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Abstract

Electricity generation as well as electricity demand are dependent on the weather and climate, and this dependency is expected to further increase in the future. Challenges in energy systems arising from this dependency can be studied using large-scale weather patterns (WPs). These WPs can help reveal the atmospheric drivers of the challenges, but there exist many different classifications of large-scale WPs. Although WPs are widely used in energy-related studies, to our knowledge, no systematic review has yet evaluated the applicability of weather pattern classifications to analyzing extreme events and variability in energy systems. In this study, we aim to fill this gap by reviewing and combining literature dealing with both WP classifications and weather-induced challenges in energy systems. A total of 69 studies are included, which use different classification methods to study weather-induced challenges on energy systems. Overall, most challenges to the energy system arise during blocking weather patterns. Furthermore, we find that stable large-scale WPs allow for better forecasts of wind power generation if combined with other predictors. This review reveals research gaps underscoring the need to consider the whole energy system, including demand and the electricity grid, not only the generation of wind power and photovoltaics.

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Abstract

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Keywords: weather patterns, weather regimes, high residual load events, energy drought, weather variability, forecasting, energy system

1. Introduction

Both electricity generation and electricity demand are dependent on the weather and climate. On the generation side, especially the variable renewable energy (VRE) technologies, wind and photovoltaics (PV), depend on weather conditions. The contribution of these low-emission technologies to the total generation profile is rising and will continue to rise, reaching an expected 55% in 2050 globally due to climate change mitigation policies [1]. As a result, the influence of weather on entire electricity systems, including the electricity grid and dispatch of generation and storage units, is increasing. This influence is further exacerbated by increasing weather dependencies on the demand side, specifically regarding heating and cooling demand. Electrification of heating through heat pumps and an increasing cooling demand due to rising temperatures will intensify the dependence of electricity systems on weather and climate [2].

The different weather-induced challenges for energy systems include extreme events in energy systems, e.g. renewable energy droughts, as well as variability of demand and especially generation [3]. These challenges arise among others, from extreme values and variability of wind speed, temperature, and cloud cover, affecting the electricity demand and the generation of wind and PV [4]. Forecasting of electricity generation and demand is a necessity to overcome these challenges and ensure a secure and stable system operation[5], [6], [7].

One way to study these weather-induced challenges for energy systems is by using large-scale weather patterns (WPs). Large-scale WPs are recurring meteorological situations with distinct spatial and temporal patterns, typically on time scales of days and spatial scales of hundreds of kilometers [8]. These patterns can be used to reveal atmospheric drivers of problematic situations in energy systems [9], [10]. Since electricity systems are often interconnected between different countries [4], weather conditions in both the country of interest and in neighboring countries are relevant to studying weather-induced challenges. Additionally, different weather phenomena affecting the energy system can occur simultaneously [11], [12], [13]. Large-scale WPs provide a way to capture and analyze these diverse meteorological conditions across wide areas at the same time. This is possible because large-scale WPs group diverse meteorological conditions into representative patterns, reducing complexity for analysis. These patterns depict atmospheric conditions over a broad area of up to 1000 km, which are persistent up to several days [14]. They directly determine surface weather and therefore also electricity systems [15], [9], [16], [17]. In contrast to large-scale WPs, there are also local WPs, see e.g. [18], [19]. We do not consider these local-scale WPs in this review. Therefore, we omit the term "large-scale" in the following and only write WPs to talk about large-scale WPs.

There exist many different classifications of WPs for analyzing energy systems. They differ in method, analyzed (climatological) variables, number of patterns, studied area and time span, and temporal resolution. Consequently, the resulting pattern sets have different persistence, impacts on energy systems, and applications. In [20], it is distinguished between three groups of classifications: subjective, mixed, and objective classifications. The 29 Grosswetterlagen (GWL) [21], as well as the 27 Lamb WPs [22] belong to the subjective classifications as they rely on visual inspection of weather maps and expert knowledge. These long-existing classifications themselves are not used for analyzing weather-induced challenges in energy systems. It's different with their newer objectivized versions [23] and [24], which are part of the mixed group. The approach of [23], which applied a pattern correlation as a distance measure for the GWLs, as well as the approach of [24], which introduced numerical criteria for atmospheric conditions to Lamb WPs, are used for energy-related topics [20], [25], [26], [27], [28] [29], [30]. Both circulation indices and WPs derived by clustering algorithms belong to the group of objective classifications. Circulation indices describe quasi-periodic oscillatory variations in the atmospheric circulation, which are large-scale movements of air driven by unequal distribution of thermal energy from the sun [31].

The literature on WPs in the scope of energy research can be grouped into two categories of topics:

(To 1) Weather-induced extreme events in electricity systems

(To 2) Weather-induced variability of electricity generation and demand

To the best of our knowledge, none of the existing review papers have examined the potential to investigate the influences and challenges of weather on energy systems through the use of WPs and thereby included both (To 1) and (To 2), as well as the categorization methods of different patterns. The conference paper [32] reviewed the use of WPs to study the variability of wind and PV and its balancing. But this article is missing Topic 2, a comparison of the different classification methods and discussions of their trade-offs. Other reviews like [33], [34], [3], [35] [36] study the influence of weather or climate on energy systems but do not include WPs. On the contrary, [20],[37] and [38] discuss WPs and their classification but not their use for energy-related topics. It would, however, be useful to combine these research fields because insights into how various WP classifications affect energy-system assessments can enhance both the robustness of planning and the security of system operation by improving predictive skill, supporting the identification of extreme events in energy systems, and enhancing the understanding of weather-induced variability.

This review article aims to overcome this gap by conducting a systematic literature review. The goal is to give an overview of the different types of WPs, their classification, and their practicability for the different energy-related approaches they are used for. Therefore, we answer the following research questions:

(RQ1) In what way can WPs help in the analysis of weather-related impacts on energy systems, and which classifications are most suitable?

- (RQ1 a) For weather-induced energy system extreme events?
- (RQ1 b) For weather-induced variability of energy generation and demand?
- (RQ1 c) For forecasting the situations in (RQ1) and (RQ2)?

(RQ2) Which aspects of energy systems have been studied using WP-based approaches?

A systematic literature review is used in this article to answer the research questions. First, a search string is iteratively developed, consisting of two parts. The first part ensures that only studies that use WPs are included. As WPs have different names in the literature, also literature dealing with "weather regimes", "circulation patterns", and "atmospheric states" are taken into account. The second part of the search string filters all literature that is related to energy topics. As the term "energy" also appears in the context of atmospheric processes and is therefore not exclusively related to electrical energy, the term "electricity" and compound words containing energy are used. The resulting search string is

(("weather regime" OR "WP" OR "circulation pattern" OR "atmospheric states")
AND
("electricity" OR "energy system" OR "power system" OR "energymodel" OR "wind power"))

This search string was used for the Scopus database, where 324 English peer-reviewed journal papers were found on 5 August 2025. These articles were filtered by the following inclusion criteria: (1) the study addresses weather-induced challenges in energy systems, and (2) the study applies WP approaches. After abstract screening and full-text screening, there were 69 articles left, see Figure 1. These 69 articles are included in this literature review.

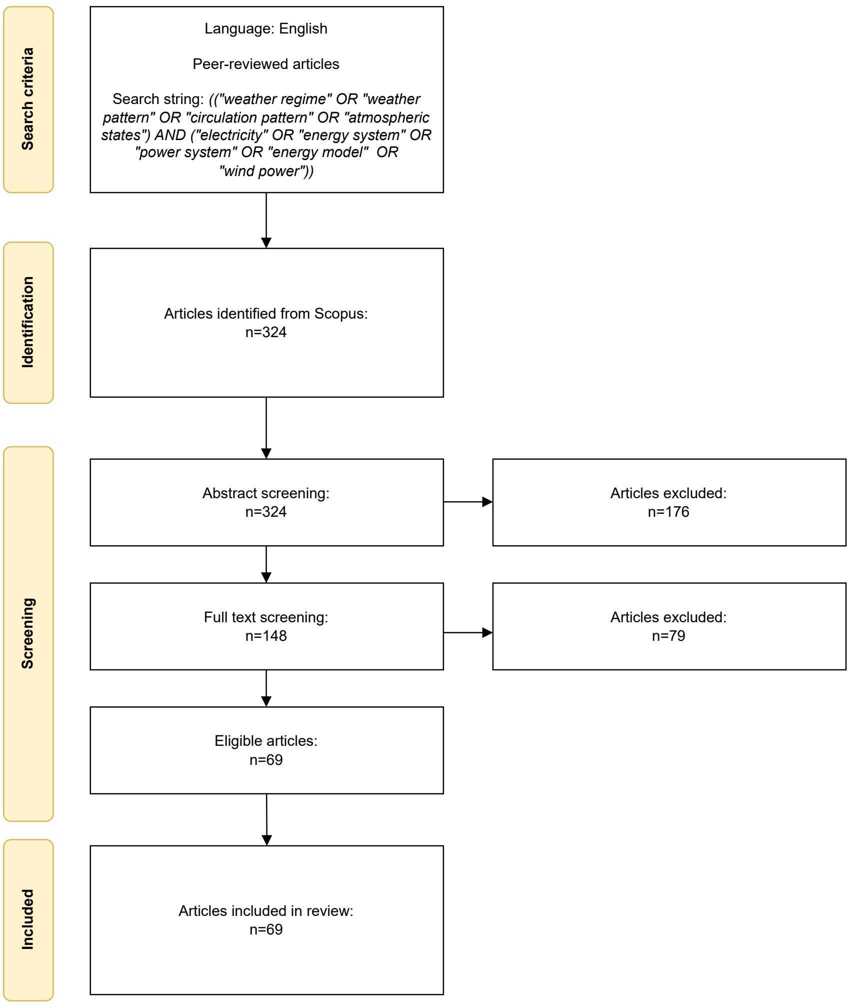

Figure 1: Filtering Process of the systematic literature research.

The remainder of this article is structured as follows: The review methodology is presented in section 1. In section 2, the different classifications of WPs used for energy-related topics are described. Sections 3-5 review the results on Topics 1-2. In 6, the central findings are discussed.

2. Weather patterns and their classification

In this section, we give an overview of the different classification methods for WPs in energy-related applications. How often the different methods are used is depicted in Figure 2. Apart from the subjective GWL and Lamb classifications, there are circulation indices and patterns derived by clustering algorithms. In the reviewed literature, circulation indices are either derived by principal component analysis (PCA), also called empirical orthogonal function (EOF), [39], [40], [41], [42] or by sums of squares of differences (SSD) at two points [43], [44]. In both cases, the classification relies on sea level pressure as the primary indicator of the atmospheric circulation state. Moreover, there are different clustering algorithms that are used for the classification of WPs in the reviewed literature. An overview of the clustered WPs is shown in Figure 3. Most of the studies that used clustered WPs applied the k-means clustering algorithm (more than 30 studies), where around 15 studies used self-organizing maps (SOM) as a clustering algorithm. Moreover, once fuzzy clustering is conducted [45]. All three clustering methods belong to the nonhierarchical clustering methods, such that the desired number of clusters has to be predefined [46]. The numbers of clusters that are used in studies deriving year-round WPs are given in Figure 4. k-means is a well-known clustering method, where in each step, each data point is assigned to its closest cluster center [46]. After this, cluster centers are recalculated for the new defined clusters. SOM is an artificial neural network, and its resulting clusters are given by a two-dimensional map of nodes [46], [47]. Fuzzy clustering allows data points to be part of more than one cluster [46]. For a detailed description of the k-means, SOM, and fuzzy clustering algorithms, see [48], [47] and [49]. In the following, first, the data used for classification is described. Then, the different k-means-based classifications used in the literature are presented. Finally, the different SOM-based classifications are explained.

2.1. Data used for classification

Here, we focus specifically on WP classifications used in energy-related studies. Most studies rely on reanalysis data, e.g., ERA5 [50], ERA-Interim [51], or JRA-55 [52], for the classification of WPs. Reanalysis data are spatially and temporally continuous data fields generated through data assimilation of weather observations [52]. According to [53] and [54], the choice of the reanalysis almost doesn't affect the classification. Only a few studies use historical data [15], [55], outputs of numerical weather predictions [56], [45] or ensemble data [57], [58]. Around 40 years of data are typical, but the minimum is one year [59] and some studies also use more than 100 years [15], [43], [58], [60]. The temporal resolution of the WPs varies between hourly and monthly. The geographical focus of most of the reviewed papers is Europe or parts of Europe. In contrast, none of the studies considered South America. South Africa is the only African country where WPs for energy-related topics are studied. The spatial scope for WP classification of studies using k-means clustering is, in general, bigger than that of studies using SOM, see figure 5. For circulation indices, an entire hemisphere of data is used. According to [61], the choice of the spatial scope has impacts on temperature and precipitation.

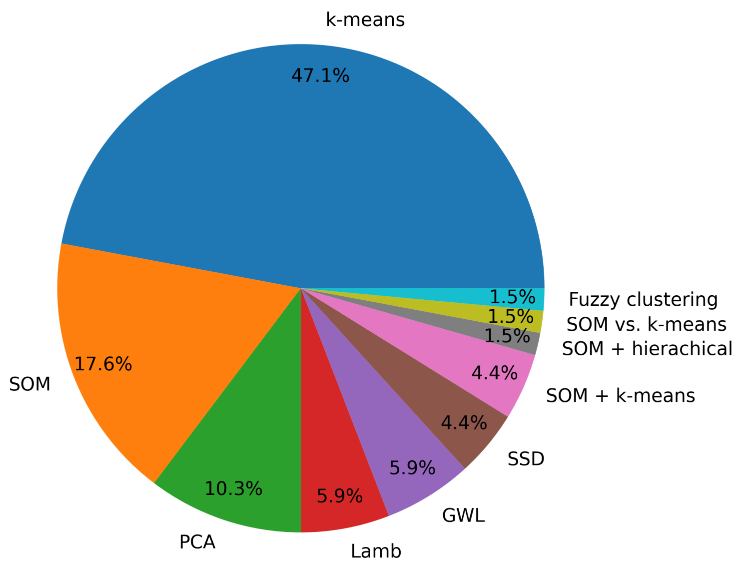

Figure 2: Overview of classification methods used in energy-related studies.

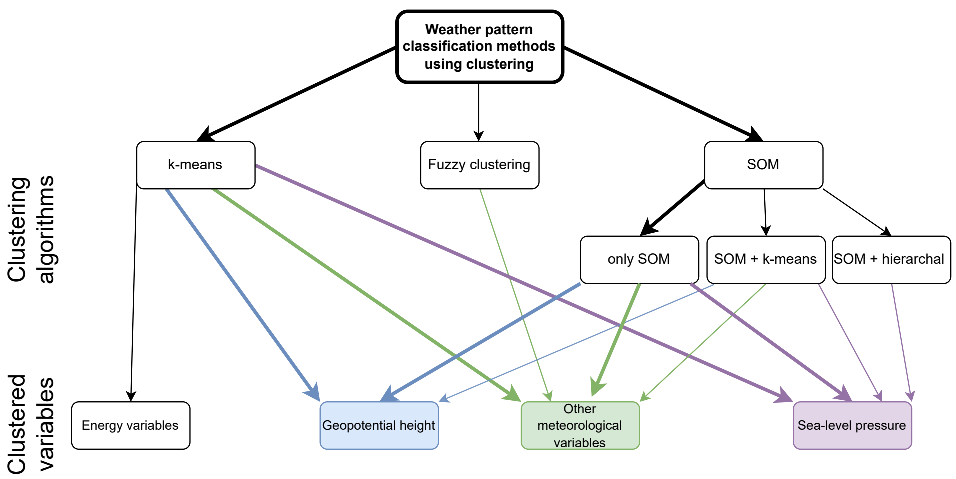

Figure 3: Overview of classification of clustered WPs in energy-related studies. Thicker arrows indicate that a classification method is used frequently.

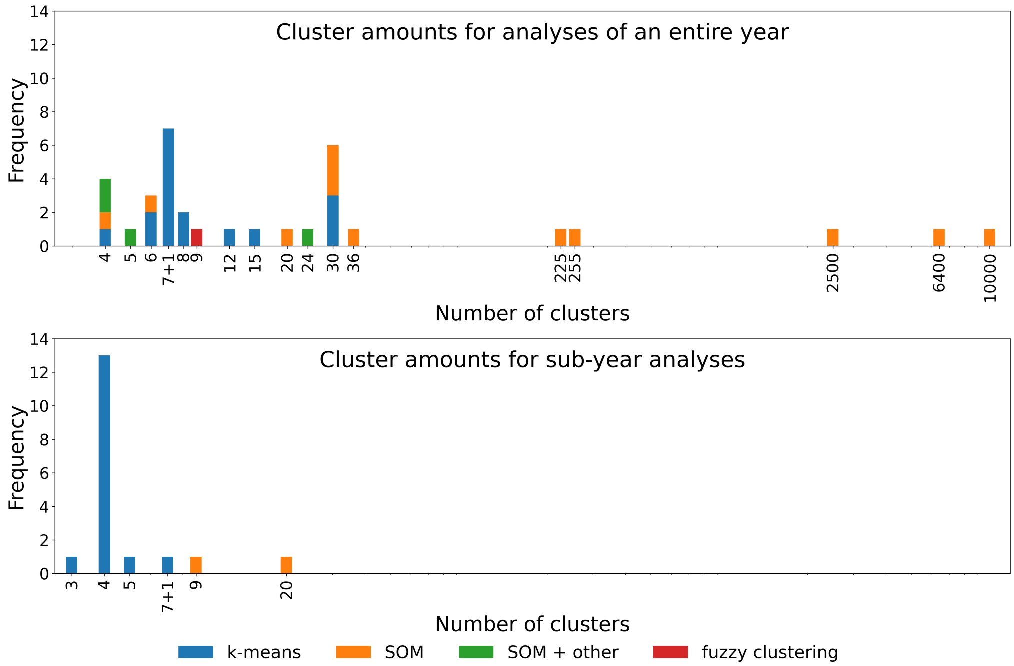

Figure 4: Cluster amounts for year-round and sub-year WP classification in the reviewed studies on a logarithmic scale.

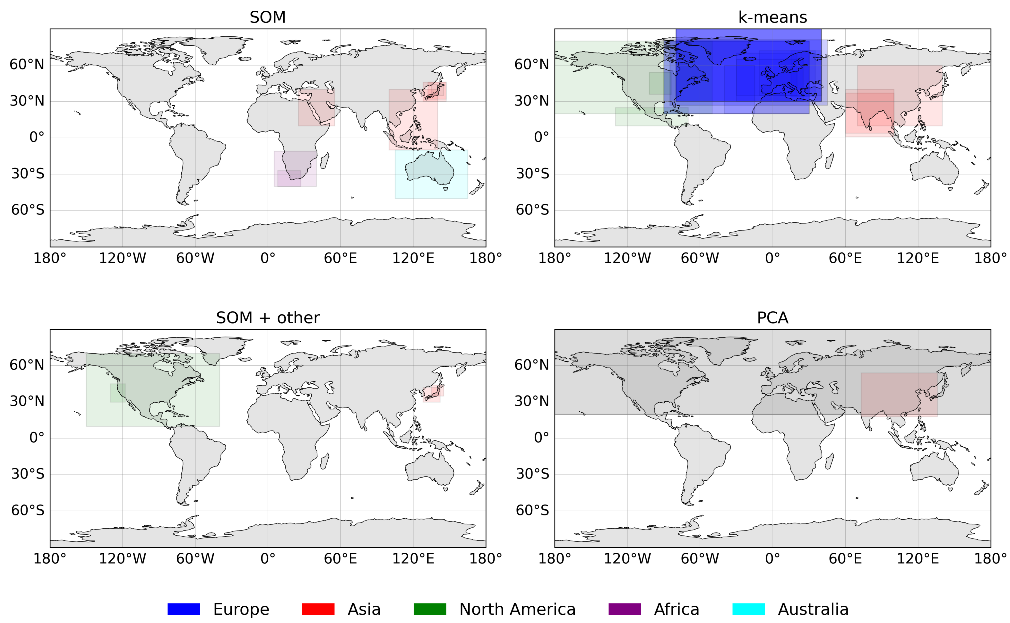

Figure 5: Spatial scope for classifying WPs used in the reviewed papers.

2.2. *WPs based on k-means*

K-means clustering is commonly applied to meteorological variables such as 500 hPa geopotential height, sea level pressure, wind speed, temperature, and solar irradiance, typically producing between 3 and 30 clusters. Geopotential height represents the altitude of a pressure level in the atmosphere and is widely used to describe WPs. Many k-means-based studies restrict their analysis to months within a single season. More than 75% of the studies using k-means as a clustering algorithm cover Europe or parts of it as spatial scope where the rest of the studies cover regions in North America and Asia.

Often one or more preprocessing steps are applied before the clustering. The first of these optional steps is the often-used removal of the seasonality of the data by calculating anomaly or normalizing [62], [15], [63]. Another step is the area weighting of the data by the cosine of the latitude, which is done because of the different sizes of the grid cells due to the curvature of the Earth [62]. Only very few studies mention this preprocessing step. A few studies also conduct a low-pass filtering to filter out high frequencies of the used variable and therefore derive more persistent WPs [64]. The last possible preprocessing step is applying a PCA. PCA is used for the reduction of the number of dimensions, e.g. in [12] [14], [6], [10], [7].

Depending on the studied seasons [14] and the temporal resolution [20], different numbers of clusters may be appropriate. In the reviewed literature, the choice of number of clusters was determined using various measures, including the elbow method, which is the within-cluster sum-of-squares [53], [65], [66], the silhouette score [67], [12], the explained variation score [68], anomaly correlation coefficient [14] and the k-means gap method [9]. Moreover, many studies used sensitivity analysis or determined the number of clusters visually and subjectively [60], [69], [62], [60].

Two different classification methods based on k-means of 500 hPa geopotential height are used very frequently to analyze weather-induced challenges for energy systems in Europe. The first one is the classification of Cassou et al. [70] which results in four winter WPs. Here, two of the WPs correspond to the positive and negative phases of the circulation index North Atlantic Oscillation (NAO) [70]. For this classification, anomalies of the daily data are calculated, and a PCA is conducted before clustering. The number of clusters in [70] is determined with the aid of the Brownian noise statistics [71].

The second widespread method from Grams et al. [14] classifies seven year-round WPs. In addition to normalizing the 3- or 6-hourly data, a low-pass filter and PCA is used for preprocessing. Seven clusters are chosen because the anomaly correlation coefficient then remains below the desired threshold. After clustering, a weather regime index is used to decide which time steps are finally assigned to their cluster and which time steps are not suitable enough and are therefore assigned to a so-called No-cluster. This further ensures the persistence of the WPs. The result of this clustering are four blocking patterns and three cyclonic patterns. Blocking and cyclonic patterns are defined according to their pressure anomalies and stability. Blocking patterns are stable high-pressure anomalies associated with low large-scale winds, where cyclonic patterns are low-pressure anomalies with less persistence and are associated with high large-scale winds. [14] [72]

There are also a few variants of classical k-means clustering of meteorological data. Study [15] used a simulated annealing variant of k-means to increase reproducibility of the clustering technique [73]. [74] clustered demand and residual load instead of climatological variables. The resulting patterns explain variability as well as extremes of energy variables better, but these patterns are strongly dependent on the installed capacities of renewable energy technologies.

2.3. WPs based on SOM

SOM is used to cluster 500 or 850 hPa geopotential height, sea level pressure, temperature, or wind speed or velocity into 4 [75] to 10 000 [76] clusters. In contrast to k-means, SOM is mainly used for regions in Asia. Besides the calculating of anomalies before clustering in [17] and [77], no preprocessing steps are used in the SOM-based papers.

While several SOM-based papers use numbers of clusters in the same range as k-means-based papers, there is also one author using more than 100 clusters in his studies [55], [78], [13], [77]. The reason is that for a small number of clusters, there is no clear benefit of using SOM instead of k-means, and that a high number of clusters can help to analyze the influences of weather and climate in more detail [13]. Additionally, the authors of [79] state that for a small number of clusters, SOM is not able to produce independent cluster centers; instead, they are symmetrically paired. Most of the studies used sensitivity analysis and visual, subjective methods to determine the number of clusters. Moreover, the method of [80] based on Euclidean distance of time steps to the cluster center is used in [81] .

For SOM, there are variations of the clustering algorithm used for energy-related topics, too. In the studies [76] and [78], a torus-type SOM is used. The map of the torus-type SOM is missing edges, leading to better pattern classification results but higher computational times [76]. Another variation is the change of the distance metric from Euclidean distance to structural similarity index to capture spatial features like highs or lows [75].

Where article [82] states that k-means is slightly preferable for energy-related topics for the scope of Minnesota in USA, article [83] in Australia and article [20] can't find this result for climate-related topics and emphasize the disadvantage that k-means clustering is sensitive to initial cluster centers. Some studies also combined SOM and k-means or other clustering methods [79], [55], [55]. Starting with a large number of clustered SOM nodes, it is continued by clustering this nodes into a smaller number of clusters with id of k-means. This can help to overcome both weaknesses, that SOM has problems with small number of clusters, and that k-means is sensitive to initial values. To determine the number of clusters, [79] assessed the reproducibility of clusters via a classifiability index and came to four final patterns of geopotential height.

3. Energy system extreme events

In this section, studies dealing with WPs and energy system extreme events, defined as events with significant impacts on energy systems, are reviewed. Therefore, we distinguish between renewable energy droughts or surplus events, which only focus on the generation side, and high or low residual load events, which also incorporate demand. Residual load refers to the difference of electricity demand and renewable energy generation [78]. Thus, high residual load events occur during periods of high demand and low wind and PV generation. The goal of using WPs for energy system extreme events is to obtain a set of patterns that are associated with extreme events and another set that contains patterns associated with "normal" conditions.

Table 1: Overview of papers using WPs to study weather-induced extreme events in energy systems. (x) indicates that the respective topic is not studied explicitly, e.g., only wind speed is studied instead of wind power. Abbreviations: not mentioned (n.m.), temperature (t), wind speed/velocity (w), residual load (rl).

Paper			Data for WP Classification				WP Classification		Preprocessing			Energy					
First author	Publication year	Region	geopot. height	sea level pressure	others	Included months	Method	Number of WPs	Normalizing	Filter	PCA	Wind	PV	Other generation	Demand	Dispatch + Invest	Gird
Grochowicz	2024	Europe	x		t,w	6	k-means	4			x	x	x	x	x	x	x
Wiel	2019	Europe	x			3	k-means	4	x		x	x	x		x		
Mockert	2022	Europe	x			alle	k-means	7+1	x	x	x	x	x		x		x
Bloomield	2020	Europe			d, rl	5	k-means	4	x	x	x	x	x		x		
Beerli	2019	Europe	x			all	k-means	7+1	x		x	(x)	(x)		(x)		
Cheneka	2021	Belgium		x		all	SOM	30				x					
Couto	2021	Portugal		x		all	Lamb	26				x					
van Duinen	2025	Europe	x			5	k-means	4	x		x	x	x	x	x		
Dijkstra	2025	India			w	all	k-means	30				x	x				
Souto	2024	GB		x		all	k-means	30	x								x
Millin	2024	USA	x			5	k-means	5	x		x				x		
Lücke	2024	GB		x		5	k-means	4	x		x	x			x		
Ho-Tran	2024	Europe	x	x		all	GWL	29		x		x	x				
Ho-Tran	2024	Germany	x	x		all	GWL	29				x	x				
Ohba	2023	Japan			w	all	SOM	225				x	x		x		
Otero	2022	Europe	x			6	k-means	7+1	x	x	n.m.	x	x		x		
Mockert	2023	Europe	x			all	k-means	7+1	x	x	n.m.	x	x		x		
Tedesco	2023	Europe	x			5	k-means	4	x		x	(x)			(x)		
Cradden	2018	Ireland	x			5	k-means	4	x			x			x		
Drücke	2021	Germany	x	x	x	all	GWL	29		x		x	x				
Rapella	2023	Europe	x			all	PCA		x								
Richardson	2023	Australia		x	t	all	SSD		x								
Sundar	2023	Western USA	x			4	SOM	6	x			x	x	x	x	x	
Agel	2021	Northeast USA	x			all	k-means	4	x						x		
Weide-Luiz	2022	Europe	x	x		all	GWL	29		x							
Thornton	2017	GB		x		all	k-means	4	n.m.	n.m.	n.m.	x			(x)		
Thomas	2021	Mexico	x			all	k-means	8	x		x	x					
Gao	2025	Asia	x			all	k-means	12	x		x	x					
Ohba	2022	Tohoku (Japan)			w	all	SOM	255				x	x				
Huva	2015	Australia		x		all	SOM	30				x	x	x	x	x	(x)
Souto	2023	UK		x		all	k-means	30									x
Weber	2019	Europe		x		all	Lamb	27				(x)					

Renewable energy generation is highly sensitive to climatic factors: PV depends on solar irradiance and is moreover influenced by temperature through its efficiency and by precipitation, which can affect efficiency by cleaning or covering the modules. Wind power is directly linked to wind speed. On the other hand, demand is strongly correlated with temperature, as heating and cooling needs depend on weather and seasonal conditions. Additionally, other parts of the energy system are weather-dependent. There are direct dependencies, such as the temperature sensitivity of the cooling of thermal power plants, and the transmission capacity of the grid, or precipitation dependencies of run-of-river and pumped hydro power plants. Furthermore, there are also indirect dependencies. Renewable energy droughts or surpluses, as well as high demand, can cause grid congestion. The dispatch of non-volatile power plants is also influenced by these events. [36]

An overview of the reviewed papers on energy system extreme events is given in Table 1

3.1. Renewable energy droughts and surpluses

Four studies analyzing renewable energy droughts and surpluses used WPs classified by k-means [84], [9], [85], [68]. None of them incorporated dispatch models or the electricity grid. The European study [84] used the classification method of [14], deriving 7+1 year-round WPs. It is focused on dark doldrums, where both wind generation and PV are low. In this paper, especially the WPs' life cycle is studied, which reveals that they are well established when dark doldrums set in. Moreover, it is found that dark doldrums occur most of time during blocking events. The other three papers cover China [85], India [68] and Mexico [9]. For China three patterns of 500 hPa geopotential height, derived from normalized data preprocessed by PCA, are used per season. In India 30 patterns of 850 hPa wind velocity, derived without preprocessing, are used for the whole year. Both papers conclude that the studied WPs can be associated with renewable energy droughts. For Mexico, eight patterns of 500 hPa geopotential height clustered by k-means with normalization and PCA preprocessing steps, are derived to study the influence on extreme wind power events. It was revealed that two of these patterns lead to low wind power anomalies in the overall area [9].

SOM is employed for Australia [80], Japan [13] and Belgium [86]. For Belgium, analyzing 30 WPs of sea level pressure, it is found that blocking patterns are correlated with low wind production, and cyclonic patterns are correlated with high wind power production [86]. 30 patterns of sea level pressure are utilized for Australia too, revealing that large pressure gradients lead to low production of both wind and PV [80]. Further, it was concluded from the results of a dispatch and invest energy model that an electricity generation by only non-dispatchable technologies in Eastern Australia is not possible because the amount of needed installed capacities is unrealistic [80]. In [13] 225 WPs of wind velocity over Japan are clustered by SOM of which four are leading to the most occurrences of dark doldrums.

An Australian as well as a European study utilized different circulation indices [44], [87]. Both studies analyzed the impact of El Niño and the Southern Oscillation (ENSO) on energy-related climatological variables. In [44] wind and solar irradiation in Australia are studied, and additionally to ENSO, Indian Ocean Dipole (IOD) and Southern Annular Mode (SAM) are considered. The results suggest that these circulation indices are not able to predict large-scale energy droughts in the whole of eastern Australia, but might be more useful for regional droughts. For the European study [87] NAO and Atlantic Multidecadal Oscillation (AMO) are used besides ENSO. It is found that high winds correlate with all of these three circulation indices, but low wind events only correlate withe ENSO and AMO, not with NAO.

The 29 patterns of objectivized GWL are used in [28], and [30] for Germany and in [29] for Europe to analyze their impacts on wind and solar production. The electricity grid or market are not incorporated in these studies. It is found that VRE generation relates to WPs in Germany: Cyclonic patterns lead to high VRE generation, blocking patterns to low generation [28], [30]. According to [29], during short-duration events of one day, other patterns are prevailing in Europe than during long-duration events of 10 days. Additionally it is found in [88], that the night low level jet, which influences wind power production in both directions, depends, among others, on these 29 WPs. In the papers [25] and [89], the objectivized Lamb classification is used to study long-lasting low and high wind speed events for Europe and Portugal, respectively. They find that periods of high wind are typically more persistent than periods of low wind. Furthermore, they agree with other studies that blocking patterns are more favorable for energy systems, as they find that long-lasting low wind periods are caused by blocking patterns.

3.2. High residual load events

For analyzing high residual load events, not only wind and PV are considered, but also demand, which is driven by temperature. Most of the residual load events are studied by k-means-based WPs and consider European regions as the geographical [84]. The studies [11], and [8] utilized the classification method of Grams et al. [14] to derive 7+1 WPs and analyzed their impact on wind power, PV, and demand or the respective meteorological variables. Both studies agree that there are higher probabilities of high residual load events during blocking WPs. According to [84], especially a WP called Greenland Blocking is associated with low wind generation and PV, and additionally, low temperatures. This WP and another one called European Blocking are assessed to be a special challenge for energy systems, as they simultaneously increase the risk of high residual load events in countries adjacent to each other [11]. In these situations, the interconnectedness of the European energy system can not help to balance the high residual load.

The studies [67], [63], [57], [90] and [91] followed the method of Cassou et al. [70] for their classification of four European WPs. The approach of [12] works similarly, but considering sea level pressure instead of geopotential height, and [16] clustered mean sea level pressure into four patterns as well. In addition to geopotential height, wind and temperature are clustered into four clusters in [67]. All of these studies focus on the winter months, and about half of these studies consider PV supplementary to wind power production.

According to these studies, blocking patterns are the dominant drivers of high residual load events in Europe. In [67], the European power system is modeled, including renewable and nuclear generation, the transmission system, and storage. They consider the energy system in 2030, allow for capacity and transmission expansion, and optimize investments to minimize total system costs. They identify "system-defining events" via shadow prices, as large investments in generator capacities signal high residual load events. They find that more than half of the identified events can be assigned to one of the blocking patterns named Scandinavian Blocking, and that even though the meteorological conditions causing these events cover a small area, their model outputs high shadow prices over the entire continent. While [91] does not explicitly include energy variables, they investigate the co-occurrence of extremely low temperatures and weak wind, and find that blocking patterns cause the most extreme events. The authors of [63] come to the same conclusion, however they state that these events arise from smaller-scale meteorological features as opposed to intensified magnitudes of the common patterns. The article [57] studies periods of high residual load that occur in multiple European countries simultaneously. They find that blocking patterns cause the highest co-occurrence of these events, although there are regional differences: Northern Europe is primarily affected by another blocking pattern than the Iberian Peninsula. Both [12] and [16] study high residual load events in Great Britain and find that the most severe events take place during the WP corresponding to the negative phase of NAO. Study [12] also investigate possible future conditions of the power system, looking at increased wind energy capacities, and find that the most severe days in their analysis are insensitive to this capacity expansion.

In [74], demand and residual load are used to define the WPs. The most influential identified pattern resembles the WP corresponding to negative phase of NAO but is shifted to the east. It should be noted that, contrary to literature findings, other blocking patterns are found not to have a strong influence on demand or residual load, and it is suggested that averaging individual circulations to define a single WP could cause this discrepancy.

A torus-type SOM of wind velocities is used by [55] for the region of Japan. The results of this approach of 225 WPs show that weather conditions and patterns responsible for high residual load will change in the future because of further VRE installations.

3.3. Other energy system extreme events

In addition to residual load and VRE droughts or surpluses, two studies analysed power system failures and their meteorological drivers in Great Britain [60], [15]. For classification of 30 WPs, it is used k-means clustering of normalized sea level pressure from historical data of more than 150 years in these studies. Study [60] uses the WPs and historical lightning induced power failures to determine time-dependent probabilities of lightning activity. They model the transmission system and analyze failure rates of lightning protection system components, considering design criteria and asset condition. Paper [15] extends the meteorological drivers to include not only lightning but also wind and gale, and snow and ice. Focusing on the winter months, they identify the WPs that are most likely to cause outages. Power outages caused by wind and gale, and lightning are obviously linked to WPs with high wind, temperature, and precipitation. Outages caused by snow and ice are linked to WPs with high snowfall and precipitation, and lower than average temperatures.

Two papers studied extreme demand events in different regions of the USA using either four winter WPs or four heat wave WPs based on k-means. For clustering, geopotential height is used in both cases. It is preprocessed by PCA and, for winter WPs, also normalized. The results of the winter WPs show that residual load is dependent on these patterns and blocking is responsible for high residual load [10]. The results of the heat wave WPs reveal that electricity demand is especially increasing if high temperatures are combined with high humidity [92].

4. Variability of energy generation and demand

Understanding WP-dependent variability of RES generation and demand can guide decisions on wind farm development and investment planning [42], [56], [66], as this variability poses challenges to balancing generation and demand [93]. Therefore, it is necessary to use WPs that explain a large share of the variability. Moreover, the prediction of short-term variability is important to operate energy systems reliably. For this reason, WPs that improve forecasts of energy variables are valuable for energy system operation. Variability arises from fluctuations in wind speed, solar irradiance, and temperature, which affect renewable output and electricity consumption. Table 2 presents an overview of the papers that use WPs to study the variability of energy generation and demand. Most of these studies only focus on wind power; a few take PV or demand into account. There are different time scales of variability in the reviewed papers: Starting from short-term time scales of power ramps, followed by subseasonal to seasonal variability, and finally long-term variability on the year-to-year time scale. Moreover, there are papers dealing with the spatial balancing of variability. They investigate whether challenging situations occur in neighboring countries in parallel or if electricity generation in other countries can be used for balancing these situations.

Table 2: Overview of papers using WPs to study variability in electricity generation and demand. (x) indicates that the respective topic is not studied explicitly, e.g., only wind speed is studied instead of wind power. Abbreviations: not mentioned (n.m.), 500 hPa geopotential height (z500), sea level pressure (slp), historical (h), ensemble (ens.), output of numerical weather prediction (NWP), subseasonal to seasonal (S2S)

Paper			Data for WP classification			WP Classification		Preprocessing				Energy				
First author	Publication year	Type of variability	Studied region	Variables	Type of data	amount of years	Method	number of patterns	Normalizing	Filter	PCA	Wind	PV	Other generation	Demand	Dispatch
Grams	2017	balancing	Europe	z500	reanalysis	36	k-means	7+1	x	x	x	x	x			
Cortesi	2019	S2S	Europe	slp	reanalysis	36	k-means	4/ month	x	x		(x)				
Cheneka	2021	ramps	Belgium	slp	reanalysis	14	SOM	30				x				
De Felice	2023	balancing	Europe	z500	reanalysis	36	k-means	7+1	x	x	x	x	x	x	x	x
Mühlemann	2022	balancing	Europe	z500	reanalysis	41	k-means	7+1	x	x	x	x		x		
Torralba	2021	long-term	Europe	slp	reanalysis	38	k-means	3,4,5,6				(x)				
Dalton	2021	ramps	South Africa	z850	reanalysis	4	SOM	36				x				
Yang	2022	ramps	South China Sea	slp	reanalysis	62	SOM	4				x				
Kirchner-Bossi	2015	long-term	Spain	z500	reanalysis	50	PCA		x			x				
Garrido-Perez	2020	S2S	Iberia + UK	z500	reanalysis	29	k-means	8	x		x	x				
Zhao	2023	long-term	China	n.m.	n.m.	n.m.	n.m.		n.m.	n.m.	n.m.	(x)				
Ohba	2016	ramps	Tohuku	slp	reanalysis	36	SOM + 2nd	24	x			x				
Ohba	2019	ramps	Japan	slp	h + ens.	59x10x6	SOM + 2nd	9				x				
Cheneka	2023	ramps	North Sea	slp	ens.	107	SOM	30				x				
Pickering	2020	balancing	Schweiz	z500	reanalysis	36	k-means	7+1	x	x	x	x				
Couto	2015	ramps	Portugal	others	NWP	1	k-means	6	x		x	x				
Yu	2019	S2S	China	others	reanalysis	33	PCA	n.m.	x			(x)				
Liu	2023	S2S	North America	z500	reanalysis	39	SOM + 2nd	3 to 25				x				

4.1. Power ramps

All of the reviewed papers dealing with power ramps only included wind speed or wind power on the energy side. The analyzed areas are rather small, namely either countries or sub-country regions. The studies used a clustering algorithm and mostly sea level pressure.

Three papers study wind power ramps in Asia with the aid of WPs of clustered sea level pressure [75], [77], [55]. The first study covers the South Chinese Sea and uses SOM to derive 4 WPs [75]. The other two studies analyze WPs in Japan and use first SOM to cluster 400 patterns and then apply a second clustering algorithm. In [77] the analyzed region is the Tohoku region, the second clustering is done by k-means and the final number of WPs is 24. The study [55], however, used hierarchical clustering and ensemble data to get 4 final WPs, and the scope was the entire Japanese country. All three papers state that wind power ramps relate to the respective WPs. Moreover, according to [75], the WPs associated with most ramp events differ between the seasons.

In different regions in Europe, SOM and k-means are used to study the relation of power ramps and WPs. 30 SOM nodes are clustered for a region in Belgium and over the North Sea [86], [58], showing that wind power ramps occur when WPs change. Ramp-up events are associated with the transition from weak to deep low-pressure systems, and ramp-down events with a transition from low-pressure systems to blocking patterns [86]. By using k-means and several meteorological variables (wind velocity, atmospheric instability, sea level pressure gradient) to derive 6 clusters for the spatial scope of Portugal, [59] agrees that ramp events are associated with changes in WPs.

The study [94] found several SOM nodes of a 30-node SOM map in South Africa to be associated with ramp-up and others with ramp-down events.

Additionally, there are three papers that use WPs to forecast power ramps by applying clustering algorithms on Portuguese or Japanese areas [59], [7], [13]. They all state that including WPs is beneficial for forecasting power ramps. Moreover, the usability of WPs is further increased by the fact that they accelerate the generation of probabilistic forecasts from a large number of ensemble forecasts [76].

4.2. Subseasonal to seasonal variability

Subseasonal to seasonal variability is studied only in European regions and only for wind power in the reviewed papers. PCA, k-means, or a combination of SOM and k-means is used to cluster reanalysis data of sea level pressure or 500h hPa geopotential height [79], [53], [62], [95]. The papers [79], [53], [95], and [62] predicted wind power variability and came to different results. The study [62] states that by using the 8 geopotential height clusters over Great Britain and Iberia as predictors, explain more than half of the month-to-month variance. These clusters are derived by k-means with normalization and PCA Preprocessing. The reconstruction of wind power based on 4 patterns of geopotential height over North America, clustered by the combination of SOM and k-means, only explained less than half of the variance [79]. The study [53], which used four k-means clusters per month derived from normalized and filtered sea level pressure over Europe, states that around half of the variance can be explained by the WPs.

4.3. Long-term variability

Long-term variability is studied too by using WPs. The studies [41] and [96] used circulation indices in Spain and China. Where in Spain the influence of the modes differs much between different locations, in China there seems to be a clearer impact of the modes on long-term variability.

4.4. Spatial balancing of variability

As electricity systems are often interconnected between neighboring countries, generation variability in one country can be balanced by the aid of another country. This is only possible if the challenging conditions do not happen at the same time in these countries. Therefore, some papers analyze this spatial balancing of VRE variability by using WPs. All of these studies cover Europe and use the classification methodology of Grams et al.[14]. Mainly focusing on wind, in [14] it was found that the Balkans could be a possible counterpart of the North Sea regarding wind variability. For Solar energy the study [64] showed that there are WPs where low generation prevails all over Europe, such that balancing in 2030 as well as in 2050 is not possible. Only in [97] a dispatch model and different generation technologies are used. The results of this paper are that Italy and Iberia could be a counterpart of northern regions. Moreover, this paper states that blocking patterns cause higher CO_2 emissions than cyclonic patterns. The study [98] only looked at Switzerland and wind power generation and came to the result that balancing is possible within Switzerland.

5. Other energy-related research topics studied with WPs

Additionally to energy system extreme events and variability of electricity generation and demand, also a few other topics are studied with the aid of WPs. An overview is given in Table

Table 3: Overview of papers using WPs to study other energy-related research topics thanen ergy system extreme events and variability. (x) indicates that the respective topic is not studied explicitly, e.g., only wind speed is studied instead of wind power. Abbreviations: not mentioned (n.m.),sea level pressure (slp), 500 hPa geopotential height (z500), temperature (temp).

Paper				Data for Classification				WP Classification		Preprocessing		Energy			
Author	Publication year	Approach	Region	viables	used months	type of data	number of years	Method	number of patterns	Normalizing	PCA	Wind	PV	Other generation	Demand
Bloomfield	2021	Forecasting	Europe	z500, demand	3	reanalysis	38	k-means	4		x	x			x
Brayshaw	2011	Forecasting	GB	z500	all	reanalysis	50	PCA	2	x		x			
Jerez	2013	Forecasting	Iberia	z500	all	reanalysis	50	PCA	2	x		x	x		
Mararakanye	2022	Forecasting	South Africa	z850	all	reanalysis	3	SOM	20			x			
Özen	2022	Forecasting	East of Turkey	slp	all	NWP output	3	Lamb	27			(x)			
Garrido-Perez	2020	Forecasting	Iberia + UK	z500	all	reanalysis	29	k-means	8	x	x	x			
Clare	2024	Forecasting	Denmark + Shetland	slp + wind	all	reanalysis	9	k-means	6			x			
Coburn	2023	Forecasting	kuwait	slp vs temp	all	reanalysis	5	SOM vs k-means	5 to 25			(x)			
Yang	2017	Forecasting	China	wind + others	all	NWP output	n.m.	fuzzy clustering	9			x			
Mararakanye	2022	Forecasting	South Africa	z500	n.m.	n.m.	3	SOM	20			x			
Ouarda	2021	Forecasting	Canada (Quebec)	z500	winter	n.m.	50	PCA		x		(x)			
Curtis	2016	prices	Ireland	slp	all	n.m.	>150	SSD		x		x		x	x
Correia	2017	wind ressources	Portugal	z500	all	reanalysis	50	PCA		x		x			
Han	2022	prices	Europe	slp	all	reanalysis	-	Lamb	27						
Naegele	2024	wind ressources	Shagaya Park, Japan	wind	all	forecasting data	2	SOM	6			x			
Liu	2023	wind ressources	North America	z500	all	reanalysis	39	SOM + k-means	4			x			
Curtis	2016	CO_2	Ireland	spl	all	reanalysis	36	SSD				x			x
Dong	2018	wind ressources	USA (Southern Plains)	z500	2	reanalysis	38	k-means	4	x		x			
Okada	2022	Forecasting	Japan	slp	n.m.	reanalysis	n.m.	n.m.	n.m.		x	x			

3.

The influence of WPs on both supply and demand is reflected in the electricity market. Generally, electricity prices as well as thermal generation costs are lower during NAO+ in Ireland, compared to NAO- [99]. Similarly, study [26] finds that low wind conditions lead to higher market prices in Germany and Austria since wind generation is the main contributor to VRE generation. Moreover, they associated Lamb WPs with the long-term behavior of electricity prices.

Beyond electricity generation itself, [43] found that system-wide CO_2 emissions in Ireland can be linked to WPs. In general, CO_2 emissions depend on carbon and fossil fuel prices, demand as well as both thermal and renewable generation capacity. They found large variations in CO_2 emissions depending on the prevailing NAO phase, since wind generation (and demand) determines the dispatch of fossil fuel-based generation.

There are a few papers that study the overarching relationship of WPs and wind resources. The article [42] finds a relation of the circulation indices NAO and East Atlantic (EA), which varies between different timescales and locations within Portugal. [56], [66], and [79] use K-means, SOM, or a combination of both to show that WPs can be related to wind resources and could therefore be beneficial for forecasting wind power production.

Other studies go a step beyond this and integrate WPs in their forecasting method of wind generation. The central motivation in much of the literature is to exploit the recurrent nature of WPs [63], [8], [6]. Since WPs are atmospheric oscillations, they exhibit a degree of predictability on sub-seasonal to seasonal timescales, with lead time of weeks to months [79], [39].

The reviewed papers realize the forecasting with the aid of WPs by linear regression [82], k-Nearest-Neighbor [5], or gradient boosting [27]. In paper [39], a Markov matrix is used instead to calculate the next time step based on the current. Paper [65] calculated the wind speed weighted mean of the cluster centers' wind generation for forecasting, and paper [45] combines different forecasting methods. The studied spatial scope is rather small for most of the papers, consisting in most cases of one to several wind parks. Only in [65], a Europe-wide scope is studied. For forecasting, different time horizons are chosen in the different studies, from short-term to monthly to long-term forecasts.

The article [5] shows that incorporating WPs classified by SOMs into the forecasting method improves day-ahead wind power forecasts in South Africa, especially during stable high-pressure conditions. Similarly, [27] and [45] confirm the improvement of forecasts by WPs, also for Lamb and fuzzy clustering pattern classifications. However, [27] emphasizes that not only WPs improve the forecast, but also, for example, outlier detection and missing data imputation. WPs alone are not ultimate to forecast wind power production or wind speed by regression methods, but they improve the forecast when combined with other parameters. In [39], month-ahead monthly mean and modelled wind power forecasts in Great Britain are compared, with and without the consideration of the NAO phase. It is found that including NAO information improves the predictions. According to [82], the WPs derived by k-means clustering are only advantageous or forecasting wind speed compared to observations if less than 6 years of observations are available to fit the regression model. Otherwise, observations are slightly better.

Even for the spatial scope of an entire continent and a multi-year forecasting, the inclusion of clustered WP information is a reliable method for long-term wind power predictions, as shown by [65] for Europe. For this approach, 6 WPs clustered by k-means are used. Moreover, they state that using WPs results in a fast and effective approach because it reduces the number of runs of the numerical weather prediction model.

In the article [40], not only wind power, but also PV is reconstructed with the aid of circulation indices. The reconstruction and the original generation time series correlate up to 80%. Study [6] forecasts demand-net-wind anomalies. Therefore, WPs derived by k-means clustering are used. Forecasting by WPs derived from 500 hPa geopotential height is compared to forecasting by WPs derived from demand-net-wind. It is found, that demand-net-wind-based WPs have a higher forecasting potential. Moreover, they found, that point forecasts outperform the WP forecasts at short lead times. At longer lead times of more than 12 days, pattern-based forecasts show a better skill. In paper [100], it is found that wind power forecasting errors differ not only between seasons but also between the 20 identified SOM nodes of 500 hPa geopotential height.

6. Discussion

In the reviewed papers, different clustering algorithms, especially k-means and SOM, circulation indices, or the objectivized Lamb and GWL classifications are used for the classification of WPs. Their research questions are within the topics of energy system extreme events, variability of generation and demand, or other energy-related research questions, including forecasting generation and demand.

There is limited research on comparing the different clustering methods for energy-related topics. In [82], it is found that k-means is slightly better for predicting wind speed in Minnesota. Comparisons for other regions and research topics are lacking. The disadvantage of objectivized

GWL is that it's developed for Germany (and surrounding countries), and therefore it is not applicable to other parts of the world than Europe. Where the number of patterns for objectivized GWL and Lamb is fixed, for k-means and SOM-based classifications, the number of clusters has to be defined before clustering. The same applies to the meteorological variables used in the classification, which are also fixed for Lamb and GWL. These two facts make the clustering algorithm-based classifications more flexible and allow for studying different situations and aspects. For k-means-based WPs, 3 to 30 clusters are used. When analyzing a single season or month, the optimal number of clusters is typically smaller (3–5 WPs) compared to studies covering the entire year (6–30 clusters). This difference reflects the need for more patterns to capture the greater atmospheric variability across a full year. Moreover, 30 clusters are only used in classifications without PCA preprocessing, whereas studies with preprocessing found fewer than 15 patterns to be favorable. If the aim is to study more persistent WPs that last several days, preprocessing by PCA, normalization, and low-pass filters might be useful. The number of clusters used for SOM clustering is generally higher. Only three studies used fewer than 20 patterns, where one of these chose 4 patterns to follow a study that conducted k-means [75]. Moreover, one of the studies that chose less than 20 clusters only considered 4 months, whereas the other studies considered the whole year. Most studies use between 20 and 40 clusters. In contrast, the studies by Ohba covering Japan or regions in Japan [13], [55], [76]-[78] use 200-10 000. In summary, the studies indicate that 20 to 40 patterns are favorable for year-round SOM classifications in all areas besides Japan.

In general, the reviewed papers found a link between specific WPs and energy system extreme events. The WPs that are associated with stressful events in energy systems in the reviewed papers are the blocking patterns. The cyclonic patterns are associated with more favorable conditions for energy systems. This holds for most regions on five different continents, which are studied in the literature, as the literature mainly focuses on regions in midlatitudes. However, the reviewed studies agree that there are also cases where stressful events occur during cyclonic patterns and more favorable conditions occur during blocking patterns. Therefore, WPs alone are not a sufficient indicator for individual energy system extreme events; rather, they provide information about their likelihood. For energy system planning, it would be more beneficial if some of the patterns are not only associated with extreme events but are clearly responsible for them. Circulation indices, such as NAO, are found to be more helpful for local studies than for larger ones [44]. These modes also influence electricity prices, which are higher during negative NAO phases [99], and system-wide CO_2 emissions [43].

Variability of generation and demand is studied in the reviewed articles for different time scales. For wind power ramps, there are disagreements about how they are associated with WPs. Some studies report that they occur during particular WPs, while others link them to changes between WPs. However, studies using WPs to predict power ramps agree that WPs improve these forecasts. For the longer time scale, namely subseasonal to seasonal, up to two thirds of the variability of wind power generation can be explained by WPs. Comparing the studies [79], [62] indicates that k-means alone could outperform the combination of SOM and k-means, as it explains more variability. However, the two studies don't use the same coefficients for the regression and have additionally different spatial scopes, which could also be reasons for this observation. Therefore, more research is needed to conclude whether the combined method is beneficial. For spatial balancing of variability, only the classification methodology of 7+1 year-round WPs is used. This topic is only studied in Europe. One possible reason is the strong interconnectivity of the European energy system in comparison to other energy systems around the world. Comparing these European studies, especially [14] and [97] on this topic, shows that incorporating a dispatch model in addition to wind and PV generation can lead to different results. Therefore, looking only at the generation side can be helpful for a first estimate, but is not sufficient to study weather-induced challenges on energy systems. Additionally, including the electricity grid would even give more realistic insights.

Due to their recurrent nature and predictability on subseasonal to seasonal time scales, WPs are used in the literature for forecasting, especially wind power forecasting. All of the reviewed papers on this topic report improved forecast performance using k-means, SOM, Lamb, and fuzzy classification methods, as well as using circulation indices. But they also made clear that forecasts should not only rely on WPs but also on other predictors, e.g., point forecasts [5] or hour of the day [5]. Most of the studies were about regional forecasts, but WPs also seem to be beneficial for continent-wide forecasts, see [65]. Additionally, using WPs can make forecasts more effective by reducing the number of runs of numerical weather predictions[65] .

On the energy side, wind power generation is the most studied aspect, followed by PV generation. Several papers also consider energy demand. Other types of electricity generation, such as conventional or hydro power plants, are rarely incorporated. Similarly, dispatch and investment models are seldom applied and are absent in studies focusing on Asia. Analyses of the electricity grid are even less common. They are only explicitly incorporated in European studies, and only for research questions about renewable energy droughts and power system failures. This means that most papers only study part of the power system, which is not sufficient to study power system stress [67]. Including all components of energy systems would give a better representation of the weather-induced challenges, as the additional components could mitigate or worsen the impacts of the weather. Moreover, there are also several papers that only study meteorological variables to draw conclusions on the energy system. Besides that, most of the reviewed papers study Europe or parts of Europe, while none study South America, and South Africa is the only African country studied.

The following factors may limit the validity of the present study. First of all, the search method poses limits. On the one hand, there are many different terms for WPs, e.g., weather regimes and circulation types. Many of these are at least partly integrated in the search string, but there could be studies that used none of these terms and therefore were not found. On the other hand, we only focused on large-scale WPs, neglecting local-scale WPs. This might be one of the reasons why more studies dealing with wind power were found than studies dealing with PV. Moreover, as no forward and backward search was conducted, some articles might have been overlooked. Additionally, the validity of the findings might be limited due to publication bias.

Through this literature review, we have identified some research gaps that should be addressed by future research. First, the continents South America and Africa are largely underrepresented in the existing literature. Second, there is a lack of studies comparing different classifications. The current literature does not clearly indicate which classification is preferable for analyzing energy system extreme events, for studying variability, and for forecasting energy variables. Instead, several classifications are used for these approaches, and they seem to work properly in different regions by capturing influences of atmospheric processes on energy systems. However, there is no classification that results in one or more WPs that uniquely contain energy system extreme events, that can explain more than two-thirds of weather-induced variability in energy systems, or that can forecast energy variables without the aid of other indicators, which would help provide more accurate and reliable assessments of weather-induced impacts on energy systems. Third, only a few studies consider the whole energy system. Especially, the grid is rarely incorporated, and demand is also not studied much. According to [67], it is essential to incorporate a detailed representation of the energy system for higher resilience. In addition to wind power and PV, demand is also influenced by the weather. Anomalously high temperatures in summer or anomalously low temperatures in winter cause high electricity demand through increased use of air conditioning or heating, and vice versa. Therefore, demand can mitigate or worsen the missing energy in the system coming from renewable energy [36]. Consequently, it is important to include demand for studying energy system extreme events, as well as for weather-induced variability. Moreover, adding demand forecasting might lead to more meaningful results than only forecasting wind power. Similarly, the electricity grid influences weather-induced challenges in energy systems. It can help to balance energy across different regions in cases of low generation or high demand [36]. On the other hand, the electricity grid limits how much of the harvested energy can be transported to consumers. When only considering wind generation, it is not clear if the system can ensure continuity of supply because transmission constraints are ignored. Plus, these constraints are temperature-dependent [101]. Therefore, future studies should integrate electricity demand and the electricity grid to provide a full understanding and a more realistic picture of weather-induced challenges in energy systems.

Declaration of interests

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

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used ChatGPT and Copilot in order to rephrase passages for better readability and to check the correctness of the reference list. Moreover, the authors used perplexity for paper screening. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

List of abbreviations

AMO Atlantic Multidecadal Oscillation

EA East Atlantic

ENSO El Niño and the Southern Oscillation

ens. ensemble

EOF empirical orthogonal function

GWL Grosswetterlagen

h historical

IOD Indian Ocean Dipole

NAO North Atlantic Oscillation

n.m. not mentioned

NWP output of numerical weather prediction

PV photovoltaics

PCA principal component analysis

rl residual load

SAM Southern Annular Mode

slp sea level pressure

S2S subseasonal to seasonal

SOM self-organizing maps

SSD sums of squares of differences

t temperature

VRE variable renewable energy

w wind speed/velocity

WP weather patterns

z500 500 hPa geopotential height

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No data was used for the research described in the article.

CRediT author statement

Kira Layer: Conceptualization, Methodology, Writing – original draft, Visualization, Investigation. **Stephanie Gutmayer:** Writing – original draft, Visualization, Investigation. **Thorben Sandmeier:** Writing – review & editing, Supervision. **Jan Cermak:** Writing – review & editing. **Jonas Ringger** Investigation. **Wolf Fichtner:** Writing – review & editing, Funding acquisition, Supervision

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