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Decadal Prediction for the European Energy Sector

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ABSTRACT

The timescale of decadal climate predictions, from a year-ahead up to a decade, is an important planning horizon for stakeholders in the energy sector. With power systems transitioning towards a greater share of renewable energy sources, these systems become more sensitive to the variability of weather and climate, thus necessitating the provision of long-range climate predictions to ensure effective planning and operation. As decadal predictions sample both the internal variability of the climate and the externally forced response, these forecasts potentially provide useful information for the upcoming decade. Here, we show for the first time that it is possible to make skillful decadal predictions for a range of energy sector relevant climate variables over the European region. We apply post-processing techniques and identify skill in certain regions during both summer and winter for temperature, solar irradiance, and precipitation. We also show significant skill for 850 hPa zonal wind speed and the North Atlantic Oscillation during the extended winter period (October–March). We demonstrate how these forecasts can be used for important energy indicators, such as offshore wind capacity factors, comparing the skill of direct model output (using forecast variables directly) and pattern-based approaches (e.g., using the NAO index). We find significant skill for predictions of modeled European energy variables, including Northern European offshore wind capacity factors ($r = 0.73$), UK electricity demand ($r = 0.84$), solar photovoltaic capacity factors in Spain ($r = 0.63$), and precipitation in Scandinavia ($r = 0.64$). Our results highlight the potential for skilful prediction of energy-sector relevant quantities on decadal timescales. This could benefit both the planning and operation of the future energy system.

1 | Introduction

Decadal predictions forecast climate over the next 1–10 years and are therefore potentially valuable to many industries adapting to climate change and climate variability. The potential value of decadal forecasts is particularly high for the energy sector as stakeholders deploy low-carbon technologies which increase the weather sensitivity of the system, both in terms of electricity generation (e.g., wind farms and solar photovoltaics) and demand (e.g., electrification of heating and transport). For wind power in the UK alone, the government aims to have deployed up to 60 gigawatts (GW) of offshore wind by 2030 (Labour 2024), and similarly ambitious targets for weather-sensitive renewables exist across Europe (European Commission 2021). As a result, decadal predictions present an opportunity to quantify and improve our understanding of the potential impacts of climate on the energy system in the next few years.

Decadal predictions from numerical models have been produced since the mid-2000s (Smith et al. 2007), with leading weather centres now producing decadal forecasts on an operational basis (Hermanson et al. 2022). Skilful predictions for the winter North Atlantic Oscillation (the NAO, a key index of the regional large-scale atmospheric circulation) have been demonstrated by numerous studies (Scaife et al. 2014; Dunstone et al. 2016; Smith et al. 2020; Athanasiadis et al. 2020), though there remain concerns that this skill may somewhat depend on the period evaluated (Christiansen et al. 2022; Marcheggiani et al. 2023). The predictable "signal" in the models is much smaller than expected—a phenomenon known as the signal-to-noise paradox (Scaife and Smith 2018). This implies that while the forecast ensemble mean often correlates strongly with observations, the magnitude of the associated variation is too weak. For predictions of the NAO and other circulation indices in the North Atlantic, this can be addressed by rescaling (e.g., Eade et al. 2014; Smith et al. 2020). While for predictions of other climate variables, such as temperature or wind speed, associated methods such as "NAO-matching" (Smith et al. 2020) can be applied prior to use.

The NAO has strong connections to European winter climate and therefore being able to skilfully predict the NAO suggests that predictive skill should exist for a range of surface climate properties of broad relevance to the energy sector (particularly temperature, wind speed, precipitation, and insolation). Previous studies have indeed confirmed that these properties of European surface climate are well correlated with the NAO at monthly and seasonal timescales (Brayshaw et al. 2011; Ely et al. 2013; Clark et al. 2017; Thornton et al. 2017, 2019). Despite this, there has been limited research in the area of decadal climate services for the European energy sector. Early studies assessing the skill of decadal wind speed predictions were inconclusive (e.g., Haas et al. 2015; Moemken et al. 2016), although this is likely, in part, due to the small ensemble sizes considered, such as the 10 members from a single model in Moemken et al. (2016) compared to over 100 members from more recent multi-model ensembles (e.g., Marcheggiani et al. 2023). In contrast, at sub-seasonal and seasonal timescales, there has been increasing development of climate services for the European energy sector (Thornton et al. 2019; Bett et al. 2022; Cionni et al. 2022). Some authors opt to use 'pattern-based' methods, where NAO predictions are combined with observed statistical relationships to map this index onto an energy variable (e.g., Clark et al. 2017; Thornton et al. 2019), while others use surface climate data from the forecast directly (e.g., Gonzalez et al. 2021).

Recent studies are beginning to address the use of decadal forecasts for specific applications, including applications to hydropower (Tsartsali et al. 2023) and hurricane damage (Lockwood et al. 2023a). Here we seek to extend this research by assessing the skill of decadal predictions for a range of energy sector relevant variables over Europe. This is the first time that a large multi-model ensemble of decadal forecasts has been comprehensively assessed in this way. Specifically, we build on previous studies by extending the evaluation of NAO forecast skill using a larger ensemble over a longer period, and by assessing the skill of predicting climate variables as well as large-scale atmospheric patterns (temperature, 850 hPa zonal wind speed, precipitation, and insolation). We then demonstrate the potential to develop decadal-scale climate services for energy through a series of energy relevant forecasts for particular regions of Europe. These are directly motivated by energy system considerations and include:

- winter electricity demand in Great Britain (a key concern for system adequacy, c.f., Clark et al. 2017);
- offshore wind capacity factors over Northern Europe (a region of rapidly growing wind farm capacity, Chirosca et al. 2022);
- solar power capacity factors in Spain (the region with the greatest potential for solar development in Europe, Perpiña Castillo et al. 2016); and
- precipitation for hydropower in Scandinavia (which contributes the largest proportion of electricity generation in this region, Graabak et al. 2017).

In each application, we contrast the performance of using pattern-based approaches (i.e., using the decadal forecast to predict an atmospheric circulation pattern and then linking this to the impact using observed statistical relationships) versus using the relevant climate variables directly.

The remainder of the paper is structured as follows. Section 2 provides an overview of the methodology and datasets. Section 3 presents the skill evaluation, first for the NAO, then for the climate variables, and finally for the energy-sector properties. The paper concludes with a discussion in Section 4.

2 | Methods and Data

Our study has two sections. First, we consider the skill of a large multi-model ensemble of decadal predictions for predicting climate variables over Europe. Second, we demonstrate how decadal predictions can be used to provide skillful predictions of energy sector relevant variables for different regions of Europe.

2.1 | Data

We use a multi-model ensemble of decadal predictions from systems contributing to the Decadal Climate Prediction Project (dcpp-A, Boer et al. 2016). For each variable, we use all data available (Table S1). We considered outputs from 12 different forecasting centers, with a maximum ensemble size of 178 members (for surface temperature and mean sea level pressure) and a minimum ensemble size of 107 members (for zonal wind speed on pressure levels). We assess skill for hindcasts initialized between 1961 and 2014, which corresponds to predictions for 1962 to 2023.

As the forecast systems have different start months (e.g., October, November, January), the year 2–9 forecast is considered as it has a minimum lead time of 11 months, which ensures a focus on decadal predictability. We use monthly mean data regridded to a $2.5° \times 2.5°$ grid following Marcheggiani et al. (2023).

The skill of the decadal predictions is assessed against reanalysis data from ERA5 (Hersbach et al. 2020) between 1960 and 2023. Before comparison with model data, observations from ERA5 were regridded to the same $2.5° \times 2.5°$ grid to allow direct comparison.

In addition to evaluating forecast performance in meteorological terms, we also evaluate forecast performance using "energy reanalysis". These datasets derive energy variables (e.g., wind power capacity factors) from meteorological variables (e.g., 10 m wind speed) using known empirical (e.g., temperature and electricity demand) and physical (e.g., wind speed and wind power capacity factors) relationships (Bloomfield et al. 2022). Here we use the University of Reading ERA5-derived (UREAD-ERA5) dataset (Bloomfield and Brayshaw 2021). As the energy reanalysis is itself a model-derived estimate of energy properties from meteorological inputs, it is expected that it will emphasize the "signal" of resolved climate phenomena on energy impacts (e.g., average UK wind speed will be approximately related to UK wind power capacity factors) over other drivers associated with unresolved meteorological phenomena (e.g., local wind conditions) and/or exogenous non-meteorological processes (e.g., shutdowns due to curtailment, maintenance or damage). Predictions of real-world energy properties are thus subject to additional "noise" (Bloomfield et al. 2021).

2.2 | Methods

2.2.1 | Variables and Indices

We focus on six climate variables of interest to the European energy sector: surface temperature (related to electricity demand), surface solar irradiance (related to solar power capacity factors), 10 m wind speed (linked to wind power capacity factors), precipitation (related to hydropower generation), zonal wind speed at 850 hPa (also linked to wind power capacity factors), and the mean sea level pressure (MSLP, the large-scale atmospheric circulation).

We assess the decadal prediction skill for the NAO for forecast years 2–9 in a similar way to Smith et al. (2020) and Marcheggiani et al. (2023), though here we consider a longer extended winter period (October through to March, ONDJFM) to align with planning time scales typical of the energy sector (e.g., NESO 2024). The NAO is defined as the difference in MSLP between two boxes located over the Azores (28°–20° W, 36°–40° N) and Iceland (25°–16° W, 63°–70° N), as defined in Dunstone et al. (2016). We focus on years 2–9 of the hindcasts, as limited predictive skill was found for shorter forecast ranges (e.g., years 2–3 and year 2). Although weaker but significant skill was found for years 2–5 of the hindcasts (not shown). In addition to the NAO, we also consider the UK North–South pressure difference (hereafter the delta P index), first defined in Thornton et al. (2017), which measures the strength of the average westerly winds over northern Europe. This is measured as the area-weighted pressure difference between two boxes: one north of Europe (27° W–21° E, 57° N–70° N) and the other over southern Europe (27° W–21° E, 38° N–51° N).

For the four climate variables, the correlation skill is calculated for regions of relevance to the energy sector. The regions are as follows:

- Temperature: 10° W–3° E, 50°–60° N, based on Clark et al. (2017).
- Wind speed (10 m and zonal at 850 hPa): 10° W–20° E, 50°–65° N, cover Northern Europe offshore wind regions.
- Solar irradiance: 11° W–2° E, 35°–45° N, covers Spain.
- Precipitation: 2°–23° E, 56°–71° N, based on Landgren et al. (2014).

2.2.2 | Ensemble Post-Processing

To overcome the signal-to-noise paradox, the ensemble size is increased by lagging in the same way as Smith et al. (2020), where each hindcast is combined with those from the three previous start dates.

Furthermore, the variance of the lagged ensemble mean NAO is adjusted to be the same as the predictable component of the observations (Eade et al. 2014; Scaife and Smith 2018). Following Smith et al. (2020), the ratio of predictable components (RPC) and the ratio of predictable signals (RPS) are estimated as follows:

$$\mathrm{RPC} = \frac{\sigma^{o}_{\mathrm{sig}}/\sigma^{o}_{\mathrm{tot}}}{\sigma^{f}_{\mathrm{sig}}/\sigma^{f}_{\mathrm{tot}}} \approx \mathrm{ACC}\frac{\sigma^{f}_{\mathrm{tot}}}{\sigma^{f}_{\mathrm{sig}}},$$

$$\mathrm{RPS} = \frac{\sigma^{\mathrm{o}}_{\mathrm{sig}}}{\sigma^{\mathrm{f}}_{\mathrm{sig}}} = \mathrm{RPC}\frac{\sigma^{\mathrm{o}}_{\mathrm{tot}}}{\sigma^{\mathrm{f}}_{\mathrm{tot}}}.$$

where σ_{tot} and σ_{sig} are the standard deviations of the total variability (the full ensemble) and predictable signal (the ensemble mean) respectively, in the observations 'o' and forecasts 'f'. The ACC is the anomaly correlation coefficient, which represents the predictable component of the observations. A perfect forecasting system would have an RPC of one, however in the case of a low signal-to-noise ratio, where the models overestimate the unpredictable component of variability, the value of RPC will be greater than one. We therefore scale the variance of the ensemble-mean forecast by the RPS to match the observed variance of the predictable signal.

As the surface variables considered are well correlated with the NAO during the extended winter period (Scaife et al. 2014; Clark et al. 2017; Thornton et al. 2019), a technique outlined in Smith et al. (2020), known as NAO-matching, can be used to extract the predictable signal in the ensemble. NAO-matching aims to do this by selecting from the lagged ensemble a subset of members at each time step, which have the closest NAO magnitude to that of the variance-adjusted ensemble mean NAO. In this way, the correct balance of dynamic and thermodynamic drivers on regions impacted by the NAO is maintained. Full details are provided in Smith et al. (2020). This method has been shown to improve predictive skill at decadal timescales for temperature and precipitation over Europe (Smith et al. 2020; Moulds et al. 2023). When looking at skill for surface variables over the extended winter period (ONDJFM) we assess the NAO-matched fields. As the predictive skill for the summer NAO is much lower (e.g., Dunstone et al. 2023), for summer (AMJJAS) the lagged fields are presented without NAO-matching.

2.2.3 | Significance

Following Smith et al. (2020), uncertainties in the raw model forecasts are quantified as the ensemble standard deviation for each start date. For the lagged and variance-adjusted forecasts,

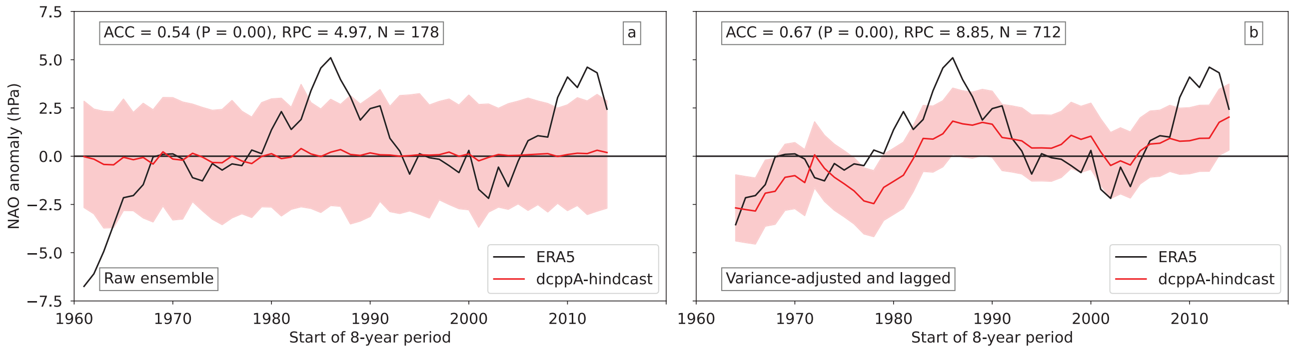

FIGURE 1 | (a) Time series of the extended winter (ONDJFM) NAO for observed 8-year running means (black) and forecast years 2–9 of the hindcasts (red) initialised from 1961 to 2014. The confidence interval is calculated as the 5%–95% range of uncertainty of the ensemble members (red shading). The anomalies are relative to the mean of all year 2–9 hindcasts. The Pearson's anomaly correlation coefficient (ACC) of the ensemble mean, its significance (see Section 2.2), the ratio of predictable components (RPC), and the ensemble size (N) are indicated. (b) Same as (a), but the hindcasts are lagged and variance-adjusted to account for known issues of signal-to-noise (see Section 2.2). The confidence interval is calculated from the root-mean-square error between the observed and ensemble mean model NAO (red shading, see Section 2.2).

uncertainties are computed from the root mean square error (RMSE) between the ensemble mean and the observations, as required for reliable forecasts (Doblas-Reyes et al. 2009; Smith et al. 2020).

For significance testing of time series and spatial skill fields, a block bootstrap approach, following the methods of Smith et al. (2020), is used. This accounts for uncertainties arising from a limited time series length and a finite ensemble size by creating 1000 additional hindcasts which randomly sample (with replacement) blocks of time (e.g., 5 overlapping 8-year running means) and ensemble members.

3 | Results

3.1 | Assessment of Decadal Skill of the NAO

Time series of the observed (ERA5) and model-forecast (dcpp-A) NAO anomalies are shown in Figure 1 for the extended winter period (ONDJFM) and years 2–9 of the hindcasts. As shown in Figure 1a, the magnitude of the variations in the multi-model ensemble mean NAO anomalies for the raw ensemble is small compared to the observations. Despite this, there is significant skill when predicting the phase of the variability (ACC $=0.54$, $p<0.01$). The significant correlation skill suggests that skillful decadal predictions of the North Atlantic circulation are possible, but are characterized by a low signal-to-noise ratio (RPC $=4.97$). Following the process described in Section 2.2.2, a lagged and variance adjusted ensemble better captures the magnitude of the observed variability of the NAO, with ACC $=0.67$ and $p<0.01$ in Figure 1b.

The observed relationships between the decadal variability of the NAO (8-year running mean) and surface variables: temperature, 10 m wind speed, solar irradiance, and precipitation are shown in Figure 2. All of the surface variables in Figure 2 are well correlated with the NAO, although the sign and magnitude of this vary with the region considered. Temperature is positively correlated with the NAO across Europe, with $r=0.58$ ($p=0.04$) over the UK (Figure 2a). Both 10 m wind speed and precipitation show the typical NAO dipole structure, where more positive NAO anomalies are highly correlated with wind speed and precipitation over Northern Europe and negatively correlated with wind speed and precipitation over Southern Europe (Hurrell et al. 2003). This is reflected in the strong correlations over Northern Europe and Scandinavian regions respectively ($r=0.84$ and $r=0.83$ in Figure 2b,d). Solar irradiance, in Figure 2c, shows the inverse relationship, with positive correlations over southern Europe ($r=0.63$ over Spain) and negative correlations over parts of North Western Europe.

As discussed in Bett et al. (2022), the skill can be expected to translate into energy-sector properties that directly depend on these surface climate properties (e.g., 8-year winter-mean wind and solar capacity factors). While this is clearly useful (and is used in Section 3.3), many energy applications require more nuanced climate inputs (such as capacity expansion planning or system reliability assessment, see, e.g., Hilbers et al. 2019, 2023 for examples). The following section therefore addresses the skill in predicting climate variables directly from the numerical forecast output.

3.2 | Assessment of Decadal Skill for Climate Variables

Consider first the winter case (Figure 3). As discussed in Section 2, the NAO-matched ensemble is shown. Prediction skill for surface temperature is significant across the entire North Atlantic region in Figure 3a. There is some skill in predicting precipitation in the Mediterranean region and over Scandinavia, see Figure 3d ($r=0.56$, $p=0.02$). Decadal prediction skill for solar irradiance is high over much of Europe, particularly over France, the UK, and Spain ($r=0.56$, $p=0.01$, Figure 3c). The picture for wind speed, however, is more complex. In particular, there is evidence for limited skill for 10 m wind speed over Northern Europe, though the pattern is weak and rather noisy (Figure 3b). In contrast, there is strong and significant skill for zonal wind speed at 850 hPa over much of the same region (U850, Figure 3c, $r=0.59$, $p<0.01$) where much of the continent's offshore wind capacity is situated. One possible explanation is the surface heterogeneity (e.g., due to orography or land/sea contrasts), which might make prediction more challenging than higher up in the

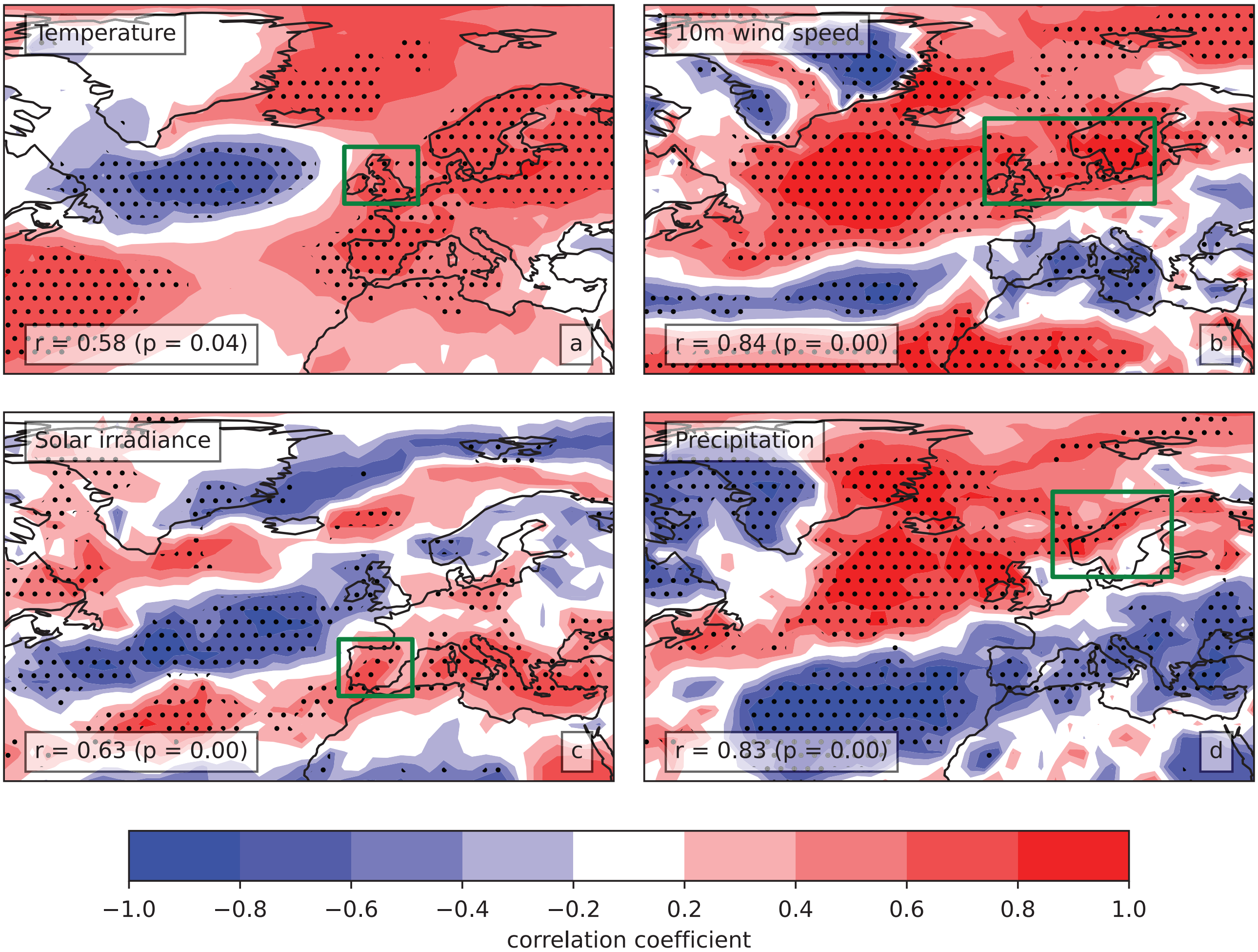

FIGURE 2 | Observed 8-year running mean correlations between extended winter (ONDJFM) NAO and temperature, 10 m wind speed, solar irradiance, and precipitation anomalies over Europe, between 1960 and 2023. Observations are from ERA5. The Pearson's anomaly correlation coefficient (r), along with the significance (p), is indicated for the regions of interest outlined in Section 2.2.1. Statistical significance at the 95% confidence level is shown by stippling.

atmosphere where predictable signals may be stronger. The results for regional skill (e.g., green boxes in Figure 3) are not sensitive to the exact choice of region.

Skill maps are shown for the extended summer period (AMJJAS) in Figure 4. As for winter, decadal prediction skill of UK extended summer temperatures is high ($r = 0.93$, $p < 0.01$). No significant skill was found for 10 m wind speed or zonal wind speed at 850 hPa during the summer, consistent with the lack of predictive skill for the summer NAO found for seasonal forecasts in Dunstone et al. (2023). Significant prediction skill is also found for solar irradiance across much of Europe, including over Spain ($r = 0.84$, $p < 0.01$). Precipitation over Scandinavia is well forecast ($r = 0.70$, $p < 0.01$), as well as over the western Mediterranean.

In summary, significant prediction skill is identified for a range of energy-relevant variables (temperature, solar irradiance, precipitation) during both the winter and summer. During the winter, there is significant skill for the zonal wind speed at 850 hPa over Northern Europe even though the skill of predicting 10 m wind speed over the same region is weak.

3.3 | Assessment of Decadal Skill for Energy-Sector Applications

In the following section, four case study applications of decadal forecasts for the energy sector are demonstrated by linking meteorological forecast variables to energy variables. In each case, the relationships are assumed to be broadly linear, and the strength of the association is measured with the Pearson correlation coefficient.

For each case study, three different meteorological predictors are considered: firstly, a relevant climate variable (e.g., temperature, solar irradiance, U850/10 m wind speed, or precipitation averaged over a suitable domain from Section 2.2.1), secondly, the NAO index, and thirdly, the delta P index. The results from the strongest meteorological predictor are presented first before contrasting the performance against the other meteorological predictors. To assist interpretation, the performance of each prediction pathway is also broken down by presenting the association (Pearson correlation coefficient) between (1) the meteorological predictor and the target energy predictand in the observational data and (2) the forecast meteorological predictor

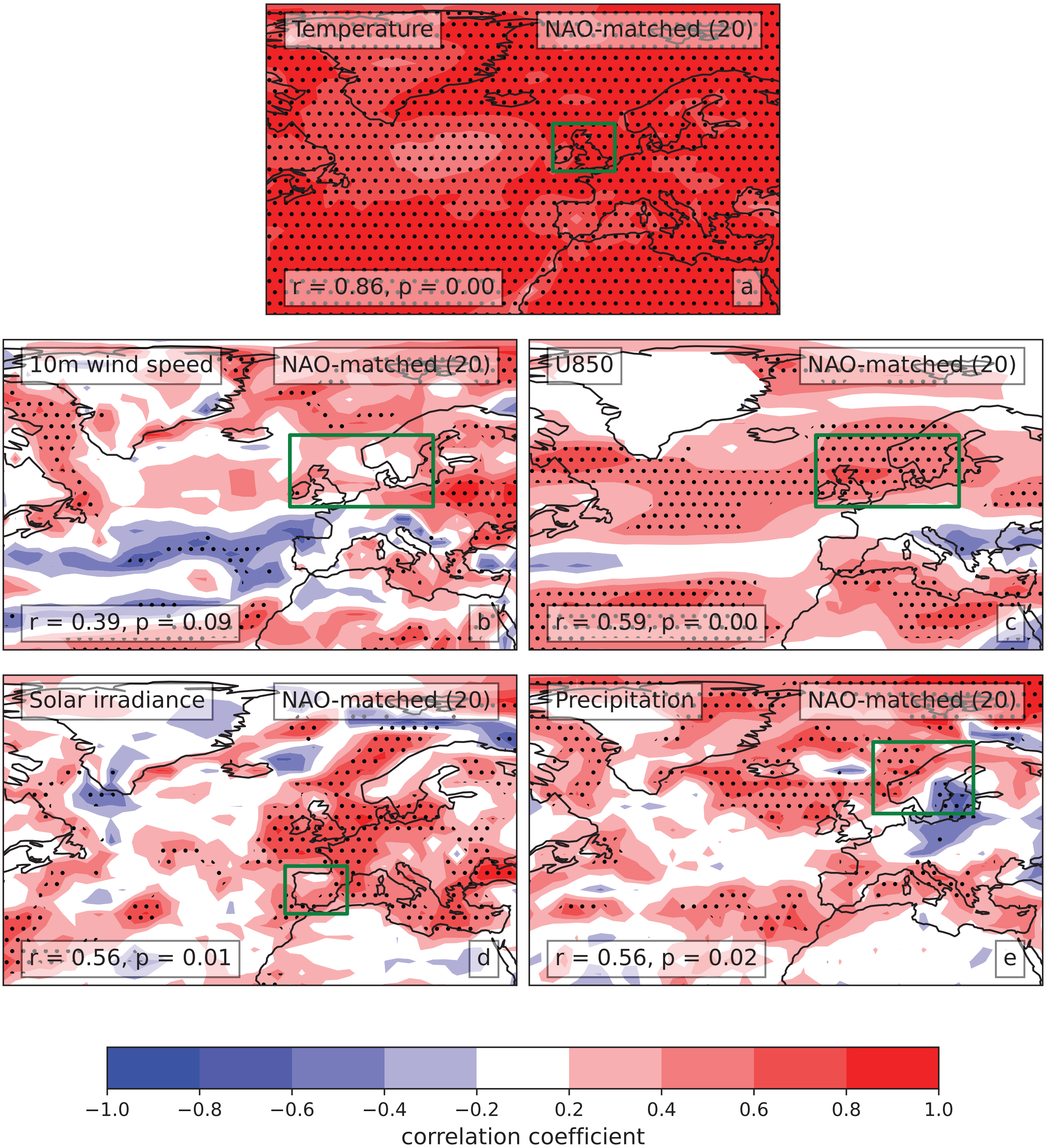

FIGURE 3 | Correlation skill for temperature, 10 m wind speed, zonal wind speed at 850 hPa, solar irradiance, and precipitation during the extended winter (ONDJFM) period for years 2–9 of the NAO-matched hindcast ensemble means. Stippling denotes significance at the 95% threshold (1000 bootstrapped samples) where the anomaly correlation coefficient (ACC) is significantly different from zero. The Pearson's anomaly correlation coefficient (*r*), along with the significance (*p*), is indicated for the regions of interest (green boxes), as outlined in Section 2.2.1. Textbox in the upper right corner displays the methodology used and the number of ensemble members.

and the observed meteorological predictor. These results are summarised in Table 1.

3.3.1 | GB Electricity Demand

Consistent with previous well-established literature (Taylor and Buizza 2003; Thornton et al. 2016, 2017, 2019; Bloomfield et al. 2022), there is a strong correlation between 8-year winter-mean GB temperature and electricity demand ($r = -0.98$, $p < 0.01$; not shown). Though this is likely an overestimate of the true correlation due to the "reconstructed" energy datasets used (the demand estimates were based on daily temperature data) it is nevertheless reasonable to expect a very strong negative relationship. As such, skilful forecasts of GB winter temperature are potentially beneficial for energy system operators

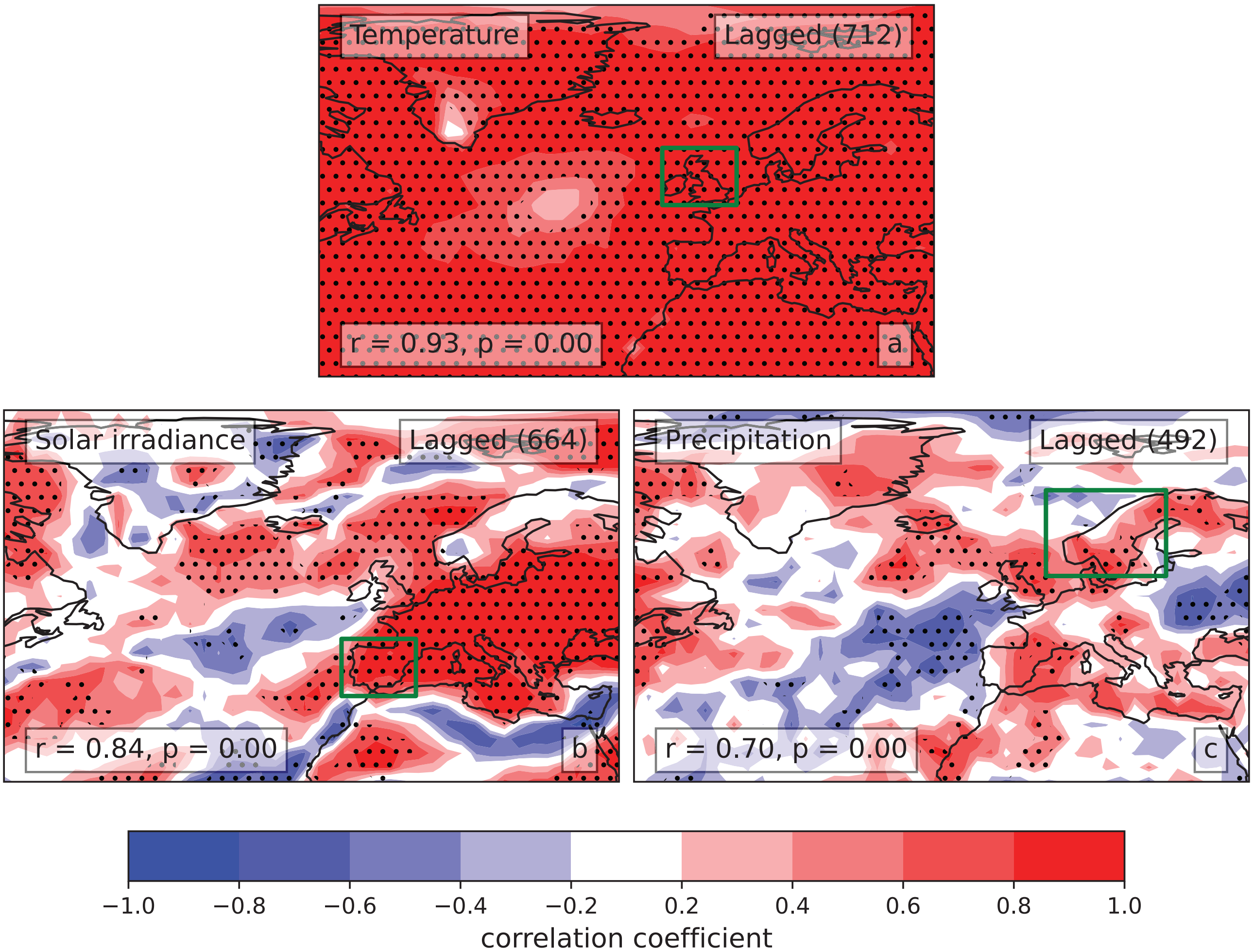

FIGURE 4 | Correlation skill for temperature, solar irradiance, and precipitation during the extended summer (AMJJAS) period for years 2–9 of the lagged hindcast ensemble means. Stippling denotes significance at the 95% threshold (1000 bootstrapped samples) where ACC is significantly different from zero. The Pearson's anomaly correlation coefficient (r), along with the significance (p), is indicated for the regions of interest (green boxes), as outlined in Section 2.2.1. Textbox in the upper right corner displays the methodology used and the number of ensemble members.

seeking to make planning decisions to ensure security of supply.

To demonstrate this skill in a forecasting context, Figure 5a shows the relationship between the forecast and observed ONDJFM 8-year mean temperatures over the GB region (here, the NAO-matched forecast is used—see Section 2 for detailed discussion). The predictions of GB temperature show significant skill ($r=0.89$, $p<0.01$), and this is further associated with GB electricity demand in Figure 5b ($r=-0.84$, $p<0.01$). It is therefore clear that the NAO-matched 2–9-year extended winter temperature forecast offers significant skill in predicting future GB electricity demand.

For comparison, the skill associated with two alternative pattern-based prediction schemes is outlined in Table 1 (i.e., using a forecast of the NAO or delta P index). While both indices (NAO and delta P) are well correlated with GB electricity demand ($r=-0.62$, $r=-0.64$) and are skilfully predicted ($r=0.67$, $r=0.80$), neither achieves the level of skill in predicting electricity demand demonstrated by the NAO-matched temperature approach ($r=0.75$, $p=0.01$ and $r=0.42$, $p=0.05$ respectively; see Table 1).

The relative lack of skill in the pattern-based approaches can likely be understood as a consequence of strong forced trends in temperature (i.e., year-on-year temperature rise) which overlay the variations associated with circulation (i.e., variations in the temperature associated with the NAO or delta P index). In particular, while the pattern-based approaches are well-suited to capturing the effects of circulation variability, they are unable to capture the increases in temperature associated with greenhouse gas forcing. The NAO-matching approach, in contrast, captures both aspects and thus provides a more skillful prediction overall.

3.3.2 | Northern European Offshore Wind

Offshore wind power generation is an increasing source of electricity supply for many countries in North West Europe. In 2023, wind power (onshore and offshore) covered around 20% of European electricity demand (Costanzo and Brindley 2024). Here, we consider the predictability of offshore wind capacity factors over a wide Northern European region (grey shading in Figure 6d, including the Exclusive Economic Zones of the United Kingdom, Norway, Sweden, Finland, Denmark,

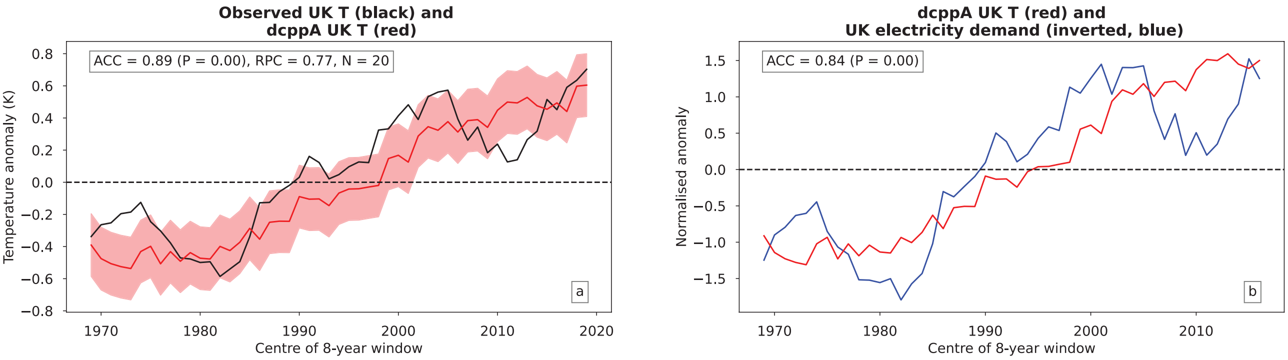

FIGURE 5 | (a) Observed (black, ERA5) and model (red, dcpp-A) time series for GB mean temperature anomalies (region defined in Section 2.2.1). The dcpp-A hindcast is NAO-matched (see Section 2.2.2). Forecast uncertainty is obtained from the root-mean-square error between the observed and model UK mean temperature anomalies (red shading, see methods) (b) Time series of UK mean temperature anomalies (red, dcpp-A) and UK weather-dependent electricity demand (blue, UREAD-ERA5). Both are presented as normalised anomalies. All time series are for the extended winter (ONDJFM) and are computed as 8-year running means (forecast years 2–9). Block bootstrapping is used for significance (see Section 2.2).

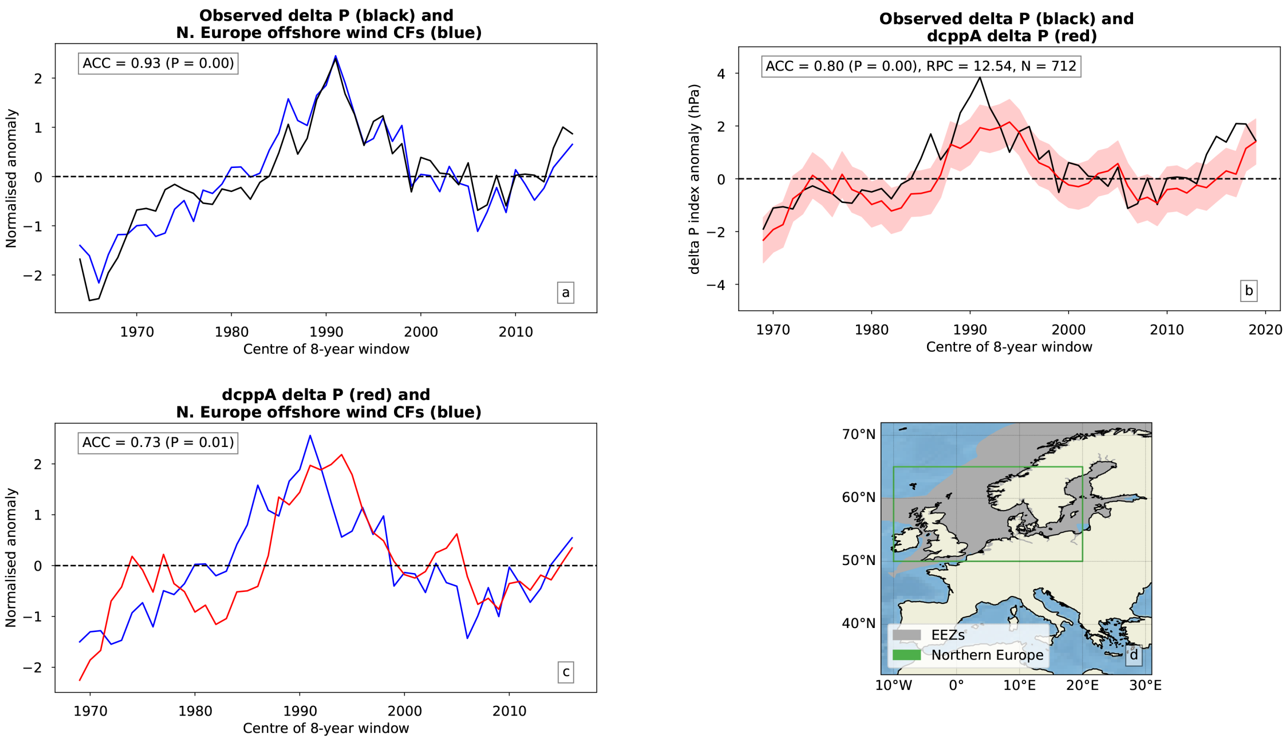

FIGURE 6 | (a) Observed time series of the delta P index (black, ERA5) and offshore wind power capacity factors aggregated over the Northern European EEZ regions (blue, from UREAD-ERA5) as detailed in Section 3.3.2. (b) Observed (black, ERA5) and model (red, dcpp-A) time series for the delta P index. The dcpp-A delta P index predictions are lagged and variance adjusted, as shown in methods. Forecast uncertainty is obtained from the root-mean-square error between the observed and model delta P index (red shading, see Section 2.2). (c) Time series of model delta P index anomalies (red, dcpp-A) and wind power capacity factors (blue, UREAD-ERA5) for the Northern European EEZs. All are for the extended winter (ONDJFM) and 8-year running means (forecast years 2–9). Block bootstrapping is used for significance (see Section 2.2). (d) Map showing the Exclusive Economic Zones (EEZs, countries outlined in Section 3.3.2) over which the offshore wind capacity factors are aggregated and the Northern Europe grid box used to calculate mean 10 m wind speed/U850, as presented in Table 1.

Germany, Netherlands, Belgium, Estonia, Latvia, Lithuania, and Poland), which includes the North Sea and Baltic Sea, two of the most heavily developed regions for offshore wind power in Europe (Gusatu et al. 2020).

To demonstrate a potential pathway for skilfully predicting offshore wind resources on decadal timescales, we focus on a pattern-based technique using the delta P index in Figure 6. There is a clear relationship between the delta P index and Northern European offshore wind capacity factors ($r = 0.93$, Figure 6a) and the hindcast skill for predicting the delta P index is similarly strong ($r = 0.80$, Figure 6b). Consequently, decadal predictions of extended winter offshore wind capacity factors exploiting these relationships lead to a highly skilful forecast

($r = 0.73$, $p = 0.01$, Figure 6c). Despite lower hindcast skill, the skill for predicting the offshore wind capacity factors using the NAO is similarly skilful ($r = 0.57$, $p = 0.03$, Table 1).

There is a strong relationship between the zonal wind speed at 850 hPa and offshore wind capacity factors over Northern Europe ($r = 0.90$) and significant hindcast skill for predictions of U850 in this region ($r = 0.76$, $p < 0.01$, Table 1 and Figure 3b). Therefore, U850 shows similar skill for predicting offshore wind capacity factors over Northern Europe as the delta P or NAO index ($r = 0.72$, $p < 0.01$). In contrast, it is noted that considerably less skill is found if 10 m wind speed is used as the predictor variable ($r = 0.46$, $p > 0.05$; Table 1) consistent with the earlier discussion of limited skill in 10 m wind speed forecasts (Section 3.2 and Figure 3b). While not explored in this study, alternative methodologies for predicting the wind speed, such as deriving the geostrophic wind from mean sea level pressure gradients, as used in Krieger et al. (2022), could warrant further investigation for identifying predictors of offshore wind capacity factors. Additionally, further investigation (beyond the scope of this study) is necessary to understand the relative lack of skill in wind speed at the surface when compared to the zonal wind speed at 850 hPa.

Decadal predictions of offshore wind capacity factors in Northern Europe can achieve similar skill using either direct model output (e.g., U850) or pattern-based approaches (e.g., by using the delta P or NAO index).

Table 1 The skill of different climate predictors for predicting modelled energy variables across different regions of Europe. Column 3: Pearson correlation coefficient (r_p) between observed energy variables (E_{obs} from UREAD-ERA5/ERA5) and extended winter (ONDJFM) mean climate variables (C_{obs}). Column 4: the correlation between observed (C_{obs}) and hindcast (C_{hc}) climate variable (i.e., the hindcast skill for predicting the climate variable). Column 5: the hindcast skill for predicting the observed energy variable (strength of the correlation between E_{obs} and C_{hc}). The observed relationship considers the period from 1960 to 2020. The climate index skill and energy variable skill considers the period 1965–2020 (all hindcasts are lagged from 1961). Bold values indicate the correlation is significant at the 5% level using block bootstrapping for significance (see Section 2.2). Insignificant correlation values are non-bold and marked with a star (*). Where surface climate variables (e.g., temperature, 10 m wind speed) are used as predictors, the NAO-matched ensemble is used. For the zonal wind at 850 hPa (U850), the lagged ensemble is used.

3.3.3 | Spanish Solar Power Capacity Factors

Southern Europe, and Spain in particular, has been identified as one of the most suitable regions for European solar power development due to the favorable climate and availability of land (Montoya et al. 2014; Perpiña Castillo et al. 2016; Gómez-Calvet et al. 2019). While solar generation is typically lower during the winter than the summer, the scale of Spain's solar resource means that winter variability remains important (Maguire 2024). There is a notable trend of increasing solar irradiance since the late 1970s, captured in both station observations and the ERA5 reanalysis (Wohland et al. 2020). This brightening trend coincides with the successful implementation of air pollution policies leading to reduced aerosol emissions in the late 20th century (Wild 2012). Ideally, any predictor of solar irradiance (and therefore solar power capacity factors) would capture both the brightening trend and the decadal variability.

The predictability of extended winter solar power capacity factors over Spain using the NAO index is summarised in Figure 7. As shown in Figure 7a, the variability of the observed NAO index is well correlated with solar power capacity factors in this region

TABLE 1 | Climate predictors for modelled energy variables.

Energy variable	Climate index (C)	Obs relationship, r_P (E_{obs}, C_{obs})	Climate index skill, r_P (C_{obs}, C_{hc})	Energy variable skill, r_P (E_{obs}, C_{hc})
Electricity demand (UK)	Temperature	**−0.98**	**0.89**	**0.84**
	NAO	**−0.62**	**0.67**	**0.75**
	delta P	**−0.64**	**0.80**	**0.42**
Offshore wind capacity factors (Northern Europe)	U850	**0.90**	**0.76**	**0.72**
	10 m wind speed	**0.96**	0.46*	0.46*
	NAO	**0.87**	**0.67**	**0.57**
	delta P	**0.93**	**0.80**	**0.73**
Solar power capacity factors (Spain)	Solar irradiance	**0.98**	**0.58**	0.37*
	NAO	**0.69**	**0.67**	**0.63**
	delta P	**0.73**	**0.80**	0.53*
Precipitation (Scandinavia)	Precipitation	—	—	**0.59**
	NAO	**0.76**	**0.67**	**0.64**
	delta P	**0.80**	**0.80**	**0.60**

($r = 0.69$, Table 1), confirming that there is a strong relationship between these properties. As discussed in Section 3.1, the decadal forecasts are known to have a high level of skill in predicting NAO ($r = 0.67$, Table 1) and it is therefore unsurprising that a pattern-based NAO forecast can be used to construct a skilful solar capacity factor prediction ($r = 0.63$, Table 1 and Figure 7b). Additionally, the positive trend in the NAO from the 1970s onwards (Figure 7b) coincides with the brightening trend in solar irradiance, which may contribute to the overall skill of the NAO.

In contrast, the two other prediction pathways (the delta P index and surface solar insolation) both lead to reduced overall skill compared to the NAO pattern-based forecast ($r = 0.53$ and $r = 0.37$ respectively), as summarised in Table 1. In the case of surface solar insolation, although there is a very strong correlation between insolation and solar capacity factors ($r = 0.98$) the ability to predict insolation is relatively weak ($r = 0.58$, Table 1) and appears to significantly reduce the overall skill.

3.3.4 | Scandinavian Hydropower

We consider the predictability of precipitation over Scandinavia as a simplified proxy for hydropower inflow. Scandinavia is a region heavily reliant on hydropower, with approximately 96% of generation in Norway and half of the generation in Sweden deriving from this source (Graabak et al. 2017; Uniper 2024).

The skill of an NAO pattern-based forecast is shown in Figure 8 and summarised in Table 1. The observed NAO is well correlated with precipitation over Scandinavia in Figure 8a ($r = 0.76$, $p < 0.01$). The strength of this relationship is similar when using the hindcast NAO as a predictor in Figure 8b ($r = 0.64$, $p < 0.01$).

The two other forecast pathways investigated lead to similar levels of overall skill (Table 1). Moreover, both the pattern-based forecasts exhibit similar levels of skill to using the precipitation data directly ($r = 0.59$). Overall, this suggests it is possible in principle to make moderately skillful hydropower inflow forecasts for ONDJFM averaged over the window 2–9 years ahead, and this is relatively insensitive to the details of the prediction methodology.

4 | Discussion and Conclusions

This paper has, for the first time, demonstrated that skilful decadal predictions of energy relevant climate variables over Europe can be made during both winter (ONDJFM) and summer (AMJJAS) seasons. A large multi-model ensemble of

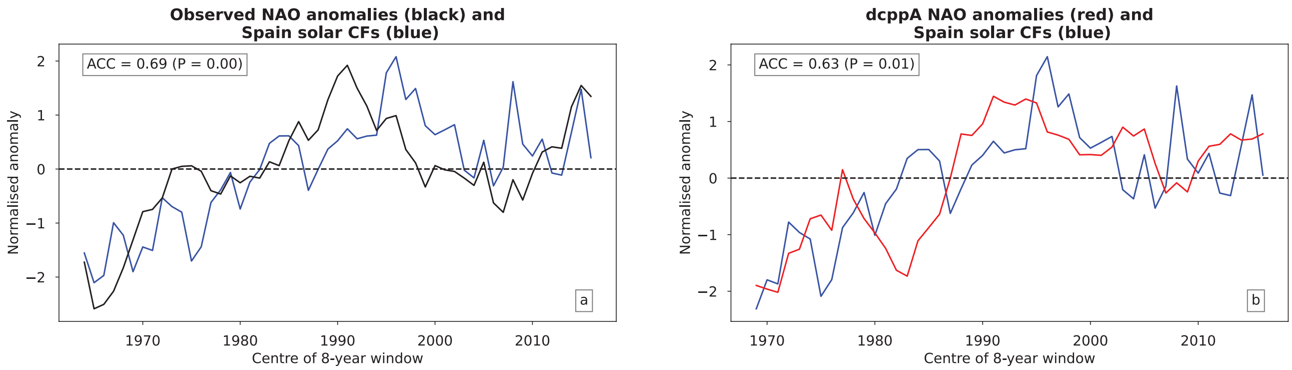

FIGURE 7 | (a) Observed time series of the NAO index (black, ERA5) and Spanish solar power capacity factors (blue, UREAD-ERA5). (b) Time series of model NAO anomalies (red, dcpp-A) and Spanish solar power capacity factors (blue, UREAD-ERA5). Both are presented as normalised anomalies. The dcpp-A NAO predictions are lagged and variance adjusted, as shown in methods. All time series are for the extended winter (ONDJFM) and are computed as 8-year running means (forecast years 2–9). Block bootstrapping is used for significance (see Section 2.2).

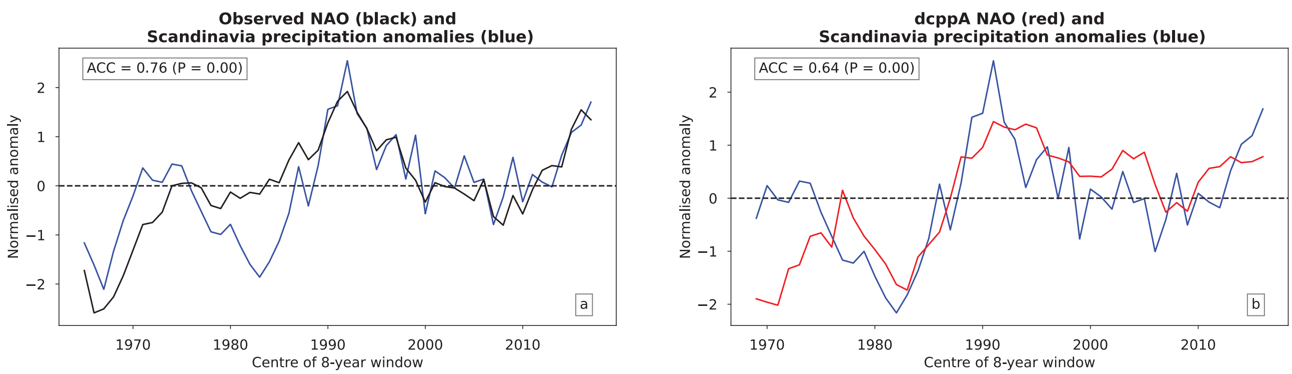

FIGURE 8 | (a). Observed (ERA5, black) time series of NAO index anomalies and precipitation anomalies over Scandinavia (blue, ERA5). (b) Time series of model NAO index anomalies (red, dcpp-A) and observed Scandinavia precipitation anomalies (ERA5). The dcpp-A NAO predictions are lagged and variance adjusted, as outlined in methods. All time series are for the extended winter (ONDJFM) and are computed as 8-year running means (forecast years 2–9). Block bootstrapping is used for significance (see Section 2.2).

decadal climate predictions was used to predict surface temperature, solar irradiance, precipitation, wind speed, and the atmospheric circulation. A series of four case studies featuring relevant energy applications were developed and the relative merits of different methods were considered. The key results of this study are as follows:

- There is a significant correlation skill in decadal predictions of Atlantic atmospheric circulation over the extended winter season (ONDJFM). Two specific indices (NAO and delta P) were examined with correlation skills of $r = 0.67$ and $r = 0.80$, respectively.
- There is significant decadal prediction skill in relevant regions of Europe for surface temperature, solar irradiance, and precipitation during both the extended winter (ONDJFM) and summer (AMJJAS) periods. Significant skill is also found for predictions of zonal wind speed at 850 hPa over Northern Europe during winter.
- Decadal predictions of the large scale circulation patterns, such as the NAO or delta P index, can be used to forecast modeled energy variables, including Northern European offshore wind capacity factors ($r = 0.73$, $p = 0.01$), Spanish solar capacity factors ($r = 0.63$, $p = 0.01$), and Scandinavian precipitation anomalies ($r = 0.64$, $p < 0.01$).
- When there is significant decadal prediction skill for an energy-related surface variable, such as UK mean temperature ($r = 0.89$, $p < 0.01$), the direct model output can be used to forecast the corresponding modelled energy variable, such as UK electricity demand ($r = 0.84$, $p < 0.01$). Similarly, for zonal wind speed at 850 hPa, the hindcast can be used as a predictor for modelled Northern Europe offshore wind capacity factors ($r = 0.72$, $p < 0.01$).

Although there is considerable potential for constructing skilful decadal forecasts for energy applications over Europe, careful selection is required. For example, although 10 m wind speed is perhaps the most obvious choice for decadal forecasts of modelled Northern European offshore wind capacity factors, its relative lack of skill (compared to U850 or other large-scale pressure pattern indices) renders it a poor choice overall for this purpose. The appropriate selection of predictors is essential, and the absence of skill in a particular surface field does not, in itself, preclude the possibility for skilful predictions through other pathways.

While beyond the scope of the analysis presented here, understanding the physical drivers of NAO/delta P index predictability warrants further investigation. While some studies have proposed external forcings as an explanation for this skill (e.g., in Klavans et al. 2021 and Christiansen et al. 2022), other studies have identified climate variability as a driver of predictability, such as Strommen et al. (2023) and Sun et al. (2015). Sun et al. (2015) demonstrated that a large proportion of decadal NAO variability can be explained using a delayed oscillator model linking the Atlantic Meridional Overturning Circulation to Atlantic sea surface temperature variability. Identifying the relative contributions of these two mechanisms is therefore crucial for understanding the benefit of these decadal forecasts.

Decadal forecast information could be useful for both the electricity and gas sectors. The National Energy System Operator (NESO) creates a margin (the difference between the total renewable/conventional supply and electricity demand) forecast for the upcoming 6-month winter/summer period based on historical weather data. In this case, decadal forecasts could be used to inform how this distribution may shift over the next 5 or 10 years. There are also applications for the gas sector, as national gas contracts are secured on seasonal, 5-year, and 10-year timescales. As gas demand is closely tied to the average temperature over a given season or multiple years, decadal forecast information could be used to inform the pricing of contracts (Thornton et al. 2016, 2019).

Using direct model output demonstrated significant skill for modelled energy variables, including UK electricity demand (via temperature), Northern European offshore wind capacity factors (via zonal wind speed at 850 hPa), and high skill for Scandinavian precipitation ($r = 0.59$, $p = 0.01$). Pattern-based predictions were found to be more skilful for modelled Spanish solar capacity factors in agreement with previous studies on seasonal (Clark et al. 2017; Thornton et al. 2019) and decadal (Lockwood et al. 2023a; Tsartsali et al. 2023) timescales.

While this analysis has focused on predicting the mean state of the climate, the ability of decadal predictions to forecast extreme events for the energy sector, such as multi-year wind droughts or successive cold winters, has not yet been explored. An improved understanding of how shifts in the mean state relate to the likelihood of seeing extremes, as in Lockwood et al. (2023b), may help to provide early warning of potentially challenging decades.

We have shown that both circulation patterns (e.g., the NAO and delta P index) and key climate variables (e.g., temperature, zonal wind speed, irradiance, and precipitation) are highly predictable on decadal timescales during the extended winter (October–March). We find that these predictions, where the climate variable is well correlated with an energy variable, can be used to create skilful forecasts of modelled energy variables (e.g., weather dependent electricity demand, offshore wind capacity factors etc.) across different regions of Europe. While there are challenges in creating operational decadal predictions, such as coordinating the exchange of forecasts across different modelling centres (as described in Hermanson et al. 2022), this study highlights the potential of these forecasts to enhance energy sector resilience. As decadal forecasting skill is now demonstrated across a diverse range of energy relevant climate properties, the challenge for future research lies in refining and exploiting that skill to support opportunities in long-term energy planning and risk management.

Author Contributions

Benjamin W. Hutchins: conceptualization, data curation, formal analysis, investigation, methodology, resources, visualization, software, writing – original draft, writing – review and editing. **David J. Brayshaw:** conceptualization, supervision, funding acquisition, writing – review and editing, methodology, project administration. **Len C. Shaffrey:** conceptualization, supervision, funding acquisition, writing – review and editing, methodology. **Hazel E. Thornton:** conceptualization, supervision, methodology, funding acquisition, software, writing – review and editing. **Doug M. Smith:** methodology, software, conceptualization, writing – review and editing, supervision.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The CMIP6 decadal climate prediction project (dcpp) experiments can be accessed freely from the Earth System Grid Federation. The ERA5 reanalysis dataset (Hersbach et al. 2020) is freely available through the Copernicus Climate Change Service Climate Data Store. The energy reanalysis dataset was produced by Bloomfield et al. (2022) and can be accessed here (https://researchdata.reading.ac.uk/321/).

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.