Daily Wind Patterns: Understanding of Processes

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Introduction

Wind is an important variable for several processes, including wind erosion and evapotranspiration estimation. Vining and Allen (1993) describe the need to consider a range of air resource related variables, including wind, in integrated resource management planning. Therefore, it is desirable that the patterns of wind speed changes over a day be investigated and described. Like most climatic variables, wind tends to be both random and cyclic as time varies. Sine waves have often been used to describe average diurnal wind speed variations. Work by Gregory, et al. (1994) indicates that wind speed at Lubbock, TX is near constant during dark hours, and follows a curvilinear pattern during daylight hours. Later work by Gregory, et al. (1996) shows that diurnal wind patterns at five locations in the Great Plains follow a pattern similar to that observed at Lubbock, TX.

The intent of this investigation is to examine diurnal wind speed patterns for various sites in different climates across the United States, applying the previously developed model to see whether it holds over a wider geographic range.

The model used to generate wind speed data to compare to the measured data is described in detail by Gregory, et al. (1994). It takes the form of:

$$ZD = A_1 - A_4(H - A_3)^2 \tag{1}$$

$$\text{If } ZD > 0\text{, then } ZD = 0 \tag{2}$$

$$WS = A_2 + ZD \tag{3}$$

Where WS = predicted wind speed
H = hour of day
A_1 = the amplitude of the daytime wave
A_2 = the wind speed at night
A_3 = the time of day that maximum wind occurs, and
A_4 is inversely related to length of daylight hours squared and directly related to A_2.

The strength of the model is its ability to predict strong downmixing of momentum from upper level winds to the surface as nighttime inversions break from solar heating. A_1 represents the potential of strength for downmixing by controlling the increase in wind speed from daybreak to time of maximum wind speed. One reason for selecting climate stations in various locations around the country was to examine the changes in potential downmixing depending on location, and how those changes would potentially affect the model's ability to predict diurnal wind speed.

We must also account for variations away from mean wind speed values. Gregory (1989) developed an equation to predict probability of wind speed variations away from mean daily values assuming a constant standard deviation over all months of data for a site. Probability is given by:

$$Pc = 100(1-e^{-K_1(1-e^{-K_2 S^{K_3}}) S^{K_3}}) \qquad (4)$$

Where Pc = Cumulative probability
S = Speed ratio (magnitude of speed of interest over mean speed for a given day), and
$K_{1,2,3}$ = coefficient values

The standard deviation of the wind data is proportional to the magnitude of the average wind speed for the time duration being considered. The coefficient of variation is approximately constant from month to month. This relationship causes the probability distribution for a given time period to be the same as other time periods when the wind speed is compared to the mean value for the given time period. Therefore, we should be able to scale the scatter of wind speed for hourly as well as monthly average wind speed.

Hourly wind values averaged over each month were calculate for data from 10 sites across the United States: Spokane, WA, Phoenix, AZ, Fresno, CA, Salt Lake City, UT, Casper, WY, Bismarck, ND, Des Moines, IA, Baton Rouge, LA, Albany, NY, and Atlanta, GA. The data are from the climate database of the Natural Resources Conservation Service Water and Climate Center. The period of record for all stations was from 1982 to 1990. These locations were chosen for a number of reasons: geographic distribution, local topographic variations (for example, mountainous west versus plains-cornbelt), site elevation, local climate, and data availability. While these sites represent only a limited cross-section of locations across the country, analysis of these data should provide some insight into the characteristics of diurnal wind speed patterns in diverse climate regimes.

Discussion of Hourly Analysis

Results of the hourly analysis of wind speed are shown for January and July in Table 1. An example plot of the average and predicted data for Bismarck, ND is shown in figure 1. At most locations, the developed model appears to accurately describe the average diurnal variations of wind speed. Albany, Atlanta, and Des Moines had R2 values above 0.90 for both months analyzed. Earlier research hypothesized that high accuracy from the model could be expected in the Great Plains, where wind speeds for much of the year are influenced by downmixing from the jet stream. Surprisingly, data for Atlanta, Baton Rouge, and Albany also showed good correlation between measured and estimated values. Atlanta and Baton Rouge have elevations near sea level and experience high relative humidity. Both factors should dampen the downmixing process. Also, these locations are generally not under the main jet stream core during January or July; however, their predictable wind patterns imply that more than location under a jet stream core, thickness of the overlying atmosphere, or relative humidity will influence diurnal wind patterns.

Table 1: Hourly wind speed analysis correlation coefficients (R^2) for January and July

January Location	R^2	July Location	R^2
Albany	0.96	Albany	0.96
Atlanta	0.93	Atlanta	0.94
Baton Rouge	0.94	Baton Rouge	0.82
Bismarck	0.89	Bismarck	0.96
Casper	0.89	Casper	0.97
Des Moines	0.90	Des Moines	0.95
Fresno	0.67	Fresno	0.51
Phoenix	0.88	Phoenix	0.77
Salt Lake City	0.69	Salt Lake City	0.87
Spokane	0.87	Spokane	0.88

Diurnal wind patterns at locations near to strong orographic influences did not follow the patterns predicted by the model. In particular, wind at Fresno in July followed a pattern of increasing speed during daylight hours and decreasing speed during nighttime hours. The other locations with the potential for orographic influence (Phoenix and Salt Lake City) showed R^2 values lower than the Great Plains locations, but the measured wind patterns generally followed the model predictions. Casper has high winds due to mountain gaps upwind; however, Casper also displays a strong downmixing pattern.

The conclusion is that the model appears to function effectively for data from January and July with only a few exceptions. The comparisons for January at all locations compare favorably with those from July. Thus, the functions that drive diurnal wind speed patterns, whether they be synoptic or local in scale, appear to function similarly without regard to time of year, at least in January and July. It is also obvious that average diurnal wind speed patterns are cyclic by do not follow a sine wave. Finally, the processes that cause these wind patterns may have a universal nature. Recent measurements of wind on Mars have provided data with a similar pattern (personal communication with Dr. Gregory Wilson, Arizona State University, 1997).

Discussion of Probability Distributions

Results of the probability analysis for Baton Rouge are shown in Figure 2. These results are for both 1:00 a.m. and 2:00 p.m. local time. Note that neither day nor night variations nor monthly variations caused the probability functions to fail. These relationships hold for the analyses at each of the locations. Based on the relationship between the standard deviation of the wind speed and the wind speed, we can assume that variations in the probability of a specified wind speed could be explained by a single probability function using the ratio of the specified speed to the average speed. These analyses bring the conclusion that one probability function does explain variations in the wind speed ratio.

This result is fortunate because it enables one to model wind speed variations with a relatively simple model. This model, however, should not be used to model extreme winds for design purposes since extreme winds are only a small fraction of all winds and tend to be caused by extreme weather conditions.

Figure 1: Average (checkered line) and predicted values of hourly wind speed for Bismarck, ND for January data.

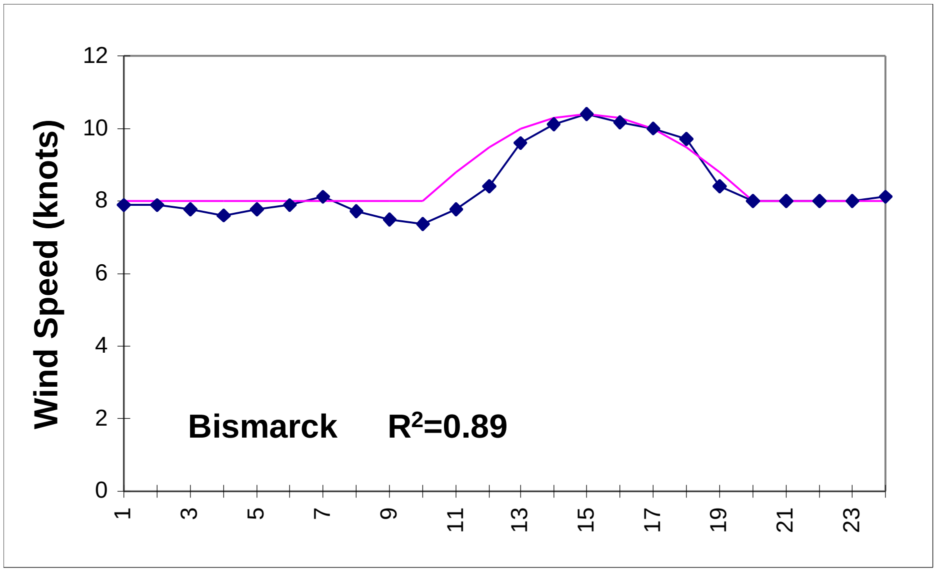


Figure 2: Average (checkered line) and predicted values of hourly wind speed for Fresno, CA for July data.

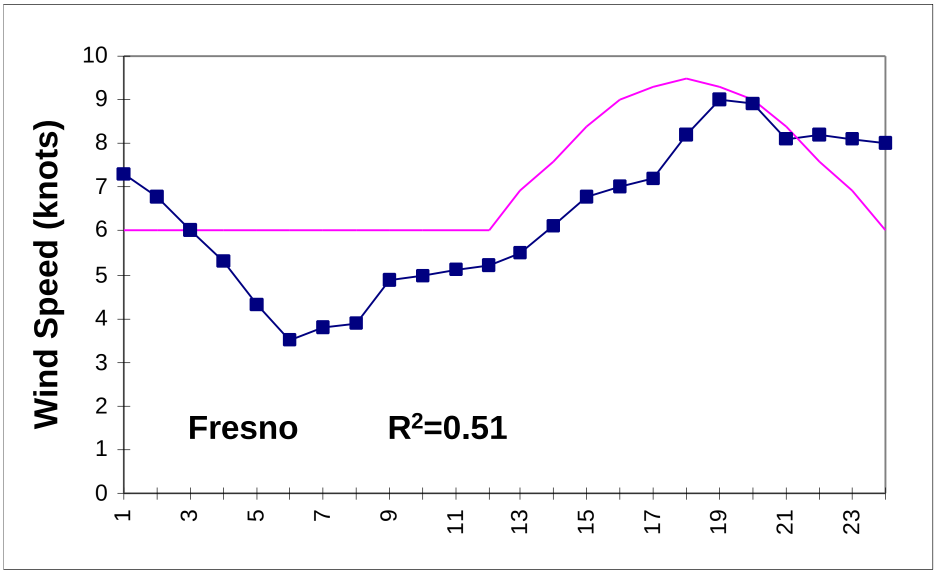
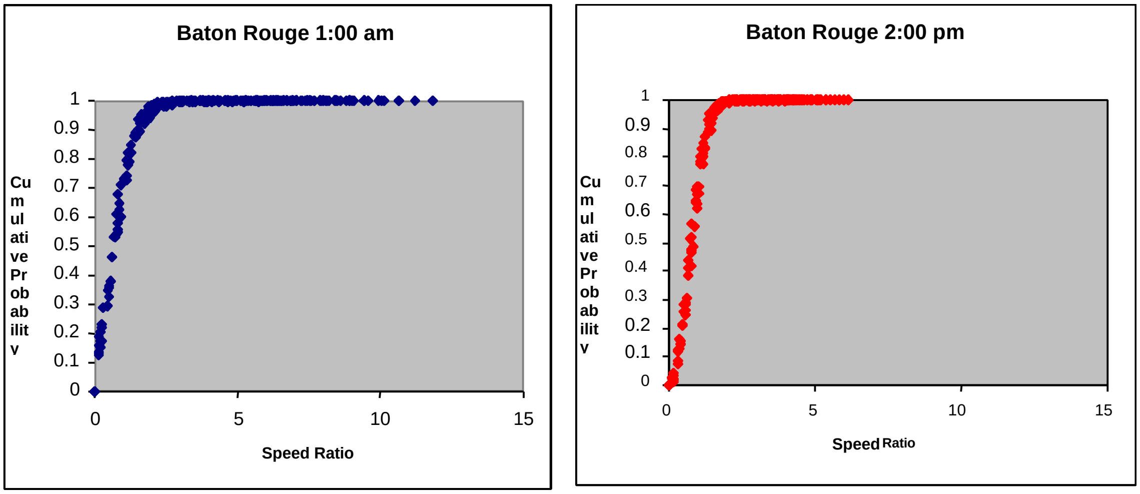


Figure 3: Cumulative probability plots for Baton Rouge.



Limitations

It is important to recognize that the data (both measured and modeled) represent long term averages (9 years, from 1982 to 1990, in all cases). Clearly, the relationships described by the equations would not hold well if we were dealing with data for a specific day. Cloud cover, synoptic conditions, frontal passage, and local effects will influence instantaneous wind speed more than long term conditions. The results do show, though, that at locations where local orographic features are not in a position to influence local climate, the model accurately predicts average wind speeds. We conclude that the simple equations used in this analysis can be adequate predictors of monthly average wind speeds in many regions of the continental United States. These equations could be used in a variety of models to simulate average wind speed. This model should prove effective in estimating wind speed for use in wind erosion, evapotranspiration, and pollution dispersion models. At locations where local geographic features affect wind speed, more specific predictive equations will need to be developed to address those concerns affected by locality.

Finally, no attempt was made at this time to relate coefficients in the equations to other variables, such as elevation, relative humidity, influence of jet stream location, etc. Values for A1, A2, A3, and A4 were successfully related to a yearly cycle by Gregory, et al. (1996) for Great Plains sites. More research is needed to develop these relationships for the whole of the United States. This research could have value in relating climate change to global temperature changes and anticipated shifts in jet stream patterns.

References

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