Revealing The Impact Of Climate Variability On The Wind Resource Using Data Mining Techniques

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1. The wind resource

Climate research tells us that large-scale climate variability can influence local conditions, from precipitation to snow cover, air temperatures and wind speeds. Teasing out these links requires careful statistical treatment of the data. Up to now, we are not aware of a technique that detects trends from wind speed and direction together.

In this study, we develop a method to identify dominant wind conditions at a site and relate those winds to larger-scale atmospheric and climate forcing. We use data from the 80-m tall M2 tower at the National Wind Technology Center (NWTC) near Boulder, Colorado, about 2 km west of the Front Range. The M2 tower has been collecting wind speed and direction measurements at 2, 5, 10, 20, 50 and 80 m above ground since late 1996. The record also includes temperature and stability data. All of this data is publically available online (*http://www.nrel.gov/midc/nwtc_m2/*).

Figure 1. *One of several pairs of turbines and meteorological towers at the NWTC. Inset: 14-year wind rose, 80 m above ground*

Prevailing winds at the NWTC are from the west through north west, over the Colorado Front Range (***Figure 1***). Less frequently, winds come from the south or north, roughly parallel to the Front Range, although these are slower than the westerly winds.

2. Grouping wind data into clusters

We find groups in hourly-average wind data as follows:

1. Convert wind speed and direction observations (***Figure 1***) into east-west and north-south wind components (***Figure 3***)
2. Remove data below turbine starting speed, 3.5 m s^{-1}
3. Classify hourly wind component data in to 2 groups using *k*-means clustering with 2 clusters (*k* = 2)
4. Score the solution using the Bayesian Information Criterion (BIC). The BIC increases as the fit to the data improves, but decreases as the number of clusters increases
5. Repeat steps 3) and 4) with more clusters (3 ≤ *k* ≤ 20) to get a range of solutions
6. Find the knee point in BIC as *k* increases, using the angle-based BIC method [ZHF08]. This is the optimum solution.
7. Assign observations to the nearest cluster

At the NWTC the optimum solution for 1997-2010 is 4 clusters. This is found independently at each height (***Figures 2 and 3***).

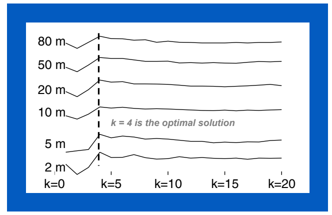

Figure 2. *Cluster quality metric, BIC at each height. The knee point at k=4 indicates the same, optimal number of clusters at each height.*

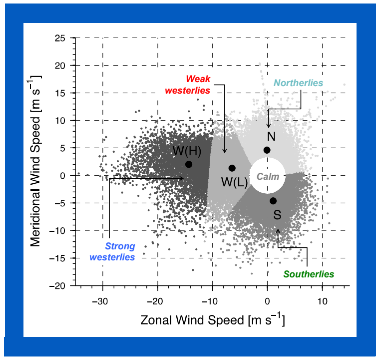

Figure 3. *The optimal wind clusters at 80 m height. Bold markers show cluster centroids.*

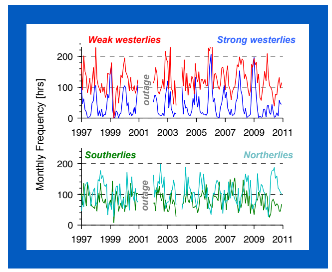

Figure 4. *Hours per month each cluster was detected at 80 m.*

Our method identifies clusters from east-west and north-south wind speeds. The groups that we found partly correspond to different stability regimes (***Figure 5***). Including stability in the clustering is possible, but would be a significant increase in computational effort. This might be beneficial for some applications, for example selecting scenarios for mesoscale modeling or computational fluid dynamics flow modeling.

The frequency of winds in each cluster follows a distinct annual pattern. Winds from the west peak during winter months, while summer months are dominated by weaker flows from the west, north and south (***Figures 4 and 6***).

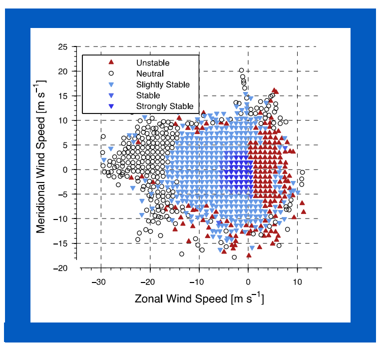

Figure 5. *Mode of stability for flows in 1 m s^{-1} by 1 m s^{-1} bins.*

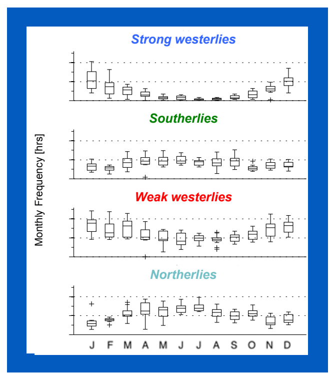

Figure 6. *The annual cycle of winds at 80 m above ground*

3. The impact of climate variability

The monthly-average wind resource at 80 m above ground at the NWTC correlates with ΔZ_{500} and the PNA, AO and Niño 3.4 climate indices (***Figure 7***). The correlation between the mean wind speed and the pressure gradient is $R^2 = 0.4$ ($p < 0.01$). The residuals are weakly correlated with the Niño 3.4 climate index.

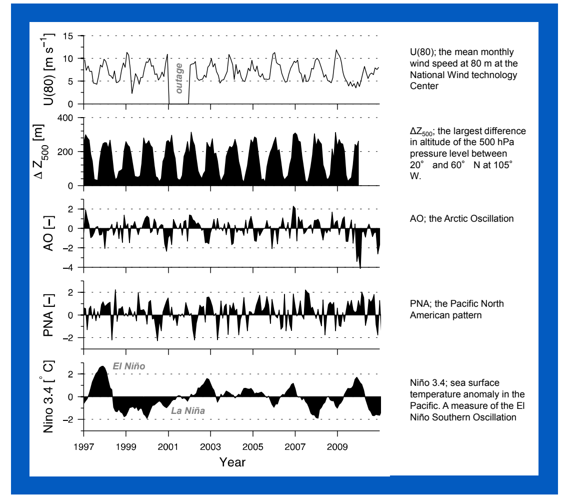

Figure 7. *Changes in monthly mean wind speed at 80 m above ground follow the pressure gradient ΔZ_{500} and several climate indices (PNA, AO, Niño 3.4).*

We compared the standardized departure of the time series of each cluster frequency (***Figure 4***) to the pressure gradient and climate indices (***Figure 7***) using multivariate linear regression. The result is a correlation coefficient and p-value for each variable and an overall R^2 (***Table 1***) so we can quantify both impact and significance of each factor on the cluster frequency.

Wind Cluster	Positive Correlations	Negative Correlations	R^2 at 80 m
Strong westerlies	ΔZ_{500}	Niño 3.4	0.45
Weak westerlies	ΔZ_{500}	PNA	0.34
Southerlies	-	ΔZ_{500}, PNA	0.15
Northerlies	-	ΔZ_{500}	0.28

Table 1. *Significant correlations (p<0.05)between wind cluster frequency anomalies and climate indices*

Anomalies in the pressure gradient are significantly correlated with each group of winds. Different climate indices are also correlated with anomalies in different flows. Apart from the local north-south pressure gradient, the Niño 3.4 and PNA climate indices are correlated with wind activity at the NWTC. This correlation with the pressure gradient and Niño 3.4 index activity is similar to observations in Minnesota [Kli07]. Our method allows us to draw a more nuanced picture than before, showing that some winds are not as heavily influenced as others by climate variability.

4. Conclusions

Long time series of wind speed and wind direction at the NWTC can be segregated into 4 distinct groups using the *k*-means clustering algorithm. The same groups (two westerly, one northerly and one southerly) emerge independently at each measurement height, and each group has a different annual cycle.

The frequency of all clusters are strongly influenced by the local north-south pressure gradient. Some of the wind phenomena show significant correlation with larger scale climate variability. For example, variation in strong westerly winds is negatively correlated with variation in the Niño 3.4 climate index. Therefore, at this site, El Niño conditions tend to reduce the frequency of the strong westerly winds.

This technique could be applied to other sites and for a range of different applications. Where a long time series is available, such as at reference sites, winds could be compared to climate indices. Alternatively, where only one year of data is available, the method could be used to help in selecting the optimal flow cases to simulate using computational fluid dynamics tools or mesoscale modeling. We also intend to develop a method to predict annualized energy production in each of these clusters, and show how energy production may be influenced by climate variability.

Acknowledgments

AO, Niño 3.4 and PNA climate index data were downloaded from the NOAA Climate Prediction Center website, http://www.cpc.ncep.noaa.gov. Pressure gradient ΔZ_{500} was derived from NCEP Reanalysis data provided by NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from http://www.esrl.noaa.gov/psd/

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