

Decadal predictions of wind, solar and compound power indicators to support the European renewable energy sector

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Abstract. Renewable energy production is strongly influenced by climate variability and change, making the energy sector sensitive to fluctuations on decadal timescales. Decadal climate predictions, which aim to forecast climate variability over the next few years, therefore offer potential value for anticipating near-term changes in wind and solar resources and supporting climate-informed energy planning. However, the predictive skill of decadal forecasts for energy-relevant indicators remains poorly quantified, which is crucial to know the potential usability of any forecast product.

This study evaluates the skill of decadal climate predictions over Europe for forecast years 1–3 using a multi-model ensemble from the Coupled Model Intercomparison Project Phase 6 (CMIP6) Decadal Climate Prediction Project (DCPP). We assess three energy-relevant indicators: photovoltaic potential (PVpot), wind capacity factor (WCF), and a compound indicator describing the number of energy drought days (NED), defined as days with inefficient production from both wind and solar resources. The skill is evaluated against the ERA5 reanalysis, and the added value of the model initialization is estimated by comparing the decadal predictions against the non-initialized historical forcing simulations. PVpot exhibits the highest and most spatially homogeneous skill for annual, spring and summer aggregations, closely reflecting the high predictability of surface solar radiation. WCF shows low and spatially heterogeneous skill, consistent with the high intrinsic variability of wind. The compound NED indicator displays strong seasonal dependence: its predictability is largely controlled by solar conditions in high-radiation seasons and by wind in winter and autumn. Model initialization generally provides added value where historical simulations already show some skill, especially for PVpot, while its impact is lower for WCF. This work shows the specific seasons, regions and energy indicators for which decadal predictions can provide actionable climate information to support renewable energy applications.

1 Introduction

The renewable energy sector has gained increasing importance in Europe in recent years, with wind and solar representing a growing fraction of total electricity generation (European Environment Agency, 2022). Continued policy support and decarbonisation targets are expected to further accelerate this expansion in the coming decades (International Energy Agency, 2024). Renewable energy production depends strongly on variations in key climate variables such as near-surface air temperature, solar radiation or surface wind speed (Solomon, 2007), and ambitious deployment targets across Europe further highlight the

25 need for climate-informed planning in the energy sector (e.g., Ely et al., 2013; Gonzalez et al., 2019). While long-term climate
projections are essential for strategic planning, and short-term forecasts support daily operations, the intermediate horizon of
the next few years remains comparatively underexploited (Smith et al., 2019). Decadal climate predictions, which bridge the
gap between seasonal forecasts and long-term projections, are emerging as a valuable tool for sectors that must adapt to both
climate variability and climate change (Meehl et al., 2009; Boer et al., 2016). In the energy sector, such information could
30 support infrastructure development, system resilience, and risk management decisions (European Commission, 2020). Despite
this potential, the explicit integration of decadal climate information into wind and solar energy assessments remains limited,
highlighting a gap between advances in decadal prediction science and their application in the renewable energy sector.

Previous studies have evaluated the forecast skill of decadal prediction systems for essential climate variables and extreme
indices (Delgado-Torres et al., 2022, 2023; World Meteorological Organization, 2024), and have also explored the role of
35 statistical downscaling in improving regional skill (Moreno-Montes et al., 2026). In parallel, decadal forecasts have been
applied to sector-specific climate services, including agriculture (Solaraju-Murali et al., 2022; Delgado-Torres et al., 2025),
water management (Paxian et al., 2022), marine fisheries (Payne et al., 2022), and hydropower (Tsartsali et al., 2023), as
well as multi-sector studies demonstrating the application of decadal predictions (Dunstone et al., 2022; Done et al., 2021).
However, research on decadal climate services explicitly focused on the energy sector remains limited. Early assessments have
40 reported regionally dependent skill for decadal predictions of wind-related variables, including near-surface wind speed and
wind energy output, with skill often enhanced through downscaling approaches (Haas et al., 2015; Moemken et al., 2016).
More recent work has highlighted relatively high skill for surface solar radiation, while wind speed skill remains generally
low over Europe (Hutchins et al., 2025). By comparison, climate services for the energy sector have been more extensively
explored at sub-seasonal to seasonal timescales (Clark et al., 2017; Torralba et al., 2017b; Bloomfield et al., 2021; Bett et al.,
45 2022; Cionni et al., 2022; Lledó et al., 2022; Soret et al., 2026) and with long-term climate projections (Carvalho et al., 2021;
Hou et al., 2021).

In this study, we assess the skill of decadal predictions for energy-relevant indicators derived separately for solar and wind
energy over forecast years 1–3, and we further explore compound indicators that combine information from both sources. This
3-year forecast period is particularly relevant for short- to medium-term energy planning applications, including maintenance
50 scheduling, estimation of expected renewable energy production, and management of seasonal energy mixes. Both annual
and seasonal indicators are considered: annual means highlight low-frequency signals relevant for year-ahead planning, while
seasonal means allow the identification of season-dependent predictability. Analyzing each energy source independently allows
us to characterize source-specific predictability, while the combined indicators capture the co-variability of wind and solar
resources and its implications for energy system operations. Compound events are particularly relevant because simultaneous
55 deficits in multiple energy resources can exacerbate the risk of energy shortages and stress the energy system (Zscheischler
et al., 2018; Otero et al., 2022). Previous studies have shown that combining wind and solar resources can enhance system
robustness through their temporal and spatial complementarity (Heide et al., 2010; Monforti et al., 2014; Jerez et al., 2019;
Kapica et al., 2024). Decadal predictions of compound hot-dry extreme events have recently been explored by Aranyossy et al.
(2025). However, to the best of our knowledge, an assessment of the forecast quality of decadal predictions for compound

power indicators remains lacking, limiting the understanding of their utility for energy system planning and risk management over multi-year timescales.

This study is organized as follows. Section 2 describes the datasets used to compute the indicators including observation-based reference datasets, decadal predictions and historical simulations. Section 3 presents the methodology to compute the solar- and wind-based indicators, and compound indicators. Section 4 presents the results together with the discussion and a comparison with previous studies. Finally, Section 5 summarizes the main findings, discussing their implications and suggesting directions for future research.

2 Data

In this study, five different decadal forecast systems contributing to the Decadal Climate Prediction Project (DCPP; Boer et al., 2016) of the Coupled Model Intercomparison Project Phase 6 (CMIP6; Eyring et al., 2016), are used. These forecast systems are the EC-Earth3 (with three different initialization strategies), IPSL-CM6A-LR and MPI-ESM1.2-HR. In addition, to analyze the impact of initialization, the indicators are computed for the three corresponding CMIP6 non-initialized historical forcing simulation models (7 EC-Earth3 members, 11 IPSL-CM6A-LR members, and 2 MPI-ESM1.2-HR members). The main characteristics of the DCPD forecast systems and the historical simulation models, including ensemble size, spatial resolutions, initialization months (for the DCPD-A), and references, are detailed in Table S1 of the Supplementary Material. Additionally, the ERA5 reanalysis (Hersbach et al., 2020) dataset is used as the observation-based reference. This observational reference has been selected taking into account its temporal and spatial coverage and because it is widely used by the energy community (Ramon et al., 2024).

Depending on the energy source, different temporal resolutions and variables are used. For solar energy indicators, daily values of surface downwelling shortwave radiation (RSDS), near-surface air temperature (TAS), and surface wind speed (SFCWIND) are employed. For wind energy indicators, instantaneous 6-hourly surface wind (6h-SFCWIND) data are used. As sub-daily data are required to compute the wind indicators (Lledó et al., 2022), the number of available models is reduced.

Start dates from 1960 to 2016 are used for decadal predictions, focusing the analysis on forecast years 1–3. Therefore, to match the period, we use the ERA5 data, as well as the historical forcing simulations concatenated with the scenario ssp245 (O'Neill et al., 2016), during 1961–2019. Historical simulations provide data until 2014, and ssp245 is used for the rest of the years (2015–2019).

The analysis focuses on Europe, defined by the spatial domain spanning longitudes 30°W–12°E and latitudes 35°N–65°N.

3 Methodology

To provide information at a spatial scale relevant for regional applications, a statistical downscaling approach is applied to model simulations to increase the horizontal resolution, bringing them to the ERA5 grid (0.25°). This downscaling procedure consists of a combination of spatial interpolation and calibration using Empirical Quantile Mapping (EQM), described below.

This method is adopted, as previous studies have shown that more complex downscaling techniques often provide limited added value in terms of predictive skill compared to simpler approaches (e.g., Manzananas et al., 2018; Gutiérrez et al., 2019; Moreno-Montes et al., 2026), while minimising the risk of introducing artificial skill. To assess the sensitivity of the results to the spatial resolution used for the analysis, all indicators and skill metrics are additionally computed on the native spatial resolution of the coarsest prediction system considered (IPSL-CM6A-LR: $2.5^\circ \times 1.25^\circ$).

After interpolation and before calibration, wind energy indicators are derived from 6h-SFCWIND data converted to wind speeds at 100 m (6-hWIND). A representative hub height of 100 m is assumed for modern wind turbines (Wiser et al., 2023). To estimate hub-height winds from surface winds, a power law is applied (Brower, 2012), using a shear exponent of $\alpha = 0.143$ (Touma, 1977) over land and $\alpha = 0.11$ over water (Hsu et al., 1994), under the assumption of neutral atmospheric stability.

In addition, ERA5 wind speeds are adjusted using the Global Wind Atlas (GWA) to better represent long-term mean conditions at hub height. Figure S1 shows the climatological ratio between ERA5 and GWA mean 6-hWIND over 1961–2019, which is applied as a multiplicative pointwise correction factor (GWA/ERA5) to adjust the mean wind speed while preserving the temporal variability of the ERA5 data (Lledó et al., 2022).

Once wind-specific corrections have been applied, model outputs are adjusted to the observed climatology by removing the model mean and replacing it with the corresponding observed mean. These climatologies are computed over a common reference period (1963–2017), defined by the availability of all forecast years included in this study (i.e. 1–3) across the selected start dates (1960–2016). This adjustment reduces the impact of model drift while preserving the temporal variability of the simulations (Boer et al., 2016).

The adjusted decadal predictions and historical simulations are then calibrated against ERA5 using EQM (Panofsky and Brier, 1958). By adjusting empirical quantiles at 1% intervals (from the 1st to the 99th percentile), EQM corrects the distribution of the variable, including the mean, variance, and higher-order moments. Calibration is performed independently at each grid point, per forecast year and member for decadal predictions, and per calendar year and member for historical simulations. In both cases, empirical distributions are estimated using a 30-day moving window centered on the target date to preserve seasonality while ensuring a sufficient sample size. Both the climatological adjustment and EQM calibration are performed within a leave-one-year-out cross-validation framework. For each target year, the climatological means and EQM transfer function are estimated using all other years in the calibration period. This prevents information from the target year from being used in the calibration and avoids artificial skill inflation (Elsner and Schmertmann, 1994). For 6-hWIND, the calibration is performed separately for each time of the day, since wind distributions differ markedly across the diurnal cycle (Kalverla et al., 2019; Weide Luiz and Fiedler, 2022).

The calibrated climate variables are then used to compute the energy indicators. All indicators are calculated separately for each climatological season and for the whole year. We define three indicators: photovoltaic potential (PVpot) for solar energy, capacity factor for wind energy (WCF), and the Number of Energy Droughts (NED). The intermediate metric Number of Effective days (Neff) is first computed for each resource and subsequently combined to derive NED. Indicators are computed for each forecast system and for the ERA5 reanalysis, which we use as a reference to assess predictive performance. Results

125 for wind-related indicators are analyzed over land and over sea-adjacent regions, as both onshore and offshore wind resources are of practical interest for current and future wind energy deployment.

Following previous studies (Mavromatakis et al., 2010; Jerez et al., 2015), PVpot is computed as a dimensionless metric that combines RSDS, TAS and SFCWIND to represent the performance of photovoltaic cells under ambient environment. PV power generation at a specific location is determined by multiplying PVpot with the nominal installed capacity of that location. 130 The PVpot is mainly driven by RSDS, with adjustments for TAS, which lowers module efficiency at higher temperatures (Radziemska, 2003), and SFCWIND, which can partially offset thermal losses through convective cooling. Although equation S1 provides PVpot as a unitless quantity, in this study it is converted to percentage values to facilitate visual interpretation. Even though daily inputs are less precise than hourly due to aggregation, they keep seasonal and annual errors small and avoid the much larger biases seen with monthly data (Müller et al., 2019; Bett and Thornton, 2016).

135 WCF is defined as the ratio between the energy actually produced and the energy that would be generated if the turbine operated continuously at its rated power. WCF depends on the turbine's power curve, which varies by turbine type and site conditions; the standard power curves defined by the International Electrotechnical Commission (IEC) 61400-1 are shown in Figure S2. In this study, an IEC Class I turbine is adopted as a common reference, as a sensitivity analysis presented no notable differences among the skill performance of the different turbines (not shown). Given the high temporal resolution of turbine 140 power curves and their strong nonlinearity, the use of 6-hourly wind data reduces aggregation bias. Although daily means are often adequate (MacLeod et al., 2018), sub-daily data better preserve variability and yield more accurate WCF estimates (Lledó et al., 2022). WCF is derived using the R-based CSIndicators package (Pérez-Zanón et al., 2023).

PVpot and WCF are defined differently, so their absolute values should not be compared across energy sources. To enable a meaningful cross-resource comparison, Neff is defined as the number of days meeting efficiency-related thresholds, providing 145 a common performance indicator with direct operational relevance.

For solar energy production, Neff efficiency thresholds are defined using a minimum RSDS and a maximum cell temperature (T_{cell}: Chenni et al., 2007). The RSDS threshold is based on the concept of peak sun hours (PSH), defined as the equivalent number of hours per day with an irradiance of 1000 W m⁻² (Duffie and Beckman, 1980). A commonly used lower limit for meaningful PV generation is 5 PSH per day, which corresponds to a daily mean RSDS of 208 W m⁻² (Ghosh et al., 2022). 150 Since higher TAS increases T_{cell} and reduces PVpot, an upper operating threshold of T_{cell} = 45 °C is applied (see equation S2), at which the PV module works at 90% of its rated efficiency, with PV generation progressively declining above this threshold (Ghosh et al., 2024).

For wind energy, Neff is defined using both operational and performance criteria. Although IEC Class I turbines operate between cut-in (2 ms⁻¹) and cut-out (25 ms⁻¹) wind speeds, winds just above cut-in typically yield little energy production. 155 Therefore, effectiveness is defined using a minimum threshold of WCF ≥ 25%, which excludes periods of low-efficiency production and can be associated with economically relevant wind power generation (Boccard, 2009; Kealy et al., 2015). This threshold is translated into an equivalent minimum wind speed using the turbine power curve, and effective time steps are counted when wind speeds exceed this value while remaining below cut-out. To ensure consistency with solar indicators, 6-

hourly wind data are aggregated to daily values, defining a day as effective when at least 3 of 4 time steps meet the threshold
160 (Figure S3).

Based on the effective number of days in which any energy source can operate efficiently, we define the combined indicator NED, which corresponds to the number of days when neither source produces efficiently. In addition, Neff is calculated separately for each energy source (solar-Neff and wind-Neff).

Once the corresponding indicators are calculated for each forecast year, the forecast years 1-3 are averaged in order to
165 obtain a mean value over the entire forecast period for each forecast system. To ensure a consistent comparison with decadal predictions, a rolling mean with a window length equal to the number of forecast years (3) is applied to the historical simulations and ERA5 time series. Subsequently, multi-model ensembles are constructed for decadal predictions (DCPP) and historical simulations (HIST) following the multi-model mean approach (Delgado-Torres et al., 2022).

The performance of the DCPP is evaluated against the ERA5 reanalysis using the Anomaly Correlation Coefficient (ACC;
170 Wilks, 2011). ACC ranges from -1 (perfect inverse correlation) to 1 (perfect correlation). A one-sided t-test is applied to determine if ACC values differ significantly from zero (Wilks, 2011). Following Storch and Zwiers (1999), the effective number of degrees of freedom is used to account for autocorrelation in the time series. To assess the impact of initialization, the residual correlation (ResCorr; Smith et al., 2019) between the DCPP and ERA5 is calculated relative to the HIST. ResCorr is calculated by linearly removing the variability associated with HIST from both DCPP and ERA5 and correlating the resulting residuals.
175 Its significance is assessed using a two-sided t-test with effective degrees of freedom to account for temporal autocorrelation. Positive values of ResCorr indicate that decadal predictions can capture more observed variability that is not already captured by the historical simulations.

Since the DCPP and HIST ensembles have different numbers of members, we perform an additional sensitivity analysis to assess the impact of ensemble size on the estimated added value of initialization. The analysis is applied to the multi-
180 model mean used throughout the study; therefore, ensemble-size adjustments are performed independently for each model before constructing the multi-model average. For each forecast system, the same number of DCPP and HIST members are selected, corresponding to the minimum ensemble size available in both systems (7 for EC-Earth3, 10 for IPSL-CM6A-LR, and 2 for MPI-ESM1.2-HR). For this analysis, the 7 EC-Earth3 decadal prediction members are taken from the three different initializations for their comparison with the non-initialized EC-Earth3 historical simulations. For each resampling, an equal-
185 member multi-model ensemble is constructed and used to estimate ResCorr. The procedure is repeated 5000 times, and the sensitivity to ensemble size is quantified as the difference in residual correlation:

$$\Delta\text{ResCorr} = \text{ResCorr}_{\text{equal-members}} - \text{ResCorr}_{\text{full-ensemble}}.$$

The median of the resulting $\Delta\text{ResCorr}$ distribution is used as the central estimate at each grid point, while the 2.5th and 97.5th percentiles define a 95% bootstrap interval. Regions where this interval does not include zero are considered robustly
190 sensitive to ensemble size.

Additionally, we assess the positive bias in ResCorr associated with the finite size of the HIST ensembles, following Smith et al. (2019). Since the multi-model mean is constructed by averaging each prediction system independently, the HIST ensemble

of each model is randomly divided into two equal subsets (3+3 members for EC-Earth3, 5+5 for IPSL-CM6A-LR, and 1+1 for MPI-ESM1.2-HR). For EC-Earth3 and IPSL-CM6A-LR, which have 7 and 11 HIST members, respectively, one member is randomly excluded in each repetition. The corresponding subsets are then averaged across prediction systems to construct two independent multi-model HIST estimates (A and B). For each repetition, a biased ResCorr estimate is calculated using HIST A as the reference for both DCP and ERA5. An unbiased ResCorr estimate is then calculated using the two independent HIST estimates, with HIST A used as the reference for DCP and HIST B for ERA5. The finite-ensemble bias is estimated as the difference between these two ResCorr values. The procedure is repeated 5000 times, and the median estimated bias is subtracted from the original ResCorr. The uncertainty associated with the ensemble partitioning is quantified as the standard deviation of the bias estimates across the 5000 repetitions.

Finally, after computing the indicators for each grid point, a regionalization is applied to analyze trends and correlations at the regional scale. For each sub-region, indicators are first spatially area-weighted averaged to obtain a single representative time series, from which regional trends, correlations and ResCorr are calculated. This step is motivated by the known contribution of externally forced trends and low-frequency variability to decadal prediction skill in some variables (e.g. van Oldenborgh et al., 2012), and allows us to assess how long-term changes influence the estimated predictability. Trends are estimated using a linear fit, while statistical significance is assessed independently using a modified Mann-Kendall test that accounts for temporal autocorrelation following Hamed and Rao (1998). Europe is divided in seven sub-regions (Figure S4), following the regionalization of Priestley et al. (2024): Iberia, Western Europe, Mediterranean, Central Europe, Eastern Europe, Scandinavia, Great Britain and Ireland.

4 Results and discussion

The results are presented in three separate sections for each indicator: PVpot, WCF, and NED. The ACC of the indicator between DCP and ERA5, the ACC between HIST and ERA5, and the ResCorr between DCP and ERA5 relative to HIST are shown for the annual mean and individual seasons. Equivalent results obtained on the native resolution of the coarsest prediction system are shown in Figures S5, S10 and S13. For each indicator, the climatology and multiannual standard deviation are presented to provide context on the mean state and variability of the indicator (Figures S6, S11 and S15). Additionally, regional trends, correlations and ResCorr for each indicator are shown in Figures 2, 4 and 6. The ACC maps of the underlying variables (RSDS, TAS and SFCWIND) are shown in Figure S7, while their regional trends are presented in Figure S9. Finally, the robustness of the ResCorr results is further assessed by examining both the sensitivity to differences in ensemble size between DCP and HIST and the positive bias associated with the finite size of the HIST ensembles, following the procedures described in Section 3. The corresponding results, including the sensitivity to equal-member resampling, the bias-corrected ResCorr, and the uncertainty associated with the finite-ensemble correction, are presented in Figures S8, S12 and S17.

4.1 Photovoltaic potential (PVpot)

Figure 1a-e shows the ACC between DCP and ERA5 of PVpot for the annual mean and each season. The annual mean (Figure 1a) and JJA (Figure 1d) show the highest fractions of significant area, with positive skill over most of the region, except in parts of the UK, southern Europe and Scandinavia. In MAM (Figure 1c), the ACC is not significantly positive in northern Europe and Iberia and the percentage of significant area is lower than in the annual mean and JJA, although the skill patterns are similar. On the other hand, DJF (Figure 1b) shows the lowest fraction of significant points, with significant skill only over parts of Iberia and Italy. ACC values during SON (Figure 1e) are significant in regions along the Atlantic coast and parts of Poland and the Baltic countries. Across all seasons, skill tends to be lower in mountainous regions, particularly over the Alps. Similar skill patterns are obtained at the coarser resolution (Figure S5a-e), indicating that the main results are robust to spatial resolution.

The climatology of PVpot (Figure S6a-e) shows higher values over southern Europe than at higher latitudes, reflecting the meridional gradient in solar irradiance, in line with previous studies (e.g. Šúri et al., 2007; Castillo et al., 2016). The associated multiannual standard deviation is low across the domain (Figure S6f-j), indicating that PVpot variability is small and largely controlled by mean climatological conditions.

Although the percentage of significant grid points is slightly lower for PVpot than for its main driver RSDS (Figure S7a-e), both variables show very similar spatial skill patterns. The reduction in PVpot skill relative to RSDS is more noticeable over southern Europe in the annual mean (Figure S7a and Figure 1a), over parts of central Europe in MAM (Figure S7c and Figure 1c), and over Iberia in SON (Figure S7e and Figure 1e). This loss of skill reflects the fact that PVpot is not only driven by RSDS but is also modulated by TAS and, with a smaller contribution, by SFCWIND. While TAS generally shows high and spatially homogeneous skill across most seasons (except in DJF; Figure S7g), and SFCWIND exhibits weaker and more heterogeneous skill (Figure S7k-o), their combined effect slightly decreases the overall PVpot predictability compared to RSDS alone.

The seasonal contrast in skill suggests a link with large-scale atmospheric conditions. Skill is higher in JJA and MAM, when more persistent radiative conditions typically dominate, and lower in DJF and in mountainous regions, when variability is stronger. However, these relationships are not spatially uniform and should be interpreted cautiously. Besides, the similarity between the annual and JJA skill patterns reflects the dominant contribution of high-radiation seasons to the annual PVpot signal. Since PVpot is strongly controlled by RSDS, and solar irradiance peaks during spring and summer, the annual mean largely integrates the predictability of these seasons. In addition, annual averaging reduces short-term variability and increases signal-to-noise ratios, resulting in higher predictability and thus higher skill values.

Few studies have assessed decadal predictability for solar-energy indicators. Hutchins et al. (2025) have reported high summer skill for RSDS over southern and central Europe, broadly consistent with our results. They have also identified additional winter predictability using a NAO-based approach, which is not captured when evaluating PVpot from the multi-model ensemble. Focusing on seasonal predictions, Bett et al. (2022) have found higher predictability for RSDS in summer and lower in winter, in line with the seasonal contrast observed here for decadal predictions.

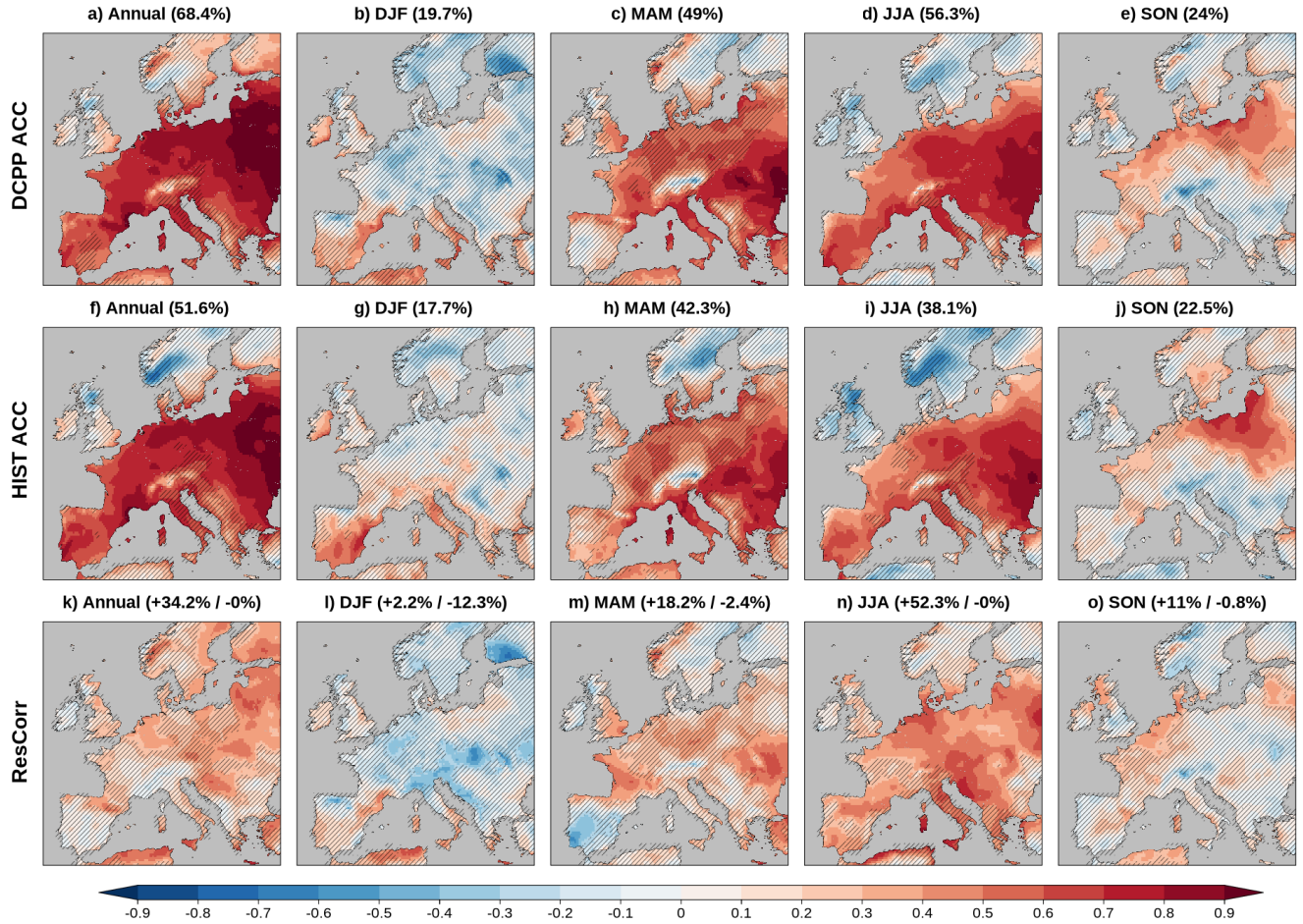


Figure 1. First row: ACC between DCP and ERA5 for PVpot for the annual mean (a) and seasonal means (b–e) for forecast years 1–3. Second row: ACC between HIST and ERA5 for the annual mean (f) and seasonal means (g–j). The percentages of significant grid points are indicated in brackets, and hatched regions denote non-significant correlations. Third row: ResCorr between DCP and ERA5 relative to HIST for the annual mean (k) and seasonal means (l–o). Percentages indicate the fractions of significantly positive (red) and significantly negative (blue) values. Positive (negative) ResCorr indicates higher (lower) skill for DCP compared to HIST. Correlations are computed against ERA5 during the 1961–2019 period. ACC significance is assessed using a one-sided t-test at the 95% confidence level, accounting for time-series autocorrelation, while ResCorr significance is assessed using a two-sided t-test with effective degrees of freedom to account for temporal autocorrelation.

The ACC between HIST and ERA5 is shown in Figure 1f–j and the added value of the DCPD relative to HIST assessed using the ResCorr is shown in Figure 1k–o. HIST reproduces the main spatial patterns identified in DCPD, although with a lower fraction of significant area, particularly in the annual mean (Figure 1f) and JJA (Figure 1i). In DJF, DCPD skill (Figure 1b) is lower than HIST skill (Figure 1g) in areas such as southern Iberia. In the annual mean (Figure 1k) and JJA (Figure 1n), ResCorr is significantly positive over large parts of the domain, indicating that model initialization enhances PVpot skill relative to historical simulations. During MAM and SON (Figure 1m,o), positive ResCorr values are restricted to specific regions, mainly over eastern Europe and parts of the Atlantic coast in MAM and over parts of northwestern Europe in SON. Similar conclusions are obtained at the native resolution of the coarsest prediction system (Figure S5f–o), where both the ACC of HIST and the ResCorr show broadly consistent patterns. Figure S8 shows that the median ResCorr differences obtained when subsampling the ensembles are generally close to zero and non-significant across Europe. This indicates that the added value of initialization identified in Figure 1k–o is largely insensitive to the unequal ensemble sizes of the prediction systems. However, accounting for the positive bias associated with the finite size of the HIST ensembles substantially reduces ResCorr, particularly for the annual mean, MAM and JJA (Figure S8f–j), indicating that the standard ResCorr may overestimate the added value of initialization. Nevertheless, the bias-corrected ResCorr is also subject to considerable uncertainty. The correction requires splitting the already small HIST ensembles into two independent subsets, including only one member per subset (1+1) for MPI-ESM1.2-HR. The relatively large standard deviation (Figure S8k–o), particularly in MAM and JJA, reflects this uncertainty. Therefore, both the standard and bias-corrected ResCorr estimates should be interpreted with caution.

Figure 2 summarizes the regional behaviour of PVpot long-term trends across the seven European sub-regions (Figure S4), showing ERA5 trends (a), DCPD trends (b), their correlations (c), and their ResCorr relative to HIST (d) for the annual mean and each season. For Iberia, Western Europe, the Mediterranean, Central Europe and Eastern Europe, ERA5 and DCPD generally show positive significant trends in the annual mean, MAM and JJA, resulting in significant positive correlations. In contrast, correlations are mostly weak and non-significant in DJF and SON, when observed trends are small or absent. Scandinavia and Great Britain and Ireland exhibit little skill overall, with significant correlations only in a few cases. ResCorr values are generally positive where correlations are significant, particularly in JJA and over Western and Eastern Europe during MAM, and in Eastern Europe and Scandinavia during annual mean, indicating that initialization contributes additional skill beyond the common trend signal. Overall, PVpot skill is closely linked to the ability of DCPD to reproduce the observed long-term trends.

PVpot trends follow similar patterns to those from RSDS (Figure S9a–b) for both ERA5 and DCPD, showing again that the variable is the main driver of the indicator. TAS trends (Figure S9c–d) are significantly positive in all the seasons and regions for both datasets, but these trends are not aligned with the PVpot trends.

The strong contribution of long-term trends to significant skill has been identified in several studies for decadal predictions (Meehl et al., 2009; Suckling et al., 2017) and historical simulations (Donat et al., 2023). Some studies have applied approaches to reduce model drift or systematic errors (Kharin et al., 2012), and others have shown that the skill of TAS is substantially reduced after removing the forced trend, whereas precipitation skill is less affected (Bellucci et al., 2015; Delgado-Torres et al., 2022). However, removing the trend may also influence forecast reliability and modify the balance between externally

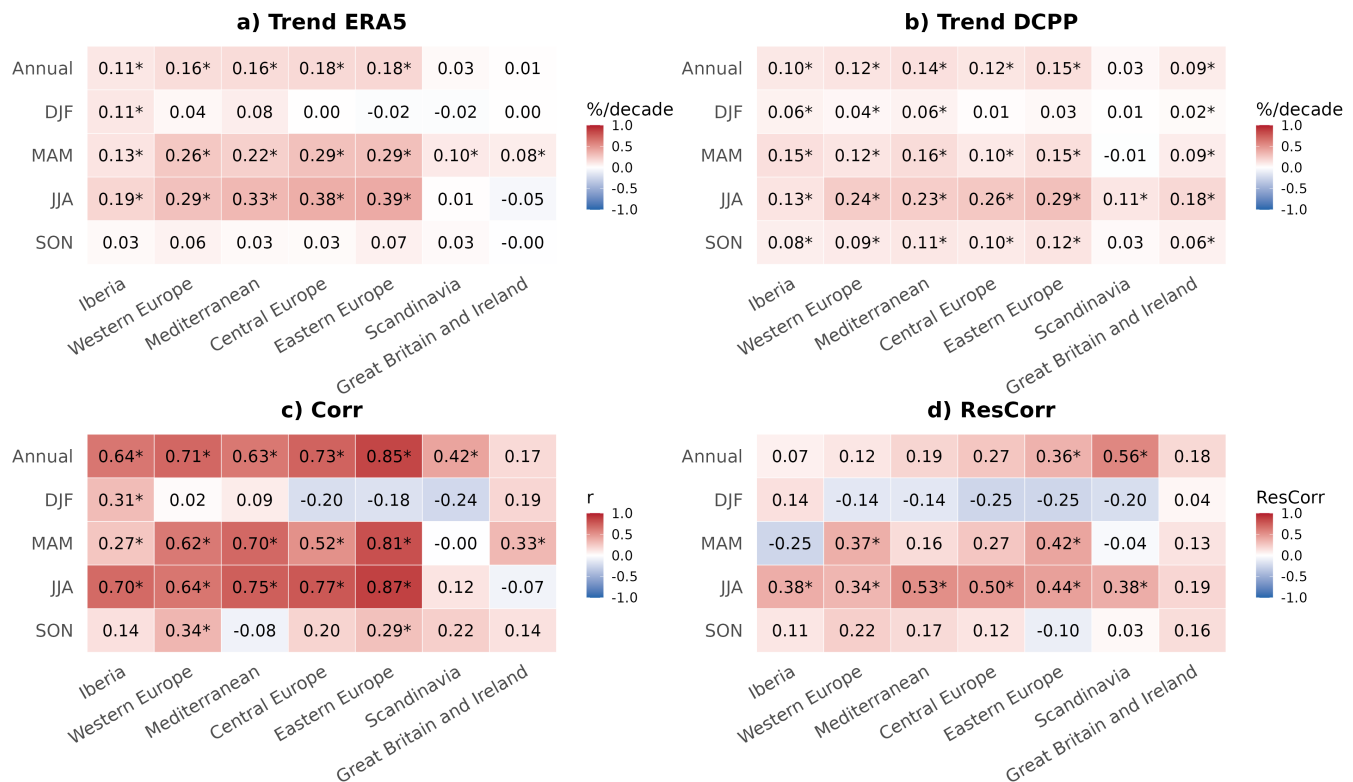


Figure 2. PVpot trends derived from ERA5 for 1961–2019 using a three-year rolling mean (a) and from DCPP for the start dates 1960–2016 over forecast years 1–3 (b), the correlation between ERA5 and DCPP (c), and the ResCorr between DCPP and ERA5 relative to HIST (d), shown for the annual mean and each season across the seven European sub-regions (Figure S4). Statistically significant trends, correlations and ResCorr values at the 95% confidence level are marked with an asterisk.

forced and internally driven variability (Corti et al., 2012; Smith et al., 2012). Rather than adopting a single approach, we explicitly present both perspectives. The ACC quantifies the total predictive skill, including the contribution from externally forced trends, which are themselves relevant for decision-making in a climate services context (Donat et al., 2023; Vaughan and Dessai, 2014; Delgado-Torres et al., 2025). The ResCorr isolates the added value of initialization beyond the historical simulations, providing insight into climate variations not captured by the historical simulations. Together, these two metrics offer a more complete assessment of decadal prediction performance for energy-relevant indicators.

The predominantly positive PVpot trends over southern and central Europe are consistent with recent historical analyses. Segado-Moreno et al. (2026) have reported weak to positive RSDS trends over southern and central Europe when comparing observations from 1994–2004 and 2004–2023, in line with the patterns found here for the longer period 1961–2019. By contrast, studies focusing on future climate change suggest different responses, with projected decreases over northern Europe and weaker or near-neutral changes in the south (Jerez et al., 2015; Hou et al., 2021). Although these future-oriented results are not directly comparable to the present analysis, they provide context suggesting that the positive PVpot trends identified here

over southern Europe are consistent with behaviours projected to strengthen in the future, whereas the future negative signals over northern Europe are not yet clearly expressed in the historical record.

305 4.2 Wind energy capacity factor (WCF)

Figure 3a-e shows the ACC of WCF between DCPD and ERA5 for the annual mean and each season. Overall, the percentage of grid points with significant skill is low across Europe, with the highest values in JJA (Figure 3d), followed by the annual mean (Figure 3a) and MAM (Figure 3c). Eastern Europe consistently exhibits high skill, although the spatial patterns vary seasonally. In the annual mean, DJF and MAM (Figure 3a-c), significant positive skill is present over parts of southern France, and over
310 Iberia in DJF. In MAM, northern Germany and northern Poland also show areas of significant skill. In JJA, skill extends across much of central Europe, whereas in SON (Figure 3e) it is limited to parts of Poland and the Baltics. These regions of significant skill are also present in the coarsest-resolution results (Figure S10a-e).

Figure S11 shows the climatology (Figure S11a-e) and multiannual standard deviation (Figure S11f-j) of WCF for the annual and seasonal means. The climatological patterns reflect the distribution of wind resources over Europe, with higher WCF
315 values over northern Europe and lower values over southern and Mediterranean regions, together with a clear seasonal cycle (Bett and Thornton, 2016) and higher values offshore than onshore. Unlike PVpot, WCF exhibits a non-negligible multiannual standard deviation, with the largest values (up to 5–6 percentage points) occurring mainly in DJF and over northern Europe, reflecting stronger year-to-year wind variability. This reflects the intrinsically high variability of wind and the non-linear turbine power curve, which translates wind fluctuations into larger variations in WCF.

320 The spatial distribution and the percentage of significant grid points for WCF closely resemble those obtained for SFCWIND (Figure S7k-o), with only minor higher values for WCF. This similarity is expected as wind speed is the main driver of WCF.

Low predictive skill for wind-related variables is physically expected given the intrinsic characteristics of atmospheric circulation. Climate predictability partly depends on the nature and variability of the variable considered (Alizadeh, 2022). Variables that are strongly constrained by large-scale energy balances and evolve more slowly, such as TAS and RSDS, tend to be more
325 predictable (Trenberth et al., 2009). In contrast, variables with higher variability and stronger dependence on regional and synoptic processes, such as SFCWIND or precipitation (PR), generally exhibit larger uncertainty (Gettelman and Rood, 2016; Slingo and Palmer, 2011). This behaviour is consistent with previous studies showing comparatively higher skill for decadal predictions for TAS than for PR (e.g. Smith et al., 2019; Delgado-Torres et al., 2022; Moreno-Montes et al., 2026).

Previous studies have examined the predictability of wind-related indicators for decadal predictions over Europe. Haas et al.
330 (2015) and Moemken et al. (2016) have reported significant skill for regional peak winds and wind energy output (Eout) over central Europe, particularly for annual means and short lead times, using a statistical–dynamical downscaling approach applied to a single model. However, these results are not directly comparable to the present assessment of WCF, which relies on a simpler statistical downscaling approach based on interpolation and calibration, and on a different wind-energy metric. More recently, Hutchins et al. (2025) have reported limited and spatially heterogeneous skill for surface wind over Europe,
335 with significant predictability mainly confined to parts of central and eastern Europe, consistent with the patterns identified here.

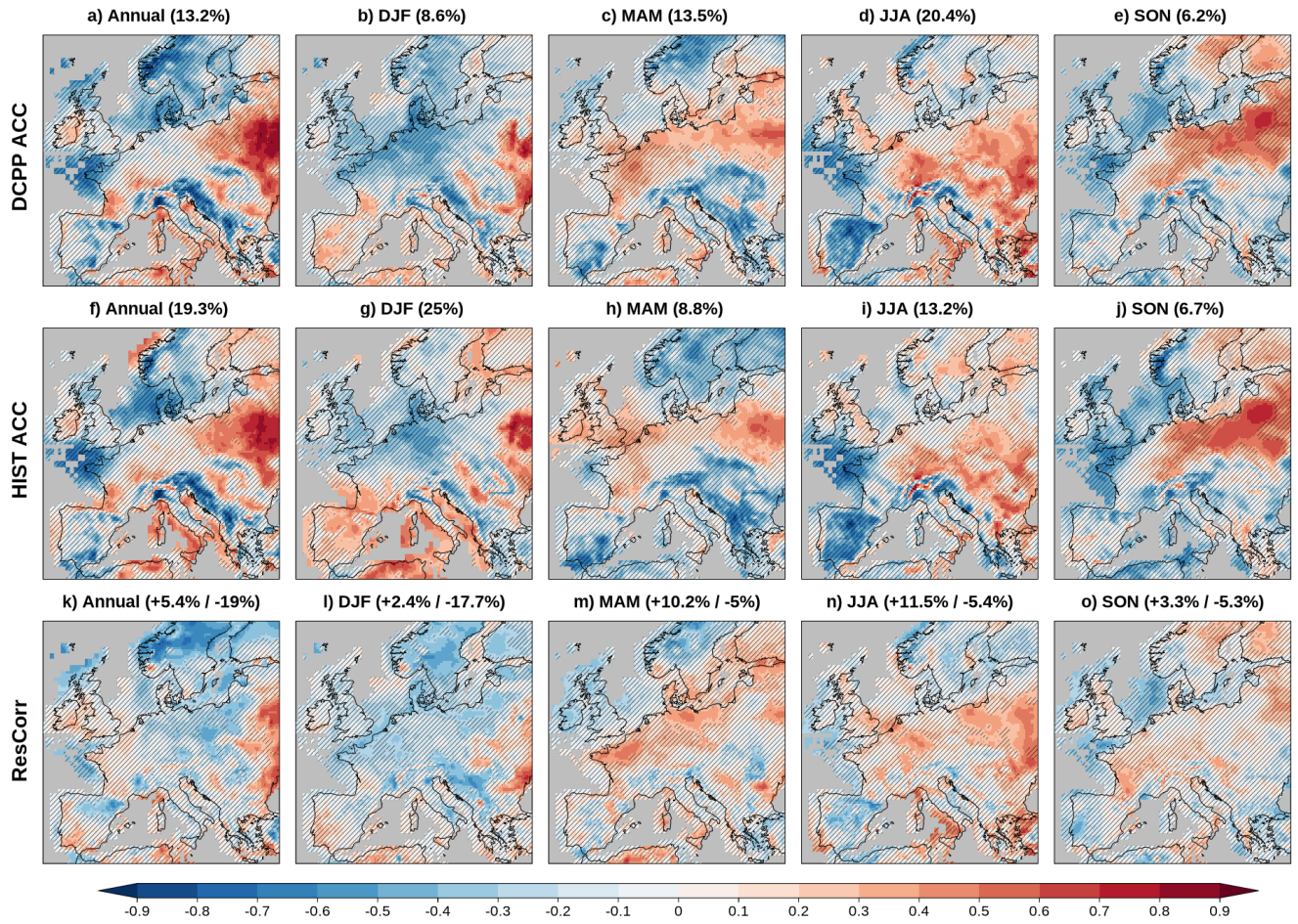


Figure 3. First row: ACC between DCP and ERA5 for WCF for the annual mean (a) and seasonal means (b–e) for forecast years 1–3. Second row: ACC between HIST and ERA5 for the annual mean (f) and seasonal means (g–j). The percentages of significant grid points are indicated in brackets, and hatched regions denote non-significant correlations. Third row: ResCorr between DCP and ERA5 relative to HIST for the annual mean (k) and seasonal means (l–o). Percentages indicate the fractions of significantly positive (red) and significantly negative (blue) values. Positive (negative) ResCorr indicates higher (lower) skill for DCP compared to HIST. Correlations are computed against ERA5 during the 1961–2019 period. ACC significance is assessed using a one-sided t-test at the 95% confidence level, accounting for time-series autocorrelation, while ResCorr significance is assessed using a two-sided t-test with effective degrees of freedom to account for temporal autocorrelation.

The ACC between HIST and ERA5 is shown in Figure 3f–j, while the impact of initialization is assessed through the ResCorr in Figure 3k–o. HIST exhibits a higher percentage of significantly positive grid points than DCP in DJF (Figure 3g), particularly over Mediterranean regions. In contrast, the percentage of significantly positive grid points is slightly lower for HIST than for DCP in MAM and JJA (Figure 3h–i). The ResCorr indicates that initialization enhances skill over eastern Europe

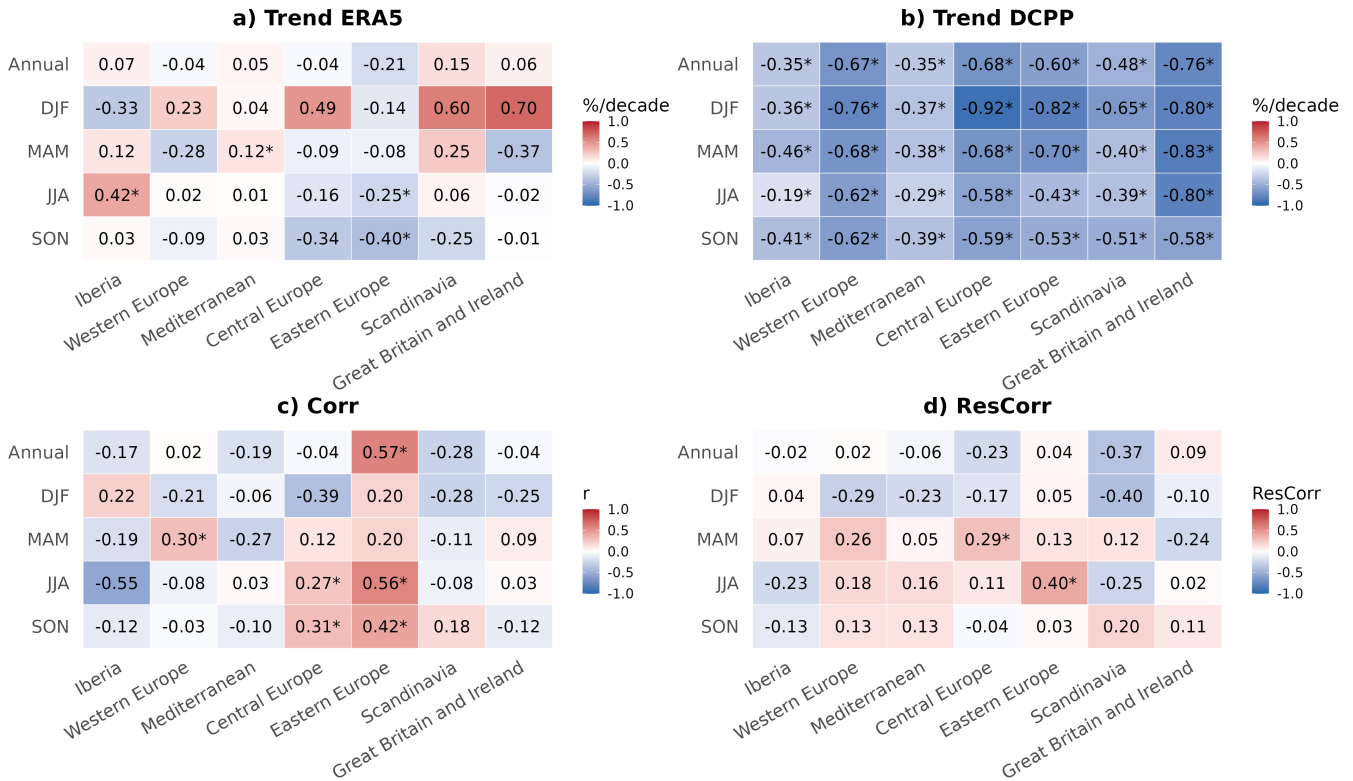


Figure 4. WCF trends derived from ERA5 for 1961–2019 using a three-year rolling mean (a) and from DCPP for the start dates 1960–2016 over forecast years 1–3 (b), the correlation between ERA5 and DCPP (c), and the ResCorr between DCPP and ERA5 relative to HIST (d), shown for the annual mean and each season across the seven European sub-regions (Figure S4). Statistically significant trends, correlations and ResCorr values at the 95% confidence level are marked with an asterisk.

in the annual mean (Figure 3k), over northern Germany and western France in MAM (Figure 3m), and over eastern Europe in JJA (Figure 3n). Outside these regions, ResCorr values are generally weak and spatially incoherent. Similar conclusions are obtained at the native resolution of the coarsest prediction system (Figure S10f-o), which shows the same large-scale patterns, supporting the robustness of these results. Figure S12 further shows that the ResCorr patterns are largely insensitive to ensemble size, with generally small and non-significant differences across Europe. Accounting for the finite size of the HIST ensembles modifies ResCorr locally but generally preserves its weak and spatially heterogeneous character (Figure S12f-j).

Applying the same regionalization used for PVpot, regional trends of WCF differ markedly between ERA5 and the DCPP (Figure 4a-b). ERA5 shows no uniform behaviour, with both significantly positive and negative trends depending on region and season, whereas the DCPP exhibits predominantly significant negative trends across all regions and seasons. WCF trends follow similar patterns to those of SFCWIND (Figure S9e-f) for both ERA5 and the DCPP.

Consequently, regional correlations between ERA5 and the DCPP (Figure 4c) are significantly positive mainly where both datasets display coherent negative trends. This is most evident in Eastern Europe, with significant correlations for the annual

mean, JJA and SON, and weaker agreement in DJF and MAM, consistent with the regions showing skill in Figure 3. Similar behaviour appears in Central Europe in JJA and SON, with additional agreement in Western Europe in MAM and weaker in Iberia in DJF. Elsewhere, differences in trend sign or magnitude lead to weak or negative correlations. Overall, these results emphasize the key role of trend consistency in explaining regional skill.

ResCorr regional values (Figure 4d) are generally non-significant, with a few isolated exceptions. A significantly positive ResCorr appears in Eastern Europe in JJA, aligned with the agreement in negative trends between ERA5 and the DCP (Figure 4a–b) and the significantly positive correlation in Figure 4c. In addition, ResCorr is significantly positive in Central Europe in MAM; however, this signal is driven by localized positive values (Figure 3h) and may be influenced by sampling variability. Other regions show non-significant but positive ResCorr values, suggesting local improvements due to initialization. In regions with weak or negative correlations, however, they mainly reflect a reduction in negative skill rather than a transition to meaningful predictive skill.

The WCF trends found are consistent with signals reported in previous studies. Using CMIP6 historical simulations, Miao et al. (2023) identified negative historical wind speed trends over Europe across a broad CMIP6 ensemble, including the three CMIP6 models analysed in the present study. Similarly, Pryor and Barthelmie (2010), analysing future climate scenarios, reported a projected weakening of near-surface winds over Europe, particularly towards the late 21st century. Although these projections are not directly comparable with the present analysis, they point to a tendency towards declining wind resources that may already be weakly emerging in current conditions. Observational and reanalysis-based studies (e.g. Vautard et al., 2010; Torralba et al., 2017a) have reported spatially heterogeneous near-surface wind trends across Europe. Our results are broadly consistent in showing negative trends over central and eastern Europe and weak signals over southern regions. However, differences remain over northern Europe and the British Isles, where these previous studies reported neutral or negative trends while positive trends are found here, likely due to differences in datasets, periods and methodologies. Together, these studies, based on different datasets and periods, indicate that declining wind signals have been reported in both modelling and observational contexts, while also highlighting the substantial uncertainty in the magnitude and spatial structure of historical wind changes.

4.3 Number of energy droughts (NED)

Figure 5a–e shows the ACC between DCP and ERA5 of NED. The highest fraction of significant ACC values occurs in JJA (Figure 5d), when most of eastern Europe and parts of central Europe and Iberia exhibit significant skill. The annual mean (Figure 5a) and MAM (Figure 5c) also show significant values over parts of eastern Europe and Iberia. In SON (Figure 5e), skill is generally weak and confined to parts of eastern Europe and the Baltics. Overall, the skill patterns are broadly consistent with those obtained at the coarsest resolution (Figure S13a–e).

Figure S14 presents the corresponding ACC for solar-Neff (Figure S14a–e) and wind-Neff (Figure S14f–j). The skill patterns of solar-Neff closely resemble those of PVpot (Figure 1a–e), while wind-Neff shows patterns similar to those of WCF (Figure 3a–e). Consequently, the spatial distribution of NED skill reflects the seasonally varying contribution of solar- and wind-related conditions. For the annual mean (Figure 5a), significant NED skill over parts of eastern Europe and Iberia broadly coincides

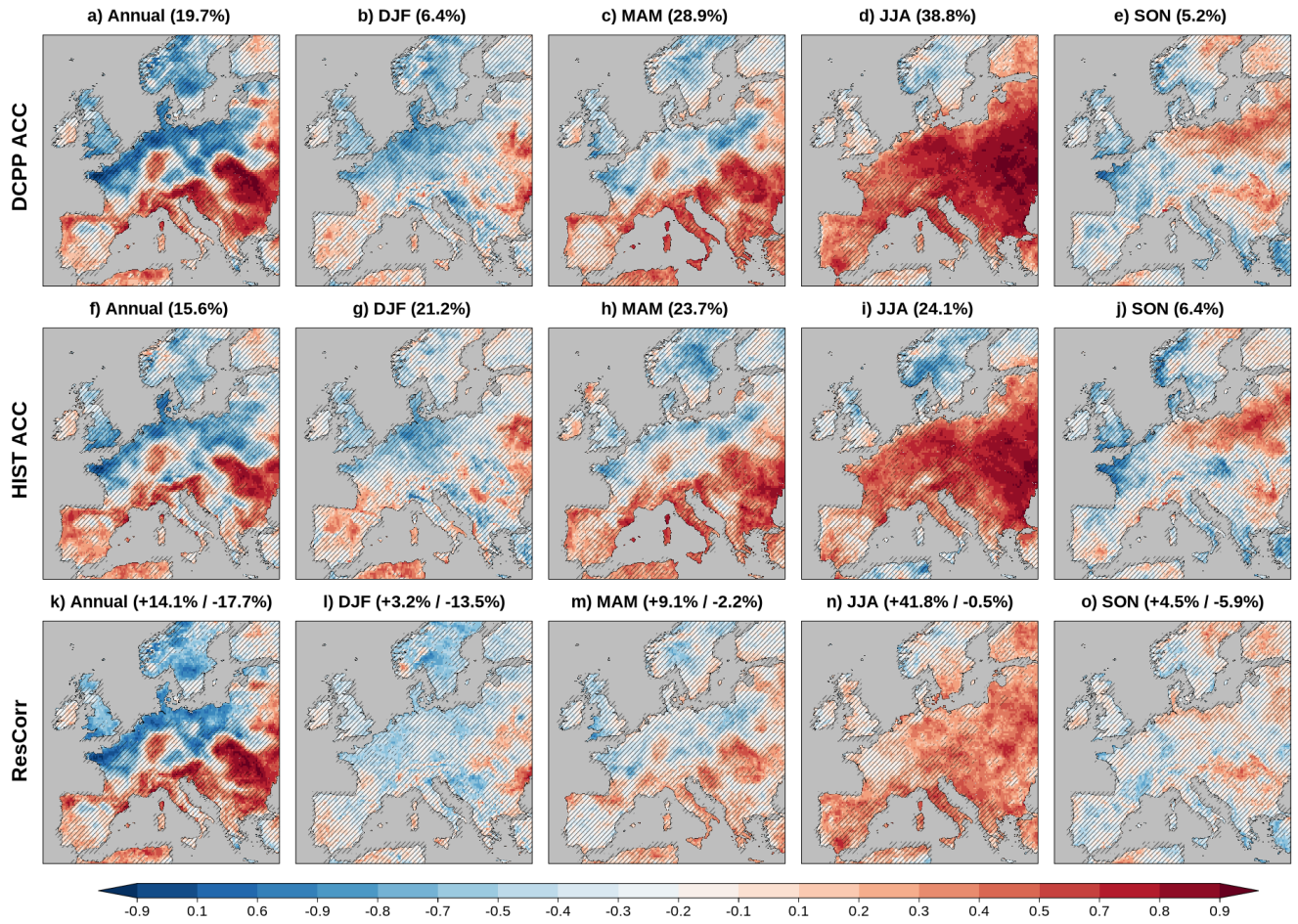


Figure 5. First row: ACC between DCPD and ERA5 for NED for the annual mean (a) and seasonal means (b–e) for forecast years 1–3. Second row: ACC between HIST and ERA5 for the annual mean (f) and seasonal means (g–j). The percentages of significant grid points are indicated in brackets, and hatched regions denote non-significant correlations. Third row: ResCorr between DCPD and ERA5 relative to HIST for the annual mean (k) and seasonal means (l–o). Percentages indicate the fractions of significantly positive (red) and significantly negative (blue) values. Positive (negative) ResCorr indicates higher (lower) skill for DCPD compared to HIST. Correlations are computed against ERA5 during the 1961-2019 period. ACC significance is assessed using a one-sided t-test at the 95% confidence level, accounting for time-series autocorrelation, while ResCorr significance is assessed using a two-sided t-test with effective degrees of freedom to account for temporal autocorrelation.

with regions where both solar-Neff (Figure S14a) and wind-Neff (Figure S14f) show positive skill. Over parts of southeastern Europe, including the Carpathian region and Greece, localized NED skill is more consistent with solar-Neff than with wind-Neff. In MAM (Figure 5c), NED skill over southern Europe generally follows the solar-Neff signal, although NED remains non-significant in several regions where solar-Neff shows skill. During JJA (Figure 5d), the widespread NED skill closely

resembles the solar-Neff pattern, with lower values over parts of western Europe. Over most of Europe in DJF and in northern regions in SON, as solar-Neff remains close to zero (Figure S16b,e), ACC cannot be computed (Figure S14b,e) and NED ACC is primarily determined by wind-Neff (Figure S14g,j). In SON, outside these regions, the weak NED skill is more consistent with wind-Neff (Figure S14j), although some contribution from solar-Neff (Figure S14e) is also apparent.

395 To provide context for these skill patterns, Figure S15 shows the climatology and multiannual standard deviation of NED, while Figure S16 shows the climatology of solar-Neff (Figure S16a-e) and wind-Neff (Figure S16f-j). NED is generally highest in DJF (Figure S15b) and SON (Figure S15e) and lowest in JJA (Figure S15d), reflecting the strong seasonal cycle of solar-Neff (Figure S16b,d,e). Spatially, higher NED values are found in mountainous regions and, during summer, over northern Europe. Wind-Neff is consistently low over mountainous areas and largely explains several regional NED features, while solar-Neff
400 mainly follows a latitudinal gradient. The largest NED variability occurs in DJF (Figure S15g), in central and eastern Europe in JJA (Figure S15i) and in some regions of northern Europe in SON (Figure S15j).

The relatively high climatological values of the NED indicator mainly reflect the use of fixed, efficiency-based thresholds to define effective energy production. Previous studies have analyzed compound energy droughts using percentile-based metrics (e.g. Otero et al., 2022), which characterise relative extremes within each region. Despite these different definitions, the main
405 seasonal patterns they report of higher drought frequencies in winter over southern Europe and in summer over northern regions are broadly consistent with our results. Here, fixed thresholds motivated by operational efficiency are adopted, an approach used in previous studies like Richardson et al. (2023). In our case, the prior calibration of all climate variables against ERA5 reduces systematic biases relative to the observational reference, including biases in mean values and variability. This helps avoid artificial shifts in the frequency of threshold exceedances caused by biases in the raw model data.

410 The ACC obtained with HIST is shown in Figure 5f–j, while the impact of initialization is assessed through ResCorr (Figure 5k–o). Overall, HIST reproduces the main spatial patterns found in DCP, although the relative skill varies by season. HIST shows a slightly lower percentage of significantly positive grid points than DCP in MAM (Figure 5h) and particularly in JJA (Figure 5i), whereas this percentage is higher for HIST in DJF (Figure 5g). JJA (Figure 5n) exhibits widespread positive ResCorr values across central, southern and eastern Europe, consistent with the substantially larger fraction of significant ACC
415 values in DCP (38.8%) than in HIST (24.1%). ResCorr values are generally weak and spatially heterogeneous in the rest of the seasons. Similar conclusions are obtained at the native resolution of the coarsest prediction system (Figure S13f–o), with broadly consistent HIST ACC and ResCorr patterns. The main exception is DJF (Figure S13g), where HIST exhibits substantially fewer significant ACC values at the coarser resolution. This suggests that part of the additional skill identified in the high-resolution results during this season may reflect spatial noise rather than robust large-scale predictability. Figure S17
420 shows that the ResCorr differences obtained when subsampling the ensembles are generally close to zero and non-significant across Europe, indicating that the NED results are largely insensitive to the unequal ensemble sizes of the prediction systems. Accounting for the finite size of the HIST ensembles substantially reduces some of the strongest ResCorr patterns, particularly for JJA (Figure S17i). The uncertainty of this correction is also relatively high (Figure S17n), indicating that the magnitude of the finite-ensemble correction should be interpreted with caution.

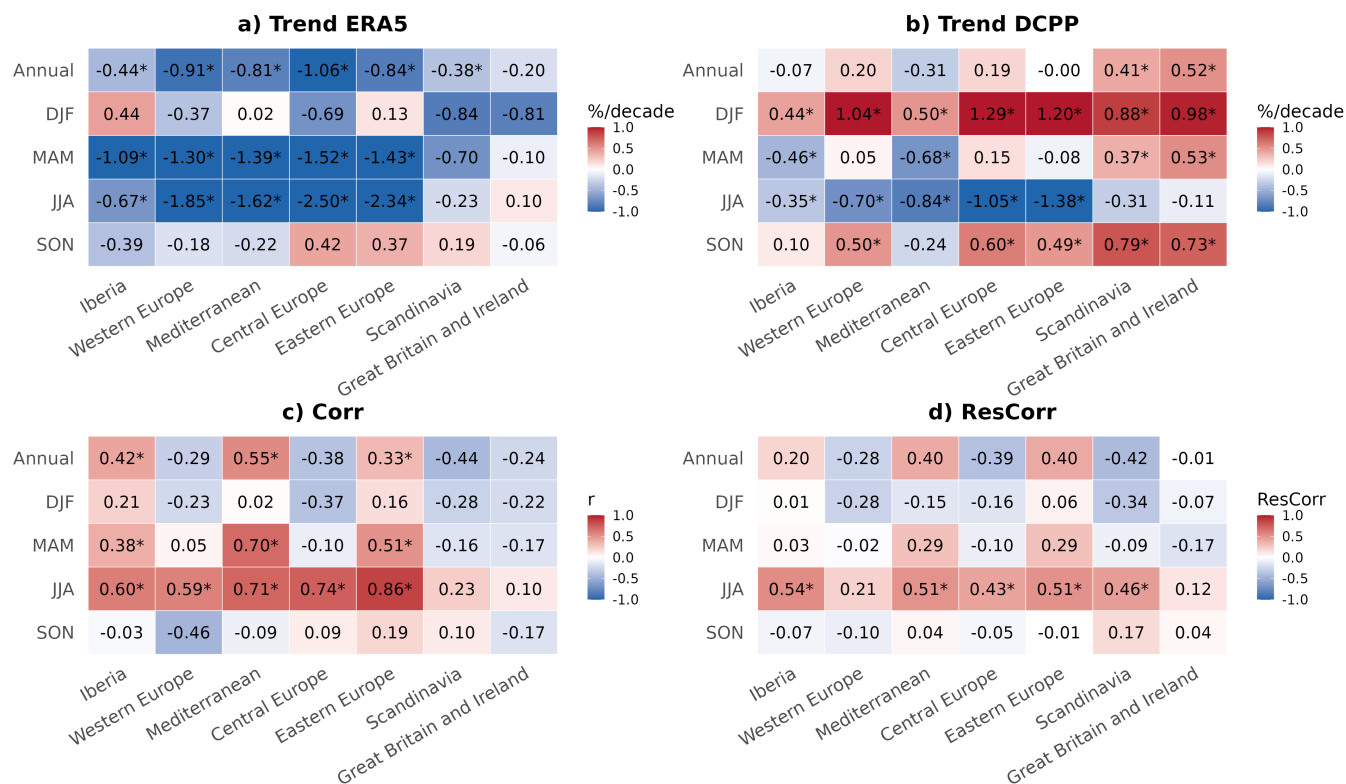


Figure 6. NED trends derived from ERA5 for 1961–2019 using a three-year rolling mean (a) and from DCPP for the start dates 1960–2016 over forecast years 1–3 (b), the correlation between ERA5 and DCPP (c), and the ResCorr between DCPP and ERA5 relative to HIST (d), shown for the annual mean and each season across the seven European sub-regions (Figure S4). Statistically significant trends, correlations and ResCorr values at the 95% confidence level are marked with an asterisk.

Figure 6 shows the regional trends of NED for ERA5 (a), for the DCPP (b), the corresponding correlations (c), and the ResCorr (d) across the seven sub-regions defined above. In some regions and seasons, ERA5 and DCPP exhibit similar trends, while in others they show opposite signs. In JJA, Iberia, Western Europe, Mediterranean, Central and Eastern Europe display significant negative trends in both datasets, which results in significantly positive correlations (Figure 6c). A similar behaviour is found for the annual mean and MAM in Iberia, Western Europe and Mediterranean. In the remaining regions and seasons, ERA5 and DCPP trends generally differ in sign, typically negative in ERA5 and positive in the DCPP, resulting in correlations that are weak or negative.

ResCorr (Figure 6d) partly mirrors the correlation patterns shown in Figure 6c. Regions and seasons with significantly positive ResCorr values (notably Iberia, Mediterranean, Central and Eastern Europe in JJA) or high but not significant ones (Mediterranean and Eastern Europe in the annual mean) generally correspond to cases where correlations are also significantly positive. This indicates that, in these cases, initialization enhances skill beyond the externally forced signal already contributing to the correlation. However, there are also cases with significantly positive correlations but low or negative ResCorr values (e.g.

Iberia in MAM and the annual mean). In these situations, the agreement in trends between ERA5 and the DCPD explains most of the skill, while initialization adds little or even decreases predictive value.

To better understand the contribution of solar-Neff and wind-Neff to NED variability and trends, solar-Neff and wind-Neff trends are analysed separately (Figure S18). The results show a clear seasonal dependence. In JJA, the strong negative NED trends in both ERA5 and DCPD are primarily associated with marked increases in solar-Neff (Figure S18a-b), while wind-Neff changes are weaker (Figure S18c-d). In MAM, solar-Neff also drives NED trends in ERA5, although with smaller magnitude, whereas in DCPD this signal is less clear due to strong negative trends in wind-Neff. In DJF, solar-Neff shows negligible variability over most regions, and NED trends are therefore directly anticorrelated with wind-Neff. In SON, both components exhibit mixed signals in ERA5, while in DCPD negative wind-Neff trends tend to dominate, leading to positive NED trends. In the annual means, the strong negative trends in NED in ERA5 seem to be dominated by positive solar-Neff trends, while the mixed DCPD signals are influenced by both energy sources.

The negative NED trends identified in ERA5 for the recent past are consistent with the ERA5-based analysis of Meng et al. (2025), who have reported a decrease in the frequency of renewable energy droughts under present-day conditions, despite differences in indicator definition. Additionally, DCPD trends show some qualitative similarities with the future evolution of energy droughts projected by Kapica et al. (2024), particularly in MAM and over parts of northern and eastern Europe in DJF. However, Kapica et al. (2024) have used a percentile-based definition of droughts, whereas the NED metric employed here is based on fixed physically motivated thresholds. The comparison is therefore limited to broad spatial patterns, and important regional differences remain, particularly in SON.

5 Conclusions

The renewable energy sector is strongly influenced by variability and long-term changes in key climate variables such as temperature, solar radiation and wind speed. However, the intermediate timescale of the coming years remains comparatively underexplored, and there is a clear need for tailored climate information to bridge the gap between decadal prediction advances and their application in renewable energy planning.

This study evaluates the predictive skill of a multi-model ensemble of decadal predictions (DCPD) for energy-relevant indicators over Europe, focusing on photovoltaic potential (PVpot), wind capacity factor (WCF), and the compound indicator number of energy droughts (NED) for forecast years 1–3. Skill is assessed using the ACC between the DCPD and ERA5, and the impact of model initialization is estimated with the ResCorr relative to historical simulations. In addition to grid-point analyses, sub-regional mean trends and correlations are examined to explore the relationship between long-term changes and predictive skill.

PVpot shows the highest and most spatially coherent skill among the indicators analyzed. Skill is significantly positive over large parts of the region at the annual scale and during MAM and JJA, while it is weaker and more spatially limited in DJF and SON. The spatial and seasonal patterns of PVpot skill closely follow those of surface downwelling shortwave radiation

(RSDS), its main driver. PVpot skill is slightly lower than RSDS skill because the indicator is also modulated by near-surface
470 air temperature (TAS) and surface wind speed (SFCWIND), which act as secondary constraints on predictability.

Initialization enhances PVpot skill in the annual mean and particularly in JJA, mainly by strengthening regions that already exhibit skill in the multi-model ensemble of historical simulations (HIST). In DJF and SON, the added value of initialization is limited and spatially heterogeneous, with localized improvements and degradations.

WCF exhibits lower and more spatially heterogeneous skill than PVpot, reflecting the higher intrinsic variability of wind
475 and its strong sensitivity to synoptic-scale circulation. Significant skill is consistently found over parts of eastern Europe across seasons, while other regions show weaker and more seasonally dependent skill, including central Europe in JJA and northern Europe in MAM and SON. The spatial distribution of WCF skill closely mirrors that of SFCWIND, confirming wind variability as the primary control on WCF predictability.

The impact of initialization is regionally dependent and generally limited. The clearest skill enhancements are found in JJA
480 over parts of eastern Europe, while in other seasons the impact of initialization is weaker and spatially heterogeneous. As for PVpot, initialization mainly improves skill where historical simulations already show some skill. The generally low WCF skill is consistent with the weak agreement between ERA5 and DCPD trends in many regions and seasons, together with the high intrinsic variability of wind.

The compound indicator NED displays predictability characteristics that reflect the combined influence of solar and wind
485 resources. NED skill is highest in JJA, followed by the annual mean and MAM, and is generally limited in DJF and SON. NED predictability does not require simultaneous skill in both components: in some regions it emerges where both solar-Neff and wind-Neff are predictable, while in others it is dominated by a single source. This highlights the importance of considering the relative contribution of both resources when assessing compound energy drought predictability.

Seasonal differences in NED skill reflect the relative contribution of wind and solar components. In JJA, NED predictability
490 is mainly driven by solar-Neff. In DJF, variability over much of Europe is largely driven by wind conditions, while in MAM and SON the relative contribution of both components varies regionally. As a result, the impact of initialization on NED is also seasonally dependent, enhancing skill when the dominant energy source is predictable, while providing little added value otherwise. This is consistent with the broader finding that initialization generally enhances existing predictability rather than creating skill where historical simulations show none. These results demonstrate the potential of decadal predictions to provide
495 actionable information for anticipating energy droughts, although forecast quality remains strongly dependent on season and region.

By evaluating compound energy indicators, explicitly separating total skill from the added value of initialization, and analysing results at the regional scale, this study advances beyond variable-based assessments and provides a more application-oriented understanding of decadal predictability for renewable energy. These findings highlight both the potential and the
500 limitations of decadal predictions for energy-related applications and underscore the need to clearly communicate where and when such information is reliable. In addition, the main conclusions were robust across spatial resolutions, and the ResCorr results were largely insensitive to differences in ensemble size between DCPD and HIST. However, the finite size of the HIST ensembles represents an additional source of uncertainty in ResCorr. Accounting for this finite-ensemble bias generally re-

duces positive ResCorr values, indicating that the standard estimate may overestimate the added value of initialization in some regions. Nevertheless, the bias correction itself is uncertain due to the small number of members available in each ensemble partition, as reflected by the relatively large standard deviation across partitions. Therefore, the standard and bias-corrected ResCorr estimates should be interpreted with caution.

Several limitations should be noted. ERA5 is the only reference dataset used, and reanalysis uncertainties, especially for wind, may affect skill estimates. However, ERA5 has been identified as one of the most reliable reanalysis datasets for near-surface wind variability, particularly in terms of correlation with observations and representation of temporal variability at turbine-relevant heights (Ramon et al., 2019), and the Global Wind Atlas has been used to correct it for a more accurate representation. Secondly, the higher resolution obtained through statistical downscaling does not necessarily imply additional local-scale predictability, particularly where relevant processes are not resolved by the original models, such as wind variability in regions with complex orography. This limitation should be considered when interpreting downscaled information for local-scale energy applications. Thirdly, fixed, efficiency-based thresholds, although operationally motivated, may limit sensitivity and transferability across regions or technologies. Moreover, temporal aggregation choices influence the indicators, particularly for wind, given the finer temporal resolution of turbine power curves. In addition, the power-law extrapolation used to estimate 100 m wind speeds assumes neutral stability and may be less representative under non-neutral atmospheric conditions, which could affect the reliability of local-scale decadal predictions. Finally, the ACC and ResCorr metrics capture correlation-based skill but do not fully describe other aspects relevant for operational decision-making, such as reliability or the representation of extreme events. Other metrics might be selected depending on the climate forecast products required by the energy users.

Future work could assess how sensitive the indicators are to the choice of thresholds (e.g. different RSDS or WCF limits), and compare results using alternative reanalyses or observation-based datasets. The framework could also be extended to include electricity demand, which would allow a more comprehensive assessment of supply–demand imbalances and increase the relevance of the indicators for system operators and energy planners. Furthermore, as decadal prediction systems are known to be affected by signal-to-noise problems (Scaife and Smith, 2018), future studies could further investigate the impact of signal-to-noise characteristics of the calibrated ensemble or apply correction methods such as the NAO-matching proposed by Smith et al. (2020).

Code availability. We acknowledge the use of the startR, s2dv, CSTools, multiApply, and CSIndicators R-language-based software packages, all of them available on the Comprehensive R Archive Network (CRAN; <https://cran.r-project.org/>, last access: 2 March 2026). The code used during the study is available from the corresponding author on reasonable request.

Data availability. All datasets used in the study are publicly available. ERA5 reanalysis data are available from the Copernicus Climate Data Store (CDS; <https://cds.climate.copernicus.eu/>, last access: 2 March 2026). The decadal predictions, historical simulations and climate projections are available on the Earth System Grid Federation system (ESGF; <https://esgf.github.io/>, last access: 2 March 2026).

535 *Author contributions.* SMM and CDT designed the study. SMM carried out the analysis and wrote the first draft. All authors contributed equally to the interpretation of results and writing thereafter.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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References

- Alizadeh, O.: Advances and challenges in climate modeling, *Climatic Change*, 170, 18, 2022.
- Aranyosy, A., De Luca, P., Delgado-Torres, C., Solaraju-Murali, B., Samso Cabre, M., and Donat, M. G.: Multi-annual predictions of hot,
550 dry and hot-dry compound extremes, *Earth System Dynamics*, 16, 2225–2251, 2025.
- Bellucci, A., Haarsma, R., Gualdi, S., Athanasiadis, P., Caian, M., Cassou, C., Fernandez, E., Germe, A., Jungclaus, J., Kröger, J., et al.: An assessment of a multi-model ensemble of decadal climate predictions, *Climate Dynamics*, 44, 2787–2806, 2015.
- Bett, P. E. and Thornton, H. E.: The climatological relationships between wind and solar energy supply in Britain, *Renewable Energy*, 87, 96–110, 2016.
- 555 Bett, P. E., Thornton, H. E., Troccoli, A., De Felice, M., Suckling, E., Dubus, L., Saint-Drenan, Y.-M., and Brayshaw, D. J.: A simplified seasonal forecasting strategy, applied to wind and solar power in Europe, *Climate services*, 27, 100 318, 2022.
- Bloomfield, H. C., Brayshaw, D. J., Gonzalez, P. L., and Charlton-Perez, A.: Sub-seasonal forecasts of demand and wind power and solar power generation for 28 European countries, *Earth System Science Data*, 13, 2259–2274, 2021.
- Boccard, N.: Capacity factor of wind power realized values vs. estimates, *energy policy*, 37, 2679–2688, 2009.
- 560 Boer, G. J., Smith, D. M., Cassou, C., Doblas-Reyes, F., Danabasoglu, G., Kirtman, B., Kushnir, Y., Kimoto, M., Meehl, G. A., Msadek, R., et al.: The decadal climate prediction project (DCPP) contribution to CMIP6, *Geoscientific Model Development*, 9, 3751–3777, 2016.
- Brower, M.: *Wind resource assessment: a practical guide to developing a wind project*, John Wiley & Sons, 2012.
- Carvalho, D., Rocha, A., Costoya, X., DeCastro, M., and Gómez-Gesteira, M.: Wind energy resource over Europe under CMIP6 future climate projections: What changes from CMIP5 to CMIP6, *Renewable and Sustainable Energy Reviews*, 151, 111 594, 2021.
- 565 Castillo, C. P., e Silva, F. B., and Lavalle, C.: An assessment of the regional potential for solar power generation in EU-28, *Energy policy*, 88, 86–99, 2016.
- Chenni, R., Makhoul, M., Kerbach, T., and Bouzid, A.: A detailed modeling method for photovoltaic cells, *Energy*, 32, 1724–1730, 2007.
- Cionni, I., Lledo, L., Torralba, V., and Dell’Aquila, A.: Seasonal predictions of energy-relevant climate variables through Euro-Atlantic Teleconnections, *Climate Services*, 26, 100 294, 2022.
- 570 Clark, R. T., Bett, P. E., Thornton, H. E., and Scaife, A. A.: Skilful seasonal predictions for the European energy industry, *Environmental Research Letters*, 12, 024 002, 2017.
- Corti, S., Weisheimer, A., Palmer, T., Doblas-Reyes, F., and Magnusson, L.: Reliability of decadal predictions, *Geophysical Research Letters*, 39, 2012.
- Delgado-Torres, C., Donat, M. G., Gonzalez-Reviriego, N., Caron, L.-P., Athanasiadis, P. J., Bretonnière, P.-A., Dunstone, N. J., Ho, A.-C.,
575 Nicoli, D., Pankatz, K., et al.: Multi-model forecast quality assessment of CMIP6 decadal predictions, *Journal of Climate*, 35, 4363–4382, 2022.
- Delgado-Torres, C., Donat, M. G., Soret, A., González-Reviriego, N., Bretonnière, P.-A., Ho, A.-C., Pérez-Zanón, N., Samso Cabre, M., and Doblas-Reyes, F. J.: Multi-annual predictions of the frequency and intensity of daily temperature and precipitation extremes, *Environmental Research Letters*, 18, 034 031, 2023.
- 580 Delgado-Torres, C., Octenjak, S., Marcos-Matamoros, R., Pérez-Zanón, N., Baulenas, E., Doblas-Reyes, F. J., Donat, M. G., Lwiza, L. M., Milders, N., Soret, A., et al.: Supporting food security with multi-annual climate information: Co-production of climate services for the Southern African Development Community, *Science of The Total Environment*, 975, 179 259, 2025.

- Donat, M. G., Delgado-Torres, C., De Luca, P., Mahmood, R., Ortega, P., and Doblas-Reyes, F. J.: How credibly do CMIP6 simulations capture historical mean and extreme precipitation changes?, *Geophysical Research Letters*, 50, e2022GL102466, 2023.
- 585 Done, J. M., Morss, R. E., Lazrus, H., Towler, E., Tye, M. R., Ge, M., Das, T., Munévar, A., Hewitt, J., and Hoeting, J. A.: Toward usable predictive climate information at decadal timescales, *One Earth*, 4, 1297–1309, 2021.
- Duffie, J. A. and Beckman, W. A.: *Solar engineering of thermal processes*, Wiley New York, 1980.
- Dunstone, N., Lockwood, J., Solaraju-Murali, B., Reinhardt, K., Tsartsali, E. E., Athanasiadis, P. J., Bellucci, A., Brookshaw, A., Caron, L.-P., Doblas-Reyes, F. J., et al.: Towards useful decadal climate services, *Bulletin of the American Meteorological Society*, 103, E1705–E1719, 590 2022.
- Elsner, J. B. and Schmertmann, C.: Assessing forecast skill through cross validation, *Weather and Forecasting*, 9, 619–624, 1994.
- Ely, C. R., Brayshaw, D. J., Methven, J., Cox, J., and Pearce, O.: Implications of the North Atlantic Oscillation for a UK–Norway renewable power system, *Energy Policy*, 62, 1420–1427, 2013.
- European Commission: *Powering a climate-neutral economy: An EU strategy for energy system integration*, 2020.
- 595 European Environment Agency: *Share of energy consumption from renewable sources in Europe*, Published: 26.10. 022, 2022.
- Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., and Taylor, K. E.: Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization, *Geoscientific Model Development*, 9, 1937–1958, 2016.
- Gettelman, A. and Rood, R. B.: *Demystifying climate models: A users guide to earth system models*, Springer, 2016.
- Ghosh, S., Dey, S., Ganguly, D., Baidya Roy, S., and Bali, K.: Cleaner air would enhance India’s annual solar energy production by 6–28 600 TWh, *Environmental Research Letters*, 17, 054007, 2022.
- Ghosh, S., Ganguly, D., Dey, S., and Chowdhury, S. G.: Future photovoltaic potential in India: navigating the interplay between air pollution control and climate change mitigation, *Environmental Research Letters*, 19, 124030, 2024.
- Gonzalez, P. L., Brayshaw, D. J., and Zappa, G.: The contribution of North Atlantic atmospheric circulation shifts to future wind speed projections for wind power over Europe, *Climate Dynamics*, 53, 4095–4113, 2019.
- 605 Gutiérrez, J. M., Maraun, D., Widmann, M., Huth, R., Hertig, E., Benestad, R., Roessler, O., Wibig, J., Wilcke, R., Kotlarski, S., et al.: An intercomparison of a large ensemble of statistical downscaling methods over Europe: Results from the VALUE perfect predictor cross-validation experiment, *International journal of climatology*, 39, 3750–3785, 2019.
- Haas, R., Reyers, M., and Pinto, J. G.: Decadal predictability of regional-scale peak winds over Europe using the Earth System Model of the Max-Planck-Institute for Meteorology, *Meteorol. Z.*, 25, 739–752, 2015.
- 610 Hamed, K. H. and Rao, A. R.: A modified Mann-Kendall trend test for autocorrelated data, *Journal of hydrology*, 204, 182–196, 1998.
- Heide, D., Von Bremen, L., Greiner, M., Hoffmann, C., Speckmann, M., and Bofinger, S.: Seasonal optimal mix of wind and solar power in a future, highly renewable Europe, *Renewable Energy*, 35, 2483–2489, 2010.
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., et al.: The ERA5 global reanalysis, *quarterly journal of the royal meteorological society*, *Quarterly Journal of the Royal Meteorological Society*, 615 2020.
- Hou, X., Wild, M., Folini, D., Kazadzis, S., and Wohland, J.: Climate change impacts on solar power generation and its spatial variability in Europe based on CMIP6, *Earth System Dynamics*, 12, 1099–1113, 2021.
- Hsu, S., Meindl, E. A., and Gilhousen, D. B.: Determining the power-law wind-profile exponent under near-neutral stability conditions at sea, *Journal of Applied Meteorology* (1988-2005), pp. 757–765, 1994.

- 620 Hutchins, B. W., Brayshaw, D. J., Shaffrey, L. C., Thornton, H. E., and Smith, D. M.: Decadal prediction for the European energy sector, *Meteorological Applications*, 32, e70 054, 2025.
- International Energy Agency: Renewables 2023, 2024.
- Jerez, S., Tobin, I., Vautard, R., Montávez, J. P., López-Romero, J. M., Thais, F., Bartok, B., Christensen, O. B., Colette, A., Déqué, M., et al.: The impact of climate change on photovoltaic power generation in Europe, *Nature communications*, 6, 10 014, 2015.
- 625 Jerez, S., Tobin, I., Turco, M., Jiménez-Guerrero, P., Vautard, R., and Montávez, J. P.: Future changes, or lack thereof, in the temporal variability of the combined wind-plus-solar power production in Europe, *Renewable energy*, 139, 251–260, 2019.
- Kalverla, P. C., Duncan Jr, J. B., Steeneveld, G.-J., and Holtslag, A. A.: Low-level jets over the North Sea based on ERA5 and observations: together they do better, *Wind Energy Science*, 4, 193–209, 2019.
- Kapica, J., Jurasz, J., Canales, F. A., Bloomfield, H., Guezgouz, M., De Felice, M., and Kobus, Z.: The potential impact of climate change
630 on European renewable energy droughts, *Renewable and Sustainable Energy Reviews*, 189, 114 011, 2024.
- Kealy, T., Barrett, M., and Kearney, D.: How profitable are wind turbine projects? An empirical analysis of a 3.5 MW wind farm in Ireland, *International journal on recent technologies in mechanical and electrical engineering*, 2015.
- Kharin, V., Boer, G., Merryfield, W., Scinocca, J., and Lee, W.-S.: Statistical adjustment of decadal predictions in a changing climate, *Geophysical Research Letters*, 39, 2012.
- 635 Lledó, L., Ramon, J., Soret, A., and Doblas-Reyes, F.-J.: Seasonal prediction of renewable energy generation in Europe based on four teleconnection indices, *Renewable Energy*, 186, 420–430, 2022.
- MacLeod, D., Torralba, V., Davis, M., and Doblas-Reyes, F.: Transforming climate model output to forecasts of wind power production: how much resolution is enough?, *Meteorological Applications*, 25, 1–10, 2018.
- Manzanas, R., Gutiérrez Llorente, J. M., van Meijgaard, E., Calmanti, S., Magariño Manero, M. E., Cofiño González, A. S., Herrera García, S., et al.: Dynamical and statistical downscaling of seasonal temperature forecasts in Europe: Added value for user applications, 2018.
- 640 Mavromatakis, F., Makrides, G., Georghiou, G., Pothrakis, A., Franghiadakis, Y., Drakakis, E., and Koudoumas, E.: Modeling the photovoltaic potential of a site, *Renewable energy*, 35, 1387–1390, 2010.
- Meehl, G. A., Goddard, L., Murphy, J., Stouffer, R. J., Boer, G., Danabasoglu, G., Dixon, K., Giorgetta, M. A., Greene, A. M., Hawkins, E., et al.: Decadal prediction: can it be skillful?, *Bulletin of the American Meteorological Society*, 90, 1467–1486, 2009.
- 645 Meng, Y., Schmidt, J., Zscheischler, J., and Bevacqua, E.: Climate-driven compounding effects and historical trends in renewable electricity droughts in Europe, *Applied Energy*, 401, 126 623, 2025.
- Miao, H., Xu, H., Huang, G., and Yang, K.: Evaluation and future projections of wind energy resources over the Northern Hemisphere in CMIP5 and CMIP6 models, *Renewable energy*, 211, 809–821, 2023.
- Moemken, J., Reyers, M., Buldmann, B., and Pinto, J. G.: Decadal predictability of regional scale wind speed and wind energy potentials
650 over Central Europe, *Tellus A: Dynamic Meteorology and Oceanography*, 68, 29 199, 2016.
- Monforti, F., Huld, T., Bódis, K., Vitali, L., D’isidoro, M., and Lacal-Arántegui, R.: Assessing complementarity of wind and solar resources for energy production in Italy. A Monte Carlo approach, *Renewable Energy*, 63, 576–586, 2014.
- Moreno-Montes, S., Delgado-Torres, C., Duzenli, E., Pérez-Zanón, N., Marcos-Matamoros, R., and Soret, A.: Comparative analysis of statistical downscaling methods for multi-model decadal climate predictions over Western Europe, *Climate Services*, 42, 100 639, <https://doi.org/https://doi.org/10.1016/j.cliser.2026.100639>, 2026.
- 655 Müller, J., Folini, D., Wild, M., and Pfenninger, S.: CMIP-5 models project photovoltaics are a no-regrets investment in Europe irrespective of climate change, *Energy*, 171, 135–148, 2019.

- O'Neill, B. C., Tebaldi, C., Van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J.-F., Lowe, J., et al.: The scenario model intercomparison project (ScenarioMIP) for CMIP6, *Geoscientific Model Development*, 9, 3461–3482, 2016.
- 660 Otero, N., Martius, O., Allen, S., Bloomfield, H., and Schaefli, B.: A copula-based assessment of renewable energy droughts across Europe, *Renewable Energy*, 201, 667–677, 2022.
- Panofsky, H. A. and Brier, G. W.: Some applications of statistics to meteorology, Mineral Industries Extension Services, College of Mineral Industries . . . , 1958.
- Paxian, A., Reinhardt, K., Pankatz, K., Pasternack, A., Lorza-Villegas, M. P., Scheibel, M., Hoff, A., Mannig, B., Lorenz, P., and Früh, B.:
 665 High-resolution decadal drought predictions for German water boards: a case study for the Wupper catchment, *Frontiers in Climate*, 4, 867 814, 2022.
- Payne, M. R., Danabasoglu, G., Keenlyside, N., Matei, D., Miesner, A. K., Yang, S., and Yeager, S. G.: Skilful decadal-scale prediction of fish habitat and distribution shifts, *Nature Communications*, 13, 2660, 2022.
- Pérez-Zanón, N., Ho, A.-C., Chou, C., Lledó, L., Marcos-Matamoros, R., Rifà, E., and González-Reviriego, N.: CSIndicators: Get tailored
 670 climate indicators for applications in your sector, 2023.
- Priestley, M. D., Stephenson, D. B., Scaife, A. A., Bannister, D., Allen, C. J., and Wilkie, D.: Forced trends and internal variability in climate change projections of extreme European windstorm frequency and severity, *Quarterly Journal of the Royal Meteorological Society*, 150, 4933–4950, 2024.
- Pryor, S. C. and Barthelmie, R. J.: Climate change impacts on wind energy: A review, *Renewable and sustainable energy reviews*, 14,
 675 430–437, 2010.
- Radziemska, E.: The effect of temperature on the power drop in crystalline silicon solar cells, *Renewable energy*, 28, 1–12, 2003.
- Ramon, J., Lledó, L., Torralba, V., Soret, A., and Doblas-Reyes, F. J.: What global reanalysis best represents near-surface winds?, *Quarterly Journal of the Royal Meteorological Society*, 145, 3236–3251, 2019.
- Ramon, J., Lledó, L., Ferro, C. A., and Doblas-Reyes, F. J.: Uncertainties in the observational reference: Implications in skill assessment and
 680 model ranking of seasonal predictions, *Quarterly Journal of the Royal Meteorological Society*, 150, 897–910, 2024.
- Richardson, D., Pitman, A., and Ridder, N.: Climate influence on compound solar and wind droughts in Australia, *npj Climate and Atmospheric Science*, 6, 184, 2023.
- Scaife, A. A. and Smith, D.: A signal-to-noise paradox in climate science, *npj Climate and Atmospheric Science*, 1, 28, 2018.
- Segado-Moreno, L. C., Ruiz-Arias, J. A., Montávez, J. P., and Betak, J.: Past, current and future solar radiation trends in Europe: Multi-source
 685 assessment of the role of clouds and aerosols, *Remote Sensing of Environment*, 333, 115 122, 2026.
- Slingo, J. and Palmer, T.: Uncertainty in weather and climate prediction, *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 369, 4751–4767, 2011.
- Smith, D., Eade, R., Scaife, A., Caron, L.-P., Danabasoglu, G., DelSole, T., Delworth, T., Doblas-Reyes, F., Dunstone, N., Hermanson, L., et al.: Robust skill of decadal climate predictions, *Npj Climate and Atmospheric Science*, 2, 13, 2019.
- 690 Smith, D. M., Scaife, A. A., and Kirtman, B. P.: What is the current state of scientific knowledge with regard to seasonal and decadal forecasting?, *Environmental Research Letters*, 7, 015 602, 2012.
- Smith, D. M., Scaife, A. A., Eade, R., Athanasiadis, P., Bellucci, A., Bethke, I., Bilbao, R., Borchert, L. F., Caron, L.-P., Counillon, F., et al.: North Atlantic climate far more predictable than models imply, *Nature*, 583, 796–800, 2020.
- Solaraju-Murali, B., Bojovic, D., Gonzalez-Reviriego, N., Nicodemou, A., Terrado, M., Caron, L.-P., and Doblas-Reyes, F. J.: How decadal
 695 predictions entered the climate services arena: an example from the agriculture sector, *Climate services*, 27, 100 303, 2022.

- Solomon, S.: Climate change 2007-the physical science basis: Working group I contribution to the fourth assessment report of the IPCC, vol. 4, Cambridge university press, 2007.
- Soret, A., Gonzalez, P., Bloomfield, H., Masato, G., Goutham, N., Plougonven, R., and Torralba, V.: Subseasonal-to-seasonal climate predictions for energy, in: Sub-seasonal to Seasonal Prediction, pp. 779–807, Elsevier, 2026.
- 700 Storch, H. v. and Zwiers, F. W.: Statistical Analysis in Climate Research, Cambridge University Press, 1999.
- Suckling, E. B., van Oldenborgh, G. J., Eden, J. M., and Hawkins, E.: An empirical model for probabilistic decadal prediction: global attribution and regional hindcasts, *Climate Dynamics*, 48, 3115–3138, 2017.
- Šúri, M., Huld, T. A., Dunlop, E. D., and Ossenbrink, H. A.: Potential of solar electricity generation in the European Union member states and candidate countries, *Solar energy*, 81, 1295–1305, 2007.
- 705 Torralba, V., Doblas-Reyes, F. J., and Gonzalez-Reviriego, N.: Uncertainty in recent near-surface wind speed trends: a global reanalysis intercomparison, *Environmental Research Letters*, 12, 114 019, 2017a.
- Torralba, V., Doblas-Reyes, F. J., MacLeod, D., Christel, I., and Davis, M.: Seasonal climate prediction: a new source of information for the management of wind energy resources, *Journal of Applied Meteorology and Climatology*, 56, 1231–1247, 2017b.
- Touma, J. S.: Dependence of the wind profile power law on stability for various locations, *Journal of the Air Pollution Control Association*, 27, 863–866, 1977.
- 710 Trenberth, K. E., Fasullo, J. T., and Kiehl, J.: Earth’s global energy budget, *Bulletin of the american meteorological society*, 90, 311–324, 2009.
- Tsartsali, E., Athanasiadis, P., Materia, S., Bellucci, A., Nicoli, D., and Gualdi, S.: Predicting precipitation on the decadal timescale: A prototype climate service for the hydropower sector, *Climate Services*, 32, 100 422, 2023.
- 715 van Oldenborgh, G. J., Doblas-Reyes, F. J., Wouters, B., and Hazeleger, W.: Decadal prediction skill in a multi-model ensemble, *Climate dynamics*, 38, 1263–1280, 2012.
- Vaughan, C. and Dessai, S.: Climate services for society: origins, institutional arrangements, and design elements for an evaluation framework, *Wiley Interdisciplinary Reviews: Climate Change*, 5, 587–603, 2014.
- Vautard, R., Cattiaux, J., Yiou, P., Thépaut, J.-N., and Ciais, P.: Northern Hemisphere atmospheric stilling partly attributed to an increase in surface roughness, *Nature geoscience*, 3, 756–761, 2010.
- 720 Weide Luiz, E. and Fiedler, S.: Spatiotemporal observations of nocturnal low-level jets and impacts on wind power production, *Wind Energy Science*, 7, 1575–1591, 2022.
- Wilks, D. S.: Forecast verification, in: *International geophysics*, vol. 100, pp. 301–394, Elsevier, 2011.
- Wiser, R., Bolinger, M., Hoen, B., Millstein, D., Rand, J., Barbose, G., Darghouth, N., Gorman, W., Jeong, S., O’Shaughnessy, E., et al.: Land-based wind market report: 2023 edition, Tellus A: Dynamic Meteorology and Oceanography, 2023.
- 725 World Meteorological Organization: WMO Global Annual to Decadal Climate Update, 2024–2028, Tech. rep., World Meteorological Organization, Geneva, Switzerland, <https://wmo.int/publication-series/wmo-global-annual-decadal-climate-update-2024-2028>, 2024.
- Zscheischler, J., Westra, S., Van Den Hurk, B. J., Seneviratne, S. I., Ward, P. J., Pitman, A., AghaKouchak, A., Bresch, D. N., Leonard, M., Wahl, T., et al.: Future climate risk from compound events, *Nature climate change*, 8, 469–477, 2018.