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

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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 for all the renewable energy sources, for an intelligent management of solar power, it is essential to have reliable and accurate information about weather/climate conditions that affect the production of electricity. This type of information can include both an estimate of past weather as well as a prediction for the next days and months. 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 as well as to help secure future power contracts. This need will likely increase in a low-carbon economy, which is one the goals of the European Union.

This paper illustrates how the state-of-art seasonal climate forecasts provide a useful prediction for the average PV power production over European regions. The quality of the forecasts is evaluated by exploiting their probabilistic nature. Such assessment provides useful insights on their advantages and limitations of these forecasts. Subsequently we describe how to assess the potential usefulness of seasonal climate forecasts for the solar industry by proposing an approach that takes into account not only their accuracy but also other potentially relevant factors. This novel approach – called index of

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1 opportunity – is described and an example is presented for solar power over Europe.

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/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. Also hydro power generation, which produces more than the 10% of European electricity, although can be considered a more controllable energy source, it is affected by availability of water in rivers and reservoirs, both tightly linked with precipitation and snow melting.

This tight link between generation and weather implies that, the more energy produced by RES, the more electric utilities and grid operators needs to take actions to prevent drawbacks and faults due to less favourable weather conditions.

Moreover, a high penetration of RES makes the grid balancing (i.e. the need to keep power generation and demand balanced at any point in time) more challenging. Predicting the energy produced by RES for the incoming hours, weeks, and months is therefore critical given that the supply of variable sources (mostly wind and solar power) cannot be adjusted to match the demand of electricity. The variability of RES within a country can, to some extent, be managed by taking advantage of the interconnections between power systems (cross-border transmission cables) which allows neighbouring countries to exchange electricity to meet their internal demands and thus reducing the effects of the variable generation.

Solar power, specifically photovoltaic power, has a fundamental role in the RES mix. With a global installed capacity increase from 177 GW to about 300 GW between 2014 and 2016[5], solar power in Europe could reach more than 600 GW by 2020 [2]. The installed capacity in Europe has grown

[5] `http://www.ren21.net/wp-content/uploads/2016/06/GSR_2016_KeyFindings1.pdf`

by 100 GW and solar power currently supplies on average 4% of the Europe's energy demand. Furthermore, solar power developments are increasing its competitiveness, generating electricity at price levels even lower than onshore wind power in some countries [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 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) for example in relation to system adequacy analysis, hedging, asset management and risk assessment [5]. A production forecast could also be useful to help deal with the variability which might exacerbate the grid imbalance when a non-dispatchable energy source such as solar generates a significant amount of national electricity. In such cases, having a forecast that can help detect in advance the cases of production lower or higher than normal can be beneficial for the management of the grid. Such potential advantage will be more prominent considering the expected change in the European energy systems in the next decades. According to SolarPower Europe [2] in 2020 the three countries with most installed PV capacity (Germany, Italy and UK) will increase their PV capacity up to 26% (17.7GW). The scenario REF2016 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 [6].

The information provided by climate forecasts at the seasonal time scale can plays an important role in supporting long-term decision-making processes. Due to advances in our knowledge of the earth system as well as the dramatic increase of available computational power the quality of these forecasts has improved significantly in the last decades [7].

It is well-known that the quality and then the applicability of weather forecasts decreases drastically after 5-7 days. Nonetheless, if we look at the "climate" instead of "weather" information, climate forecasts can show predictive skill. Seasonal climate forecasts are numerical model-based predictions where each forecast is started from an estimate of the initial state of the Earth system derived from Earth observations. To address the inherent uncertainty, many forecasts are initialised each with slightly different conditions: the combination of all these forecasts is defined as an "ensemble". These systems are able to provide longer term predictions of the climate up to several months ahead. This is possible due to the capability to model the slowly-varying interactions of the earth system such as the oceans and the land surface (for a solid introduction to predictability of weather/climate and seasonal climate forecasts see [8] and [9]). 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 does not cover a short timespan (minutes or hours) or a small area (e.g. a city) but rather information for a longer period, e.g. for the next season (e.g. seasonal average) and larger areas (e.g. mid-size country). Secondly, whilst weather forecasts are normally deterministic, climate forecasts provide probabilistic information, as they consist of an ensemble of simulation, a way to deal effectively with the uncertainty. These differences also imply distinct approaches to include the information into decision-making processes for the energy sector. This is both due to the different types of resolution (e.g. a seasonal average instead of hourly one) and because at longer timescales there are different types of operations with other peculiarities as opposed to 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 [10].

The reliability and quality of seasonal climate forecasts often vary with respect to the period of the year, the predicted meteorological variable and the geographical domain. Although there is a shared agreement on "why and when" seasonal forecasts are good (see for example [11] and [7]), it is often considered good practice to apply post-processing (e.g. bias correction) or multi-variate statistical methods (see for example the approach used in [12]) to enhance the forecasts' information.

The capability of NWP models in predicting solar radiation at short and medium timescales (up to few days) has been analysed in several papers (see for example [13], [14] and [15]) as well as studies focusing on the use of NWP for solar power forecasting ([16]).

In recent years, a number of European projects have assessed and analysed the potential usefulness and usability of climate forecasts across a number of sectors including energy. While some focused on long-term climate change scenarios (e.g. CLIM-RUN [17] and ECLISE [18]) others, such as SPECS [19], EUPORIAS [20] and, more recently, the Copernicus Climate Change Services contracts (CLIM4ENERGY [21] and ECEM [22] on the energy sector), targeted seasonal climate forecasts as an input for operational activities in the renewable energy sector. These efforts have been largely underpinned by the need to efficiently manage the renewable energy sector which is becoming more prominent in Europe[6] as well as the opportunities arising from new operational forecasting systems[7].

In the scientific literature, there are only a few studies that have looked into the use of seasonal climate forecasts for RES. For example, Garcia-Morales and Dubus [23] evaluated the quality of seasonal forecasts for hydroelectric power management; Brayshaw et al. [24] assessed the use of forecasts to estimate power output in the UK; De Felice et al. [12] applied seasonal climate forecasts to predict electricity demand in Italy during summer. Finally, an extensive literature review on the use of seasonal climate forecasts in Europe can be found in Bruno Soares and Dessai [25]. Considering the entire energy sector and not only RES, the number of studies on the use of seasonal forecasts is steadily increasing, see for example Clark et al. [26] and Torralba et al. [27]. However, many of those works 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, i.e. help to better inform and support the users' decisions. An example is the paper by Weisheimer and Palmer [28], which assess the "goodness" of seasonal climate forecasts at the global level, classifying their usefulness for decision-making only considering their statistical reliability, i.e. its statistical consistency.

This paper aims to provide and discuss a methodology to evaluate the usefulness of seasonal climate forecasts for the solar power industry considering the main factors that are relevant to an industry user.

In section 2 we present an analysis on the predictability of solar power in Europe, also presenting the methodology we have used to measure the solar power potential. After the description of the index of usefulness in section

[6] 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`

[7] These are provided by the producing centres of seasonal forecasts. See full list of these centres here: `http://www.wmo.int/pages/prog/wcp/wcasp/gpc/gpc.php`

3, in section 4 we discuss its 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 (e.g. MERRA by NASA or ERA-INTERIM by ECMWF) due to their higher accuracy [29].

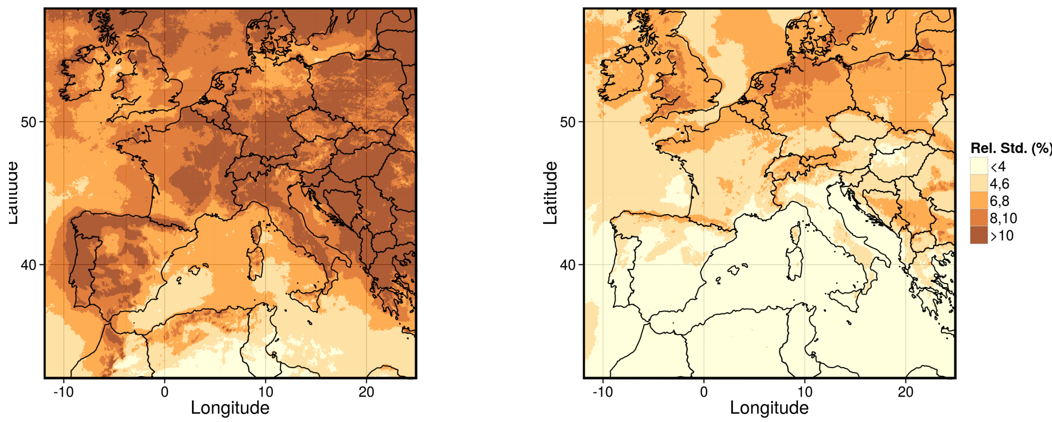
In this study, we use the SARAH (Surface Solar Radiation Data Set-Heliosat) dataset. It was released in 2015 by CM SAF (Satellite Application Facility on Climate Monitoring) and provides data for the period of 1983 to 2013 including the hourly to monthly averages in a regular grid at a resolution of $0.05° \times 0.05°$ [30, 31].

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 System 4 forecast system which was operational from November 2011 until November 2017[32]. 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.

Although solar radiation is the prominent variable to estimate the power output of a PV plant, also air temperature plays an important role due to its role in the efficiency of the PV panel [16]. To this end, in our analysis we have used 2-metre temperature data from E-OBS dataset [33].



(a) winter (DJF)

(b) summer (JJA)

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

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 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 [34]. It is defined as:

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

where G is the solar radiation (from satellite measurements or climate forecasts) and G_{STC} is the solar radiation 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 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. [35] 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 [36], 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 $48°C$.

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 [37] particularly the Brier Skill Score (BSS), a well-known and widely used skill metric for the probabilistic forecasts. The BSS is based on the Brier Score (BS) [38], that basically corresponds to the mean squared error of the probability forecast in predicting a binary event.

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.

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

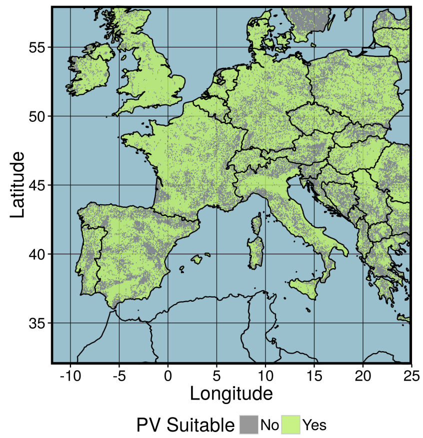


Figure 2: Areas suitable for PV-panel installation. The map has a 1km of resolution and it is based on Corine Land Cover Data (CLC2006) following the procedure proposed by Hansen and Thorn [39]

[39] and it consists of an analysis of the PV potential per square km in Europe using the Corine Land Cover data (CLC2006). After estimating the potential density of PV panels (see Figure 2) we omitted all the grid points where the density of PV panels is zero (e.g. high-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 PV potential 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).

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

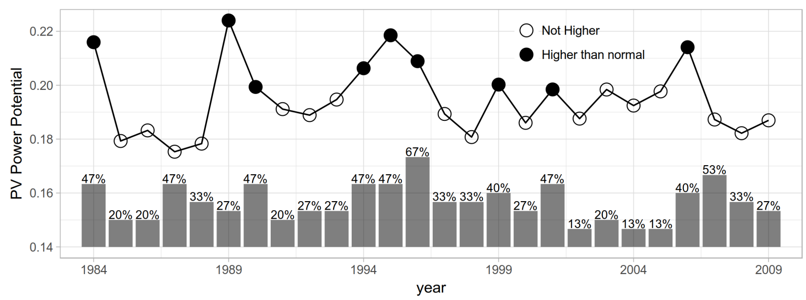
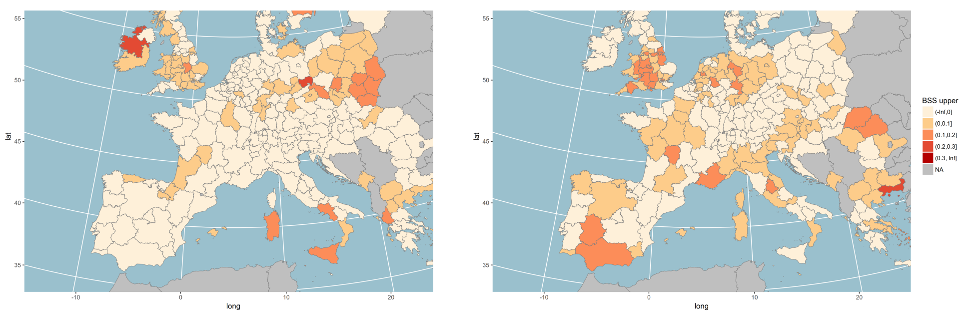


Figure 3: Example for West Midlands in summer. The line represents the PV power potential based on the observed meteorological variables. The bar plot instead shows the probability given by the seasonal climate forecasts issued in May of a PV power potential higher than normal (i.e. greater than the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



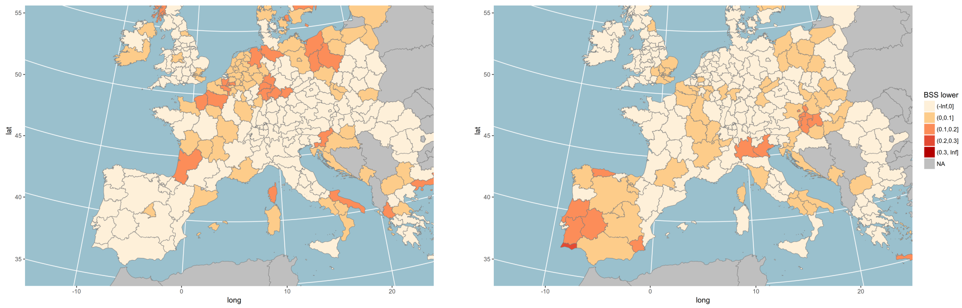
(a) winter (DJF) (b) summer (JJA)

Figure 4: PV power potential BSS Upper Event

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).

The following section presents our approach for calculating an index of opportunity of seasonal forecasting to help inform and improve the operational decisions and activities pursued within the solar power industry.



(a) winter (DJF)

(b) summer (JJA)

Figure 5: PV power potential BSS Lower Tercile

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 (cf. Bruno Soares and Dessai [25]). However, as emphasized by Murphy et al. [40], for seasonal forecasts to be useful they should be able to have a positive influence on the decision-making. As such, it is critical to understand how this type of forecasts can potentially help 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 users 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 [40, 41, 42]. Furthermore, broader aspects related to the specific organizational 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 [41, 43, 42].

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 users 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 [44, 45, 46].

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 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 reffig:indexofopportunity. 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 assume that 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. This

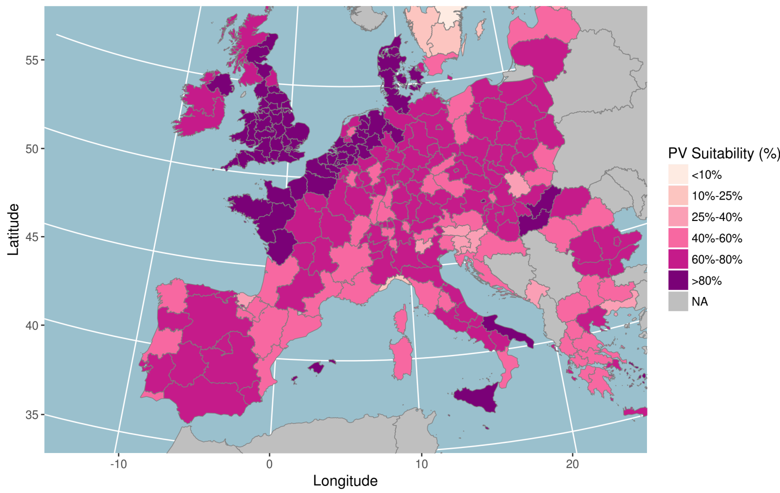


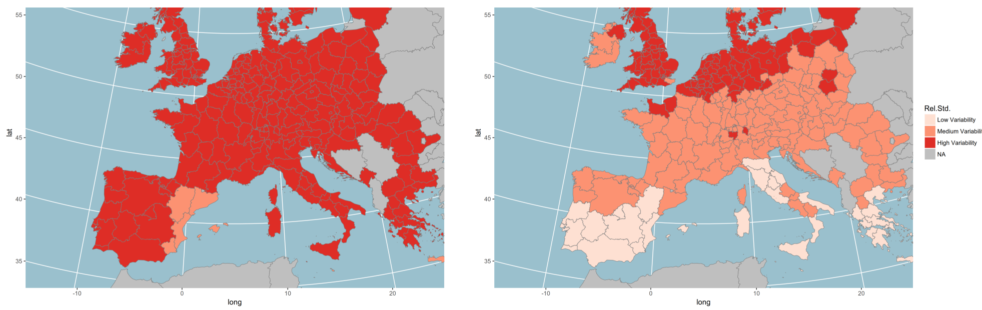
Figure 6: Percentage of land suitable for PV panels for each European region (NUTS-2).

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.

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 the values at regional level, therefore obtaining for each European region the share of land that is potentially suitable for PV installations (see Figure 6). 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 7. The thresholds have been set to have each category of the same size.

The three factors were combined based on the function depicted in the diagram in Figure 8. For a specific region, we can obtain the value of the index firstly selecting one of the three panels according the inter-annual variability



(a) winter (DJF) (b) summer (JJA)

Figure 7: Relative standard deviation of PV potential production at regional level. We can observe how the variability is higher during the winter period due to more frequent cloudy conditions.

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 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 8 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.

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

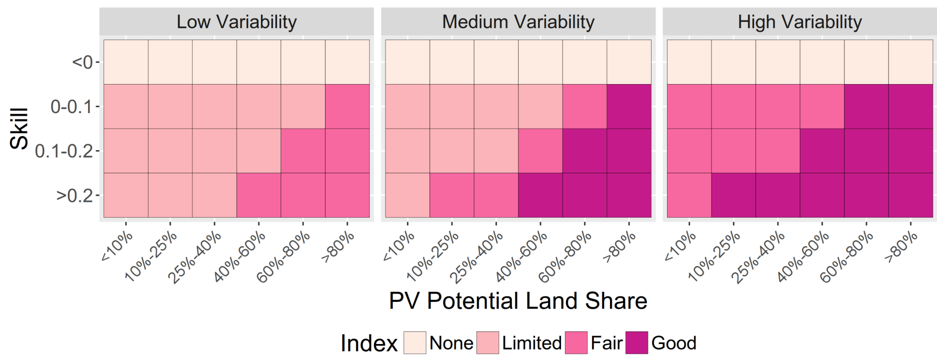
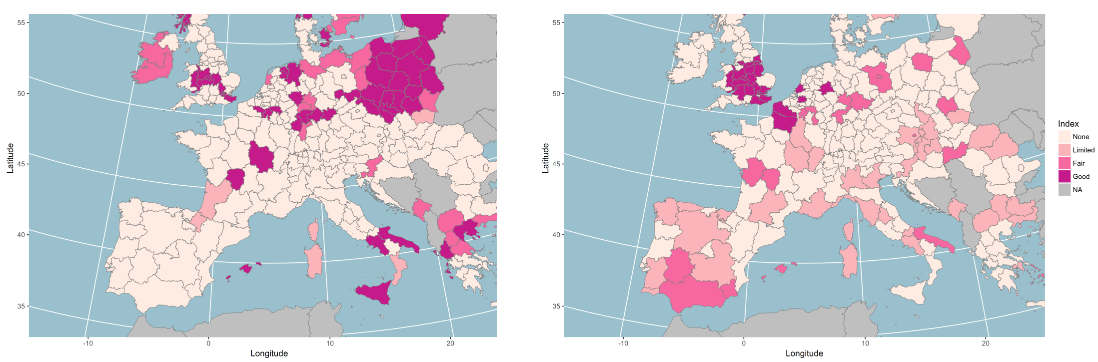


Figure 8: Index of Opportunity: the three panels refers to the variability of PV power potential (low, medium and high variability).



(a) winter (DJF)

(b) summer (JJA)

Figure 9: Index of Opportunity

useful in areas such as Poland and, in general, in the Northwestern Europe. 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 [47].

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 three possible events: generation above the second tercile (i.e. 66^{th} percentile), below the first tercile (i.e. 33^{th} percentile) and between the two. 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 [37] and, for a applicative comparison for the energy sector, to the results of the C3S ECEM contract [48, 49].

As for the other factors, the choice of the skill score 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 users decision-making. 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 [50] that are well-known to have an impact of solar radiation and therefore PV power [51, 52].

6. Acknowledgments

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ENSEMBLES (http://ensembles-eu.metoffice.com) and the data providers in the ECA&D project (http://www.ecad.eu). The authors thank Dr. Maurizio Pollino for the GIS analysis on the CLC2006 dataset.

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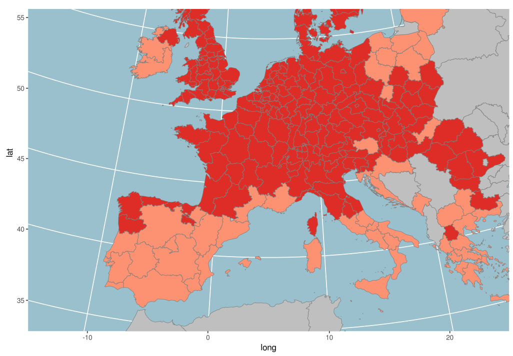
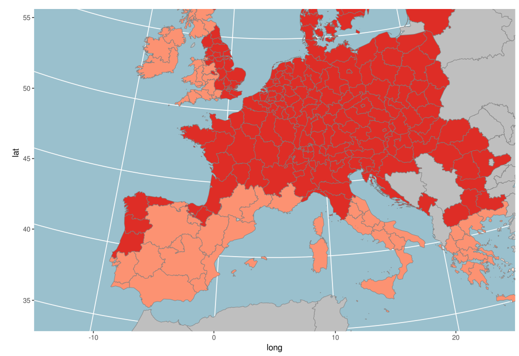
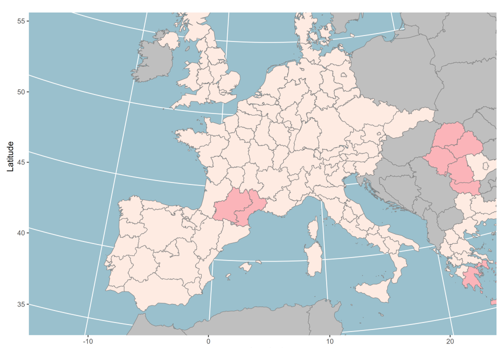
Supplemental Materials: Scoping the potential usefulness of seasonal climate forecasts for solar power management



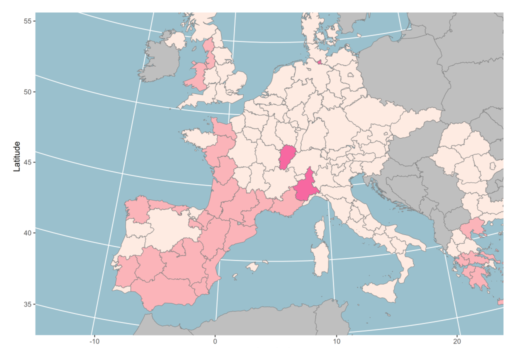
(a) Variability - Spring (MAM)



(b) Variability - Autumn (SON)

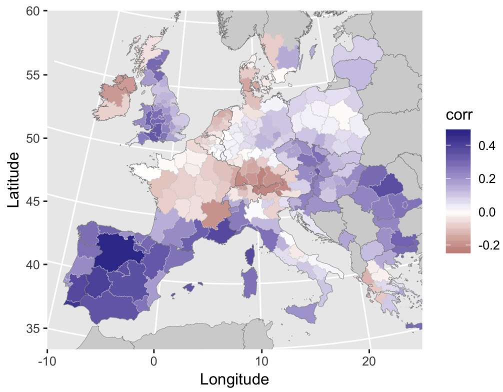


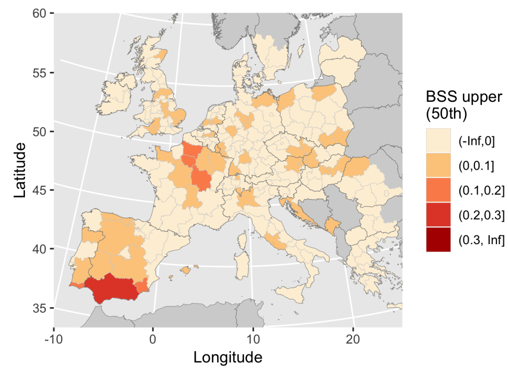
(c) Index - spring (MAM)



(d) Index - autumn (SON)

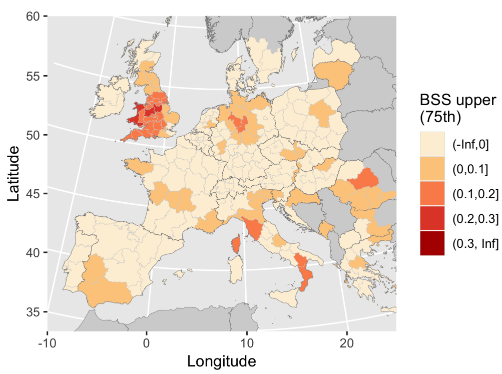
Figure S1: Inter-annual variability and Index of Opportunity for spring and autumn seasons.

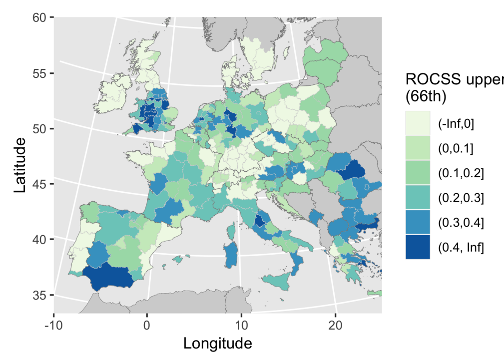




(a) Correlation

(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.