OFFSHORE WIND RESOURCE ASSESSMENT BY CHARACTERIZING WEATHER REGIMES BASED ON SELF-ORGANIZING MAP

Shangshang Yang, Huiling Yuan and Li Dong

1 School of Atmospheric Sciences and Key Laboratory of Mesoscale Severe Weather/Ministry of Education, Nanjing University, Nanjing, People’s Republic of China
2 Frontiers Science Center for Critical Earth Material Cycling, Nanjing University, Nanjing, People’s Republic of China
3 Department of Earth and Space Science, Southern University of Science and Technology, Shenzhen, People’s Republic of China
4 Academy for Advanced Interdisciplinary Studies, Southern University of Science and Technology, Shenzhen, People’s Republic of China

E-mail: yuanhl@nju.edu.cn
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Abstract

As offshore wind power is continuously integrated into the electric power systems in around the world, it is critical to understand its variability. Weather regimes (WRs) can provide meteorological explanations for fluctuations in wind power. Instead of relying on traditional large-scale circulation WRs, this study focuses on assessing the dependency of wind resources on WRs in the tailored region clustered based on the finer spatial scale. For this purpose, we have applied self-organizing map algorithm to cluster atmospheric circulations over the South China Sea (SCS) and characterized wind resources for the classified WRs. Results show that WRs at mesoscale can effectively capture wind resources driving wind power production variability, especially on multi-day timescale. Capacity factor reconstruction during four seasons illustrates that WRs highly influence most areas in winter and southern part of SCS in summer, and WRs can serve as a critical source of predicting the potential of wind resources. In addition, we further qualify the wind power intermittency and complementarity under different WRs, which have not been assessed associated with WRs. During WRs with changeable atmosphere conditions, the high complementarity over coastal areas can reduce the impact of intermittency on wind power generation. The proposed approach is able to be implemented in any region and may benefit wind resource evaluation and characterization.

1. Introduction

As a clean, renewable, and sustainable energy, wind energy plays an important role in accelerating decarbonization to mitigate climate change (Rogelj et al 2015, Kern et al 2016, Luderer et al 2022), which helps achieve various sustainable development goals worldwide (Kammen et al 2016, Gielen et al 2019, Xu et al 2019). With the increasing share of renewable energy in total power generation, wind energy is in urgent need of development, especially offshore wind power (Sahu et al 2018, Costoya et al 2020, Soares-Ramos et al 2020). However, wind power highly depends on changeable weather, indicating that wind energy varies at different timescales (Pryor et al 2006, Jenn et al 2016, Kiviluoma et al 2016).

The main meteorological driver of offshore wind power is wind speed, which mainly depends on the atmosphere circulation. Hence, it is essential to improve our understanding of the relationship between the atmosphere circulation and wind power production for assessment and further implementation of wind resources (Thornton et al 2017, Gonzalez et al 2019, Soares et al 2019). Numerical weather models can provide interpretations of variations in wind power generation, and simulate more detailed wind farm scales to more accurately estimate wind energy potentials (Barrie et al 2010, Miller et al...
2015, Miller and Kleidon 2016, Sanz et al 2017, Volker et al 2017, Minz et al 2020, 2021). Simple but physically meaningful kinetic energy budget can also provide useful insights into wind energy production (Miller et al 2015, Miller and Kleidon 2016, Kleidon and Miller 2020, Minz et al 2020, 2021). In addition, weather regimes (WRs) based on atmospheric circulation in reanalysis data can effectively capture meteorological variability when the spatial scale is large and timescales are weekly, seasonal and annual (Grams et al 2017, van der Wiel et al 2019a, Garrido-Perez et al 2020).

Previous studies used large-scale atmospheric circulation patterns such as North Atlantic Oscillation, and the East Atlantic and Scandinavian modes to assess wind resources (Brayshaw et al 2011, Jerez and Trigo 2013, Jerez et al 2013, Zubiate et al 2017). Detailed WRs using extended classification or cluster method are capable of capturing characteristics of surface weather systems with more details (Cradden and McDermott 2018, Dong 2018, Millstein et al 2019, Bloomfield et al 2020). Other studies have contributed with insight into the meteorological effects on wind resource characteristics, such as ramp events (Ohba et al 2016, 2022, Bloomfield et al 2018), regional imbalance in wind power (Gibson et al 2015), and spatial planning with the guide of WRs (Grams et al 2017). These classifications focus on wind power response to large-scale circulations and months when WRs have their largest influence. However, the relationship between meteorology and wind power is complex and varies with different regions and seasons. The WR clustering scheme on finer (i.e. sub-country) spatial scales in the tailored region is urgently needed for capturing multiple timescale variability of wind power and comparing characteristics of wind resource. Furthermore, taking into account the close relationship among WRs, ramp events and wind power complementation, there is a lack of attempts to quantify these wind resource characteristics for WRs.

This study focuses on how seasonal WRs in an interested region influence wind energy variability at different timescales. The study region is the South China Sea (SCS), which has great potential for wind power and is a key area for wind power development (Wang et al 2018, Liu et al 2019). At the same time, the SCS is influenced by multiple weather systems with complex weather patterns. It is of interest to investigate wind resource assessment over the SCS associated with WRs. Consequently, there are three main contributions of the paper: (a) developing a new set of specific regional WRs with a robust relation to wind over SCS; (b) identifying regions and seasons strongly influenced by WRs using reconstruction method; (c) further assessing wind resource characteristics by quantifying wind power intermittency and complementarity under WRs.

In the following, we first describe the datasets and methodology used to cluster WRs and estimate wind power production in section 2. In section 3, we show the clustered WRs and characterize wind power using WRs. We then qualify wind power intermittency and complementarity under WRs. Finally, we conclude our results and discuss future work in section 4.

2. Clustering of weather regimes and calculation of wind resource characteristics based on reanalysis data

2.1. Overview

In this section, we introduce the study region, the reanalysis data, the clustering method and specific considerations in terms of similarity measure, clustering area and classification seasons. Then we describe the procedure of converting wind speed into capacity factor using the energy model and an adjusted power curve. Finally, we introduce the definition of wind power intermittency and complementarity, and how to calculate them for classified WRs. Figure 1 illustrates the flowchart of our study.

2.2. Meteorological data and study region

We used the ERA5 reanalysis dataset to represent weather conditions and calculate wind power (Hersbach et al 2020). ERA5 has been proved to be very effective in the numerical simulations of offshore wind power generations (Kalverla et al 2020, Soares et al 2020, Fan et al 2021). The latest full ERA5 record from 1959 to 2021 is used. Figure 2 shows the study region, SCS. The WR clustering is conducted over a larger region (right panel in figure 2). The east and northeast winds are evident over most areas of the SCS and the mean wind speed at 100 m is greater than 7 m s⁻¹, indicating the SCS has abundant wind resources.

2.3. Weather regime clustering

WRs are obtained using a clustering method called self-organizing mapping (SOM). SOM is proposed by Kohonen (1982), and it is able to cluster high-dimensional data according to similarity and is widely used in weather related research (Horton et al 2015, Lee et al 2017, Gibson et al 2017b). Daily mean sea level pressure (MSLP) from 1959 to 2021 in ERA5 is clustered using SOM.

Traditional SOM uses Euclidean distance (ED) as similarity measure. However, without considering spatial correlation, ED makes it difficult to distinguish specific weather patterns (Doan et al 2021). We change the ED to structural similarity index (SSIM) in assessing WRs. SSIM is able to consider the similarity
of spatial features based on weather states, such as the locations of highs or lows. Doan et al (2021) provided a detailed description of the SOM based on SSIM and a comprehensive comparison to illustrate the advantages of this method.

To avoid large-scale clustering that would be disturbed by weather systems that have no direct impact on the SCS. We select a relatively small area to cluster weather systems that directly affect the SCS. The optimal expanded region (figure 2) is chosen to carry out the WR clustering. Considering seasonal variations of wind energy, WRs are classified for four seasons, respectively. There are several methods to determine the optimal number of clusters (Michelangeli et al 1995, Rousi et al 2015). In this study, the optimal number of 4 is used for the WR clustering, which is effective in identifying the wind energy characteristics over the SCS, consistent with the previous study (Torralba et al 2021).

2.4. Converting ERA5 wind speed into capacity factor

Wind power production is calculated using ERA5 reanalysis wind speed and is linked to WRs. We combine the energy models from previous studies (van der Wiel et al 2019b, Bloomfield et al 2020, Hayes et al 2021). Our focus is on the response of capacity factor variability to WRs. For each grid and hour, the wind speed needs to be extrapolated to the hub height (assumed to be 80 m in this study) using the logarithmic profile law (Manwell et al 2010, Emies 2018).

\[
\nu(Z) = \nu_{ref} \frac{\ln\left(\frac{Z}{Z_*}\right)}{\ln\left(\frac{Z_{ref}}{Z_*}\right)}
\]

(1)

where \(Z_*\) is the roughness of the sea surface water and is estimated as 0.2 mm (Mattar and Borvaran 2016, Nagababu et al 2017, Reboita et al 2018).
The Vestas V80 2 MW offshore turbine is selected to calculate wind production. The power curve of turbine is obtained at www.renewables.ninja (last access: 10 October 2022) (Staffell et al. 2016). We adjusted the original turbine power curve, which is able to represent a farm of several geographically dispersed turbines and consider wake loss. This method is proven effective in modeling offshore power generation (Hayes et al. 2021). The detailed adjustment method is described in supplementary material A. Based on the adjusted power curve in our model, the wind speed at hub height is converted into the capacity factor for each grid and hour.

2.5. Wind power intermittency and complementarity
In addition to wind power output in wind resource assessment, other characteristics of wind resources are also important. We qualify wind power intermittency and complementarity under each WR. The wind power intermittency is mainly caused by ramp events, which greatly impact the stability and management of wind resource. When a ramp event occurs, there is an intermittent period of wind power generation that is undesired. A ramp event refers to a large variation in wind power generation by at least 50% in 4 h or less (Gallego-Castillo et al. 2015). We calculate the mean daily frequency for different WRs.

Interconnecting wind farms at different regions is an effective method to slow down the variability and intermittency of wind power generation (Gunturu and Schlosser 2012, Fant et al. 2016). The wind power complementarity or complementarity score (CS) represents the degree of the opposite change of wind power in different regions (Ren et al. 2019) and is used to evaluate the effectiveness of wind farm interconnection (supplementary material C gives detailed calculation of CS).

3. Results of weather regimes and related wind resource characteristics

3.1. Weather regimes over the South China Sea
The WRs over the SCS for four seasons are classified (figure 3), where WR1, WR2, WR3, and WR4 are ranked by the occurrence frequency from high to low. Obviously, the identified WRs significantly alter wind conditions over the SCS (see tables S1–S4 in the supplementary material D for detailed descriptions of each WR).

The WRs with large wind anomalies are basically related to the East Asian monsoon and tropical cyclones. For example, WR1 in winter, fall, and spring are primarily affected by winter monsoons, as the MSLP is higher over the northern SCS and lower over the southern SCS, leading to strong and stable northeasterly winds. WR1 in summer is typically related to the East Asian summer monsoon, which features a low pressure center over the northeast SCS and a high pressure center over the southwest SCS. With this configuration, the southwesterly airflow is strong. Furthermore, WR2 in summer and WR4 in fall are mainly affected by tropical cyclones, and thus accompanied by strong southwesterly airflow over the southern SCS. Due to non-uniform distribution of tropical cyclones over the SCS, there are also WRs associated with tropical cyclones but with poor wind conditions. The tropical cyclones
Figure 3. Wind anomalies (shaded, in m s\(^{-1}\)) and direction (vector) at 100 m above ground, and MSLP (contours with a 2 hPa interval) under different WRs (the first four columns) in each season (from top to bottom rows: spring, summer, fall, and winter). Panels in the fifth column show the frequency proportion of WRs in each month or season.

Figure 3. Wind anomalies (shaded, in m s\(^{-1}\)) and direction (vector) at 100 m above ground, and MSLP (contours with a 2 hPa interval) under different WRs (the first four columns) in each season (from top to bottom rows: spring, summer, fall, and winter). Panels in the fifth column show the frequency proportion of WRs in each month or season.

linked to WR2 in fall are present over the eastern SCS, causing large wind anomalies in the eastern SCS while small wind anomalies are present over the remaining SCS. Besides, WR2 in spring and WR4 in summer are affected by the high pressure over the eastern SCS, leading to the easterly airflow and thus reduced wind resources. Nevertheless, the impacts of weather systems on the wind resources show spatial heterogeneity over the SCS. For example, for WR3 in spring and WR3 in summer, due to frequent troughs in South China, the southerly wind over the Beibu Gulf and along the coast of Guangdong Province is fairly strong, whereas the winds elsewhere in that region are relatively weak.

3.2. Overall situation of wind resources under weather regimes

The average capacity factors and the wind speed distribution over the SCS under different WRs for four seasons are examined (figure 4). The hourly 80 m wind speed, area-averaged over all reanalysis grid cells over the SCS, are fitted to the Weibull distributions for each WR in four seasons, respectively. Pattern of capacity factors for each WR is consistent with the averaged wind speed distributions. Generally, WR1 in fall and winter features high capacity factors due to prevailing winter monsoons over the SCS. In particular, WR1 during winter exhibits the highest capacity factors over most of the SCS, which is most ideal for wind power production, with the peak wind speed exceeding 10 m s\(^{-1}\). In addition, WR2 in summer also features enhanced capacity factors due to tropical cyclones. For instance, the average capacity factors over the northern SCS is greater than 0.6. Besides, WR1 in summer is also associated with high capacity factors attributable to the summer monsoons over the SCS, with the average capacity factors greater than 0.3 in most areas. Due to the presence of the southern trough of China, WR3 in spring and summer also present high capacity factors over the Beibu Gulf of Hainan and the coastal areas of Guangdong Province. Nevertheless, for WR4 in Spring and WR3 in fall, there is no weather system directly promoting wind speed over the SCS, leading to the overall low wind energy density. For example, the average capacity factors are less than 0.2 for WR4 in spring and summer. WR2, WR3, and WR4 of spring feature a wind speed magnitude within the range of 0–8 m s\(^{-1}\).
3.3. A case study: how WRs influence wind power production on multi-day timescales

As a case study, the hourly capacity factor in 2012 (figure 5) fluctuates on multi-day timescales throughout the four seasons. The peak capacity factor shows large discrepancies for different seasons and WRs. In the spring of 2012, the largest capacity factor appears to be associated with WR1, but around 15 April 2012, the occurrence frequency of WR1 starts to reduce with an averaged capacity factor being lower than 0.1. In the summer, the peak capacity factor, usually greater than 0.5, is frequently associated with WR2, which is related to tropical cyclones. During the winter, the peak capacity factor generally coincides with WR1, while the capacity factor drops sharply as WR2, WR3, and WR4 take place, with the capacity factor falling below 0.3 in several instances. This case study provides a perfect prototype for objective wind resource assessment over the SCS, with the aid of clustering approach. In other words, the identified WRs have high potential in predicting possible periods of high or low capacity factors.

3.4. Capacity factor reconstruction using weather regimes

The reconstruction method is used to evaluate the effectiveness of WRs in characterizing a target variable as demonstrated in many studies (Cortesi et al 2019, Garrido-Perez et al 2020, Torralba et al 2021). The detailed description of this method is in supplementary material B. In this study, the reconstruction method identifies the sensitive areas of capacity factors influenced by WRs, by measuring the correlation between the seasonal capacity factor directly calculated from ERA5 and that reconstructed based on WRs (figure 6). The one-sided t test is performed to evaluate the statistical significance of the correlation coefficients.

During winter (summer), the correlation coefficients over most areas of the northern (southern)
Figure 5. The hourly capacity factor over the SCS during four seasons in 2012. The time axis is highlighted in colors that correspond to the classified WRs.

Figure 6. Pearson correlation coefficients between the seasonal capacity factor directly calculated from ERA5 and that reconstructed based on WRs during 1959–2021. Areas with statistical significance greater than 95% are highlighted in black grids.
SCS are greater than 0.7 at the 95% significance level, indicating that the identified WRs are capable of representing the dominant weather systems and defining capacity factors in both seasons. In addition, the highest correlation in winter suggests that the WR classification approach can explain the variations of capacity factors with the optimal accuracy for winter. In spring, the correlation coefficients over the northern SCS and the Beibu Gulf are greater than 0.5, but those over the southern SCS are not statistically significant. For spring and fall, the correlations are generally good over the northern SCS, whereas they start deteriorating over the southern SCS. This is largely due to the presence of complex weather systems during spring and fall, including tropical cyclones and monsoons. Furthermore, there are additional factors dominating capacity factors of those areas, such as topography and land sea breeze.

3.5. Wind power intermittency and complementarity under weather regimes

As the wind power is eventually merged into the grid, along with other forms of power resources (such as solar and hydro power), it is vital for wind farms to assess the uncertainties of wind resources and balance the overall power integrated into the grid. Occurrence frequencies of ramp events are adopted to quantify the wind power intermittency during various WRs (figure 7(a)). Ramp events occur frequently in coastal areas and the intermittency of wind resource varies greatly among different WRs. For instance, during WR1 in both fall and winter, wind resources are dominated by winter monsoons, such that the intermittency of wind power is high over the northern SCS and the Taiwan Strait, with occurrence frequencies of ramp events exceeding 0.05. For WR3 in spring and summer, wind resources are primarily affected by the trough in South China. Thus, ramp events occur frequently over the northern SCS. In particular, due to the southerly wind prevailing over the Beibu Gulf, the intermittency of wind resources over the Beibu Gulf is higher than other places.

The complementarity of wind resources can effectively mitigate the intermittency of wind resources, referring to the practice of Ren et al (2019). The complementarity of wind resources over the SCS is generally high (figure 7(b)), but there is a large gap among different WR scenarios. The complementarity of wind resources during WR4 in summer, WR3 in fall and WR1 in winter is generally the lowest, with the values lower than 0.25 over central area of the SCS. On the other hand, the complementarity of WR2 in summer, WR1 in fall and WR3 in winter is generally high, with the averaged values greater than 0.4. Moreover, the regional differences in complementarity of wind resources are also relatively large. The complementarity of wind resources over coastal areas is higher than 0.4 for most WRs, while it is low over the central area of the SCS as the offshore wind direction is often relatively stable. Nevertheless, the
central area of the SCS also features WRs associated with good complementarity of wind resources, such as WR2 in summer and WR2 in winter, with the averaged value higher than 0.35.

From the perspective of WRs, the complementarity can effectively mitigate the intermittency of wind resources. For instance, wind power over the Beibu Gulf often occurs with wind ramp events. However, high complementarity in most WRs shows the fluctuations caused by wind power, which can be balanced by spatial deployment based on the understanding of meteorological variations. Wind resources in coastal areas under WR1 in spring, WR2 in summer and WR3 in winter are highly complementary, when the intermittency of wind is high. Under these WRs, the interconnection of wind farms can effectively reduce ramp events of wind power generation.

4. Conclusions and discussion

This study comprehensively characterized the wind resources over the SCS by clustering the WRs via the SOM method using the latest full ERA5 dataset (1959–2021). The WRs are characterized over the region of interest instead of using large-scale circulation pattern, and extended to the four seasons, which maximizes the response of wind resources to the atmosphere circulation and obtaining a year-round view of wind resource characteristics.

The wind resources associated with monsoons and tropical cyclones are generally excellent, while it can be reduced due to the adverse circulation condition, such as the subtropical high system propagating westward with the accompanied easterly wind. A case study on 2012 conditions shows that WRs effectively provide a meteorological explanation for wind power fluctuations on multi-day timescales. The occurrence of specific WRs can bring about a rapid rise or fall in the capacity factor. The analysis of the reconstructed capacity factors based on the identified WRs indicates that WRs are very effective in characterizing capacity factors over most areas of the SCS, with the correlation coefficients greater than 0.5.

In addition, the intermittency, and complementarity of wind resources are evaluated for the classified WRs. Under WR1 in spring, WR2 in summer and WR3 in winter, the wind speed change over coastal areas rapidly, resulting in many ramp events. Meanwhile, the complementarity of wind resources over coastal areas during these WRs is also high, hence the intermittency of wind power generation can be reduced.

The WRs can be used as an alternative standard for the operational objective assessment of the SCS wind resources, and the results derived from this study can also help planners and decision makers make preliminary planning. In the future, our WRs are expected to be related to more refined regional scale wind energy variability. The response of regional wind power production in the period when WR changing is interesting. More explicit estimation of wind energy potential is also crucial in regional scale. In particular, we are interested in using Kinetic Energy Budget of the Atmosphere model for robust estimates (Kleidon and Miller 2020, Minz et al 2020, 2021). Previous studies suggested that WRs are more skilled in predicting extreme weather events, such as drought and cold wave (Ferranti et al 2018, Lavaysse et al 2018). It is also of interest to investigate the methods of predicting wind power capacity factors or wind energy density for 1–4 weeks over the SCS, by exploring the potential of WRs. In addition, the prediction of wind energy resources over other regions by WRs at different time scales needs to be further studied.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form.

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ORCID iD

Huiling Yuan @ https://orcid.org/0000-0003-4725-9039

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