SPATIAL COHERENCE AND DECAY OF WIND SPEED AND POWER IN THE NORTH-CENTRAL UNITED STATES

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Abstract: Hourly wind data from a network of climate stations in the north-central United States (drawn from the states of Illinois, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota, and Wisconsin) are analyzed to evaluate the efficacy of spatial analyses of near-surface wind speed and power. Spatial autocorrelation functions (acfs) were calculated at a number of timescales: annual, monthly, daily, and hourly. Annual wind speeds have virtually no coherent distance-decay relationship; monthly data produce a more consistent relationship, but still exhibit a large amount of scatter. Both daily and hourly data have classical decay with increasing distance between stations and there appears to be an optimal level of temporal aggregation, near the daily timescale, for spatial analysis of wind. In general, however, spatial acfs overestimate the spatial coherence of both wind speed and power. Temporal nonstationarities in wind data (i.e., diurnal and annual cycles) bias spatial autocorrelation functions and need to be removed before using spatial acfs to estimate characteristics of wind fields. Because mean absolute differences (MADs) of interstation wind speed and power are less affected by temporal nonstationarities, they produce more robust representations of the spatial variability of wind speed and power. As a result, spatial MADs are recommended over spatial acfs for analyzing spatial coherence and decay of any spatial variable that contains nonstationarities. Methods for improving the spatial analysis of wind are discussed. [Key words: wind energy, spatial autocorrelation, spatial analysis, nonstationarity, north-central United States.]

INTRODUCTION

Many areas of the United States experience wind speed fluctuations that are related to atmospheric variability on a number of timescales (e.g., diurnal, annual, decadal). Wind energy resources, therefore, are sensitive to both natural climatic variability and any climatic changes that are occurring (Palutikof et al., 1987; Robeson and Shein, 1996). Given adequate temporal resolution and duration, wind-energy resources can be assessed at locations where wind speed is

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measured, although unresolved (long-term) temporal variability beyond the period of record remains problematic. In many cases, however, wind speed and power need to be estimated at locations where no data are available. In such instances, wind data must be interpolated spatially.

Often, short-term observations from a candidate site are used in combination with observations from another nearby site (with longer-term data) to assess the issue of temporal variability and to improve the resolution of probability density functions. A simple transfer function that relates wind speeds at the nearby site to wind speeds at the candidate site can then be used to reconstruct and evaluate long-term variability at the candidate site (Justus et al., 1979). This spatial estimation approach, while worthwhile, has a number of limitations. First, the temporal representativeness of the candidate-station data, and therefore the transfer function, is difficult to assess, especially if only a few months of data are collected (Barros and Estevan, 1983; Brown et al., 1984; Skibin, 1984; Haslett and Raftery, 1989). Additional limitations are related to estimation of the transfer function, which leads to fundamental questions related to spatial estimation of wind speed and power. Paramount among these are (1) how nearby should the “nearby” station be and (2) what temporal resolution of data is optimal for developing the transfer function? This research aims to address these two issues by evaluating the spatial variability of wind speed and wind power at a number of timescales using data from the north-central United States. Spatial autocorrelation functions (acfs) and mean absolute differences (MADs) are used to characterize the spatial coherence and decay of wind speed and power. Methods for improving the spatial analysis of wind also are discussed.

STUDY REGION AND DATA

Study Region

Although most wind-power development in the United States has occurred in California where wind speeds along many coastal mountain-valley systems are relatively high and predictable, considerable wind-power potential has been identified in the north-central United States (Elliot et al., 1987; Brower et al., 1993; Gipe, 1995). Using traditional wind-power classification methods that are based on mean wind speed, a large proportion of the Great Plains has a wind-power rating of Class 4 or 5 (Table 1). In particular, large sections of North Dakota, South Dakota, southwestern Minnesota, northwestern Iowa, north-central Nebraska, and central Kansas have wind-power sites that are viable using existing turbine technology (Brower et al., 1993). Since the north-central United States has relatively low topographic relief, it is an instructive region to develop spatial models of wind speed and power. At the same time, the north-central United States has a range of wind climates and, therefore, provides an excellent opportunity to examine historical space-time variability in a number of areas where wind energy is being developed. The study area also is large enough to examine the role of regional-scale climatic forcing. Overall, however, there has been a surprising lack of both theoretical and applied research on the relation-
Table 1. Wind-Power Classes Based on Mean Wind Speeds at 10 m\(^3\)

<table>
<thead>
<tr>
<th>Wind class</th>
<th>Speed (m s(^{-1}))</th>
<th>Speed (mi hr(^{-1}))</th>
<th>Power (W m(^{2}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0–4.4</td>
<td>0.0–9.8</td>
<td>0–100</td>
</tr>
<tr>
<td>2</td>
<td>4.4–5.1</td>
<td>9.8–11.5</td>
<td>100–150</td>
</tr>
<tr>
<td>3</td>
<td>5.1–5.6</td>
<td>11.5–12.5</td>
<td>150–200</td>
</tr>
<tr>
<td>4</td>
<td>5.6–6.0</td>
<td>12.5–13.4</td>
<td>200–250</td>
</tr>
<tr>
<td>5</td>
<td>6.0–6.4</td>
<td>13.4–14.3</td>
<td>250–300</td>
</tr>
<tr>
<td>6</td>
<td>6.4–7.0</td>
<td>14.3–15.7</td>
<td>300–400</td>
</tr>
<tr>
<td>7</td>
<td>&gt;7.0</td>
<td>&gt;15.7</td>
<td>&gt;400</td>
</tr>
</tbody>
</table>

\(^{a}\)Assumptions about wind-speed distributions also are used to develop the classes. Class 5 sites are considered feasible using existing turbine technology, while Class 3 and 4 sites are expected to be feasible in the near future (adapted from Brower et al., 1993).

ships between climatic variability and wind. Of the 653 entries in a recent annotated bibliography of global warming (Handel and Risbey, 1992), not one citation refers to the effect of climatic change on wind or vice versa.

The north-central United States experiences wind-speed variability that is dominated by (interannual, annual, and shorter-term) variability in synoptic-scale weather systems (Robeson and Shein, 1996). Therefore, any climatic change or variability that influences mid-latitude weather systems will influence wind speeds, and therefore wind-energy resources, in this area. Since cyclone paths and frequencies have varied considerably in the past (Agee, 1991) and most scenarios of climatic change simulate changes in cyclone paths (although there is considerable uncertainty in estimating the changes that will occur; König et al., 1993; Hall et al., 1994; Lambert, 1995), the north-central United States is particularly sensitive to synoptic-scale climatic variability (i.e., more so than regions that rely on regional-scale circulations caused by thermal or topographic forcing). As a result, estimating the space-time variability of wind in this region is extremely important for diagnosing the impacts of climatic variability on wind-energy resources. Analyses of temporal variability of wind resources in the north-central United States have shown that substantial changes have occurred in a number of wind-energy statistics (on a number of timescales) over the period 1961 to 1990 (Robeson and Shein, 1996; Shein, 1995; Shein and Robeson, 1996). It is not clear, however, whether large-scale climatic forcing or local-scale changes are responsible for the observed changes. This research represents some of the first steps in evaluating space-time variability of wind resources in the north-central United States.

**Data**

The data used here are derived from the Solar and Meteorological Surface Observation Network (SAMSON) CD-ROM that was compiled by the National
Renewable Energy Laboratory (NREL, 1993; the CDs are available from the National Climatic Data Center, Asheville, North Carolina). Station histories and data from all SAMSON stations in the north-central United States were examined; two stations (St. Cloud, Minnesota, and Norfolk, Nebraska) were not used because of excessive missing data. The remaining 37 stations (Fig. 1) represent an approximate station density of 26 stations per 10 km² with an average nearest-neighbor distance of 152 km. Most of the 1961–1990 period of record consists of hourly observations, allowing wind power to be estimated at relatively high temporal resolution. Prior to analysis, a series of adjustments were made to the data. All data were screened for gross observational errors and obvious inhomogeneities; only a few keypunch errors were found. The time series for each station contained few missing observations, usually much less than 0.1%. For several years, primarily in the late 1960s and early 1970s, most of the stations used a three-hour observation schedule; however, the high temporal correlation of hourly wind speeds (Brett and Tuller, 1991) allows these values to be interpolated with relatively little error (Shein, 1995). As a result, data for nearly all hours from 1961 to 1990 are available at the 37 stations (Fig. 1).

Vertical Wind-Speed Adjustments

Before calculating wind power or performing any statistical analysis, wind-speed values need to be adjusted to a common height above the ground. In particular, when using stations whose anemometer heights have changed over time or when comparing stations that have measurements of wind speed at different heights, a wind-profile law can be applied to adjust the data to a common elevation. Two closely linked alternatives are available: the log and the power profiles. The log profile makes use of the well-known logarithmic increase in wind speed with height:

$$u_2 = u_1 \left( \frac{\ln(z_2/z_0)}{\ln(z_1/z_0)} \right)$$  (1)

where $u_2$ and $u_1$ are wind speeds (m s⁻¹) at heights $z_2$ and $z_1$ (m) above the ground, and $z_0$ (m) is a roughness length that is representative of the underlying surface (Arya, 1988; Oke, 1987). Similarly, the power profile,

$$u_2 = u_1 (z_2/z_1)^{\alpha}$$  (2)

where $\alpha$ is a roughness exponent, can be used to extrapolate winds to other heights (Touma, 1977). Over relatively small changes in height (i.e., small values of $z_2 - z_1$), either approach will produce similar wind-speed values, assuming that appropriate roughness parameters, $z_0$ and $\alpha$, have been specified (Fig. 2). When extrapolating to greater heights, however, small differences in roughness parameters become increasingly important and using the log profile is recommended (Arya, 1988). Most of the wind-speed observations used in this study were taken at 6.1 m (20 ft),
while other observations, particularly during the early part of the record, were taken at heights ranging as high as 16 m. Therefore, to reduce height-extrapolation errors, all observations are adjusted to 10 m, which is a useful intermediate level and the WMO-recommended height for wind-speed observations. It is important to note that neither equation 1 nor equation 2 (as specified) incorporates information on atmospheric stability; therefore, neutral stability is being assumed. Although stability certainly plays an important role in determining wind-speed variations with height, the information needed to estimate and apply stability corrections is not available for much of the wind-speed data to be used here. In addition, the relatively small height corrections (i.e., most are less than 4 m) reduce the relative magnitude of stability corrections.

Another potential limitation of using historical wind-speed data is the influence of changing surface roughness over the period of record. While surface roughness certainly varies to some extent at all sites (surface roughness changes as the texture of the underlying surface changes, and therefore varies with obstacle geometry—e.g., length and density of grass—and even with wind speed), it is nearly impossible to reconstruct the values of either $z_0$ or $\alpha$ reliably from station histories or even topographic maps. Historical topographic maps were con-
sulted, however, to examine the local environment of each station. All stations are at airport sites and therefore, to some extent, are associated with cities. Several of the cities (e.g., St. Louis and Milwaukee) have expanded rapidly over the period from 1961 to 1990, engulfing the airports, and this has implications for both roughness changes and for interpolating to rural wind-energy sites (Wieringa, 1980). Since all of the sites are located at airports, though, we will assume that (1) sufficient fetch is available in all directions and (2) surface roughnesses associated with short grass prevailed throughout the period of record. For this research, therefore, the power-profile relationship (Eq. 2) with $\alpha = 1/7$ (a value typical of short-grass surfaces; Touma, 1977) was used to adjust all of the wind-speed values to 10 m. The power profile with $\alpha = 1/7$ produces very similar adjustments to the log profile with a roughness length of 3 to 4 cm (Fig. 2), which is typical of airport environments (Wieringa, 1980).

Calculating Wind Power from Wind Speed

After wind-speed values are adjusted to a common height, it is important to calculate wind power at fine temporal resolution. Wind power ($P$, in Watts) is a cubic function of wind speed ($u$, in m s$^{-1}$):
where \( A \) is the area swept by the turbine rotor and \( \rho \) is air density (kg m\(^{-3}\)). Air density is estimated as a function of station elevation (Elliot et al., 1987). Dividing both sides of equation 3 by the turbine area provides a convenient and turbine-independent measure of potential wind “power” (actually wind-power density, in Wm\(^{-2}\)). While typical turbine-conversion efficiencies are 35% of potential power (Gipe, 1995), potential wind power is used here. Given the cubic dependence of wind power on wind speed, it can be critically important to estimate wind power prior to any temporal aggregation of wind speed (the average of a series of values that have been cubed is greater than or equal to the cube of the average of that same series). As a result, standard classification systems based on wind-speed averages, even when combined with assumptions about wind-speed probability distributions, can be limiting, misleading, or even erroneous. It is important, therefore, to estimate wind resources and their spatial distribution using fine temporal-resolution data. The wind-power data used below were constructed by using hourly wind-power values.

**MEASURES OF SPATIAL COHERENCE AND DECAY**

To estimate spatial characteristics of wind speed and power using data from the north-central United States (Fig. 1), a variety of measures of spatial association are used. Spatial coherence can be defined and examined in a variety of ways. For instance, in a study of the spatial characteristics of solar radiation in the eastern and central United States, Suckling (1997) defines “spatial coherence” as how quickly the values of solar radiation change with distance from a given location. Here, however, we use the term “coherence” to refer to the amount of scatter associated with the distance-decay relationship and use “spatial decay” to refer to how quickly the values change with distance. The spatial decay may be estimated in various directions from any given point (i.e., be anisotropic; Thiébault, 1976) or may vary with location over the spatial domain (i.e., be heterogeneous). Since the spatial domain in this study is limited, only isotropic and homogeneous decay functions will be used. For all of the measures of spatial association used here, the relationships are estimated using station pairs, of which there are 666 possible combinations (the number of combinations of 2 stations taken from 37 different stations). The major spatial features and limitations of each method are discussed.

*Spatial Autocorrelation*

Spatial autocorrelation is one of the most widely used quantities for estimating the structure of spatially distributed variables (Cliff and Ord, 1981; Thiébault and Pedder, 1987; Odland, 1988). The spatial autocorrelation function (acf) is formed by plotting the correlation between a variable measured at one location and that same variable measured at another location as a function of distance (the spatial acf is sometimes known as a spatial correlogram). As a result, the
spatial acf indicates both the relative strength (coherence) and decay of the correlative relationship with distance. In addition, spatial acfs can be used to form optimal weighting functions in spatial interpolation methods such as “optimal statistical objective analysis” (Thiébaux and Pedder, 1987), which is closely related to kriging (Cressie, 1993; Robeson, 1997).

Using data from the network of stations discussed previously (Fig. 1), spatial acfs were estimated for a variety of timescales: annual, monthly, daily, and hourly. Both wind speed and power have similar spatial acfs; therefore, only wind speed will be discussed. Annual wind speeds have virtually no coherent distance-decay relationship, as estimated by spatial autocorrelation (Fig. 3a). Correlations for nearest-neighbor stations range from −0.2 to 0.7 and there is very little spatial coherence at any distance. Nearby stations, therefore, do not have annual average wind speeds that covary to a greater extent than stations that are farther away. As an example, if a station such as Huron, South Dakota, has above-average wind speed during a given year, then nearby stations such as Sioux Falls, South Dakota, or Pierre, South Dakota, will not necessarily have above-average wind speed (and neither will stations that are farther away). Annual wind speed and power clearly are not spatially coherent and, therefore, cannot be estimated reliably using this network of stations (or, possibly, any network). In this respect, it is useful to consider whether wind speed and power are unlike other climatological variables such as air temperature and precipitation, which are considered to be spatially coherent on annual timescales (although this assertion should be tested more thoroughly; Gunst (1995), for instance, has shown that annually averaged air-temperature anomalies in the United States lack high spatial coherence). The lack of spatial coherence of annual wind speed likely suggests that local-scale processes are more dominant than those at regional or synoptic scales in determining interannual wind variability, although the study area may be too small to assess the spatial effects of interannual synoptic-scale variability. Monthly wind speed and power are more coherent than annual wind speeds, but neither the coherence nor the spatial decay is strong (Fig. 3b). Correlations between nearest-neighbor stations range from 0.4 to 0.9. In addition, if a function were fit to the monthly acf, the function would not produce an autocorrelation that approached one as the distance approached zero, indicating that even stations that are very close are not necessarily highly correlated at the monthly timescale.

Daily and hourly wind speed and power have distance-decay relationships that are very coherent spatially (Figs. 3c–d). Spatial acfs estimated using hourly data decay more rapidly (with distance) than daily ones (nearest-neighbor correlations for daily data are approximately 0.9, while those for hourly data are approximately 0.7), suggesting that daily data represent a near-optimal timescale for spatial analysis of wind speed and power. This conclusion also follows from the dominant forcings for wind speed in this region being synoptic-scale systems, which have characteristic timescales that are measured in days. Daily data have been found to be an optimal level of aggregation for spatial prediction of wind speed in Ireland as well (Haslett and Raftery, 1989). The structure of the spatial acf for daily data in Ireland also is very similar to the data used here. Hourly wind speed is spatially coherent (Fig. 3d), but the distance decay is more rapid than for daily data, likely because of more-local influences dominating hourly wind-speed variability.
Fig. 3. Spatial autocorrelation functions for (a) annual, (b) monthly, (c) daily, and (d) hourly wind speeds for the 37 stations over the period 1961 to 1990. The daily and hourly data show the greatest spatial coherence; however, much of this coherence is caused by nonstationarities in the data (e.g., diurnal and annual cycles).

From the results presented so far, therefore, it appears that the optimal timescale for spatial analysis of wind speed and power in the north-central United States is near-daily (this result, of course, is dependent on the application of the spatial analysis). To varying extents, however, monthly, daily, and hourly wind-speed and power time series contain nonstationarities (statistical properties such as mean or variance that change through time) that bias estimates of spatial autocorrelation.
Fig. 4. Wind speed at Pierre, South Dakota, over the period 1961 to 1990: (a) mean value for each hour of the day (open circles) with "error bars" indicating one standard deviation on either side of the mean, and (b) mean value for each day of the year. These two nonstationarities in the mean wind speed cause overestimation of spatial autocorrelation functions. Note that the diurnal cycle of wind speed has stationary variance. All 37 stations have similar diurnal and annual cycles of wind speed.

Both the mean and variance of wind speed and power vary not only over the course of a day, affecting hourly data (Fig. 4a), but also on an annual basis, affecting hourly, daily, and monthly data (Fig. 4b). These nonstationarities can cause a consistent
Fig. 5. Illustration of the problems associated with estimating spatial autocorrelations of time-series data that contain temporal nonstationarities: (a) two time series that have different mean values and amplitudes, yet have perfect "spatial" correlation; and (b) two time series that have very similar values and relatively high spatial correlation, yet have variability about the diurnal cycle that is inversely related (a random time series has been added to the higher-amplitude series in Fig. 5a and the same random time series has been subtracted from the lower-amplitude series in Fig. 5a). In both cases, the estimated spatial correlation would be high because of the existence of the diurnal cycle and not because the locations were experiencing similar wind speeds or wind-speed variability.

overestimation of spatial autocorrelation. As an example, wind-speed values are typically higher during the afternoon than at night. Two stations, therefore, that are quite distant but experience diurnal cycles could have relatively high "spatial" cor-
relation (Fig. 5a), even if the variability about the nonstationary mean were inversely correlated (fig. 5b). Similarly, data from any two stations that had annual cycles that were in phase also would appear to be correlated. Similar problems with using time-series data that have nonstationarities to estimate spatial autocorrelation have been found in air-temperature data (Gunst, 1995). All of this evidence leads one to the conclusion that spatial acfs of data with nonstationarities overestimate spatial relationships and should be used cautiously. Similarly, spatial interpolation methods that make use of spatial acfs, such as optimal statistical objective analysis, must be implemented carefully in order to reduce the effects of temporal nonstationarities. Alternatives to using spatial acfs for estimating spatial coherence and decay are discussed below.

**MAD Distance Decay**

As an alternative to spatial autocorrelation, mean absolute differences (MAD$_{ij}$) for each station pair $i$ and $j$ can be calculated:

$$
MAD_{ij} = \frac{1}{n_i} \sum_{k=1}^{n_i} |u_{ik} - u_{jk}| 
$$

where $u_{ik}$ is the wind speed for station $i$ at time $k$, $u_{jk}$ is the wind speed for station $j$ at time $k$, $n_i$ is the number of time series values, and $n_s$ is the number of stations in network. By plotting MAD$_{ij}$ as a function of distance between stations $i$ and $j$, the spatial coherence and decay in wind speed and power coherence are clearly shown in meaningful units (Figs. 6 and 7). Since the calculation of MAD$_{ij}$ does not use deviations from a temporal mean (as correlation does), it is less affected by the presence of nonstationarities such as diurnal and annual cycles. In addition, unlike correlation, the variance of the two series is incorporated into MAD$_{ij}$, which makes the values physically interpretable. MAD$_{ij}$ is very similar to a variogram (Cressie, 1993), except that absolute values of differences, rather than the square of differences, are used. Absolute values are used since squaring the differences exaggerates the influence of large differences.

Overall, MAD for wind speed and power produces patterns of decay and coherence that are similar to the spatial acfs, with some notable differences (compare Fig. 3 with Figs. 6 and 7). Like the spatial acf for annual data, annual MADs for both wind speed and power show little spatial coherence and no discernible distance decay. Monthly MADs also show little coherence and no distance decay, suggesting that the weak distance decay in monthly acfs is a result of the temporal nonstationarity induced by the annual cycle of wind speed and power. Unlike correlation, MAD estimates the differences between the values of two variables directly (i.e., it is not estimating the degree to which the two variables covary); therefore, the lack of a distance-decay relationship indicates that wind speed and power values from nearby locations are no more similar than those that are more distant from each other. As a result, spatially interpolating and map-
Fig. 6. Mean absolute deviations of wind speed estimated at every possible combination of the 37 stations, plotted as a function of interstation distance for (a) annual, (b) monthly, (c) daily, and (d) hourly averages.

Pinning annual and monthly averages of wind speed and power would appear to be an unproductive and possibly misleading activity for locations in the north-central United States (i.e., these variables cannot be "regionalized"). Maps that utilize proportionally sized circles that represent wind speed and power at station locations would be appropriate alternatives to isoline maps.

MADs for daily wind speed and power are both fairly coherent and have fairly strong distance decay, with the MAD not quite approaching zero as the distance goes to zero—a feature of spatial variance known as the "nugget effect" in the geostatistical literature (Cressie, 1993). The nugget effect (or variance) is a combination of measurement errors and localized spatial variability that is not resolved by the sampling network. Like daily data, hourly wind speed and power both show relatively strong distance decay, as estimated by MAD; however, hourly wind power is much less coherent spatially than hourly wind speed (i.e., there is much more scatter in Fig. 7d than in Fig. 6d). In addition, MADs for hourly data also do not approach zero for near-zero distances. The daily timescale, therefore, once again appears to be near-optimal in terms of spatial analysis of both wind speed and power.
SUMMARY AND CONCLUSIONS

From the results presented here, annual and monthly wind-speed and power variations are not spatially coherent and do not have a distance-decay relationship. Both the spatial acf and MADs show that the spatial variability of annual wind data is not a function of distance. Monthly averages of wind speed and power, on the other hand, have some spatial coherence when their spatial variability is estimated using spatial acfs, but little coherence when MAD is used. Since spatial acfs have been shown to be biased estimators of spatial similarity for data with temporal nonstationarities, the monthly MADs are a better indicator of spatial similarity. By subtracting a global mean from the two time series being compared, correlation indicates similarity whenever two series are above or below their respective means together. This occurs in monthly wind data because all of the stations in this network have an annual cycle. As a result, values in February are nearly always above the 1961 to 1990 mean and values in August are nearly always below the mean, producing a relatively high “spatial” correlation. The same problem also biases daily and hourly acfs. Hourly data are most affected because they also include the nonstationarity associated with the diurnal cycle of wind speed. By examining absolute differences between stations, MAD produces more-robust estimates of
spatial coherence and decay. Since daily data produce the most coherent MAD distance-decay relationships, the daily timescale appears to be near-optimal for spatial analysis of wind speed and power. The nearest-neighbor mean-absolute differences are approximately 1 m/s for wind speed and approximately 100 W/m² for wind power, however, suggesting that spatial interpolation of wind speed and power would produce relatively large errors. For the stations analyzed here, wind-speed errors of 1 m/s (at 10 m) represent a relative error of nearly 20%. Improved methods for spatial analysis of wind speed and power, therefore, are needed.

As with other climatological variables (Daly et al., 1994; Willmott and Matsuura, 1995; Dodson and Marks, 1997), incorporating ancillary data that are related to wind variability, but observed at higher resolution, is likely to improve the spatial analysis of wind speed and power. In particular, high-resolution digital elevation models and satellite-derived landcover could produce vast improvements in spatial models of wind speed and power variability. Elevation data can be used to model the topographic exposure of a particular location (i.e., whether an area is exposed or sheltered relative to surrounding locations), while landcover data can be used to estimate the “roughness” of the surface (Brower et al., 1993). Elevation data are likely to be most important for wind-power assessment, however, since all wind-power sites would have roughnesses associated with short-grass surfaces.

The results presented here also raise doubts about the spatial representativeness of annual or monthly wind-speed climatologies. Mapping of annual and monthly wind data seems problematic, since locations close to a station where wind speed is measured are no more likely to have similar wind speeds than locations that are farther away. Climatologies that include spatial analyses of monthly or annual wind data, for instance, may need to be revisited, with additional analyses performed using daily data, where possible. In addition, the lack of spatial coherence and decay in longer-term averages of wind data may help to explain, for example, the relative lack of agreement between modeled and measured wind-power potential found by Brower et al. (1993). If monthly or annual wind-speed data are being used in other regions, it is recommended that their spatial coherence and decay be estimated before spatial analyses are performed.

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