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Characterizing the winter meteorological drivers of the European electricity system using targeted circulation types

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Abstract

Renewable electricity is a key enabling step in the decarbonization of energy. Europe is at the forefront of renewable deployment and this has dramatically increased the weather sensitivity of the continent's power systems. Despite the importance of weather to energy systems, and widespread interest from both academia and industry, the meteorological drivers of European power systems remain difficult to identify and are poorly understood. The present study presents a new and generally applicable approach, targeted circulation types (TCTs). In contrast to standard meteorological weather-regime or circulation-typing schemes, TCTs convolve the weather sensitivity of an impacted system of interest (in this case, the electricity system) with the intrinsic structures of the atmospheric circulation to identify its meteorological drivers. A new 38 year reconstruction of daily electricity demand and renewable supply across Europe is used to identify the winter large-scale circulation patterns of most interest to the European electricity grid. TCTs provide greater explanatory power for power system variability and extremes compared with standard meteorological typing. Two new pairs of atmospheric patterns are highlighted, both of which have marked and extensive impacts on the European power system. The first pair resembles the meridional surface pressure dipole of the North Atlantic Oscillation (NAO), but shifted eastward into Europe and noticeably strengthened, while the second pair is weaker and corresponds to surface pressure anomalies over Central Southern and Eastern Europe. While these gross qualitative patterns are robust features of the present European power systems, the detailed circulation structures are strongly affected by the amount and location of renewables installed.

KEYWORDS

circulation, electricity, Europe, power, regimes, renewables, weather types

1 | INTRODUCTION

A global transition to low-carbon energy sources is underway in an attempt to meet Paris Agreement targets, and the rapid decarbonization of electricity systems is widely seen as a key enabling step (Rogelj *et al*., 2015). Europe sits at the forefront of this transition, with the region being one of the world's biggest energy consumers and greenhouse gas emitters (Liobikiene and Butkus, 2017), but also having some of the best resources and most ambitious targets for renewable power penetration (Resch *et al*., 2008). A key feature of many renewables (such as wind, solar and hydro generation), however, is that they are meteorologically sensitive and increase the exposure of the entire power system to variations in weather and climate in a highly non-localized manner (Bloomfield *et al*., 2016, 2018; Wohland *et al*., 2017; Collins *et al*., 2018; Zeyringer *et al*., 2018; van der Wiel *et al*., 2019b). It is therefore important to identify and understand the large-scale meteorological drivers associated with structured fluctuations in both demand and renewable generation both to anticipate periods of over- and under-supply and to plan future deployment.

There have been many attempts to classify European meteorological variability through sets of synoptic-scale (about 1,000 km) weather patterns on daily time scales. Such techniques are often referred to as "circulation types" or "weather regimes" and began from subjective catalogues such as Grosswetterlagen (Baur, 1949), though recently it has become popular to calculate objective circulation types using techniques such as *k*-means clustering (e.g. Neal *et al*., 2016). A particular method based on winter geopotential height anomalies in the mid-troposphere and leading to four winter Euro-Atlantic weather patterns (Michelangeli *et al*., 1995; Cassou, 2008) has attracted widespread interest in weather research and the energy industry. The four patterns are typically referred to as the positive and negative phases of the North Atlantic Oscillation (NAO), the Atlantic Ridge and Scandinavian Blocking, though this naming convention is somewhat subjective. Each weather pattern can be associated with a set of surface meteorological impacts (e.g. anomalous temperature and wind speeds; van der Wiel *et al*., 2019a).

Research in the energy–meteorology community has focused on identifying power system responses to these existing weather-based classification schemes. The NAO is the best studied pattern for Europe with demonstrated connections to electricity demand (Ely *et al*., 2013; Thornton *et al*., 2017; Bloomfield *et al*., 2018), wind power (Brayshaw *et al*., 2011; Zubiate *et al*., 2016; Cradden *et al*., 2017; Bloomfield *et al*., 2018) and solar power (Colantuono *et al*., 2014) across various European countries. Physically this is consistent with the NAO's association with the shifting path of extra-tropical cyclones travelling across the North Atlantic (Hurrell *et al*., 2003): NAO+ (the positive phase of the NAO) generally results in warm, wet and windy conditions over Northern Europe and leads to reduced demand and increased wind power generation (Ely *et al*., 2013; Cradden *et al*., 2017; Bloomfield *et al*., 2018; Ravestein *et al*., 2018), while Southern Europe experiences below-average wind speeds and, therefore, wind power generation (Jerez *et al*., 2013; Zubiate *et al*., 2016). In NAO− (the negative phase of the NAO), the situation is broadly reversed. Other studies confirm more generally that so-called blocked conditions (such as Scandinavian Blocking and Greenland Blocking, or NAO−) are associated with above-average demand and below-average wind and solar generation in Central and Northern Europe (Grams *et al*., 2017; van der Wiel *et al*., 2019a). More zonal flow conditions (such as NAO+) lead to above-average wind generation in Central–Northern Europe and below-average generation in Southern Europe (Grams *et al*., 2017). In each case, however, it must be emphasized that this link is probabilistic rather than deterministic: exceptions from these general patterns can occur in individual cases.

An expected limitation of traditional weather classifications for studying weather impacts on human and environmental systems, however, is that weather classifications are typically based on atmospheric circulation (often geopotential height anomalies in the mid-troposphere or mean sea level pressure—MSLP) rather than relevant aspects of surface climate (e.g. temperatures and wind speeds in particular locations) or their consequent impacts on a system of interest. Thus, while weather classifications can be used to summarize efficiently the variations in atmospheric circulation, there is no reason to assume that the circulation types identified must correspond to the atmospheric circulation patterns of the greatest consequence for a particular region or system. Previous studies have shown, for example, that the weather pattern driving a key power system property, peak "demand net wind" in Great Britain depend intimately on the characteristics of the power system itself. In this case, the amount of wind power capacity installed is particularly important (Bloomfield *et al*., 2018). Consider also the winter NAO: while the NAO is indeed a dominant atmospheric circulation pattern affecting European climate, it has little consequence for wind power resources over northern France as this region lies between regions where there are strong associations of the NAO with surface winds (Zubiate *et al*., 2016). From these examples, it is clear that the patterns of atmospheric variability driving the largest impact on the power system are not necessarily identical to intrinsic patterns of atmospheric circulation types; instead, they are a complicated convolution of the atmosphere's variability with the power system's weather sensitivities.

Extrapolating these essentially local considerations to a geographically extended European power system containing many different weather sensitivities together, it is clear that the atmospheric patterns that best explain its response to weather fluctuations cannot necessarily be assumed to be merely identical to the atmosphere's own preferred circulation types. Instead, they will be a convolution of the atmospheric circulation with the pattern of weather sensitivity of the power system itself.

A new approach to weather typing is presented that directly identifies the most relevant winter atmospheric circulation patterns for the European power system. This is referred to as targeted circulation types (TCTs), thereby avoiding the word "regime" due to its implications of well-defined discrete internal states. Whereas traditional weather patterns are derived from statistical analysis of purely meteorological fields (e.g. geopotential height or MSLP), TCTs are instead derived from the power system's weather response (in this case, meteorological data which have first been transformed into estimates of national demand, wind and solar generation across Europe). As will be discussed, TCTs require choices to be made concerning which aspects of the power system behaviour are of most relevance but, once defined, provide a natural framework for estimating the most significant weather drivers of interest affecting a geographically extended infrastructure system with complicated meteorological sensitivities. While the application and insights presented here are discussed in terms of the European power system, the TCTs methodology is fully general (and no more complicated than existing weather typing methods) such that TCTs could be readily defined for any relevant human or environmental system affected by weather in a similar way.

The paper is structured as follows. The present paper first introduces a new data set for studying the European power system response to winter weather (Sections 2.1–2.3). These build upon well-established methods and are used to construct a self-consistent, multi-decadal record of renewable generation and electricity demand by country across the European region. Section 2.4 briefly recaps the widely used weather typing approach of "Michelangeli–Cassou" patterns (MCPs); and Section 2.5 extends this into the new TCT approach. The results of the TCT analysis are presented in three parts. Sections 3 and 4 contrast the new TCTs with the traditional MCPs in terms of their impact on demand; while Section 5 demonstrates how the changing nature of the power system due to renewable integration affects the atmospheric circulation patterns of most interest for quantification and prediction. A practical application of the TCT approach in a climate service for energy context is discussed in Section 6; conclusions are presented in Section 7.

2 | DATA AND METHODS

A central feature of TCTs is that they are constructed from data sets corresponding to the impact of weather on a system of interest rather than the raw meteorological data itself, with multi-decadal data sets being required for robust pattern identification. Unfortunately, for many aspects of critical infrastructure direct observations of the system itself are short, sparse and/or inhomogeneous. As a result, it has become common to produce "reconstructions" of weather-sensitive aspects using meteorological reanalyses (e.g. in electricity and telecommunications; Ely *et al.*, 2013; Cannon *et al.*, 2015, Staffell and Pfenninger, 2016; Troccoli *et al.*, 2018; Brayshaw *et al.*, 2019). Here, the ERA5 reanalysis (Hersbach, 2018) spanning the period 1980–2018 is used to generate a new and self-consistent reconstruction of daily European power system data (national total electricity demand, wind power generation and solar power generation for each of 28 European countries), as well as for deriving the associated MCP and TCT circulation types. The following subsections briefly summarize each aspect of this individually. The corresponding data sets produced are available from the Reading Research and Data Repository (https://doi.org/10.17864/1947.227). For brevity, the methods used in this reconstruction are described concisely in this section with full details available in Supporting Information File S1.

The power system structure for the national-aggregate models is based on data from the ENTSOe (2019) transparency platform and the commercially available windpower.net (2019) database. The bulk of the analysis presented assumes a power system baseline equivalent to 2017, unless noted, though a series of sensitivity experiments with differing renewables capacities are also referred to, with full details in Supporting Information File S1.

2.1 | Electricity demand model

Temperature is well established as the primary weather driver of electricity demand with very cold or very warm temperatures driving increases in demand corresponding to heating and cooling, respectively (Taylor and Buizza, 2003). To quantify this, a multiple linear regression model of demand is constructed separately for each country. Each model contains parameters corresponding to both heating and cooling degree-days, as well as confounding human behavioural factors (day of the week, long-term socioeconomic trends). Each model is trained on two years of observed "daily total load" data (2016–2017) from the ENTSOe transparency platform and validated on 2018. Note that in some countries the total load data may include a contribution from embedded renewable generation, which should be noted in the interpretation of results. This approach is very similar to that used in previous studies (Bloomfield *et al.*, 2016, 2018) and validates well against observations on daily timescales with $R^2 > 0.86$ for all countries, and an average root mean square error (RMSE) of 7% of the national-aggregate demand in all cases. For full details of the regression co-efficients and corresponding skill scores, see Supporting Information File S1.

After the model parameters have been estimated, they are applied retrospectively to the full reanalysis period, but the parameters representing human behaviours are neglected to highlight better the weather-driven components (e.g. the day-of-the-week and socioeconomic trends are neglected). The resulting time series can therefore be interpreted as the demand that would have been expected on each weather-day in the period 1980–2018, with no day-of-the-week effects and the prevailing socioeconomic conditions of 2017.

2.2 | Wind power model

The wind power is modelled physically using 100 m wind speeds from ERA5, extending Lledo *et al.* (2019) and follows on from previous studies (Cannon *et al.*, 2015).

The gross characteristics of near-surface wind have been well studied in the wind energy community and authoritative data sets, such as the high-resolution Global Wind Atlas (2019), and are widely used in practical wind-resource assessment. Though not a focus of the present work, ERA5's near-surface wind speeds over land areas tend to be somewhat lower than many other estimates, leading to potentially profound differences in wind power estimates due to the highly nonlinear nature of the wind-power curve (see Supporting Information File S1). An additive bias correction is therefore applied to each individual ERA5 grid point to adjust the long-term mean wind speed to match the corresponding value from the Global Wind Atlas.

The bias-corrected ERA5 100 m wind speeds are then used to estimate the wind power capacity factor at each grid point using one of three different power curves. The three curves correspond to typical turbines in each standardized wind power classification ranges (low, medium and high wind-speed regions; IEC, 2005) and the selection is made based on the long-term mean wind speed at each grid box. Finally, national aggregate wind power generation is calculated by weighting each grid box by the amount of wind power installed there. The resulting daily generation estimates capture the weather-driven variability of the wind power generation well (average $R^2 = 0.92$, average RMSE = 10%). For full details of skill scores, see Supporting Information File S1.

2.3 | Solar photovoltaic (PV) model

The solar PV model follows the empirical formulation of Evans and Florschuetz (1977), but with substantial adaptation to newer solar PV technologies operating at the country scale. The meteorological inputs are grid point temperature and incoming surface solar irradiance, from which national solar power generation is calculated assuming that each country's solar PV capacity is uniformly distributed over its land area (unlike wind power, good information on the within-country distribution of solar capacity is not available). At the daily level, all countries have an R^2 of approximately 0.93 and RMSE of 3%, confirming that the model captures the overall behaviour of the national solar power generation well. For full details of the skill scores, see Supporting Information File S1.

The solar PV model is presented here for completeness in recognition of the growing volume of solar PV capacity across Europe. Corresponding analysis including solar PV is presented in Supporting Information File S1. However, at 2017 installed capacity levels, solar PV is found to have only modest qualitative impacts on the analysis. For simplicity, the remainder of the text therefore focuses on the impact of demand and wind power alone unless explicitly noted.

2.4 | Classification of "Michelangeli–Cassou" patterns (MCPs)

MCPs have been computed following the method of Cassou (2008). In this method each day's gridded meteorological data from November to March for the period 1980–2018 is assigned to one of the four North Atlantic weather regimes (see Section 3 for the regime patterns). The meteorological field used for the assignment is area-weighted, daily-mean, 500 hPa geopotential height (Z500) anomalies from ERA5 over the domain 90 ° W–30 ° E, 20 ° N–80 ° N. Rather than performing the *k*-means clustering on the Z500 anomalies, the clustering is performed in empirical-orthogonal function (EOF) phase space to speed up the computation significantly (Wilks, 2011, has a mathematical description of the EOF analysis). The first 14 EOFs are retained, corresponding to 89% of the total variance. The principal component time series associated with the 14 EOFs is then used as the co-ordinates of a reduced phase space on which the *k*-mean clustering algorithm is performed to obtain four centroids, and it assigns each day to one of the four centroids (the method of Michelangeli *et al.*, 1995, is used to determine the optimal number of clusters). The *k*-means clustering algorithm separates the data into a predefined number of groups in such a way that each observation belongs to the nearest cluster (in this case, the sum of the squared Euclidean distances from the centroid) with the within cluster variances being minimized (Wilks, 2011, has further details). Following convention, the four weather regimes are referred to as the positive and negative phases of the NAO, the Atlantic Ridge and Scandinavian Blocking, and are consistent with the patterns found in other studies (Cassou, 2008; van der Wiel *et al.*, 2019a).

2.5 | Classification of TCTs

TCTs are constructed analogously to the MCPs using the *k*-means clustering algorithm. However, in this case, the inputs are daily time series of national power system indicators (e.g. national demand or residual load) for each of 28 European countries. The same time period is used for analysis as for the MCPs, November–March from 1980 to 2018. Performing *k*-means clustering on these 28 time series is significantly less computationally demanding than for the gridded Z500 anomalies in the MCP methodology. However, in order to match the MCP methodology closely, the first 14 EOFs of the 28 time series are taken and the clustering is performed in this reduced phase space (though tests confirm that for this application the patterns produced are insensitive to omitting this data reduction step; data not shown). The MCP centroid clusters (presented in Section 3) correspond to gridded maps of Z500 anomalies. Whereas, for the TCT method, the cluster centroids correspond to a map of the 28 country-aggregate time series anomalies (see Section 4 for examples). Four clusters are typically found to be a good representation of the resulting data sets (again, following the method of Michelangeli *et al.*, 1995, to determine the optimal number of clusters) and, therefore, four clusters are used for consistency and convenience throughout.

An important consideration in TCTs is that they are sensitive to the nature of the weather sensitivity of the human or environmental system being considered. The input variable to the TCT analysis has important implications for how the resulting patterns should be interpreted. At the simplest level, the choice of power system variable is of paramount importance in determining the patterns that will be produced. In Section 4, the focus will be on using TCTs to understand weather variations in national demand. The role of renewables in changing the weather sensitivity of the power system is then investigated in Section 5 by comparing the demand-only TCTs with residual-load TCTs, where "residual load" corresponds to the remaining demand once the contribution from renewables has been deducted and can be interpreted as the amount of generation required from traditional generators. Two sets of residual-load TCTs are considered: one with the present-day level of wind capacity and another with three times the present installed wind capacity. For corresponding analysis including solar PV, see Supporting Information File S1.

A more subtle issue in TCT design, however, is associated with the marked differences in the size of individual national power systems. Consider, for example, a set of TCTs based on raw national demand across Europe (Figure 1a–d). The patterns are dominated by a small number of countries, typically those with the greatest demand (France, Germany and the United Kingdom (UK)). For some applications, this may be the most relevant way to define a set of Europe-wide TCTs as the associated weather patterns are associated with the largest absolute demand fluctuations. Alternative definitions are, however, possible and it is reasonable to expect that a, say, 1 GW, demand change in a country with a large power system (e.g. France or UK) is less remarkable (and, therefore, easier to manage) than a similar size anomaly for a much smaller power system such as Slovakia or Hungary.

In the present study, the focus is on power system balancing across the European power system region recognizing that different actors have responsibility for different subdomains within the overall region. A scale-agnostic approach to weather impacts on national power systems is therefore taken. Each power system variable (i.e. demand or residual load) is normalized before the calculation of the TCTs as follows. A locally estimated scatterplot smoothing (LOESS) filter (with a one month window) is first applied to each national energy variable's annual climatology to calculate a smoothed annual climatology. This is then removed to calculate the time-varying anomaly for each year. Each country's anomaly time series is then divided by its own standard deviation (SD) climatology (separately for each day of the year). A value of +1 in the resulting time series therefore indicates a +1 SD departure above the norm for that day of the year for that country, such that the normalized values can be interpreted as corresponding to the magnitude of

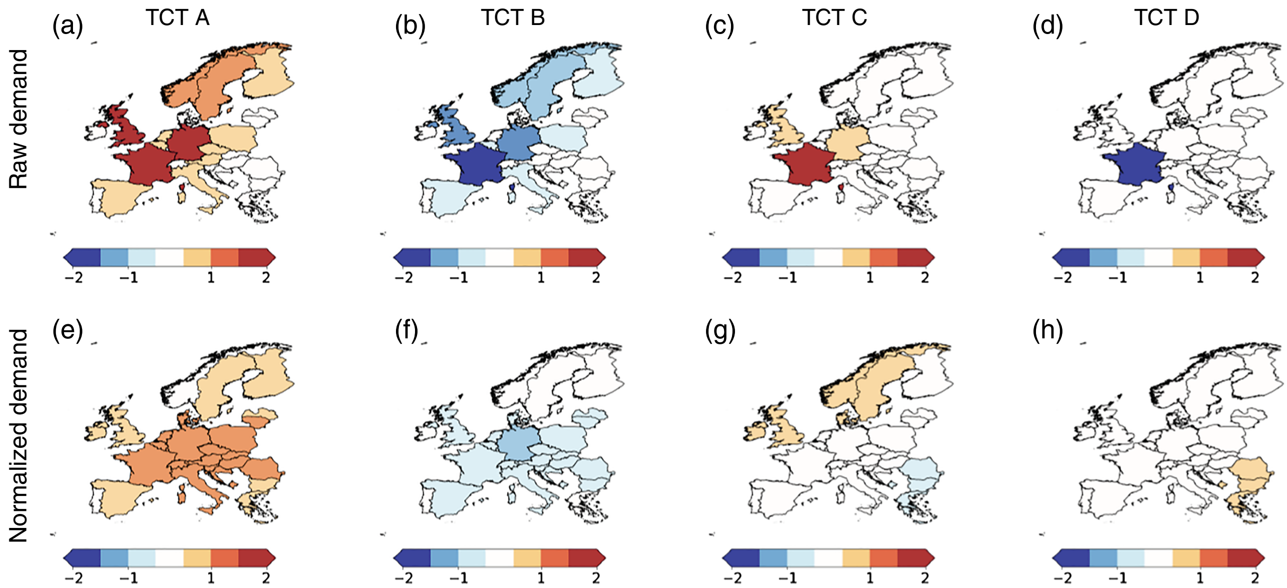

FIGURE 1 Targeted circulation type (TCT) patterns based on daily national aggregate demand across Europe (November–March): (a–d) TCTs constructed using raw demand data from each country; (e–h) TCTs constructed using demand data that have first been normalized by the size of each country's power system. The colour scale is defined in normalized demand units (i.e. +1 indicates a +1 standard deviation departure above the climatological norm for a given country)

the relative local impact on each power system. As shown in Figure 1e–h, the resulting TCTs are similar but not identical to the TCTs calculated on raw national demand data (particularly patterns 1 and 2), but with a much more diverse spread of countries are involved.

3 | IMPACT OF STANDARD WEATHER TYPES ON EUROPEAN POWER SYSTEMS

In the subsequent sections, the power system impacts of the well-known MCPs are contrasted with the new TCT equivalents. First, a brief review is presented concerning the impact of the standard MCP weather types on the European surface climate (temperature, wind speed) and key power system metrics (demand, residual load), as summarized in Figure 2.

The first column of Figure 2 corresponds to the so-called NAO− pattern, as well as to a strong meridional pressure anomaly dipole in the North Atlantic (Figure 2i), consistent with a weakening of the westerly flow (Figure 2q) and colder temperatures (Figure 2m) in parts of Northwestern Europe. The region of lower than normal winter temperatures is consistent with stronger than normal demand (between +0.5 and +1 SD in Northern Europe and Great Britain; Figure 2a). The area of anomalously cold temperatures is, however, confined to the northern edges of the domain, and the demand over most of Europe is near normal (e.g. France, Germany, Spain, Poland and Italy). A similar pattern is observed for residual load (Figure 2e), because, in general, the wind speed anomalies complement the temperature anomalies (both acting to increase residual load through increased demand or decreased wind power). Interestingly, Ireland, Denmark and Latvia, where one would expect the impact of NAO− on demand (temperature; Figure 2m) and wind power (wind speed; Figure 2q) to exacerbate each other, appear as positive demand anomalies, but not as positive residual load anomalies. This is consistent with the "signal" of the NAO− on the demand and residual load being relatively modest compared with the range of meteorological conditions present for days clustered within the NAO− type.

In contrast to the NAO−, for the NAO+ pattern (Figure 2, second column), the gross sense of the meridional MSLP dipole over the North Atlantic is reversed (Figure 2j), and the centres of action shifted eastward towards Europe. Broadly speaking, the NAO+ pattern is characterized by the opposite response to the NAO− in temperature and wind speed over Europe, with warmer and windier conditions in the north and slightly less windy in the south (Figure 2n, r). The temperature response is most extensive over the European land mass (including large parts of France, Germany, Austria, Slovakia and so on). As a result, the NAO+ is associated with weaker demand across a wider area of Central Europe (from France to Poland). Interestingly, the UK, Ireland and Scandinavian countries where the temperature anomalies are strongest shown near-normal demand

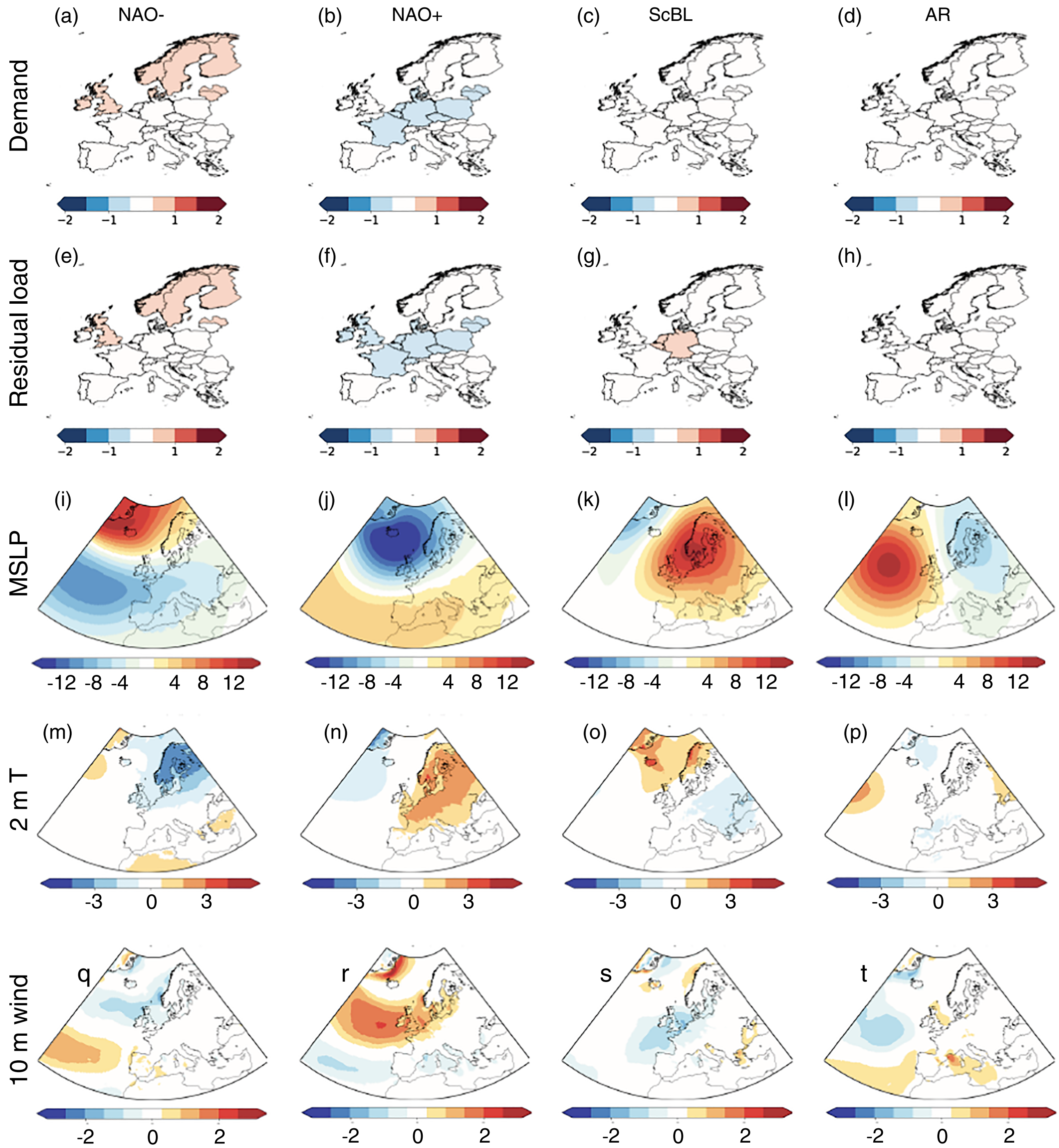

FIGURE 2 Surface response to each of the four standard "Michelangeli–Cassou" patterns (MCPs) for weather regimes (columns), expressed as anomalies with respect to climatology (November–March). Row 1 shows normalized demand; row 2 shows normalized residual load (demand minus wind power). The colour bar units for rows 1 and 2 correspond to SD of each country's anomaly time series (see Figure 1 and the discussion in Section 2.5). Rows 3 to 5 show mean sea level pressure (MSLP) (hPa), 2 m temperature (K) and 10 m wind speed ($m{\cdot}s^{-1}$), respectively

(compare Figure 2b with n). The overall pattern of demand anomalies is typically exacerbated by the inclusion of wind power (Figure 2f).

The Scandinavian Blocking and Atlantic Ridge circulation types are shown in the third and fourth columns of Figure 2, respectively. The former is characterized by a high-pressure centre near Denmark (Figure 2k, typically associated with strengthening the climatological westerly winds to the north and weakening to the south; data not shown), and the latter by a zonal pressure anomaly dipole (Figure 2l) associated with anomalously northerly winds around the North Sea region. The imprint of both patterns can be seen in both surface temperature and wind speed, though the corresponding anomalies over land are rather weak (Figure 2o, p, s and t). As such, neither pattern produces significant large-scale responses in either demand or residual load (Figure 2c, d, g and h). This is, perhaps, somewhat surprizing given the well-documented role of, for example, Scandinavian blocking in extreme weather (and associated power demand) over the UK and Western Europe (e.g. Brayshaw *et al.*, 2012; Thornton *et al.*, 2017, 2019) and highlights the danger of compositing of many similar but subtly different individual circulations into a single weather type in terms of understanding their impact (e.g. individual meteorological events assigned to a particular weather type may look very different to each other and the canonical "average" weather pattern for the type; see also van der Wiel *et al.*, 2019a).

Several conclusions can be drawn from this brief review of MCPs applied to the European power system. In general, the strongest surface climate impacts associated with the MCPs are not co-located with the most sensitive regions of the European power system. For example, the NAO patterns produce the strongest wind speed anomalies in the mid-Atlantic, rather than over sites where wind farms are located. Moreover, while evidence from previous studies indicates a key role for these general types of weather phenomena (NAO, blocking) in driving the European power system, it seems that the MCP clusters fail to provide an adequate representation of this. In consequence, the magnitude of the composite

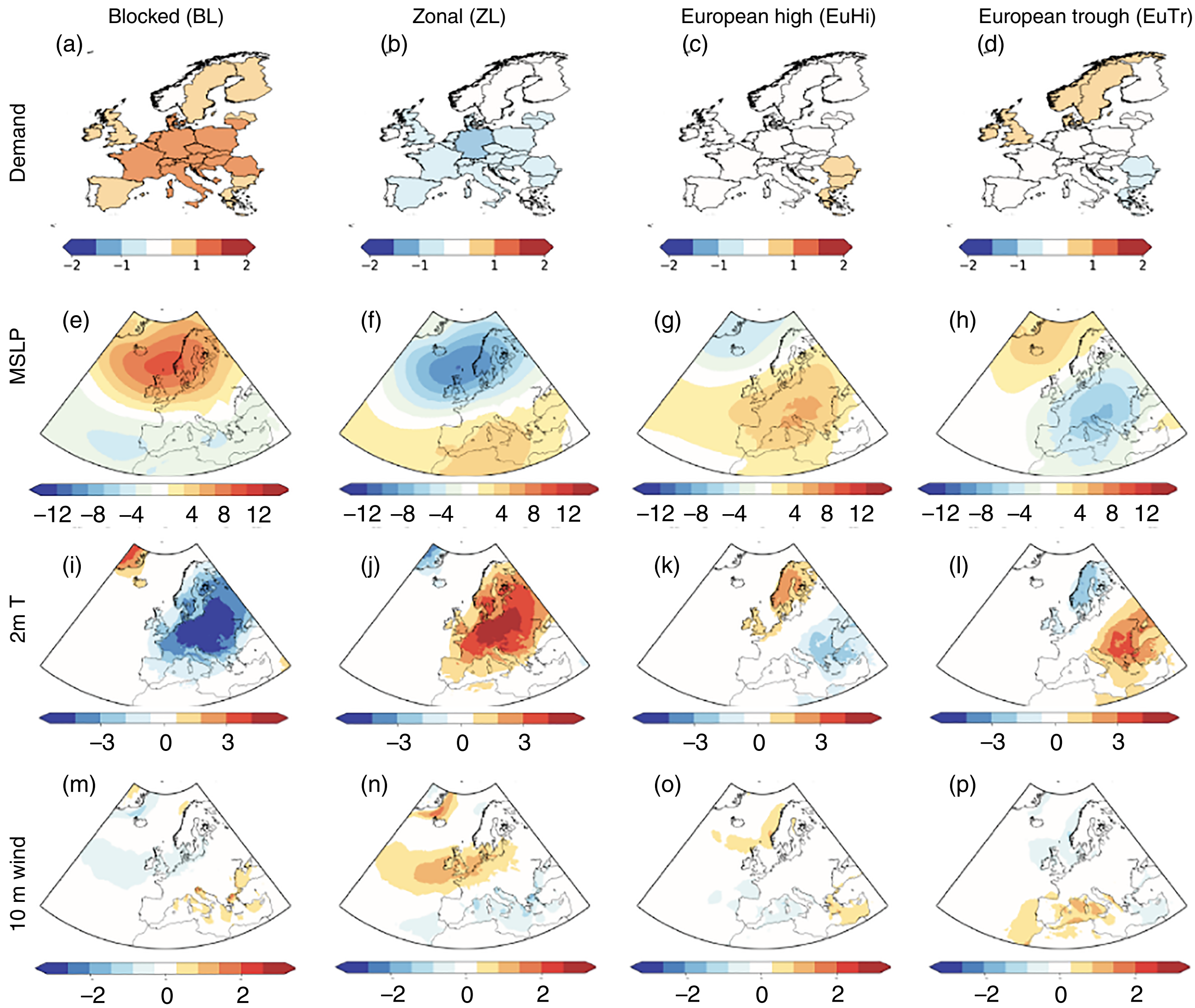

FIGURE 3 Surface response to each of the four targeted circulation types (TCTs) (columns) constructed using normalized demand, expressed as anomalies with respect to climatology (November–March). Row 1 shows normalized demand (units correspond to SD of each country's anomaly time series; see Figure 1 and the discussion in Section 2.5). Rows 2–5 show mean sea level pressure (MSLP) (hPa), 2 m temperature (K) and 10 m wind speed ($m{\cdot}s^{-1}$), respectively

TABLE 1 Days allocated to each pattern-type combination from November to March 1980–2018

Circulation type	TCT-D blocked (19%)	TCT-D zonal (32%)	TCT-D EuHi (21%)	TCT-D EuTr (28%)	Total
MCP NAO− (19%)	346	241	384	125	1,096
MCP NAO+ (32%)	76	1,062	203	458	1,799
MCP ScBL (28%)	401	315	225	644	1,585
MCP AR (21%)	261	231	355	373	1,220
Total	1,084	1,849	1,167	1,600	5,700

Notes: Rows indicate the standard "Michelangeli–Cassou" patterns (MCPs); columns indicate targeted circulation types (TCTs) calculated using normalized demand.
AR: Atlantic Ridge; EuHi: European High; EuTr: European Trough; NAO: North Atlantic Oscillation; ScBL: Scandinavian blocking.

demand and residual load responses to the standard MCP approach to weather typing is weak (in no case the anomalies exceed 1 SD), suggesting that their explanatory power for understanding and predicting weather impacts on European power is rather limited.

4 | TCTs AND EUROPEAN POWER DEMAND

Figure 3 shows the TCTs based on the November–March normalized demand anomalies and Table 1 indicates how the days classified into TCT patterns compare with traditional MCP analysis. For convenience and in analogy with the MCP names, the four TCT patterns produced are referred to as Blocked (BL), Zonal (ZL), European High (EuHi), and European Trough (EuTr), respectively.

An initial comparison of the TCT circulation patterns (i.e. MSLP anomalies) with the MCP circulation patterns (compare Figure 3e–h with Figure 2i–l) suggests many elements of qualitative similarity. For example, a meridional pressure dipole is prominent in the first two columns of either method (i.e. NAO−/NAO+ or ZL/BL) and there is a relatively strong leading diagonal (top left to bottom right) in Table 1. This similarity is expected given that the TCT method depends on the atmospheric circulation insofar as the same underlying meteorological data used in MCP analysis are also used to estimate the power system variable (demand) and the associated TCT clustering. It is, however, clear that the transformation of raw weather into its power system impact modifies the pattern set substantially, both qualitatively and quantitatively. In particular:

- The TCT patterns are more pair-wise symmetric than the MCPs (i.e. BL is broadly the opposite of ZL, also for EuHi *versus* EuTr; Figure 3).
- The TCT patterns appear to blend elements of the MCPs (e.g. the BL TCT appears to be a mixture of the MCPs for NAO− and Scandinavian Blocking, compare Figure 3e with Figure 2i, k; and also see the "Zonal" column of Table1).
- The Atlantic Ridge MCP appears to have no direct TCT equivalent and Atlantic Ridge days are split almost evenly over the TCTs (table 1, penultimate row).

The TCT patterns are each briefly discussed below.

4.1 | Blocked

The MSLP composite for the BL TCT (Figure 3e) has similarities to both the NAO−, Scandinavian Blocking and Atlantic ridge MCPs, though none is a direct equivalent (compare Figure 3 with Figure 2 (row 3); and see table 1). In the BL TCT, stronger positive normalized demand anomalies are seen over Central Europe than those associated with any individual MCP. This is consistent with a stronger negative temperature anomaly over a much larger region of continental Europe than any MCP.

4.2 | Zonal

Figure 3 (column 2) shows the ZL TCT has a close resemblance to the NAO+ MCP (see also column 2 of table 1) and results in negative normalized demand anomalies over Central Europe. Though the TCT pattern closely resembles the MCP NAO+, however, the demand anomalies in the TCT pattern cover a larger area of Europe than those seen in the NAO+ MCP (Figure 2b). This is consistent with the TCT having a stronger temperature signature than the closest corresponding MCP.

4.3 | European high

The pattern associated with the EuHi TCT (Figure 3g) resembles the inverse of the EuTr TCT (Figure 3h) when the MSLP and temperature composites are compared, with inverse impacts seen on demand. The MSLP anomalies associated with the TCT pattern resembles a blend of two MCPs (NAO+ and Scandinavian Blocking; *cf.*

Figure 3g with Figure 2j, k; also see Michelangeli–Cassou 1, column 4) despite the European impact of these two MCPs usually being considered as rather distinct.

4.4 | European trough

The EuTr TCT, like the BL TCT, also has some similarities to the NAO− MCP as they both relate to a change in the meridional pressure gradient over Europe, though the centres of action are very different (*cf*. Figure 3h with Figure 2). A dipole structure of normalized demand and temperature anomalies is seen in EuTr with centres over Northwestern Europe and the Eastern Mediterranean. The temperature composite associated with EuTr is similar to the NAO−, though the increase in temperatures in Southeastern Europe is stronger (and the decrease in temperatures in Northwestern Europe weaker) than the NAO− MCP.

This analysis demonstrates that although the standard MCPs are associated with impacts on European power demand, they are far from the best method for identifying the atmospheric circulation patterns to which demand is sensitive. In contrast, the new TCT approach constructs a set of patterns with a significantly stronger connection to the property of interest, and, therefore, more explanatory power. In this case, the TCTs can be viewed as two distinct MSLP pattern structures each with a positive and negative phase and are associated with markedly different surface temperature impacts specifically targeted over the European landmass (rather than surrounding oceans as seen in MCP). Interestingly, one of the MCPs (the so-

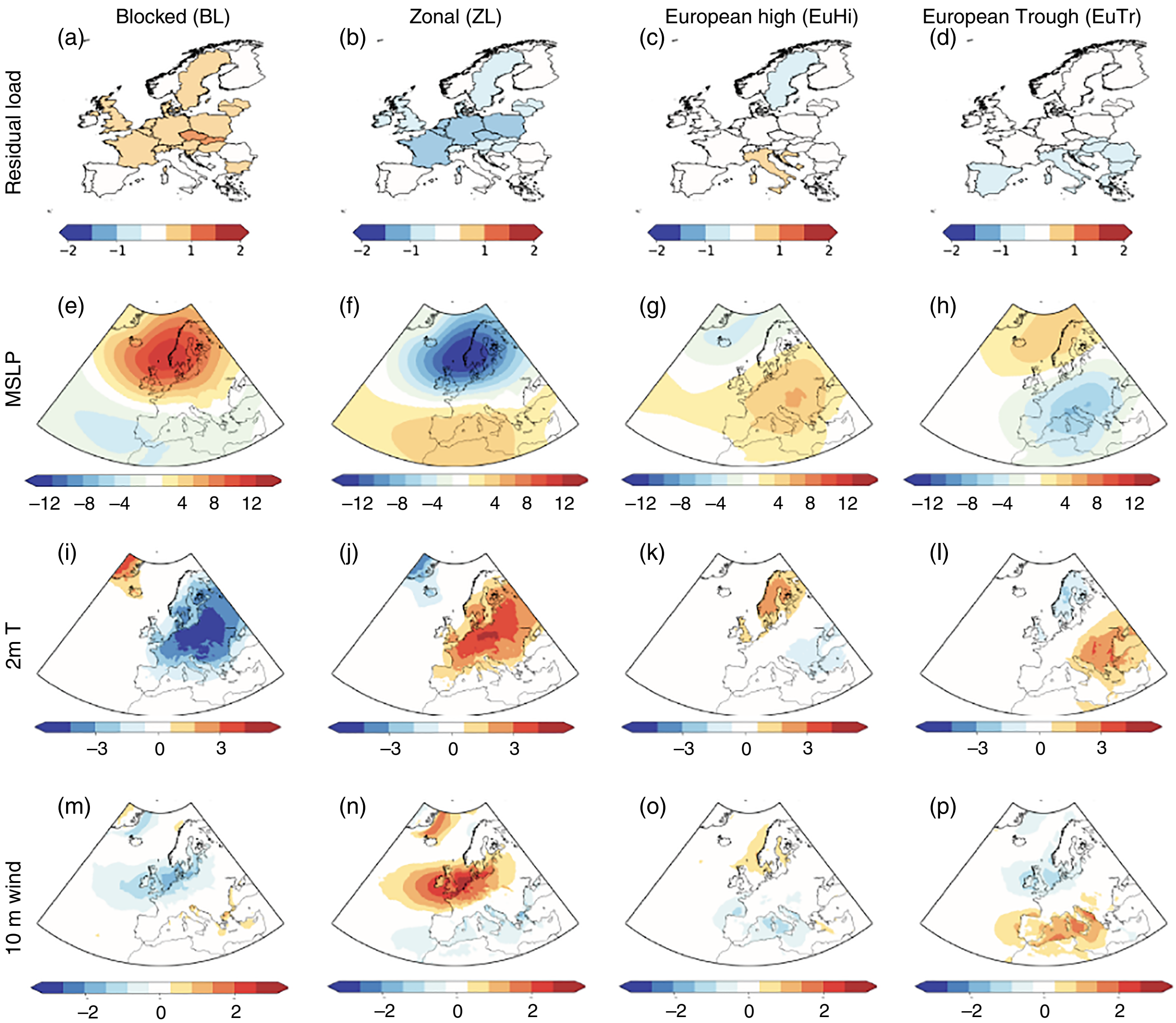

FIGURE 4 As for Figure 3, but for the targeted circulation types (TCTs) constructed using normalized residual load (demand minus wind power)

called Atlantic Ridge) does not feature at all in the corresponding set of TCT patterns, indicating that it has minimal relevance for European demand variability.

A key issue with TCTs, however, is that they are expected to change as the power system evolves over time (i.e. as the power system's weather sensitivity changes due to the introduction of renewables). It is interesting to note that the composites for all four TCT patterns presented in this section (Figure 3) have only modest 10 m wind speed anomalies (Figure 3m–p). This is perhaps to be expected as this set of TCT patterns is derived from the normalized national demand data, which, in the present study, depend only on temperature (see Section 2.1 and Supporting Information File S1). The influence of including wind power on the nature of the TCT patterns is therefore discussed in the next section.

5 | IMPACT OF RENEWABLES

TCTs, by design, reflect the weather sensitivity of the system or property that is being impacted upon by the atmospheric circulation. Thus, as renewable power technologies are integrated into the power system, the TCTs (and, by extension, the weather patterns of most interest) also change. Figure 4 shows the set of TCTs calculated using normalized national residual load based on the present-day distribution of wind power capacity (as discussed above, for simplicity only demand minus wind power is considered rather than including solar PV; results including solar PV are presented in Supporting Information File S1). Contrasting this set of TCTs with the previous TCTs derived from demand data alone (Figure 3) shows how the present-day level of wind power capacity has affected the overall large-scale meteorological sensitivity of the European power system.

There are clear similarities between the circulation patterns associated with residual-load and demand-only TCTs (*cf.* Figure 4e–h with Figure 3e–h), and days tend to appear in the same pattern cluster (see the strong leading diagonal from top-left to bottom-right in 2). The naming convention used for the demand-only TCTs (BL, ZL, EuHi, EuTr) is therefore retained. There are, however, important differences in the patterns produced: nearly 40% of days are reclassified between the demand- and residual-load TCT sets and the corresponding MSLP patterns are subtly modified (Figure 5) consistent with significant changes in the surface temperature and, in particular, the surface wind (compare Figure 4i–p with Figure 3i–p). The changes in each of the TCT patterns are discussed below.

5.1 | Blocked

The MSLP composite is similar in structure to the equivalent demand-only TCT pattern (compare Figure 4e with Figure 3e; the difference is shown in Figure 5a), with approximately 85% of days in the demand-only BL TCT cluster remaining in the corresponding residual-load TCT cluster. The residual-load TCT is, however, stronger in magnitude with an eastward-shifted centre of action extending the pattern more strongly into Europe, consistent with several demand-only TCT EuHi and EuTr days reassigned into the new BL TCT (see Table 2). These differences are consistent with the climatological mid-latitude westerly winds from the Atlantic being further weakened compared with the demand-only BL TCT and, in consequence, greatly weakened surface winds in a zonal band over Ireland, Great Britain and the North Sea, extending into Denmark, northern France and Germany (compare Figure 4m with Figure 3m)—all of which feature substantial installations of wind power capacity. The temperature anomaly associated with the residual-load BL TCT is, by contrast, weaker than the corresponding demand-only TCT (compare Figure 4i and Figure 3i), consistent with temperature playing a less dominant role in determining the structure of residual-load TCTs.

5.2 | Zonal

As with the BL TCT, the ZL TCT shares many similarities between the residual-load and demand-only TCTs (*cf.* Figure 4f with Figure 3f; the difference is shown in

TABLE 2 Days allocated to each pattern-type combination

TCT pattern	Demand BL (19%)	Demand ZL (32%)	Demand EuHi (21%)	Demand EuTr (28%)	Total
RL BL (27%)	941	10	225	390	1,566
RL ZL (22%)	0	1,057	77	143	1,277
RL EuHi (25%)	54	457	736	159	1,406
RL EuTr (26%)	89	325	129	908	1,451
Total	1,084	1,849	1,600	1,167	5,700

Notes: Rows indicate the targeted circulation types (TCTs) using normalized residual load; columns indicate TCTs calculated using normalized demand. BL: Blocked; ZL: Zonal; EuHi: European High; EuTr: European Trough; RL: residual load.

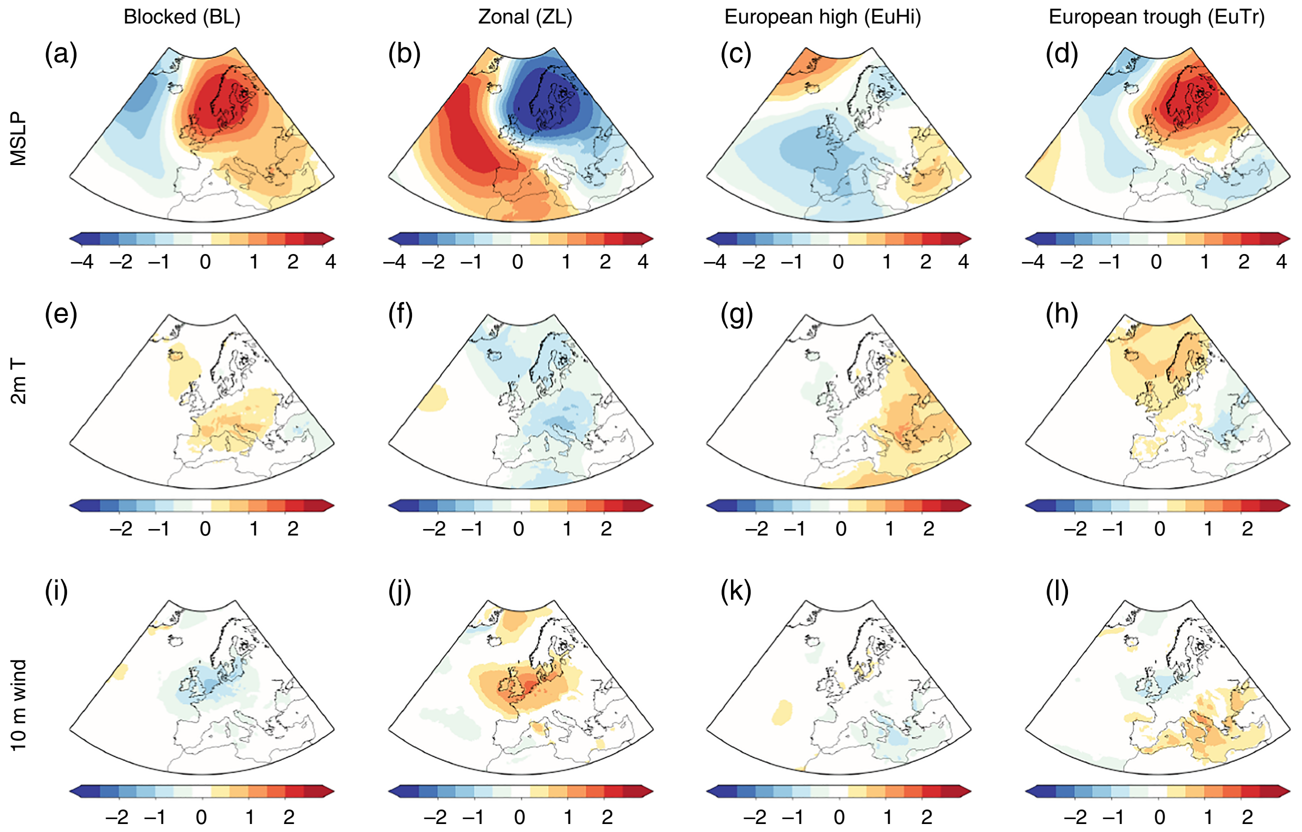

FIGURE 5 Difference in the surface climate response between the targeted circulation types (TCTs) defined on normalized residual load compared with demand (columns). Rows 1–3 show mean sea level pressure (MSLP) (hPa), 2 m temperature (K) and 10 m wind speed ($m{\cdot}s^{-1}$), respectively. Note that the colour scale has changed from previous figures

Figure 5b), though the pattern is again strengthened and shifted eastward in the residual-load case. Consistent with this, the surface temperature anomaly associated with the residual-load TCT is weakened and the wind speed anomaly strengthened (*cf.* Figure 4j and Figure 4n against the corresponding panels in Figure 3).

5.3 | European High and European Trough

For brevity, it is noted that the differences in patterns EuHi and EuTr between the residual-load and demand-only TCTs are consistent with those noted for the BL and ZL TCTs above (compare Figure 4, columns 3 and 4, with Figure 3, columns 3 and 4). As before, the pressure patterns are modified by the change of TCT analysis variable (though the nature of this modification is more subtle than for the BL and ZL TCTs), leading to a strengthening of the surface wind speed anomalies at the expense of temperature.

Two further TCT analyses are performed using residual-load corresponding to (1) demand minus the sum of wind and solar; and (2) demand minus wind power, but with treble the present-day installed wind capacities. The inclusion of these additional power system ingredients into the TCT variable is found to have a modest impact on the resulting pattern classification (see Supporting Information File S1). This lack of sensitivity is attributed to the relatively modest change each increase in installed capacity makes to the overall sensitivity of the residual load to weather drivers. This is illustrated below for the case of wind.

Figure 6a–c shows the extent to which daily-total residual load is correlated to surface temperature and wind speed as a function of the wind capacity installed in a selection of countries (Germany, France and Spain; the installed capacity is scaled assuming a constant geographical distribution of wind farms within each country). Each country's demand has a different sensitivity to 2 m temperature (this can be seen by the varying magnitudes of the regression coefficients in Table S1 in Supporting Information File S1). This differing temperature sensitivity represents the contrasting construction of energy systems across Europe, with countries including a larger proportion of domestic heating (e.g. France) having the largest sensitivities to temperature. In such countries the temperature sensitivity is still prevalent even

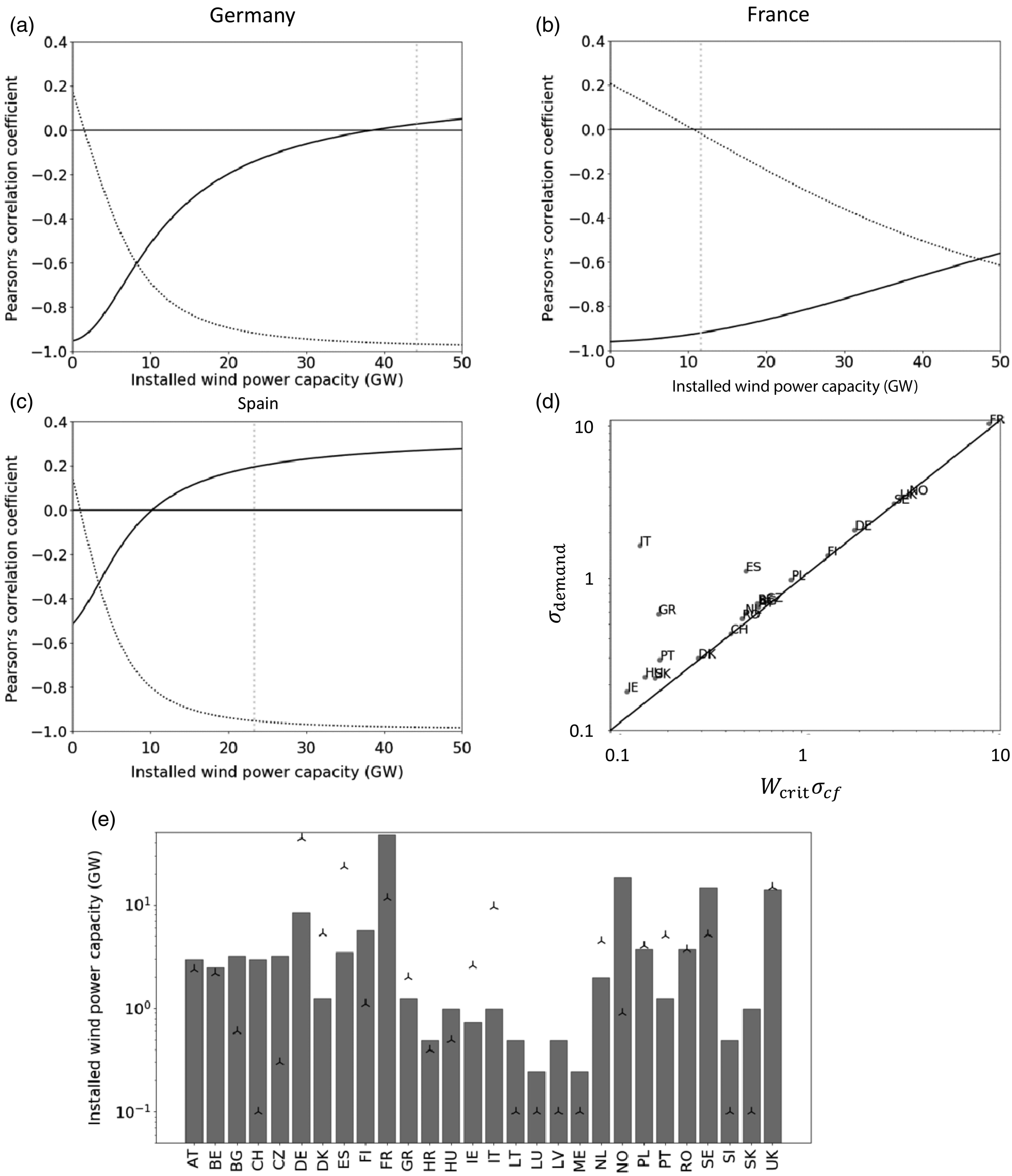

FIGURE 6 Correlation of the November–March normalized daily residual load with daily 2 m temperature (solid) and daily 10 m wind speed (dashed) across a range of installed wind capacities, showing (a) Germany, (b) France and (c) Spain. In each case, the 2017 installed wind power capacity is indicated by a vertical dotted line. (d) The SD of daily wind power compared with the SD of demand when each country's wind power capacity is rescaled to the critical point such that the daily residual load is equally dependent on 10 m wind and 2 m temperature (i.e. $W_{\mathrm{crit}}\sigma_{\mathrm{cf}}$ *versus* σ_{demand}; see the main text for a discussion). Each point represents a country; the 1:1 line is shown. (e) The critical point for wind power capacity by country (bars) and the current installed capacity for each country (turbine symbols; as recorded by thewindpower.net database in 2017)

with substantial amounts of installed wind power generation (Figure 6b). Note that in some countries the total load data may include a contribution from embedded renewable generation, which should be noted in the interpretation of results.

In each country shown in Figure 6, there is a transition point for installed wind power capacity which, once exceeded, the residual load correlate more strongly with wind rather than temperature (where the two curves intersect, hereafter referred to as W_{crit}). W_{crit} is different for different countries (< 5–10 GW for Germany and Spain, but closer to 45–50 GW for France; Figure 6a–c; see also the bars in Figure 6e), but can be intuitively estimated through a simpler heuristic. As shown in Figure 6d, for almost all countries the transition W_{crit} occurs approximately the point at which day-to-day variations in wind power are comparable in magnitude with day-to-day variations in demand, that is:

$$W_{\text{crit}} \approx \frac{\sigma_{\text{demand}}}{\sigma_{\text{cf}}}, \tag{1}$$

where σ_{demand} and σ_{cf} denote the SD of daily demand and daily wind power capacity factor, respectively.

For installed capacity $W \lesssim W_{crit}$ the weather sensitivity of the residual load (and, by extension, the overall power system) changes rather rapidly with installed wind power capacity (increasing sensitivity to wind, reducing the sensitivity temperature). However, for $W \gg W_{crit}$ the weather sensitivity is relatively uniform consistent. As shown in Figure 6e, eight (of 28) countries studied are already in this $W \gg W_{crit}$ regime (particularly those with the highest installed wind power capacities), with a further six near the transition point ($W \approx W_{crit}$). This is therefore consistent with the marginal impact of trebling the existing wind power capacity distribution having minimal effect on the weather drivers of residual load and, hence, the gross characteristics of the TCTs produced (as those countries where most of this additional capacity is installed are already well above W_{crit}).

TCT patterns are by construction sensitive to the choice of variable used and the inclusion of renewables has already changed the nature of the day-to-day weather sensitivity of the European power system: from a predominantly temperature-sensitive behaviour (demand only TCTs) to a mixed temperature-and-wind-sensitive system (residual load TCTs). It is, however, likely that further installations of wind power will not dramatically change these gross weather sensitivities unless they are sited in a way which is fundamentally different to the present wind power capacity distribution (as might be the case if, for example, strategies to minimize day-to-day variations in renewable supply are taken up; Santos-Alamillos *et al.*, 2017). From a meteorological perspective, the changes introduced by wind integration are subtle, principally associated with changes in the magnitude and position of the meridional pressure dipole (and, hence, surface westerlies associated with the mid-latitude eddy-driven jet), but there is a significant reassignment of days between TCT clusters. This emphasizes the importance of the careful selection of the variable on which TCTs are based, with profound consequences for the strength of the impact on the target system.

6 | APPLICATION TO CLIMATE SERVICES FOR ENERGY

Weather typing is a technology that has been applied in many different situations, from power system design (Grams *et al.*, 2017; van der Wiel *et al.*, 2019a) to forecasting (Ferranti *et al.*, 2015; Neal *et al.*, 2016). A typical framework for these applications is determining the probability of an event of interest occurring (e.g. above normal demand) given information describing the prevailing weather type. TCTs offer a new approach to weather typing, so assuming that TCT occurrence can be accurately estimated (e.g. from an numerical weather prediction or climate model projection), it is valuable to discuss briefly how such information might be useful from the perspective of a user-based application rather than merely an academic tool for process understanding.

Figure 7 provides a user-based perspective of TCTs: the probability of finding demand in the upper climatological tercile given a prevailing weather type. As can clearly be seen, the standard MCPs provide only modest shifts in the probability of above-normal demand: typically 10–20% chance in NAO+ (Figure 7b) and 50–70% chance in NAO− (Figure 7a) against a climatological expectation of 33% (the other MCPs have even less effect). Moreover, the geographical impact of the strongest MCP signals is very limited (e.g. restricted to Norway, Sweden, Finland and Denmark in NAO−, though a wider region experiences a weaker signal). By contrast, each of the TCTs has a strong and geographically extensive impact over most of Europe, particularly for the BL and ZL TCTs. For example, the BL TCT has > 80–90% chance of producing demand in the upper tercile over most of Central Europe (Figure 7e), while for the ZL TCT, the corresponding probability is < 10% (Figure 7f). Even the weaker TCT patterns (i.e. EuHi and EuTr) have significant explanatory power over Southeastern Europe (e.g. Greece, Bulgaria, Romania) (Figure 7g).

Figure 8 takes this further to consider the tails of the distribution: the probability of finding demand in the upper 10% of the climatological distribution (the so-called

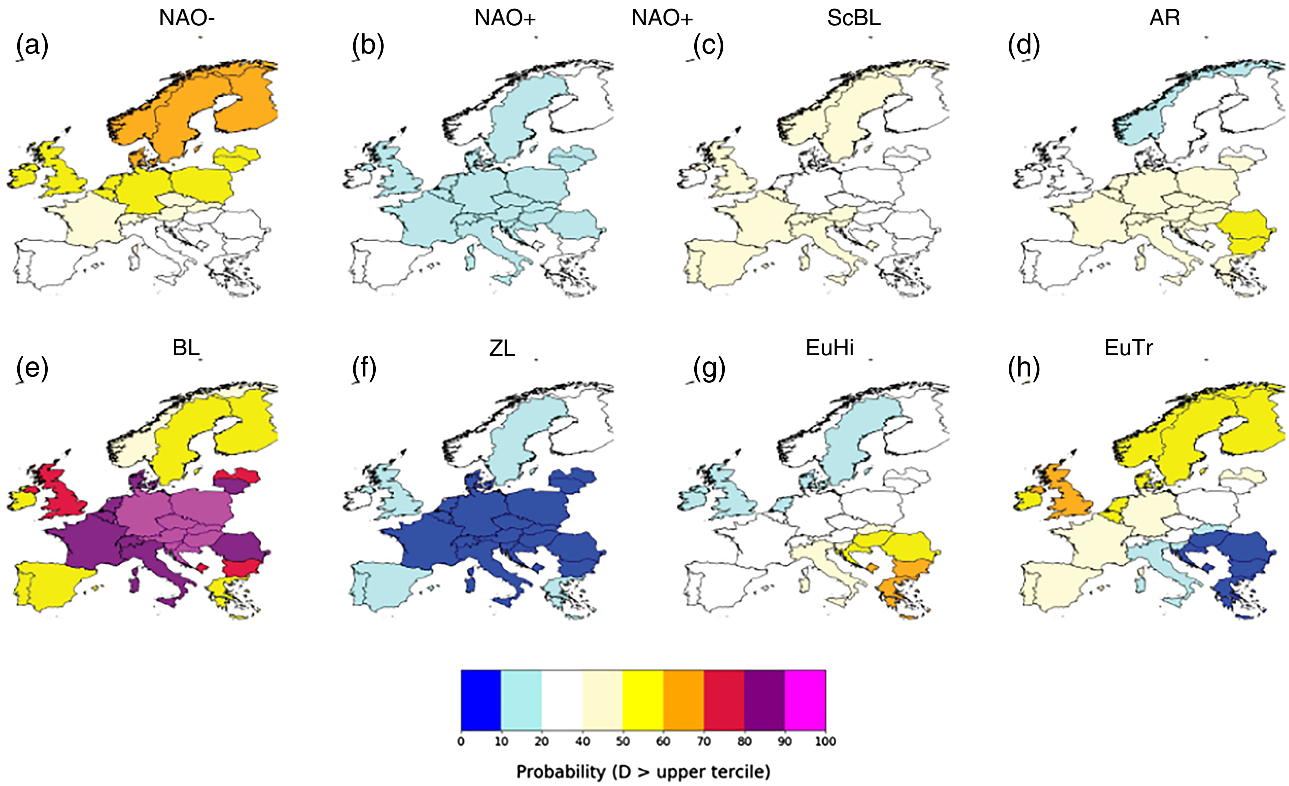

FIGURE 7 Probability of each country's demand being in the upper climatological tercile in each "Michelangeli–Cassou" pattern (MCP) (top) and targeted circulation type (TCT) (bottom). The TCT patterns used are constructed from normalized demand

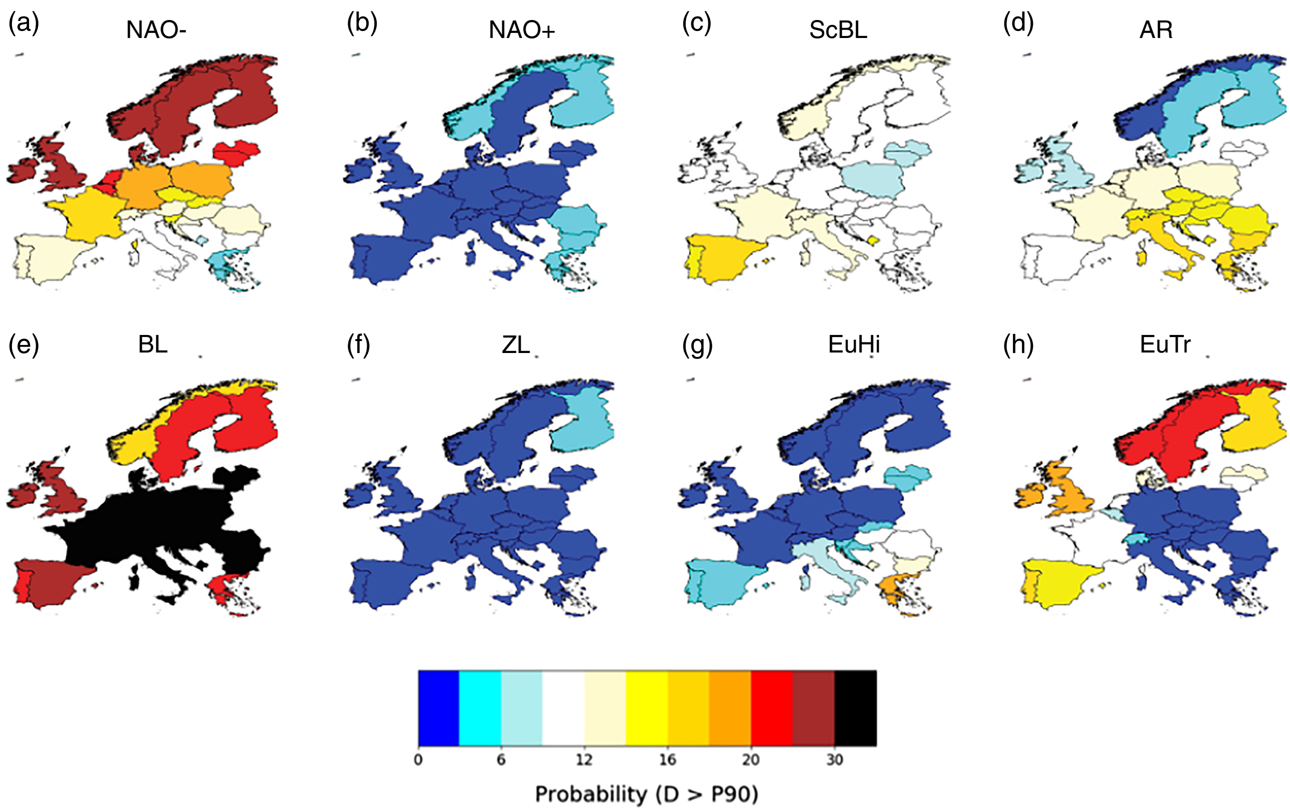

FIGURE 8 As for Figure 7, but for the upper climatological decile (i.e. the so-called P90 value)

P90 value). As before, explanatory power using the standard MCPs is available but limited: high demand levels are three times less likely than the climatological expectation in NAO+ ($P < 3\%$ over much of Europe) and about three times more likely in some regions during NAO− ($P > 25\%$ for Great Britain, Ireland, Denmark, Norway and Sweden). By contrast, the TCTs have a strong link to demand anomalies across almost all of Europe ($P > 30\%$ in the Blocked TCT for a zonal band from France to Romania, $P < 3\%$ for almost the whole of Europe for the Zonal TCT, and more complex but equally strong responses for the EuHi and EuTr TCTs).

A selection of other probability levels and variables (residual load) are presented in Supporting Information File S1.

In summary, the TCTs provide a much stronger and more convincing link between the synoptic or large-scale atmospheric circulation and its impacts relevant to power system stakeholders, with potentially significant benefits for improving predictions and simulations of power system impacts. The ability correctly to simulate and project onto TCTs in numerical weather predictions and climate model projections will be addressed in subsequent papers.

7 | CONCLUSIONS

Power systems across the world are going through a period of extreme and rapid change as they shift from carbon-intensive to low-carbon technologies. Renewable energy, particularly wind and solar, have already become a key part of the generation in many areas of Europe, and improved understanding of the underlying large-scale meteorological variability that cause fluctuations both demand and renewable supply is therefore essential. Previous studies of the meteorological impact on the power system have typically begun from a perspective of weather typing: defining circulation patterns based purely on meteorological properties such as geopotential height. While such schemes are powerful tools, they neglect important considerations concerning the weather sensitivity of the power system itself. A new approach referred to as targeted circulation typing (TCT) is therefore presented and compared with a widely used weather-typing approach. In the present study, the TCT method is applied to normalized indices of nationally aggregated demand and residual load (demand net renewables) derived from the ERA5 reanalysis and spanning 28 European countries. It is, however, emphasized that the technique itself is readily applicable to other geographically extended systems with complicated meteorological sensitivities. This work could also easily be extended to identify TCTs for the summer. Once a set of TCTs has been identified using observed impact data, they could be used with climate model simulations in order to understand potential future changes in the frequency of occurrence and resulting impacts of the patterns.

The circulation patterns revealed by the TCT analysis convolve the structures of day-to-day meteorological variability with the sensitivity of the European power system to weather. As such, they share important similarities with the standard weather patterns, but also significant differences in the location, magnitude and type of circulation structures revealed. This indicates that, although standard weather patterns are associated with impacts on the European power system, they are far from the optimal method for detecting or representing meteorological impacts on the power system. Weather patterns in general (and "Michelangeli–Cassou" patterns (MCPs) in particular) often have limited surface impacts in the region of interest. For example, in the North Atlantic Oscillation (NAO) MCPs, the impact on the European power system is limited as the strongest wind anomalies typically occur over the North Atlantic, while temperature anomalies are restricted to the far north. This situation is even more marked in the Atlantic Ridge MCP, which appears to have almost no impact on European power.

In contrast to the standard weather types, the TCTs reveal two pairs of circulation patterns that are highly relevant to a pan-European power system. The first pair resembles the meridional dipole of the NAO, but in a symmetric sense (positive and negative phases, compared with the asymmetric NAO+ and NAO− patterns in the MCP method), and are referred to as "Zonal" and "Blocked". Compared with the standard NAO MCPs, the pressure dipole is shifted eastward into Europe and strengthened (particularly when the role of wind generation is included): both are consistent with a more extensive surface temperature and surface wind signature, covering most of Central Europe (and, in particular, the heavily developed wind-generating regions over Ireland, Great Britain, the North Sea and northern Germany). Although not discussed in detail, this corresponds to a strengthening or weakening of the climatological wintertime westerly wind (advecting relatively mild maritime air into the continent), such that a weakening of the westerly wind leads to anomalously high residual load experienced over most of Europe simultaneously. The second pair of TCTs, referred to as "European High" and "European Trough", are weaker in their influence, but are again symmetric with anomalously high (or low) MSLP over Central Southern/Eastern Europe, corresponding to a northeast–southwest residual load dipole over Europe.

TCTs are by design sensitive to the variable used in their construction (here, normalized national demand or residual load), and an egalitarian view has been applied (power system anomalies are inversely weighted by the scale of the power system in which they occur). Through their use, however, it is demonstrated that the inclusion of renewables has already changed the nature of the day-to-day weather sensitivity of the European power system from a predominantly demand-oriented (and, therefore, temperature-sensitive) system to a mixed temperature-and-wind-sensitive system. It is suggested, however, that further installations of wind power are unlikely qualitatively to change these weather sensitivities further unless they are sited in a way that is fundamentally different to the present wind power capacity distribution (as suggested by Santos-Alamillos *et al.*, 2017, as a strategy, for example, to maximize the output from renewables or minimize their meteorological volatility). Significant increases in solar photovoltaic (PV) may, however, lead to more significant changes in TCT structure as solar PV have not yet reached sufficiently high penetration levels to influence the gross meteorological sensitivity at this national pan-European level. From a user perspective, the TCTs offer considerably more explanatory power than standard weather patterns for estimating national demand or residual load over most of Europe: if the prevailing TCT is known, then there is an extremely strong connection to the probability of high demand or residual load over much of Europe.

The TCT approach, here applied to the European power system, is applicable to other geographically extended human and environmental systems with complicated meteorological sensitivities, for example, agricultural or energy commodities and water resources. TCTs therefore present new opportunities for developing a deeper understanding of meteorological impacts and may provide opportunities for enhanced predictive skill across a range of applications such as energy and trade in agricultural or energy commodities.

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SUPPORTING INFORMATION

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

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