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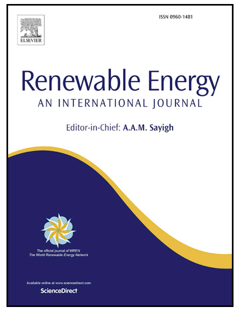

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Scoping the potential usefulness of seasonal climate forecasts for solar power management

Matteo De Felice[1], Marta Bruno Soares[2], Andrea Alessandri[3,1], Alberto Troccoli[4]

Abstract

Solar photovoltaic energy is widespread worldwide and particularly in Europe, which became in 2016 the first region in the world to pass the 100 GW of installed capacity. As with all the renewable energy sources, for an effective management of solar power, it is essential to have reliable and accurate information about weather/climate conditions that affect the production of electricity. Operations in the solar energy industry are normally based on daily (or intra-daily) forecasts. Nevertheless, information about the incoming months can be relevant to support and inform operational and maintenance activities.

This paper discusses a methodology to assess whether a seasonal climate forecast can provide a useful prediction for a specific sector, in this paper the European solar power industry. After evaluating the quality of the forecasts in providing probabilistic information for solar radiation, we describe how to assess their potential usefulness for a generic user by proposing an approach that takes into account not only their accuracy but also other potentially relevant factors. This approach is called index of opportunity and is then illustrated by presenting an example for the European solar power sector. The index of opportunity provides indications about where and when seasonal climate forecasts can benefit the decision-making in the photovoltaic sector. Even more importantly, it suggests an approach on how to evaluate their

Email address: `matteo.defelice@enea.it` (Matteo De Felice)

[1]ENEA, Roma, Italy

[2]University of Leeds, School of Earth and Environment, Leeds, UK

[3]Koninklijk Nederlands Meteorologisch Instituut (KNMI), De Bilt, Netherlands

[4]World Energy & Meteorology Council c/o University of East Anglia, Norwich, NR4 7TJ, UK

usefulness for the user's decision-making. This approach has the advantage of not limiting the definition of the usefulness only to the quality of the forecasts but rather considering, in an explicit way, all the factors that must be combined with the forecast's quality to define what is useful or not for the user.

Keywords: Solar Power, Climate, Climate Services, Forecasting

1. Introduction

The fluctuations of the electricity produced by the majority of renewable energy sources (RES) is closely related to weather and climate variability. Sources like solar and wind power, which together accounted for approximately 12% of the European electricity generation in 2016 [1], are inherently non-dispatchable and influenced by the availability of solar radiation and wind, respectively. In addition, hydro power generation, which produces more than 10% of Europe's electricity, although a more controllable energy source, is also affected by the availability of water in rivers and reservoirs which is tightly linked with precipitation and snow melting.

This strong link between power generation and meteorology implies that an increase in energy produced by RES requires actions by the electric utilities and grid operators to prevent drawbacks and faults due to less favourable weather conditions.

Solar power, specifically photovoltaic power, has a fundamental role in the RES mix. With a global installed capacity increase from 177 GW to about 400 GW between 2014 and 2017[5], solar power could reach more than 600 GW by 2020 [2]. In Europe, the installed capacity in Europe has grown by 100 GW and solar power currently supplies on average 4% of the Europe's energy demand [2]. The EU Reference Scenario 2016 [6] from the European Commission envisages an increase of solar capacity in 2050 (in relation to 2015) of 116% for Germany, 200% for Italy and 16% for UK [3].

Solar power is affected by the availability of solar radiation making the power supply particularly vulnerable to clouds and, more generally, to the occurrence of low-pressure systems. Furthermore, the efficiency of photovoltaic

[5] `http://www.ren21.net/gsr-2018/`

[6] Available here: `https://ec.europa.eu/energy/sites/ener/files/documents/ref2016_report_final-web.pdf`

panels is directly related to their temperature adding a further dependence to air temperature and wind speed due to cooling effects [4].

Forecasting the expected production of solar power for the next hours/days is normally necessary for the scheduling of non-renewable power plants and for decision-making processes within the energy market. However, there are also decisions that are made at longer timescales (e.g. 2-3 months ahead) and influenced by weather/climate such as in relation to system adequacy analysis, hedging, asset management and risk assessment [5]. A tool that could help to predict the climate information at long time-scales is the climate forecast generated by an Earth system model.

Seasonal climate forecasts are numerical model-based predictions where each forecast is initiated from an estimate of the initial state of the Earth system derived from Earth observations. Due to advances in the knowledge of the Earth system as well as the dramatic increase of available computational power, their quality has improved significantly in the last decades [6]. These systems are able to provide predictions of the climate up to several months ahead [7, 8]. Although climate forecasts can be perceived as an extension of weather forecasts with respect to the timescale of the information provided, the shift from "weather" to "climate" information leads to two big differences. Firstly, the information covers a longer period (e.g. the next season) and larger areas (e.g. mid-size country). Secondly, climate forecasts provide probabilistic information, as they consist of an ensemble of simulation, a way to deal effectively with the uncertainty.

The type of information provided by climate forecasts also requires a different approach when using the information for decision-making in the energy sector. This is due to the different types of resolution (e.g. a seasonal instead than hourly average) and the longer timescales which influence other types of operations than those pursued at hourly or daily timescales.

The intrinsic probabilistic nature of seasonal climate forecasts also requires different methods to assess the quality of the information which are technically different from the verification methods applied to deterministic (weather) forecasts [9]. Although there is a shared agreement on "why and when" seasonal forecasts are good (see for example [10] and [6]), it is often considered good practice to apply post-processing (e.g. bias correction) or multi-variate statistical methods (e.g. [11]) to enhance the forecasts' information.

In recent years, many projects in Europe have assessed and analysed the potential usefulness and usability of climate forecasts across a number of sectors including energy focusing on long-term climate change scenarios (e.g. [12] and [13]) and seasonal climate forecasts as an input for operational activities in the renewable energy sector (e.g. [14, 15, 16, 17]). These efforts have been largely underpinned by the need to efficiently manage the renewable energy sector as it is becoming more prominent in Europe[7] as well as the opportunities arising from new operational forecasting systems[8].

In the scientific literature, there are only a few studies that have looked into the use of seasonal climate forecasts for RES (e.g. [18, 19, 11, 20]). However, many of those analyse the information provided by the forecasts from a statistical perspective and tend to exclude assessments of how the predicted climate information can be potentially useful to the user, i.e. help to better inform and support their decisions. An example is [21], which assesses the "goodness" of seasonal climate forecasts at the global level, classifying their usefulness considering their statistical reliability, i.e. its statistical consistency, without taking into account explicitly the decision-making of their users.

This paper proposes a methodology to understand the usefulness of seasonal climate forecasts for the solar power industry considering the main factors that are perceived as relevant to an industry user. In Section 2 we present an analysis on the predictability of solar power in Europe. Section 3 presents an approach, called index of opportunity, illustrated with an example on European solar power. In Section 4 we discuss the results and its potential application on European regions. Finally, in Section 5 we provide some final remarks.

2. Predicting solar power in Europe

Solar radiation is the most important meteorological driver for photovoltaic power plants. It can be measured using ground sensors or estimated by satellite measures or atmospheric reanalyses. As the scope of this study is the European continent a homogeneous dataset spanning a long period was required, to this end we opted for a satellite-based product. In addition, the use of satellite data is often preferred with respect to reanalyses

[7] In the period 1990-2014 the production from RES in Europe has increased by 174%. For more see the recent EUROSTAT statistics available here `http://bit.ly/1TE3Ms5`

[8] An example is the Copernicus Climate Change Service (C3S) seasonal multi-system freely available at `https://climate.copernicus.eu/seasonal-forecasts`

(e.g. MERRA by NASA or ERA-INTERIM/ERA5 by ECMWF) due to their higher accuracy [22].

In this study, we use the SARAH (Surface Solar Radiation Data Set-Heliosat) dataset. It was released in 2015 by CM SAF (Satellite Application Facility on Climate Monitoring) and provides data for the period of 1983 to 2013 including the hourly to monthly averages in a regular grid at a resolution of $0.05° \times 0.05°$ [23, 24]. Although solar radiation is the prominent variable to estimate the power output of a PV plant, air temperature plays an important role too due to its role in the efficiency of the PV panel [25]. To this end, in our analysis we have used 2-metre temperature data from E-OBS dataset [26].

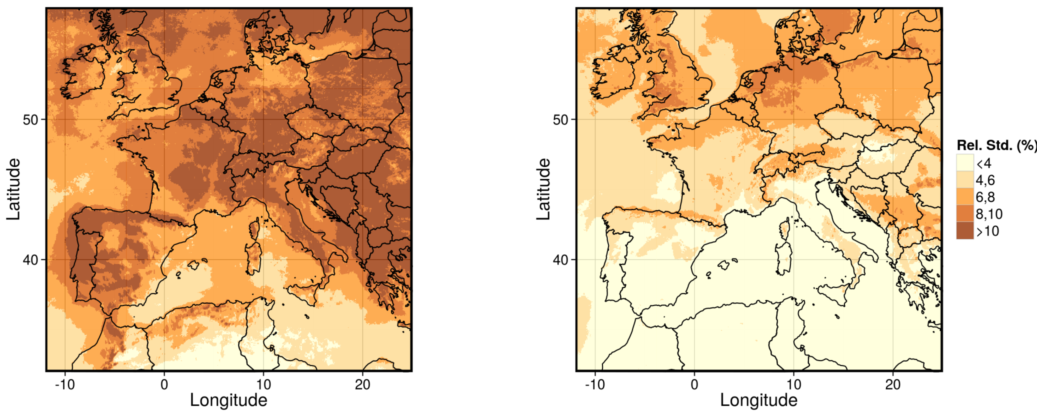
Solar radiation shows a strong seasonality in both its average and variability, due to astronomical and atmospheric effects. The inter-annual variability for the winter and summer seasons, expressed as the percentage ratio between the standard deviation and the mean (hereinafter relative standard deviation), is shown in Figure 1. The Mediterranean region shows a lower variability than the rest of Europe due to more frequent clear sky conditions. Another evident characteristic is the higher variability in the mountain regions, as for example in the Pyrenees, Apennines, Alps and the Carpathian Mountains.

2.1. Predicting Solar Power using Seasonal Climate Forecasts

The seasonal forecasts used in this work were produced by the ECMWF[9] System 4 forecast system which was operational from November 2011 until November 2017 [27]. The System 4 system provides every month a forecast for the incoming months as a set of different realisations (named ensemble members) with a temporal resolution of 6 hours.

Our analysis focuses on the potential predictability of solar power at regional level given the difficulty to simulate the actual production at site-level due to the lack of information on existing PV plants (geographical coordinates, panel orientation, on-site measurements, solar panels typology, etc.) for all the European countries. We compared for each European region (considering NUTS 2 classification, the second level of the European Nomenclature of territorial units for statistics) the: a) solar power potential obtained

[9]The European Centre for Medium-Range Weather Forecasts (ECMWF) is an intergovernmental organisation established in 1975 and supported by 34 states.



(a) Winter (December, January and February)

(b) Summer (June, July and August)

Figure 1: Relative Standard Deviation of daily solar radiation for summer and winter seasons from SARAH dataset for the period 1983-2013. It is clearly visible how the Mediterranean regions show a lower variability than the rest of Europe due to a general clearer sky

using satellite solar radiation and the observed air temperature, and b) the solar power potential computed using the same two variables from the seasonal climate forecast output instead.

The photovoltaic power potential is a dimensionless metric function of all the factors affecting solar power production [28]. It is defined as:

$$\mathrm{PV}_{\mathrm{pot}}(t) = \eta(t)\frac{G}{G_{STC}} \tag{1}$$

where G is the solar irradiance (derived from satellite measurements or climate forecasts) and G_{STC} is the solar irradiance at standard conditions (the conditions when the PV module produces its nominal power) which is equal to $1000W/m^2$; $\eta(t)$ is the performance ratio, a coefficient that models the changes in efficiency of the PV panel, defined as:

$$\eta(t) = 1 + \gamma(T_{cell}(t) - T_{STC}(t)) \tag{2}$$

where γ is the temperature coefficient, which is normally provided by the manufacturer. In our case we set it to $0.0045°C^{-1}$, which is an average value considering the possible photovoltaics technologies (see Dubey et al. [29] for more details on this aspect). T_{STC} is the temperature at standard conditions (here $25°C$) and T_{cell} is the PV cell temperature that, following the definition in Ross [30], can be expressed as:

$$T_{cell} = T_{air} + G\frac{NOCT - 20}{800} \tag{3}$$

where T_{air} is the air temperature and NOCT is the Nominal Optimal Cell Temperature that we assume here as $48°C$.

2.2. Probabilistic Analysis

We analyse the seasonal climate forecasts in predicting PV power production for a 3-month seasonal average with one month of lead time (i.e. forecasts issued on the first of February for the spring season, the first of May for summer, etc.). In this analysis, we focus on the seasonal averages, derived by averaging all the values of each ensemble member for each season.

Given the probabilistic nature of seasonal forecasts we followed the approach and skill measures described in Wilks [31] particularly the Brier Skill Score (BSS), a well-known and widely used skill metric for the probabilistic forecasts [10, 32]. Although there are several frameworks and metrics that can be potentially applied to assess the quality of a probabilistic forecast, we opted for the use of the Brier Score [33] for a binary event. We decided to focus our analysis on a binary event (e.g. solar power production higher than normal), rather than on a continuous variable (e.g. the amount of generated electricity), to be able to simplify the decision-making model to better concentrate this work on the link between the quality of a forecast and its perceived usefulness for a user, as we will see later in Section 4. Using a categorical (e.g. binary) predictand instead of a continuous one also makes easier the analysis of the joint distribution of observations and forecasts. Moreover, the Brier Score is used also for its useful reliability-sharpness decomposition [31] and for the fact of being a proper score [34].

The BSS is based on the Brier Score (BS), that basically corresponds to the mean squared error of the probability forecast in predicting a binary event. The formula for the BS is the following:

$$BS = \frac{1}{n}\sum_{k=1}^{n}(y_k - o_k)^2 \tag{4}$$

where o is the observation, with $o = 1$ when the event occurs and $o = 0$ when it does not. Instead y is the probability forecast, with k the index for the n time steps.

The skill score (BSS) is obtained comparing the BS of the forecast with the BS of a reference forecast, in this case the climatological relative frequency. A BSS of 1 indicates a perfect forecast while a score of 0 means no difference between the forecast and the reference forecast. When the value is negative, it means that the forecast performs worse than the reference forecast. The formula for the BSS is then:

$$BSS = 1 - \frac{BS}{BS_{ref}} \tag{5}$$

where BS and BS_{ref} are respectively the Brier Score of the forecast and the reference forecast.

All the datasets here used have been interpolated on a common grid, the one of the SARAH dataset. Consequently, also the PV power potential is computed point by point on a regular grid and then we choose to aggregate it, using the mean, at regional level. Moreover, to make this analysis more realistic and therefore meaningful for each region we average only the grid points where, based on the land-cover information, PV panel may be installed. This is based on the methodology proposed by Hansen and Thorn [35] and it consists of an analysis of the potential for PV farms per square km in Europe using the Corine Land Cover data (CLC2006). This potential represents an estimate of the regional PV energy suitability (i.e. the area available for PV) taking into account geographical and physical conditions. After estimating the potential density of PV panels we classify all the grid points as suitable (or not) for PV power installation (see Figure 2), we filter out all the grid points that are not suitable (i.e. where the density of PV panels is zero as for example in mountain areas) from the regional averages. Figure 2 shows a map illustrating, with one km resolution, all the areas that are suitable for PV panels, i.e. when the potential for PV farms is greater than zero.

The BSS is used here to measure the skill of the seasonal forecast in predicting two binary events: *upper event* and *lower event*. The two events are defined according to the lower and upper terciles of the average regional PV power potential, i.e. the upper (lower) event is defined when the PV potential is above (below) the 66^{th} (33^{th}) percentile of all the PV potential observed in the considered period (1983-2013).

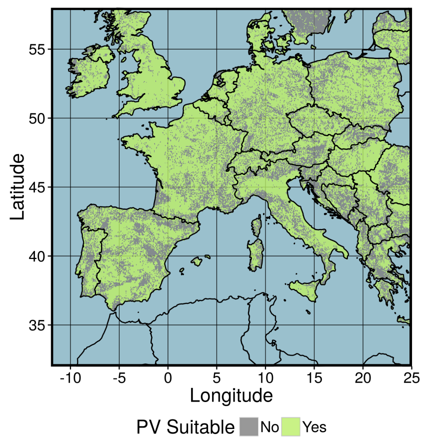


Figure 2: Areas suitable for PV-panel installation. The map has a 1 km of resolution and it is based on Corine Land Cover Data (CLC2006) following the procedure proposed by Hansen and Thorn [35]. The grey grid points represent the areas where the potential density of PV is zero.

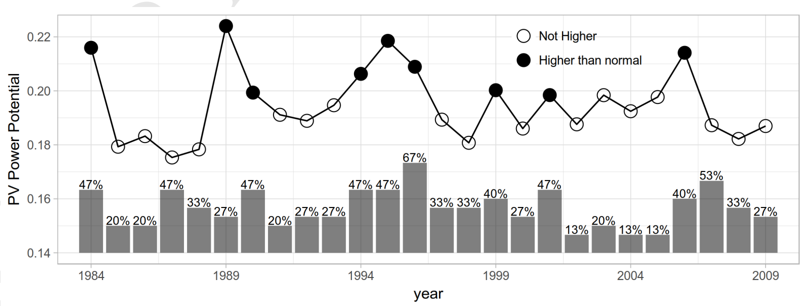
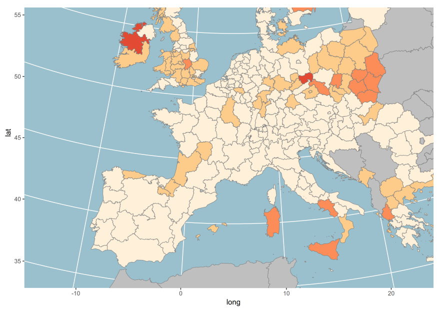
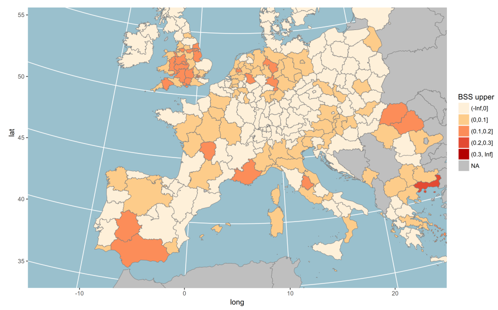


Figure 3: Example for West Midlands in summer. The line represents the PV power potential (see Eq. 1) based on the observed meteorological variables. The bar plot instead shows the probability given by the seasonal climate forecasts issued in May of a PV power potential higher than normal (i.e. greater than the 66^{th} percentile) for the incoming summer.



(a) Winter (December, January and February)



(b) Summer (June, July and August)

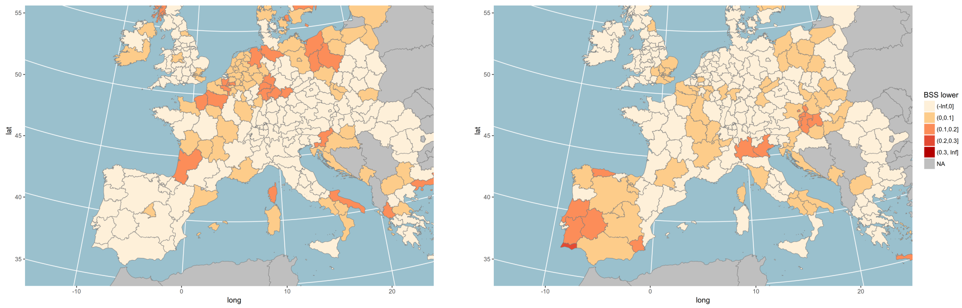
Figure 4: Brier Skill Score for the PV power potential higher than normal (i.e. above the 66^{th} percentile).

An example on how the events are defined is in Figure 3, where the photovoltaic power potential is shown for a county in the West Midlands region (England) for the summer. The black dots represent the *upper event*, i.e. when the potential is above the 66^{th} percentile (0.20 in this example). The bar plot at the bottom indicates the probability predicted by the seasonal forecast for having the PV power potential higher than normal. In this example the skill score is equals to 0.27.

The BSS of the seasonal forecast for the two events is shown for all the European regions in Figures 4 and 5.

The coloured areas represent the regions where the seasonal forecast provides probabilistic information that is better than climatology i.e. the information coming from the observed frequency of the event in the past. In both of these figures we can see that in some areas of Europe there is skill in multiple regions such as in the Iberian Peninsula during summer months for both of the events or in the United Kingdom for the higher event (i.e. the prediction that the PV output will be higher than normal).

A detailed skill assessment of solar power generation (and, more in general, energy and climate variables) can be found instead in two deliverables of the ECEM contract [36, 37]. Both the documents focused on solar irradiance given that, for seasonal averages, it is highly correlated with the solar power production. The assessment in [36] is based both on the point-by-point correlation between the seasonal forecasts and the ERA-INTERIM reanalysis for solar irradiance (Figure 16 of [36]) and on the use of a set of skill-scores



(a) Winter (December, January and February)

(b) Summer (June, July and August))

Figure 5: Brier Skill Score for the PV power potential lower than normal (i.e. below the 33^{th} percentile).

for country averages. In the latter analysis (shown in Table 2 and 3 of [36]]) they have found that for the winter forecasts the correlation is significantly greater than zero for Eastern Europe (Albania, Bosnia-Herzegovina, Bulgaria, Croatia, Czechia, Greece, Hungary, Macedonia, Montenegro, Serbia, Slovakia) and instead for ROC skill-score (see Wilks [31] for the description of this metric) only in Serbia and Poland. On the contrary, the authors have found that for summer forecasts no areas shows a skill-score significantly greater than zero.

A proper skill assessment is a vital step to evaluate a seasonal climate forecast, however, skill metrics alone are not enough to define if a forecast is useful or not for a user. In the following section we discuss and present an approach for calculating an index of opportunity of seasonal forecasting, based on multiple factors including a skill score, to help inform and improve the operational decisions of a target generic user.

3. Index of opportunity: a hypothetical example for the solar power industry

As mentioned above, seasonal climate forecasts can be potentially used as a tool to improve the decision-making in sectors where climate plays an important role (see [20]). However, as emphasized by [38], for seasonal forecasts to be useful should be able to influence the decision-making: assessing their accuracy (as we did in Section 2.1) is generally not sufficient. As such, it is critical to understand how this type of forecasts can potentially help to inform the operations and decision processes within the solar power industry. In this context, the potential usefulness of seasonal forecasts to the end-users will be influenced by a number of aspects such as how much is the information provided by the forecast needed to inform the user's operations and decisions; what is the impact of a good (bad) forecast to the user; how precise and accurate does the forecast needs to be to be applied by the user [38, 39, 40]. Furthermore, broader aspects related to the specific organisational context within which the forecasts are to be applied (e.g. governance structures, institutional and regulatory contexts, trusting relationships with the forecasts' providers) also influence how potentially useful and, ultimately, usable seasonal forecasts can become [39, 40, 41].

However, the use of seasonal forecasts to inform activities within the solar energy sector in Europe is limited. To evaluate the potential usefulness of seasonal climate forecasts, we propose an index that, taking into account multiple factors, can help understand the capability of the seasonal forecast information to inform the solar power industry.

The main premise of this index is that it is based on the user's organisational context and knowledge in order to capture the factors most relevant to the user. This means that the index is an indicator tailored to a specific user and a specific decision-making process and, as result, it is not a generalised index of usefulness. The first step is therefore to understand what are the critical factors to the user which can include, for example the need to detect periods with anomalous low generation or to give priority to the regions with the greater installed capacity.

Such index models a specific decision-making process in a particular organisational setting. As such, the construction of the index can be considered as part of the tailoring process characteristic of a climate service [42, 43, 44].

Here we propose a hypothetical index based on the following three assumptions:

- Skill: we assume that the more skillful the forecast is the more useful it is. On the contrary, we consider a forecast with zero or negative skill useless;

- PV potential capacity: we assume that in a region where there is a large amount of potential PV installed capacity a good forecast will be potentially more useful than in areas with a low potential;

- Inter-annual variability of solar power potential: we assume that a

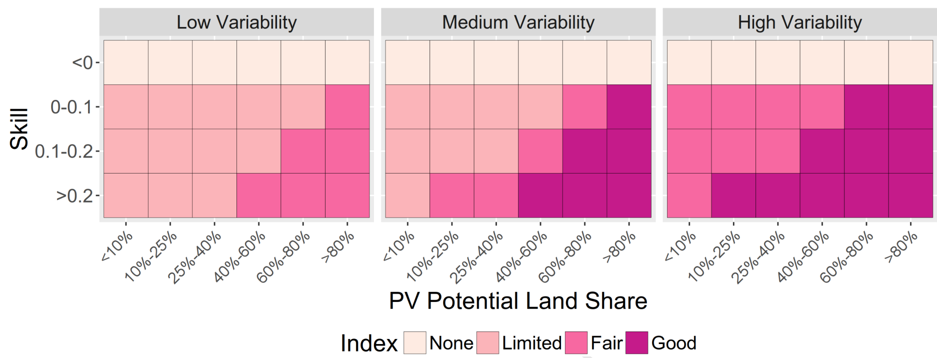


Figure 6: Index of Opportunity: the three panels refers to the variability of PV power potential (low, medium and high variability).

seasonal forecast should help to cope with the high variability of solar power generation (i.e. a large standard deviation).

These three aspects are the "information layers" that have been combined to create the index shown in Figure 6. Each of these aspects is associated to a specific factor: *Skill*, *PV Potential Land Share*, and *Variability*. The factors have been divided into categories through the following procedures:

Skill. The skill for power production has been presented in Section 2.1 by using the Brier Skill Scores for two events represented by the upper and lower terciles (i.e. PV power production above and below normal). We summarise the skill by considering the average between the two values, therefore assuming that the prediction of upper and lower events has the same level of importance for the user. We make two assumptions: 1) any positive score is useful to some extent, because it means that the climate forecast provides probabilistic information more accurate than the climatology, i.e. the observed past; 2) a forecast is never useful when its skill is negative. Based on those assumptions, this factor has been divided in four categories: negative score, score between 0 and 0.1, between 0.1 and 0.2, and score greater than 0.2. The choice of the intervals is arbitrary, considering that what is being proposed is an example for a generic user.

PV Potential Land Share. To estimate the potential land share of PV we have used the data presented in Section 2.1 (see Figure 2) and we have aggregated

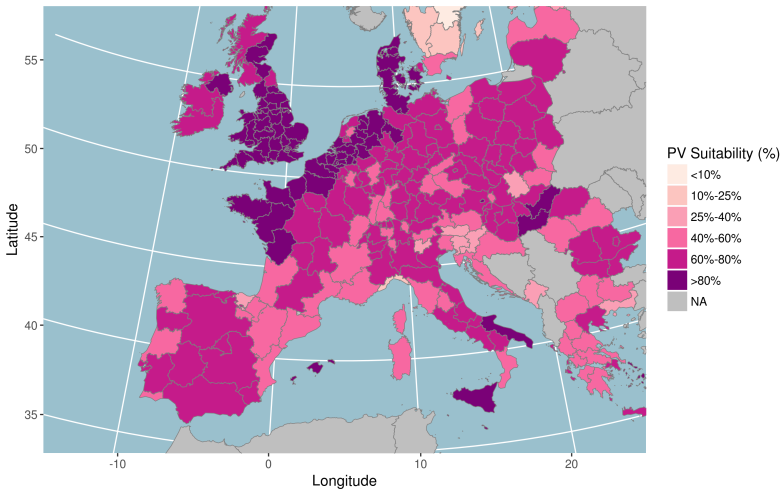
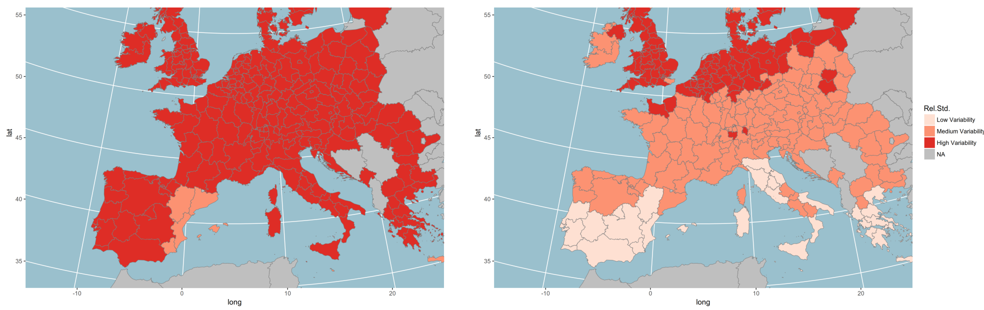


Figure 7: Percentage of land suitable for PV panels for each European region (NUTS2). The suitability is defined as the percentage of the grid points that are suitable for PV panels (see Figure 2).

the values at regional level, therefore obtaining for each European region the share of land that is potentially suitable for PV installations (see Figure 7). This factor has been divided into six categories to try to characterise the diverse suitability for PV installation of the European regions.

Variability. This factor represents the inter-annual variability of solar power potential. The relative standard deviation has been used to measure the variability, as done for the solar radiation in Section 2. We have divided the variability in three categories, according to the terciles computed on the entire distribution for all the seasons, i.e. high (low) variability is defined as the relative standard deviation above (below) the 66^{th} (33^{th}) percentile of all the relative standard deviations in all the seasons. The calculation has been done considering regional aggregated data and the output is shown in Figure 8. The thresholds have been set to have each category of the same size.

The three factors are combined based on the function depicted in the diagram in Figure 6. For a specific region, we can obtain the value of the index firstly selecting one of the three panels according the inter-annual variability of the region (Low, Medium or High) and then looking at the color in the row and columns according to, respectively, the forecast skill and the PV potential land share in the specific region. The potential usefulness is classified in four



(a) Winter (December, January and February)

(b) Summer (June, July and August)

Figure 8: Relative standard deviation of PV potential production at regional level. The three categories are defined according to the terciles of all the values of relative standard deviation for all the regions and all the seasons. We can observe how the variability is higher during the winter period due to more frequent cloudy conditions.

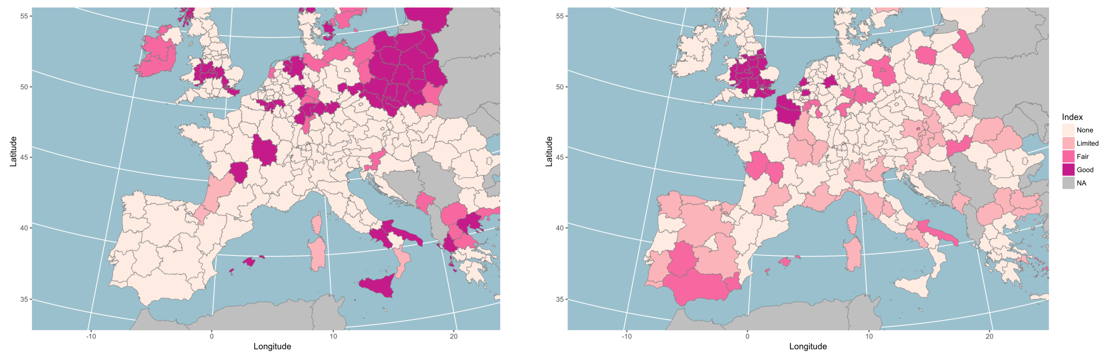
levels, ranging from 'None' (the lightest shade) to 'Good' (the dark purple), according to three variables. As stated before, this index is a specific example and it reflects the idea that: 1) a forecast is never useful when its skill is negative; 2) a forecast is more useful in the regions where the potential land share is high (for example when it is higher than 80% the index is always at least 'Fair'); 3) the higher the observed generation variability, the more useful is the forecast (in Figure 6 we can see that the index is never 'Good' when we have Low Variability, on the opposite when the variability is High, the usefulness is always at least 'Fair');

The index of opportunity has been computed for all the European regions at NUTS 2 level.

4. The potential usefulness of seasonal climate forecasts for solar power

The index of opportunity proposed in the previous section is illustrated in Figure 9 for the two main seasons – winter and summer – across European NUTS 2 level regions.

According to our example, the index indicates that seasonal forecasts can provide some potential benefits during both seasons in different parts of Europe. For example, during winter months, the forecasts are potentially useful in areas such as Poland and, in general, in the Northwestern Europe.



(a) Winter (December, January and February) (b) Summer (June, July and August)

Figure 9: Index of Opportunity proposed in Section 3 across European NUTS 2 regions.

In the southeastern part of the continent, the index highlights some potential benefits in Greece and in the southern Italian regions. During summer months, the areas with a fair-to-good value of the index are located in the Iberian Peninsula, in the central-southern England regions and in the north of France. In general, during summer the index shows potential benefits in most of the Mediterranean areas.

If we take into account in our analysis the actual installed capacity of solar PV, we can also observe that the benefit of the climate forecast can be seen as a support to a higher penetration of PV in the areas where the installed capacity is still low compared to the other regions. Poland for example, according to the Polish Energy Regulatory Office, has 100 MW of installed solar power in 2017, a number about 400 times lower than Germany and about 100 times lower than the UK, two countries that shows a similar solar potential [45].

In addition, despite the interconnection between European power grids, multiple electricity markets exist, varying in geographical scope and in the typology of the performed operations and the implemented regulations. This diversity of the policy and governance structures across countries/regions requires a closer attention to the underlying assumptions (i.e. the considered factors) to be included in an index of opportunity. In this study, the assumptions included in the index have been selected in order to exemplify the approach. However, these should ultimately be discussed and defined with the end-users, according to what they regard as critical aspects in their specific decision-making processes and in order to fit their information needs.

As such, future research efforts should aim to develop and test the proposed index of opportunity with decision-makers within the solar power industry in Europe to ascertain the usability of such approach in helping them make better informed decisions supported by seasonal climate forecasts.

4.1. Remarks on the choice of the skill score

In the proposed index the skill score is an important factor because it summarises the capability of the forecast to provide an accurate estimate of the potential generation. Here we have used the Brier Skill Score metric considering two possible events: generation above the second tercile (i.e. 66^{th} percentile) and below the first tercile (i.e. 33^{th} percentile). However, there exists a wide range of skill scores, each one focusing on a different aspect. Providing a summary of the most common used scores for probabilistic forecasts is not in the scope of this paper, for an in-depth description and discussion, the authors refer to Wilks [31] and, for a applicative comparison for the energy sector, to the results of the C3S ECEM contract [36, 37].

As for the other factors, the choice of the skill score and the thresholds used to categorise it should be carried out in collaboration with the user trying to define which are the statistical features of the forecast most relevant for the specific decision-making. An example showing the results of the application of different skill scores on the PV power potential is given in the Supplementary Material in Fig. S2.

5. Concluding remarks

This paper describes how to create an index of opportunity, designed to be able to combine multiple factors related to the usefulness for a specific user of a forecast in predicting the seasonal PV potential production. A specific hypothetical example based on the authors' experience is presented to help illustrate the potential for using such an index. However, the development of this type of index should always be pursued in close collaboration with the users of the seasonal climate forecasts.

This study provides some insights on where and when seasonal climate forecasts can benefit the decision-making for the photovoltaics sector and, more important, it suggests an approach on how to evaluate their usefulness for the user's decision-making. This approach has the advantage of not limiting the definition of the usefulness only to the quality of the forecasts but rather considering, in an explicit way, all the factors that must be combined with the forecast's quality to define what is useful or not for the user.

This approach can also be regarded as a step needed for an effective integration of seasonal climate forecasts in the decision-making processes in the European renewable energy sector, especially considering the challenges that the European power systems operators are facing with the increasing penetration of PV power and, in general, renewable energy sources.

This work is also motivated by the fact that the use of the seasonal climate information by the solar power industry is probably going to increase due to the recent improvements of seasonal forecasting systems in predicting phenomena like the North Atlantic Oscillation [46] that are well-known to have an impact of solar irradiance and therefore PV power [47, 48].

6. Acknowledgments

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[1] Eurostat, `http://ec.europa.eu/eurostat/web/energy/data/shares`, 2017 (accessed 21/07/2017).

[2] SolarPower Europe, Global Market Outlook for Solar Power 2016-2019, Technical Report, SolarPower Europe, 2016.

[3] "European Commission", "DG ENER", "DG CLIMA", "DG MOVE", EU Reference Scenario 2016: Energy, Transport and GHG emissions. Trends to 2050, Technical Report, European Commission, 2016.

[4] C. Schwingshackl, M. Petitta, J. Wagner, G. Belluardo, D. Moser, M. Castelli, M. Zebisch, A. Tetzlaff, Wind Effect on PV Module Temperature: Analysis of Different Techniques for an Accurate Estimation, Energy Procedia 40 (2013) 77 – 86.

[5] D. S. Kirschen, G. Strbac, Fundamentals of power system economics, John Wiley & Sons, 2004.

[6] F. J. Doblas-Reyes, J. García-Serrano, F. Lienert, A. P. Biescas, L. R. L. Rodrigues, Seasonal climate predictability and forecasting: Status and prospects, Wiley Interdisciplinary Reviews: Climate Change 4 (2013) 245–268.

[7] T. Palmer, R. Hagedorn, Predictability of weather and climate, Cambridge University Press, 2006.

[8] J. Shuila, J. Kinter III, Predictability of seasonal climate variations: A pedagogical review (2006).

[9] T. Gneiting, M. Katzfuss, Probabilistic forecasting, Annual Review of Statistics and Its Application 1 (2014) 125–151.

[10] A. Alessandri, A. Borrelli, A. Navarra, A. Arribas, M. Déqué, P. Rogel, A. Weisheimer, Evaluation of Probabilistic Quality and Value of the ENSEMBLES Multimodel Seasonal Forecasts: Comparison with DEMETER, Monthly Weather Review 139 (2011) 581–607.

[11] M. De Felice, A. Alessandri, F. Catalano, Seasonal climate forecasts for medium-term electricity demand forecasting, Applied Energy 137 (2015) 435–444.

[12] CLIM-RUN Project - Climate Local Information in the Mediterranean region Responding to User Needs, 2011-2014. [Online; accessed 14-September-2016].

[13] ECLISE: Enabling CLimate Information Services for Europe, 2011-2013. [Online; accessed 14-September-2016].

[14] SPECS: Seasonal-to-decadal climate Prediction for the improvement of European Climate Services, 2012-2017. [Online; accessed 14-September-2016].

[15] EUPORIAS: European Provision Of Regional Impacts Assessments on Seasonal and Decadal Timescales, 2012-2017. [Online; accessed 14-September-2016].

[16] CLIM4ENERGY - A service providing climate change indicators tailored for the energy sector, 2015-2017. [Online; accessed 14-September-2016].

[17] A. Troccoli, C. Goodess, P. Jones, L. Penny, S. Dorling, C. Harpham, L. Dubus, S. Parey, S. Claudel, D.-H. Khong, P. E. Bett, H. Thornton, T. Ranchin, L. Wald, Y.-M. Saint-Drenan, M. De Felice, D. Brayshaw, E. Suckling, B. Percy, J. Blower, Creating a proof-of-concept climate service to assess future renewable energy mixes in europe: An overview of the C3S ECEM project, Advances in Science and Research 15 (2018) 191–205.

[18] M. B. García-Morales, L. Dubus, Forecasting precipitation for hydroelectric power management: how to exploit GCM's seasonal ensemble forecasts, International Journal of Climatology 27 (2007) 1691–1705.

[19] D. J. Brayshaw, A. Troccoli, R. Fordham, J. Methven, The impact of large scale atmospheric circulation patterns on wind power generation and its potential predictability: a case study over the UK, Renewable Energy 36 (2011) 2087–2096.

[20] M. B. Soares, S. Dessai, Barriers and enablers to the use of seasonal climate forecasts amongst organisations in Europe, Climatic Change (2016) 1–15.

[21] A. Weisheimer, T. Palmer, On the reliability of seasonal climate forecasts, Journal of The Royal Society Interface 11 (2014) 20131162.

[22] A. Boilley, L. Wald, Comparison between meteorological re-analyses from ERA-Interim and MERRA and measurements of daily solar irradiation at surface, Renewable Energy 75 (2015) 135–143.

[23] R. Müller, U. Pfeifroth, C. Träger-Chatterjee, R. Cremer, J. Trentmann, R. Hollmain, Surface Solar Radiation Data Set - Heliosat (SARAH), 2015.

[24] R. Müller, U. Pfeifroth, C. Träger-Chatterjee, J. Trentmann, R. Cremer, Digging the METEOSAT Treasure—3 Decades of Solar Surface Radiation, Remote Sensing 7 (2015) 8067–8101.

[25] M. De Felice, M. Petitta, P. M. Ruti, Short-term predictability of photovoltaic production over Italy, Renewable Energy 80 (2015) 197–204.

[26] M. Haylock, N. Hofstra, A. Klein Tank, E. Klok, P. Jones, M. New, A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006, Journal of Geophysical Research: Atmospheres 113 (2008).

[27] F. Molteni, T. Stockdale, M. Balmaseda, G. Balsamo, R. Buizza, L. Ferranti, L. Magnusson, K. Mogensen, T. Palmer, F. Vitart, The new ECMWF seasonal forecast system (System 4), ECMWF Technical Memorandum 656 (2011).

[28] F. Mavromatakis, G. Makrides, G. Georghiou, A. Pothrakis, Y. Franghiadakis, E. Drakakis, E. Koudoumas, Modeling the photovoltaic potential of a site, Renewable energy 35 (2010) 1387–1390.

[29] S. Dubey, J. N. Sarvaiya, B. Seshadri, Temperature dependent photovoltaic (PV) efficiency and its effect on PV production in the world–a review, Energy Procedia 33 (2013) 311–321.

[30] R. Ross, Flat-plate photovoltaic array design optimization, in: 14th IEEE Photovoltaic Specialists Conference, San Diego, CA, pp. 1126–1132.

[31] D. S. Wilks, Statistical Methods in the Atmospheric Sciences, volume 100, Academic Press, 2011.

[32] E. Becker, H. Van Den Dool, Probabilistic seasonal forecasts in the North American Multimodel Ensemble: A baseline skill assessment, Journal of Climate 29 (2016) 3015–3026.

[33] G. W. Brier, Verification of forecasts expressed in terms of probability, Monthly weather review 78 (1950) 1–3.

[34] J. Bröcker, L. A. Smith, Scoring probabilistic forecasts: The importance of being proper, Weather and Forecasting 22 (2007) 382–388.

[35] A. C. Hansen, P. Thorn, PV potential and potential PV rent in European regions, ENSPAC Research Papers on Transitions to a Green Economy, Roskilde University, 2013.

[36] ECEM, D2.2.1: Skill assessment of energy-relevant climate variables in a selection of seasonal forecast models. Report using final data sets., Technical Report, Copernicus Climate Change Service, 2018. https://doi.org/10.5281/zenodo.1293863.

[37] ECEM, D3.4.1: Assessment of seasonal forecasting skill for energy variables, Technical Report, Copernicus Climate Change Service, 2018.

[38] A. H. Murphy, What Is a Good Forecast? An Essay on the Nature of Goodness in Weather Forecasting, Weather and Forecasting 8 (1993) 281–293.

[39] J. Clements, A. Ray, G. Anderson, The value of climate services across economic and public sectors: A review of relevant literature, United States Agency for International Development (USAID): Washington. http://www. climate-services. org/wp-content/uploads/2015/09/CCRD-Climate-Services-Value-Report_FINAL. pdf (accessed 9 December 2015) (2013).

[40] M. Bruno Soares, M. Daly, S. Dessai, Assessing the value of seasonal climate forecasts for decision-making, Wiley Interdisciplinary Reviews: Climate Change 9 (2018) e523.

[41] M. C. Lemos, C. J. Kirchhoff, V. Ramprasad, Narrowing the climate information usability gap, Nature climate change 2 (2012) 789.

[42] C. Vaughan, S. Dessai, Climate services for society: origins, institutional arrangements, and design elements for an evaluation framework, Wiley Interdisciplinary Reviews: Climate Change 5 (2014) 587–603.

[43] C. Buontempo, H. M. Hanlon, M. B. Soares, I. Christel, J.-M. Soubeyroux, C. Viel, S. Calmanti, L. Bosi, P. Falloon, E. J. Palin, et al., What have we learnt from EUPORIAS climate service prototypes?, Climate Services (2017).

[44] P. Falloon, M. B. Soares, R. Manzanas, D. San-Martin, F. Liggins, I. Taylor, R. Kahana, J. Wilding, C. Jones, R. Comer, et al., The land management tool: Developing a climate service in Southwest UK, Climate Services (2017).

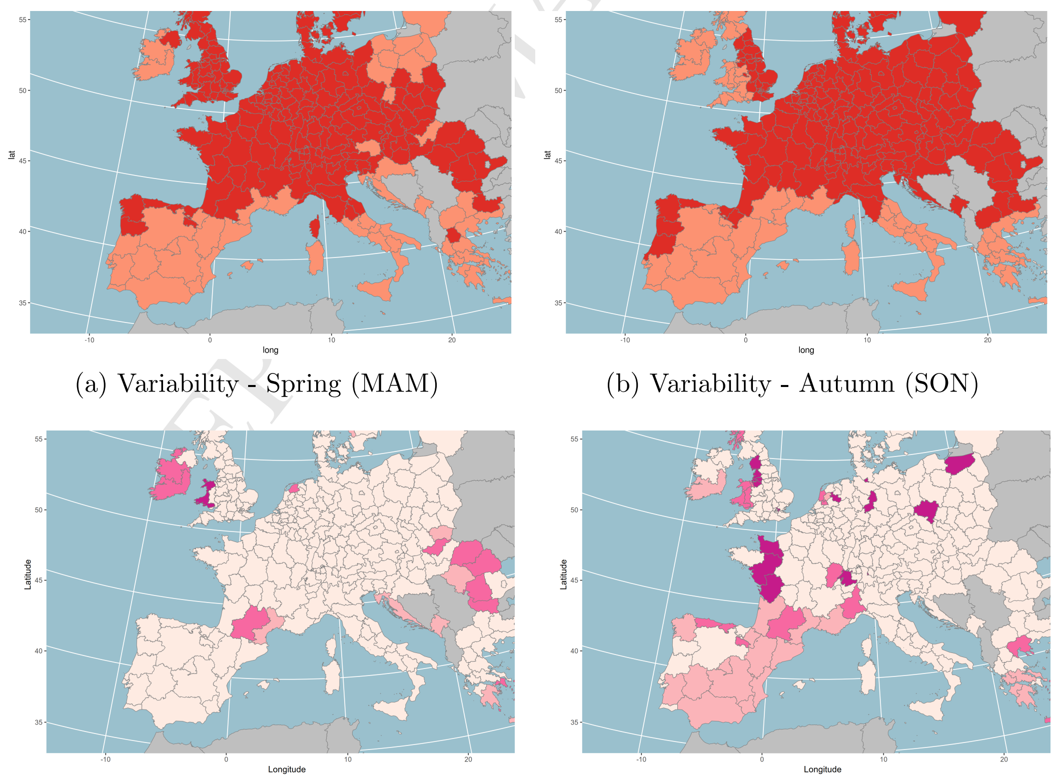
[45] M. Šúri, T. Huld, E. D. Dunlop, H. Ossenbrink, Potential of solar electricity generation in the European Union member states and candidate countries, Solar Energy 81 (2007) 1295–1305.

[46] A. Scaife, A. Arribas, E. Blockley, A. Brookshaw, R. Clark, N. Dunstone, R. Eade, D. Fereday, C. Folland, M. Gordon, et al., Skillful long-range prediction of European and North American winters, Geophysical Research Letters 41 (2014) 2514–2519.

[47] D. Pozo-Vázquez, NAO and solar radiation variability in the European North Atlantic region, Geophysical Research Letters 31 (2004) 1–4.

[48] B. François, Influence of winter north-atlantic oscillation on climate-related-energy penetration in europe, Renewable Energy 99 (2016) 602–613.

Supplemental Materials: Scoping the potential usefulness of seasonal climate forecasts for solar power management



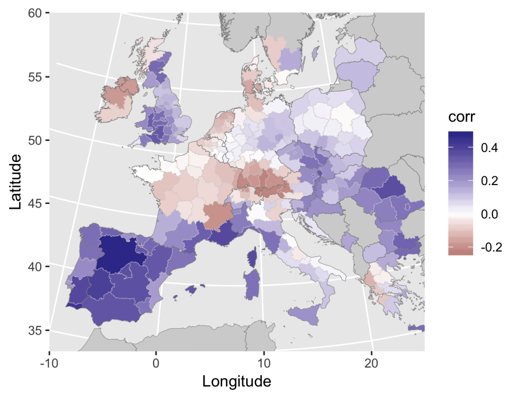
(a) Variability - Spring (MAM)

(b) Variability - Autumn (SON)

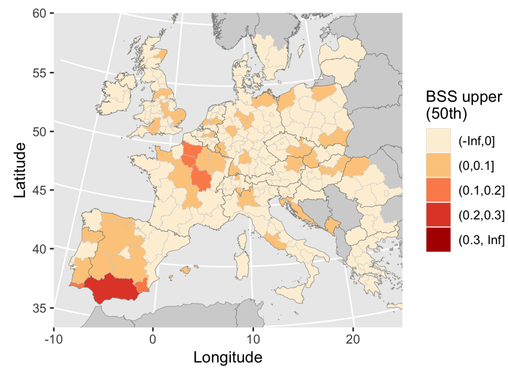
(c) Index - spring (MAM)

(d) Index - autumn (SON)

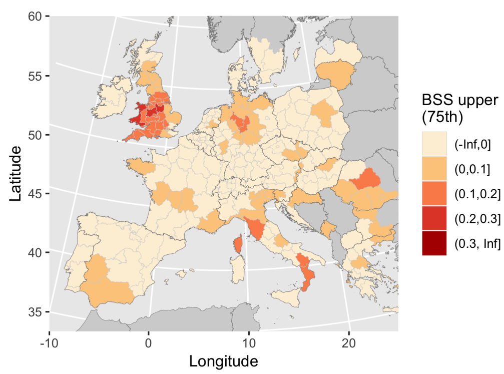
Figure S1: Inter-annual variability and Index of Opportunity for spring and autumn seasons.



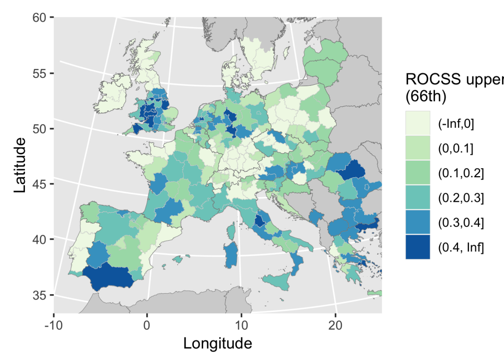
(a) Correlation



(b) BSS upper median



(c) BSS upper 75^{th} percentile



(d) ROC Skill Score upper (66^{th})

Figure S2: Four different metrics are used to compare the forecast of PV power potential as done in Figures 4 and 5. a) The correlation is applied on the mean of all the ensemble members, it is not a probabilistic skill but however is widely used; b) The Brier Skill Score with the event defined as the generation above the median; c) Same as b) but using the 75^{th} percentile; d) The ROC skill score for the generation above the second tercile.

- This work explains how to use better climate forecasts in the energy sector
- To assess the usefulness of climate forecasts estimating the accuracy is not enough
- This approach considers many factors to assess the usefulness of climate forecasts