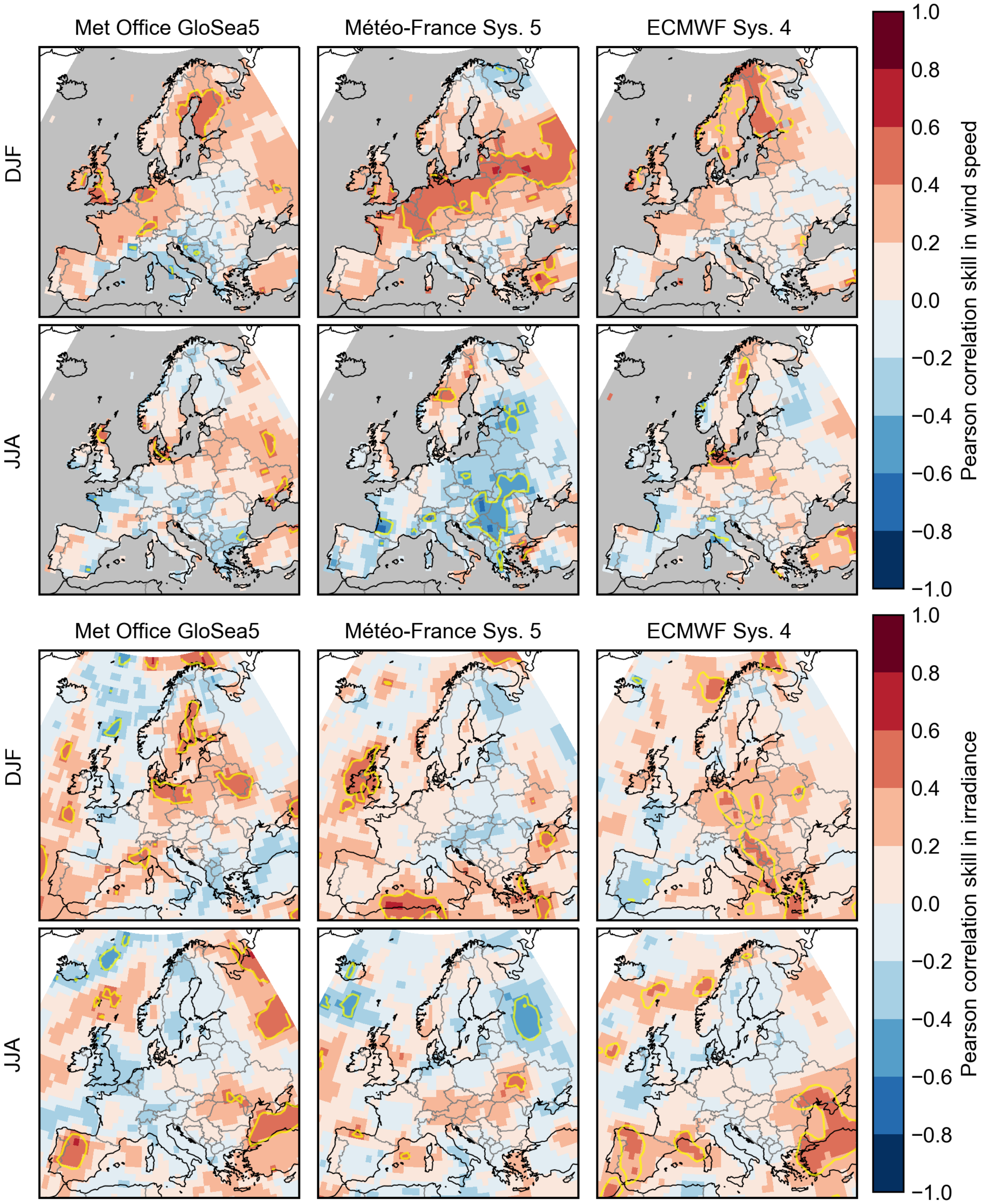

Figure B.8: Correlation skill of seasonal forecasts of wind (upper rows) and irradiance (lower rows), from the three hindcasts we use here (columns, as labelled), against the ECEM observational data. Forecasts are for the 3-month averages of winter (DJF) and summer (JJA) as labelled, at a lead time of one month (i.e. November and May initialisation respectively). The yellow contour marks a notional threshold for significance, using the Fisher z-test at the 5% level.