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A reversal in global terrestrial stilling and its implications for wind energy production

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33 **Wind power, a rapidly growing alternative energy source, may be threatened by reductions**
34 **in global average surface wind speed over land since the 1980s, known as terrestrial stilling.**
35 **However, this stilling is largely unexplained so far. Here we use wind data from *in-situ***
36 **stations worldwide to show that the stilling reversed around 2010 and global wind speeds**
37 **over land have recovered. We illustrate that decadal-scale variations of near-surface wind**
38 **are likely determined by internal decadal ocean/atmosphere oscillations, rather than the**
39 **previous hypothesis of vegetation growth and/or urbanization. The strengthening has**
40 **increased potential wind energy by $17 \pm 2\%$ for 2010-2017, increasing U.S. wind power**
41 **capacity factor by $\sim 2.5\%$ that is as significant as technology innovations. In the longer-term,**
42 **use of ocean/atmosphere oscillations to anticipated future wind speeds, could allow**
43 **optimization of turbines for expected speeds during their productive life spans.**

44
45 Reports of a global decline in land surface wind speed of 8% from ~ 1980 to 2010 have raised
46 concerns about outputs from future wind power¹⁻⁵. Wind power (p) varies with the cube of wind
47 speed (u) according to the formula

$$p = \frac{\rho s f}{2} u^3 \quad (1),$$

49 where ρ is air density, s the swept area of the turbine, and f an efficiency factor⁶. The decline
50 has been manifest in the northern mid-latitude countries where the majority of wind turbines are
51 installed including China, the U.S. and Europe¹. If the observed trend from 1980 to 2010 were to
52 continue to the end of the century, global u would reduce by 21%, halving the amount of power
53 available in the wind (using Equation (1)). Understanding the drivers of this long-term decline in
54 wind speed is critical not merely to maximize wind energy production⁷⁻⁹ but also to address other
55 globally significant environmental problems related to stilling, including reduced aerosol

56 dispersal, changes in evapotranspiration rates, and adverse effects on animal behavior and
57 ecosystem functioning^{1,3,4,10}.

58
59 The potential causes for global terrestrial stilling are complex and remain contested^{2,3,11,12}. Many
60 regional-scale studies^{13-15G&W} using reanalysis datasets have found correlations of u with various
61 climate indices. Those studies hypothesize that terrestrial stilling is caused by decreased driving
62 force due to the change in large scale circulations¹¹. This is supported by a consistency in wind
63 speed changes at the surface and at higher levels in the reanalysis datasets^{11,14}. Nevertheless,
64 there are large uncertainties in these datasets^{2,11,14}, and more importantly, global terrestrial
65 stilling is either not reproduced or has been largely underestimated in global reanalysis
66 products^{2,11} (Supplementary Fig. 1) and/or climate model simulations for IPCC AR5
67 (Supplementary Fig. 2). Acknowledging that wind speed reanalysis datasets do not represent land
68 surface dynamics, the discrepancies between the decreasing trends derived from *in-situ* stations
69 and from reanalysis or climate model simulations lead to the hypothesis that global terrestrial
70 stilling is caused by increased drag related to increased surface roughness from the greening of
71 the Earth and/or urbanization^{2,16}, both of which would suggest further future declines.

72
73 However, conversely, recent studies have described wind speed reversal at local scales^{17,18} or an
74 increase of global wind speed during a particular year¹⁹, despite uncertainty over the global trend
75 of wind speed change^{5,11}. The recent reversal over land, if evidenced to be true at global scale,
76 could elucidate the causes of global terrestrial stilling and potentially improve future wind energy
77 projections.

79 **Analysis**

80 We integrate direct *in-situ* observations of u from ground weather stations from 1978 to 2017
81 together with statistical models for detection of trends. The stations, mainly distributed in the
82 northern mid-latitudes countries, were carefully selected from the Global Summary of Day
83 (GSOD) database following strict quality control procedures (Supplementary Fig. 3; see *Methods*
84 for details). To test for a continuation of the terrestrial stilling after 2010 (refs 1-3), we use a
85 piecewise linear regression model to examine the potential trend changes^{26,27}.

86

87 **Scope of a reversal in global terrestrial stilling**

88 The analysis shows that global mean annual u decreased significantly at a rate of -0.08 m s^{-1} (or -
89 2.3%) per decade during the first three decades beginning in 1978 (P-value < 0.001; Fig. 1a,
90 Supplementary Table 1). While the decreasing trend has previously been shown²⁻⁴ and confirms
91 global terrestrial stilling as an established phenomenon during the period of 1978-2010, we find
92 that u has significantly increased in the current decade. This turning point is statistically
93 significant at $P < 0.001$ with a goodness of fit of an $R^2 = 90\%$ (Fig. 1a). The recent increasing
94 rate of $0.24 \text{ m s}^{-1} \text{ decade}^{-1}$ ($P < 0.001$) is three-fold the decreasing rate before the turning point in
95 2010.

96

97 To exclude the possibility that the turning point is caused by large wind speed changes at only a
98 few sites, we repeat our analyses 300 times by randomly resampling 40% of the global stations
99 each time (grey lines in Fig. 1a; 40% of the stations are selected to ensure a sufficient sample
100 size ($n > 500$)). We find significant turning points in each randomly-selected sub-sample ($P <$
101 0.001 ; $R^2 \geq 76\%$). Run-specific turning points occur between 2002 and 2011, with most (95%) of

102 them between 2009 and 2011 (Fig. 1b). In addition, mean annual u changes before and after a
103 specific turning point based on the 300 sub-sample estimates are $-0.08 \pm 0.01 \text{ m s}^{-1}$ per decade
104 and $0.24 \pm 0.03 \text{ m s}^{-1}$ per decade, respectively (Fig. 1c), identical to those values based on all the
105 global samples.

106

107 Spatial analyses further confirm that the recent reversal is a global-scale phenomenon
108 (Supplementary Fig. 4a-c). A majority (79%) of the stations where u decreased significantly
109 during 1978-2010 (Supplementary Fig. 4b) have positive trends in u after 2010 (Supplementary
110 Fig. 4c). The stations are mainly distributed over North America, Europe, and Asia. Significant
111 turning points exist in all the three regional mean annual u time series ($P < 0.001$, Supplementary
112 Fig. 4d-f), but they vary in the specific year of occurrence. For example, a turning point occurs
113 earlier in Asia (2001, $R^2 = 80\%$, Supplementary Fig. 4f) and Europe (2003, $R^2 = 56\%$,
114 Supplementary Fig. 4e) than in North America (2012, $R^2 = 80\%$, Supplementary Fig. 4d).
115 Nevertheless, all the three regions have the most significant increase in u after ~2010
116 (Supplementary Fig. 4d-f).

117

118 The existence of turning points is robust regardless of season (Supplementary Table 1 and
119 Supplementary Fig. 5) or wind variable chosen for analysis (Supplementary Fig. 6), and shows
120 no dependence on quality control procedures for weather station data (Supplementary Fig. 7).
121 For maximum sustained wind and wind gusts, the turning points appear earlier and the recent
122 increasing rates are weaker (Supplementary Fig. 6). Furthermore, we show that our findings are
123 robust and repeatable (Supplementary Fig. 8) using a different data set—the HadISD database,
124 which follows station selection criteria and a suite of quality control tests established by Met

125 Office Hadley Centre²⁸. We also find that the tendency for an increasing number of stations
126 becoming automated during recent decades (Supplementary Figs 9 and 10) does not affect the
127 result (Supplementary Fig. 11). Finally, to test the effect of inhomogeneity, we remove all the
128 stations with change points detected by the Pettitt tests²⁹, finding that the results do not change
129 after the analysis is repeated (Supplementary Fig. 12). All these lines of evidences provide
130 independent supports that the trends in u are not caused by changes in measurement methods and
131 inhomogeneity.

132

133 **Causes of the reversal in global terrestrial stilling**

134 A variety of theories have been presented previously to explain stilling, many of which focus on
135 the drag force of u linked to increased terrestrial roughness caused by urbanization and/or
136 vegetation changes^{2,12}. These theories have been disputed³⁰ (also see Supplementary Figs 13 and
137 14). Our finding that global stilling changed after 2010, especially the increasing rate which is
138 three times that of the decreasing rate before 2010 (Fig. 1a), further refutes these theories
139 because terrestrial roughness did not suddenly change in 2010. More likely, the variation in u
140 (including prior stilling and the recent reversal) is determined mainly by driving forces
141 associated with decadal variability of large-scale ocean/atmospheric circulations.

142

143 Wind is physically created by pressure gradient which is due to uneven heating of the Earth
144 surface (temperature anomalies or heterogeneity), and the latter is to a large extent described by
145 climate indices for oscillations. To test such associations, we first include twenty-one climate
146 indices in the pool of indicators for ocean/atmosphere oscillations (Supplementary Table 2 and
147 *Methods*). To avoid overfitting, we apply stepwise regression³² to identify six largest explanatory

148 power factors for the decadal variations of u over the globe, North America, Europe, and Asia,
149 respectively (see Supplementary Table 3). The reconstructed u obtained from the stepwise linear
150 regression matches well with the observed u (Supplementary Figs 15 and 16, and discussion in
151 *Methods*). Finally, we train our models only using the detrended time series before the turning
152 points (2010 for the globe, 2012 for North America, 2003 for Europe, and 2001 for Asia), finding
153 that the models are capable of reproducing the positive trends after the turning points, not only
154 for the globe ($P < 0.001$; Fig. 2a), but also for all the three regions ($P < 0.001$; Fig. 2b-d). The
155 magnitude of the increasing rate after the turning points is well modelled (Fig. 2). These results
156 suggest a predictive relationship between wind changes and ocean/atmosphere oscillations,
157 which would be very valuable for the wind energy sector.

158

159 To uncover the mechanisms behind the decadal variations of u , we construct the composite
160 annual mean surface temperature for the years that exhibit negative (Fig. 3a) and positive (Fig.
161 3b) anomalies of detrended u . During the years of negative u anomalies (Fig. 3a) the following
162 are observed: (a) positive anomalies of temperature prevail over the Tropical Northern Atlantic
163 (TNA region, 5.5°N to 23.5°N, 15°W to 57.5°W), showing a positive value for Tropical Northern
164 Atlantic Index (TNA); (b) the west (east) Pacific is warmer (colder) than normal years,
165 demonstrating a negative value for Pacific Decadal Oscillation (PDO); and (c) positive anomalies
166 of temperature occur near the Azores and negative anomalies occur over Greenland, indicating a
167 negative value for North Atlantic Oscillation (NAO). The opposite pattern (i.e. negative TNA,
168 positive PDO and NAO) occurs during the years of positive u anomalies (Fig. 3b). Furthermore,
169 TNA has strong, significant, and negative correlations with regional u , in particular, over North
170 America (Fig. 3c). PDO has significant positive correlations with regional u globally (Fig. 3e).

171 NAO has overwhelmingly significant positive correlations with regional u in the U.S. and
172 Northern Europe, but negative correlation with regional u in Southern Europe (Fig. 3d). These
173 patterns are consistent with the finding that the greatest explanatory power factor is TNA for
174 North America ($R = -0.67$, $P < 0.001$), PDO for Asia ($R = 0.50$, $P < 0.01$), and NAO for Europe
175 ($R = 0.37$, $P < 0.05$) (more discussions refer to *Methods*). The ocean/atmosphere oscillations,
176 characterized as the decadal variations in these climate indices (mainly TNA, NAO, PDO), can
177 therefore explain the decadal variation of u (i.e., the long-term stilling and the recent reversal)
178 (Figs 2 and 3f-h).

179

180 There are some theories²⁰⁻²³ for potential physical mechanisms how these oscillations affect
181 regional u over land. With respect to TNA, prior studies demonstrate that the positive phase of
182 TNA is linked with a weakened Hadley circulation (more details refer to ref. 21). During the
183 positive phase of TNA there is a cold anomaly over the eastern coast of the U.S. (Fig. 3a and ref.
184 21). This pattern leads to a southward component of surface wind and a stable environment of
185 weak convergence from the tropics to the mid-latitudes, resulting a reduction of u in the mid-
186 latitudes, the U.S. in particular (Fig. 3c and Supplementary Fig. 17a,b). As for NAO, its negative
187 and positive phases have different jet stream configurations and wind systems in Northern versus
188 Southern Europe (Supplementary Fig. 17c,d; details refer to ref. 20). During the positive
189 (negative) phase, the pressure gradient across the North Atlantic²⁰ generates strong winds and
190 storms across Northern (Southern) Europe (Supplementary Fig. 17c,d), explaining the
191 contrasting correlations of NAO to u in Northern and Southern Europe (Fig. 3d, Supplementary
192 Fig. 18). For PDO, the temperature gradient during the negative (positive) phase generates an
193 easterly (westerly) component of surface wind (details refer to refs 22, 23), which weakens

194 (strengthens) the prevailing westerly winds in the mid-latitudes (Supplementary Fig. 17e,f) and
195 explains the widespread and significant positive correlations between PDO and u across the
196 whole mid-latitudes (Fig. 3e). However, despite these potential physical mechanisms²⁰⁻²³, the
197 relationships between these oscillations and long-term wind speeds over land are still uncertain
198 and require more investigations.

199
200 Finally, it is critical to determine why global reanalysis products do not reproduce or
201 underestimate the historical terrestrial stilling (Supplementary Fig. 1), which is a major basis for
202 the previous studies^{2,12} rejecting the ocean/atmosphere oscillations as a dominant driver for
203 terrestrial stilling. Global reanalysis products are generated at numerical weather prediction
204 centers with their most-advanced data assimilation systems. But most of them cannot properly
205 assimilate near-surface winds over land due to inappropriate model topography and inaccuracy
206 of atmospheric boundary layer processes implemented into the data assimilation systems. ERA-
207 Interim³⁵, one of the best products available, can only assimilate surface winds over seas from
208 scatterometers, ships and bouys. The capacities of these products in reproducing the near-surface
209 wind speed over land are thus generally poor and rely on climate models. We find that in the
210 regions where AMIP model simulations (i.e. atmospheric simulations forced with observed sea
211 surface temperature) capture the stilling, such as Europe and India (Fig. 4a,b in ref. 30), the
212 global reanalysis products are also capable of reproducing the stilling in these regions (Fig. S1c);
213 while in regions where AMIP simulations do not capture the stilling, such as North America^{30,36},
214 the global reanalysis products also fail to reproduce the stilling^{2,11} (Fig. S1b). Therefore, it is the
215 model limitations that prevent global reanalysis products from reproducing the observed near-
216 surface wind speed changes in some regions satisfactorily. More efforts are required to improve

217 surface process parameterization scheme and its connection to ocean/atmosphere circulations in
218 climate models and operational weather data assimilation systems.

219

220 **Implications for wind energy production**

221 In wind power assessments, near-surface wind observations from weather stations (u at the
222 height of $z_r = 10$ meters) are often used to estimate wind speeds at the height of a turbine (u_{tb} at
223 the height of $z_{tb} = 50$ -150 meters) using an exponential wind profile power law relationship:

$$224 \quad u_{tb} = u \left(\frac{z_{tb}}{z_r} \right)^\alpha \quad (2)$$

225 where the α is commonly assumed to be constant (1/7) in wind resource assessments because the
226 differences between these two levels are unlikely great enough to introduce considerable errors
227 in the estimates⁵.

228

229 Changes in wind speed matter not only on average but also in the percentage of time wind speeds
230 are high or low. A $u_{tb} > 3 \text{ m s}^{-1}$ is a typical minimum velocity needed to drive turbines efficiently,
231 so wind speeds below 3 m s^{-1} are typically wasted from the power generation perspective.
232 Although periods of high wind speed greatly increase the physical capacity to generate power
233 according to formula (1), turbines are built with a maximum capacity, so periods of high wind
234 speed can also “waste” the uses of wind with the threshold depending on the capacity of the
235 turbine.

236

237 On average, the increase of global mean annual u from 3.13 m s^{-1} in 2010 to 3.30 m s^{-1} in 2017
238 (Fig. 1a; see *Methods* for details) increases the amount of energy entering a hypothetical wind

239 turbine receiving the global average wind by $17 \pm 2\%$ (uncertainty is associated with subsamples
240 in Fig. 1a; regionally, $22 \pm 2\%$ for North America, $22 \pm 4\%$ for Europe, and $11 \pm 4\%$ for Asia). At
241 the hourly scale, the frequency of low u decreases while the frequency of high u increases (Fig.
242 4a). Using one General Electric GE 2.5 – 120 turbine³⁷ (Supplementary Fig. 19) to illustrate, the
243 effects of changes in global average u increase potential power generation from 2.4 million kWh
244 in 2010 to 2.8 million kWh in 2017 (+17%). If the present trend persists for at least another
245 decade, in the light of the robust increasing rate during 2000-2017 (Fig. 1a) and the long cycles
246 of natural ocean/atmosphere oscillations²⁰⁻²⁴ (Supplementary Fig. 20), power would rise to 3.3
247 million kWh in 2024 (+37%), resulting in a +3% per decade increase of global-average capacity
248 factor (mean power generated divided by rated peak power) on average. This change is even
249 larger than the projected change in wind power potential caused by climate change under multi-
250 scenarios³⁸.

251

252 During the past decade, the capacity factor of the U.S. wind fleet³⁹ has steadily risen at a rate of
253 +7% per decade (Fig. 4b), previously attributed solely to technology innovations⁴⁰. We find that
254 the capacity factor for wind generation in the U.S. is highly and significantly correlated with the
255 variation in the cube of regional-average u (u^3 , $R = 0.86$, $P < 0.01$; Fig. 4b). To isolate the u -
256 induced increase in capacity factor from that due to technology innovations, we use the regional
257 mean hourly wind speed in 2010 and 2017 to estimate the increase of capacity factor for a given
258 turbine, thereby controlling for technology innovations. It turns out that the increased u^3 explains
259 ~50% of the increase of the capacity factor (see *Methods* for details). Therefore, in addition to
260 technology innovations, the strengthening u is another key factor powering the increasing

261 reliability of wind power in the U.S. (and other mid-latitude countries where u is increasing, such
262 as China and European countries).

263

264 To illustrate the consequences, one turbine (General Electric GE 1.85 – 87 (ref. 41)) installed at
265 one of our *in-situ* weather stations in the U.S. in 2014 (inset plot in Fig. 4c), which was expected
266 to produce 1.8 ± 0.1 million kWh using four years of u records before the installation (2009-
267 2013)⁴¹, actually produced 2.2 ± 0.1 million kWh between 2014-2017 (+25%). This system has
268 the potential to generate 2.8 ± 0.1 million kWh (+56%) if u recovers to the 1980s level (red bars
269 in Fig. 4d; see *Methods* for details). Globally, 90% of the global cumulative wind capacity has
270 been installed in the last decade²⁵, during which global u has been increasing (see above).

271

272 **Discussion**

273 Although the response of ocean/atmosphere oscillations to anthropogenic warming remains
274 unclear²³, the increases in wind speeds should continue for at least a decade because these
275 oscillations change over decadal time frames²⁰⁻²⁴. Climate model simulations constrained with
276 historical sea surface temperature also show a long cycle in u over land (Supplementary Fig. 20).
277 Our findings are therefore good news for the power industry for the near future.

278

279 However, oscillation patterns in the future will likely cause returns to declining wind speeds, and
280 anticipating these changes should be important for the wind power industry. Wind farms should
281 be constructed in the areas with stable winds and high effective utilization hours (e.g. $3 - 25 \text{ m s}^{-1}$).
282 If high wind speeds are likely to be common, building turbines with larger capacities could be
283 justified. For example, capturing more available wind energy (blue bars in Fig. 4d) could be

284 achieved through the installation of higher capacity wind turbines (e.g. General Electric GE 2.5 –
285 120, green bars in Fig. 4d), greatly increasing total power generation. Most turbines tend to
286 require replacement after 12-15 years⁴². Further refinement of the relationships uncovered in this
287 paper could allow choices of turbine capacity, rotor and tower that are optimized not just to wind
288 speeds of the recent past but to likely future changes during the lifespan of the turbines.

289

290 In summary, we find that after several decades of global terrestrial stilling, wind speed has
291 rebounded, increasing rapidly in the recent decade globally since 2010. Ocean/atmosphere
292 oscillations, rather than increased surface roughness, are likely the causes. These findings are
293 important for those vested in maximizing the potential of wind as an alternative energy source.
294 The development of renewable energy sources including wind power^{6-9,25} is central to energy
295 scenarios⁸ that help keep warming well below 2 °C. One megawatt (MW) of wind power reduces
296 1,309 tonnes of CO₂ emissions and also saves 2,000 liters of water compared with other energy
297 sources^{9,25}. Since its debut in the 1980s, the total global wind power capacity reached 539
298 gigawatts by the end of 2017, and the wind power industry is still booming globally. For instance,
299 the total wind power capacity in the U.S. alone is projected to increase fourfold by 2050 (ref. 9).
300 The reversal in global terrestrial stilling bodes well for the expansion of large-scale and efficient
301 wind power generation systems in these mid-latitude countries in the near future.

302

303

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401

402 **Additional information**

403 Supplementary information is available in the online version of the paper. Reprints and
404 permissions information is available online at www.nature.com/reprints.

405 Correspondence and requests for materials should be addressed to Z. Zeng.

406

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416

417 **Author contributions**

418 Z. Zeng and E. Wood designed the research. Z. Zeng and L. Yang performed analysis; Z. Zeng,
419 A. Ziegler, T. Searchinger wrote the draft; and all the authors contributed to the interpretation of
420 the results and the writing of the paper.

421

422 **Data availability.** The data for quantifying wind speed changes are the Global Surface Summary
423 of the Day database (GSOD, <ftp://ftp.ncdc.noaa.gov/pub/data/g sod>), and the HadISD (version
424 v2.0.2.2017f) global sub-daily database (<https://www.metoffice.gov.uk/hadobs/hadisd/>). The

425 time series of climate indices describing monthly atmospheric and oceanic phenomena are
426 obtained from the National Oceanic and Atmospheric Administration
427 (<https://www.esrl.noaa.gov/psd/data/climateindices/list/>). Simulated wind speed changes in
428 Coupled Model Intercomparison Project Phase 5 (CMIP5) are available in the Program for
429 Climate Model Diagnosis and Intercomparison (<https://esgf-node.llnl.gov/projects/cmip5/>).
430 Simulated wind speed changes constrained by historical sea surface temperature are provided by
431 the IPSL Dynamic Meteorology Laboratory. Wind records in reanalysis products include the
432 ECMWF ERA-Interim Product (<apps.ecmwf.int/datasets/data/interim-full-daily/>), the ECMWF
433 ERA5 Product ([https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels-](https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels-monthly-means)
434 [monthly-means](https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels-monthly-means)) and the NCEP/NCAR Global Reanalysis Product
435 (<http://rda.ucar.edu/datasets/ds090.0/>). The processed wind records and the relevant code are
436 available in Supplementary Data 1 and 2. All datasets are also available on request from Z. Zeng.

437

438 **Code availability.** The program used to generate all the results is MATLAB (R2014a) and
439 ArcGIS (10.4). Analysis scripts are available by request from Z. Zeng. The code producing wind
440 records are available in Supplementary Data 1 and 2.

441

442 **Competing financial interests**

443 The authors declare no competing financial interests.

444

445 **Figure Legends.**

446 **Figure 1. Turning point for mean global surface wind speed (u).** (a) Global mean annual u
447 during 1978-2017 (black dot and line). The piecewise linear regression model indicates a
448 statistically significant turning point in 2010. The red line is the piecewise linear fit ($R^2 = 90\%$, P
449 < 0.001). The dashed line indicates the turning point. The trends before and after the turning
450 point are shown in the inset. Each grey line ($n = 300$) is a piecewise linear fit for a randomly
451 selected subset (40%) of the global stations. (b) Frequency distribution of the estimated turning
452 points derived from the 300 resampling results. (c) Frequency distribution of the trends in mean
453 annual u before and after the turning point from the 300 resampling results. The result is based
454 on the weather stations in the GSOD database.

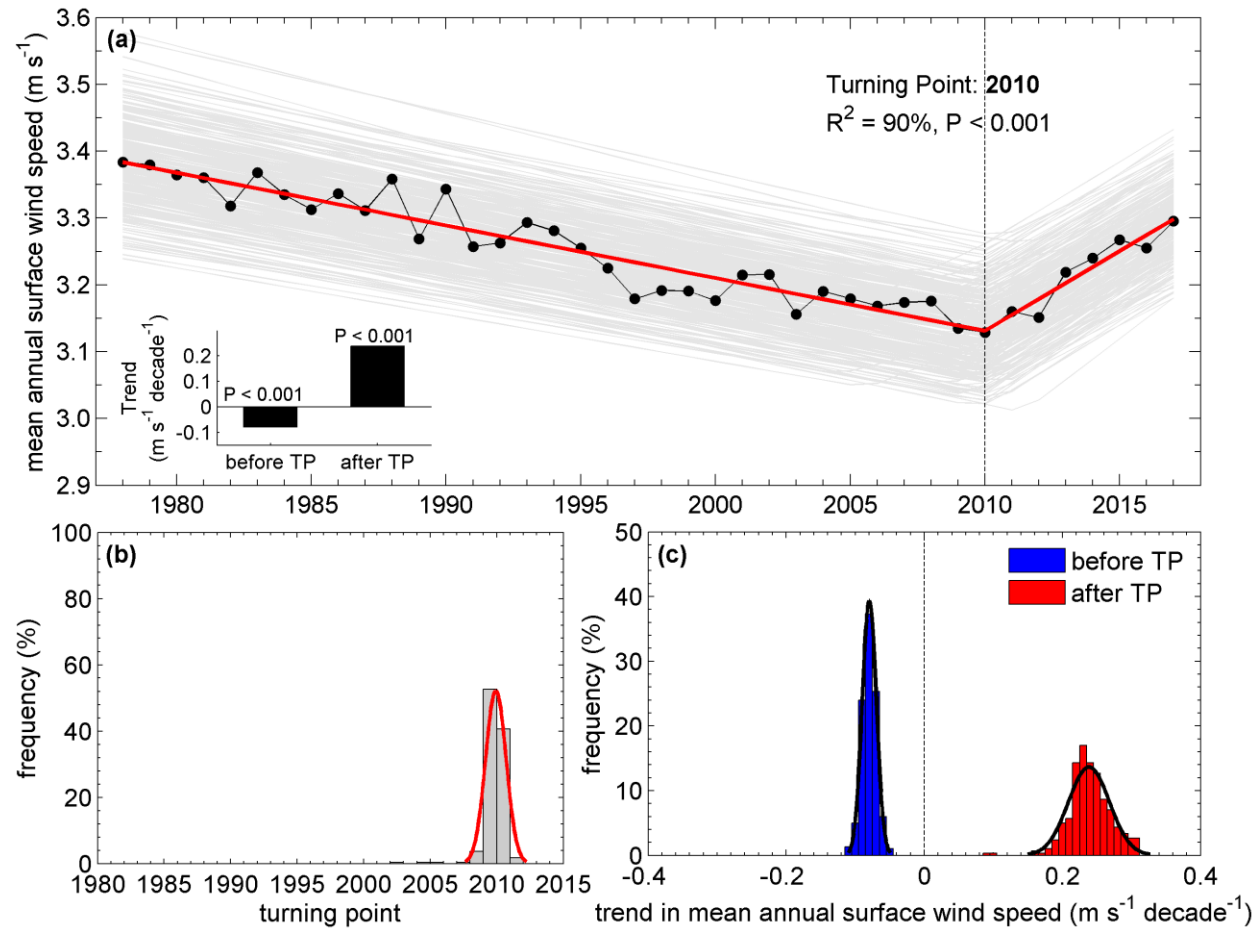
455 **Figure 2. Factors driving the decadal variations in u .** Observed (black) and reconstructed (red)
456 detrended mean annual u over the following: (a) the globe, (b) North America, (c) Europe, and (d)
457 Asia. The models are trained only using the detrended time series before the turning points. The
458 dashed line indicates the turning point (2010 for the globe, 2012 for North America, 2003 for
459 Europe, and 2001 for Asia). For the globe and each of the three continents, we select six largest
460 explanatory climate indices for the decadal variations of u with a stepwise forwarding regression
461 model. The selected climate indices are then used to reconstruct decadal variations of u via a
462 multiple regression. Uncertainties are the inter-quartile range of the results based on a randomly
463 selected 40% subset of the station pools (repeated 300 times). Inset plots indicate the locations of
464 the stations. Inset black numbers are coefficients of determination between observed and
465 reconstructed u before the turning points. Inset red numbers are correlation coefficient and its
466 significance between observed and reconstructed u after the turning points.

467 **Figure 3. Mechanisms for the decadal variation in u .** Normalized mean annual surface
468 temperature for the years with negative **(a)** and positive **(b)** anomalies of detrended wind.
469 Characteristic regions for Pacific Decadal Oscillation (PDO), North Atlantic Oscillation (NAO)
470 and Tropical Northern Atlantic Index (TNA) are outlined by green, red, and blue boxes,
471 respectively. Surface temperature over land is obtained from Climate Research Unit TEM4 with
472 a spatial resolution of 5° by 5° (ref. 50), and that over ocean is from NOAA Optimum
473 Interpolation (OI) Sea Surface Temperature V2, with a spatial resolution of 1° by 1° (ref. 51).
474 Spatial patterns of the correlation between the regional ($5^\circ \times 5^\circ$) mean annual u and the following:
475 **(c)** TNA; **(d)** NAO; and **(e)** PDO for 1978-2017. Dotting represents significant at $P < 0.05$ level.
476 Decadal variations are shown in panels **(f)** for TNA and regional u in North America; **(g)** for
477 NAO and regional u in Europe; and **(h)** for PDO and regional u in Asia. The thin lines are annual
478 values; and the thick lines are 9-year-window moving averages. The black lines are wind speed;
479 and each of the colored lines are TNA, NAO, and PDO, respectively.

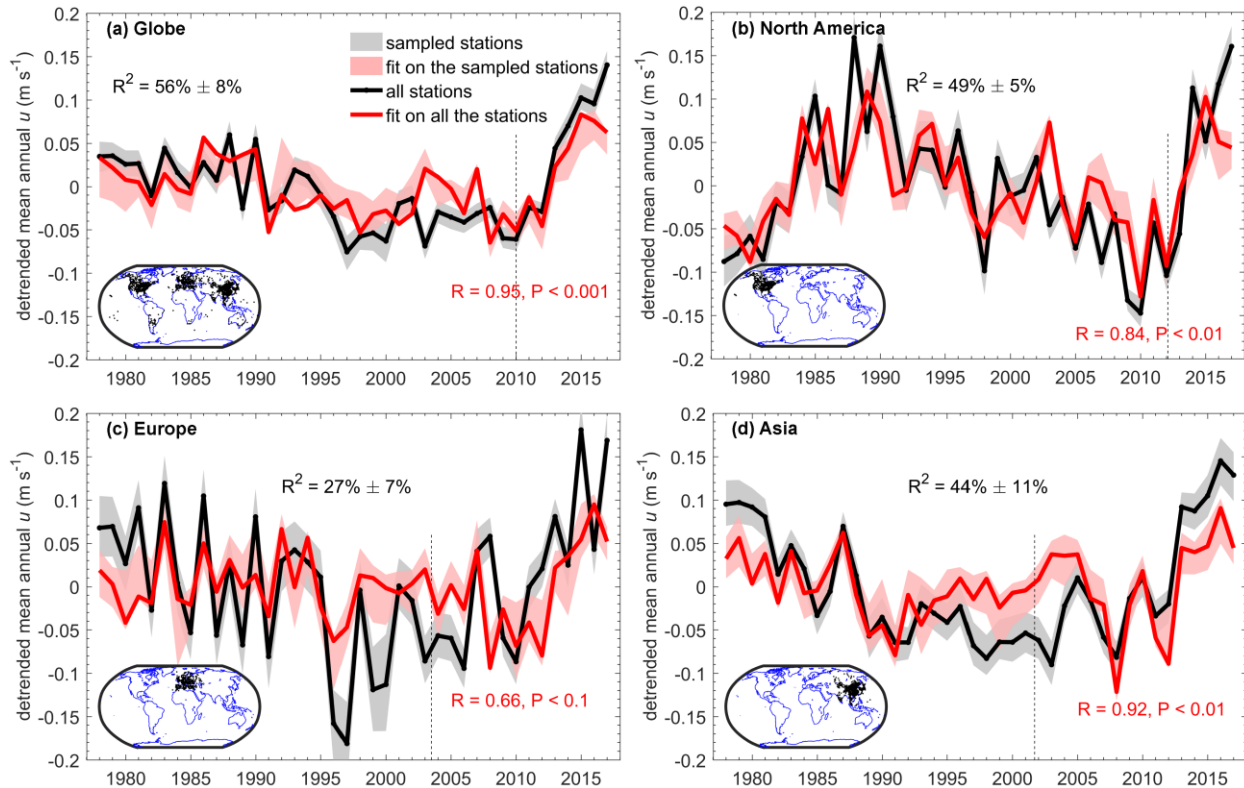
480 **Figure 4. Implications of the recent reversal in global terrestrial stilling for wind energy**
481 **industry.** **(a)** Frequency distribution of global average hourly u in 2010 and 2017, and the year
482 2024 assuming the same increasing rate. **(b)** Time series of the overall capacity factor for wind
483 generation in the U.S. (black line) and the three-order of the regional-average u (u^3 ; blue line)
484 from 2008 to 2017. The inset scatter plot shows the significant relationship between the overall
485 capacity factor and the regional u^3 ($R = 0.86$, $P < 0.01$). The inset black numbers show the trend
486 in the overall capacity factor for wind generation, and the inset red numbers show the u -induced
487 increase of capacity factor in the U.S.. **(c)** Mean annual u observed at a weather station near an
488 installed turbine at Deaf Smith County, the U.S. (< 1 km). The inset plot shows the location. The
489 turbine was installed in 2014. The background colors separate different periods: P0, the 1980s

490 level when u is relative strong (1978-1995); P1, the evaluation years before the installation of the
491 turbine (2009-2013); P2, the operation years when the turbine is generating power (2014-2017).
492 **(d)** Mean annual wind power production at Deaf Smith County, the U.S. from different wind
493 turbines during different periods (grey: General Electric GE 1.85 – 87; green: General Electric
494 GE 2.5 – 120 turbine; blue: the theoretical maximum ratio of power that can be extracted by a
495 wind turbine given diameter of 120 m and hub height of 120 m). Error bars show the interannual
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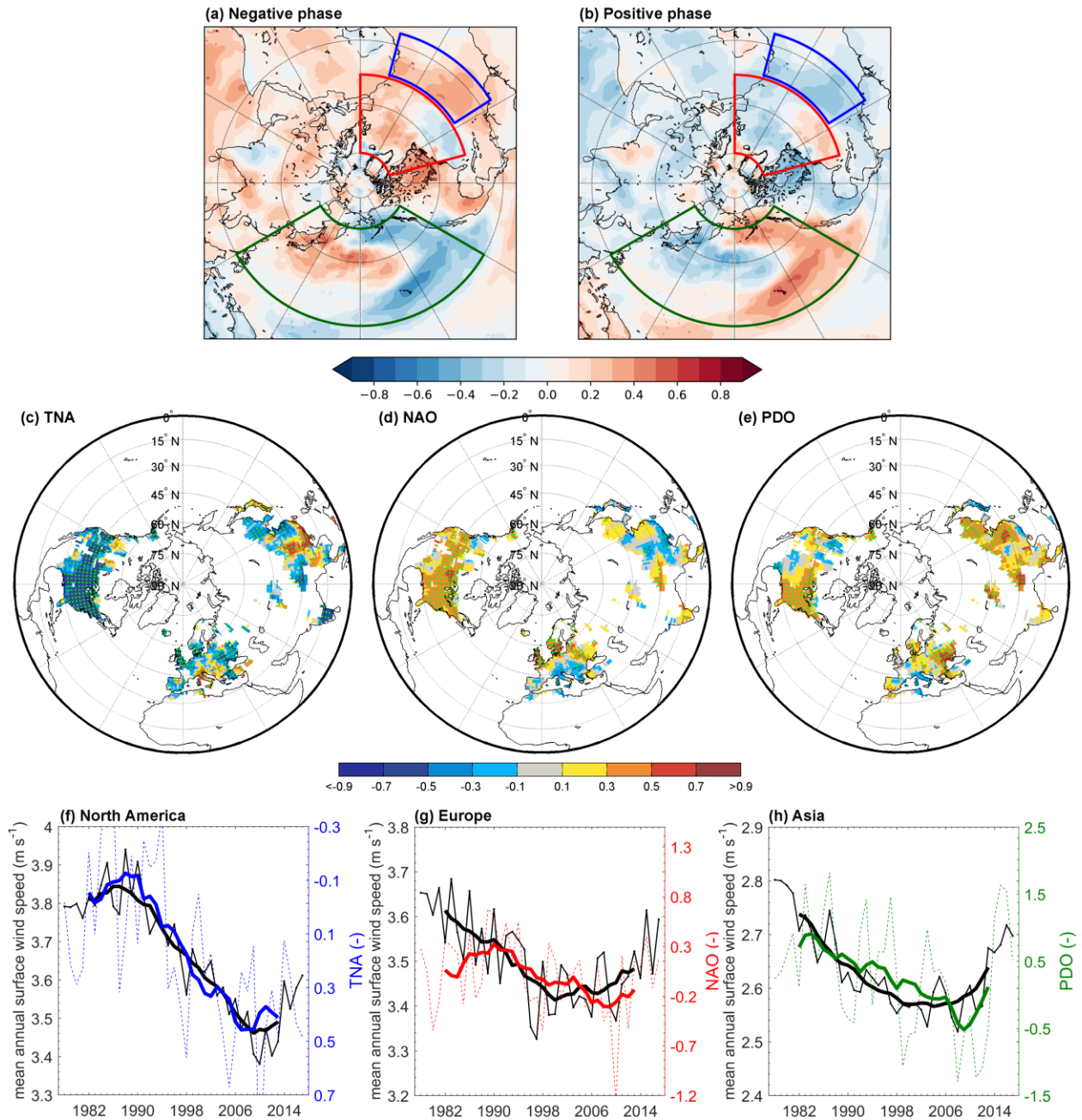
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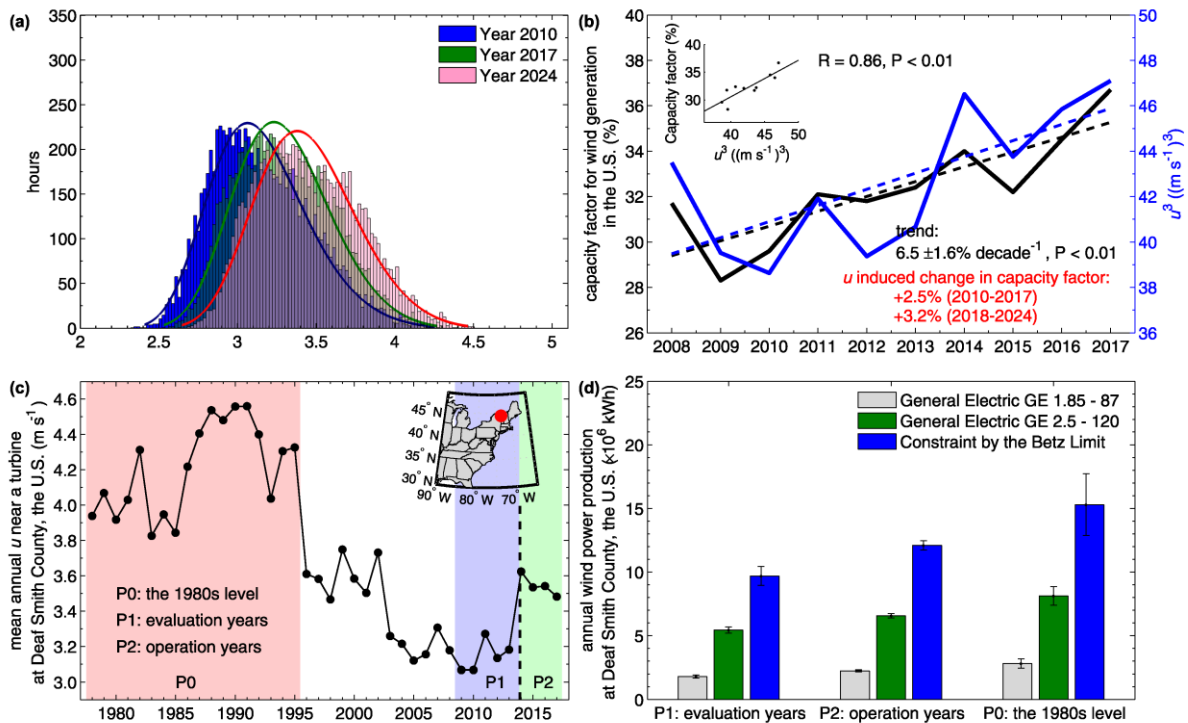


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