Received: 22 February 2022 | Revised: 20 June 2022 | Accepted: 21 July 2022

DOI: 10.1002/met.2089

Meteorological Applications
Science and Technology for Weather and Climate
Open Access
RMetS

RESEARCH ARTICLE

# Characterizing renewable energy compound events across Europe using a logistic regression-based approach

**Noelia Otero**[1] | **Olivia Martius**[1] | **Sam Allen**[2] | **Hannah Bloomfield**[3,4] | **Bettina Schaefli**[1]

[1]Department of Geography and Oeschger Centre for Climate Change Research, University of Bern, Bern, Switzerland

[2]Department of Mathematical Statistics and Actuarial Science, University of Bern, Bern, Switzerland

[3]Department of Meteorology, University of Reading, Reading, UK

[4]Department of Geographical Sciences, University of Bristol, Bristol, UK

**Correspondence**
Noelia Otero, Department of Geography, Hallerstrasse 12, 3012 Bern, Switzerland.
Email: noelia.otero@giub.unibe.ch

**Abstract**

The transition towards decarbonized power systems requires accounting for the impacts of the climate variability and climate change on renewable energy sources. With the growing share of wind and solar power in the European power system and their strong weather dependence, balancing the energy demand and supply becomes a great challenge. We characterize energy compound events, defined as periods of simultaneous low renewable production of wind and solar power, and high electricity demand. Using a logistic regression approach, we examine the influence of meteorological and atmospheric drivers on energy compound events. Moreover, we assess the spatial coherence of energy compound events that pose a major challenge within an interconnected power grid, as they can affect multiple countries simultaneously. On average, European countries are exposed to winter energy compound events more than twice per year. The combination of extremely low temperatures and low wind speeds is associated with a higher probability of occurrence of energy compound events. Furthermore, we show that blocked weather regimes have a major influence on energy compound events. In particular, Greenland and European blocking lead to widespread energy compound events that affect multiple countries at the same time. Our results highlight the relevance of weather regimes resulting in synchronous spatial energy compound events, which might pose a greater risk within a potential fully interconnected European grid.

**KEYWORDS**

energy compound events, extremes, renewable energies, weather regimes

## 1 | INTRODUCTION

Climate change mitigation strategies are driving a global transition towards low carbon energy sources, for which the role of renewable energy is essential (Cronin et al., 2018). To meet the Paris Agreement targets, Europe is undergoing a rapid clean energy transition with an increasing growth in renewable capacity in recent years (IRENA, 2018). Transitioning to a low-carbon energy system will require the impacts of climate variability and

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.
© 2022 The Authors. *Meteorological Applications* published by John Wiley & Sons Ltd on behalf of Royal Meteorological Society.

climate change on renewable energy sources (RES) to be thoroughly understood (Collins et al., 2018; IRENA, 2018). In this context, wind and solar power, with a rapid growth over the past years (EEA, 2020), are expected to be increasingly important contributors to the energy mix in Europe. With the increasing share of RES that are strongly weather-dependent, balancing the energy demand and supply becomes a great challenge (Bloomfield et al., 2016; EEA, 2017; von Bremen, 2010). The fluctuating nature of RES represents a challenge for reliable energy production as both sources are directly dependent on weather conditions with a high spatio-temporal variability (Francois, 2016; Jurasz et al., 2021; von Bremen, 2010). Moreover, electricity demand is particularly sensitive to weather conditions (i.e., heating and cooling), with the temperature being one of the main drivers of demand patterns (Bloomfield et al., 2018; Garrido-Perez et al., 2021).

The influence of large-scale atmospheric patterns on European energy systems has been the subject of several studies (Bloomfield et al., 2018, 2020; Brayshaw et al., 2011; Ely et al., 2013; Francois, 2016; Grams et al., 2017; Thornton et al., 2017). In particular, it has been shown that persistent atmospheric blocking leads to anomalously low wind speeds and cold temperatures, resulting in higher residual load (i.e., energy demand minus energy production, Bloomfield et al., 2018; van der Wiel, Bloomfield, et al., 2019). The North Atlantic Oscillation (NAO), one of the most important modes of atmospheric variability over the North Atlantic sector in winter, plays a significant role in European power systems (e.g., Brayshaw et al., 2011; Ely et al., 2013; Francois, 2016; Grams et al., 2017; Jerez et al., 2013). Ravestein et al. (2018) showed the association between the NAO variability with periods of persistent low wind speeds over Europe, and thus a reduced wind power generation and colder temperatures. Recently, Allen et al. (2021) exploit this association when statistically post-processing wind speed forecasts. In Europe, mean wind generation shows strong weather regime dependent fluctuations: cyclonic regimes that can explain periods of overproduction and blocked regimes that can explain underproduction (Grams et al., 2017).

Extreme meteorological stress on the electricity system poses a serious risk to the European energy security. This includes periods of low renewable production and high demand. Raynaud et al. (2018) analysed periods of low production from renewable power sources, "energy production droughts," along with periods of high demand, "energy supply droughts," over a number of European regions. They found a large variability in the frequency of energy droughts between energy sources and the considered regions. They showed that wind droughts were more frequent but shorter than solar droughts that last longer as a result of the seasonality, while hydropower droughts were more regionally dependent. Bloomfield et al. (2020) investigated the meteorological conditions leading to the top 10 events of peak demand and residual load over Europe. They found that peak winter demand occurred with high atmospheric pressure over Russia and Scandinavia and temperatures and wind speeds below normal conditions across Europe. They noted a considerable spatial variability in dates of national peak demand events and renewable energy generation. Using large ensemble simulations from global climate models, van der Wiel, Bloomfield, et al. (2019) analysed the meteorological sensitivity of European renewable sources. From these simulations, they extracted 1-in-10 year low renewable energy production events and 1-in-10 year high energy residual load events to examine the meteorological conditions during low renewable production and high residual load. They showed that atmospheric blocking situations lead to long-lasting periods of low energy production. In a similar framework, van der Wiel, Stoop, et al. (2019) investigated whether four weather regimes capture the influence of meteorological variability in winter on the European energy sector.

Detailed analysis from previous works has emphasized the complex relationship between meteorology and energy production and load, including critical situations (e.g., extreme events) at local and regional scales (Bloomfield et al., 2019a; van der Wiel, Stoop, et al., 2019). Such complexity calls for tailored studies to better understand and quantify the impacts of climate variability on an energy system largely based on RES. In particular, understanding the weather conditions associated with a major risk of a power system failure, that is, an imbalance between electricity demand and energy production, is crucial within the context of a clean energy transition. In their study, van der Wiel, Bloomfield, et al. (2019) pointed out that high residual load events can be thought of as examples of compound events that arise from a combination of multiple drivers and/or hazards (Raymond et al., 2020; Zscheischler & Seneviratne, 2017).

In contrast to their approach, we do not rely on one single quantity to assess critical energy events, but instead, we use a country-wide bivariate definition of energy compound events based on two quantities: energy production and energy demand. We define an energy compound event as an episode of simultaneously low power production and high electricity demand. This approach allows us to focus on extreme episodes of energy compound events, as concurrent low production and high demand might not necessarily coincide with a high residual load. Indeed, high residual load values

might include episodes of low production but moderate (not extremely high) demand (or vice versa).

With the increasing interconnection between European electricity grids (EEA, 2019) that are largely based on RES dependent on weather conditions, assessing such critical situations that can make the power system more vulnerable is essential. A more interconnected European grid can be a strategic response to the multi-day variability challenge of RES supply (Grams et al., 2017), but it can also increase their vulnerability under particular situations (EEA, 2019). Therefore, it is important to consider the spatial coherence of energy compound events that can simultaneously affect multiple regions.

Building upon previous research that has shown the influence of weather regimes on RES supply and demand (e.g., Bloomfield et al., 2019a; Grams et al., 2017; van der Wiel, Stoop, et al., 2019), we characterize energy compound events in terms of their frequency, their drivers, and their spatial coherence across 27 European countries. Unlike most of the previous studies that analysed the mean meteorological conditions based on composite maps corresponding to energy events (e.g., low production or high residual load), we apply a logistic regression approach, which has been used in studies of multivariate compound events (e.g., Bevacqua et al., 2021; Martius et al., 2016), to assess the influence of weather conditions on extreme energy events. Moreover, using the logistic regression models, we quantify the odds of occurrence of energy compound events given a combination of certain weather conditions. The goals of this study are therefore twofold. First, we characterize energy compound events across Europe in terms of their frequency of occurrence and the dominant meteorological drivers associated with these events, and use a logistic regression approach to quantify the influence of meteorological drivers on the odds of occurrence of energy compound events. Second, we investigate for the first time the spatio-temporal occurrence of energy compound events across multiple countries, which can pose a high risk to the power system, especially in interconnected regions.

The remainder of this paper is organized as follows. The data, including the relevant energy indicators and weather regimes, are introduced in Section 2. In Section 3, the definition of energy compound events and the logistic models are described. The results are presented in Section 4, and Section 5 concludes with a general discussion and conclusions.

## 2 | DATA

We use daily time series of European energy indicators, including electricity demand, solar and wind power at a national level, created by Bloomfield et al. (2019b). These data are a reconstruction of energy indicators obtained from the ERA5 reanalysis data (Hersbach, 2018) during 1979–2019 and are available from the Reading Research and Data Repository (https://researchdata.reading.ac.uk/273/). The data have been used in previous studies (Bloomfield et al., 2019a, 2020; Otero et al., 2021). In the following subsections, we briefly summarize the methods used for the weather-to-energy conversion data, and the reader is referred to Bloomfield et al. (2019a) for further details.

Also, from ERA5, country averages of 2 m temperature (T2m), near-surface wind speed of 10 m (WS), and incoming shortwave radiation (SSRD) were used in the statistical analysis, because they are considered to be the main predictors of both energy production and electricity demand. In addition, the corresponding gridded fields with 1° by 1° spatial resolution, along with mean sea level pressure, were used for the composite analyses. Moreover, 500 hPa geopotential height (Z500) has been used for the weather regimes classification (Grams et al., 2017).

As shown in previous studies, there is a strong seasonality of energy peak demand and low production (Bloomfield et al., 2019a; van der Wiel, Stoop, et al., 2019). We performed sensitivity tests that confirmed that these critical events were limited to winter months for most countries, and our analysis, therefore, focuses on an extended winter season (October–March, ONDJFM).

### 2.1 | Energy demand

The electricity demand was reconstructed based on a multiple linear regression model trained with observed demand, in giga ($10^9$) watts (GW) units. The training data were available for two complete years (2016–2017) and extracted from the ENTSOe transparency platform (ENTSOE, 2019). The regression model uses both weather-dependent and human-behaviour-dependent factors (e.g., the day-of-the-week and long-term socio-economic trends Bloomfield et al., 2019a). The weather-dependent model parameters are heating-degree days (HDDs) and cooling-degree days (CDDs). An HDD occurs when a country-average T2m falls below 15.5° (the threshold at which residential heating is required), whereas a CDD occurs when a country-average T2m is above 22° and energy is required for residential cooling (Bloomfield et al., 2019a). Within the model, T2ms is the only weather-dependent variable that contributes to fluctuations in demand (Bloomfield et al., 2019a). This type of statistical regression approach to reconstruct

long-time series of electricity demand has been used in a number of similar studies (Francois, 2016; Raynaud et al., 2018; Thornton et al., 2017).

We use the weather-dependent model version that neglects the predictors representing human behaviour (e.g., the weekday and socioeconomic predictors) to highlight the weather dependence (see further details in Bloomfield et al., 2019a).

## 2.2 | Wind and solar power

The capacity factors, defined as the ratio of the total produced energy to the total installed capacity (%), obtained from both wind and solar power models were used to calculate the daily national wind and solar power production. To do so, for each country, we used as the baseline the installed capacity of wind and solar corresponding to 2017 (Figure S1; Bloomfield et al., 2019a, 2020). The wind and solar power datasets captured the overall behaviour of the national wind and solar power generation well (see Bloomfield et al., 2019a, and references therein for further details).

Wind power capacity factors were obtained from a physical model that uses bias-adjusted wind speeds (using the Global Wind Atlas as the "truth") at an altitude of 100 m above ground from the ERA5 reanalysis (Bloomfield et al., 2019a). Calibrated wind speeds are then passed through a power curve to convert to wind power capacity factors. Three different power curves were used for different grid cells of the underlying climate data set to allow the maximum potential to be extracted from each grid cell's wind speeds. In each grid cell, either a class 1, 2, or 3 wind turbine was assigned based on the 1979–2019 mean wind speed. Country-level wind power generation is calculated by weighting each grid box by the amount of wind power installed there (in the reference year 2017).

Solar power capacity factors were modelled following the empirical formulation of Evans and Florschuetz (1977), using T2m and incoming surface solar radiation as inputs. The solar power capacity factors were created at each grid point and then aggregated to national level, assuming a uniform distribution of solar panels across the country (as at the time of model creation, there were no available data on panel locations).

## 2.3 | Weather regimes

We use an extended classification of weather regimes (WRs) provided by Grams et al. (2017), in which a total of 7-year-round WRs are identified based on 10-day low-pass-filtered 500 hPa geopotential height anomalies (Z500) that remove short-term variability (Grams et al., 2017). The WRs are identified based on a standard empirical orthogonal function (EOF) analysis on 3-hourly Z500 anomaly patterns, followed by a k-means clustering of the leading EOFs that attributes each time step to a specific cluster in the EOF phase space. For our study, we derive the daily weather regime life cycle from the 3-hourly categorization. The WRs represent strong zonal flow conditions and blocking over Greenland, Scandinavia, and Central Europe. This classification also includes a "no regime" type for those time steps at which none of the seven regimes fulfils the criteria (Grams et al., 2017).

Three of the seven WRs are cyclonic: the Atlantic trough regime (AT); the Zonal regime (ZO); and the Scandinavian trough (ScTr). The cyclonic WRs show as predominant feature a negative Z500 anomaly. Four of the seven regimes are considered as blocked: the Atlantic ridge regime (AR); the European blocking regime (EuBL); the Scandinavian blocking (ScBL); and the Greenland blocking (GL; Grams et al., 2017). The cyclonic types (AT, ZO, ScTr) are dominant in winter, whereas the blocked regimes tend to dominate in summer (Grams et al., 2017). Figure S2 (see the supplementary material) provides a general overview of the relative frequencies of WRs throughout the year for the period of study.

Grams et al. (2017) showed that the seven WRs capture the seasonal variability of the large-scale circulation states over the Euro-Atlantic region. Moreover, they found a direct year-round relationship between the WRs and the surface wind distribution over the North Euro-Atlantic sector (see further details in Grams et al., 2017). Recent studies have shown the usefulness of this extended WR classification. For example, Domeisen et al. (2020) assessed the variability of the tropospheric response to sudden stratospheric warming events in the North Atlantic European region in terms of the WRs. In the context of sub-seasonal predictions, Büeler et al. (2021) evaluated the forecast skill of these seven WRs in sub-seasonal reforecasts from the European centre for medium-range weather forecasts (ECMWF).

# 3 | METHODS

## 3.1 | Energy compound events

An energy compound event (ECE) is defined here as a period of time when low wind and solar energy production (LWS) occurs simultaneously with high electricity demand (HD). For each country, the occurrence of an ECE can be expressed as follows:

$$E(t) = \begin{cases} 1 & \text{if } P_{WS}(t) \leq \text{LWS}_{10} \text{ and } D(t) \geq \text{HD}_{90} \\ 0 & \text{otherwise} \end{cases}, \quad (1)$$

where $E(t)$ is a daily time series characterizing whether an ECE occurs ($E(t) = 1$) or does not occur ($E(t) = 0$) at each time $t$. $P_{WS}(t)$ represents the wind and solar power production at time $t$, while $D(t)$ is the corresponding electricity demand. $\text{LWS}_{10}$ is the threshold used to define LWS events and is fixed as the 10th percentile of $P_{WS}(t)$, at the country of interest. Similarly, $\text{HD}_{90}$ is the threshold used to define HD events and is fixed as the 90th percentile of the distributions of $D(t)$. Thus, $E(t) = 1$ when $P_{WS}(t)$ is below the 10th percentile of all $P_{WS}(t)$ values and $D(t)$ is above its 90th percentile. Since we focus on the extended winter, ONDJFM, the $\text{LWS}_{10}$ and $\text{HD}_{90}$ are country- and season-specific thresholds. Although the number of instances that $P_{WS}(t)$ falls below $\text{LWS}_{10}$ and $D(t)$ exceeds $\text{HD}_{90}$ will individually be the same for each country, the number of times that this occurs simultaneously will vary across the countries (see Figure 1).

## 3.2 | Logistic regression

We apply a binary logistic modelling approach to quantify the influence of key driving factors of ECEs across Europe, including both meteorological predictors and WRs. Preliminary analysis showed that combining meteorological variables and WRs in the same model might hide the significant influence of WRs on the ECEs, as the meteorological covariates already explain a large proportion of information contained in the WRs. Therefore, we fit two independent models to quantify the influence of (1) local meteorological variables and (2) WRs. The formulation of the two models can be summarized as follows:

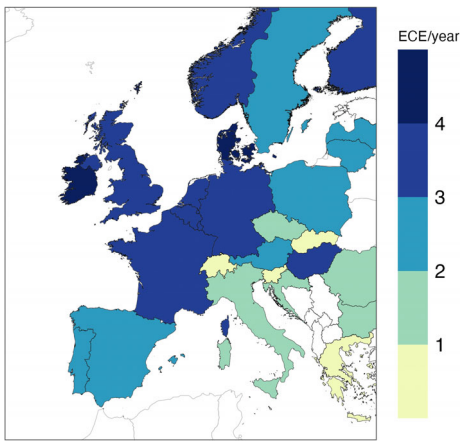


**FIGURE 1** Observed frequency of occurrence (per year) of energy compound events (ECEs) for each country over the period of study 1979–2019.

1. Meteorological logistic regression model

$$\text{logit}(P(t)) = \ln\left(\frac{P(t)}{1-P(t)}\right) = \beta_0 + \beta_1 \text{T2m}(t) + \beta_2 \text{WS}(t) + \beta_3 \text{SSRD}(t), \quad (2)$$

where $\text{T2m}(t)$, $\text{WS}(t)$, and $\text{SSRD}(t)$ represent the T2m, 10 m wind speed, and incoming shortwave solar radiation, at time $t$, and $P(t)$ is the predicted probability that an ECE will occur given these covariates at this time. $\beta_1$, $\beta_2$, and $\beta_3$ are the regression coefficients corresponding to T2m, WS, and SSRD. The meteorological covariates were standardized prior to the model fitting. This enables a direct comparison between their odds ratios (i.e., $\exp[\beta]$), interpreted as a multiplicative factor by which the odds of an ECE occurring increase (or decrease, if $\exp[\beta] < 1$) as the corresponding covariate increases by one unit (i.e., one standard deviation), keeping constant the rest of the covariates included in the model.

2. Regime-dependent logistic regression model

$$\text{logit}(P(t)) = \ln\left(\frac{P(t)}{1-P(t)}\right) = \sum_{\text{wr}=1}^{7} \alpha_{\text{wr}} X_{\text{wr}}, \quad (3)$$

where $P(t)$ is the predicted probability that an ECE will occur given a certain WR, and $\alpha_{\text{wr}}$ are the regression coefficients corresponding to each weather regime. The WRs are introduced as categorical factors in the logistic regression, and hence it introduces seven auxiliary variables into the model (i.e., $X_{\text{wr}}$ are either 0 or 1 depending on whether that regime occurs). Note that one of the categories is set as a reference (in our case, the reference is 0, i.e., "no regime"). Therefore, the odds ratios ($\exp[\alpha_{\text{wr}}]$) are interpreted as multiplicative factors that increase (for positive $\alpha_{\text{wr}}$) or decrease (for negative $\alpha_{\text{wr}}$) (with respect to the reference category) the probability of occurrence of an ECE for a given WR.

The parameters of the logistic regression models are estimated using maximum likelihood (ML) estimation. Since the ECEs we consider are rare, we follow Firth's method (Firth, 1993) and introduce a likelihood penalty to reduce the bias of the ML estimates that arises due to a small effective sample size. This implementation was carried out with the R package logistf (Puhr et al., 2017).

The performance of the logistic regression models was assessed through common metrics: the Brier score (BS; Wilks, 2011) and the Brier skill score (BSS; Wilks, 2011).

The BS is estimated as:

$$\mathrm{BS} = \frac{1}{N}\sum_{t=1}^{N}(P(t) - E(t))^2, \quad (4)$$

where $N$ is the total number of observations, $P_t$ is the predicted probability of occurrence of an ECE, and $E_t$ is the observed occurrence of an ECE (i.e., $E_t = 1$ if the event occurs, and 0 otherwise). BS ranges between 0 and 1, with lower values indicating a better performance (Wilks, 2011). The BSS is calculated as:

$$\mathrm{BSS} = 1 - \frac{\mathrm{BS}}{\mathrm{BS}_{\mathrm{ref}}}, \quad (5)$$

where $\mathrm{BS}_{\mathrm{ref}}$ is the Brier score of a reference forecast. The BSS can be interpreted as the relative improvement in BS over the reference forecast. Here we use the climatological event frequency (i.e., during the period of study) as reference.

In addition to the listed metrics, we have used reliability diagrams, which plot the observed event frequency against the predictive probability, and can be used as a direct diagnostic tool for assessing the model performance. The reliability diagrams assess how reliable or calibrated the predictions issued by the logistic regression model are, whereas the BS and BSS are typically used to compare competing models or predictions.

# 4 | RESULTS

## 4.1 | Characteristics of ECEs

We begin our analysis by examining the observed frequency of occurrence of ECEs for each country along with the local meteorological conditions that characterize these events. As illustrated in Figure 1, European countries are exposed to an ECE more than two times per winter on average. The highest frequency is observed in northern and central European countries, which are exposed to more than three ECEs per winter on average. Despite the high installed capacity of solar and wind in some countries (e.g., Germany), the frequency of ECE indicates the existing risks of mismatch between renewable production and load. The lowest frequency is observed in a few countries (e.g., Slovakia, Switzerland, Greece) with less than one ECE per winter.

Next, we characterize the ECEs in terms of the local meteorological conditions that dominate during the occurrence of an event. For each country, the means of T2m, WS, and SSRD during ECEs ($E(t) = 1$) were calculated. To assess how "extreme" the weather conditions during an ECE might be, we show the average values of the three meteorological variables when an ECE occurs, expressed in terms of percentiles of their climatological distributions. Additionally, we analysed the mean meteorological conditions during an ECE for each WR. As illustrated in Figure 2, ECEs are characterized by extremely low temperatures (<5th percentile) everywhere, accompanied by generally low wind speeds (<10th percentile). We notice a larger variability of SSRD conditions during ECEs, but in general SSRD does not seem to have a strong effect, as it is close to the 50th percentile in most of the central and southern countries. It must be noted that in winter, solar power is a very small input to the renewable generation compared with wind power, and hence does not have as large an effect on the total energy generated by RES. On average, moderate–high (>60th) SSRD conditions are observed during an ECE in northern countries, due to the presence of blocked regimes (e.g., GL, EuBL, AR) that lead to increased SSRD (Figure S3), accompanied by extremely low temperatures and low wind speeds in most of the countries (Figures S4 and S5). Overall, the dominant conditions that result in ECEs in most of Europe are extreme cold temperatures and low wind speed. However, we observed distinct patterns in a few countries (e.g., Switzerland, Slovakia), where ECE are associated with moderate–high wind speed (>50th) conditions and low SSRD (<10th), pointing out the negative correlation between solar and wind power: windy conditions are generally associated with cloudy days (lower solar radiation). Moreover, it must be noted that in these countries, low power production episodes (LWS) are mainly driven by solar power, due to the small installed wind power capacity (Figure S1), which can explain these dominant conditions during an ECE.

## 4.2 | Logistic regression

In this section, we examine the influence of meteorological and atmospheric drivers on ECEs based on the logistic regression models. Then, we continue our analysis with a focus on spatio-temporal ECEs that can affect multiple countries.

### 4.2.1 | Meteorological logistic regression model

The logistic regression models that used meteorological covariates as predictors obtained low BS in most countries, ranging from 0.01 to 0.017 (Table S1). Although these small values are largely attributable to the rarity of ECEs, the BSS values are positive at all locations, ranging from 0.13 (Bulgaria) to 0.57 (Ireland), which suggests the

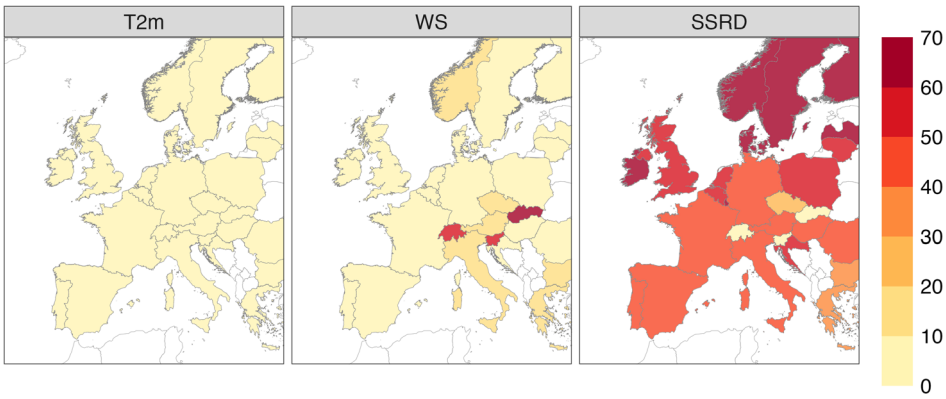


**FIGURE 2** Country-based percentiles of 2 m temperature (T2m), 10 m wind speed (WS), and surface solar radiation (SSRD) corresponding to their means values during an energy compound event.

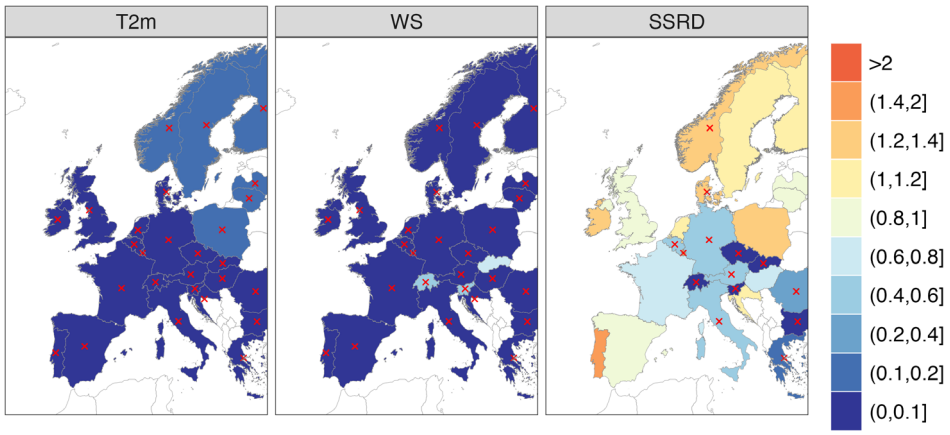


**FIGURE 3** Odds ratio corresponding to temperature, 10 m wind speed, and surface solar radiation obtained from the country-based logistic regression models. Red crosses indicate statistically significant coefficients according to the Wald test at the 5% significance level. Odds ratios <1 indicate a negative relationship (i.e., associated with a decrease in the outcome), and odds ratio >1 indicate a positive relationship (i.e., associated with an increase in the probability of an energy compound event).

predictions obtained using the logistic regression model are significantly more informative than the climatological event frequency. The differences in the model performance in terms of BSS are also reflected in the reliability diagrams that show the different model performance across the countries (Figure S6). The best model performance is found in Ireland, Portugal, and France, where the predictions are closer to the observations, in contrast to a relatively poorer performance shown in a few countries (e.g., Bulgaria, Switzerland; Figure S6). This lack of accuracy might be explained by the small number of events in those countries due to a limited amount of installed capacity for both wind and solar power, which makes challenging the characterization of ECEs.

### 4.2.2 | Influence of meteorological drivers on ECEs

Figure 3 shows the odds ratio associated with temperature, wind speed, and solar radiation. The temperature and wind speed were found to be statistically significant predictors of ECEs in most countries, and their associated odds ratio were generally below 1, which indicates an increasing probability of occurrence of an ECE for decreasing temperature and wind speed conditions. This is consistent with peak winter demand events due to cold temperatures that can be accompanied by below normal wind speed conditions that result in low wind power production (Bloomfield et al., 2018). We observe a larger variability across the countries for the odds ratio of solar radiation, in terms of the sign, which points to a different effect of incoming radiation on the occurrence of an ECE. In a number of countries, the odds ratio corresponding to solar radiation is close to one (e.g., the United Kingdom, Netherlands, Sweden), which suggests that solar radiation has little effect on the occurrence of an ECE in comparison with temperature and wind speed. In most central and southern countries, there is a higher probability of occurrence of an ECE with decreasing solar radiation, while in some northern and western countries, the odds of occurrence of an ECE are higher with

increasing solar radiation. This might be explained by the prevailing atmospheric patterns that can lead to more insolation, but also colder temperatures (i.e., higher demand), and thus, a higher probability of an ECE. Increasing solar radiation could be translated into more solar power production to help meet the demand. However, we must note that in winter the potential for solar generation is lower than in summer, especially in the northern countries (Bloomfield et al., 2018). Furthermore, in most countries, the installed capacity of solar generation is relatively low (compared with the installed wind power capacities; Figure S1).

Similarly to other examples of compound events, the combination of hazardous weather conditions might result in the occurrence of an ECE, intensifying the risks of power failures. Thus, we further examine the odds of an ECE occurring (see Equation 2) given certain combinations of meteorological conditions. The logistic model allows us to quantify the probability of occurrence of an ECE for a combination of meteorological conditions. Figure 4 shows the predicted probabilities as a function of the observed meteorological conditions of T2m, WS, and SSRD for some selected countries. In most cases, the probability of occurrence of an ECE considerably increases for extremely low temperatures along with low wind speeds. In particular, in the case of central European countries (e.g., France, Germany, Austria), the maximum probability of an ECE occurs for observed temperatures $<-10°C$ and $<-5°C$ in the case of northwestern countries (Ireland and the United Kingdom). Also, in the southern countries (e.g., Portugal), low temperatures are associated with a high ECE probability. Note that the meteorological conditions represent the country averages. In general, moderate–high values of SSRD seem to be associated with a higher probability of ECEs.

#### 4.2.3 | Regime-dependent logistic regression model

The regime-dependent logistic regression model showed a poorer performance compared with the meteorological models, with little predictive skill (Table S2). This indicates that the WRs are less able to capture the behaviour of the ECEs. Nevertheless, the weather logistic models can be used in a descriptive way as they provide further insights into the influence of atmospheric circulation patterns on the occurrence of ECEs.

Figure 5 shows the distinct behaviour of the WRs, in terms of odds ratios, which reflects the variability between the high demand and low renewable production across the countries under the WRs. The cyclonic types (i.e., AT, ZO, ScTr) significantly decrease the probability of the occurrence of an ECE. In particular, the lowest odds ratio is shown by the ZO and AT in the northern and central countries (e.g., Norway, the United Kingdom, France). Overall, the odds of an ECE also decrease under the presence of ScTr in most of Europe. A contrasting pattern is found in the odds ratios corresponding to the blocked types (AR, EuBL, ScBL, and GL), during which the westerly flow is disrupted by stationary anticyclones, resulting in reduced wind speed (i.e., decreasing power production). In general, the odds of ECEs slightly increase in the presence of AR and ScBL, mostly in the eastern countries where these WRs are statistically significant. A larger effect is observed in the odds ratios corresponding to EuBL and GL that significantly increase the odds of an ECE in most of Europe, especially in Central Europe. The EuBL has a major effect on the odds of occurrence of ECE, while GL plays a major role in the odds of ECE in the northern countries (e.g., Sweden, Norway, Finland; see Figure 6).

Our results show that the probability of occurrence of an ECE decreases for certain cyclonic conditions, particularly AT and ZO (coincident with the positive NAO), as a result of higher renewable production, mostly driven by increased wind power production. These findings are consistent with previous work that showed the strong influence of blocked regimes on episodes of peak demand and low production (Bloomfield et al., 2018; van der Wiel, Stoop, et al., 2019). Grams et al. (2017) showed that winter cyclonic regimes are associated with overproduction of wind power generation in northern and western Europe, and with a risk of underproduction of wind power production in southeastern Europe. Moreover, cyclonic regimes favour mild winter conditions due to the air mass advection from over the Atlantic Ocean into the continent (Grams et al., 2017), which results in positive temperature anomalies. Similarly, van der Wiel, Stoop, et al. (2019) showed high wind and solar production (on average) and less electricity demand during the positive phase of the NAO. Consistently, here we show a significant influence of some WRs, particularly the EuBL and GL, which increase the odds of occurrence of an ECE across Europe.

### 4.3 | Spatio-temporal ECEs

The analysis presented above focused on local ECEs (i.e., an ECE occurring at a country-level scale). However, synchronous ECEs that occur across multiple countries can pose a serious risk to the European power system. The analysis of weather conditions that can result in spatio-temporal characteristics of ECEs is of major interest to build an interconnected power grid largely

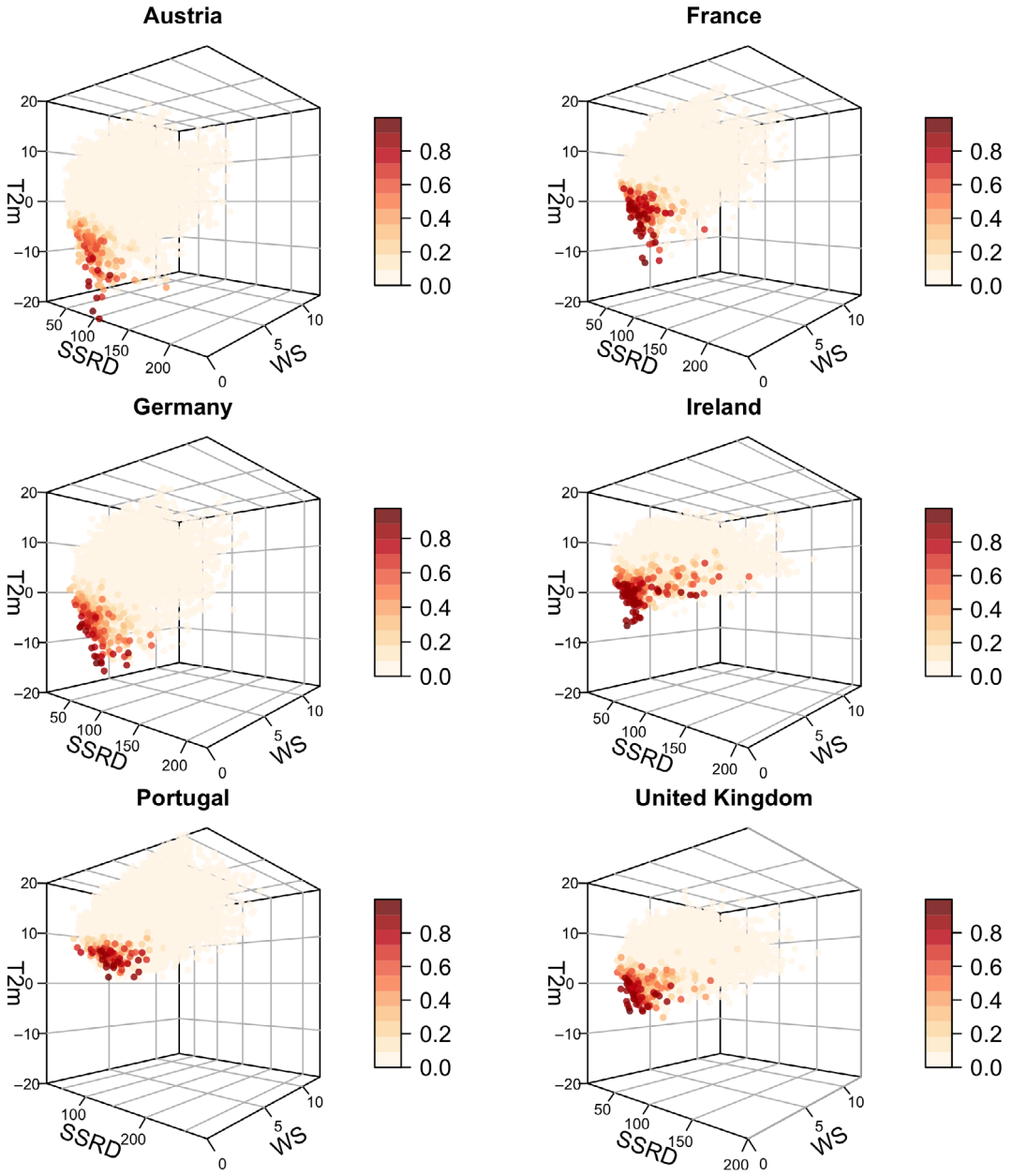


**FIGURE 4** Probability of occurrence of an energy compound event (ECE) derived from the logistic regression models as a function of 2 m temperature (T2m; °C), wind speed (WS; m/s), and surface solar radiation (SSRD; W/m$^2$) for a representative number of countries.

dependent on RES. Therefore, this section provides further insights into the spatio-temporal ECEs and the links with atmospheric drivers. To assess the spatial relationship of ECEs, we first quantified the co-occurrence of ECEs across the countries. For that, monthly frequencies of ECEs were used to calculate the Pearson's correlation coefficients between each country pair. Figure 6 shows the correlation coefficients for each pair of countries. ECEs are significantly positively correlated across a large number of countries. The highest correlation coefficients are observed across the northwestern countries, such as France, Belgium, Luxembourg, and the Netherlands. Similarly, the frequency of ECEs is strongly correlated across the southern countries (e.g., Spain, Portugal, Italy) and northern central countries (e.g., Germany, Czech Republic, Poland, Latvia, Denmark). The correlation coefficients do not explicitly restrict attention to concurrent ECEs; however it allows us to get a better picture of the spatial relationship between critical energy events across Europe. Furthermore, we empirically calculated the frequency of country-pair ECEs (i.e., by simply counting the simultaneous ECEs for each pair of countries), which showed similar spatial patterns (Figure S7) than those obtained from correlation analysis (Figure 6).

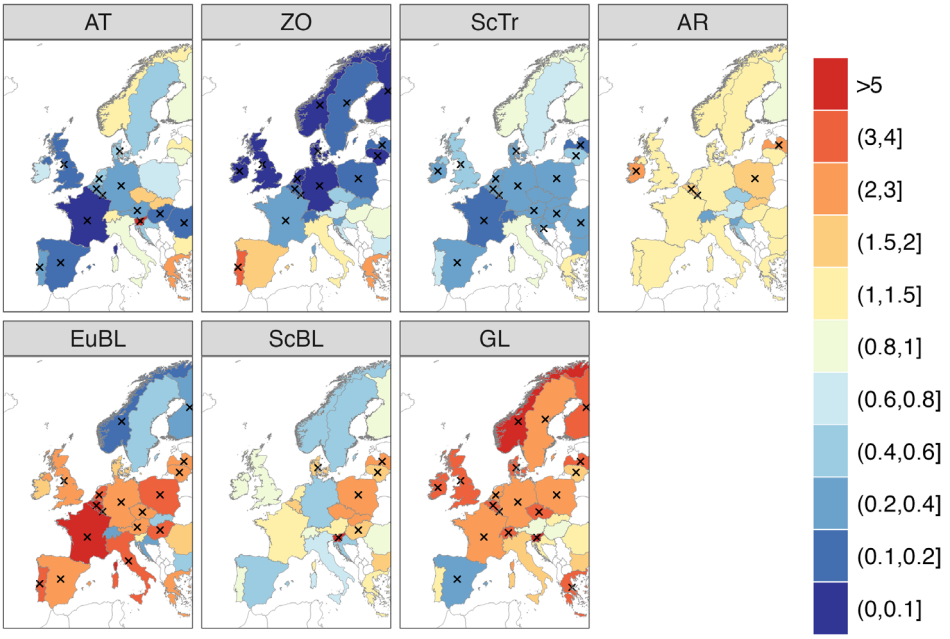


**FIGURE 5** Odds ratio corresponding to the weather regimes (with respect to the reference level, i.e., no regime): Atlantic trough (AT), zonal (ZO), Scandinavian trough (ScTr), Atlantic ridge (AR), European blocking (EuBL), Scandinavian blocking (ScBL), and Greenland blocking (GL). Black crosses indicate statistically significant coefficients according to the Wald test at the 5% significance level. Odds ratios <1 indicate a negative relationship (i.e., associated with a decrease in the outcome), and odds ratios >1 indicate a positive relationship (i.e., associated with an increase in the outcome).

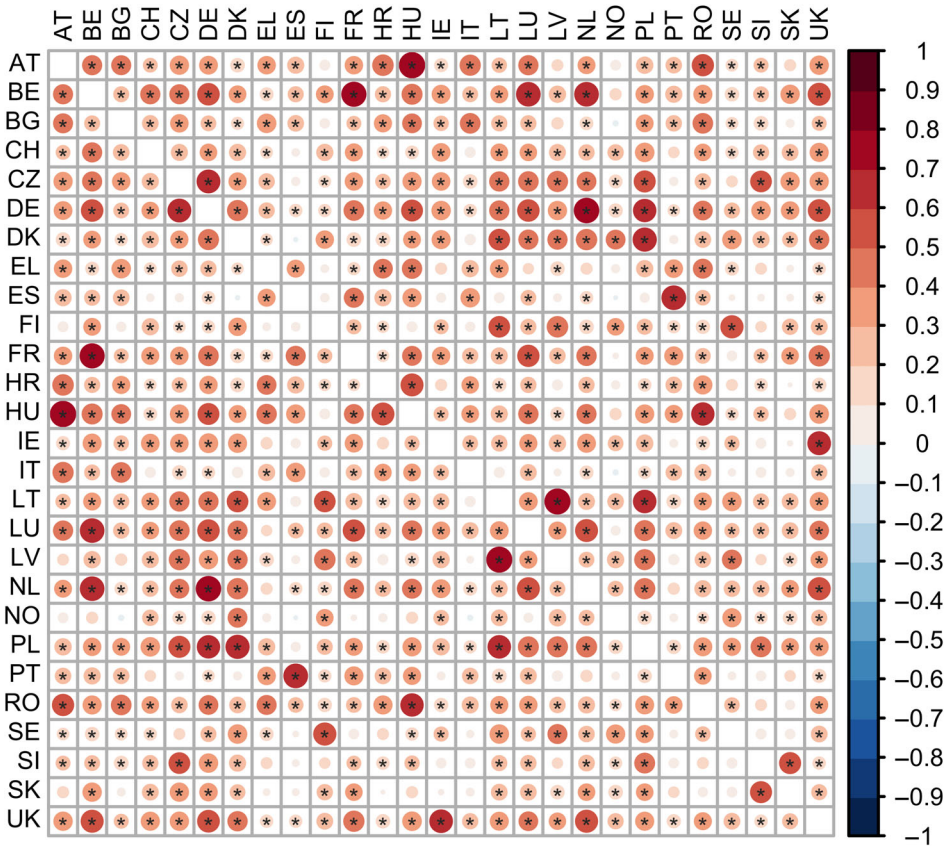


**FIGURE 6** Pearson's correlation coefficients calculated between the monthly frequencies of energy compound events (ECEs) for each pair of countries, with country names represented by ISO codes. Black asterisks indicate statistical significant correlations at the 95% significance level of the *t*-test.

### 4.3.1 | Climate drivers of spatio-temporal ECEs

Figure 7a illustrates the relative frequency of ECEs occurring during each WR. Note that the number of ECEs differs across the countries, as shown in Figure 1. On average, 25% of the ECEs occur during "no regime" (no), which can be due to the high proportion of days that are categorized as a "no" regime during the period of study (Figure S2). Despite the variability in the proportion of ECEs occurring during the WRs across the countries, it

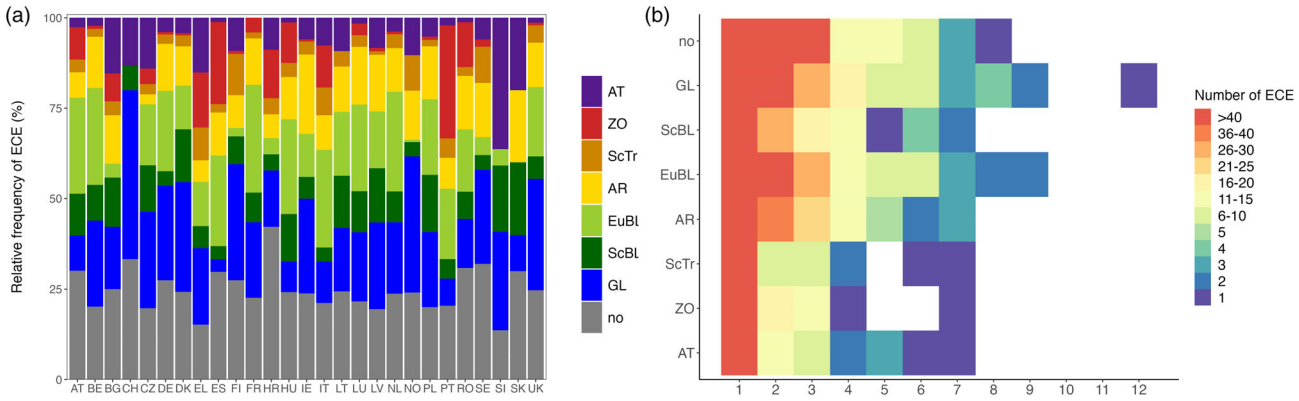


**FIGURE 7** (a) Relative frequency of occurrence of an energy compound event (ECE) under each weather regimes (WRs) with respect to the total number of ECEs for each country. (b) Frequency of ECEs corresponding to each WR, as a function of the number of countries affected by the ECE.

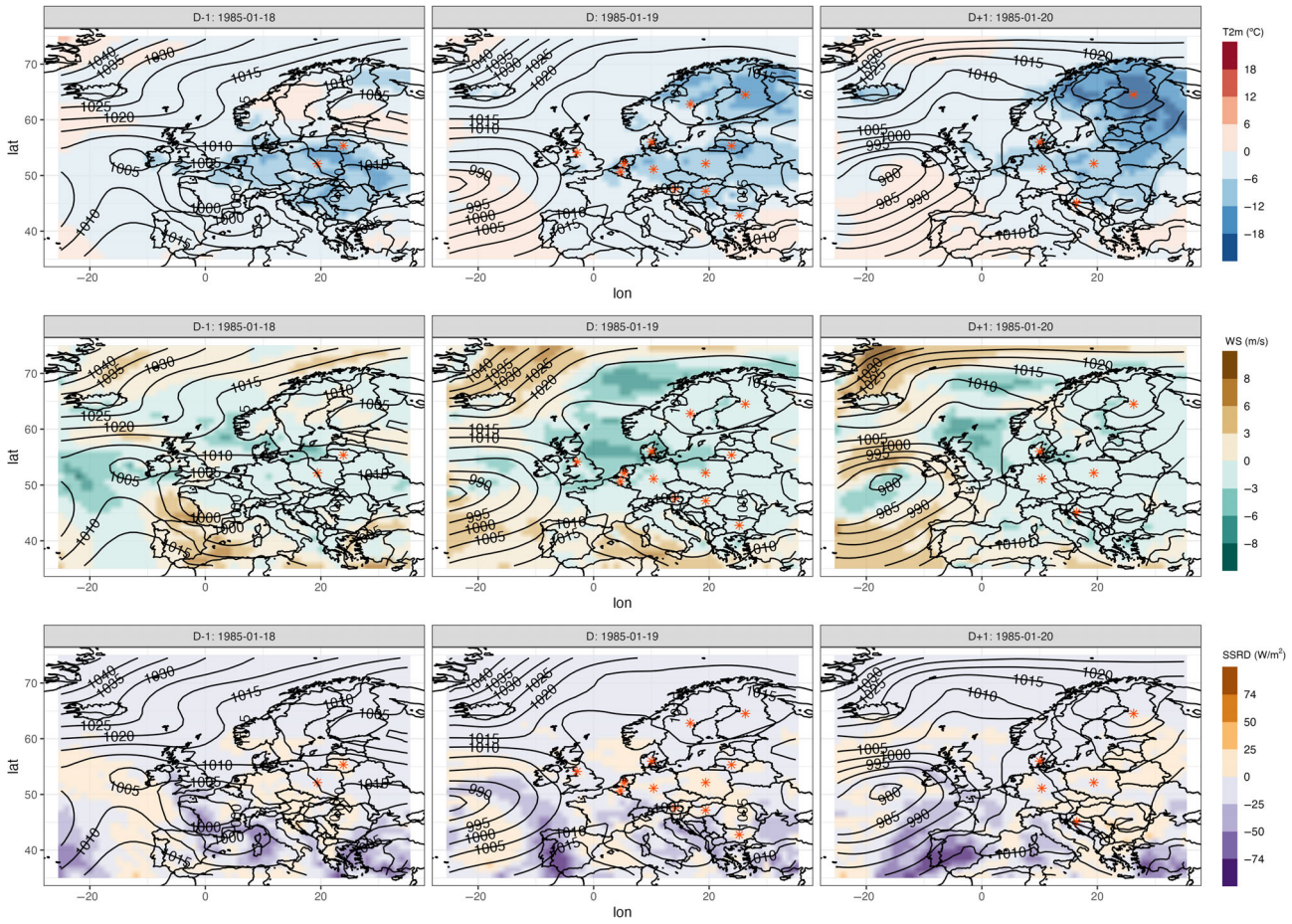


**FIGURE 8** Anomaly composites of 2 m temperature, 10 m wind speed, and incoming surface solar radiation for the first selected event, during which 12 countries experienced an energy compound event (ECE). Red stars indicate the countries simultaneously affected by an ECE. The dominant weather regime was the blocked regime Greenland blocking.

can be observed that a large percentage of ECEs occur during blocked WRs. In particular, 21% of ECEs occur during the GL and 15% during EuBL. Overall, there is a high frequency of ECEs during GL in northern countries (e.g., Norway, Finland, Denmark), while ECEs occur more often during EuBL in central and southern countries (e.g., France, Netherlands, Austria, Italy). During GL and EuBL conditions, most of Europe experiences extremely cold temperatures (Figure S4) and generally low wind speeds (Figure S5). As shown in Grams et al. (2017), the

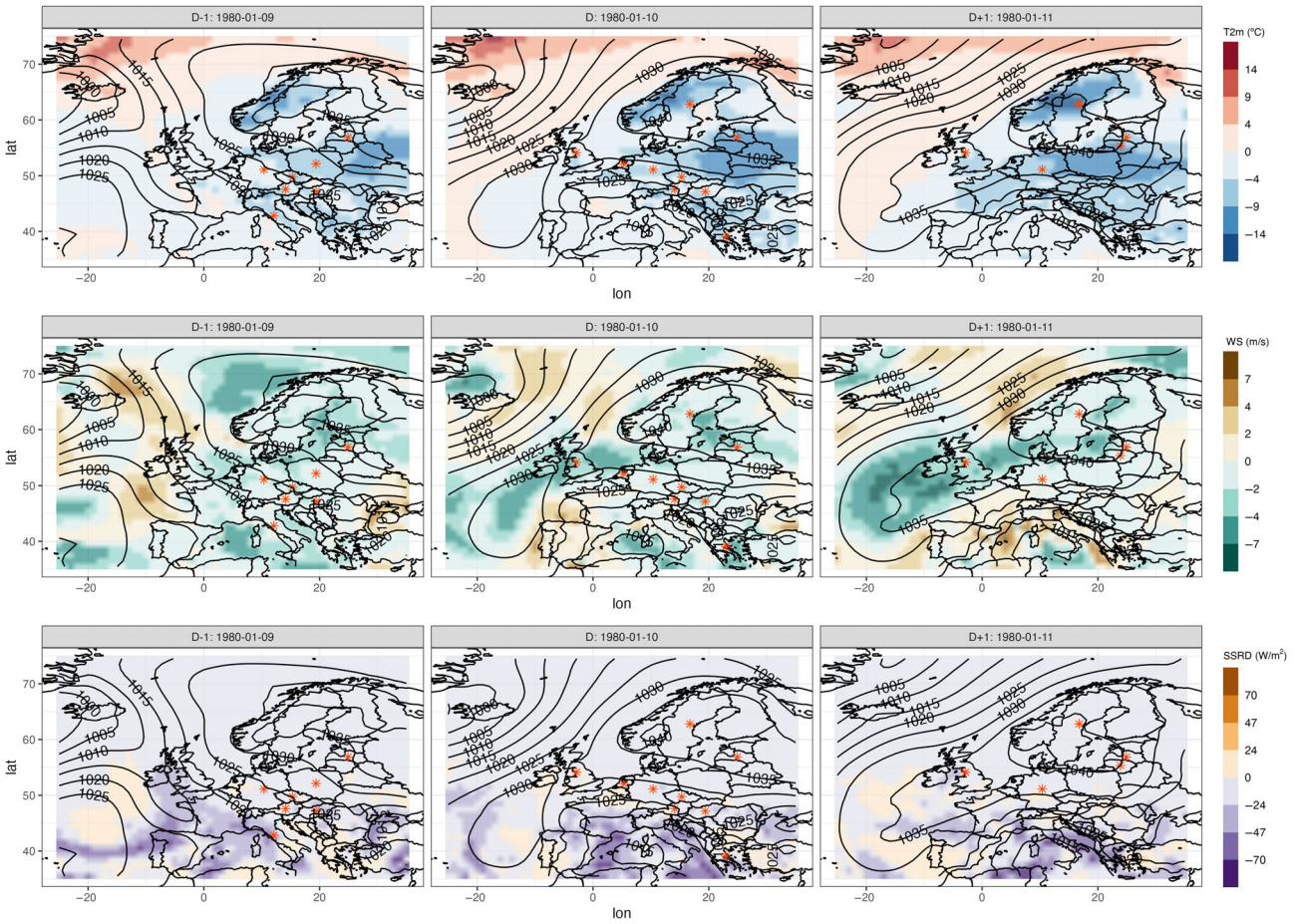


**FIGURE 9** Anomaly composites of 2 m temperature, 10 m wind speed, and incoming surface solar radiation for the second selected event, during which nine countries experienced an energy compound event.

minimum mean wind underproduction occurs during EuBL, especially in the northern countries, which along with low temperatures, explain a major percentage of ECE under EuBL. Similarly, GL leads to high demand, but also reduced wind speed (less wind production). Also, in Figure 7b, we show the frequency of WRs as a function of the number of countries that experienced synchronous ECEs. In general, the number of countries simultaneously affected by an ECE increases with blocked regimes. For example, ECEs affecting more than seven countries at the same time were predominately associated with GL, EuBL, and AR regimes.

Based on the frequency analysis shown in Figure 7, we analysed the meteorological conditions during spatial ECEs. For that, we first selected the ECEs that affected a large number of countries. Then, we used seasonal anomaly composites of temperature, wind speed, and solar radiation corresponding to the previous day, the day after, and the selected day of the ECE.

Figure 8 shows the anomaly composites of temperature, wind speed, and solar radiation corresponding to an event in January 1985 that led to a total of 12 European countries with an episode of concurrent low production and high demand. The GL regime was the dominant WR during the event, with a blocking high-pressure system near southern Greenland and a low-pressure system over the Atlantic, which corresponds to the negative phase of the NAO. The GL leads to considerably reduced zonal flow over northern Europe, where persistent negative wind speed anomalies are observed (Figure 8, central row). Moreover, GL was associated with cold conditions in the northern and eastern European countries, as shown by the negative temperature anomalies (Figure 8, first row). It can be noticed that the day before and the day after the selected ECE (D − 1, D + 1, Figure 9), the magnitude of the anomalies of wind speed is relatively small and positive (0.5–1 m/s) in some locations in northern Europe compared with the anomalies observed during the selected day. Negative temperature anomalies ($>-10°C$) combined with reduced wind speeds lead to ECEs in most of northern and eastern Europe. Interestingly, some central European countries experienced weak positive anomalies of solar radiation, which might suggest that solar power generation could partly compensate

for the decrease of wind power during the demand peaks. However, it is important to stress the reduced availability of solar resource in winter due to the seasonal cycle. Moreover, it must be noticed that the installed solar capacity is much smaller than the installed wind capacity (Figure S1), meaning a large proportion of low renewable energy production is driven by wind power generation.

Similarly to the GL, a blocked EuBL regime was associated with spatially concurrent ECEs (Figure 9). During the EuBL, a blocking ridge expands over central and western Europe. These WRs lead to large negative anomalies of wind speed over most of Europe, particularly in the central and northern countries. Moreover, during EuBL, a large part of Europe experienced colder temperatures, with the largest negative anomalies of temperatures in northern Europe (Figure 9). In agreement with early studies, we show that the European power system is particularly sensitive to blocked regimes, which favour combined meteorological conditions that might result in spatio-concurrent ECEs.

## 5 | DISCUSSION AND CONCLUSIONS

Assessing the balance between renewable energy production and energy demand requires considering the climate drivers that can threaten the reliability of energy production. Here, we analysed winter ECEs, defined as simultaneous episodes of low renewable energy production (wind plus solar power generation) and high electricity demand across a total of 27 European countries. We use a threshold-based approach to identify ECEs.

Based on a logistic regression approach, we assessed the influence of local meteorological covariates and atmospheric drivers (WRs) on energy compound events (ECEs), separately for each country. Furthermore, we examined the spatial coherence of ECEs that affect multiple countries and can have a major impact on the energy power system.

We showed that European countries are exposed to an ECE more than two times per year on average. In general, the ECEs are characterized by extremely low temperatures (<5th percentile of the climatological distribution) and low wind speed (<10th percentile of the climatological distribution), which translate into a higher energy demand and lower wind power production.

Results from the meteorological logistic regression model, fitted with meteorological variables covariates, indicated the significant influence of temperatures and wind speed on the odds of ECEs that increase with very low temperature and low wind conditions. Overall, the solar radiation had a small effect on the probability of an ECE occurring. The regime-dependent logistic models, fitted with weather regime covariates, showed distinct patterns in the odds ratios corresponding to the different WRs. We found that the odds of ECEs tend to increase under the presence of blocked regimes. In particular, EuBL and GL significantly increase the odds of an ECE over most of Europe. In general, the cyclonic regimes were associated with a low probability of occurrence of ECEs. These results are consistent with previous work that showed overproduction of wind power during winter cyclonic regimes and underproduction of wind power production in southeastern Europe (Grams et al., 2017).

In recent years, the European electricity grids have increased their level of interconnection (EEA, 2019). Due to the potential risks of spatially ECEs, which simultaneously affect multiple countries, we have further analysed these events and their atmospheric drivers. With a simple approach, based on correlation coefficients between monthly frequencies of ECEs across country pairs, we showed the spatial relationship between the ECEs in a large number of countries. Large correlations were found between neighbouring countries (e.g., France, Belgium, Luxembourg), likely as a result of similar climate conditions, and thus, consumption patterns, which lead to a higher demand (and higher probability of occurrence of an ECE). Moreover, we showed the link between spatial ECEs and blocked regimes, specifically the GL and EuBL that occurred more often during widespread ECEs. This analysis illustrated that blocked regimes can result in synchronous ECEs that affect multiple regions.

It is worth noting that the results presented here assume a power system baseline equivalent to 2017. We acknowledge that assessing ECEs under a different scenario of installed wind and solar capacities will be required to account for changes in the electricity demand patterns induced by a warmer climate or evolved energy system to meet climate mitigation targets. Therefore, future work might investigate other renewable energy power system scenarios under a changing climate. Using climate scenarios, Garrido-Perez et al. (2021) showed a seasonal shift in the electricity demand peaks from winter to summer in Spain, where the frequency and severity of extreme electricity demand days are expected to increase. The methodology presented here could be used to analyse changes in the frequency of ECEs in summer, which might be particularly interesting in southern and western European countries that will experience an increased electricity demand under a warmer climate (Wenz et al., 2017).

To conclude, we have shown that European countries are exposed to ECEs during which it might be challenging to achieve a balanced electricity transmission system, due to simultaneous episodes of high demand and low

production. More importantly, our study illustrated that synchronous ECEs can affect multiple countries. In particular, the European power system seems to be vulnerable to blocked WRs that have a large influence on European renewable energy production and demand.

Given the rapid growth of wind and solar power generation, and with the promising skill shown by WRs for sub-seasonal forecasting (Büeler et al., 2021), our study highlights the relevance of considering WRs that might result in spatially coincident ECEs that pose a major risk for interconnected regions. We believe that the energy sector could greatly benefit from skilful forecasts of WRs that have shown a major influence on ECEs.

## AUTHOR CONTRIBUTIONS

**Noelia Otero:** Conceptualization (lead); formal analysis (lead); investigation (lead); methodology (lead); software (lead); visualization (lead); writing – original draft (lead). **Olivia Martius:** Supervision (equal); writing – review and editing (equal). **Sam Allen:** Methodology (supporting); writing – review and editing (equal). **Hannah Bloomfield:** Data curation (lead); writing – review and editing (equal). **Bettina Schaefli:** Supervision (equal); writing – review and editing (equal).

## ACKNOWLEDGEMENTS

The authors would like to thank Christian Grams for providing the Weather regimes dataset.

## CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

## ORCID

*Noelia Otero* https://orcid.org/0000-0003-3217-3945
*Hannah Bloomfield* https://orcid.org/0000-0002-5616-1503

## REFERENCES

Allen, S., Evans, G., Buchanan, P. & Kwasniok, F. (2021) Incorporating the North Atlantic Oscillation into the post-processing of MOGREPS-G wind speed forecasts. *Quarterly Journal of the Royal Meteorological Society*, 147, 1403–1418. https://doi.org/10.1002/qj.3983

Bevacqua, E., Michele, C.D., Manning, C., Couasnon, A., Ribeiro, A., Ramos, A. et al. (2021) Guidelines for studying diverse types of compound weather and climate events. *Earth's Futures*, 9, e2021EF002340. https://doi.org/10.1029/2021EF002340

Bloomfield, H., Brayshaw, D. & Charlton-Perez, A. (2019a) Characterizing the winter meteorological drivers of the European electricity system using targeted circulation types. *Meteorological Applications*, 27, e1858. https://doi.org/10.1002/met.1858

Bloomfield, H., Brayshaw, D. & Charlton-Perez, A. (2019b) *ERA5 derived time series of European country-aggregate electricity demand, wind power generation and solar power generation*. University of Reading. Dataset. https://doi.org/10.17864/1947.227

Bloomfield, H., Brayshaw, D., Shaffrey, D. & Thornton, L.C.H. (2016) Quantifying the increasing sensitivity of power systems to climate variability. *Environmental Research Letters*, 11, 124025. https://doi.org/10.1088/1748-9326/11/12/124025

Bloomfield, H., Brayshaw, D., Shaffrey, D. & Thornton, L.C.H. (2018) The changing sensitivity of power systems to meteorological drivers: a case study of Great Britain. *Environmental Research Letters*, 13, 054028. https://doi.org/10.1088/1748-9326/aabff9

Bloomfield, H., Suitters, C. & Drew, D.R. (2020) Meteorological drivers of European power system stress. *Journal of Renewable Energy*, 2020, 12. https://doi.org/10.1155/2020/548101

Brayshaw, D., Troccoli, A., Fordham, R. & Methven, J. (2011) The impact of large scale atmospheric circulation patterns on wind power generation and its potential predictability: a case study over the UK. *Renewable Energy*, 36, 2087–2096. https://doi.org/10.1016/j.renene.2011.01.025

Büeler, D., Ferranti, L., Magnusson, L., Quinting, J.F. & Grams, C.M. (2021) Year-round sub-seasonal forecast skill for Atlantic–European weather regimes. *Quarterly Journal of the Royal Meteorological Society*, 147, 1–27. https://doi.org/10.1002/qj.4178

Collins, S., Saygin, D., Deane, J., Miketa, A., Gutierrez, L., Gallachóir, B. et al. (2018) Planning the European power sector transformation: the remap modelling framework and its insights. *Energy Strategy Reviews*, 22, 147–165. https://doi.org/10.1186/s12940-017-0325-2

Cronin, J., Anandarajah, G. & Dessens, O. (2018) Climate change impacts on the energy system: a review of trends and gaps. *Climatic Change*, 151, 79–93. https://doi.org/10.1007/s10584-018-2265-4

Domeisen, D., Grams, C. & Papritz, L. (2020) The role of North Atlantic–European weather regimes in the surface impact of sudden stratospheric warming events. *Geophysical Research Letters*, 38, L06702. https://doi.org/10.1029/2010GL046582

EEA. (2017). Renewable energy in Europe 2017—recent growth and knock-on effects. *EEA Report*, 3/2017.

EEA. (2019). Adaptation challenges and opportunities for the European energy system. *EEA Report*, 01/2019.

EEA. (2020). Trends and projections in Europe 2020. *EEA Report*, 13/2020.

Ely, C., Brayshaw, D., Methven, J., Cox, J. & Pearce, O. (2013) Implications of the North Atlantic Oscillation for a UK–Norway renewable power system. *Energy Policy*, 62, 1420–1427. https://doi.org/10.1016/j.enpol.2013.06.037

ENTSOE. (2019). *Entsoe transparency platform*. https://www.entsoe.eu/publications/statistics-and-data/.

Evans, D. & Florschuetz, L. (1977) Cost studies on terrestrial photovoltaic power systems with sunlight concentration. *Solar Energy*, 19, 255–262.

Firth, D. (1993) Bias reduction of maximum likelihood estimates. *Biometrika*, 80, 27–38.

Francois, B. (2016) Influence of winter North-Atlantic Oscillation on climate-related energy penetration in Europe. *Renewable Energy*, 99, 602–613. https://doi.org/10.1016/j.renene.2016.07.010

Garrido-Perez, J., Barriopedro, D., García-Herrera, R. & Ordóñez, C. (2021) Impact of climate change on Spanish electricity demand. *Climatic Change*, 165(50), 1–18. https://doi.org/10.1007/s10584-021-03086-0

Grams, C., Beerli, R., Pfenninger, R., Staffell, I. & Wernli, H. (2017) Balancing Europe's wind-power output through spatial deployment informed by weather regimes. *Nature Climate Change*, 7, 557–562. https://doi.org/10.1038/nclimate3338

Hersbach, H. (2018) *Operational global reanalysis: Progress, future directions and synergies with NWP*. Reading, UK: European Centre for Medium Range Weather Forecasts, 18765.

IRENA. (2018) *Irena, renewable energy prospects for the European Union*. Abu Dhabi: IRENA.

Jerez, S., Trigo, R., Vicente-Serrano, S., Pozo-Vázquez, D., Lorente-Plazas, R., Lorenzo-Lacruz, J. et al. (2013) The impact of the North Atlantic Oscillation on renewable energy resources in southwestern Europe. *Journal of Applied Meteorology and Climatology*, 52, 2204–2225. https://doi.org/10.1175/JAMC-D-12-0257.1

Jurasz, J., Mikulik, J., Dąbek, P., Guezgouz, M. & Kaźmierczak, B. (2021) Complementarity and 'resource droughts' of solar and wind energy in Poland: an ERA5-based analysis. *Energies*, 14, 1118. https://doi.org/10.3390/en14041118

Martius, O., Pfahl, S. & Chevalier, C. (2016) A global quantification of compound precipitation and wind extremes. *Geophysical Research Letters*, 43, 7709–7717. https://doi.org/10.1002/2016GL070017

Otero, N., Martius, O., Allen, S., Bloomfield, H. & Schaefli, B. (2021) A copula-based assessment of renewable energy droughts across Europe. *EarthArXiv*. https://doi.org/10.31223/X5S62C

Puhr, R., Heinze, G., Nold, M., Lusa, L. & Geroldinger, A. (2017) Firth's logistic regression with rare events: accurate effect estimates and predictions? *Statistics in Medicine*, 36(17), 2302–2317. https://doi.org/10.1002/sim.7273

Ravestein, P., van der Schrier, G., Haarsma, R., Scheele, R. & van den Broek, M. (2018) Vulnerability of European intermittent renewable energy supply to climate change and climate variability. *Renewable and Sustainable Energy Reviews*, 97, 497–508. https://doi.org/10.1016/j.rser.2018.08.057

Raymond, C., Horton, R., Zscheischler, J., Martius, O., Aghakouchak, A., Bowen, J.B.S.G. et al. (2020) Understanding and managing connected extreme events. *Nature Climate Change*, 10, 611–621. https://doi.org/10.1038/s41558-020-0790-4

Raynaud, D., Hingray, B., François, B. & Creutin, J. (2018) Energy droughts from variable renewable energy sources in European climates. *Renewable Energy*, 125, 578–589. https://doi.org/10.1016/j.renene.2018.02.130

Thornton, H., Scaife, A.A., Hoskins, B. & Brayshaw, D. (2017) The relationship between wind power, electricity demand and winter weather patterns in Great Britain. *Environmental Research Letters.*, 12, 064017. https://doi.org/10.1088/1748-9326/aa69c6

van der Wiel, K., Bloomfield, H., Lee, R., Stoop, L., Blackport, R., Screen, J. et al. (2019) The influence of weather regimes on European renewable energy production and demand. *Environmental Research Letters*, 14, 094010. https://doi.org/10.1088/1748-9326/ab38d3

van der Wiel, K., Stoop, L., Zuijlen, B.V., Blackport, R., den Broek, M.V. & Selten, F. (2019) Meteorological conditions leading to extreme low variable renewable energy production and extreme high energy shortfall. *Renewable and Sustainable Energy Reviews*, 111, 261–275. https://doi.org/10.1016/j.rser.2019.04.065

von Bremen, L. (2010) Large-scale variability of weather dependent renewable energy sources. In: A, Troccoli (ed.), *Management of weather and climate risk in the energy industry* (pp. 189–206). The Netherlands, Dordrecht: Springer. https://doi.org/10.1007/978-90-481-3692-613

Wenz, L., Levermann, A. & Auffhammer, M. (2017) Effects of 2000–2050 global change on ozone air quality in the United States. *Proceedings of the National Academy of Sciences*, 114, E7910–E7918. https://doi.org/10.1073/pnas.1704339114

Wilks, D. (2011) *Statistical methods in the atmospheric*, 3rd edition. Oxford: Academic Press.

Zscheischler, J. & Seneviratne, S. (2017) Dependence of drivers affects risks associated with compound event. *Science Advances*, 3(6), 1–11. https://doi.org/10.1126/sciadv.1700263

## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

**How to cite this article:** Otero, N., Martius, O., Allen, S., Bloomfield, H., & Schaefli, B. (2022). Characterizing renewable energy compound events across Europe using a logistic regression-based approach. *Meteorological Applications*, *29*(5), e2089. https://doi.org/10.1002/met.2089