Stilling and Recovery of the Surface Wind Speed Based on Observation, Reanalysis, and Geostrophic Wind Theory over China from 1960 to 2017

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ABSTRACT

Surface wind speed (SWS) from meteorological observation, global atmospheric reanalysis, and geostrophic wind speed (GWS) calculated from surface pressure were used to study the stilling and recovery of SWS over China from 1960 to 2017. China experienced anemometer changes and automatic observation transitions in approximately 1969 and 2004, resulting in SWS inhomogeneity. Therefore, we divided the entire period into three sections to study the SWS trend, and found a near-zero annual trend in the SWS in China from 1960 to 1969, a significant decrease of $-0.24 \text{ m s}^{-1} \text{ decade}^{-1}$ from 1970 to 2004, and a weak recovery from 2005 to 2017. By defining the 95th and 5th percentiles of daily mean wind speeds as strong and weak winds, respectively, we found that the SWS decrease was primarily caused by a strong wind decrease of $-8\% \text{ decade}^{-1}$ from 1960 to 2017, but weak wind showed an insignificant decreasing trend of $-2\% \text{ decade}^{-1}$. GWS decreased with a significant trend of $-3\% \text{ decade}^{-1}$ before the 1990s; during the 1990s, GWS increased with a trend of $3\% \text{ decade}^{-1}$ whereas SWS continued to decrease with a trend of $10\% \text{ decade}^{-1}$. Consistent with SWS, GWS demonstrated a weak increase after the 2000s. After detrending, both SWS and GWS showed synchronous decadal variability, which is related to the intensity of Aleutian low pressure over the North Pacific. However, current reanalyses cannot reproduce the decadal variability and cannot capture the decreasing trend of SWS either.

1. Introduction

Roderick et al. (2007) discovered the global stilling phenomenon of surface wind speed (SWS) over land; that is, the mean SWS over global land regions declined over 30–40 years prior to 2000, with typical rates from -0.2 to $-0.1 \text{ m s}^{-1} \text{ decade}^{-1}$. This conclusion has been verified in many other studies (Achberger et al. 2006; Dumitrescu et al. 2014; Earl et al. 2013; McVicar et al. 2008; Minola et al. 2016; Vautard et al. 2010). Recent studies have found SWS recovery phenomena since the last decade over Saudi Arabia (Azorin-Molina et al. 2018a), South Korea (Kim and Paik 2015), and China (Li et al. 2018; Lin et al. 2013). More details about global wind speed change in recent years can be found in the overviews of Wu et al. (2018a) and Hartfield et al. (2018).

SWS changes have important impacts on the natural climate and human societies. The decline in SWS could reduce atmospheric evaporative demand and have an important influence on different catchment regions (Wang and Dickinson 2012; Yang et al. 2014). Decreased pan evaporation caused by SWS decreases in wet catchments results in a complementary increase in streamflow but has a negligible impact on streamflow for dry catchments (McVicar et al. 2012a,b). SWS could also influence human-perceived temperature, which affects human comfort under different conditions and thus affects human work and life (Dunne et al. 2013; Mora et al. 2017). Furthermore, SWS strongly affects erosion by displacing or removing topsoil from the land surface, which could influence aeolian geomorphology areas affected by desertification (Dong et al. 2009).

In addition to mean SWS, extreme wind changes are also important. Weak wind can increase the residence time of $\text{PM}_{2.5}$ and other aerosol particles (Wang et al. 2016, 2018), while strong winds, such as those from wind storms, can blow dust (Cowie et al. 2013), damage buildings and crops, induce property losses, and increase

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casualties (Vose et al. 2014). However, most existing studies on SWS over China are usually focused on mean values (Chen et al. 2013; Fu et al. 2011; Li et al. 2017), and there have been few systematic studies on extreme wind changes over China in the past 50 years.

SWSs are directly measured by wind anemometers and are vulnerable to the influence of data inhomogeneities caused by gradual urbanization around weather stations (McVicar et al. 2008; Rayner 2007), instrument changes (Azorin-Molina et al. 2018b), and station relocations (Wan et al. 2010). Wind anemometers experienced two significant changes in China: the first one is the change from Wilde anemometers to EL or EN electric wind anemometers in approximately 1969 (Li et al. 2008), and the other one is that Chinese meteorological observation method underwent large-scale transformations from manual observations to automatic observations during the 2004–05 period (Cao et al. 2016). However, there have been few studies of the anemometer replacement influence on SWS over China.

Besides observations, reanalyses also provide SWS products. Reanalyses have been widely used in climate studies (Liu et al. 2018; Zhou et al. 2018) and are not sensitive to local land cover change (Li et al. 2017; Parker 2016), so SWS reanalyses that do not assimilate observed SWS are often taken as a reflection of atmospheric circulation changes. However, reanalyses could suffer from inhomogeneities caused by changes in the number of assimilated stations over time (Krueger et al. 2013), and atmospheric circulations of reanalyses are also influenced by the performance of the assimilation systems (Parker 2016; Wohland et al. 2019).

Studies have shown that aerosols could decrease the surface pressure gradient and SWSs and increase the duration of time that aerosols are in air, which forms a positive feedback between aerosols and SWS (Xu et al. 2006; Yang et al. 2017). However, most reanalyses do not include annual aerosol changes (Wang et al. 2015). The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2), is the first reanalysis that assimilates aerosol optical depth estimates from satellite retrievals and model simulations based on emission inventories. One interesting matter is whether the introduction of annual aerosol changes in reanalyses could improve the simulation efficiency of SWS, which is also a topic we focus on in this study.

To overcome the aforementioned shortcomings of observations and reanalysis SWSs, we proposed using geostrophic wind as reference data. Geostrophic wind is the wind under the balance of the pressure gradient force and Coriolis force during the movement of wind (Markowski and Richardson 2010). Therefore, the geostrophic wind speed (GWS) calculated from the

observed surface pressure is not the actual wind, but it could describe the SWS changes that occur under the direct influence of atmospheric circulation.

Geostrophic wind theory is a mature theory in the atmospheric sciences. Schmidt and von Storch (1993) first used GWS to study storm trends of the German Bight on climatic time scales, and subsequently the method was widely used to study storminess such as that over the northeast Atlantic (Alexandersson et al. 1998; Wang et al. 2009), and Europe (Matulla et al. 2008). Krueger and von Storch (2011) evaluated the applicability of using percentiles of GWS to depict storm activity, and GWS has recently been used to homogenize SWS (Minola et al. 2016; Wan et al. 2010).

The observed SWS, global atmospheric reanalysis, and GWS have their own strengths and limitations. In this study, we combined SWS values from the three estimates to study the stilling and recovery of SWS over China from 1960 to 2017. We explored SWS and weak and strong wind changes and then assessed atmospheric circulation influences on SWS through GWS. Furthermore, we explored the reason for the recent wind recovery and discussed the influence of anemometer changes on SWS. Finally, we evaluated the existing major reanalysis model capacity for SWS over China based on observations and GWS.

2. Data and methods

a. Surface wind speed data

Daily SWS data collected at 2419 meteorological stations from 1960 to 2017 in China were obtained from the China Meteorological Data Service Center (CMDC; <http://data.cma.cn/en/?r=data/>). The SWS were recorded at a standard height of 10 m, and we converted the daily data into monthly data for analysis. The stations with less than 25% of monthly values missing during the studied periods were used, resulting in 2333 stations remaining. To reduce the impact of statistical errors caused by the uneven distribution of stations, we followed Zhou and Wang (2017) to first divide all stations into $1.25^\circ \times 1.25^\circ$ grids (to match the reanalyses) and then obtained the national and regional averages.

b. Sea level pressure data

Similar to the wind speed data, the daily sea level pressure (SLP) data were from 2333 stations of the CMDC, and we used these SLP data to calculate the GWS values as much as possible. Near the Chinese borders, we also collected SLP data from the Global Surface Summary of the Day (GSOD), and then we could obtain accurate GWS values as much as possible

TABLE 1. Summary of the five reanalysis products.

Reanalysis	Institution	Model resolution	Data resolution	Period
ERA-Interim	ECMWF	T255 (~80 km)	$3/4^\circ \times 3/4^\circ$	1979 and afterward
JRA-55	JMA	T319 (~55 km)	$5/4^\circ \times 5/4^\circ$	1958 and afterward
CFSR	NCEP	T382 (~38 km)	$1/2^\circ \times 1/2^\circ$	1979–2010
MERRA	NASA/GMAO	$1/2^\circ \times 2/3^\circ$ (~55 km)	$1/2^\circ \times 2/3^\circ$	1979–February 2016
MERRA-2	NASA/GMAO	$1/2^\circ \times 2/3^\circ$ (~55 km)	$1/2^\circ \times 2/3^\circ$	1980 and afterward

near the Chinese borders. To calculate the GWS at a station, we needed to first calculate the pressure gradient force; as with previous studies, we assume that the pressure is a function of position (Krueger et al. 2019; Krueger et al. 2013; Wang et al. 2009):

$$P = ax + by + c, \quad (1)$$

where P denotes the instantaneous SLP values,

$$x = R_e \lambda \cos \Phi, \quad (2)$$

$$y = R_e \Phi, \quad (3)$$

where R_e represents Earth's radius, λ is longitude, and Φ is latitude. There are three parameters (a , b , and c) in Eq. (1), so we need at least three stations to calculate the pressure gradient force:

$$P_1 = ax_1 + by_1 + c, \quad (4)$$

$$P_2 = ax_2 + by_2 + c, \quad \text{and} \quad (5)$$

$$P_3 = ax_3 + by_3 + c, \quad (6)$$

and then we can derive GWS as follows:

$$u_g = -\frac{1}{\rho f} \frac{\partial P}{\partial Y} = -\frac{b}{\rho f}, \quad (7)$$

$$v_g = \frac{1}{\rho f} \frac{\partial P}{\partial X} = \frac{a}{\rho f}, \quad \text{and} \quad (8)$$

$$w_g = (u_g^2 + v_g^2)^{1/2}, \quad (9)$$

where w_g denotes GWS, u_g and v_g represent the components of the zonal and meridional directions, respectively, ρ is the density of air, and f is the Coriolis parameter.

As illustrated above, GWS can be calculated from the SLPs at three stations near the studied stations. However, GWS calculated by this method is very sensitive to SLP observation errors. To reduce the errors caused by the randomness of choosing three stations, we used station combinations that were within a circle with a radius of 3° latitude and longitude centered at the middle of the studied station. The reason for choosing 3°

as the radius is that smaller triangles have a better description of GWS (Krueger and von Storch 2011). We selected stations within 3° for each studied station to first build pressure triangles, and then we used the 10th percentiles from approximately 1000 studied pressure triangles to calculate the GWS. The choice of 10th percentiles of station combinations was consistent with the study conducted by Zhang et al. (2019). Following this method, we could derive the GWS at each studied station.

c. Climate indices

Studies have shown that the Siberian high and North Pacific Oscillation have a subsequent influence on weather and climate over China (Chang and Lu 2012; Choi et al. 2011). To explore the potential connection of wind speed to large-scale circulation variability and possible teleconnections, we examined the following three climate indices: the Siberian high index (SHI), the Siberian high position index (SHPI), and the North Pacific index (NPI). The SHI and SHPI reflect the Siberian high intensity and position in winter, respectively, and the two indices were calculated following Jia et al. (2015). The NPI reflects the intensity variation of Aleutian low pressure over the North Pacific, and the index is available online (<https://climatedataguide.ucar.edu/climate-data/north-pacific-np-index-trenberth-and-hurrell-monthly-and-winter>).

d. Reanalysis data

We also studied the SWS from five frequently used reanalyses: the European Centre for Medium-Range Weather Forecasts (ECMWF) interim reanalysis (ERA-Interim; Dee et al. 2011); the National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR; Saha et al. 2010); the Japanese Meteorological Agency 55-Year Reanalysis (JRA-55; Kobayashi et al. 2015); and the National Aeronautics and Space Administration Modern-Era Retrospective Analysis for Research and Applications (MERRA; Rienecker et al. 2011) and its updated version, MERRA-2 (Reichle et al. 2017). More information about the five reanalyses is shown in Table 1. These reanalysis data are all gridded data, and the coarsest resolution is $1.25^\circ \times 1.25^\circ$ (JRA-55). We also converted all reanalyses into a $1.25^\circ \times 1.25^\circ$ grid via the nearest area-weighted method

(a bilinear interpolation function on two-dimensional grids) to facilitate comparison.

According to our knowledge, until recently only JRA-55 assimilated observed SWS over land into the reanalysis (Torralba et al. 2017), but they all assimilate SWS over oceans (Fujiwara et al. 2017). Additionally, MERRA-2 is the only reanalysis assimilating aerosol optical depth dataset derived from satellite retrievals and model simulations (Wang et al. 2015). The SWS in the reanalyses represents the simulation ability of atmospheric circulation and near-surface layer processes.

e. Surface wind speed regionalization

We used the rotated empirical orthogonal function (REOF) (Burroughs and Miller 1961; Richman 1986) to investigate the SWS regional characteristics in China. Compared to the empirical orthogonal function (EOF), the REOF could partly overcome the limitation that each EOF more uniformly describes the variable structure of the whole field in traditional EOF analyses (Horel 1981), and these functions have been widely used in various climate regions (Chen and Tung 2018; Horel 1981; Lian and Chen 2012). Wind speed data were decomposed by the EOF according to the standardized values of the monthly mean. Then, the eigenvalue calculation errors proposed by North et al. (1982) were used for the significance test. Because the total variance contribution of the first 10 EOFs was more than 85%, we selected the first 10 principal components to perform REOF decomposition. Figure 1 shows the results of REOF decomposition, according to which we divided China into six regions: 1) northeastern China, 2) northern China, 3) northwestern China, 4) the Tibetan Plateau, 5) southern China, and 6) southeastern China.

f. Trend analysis

The Theil–Sen trend estimator is used to unbiasedly estimate the trend of a time series (Sen 1968; Theil 1992), and the Mann–Kendall test is used to test the significance of the trends (Zhou and Wang 2016). Therefore, in our study, we used the Theil–Sen trend estimator to calculate the trend and the Mann–Kendall test to examine the significance. As illustrated in section 1, Chinese anemometers underwent significant changes in approximately 1969 and 2004; therefore, we divided the entire time into three periods of 1960–69, 1970–2004, and 2005–17 to study the recovery phenomena and discuss the influence of anemometer changes on SWS.

3. Results

a. Climatology of SWS over China

Figure 2 shows the spatial pattern of multiyear averaged SWS and standard deviations in four seasons in

FIG. 1. Surface wind speed (SWS) regionalization in China. The six different colors express different regional distributions of station locations. Regionalization was conducted by the rotated empirical orthogonal function (REOF) method.

China from 1960 to 2017. SWS is highest in northeastern China, with an annual mean value of approximately 4 m s^{-1} , and it was much weaker (approximately 1 m s^{-1}) in other areas. SWSs were strongest in spring and weakest in autumn. The seasonal pattern was similar to the annual spatial pattern. Further, we calculated the standard deviations of SWS monthly anomaly to study the variability of SWS (Fig. 2b), and the standard deviations show similar spatial patterns with those of the mean values. However, the variability of SWS in winter was high, although its mean values were much lower. The relatively higher standard deviations in winter may be related to atmospheric circulation changes, which will be discussed later.

Figure 3 shows the probability density function (PDF) of daily SWS over China. The PDF in six subregions showed a similar distribution, while the fraction of high SWS is higher in northeastern and northern China. Over China, the 95th percentile corresponded to 5 m s^{-1} , which has been used as a threshold for dust emissions (Cui et al. 2018) and has been used in many extreme climate studies (Xu et al. 2006). Therefore, we chose the 95th percentile of daily mean SWS as a reference to define strong wind. Consistently, we used the 5th percentile to define weak wind, which is a key parameter for air stagnation (Wang et al. 2018).

For the SWS, the mean strong winds in northeastern China and northern China were the highest (Fig. 4a), with annual mean values reaching $6\text{--}7 \text{ m s}^{-1}$, while it was $2\text{--}3 \text{ m s}^{-1}$ in southern China. The spring and winter strong winds were much larger than those in other seasons. The weak wind varied from 0 to 2 m s^{-1} and showed a similar spatial pattern (Fig. 4b). The weak wind in spring was the

FIG. 2. (left) Multiyear average and (right) standard deviations in the SWS from 1960 to 2017. Shown are (a₁), (b₁) annual means and averages in (a₂), (b₂) spring, (a₃), (b₃) summer, (a₄), (b₄) autumn, and (a₅), (b₅) winter.

largest, and it was the lowest in winter, which was a key factor for extreme pollution events in winter (Cai et al. 2017).

b. Trends of SWS and GWS over China

Figure 5 shows the SWS annual and seasonal time series from 1960 to 2017 in six regions. The sudden jump in SWS

in approximately 1969 was likely due to instrument replacement (Han et al. 2016). In the 1960s, the Wilde anemometers were used to measure SWS (Li et al. 2008), and Wilde anemometers have high inertia, which requires higher wind to start the device, and slowing down is difficult when the wind stops. To more clearly capture SWS changes

FIG. 3. Probability density distribution of the SWS in different regions of China.

and discuss the influence of instrumentation on the observed SWS over different parts of China, we evaluated the SWS daily PDF over China for three different periods (Fig. 6). It was also found that a much higher fraction of strong wind and a lower fraction of weak wind occurred in the 1960s than during the other periods (Fig. 6).

During the 2004–05 period, Chinese meteorological stations experienced large-scale automations. Manual observations mainly adopt EL or EN electric wind anemometers, where the starting wind speed is less than 1.5 m s^{-1} . The photoelectric wind direction sensor is used for automatic observations and has a weaker starting wind speed of less than 0.3 m s^{-1} and a faster response to SWS changes. Automatic observations make it easier to capture SWS changes in breezes compared to manual observations. This might be the reason for the highest fraction of weak wind during the 2005–17 period (Fig. 6).

The inhomogeneity in the observed SWS caused by instrument replacement is important for trend analysis. Therefore, we divided the entire timeframe into three periods of 1960–69, 1970–2004, and 2005–17 to study the SWS changes. We found the near-zero annual trend before 1969, a monotonic decreasing trend from 1970–2004, and a recent break in stilling (recovery) from the early twenty-first century to the present (Fig. 5 and Table 2).

Because GWS is larger than SWS and more or less a representation of upper-air winds, we calculate normalized trends to explore SWS and GWS trends. The normalized trend here means that time series are first normalized by zero-mean normalization (time series are subtraction of the average and then divided by the standard deviation) and then trends are calculated. Figure 7 shows the temporal-spatial distributions of the SWS and GWS normalized trends. There was a unanimous decreasing trend in SWS

over China during the entire study period, and the decreasing trend was concentrated from -8% to -6% decade $^{-1}$. During the 2005–17 period, the SWS over most of China showed an increasing trend from 6% to 12% decade $^{-1}$, and the SWS recovery phenomenon mainly occurred in southern China. The SWS trends over the six subareas and whole China are listed in Table 2.

Before the 1970s, there was a significant lack of surface pressure recordings, so GWS was not available before this time. Compared to SWS, GWS showed a more obvious spatial pattern during the entire studied period (Fig. 7b). The GWS trend was concentrated from -3% to 3% decade $^{-1}$ from 1960 to 2017 (Fig. 7b), which was much weaker than the SWS trend. During the 1960–69 period, the Chinese SWS showed a significant decreasing trend (-9% decade $^{-1}$) based on available data. In the 1970–2004 period, GWS showed an obvious spatial pattern, and the trend was also concentrated from -3% to 3% decade $^{-1}$. The GWS showed a weaker increasing trend (3% – 6% decade $^{-1}$) over the southern regions of China after 2005, and in other areas, there were also no obvious trend changes.

Anemometer automation can underestimate SWS to some degree compared to manual observations (Azorin-Molina et al. 2018b), but to date there have been no studies on changes in the influence of automatic observations on SWS recovery over China. In our research, we found that GWS showed a recovery phenomenon in the southern regions of China, which was where the main SWS areas also showed recoveries in the last decade. Furthermore, GWS showed recovery even before the 2000s, and it accounted for more than half of the trend variations in the SWS trend changes during the SWS recovery period, which indicated that atmospheric circulation was the main cause of SWS recovery over China during this period. Both SWS and GWS presented recovery phenomena in northwestern, southern, and southeastern China. Detailed GWS trends in different periods and areas are also summarized in Table 2.

c. Trends of weak and strong SWS and GWS

Contrary to the mean SWS, the observed weak SWS showed an increasing trend of 6% decade $^{-1}$ during the 1960–2017 period, except in small regions of northeastern and northwestern China (Fig. 8a). Therefore, SWS decrease was not mainly caused by weak wind from 1960 to 2017. In contrast, strong wind showed a significant decreasing trend of -6% decade $^{-1}$ throughout China.

The observed weak wind presented a slight decreasing trend of -2% decade $^{-1}$ over China in the five studied decades, while the strong wind showed a more rapid

FIG. 4. Multiyear average of surface (left) strong wind and (right) weak wind from 1960 to 2017. Shown are (a1),(b1) annual means and averages in (a2),(b2) spring, (a3),(b3) summer, (a4),(b4) autumn, and (a5),(b5) winter.

decreasing trend of $-8\% \text{ decade}^{-1}$ (Fig. 8b). The decreasing trend in the strong wind was mainly concentrated in the 1970–2004 period, although the strong wind at some stations increased during the 2005–17 period. The reason why the SWS decrease occurred for mostly strong winds is discussed in section 4.

The weak geostrophic wind showed a similar spatial pattern with a weak surface wind during the last five decades over most of China (Fig. 8c), with an increasing trend mainly concentrated from 0% to $3\% \text{ decade}^{-1}$. Similar to weak SWS, weak GWS in some parts of northeastern China and northern China exhibited a decreasing trend, and the

FIG. 5. Annual and seasonal mean SWS in China and its six subregions from 1960 to 2017. The three different shaded areas indicate three different studied periods due to replacement of the surface wind speed measurement instrument. (a) Annual surface wind speed variations; (b)–(e) as in (a), but for spring, summer, autumn, and winter, respectively.

magnitude was also smaller, reaching from -3% to 0% decade $^{-1}$. The other periods showed similar patterns with the patterns exhibited by all five studied decades, except for the first study period (1960–69), which showed a significant decreasing trend over China. In the 1960–69 period, the decreasing trend was mainly concentrated from -15% to -12% decade $^{-1}$, which was much higher than the subsequent increasing trend. The weak geostrophic wind also exhibited a significant increasing trend of 6% – 9% decade $^{-1}$ over southern parts of China, as the observed weak wind showed, which also illustrated that the increasing weak wind was mostly driven by atmospheric circulation.

Strong geostrophic wind showed a negligible decreasing trend of -1% decade $^{-1}$ over China during the past five decades (Fig. 8d), and this pattern was very similar to that during the 1970–2004 period. During the 1960–69 period, the strong GWS also showed an obvious decreasing trend over China based on available data, and in the last decade the GWS expressed a slight increasing trend over southern China. Details of the weak and strong wind trends are listed in Table 3.

d. SWS and GWS associations with atmospheric circulation

Figure 9 shows the SWS, detrended SWS, normalized GWS, and detrended normalized GWS annual mean

time series over six regions. Compared to the original wind time series, the detrended wind time series could reflect wind variabilities more directly. Because GWS value was 2–3 times larger than SWS over the midlatitude regions, to minimize the influence of GWS mean value difference on regional mean values GWS was normalized by min–max normalization (time series are subtraction of the minimum value and then divided by the range of time series) first, and then the regional averages were obtained. GWS decreased with a significant trend of -3% decade $^{-1}$ ($p = 0.001$) from the 1970s to the 1990s. During the 1990s, GWS increased with a trend of 3% decade $^{-1}$ whereas SWS continued to decrease with a trend of 10% decade $^{-1}$. Consistent with SWS, GWS demonstrated a weak increase after the 2000s. Although SWS and GWS did not show same trend changes, both of the detrended wind time series generally showed synchronous variations over China, illustrating that atmospheric circulation did not influence SWS trend changes but dictated the SWS variations over China.

To further explore the potential connection of wind speed with the large-scale circulation variability and to possible teleconnections, we examined decadal correlation coefficients with three climate indices: SHI, SHPI, and NPI. Both of the detrended and original wind time series were first smoothed by running means with a

FIG. 6. Probability density distribution of the SWS during three periods over different regions of China. (a) SWS probability density distribution over northeastern China; (b)–(g) as in (a) but for northern China, northwestern China, the Tibetan Plateau, southern China, southeastern China, and all of China, respectively.

window length of 10 years, and then the Pearson correlation coefficients were calculated. Because the Siberian high was mostly occurred in winter, we focused SWS variations in winter here (except for special declarations, the following SWS time series all refer to SWS in winter over all of China). SWS did not correlate with three indices generally (Figs. 10a–c). However, the detrended SWS showed negative correlation with SHPI and significant positive correlation with NPI, which further demonstrated that these three indices did not

influence SWS trend changes, but they were factors influencing SWS decadal variabilities.

Then we investigated GWS relationships with three indices also at decadal scales (Figs. 10d–f). As in Fig. 9, GWS was also normalized by min–max normalization first, and then the correlation coefficients were calculated. Because GWS did not show much trend change, the correlation coefficients of detrended GWS and GWS with three indices did not show much difference, and they generally showed significant correlations with three

TABLE 2. Surface wind speed and geostrophic wind speed trends ($\text{m s}^{-1} \text{decade}^{-1}$). The bold font indicates the Mann–Kendall test results with a significance level of 0.05.

	1960–69		1970–2004		2005–17		1960–2017	
	SWS	GWS	SWS	GWS	SWS	GWS	SWS	GWS
Northeastern China	0.14	—	−0.29	0.05	0.04	0.11	−0.24	0.05
Northern China	0.23	—	−0.27	−0.01	0.02	−0.09	−0.17	−0.01
Northwestern China	−0.01	—	−0.30	0.78	0.11	−0.02	−0.16	—
Tibetan Plateau	−0.08	—	−0.24	−0.05	−0.06	−0.14	−0.12	—
Southern China	−0.04	—	−0.21	−0.02	0.04	0.09	−0.13	0.03
Southeastern China	−0.03	—	−0.24	0.04	0.06	0.07	−0.12	0.08
China	−0.04	—	−0.24	0.07	0.02	−0.05	−0.15	0.08

FIG. 7. (a1)–(a4) The normalized linear trends ($\% \text{ decade}^{-1}$) of the SWS in different periods over China, where the surface wind speed linear trends are during 1960–69, 1970–2004, 2005–17, and 1960–2017, respectively. The black dots indicate that these areas passed the significance test at the 0.05 level based on the Mann–Kendall test. (b1)–(b4) As in (a1)–(a4), but for the geostrophic wind speed linear trends.

indices, illustrating that these three indices mostly influenced GWS decadal variations.

Figure 10 shows the Chinese SWS variations with large-scale climate indices, and the local wind variations with three climate indices are presented in Table 4. The SHI influence on regional SWS was more prominent over northeastern and northwestern China, and the SWS variations were significantly positively correlated with NPI over all of China, which illustrated that the decadal SWS variation was significantly affected by the intensity of Aleutian low pressure over the North Pacific.

The above section explored SWS and GWS variabilities with atmospheric circulation from the point of climate model indices. In section 3b, we also found that atmospheric circulation was not the main cause of SWS decrease in China during the last five decades, but it was the main cause for recent recovery. To more intuitively investigate the influence of atmospheric circulation on SWS, we studied the atmospheric circulation fields during the three periods in next section.

The atmospheric circulation fields were different in different seasons (Li et al. 2011), and we investigated summer and winter separately, as these two seasons had

FIG. 8. Weak wind and strong wind linear trends in the SWS and GWS in different periods over China. (a₁)–(a₄) The linear trends in the weak surface wind speed during 1960–69, 1970–2004, 2005–17, and 1960–2017, respectively. The black dots indicate that these areas passed the significance test at the 0.05 level based on the Mann–Kendall test. (b₁)–(b₄) The linear trends in the strong surface wind speed. (c₁)–(c₄) The relative linear trends in the weak geostrophic wind speed. (d₁)–(d₄) The relative linear trends in the strong geostrophic wind speed.

the most obvious contrast in terms of atmospheric circulation fields. The GWS did not show obvious trend changes over China from 1970 to 2004 (Fig. 9b). Thus, from the perspective of atmospheric circulation, the

SLP pattern did not change much in this period. Furthermore, the GWS showed a recovery phenomenon beginning in the early twenty-first century, so we chose 1970–2004 as the basic period to study SLP pattern

TABLE 3. Extreme surface wind speed and geostrophic wind speed trends (% decade^{−1}). The bold font indicates the Mann–Kendall test results with a significance level of 0.05.

	1960–69		1970–2004		2005–17		1960–2017	
	SWS	GWS	SWS	GWS	SWS	GWS	SWS	GWS
Weak wind								
Northeastern China	−2	—	−11	1	10	3	−4	0
Northern China	6	—	−8	0	22	0	0	0
Northwestern China	−9	—	−22	2	0	9	−11	0
Tibetan Plateau	−17	—	−12	−5	2	0	−2	−4
Southern China	−10	—	−11	0	41	4	−2	0
Southeastern China	−1	—	−14	2	21	3	1	2
China	−6	—	−11	0	26	3	−2	0
Strong wind								
Northeastern China	2	—	−10	0	−5	0	−8	0
Northern China	7	—	−10	−1	−5	−2	−8	−1
Northwestern China	3	—	−13	−1	−2	0	−9	−2
Tibetan Plateau	−3	—	−10	−2	−9	−1	−7	−2
Southern China	−4	—	−10	−1	−6	0	−8	−1
Southeastern China	−1	—	−12	0	−3	−5	−9	0
China	−2	—	−10	−1	−6	−1	−8	−1

FIG. 9. Time series of annual mean SWS and normalized GWS over (a)–(f) six subregions and (g) all of China from 1970 to 2017.

changes. Because the observed SLPs were not continuously distributed throughout China, we used monthly SLP data from the NCEP–National Center of Atmospheric Research (NCAR) Reanalysis 1 (Kalnay et al. 1996) to study the SLP field. The studies showed that the NCEP–NCAR reanalysis performed well in terms of describing the atmospheric circulation pattern (Fu et al. 2016; Simmonds and Keay 2000; Waliser et al. 1999).

Figure 11 shows the SLP differences in the periods of 1960–69 and 2005–17 periods compared to the 1970–2004 period. We found that compared to 1970–2004, the mean SLP was lower in the summer of 1960–69, especially in northwestern China, and this value reached 4–5 hPa. The SLP pattern in the summer of 2005–17 showed different phenomena compared with 1960–69: in northern China and the Tibetan Plateau, the SLPs were 1–2 hPa higher than those in 1970–2004, and in other parts of China, the SLPs were 1 hPa lower than those in 1970–2004. Therefore, the pressure gradient weakened over China in the last decade, and the southerly winds decreased.

Compared to summer, the SLP patterns in winter were more similar during the 1960–69 and 2005–17 periods, where both periods showed a higher SLP in northern China and lower SLP in southern China. During 2005–17, the Mongolian high also strengthened, while the SLP decreased in southern China, which increased the pressure gradient and prevailing northwesterly winds. From the SLP patterns, we can infer that SWS recovery should mainly occur in the winter compared to summer, which was also illustrated in Fig. 5.

e. SWS in the reanalyses

We selected five commonly used reanalyses in climate studies: JRA-55, MERRA, MERRA-2, CFSR, and ERA-Interim. In this section, we mainly evaluated the model capabilities of the reanalyses in terms of climatology, temporal variability and trend. The observed SWS and GWS calculated from SLP were used as reference data. The introduction of GWS could provide a more objective assessment compared with the comparisons between only the observations and reanalyses.

FIG. 10. Time series of detrended winter SWS (blue lines) and winter SWS (black lines) over China with (a) SHI, (b) SHPI, and (c) NPI; red lines show indices variations. (d)–(f) As in (a)–(c), but for normalized GWS.

For climatology, the reanalyses (except JRA-55) generally had a stronger SWS than the observations (Fig. 12), and all of the reanalyses showed a similar spatial pattern to the observations: SWSs were stronger in northern China and weaker in southern China. According to our knowledge, except for JRA-55, the other four reanalyses did not assimilate the SWS observations over land (Torralba et al. 2017). Additionally, the assimilation of the SWS in JRA-55 was focused on the screen-level analysis, which minimized the difference between model forecasts and observations; these were not used as initial conditions for forecasts and were separate from the atmospheric analysis (Kobayashi et al. 2015).

As Torralba et al. (2017) illustrated, JRA-55 showed a negative near-surface wind speed bias in the regions where the vegetation type is categorized as trees. The bias originates from the lowermost atmospheric level, which is placed too high over regions with trees, thus reducing the wind speed when interpolated from that level down to the altitude of 10 m and are not fully corrected in the data assimilation process. This explains why JRA-55 was the reanalysis most similar to the observations, but there were also negative biases in some areas, such as over southern China and northeastern China. This issue may be addressed by correcting the surface roughness height where there were trees and

improving the data assimilation system. The climatology and spatial patterns in the other four reanalyses indicated that they had the ability to simulate SWS, but the systematically overestimated bias also showed deficiencies in the presentation of land–atmosphere interactions.

We then examined the correlations of five reanalyses with the observations using monthly anomalies from 1980 to 2017. Overall, the SWS in all reanalyses had high correlations with the observed SWS, except in northwestern China, which indicated that the reanalyses could essentially simulate the SWS seasonal variations (Fig. 13). Because of

TABLE 4. Detrended surface wind speed and geostrophic wind speed decadal correlation coefficients with three climate indices. The bold font indicates the Student's *t* test results with a significance level of 0.05.

	Surface wind speed			Geostrophic wind speed		
	SHI	SHPI	NPI	SHI	SHPI	NPI
Northeastern China	0.31	−0.02	0.59	0.70	−0.38	0.11
Northern China	0.16	−0.27	0.46	0.52	−0.37	0.30
Northwestern China	0.31	−0.09	0.66	0.34	−0.32	0.35
Tibetan Plateau	−0.23	−0.43	0.46	0.30	−0.15	0.50
Southern China	0.08	−0.23	0.57	0.62	−0.33	0.45
Southeastern China	0.12	−0.24	0.59	0.68	−0.35	0.35
China	0.13	−0.23	0.59	0.60	−0.33	0.41

FIG. 11. Sea level pressure differences based on the period 1970–2004: (a) summer differences in 1960–69, (b) summer differences in 2005–17, (c) winter differences in 1960–69, and (d) winter differences in 2005–17. The pink contour lines represent the average pattern of the mean sea level pressure during the studied period, and the interval unit is 2 hPa.

the assimilation of observations, JRA-55 had the highest correlations with the observations, which exceeded 0.7 over most of China, and the other four reanalyses showed similar patterns. Although MERRA-2 considered annual aerosol changes when the other reanalyses used climatological aerosols, this dataset did not make obvious progress in terms of modeling SWS annual variations.

Figure 14 shows the annual and decadal normalized wind speed anomalies via the observations, GWS, and five reanalyses over China and six subareas. To maintain data consistency, all of the wind speed time series were normalized by min-max normalization first, and then the multiyear average anomalies were calculated. The decadal variations were obtained by smoothing annual values with a running mean window length of 10 years. Overall, all reanalyses had synchronous annual variations with the observed SWS and GWS, but decadal variability did not show much change as other data showed. All of the five reanalyses had deficiency in describing atmospheric circulation, and none of them could exhibit the recovery phenomenon as shown by the SWS and GWS since the last decade.

4. Conclusions and discussion

In this study, the observed SWS and the GWS calculated from surface pressure at more than 2000 stations across China were used to study the stilling and recovery

of SWS over China from 1960 to 2017. China experienced anemometer changes and automatic observation transitions in approximately 1969 and 2004, resulting in the inhomogeneity of SWS. Therefore, we divided the entire period into three sections to study the SWS trend, and found that the annual SWS showed a significant decreasing trend of $-0.24 \text{ m s}^{-1} \text{ decade}^{-1}$ over China during the 1970–2004 period, while the decreasing trends during the 1960–69 and 2005–17 periods were only -0.04 and $-0.05 \text{ m s}^{-1} \text{ decade}^{-1}$, respectively.

GWS decreased with a significant trend of $-3\% \text{ decade}^{-1}$ ($p = 0.001$) before the 1990s; during the 1990s, GWS increased with a trend of $3\% \text{ decade}^{-1}$ whereas SWS continued to decrease with a trend of $10\% \text{ decade}^{-1}$. Consistent with SWS, GWS demonstrated a weak increase after the 2000s. The GWS trend analysis and further circulation pattern analysis indicate that atmospheric circulation was not the key cause of SWS stilling during 1960–2017 but was the main cause of SWS recovery over China since the early twenty-first century. Both of GWS and SWS showed synchronous decadal variability, which is significantly affected by the intensity variation of the Aleutian low pressure over the North Pacific.

By defining the 95th and 5th percentiles of daily mean wind speeds as strong and weak winds, respectively, we found that the SWS decrease over China in the last five

FIG. 12. The annual mean SWS in the observations, and five reanalyses' differences with observation, from 1980 to 2017: (a) observation, (b) JRA-55, (c) MERRA (1980–2015), (d) MERRA-2, (e) CFSR (1980–2010), and (f) ERA-Interim.

decades was mainly caused by a decrease in strong wind, reaching $-8\% \text{ decade}^{-1}$, while weak surface winds showed a slight decreasing trend of $-2\% \text{ decade}^{-1}$ in the last five decades. The subperiod study also showed that the weak wind recovery reached $26\% \text{ decade}^{-1}$ over all of China. Neither strong nor weak geostrophic wind showed an obvious trend in 1960–2017.

Strong surface wind showed a higher decreasing trend than weak surface wind, while strong geostrophic wind did not show an obvious trend change, and weak wind showed a relatively a slightly increasing trend. The increase in surface roughness may be one of the main reasons for this phenomenon. The SWS decline induced by surface roughness increases

has become increasingly in the last four decades over China (Zhang et al. 2019). Observations (Li et al. 2011) and theoretical analysis (Fan et al. 2005) showed that surface roughness had a stronger influence on strong winds than weak winds, which was consistent with our results. A decrease in strong geostrophic wind showed that strong surface wind should also decrease if only under the influence of atmospheric circulation, but SWSs were more likely to be influenced by increasing surface roughness. Therefore, the strong surface wind decreased more quickly than the strong geostrophic wind.

The five studied reanalyses could simulate SWS interannual variations but had deficiencies in terms of

FIG. 13. The correlation coefficients between the monthly anomalies of observed and reanalysis SWS: (a) JRA-55, (b) MERRA (1980–2015), (c) MERRA-2, (d) CFSR (1980–2010), and (e) ERA-Interim.

describing climatology and trends. The SWSs in the reanalyses were all higher than the observations except JRA-55. Due to the assimilation of observations, JRA-55 was the reanalysis that was most relevant with the observations and depicted a recovery phenomenon since the early twenty-first century. The other four reanalyses did not show the recovery phenomenon as shown by the SWS and GWS since the last decade.

GWS was first used over sea surfaces or flat land near coastal regions (Alexandersson et al. 1998; Schmidt and von Storch 1993; Wang et al. 2008). Recently, Wan et al. (2010) and Minola et al. (2016) used GWS to homogenize SWS over Canada and Sweden, respectively, and these studies used GWS over land at a large

scale. Compared to Sweden, the topography in Canada was more complex, especially over western Canada, where the Cordilleran Mountains are located, and we found that the results were relatively reliable, and the geostrophic wind theory were also applicable over complex land surface. Then, we extended the use of the geostrophic wind theory over China. It is known that the ability of the geostrophic wind to describe the real atmospheric flow diminishes where ageostrophic effects are high. The Tibetan Plateau is one of the most complex regions in the world, and we found that GWS over the Tibetan Plateau also had significant correlations with the SHI and NPI decadal variations similar to over other regions (Table 4), which indicated that GWS over heterogeneous terrain could depict

FIG. 14. Annual (solid lines) and decadal (dotted lines) mean normalized SWS anomalies via the observations and five reanalyses, and GWS over (a)–(f) six subregions and (g) China from 1980 to 2017. All of the time series were normalized by min–max normalization first, and then, the multiyear average anomalies were calculated.

atmospheric circulation changes basically. However, quantitative assessment of ageostrophic effects on GWS needs further studies.

In addition to atmospheric circulation, many other studies have explored the causes for SWS variations based on other factors, such as surface roughness and aerosols. Wu et al. (2018b) found that surface friction caused by surface roughness increase could decrease the SWS by an average of -1.1 m s^{-1} from 1981 to 2010 in eastern China. Vautard et al. (2010) found that surface roughness could explain between 25% and 60% of the SWS variations over Eurasia. By assuming a parameter K that was related to surface roughness, Zhang et al. (2019) found that surface friction dominated the SWS decline over the North Hemisphere lands in the past four decades, and aerosol emissions contributed no more than 10% to SWS stilling (Bichet et al. 2012; Jacobson and Kaufman 2006). Additionally, it remains unclear whether the short-term trends in this study are internal variations or if they include external forcing like surface roughness changes in recent decades (Vautard et al. 2010), which need to be explored further.

It is worth mentioning that even though some conventional data quality controls such as checking for

climatological outliers and temporal and spatial consistency have been applied for the data released by CMDC (Cao et al. 2016), they did not do homogeneity tests. This study identified the replacement of anemometers around the year of 1969 and 2004, which influenced the mean values and distribution of SWS in China. However, it is still a challenge to accurately detect and adjust the inhomogeneity. Given the lack of hourly data, we used daily mean values to estimate upper quantiles of SWS, and daily averages could smooth out the peaks in the pressure gradients and surface winds, which could induce the uncertainty in our study and requires further study.

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