

Supplementary Information for

Detecting and Calibrating Large Biases in Global Onshore Wind Power Assessment Across Temporal Scales

Chengzhi Hou¹, Zhiwei Xu^{1*}, Kristopher B. Karnauskas^{2,3}, Danqing Huang⁴, Huayu Lu¹

¹School of Geography and Ocean Science, Nanjing University, Nanjing, China

²Department of Atmospheric and Oceanic Sciences, University of Colorado, Boulder, CO,
USA

³Cooperative Institute for Research in the Environmental Sciences, University of Colorado,
Boulder, CO, USA

⁴School of Atmospheric Sciences, Nanjing University, Nanjing, China

*Corresponding author: Zhiwei Xu, Email: zhiweixu@nju.edu.cn

List of Supplementary Items

Supplementary Tables 1 to 4

Supplementary Figures 1 to 20

Supplementary Notes 1 to 3

Supplementary References

19 **Table of contents**

20	Supplementary Tables	4
21	Supplementary Table 1	4
22	Supplementary Table 2	5
23	Supplementary Table 3	6
24	Supplementary Table 4	7
25	Supplementary Figures	8
26	Supplementary Figure 1	8
27	Supplementary Figure 2	9
28	Supplementary Figure 3	10
29	Supplementary Figure 4	11
30	Supplementary Figure 5	12
31	Supplementary Figure 6	13
32	Supplementary Figure 7	14
33	Supplementary Figure 8	15
34	Supplementary Figure 9	16
35	Supplementary Figure 10	17
36	Supplementary Figure 11	18
37	Supplementary Figure 12	19
38	Supplementary Figure 13	20
39	Supplementary Figure 14	21
40	Supplementary Figure 15	22
41	Supplementary Figure 16	23
42	Supplementary Figure 17	24
43	Supplementary Figure 18	25
44	Supplementary Figure 19	26
45	Supplementary Figure 20	27
46	Supplementary Notes	28
47	Supplementary Note 1	28

48	Supplementary Note 2.....	29
49	Supplementary Note 3.....	31
50	Supplementary References	32
51		

Supplementary Tables

Supplementary Table 1 | Summary of previous studies using wind speed data with different temporal resolutions for wind power density (WPD) assessments.

Study	Temporal resolution	Data source	Study Area
Akinsanola et al., 2021 ¹	daily	CMIP6	West Africa
Archer and Jacobson, 2005 ²	daily	Observations	Global
Costoya et al., 2021 ³	daily	RCMs	China South Sea
Gil Ruiz et al., 2021 ⁴	10 min, 1 h	Observations, ERA5	Coastal Colombia
Hayes et al., 2021 ⁵	1 h	ERA5	Europe
Hosking et al., 2018 ⁶	daily	RCMs	Europe
Johnson & Erhardt, 2016 ⁷	3 h	RCMs	USA
Karnauskas et al., 2018 ⁸	monthly	CMIP5	Global
Li D. et al., 2020 ⁹	3 h	GCMs	East Asia
Li M. et al., 2022 ¹⁰	daily	Observations	China
Liu et al., 2019 ¹¹ , 2023 ¹²	6 h	Observations	China
Lu et al., 2009 ¹³	6 h	RCMs	Global
Miao et al., 2020 ¹⁴	monthly	Observations, Climate Reanalysis	Northern Hemisphere
Pryor & Barthelmie, 2011 ¹⁵	3 h	RCMs	USA
Pryor et al., 2005 ¹⁶	30 min	RCMs	USA
Sherman et al., 2017 ¹⁷	1 h	Observations, MERRA	China
Tian et al., 2019 ¹⁸	daily, monthly	Observations, CMIP5	Global

Note: References listed in this table are detailed in the Supplementary References section.

Abbreviations:

GCMs: General Circulation Models

RCMs: Regional Climate Models

CMIP: Coupled Model Intercomparison Project

ERA5: Fifth-generation European Centre for Medium-Range Weather Forecasts atmospheric reanalysis of the global climate

MERRA: Modern-Era Retrospective analysis for Research and Applications

Supplementary Table 2 | Surface roughness lengths (z_0) for different land-use and land-cover types.

Land-use and land-cover (LULC)	z_0 (meter)
Densely populated urban districts	1.6
Tree cover	0.50
Built-up	0.40
Shrubland	0.10
Cropland	0.03
Grassland	0.008
Snow or ice-covered surface	0.003
Open ground with smooth surface, e.g., desert, bare land, sparse vegetation cover	0.0024
Permanent water bodies	0.0002

Note: Values are based on established classifications from previous studies and are used for wind power density (WPD) calculations in this study.

Supplementary Table 3 | Statistical characteristics of the calibration coefficient K (daily-1 hour) for different wind power density (WPD) levels, based on wind speed observational data.

WPD levels (WPL, W m^{-2})	Statistical information of K (daily-1 hour)					
	min	25 th percentile	50 th percentile	75 th percentile	max	mean
0-50	1.15	1.81	2.12	2.61	4.98	2.31
50-100	1.11	1.51	1.65	1.83	4.10	1.71
100-200	1.07	1.39	1.49	1.62	3.50	1.52
200-300	1.07	1.32	1.39	1.48	2.12	1.41
300-400	1.07	1.27	1.33	1.40	2.13	1.34
>400	0.96	1.15	1.21	1.28	1.64	1.22

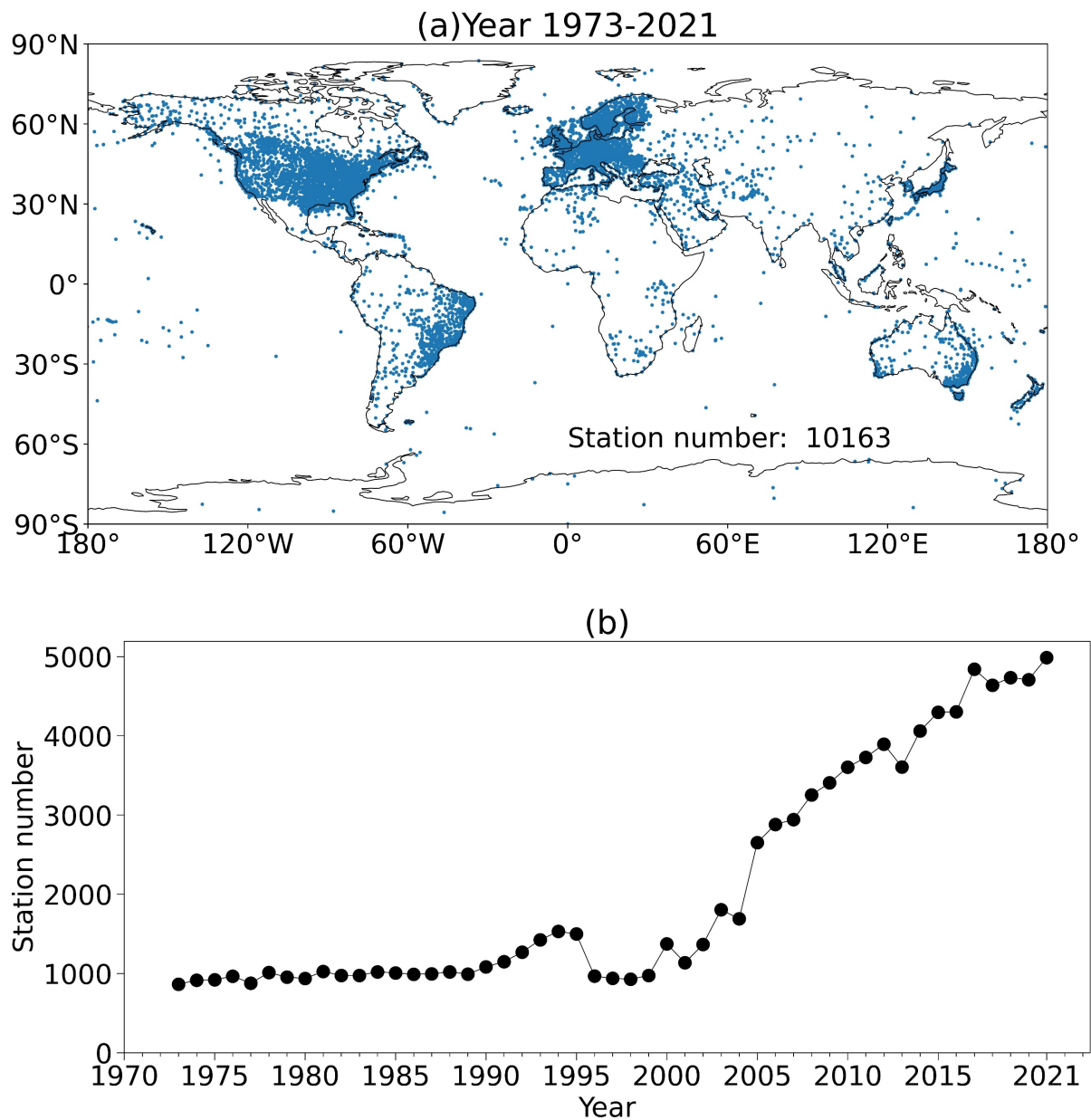
Note: The median value (50th percentile) of K (daily-1 hour) was used for calibration in this study.

Supplementary Table 4 | Statistical characteristics of the calibration coefficient K (daily-3hour) for different wind power density (WPD) levels, based on wind speed data from the fifth-generation European Centre for Medium-Range Weather Forecasts atmospheric reanalysis of the global climate (ERA5).

WPD levels (WPL, W m^{-2})	Statistical information of K (daily-3hour)					
	min	25 th percentile	50 th percentile	75 th percentile	max	mean
I (0-50)	1.00	1.25	1.41	1.73	4.76	1.61
II (50-100)	1.00	1.15	1.20	1.29	2.42	1.24
III (100-200)	1.01	1.13	1.18	1.24	1.98	1.20
IV (200-300)	1.01	1.08	1.12	1.17	2.37	1.14
V (300-400)	1.00	1.06	1.09	1.14	1.51	1.11
VI (>400)	0.53	1.02	1.05	1.09	1.97	1.06

Note: The median value (50th percentile) of K (daily-3hour) was used for calibration in this study.

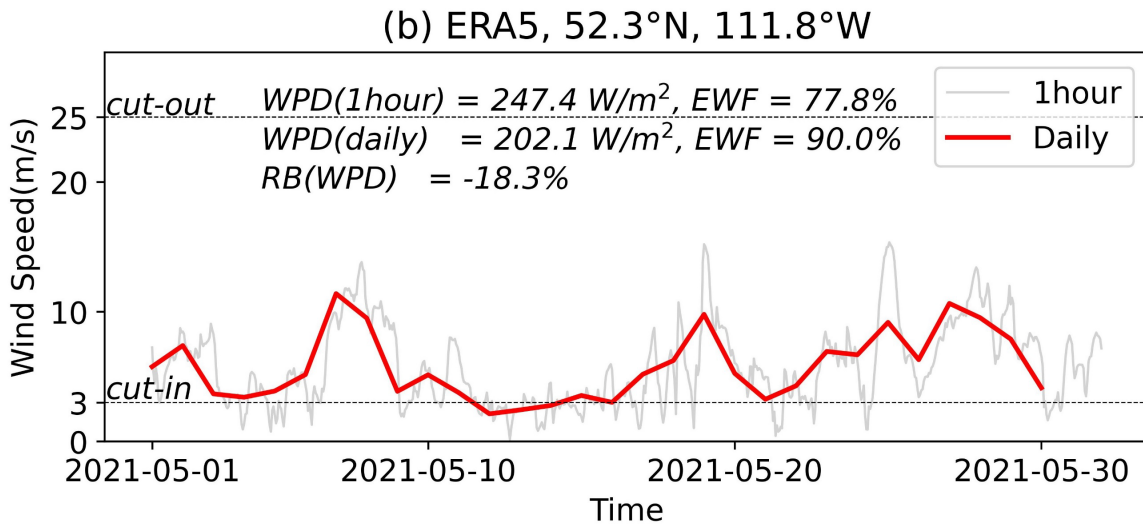
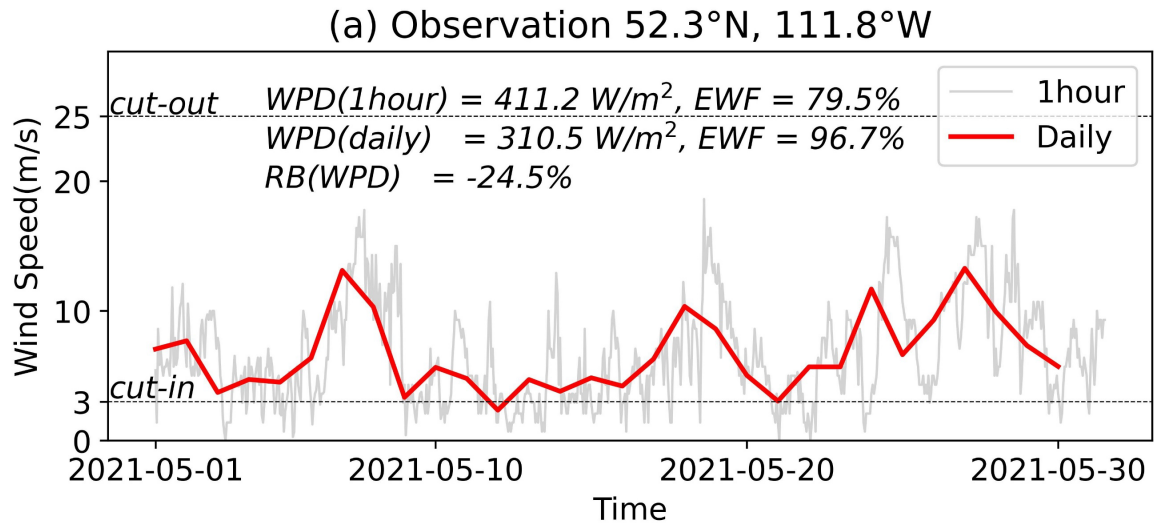
82 **Supplementary Figures**



83

84 **Supplementary Figure 1 | Global distribution of high temporal-resolution wind speed data**
85 **(20-min, 30-min, 1-hour) from the National Climatic Data Center (NCDC). (a)** Spatial
86 distribution of meteorological stations with valid wind speed records from 1973 to 2021. **(b)**
87 Total number of stations from 1973 to 2021.

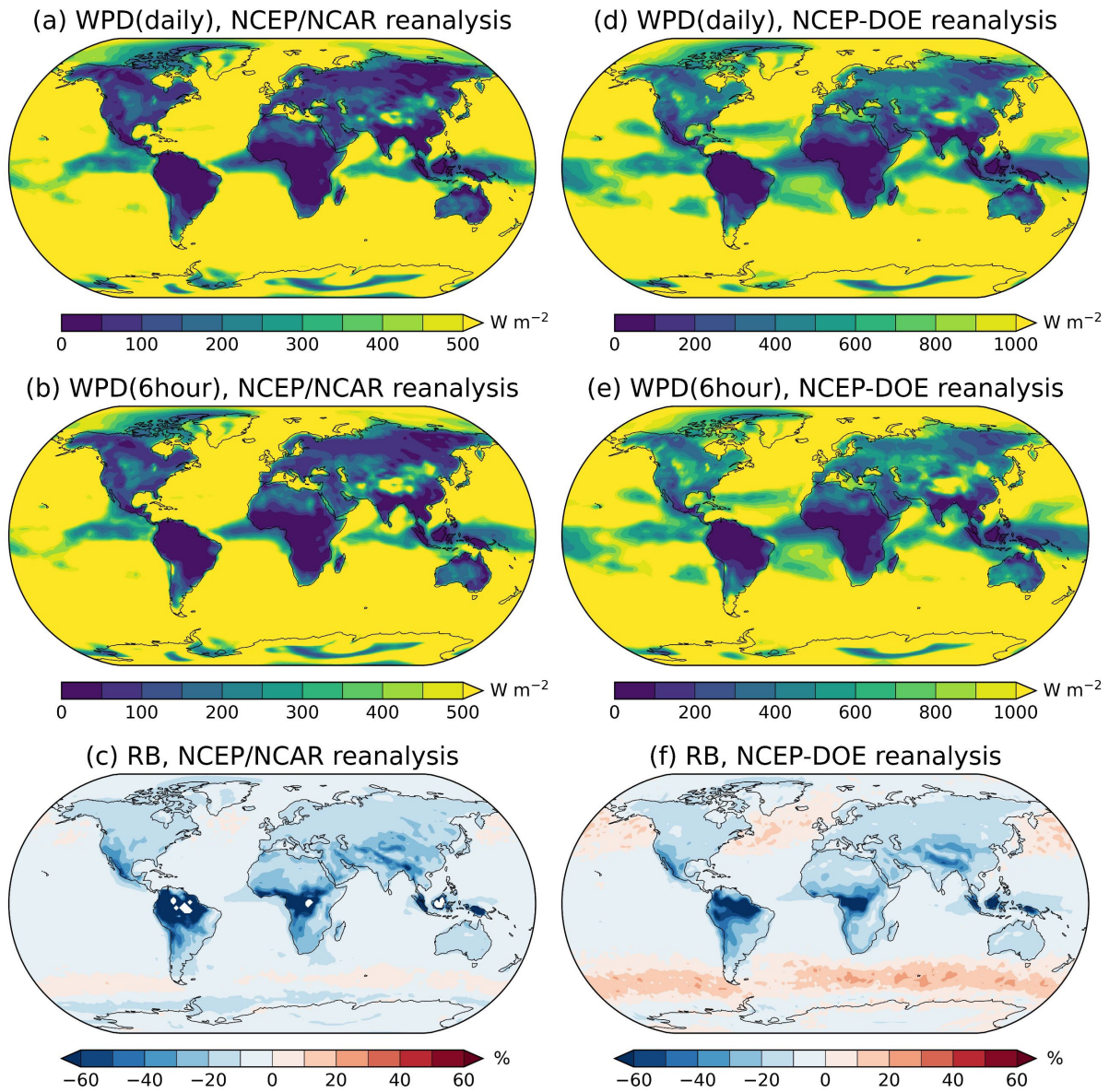
88



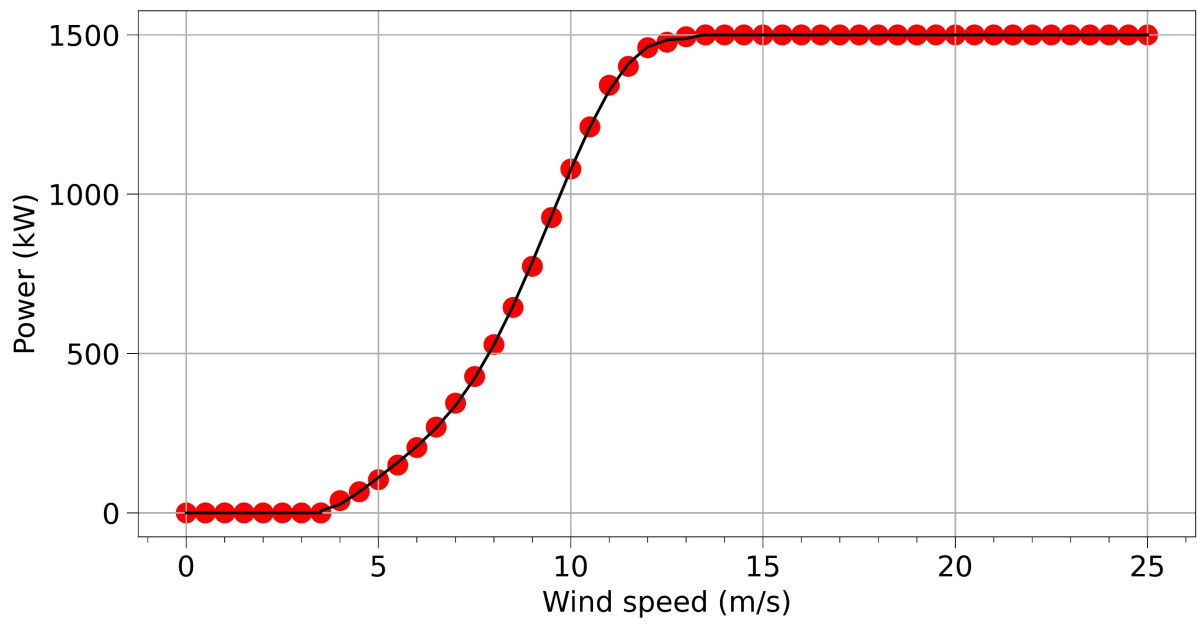
89

90 **Supplementary Figure 2 | Time series of wind speed at the hub height (100 m) for a rural**
 91 **station in southern Canada during May 2021.** (a) Observational wind speed data at the site
 92 (52.3°N, 111.8°W, station ID: 71006099999). (b) Wind speed data for the same location from
 93 the fifth-generation atmospheric reanalysis produced by the European Centre for Medium-
 94 Range Weather Forecasts (ERA5). Note that wind power density (WPD) values in this figure
 95 are calculated for May 2021 only, whereas annual WPD (based on wind speed time series from
 96 2014 to 2021) is presented in [Fig. 2a](#) of the main text. Effective wind frequency (EWF) indicates
 97 the proportion of wind speeds within the operational range between 3 m s^{-1} (cut-in speed) and
 98 25 m s^{-1} (cut-off speed). Relative bias (RB, %) quantifies the underestimation of WPD when
 99 using daily versus 1-hour wind speed data at this site.

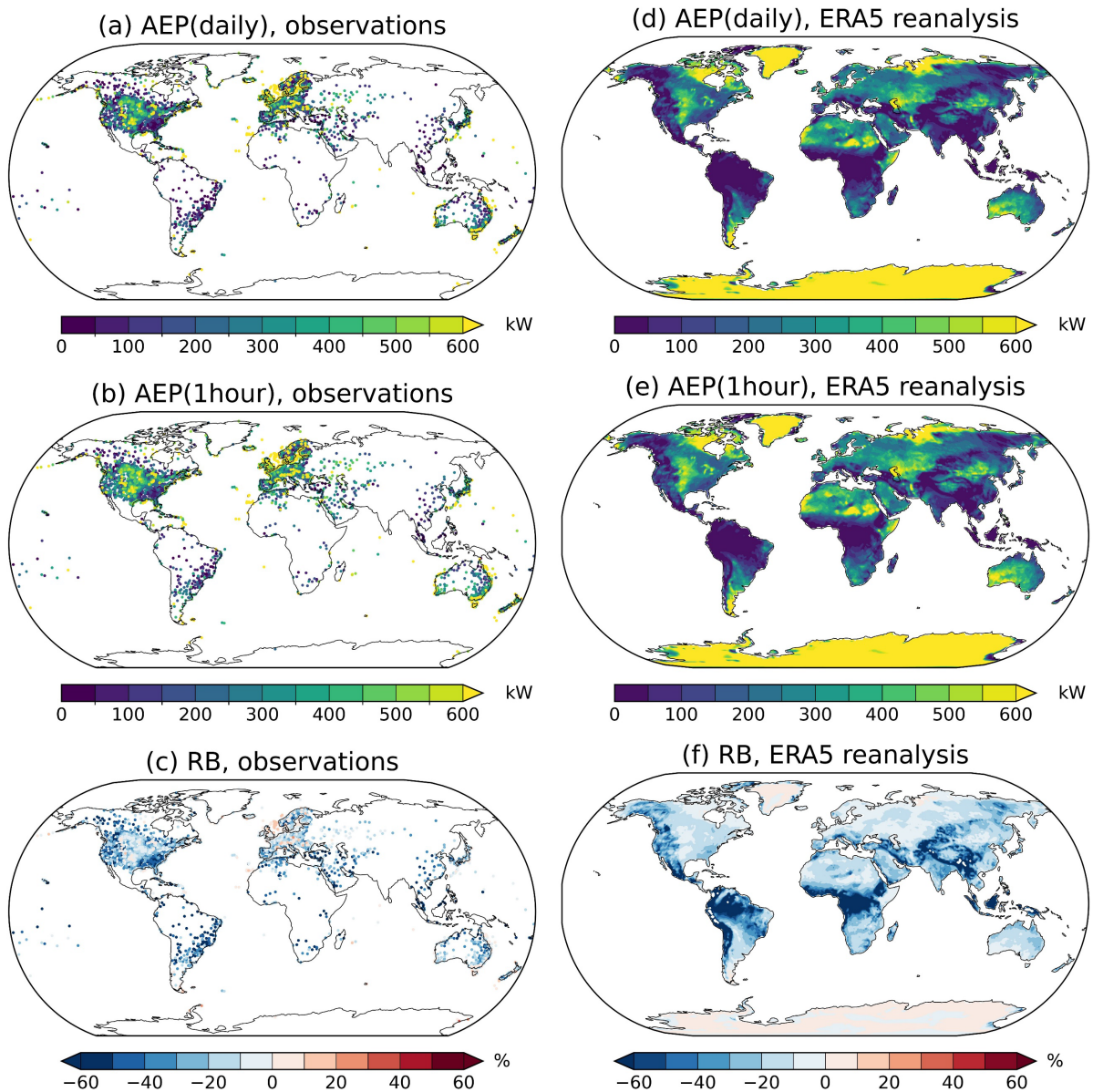
100



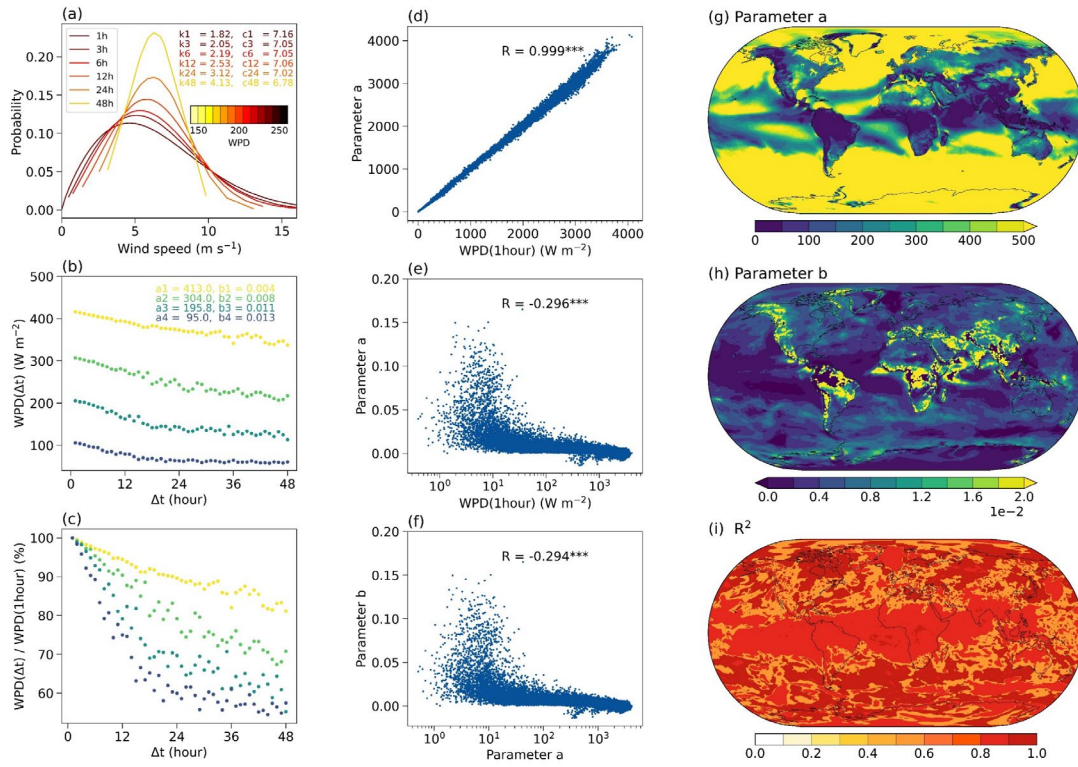
Supplementary Figure 3 | Wind power density (WPD) at the hub height (100 m) calculated using National Centers for Environmental Prediction/National Centers for Atmospheric Research (NCEP/NCAR) and NCEP-US Department of Energy (NCEP-DOE) reanalysis datasets at 6-hour and daily temporal resolutions. The maps show WPD estimates derived from the NCEP/NCAR reanalysis using daily (a) and 6-hour (b) wind speed data, along with their relative bias (RB, %) (c). Similarly, WPD estimates from the NCEP-DOE reanalysis using daily (d) and 6-hour (e) wind speed data are shown, with their corresponding relative bias (RB, %) (f).



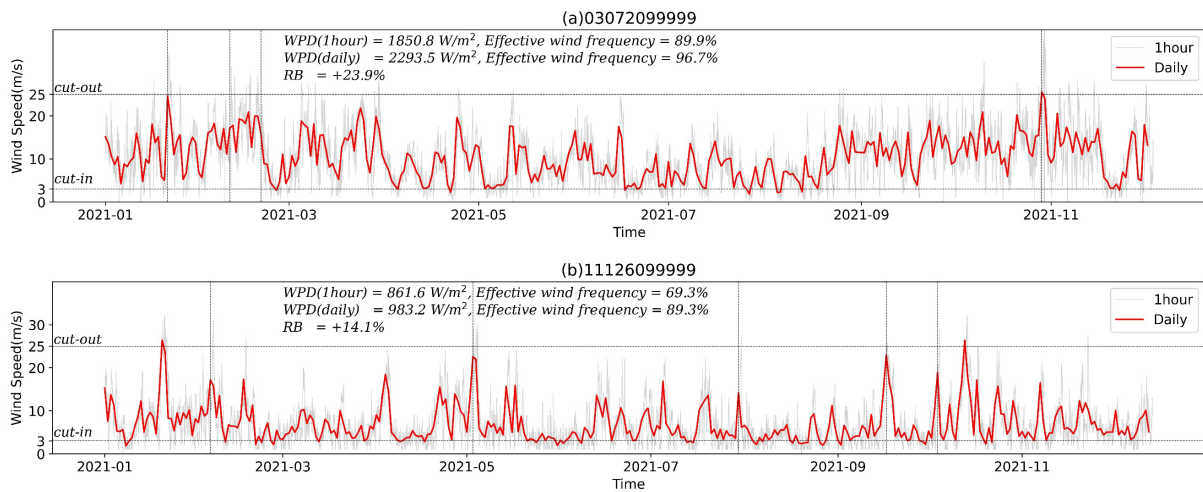
Supplementary Figure 4 | Power curve for the General Electric GE1.5s wind turbine. The power curve includes the following parameters: rated power (1500 kW), cut-in wind speed (3.5 m s⁻¹), rated wind speed (12.0 m s⁻¹), cut-out wind speed (25 m s⁻¹), diameter (70.5 m), swept area (3904.0 m²), and hub height (100 m).



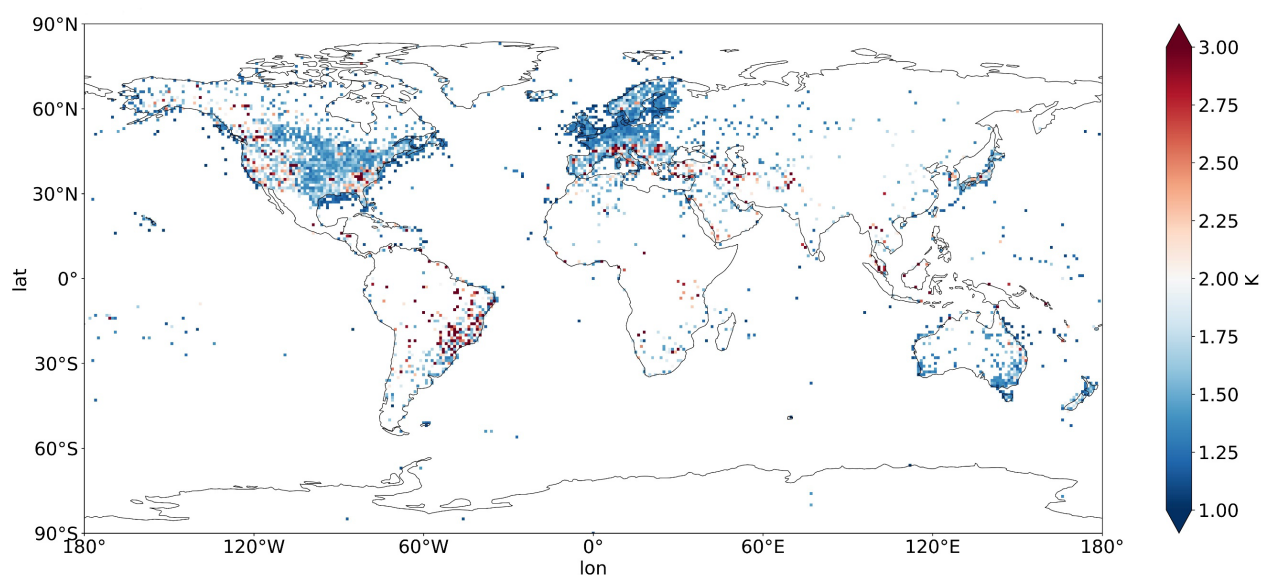
Supplementary Figure 5 | Global actual electrical power production (AEP) at 100 m hub height from observations and climate reanalysis using the General Electric GE 1.5s power curve. The maps show AEP (kW) derived from observational data at daily (a) and 1-hour (b) resolutions, along with their relative bias (RB, %) (c). Similarly, AEP derived from the fifth-generation atmospheric reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ERA5) using daily (d) and 1-hour (e) resolutions are shown, with their corresponding relative bias (RB, %) (f).



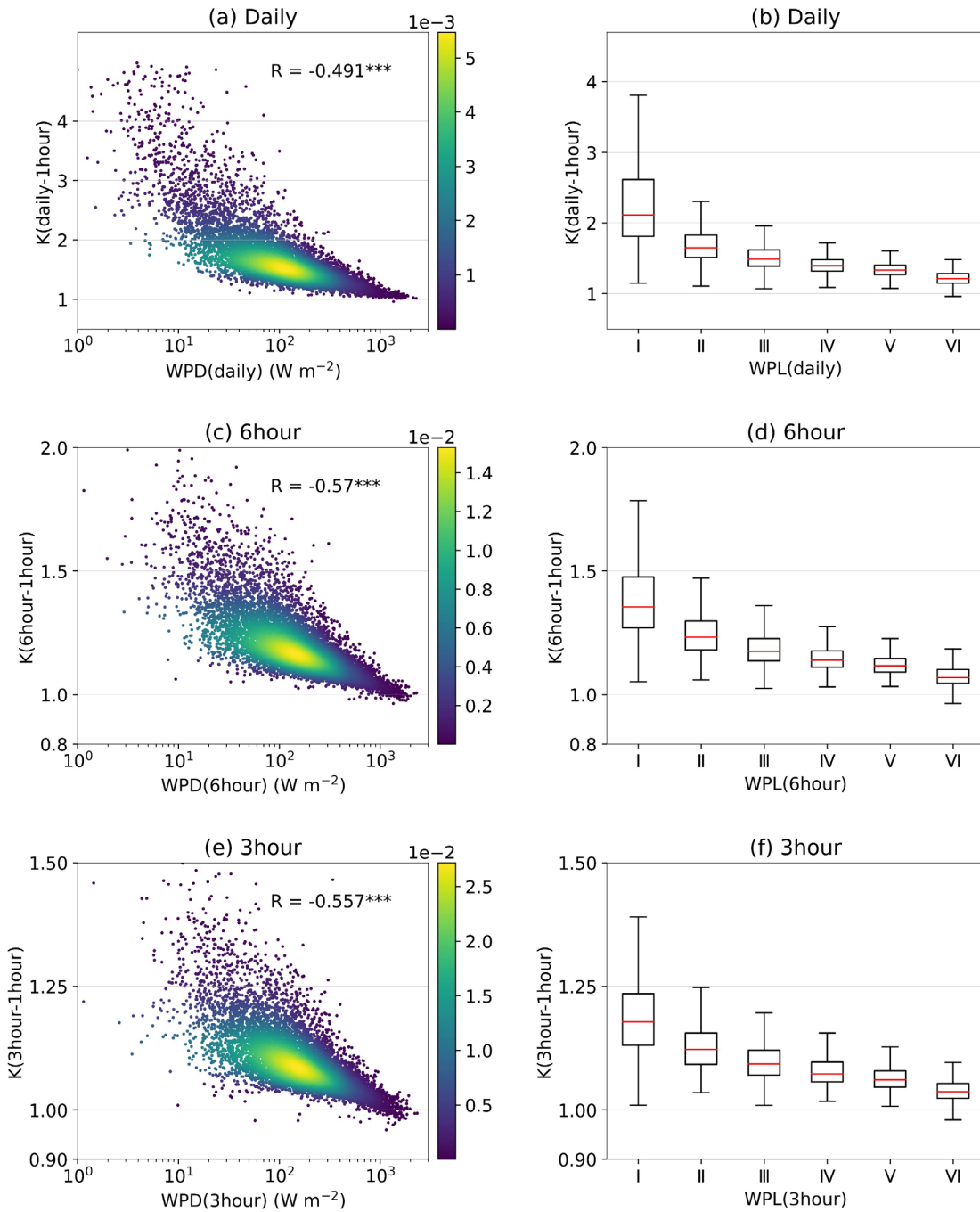
Supplementary Figure 6 | Relationship between wind power density (WPD) and temporal resolutions (Δt) based on climate reanalysis. (a) Wind speed distributions for different Δt values (1-hour to 48-hour) fitted with Weibull probability density function, using wind speed data from January to December 2021 at a grid in northern China (40°N , 100°W), based on the fifth-generation atmospheric reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ERA5). Parameters k and c describe the Weibull shape and scale, respectively, and the numbers in the panel following k and c (e.g., 1, 3, 6, ...) indicate the corresponding Δt values (e.g., 1-hour, 3-hour, 6-hour, ...). WPD were calculated using the statistical method. (b) Exponential fits of WPD versus Δt for four global sites representing different WPD levels: Site 1 (eastern USA, 32°N , 81°W , $\sim 400 \text{ W m}^{-2}$), Site 2 (eastern Europe, 47°N , 46°E , $\sim 300 \text{ W m}^{-2}$), Site 3 (Mongolia, 46°N , 101°E , $\sim 200 \text{ W m}^{-2}$), and Site 4 (Tibetan Plateau, 36°N , 83°E , $\sim 100 \text{ W m}^{-2}$). Parameters a and b for each site are labeled as a_1 , a_2 , a_3 , a_4 and b_1 , b_2 , b_3 , b_4 , respectively. (c) Ratio of WPD(Δt) to WPD(1-hour) as a function of Δt , corresponding to the sites in panel (b). (d-f) Scatter plots illustrating relationships among WPD(1-hour), parameter a , and parameter b . *** indicates a correlation exceeding the 99.9% significance level (t -test). (g-i) Global distributions of parameters a , b , and the exponential fitting coefficient R^2 , respectively.



Supplementary Figure 7 | Time series of hub-height (100 m) wind speeds at 1-hour and daily resolutions for two high-wind sites. (a) Site 1: 56.8°N, 83.3°W, station ID: 03072099999. (b) Site 2: 47.2°N, 11.5°E, station ID: 11126099999. Wind power density (WPD) and effective wind frequency (EWF) values shown in this figure were calculated based on wind speed data from January to December 2021. These two sites show examples with positive relative bias (RB, %) values, indicating an apparent overestimation of WPD when using daily versus 1-hour wind speed data. However, this effect is attributed to artificially high-speed winds resulting from averaging wind speeds above the cut-out threshold, which do not contribute to actual electricity production.

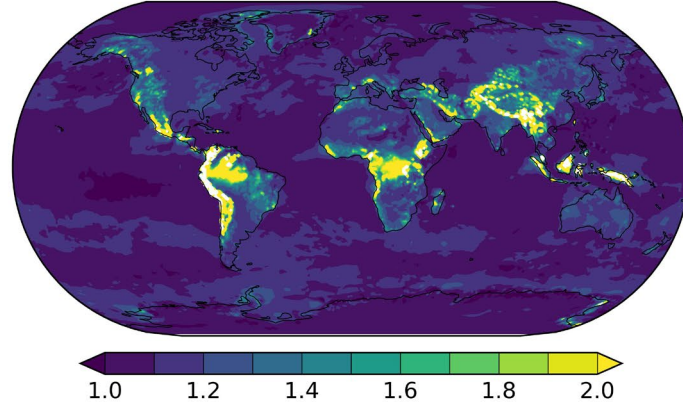


Supplementary Figure 8 | Global $1^\circ \times 1^\circ$ gridded dataset of calibration coefficient K (daily-1 hour) based on observational data. This gridded dataset is based on [Fig. 3a](#) of the main text. The K (daily-1 hour) values represent current wind conditions and are applicable for correcting wind power density (WPD) estimates. However, recalibration may be necessary if wind conditions undergo significant changes due to future climate change. Source data are provided as a Source Data file.

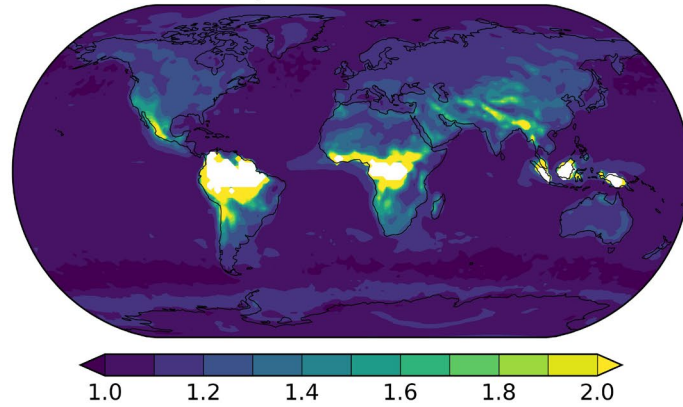


Supplementary Figure 9 | Calibration coefficient $K(\Delta t\text{-1hour})$ for wind power density (WPD) at daily, 6-hour, and 3-hour resolutions based on observations. (a, c, e) Scatter plots of $K(\Delta t\text{-1hour})$ values for WPD at daily, 6-hour, and 3-hour resolutions, respectively. (b, d, f) Boxplots of $K(\Delta t\text{-1hour})$ values across WPD levels (WPL, grades I–VI: 0-50, 50-100, 100-200, 200-300, 300-400, >400 W m^{-2}).

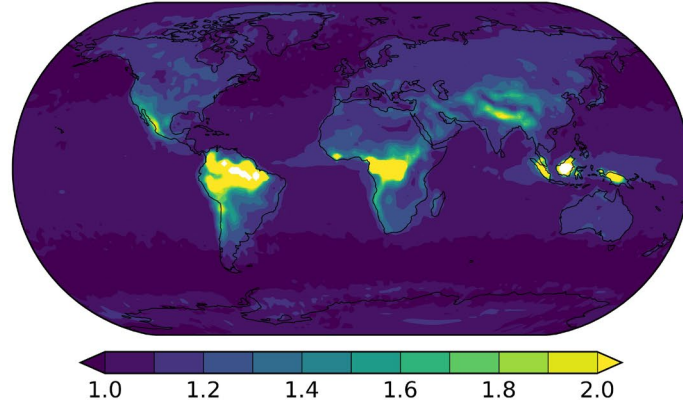
(a) K (daily-1hour), ERA5



(b) K (daily-6hour), NCEP/NCAR



(c) K (daily-6hour), NCEP-DOE



171

172

173

174

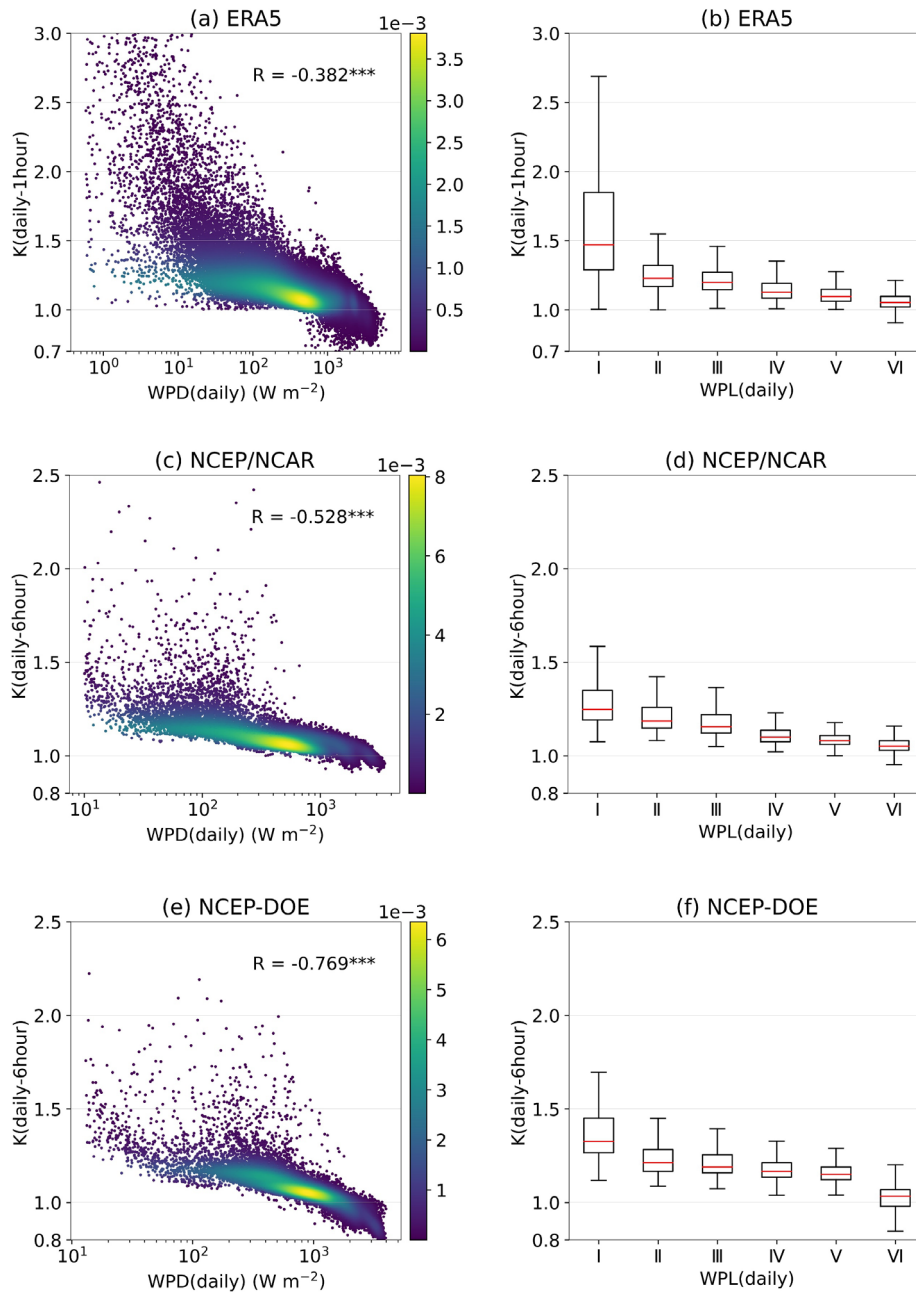
175

176

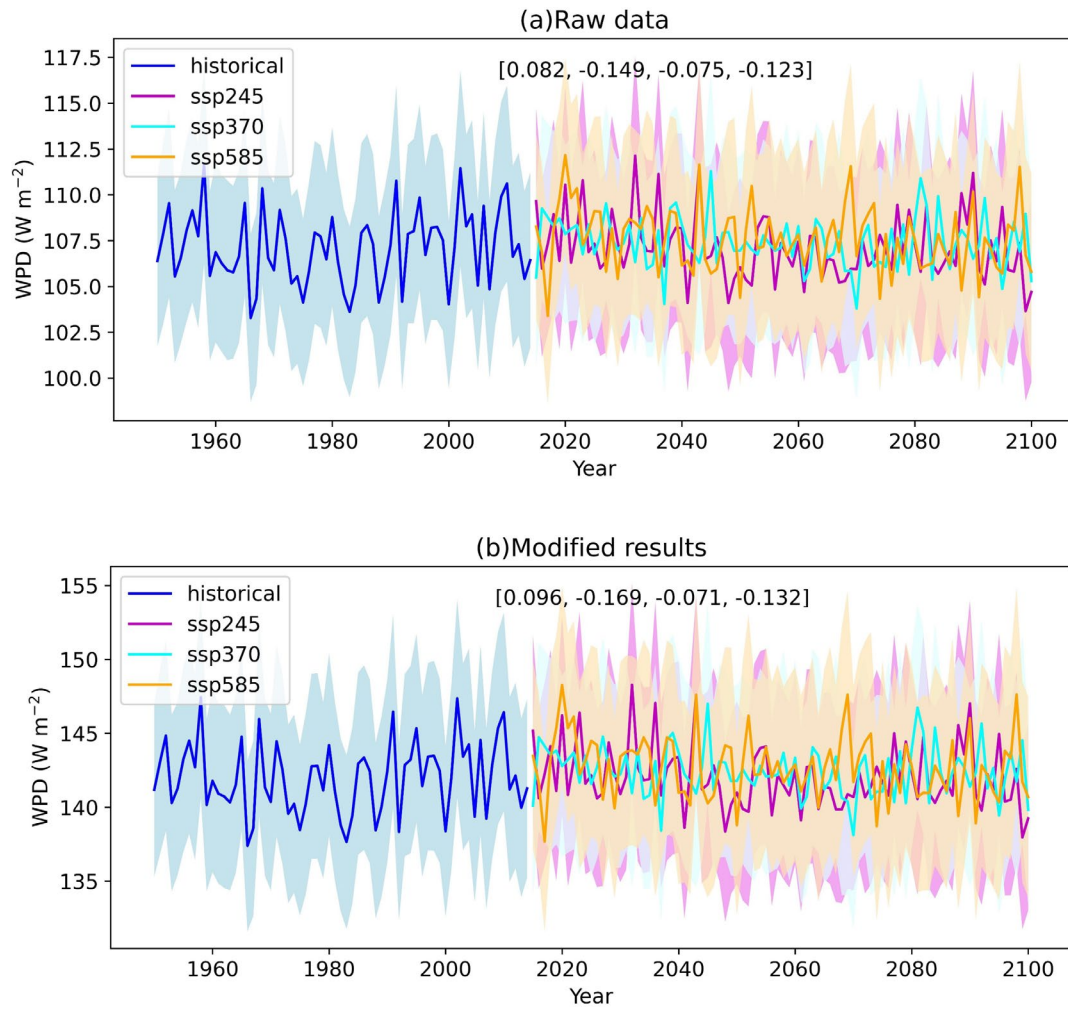
177

178

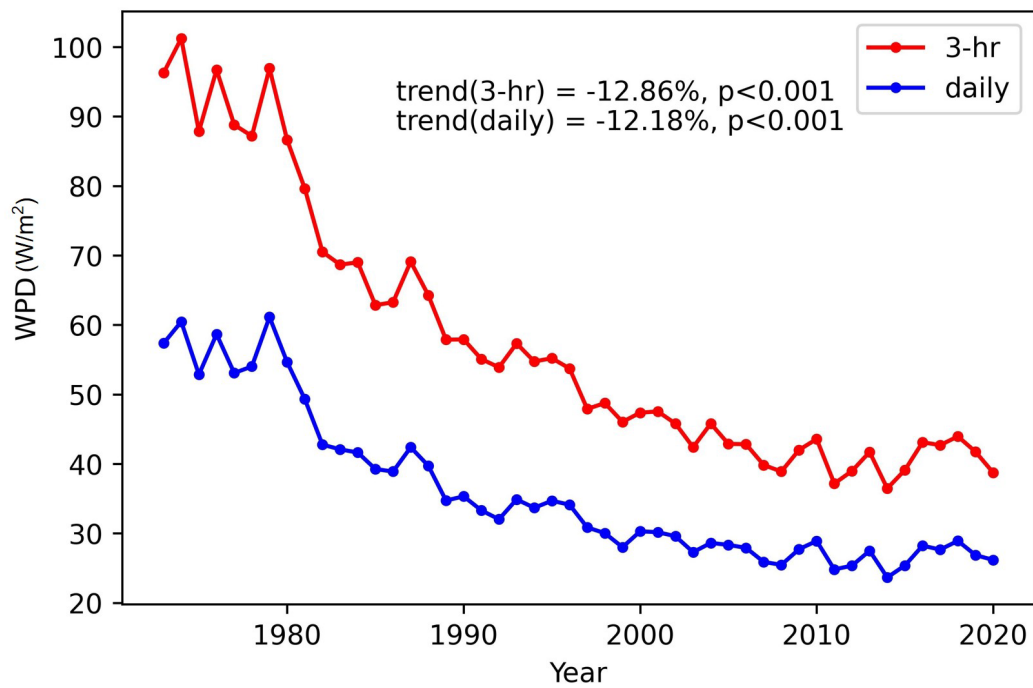
Supplementary Figure 10 | Global distribution of calibration coefficient K based on different climate reanalysis datasets. (a) K (daily-1hour) calculated from the fifth-generation atmospheric reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ERA5). (b, c) K (daily-6hour) calculated from the National Centers for Environmental Prediction/National Centers for Atmospheric Research (NCEP/NCAR) and the NCEP-US Department of Energy (NCEP-DOE) climate reanalysis datasets, respectively.



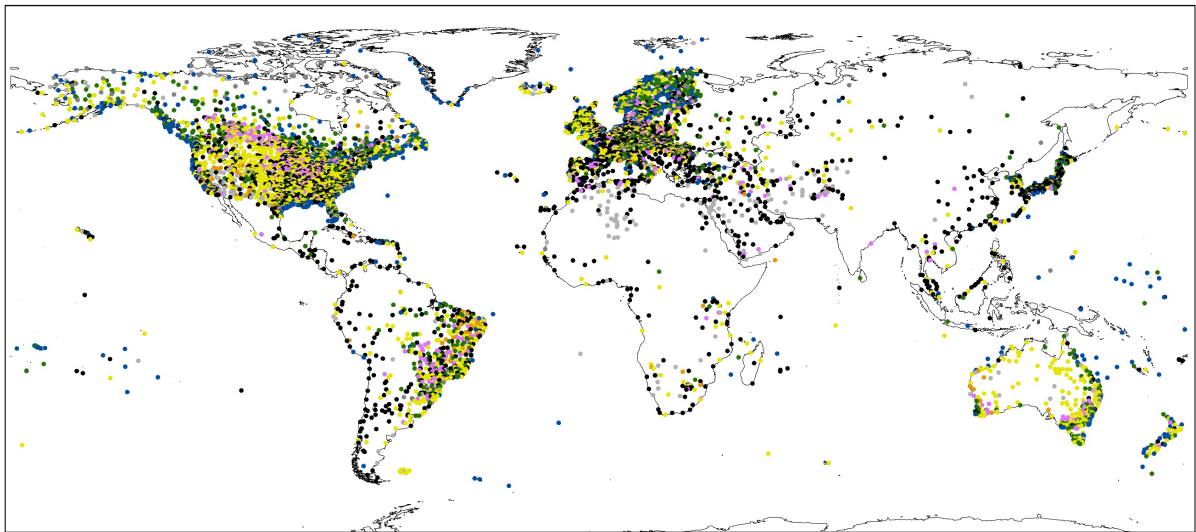
Supplementary Figure 11 | Relationship between wind power density (WPD) and calibration coefficient K based on climate reanalyses. (a) Scatter plot of $WPD(\text{daily})$ versus $K(\text{daily-1hour})$ derived from the fifth-generation atmospheric reanalysis of the European Centre for Medium-Range Weather Forecasts (ERA5). (c, e) Scatter plots of $WPD(\text{daily})$ versus $K(\text{daily-6hour})$ calculated from the National Centers for Environmental Prediction/National Centers for Atmospheric Research (NCEP/NCAR) and the NCEP-US Department of Energy (NCEP-DOE) reanalysis datasets, respectively. (b, d, f) Boxplots of K across WPD levels (WPL grades I–VI: 0–50, 50–100, 100–200, 200–300, 300–400, >400 W m^{-2}) for each dataset.



Supplementary Figure 12 | Global onshore wind power density (WPD) trends during the historical period (1950-2014) and future projections (2015-2100) under different Shared Socioeconomic Pathway (SSP) scenarios. (a) WPD trends derived from raw daily-resolution wind speed data. **(b)** Calibrated WPD trends using $K(\text{daily-3hour})$. The climate models used for assessing relative changes in WPD under future climate scenarios include BCC-CSM2-MR, CMCC-ESM2, CNRM-CM6-1, EC-Earth3, INM-CM4-8, IPSL-CM6A-LR, MIROC6, and MRI-ESM2-0, all of which participate in the Coupled Model Intercomparison Project Phase 6 (CMIP6). Antarctica is excluded from the analysis due to its current unsuitability for wind power development. The numbers in the panels, from left to right, represent WPD trends (unit: W m^{-2} per year) for the historical period and future projections under the SSP245, SSP370, and SSP585 scenarios, respectively.



Supplementary Figure 13 | Time series and trends of wind power density (WPD) at 3-hour and daily resolutions over China from 1973 to 2020.



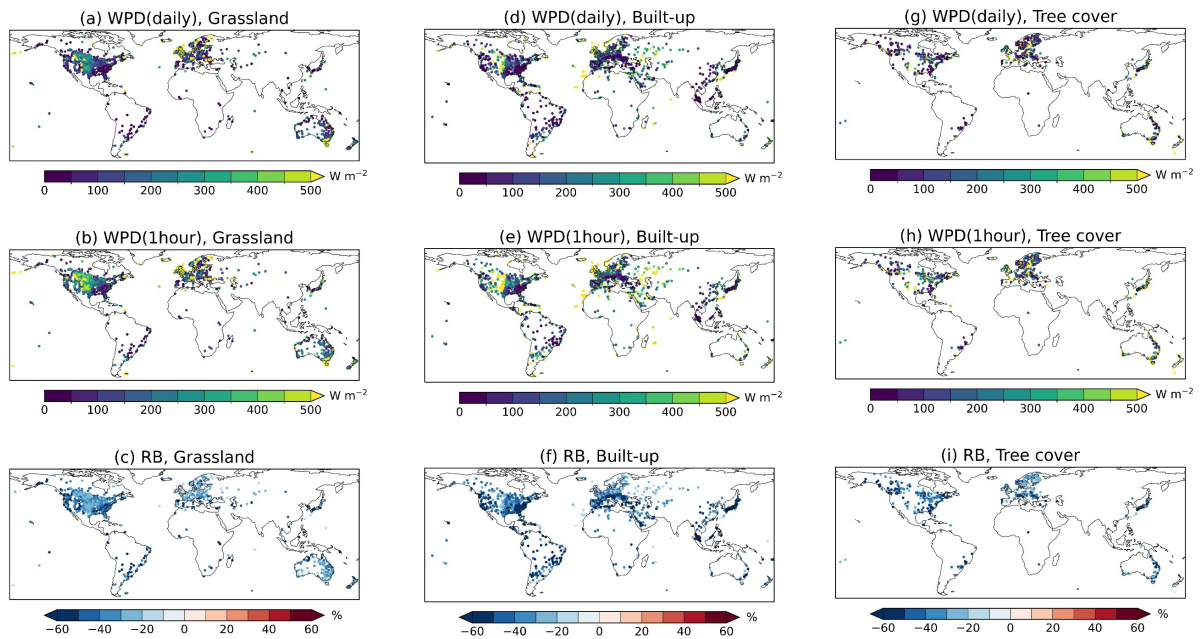
Legend

- Tree cover • Grassland • Built-up • Snow and ice • Others
- Shrubland • Cropland • Bare/sparse vegetation • Permanent water bodies

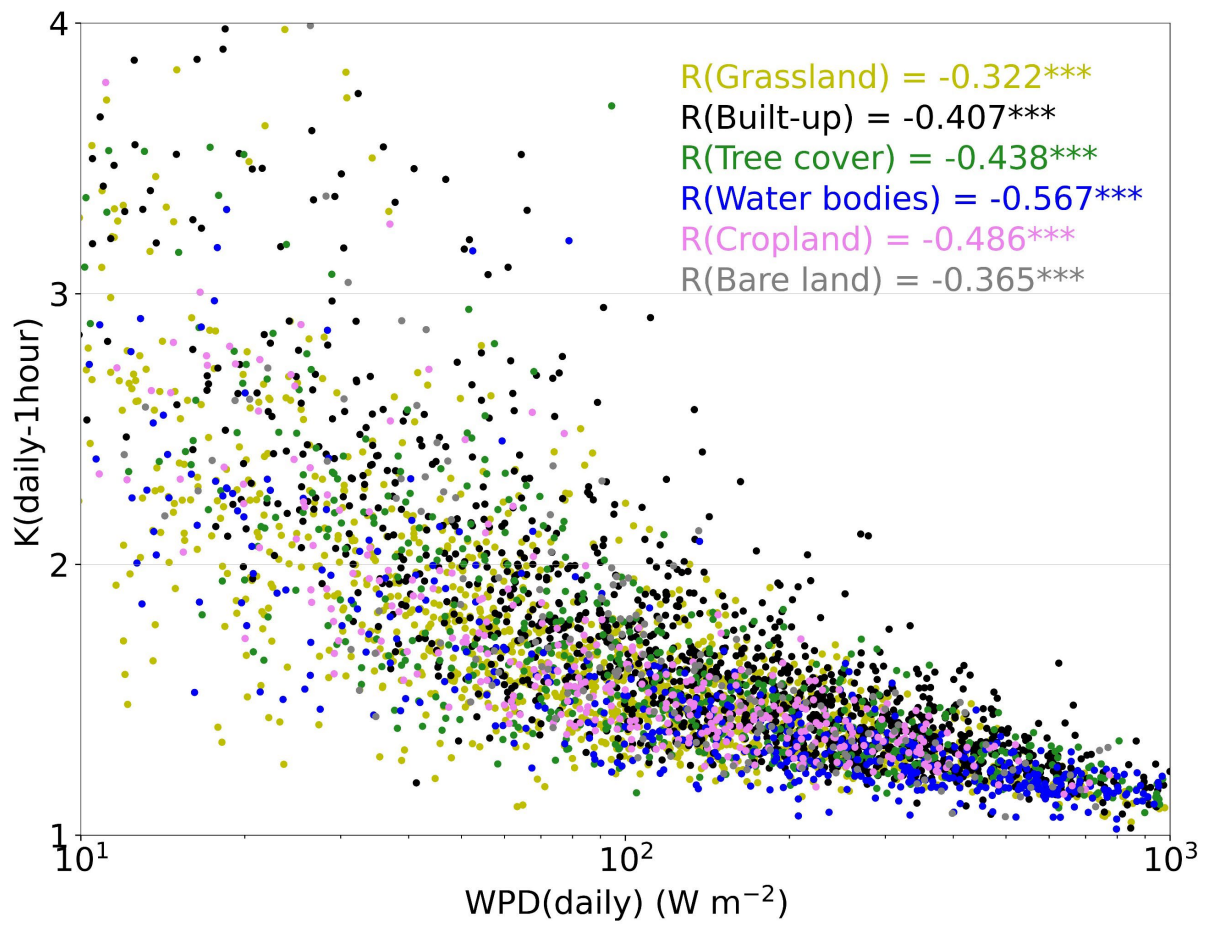
206

207 **Supplementary Figure 14 | Global distribution of land-use and land-cover (LULC) types**
 208 **around the National Climatic Data Center (NCDC) sites, derived from the European**
 209 **Space Agency (ESA) WorldCover dataset.**

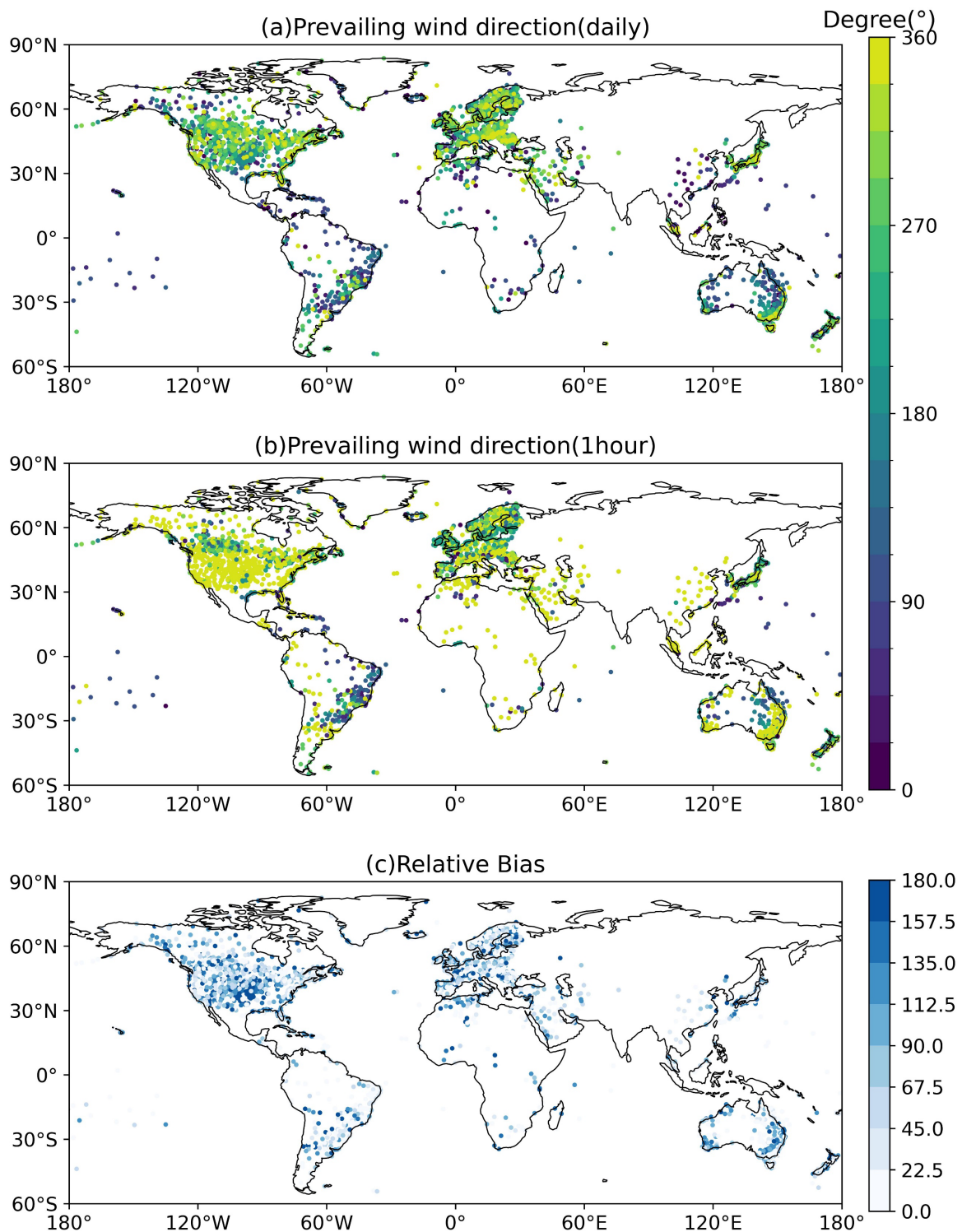
210



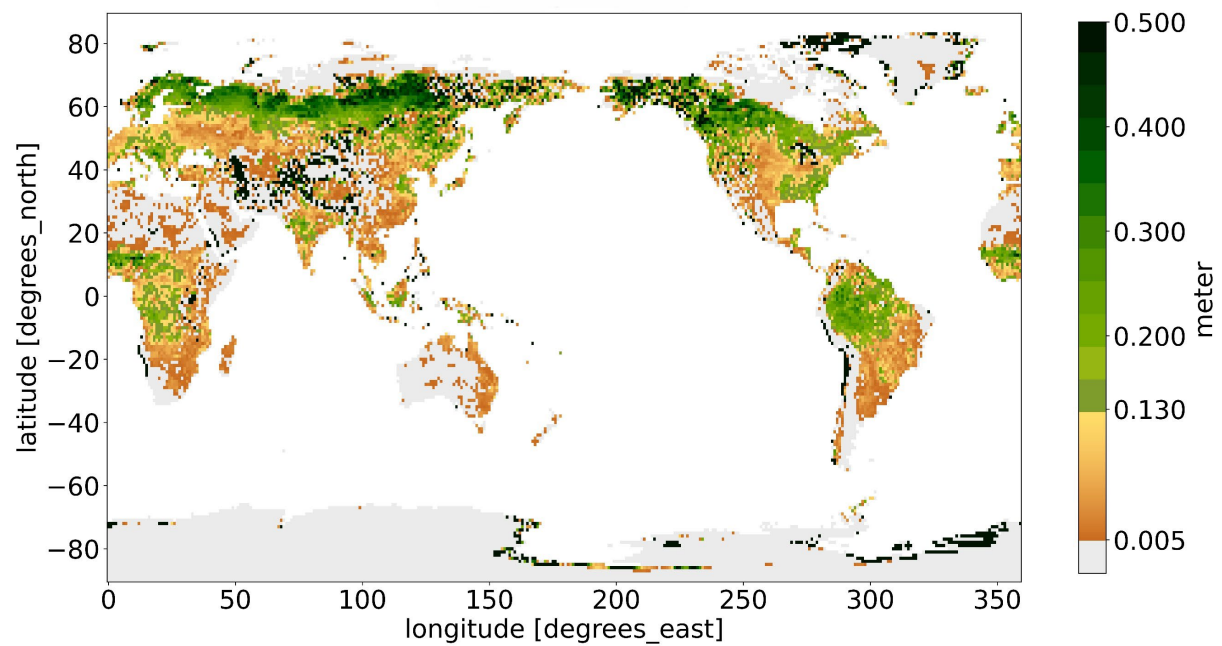
Supplementary Figure 15 | Wind power density (WPD) at the hub height (100 m) calculated from daily and 1-hour observational data, shown for different LULC types. (a, b, c) Global WPD distribution for grassland derived from daily and 1-hour observational data, along with their relative bias (RB, %). (d, e, f) Global WPD distribution for built-up derived from daily and 1-hour observational data, along with their relative bias (RB, %). (g, h, i) Global WPD distribution for tree cover derived from daily and 1-hour observational data, along with their relative bias (RB, %).



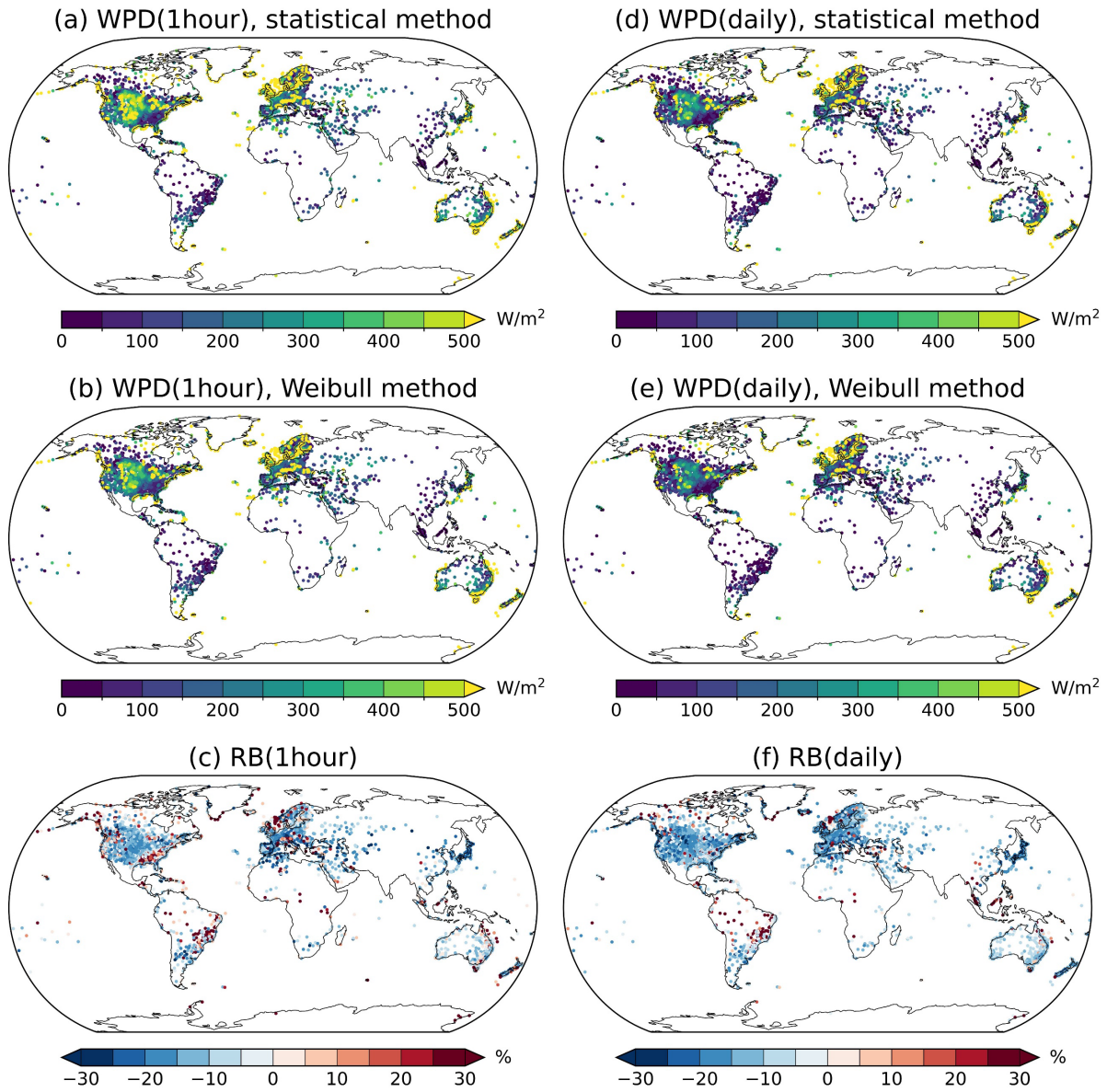
Supplementary Figure 16 | Calibration coefficient $K(\text{daily-1hour})$ for various land-use and land-cover (LULC) based on observations.



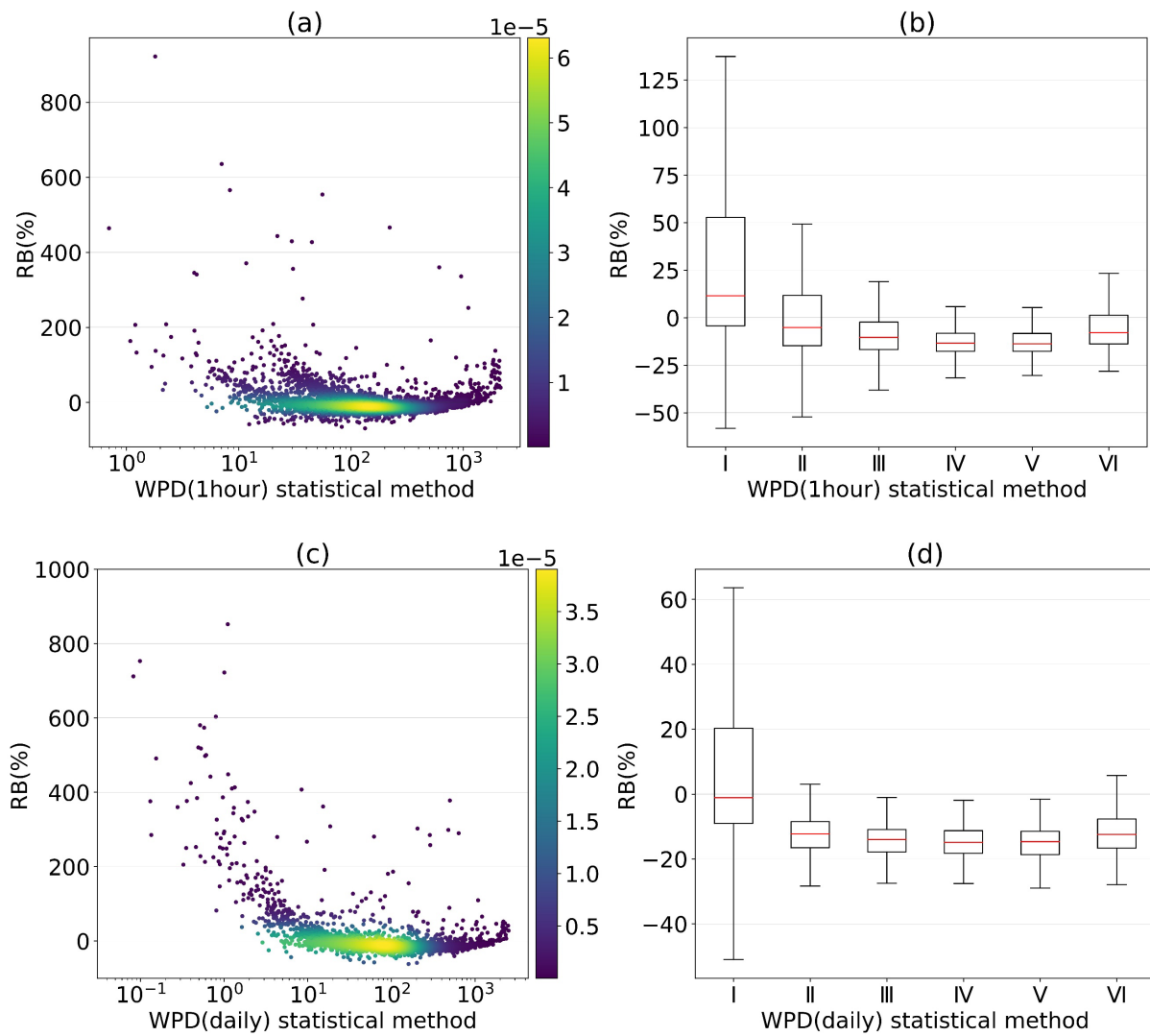
Supplementary Figure 17 | Prevailing wind directions for wind power production based on 1-hour and daily observational data and their differences. (a, b) Prevailing wind directions for wind power production derived from daily and 1-hour observational data, respectively. **(c)** Relative bias (unit: degree) between them.



Supplementary Figure 18 | Global distribution of surface roughness length (z_0) estimated from the fifth-generation European Centre for Medium-Range Weather Forecasts atmospheric reanalysis of the global climate (ERA5).



Supplementary Figure 19 | Comparison of wind power density (WPD) calculated using statistical and Weibull methods for different temporal resolutions. (a, b) WPD estimated using the statistical method and Weibull method based on 1-hour wind speed observational data, respectively. (c) Relative bias (RB, %) between WPD values in panels (a) and (b). (d, e) WPD estimated using the statistical method and Weibull method based on daily wind speed observational data, respectively. (f) Relative bias (RB, %) between WPD values in panels (d) and (e).



Supplementary Figure 20 | Relative bias (RB, %) between wind power density (WPD) calculated using the statistical method and estimated using the Weibull method for 1-hour and daily temporal resolutions. (a) Scatter plot of RB between Weibull-derived and statistically calculated WPD(1-hour), expressed relative to statistically calculated WPD(1-hour). **(b)** Boxplot of RB for WPD(1-hour) across WPD levels (WPL grades I–VI: 0-50, 50-100, 100-200, 200-300, 300-400, >400 W m^{-2}). **(c)** Scatter plot of RB between Weibull-derived and statistically calculated WPD(daily), expressed relative to statistically calculated WPD(daily). **(d)** Boxplot of RB for WPD(daily) across WPL grades I–VI.

Supplementary Notes

Supplementary Note 1 | Influence of temporal resolution on wind power density trends

To evaluate whether temporal resolution (Δt) affects wind power density (WPD) trend estimates, we first used China as an example, where declining trends in historical WPD have been widely reported¹⁹. Using daily and 3-hour wind speed data from 1973 to 2020, we observed consistent decreasing trends in WPD, with only minor differences in trend rates (Supplementary Fig. 13). This suggests that Δt has a minimal impact on historical WPD trend estimation.

We extended the analysis to future scenarios using multi-model outputs from the Coupled Model Intercomparison Project Phase 6 (CMIP6), including BCC-CSM2-MR, CMCC-ESM2, CNRM-CM6-1, EC-Earth3, INM-CM4-8, IPSL-CM6A-LR, MIROC6, and MRI-ESM2-0. Results from the multi-model mean indicate statistically insignificant global onshore WPD trends for 2015–2100 across various Shared Socioeconomic Pathway (SSP) scenarios (Supplementary Fig. 12). Importantly, applying the calibration coefficient K did not notably alter these trends.

While coarse-resolution wind speed data are sufficient for detecting long-term WPD trends, they are inadequate for accurately quantifying absolute WPD values. High-resolution data remain essential for precise projections of future wind energy resources²⁰. When high-resolution data are unavailable, applying K can improve the reliability of coarse-resolution WPD estimates while reducing computational demands.

Supplementary Note 2 | Influence of land-use and land-cover on wind power density calculations and calibration coefficient K

To enhance the accuracy of wind power density (WPD) calculations, we used the logarithmic wind profile equation to extrapolate hub-height (100 m) wind speeds. In applying the logarithmic law, we considered land-use and land-cover (LULC)-specific surface roughness length (z_0), based on established values²¹⁻²⁴ (Supplementary Table 2). LULC classifications for observation sites were determined using the European Space Agency (ESA) WorldCover data²⁵, and validated against high-resolution remote sensing imagery to ensure their accuracy in representing local conditions around the National Climatic Data Center (NCDC) sites (Supplementary Fig. 14). The LULC-specific z_0 values were then applied in equation (4) to extrapolate hub-height wind speeds for observation sites.

The fifth-generation European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis of the global climate (ERA5) provides both 10 m and 100 m wind speeds, enabling the global calculation of z_0 for each grid using equation (4). The resulting global z_0 map (Supplementary Fig. 18) aligns well with established LULC-specific roughness values (Supplementary Table 2). Globally, z_0 varies significantly: low z_0 values (<0.005) are common in deserts (e.g., Sahara, Arabian Desert, Australian Outback) and snow/ice-covered areas (e.g., Antarctica, Greenland); moderate z_0 values (0.005–0.15) are found in grasslands, shrublands (e.g., central USA, southern Africa, central Asia), and croplands (e.g., eastern Asia, eastern Australia, southeastern Brazil); while high z_0 values (>0.15) are often associated with dense tree cover, including tropical rainforests (e.g., Amazon, Congo, Southeast Asia) and boreal forests (e.g., Siberia, northern Canada). This global z_0 map derived from ERA5 was subsequently applied to extrapolate hub-height wind speeds from the Coupled Model Intercomparison Project Phase 6 (CMIP6) model outputs, improving the reliability of WPD calculations across diverse landscapes.

To examine whether the impact of temporal resolution (Δt) on WPD is consistent across different landscapes, global NCDC sites were categorized based on their LULC types. The

corresponding WPD(daily) and K (daily-1hour) were then subdivided and analyzed. As shown in [Supplementary Fig. 15](#), the underestimation of WPD(daily) compared to WPD(1-hour) is consistent across common LULC types, including grassland, tree cover, and built-up areas, which together account for more than 90% of all sites. Although variations in surface roughness among different LULC types influence the extrapolation of hub-height wind speeds and absolute WPD values, WPD distributions across LULC types are broadly overlapping ([Supplementary Fig. 16](#)). Generally, grasslands exhibit slightly lower WPD values (the lowest among the analyzed LULC types), leading to relatively higher biases between WPD(daily) and WPD(1-hour), making WPD calculations in grasslands more sensitive to Δt .

More importantly, a consistent and significant negative correlation ($p < 0.001$) was observed between K (daily-1hour) and WPD(daily) across all LULC types, with correlation coefficients ranging from -0.32 to -0.57 ([Supplementary Fig. 16](#)). This result indicates that the impact of Δt on WPD is broadly consistent across diverse landscapes, and that the relationship between WPD and K remains unchanged across LULC types. These findings again underscore that the relationship between WPD and Δt is primarily governed by wind speed distribution characteristics (parameter a) rather than land surface attributes.

Supplementary Note 3 | Influence of temporal resolution on primary wind direction for wind power production

Primary wind direction plays a crucial role in optimizing wind farm layouts, turbine alignment, and overall efficiency²⁶⁻²⁸. However, few studies have systematically explored how temporal resolution affects wind direction determination²⁹⁻³¹. To address this, we compared primary wind directions derived from 1-hour and daily wind speed data for 1973–2021 ([Supplementary Fig. 17](#)).

The results derived from 1-hour and daily data are generally consistent, both aligning well with prevailing circulation patterns. For example, westerly winds dominate in mid-latitudes, with primary wind directions typically from the northwest. Southwest winds prevail in coastal northern Europe. Northeast trade winds, influenced by the Subtropical High, affect regions such as the Sahara Desert and the Cuban Islands. Meanwhile, southeast trade winds dominate areas like Brazil and northern Australia in the tropical Southern Hemisphere.

Biases between 1-hour and daily-derived primary wind directions are minimal in trade wind regions but more pronounced in mid-latitudes ([Supplementary Fig. 17](#)), where rapid wind direction shifts caused by extratropical cyclones are common³². Those rapid wind rotations may not be fully captured when wind observations have large intervals or coarse averaging times. Notably, such biases can reach 45°-90°, which can significantly impact wind farm layouts, given that even a 10° misalignment may reduce power output by up to 43%³³. Therefore, coarse-resolution data should be used cautiously when determining primary wind direction for wind power generation³⁴. Further research is needed to better understand these discrepancies, particularly in mid-latitude regions, to refine turbine placement strategies.

Supplementary References

1. Akinsanola, A. A., Ogunjobi, K. O., Abolude, A. T. & Salack, S. Projected changes in wind speed and wind energy potential over West Africa in CMIP6 models. *Environ. Res. Lett.* **16**, 44033 (2021).
2. Archer, C. L. & Jacobson, M. Z. Evaluation of global wind power. *J. Geophys. Res.* **110**, D12110 (2005).
3. Costoya, X., DeCastro, M., Carvalho, D., Feng, Z. & Gómez-Gesteira, M. Climate change impacts on the future offshore wind energy resource in China. *Renew. Energy*. **175**, 731-747 (2021).
4. Gil Ruiz, S. A., Barriga, J. E. C. & Martínez, J. A. Wind power assessment in the Caribbean region of Colombia, using ten-minute wind observations and ERA5 data. *Renew. Energy*. **172**, 158-176 (2021).
5. Hayes, L., Stocks, M. & Blakers, A. Accurate long-term power generation model for offshore wind farms in Europe using ERA5 reanalysis. *Energy*. **229**, 120603 (2021).
6. Hosking, J. S. et al. Changes in European wind energy generation potential within a 1.5 °C warmer world. *Environ. Res. Lett.* **13**, 54032 (2018).
7. Johnson, D. L. & Erhardt, R. J. Projected impacts of climate change on wind energy density in the United States. *Renew. Energy*. **85**, 66-73 (2016).
8. Karauskas, K. B., Lundquist, J. K. & Zhang, L. Southward shift of the global wind energy resource under high carbon dioxide emissions. *Nat. Geosci.* **11**, 38-43 (2018).
9. Li, D. et al. Historical Evaluation and Future Projections of 100-m Wind Energy Potentials Over CORDEX-East Asia. *J. Geophys. Res. Atmos.* **125**, e2020JD032874 (2020).
10. Li, M. et al. An assessment of observed wind speed and wind power density over China for 1980–2021. *Wind Energy*. **25**, 2052-2070 (2022).
11. Liu, F. et al. On wind speed pattern and energy potential in China. *Appl. Energy*. **236**, 867-876 (2019).
12. Liu, F., Wang, X., Sun, F. & Kleidon, A. Potential impact of global stilling on wind energy production in China. *Energy*. **263**, 125727 (2023).
13. Lu, X., McElroy, M. B., Kiviluoma, J. & Anderson, J. G. Global Potential for Wind-Generated Electricity. *Proc. Natl. Acad. Sci. USA*. **106**, 10933-10938 (2009).
14. Miao, H. et al. Evaluation of Northern Hemisphere surface wind speed and wind power density in multiple reanalysis datasets. *Energy*. **200**, 117382 (2020).
15. Pryor, S. C. & Barthelmie, R. J. Assessing climate change impacts on the near-term stability of the wind energy resource over the United States. *Proc. Natl. Acad. Sci. USA*. **108**, 8167-8171 (2011).
16. Pryor, S. C., Barthelmie, R. J. & Kjellström, E. Potential climate change impact on wind energy resources in northern Europe: analyses using a regional climate model. *Clim. Dyn.* **25**, 815-835 (2005).

17. Sherman, P., Chen, X. & McElroy, M. B. Wind-generated Electricity in China: Decreasing Potential, Inter-annual Variability and Association with Changing Climate. *Sci. Rep.* **7**, (2017).
18. Tian, Q., Huang, G., Hu, K. & Niyogi, D. Observed and global climate model based changes in wind power potential over the Northern Hemisphere during 1979–2016. *Energy*. **167**, 1224-1235 (2019).
19. Li, M. et al. An assessment of observed wind speed and wind power density over China for 1980–2021. *Wind Energy*. **25**, 2052-2070 (2022).
20. Liu, L. et al. Climate change impacts on planned supply–demand match in global wind and solar energy systems. *Nat. Energy*. **8**, 870-880 (2023).
21. Bañuelos-Ruedas, F., Angeles-Camacho, C. & Rios-Marcuello, S. Analysis and validation of the methodology used in the extrapolation of wind speed data at different heights. *Renew. Sustain. Energy Rev.* **14**, 2383-2391 (2010).
22. Emeis, S. Vertical variation of frequency distributions of wind speed in and above the surface layer observed by sodar. *Meteorol. Z.* **10**, 141-149 (2001).
23. Masters G M. Renewable and Efficient Electric Power Systems (Wiley, 2004).
24. Manwell, J. F., McGowan, J. G. & Rogers, A. L. Wind Energy Explained: Theory, Design and Application (Wiley, 2010).
25. Zanaga, D. et al. ESA WorldCover 10 m 2021 v200. <https://doi.org/10.5281/zenodo.7254221> (2022).
26. Erdem, E. & Shi, J. Comparison of bivariate distribution construction approaches for analysing wind speed and direction data. *Wind Energy*. **14**, 27-41 (2011).
27. Schindler, D. & Jung, C. Copula-based estimation of directional wind energy yield: A case study from Germany. *Energy Conv. Manag.* **169**, 359-370 (2018).
28. Song, M., Chen, K., Zhang, X. & Wang, J. Optimization of wind turbine micro-siting for reducing the sensitivity of power generation to wind direction. *Renew. Energy*. **85**, 57-65 (2016).
29. Gugliani, G. K., Sarkar, A., Ley, C. & Mandal, S. New methods to assess wind resources in terms of wind speed, load, power and direction. *Renew. Energy*. **129**, 168-182 (2018).
30. Herbert-Acero, J., Probst, O., Réthoré, P., Larsen, G. & Castillo-Villar, K. A Review of Methodological Approaches for the Design and Optimization of Wind Farms. *Energies*. **7**, 6930-7016 (2014).
31. Stephen, B., Galloway, S., McMillan, D., Anderson, L. & Ault, G. Statistical profiling of site wind resource speed and directional characteristics. *Iet Renew. Power Gener.* **7**, 583-592 (2013).
32. Shaw, T. A. et al. Storm track processes and the opposing influences of climate change. *Nat. Geosci.* **9**, 656-664 (2016).
33. Porté-Agel, F., Wu, Y. & Chen, C. A Numerical Study of the Effects of Wind Direction on Turbine Wakes and Power Losses in a Large Wind Farm. *Energies*. **6**, 5297-5313 (2013).
34. Masseran, N. & Razali, A. M. Modeling the wind direction behaviors during the monsoon seasons in Peninsular Malaysia. *Renew. Sustain. Energy Rev.* **56**, 1419-1430 (2016).