Evaluation and Projection of Surface Wind Speed Over China Based on CMIP6 GCMs

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Abstract Surface wind speed has great impacts on the economy, environment, and society around the world. Based on 24 global climate models (GCMs) from Coupled Model Intercomparison Project Phase 6 (CMIP6), this paper assesses the historical surface wind speed over China, and quantifies the advancements of CMIP6 over CMIP5. In addition, future changes of surface wind speed under the Shared Socioeconomic Pathway scenarios of 1.2, 2.4, and 5.8 (SSP1-2.6, SSP2-4.5, and SSP5-8.5) are also provided, using 18 out of the 24 models with all three scenarios. Results show that multimodel ensemble mean of CMIP6 can well capture the spatial distributions of the annual, summer, and winter surface wind speed and generally performs better than both the median of the individual CMIP6 GCMs and multimodel ensemble mean of CMIP5 in monthly, seasonal, and annual wind climatology. However, CMIP6 GCMs fail to reproduce the observed decreasing trends, in terms of magnitude and/or sign. Meanwhile, the annual cycle of the surface wind speed simulated by CMIP6 GCMs falsely demonstrates the maximum in winter instead of spring. In the context of global warming, surface wind speed is projected to decrease in most parts of China in the middle and late 21st century under the three scenarios. Moreover, the trends of wind speed averaged over China will decrease significantly in both annual and winter under all three scenarios, but it will increase significantly in summer under SSP5-8.5.

1. Introduction

The wind climate has a major impact on water cycles (McMahon et al., 2013; Rayner, 2007; Roderick et al., 2007), the wind energy industry (Ding et al., 2020; Kulkarni & Huang, 2014; Tian et al., 2019; Zeng et al., 2019), and wind-related natural disasters, such as tornados, typhoons (Cao & Wang, 2013; Tamura et al., 2019), and storm surges (Debernard & Røed, 2008). Therefore, it is of great importance to understand the changes of the wind speed, especially for China with the largest new and cumulative wind power capacities in the world (Renewables, 2019; Sönnichsen, 2020).

Under the context of global climate change, the changes in pattern and strength of surface wind speed have been observed across the globe (Zeng et al., 2019) and in some local areas, such as the contiguous United States (Pryor et al., 2009; Pryor & Ledolter, 2010), Canada (Tuller, 2004; Wan et al., 2010), Sweden (Molina et al., 2014), Czech Republic (Brázdil et al., 2009), Spain and Portugal (Azorin-Molina et al., 2014), Australia (McVicar et al., 2008; Troccoli et al., 2012), and China (Fu et al., 2011; Guo et al., 2011; Jiang, Luo, Zhao, & Tao, 2009). Results from the studies reported the decreasing of surface wind speed (termed “global stilling”) over the globe and the specific regions. But recently, a reversal in global stilling is reported by Zeng et al. (2019), and they found that the rebound of surface wind speed has increased the potential global wind energy by 17 ± 2% during 2010–2017.

Global climate model (GCM) is the primary tool to investigate climate change. It has been extensively used especially after the Coupled Model Intercomparison Project (CMIP) came into operation, which aims to understand the past climate changes, make projections, and estimate future uncertainty. The models participating in Phases 3 and 5 of CMIP (CMIP3 and CMIP5) (Meehl et al., 2007; Taylor et al., 2012) have been widely used in recent decades. For example, by using four CMIP3 GCMs, small changes in the annual maximum daily wind speed over the Netherlands were projected under the Special Report on Emissions Scenarios (SRES) A1B, A2, and B1 (van den Hurk et al., 2007). De Winter et al. (2013) and Kumar et al. (2014) used CMIP5 GCMs to investigate the annual maximum wind speed and its return value in the North Sea and globally, respectively. In addition, significant decreases of the mean surface wind speed in the northern
Indian Ocean (IO) under 4.5 and 8.5 Representative Concentration Pathway scenarios (RCP4.5 and RCP8.5) in the middle and late 21st century are reported by Mohan and Bhaskaran (2019). Over the Bay of Bengal region, it is found that the CMIP5 models fail to represent the current wind climate satisfactorily (Krishnan & Bhaskaran, 2019). The relatively poor skill especially for the long-term temporal trends over the Northern Hemisphere is also found in Tian et al. (2019).

The surface wind speed over China was also investigated. For instance, Chen et al. (2012) assessed the performance of nine CMIP5 GCMs in simulating the surface wind speed during 1971–2005 and found that all the models tend to underestimate the interannual variability and fail to reproduce the observed decline trend. By comparing the climatology of the East Asian winter monsoon simulated by 41 CMIP5 and 24 CMIP3 GCMs, Wei et al. (2013) revealed that CMIP5 models perform better in simulating the near-surface wind speed. Jiang et al. (2017, 2018) and Jiang, Luo, and Zhao (2009) applied CMIP3 and CMIP5 GCMs to validate and project the surface wind speed over China, and the results show that these GCMs can capture the spatial patterns of annual and seasonal mean wind speed, but underestimate their decline trends.

The Phase 6 of CMIP (CMIP6) is in process (Eyring et al., 2016), with 112 GCMs from 33 institutions worldwide participating in it. Compared with CMIP5, the most evident difference in CMIP6 is the choice of new future scenarios, with the combination of radiative forcing levels of the RCPs used in CMIP5 and the Shared Socioeconomic Pathways (SSPs) (O’Neill et al., 2016). For example, SSP1-2.6, SSP2-4.5, and SSP5-8.5 in CMIP6 share similar 2,100 radiative forcing levels with RCP2.6, RCP4.5, and RCP8.5 scenarios in CMIP5, which represent the low-, medium-, and high-emission scenarios, respectively, reaching ~2.6, ~4.5, and ~8.5 W/m² radiative forcing at stabilization in 2100. Moreover, compared with those in CMIP5, GCMs participating in CMIP6 have finer resolutions and more complicated physical processes. With the availability of the state-of-the-art GCMs, some researchers have analyzed the simulations in China, including the mean climate and climate extremes (Wang et al., 2019; Xin et al., 2020; Zhou et al., 2020). However, few comprehensive studies on the surface wind speed over China have been conducted. In addition, compared to other climate variables, such as temperature and precipitation, wind speed has received less attention, partly due to the relatively poor representation of wind speed in the reanalysis data sets (Miao et al., 2020; Torralba et al., 2017; Yu et al., 2019; Zeng et al., 2019) and the scarcity of high-quality observation data sets.

The remainder of this paper is organized as follows. Section 2 describes the data sets and methods. Comparison of the present-day surface wind speed between CMIP5 and CMIP6 GCMs, and projection of surface wind speed based on the CMIP6 models are provided in section 3. Section 4 presents the key conclusions and discussions.

## 2. Data and Methods

### 2.1. Data

Currently, the outputs of 24 GCMs about monthly historical surface wind speed are provided in the CMIP6 archive (https://esgf-node.llnl.gov/search/cmip6/). However, in terms of the three ScenarioMIP experiments (SSP1-2.6, SSP2-4.5, and SSP5-8.5, which represent low-, medium-, and high-emission scenarios, respectively), the outputs are only available for 18, 19, and 19 CMIP6 GCMs, respectively. BCC-ESM 1, GISS-E2-1-G, GISS-E2-1-H, MCM-UA-1-0, and MPI-ESM 1-2-HAM lack the simulations under both the SSP2-4.5 and SSP5-8.5 scenarios, and GFDL-CM4 lacks the simulations under all the three SSPs scenarios. Therefore, 18 CMIP6 GCMs with all the three scenarios are used for projection in this study.

Historical simulations of monthly surface wind speed from 37 CMIP5 GCMs (obtained from https://esgf-node.llnl.gov/search/cmip5/) are used to evaluate the potential improvements in CMIP6. Table 1 lists a brief introduction of the institution, country, and horizontal resolution of each GCM in CMIP5 and CMIP6, indicating generally finer resolutions in CMIP6 GCMs. To ensure all the GCMs weighted equally in the multimodel statistics, only one realization “r1i1p1f1,” which means the first realization (r1), first initialization (i1), first physics and first forcing (p1f1), from the CMIP6 GCM and “r1i1p1” from the CMIP5 GCM are used.

A high-quality gridded 10 m wind speed monthly observation data set of CN05.1 is used to assess the GCMs in simulating the present-day surface wind (Wu & Gao, 2013). This dataset is constructed based on the
Table 1
List of 37 CMIP5 and 24 CMIP6 GCMs Used in This Study

| Institute/country | CMIP5 model | CMIP5 model horizontal resolution (longitude × latitude) | CMIP6 model | CMIP6 model horizontal resolution (longitude × latitude) |
|-------------------|-------------|----------------------------------------------------------|-------------|----------------------------------------------------------|
| Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM)/Australia | ACCESS1-0 | 192 × 144 | ACCESS-CM2 | 192 × 145 |
| Beijing Climate Center (BCC)/China | BCC-CSM1-1 | 128 × 64 | BCC-ESM 1 | 128 × 64 |
| Beijing Normal University (BNU)/China | BNU-ESM | 128 × 64 | — | — |
| Chinese Academy of Meteorological Sciences (CAMS)/China | — | — | CAMS-CSM1-0 | 320 × 160 |
| Canadian Centre for Climate Modelling and Analysis (CCCMA)/Canada | CanESM2 | 128 × 64 | CanESM5 | 128 × 64 |
| Centro Euro-Mediterraneo per I Cambiamenti Climatici (CMCC)/Italy | CMCC-CESM | 96 × 48 | — | — |
| Centre National de Recherches Météorologiques (CNRM)/France | CNRM-CM5 | 256 × 128 | — | — |
| EC-Earth Consortium/Europe | — | — | EC-Earth3 | 512 × 256 |
| Institute of Atmospheric Physics (IAP)/China | HadCM3 | 96 × 72 | — | — |
| Geophysical Fluid Dynamics Laboratory (GFDL)/United States | GFDL-CM2.1 | 144 × 90 | GFDL-CM4 | 288 × 180 |
| Goddard Institute for Space Studies (GISS)/United States | GISS-E2-H | 144 × 90 | GISS-E2-1-H | 144 × 90 |
| Met Office (UKMO)/United Kingdom | HadGEM2-AO | 192 × 144 | KAGE-1-0-G | 192 × 144 |
| Institute for Numerical Mathematics (INM)/Russia | INM-CM4 | 180 × 120 | INM-CM4-8 | 180 × 120 |
| Institute Pierre-Simon Laplace (IPSL)/France | IPSL-CM5A-LR | 96 × 96 | IPSL-CM5A-LR | 144 × 143 |
| National Institute of Meteorological Sciences (NIMS)/South Korea | HadGEM2-AO | 192 × 144 | KAGE-1-0-G | 192 × 144 |
| University of Arizona (UA)/United States | MIROC4h | 640 × 320 | MIROC6 | 256 × 128 |
| Model for Interdisciplinary Research on Climate (MIROC)/Japan | MIROC5 | 256 × 128 | MIROC-ESM | — |
| Max Planck Institute (MPI) for Meteorology/Germany | MPI-ESM1-2-LR | 192 × 96 | — | — |
| Meteorological Research Institute (MRI)/Japan | MRI-ESM2 | 320 × 160 | — | — |
| Nanyang University of Information Science and Technology (NUIST)/China | NorESM1-M | 144 × 96 | — | — |
| Norwegian Climate Centre/China | NorESM1-ME | 144 × 96 | — | — |

“anomaly approach” interpolation, with observations from 2,416 meteorological stations through quality control procedures and homogenization. Specifically, a gridded climatology was first calculated using thin-plate smoothing splines, and then the daily anomalies at stations are interpolated to grids using an angular weighting method. Adding the daily anomalies to the climatology produces the final gridded data (Shi et al., 2018).
CN05.1 comprises eight variables, including daily mean, maximum and minimum temperature, precipitation, wind speed, evaporation, relative humidity, and sunshine durations. Previous studies have shown that CN05.1 is comparable to CN05 (Xu et al., 2009), EA05 (Xie et al., 2007), and APHRO (Yatagai et al., 2009) and is widely used in the validation of climate models over China (Luo et al., 2020; Xu et al., 2018; Zhou et al., 2019).

The analysis on wind speed from CN05.1 is similar to other observations, such as the Global Surface Summary of Day (GSOD) and HadISD (Dunn et al., 2014). As shown in supporting information Figure S1, similar spatial patterns of surface wind speed can be found in the three datasets, including high values in northern China and low values over the Sichuan Basin, south edge of Yunnan Province, and southeastern China. This spatial pattern is consistent with that in Miao et al. (2020). Similar interannual variation and approximate values are also observed in the temporal evolution of these datasets, with the correlation coefficients between CN05.1 and HadISD/GSOD are 0.97/0.96, respectively, with \( p < 0.01 \) (Figure S2). But due to their relative sparse stations and short periods over China, especially over western China, GSOD and HadISD are not used in this study.

2.2. Methods

Since the CMIP5 and CMIP6 GCMs and CN05.1 have different horizontal resolutions ranging from \( \sim 0.7 \times \sim 0.7^\circ \) (latitude \( \times \) longitude) to 3.75 \( \times \) 3.75\(^\circ\) (latitude \( \times \) longitude), to facilitate the comparison, they are interpolated to a common 1 \( \times \) 1\(^\circ\) (latitude \( \times \) longitude) grid, using a bilinear (for low-resolution GCMs) or an area-weighted (for high-resolution GCMs and CN05.1) interpolation algorithm (Jiang et al., 2016).

Considering the temporal coverage of CN05.1 and CMIP5 and CMIP6 GCMs, the period of 1961–2005 is selected for evaluation. For the projections, only the CMIP6 outputs are used, and the periods of 1995–2014, 2046–2065, and 2080–2099 are chosen to represent the present-day, middle and late 21st century, respectively.

The Mann-Kendall (Kendall, 1948; Mann, 1945) test with Sen’s (1968) slope estimates is used to estimate trends in seasonal and annual mean wind speed, which has been widely used in wind analysis (Dadasercelik & Cengiz, 2014; Li et al., 2018; You et al., 2014). \( P < 0.05 \) is used to judge whether a trend is statistically significant. The metrics, including pattern correlation coefficient, absolute bias, and root-mean-square error (RMSE) between the observation (CN05.1) and the two CMIP data sets, are used to evaluate the models’ performance.

In assessing the monthly, seasonal, and annual mean wind speed over China, a normalized RMSE, similar to the relative error defined by Gleckler et al. (2008), is applied in this study. The normalized RMSE (RMSE\(^\prime\)) is defined as follows:

\[
\text{RMSE}' = \frac{\text{RMSE}}{\text{RMSE}_{\text{median}}}
\]

The RMSE’s are calculated for each model (or multimodel ensemble) at each time slice. RMSE\(_{\text{median}}\) is the median of all models at a certain time slice. A lower value of the RMSE\(^\prime\) indicates a better performance, and vice versa. Specifically, a model’s RMSE\(^\prime\) at a certain time slice less than 1 indicates that the RMSE is less than the median RMSE of all the models at the same time slice.

In assessing the spatial distribution over China, empirical orthogonal function (EOF) analyses are applied. First, we calculate the RMSEs between the first four EOF modes of the simulations in each model and the first one leading mode (EOF1) of the observation, respectively. Then, the EOFs with the minimal RMSEs are selected. In addition, the skill scores are calculated based on the reciprocals of RMSEs to evaluate the GCMs’ skills in both the spatial distribution and temporal evolution of wind speed.

3. Results

3.1. Changes of Surface Wind Speed During 1961–2005

The spatial distributions of annual, summer (June-July-August, JJA), and winter (December-January-February, DJF) surface wind speed derived from the observation and the ensemble means of CMIP5 and CMIP6 models (referred as MME_5 and MME_6 hereafter) during 1961–2005 over China are shown in
Figure 1. The high values (>5 m/s) of annual mean surface wind speed are observed over the Tibetan Plateau, and the low values (<2 m/s) are mostly observed over the Sichuan Basin and southeastern China (Figure 1a). This result is consistent with previous studies (Guo et al., 2011; Jiang, Luo, Zhao, & Tao, 2009). Overall, the observed spatial patterns of summer and winter surface wind speed are quite similar to that of the annual mean (Figures 1a–1c). The main differences between the annual and summer (winter) surface wind speed are higher (lower) values over the most part of Xinjiang Province and lower (higher) values over the northern part of the Tibetan Plateau in summer (winter) compared to that in the annual mean (Figures 1b and 1c).

The MME_5 and MME_6 well reproduce the spatial patterns of annual and winter surface wind speed, characterized by high values in the Tibetan Plateau and Inner Mongolia. The spatial correlation coefficients of annual, summer, and winter surface wind speed in MME_5 are 0.74, 0.56, and 0.79, respectively, while those in MME_6 are 0.76, 0.68, and 0.80, respectively. However, the ensembles underestimate the annual mean surface wind speed over the whole China, with a maximum less than 4 m/s (Figures 1d and 1g). The summer surface wind speed is also underestimated over the whole country, with high values (2–3 m/s) in the central Xinjiang Province and the central and southern Tibetan Plateau (Figures 1e and 1h). In DJF, the underestimation is mainly found in the south of the Yellow River (Figures 1f and 1i). MME_6 has a better performance than MME_5, especially in DJF.

Figure 2 presents the spatial patterns of annual, summer, and winter surface wind speed trends during 1961–2005 from the observation, MME_5, and MME_6. The observed surface wind speed decreases significantly in most parts of China, with large decreasing trends (−0.3 (m/s)/decade) in western China between 30°N and 40°N, east of 110°E (Figures 2a–2c). MME_5 and MME_6 show their poor ability to reproduce the trends, with the magnitudes ranging from −0.05 (m/s)/decade to 0.05 (m/s)/decade. MME_5 simulates increasing...
trends of annual and winter surface wind speed in north of the Yangtze River and southeastern coasts, while it simulates decreasing trends in most parts of western China and south of the Yangtze River (Figures 2d and 2f). In JJA, MME_5 simulates a positive trend extending from northeastern China to southwestern China and a negative trend over west of 110°E and along the southeastern coasts, where the observed trends are both negative (Figure 2e). Compared to MME_5, the area with decreasing trend in MME_6 expands but still differs from the observation (Figures 2g–2i). Generally, the surface wind speed trends are not well simulated by the CMIP3 (Jiang, 2009), CMIP5 (Chen et al., 2012; Tian et al., 2019), and the new generation models of CMIP (CMIP6), which is maybe caused by the following: (1) The surface boundary conditions of CMIP GCMs do not include surface roughness, which can increase the friction force on the surface and weaken the wind speed due to urbanization, the trees and forest, and other types of underlying surface (Vautard et al., 2010), and (2) the current GCMs have a relatively low ability to represent some features of the atmospheric flow (Chen et al., 2012). For example, the CMIP5 GCMs fail to reproduce the slowed East Asia monsoon (Saha et al., 2014), which may result in the decline trend of surface wind speed in China (Jiang et al., 2017).

The monthly surface wind speed averaged over China is evaluated and presented in Figure 3. The observed surface wind speed shows distinct seasonal variations, with the strongest wind in spring (a maximum of 3.7 m/s in April) and the weakest wind in autumn (a minimum of 2.7 m/s in September), which is consistent with Guo et al. (2011). While both the MME_5 and MME_6 simulations show peaks in January (2.5 m/s in MME_5 and 2.4 m/s in MME_6) and troughs in June (1.4 m/s in MME_5 and 1.5 m/s in MME_6). The values from March to October in MME_6 are closer to the observations than MME_5. The medians of CMIP6 simulations (lines in the boxes) show a minimum (1.4 m/s) in June and a maximum (2.3 m/s) in January. Generally, the interquartile model spreads (boxes) and the full intermodel ranges (whiskers) of the CMIP6 GCMs are larger in winter and smaller in May and September. This result indicates the larger uncertainties in winter and the relatively smaller uncertainties in the transition months (May and September).

Figure 4 presents the relative RMSEs of the monthly, seasonal, and annual mean surface wind speed in the 24 CMIP6 GCMs, MME_5, and MME_6 during 1961–2005 over China. Among the individual CMIP6 GCMs,
CAMS-CSM1-0 performs the best, followed by MPI-ESM1-2-LR, while GFDL-ESM 4, GISS-E2-1-G, INM-CM5-0, KAGE-1-0-G, and MIROC6 perform poorly in all the months, seasons, and the annual mean. The performance of MME_5 and MME_6 is better than compared to most individual models, which confirms the finding of Tebaldi and Knutti (2007): The multimodel mean or median can partly cancel the errors, resulting in a better performance. In addition, MME_5 and MME_6 show similar relative RMSEs in most months, seasons, and annual mean, except in May, July, and autumn (September-October-November) with lower values in MME_6, which indicates the better performance of CMIP6 models.

To quantify the agreement between the individual CMIP6 GCMs and the observation, pattern correlation coefficients, biases, and RMSEs of the annual mean surface wind speed are calculated during 1961–2005 (Table 2). Several GCMs exhibit better agreements (smaller biases/ RMSEs and higher correlations) with the observation, including BCC-CSM2-MR, CAMS-CSM1-0, CanESM5, FGOALS-f2-L, and MRI-ESM2-0. Note that three of them (BCC-CSM2-MR, CAMS-CSM1-0, and FGOALS-f2-L) are from China, and developed by National/Beijing Climate Center, Chinese Academy of Meteorological Sciences, and Institute of Atmospheric Physics, respectively. MIROC6 has a high correlation (0.76), but it simulates the largest bias (−1.86). GISS-E2-1-G and KACE-1-0-G generate large negative biases (≤−1.80 m/s) and RMSEs (>2). The only positive bias appears in FGOALS-f3-L. In general, the GCMs with large biases also have large RMSEs. Compared to the individual models, MME_5 and MME_6 show high correlations and relatively small biases and RMSEs, and MME_6 performs better.

Figure 3. Boxplots of monthly mean surface wind speed (units: m/s) during 1961–2005 over China from CMIP6 models. Red, green, and orange dots indicate the monthly mean wind speeds from the observation, and ensemble means of CMIP5 and CMIP6, respectively.

Figure 4. The monthly, seasonal, and annual mean relative root-mean-square errors during 1961–2005 over China simulated by individual CMIP6 models, and ensemble means of CMIP5 and CMIP6.
The pattern correlation coefficients, biases, and RMSEs in JJA and DJF are also calculated and shown in Table 2. The correlation coefficients in most individual CMIP6 GCMs are lower in JJA than those in annual, except for the simulations of ACCESS-ESM 1-5, MPI-ESM 1-2-HAM, and NESM3 (Table 2). In addition, different from the positive correlation coefficients in all of the models in annual mean, INM-CM4-8 and INM-CM5-0 show negative correlations. In general, ACCESS-ESM1-5, CAMS-CSM1-0, and MRI-ESM 2-0 perform better among the CMIP6 models. MCM-UA-1-0 is the only one model with positive bias. Considering the multimodel ensemble, MME_6 shows higher correlation and smaller bias and RMSE than MME_5, which is the same as that in the annual mean. As shown in Table 2, most individual CMIP6 GCMs have better performance in DJF than those in both annual and JJA, with higher correlations and smaller biases/RMSEs. In terms of multimodel ensemble, the bias in MME_5 is smaller than that in MME_6, which differs from the conditions of annual and summer simulations.

To assess the capacity of the individual CMIP6 GCMs in simulating the surface wind speed during 1961–2005 comprehensively, we calculate and rank the spatial scores based on the RMSEs of climatology and EOFs, as well as the temporal scores based on the RMSEs of annual cycles and interannual variabilities (Figure 5). The ability of the individual CMIP6 GCMs varies in capturing the spatial and temporal characteristics of the surface wind speed over China. In both the spatial and temporal ranks, CAMS-CSM1-0, FGOALS-f3-L, BCC-CSM2-MR, and MCM-UA-1-0 show better skills, while GISS-E2-1-G presents lower skills. The skill scores of MME_6 are higher than MME_5 in both ranks, suggesting the advancements of MME_6 in reproducing both the spatial and temporal features of surface wind speed. Note that both MMEs score high in the spatial ranks, but medium in the temporal ranks.

Over all, CAMS-CSM1-0 performs best based on the analysis. For the model, the atmospheric component of it is modified from ECMWF-HAMburg (ECHAM5 [v5.4]), but two major revisions have been made: (1) In the
passive tracer transport, a Two-step Shape Preserving Advection Scheme is employed to reduce precipitation overestimation over the Tibetan Plateau’s southern edges (Yu, 1994; Yu et al., 2015), and (2) a correlated $k$-distribution scheme is used for radiation transfer parameterization, this scheme can greatly improve the performance of GCMs to simulate terrestrial energy balance (Zhang, Shi, et al., 2006; Zhang, Suzuki, et al., 2006). These modifications may contribute to the good performance of CAMS-CAMS1-0 over China.

3.2. Projection of Surface Wind Speed in the 21st Century

Figures 6a–6f display the spatial distributions of the projected changes in the annual mean surface wind speed over China in the middle and late 21st century under SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios. Significant decreases in surface wind speed can be found, with higher magnitude and larger area under high-emission scenarios. Specifically, under SSP1-2.6, surface wind speed increases mainly over Inner Mongolia, northwestern China, and on the southern boundary of the Tibetan Plateau, while decreases over Northeast China, East China, the Tarim Basin, and most parts of the Tibetan Plateau in the middle and late 21st century (Figures 6a and 6d). The area with large increase of surface wind speed (>0.1 m/s) over northern Northwest China during 2046–2065 (Figure 6a) will expand to northern Inner Mongolia during 2080–2099 (Figure 6d). The decrease of surface wind speed (<−0.1 m/s) is found in south of the Yangtze River and southwestern China in the mid-21st century, with good agreement among the simulations (Figure 6a), and mainly along the Yangtze River, southeastern coast, and the western boundary of the Tibetan Plateau in the late-21st century (Figure 6d).

Under SSP2-4.5, the spatial patterns of surface wind speed changes in the two periods of 2046–2065 and 2080–2099 are similar (Figures 6b and 6e), characterized by an increase over Inner Mongolia, northern Northwest China, and the southwestern North China Plain and a decrease over northern Northeast China, the Sichuan Basin, and the south of the Yangtze River. Under SSP5-8.5, the decreased surface wind speed is found over eastern Northeast China and south of 40°N in both periods, with larger magnitude (<−0.3 m/s/decade) over the Tibetan Plateau in the late-21st century (Figures 6c and 6f).

The spatial distributions of the annual mean surface wind speed trends from 2015 to 2099 under the three scenarios are presented in Figures 6g–6i. The magnitude of surface wind speed trend increases with the increasing greenhouse gas emissions. Under SSP1-2.6, a relatively small decreasing trend (<−0.01 (m/s)/decade) is found over most parts of China, except for a weak increasing trend in Xinjiang Province, northern Inner Mongolia, and on the southern boundary of China (Figure 6g). Under SSP2-4.5, a significant decreasing trend in the west of 100°E and a significant increasing trend over eastern Northeast China and southern North China Plain are found (Figure 6h). Under SSP5-8.5, besides the regions west of 105°E, significant decreasing trends are also found in the regions extending from the Daxinganling to east of the Great Bend of the Yellow River, with large values (<−0.03 (m/s)/decade) over the Tibetan Plateau, while the projected increasing trend is mainly projected in eastern Northeast China and the regions east of 105°E and south of ~40°N (Figure 6i).
In JJA, the spatial distributions of surface wind speed in the middle and late 21st century are quite similar under SSP1-2.6 and SSP2-4.5 scenarios, characterized by the decreased surface wind speed in Northeast China, the Sichuan Basin, south of the Yangtze River and over the Tibetan Plateau, and the increased wind speed in the northern Xinjiang Province (Figures 7a, 7b, 7d, and 7e). Under SSP5-8.5, compared to mid-21st century, the areas with increased surface wind speed enlarge in the late-21st century, extending from northern Northeast China to East China (Figures 7c and 7f). Furthermore, the surface wind speed trends under SSP1-2.6 and SSP2-4.5 show mixed patterns of increase and decrease over China, with significant increases over the eastern Loess Plateau and Qinling Mountains under both scenarios, and along the southern coast under SSP2-4.5 (Figures 7g and 7h). Under SSP5-8.5, there are significant increasing trends (>0.01 (m/s)/decade) across East China and the northern Tibetan Plateau, and decreasing trends over the northern boundary of China, Northwest China, and the southern Tibetan Plateau with the largest value (<−0.03 (m/s)/decade) (Figure 7i).

In DJF, the surface wind speed is projected to increase over the north of 35°N, and decrease mainly in East China and the southern Xinjiang Province under the three scenarios (Figures 8a–8f). As the greenhouse gas emission increases, the area of increased surface wind speed moves eastward, and the area of the decreased wind speed over the Tibetan Plateau becomes larger (Figures 8b, 8c, 8e, and 8f). Under SSP1-2.6, the decreasing trends in the most parts of China and weak increasing trends over some isolated regions are found (Figure 8g). The spatial distributions of trends under SSP2-4.5 and SSP5-8.5 are similar, demonstrating significant decreasing trends in south of the Yangtze River and over the Tibetan Plateau and significant increasing trends in Northeast China (Figures 8h and 8i). In general, the magnitude of trends is larger under SSP5-8.5, compared to SSP2-4.5.

The temporal evolutions of the annual, summer (JJA), and winter (DJF) surface wind speed averaged over China during 1961–2099 are presented in Figures 9a, 9c, and 9e. The time series of both the annual and
winter wind speeds represent decreasing trends over China during 2015–2099 under the three scenarios, with the largest trends (−0.008 (m/s)/decade in annual mean and −0.012 (m/s)/decade in DJF) under SSP5−8.5 (Figures 9a and 9e). But the interannual variations in DJF are larger than those in annual. Unlike the annual and winter surface wind speeds, the summer surface wind speed shows increasing trends under all the three scenarios, with the largest trend (0.004 (m/s)/decade) under SSP5−8.5, and the anomalies of wind speed are negative (Figure 9c). The trends in annual and DJF under the three scenarios and that in JJA under SSP5−8.5 during 2015–2099 are all significant at the 95% confidence level (Figure 9f). The uncertainties of CMIP6 GCMs in the middle and late 21st century are displayed by boxplots in Figures 9b and 9d. The results show that the interquartile model spreads (boxes) and the full intermodel ranges (whiskers) of the CMIP6 simulations are the smallest in JJA, and the largest in DJF, which is opposite to Jiang (2009) based on CMIP5 models.

4. Summary and Discussion

This paper investigates the performance of CMIP6 GCMs in simulating the historical surface wind speed and projecting its future changes over China. Our key conclusions can be summarized as follows:

1. The multimodel ensemble of CMIP6 GCMs can well capture the observed annual and seasonal spatial pattern of surface wind speed over China. The pattern correlation coefficients are 0.75 in annual, 0.65 in JJA, and 0.80 in DJF, respectively. The MME_6 has a good performance in simulating the monthly, seasonal, and annual mean climatology, and the simulation is better than the median of all the CMIP6 GCMs in each time slice.

2. The MME_6 fails to reproduce the decreasing trends during 1961–2005 over the entire China, with the smaller magnitude of wind decrease and opposite trends over some regions compared with the observation, which is also found in CMIP3 and CMIP5 models (Chen et al., 2012; Jiang, 2009; Tian et al., 2019). The maximum monthly wind speed in MME_6 occurs in winter, which is inconsistent with the observation where the maximum in spring.
3. Comparison with the models from CMIP5 and CMIP6, MME_6 outperforms MME_5 in general, which may be related to the higher resolution and the better representation of physical processes (Eyring et al., 2016).

4. Based on six metrics (relative RMSE, pattern correlation, bias, RMSE, and spatial and temporal scores), CAMS-CSM1-0 performs best in simulating the historical surface wind speed over China among all the CMIP6 GCMs. This model is developed by the Chinese Academy of Meteorological Sciences (CAMS) and consists of several state-of-the-art component models (Rong et al., 2019). Other Chinese GCMs also perform well, including BCC-CSM2-MR and FGOALS-f2-L with large pattern correlation coefficients and small biases/RMSEs.

5. Significant decrease of surface wind speed over the most parts of China is projected in the middle and late 21st century. The decreasing trends are also found over the most part of China under SSP1-2.6 and SSP2-4.5 during 2015–2099, while increasing trends are presented over East China in annual and JJA under SSP5-8.5. With the increase of radiative forcing in projections, surface wind speed trends in annual and winter over the Tibetan Plateau and those in summer over eastern China have larger magnitudes. The distributions of wind speed trends are consistent with those in CMIP3 and CMIP5 models (Jiang et al., 2018).

Since there are still large biases in the simulation of historical surface wind speed in the current CMIP6 GCMs, future wind speed projection should be interpreted with caution, which is directly related to the future wind energy plan. In addition, large uncertainties exist in the simulation and future climate change projection, and are especially problematic at regional and local scales. Although CMIP6 GCMs have finer spatial resolutions and more comprehensive physical processes than their precedents, their performance in capturing the local and regional forcing is still poor, especially in regions with complex terrain like China. This emphasizes the importance of high-resolution regional climate models (RCMs), which show great improvements in representing the fine-scale forcing and terrain over China (e.g., Gao et al., 2001, 2006, 2013; Qian & Leung, 2007; Zou & Zhou, 2013). Therefore, using regional climate models with higher

Figure 8. Same as Figure 6, but for winter (DJF).
resolution may help obtain more reliable information on the climate change over China. Thus, our future work will proceed in this direction.

Data Availability Statement
The CMIP5 and CMIP6 model data used in this work are available from https://esgf-node.llnl.gov/search/cmip5/ and https://esgf-node.llnl.gov/search/cmip6/, respectively. The observational data (CN05.1) used in this paper are available online (https://doi.org/10.5281/zenodo.4150708).

Acknowledgments
This research was jointly supported by the National Key Research and Development Program of China (No. 2017YFA0605002) and the National Natural Science Foundation of China (Nos. 4185063 and 41375104). We also acknowledge the World Climate Research Program’s Working Group on Coupled Modelling, which is responsible for CMIP. And we thank climate modeling groups for producing and making model output available.

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Figure 9. Temporal evolution of (a) annual, (c) summer, and (e) winter wind speed anomaly (units: m/s) over China during 1961–2099 relative to the present day, the ranges of wind speed changes by (b) the middle and (d) late century, and (f) the trends of it (units: (m/s)/decade) during 2015–2099 under SSP1-2.6 (green), SSP2-4.5 (blue), and SSP5-8.5 (red). The star in (f) indicates the significant trends with $p < 0.05$. 

WU ET AL.
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