Statistical Methods for Quantifying Uncertainty in ENSO on Wind Power in the Northern Great Plains

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ABSTRACT

The El Niño Southern Oscillation (ENSO) is a well-known source of inter-annual climate variability for both precipitation and temperature in the northern Great Plains. The northern Great Plains also have the largest wind resource in the United States. With the continued growth of wind energy, ENSO's effect on wind speed needs to be examined because of our current lack of understanding about how wind speeds are affected by inter-annual variability. After having previously established that a teleconnection to ENSO exists, we set out to quantify the uncertainty in this relationship with this study. Our method uses the sign test and resampling of hourly airport wind speed measurements for the past half-century at 4 airports in both North Dakota and South Dakota. Airport data are useful in this case because they have very long and continuous measurement of hourly wind speed. With this data, we were able to show that ENSO did have an effect on wind speeds as well as on wind power. The warm phase of El Niño, in particular, was correlated with the largest reductions in wind speed in South Dakota. In North Dakota, it was the cold phase that produced the largest reduction in wind power. The largest differences occurred in April, while the smallest differences occurred in July. It is our hope that this method will also be a useful tool for wind farm developers across the country to more accurately assess the value of their site based on limited in-situ data.

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1. Introduction

There are many current stresses for residents of the Great Plains, including climate change, economic volatility, and market pressures. Climate variability is just one additional stress that is increasingly affecting Great Plains residents. The present study is motivated by a desire to better understand the impact of the El Niño-Southern Oscillation (ENSO) cycle on the climate and economics of the Great Plains.

ENSO has been shown to have significant impacts on various atmospheric parameters and phenomena throughout continental United States. Past studies have shown the association of ENSO with temperature (Ropelewski and Halpert 1986; Sittel 1994), precipitation (Ting and Wang 1997; Montroy et al. 1997, Schubert et al. 2003, and severe storms (Bove et al. 1998; Etkin et al. 2001). Climate variability has the possibility of affecting, either positively or negatively, many economic sectors in the Great Plains, including agriculture, ranching and livestock, natural systems, and water.

A new sector of economic development, wind power, is injecting a much needed economic boost while promoting sustainability in the northern Great Plains, which has the largest natural wind resource in the United States. Harvesting the wind's power to make electricity has prompted commercial utilities and individual farmers to install mid-size wind turbines. This trend is following suit with the increased worldwide use of wind turbine generators as the cost of producing energy from wind continues to decline. As the northern Great Plains continues to develop its wind industry, issues related to the site specific dependability and economics of these intermittent resources are going to become crucial to utility planning. Although modern wind turbines have long lifetimes, the site planning data used to estimate potential energy production is often based on as little as 12 months of data. A limited understanding of wind climatology could cause energy production potential to be either over- or under-estimated if local measurements were unknowingly influenced by the ENSO cycle.

Accurate wind climatology is extremely important to the wind energy industry because the power available in a gust of wind is:

$$P = 0.5 * \rho * A * V^3 \quad \text{(Gipe 2004)}$$

P = power in watts

ρ = air density (about 1.225 kg/m^3 at sea level)

A = rotor swept area, exposed to the wind (m^2)

V = wind speed in meter/sec

Therefore, the power in a free flowing stream of wind is directly related to the cube of the wind speed[1]. If wind speed measurements used for locating turbines are limited or inaccurate, the resulting power over the lifetime of the wind farm will likely differ from

1 In practice, P is roughly proportional the square of the wind speed. This is because in practice power is limited by the mechanical limitations of the turbine and the second law of thermodynamics. Each turbine also has a threshold below/above which P = 0.

the expected performance goals. There are obviously financial and grid management consequences if a site does not produce as much energy as expected, but there are also consequences if the site produces more energy then expected.

An electric utility must provide a reliable and continuous source of electricity to its customers. Due to wind energy's intermittent nature, it has been restricted to supplementing a small portion of the total U.S. energy demand. Currently, slightly more than 0.4% of total U.S. electricity generation is supplied by wind energy. Nevertheless, wind energy has lately demonstrated environmental and economic benefits as an energy resource and is growing in significance as a component of the US electric supply system. As wind energy continues to capture a larger percentage of the U.S. energy market, the forecasting and understanding of wind characteristics in time and space must also become more reliable. Without accurate wind climatology, the wind industry will not able to become as effective and competitive in the energy industry as coal, nuclear, natural gas, and other means of electricity generation.

Despite the growing importance of wind climatology, ENSO's effect on wind speed has received virtually no attention when compared to atmospheric teleconnections more closely related to crop production, such as precipitation and temperature. Enloe et al. (2004) have previously documented ENSO impacts on extreme winds over the entire United States. These authors, however, did not have sufficient data to draw any conclusions about the impacts of ENSO on the northern Great Plains. In order to help fill this void, our study last summer explored the potential role of El Niño as a source of seasonal to inter-annual variability in the winds at four sites in South Dakota (Harper 2005, SOARS® paper). Their approach, which is commonly applied in teleconnections research, involves dividing the time series of the variable of interest (e.g. wind speed) into groups based on the simultaneous value of another variable (e.g. occurrence/non-occurrence of an El Niño event). Then the median values of the groups were compared using box plots. This approach is more appropriate than ordinary correlation because we suspected the relationship between tropical SST and North American wind speeds may be non-linear. Additionally, the extremes wind speeds are of particular importance because the amount of power produced is very sensitive to high and low wind speeds. Harper found that an ENSO signal in the wind speed likely does exist because when the same procedure was used after one randomization, the difference in magnitude was smaller than observed with the grouped data. Therefore, we were convinced that further quantifying the uncertainty of ENSO effect on wind speed would prove to be productive.

We set out to discover three main things with this research. First we needed to confirm that the teleconnection between ENSO and wind speeds in South Dakota we found last year are in fact a real correlation and not simply an artifact of the data we used. Next we needed to get an idea of how much ENSO changes wind speed. Finally we needed to investigate what this change in wind speed means for power production.

The process for determining ENSO months for the period 1950 – 2000 and the wind speed data set are described in section 2 while our four stages of statistical analysis are described in section 3. Section 4 consists of our results. A discussion follows in section 5 after which the conclusions are presented in section 6.

2. Data

Hourly wind speed data were obtained from the TD6421 Enhanced Hourly Wind Station Data for the Contiguous United States dataset developed by the National Climatic Data Center. The wind speed data is taken at the original anemometer height in m sec^{-1} x 10. Our data is recorded as discrete speeds with a precision of approximately 0.5 m/s. The data represent observations from four airport anemometers located at Huron Regional Airport (44.38N, 98.22W), Pierre Municipal Airport (44.38N, 100.28W), Bismark Airport (46.81N, 100.78W), and Williston Airport (48.16, 103.63W) that can be found in Figures 1 and 2 as denoted by the four pointed stars. These sites were selected to examine wind characteristics along a range of different latitudes and longitudes in the northern Great Plains. All four of the stations have some missing data (Table 1), but are relatively complete in their record. The data from the Ellsworth Air Force Base was initially included in our analysis, but was later dropped due to step functions identified in the data that may indicate a change in the station surroundings or the physical movement of the station and non-Weibull wind distributions patterns that may indicate corrupted data. Our study was also constrained by the ENSO index data we used, which spanned the period from January 1950 – December 1999 (Trenberth 1997). Altogether 1,453,059 hours of wind speed data were analyzed.

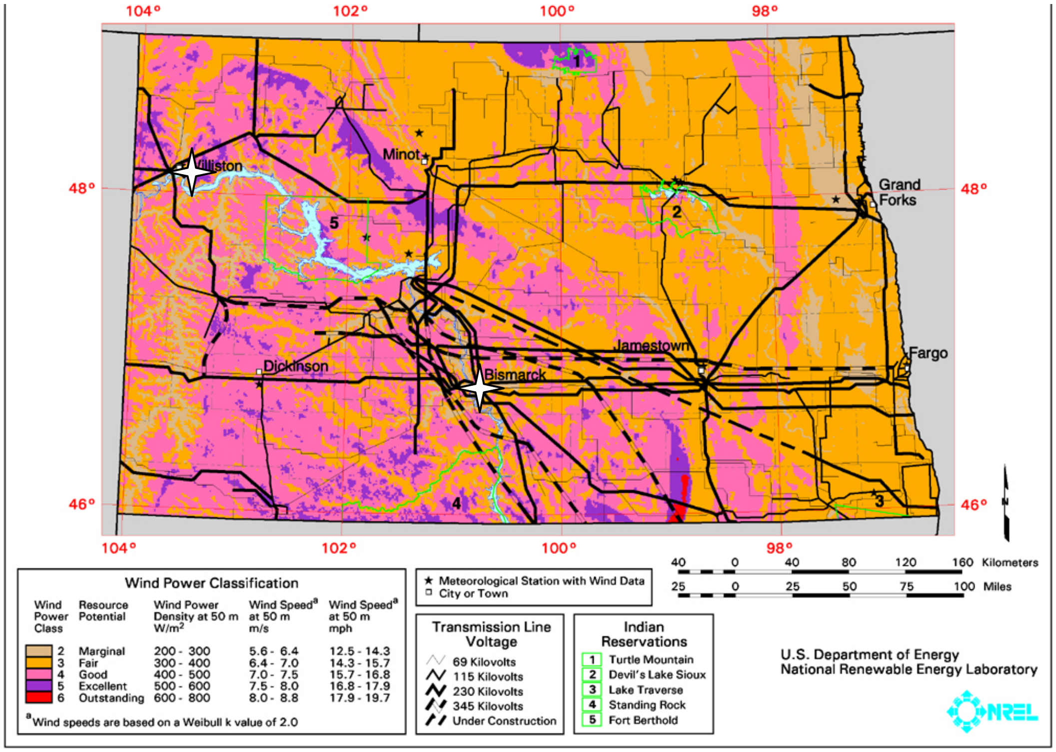

Figure 1: North Dakota - Wind Resource Map. Note the locations of Bismarck in the South central and Williston in the North West part of the state. Map generated by the U.S. Department of Energy National Renewable Energy Laboratory.

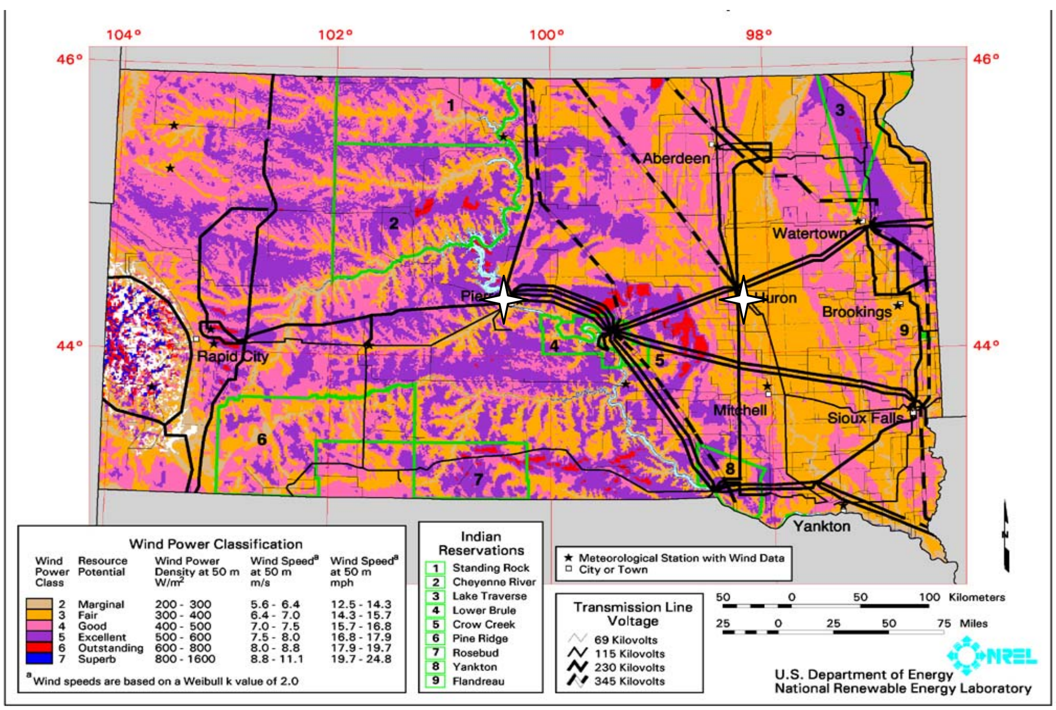

Figure 2: South Dakota - Wind Resource Map. Note the locations of Huron in the East central and Pierre in the central part of the state. Map generated by U.S. Department of Energy National Renewable Energy Laboratory.

Table 1.

Station Location	Completeness	Dates Used
Bismarck Airport	89.3%	1 January 1950 – 31 December 1999
Huron RA	89.0%	1 January 1950 – 31 December 1999
Pierre MA	89.0%	1 January 1950 – 31 December 1999
Williston Airport	84.5%	1 January 1962 – 31 December 1999

The classification of ENSO events followed in the present study is defined by the National Oceanic and Atmospheric Administration's (NOAA) Multivariate ENSO Index (MEI). The MEI Sea Surface Temperature (SST) index defines phases of ENSO based on the main observed variables over the tropical Pacific. These surface marine observations have been collected and published in the Comprehensive Ocean-Atmosphere Data Set (COADS) for many years. The MEI can be understood as a weighted average of the main ENSO features contained in the following six variables: sea-level pressure, the east-west and north-south components of the surface wind, SST, surface air temperature, and total amount of cloudiness. Extremes in ENSO typically develop during summer, climax in the fall, and subside the following spring. The periods of ENSO events used in this study are summarized in Table 2.

Table 2
Listings of El Niño and La Niña events after 1950 as defined by SST's in the Nino 3.4 region and exceeding $\pm 0.4^0$C threshold. The starting and ending month of each is given with the duration in months.

El Niño events			La Niña events		
Begin	End	Duration	Begin	End	Duration
Aug-51	Feb-52	7	Mar-50	Feb-51	12
Mar-53	Nov-53	9	Jun-54	Mar-56	22
Apr-57	Jan-58	15	May-56	Nov-56	7
Jun-63	Feb-64	9	May-64	Jan-65	9
May-65	Jun-66	14	Jul-70	Jan-72	19
Sep-68	Mar70	19	Jun-73	Jun-74	13
Apr-72	Mar-73	12	Sep-74	Apr-76	20
Aug-76	Mar-77	8	Sep-84	Jun-85	10
Jul-77	Jan-78	7	May-88	Jun-89	14
Oct-79	Apr-80	7	Sep-95	Mar-96	7
Apr-82	Jul-83	16	Jul-98	Dec-99	18
Aug-86	Feb-88	19			
Mar-91	Jul-92	17			
Feb-93	Sep-93	8			
Jun-94	Mar-95	10			
Apr-97	Apr-98	13			

3. Methodology

The main tool used to analyze the data set was the R Project for Statistical Computing. R is a language and environment for statistical computing and graphics. It is a GNU project, which is similar to the S language and environment, which was developed at Bell Laboratories by John Chambers and colleagues. R can be considered as a different implementation of commercially available S language. There are some important differences, but much code written for S runs unaltered under R. See www.r-project.org for more information.

Each month of wind speed data has been assigned one of three ENSO phases: cold (La Niña), neutral, or warm (El Niño) that correspond to the simultaneous ENSO phases in the tropical Pacific based on NOAA's MEI. Separating the data by ENSO phase we were able compute differences between the cold/warm phase and the neutral phase. The three power characteristic differences we computed were 1) mean wind speed 2) mean probability of a low wind event and 3) mean wind power production.

In order to assess the importance of our findings to the wind energy industry, we converted our results from wind speed to power using a power curve for a typical utility scale turbine. Utility scale turbines have a hub height of around 80 m and therefore typically experience higher wind speeds than those at the height where weather data are recorded. An approach commonly used to extrapolate 10 m wind speed data to 80 m is the power-law relation [available at http://rredc.nrel.gov/wind/pubs/atlas],

$$V(z) = V_R \left(\frac{z}{z_R}\right)^{\alpha} \qquad (2)$$

where V(z) is wind speed at elevation z above the topographical surface (80 m in this case, i.e. V(80)), V_R is wind speed at the reference elevation z_R (10 m above the topographical surface in the rest of this paper), and α (typically 1/7) is the friction coefficient (Archer and Jacobson 2003). Although the amount of energy in the wind is related to the cube of the wind's speed, the actual amount of energy that can be extracted is bounded by the mechanical limitations of a real wind turbine. This non-linear relationship is different, yet similar, for almost all modern wind turbines. All wind turbines have a range of wind speeds for which they extract power from the wind, but above and below which no power is produced (Figure 3). For this study a low wind event is considered any wind speed below 4 m/s.

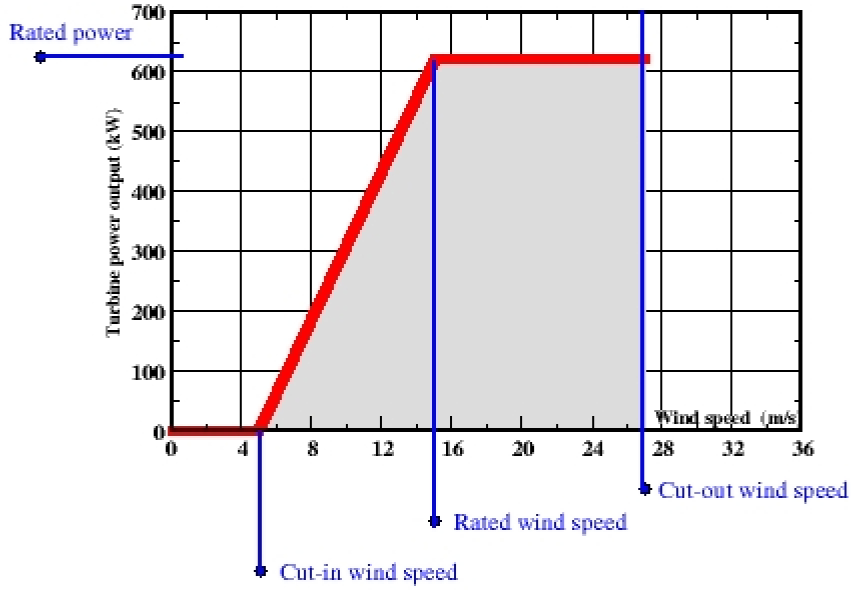

Figure 3: Idealized power curve for a wind turbine (example). From the Canadian Wind Energy Atlas.

Once the wind speed was corrected we used a power curve for a typical utility scale turbine to calculate the power produced from the 80 m wind speed. This is because of the earlier mentioned non-linearity of wind power production. In this study we used a power curve for the NORDEX N60 1.3-MW turbine approximated by a 4th order polynomial:

$$P = 0.0649s^4 - 3.8773s^3 + 74.418s^2 - 429.14s + 785.06 \qquad (3)$$

where P is the power in kW and s is the speed of the wind between 4 m s^{-1} and 26 m s^{-1} because most utility scale turbines only produce power within this range.

We then tested the significance of these power characteristics using statistical analysis. Our statistical analysis involved four analysis stages 1) global test of significance 2) local test of significance 3) confidence interval for effect size, and 4) distributional analysis.

a. Global test of Significance

The global test of significance is a global test designed to detect a significant ENSO effect. It is considered global because it treats all months simultaneously. The global test utilizes the sign of the result rather than the numeric value and is often referred to as the "sign test" (Hollander and Wolfe 1998). The sign test indicates whether there is an ENSO effect in one or more months, but does not necessarily identify which specific months. This was performed by separating the wind speed data into three categories (cold, neutral, and warm phases) mentioned before. We then plotted the monthly mean statistic of interest for all of the months on a single plot that gave us an annual trend for each phase of ENSO. Simply by examining how many times the difference changes sign, the test tells us whether there is a significant difference. This is because a plot of any monthly mean statistic is similar to flipping a fair coin 12 times. The outcome of flipping a coin can be represented by a binomial distribution. There is a .00024 chance that this event will result in 12 heads. Likewise there is a .00024 chance that all tails will result. Combined, there is a .00049 chance that one would always get the same result back, either all heads or all tails. This is the same as having all cold phase monthly mean statistics result in higher values than all the neutral phase monthly mean statistics or vice versa. In other words, if the cold phase line is always above the neutral phase line the difference has zero negative occurrences or 12 positive occurrences. It is less significant if one or more of the cold phase differences is negative. The probability of 0 – 3 points breaking with this pattern is given in Table 3.

Table 3

Occurrence	Probability	Significance
0 or 12	.00049	Significant at 1% level
1 or 11	.0063	Significant at 1 % level
2 or 10	.039	Significant at 5% level
3 or 9	.15	Not significant at 10% level

b. Local test of Significance

In contrast to the global test, the local test of significance attempts to detect an ENSO effect in a single month. It is necessarily less powerful than the global test, because it makes use of wind specific months rather than all of the data. The local test randomizes the data and then draws from that random set without replacement. In other words the data is simply permuted, or re-ordered, because there are no repeated values. Permutation techniques are not particularly concerned about populations and/or their parameters. Permutation procedures focus on the underlying mechanism that led to the data being distributed between groups in the way that they are (Efron and Tibshirani, 1993). Therefore, in order to confirm that the teleconnection between ENSO and wind speeds in the northern Great Plains that we found is in fact real for any particular month, we used the permutation approach. By randomly choosing new ENSO values for a particular month of each year we computed the same statistics of interest. This approach avoids autocorrelation because consecutive months are only minimally dependent on the previous months. By performing this permutation again and again we can increase our confidence as to whether the original data produced a unique result. We performed the permutation test 10,000 times for a particular month and then determined the level at which 95% of these results occurred. After comparing this to our original statistic of interest we could say with 95% confidence that our result could or could not have occurred randomly.

c. Confidence Interval for effect size

The confidence interval for effect size uses the bootstrap technique to attach uncertainty to a statistic once it is computed. Bootstrapping is primarily focused on estimating population parameters, and it attempts to draw inferences about the population from which the data came (Efron and Tibshirani, 1993). We used the bootstrap to calculate a confidence interval that is useful whether or not the ENSO effect is statistically significant. Consider, for example, two groups of wind speed data that have been assigned as occurring either during an anomalous event or a normal event. The bootstrap approach would focus primarily on estimating data differences between the two conditions, and would result in a confidence interval on the mean difference in estimated wind speed between an anomalous and normal event. Our approach first created two populations, the first consisting of all the warm phase mean monthly statistics and the second consisting of all the neutral phase mean monthly statistics. We then drew (with replacement) a sample of equal length for the new "warm" and "neutral" sets. Each of these is called a bootstrap sample and is different from a permutation mainly because we sampled with replacement and therefore could get repeated values. We repeat this process 10,000 times as before, and obtain 10,000 bootstrap samples. These 10,000 samples contain information that we used to put confidence intervals on the statistics we computed. By computing the 97.5 percentile of the statistic from the 10,000 bootstrap samples we can infer a 95% confidence interval on the original statistic. In other words we are 95% confident that the actual difference lies with the provided confidence interval.

d. Distributional Analysis

The distributional analysis utilizes a fitted Weibull wind speed distribution that closely models most wind regimes (Dodson 2006). It is used for purely descriptive purposes, aiding in comparing the ENSO effects in terms of lulls, mean wind speed, or mean wind power. This approach has the advantage of examining the effect of ENSO on the entire distribution of wind speed simultaneously, rather than focusing on a single wind statistic at a time as in the previous three stages. The Weibull distribution has two parameters of interest: the shape and scale. For wind speeds the shape parameter usually ranges between 1 (and exponential distribution) and 3 (a nearly normal distribution) because wind speed are usually skewed toward the low values. When two distributions are compared the one with a lower shape parameter indicates that low wind speed occur more frequently provided the two distributions have the same scale parameter. The scale parameter has no effect on the shape of the distribution, but does have an effect on the mean and variance of the distribution.

4. Results

For the four sites analyzed during this study, the largest variations in wind speed occurred in annual and diurnal cycles. The most reliable high winds normally occur in April, whereas average wind speeds are the lowest in July. This accounts for the overall peak and valley pattern seen in the plots of mean wind speed (Figure 4). The strongest daily winds typically peak during the warmest part of the day (1 pm – 3 pm), while the weakest winds are characteristically consistent during the coldest part of the day (8 pm – 7 am). These cycles are the dominant sources of variability in wind speeds.

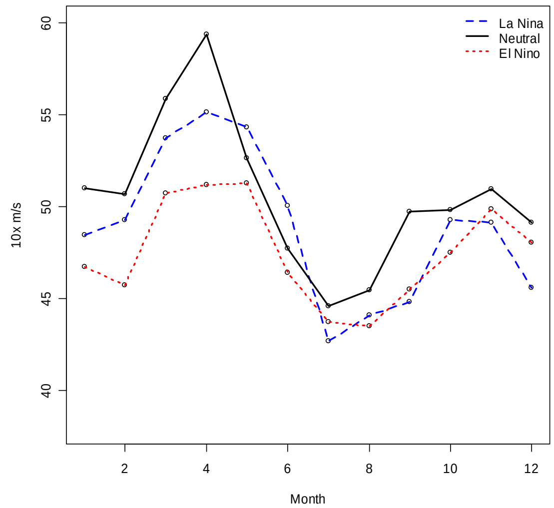

Figure 4: Mean wind speed at Huron. Note the numbers on the x-axis correspond to the months of the year. For example 2 = February, 4 = April, etc.

a. Huron

The sign test of monthly mean wind speeds suggests that a relationship with ENSO does exist. Figure 4 shows that for all twelve months the monthly mean wind speed during the warm phase was lower than during the neutral phase. Additionally, Figure 4 shows that for all months except May and June the monthly mean wind speed during the cold phase is also lower than during the neutral phase. The difference in April monthly mean wind speeds between the neutral and warm phase is 0.84 $\pm$ 0.38 m/s while the permutation analysis showed that 95% of the time this difference would be less than 0.54 m/s. The difference in July monthly mean wind speeds between the neutral and warm phase is 0.07 $\pm$ 0.24 m/s, while the permutation analysis showed that 95% of the time this difference would be less than 0.27 m/s.

Table 1: Mean wind speed difference between warm and neutral phase (Neutral – Warm)

Month	Mean wind speed (m/s)	95% confidence interval (m/s)	95% significance level (m/s)	Significant
April	0.84	0.46 – 1.3	0.54	Yes
July	0.07	-0.33 – 0.31	0.27	No

The observed statistical differences associated with mean wind speed translate to mean wind power as well as can be seen in Figure 5. Less mean wind power was produced during each month of the warm phase although this relationship was not only true for the cold phase. The difference between neutral and warm mean wind power April was less than 41 kW 95% of the time while the actual difference in April mean wind power was 67 $\pm$ 26 kW. The same difference in July mean wind was less than 22 kW 95% of the time while the actual difference in July mean wind power was 17 $\pm$ 22 kW, though.

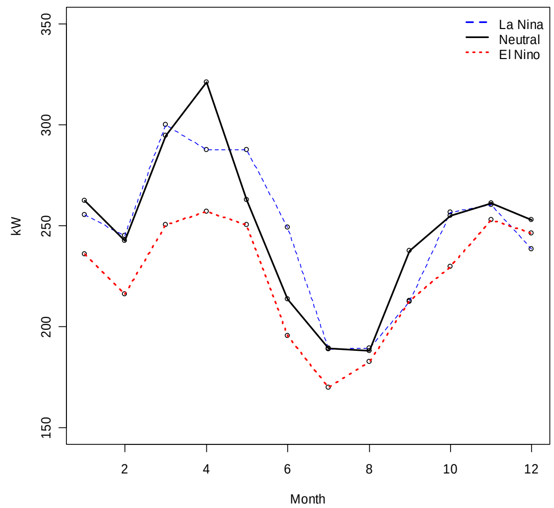

Figure 5: Mean wind power at Huron.

Table 2: Mean wind power difference between warm and neutral phase (neutral – warm)

Month	Mean wind power (kW)	95% confidence interval (kW)	95% significance level (kW)	# of iterations
April	67	41 - 93	41	10,000
July	17	-3.9 – 40	22	10,000

The observed patterns in low wind events associated with ENSO are very similar in magnitude, though inverted, to the pattern observed for mean wind speed. Once more the warm phase has a higher probability of a low wind event than the neutral phase for every month of the year, while the cold phase has the same pattern for all months except May and June as shown in Figure 6. The difference in April monthly probabilities of a low wind event between the neutral and warm phase is 9.4 $\pm$ 6.5%, while the permutation analysis illustrates that 95% of the time this difference would be less than 6.4%. But the difference in July monthly probabilities of a low wind event are between the same neutral and warm phases is 3.6 $\pm$ 6.1%, while the permutation analysis gives us an idea that 95% of the time this difference would be less than 5.2%. Additionally, the same analysis for February and September yielded differences of 9.7 $\pm$ 4.5% and 7.5 $\pm$ 5.7%, respectively.

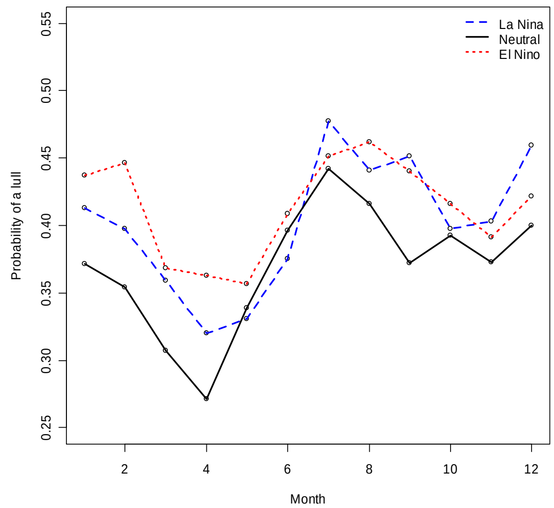

Figure 6: Low wind events at Huron.

Table 3: Probability of a low wind event difference between warm and neutral phase (neutral – warm)

Month	Probability of a lull (%)	95% confidence interval (%)	95% significance level	Significant
February	9.7	5.2 – 15	-	Yes
April	9.4	2.9 – 16	6.4	Yes
July	3.6	-2.6 – 9.7	5.4	No
September	7.5	1.8 – 13	5.4	Yes

Because we found significant results during the month of April, we also produced a Weibull curve that summarizes the monthly distribution of wind speeds. This distribution is consistent with the previous results. While the long tail is very similar for each phase, the low winds speeds differ markedly. Since a wind turbine can normally only produce power above a threshold of 4 m/s, Figure 7 explains why the neutral phase conditions produces the most power while the warm phase conditions have the highest probability of a low wind event. During a warm phase the scale parameter of the Weibull distribution tends to be smaller for the warm phase than the neutral phase and as a result the distribution is shifted toward the lower wind speeds.

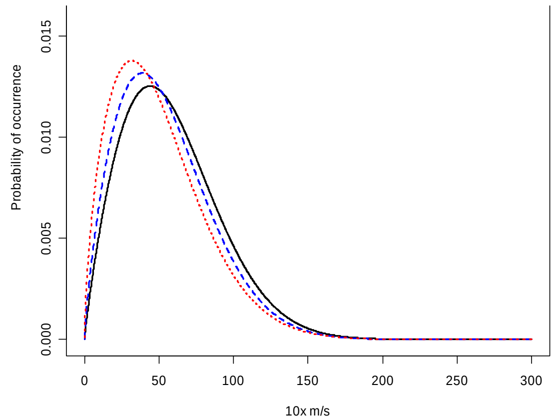

Figure 7: A fitted Weibull distribution for the month of April at Huron.

b. Other Stations

The ENSO effect at Pierre was more difficult to identify, but the results are similar to those found at Huron. The warm phase showed a statistical decrease for both the mean wind speed as well as mean power output (Figure 8). We were not able to identify the warm phases' effect on low wind events.

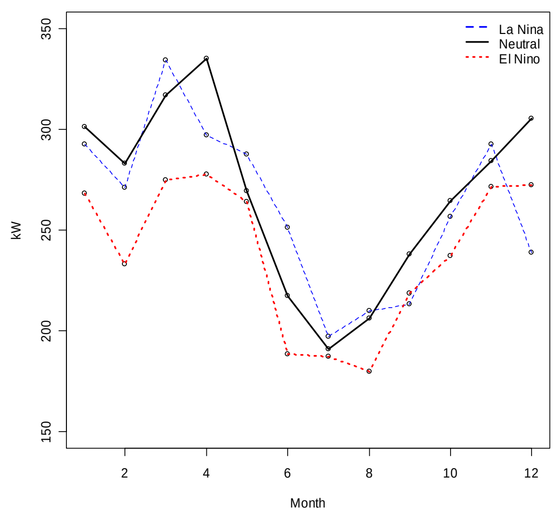

Figure 8: Mean wind power at Pierre.

We were unable to identify any statistically significant ENSO effect at Bismarck. The ENSO effect at Williston was only significant during the cold phase as shown in Figure 9. Here we saw a decrease in wind power production during La Niña conditions. We did not find the same result for either mean wind speed or low wind events.

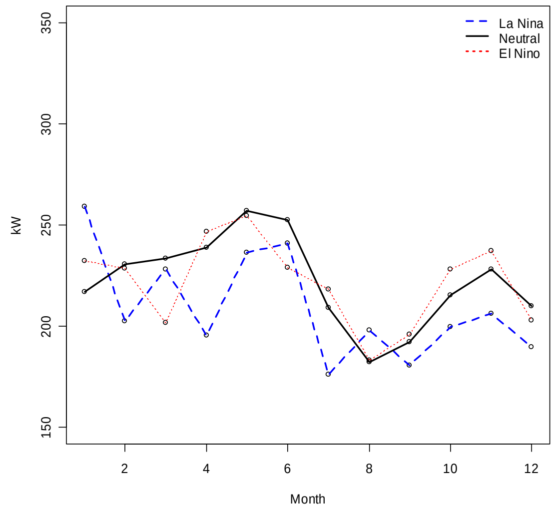

Figure 9: Mean wind power at Williston.

5. Discussion

The annual and diurnal wind cycles on the Northern Great Plains are well known to the wind industry. ENSO's effect, however, does have some discernable signals that should be considered in wind power planning. Although ENSO's effect on wind speed is smaller in magnitude, it remains an important consideration because of the exponential relationship between wind speed and power. This means that the potential power is very sensitive to wind speeds. The South Dakota stations appear to exhibit a more consistent signal and a markedly different pattern than the stations in North Dakota. For this reason we will consider them separately.

In South Dakota the warm phase has the strongest signal and tends to reduce mean wind speeds and mean wind power while also increasing the probability of a low wind event. At both Huron and Pierre we can say that we are more than 99.9% sure that the wind power production, which is the main statistic of interest for wind energy producers, is reduced during the warm phase. This decrease tends to be most significant for the months of January though April and again for September and October. In the month of April in particular the wind speeds are very likely to be below average during a warm phase. If this ENSO effect in not taken into account a wind farm could overestimate its production by as much as 72 kW per MW of capacity. This represents an error of 7.2%. The decrease in wind power generation tends to be smallest, and possibly even reversed, for the months of May though July. This results in similar Weibull scale parameters and warm phase distributions that are comparable to the neutral phase. The cold phase also exhibits a parallel pattern to that of the warm phase although it is harder to identify this effect statistically. At Huron station in particular we are more than 95% sure that the cold phase reduces mean wind speed and increases the probability of a low wind event. This decrease was most significant during the months of January, September, and December at both stations. As with the warm phase, the lower Weibull scale parameter during the cold phase indicate that the distribution is shifted toward the low wind speeds during these 3 months relative to the same months during the neutral phase (Figure 9).

In North Dakota the ENSO signal is different than the signal further south and much harder to detect. The strongest ENSO signal is present in the mean wind power statistic at Williston station. Here we are 95% sure the cold phase reduces the mean wind power relative to the neutral phase. This effect is most significant during the months of April, September, and December as we saw in South Dakota.

The difference in results between North and South Dakota suggests that latitude plays a more critical role whether the cold or warm phase reduces wind speeds. We hypothesize that this may the result of changes in latitude of the jet stream and storm tracks across the northern Great Plains. While physical mechanisms that connect wind speeds in the northern Great Plains to ENSO may be related to a storms direction and/or frequency; this connection must await further analysis.

6. Conclusion

The wind power resource in the northern Great Plains was variable at inter-annual time scales, in part at least, due to forcing associated with ENSO conditions. Shifts in the distribution of wind speed were identified in association with the El Niño and La Niña phases of ENSO. Monthly mean wind power production was found to generally decrease during the El Niño phase. Other systematic characteristics in the long-term climatology of the wind resource that are relevant to power system planning and operations were also found. Significant shifts occurred in the mean wind speed and probability of a low wind event in South Dakota. El Nino noticeably decreased both the mean wind speed and increased the probability of a low wind event while the connection with La Nina was harder to identify.

Accurate wind speed measurements are critical in order for this method to identify a teleconnection with ENSO. In addition to the importance of accurate wind speed measurements, it is also useful to consider that the ENSO index is a continuum rather than a discrete 3 phase index. This sometimes causes El Niño phases of different intensity to behave very differently from each other (Philander 2004).

7. References

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