Surface Wind Speed over Land: A Global View

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ABSTRACT

This paper provides a global analysis of surface wind speed (SWS) based on data from 1506 weather stations. It is found that the local variation in monthly normal SWS can generally be captured as a sine function of calendar month using three descriptors: the annual mean SWS, the annual amplitude of SWS, and the month of peak SWS. With station-specific descriptor values, the function accounts statistically for 97% of the variance in SWS contained in the total dataset; the corresponding root-mean-square error is 0.30 m s\(^{-1}\), or 8.2% of the SWS data mean. Global maps of the three SWS descriptors are produced by geographically interpolating the locally fit values. By reversing the above procedure, the maps may be used to provide first approximations to monthly SWS anywhere in the world.

1. Introduction

Surface wind speed (SWS) here refers to the speed of air movement reported by weather stations [i.e., preferably but not always measured in open air 10 m above the land surface and in locations with no obstructions upwind to distances of 100 times the anemometer height (Linacre 1992)]. The synthesis of temporal and geographic variation of SWS has been limited to qualitative descriptions in climatology treatises (e.g., Linacre 1992; Martyn 1992; Barry and Chorley 1998) and location-specific monthly summaries in climate atlases (e.g., USEDS 1968; Deharppoite 1983a,b, 1984; Geelin and Lewis 1992). SWS is absent from otherwise comprehensive climate data grids developed for model-based analysis of global change and terrestrial ecosystems (e.g., Kittel et al. 1995; Friend 1998; Cramer et al. 1999). This absence represents a major obstacle to reducing uncertainties in such analyses (Cramer et al. 1999), because SWS regulates many ecosystem processes (e.g., aerosol transport; surface soil erosion; atmosphere-land/vegetation exchanges of energy, water vapor, carbon dioxide, nitrogen, mercury, and all other gases; Hagen 1991; Jones 1992; Waring and Running 1998). This paper describes an attempt to capture the normal monthly and geographical variation in SWS and to provide a simple method for making initial estimates of SWS anywhere in the world.

2. Methods

Surface winds occur as a result of atmospheric pressure gradients and the earth’s rotation (the Coriolis effect and centripetal acceleration); they are slowed by friction against the earth surface, are modified by local topography through thermal differences or as a physical barrier, and are accelerated by the vertical churning of the atmosphere due to thermal convection or turbulence (Barry and Chorley 1998). Because the factors that drive the winds tend to vary seasonally (Barry and Chorley 1998), SWS is also seasonal at most locations. I hypothesized that monthly mean SWS, \( W \) (m s\(^{-1}\)), can be expressed as

\[
W = W_{yr} + A_w \sin\left(\frac{s + 3 - s_{\text{max}}}{2\pi/12}\right),
\]

where \( W_{yr} \) is the annual mean SWS (m s\(^{-1}\)); \( A_w \) is the annual amplitude (m s\(^{-1}\)); \( s \) is calendar month (January = 1.5, . . . , December = 12.5); and \( s_{\text{max}} \) is the month when SWS peaks. Locations with approximately constant SWS year-round are a special case of Eq. (1) with \( A_w = 0 \) (and with \( s_{\text{max}} \) irrelevant).

Data for multiyear mean (“normal”) monthly SWS were initially compiled in conjunction with a series of climatological studies (i.e., Yin 1998, 1999a,b,c). Those studies revealed that mathematical algorithms can be developed for estimating atmospheric water vapor pressure, bright sunshine duration, atmospheric turbidity, and solar irradiance from information of precipitation and air temperature, because the climate variables involved are of direct or indirect reciprocal cause-and-effect relationships. SWS does not share such relationships, so a similar algorithm proved unattainable for SWS. The compilation of SWS data was expanded to maximize the data base by including all stations for

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which monthly SWS was reported in Landsberg (1969–81), Environment Canada (1982), Müller (1982), Ruffner and Bair (1985), and Domrös and Peng (1988). The final dataset consisted of 1506 locations, including 25 Antarctic stations and 28 ocean stations.

The source references were global or national compilations and in general did not specify measurement methods (e.g., anemometer type, installation height, and measurement frequency), which are known to have differed among countries, changed over time, and caused inconsistencies among SWS readings (Linacre 1992). Further, the stations tend to be in or near population centers, are relatively low in density over mountainous terrain (where climatic patterns are often complex), and are rarely located along shorelines (where SWS may change drastically between the land and the adjacent ocean). These problems are common to all climate analyses and are reiterated here to emphasize the limitations of the database. Also for perspective, in comparison with 1506 stations here, the number of data stations used to develop global climate grids has ranged from more than 6000 for temperature and precipitation down to 1597 for bright sunshine duration, 802 for humidity, and 162 for solar irradiance (Friend 1998).

Equation (1) was fitted to the compiled SWS data by nonlinear regression to obtain the values of descriptors \( W_{yr}, A_w, \) and \( s_{max} \) for each data station. As none of the descriptors showed an apparent gradient with elevation (as indicated later), the station-specific values were interpolated latitudinally and longitudinally to generate isotachs over the global surface, using the “contour plot” feature of JMP Statistical Software (SAS Institute); the interpolation was done on the assumption that the spatial change in SWS and its three descriptors should be gradual (i.e., even and continuous) between neighboring stations. Such an assumption is inherent in all climate maps, for example, for precipitation or air temperature, although it is unlikely to be strictly valid even where the landscape appears uniform (unless the density of data stations would approach infinity). Deviations from the assumption should be inconsequential as long as the local variation in SWS falls within the interval of isotachs.

3. Results and discussion

Of the 1506 data stations, all but 1.4% have SWS exhibiting a seasonal pattern consistent with Eq. (1). Parameterized by the locally fit descriptor values, the equation accounts statistically for 97% of the variance in SWS contained in the total dataset; the corresponding root-mean-square error is 0.30 m s\(^{-1}\), or 8.2% of the SWS data mean.

Across the data stations, the SWS descriptor values and geographic locations show the following relationships:

- \( W_{yr} \) is correlated with \( A_w \) \((R^2 = 0.24\) in a simple linear regression function\): SWS tends to exhibit a greater
annual amplitude where its annual mean is high than where the mean is low;
- $W_{av}$ is correlated with $s_{max}$ ($R^2 = 0.15$ in a quadratic function): annual mean SWS tends to be lowest where SWS peaks in midsummer and be highest where SWS peaks in midwinter; and
- $W_{av}$ is correlated with latitude ($R^2 = 0.11$ in a quadratic function): annual mean SWS tends to be lowest at the equator and increase continuously toward the Poles.

There are no other apparent correlations, beyond the three just described, between the SWS descriptors and geographic location (latitude, longitude, elevation).

A global view of the SWS descriptors, as rendered in Figs. 1–3, leads to the following generalizations:

- The annual mean SWS is generally below 6 m s$^{-1}$ (Fig. 1). The highest annual mean speeds (>4 m s$^{-1}$) are found over the Great Central Lowland of North America, the Western Siberian Lowland and westward in the former USSR, the Arabian Peninsula, and various coastal areas. The lowest mean speeds (<2 m s$^{-1}$) are largely confined to tropical forest climates (i.e., where lowest monthly mean temperature exceeds 18°C) in South America, Africa, and southeastern Asia; and to mesothermal forest climates (i.e., where the lowest monthly mean temperature is in the range of 0°–18°C and the highest monthly mean temperature is greater than 10°C) over the rugged terrain flanking the Tibetan Plateau (see Strahler 1989 for climatic classifications). Annual mean SWS may reach 16 m s$^{-1}$ at isolated landlocked locations (Fig. 1), especially on mountain summits (Barry and Chorley 1998).
- The annual amplitude of monthly mean SWS is generally smaller than 1 m s$^{-1}$ (Fig. 2). Exceptions are found mainly off the northern Indian Ocean (the Arabian, Indian, and Malay Peninsulas), and in scattered coastal areas.
- SWS is generally highest in winter in Europe, Asia Minor, western Siberia Lowland, eastern United States, Canada’s Laurentian Highlands and eastward, and much of northwestern and southernmost South America. The highest SWS generally occurs in spring in western United States, northern Africa, and Asia (except in Siberia, in the Taklamakan Desert, and in the Indian Subcontinent where SWS tends to be highest in summer). Areas where SWS peaks in autumn are largely limited to northernmost Canada, central South America, and some areas in southernmost Africa or Australia (Fig. 3).

Many mathematical models have been developed to estimate SWS, but such models are generally highly localized and cannot be readily adapted for regional or global application (e.g., Castino et al. 1998; Cox et al. 1998; Maurizi et al. 1998; Miller and Davenport 1998; Salmon and Walmsley 1999). Until an effective generic SWS model emerges, Figs. 1–3 may be used in conjunction with Eq. (1) to provide initial estimates of monthly SWS. As noted earlier, using locally fit values for the descriptors in Eq. (1) leads to an overall root-mean-square error of 0.30 m s$^{-1}$. This margin of error would increase only mildly to 0.47 m s$^{-1}$ if, instead of...
Fig. 3. Global map of peak wind speed season. The season is converted from the month of peak SWS $s_{\text{max}}$: Dec–Feb ($12 < s_{\text{max}} \leq 3$) as winter, Mar–May ($3 < s_{\text{max}} \leq 6$) as spring, Jun–Aug ($6 < s_{\text{max}} \leq 9$) as summer, and Sep–Nov ($9 < s_{\text{max}} \leq 12$) as autumn for the Northern Hemisphere; shifting six months, e.g., Jun–Aug ($6 < s_{\text{max}} \leq 9$) as winter, for the Southern Hemisphere. See Fig. 1 for explanations.

The fitted value, the median value of each interval range in Figs. 1–3 is substituted for each descriptor (e.g., any location within the most lightly shaded area in Fig. 1 takes the value of 0.5 m s$^{-1}$ for $W_{yr}$, whereas any location in a black area takes 5.5 m s$^{-1}$; any location in the Northern Hemisphere having spring as the windiest season in Fig. 3 takes the value of 4.5 for $s_{\text{max}}$). The mean error margin should lie somewhere between 0.30 and 0.47 m s$^{-1}$ if descriptor values are prorated by the relative distances to the nearest isometric lines and if the geographic interpolations of the descriptors reflect the “ground truth.”

The global surfaces depicted in Figs. 1–3 are based on monthly normal SWS, following the tradition of climate atlases, and more recently, global data grids of other climate parameters developed to aid global change research (e.g., Kittel et al. 1995; Friend 1998; Cramer et al. 1999). As such, they represent long-term averages on a broad geographic scale, and do not reflect temporal dynamics of SWS from diurnal, daily, or yearly fluctuations, or spatial variation in SWS due to local topography. Estimates of SWS based on the figures are subject to those same constraints.

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