A continuous decline of global seasonal wind speed range over land since 1980

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ABSTRACT

To investigate changes in global wind speed phenomena, we constructed homogenized monthly time series (1980-2018) for 4,722 meteorological stations. Through examining monthly-averaged wind speeds (MWS), we found that seasonal wind speed range (SWSR; calculated as the difference between maximum and minimum MWS) has declined significantly by 10% since 1980 ($p < 0.001$). This global SWSR reduction was primarily influenced by decreases in Europe (-19%), South America (-16%), Australia (-14%), and Asia (-13%), with corresponding rate reductions of -0.13, -0.08, -0.09 and -0.06 m s$^{-1}$ decade$^{-1}$, respectively ($p < 0.01$). In contrast, the SWSR in North America rose 3%. Important is that the decrease in SWSR occurred regardless of the stilling or reversal of annual wind speed. The shrinking SWSR in Australia and South America was characterized by continuous decreases in maximum MWS and increases in the minimum. For Europe and Asia, maximum and minimum MWS declined initially after 1980, followed by substantial increases in minimum MWS (about 2000 and 2012, respectively) that preserved the long-term reduction in the range. Most reanalysis products (ERA5, ERA-Interim, and MERRA-2) and climate model simulations (AMIP6 and CMIP6) fail to reproduce the observed trends. However, some ocean-atmosphere indices (seasonality characteristics) were correlated significantly with these trends, including West Hemisphere warm pool, East Atlantic Patten, Pacific Decadal Oscillation, and others. These findings are important for increasing the understanding of mechanisms behind wind speed variations that influence a multitude of other biogeophysical processes and the development of efficient wind energy generations, now and in the future.

**Keywords:** Terrestrial wind speed, seasonality, stilling reversal, decadal variability, ocean-atmosphere circulations
1. Introduction

Wind is a critical component of many socio-economic and environmental issues, for example, wind erosion and landscape evolution (Chappell et al. 2016; Abell et al. 2020), the hydrological cycle (McVicar et al. 2012), wave phenomena (Young et al. 2019), geothermal mixing in water bodies (Woolway et al. 2019), aerosol transport and dispersal (Wen and Yeh 2010), fire spread/intensity (Cruz and Alexander 2019), and weather (Zhou et al. 2013). While strong winds are a hazard that can cause great physical damage, human casualties, and economic losses (Stawicki et al. 2013), wind is also an alternative energy source to fossil fuel burning when annual velocities are stable and of sufficient magnitude (Kaberger 2018). As a key clean and renewable energy source, wind is anticipated to supply 25-33% of the world’s electricity by 2050 (Veers et al. 2019). The global wind energy sector attaches great interest to variations in wind speed when evaluating wind resources and managing wind farms (Ulazia et al. 2019). Even slight variations in wind speed can make significant differences in wind energy production because the power generated is proportional to the third power of wind speed (Zeng et al. 2019).

Annual global terrestrial wind speeds have been rising rapidly since 2010, following decades of reductions starting from the 1960s, a phenomenon known as stilling (Vautard et al. 2010; McVicar et al. 2012; Zeng et al. 2019). The recent observed increase in global wind speed represents a boost for the wind energy sector. However, a study at finer spatio-temporal resolutions is needed to guide efficient wind energy harvesting strategies. Operationally, wind energy productions (average monthly) of a wind farm lie between the power generation in months with maximum and minimum wind speeds. Thus, a global investigation on monthly wind speed (MWS) changes should be useful for optimizing the use of wind energy worldwide, in addition to providing a better understanding of potential impacts of wind variability on other natural and human systems (Vautard et al. 2010; Bichet et al. 2012; McVicar et al. 2012; Zeng...
et al. 2019). Moreover, enhanced knowledge of MWS changes is also helpful for learning the uncertainty of reanalyses and climate models that incorporate the variability of wind speed over large spatial and long temporal scales (Torralba et al. 2017; Shaner et al. 2018). These types of products are used by the wind power industry for wind resource assessments; they are also used by many other institutions to assess climate change and variability (Huang et al. 2014; Gregow et al. 2016).

In prior work, Zeng et al. (2019) reported the reversal in wind stilling for Asia, Europe, and North America, but they did not explore seasonal variations. To date, only a handful of regional studies on seasonal wind speeds have been conducted. Some of these studies found different trends in seasonal wind speed. For instance, a study conducted in Spain and Portugal for 1961-2011 found that wind speed weakened in boreal winter and spring but rose in summer and autumn (Azorin-Molina et al. 2014). Another study found that during 1978-2013 wind speeds in Saudi Arabia decreased in the winter-spring, while those in summer-autumn reversed in 2001, following two decades of stilling (Azorin-Molina et al. 2018). In China, the daily maximum wind speed for 1975-2016 declined in boreal winter and autumn but rose in summer and spring (Zhang et al. 2020). The above studies show that trend differences occur between seasons with higher and lower wind speeds. We thus hypothesize that differences exist between seasons with the highest and lowest wind speeds. These temporal differences in wind speed changes for small areas support the notion that distinct seasonal differences may occur elsewhere globally. In addition, the differences have not been quantified, particularly those related to reversals (increase) following stilling (decrease). In this study, we explore the observed seasonal wind speed range (SWSR hereafter), which is the difference between the maximum and minimum MWS in a year.

In addition, as the changes of wind speeds in particular months are possibly driven by different factors, an investigation on the spatiotemporal changes in the seasonality of terrestrial
wind speed is helpful in advancing our understanding on the mechanisms behind the decadal variations of wind speed, including the terrestrial stilling and its recent reversal (Vautard et al. 2010; Bichet et al. 2012; McVicar et al. 2012; Zeng et al. 2019). An improved understanding of the causes of SWSR changes is also crucial for predicting the variability of wind speed over large spatial and long temporal scales (Torralba et al. 2017; Shaner et al. 2018). If the processes influencing wind speed changes have not been represented in models accurately (e.g., forecast models in reanalysis products or climate models), they may fail to reproduce the observed variability of wind speed.

The primary objectives of this study are the following: (i) to characterize the spatiotemporal changes in MWS and SWSR regionally and globally; (ii) to evaluate whether the observed spatiotemporal changes in the wind seasonality have been reproduced by model-based wind products, including global reanalysis products (ERA5, ERA-Interim, JRA-55, and MERRA-2), as well as the climate model outputs from AMIP6 and CMIP6 projects; and (iii) to explore potential causes that drive the decadal variation of wind speed, if present. While our interest in wind change phenomena is framed in the context of wind energy production, our results are relevant to any field of inquiry where wind is a crucial process.

2. Data and Methods

a. In-situ observations of terrestrial wind speed and homogenization

We analyzed the terrestrial wind speed at 10-m height in the global HadISD dataset, version v3.0.0.2018f (https://www.metoffice.gov.uk/hadobs/hadisd/; last accessed 15 May 2021; Dunn et al. 2016; Dunn 2019). The period chosen in this study was from 1980 to 2018. We performed the analysis for the period 1980 to 2018. We used the R package Climatol v3.1 (Guijarro 2017; http://www.climatol.eu/; last accessed 15 May 2021) to perform quality control, identify outliers and missing values, and to homogenize time series. Homogenization is required
because wind speed time series often have erroneous values that result from (i) station resettlement, (ii) anemometer height changes, (iii) instrumentation defects, (iv) instrumentation replacements, (v) sampling interval variation, and (vi) environment changes (Pryor et al. 2009). Invariably, these actions produce gaps in the data (not recorded or erroneous) or systematic shifts in the mean that must be reconstructed or adjusted.

First, we aggregated daily wind speed data into monthly values because high variations at a daily resolution makes identifying breakpoints challenging. We then built monthly time series for all stations, assigning months with more than five missing daily values to be “missing data” (Azorin-Molina et al. 2014). Second, we normalized the time series by dividing every value by the mean series.

In the homogenization process, all wind speed values in each series (including missing values) were created as a weighted mean of data from four nearby stations (weighted by an inverse distance function). Differences between the observed and estimated values (standard anomalies) were used to identify outliers and determine breakpoints with the Standard Normal Homogeneity Test (SNHT; Alexandersson 1986; AnClim R package). Briefly, wind speed series were split at their largest SNHT. The splitting process was repeated iteratively on series until no statistically significant breakpoints with SNHT > 25 remained (Azorin-Molina et al. 2014). Missing data in the original monthly time series was filled using data from the four nearest data available at each time step. An example of the breakpoint detection and homogenization methods adopted in this research can be found in Azorin-Molina et al. (2018; Fig. 2).

Homogenization identified 21,527 breakpoints that required corrections. Seven outliers were rejected. Through this process, we created the homogenized time series from 4,722 stations (Fig. S1), of which 1,404 are located in Europe (36°-71° N and 15° W-45° E); 1,113 in Asia (2°-71° N and 45°-170° E); 1,278 in North America (8°-71° N and 56°-168° W); 337 in...
Accordingly, the stations were divided into five regions for analysis: Europe, Asia, North America, Australia, and South America. Africa was not included in this study because of a lack of data. Here, we remind readers that because of the disproportionate number of stations in Europe, Asia, North America, Australia, and South America, the trends we explore below are not truly global; rather, they reflect trends in all associated with all data-rich regions.

b. Reanalysis products, CMIP6 and AMIP6 model simulation data

To investigate whether reanalysis assimilation products or climate model simulation outputs are capable of reproducing changes in monthly and seasonal characteristics of wind speed, we examined the state-of-the-art reanalysis ERA5 product (Hersbach et al. 2020), and three other widely-used reanalyses: ERA-Interim (Dee et al. 2011), MERRA-2 (Gelaro et al. 2017) and JRA-55 (Kobayashi et al. 2015). We also investigated trends in simulation outputs from five global climate models from the Atmospheric Model Intercomparison Project 6 (AMIP6) and the Coupled Model Intercomparison Project 6 (CMIP6) (Eyring et al. 2016; Pascoe et al. 2020). Unlike reanalysis products, based on numerical weather prediction models and assimilating prescribed quantities of ocean, land, and ice, climate models commonly consist of several sub-models, each focusing on different components. The difference between AMIP6 and CMIP6 is that observed sea surface temperatures and sea ice concentrations replace ocean and sea ice models in AMIP6 (Eyring et al. 2016).

We directly obtained the outputs of the ERA5 product from the Copernicus Climate Data Store website (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels-monthly-means?tab=form, last accessed 15 May 2021), and the selected variable was “10m monthly wind speed”. ERA-Interim is the previous version of ERA5 (https://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=sfc/, last accessed 15 May

We used the historical simulation outputs from CMIP6 and AMIP6, both driven by historical forcings, including greenhouse gases (GHG) and aerosols induced by human activities, global gridded land use, solar forcing, and volcanic activity. These outputs are useful for exploring processes that cause wind speed changes. Finally, we chose five models from CMIP6 and AMIP6 because they have the following in common: (i) a spatial resolution finer than 100 km; (ii) overlapping temporal coverage with observation time series; and (iii) historical monthly near-surface wind speed data. Finally, the output of five global climate models CNRM-CM6-1-HR, FGOALS-f3-L, MRI-ESM2-0, BCC-CSM2-MR, and CESM2 were downloaded (https://esgf-node.llnl.gov/search/cmip6/, last accessed 15 May 2021; Seiji et al. 2019). More details of these products, including institutions, resolution and period coverage, are provided in Table 1.

c. Climate indices

Some ocean-atmosphere oscillations are among the principal drivers of wind speed changes and multi-decadal variabilities (Zeng et al. 2019). Such oscillations are represented by a variety of climate indices that can express conditions and variations of the climate system. In our analysis, we considered a set of 22 indices having continuous data during the study period (1980-2018): including (a) 11 Northern hemisphere teleconnection indices, e.g., North Atlantic Oscillation (NAO; Jones et al. 1997), East Atlantic Pattern (EA; Barnston and Livezey 1987;
Bojariu and Reverdin 2002), West Pacific Pattern (WP; Barnston and Livezey 1987; Wallace and Gutzler 1981), East Pacific/North Pacific Pattern (EP/NP; Bell and Janowiak 1995), Pacific/North American Pattern (PNA; Feldstein 2002), East Atlantic/West Russia Pattern (EA/WR; Barnston and Livezey 1987; Washington et al. 2000), Scandinavia Pattern (SCA; Washington et al. 2000; Bueh and Nakamura 2007), Tropical/Northern Hemisphere Pattern (TNH; Mo and Livezey 1986), Polar/Eurasia Pattern (POL; Barnston and Livezey 1987), Pacific Transition Pattern (PT; Wallace and Gutzler 1981) and Pacific Decadal Oscillation (PDO; Mantua et al. 1997); (b) four ENSO indices (Niño 1+2, Niño 3.4, Niño 3, Niño 4; Rasmusson and Carpenter 1982); (c) three atmospheric indices (Arctic Oscillation (AO; Thompson and Wallace 1998), Antarctica Oscillation (AAO; Thompson and Wallace 2000), Southern Oscillation Index (SOI; Allan et al. 1991)); and (d) four indices related to sea surface temperature (SST) (Tropical Northern Atlantic Index (TNA; Enfield et al. 1999), Atlantic Meridional Mode (AMM; Servain et al. 1999), Tropical Southern Atlantic Index (TSA; Enfield et al. 1999) and Western Hemisphere warm pool (WHWP; Wang et al. 2007)). All these climate indices were downloaded from the NOAA. A definition of each one can be found here: https://psl.noaa.gov/data/climateindices/list/#NAOJONES%20(last accessed 15 May 2021).

d. Statistical analyses

For a specific region or the globe, we averaged maximum MWS, minimum MWS, and SWSR for all the stations within the study region to obtain regional estimates. As reanalysis products and climate model outputs are gridded data, we extracted the nearest grid point for each station for calculations. For grids with multiple stations, we only used the grid data once when calculating the MWS values. In addition, we checked the trends of 300 independent time series for each region (Zeng et al. 2019). Each time series was constructed by the mean time series from 40% of the stations in the corresponding region, and these stations were selected.
randomly (Zeng et al. 2019). This method allows us to know if the average trend resulted from large anomalies at a few sites. We used the R package “segmented” to identify the stilling turning points in time series (Muggeo VM 2003, 2016, 2017, 2008) and Mann-Kendall test (Gocic and Trajkovic 2013) to calculate the significance of trends at \( p < 0.05 \) (Matlab climate tools; Greene et al. 2019). Additionally, we used the Pearson correlation coefficient \((r)\) at a significance of \( p < 0.05 \) to evaluate the relationships between climate indices and wind speed variables on these constructed sets.

3. Results

a. Changes in the seasonality of terrestrial MWS

As shown in the time series of global-mean wind speed phenomena from 1980 to 2018 (Fig. 1), annual minimum MWS usually occurred in four boreal summer-autumn months (July-September); and annual maximum MWS often occurred in four boreal winter-spring months (January-April). This seasonality is mainly associated with the wind speed variations in the Northern Hemisphere, where 87% of the stations are located. Further, the decadal mean MWS for almost all months declined in the three decades from 1980 to 2009 (Fig. 1b-c). They then rebounded, except January, March, and September, with a mean monthly increase of +0.016 m s\(^{-1}\) (Fig. 1b). The decrease mentioned above, as well as the reversal in stilling, also occurred in decadal mean seasonal wind speeds (Fig. 1c). The fastest recovery was in summer (July-August) and the slowest in autumn (September-November) (Fig. 1c). In Europe, MWS peaked in winter (DJF), and plunged in summer and early autumn months (July-September; Fig. 2a2-2a3). Decadal boreal winter (DJF) and spring (MAM) wind speed between 1980 and 1999 was higher than other periods, which declined in the period 2000-2009 and then increased in the last decade (2010-2018). The decrease in the boreal summer (JJA) reversed in 2000, while the autumn (SON) decadal mean declined continuously from 1980-2018 (Fig. 2a3). These trends provide
some supports for a reversal in stilling in Europe.

In comparison, the highest mean wind speed values in Asia occurred in the boreal spring (March-May), whereas the lowest were associated with summer-autumn (August-October; Fig. 2b1). Further, more than half of the number of months saw a reversal (increase) in wind speed (May-Dec) after three decades of decrease (Fig. 2b2). This upward trend was more evident in the decade (2010-2018), monthly, and seasonal mean wind speeds (Fig. 2b2-2b3).

In contrast, we could not identify a reversal in stilling in the decadal monthly and seasonal wind speed data for North America, where decadal wind speeds declined during the study period, particularly after 1990 (Fig. 2c2). However, the seasonal pattern in North America was similar to that of Asia, with MWS highs in February-April and lows occurring in July-September. In Australia, like in North America, the seasonal wind speed for the most recent decade (2010-2018) was lower than that in prior decades (Fig. 2d2). The exception was the austral autumn (MAM), where MWS has been increasing since 1980. Seasonally, wind speeds increased decade by decade in the austral autumn (MAM); they decreased in the austral winter (JJA). The Australian decadal data do not indicate a reversal in stilling. South America, which is also predominantly located in the Southern Hemisphere, had MWS variations that were smaller than those in Australia during the past four decades (Fig. 2e1-2e2). Seasonal wind speeds and most of the MWS in South America rose after 2009 (Fig. 2e2-2e3). In general, these results reveal that the timing of the stilling and the recovery in South American MWS varied seasonally.

b. A continuous narrowing SWSR for 1980-2018

The most novel result we found regarding the spatiotemporal changes in the seasonality of terrestrial wind speed variable was the continuous narrowing of SWSR over the entire study period, even after the reversal of annual wind speed stilling around 2010 (Fig. 3). Globally, the
mean SWSR of all stations decreased significantly at a rate of -0.06 m s\(^{-1}\) per decade \((R^2 = 47\%; p < 0.001)\) during 1980-2018 (Fig. 3). This trend was verified by recalculation using 300 randomly selected subsets containing 40\% of stations (shadow lines in Fig. 3). The narrowing range reflects distinct variations between maximum and minimum MWS, which both increased after 2010, following a three-decade decline (Fig. 4). During the declining phase, maximum MWS (-0.06 m s\(^{-1}\) per decade, \(p < 0.05\)) dropped faster than the minimum MWS, which was largely unchanged (~0.00 m s\(^{-1}\) per decade, \(p > 0.05\)). After about 2010, the increase in maximum MWS (+0.04 m s\(^{-1}\) per decade, \(p > 0.05\)) was less than that of the minimum MWS (+0.19 m s\(^{-1}\) per decade, \(p < 0.05\); Fig. 4). The post-2010 differences not only resulted in the observed continuous decrease of SWSR (Fig. 3), but they allow for a reversal of stilling at a global scale. A total of 65\% of the individual stations recorded a decline in the SWSR (Fig. 5), of which 46\% (or 30\% of the total stations) were significant \((p < 0.05)\) (Table 2). Most of these stations (with narrowing SWSR) are located in Europe (37\%), Asia (26\%), North America (17\%), Australia (7\%), and South America (4\%).

The increase of SWSR in North America (+0.01 m s\(^{-1}\) per decade, \(p < 0.001\)) (Fig. 6e) resulted from a continuous fall in maximum MWS and decadal fluctuations in minimum MWS (Fig. 6f). In contrast, SWSR narrowed significantly in the other four regions \((p < 0.01)\) (Fig. 6a, c, g, i), but changes in maximum and minimum MWS were different (Fig. 6b, d, h, j). In Europe, maximum MWS dropped at a rate of -0.10 m s\(^{-1}\) per decade \((p > 0.05)\) during 1980-2000; the decline then slowed after 2000 (-0.05 m s\(^{-1}\) per decade, \(p > 0.05\)). The decrease in minimum MWS (-0.02 m s\(^{-1}\) per decade, \(p > 0.05\)) during 1980-2000 later reversed to a small increase (+0.01 m s\(^{-1}\) per decade, \(p < 0.05\)) following a period of great variability from 1997 to 2000. The net result was a decrease in SWSR at a rate of -0.13 m s\(^{-1}\) per decade \((p < 0.01)\) (Fig. 6a). Asia showed a similar pattern with Europe, but both maximum and minimum MWS increased greatly around 2011 (+0.11 m s\(^{-1}\) per decade, \(p < 0.05\); +0.39 m s\(^{-1}\) per decade, \(p < 0.05\),...
respectively), following three decades of weak decreases (-0.03 m s\(^{-1}\) per decade, \(p < 0.05\); +0.00 m s\(^{-1}\) per decade, \(p < 0.05\), respectively) (Fig. 6d). The pattern of increases in maximum and minimum MWS were distinct, with the minimum MWS reaching a four-decade high in 2015, but the maximum MWS only recovered to the value observed in 2005 and before (Fig. 6d). In Australia and South America, the reduction in SWSR was related to near-constant declines in maximum MWS and increases in minimum MWS throughout 1980-2018 (\(p < 0.05\), Fig. 6h-6j). In addition, we also calculated SWSR trends of six regions after fixing months (i.e., the maximum and minimum MWS are the MWS for the specified months; specified months is the one who occurred the most with maximum/minimum MWS during 1980-2018). This allowed us to see whether it was wind speed in the specified months that caused decreasing SWSR. We found that SWSR tended to fall regardless of whether the months were fixed or not, but the decline was weaker when the months were fixed (Fig. S2).

c. Relationship with ocean-atmosphere oscillations

In evaluating the relationship between the large-scale ocean-atmosphere oscillations and wind speed changes, we performed a correlation test between the ranges of climate indices and SWSR to explore if seasonal evolutions of climate indices impact SWSR. For maximum and minimum MWS, we used annual indices in the tests. We also tested the relationship between yearly indices and SWSR (Table S1). We found that the climate indices with the highest, significant \(r\) values were mainly located in the Atlantic Ocean (Table 3). Of all the indices, the one that stands out for being the most associated with global and regional wind phenomena was the WHWP, as it was correlated with the SWSR and both MWS variables for Australia, South America, and globally; it was also linked with two variables in Asia and North America. In Europe, the EA/WR correlated significantly with maximum and minimum MWS. The EA was correlated with both MWS variables in Australia, South America, and the globe. The only index
correlated with all three variables in Asia was the PDO. The TNA was significantly associated
with six variables in various regions. Other useful indices were the POL, AAO, SCA, and AMM
because of their high correlation with one variable in a region. These significant correlations
(\( \leq |0.66| \); Table 3), suggest that the processes represented by these indices may be capable of
modulating SWSR by influencing maximum and minimum MWS.

Furthermore, we identified the turning points in the climate indices to determine how they
align with the turning points of global wind speeds approximately in 2010 (Fig. 7). We found
that PDO, NAO, SOI, Niño 1+2, Niño 3.4, Niño 3, Niño 4, and AMM also reversed around
2010, with all indices decreasing and then increasing. The EA, SOI, and AMM increased and
then decreased (Fig. 7). Some studies found these indices link with each other. For example,
PDO is influenced by Aleutian low, which can be altered by ENSO significantly (Wang et al.
2012); atmospheric circulation anomalies (e.g., NAO, EA) over the North Atlantic were
suggested to show an obvious relationship with ENSO (Nakamura et al. 2015). This may
interpret why they reversed simultaneously. Other indices including WP, POL, EA/WR, EP/NP,
PNA, and AO, showed reversal around 1990 (1989-1992), with PNA dropping first and rising
afterward. The others first climbing, then fell. The remaining climate indices (SCA, PT, AAO,
TNA, TSA, and WHWP) have been rising since 1980.

d. Annual maximum and minimum MWS and SWSR from the ERA5, AMIP6, and CMIP6

Overall, the ERA5 reanalysis product captured most of the observed year-to-year variations
in SWSR at both global and regional scales (Fig. 8), but not the magnitude. The correlation
between SWSR from ERA5 and observations were significant for all regions (\( p < 0.05 \)): Europe
(0.91), North America (0.82), Globe (0.77), Australia (0.69), South America (0.52) and Asia
(0.35). However, ERA5 did not capture the continuous narrowing of SWSR throughout 1980-
2018. With regard to magnitude, the SWSR in ERA5 was lower than that in the observations in
all the regions, except for Asia after 2010 (Fig. 8).

Part of the inability to reproduce the SWSR stemmed from poor simulation of maximum
and minimum MWS (Fig. 8; right panel). The differences between maximums in ERA5 and
observations were much larger than those between the two minimums (apart from Asia),
although the maximums were more correlated. The correlation coefficients of the
maximum/minimums versus observed values were: 0.74/0.45 in North America; 0.92/0.69 in
Europe; 0.80/-0.03 in Australia; 0.25/0.73 in South America; and 0.80/0.26 for the globe,
respectively ($p < 0.05$, except for the Asian minimum MWS and South American maximum
MWS).

Similarly, most of the simulations from AMIP6 (Fig. 9) and CMIP6 (Fig. 10)
underestimated the magnitude of SWSR at both global and regional scales, except for Asia. The
underestimation of annual maximum MWS was larger than that of annual minimum MWS,
resulting in the devaluation of SWSR (Figs. 9-10). In addition, none of these models captured
the year-to-year variations of SWSR, annual maximum, and minimum MWS (Figs. 9-10). The
correlation between observed SWSR trends and those in climate models is not significant (Table
4). Nevertheless, we further checked the signs of SWSR trends in climate models (Table 4),
considering that Deng et al. (2021) found that CMIP6 models can capture the observed sign of
annual mean wind speed trends ($p < 0.1$), although there is still a disagreement between model-
simulated and observed magnitudes. Surprisingly, we found that CMIP-historical experiments
were better predictors of trends than AMIP-historical experiments, especially the experiment in
CESM2 models (Table 4). However, the identified trends were not significant ($p > 0.05$).
Additionally, AMIP6 and CMIP6 multi-model mean generally failed to reproduce the
downward SWSR trends found in observations.

4. Discussion
In studying the SWSR worldwide over the last four decades, we detected regional variations that had not been explored in detail to date. A key finding was that 65% of the stations globally recorded a narrowing in the SWSR that was often related to non-uniform changes in minimum and maximum monthly wind speeds across the regions. Previously, several regional studies inferred that observed changes in seasonal wind speeds were likely caused by large ocean-atmosphere oscillations (Troccoli et al. 2012; Azorin-Molina et al. 2014; Minola et al. 2016; Zhang et al. 2020). Our analyses demonstrate the plausibility that the narrowing SWSR is attributed to large-scale ocean-atmosphere oscillations, which are represented by various indices, including EA, TNA, WHWP, and perhaps others. The EA, which is a teleconnection pattern in all seasons across a large geographical area, together with the NAO, is suggested to describe the latitudinal and intensity of the jet stream (Woollings and Blackburn 2012; Mellado-Cano et al. 2019). Links between NAO and wind speed changes have been studied in some detail. For example, the phase of NAO can induce opposing effects (strengthening or weakening) on wind speeds in different regions (Kriesche and Adam Schlosser 2014; Yu et al. 2015; Minola et al. 2016). In comparison, relatively little research has been done on how EA potentially modulates wind speed variations. However, we did not find NAO highly correlated with wind variables in many regions, only maximum MWS in Europe and for the globe.

Indices TNA and WHWP reflect sea surface temperature variations, with the former indicating SST anomaly; the latter, areas of SST anomaly (Enfield et al. 1999; Wang and Enfield 2001). As TNA is highly related to WHWP (Wang and Enfield 2003), their influence on maximum and minimum MWS in the same regions is understandable. WHWP was significantly correlated with many regional wind variables. Furthermore, we found that indices WHWP and TNA both increased over the study period, and they were driven mainly by external forcings (Takahashi and Watanabe 2016). Such SST changes can result in wind speed variations, for
example, through strengthening Pacific trade winds by creating a pressure difference between the Atlantic and the Pacific Ocean (McGregor et al. 2014) or weakening northerly winds from the Atlantic warm pool to the Great Plains of North America (Wang et al. 2006).

Globally, the WHWP, SCA, and PDO (in the form of annual range) correlated significantly with SWSR, revealing seasonal connections between wind speed and ocean-atmosphere oscillations. Shifts of WHWP, i.e., changes of SST in its geographical area, can result in alterations of Walker and Hadley circulations by convective activity, thereby causing global climate variations (Wang and Enfield 2003; Park et al. 2019). Even a small SST anomaly variation may lead to a comparatively large atmospheric response (Wang et al 2006). In fact, the PDO was suggested to contribute to stilling and reversals of wind speed (Deng et al 2021, Zeng et al 2019). We also found that PDO was decreasing before 2010, then increased afterward (Fig. 7). This reversal is analogous to the change in MWS variables in Asia (Fig. 6), where we identified a significant correlation between PDO and three wind speed variables (Table 3). Although some climate indices did not show significant relationships with SWSR or maximum and minimum MWS, the oscillations behind these indices could also modulate wind speeds variations indirectly by influencing other circulations. For example, ENSO was the dominant external source of TNA (Chen et al. 2015); and NAO plays a role in EA/WR formation (Lim 2015).

Overall, how WHWP and other ocean-atmosphere oscillations contribute to wind speed changes is a complex issue involving many responses and feedbacks (Lee et al. 2007). To date, most studies analyzed the relationship between climate indices and wind speed by testing correlations (Azorin-Molina et al. 2016; Zeng et al. 2019; Zhang et al. 2020). Many questions about the mechanisms remain unsolved, for instance, the dominant role of various ocean-atmosphere oscillations on wind speed or the interaction of seasonal climate phenomena with wind speed variables. Therefore, quantitative analyses regarding the impacts of ocean-
atmosphere oscillations on wind speed in different regions and seasons should be explored further. Nevertheless, the moderate correlations ($r \leq 0.66$) we found between the three wind variables and some climate indices are potentially helpful for the wind energy sector in improving their ability to evaluate wind power production based on climate predictions.

In addition, the narrowing SWSR could influence the wind industry. For example, due to seasonal variations of wind speeds, some wind farms rely on storage systems or backup infrastructures to maintain a balance between generation and demand (Wohland et al. 2019). Decreasing SWSR (i.e., smaller seasonal difference) could reduce the cost of storage facilities. Moreover, a downward SWSR may affect wind energy production and this effect depends on maximum and minimum MWS changes. There are three potential and relevant trends to consider: (i) they both increase with minimum MWS increasing more; (ii) they both decrease with minimum MWS decreasing less; and (iii) the maximum decreases while the minimum increases. We assume changes only in maximum and minimum MWS; that is, wind speeds in other months remain constant. Briefly, the first scenario is the best because energy production would obviously rise due to increasing maximum and minimum MWS. The second scenario is the least favourable as production would drop. The third scenario is the most complex and needs to be quantified through additional study. Under this case, the yield of a wind farm depends on many factors, such as specific wind conditions, the power curve of wind turbines, and the hub height (Solomon et al. 2016). Currently, it is hard to judge how the SWSR will change; therefore, we should endeavor to understand the mechanisms behind SWSR in future studies, as it will benefit wind energy harvesting strategies.

Herein, we also found that wind speed changes varied from month to month. These findings partly challenge the proposal that surface roughness changes are the main reason for the stilling. For instance, our results showed that strong seasonal winds increased while weak winds decreased in the same year, which contradicts the conclusion that an increase in surface
roughness may affect strong wind speeds more than weak wind speeds (Zhang and Wang, 2019). Further, there was no evidence of a corresponding abrupt increase or decrease in roughness at the time of the observed reversals of wind speed (Zhu et al. 2016; Zeng et al. 2018; Liu et al. 2020). We recognize that evolving patterns of surface roughness do likely contribute an undetermined amount to the changes we observed (Wu et al. 2018), but more research is needed to verify the mechanisms.

(b) Comparison with wind fields in climate (re)constructions

The reanalysis product ERA5 does not capture the trends of SWSR nor those of maximum and minimum MWS. Most reanalyses fail to reproduce wind speed trends (Vautard et al. 2010; Troccoli et al. 2012; Li et al. 2018); they perform poorly in reproducing seasonal wind climatology (Torralba et al. 2017; Ramon et al. 2019). Failure to reproduce trends may be because the reanalyses do not assimilate 10-m wind speed from in-situ observations over land, only over the sea (Hersbach et al. 2020). To test this hypothesis, we examined SWSR trends in three other reanalysis products: ERA-Interim, MERRA-2, and JRA-55 (Table 4). Results showed that only JRA-55, which assimilates land surface wind speeds (Zhang et al. 2020), captured significant downward SWSR trends ($p <0.05$) in most areas. Furthermore, Wohland et al. (2019) found trends were absent in model outputs of reanalyses. We thus suggested that it is the assimilation process rather than the model characteristics or boundary conditions that introduce the trends. Alternatively, this failure may reveal that observation data currently used for initial states in reanalysis may be insufficient to predict wind speed trends successfully (Fang and Huang 2019).

Given that most reanalyses, particularly those without land surface wind speed observations, reproduced few regional SWSR trends, it is not a surprise to see that the significant trends were absent in AMIP6 and CMIP6. Similar results were also found in Tian et
al. (2019). Surprisingly, CMIP6 captured slight, albeit insignificant ($p > 0.05$), downward SWSR trends, but AMIP6 did not (Table 4). This difference between the CMIP6 and AMIP6 can be attributed to the signal-to-noise ratio of the latter model. Additionally, we further examined SWSR trends in GHG-only run and aerosols-only run experiments in CMIP6 because Deng et al. (2021) suggested GHG and aerosol can modulate wind speeds trends. Narrowing SWSR was present in both experiments, implying that GHGs and aerosols may influence SWSR trends (Table 4). GHGs can alter the meridional atmospheric circulation, thereby affecting wind speeds (Deng et al. 2021). Aerosols can induce SST variability, which links with strengthened Pacific trade winds (Takahashi and Watanabe 2016). Nevertheless, trends in CMIP6 were weak, implying that more work is needed on this issue regarding climate models.

5. Conclusion

Our analysis showed that the global seasonal wind speed range (SWSR), which is the difference between maximum and minimum monthly mean wind speeds (MWS), has declined over the past four decades (1980-2018), although global annual wind speeds have fallen and then increased over this period. The reduction in SWSR varies among continents, being most prominent in Europe (-0.13 m s$^{-1}$), followed by Australia (-0.09 m s$^{-1}$), South America (-0.08 m s$^{-1}$), then Asia (-0.06 m s$^{-1}$). SWSR increased slightly in North America. We also found that regional SWSR changes were moderately correlated with some large-scale climate indices (e.g., WHWP, EA, PDO, TNA, EA/WR, POL, SCA, AAO). However, wind changes were poorly represented in reanalysis products (ERA5, ERA-Interim, and MERRA-2) and the CMIP6 and AMIP6 climate historical simulation output fields. We also confirmed that wind speed trends vary by season and month, reflecting the temporal and spatial asynchrony of wind speed variations. Specifically, decadal seasonal MWS data from Asia, and to some extent Europe and South America, indicated a reversal in regional stilling at about the same time as the global
phenomenon (about 2010); the North American and Australian data did not. Additional studies
at finer spatial resolutions (e.g., country-level) and longer time series would contribute to a
better understanding of wind speed changes, and thus benefit the management of wind energy
resources and assessments of other wind issues related to hazards, land-use management, water
resources, and environmental management. Also needed are more wind observation stations in
under-represented parts of the world, including South America and particularly Africa, which
was excluded from our analyses because of paucity of data.
Acknowledgements

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Author contributions

Z.Z. designed the research; L.Z. performed the analysis and wrote the draft. All authors contributed to the interpretation of the results and the writing of the paper.

Declaration of Interests

The authors declare that they have no competing interests.

Data availability


Code availability

The scripts used to generate all the results are MATLAB (R2020a). Analysis scripts are available on request from Z. Zeng.
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Table 1. Overview of the reanalyses and the selected AMIP6 and CMIP6 models.

Table 2. Statistics of the stations showing upward or downward trends in the seasonal wind speed range (SWSR) for the globe and each region for 1980-2018.

Table 3. Pearson correlation coefficients (r) between climate indices and SWSR, maximum MWS and minimum MWS for the five regions and globally: NA (North America), EU (Europe), AS (Asia), AU (Australia), SA (South America), and GLO (GLOBE). For SWSR, annual ranges of climate indices were used for correlation tests; for maximum and minimum MWS, the annual mean of climate indices were used. Significant correlations (p < 0.05) are marked in bold. Trends and decadal variability of SWSR, maximum MWS, and minimum MWS for 1980-2018 are reported.

Table 4. SWSR trends (m s⁻¹ dec⁻¹) in HadISD, reanalysis products, and climate models. Significant correlations (p < 0.05) are marked in bold. An asterisk indicates a significant correlation between SWSR in that product and HadISD (i.e., observed data). Hist-GHG and Hist-Aerosol are historical well-mixed GHG-only run and historical anthropogenic aerosols-only run experimental outputs, respectively, which are not available for CNRM-CM6-1-HR and FGOALS-f3-L.
Table 1. Overview of the reanalyses and the selected AMIP6 and CMIP6 models.

<table>
<thead>
<tr>
<th>Name</th>
<th>Institution</th>
<th>Longitude×Latitude (nominal resolution)</th>
<th>Period covered</th>
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<tr>
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<td>ECMWP</td>
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<td>1979-2018</td>
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<td>NASA</td>
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<td>JRA-55</td>
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</tr>
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</table>
Table 2. Statistics of the stations showing upward or downward trends in the seasonal wind speed range (SWSR) for the globe and each region for 1980-2018.

<table>
<thead>
<tr>
<th>Region</th>
<th>(a) Number of stations</th>
<th>(b) Percentage of stations with downward trends</th>
<th>(c) Percentage of stations in (b) with significant ( p &lt; 0.05 ) downward trends</th>
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<td>81.1%</td>
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<td>70.5%</td>
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<td>North America</td>
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<td>337</td>
<td>67.1%</td>
<td>32.1%</td>
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<tr>
<td>South America</td>
<td>168</td>
<td>69.1%</td>
<td>28.6%</td>
</tr>
</tbody>
</table>
Table 3. Pearson correlation coefficients (r) between climate indices and SWSR, maximum MWS and minimum MWS for the five regions and globally: NA (North America), EU (Europe), AS (Asia), AU (Australia), SA (South America), and GLO (GLOBE). For SWSR, annual ranges of climate indices were used for correlation tests; for maximum and minimum MWS, the annual mean of climate indices were used. Significant correlations (p < 0.05) are marked in bold. Trends of SWSR, maximum MWS, and minimum MWS for 1980-2018 are reported.

<table>
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<th>Region</th>
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<th>AU</th>
<th>SA</th>
<th>GLO</th>
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<th>EU</th>
<th>AS</th>
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<th>SA</th>
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37
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Note: All indices offer 12 months of data, except EP/NP, THN and PT, which were masked with asterisks. EP/NP provides data for January-November; THN provides data for December, January and February; PT provides data for August and September. NAO (North Atlantic Oscillation), EA (East Atlantic Pattern), WP (West Pacific Pattern), EP/NP (East Pacific/North Pacific Pattern), PNA (Pacific/North American Pattern), EA/WR (East Atlantic/West Russia Pattern), SCA (Scandinavia Pattern), TNH (Tropical/Northern Hemisphere Pattern), POL (Polar/Eurasia Pattern), PT (Pacific Transition Pattern), AO (Arctic Oscillation), AAO (Antarctica Oscillation), SOI (Southern Oscillation Index); ENSO indices (Niño 1+2, Niño 3.4, Niño 3, Niño 4); PDO (Pacific Decadal Oscillation), TNA (Tropical Northern Atlantic Index), AMM (Atlantic Meridional Mode), TSA (Tropical Southern Atlantic Index), WHWP (Western Hemisphere warm pool).
Table 4. SWSR trends (m s\(^{-1}\) dec\(^{-1}\)) in HadISD, reanalysis products, and climate models.

Significant correlations (\(p < 0.05\)) are marked in bold. An asterisk indicates a significant correlation between SWSR in that product and HadISD (i.e., observed data). Hist-GHG and Hist-Aerosol are historical well-mixed GHG-only run and historical anthropogenic aerosols-only run experimental outputs, respectively, which are not available for CNRM-CM6-1-HR and FGOALS-f3-L.

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FIGURES

Figure 1. Terrestrial wind speed changes for 1980-2018. (a) Global terrestrial wind speed anomalies (m s⁻¹; relative to 1981-2010) at monthly, seasonal, and annual scales. The corresponding climatological normal (1981-2010) was removed. (b) Monthly means of wind speed for different decades. (c) Seasonal means of global terrestrial wind speed for different decades. Notice that the last decade lacks 2019.

Figure 2. The same as Figure 1 but for each region. (a1-a3) Europe, (b1-b3) Asia, (c1-c3) North America, (d1-d3) Australia, and (e1-e3) South America.

Figure 3. Global variability of seasonal wind speed range (SWSR) for 1980-2018. The red line represents the linear regression. Grey dashed lines are regression fitting lines for 300 random datasets containing half of the total stations each. Inset numbers indicate the rate (in m s⁻¹ decade⁻¹), the coefficient of determination (R²), and the level of significance (p) of the red regression line (Mann-Kendall test). The inset map represents the distribution of stations we used, and its enlargement is shown in supplementary material (Fig. S1).

Figure 4. Annual maximum and minimum monthly wind speed (MWS) averaged over all the stations for 1980-2018. A dashed line is achieved by piecewise linear fitting for the corresponding line of same color.

Figure 5. Spatial distribution of the station-based trends in the SWSR globally (60° S-72° N). Filled dots indicate significant trends at p < 0.05. Rectangles refer to each region: (1) North America, (2) Europe, (3) Asia, (4) Australia, and (5) South America.

Figure 6. Same as Figure 3-4 but for each region. (a-b) Europe, (c-d) Asia, (e-f) North America, (g-h) Australia, and (i-j) South America.

Figure 7. Time series (1980-2018) and turning points (TN) of 22 climate indices, in terms of annual mean. Black line is the time series, and the red line indicates the trend. TN is the year when the turning point occurred.

Figure 8. Time series of SWSR (left), and maximum (center) and minimum (right) MWS derived from observations and ERA5 reanalysis for 1980-2018. (a-b) Globe, (c-d) Europe,
(e-f) Asia, (g-h) North America, (i-j) Australia, and (k-i) South America. Inset numbers exhibited the slope (slope), the coefficient of determination ($R^2$), and the level of significance test ($p$) of the red regression lines for observed and simulated SWSR.

**Figure 9.** Time series of SWSR (left), and maximum (center) and minimum (right) MWS derived from observations and AMIP6 simulations for 1980-2018. (a1-a3) Globe, (b1-b3) Europe, (c1-c3) Asia, (d1-d3) North America, (e1-e3) Australia, and (f1-f3) South America.

**Figure 10.** As in Fig. 9, but for CMIP6 simulations.
Figure 1. Terrestrial wind speed changes for 1980-2018. (a) Global terrestrial wind speed anomalies (m s\(^{-1}\); relative to 1981–2010) at monthly, seasonal, and annual scales. (b) Monthly means of global terrestrial wind speed for different decades. (c) Seasonal means of global terrestrial wind speed for different decades. Notice that the last decade lacks 2019.
Accepted for publication in *Journal of Climate*. DOI: 10.1175/JCLI-D-21-0112.1.
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