Climate Services 26 (2022) 100294

Contents lists available at ScienceDirect

Climate Services

journal homepage: www.elsevier.com/locate/cliser

Seasonal predictions of energy-relevant climate variables through Euro-Atlantic Teleconnections

Irene Cionni [a,*], Llorenç Lledó [b], Verónica Torralba [c], Alessandro Dell'Aquila [a]

[a] *Agenzia nazionale per le nuove tecnologie, l'energia e lo sviluppo economico sostenibile (ENEA-SSPT), Rome, Italy*
[b] *Barcelona Supercomputing Center (BSC-CNS), Barcelona, Spain*
[c] *Fondazione Centro Euro-Mediterraneo Sui Cambiamenti Climatici (CMCC), Climate Simulations and Predictions Division, Bologna, Italy*

ARTICLE INFO

Keywords:
Seasonal forecasting
Renewable Energy
Teleconnections
Value of service

ABSTRACT

The goal of this analysis is the better understanding of how the large-scale atmospheric patterns affect the renewable resources over Europe and to investigate to what extent the dynamical predictions of the large-scale variability might be used to formulate empirical prediction of local climate conditions (relevant for the energy sector). The increasing integration of renewable energy into the power mix is making the electricity supply more vulnerable to climate variability, therefore increasing the need for skillful weather and climate predictions. Forecasting seasonal variations of energy relevant climate variables can help the transition to renewable energy and the entire energy industry to make better informed decision-making. At seasonal timescale climate variability can be described by recurring and persistent, large-scale patterns of atmospheric pressure and circulation anomalies that interest vast geographical areas. The main patterns of the North Atlantic region (Euro Atlantic Teleconnections, EATCs) drive variations in the surface climate over Europe. We analyze reanalysis dataset ERA5 and the multi-system seasonal forecast service provided by Copernicus Climate Change Service (C3S). We found that the observed EATC indices are strongly correlated with surface variables. However, the observed relationship between EATC patterns and surface impacts is not accurately reproduced by seasonal prediction systems. This opens the door to employ hybrid dynamical-statistical methods. The idea consists in combining the dynamical seasonal predictions of EATC indices with the observed relationship between EATCs and surface variables. We reconstructed the surface anomalies for multiple seasonal prediction systems and benchmarked these hybrid forecasts with the direct variable forecasts from the systems and also with the climatology. The analysis suggests that hybrid methodology can bring several improvements to the predictions of energy relevant Essential Climate Variables.

1. Practical implications

In the framework of the European Green Deal (European Commission, 2021), on 14 July 2021 the European Commission adopted a set of proposals to reduce net greenhouse gas emissions by at least 55% by 2030, compared to 1990 levels. To achieve these results the new 2030 target for renewable energies in the energy mix is set to 40% of final energy consumption. Atmospheric variability is known to affect the energy system as a whole in many aspects (supply, demand, transport and distribution, and energy markets) and at every timescale (from hour-to–hour weather to longer-term climate variability), and the importance of this dependency is only to keep growing with the projected higher shares of renewable energy entering the electricity mix. The generation capacity of solar and wind energies strictly depends on the surface solar radiation and wind speed variability. The sensitivity of electricity demand to temperature is highly significant, cold spells in winter and hot spells in summer can undercut the energy network stability. Severe weather events can strongly impact the delivery of electricity and the ability of the utility to restore power in their service territory. Therefore, it is crucial to understand how to improve the resilience of renewable energy to climate variability. The atmospheric data relevant for the energy sector include, among others, 2 meters temperature for electricity demand, surface solar radiation downward for solar power generation, 10 meters surface wind speed for wind power generation. Until a few years ago, the energy sector used weather forecasts systematically for forecasts up to 15 days and beyond this time

* Corresponding author.
E-mail address: irene.cionni@enea.it (I. Cionni).

https://doi.org/10.1016/j.cliser.2022.100294

Available online 23 April 2022

horizon it used climatological data. Typically, at operational level, climatological averages of reanalysis or in situ data were employed, assuming that the future condition for a certain month (or week) would be similar to past conditions of that month (or week). This methodology presents several limitations since climatological averages could not represent extreme events and could not account for changes in the atmospheric conditions due to the ongoing climate change. In this context, seasonal probabilistic forecasting can inform better decision-making at some temporal scales and regions. Recently, some initiatives (FP7 EUPORIAS, C3S ECEM, H2020 S2S4E, H2020 SECLI-FIRM) have exploited the possibility of using climate predictions for the energy sector, in particular at seasonal time scales. The S2S4E H2020 project, in particular, developed a climate service named DST (Decision Support Tool (DST, 2019)) with the aim to address the needs of the energy sector through the use of seasonal and sub-seasonal predictions. The seasonal climate predictions are able to project the mean conditions and some of the statistical characteristics of the climate a season or two in advance that can wisely support the decision-making process. Seasonal climate prediction can improve the decision-making of renewable energy generation and electricity demand, but also help the scheduling of the Operations and Maintenance of the renewable energy farms or traditional power plants without compromising the security and anticipate energy prices for energy traders. Despite the substantial advancement of the quality of seasonal forecasts over the past decade, some geographic regions (i.e. Europe) and seasons still have significant limitations. Improving the skill of seasonal forecast in these specific regions and seasons, to provide timely and reliable predictions for the atmospheric variables that are known to produce important impacts in the energy supply/demand stress of the European electricity system, could provide a specific added value for the different kinds of users so far involved in the energy sector business.

Taking advantage of our knowledge of large-scale weather patterns, and their possible impacts on the tendencies of energy-relevant variables, is an appealing and innovative approach to improving the overall quality and relevance of seasonal forecasts for the energy sector. Specifically, we consider the North Atlantic Oscillation, East Atlantic pattern, East Atlantic/Western Russia pattern, and the Scandinavian pattern. The methodology shows that 2 meters temperature is the variable most affected by improvements over the continent and consistent across the prediction systems, particularly in winter (up to 24% with respect to the raw prediction) and summer (up to 20%). This result can be translated into an improvement in the prediction of the demand. Wind shows regional improvements in winter (up to 16%) and spring (up to 20%) and radiation in winter (up to 24%), spring and summer and therefore improve the prediction of wind and solar production. The results have been tested also with the extreme events, showing relevant results for the prediction of extremely low temperature in winter and summer (up to 24%).

2. Introduction

Accurate and reliable information from climate predictions at seasonal time-scales can have an essential role to anticipate climate variability affecting supply of renewable energy and to stabilize and secure the energy network as a whole. Seasonal forecasts have potential value as tools for assisting decision-making in climate-sensitive socioeconomic sectors such as energy, agriculture, insurance, health or tourism to cite only a few. The value and benefits of using seasonal forecasts to support decision-making processes rests on the provision of credible products. Evaluation studies can be helpful in understanding the advantages of using seasonal forecasts against other pathways and to improve existing provisions of seasonal forecasts in order to maximize use and value to its users (Bruno Soares and Buontempo, 2019). Seasonal climate forecasts are an intermediate product between short-term weather forecasts and long term climate change simulations. Seasonal climate predictions are generally produced with dynamical prediction systems that couple atmosphere, ocean and land surface models but also their interactions. The feasibility of seasonal prediction largely relies on the existence of predictable signals at seasonal timescale arising from ocean, soil moisture, snow cover or sea-ice anomalies/processes that affect (force) the atmosphere (Doblas-Reyes et al., 2013). One of the main sources of predictability at seasonal timescales are the teleconnection patterns. These teleconnections are recurring and persistent large-scale patterns of pressure and circulation anomalies that span vast geographical areas (Hurrell et al., 2003; Trenberth et al., 2007). Prominent teleconnection patterns that are inherently related to the surface weather conditions in Europe, and known as Euro-Atlantic Teleconnections (EATCs), have been identified in the North Atlantic sector (Barnston et al., 1987). Several previous studies have recognized the strong links between the North Atlantic Oscillation (NAO) (Walker et al., 1932; Lamb et al., 1987; Hurrell, 1995) —the most relevant EATC— and surface temperature, wind speed or precipitation anomalies over Europe on interannual timescales (Trigo et al., 2002; Scaife et al., 2008; Hurrell et al., 2009; Burningham and French, 2013; Svensson et al., 2015). However, more recent studies (Moore and Renfrew, 2012; Comas-Bru and McDermott, 2014; Zubiate et al., 2017; Comas-Bru and Hernández, 2018; Hall and Hanna, 2018; Rust et al., 2015) have shown that taking into account the second, third and fourth modes of variability —namely the East Atlantic (EA), East Atlantic/Western Russia (EAWR) and the Scandinavian (SCA) patterns— greatly improves the representation of the variability and our understanding of the impacts on surface climate. Each teleconnection is composed of a fixed spatial pattern and an associated index (a time series) that describes the evolution of its amplitude and phase. The state of a teleconnection index determines to a certain extent the general atmospheric circulation and thus large-scale advections of temperature and moisture. The interplay of the EATCs exerts a strong impact on climates at different spatio-temporal scales and has important ecological, economical and societal impacts (e.g. Jerez et al., 2013; Bastos et al., 2016; Zubiate et al., 2017).

Analysis of seasonal forecast of multiple systems highlighted significant predictability for tropical climate teleconnections, but only low forecast skill in the extra-tropics, especially the North East Atlantic sector (Palmer et al., 2004) (Doblas-Reyes et al., 2013). In addition, the North Atlantic is highly affected by the 'signal-to-noise paradox' (Dunstone et al., 2016) that consist in climate model simulations that, despite a model spread larger than the observed variability of NAO signal (and therefore a low signal-to-noise-ratio), seems to capture a significant part of the observed variability of NAO. The 'signal-to-noise paradox' (Scaife and Smith, 2018; Dunstone et al., 2016) will be reduced using the average of a large ensemble of simulations and therefore will provide skillful predictions of the NAO on seasonal timescale.

Although several studies have focused on skillfully predicting the state of the NAO during winter season (Scaife et al., 2014; Stockdale et al., 2015; Dunstone et al., 2016; Johnson et al., 2019), only recently the dynamical predictions for the other EATC indices have been explored in the literature (Lledó et al., 2020). Furthermore, several pattern-based approaches have been already implemented for the improvement of dynamically produced sub-seasonal and seasonal forecasts (see Bloomfield et al., 2021 and reference therein). Skillful seasonal predictions of the EATC indices open the door to produce useful regional seasonal climate predictions for European regional weather, hence enable the development of new climate services (Hall and Hanna, 2018).

Shortage of skill is inherent to the Earth system dynamics, but there are additional shortcomings derived from modelling biases (Barnston et al., 2015; Schepen et al., 2016). In some of those cases, the use of empirical methods can substitute or integrate dynamical forecasts (Cohen et al., 2019; Strazzo et al., 2019). An empirical approach can be the characterization in observations of a relationship between predictands and predictors and the exploitation of this relationship to skillfully estimate the predictands in the future (Eden et al., 2015). Simple empirical methodologies have been used to statistically predict

El Niñ-Southern Oscillation (ENSO) evolution (Barnston et al., 1992; Van Den Dool, 1994; van den Dool, 2006) with skill levels comparable to those produced by dynamical systems (e.g. Tippett et al., 2012; van Oldenborgh et al., 2005). Recently, more complex empirical methodologies based on linear inverse models (Newman and Sardeshmukh, 2017) or recurrent neural networks (Huang et al., 2020) have been shown to be more skillful than a multi-system based on the North American Multi-Model Ensemble in some parts of the tropical band (Kirtman et al., 2014). Giuliani et al. (2019) proposed the use of artificial intelligence for producing seasonal hydrologic forecasts based on multiple global climate signals. Empirical methodologies have also been applied to statistically predict the North Atlantic Oscillation (NAO) (Wang et al., 2017) from sea ice extent anomalies, lower stratospheric circulation, and ocean surface temperatures. The work of Wang et al. (2017) also used a statistical model to derive seasonal forecasts of the European surface climate. Rodríguez-Guisado et al. (2019) developed an empirical model for seasonal forecast over the Mediterranean area based on set of global climate indices and Sánchez-García et al. (2019) elaborated a methodology for weighting the member of the dynamical seasonal forecast systems based on the prediction of winter NAO.

An alternative approach is the use of hybrid methods that combine dynamical forecasts of physical processes or circulation variables that are well described in coarse-resolution models, and statistical relationships between circulation indices and surface variables, which typically are more difficult to predict. Statistical techniques based on observations are used to post-process dynamical models with the goal of further improving dynamical models' performance (among others Lledó and Doblas-Reyes, 2020; Specq and Batté, 2020; Strazzo et al., 2019; Zhang et al., 2018).

Here we present and verify a hybrid prediction system for anticipating seasonal anomalies of surface variables that are relevant for the energy sector in Europe, employing the four aforementioned EATCs as predictors in the statistical model. This method can be thought of as a perfect prognosis method (Wilks, 2011) where the observed relationship between the EATCs and the surface variables has been modeled through a multilinear regression. Multiple studies have related surface anomalies with teleconnection indices (e.g. NAO: Hurrell, 1995; Hurrell et al., 2009; Moore and Renfrew, 2012; EAWR: Krichak et al., 2005; SCA: Bueh et al., 2007;) and weather regimes (Torralba et al., 2021). Several of those studies attempt to reconstruct surface variables through the use of EATC indices. For instance, Castro-Díez et al. (2002), limiting their study to the use of NAO, reconstructed temperature anomalies and, more recently Riaz et al. (2017), using NAO and its constituent centers of action reconstructed the climate in Germany. Rust et al. (2015) systematically studied the effect of a set of teleconnection patterns on European temperature and seek for a quantitative description of their individual contribution to temperature anomalies. In addition, northern hemispheric teleconnection patterns have been linked to climate anomalies in North America (Yu et al., 2019) and East Asia (Wang et al., 2011). In our case, we explore the possibility to combine those empirical models with seasonal predictions of the teleconnection indices. Specifically, we focus our analyses in three atmospheric variables that are known to produce important impacts in the energy supply/demand stress of the European electricity system: surface wind speed is a good proxy for wind power generation (Lledó et al., 2019); surface solar radiation together with the 2 meters temperature are the main atmospheric factors affecting solar power generation (Bett et al., 2016); and temperature is also a good indicator of electricity demand (Thornton et al., 2017). Dynamical forecasts of the four EATC indices at one month of lead time and for the four seasons of the year (as in Lledó et al., 2020) are directly fed into the statistical model that transforms values of the teleconnection indices to values of surface variables at each grid point. A similar methodology was used in Ramon et al. (2021), but in that case the goal was to produce downscaled predictions, while here the focus is on enhancing the skill at the scale of the state-of-the-art prediction systems and evaluate the quality gains. The focus of most of the studies mentioned above has been the winter season, but we are aware that forecasts for the other seasons can be relevant as well for energy users. Therefore, our aim is to elaborate an approach that can be employed throughout the year and for both observations and forecasts. The methodology for the EATC patterns and indices calculation already applied by Lledó et al. (2020) replicates the well-known Climate Prediction Center patterns and indices as much as possible (Climate Prediction Center, 2012) and does not rely on identifying the centers of action of the different teleconnections, which vary from one season to another. One example of this can be seen in JJA of the pattern named EAWR, which has a different center of action and localization with respect to the EAWR pattern defined by Lim (2015) with DJF data and by Barnston et al. (1987) with September to March data.

Section 3 describes the datasets, variables and methods employed; in Section 4 the results are discussed and in Section 5 conclusions and future developments are summarised.

Table 1
Features of the seasonal prediction systems employed.

Producing center	Prediction system	Ensemble members	Ensemble generation	Horizontal grid
CMCC	SPS3	40	burst	Regular 360x180
DWD	System2	30	burst	Regular 360x180
UKMO	GloSea5 GC2	28	lagged	Regular 360x180
MF	System6	25	lagged	Regular 360x180
ECMWF	SEAS5	25	burst	Regular 360x180

3. Materials and methods

3.1. Observations

Gridded observational reference of atmospheric variables has been obtained from the ERA5 reanalysis (Hersbach et al., 2020), the latest climate reanalysis produced by the European Center for Medium-Range Weather Forecasts (ECMWF) and based on the Integrated Forecasting System (IFS) cycle Cy41r2. ERA5 produces hourly output at a horizontal resolution of 31 km with 137 vertical levels from the surface to 0.01 hPa. ERA5 presents a higher temporal and spatial resolution than previous reanalyses and assimilates a much larger number of reprocessed datasets, resulting in an improved quality (Fujiwara et al., 2017; Ramon et al., 2019). The ERA5 data employed covers the 1981–2018 period and has been obtained from the Climate Data Store (CDS) of the Copernicus Climate Change Service (C3S) on a regular latitude-longitude grid with a resolution of 0.25° x 0.25°. The data has been regrided to match the spatial resolution of the seasonal forecasts (see Table 1).

Both circulation and surface variables are required for this study. Firstly, 500 hPa geopotential fields are used to derive four teleconnection patterns and indices. Those are obtained from a Rotated Empirical Orthogonal Function (REOF) analysis (Hannachi et al., 2007; Wilks, 2011) of the ERA5 geopotential height seasonal anomalies (without any detrending) at 500 hPa for DJF, MAM, JJA, SON over the Euro-Atlantic domain (90 W-60E and 20 N-80 N). First the geopotential height at 500 hPa anomalies have been weighted by the cosine of the latitude to account for differences in the areas of the grid points, then the EOF analysis has been performed and finally, a Varimax rotation has been applied to the eigen-vectors in order to simplify the spatial structure of the patterns preserving the orthogonality (Mestas-Nunez, 2000). The four obtained REOF modes have been reordered and their sign has been adjusted in order to resemble as much as possible the positive phases of the NAO, EA, EAWR and SCA patterns as computed by NCEP's Climate Prediction Center (Climate Prediction Center, 2012; (Barnston

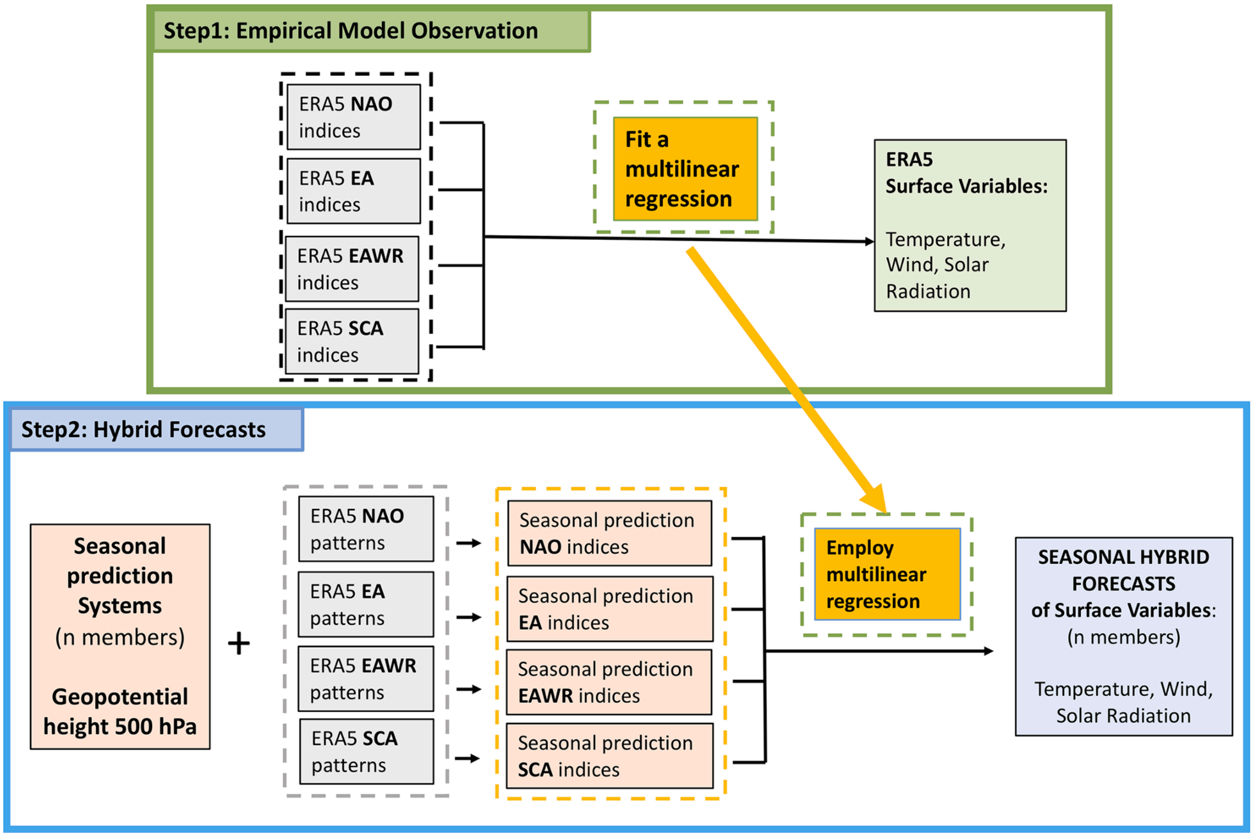

Fig. 1. Description of the methodology.

et al., 1987; Climate Prediction Center, 2012; ECMWF (2019)). Secondly, fields of three energy-related surface variables are also used to a) evaluate the empirical relationships between teleconnection indices and surface variables; b) build enhanced forecasts of those variables; and c) evaluate the skill levels of the new hybrid forecasts. The energy-related variables studied are: 2 meters temperature (t2m), surface wind (sfcwind) and surface solar radiation downward (ssrd).

3.2. Seasonal Predictions

The seasonal predictions analyzed in this study were obtained from the Climate Data Store (CDS) of the Copernicus Climate Change Service (C3S) initiative (Thepaut et al., 2018; Buontempo et al., 2019). The C3S seasonal service is based on a multi-system framework of eight forecast systems. Among the five European centres that are currently providing forecasts to C3S there are the ECMWF, the UK Met Office (UKMO), Météo-France (MF), the Deutscher Wetterdienst (DWD) and the Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC). The seasonal forecasts available at the CDS consist of a set of atmosphere and ocean variables at a 1° x 1° grid, daily or sub-daily temporal resolution and spanning up to 6-months ahead from the start date. Each prediction system provides multiple realisations in the form of several ensemble members. The techniques used to build these ensembles differ among the forecasting system (*burst* vs *lagged* ensemble, see ECMWF (2019)) but all are designed to sample the uncertainty that arises from imperfect knowledge of the initial conditions. Table 1 summarizes the most relevant features of the operational prediction systems employed.

We analyze one-month lead seasonal forecasts of t2m, sfcwind and ssrd. Therefore, we consider predictions initialized in November for the study of the season December-January-February (DJF); predictions initialized in February for the season March-April-May (MAM); predictions initialized in May for the season June-July-August (JJA) and predictions initialized in August for the season September-October-November (SON) from the C3S seasonal multi-system ensemble. The hindcast period is 1993–2018 for MAM, JJA and SON, 1993/1994–2017/2018 for DJF.

Forecasts of the EATC indices for the four seasons of the year and one month of lead time were also derived from 500 hPa geopotential height forecasts by projecting the anomalies of individual members onto the ERA5 EATC patterns, as in Lledó et al. (2020).

3.3. Surface impacts of the teleconnections

The signature of each teleconnection on the energy-relevant surface variables has been assessed through Pearson correlation analyses. The observed teleconnection indices (i.e. the rotated PCs) have been correlated with the time series of the ERA5 anomalies of 2 meters temperature, surface wind and surface solar radiation at each grid point over Europe. The observations cover the 1981–2018 period (37 years), and the statistical significance has been checked using a two-tailed Student's t-test with N-2 (35) degrees of freedom at a 99% level of confidence.

The surface impacts of the four teleconnections have also been analyzed in the seasonal prediction systems and compared to the observed (ERA5) impacts. In this case both the observed and modelled correlations are computed for a shorter period (1993–2018). The correlations between forecasted EATCs and its respective surface variable predictions have been produced considering the ensemble mean. The statistical significance of the differences is assessed with a Fisher's transformation performed on the correlations, which are computed for the same temporal range (1993–2018). Therefore, the data has been considered dependent but non-overlapping.

3.4. Construction of hybrid forecasts

In order to improve the seasonal forecasts of surface variables, we combine the dynamical seasonal predictions of EATC indices with the

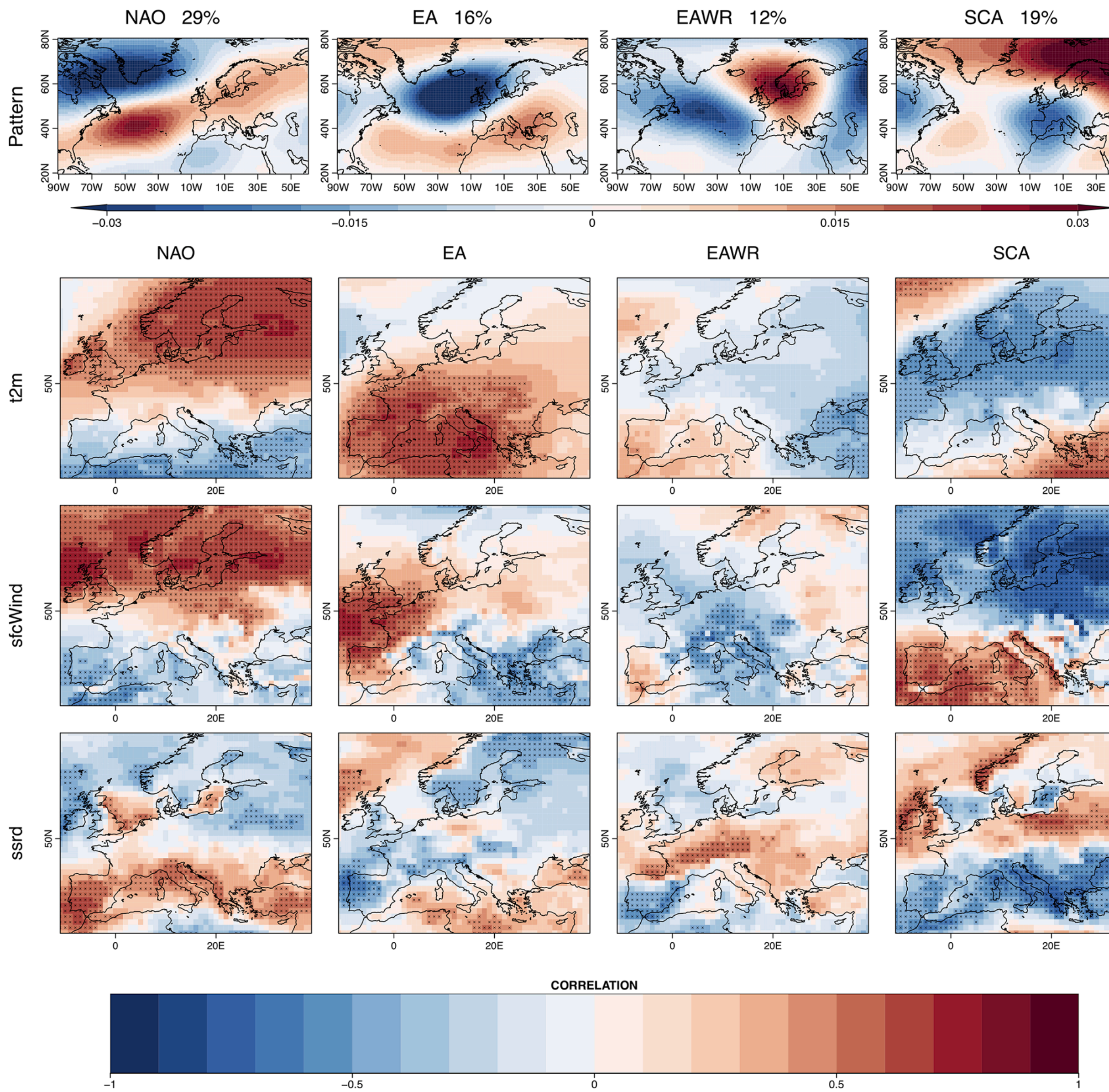

Fig. 2. The loading patterns (i.e. of norm one) of the four Euro-Atlantic teleconnections obtained for DJF from ERA5 geopotential height anomalies at 500 hPa in the 1981–2018 period and the correlation between indices associated with these patterns and surface anomalies (t2m, sfcWind and ssrd).

empirical (observed) relationship between EATCs and surface variables. This method can be thought of as a perfect prognosis method (Wilks, 2011) where the observed relationship between EATCs and surface variables has been modeled through a multilinear regression.

The schematic representation of the methodology is shown in Fig. 1.

1. The first step consists in finding an empirical relationship that relates observed EATC indices and observed surface variables. For each surface variable (t2m/sfcwind/ssrd) and for each grid point, a statistical relationship between the four observed EATC indices and the observed seasonal mean values is sought. Since the sample sizes available for training are not large, a simple model is used here. The surface anomalies at each grid point have been expressed as a multilinear combination of the EATC indices. For each time t and location (x, y), the observed anomalies have been approximated as:

$$Anom(t,x,y) \approx a(x,y) * NAO(t) + b(x,y) * EA(t) + c(x,y) * EAWR(t) + d(x,y) * SCA(t) \quad (1)$$

where NAO, EA, EAWR, and SCA are the four observed EATC indices. The multilinear regression coefficients a, b, c, and d that minimize the approximation error for each grid point are obtained using ordinary least squares. Determination coefficients of each multilinear model fit have been used as an indication of goodness of fit.

2. In the second step, the EATC index forecasts from the dynamical systems are directly plugged in into Eq. 1 to reconstruct an ensemble of forecasts (hybrid forecast) of the surface variables. The hybrid forecasts are reconstructed for each season, predictions system and member separately. The reconstruction is done in cross validation, excluding the year of interest from the training sample used for the estimation of the regression coefficients.

3.5. Forecast quality assessment

The quality of the hybrid forecasts is assessed with observed anomalies of surface variables from the ERA5 reanalysis. We consider two scores that measure the reliability and resolution of probabilistic predictions (Jolliffe and Stephenson, 2011): the Brier Score (BS) (Brier,

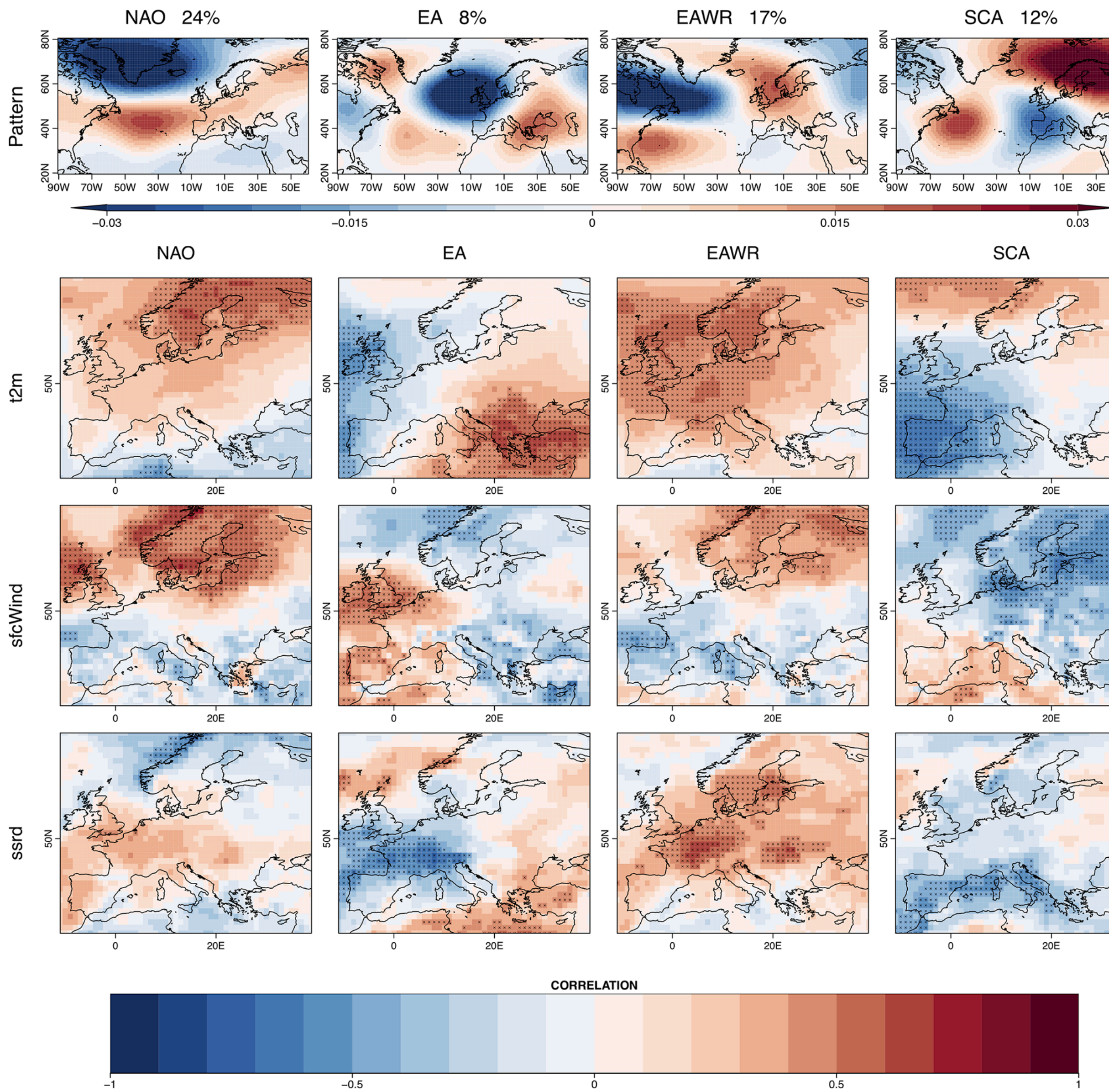

Fig. 3. The loading patterns (i.e. of norm one) of the four Euro-Atlantic teleconnections obtained for MAM from ERA5 geopotential height anomalies at 500 hPa in the 1981–2018 period and the correlation between indices associated with these patterns and surface anomalies (t2m, sfcWind and ssrd).

1950) is used to evaluate single-category forecasts (e.g. exceeding the 90th percentile), while the Ranked Probability Score (RPS), (Epstein, 1969) is used for tercile category (below normal/normal/above normal) forecasts. Both the reference climatology and the dynamical predictions of the surface variables have been used as benchmark to understand the performance enhancement of the hybrid methodology. The associated skill scores, Brier Skill Score (BSS) and Ranked Probability Skill Score (RPSS), express the improvement with respect to the reference benchmark, and are computed respectively as:

$$BSS = 1 - \frac{BS}{BS_{ref}} \tag{2}$$

where BS is the score obtained for the hybrid model forecasts and BS_{ref} the one for the dynamical predictions; and as

$$RPSS = 1 - \frac{RPS}{RPS_{ref}} \tag{3}$$

where RPS is the score obtained for the hybrid model forecasts and RPS_{ref} the one for the dynamical predictions.

The forecast quality is assessed in a leave-one-out cross-validation setting (Jolliffe and Stephenson, 2011; Wilks, 2011). The forecasts for each year are produced with a separate model trained with the corresponding observations set aside, to guarantee that an independent observation is used in the verification. see Fig. 1.

4. Results and Discussion

4.1. Observed surface impacts of the Euro-Atlantic teleconnections

Following the methodology described in Section 3 and in Lledó et al. (2020), EATC patterns and indices have been obtained from ERA5 data. The surface impacts of those four variability modes have been assessed through correlation analysis of the teleconnection indices with the surface variables. Figs. 2–5 show the geographical distribution of the correlation between the four EATC indices (NAO, EA, EAWR, SCA) and the three variables for each season of the year (DJF, MAM, JJA and SON). The percentage of variance explained by each EATC pattern is reported

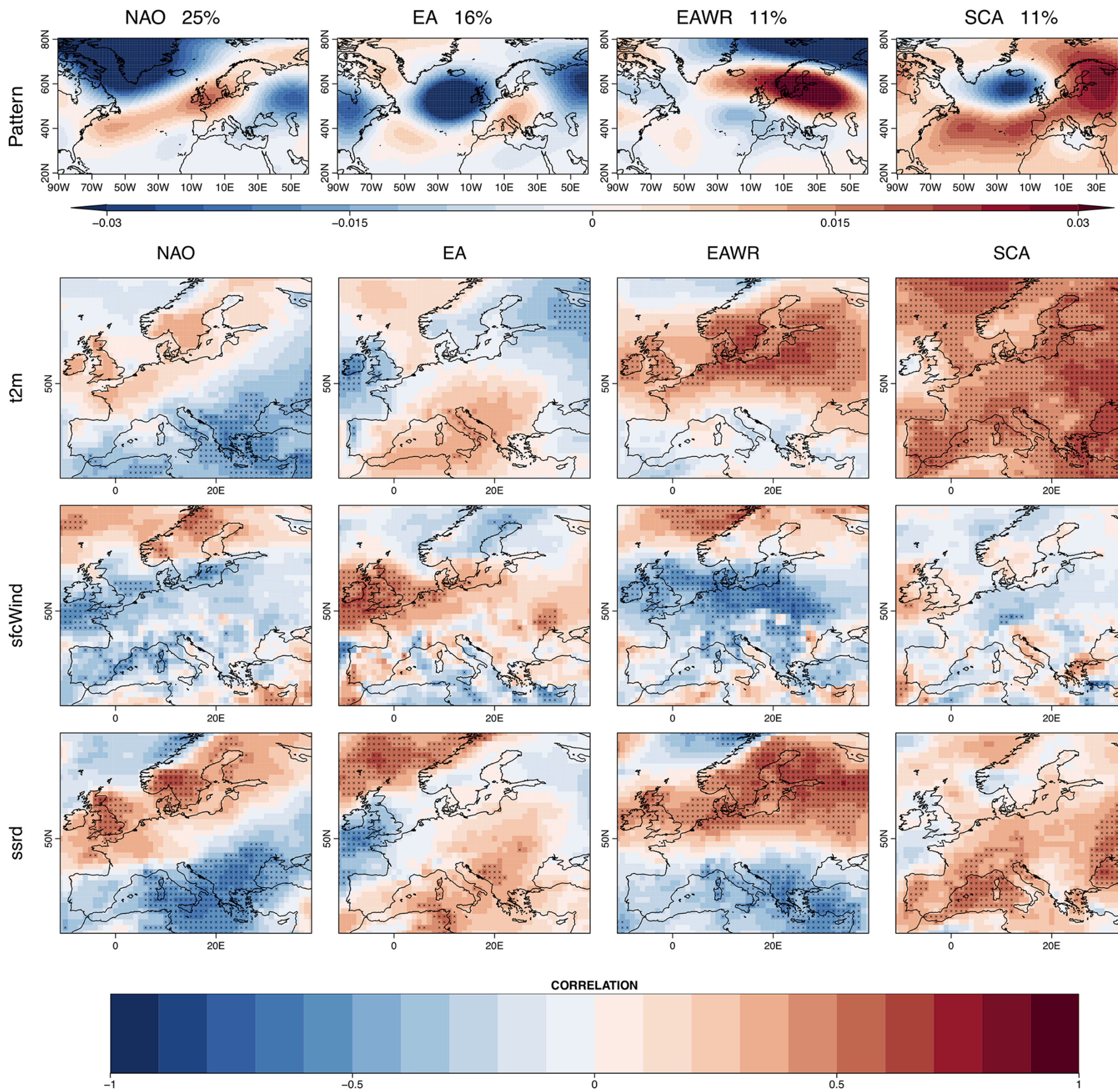

Fig. 4. The loading patterns (i.e. of norm one) of the four Euro-Atlantic teleconnections obtained for JJA from ERA5 geopotential height anomalies at 500 hPa in the 1981–2018 period and the correlation between indices associated with these patterns and surface anomalies (t2m, sfcWind and ssrd).

in the top title (2–5). The values of cumulative variance for the EATC other than NAO are always higher than the 30%. The unexplained variance is between 24% in DJF and 39% in MAM. These values support the thesis that to describe the Euro-Atlantic atmospheric circulation variability a multiple pattern approach is needed. The strongest surface impacts are seen in winter (DJF, Fig. 2). In this season, the NAO has a prominent role and its positive phase is linked to higher temperatures and higher wind speeds in northern Europe, and higher surface solar radiation in southern Europe. The widely known action of NAO in its positive phase is the strengthening of the wind field with a consequent advection of moist warm air to the northeast, producing warmer conditions over most of Europe, from Scandinavia to Central Europe (e.g. Scaife et al., 2008). During the positive NAO, these areas are generally interested by anticyclonic circulation with reduced precipitation and cloud cover. The positive phases of EA in winter are also associated with high temperatures occurring over southern and central Europe jointly with high winds over western Europe and low winds over the Mediterranean basin. The solar radiation is also affected by the EA state but the patterns are patchier: its positive phase is accompanied by reductions of radiation over the Iberian Peninsula, the Alps and parts of Scandinavia, and increased radiation over the Mediterranean basin. The SCA in winter has similar impacts to those of NAO but of reverse sign: low temperature, low wind and high solar radiation over northern Europe and high wind and low solar radiation over southern Europe. The role of the EAWR in winter is more focused, with reductions of surface wind around Italy and a dipole pattern in solar radiation in France, Germany and the Iberian Peninsula.

In spring (MAM, Fig. 3), the NAO is still correlated with temperature and wind, but mainly over Scandinavia, and the effects on surface solar radiation are not anymore significant over land. Positive phases of the EA significantly increase temperatures over southeastern Europe and decrease temperature in the western Atlantic coast (British Isles and Portugal), where the wind also increases, while the solar radiation decreases over France. The EAWR has a significant and consistent impact on temperature over most of Europe, with increases also of solar radiation in central Europe and increases of wind in Scandinavia. The positive phases of the SCA lead to a reduction of the temperature over Iberian Peninsula and surroundings, the wind speed over Scandinavia

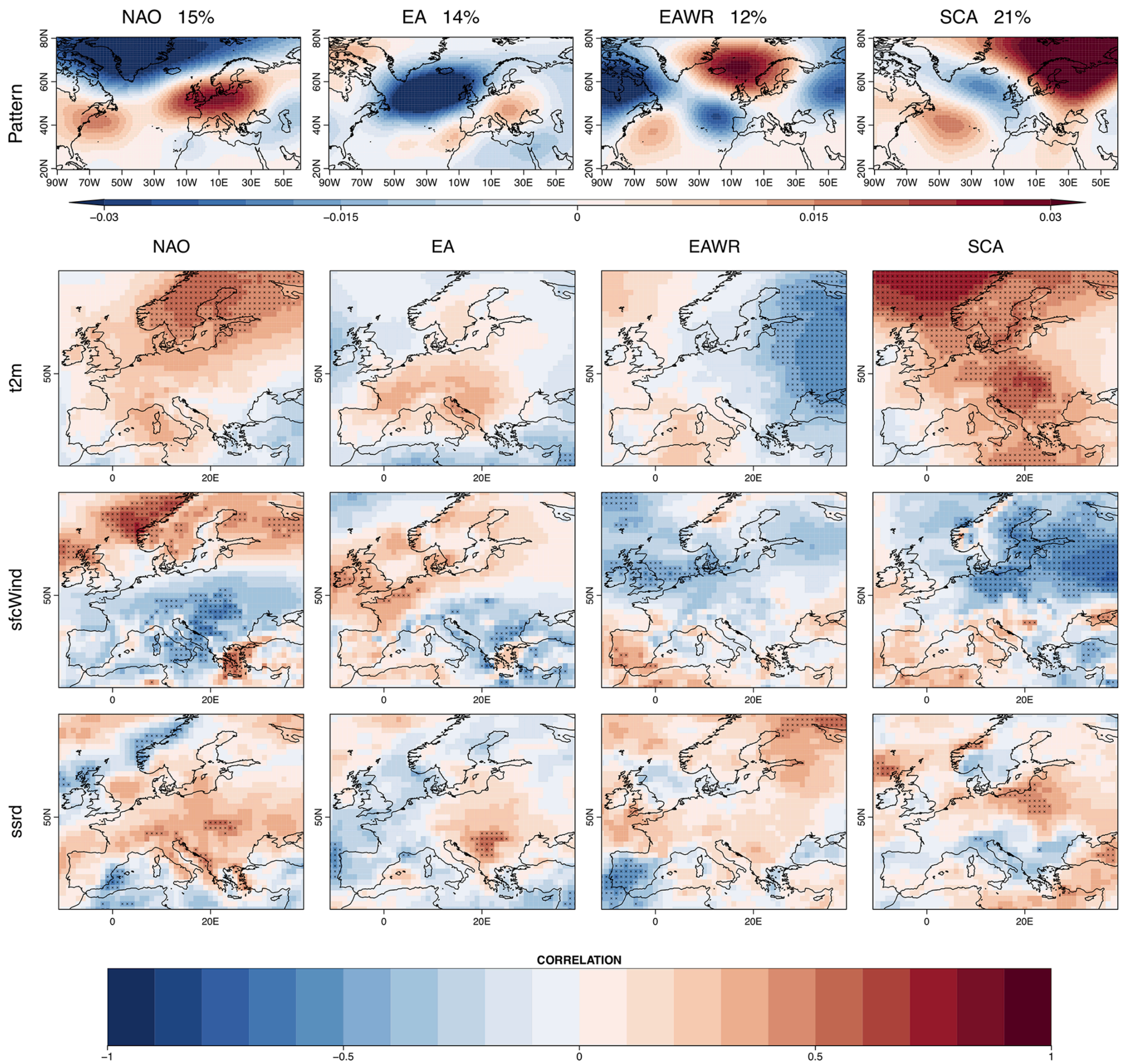

Fig. 5. The loading patterns (i.e. of norm one) of the four Euro-Atlantic teleconnections obtained for SON from ERA5 geopotential height anomalies at 500 hPa in the 1981–2018 period and the correlation between indices associated with these patterns and surface anomalies (t2m, sfcWind and ssrd).

and eastern Europe and the solar radiation over southern Europe.

In summer (JJA, Fig. 4), the positive phases of the SCA teleconnection have a very consistent effect of increasing temperatures all over the European continent, accompanied also by increased solar radiation. EAWR pattern in JJA doesn't resemble the EAWR pattern defined for winter by Lim (2015) and Barnston et al. (1987) and has a positive phase related to high temperatures, low wind and high solar radiation over northern Europe. The NAO exerts a weaker signal in this season, with a negative influence on southern Europe temperatures and radiation, and increases of solar radiation and decreases of wind over the British Isles. The signature of the EA shows the opposite NAO effect over the British Isles with high wind, low radiation and low temperature.

The signature of the four EATCs is less evident in autumn (SON, Fig. 5) than in other seasons. Positive phases of the SCA have a statistically significant effect of increasing continental temperatures and decreasing wind in northeastern Europe. The autumn NAO is associated with high temperatures and high winds over Scandinavia, and low winds over Italy. The EA and EAWR are poorly correlated with all surface variables with only small patches of significant correlations.

Fig. 2 to Fig. 5 indicate that the influence of EATC on the surface variable largely depends on the season and the region of interest. Although in some seasons the role of a certain EATC seems to be less relevant, the methodical use of all four patterns appears to offer a complete representation of the state of the atmosphere and its impact on surface variables.

4.2. Surface impacts of the teleconnections in the dynamical prediction systems

In this section, we briefly evaluate if the dynamical prediction systems are able to faithfully reproduce the teleconnection impacts that we have described in the previous section. Retrospective forecasts of the EATC indices (see Methods section) are correlated with the corresponding (i.e. ensemble mean) surface variable forecasts, and compared to the observed (ERA5) correlations. Fig. 6 shows the differences between the observed DJF correlation (ERA5) and the correlations obtained for ECMWF SEAS5 forecasts at a lead time of 1 month. Although in general terms the correlation patterns of ERA5 and ECMWF SEAS5 are

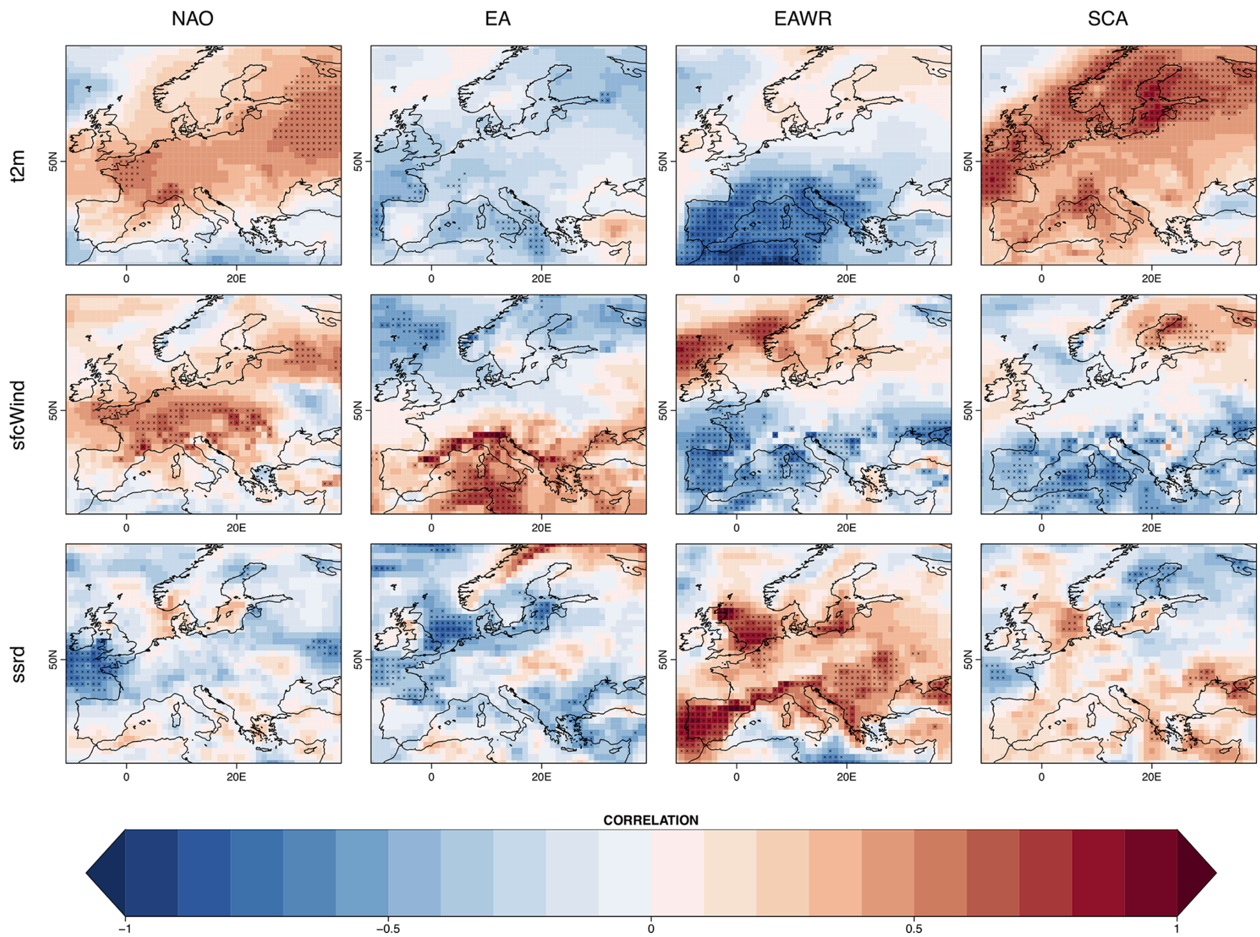

Fig. 6. Differences between the observed surface impact (observed correlation) and the modelled surface impact (correlation in the predictions) in DJF for the SEAS5 predictions issued one month ahead. Dots indicate the grid points where the correlation difference is statistically significant.

quite similar in shape and position, overall the correlations are stronger for the observations than for the models, with significant differences of up to 0.6 points in some patterns and regions.

These results indicate that the ECMWF SEAS5 system is not able to exactly reproduce the teleconnection impacts that were expected from the observational analysis. It is worth noting that the other analyzed prediction systems exhibit similar biases in terms of correlation with wind, temperature and solar radiation (not shown). The inability of the seasonal prediction systems to reproduce accurately the relationship between EATC patterns and surface impacts prompts to employ hybrid dynamical-statistical methods. The idea consists in combining the dynamical seasonal predictions of EATC indices with the observed relationship between EATCs and surface variables.

4.3. Performance under perfect knowledge of the teleconnection indices

A separate multilinear model has been fitted at each grid point for the three surface variables. The determination coefficient r^2 (i.e. the squared Pearson correlation coefficient) of the multilinear model fit is often used as an indicator of the goodness of fit. It indicates the percentage of variability in the observed predictand (surface anomaly) that is explained by changes in the observed predictors (the EATC indices). This can also be thought of as the maximum quality that one can expect from the hybrid forecasts if the state of the four EATCs is known. Fig. 7 shows a map of the determination coefficients for each surface variable and season. As it can be seen, the performance of the statistical model depends on the region, variable and season. Generally speaking, the performance is better in winter for both temperature and wind, while for solar radiation it is better in summer (the season with highest solar energy generation). The r^2 values are moderate or high in those regions where at least one of the teleconnections has a strong impact. For instance, in winter the four teleconnections have impacts spread across different regions of Europe (see second row of Fig. 2), therefore the resulting r^2 is high almost everywhere. On the other hand, the impacts on wind (third row of Fig. 2) are concentrated in the northern part of Europe, and consequently we see lower r^2 values in southern Europe. In spring, the r^2 values are higher for temperature and wind in Scandinavia where mainly NAO and EAWR have an impact (Fig. 3), while for surface solar radiation, higher coefficients are seen over France and the Alps (generally associated with EA). In summer, the proposed methodology can potentially perform well for eastern European temperatures. Surface solar radiation and wind have high r^2 values over Baltic and British Isles in agreement with the effect of EA, EAWR and NAO (Fig. 4). Autumn is the season with the worst potential performance, in accordance with weaker teleconnection impacts in that season (Fig. 5). Overall, the results show that a good knowledge of the four EATC indices would translate in skillful forecasts of the surface variables.

In regards to the energy applications, Fig. 7 draws attention to the ability of the methodology on representing temperature in winter over most of the continental Europe, especially the densely populated area over France and Germany, where the winter temperature drives the heating degree days, a proxy for energy demand needed to heat home or a business. On the other hand, the fair goodness of fit over Italy in summer can be a good proxy for energy demand needed to cool home or a business. The good representation of the temperature over Scandinavia during spring can be of interest for the decision makers in the management of water reservoirs since a high melting of the snow in this

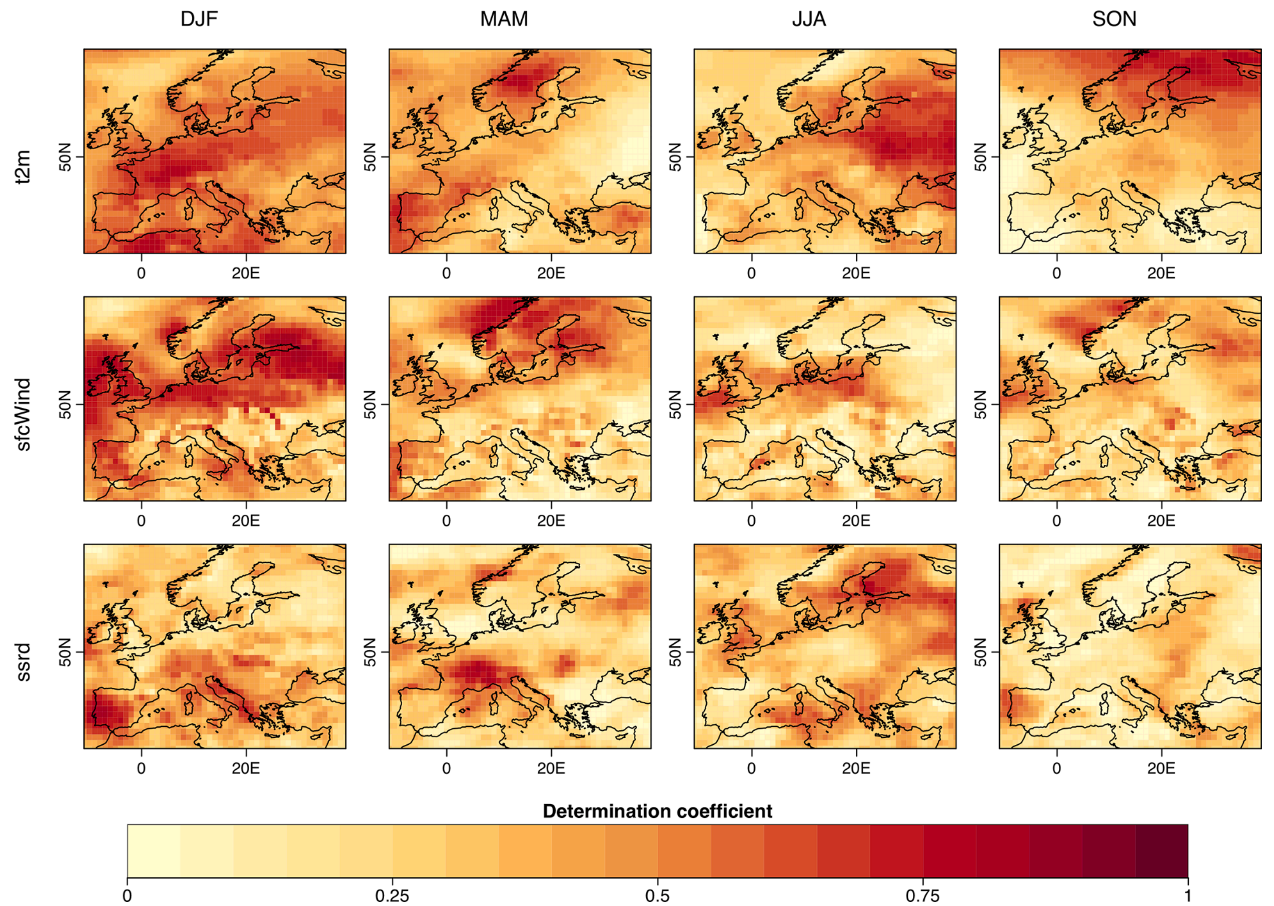

Fig. 7. Goodness of fit (r^2) of the multilinear regression for each of the surface variables (rows) and seasons of the year (columns).

season can determine the peak of the hydropower reservoir inflow. Germany, Spain, UK and France have the highest cumulative installed capacity in Europe (Wind Europe, 2021) and the wind energy generation has a peak of production from October to March (Eurostat, 2021). The fit in Fig. 7 shows that wind can be well represented by the EATCs in winter over the north of Europe and Iberian Peninsula. Solar energy generation peaks from March to October March (Eurostat, 2021). Fig. 7 shows that surface solar radiation is well fitted in MAM over Italy and south of France and JJA in the south of Italy and Mediterranean region.

4.4. Skill assessment of the hybrid forecasts

Probabilistic forecasts of the surface variables are reconstructed here by using forecasted EATC indices and the observed (ERA5) multilinear regression coefficients. As mentioned the reconstruction is done in cross validation, this procedure allows a fair evaluation of the forecast quality in an operational prospective. The hybrid (retrospective) forecasts are evaluated with respect to ERA5 observed values and its skill compared to the dynamical predictions and the reference climatology.

Figs. 8–10 show the RPSS values for each prediction system listed in Table 1, and for a lead time of one month. These figures use the raw dynamical predictions of the surface variables as the benchmark to beat, and only the positive RPSS values (i.e. improvement over the baseline) are shown. The black dots indicate the grid points where hybrid predictions are better than climatology (i.e. the hybrid forecasts perform better than both baselines). The results for temperature (Fig. 8) show important improvements in winter and summer for most prediction systems (all but CMCC). In spring, the benefits can only be seen around the Iberian Peninsula, whereas in autumn the improvements are mostly concentrated over the North Sea region.

The improvements in surface wind predictions (Fig. 9) are more modest and spatially discontinuous, but with an evident enhancement of predictive skill in spring for almost all the systems. In winter, there are patterns of improvements over North Europe for DWD, UKMO and Meteo-France. In spring, most of the systems show improvements over the Iberian Peninsula, similarly to the temperature results. DWD shows a large improvement over southern Europe. In summer, there are only small and irregular patterns of improvements; in UKMO these patterns are localized over most of the Mediterranean coast. In autumn, hybrid predictions are only better in some spots over northern Europe.

Hybrid predictions for surface solar radiation (Fig. 10) in winter have good performance over the Mediterranean region, Central Europe and Baltics (especially for DWD and UKMO). In spring, hybrid predictions are skillful in Scandinavia (almost all systems), France and Germany (UKMO and Meteo-France). In summer, UKMO and Meteo-France show improvements over northeastern Europe, whereas SEAS5 shows improvements in the Mediterranean region. In autumn, the performance of the hybrid methodology has worst performance, excluding some spotted enhancements over the Iberian Peninsula in DWD and Meteo-France and over Greece in UKMO, SEAS5 and Meteo-France.

The hybrid methodology outperforms quite uniformly among the prediction systems analyzed, showing positive values of RPSS in almost the same regions and seasons, especially for temperature. On the other hand, the significance test applied to the RPSS of hybrid prediction with respect to climatology and based on a bootstrap methodology (with replacement and N = 500) indicates a generally low statistical significance of the results. A comparison between RPSS and Fig. 7 shows that improvements in hybrid predictions generally follow the performance of the model under perfect condition. This is particularly true for the DWD system. In Lledó et al. (2020) DWD is shown to be the system that has the best EATC index forecasts at one month of lead time. This indicates that the better the system represents the EATCs the better the hybrid

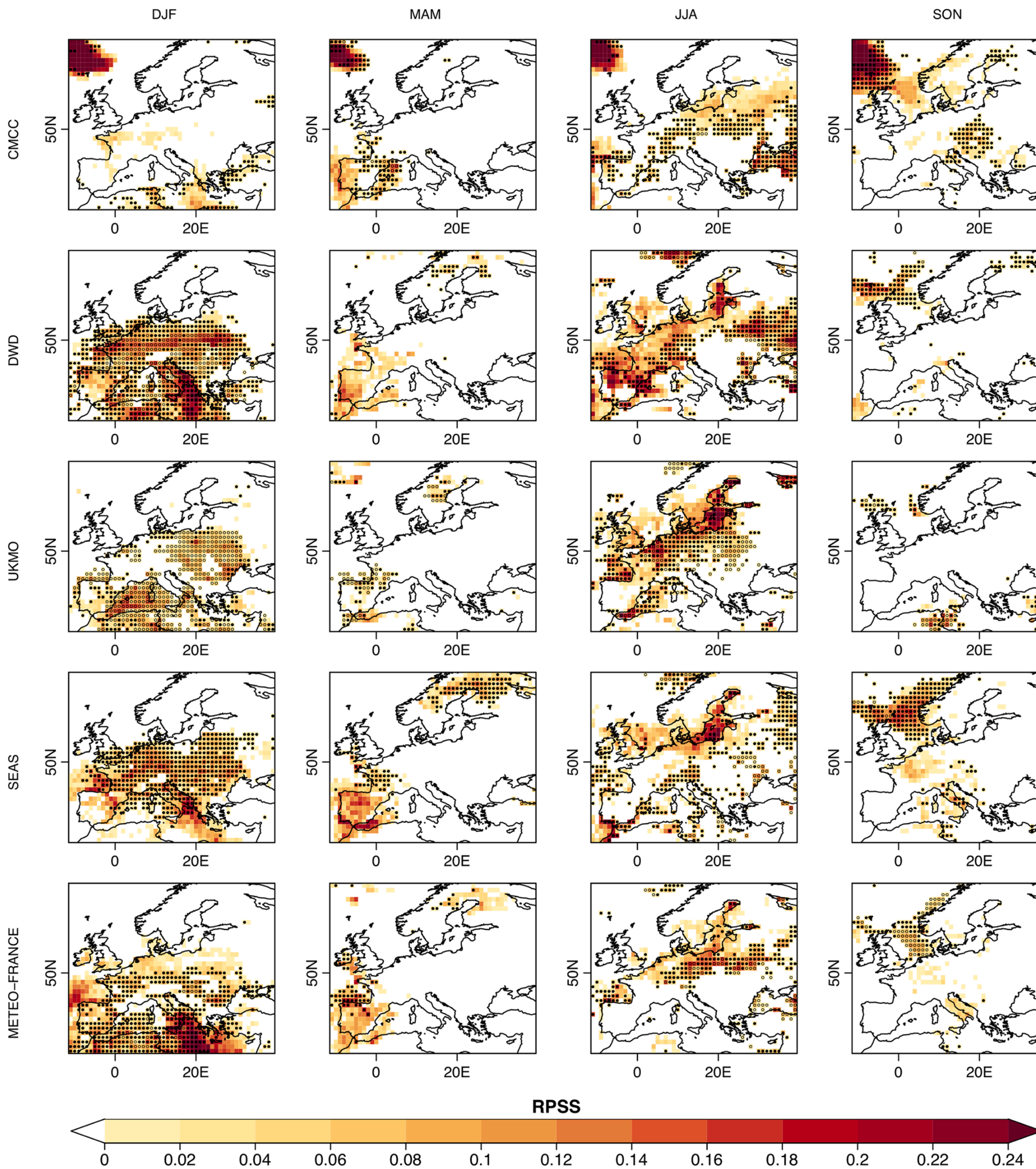

Fig. 8. Ranked Probability Skill Score of hybrid forecasts of surface temperature compared to the dynamical prediction forecasts over Europe. Hybrid forecasts from CMCC, DWD, UKMO, SEAS and M-F have been employed to reconstruct forecasts of surface temperature in DJF (first column), MAM (second column), JJA (third column) and SON (fourth column). Raw forecasts have been employed as benchmark. Empty circles indicate grid points where the hybrid predictions are better than the dynamical predictions and better than the climatology reference. Black full dots indicate grid points where the hybrid predictions are better than the dynamical predictions and significantly better than the climatology reference (p-value $>$ 0.05).

predictions are. However, if the model is not able to anticipate the correct index values, but well simulates surface variables, the hybrid methodology doesn't add any value to the raw predictions.

The renewable energy sector can be largely affected by extreme events: low wind speed or low surface solar radiation can decrease the expected production of wind and solar energy. More generally, extreme weather has a significant impact on critical infrastructures such as the electrical power lines, causing large damage on transmission and distribution facilities (Panteli and Mancarella, 2015). Extremely high or low temperatures, prolonged heatwaves or cold waves, heavy snow or ice accretion can increase the energy demand, limit the transfer capability of transmission lines, increase the energy losses or cause failures of overhead lines. High winds can also damage the transmission lines and difficult the operation and maintenance tasks of wind farms, especially the offshore wind farms. For all these reasons, it is useful to assess the capacity of seasonal forecasts to identify extreme events (Orlov et al., Feb. 2020). In particular, we want to assess the performance of the probabilistic hybrid forecasts at anticipating events where the seasonal means of t2m, sfcwind or ssrd exceed the 90th percentile of the climatology, or fall below the 10th percentile. To such end we use the BSS

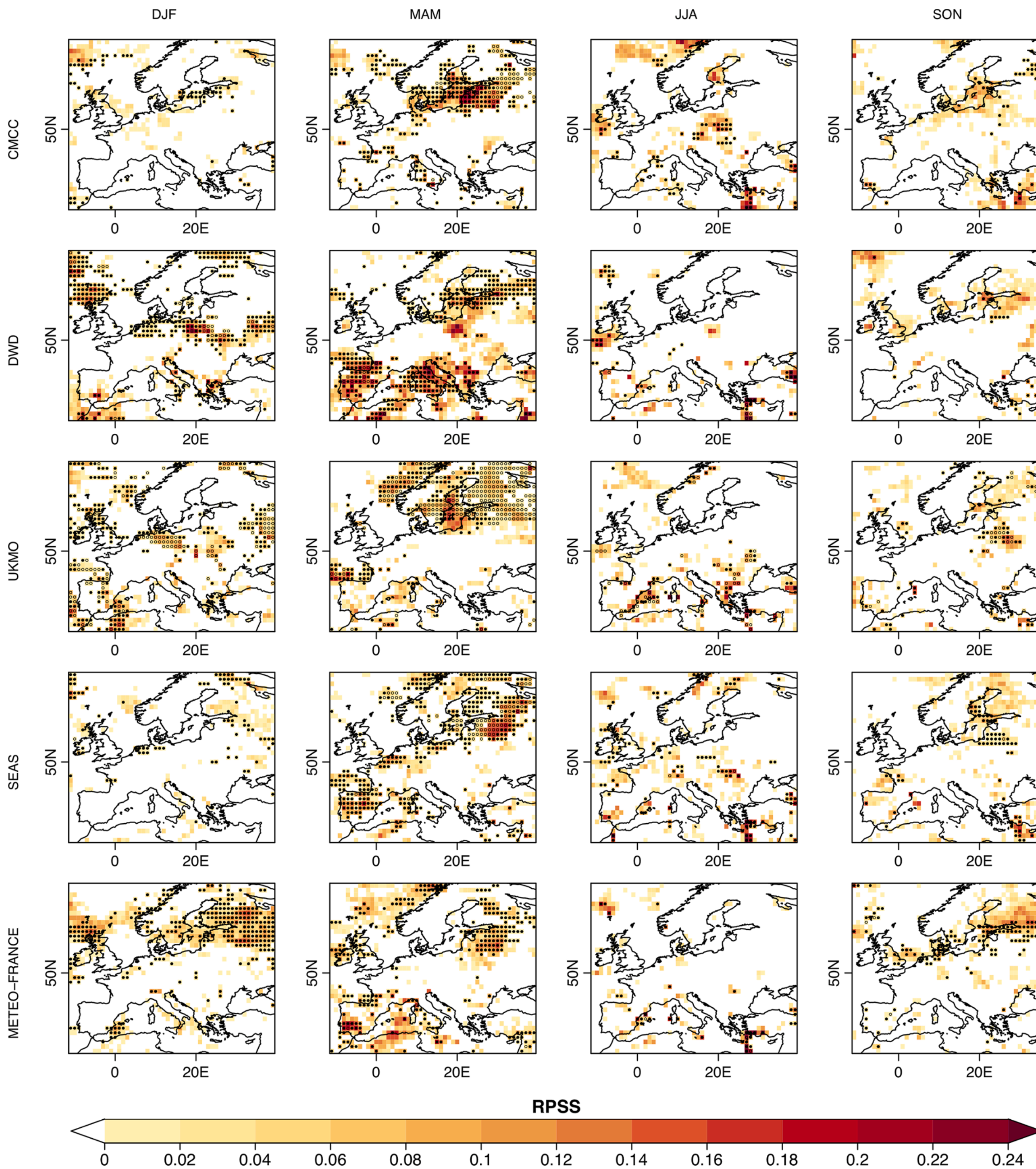

Fig. 9. As Fig. 8 for surface wind.

metric (see Methods).The analysis of the predictive skill of the 90th percentile and 10th percentile seasonal mean anomalies cannot be interpreted as the analysis of the extreme indices based on daily data. Previous study stated that there is a strong relationship between the seasonal mean temperature and the number of extreme days in a certain season (Hamilton et al., 2011). In the same way, a link between the skill in predicting the number of extreme days and the skill in predicting the seasonal mean extremes has been suggested(e.g. Hamilton et al. (2011) Bhend et al. (2016)). Nevertheless, these studies pointed out that predictive skills of daily data are generally lower than the skill of seasonal mean daily indices. In addition, recent trends due to global warming could generate overconfidence on predictive skills (Prodhomme et al., 2021). The BSS is presented for the 10th percentile forecasts and in Fig. 12 for the 90th percentile forecasts, both for the DWD system. The BSS values obtained are quantitatively relevant in some regions, up to values of more than 0.2. The hybrid methodology improves the representation of the extremely high temperatures (top row in Fig. 11) over Greece and Finland in winter; over parts of the Alps and Italy in spring; over France, the Baltic Sea and North Sea region in summer; and over the eastern Mediterranean basin in autumn. For forecasts of extremely high winds (central row in Fig. 11) consistent improvements are seen in Finland and the Baltic countries in winter and spring, with also some spots over the British Isles or the Mediterranean ares in those two seasons. Predictions for high extremes of solar radiation (bottom row in Fig. 11) are improved in winter over the Mediterranean and Scandinavia, in spring over southern Scandinavia and in summer in the western

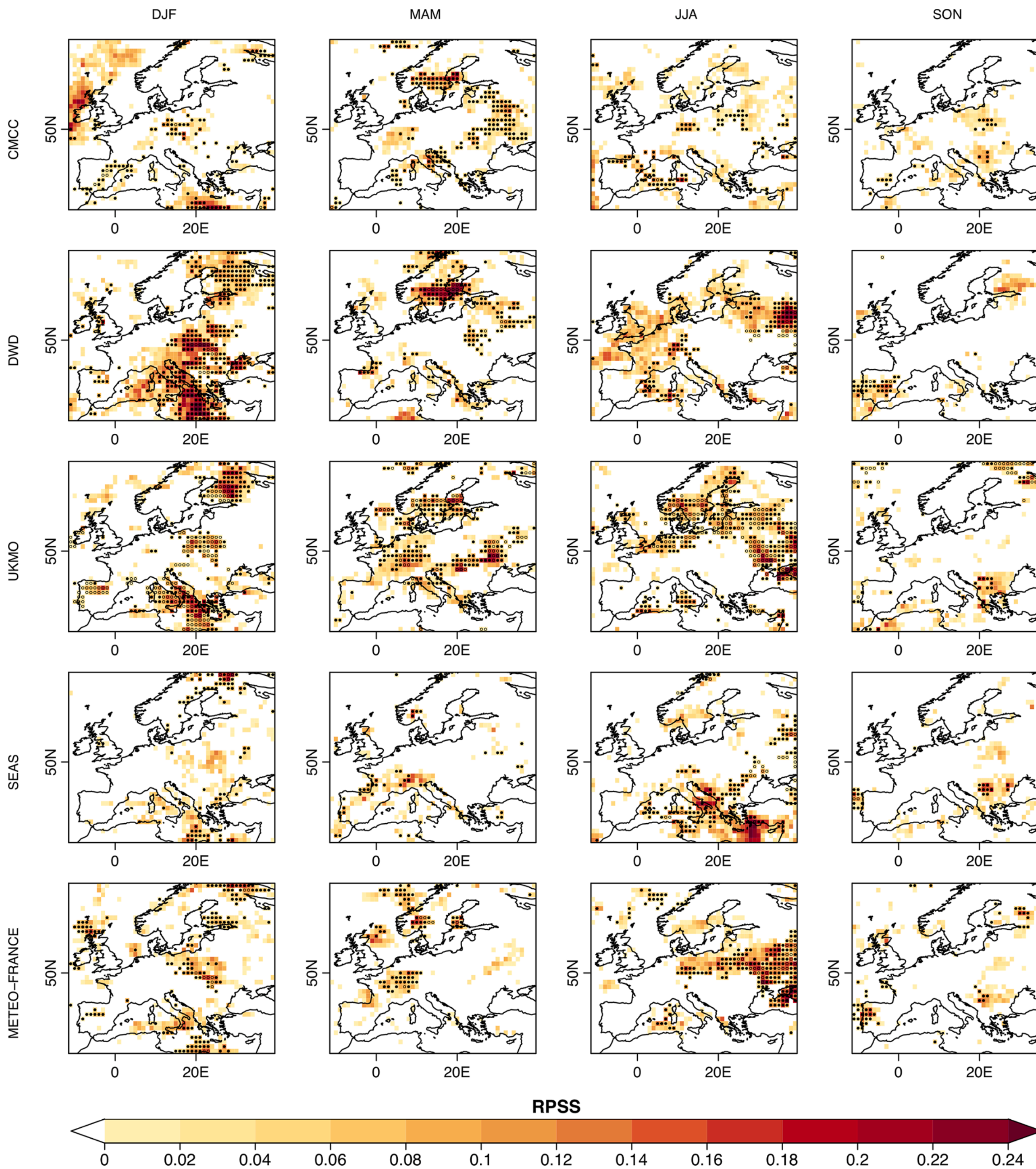

Fig. 10. As Fig. 8 for surface solar radiation.

part of the Iberian Peninsula. The performance of the hybrid method at predicting extremely low temperatures (Fig. 12) is noticeably improved in winter and summer, specially, in Scandinavia and the Mediterranean. Extremely low skills of surface winds are only enhanced at some localized areas, whereas for low extremes of solar radiation some important improvements can be seen in Sweden, Denmark, Ukraine and Romania in spring, the Iberian Peninsula in autumn and parts of central Europe in winter.There is a generally low statistical significance of the BSS of hybrid prediction with respect to climatology based on a bootstrap methodology (with replacement and N = 500).

We separated the two components (reliability and resolution) of the hybrid forecast BS and dynamical forecast BS and then evaluated the differences (Figs. 1A–4A in Supplementary Material). The improvements of the hybrid BS are mostly due to improvements in the resolution part of the BS. Despite the challenges involved in the definition of a skill threshold from which the hybrid prediction can be useful for the forecasters in the energy sectors, the improvements of the skill values up to 0.24 suggests that the hybrid forecasts show a "fair to "good" quality. We express this judgment based on the metrics defined with the energy users during the development of the Decision Support Tool (DST) in the H2020 S2S4E. In the DST, BSS and RPSS values have been expressed as a percentage (which is easier to understand than the real values of these skill scores ranging from -∞ to 1.), where a value of 1 correspond to 100% skill and this will be described based on terms (perfect, good, fair, …) that qualitatively measure the performance of the forecast. The terms used in DST are: "fair" for skill above 0 and below 15% (or 0.15),

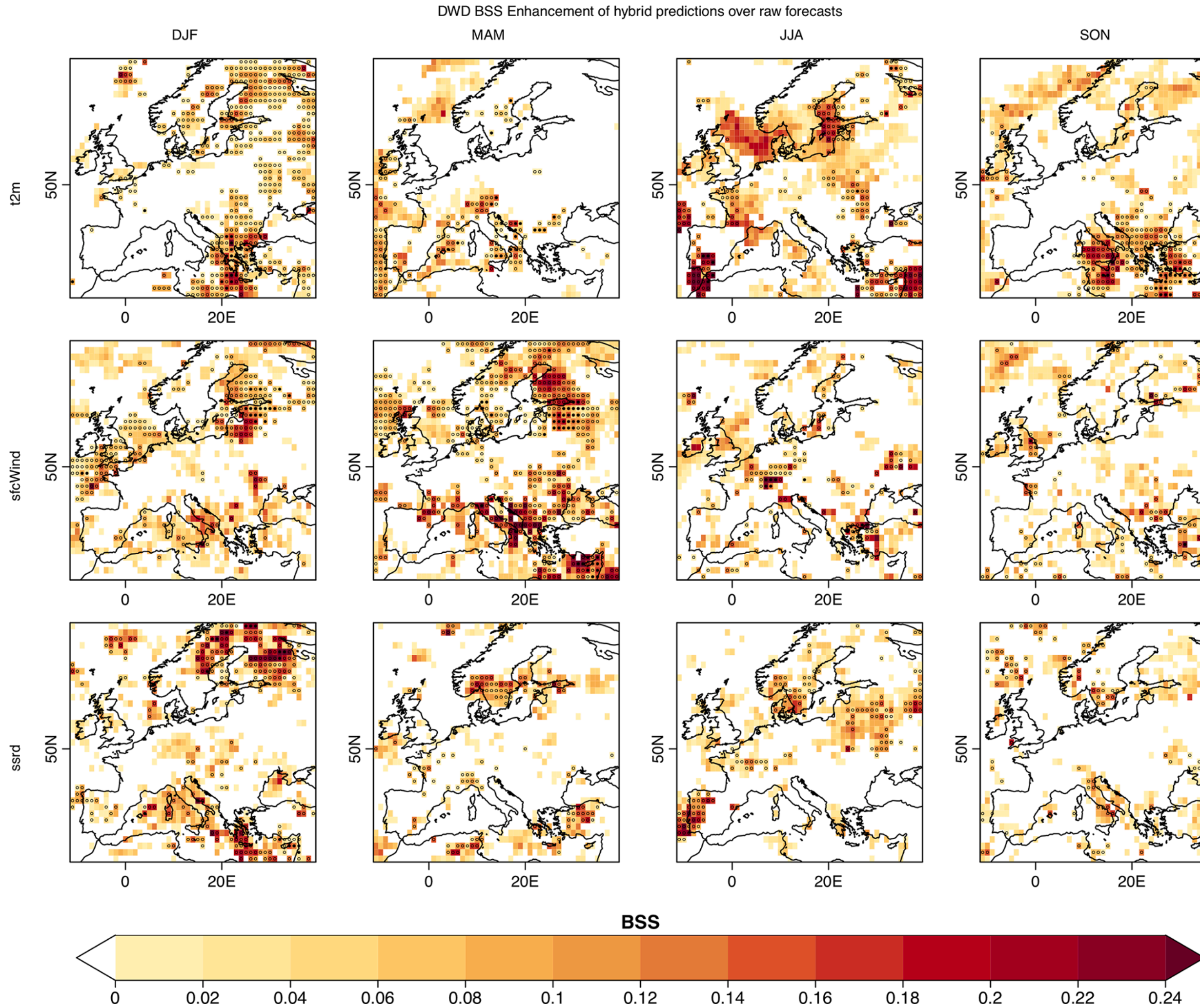

Fig. 11. Brier Skill Score of the probability of exceeding the 90th percentile forecasts for the hybrid predictions compared to the dynamical predictions. Hybrid forecasts from DWD have been employed to reconstruct forecasts of the three surface variables (rows) and four seasons of the year (columns). Empty circles indicate grid points where the hybrid predictions are better than the dynamical predictions and better than the climatology reference. Black full dots indicate grid points where the hybrid predictions are better than the dynamical predictions and significantly better than the climatology reference (p-value > 0.05).

"good" for skill between 15%-30% (0.15 and 0.30) and "very good" for skill above 30% (or 0.3).

5. Conclusions

This study investigates the possibility of improving seasonal predictions of surface variables that are known to impact energy generation and demand in Europe, by looking at the state of the general atmospheric circulation over the Euro-Atlantic region. The large-scale circulation over the continent is assessed by means of four teleconnection indices (NAO, EA, EAWR and SCA), that collectively describe the strength and location of the storm tracks and the advection of differentiated air masses.

Firstly, empirical relationships between the four circulation indices and the observed surface climate are assessed for each season of the year. We interpret these associations as a causation chain, in the following way: slowly varying components of the Earth system (e.g. sea ice extent, sea surface temperatures, ENSO state, soil moisture) determine the preferred large-scale circulation states, which in turn determine the surface conditions. The role of the EATCs is more prominent in winter and less evident in autumn, in agreement with the fraction of explained variability that the four EATCs have in these seasons (see Fig. 3 in Lledó et al. (2020)). In winter, positive phases of the NAO determine higher temperature and wind in northern Europe, which translate in an increase of wind energy production and a decrease of electricity demand. The SCA has a similar effect but of reverse sign, and the EA impacts mostly the western coast of Europe. In summer, the role of the SCA is noticeable, determining higher temperatures and higher solar radiation over most of the continent, while NAO and EAWR produce north–south dipoles on temperature and radiation.

Secondly, we obtain seasonal forecasts of the teleconnection indices issued one month ahead from five different prediction systems, and we use the empirical relationships to translate those circulation forecasts into surface impact forecasts. Thereafter, we quantify the performance of these dynamical-statistical hybrid predictions at issuing tercile probabilities. The performance improvements can only be expected in those regions where the teleconnections have strong impacts and the statistical model provides a good fit to the observed data. The hybrid forecasts of 2 meters temperature are the most skillful over the continent and consistent across the prediction systems, particularly in winter and summer. The improvements for wind speed and solar radiation are more modest and concentrated to specific regions only. Wind shows improvements in winter and spring only, and radiation in winter, spring and summer. Autumn proves to be a difficult season for all the evaluated surface variables. The performance of extreme events (above 90th percentile/below 10th percentile) is also assessed and shows

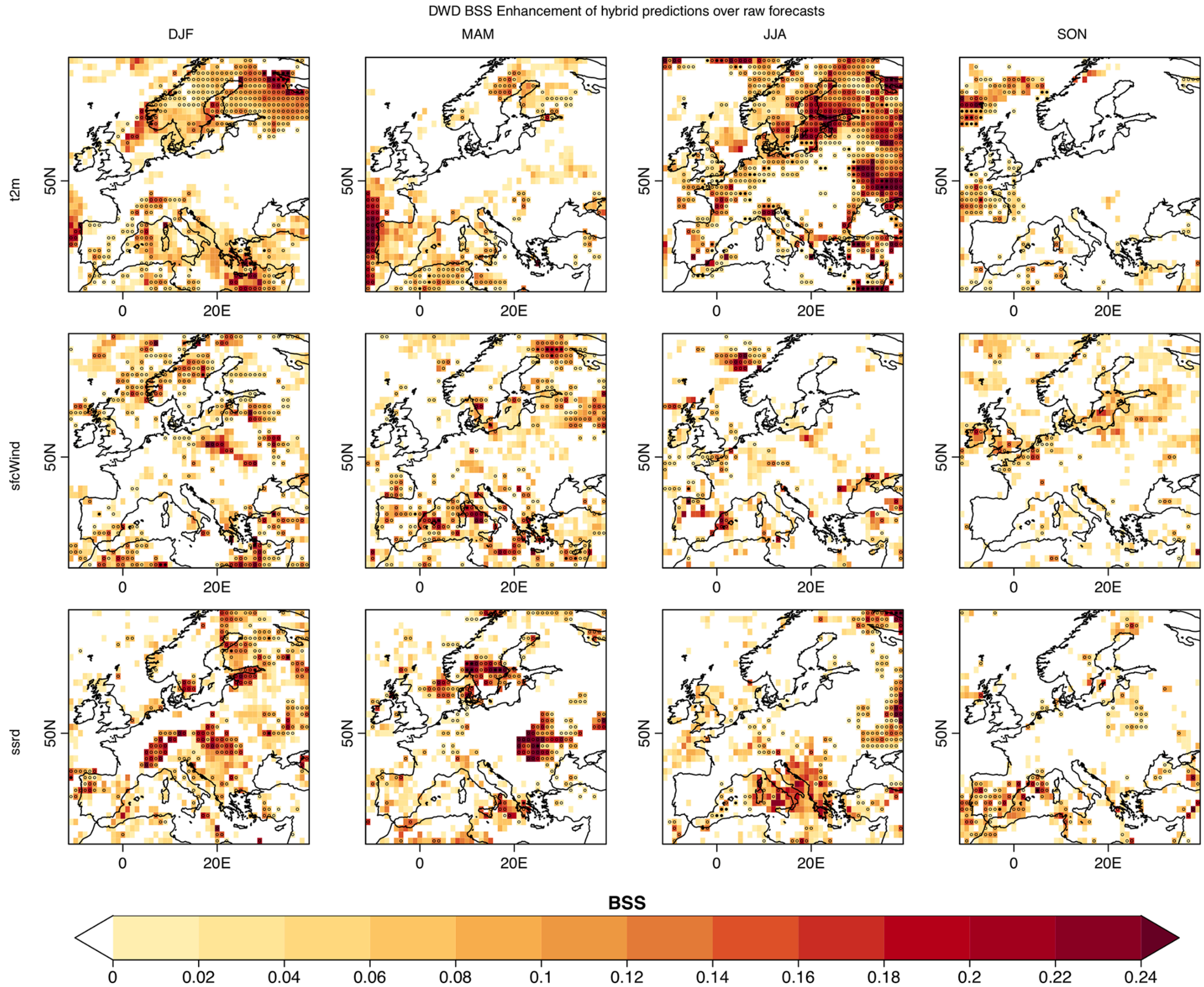

Fig. 12. Brier Skill Score of the probability of not exceeding the 10th percentile forecasts for the hybrid predictions compared to the dynamical predictions. Hybrid forecasts from DWD have been employed to reconstruct forecasts of the three surface variables (rows) and four seasons of the year (columns). Empty circles indicate grid points where the hybrid predictions are better than the dynamical predictions and better than the climatology reference. Black full dots indicate grid points where the hybrid predictions are better than the dynamical predictions and significantly better than the climatology reference (p-value > 0.05).

encouraging results especially for low temperatures in winter and summer. This is a relevant result since the ability of the seasonal forecast to predict extremely low temperature events in Europe is generally limited (Pepler et al., 2015).

Overall the hybrid methodology described in this work generates some skill improvements (up to 24% in some region, season and variables with respect to the raw prediction for both tercile categories and extremes) that can be integrated in the development of new climate services. Aside of the skill improvement, the methodology brings the additional benefit of delivering probabilistic predictions of surface variables that are consistent with the large-scale circulation forecasts, and yields a causal reasoning of why those anomalies occurred, which might be relevant to some users. Finally, the fact that the surface forecasts are derived from the few predictors unveils the common drivers that shape those variables, which are then forced to co-vary by its natural connection to the indices.

We have also shown that better predictions of the teleconnection indices result in better predictions of the surface variables. It is therefore crucial to investigate new methods to improve the EATC forecasts, for instance by improving the representation of the relevant physical processes in the dynamical systems, or by means of purely statistical methods. From a post-processing point of view, the definition of an appropriate methodology to obtain a multi-model synthesis could be one of the first ways to be attempted to improve the results. The introduction of machine learning and artificial intelligence methodologies can be pivotal for the achievement of more ambitious results.

Funding

This work was supported by the European Union's Horizon 2020 research and innovation programme [Grant Numbers. No 776787, H2020 S2S4E] and by the National Italian project PAR 2019–2021 1.8 'Energia dal Mare'.

CRediT authorship contribution statement

Irene Cionni: Conceptualization, Methodology, Formal analysis, Software, Visualization, Data curation, Writing - original draft. **Llorenç Lledó:** Software, Data curation, Methodology, Writing - original draft, Methodology, Writing - original draft. **Verónica Torralba:** Software, Writing - review & editing. **Alessandro Dell'Aquila:** Conceptualization, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The authors would like to express their gratitude to anonymous reviewers for their valuable comments.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.cliser.2022.100294.

References

Barnston, A., Livezey, R., 1987. Classification, seasonality and persistence of low-frequency atmospheric circulation patterns. Mon. Weather Rev. 115, 1083–1126.
Barnston, A., Ropelewski, C., 1992. Do statistical pattern corrections improve seasonal climate predictions in the north american multimodel ensemble models? J. Clim. 5, 1316–1325.
Barnston, A.G., Tippett, M.K., van den Dool, H.M., Unger, D.A., 2015. Toward an improved multimodel enso prediction. J. Appl. Meteorol. Climatol. 54 (7), 1579–1595.
Bastos, A., Janssens, I., Gouveia, C., Trigo, R., Ciais, P., Chevallier, F., Penuelas, J., Rodenbeck, C., Piao, S., Friedlingstein, P., Running, S., 2016. European land co2 sink influenced by nao and east-atlantic pattern coupling. Nat. Commun. 7.
Bett, P., Thornton, H., 2016. The climatological relationships between wind and solar energy supply in britain. Renewable Energy 87, 96–110.
Bhend, J., Mahlstein, I., Liniger, M., 2016. Predictive skill of climate indices compared to mean quantities in seasonal forecasts: Seasonal forecasts of climate indices. Quarterly J. R. Meteorological Soc. 143.
Bloomfield, H., Brayshaw, D., Gonzalez, P., Charlton-Perez, A., 2021. Pattern-based conditioning enhances sub-seasonal prediction skill of european national energy variables. Meteorol. Appl. 28.
Brier, G., 1950. Verification of forecasts expressed in terms of probability. Mon. Weather Rev. 78, 1–3.
Bruno Soares, M., Buontempo, C., 2019. Challenges to the sustainability of climate services in europe. WIREs Climate Change 10 (4), e587.
Bueh, C., Nakamura, H., 2007. Scandinavian pattern and its climatic impact. Q. J. R. Meteorol. Soc. 133, 2117–2131.
Buontempo, C., Hutjes, R., Beavis, P., Berckmans, J., Cagnazzo, C., Vamborg, F., Thépaut, J.-N., Bergeron, C., Almond, S., Amici, A., Ramasamy, S., Dee, D., 2019. Fostering the development of climate services through copernicus climate change service (c3s) for agriculture applications. Weather and Climate Extremes 27, 100226.
Burningham, H., French, J., 2013. Is the nao winter index a reliable proxy for wind climate and storminess in northwest europe? Int. J. Climatol. 33 (8), 2036–2049.
Castro-Díez, Y., Pozo-Vázquez, D., Rodrigo, F.S., Esteban-Parra, M.J., 2002. Nao and winter temperature variability in southern europe. Geophys. Res. Lett. 29 (8), 1–4.
Climate Prediction Center, 2012. Northern hemisphere teleconnection patterns. URL: https://www.cpc.ncep.noaa.gov/data/teledoc/telecontents.shtml [Accessed: 2021-06-30].
Cohen, J., Coumou, D., Hwang, J., Mackey, L., Orenstein, P., Totz, S., Tziperman, E., 2019. S2s reboot: An argument for greater inclusion of machine learning in subseasonal to seasonal forecasts. WIREs Climate Change 10 (2), e00567.
Comas-Bru, L., Hernández, A., 2018. Reconciling North Atlantic climate modes: Revised monthly indices for the East Atlantic and the Scandinavian patterns beyond the 20th century. Supplement to: Comas-Bru, L; Hernández, A (2018): Reconciling North Atlantic climate modes: Revised monthly indices for the East Atlantic and the Scandinavian patterns beyond the 20th century. Earth System Science Data 10, 2329–2344. https://doi.org/10.5194/essd-10-2329-2018.
Comas-Bru, L., McDermott, F., 2014. Impacts of the ea and sca patterns on the european twentieth century nao-winter climate relationship. Q. J. R. Meteorol. Soc. 140 (679), 354–363.
Doblas-Reyes, F.J., García-Serrano, J., Lienert, F., Biescas, A.P., Rodrigues, L.R.L., 2013. Seasonal climate predictability and forecasting: status and prospects. WIREs Climate Change 4 (4), 245–268.
DST, 2019. S2S4E Climate Services for Energy, Decision Support Tool. https://s2s4e-dst.bsc.es/ [Accessed: 2021-12-01].
Dunstone, N., Smith, D., Scaife, A., Hermanson, L., Eade, R., Robinson, N., Andrews, M., Knight, J., 10 2016. Skilful predictions of the winter north atlantic oscillation one year ahead. Nature Geoscience 9.
ECMWF, 2019. Seasonal forecasts and the copernicus climate change service. URL: https://confluence.ecmwf.int//display/COPSRV/Seasonal+forecasts+and+the+Copernicus+Climate+Change+Service [Accessed: 2019-11-14].
Eden, J.M., van Oldenborgh, G.J., Hawkins, E., Suckling, E.B., 2015. A global empirical system for probabilistic seasonal climate prediction. Geoscientific Model Development 8 (12), 3947–3973.
Epstein, E.S., 1969. Stochastic dynamic prediction1. Tellus 21 (6), 739–759. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.2153-3490.1969.tb00483.x.
European Commission, 2021. European Green Deal: Commission proposes transformation of EU economy and society to meet climate ambitions, Brussels, 14th July 2021. (https://ec.europa.eu/commission/presscorner/detail/en/IP_21_3541).
Eurostat, 2021. Statistics Explained. Monthly electricity generation from non-combustiblerenewables - statistics. URL: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Monthly_electricity_generation_from_non-combustible_renewables_-_statistics, 2021.
Fujiwara, M., Wright, J.S., Manney, G.L., Gray, L.J., Anstey, J., Birner, T., Davis, S., Gerber, E.P., Harvey, V.L., Hegglin, M.I., Homeyer, C.R., Knox, J.A., Krüger, K., Lambert, A., Long, C.S., Martineau, P., Molod, A., Monge-Sanz, B.M., Santee, M.L., Tegtmeier, S., Chabrillat, S., Tan, D.G.H., Jackson, D.R., Polavarapu, S., Compo, G. P., Dragani, R., Ebisuzaki, W., Harada, Y., Kobayashi, C., McCarty, W., Onogi, K., Pawson, S., Simmons, A., Wargan, K., Whitaker, J.S., Zou, C.-Z., 2017. Introduction to the SPARC reanalysis intercomparison project (s-RIP) and overview of the reanalysis systems. Atmos. Chem. Phys. 17 (2), 1417–1452.
Giuliani, M., Zaniolo, M., Castelletti, A., Davoli, G., Block, P., 2019. Detecting the state of the climate system via artificial intelligence to improve seasonal forecasts and inform reservoir operations. Water Resour. Res. 55 (11), 9133–9147.
Hall, R.J., Hanna, E., 2018. North atlantic circulation indices: links with summer and winter uk temperature and precipitation and implications for seasonal forecasting. Int. J. Climatol. 38 (S1), e660–e677.
Hamilton, E., Eade, R., Graham, R., Scaife, A., Smith, D., Maidens, A., MacLachlan, C., 12 2011. Forecasting the number of extreme daily events on seasonal timescales. AGU Fall Meeting Abstracts 117, 1011–.
Hannachi, A., Jolliffe, I., Stephenson, D., 07 2007. Empirical orthogonal functions and related techniques in atmospheric science: A review. International Journal of Climatology 27.
Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., Thépaut, J.-N., 05 2020. The era5 global reanalysis. Quarterly Journal of the Royal Meteorological Society.
Huang, Y., Yang, L., Fu, Z., 2020. Reconstructing coupled time series in climate systems using three kinds of machine-learning methods. Earth System Dynamics 11 (3), 835–853.
Hurrell, J., 1995. Decadal trends in the north atlantic oscillation. Science (New York N. Y.) 269, 676–679.
Hurrell, J., Deser, C., 03 2009. North atlantic climate variability: The role of the north atlantic oscillation. Journal of Marine Systems - J MARINE SYST 78.
Hurrell, J.W., Kushnir, Y., Ottersen, G., Visbeck, M., 2003. An Overview of the North Atlantic Oscillation. American Geophysical Union (AGU) 1–35.
Jerez, S., Jimenez-Guerrero, P., Montávez, J.P., Trigo, R.M., 2013. Impact of the north atlantic oscillation on european aerosol ground levels through local processes: a seasonal model-based assessment using fixed anthropogenic emissions. Atmos. Chem. Phys. 13 (22), 11195–11207. URL:https://acp.copernicus.org/articles/13/11195/2013/.
Johnson, S.J., Stockdale, T.N., Ferranti, L., Balmaseda, M.A., Molteni, F., Magnusson, L., Tietsche, S., Decremer, D., Weisheimer, A., Balsamo, G., Keeley, S.P.E., Mogensen, K., Zuo, H., Monge-Sanz, B.M., 2019. Seas5: the new ecmwf seasonal forecast system. Geoscientific Model Development 12 (3), 1087–1117.
Jolliffe, I.T., Stephenson, D.B. (Eds.), Dec. 2011. Forecast Verification. John Wiley & Sons Ltd.
Kirtman, B., Min, D., Infanti, J., Kinter, J., Paolino, D., Zhang, Q., Dool, H., Saha, S., Peña, M., Becker, E., Peng, P., Tripp, P., Huang, J., DeWitt, D., Tippett, M., Barnston, A., Li, S., Rosati, A., Schubert, S., Wood, E., 2014. The north american multimodel ensemble: Phase-1 seasonal-to-interannual prediction; phase-2 toward developing intraseasonal prediction. Bull. Am. Meteorol. Soc. 95, 585–601.
Krichak, S., Alpert, P., 2005. Decadal trends in the east atlantic-west russia pattern and mediterranean precipitation. Int. J. Climatol. 25, 183–192.
Lamb, P.J., Peppler, R.A., 1987. North atlantic oscillation: Concept and an application. Bull. Am. Meteorol. Soc. 68, 1218–1225.
Lim, Y.-K., 2015. The east atlantic/west russia (ea/wr) teleconnection in the north atlantic: climate impact and relation to rossby wave propagation. Clim. Dyn. 44 (11), 3211–3222.
Lledó, L., Cionni, I., Torralba, V., Bretonnière, P.-A., Samsó, M., 2020. Seasonal prediction of euro-atlantic teleconnections from multiple systems. Environ. Res. Lett. 15 (7), 074009 https://doi.org/10.1088/1748-9326/ab87d2.
Lledó, L., Doblas-Reyes, F.J., 2020. Predicting daily mean wind speed in europe weeks ahead from MJO status. Mon. Weather Rev. 148 (8), 3413–3426.
Lledó, L., Torralba, V., Soret, A., Ramon, J., Doblas-Reyes, F., 2019. Seasonal forecasts of wind power generation. Renewable Energy 143, 91–100.
Mestas-Nunez, A., 2000. Orthogonality properties of rotated empirical modes. International Journal of Climatology - INT J CLIMATOL 20, 1509–1516.
Moore, G.W.K., Renfrew, I.A., 2012. Cold european winters: interplay between the nao and the east atlantic mode. Atmospheric Science Letters 13 (1), 1–8.
Newman, M., Sardeshmukh, P.D., 2017. Are we near the predictability limit of tropical indo-pacific sea surface temperatures? Geophys. Res. Lett. 44 (16), 8520–8529.
Orlov, A., Sillmann, J., Vigo, I., Feb. 2020. Better seasonal forecasts for the renewable energy industry. Nature Energy 5, 108–110.
Palmer, T.N., Alessandri, A., Andersen, U., Cantelaube, P., Davey, M., Délécluse, P., Déqué, M., Díez, E., Doblas-Reyes, F.J., Feddersen, H., Graham, R., Gualdi, S., Guérémy, J.-F., Hagedorn, R., Hoshen, M., Keenlyside, N., Latif, M., Lazar, A., Maisonnave, E., Marletto, V., Morse, A.P., Orfila, B., Rogel, P., Terres, J.-M., Thomson, M.C., 2004. Development of a european multimodel ensemble system for seasonal-to-interannual prediction (demeter). Bull. Am. Meteorol. Soc. 85 (6),

853–872. URL:https://journals.ametsoc.org/view/journals/bams/85/6/bams-85-6-853.xml.
Panteli, M., Mancarella, P., 2015. Influence of extreme weather and climate change on the resilience of power systems: Impacts and possible mitigation strategies. Electric Power Systems Research 127, 259–270.
Pepler, A.S., Díaz, L.B., Prodhomme, C., Doblas-Reyes, F.J., Kumar, A., 2015. The ability of a multi-model seasonal forecasting ensemble to forecast the frequency of warm, cold and wet extremes. Weather and Climate Extremes 9, 68–77, the World Climate Research Program Grand Challenge on Extremes - WCRP-ICTP Summer School on Attribution and Prediction of Extreme Events.
Prodhomme, C., Materia, S., ARDILOUZE, C., White, R., Batté, L.S., Guemas, V., Fragkoulidis, G., García-Serrano, J., Jun. 2021. Seasonal prediction of European summer heatwaves. Climate Dynamics. URL:https://hal.archives-ouvertes.fr/hal-03274790.
Ramon, J., Lledó, L., Bretonnière, P.-A., Samsó, M., Doblas-Reyes, F.J., 2021. A perfect prognosis downscaling methodology for seasonal prediction of local-scale wind speeds. Environ. Res. Lett. 16 (5), 054010.
Ramon, J., Lledó, L., Torralba, V., Soret, A., Doblas-Reyes, F.J., 2019. What global reanalysis best represents near-surface winds? Q. J. R. Meteorol. Soc. 145 (724), 3236–3251.
Riaz, S.M.F., Iqbal, M.J., Hameed, S., 2017. Impact of the north atlantic oscillation on winter climate of germany. Tellus A: Dynamic Meteorology and Oceanography 69 (1), 1406263.
Rodríguez-Guisado, E., Serrano-de la Torre, A.A., Sánchez-García, E., Domínguez-Alonso, M., Rodríguez-Camino, E., 2019. Development of an empirical model for seasonal forecasting over the mediterranean. Advances in Science and Research 16, 191–199. URL:https://asr.copernicus.org/articles/16/191/2019/.
Rust, H.W., Richling, A., Bissolli, P., Ulbrich, U., 2015. Linking teleconnection patterns to european temperature? a multiple linear regression model. Meteorol. Z. 24 (4), 411–423.
Sánchez-García, E., Voces-Aboy, J., Navascués, B., Rodríguez-Camino, E., 2019. Regionally improved seasonal forecast of precipitation through best estimation of winter nao. Adv. Sci. Res. 16, 165–174. URL:https://asr.copernicus.org/articles/16/165/2019/.
Scaife, A., Smith, D., 12 2018. A signal-to-noise paradox in climate science. npj Climate and Atmospheric Science 1.
Scaife, A.A., Arribas, A., Blockley, E., Brookshaw, A., Clark, R.T., Dunstone, N., Eade, R., Fereday, D., Folland, C.K., Gordon, M., Hermanson, L., Knight, J.R., Lea, D.J., MacLachlan, C., Maidens, A., Martin, M., Peterson, A.K., Smith, D., Vellinga, M., Wallace, E., Waters, J., Williams, A., 2014. Skillful long-range prediction of european and north american winters. Geophys. Res. Lett. 41 (7), 2514–2519.
Scaife, A.A., Folland, C.K., Alexander, L.V., Moberg, A., Knight, J.R., 2008. European climate extremes and the north atlantic oscillation. J. Clim. 21 (1), 72–83. https://doi.org/10.1175/2007jcli1631.1.
Schepen, A., Wang, Q.J., Everingham, Y., 2016. Calibration, bridging, and merging to improve gcm seasonal temperature forecasts in australia. Mon. Weather Rev. 144 (6), 2421–2441.
Specq, D., Batté, L., 2020. Improving subseasonal precipitation forecasts through a statistical–dynamical approach: application to the southwest tropical pacific. Clim. Dyn. 55 (7–8), 1913–1927.
Stockdale, T.N., Molteni, F., Ferranti, L., 2015. Atmospheric initial conditions and the predictability of the arctic oscillation. Geophys. Res. Lett. 42 (4), 1173–1179.
Strazzo, S., Collins, D.C., Schepen, A., Wang, Q.J., Becker, E., Jia, L., 2019. Application of a hybrid statistical-dynamical system to seasonal prediction of north american temperature and precipitation. Mon. Weather Rev. 147 (2), 607–625.
Svensson, C., Brookshaw, A., Scaife, A.A., Bell, V.A., Mackay, J.D., Jackson, C.R., Hannaford, J., Davies, H.N., Arribas, A., Stanley, S., 2015. Long-range forecasts of UK winter hydrology. Environ. Res. Lett. 10 (6), 064006 https://doi.org/10.1088/1748-9326/10/6/064006.
Thepaut, J.-N., Dee, D., Engelen, R., Pinty, B., 2018. The copernicus programme and its climate change service. In: In: IGARSS 2018–2018 IEEE International Geoscience and Remote Sensing Symposium. IEEE.
Thornton, H., Scaife, A., Hoskins, B., Brayshaw, D., 2017. The relationship between wind power, electricity demand and winter weather patterns in great britain. Environ. Res. Lett. 12, 064017.
Tippett, M.K., Sobel, A.H., Camargo, S.J., 2012. Association of u.s. tornado occurrence with monthly environmental parameters. Geophys. Res. Lett. 39 (2).
Torralba, V., Gonzalez-Reviriego, N., Cortesi, N., Manrique-Suñén, A., Lledó, L., Marcos, R., Soret, A., Doblas-Reyes, F.J., 2021. Challenges in the selection of atmospheric circulation patterns for the wind energy sector. Int. J. Climatol. 41 (3), 1525–1541.
Trenberth, K., Jones, P., Ambenje, P., Bojariu, R., Easterling, D., Klein Tank, A., Parker, D., Rahimzadeh, F., Renwick, J., Rusticucci, M., Soden, B., Zhai, P., 2007. Observations: Surface and Atmospheric Climate Change. Cambridge University Press, pp. 235–336.
Trigo, R., Osborn, T., Corte-Real, J., 2002. The north atlantic oscillation influence on europe: Climate impacts and associated physical mechanisms. Climate Research - CLIMATE RES 20, 9–17.
van den Dool, H., 2006. Empirical Methods in Short-Term Climate Prediction. Oxford University Press.
Van Den Dool, H.M., 1994. Searching for analogues, how long must we wait? Tellus A 46 (3), 314–324.
van Oldenborgh, G.J., Philip, S.Y., Collins, M., 2005. El niño in a changing climate: a multi-model study. Ocean Science 1 (2), 81–95.
Walker, G., Bliss, E., 1932. World weather v. Memoirs of the Royal Meteorological Society 4, 53–84.
Wang, L., Ting, M., Kushner, P., 12 2017. A robust empirical seasonal prediction of winter nao and surface climate. Scientific Reports 7.
Wang, X., Wang, C., Zhou, W., Wang, D., Song, J., 2011. Teleconnected influence of north atlantic sea surface temperature on the el niño onset. Clim. Dyn. 37 (3), 663–676.
Wilks, D.S., 2011. Statistical methods in the atmospheric sciences. Elsevier Academic Press, Amsterdam, Boston.
Wind Europe, 2021. Wind-energy-in-europe-in-2020-trends-and-statistics. URL: https://windeurope.org/intelligence-platform/product/wind-energy-in-europe-in-2020-trends-and-statistics/#overview.
Yu, B., Lin, H., 2019. Modification of the wintertime pacific-north american pattern related north american climate anomalies by the asian-bering-north american teleconnection. Clim. Dyn. 53.
Zhang, W., Villarini, G., Slater, L., Vecchi, G., Bradley, A., 2018. Improved enso forecasting using bayesian updating and the north american multimodel ensemble (nmme). J. Clim. 30.
Zubiate, L., McDermott, F., Sweeney, C., O'Malley, M., 2017. Spatial variability in winter nao-wind speed relationships in western europe linked to concomitant states of the east atlantic and scandinavian patterns. Q. J. R. Meteorol. Soc. 143 (702), 552–562.