Interannual variability of the summer wind energy over China: A comparison of multiple datasets

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Abstract
Because of the increase in the nation's need for wind energy, the impacts of climate change on wind energy have been investigated. In addition to long-term changes, wind energy also shows robust interannual variations, but little effort has been devoted to understanding the underlying mechanisms. In this study, the impact of El Niño on the summer mean wind power density (WPD) over China is investigated. The abilities of five sets of reanalysis data in measuring the interannual variability of the WPD over China are assessed. Encouraging results are seen for all reanalysis datasets, with the MERRA and ERA-Interim datasets showing the best performance. The relationship between El Niño and the following summer WPD is identified over China. During El Niño decaying year summers, the WPD over south of the Yangtze River valley increases, whereas the WPD over north of the Yangtze River valley decreases. The WPD changes are dominated by an anomalous anticyclone located in the northwestern Pacific. The anticyclone leads to strong southerly winds in southern China and thereby enhances the WPD. In regions north of the Yangtze River valley, the low surface pressure gradient causes a reduction in wind speed and thereby a weak WPD. Because the year-by-year variation in El Niño-Southern Oscillation (ENSO) is highly predictable, our results shed light on the seasonal prediction of wind power over China.

KEYWORDS
anomalous anticyclone, data comparison, ENSO, interannual variation, low surface pressure gradient, wind energy, wind power density

1 | INTRODUCTION

With the development of renewable energy, wind energy has become one of the most well-established sources that is currently used in more than 100 countries around the world.1 In recent decades, an increasing number of investigations have focused on the assessment and analysis of wind energy resources, including the regional distributions of near-surface wind speed, wind power potentials, and wind power density (WPD), the changes in near-surface wind and WPD, and the future changes in near-surface wind and WPD.1–7 The world's interest in wind energy is increasing rapidly. Understanding the historical changes in wind energy and making reliable predictions of its future changes are of great importance to society.
The long-term changes in wind speed have been evaluated in previous studies. In the United States, the 10-m (10 metre above the ground) wind speed was found to have decreased significantly over the past 30–50 years according to data from approximately 1300 stations over the contiguous United States. If the annual mean wind speeds are arranged in ascending order, more than half of the annual 50th percentile 10-m wind speed and nearly half of the 90th percentile annual 10-m wind speed time series exhibit significant decreasing trends. Decreasing trends are also found in the annual mean surface wind speeds over Europe. In addition, the daily maximum wind speed also shows decreasing trends over Northwestern Europe in summer. In China, the 10-m wind speeds derived from meteorological station data also exhibited a long-term decreasing trend from 1960 to 2010.

The projection of future changes in wind energy has been a focus of previous studies. Many of these kinds of studies are based on the analysis of global and regional climate models. For example, it is projected that there will be an increasing trend in wind energy resources in parts of wind farms that have large-scale generation capacity over the United States. Over northern Europe, the mean wind speeds, 90th percentile wind speeds, and energy density in the period from 2081 to 2100 are projected to be slightly lower than those during 1961–1990. The annual and winter mean WPD in China during the early 21st century is also projected to decrease slightly.

In addition to long-term changes, the WPD also shows robust interannual variations. The year-by-year or interannual variability in WPD is important for the production of wind farms. Wind farms usually face uncertainties in predicting the energy output due to the robust interannual variations in the WPD. The year-to-year changes in WPD could cause substantial economic losses to wind farm companies. However, in comparison to future change projections, few studies have focused on the interannual variability in WPD. Pryor et al. assessed the historical variability in annual wind indices across Europe and found that the North Atlantic Oscillation (NAO) contributed to the interannual variability of the 90th percentile winter wind speeds. Additionally, the interannual variability in WPD over Europe is also attributable to variations in the Atlantic Oscillation (AO).

The El Niño–Southern Oscillation (ENSO) is a coupled ocean–atmosphere cycle with a 2- to 7-year period occurring over the tropical Pacific Ocean. The interannual variability in the global climate is mainly affected by ENSO. The sea surface temperature (SST) anomalies over the Niño-3.4 region (5°S–5°N, 120°–170°W) are used to track ENSO, which is also referred to as the ENSO index. A positive ENSO index represents the warm phase (El Niño), whereas a negative ENSO index represents the cool phase (La Niña). El Niño also plays an important role in the year-to-year variations in wind energy. For example, over the Canadian Prairies, the surface wind speed stills during winter in El Niño years. In the Great Lakes region, large interannual variability occurs in the winter and small variations occur in the summer, which are associated with El Niño events.

The wind energy over continental China also shows large interannual variations. In China, the total electricity consumption is high in the summer months and tends to increase with global warming. East China is controlled by a large summer monsoon system, and the interannual variations in wind energy in summer are greatly affected by the East Asian summer monsoon. ENSO has been demonstrated to be a major factor that modulates the interannual variations in the East Asian summer monsoon. Following the monsoon changes, the wind energy also exhibits corresponding changes. For example, more than 55% of the observational stations in China show weaker than normal near-surface wind speeds in El Niño years, but the underlying mechanisms remain unknown. The major objective of this study is to reveal how El Niño modulates the interannual variations in summer mean WPD over China. The performances of different reanalysis data in quantifying the summer mean WPD changes over China are also assessed.

The remainder of the paper is organized as follows. Section 2 describes the datasets and analysis methods used in this study. In Section 3, the main results are presented, including the interannual variability of the WPD and the effect of El Niño. The concluding remarks are presented in Section 4.

2 | DATA AND METHOD

2.1 | Data description

We use the daily mean 10-m wind speed from 756 meteorological stations as observation data. These data were obtained from the China Meteorological Administration (CMA; http://cdc.nmic.cn/home.do). The observations were quality controlled, including internal consistency checks, spatial and temporal consistency checks, identification of outliers, and correction of suspected and erroneous data, but homogenization was not conducted. We chose 503 stations with the best continuity (i.e., the missing data represent less than 5% of the data in each year) during 1960–2013 in our analysis. The monthly mean data were calculated from the daily observation data.

In this study, six reanalysis datasets were used: (1) National Centers for Environmental Prediction (NCEP)–U.S. Department of Energy (DOE) Reanalysis 2 (NCEP-2), which is an improved version of NCEP-1; (2) Modern-ERA Retrospective Analysis for Research and Applications (MERRA), which is a National Aeronautics and Space Administration (NASA) reanalysis for the satellite era using a major new version of the Goddard Earth Observing System Data Assimilation System Version 5 (GEOS-5); (3) Japanese 55-year Reanalysis Project (JRA-55), which employs four-dimensional variational data assimilation (4DVAR) with variational bias correction for satellite radiances; (4) Interim European Centre for
Medium-Range Weather Forecasts (ECMWF) Reanalysis product (ERA-Interim), which improves certain key aspects of ERA-40 and employs the 4DVAR assimilation method; (5) 20th Century Reanalysis (20CR), which is performed with the ensemble filter; and (6) SST from the Hadley Centre sea ice and sea surface temperature dataset (HadISST). Detailed information on the six reanalysis datasets is presented in Table 1. Monthly air temperature, monthly surface pressure, daily meridional wind, daily zonal wind, and monthly SST are used in this study. The monthly mean WPD is calculated from daily data in the reanalysis data.

2.2 Analysis method

2.2.1 Homogenization of the daily 10-m wind speed data

Because the original meteorology station data (MSD) station data were not homogenized, we performed a homogenization analysis of the data before they were applied. The penalized maximum F test is applied to perform the homogenization. This test can detect any discontinuities in the time series of the daily 10-m wind speed data. Each station is detected for all times. This method does not require a reference series or station because it allows a long-term trend and accounts for first-order autocorrelation. We first used the penalized maximum F test to detect the change point in the time series at each station. If significant change points are identified, the quantile-matching method is used to remove the discontinuities in the daily 10-m wind speed around the detected change points. Then, the MSD is homogenized and used to calculate the monthly WPD over China. For details of the method, please refer to Dai et al. and Wang et al.

2.2.2 Computation of WPD at the turbine hub height

The WPD depends on the air density and wind speed. WPD is used to describe wind resources and indicates how much wind energy can be harvested at a location. The WPD at each time step can be written as

$$WPD = \frac{1}{2} \rho U^3.$$  

(1)

where \(U\) is the near-surface wind speed and \(\rho\) is the air density, which is equal to 1.225 kg m\(^{-3}\) in this study.

The turbine hub height is 80 metre above the ground in China. Therefore, we first need to calculate the 80-m wind speeds. The vertical wind profile is applied to extrapolate the wind speed from 10-m up to 80-m. The empirical power law, shown in Equation 2, was first used by Elliott and has been widely used.

$$U_Z = U_{10} \left( \frac{Z}{10} \right)^{1/7},$$  

(2)

where \(U_Z\) is the wind speed at the turbine hub height \(Z\) and \(U_{10}\) is the wind speed at 10-m. This formula is often used in the surface layer chartered by neutral conditions and smooth areas without variations in the boundary layer stability. Therefore, Justus and Mikhail proposed an alternative formula (Equations 3 and 4) that accounted for variations.

**TABLE 1** Detailed information on the six reanalysis datasets used in this study

| Providers  | Time period   | Resolution  | Assimilation algorithm |
|------------|---------------|-------------|------------------------|
| NCEP-2     | NCEP + DOE    | 1979-2011   | 2.5° × 2.5°             | 3DVAR 5SI                      |
| MERRA      | NASA + GMAO   | 1979-2011   | 1.33° × 2.33°           | GEOS-5 DAS                     |
| JRA-55     | JMA           | 1979-2011   | 1.25° × 1.25°           | 4DVAR                          |
| ERA-Interim| ECMWF         | 1979-2011   | 0.75° × 0.75°           | 4DVAR                          |
| 20CR       | NOAA + DOE    | 1979-2011   | 2.5° × 2.5°             | Ensemble Kalman filter         |
| HadISST    | Met Office Hadley Centre | 1979-2011 | 1.0° × 1.0°             | RSOI                           |

Abbreviations: DOE, Department of Energy; ECMWF, European Centre for Medium-Range Weather Forecasts; GMAO, Global Modeling and Assimilation Office; JMA, Japan Meteorological Agency; NASA, National Aeronautics and Space Administration; NCEP, National Centers for Environmental Prediction; NOAA, National Oceanic and Atmospheric Administration.
where $U_Z$ is the wind speed at the turbine hub height $Z$ and $U_{10}$ is the wind speed at 10-m. In this study, we first use the alternative formula to calculate the 80-m wind speed. Then, the WPD at 80-m is calculated by using Equation 1.

Before the area-weighted mean WPD was calculated, the station data were interpolated onto a 1.25° × 1.25° resolution grid using bilinear interpolation. Because the focus of our study is interannual variability, variations longer than 9 years were filtered out from the original datasets with a Lanczos filter before the analysis. We focused on the time period from 1985 to 2004 in this study because of the availability of data.

3 | RESULTS

3.1 | The climatology of the WPD

The 20-year averaged spatial pattern of the summer mean WPD is shown in Figure 1. The large MSD values (Figure 1A) are located in Inner Mongolia, north of Xinjiang, northeast China and eastern coastal China. The values are low in the Sichuan Basin. Except for NCEP-2, the other four reanalysis datasets reasonably reproduced the observed spatial pattern with high values in northern and eastern China and low values in the Sichuan Basin (Figure 1B–F). The observed summer mean WPD mainly varied between 30 and 130 W m$^{-2}$ across China. The intensity of the summer mean WPD was approximately 30 W m$^{-2}$ larger than the observations in the reanalysis datasets over most regions, especially Inner Mongolia and coastal areas. In NCEP-2 and 20CR, the largest biases were found in the Tibetan Plateau. The WPD in JRA-55 was smaller than the observed value, and the WPD in NCEP-2 was larger than the observed value.

**FIGURE 1** Distributions of the long-term (1985–2004) summer (JJA) mean 80-m wind power density (WPD) (units: W m$^{-2}$) over China: (A) observations, (B) NCEP-2, (C) MERRA, (D) JRA-55, (E) ERA-Interim, and (F) 20CR [Colour figure can be viewed at wileyonlinelibrary.com]
The quality of the reanalysis datasets was quantitatively measured by the pattern correlation coefficient (PCC) and root mean square error (RMSE) with reference to the MSD, as given in Table 2. As listed in Table 2, the PCCs (RMSEs) of the five reanalysis datasets were 0.64, 0.86, 0.85, 0.86, and 0.813 (236.45, 55.13, 62.43, 49.59, and 77.12) for NCEP-2, MERRA, JRA-55, ERA-Interim, and 20CR, respectively. Hence, the reanalysis datasets reasonably reproduced the spatial distributions but with evident biases in intensity. MERRA and ERA-Interim were the best datasets for reproducing the climatology of the summer WPD in China.

3.2 The interannual variability in WPD

To reveal the interannual variation in the summer mean WPD, the standard deviation was first calculated. The spatial distributions of the interannual variability are shown in Figure 2. Large interannual variations in the summer mean WPD occurred in Inner Mongolia, northern Xinjiang, northeast China, eastern China, and southern China, as evidenced by the high standard deviation values in MSD (Figure 2A). Small interannual variations occurred in the southern Tibetan Plateau and Sichuan Basin, as indicated by the low standard deviation values in MSD. In all reanalysis datasets (Figure 2B–F), except for NCEP-2, large interannual variations occurred in Inner Mongolia, northern Xinjiang, northeast China, and eastern coastal China, whereas small interannual variations occurred in the other regions. In NCEP-2 (Figure 2B), standard deviations larger than the

| Abbreviations: PCC, pattern correlation coefficient; RMSE, root mean square error; WPD, wind power density. |

### TABLE 2 The PCC and RMSE of the summer mean WPD in five reanalysis datasets

|                | PCC   | RMSE (W m\(^{-2}\)) |
|----------------|-------|---------------------|
| MSD vs. NCEP-2 | 0.64  | 236.45              |
| MSD vs. MERRA  | 0.86  | 55.13               |
| MSD vs. JRA-55 | 0.85  | 62.43               |
| MSD vs. ERA-Interim | 0.86 | 49.59               |
| MSD vs. 20CR   | 0.81  | 77.12               |

**FIGURE 2** Interannual variability of the summer (JJA) mean 80-m wind power density (WPD) (units: W m\(^{-2}\)) over China: (A) observations, (B) NCEP-2, (C) MERRA, (D) JRA-55, (E) ERA-Interim, and (F) 20CR [Colour figure can be viewed at wileyonlinelibrary.com]
observations occurred throughout China, especially the Tibetan Plateau. The distributions shown by NCEP-2 are not evident in the MSD. The PCCs of the reanalysis datasets are 0.40, 0.61, 0.59, 0.49, and 0.49 for NCEP-2, MERRA, JRA-55, ERA-Interim, and 20CR, respectively, indicating that MERRA was the best at reproducing the spatial distributions of interannual variations. Additionally, the interannual variations in the reanalysis datasets were larger than the observed values except for in the JRA-55 dataset.

**FIGURE 3** The spatial pattern of the leading empirical orthogonal function (EOF) mode of the summer mean wind power density (WPD) over China in the observation. The Lanczos filter is used to filter out signals longer than 9 years. The data were normalized before performing EOF analysis [Colour figure can be viewed at wileyonlinelibrary.com]

**FIGURE 4** Summer mean wind power density (WPD) in NCEP-2 (A), MERRA (B), JRA-55 (C), ERA-interim (D), and 20CR (E) regressed onto PC1 of the observations (shaded). The box shows the area south (22°N–30°N, 104°E–118°E) of the Yangtze River, which was the point of interest in this study. Dotted regions indicate grid points where the changes are significant at the 95% confidence interval. All reanalysis datasets have been processed by 9-year high-pass filtering and standardizing. Signals longer than 9 years have been removed by the Lanczos filter. The filtered data were normalized and thus unitless [Colour figure can be viewed at wileyonlinelibrary.com]
To better understand the spatial and temporal distributions of the summer mean WPD in China, empirical orthogonal function (EOF) analysis was performed to identify the leading interannual variability modes. Because the focus of our study was interannual variability, variations longer than 9 years were filtered out from the original datasets with a Lanczos filter before the EOF was calculated. The MSD results are shown in Figure 3. The first leading EOF mode (hereafter EOF1) (Figure 3A) explains 36.4% of the variance in MSD. The leading mode of the summer mean WPD shows positive anomalies in northeastern China, south of the Yangtze River valley, and negative anomalies in other regions of China, featuring a meridional positive–negative pattern over eastern China. The EOF1 pattern of MSD passed the significance test of the North criterion and was independent from the other modes. The time series of the first leading EOF mode (hereafter PC1) is shown in Figure 3B. The MSD exhibited significant interannual variations. The PC1 of MSD was regressed on the five reanalysis datasets, and we obtained the spatial patterns of the first leading interannual variability modes derived from the five reanalysis datasets (Figure 4). All reanalysis datasets could reproduce the observed characteristics of EOF1, with positive anomalies south of the Yangtze River and negative anomalies north of the Yangtze River. Only MERRA and ERA-Interim showed significant interannual variations in these two regions. The weakness of this analysis was that the positive and negative anomalies were stronger than the observed values. In NCEP-2, positive anomalies were also observed in the Tibetan Plateau.

In Figure 4, significant anomalies occurred in the south (22°N–30°N, 104°E–118°E) Yangtze River (gray box in Figure 4A). All reanalysis datasets reasonably reproduced that observed spatial pattern. Over the north of the Yangtze River region, there were also significant anomalies. In the following analysis, we focus on these two specific regions, namely, north and south of the Yangtze River, where wind energy has developed rapidly in recent years.

**FIGURE 5** Sea surface temperature (SST) anomalies (K·a⁻¹) from the proceeding winter D(-1) JF(0) to the concurrent summer JJA(0) regressed onto PC1 of the JJA wind power density (WPD) (shaded). Dotted regions indicate grid points where the anomalies are statistically significant at the 5% level [Colour figure can be viewed at wileyonlinelibrary.com]
3.3 The effect of ENSO

To reveal the potential link of WPD variations with SST anomalies, we regressed PC1 of the summer mean WPD EOF1 with SST in Figure 5. Note that the El Niño mature phase occurs during boreal winter, namely, D (−1) JF (0). Here, −1 indicates 1 year prior to the summer mean WPD, and 0 indicates the current year. The SST anomaly features a typical El Niño pattern, with significant positive anomalies located in the equatorial central and eastern Pacific (Figure 5A). The correlation coefficient between PC1 and the ENSO index, which is defined as the regional average of SST anomalies within the 5°S-5°N, 120°-170°W box, was 0.576, which is statistically significant at the 99% confidence level. Hence, ENSO is a major factor that can affect the interannual variations in the summer mean WPD.

The evolution of El Niño includes three stages: developing (boreal summer), peaking (winter), and decaying (following spring). Following the evolution of El Niño events, a warming tropical Indian Ocean (TIO) was observed. TIO warming appeared in boreal winter (Figure 5A) and reached a maximum during MAM (0) (Figure 5B). In El Niño decaying year summers, the SST anomalies in the tropical eastern Pacific were generally neutral, whereas significant warming was evident in the TIO (Figure 5C).

To quantify the impact of El Niño on the summer mean WPD, the lead–lag correlation of PC1 with the ENSO index and the area-averaged SSTA over the TIO (10°S-10°N, 40°E-110°E) region are shown in Figure 6. We denote the year with the summer mean WPD time series at year 0 and the leading (following) year is denoted as year −1 (1). Whereas the correlation coefficient of WPD PC1 with the ENSO index decayed rapidly from boreal winter to the following summer, the significant positive correlation of WPD PC1 with the TIO index persisted from boreal winter to the following summer. The highest correlation coefficient occurred in JJA (0). This kind of relationship is evident in both the observations (Figure 6A) and the ERA-Interim reanalysis (Figure 6B). The delayed response of the TIO is also evident in Figure 5C. Hence, El Niño events have significant influences on the WPD over China during El Niño decaying year summers through the decayed warming of the TIO. El Niño decaying year summers occur through the decaying warming of the TIO. During El Niño decaying year summers, the WPD in the south (north) of the Yangtze River will increase (decrease).

Why is the WPD variation seasonally dependent on the TIO SST? During the mature phase of El Niño, an anomalous anticyclone appeared over the western North Pacific (WNP) and affected the East Asian continent in the south of the Yangtze River (Figure 7). The anomalous anticyclone persisted from D (−1) JF (0) to JJA (0). The south of the Yangtze River is controlled by this anomalous anticyclone. The winds are from the southwest in D (−1) JF (0) and MAM (0) to the south in JJA (0) over the south of the Yangtze River valley. The strong anomalous south winds

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**FIGURE 6** Lead–lag correlations between PC1 of the summer mean wind power density (WPD) and the El Niño-Southern Oscillation (ENSO) index (solid line) and the basin-wide Indian Ocean warming index (dashed line): 0 for the year of the summer WPD time series and −1 (1) for the leading (following) year. (A) Lead–lag correlations between PC1 of MSD derived from the observational stations and the ENSO index (solid) and the basin-wide Indian Ocean warming index (dashed). (B) Same as (A), except for PC1 of the MSD index derived from ERA-Interim. The basin-wide Indian Ocean warming index is defined as area-averaged sea surface temperature anomalies (SSTAs) in the tropical Indian Ocean (10°S-10°N, 40°-110°E)
contribute to the increase in the WPD in JJA (0) over this region. In the meantime, the wind over the north of the Yangtze River valley will be weakened.

The results from present studies show that the formation of the WNP anticyclone anomaly contributes to TIO warming from winter to spring, and warming could persist into decaying summers. The TIO warms similar to a battery charging capacitor. After El Niño decay, TIO warming persists through JJA (0) and exerts its climatic influence on the surrounding regions. The dynamic and thermodynamic mechanisms are used to explain how TIO warming could affect the WNP anticyclone. The basin-wide IO warming does not affect the WNP circulation in the
mature phase of El Niño but is the major cause of WNP circulation during decaying summer. The local cold SST anomalies during boreal winter and the subsequent seasons could maintain anomalous anticyclones. Significant cold SST anomalies exist in the WNP (Figure 5) during D (−1), JF (0), and MAM (0). Thus, the anomalous anticyclone in the WNP during the El Niño decaying summer may be affected by both basin-wide IO warming and local cold SST anomalies. The basin-wide IO warming will induce anticyclonic anomalies through Kelvin wave-induced Ekman pumping divergence, and the local cold SST anomalies will maintain the anticyclonic anomaly through the IO forcing effect. More detailed information can be found in the study by Li et al.

In addition, we found that the near-surface wind speed is small during JJA (0) over the north of the Yangtze River (Figure 7C). China’s topography is varied and complicated, especially in northern and western China. The near-surface wind speed is influenced by the topography. Thus, we examined the relationship between the surface pressure over land and El Niño (Figure 8). Positive anomalies were observed over the low-pressure center (Tibetan Plateau), and negative anomalies existed over the high-pressure area (low-altitude region) during JJA (0) after El Niño events. This result means that the pressure gradient decreased north of the Yangtze River. The lower pressure gradient helped the wind decrease during the following summer. Therefore, a lower WPD exists during the following summer over the northern Yangtze River.

![Figure 8](wileyonlinelibrary.com)
4 | SUMMARY

In this study, the interannual variability of the summer WPD derived from five reanalysis datasets (NCEP-2, MERRA, JRA-55, ERA-Interim, and 20CR) and observations are compared. The mechanism of the interannual variability is investigated. The major findings are summarized below.

1. The observed long-term mean summer WPD over China is large in northern and eastern China and small in the Sichuan Basin. All reanalysis datasets, except NCEP-2, reasonably reproduce the observed spatial distribution but include evident biases in intensity. Among the five reanalysis datasets, MERRA and ERA-Interim show the best performance with large PCC and small RMSE values.

2. The observed interannual variations in the summer mean WPD in China are regionally dependent, with large variations observed in Inner Mongolia, northern Xinjiang, northeastern China, eastern China, and southern China. Small variations occur in the south of the Tibetan Plateau and Sichuan Basin. All reanalysis datasets, except NCEP-2, reproduce the large variations in Inner Mongolia, northern Xinjiang, and eastern coastal China and small variations in the Sichuan Basin. However, the interannual variations in the reanalysis datasets are smaller than the observed variations. According to the results of EOF1 in MSD, a meridional positive–negative pattern is seen over eastern China with positive anomalies south of the Yangtze River and negative anomalies north of the Yangtze River. All reanalysis datasets could reproduce the observed positive and negative anomalies, but the anomalies are significant in only the MERRA and ERA-Interim datasets.

3. The interannual variability of the summer mean WPD over China is dominated by ENSO. In the south of the Yangtze River, the WPD increases during El Niño decaying year summers but decreases during La Niña decaying year summers. In the north of the Yangtze River, the opposite change occurs. During the El Niño decaying summer, an anomalous anticyclone appears in the WN Pacific. This condition affects the continent south of the Yangtze River, and a strong anomalous south wind appears, leading to an increase in the WPD south of the Yangtze River. During the El Niño decaying summer, the near-surface wind speeds are slow north of the Yangtze River, which can be explained by the low surface pressure gradient.

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REFERENCES

1. Soldatenko S, Karlin L. The climate change impact on Russia's wind energy resource: current areas of research. Energy Power Eng. 2014;06(11):371-385. https://doi.org/10.4236/epc.2014.611032

2. Groisman PY, Knight RW, Karl TR, Easterling DR, Sun B, Lawrimore JH. Contemporary changes of the hydrological cycle over the contiguous United States trends derived from in situ observations. J Hydrometeorol. 2003;5(1):64-85. https://doi.org/10.1175/1525-7541(2003)005<0064:cothc>2.0.co;2

3. Pryor SC, Schoof JT, Barthelmie RJ. Climate change impacts on wind speeds and wind energy density in northern Europe: empirical downscaling of multiple AOGCMs. Climate Res. 2005;29(3):183-198. https://doi.org/10.3354/cr029183

4. Sailor DJ, Smith M, Hart M. Climate change implications for wind power resources in the Northwest United States. Renew Energy. 2008;33(11):2393-2406. https://doi.org/10.1016/j.renene.2008.01.007

5. García-Bustamante E, González-Rouco JF, Jiménez PA, Navarro J, Montávez JP. A comparison of methodologies for monthly wind energy estimation. Wind Energy. 2009;12(7):640-659. https://doi.org/10.1002/we.315

6. McVicar TR, Roderick ML, Donohue RJ, et al. Global review and synthesis of trends in observed terrestrial near-surface wind speeds: implications for evaporation. J Hydrol. 2012;416-417:182-205. https://doi.org/10.1016/j.jhydrol.2011.10.024

7. Pryor SC, Barthelmie RJ, Kjellström E. Potential climate change impact on wind energy resources in northern Europe: analyses using a regional climate model. Climate Dynam. 2005;25(7–8):815-835. https://doi.org/10.1007/s00382-005-0072-x

8. Pryor SC, Barthelmie RJ. Climate change impacts on wind energy: a review. Renew Sustain Energy Rev. 2010;14(1):430-437. https://doi.org/10.1016/j.rser.2009.07.028

9. Walter A, Keuler K, Jacob D, et al. A high resolution reference data set of German wind velocity 1951-2001 and comparison with regional climate model results. Meteorol Z. 2006;15(6):585-596. https://doi.org/10.1127/0941-2948/2006/0162

10. Bakker AMR, van den Hurk BJM. Estimation of persistence and trends in geostrophic wind speed for the assessment of wind energy yields in Northwest Europe. Climate Dynam. 2011;39(3–4):767-782. https://doi.org/10.1007/s00382-011-1248-1

11. Yan Z, Bate S, Chandler RE, Isham V, Wheater H. An analysis of daily maximum wind speed in northwestern Europe using generalized linear models. J Climate. 2002;15(15):2073-2088. https://doi.org/10.1175/1520-0442(2002)015<2073:AAODMW>2.0.CO;2

12. Cong ZT, Yang DW, Ni GH. Does evaporation paradox exist in China. Hydrol Earth Syst Sci. 2009;13(3):357-366. https://doi.org/10.5194/hess-13-357-2009
13. Yin Y, Wu S, Chen G, Dai E. Attribution analyses of potential evapotranspiration changes in China since the 1960s. *Theor Appl Climatol.* 2009;101(1–2):19-28. https://doi.org/10.1007/s00704-009-0197-7

14. Fu G, Yu J, Zhang Y, Hu S, Ouyang R, Liu W. Temporal variation of wind speed in China for 1961–2007. *Theor Appl Climatol.* 2010;104(3–4):313-324. https://doi.org/10.1007/s00704-010-0348-x

15. Jiang Y, Luo Y, Zhao Z. Projection of wind power density in China in the 21st century by climate models. *Resources Sci (in Chinese).* 2010;32(4):640-649. https://doi.org/10.1007/s10704-010-0222-9

16. Pryor SC, Barthelmie RJ, Schoof JT. Inter-annual variability of wind indices across Europe. *Wind Energy.* 2006;9(1–2):27-38. https://doi.org/10.1002/we.178

17. George SS, Wolfe SA. El Niño stills winter winds across the southern Canadian Prairies. *Geophys Res Lett.* 2009;36(23):L23806. https://doi.org/10.1029/2009gl041282

18. Kriesche P, Schlosser CA. The association of large-scale climate variability and teleconnections on wind energy resource over Europe and its intermittency. USA: MIT Joint Program on the Science and Policy of Global Change; 2013.

19. Webster PJ, Magaña VO, Palmer TN, et al. Monsoons: processes, predictability, and the prospects for prediction. *J Geophys Res Oceans.* 1998;103(C7):14451-14510. https://doi.org/10.1029/97jc02719

20. Webster PJ, Yang S. Monsoon and ENSO: selectively interactive systems. *Q J Roy Meteorol Soc.* 1992;118(507):877-926. https://doi.org/10.1002/qj.49711850705

21. Oort AH. Observed interannual variability in the Hadley circulation and its connection to ENSO. *J Climate.* 1996;9(11):2751-2767. https://doi.org/10.1175/1520-0444(1996)009<2751:oiivih>2.0.co;2

22. Ge J, Jia X, Lin H. The interdecadal change of the leading mode of the winter precipitation over China. *Climate Dynam.* 2016;47(7-8):2397-2411. https://doi.org/10.1007/s00382-015-2970-x

23. Li X, Zhong S, Bian X, Heilman WE. Climate and climate variability of the wind power resources in the Great Lakes region of the United States. *Regions Sci (in Chinese).* 2001;45(16):1957-1979. https://doi.org/10.1007/s00382-003-1730-2

24. Wang B, Wu Z, Chang C-P, Liu J, Li J, Zhou T. Another look at interannual-to-interdecadal variations of the East Asian winter monsoon: the northern and southern temperature modes. *J Climate.* 2010;23(6):1495-1512. https://doi.org/10.1175/2009jcli3243.1

25. Wu R, Wang B. Multi-stage onset of the summer monsoon over the western North Pacific. *J Climate.* 2011;24(14):313-324. https://doi.org/10.1002/qj.864

26. Fu G, Yu J, Zhang Y, Hu S, Ouyang R, Liu W. Temporal variation of wind speed in China for 1961–2007. *Theor Appl Climatol.* 2010;104(3–4):313-324. https://doi.org/10.1007/s00704-010-0348-x

27. Li C, Mu M. Relationship between East Asian winter monsoon, warm pool situation and ENSO cycle. *Adv Atmosph Sci.* 1999;16(1):1-22. https://doi.org/10.1007/s00376-999-0039-4

28. Fan D, Wang S, Zhang W. Study on application of seasonal cycle model in China's power load forecasting. *Power Syst Technol (in Chinese).* 2002;83(11):1631-1643. https://doi.org/10.1007/s00704-000197-7

29. Kim J-W, Yeh S-W, Chang E-C. Combined effect of El Niño-southern oscillation and Pacific decadal oscillation on the East Asian winter monsoon. *Theor Appl Climatol.* 2010;104(3–4):313-324. https://doi.org/10.1007/s00382-013-1730-z

30. Wang B, Wu Z, Chang C-P, Liu J, Li J, Zhou T. Another look at interannual-to-interdecadal variations of the East Asian winter monsoon: the northern and southern temperature modes. *J Climate.* 2010;23(6):1495-1512. https://doi.org/10.1175/2009jcli3243.1

31. Wu R, Wang B. Multi-stage onset of the summer monsoon over the western North Pacific. *Climate Dynam.* 2001;17(4):277-289. https://doi.org/10.1007/s003820000118

32. Zhou T-J, Yu R. Atmospheric water vapor transport associated with typical anomalous summer rainfall patterns in China. *J Geophys Res.* 2005;110(D8):D08104. https://doi.org/10.1029/2004jd005413

33. Chen L, Li D, Pryor SC. Wind speed trends over China: quantifying the magnitude and assessing causality. *Int J Climatol.* 2013;33(11):2579-2590. https://doi.org/10.1002/joc.3613

34. Ma S, Zhou T, Dai A, Han Z. Observed changes in the distributions of daily precipitation frequency and amount over China from 1960 to 2013. *J Climate.* 2015;28(17):6960-6978. https://doi.org/10.1175/jcli-d-15-0011.1

35. Kanamitsu M, Ebisuzaki W, Woollen J, et al. NCEP–DOE AMIP-II reanalysis (R-2). *Bull Am Meteorol Soc.* 2002;83(11):1631-1643. https://doi.org/10.1175/1520-0477-3.11.10.1175/BAMS-83-11

36. Rienecker MM, Suarez MJ, Gelaro R, et al. MERRA: NASA's Modern-Era Retrospective Analysis for Research and Applications. *J Climate.* 2011;24(14):3624-3648. https://doi.org/10.1175/2011jcli4051.1

37. Kobayashi S, Ota Y, Harada Y, et al. The JRA-55 reanalysis: general specifications and basic characteristics. *J Meteorol Soc Japan Ser II.* 2015;93(1):5-48. https://doi.org/10.2151/jmsj.2015-034

38. Berrisford P, Källberg P, Kobayashi S, et al. Atmospheric conservation properties in ERA-Interim. *Q J Roy Meteorol Soc.* 2011;137(659):1381-1399. https://doi.org/10.1002/qj.864

39. Rayner NA, Parker DE, Horton EB, et al. Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *J Geophys Res.* 2003;108(D14):4407. https://doi.org/10.1029/2002jd002670

40. Wang XL. Penalized maximal F test for detecting undocumented mean shift without trend change. *J Atmos Oceanic Tech.* 2008;25(3):368-384. https://doi.org/10.1175/2007jotecha982.1

41. Dai A, Wang J, Thorne PW, Parker DE, Haimberger L, Wang XL. A new approach to homogenize daily radiosonde humidity data. *J Climate.* 2011;24(4):965-991. https://doi.org/10.1175/2010jcli3816.1

42. Wang YX, Chen H, Wu Y, Feng Y, Pu Q. New techniques for the detection and adjustment of shifts in daily precipitation data series. *J Appl Meteorol Climatol.* 2010;49(12):2416-2436. https://doi.org/10.1175/2010jamc2376.1

43. Bloom A, Kotroni V, Lagouvardos K. Climate change impact of wind energy availability in the Eastern Mediterranean using the regional climate model PRECIS. *Natural Hazards and Earth System Sciences (NHESS) & Discussions (NHESSD).* 2008. https://doi.org/10.5194/nhess-8-1249-2008

44. Nolan P, Lynch P, McGrath R, Semmler T, Wang S. Simulating climate change and its effects on the wind energy resource of Ireland. *Wind Energy.* 2012;15(4):593-608. https://doi.org/10.1002/we.489
45. Cosseron A, Schlosser CA, Gunturu UB. Characterization of the wind power resource in Europe and its intermittency. *Energy Procedia*. 2013;40:58-66. https://doi.org/10.1016/j.egypro.2013.08.008

46. Elliott D. Adjustment and analysis of data for regional wind energy assessments. *Workshop on Wind Climate*. Asheville, North Carolina: 1979; 121-131

47. Hueging H, Haas R, Born K, Jacob D, Pinto JG. Regional changes in wind energy potential over Europe using regional climate model ensemble projections. *J Appl Meteorol Climatol*. 2013;52(4):903-917. https://doi.org/10.1175/jamc-d-12-086.1

48. Tobin I, Vautard R, Balog I, et al. Assessing climate change impacts on European wind energy from ENSEMBLES high-resolution climate projections. *Clim Change*. 2014;128(1-2):99-112. https://doi.org/10.1007/s10584-014-1291-0

49. Justus CG, Mikhail A. Height variation of wind speed and wind distributions statistics. *Geophys Res Lett*. 1976;3(5):261-264. https://doi.org/10.1029/GL003i005p00261

50. Duchon CE. Lanczos filtering in one and two dimensions. *J Appl Meteorol*. 1979;18(8):1016-1022. https://doi.org/10.1175/1520-0450(1979)018<1016:Lfoat>2.0.CO;2

51. North GR, Bell TL, Cahalan RF, Moeng FJ. Sampling errors in the estimation of empirical orthogonal functions. *Mon Weather Rev*. 1982;110(7):699-706. https://doi.org/10.1175/1520-0493(1982)110<0699:Seiteo>2.0.CO;2

52. Chen ZY, Dong WL, Gao H, et al. Statistical Bulletin on Capacity of Wind Power in China in 2017. Beijing, China: CWEA.

53. Xie S-P, Hu K, Hafner J, et al. Indian Ocean capacitor effect on Indo-Western Pacific climate during the summer following El Niño. *J Climate*. 2009;22(3):730-747. https://doi.org/10.1175/2008jcli2544.1

54. Annamalai H, Liu P, Xie S-P. Southwest Indian Ocean SST variability its local effect and remote influence on Asian monsoons. *J Climate*. 2005;18(20):4150-4167. https://doi.org/10.1175/JCLI3533.1

55. Watanabe M, Jin F-F. A moist linear baroclinic model: coupled dynamical-convective response to El Niño. *J Climate*. 2003;16(8):1121-1140. https://doi.org/10.1175/1520-0442(2003)16<1121:ALBMC>2.0.CO;2

56. Yang J, Liu Q, Xie S-P, Liu Z, Wu L. Impact of the Indian Ocean SST basin mode on the Asian summer monsoon. *Geophys Res Lett*. 2007;34(2):L02708. https://doi.org/10.1029/2006gl028571

57. Hu Z-Z. Interdecadal variability of summer climate over East Asia and its association with 500 hPa height and global sea surface temperature. *J Geophys Res Atmos*. 1997;102(D16):19403-19412. https://doi.org/10.1029/97jd01052

58. Wu B, Zhou T, Li T. Seasonally evolving dominant interannual variability modes of east Asian climate*. *J Climate*. 2009;22(11):2992-3005. https://doi.org/10.1175/2009jcli2710.1

59. He C, Zhou T, Wu B. The key oceanic regions responsible for the interannual variability of the western North Pacific subtropical high and associated mechanisms. *J Meteorol Res*. 2015;29(4):562-575.

60. Xie S-P, Kosaka Y, Du Y, Hu K, Chowdary JS, Huang G. Indo-western Pacific Ocean capacitor and coherent climate anomalies in post-ENSO summer: a review. *Adv Atmospheric Sci*. 2016;33(3):411-432.

61. Wu B, Li T, Zhou T. Relative contributions of the Indian Ocean and local SST anomalies to the maintenance of the Western North Pacific anomalous anticyclone during the El Niño decaying summer. *J Climate*. 2010;23(11):2974-2986.

62. Li T, Wang B, Wu B, Zhou T, Chang C-P, Zhang R. Theories on formation of an anomalous anticyclone in western North Pacific during El Niño: a review. *J Meteorol Res*. 2018;31(6):987-1006.

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