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The Long-Term Wind Resource

Part 2 - Comparing Data Sources and Techniques for Predicting the Performance of Wind Plants

By Dennis A. Moon, Ph.D.

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By Dennis A. Moon & Scott E. Haynes

Introduction

Understanding the long-term wind resource is critical to developing and operating wind power plants. A growing body of work has shown the need for long-term reference wind data covering a span of 30 years or more. Due to natural climatic variability on the decadal or longer scale, shorter time spans may provide misleading results when characterizing long-term mean wind speeds and understanding wind variability at a site.

To understand the value of wind resource assessment over long time scales, WindLogics has been doing extensive research to compare different sources of long-term data, studying their correlation with multi-year tall tower data and analyzing the errors associated with wind resource estimates based on different sources and correlation techniques. A theme that has emerged from this work is that regardless of the type of reference dataset or the methods used to extend the data to reflect long-term trends at the site, it is the *predictive ability* of the data and methods used that matters most. In other words, statistics that characterize the correlation between the site and reference datasets are not sufficient for evaluating the relationship between the site and reference datasets – the underlying distributions (time-series, histograms, wind roses, etc.) *must* be examined as well.

Last month, we described the various sources of long-term data in detail. In this article, we show the results of using various data sets and methods. A summary of these results is discussed below, and a more detailed technical paper is available from the authors.

Analyzing Long-term Reference Datasets

The following analyses serve as a deeper investigation into the sources of error associated with long-term normalization. There are several topics that we must consider to reach a logical conclusion. For example, in looking at the Reanalysis data (or indeed, any data set), it is natural to consider the correlation of the data versus other reanalysis and observational datasets. But the true test is to look at the quality of the long-term wind estimates that can be obtained by various combinations of data and methods. To that end, four sources of long-term reference data were used to generate proxy time-series for comparison with actual observed conditions at a wide range of sites. The methods used to generate the proxy time series included linear regression and multi-variable non-linear support vector regression.

Testing Alternative Approaches with Public Towers

Thirty publicly available "tall-tower" sites, each with between three and seventeen years of wind speed data, were used to test various reference sources and methods. The process was designed to objectively compare the predictive ability of various reference data sources including the NCAR/NCEP Global Reanalysis (RNL) and North American Reanalysis (NARR) datasets, Global Surface Observations (referred to as METAR observations) and the Integrated Global Radiosonde Archive (IGRA). Many additional details about these towers and tests are available in the complete technical report.

In part I, we discussed the degree of correlation between the tower data and the various sources of long-term reference data. What really matters, of course, is predictive ability rather than correlation. While tests of correlation between the tall tower data and a reference source is interesting in a general sense, it is more important to characterize the errors that result from using the different sources in the downscaling process. In other words, if we use each source with appropriate methods to estimate the multi-year onsite conditions, how well does it do?

The analysis was performed by using a year of data for training and then applying that training relationship to predict the other years from the source dataset. For example, if we had data from 2000-2005 at a site, we would first use the data from 2000 to establish the relationship, and then apply that relationship to estimate 2001, 2002, 2003, 2004 and 2005, and characterize the resulting errors. We would then repeat this process, but using 2001 as the training year, then 2002, etc. In all cases, the training year itself was not considered in the characterization of the error.

The predicted time series was compared against the measured tower data in terms of monthly average speed. Given the number of sites and number of years at each site, the total sample size (number of estimated monthly mean values excluding the training year) for each technique was more than 3,300 site-months.

Many combinations of reference data and techniques were tested. In each case, the approach was used to predict the long-term time span and this prediction was compared against the actual tower measurements.

- **Global Reanalysis (RNL) using linear fit** - Tower wind speed measurements for the training year were matched up against RNL wind speed from the most highly correlated of the surrounding grid points, and an unconstrained linear fit was formed (y= mx + b). This fit was then used to estimate tower winds (on an every six hour basis) for the other years in the multi-year time span.
- **North American Regional Reanalysis (NARR) using linear fit** - Tower wind speed measurements for the training year were matched up against NARR wind speed from a nearby grid point and an unconstrained linear fit was formed. This fit was then used to estimate the tower winds (on an every three hour basis) for the other years in the multi-year time span. Given the high spatial resolution of the NARR grid, the four surrounding grid points are all quite close to the tower location, so the lower left grid point was selected for simplicity.
- **METAR surface data using linear fit** - Tower wind speed measurements for the training year were used to calculate a daily mean wind speed that was matched up against the daily mean wind speed from the most highly correlated of the nearby METAR stations, and an unconstrained linear fit was formed. This fit was then used to estimate the daily tower winds for the other years of the multi-year time span.
- **IGRA radiosonde data using linear fit** - The IGRA winds were linearly interpolated to a height of 750 m above ground level, tower wind speed measurements for the training year were matched up against the wind speed from the most highly correlated of the neighboring radiosonde stations, and an unconstrained linear fit was formed. This fit was then used to estimate the tower winds (on an every twelve hour basis) for the other years in the multi-year time span.
- **Global Reanalysis using Support Vector Machine (SVM) regression** - Tower wind speed measurements for the training year were matched up against the RNL meteorological conditions from the surrounding RNL grid cells. In most cases, RNL data were extracted from the four surrounding grid cells. In cases where the tower did not fall near the center of this area, groups of six or nine grid cells were used to surround the tower location. Multiple values of wind speed, direction and other weather variables were used to train with Support Vector Machine regression; a multivariate, non-linear pattern detection procedure. Once trained, SVM regression was used to estimate the tower winds (on an every six hour basis) for the other years of the multi-year time span.
- **North American Regional Reanalysis using SVM regression** - Tower wind speed measurements for the training year were matched up against the NARR meteorological conditions from the surrounding NARR grid cells. In most cases, NARR data were extracted from the four surrounding grid cells. If the tower did not fall near the center of this area, a group of six grid cells was used to surround the tower location. Multiple values of wind speed, direction and other weather variables were used to train with Support Vector Machine regression. Once trained, SVM regression was used to estimate the tower winds (on an every three hour basis) for the other years of the multi-year time span.

The error histograms for all of the techniques are shown in Figure 1. The errors are based on comparing the estimated monthly average speed to the tower-measured monthly average speed.

All the techniques do a good job at minimizing overall bias, as measured by the mean error (“ME” in the figure). However, there are considerable differences in their ability to match the monthly wind speeds, as measured by the RMS error:

- NARR and RNL-based SVM regression approaches show the smallest and tightest distribution of errors, with 0.45 and 0.47 m/s RMS error respectively.
- The RNL linear regression has a RMS error of 0.59 m/s, while NARR linear regression has a RMS error of 0.64 m/s. It is a bit surprising that the NARR did not perform better than the RNL with the linear method given the higher spatial resolution of the NARR dataset, but both datasets provided significantly improved results with the SVM regression method.
- METAR linear regression produced RMS error of 0.65 m/s. The METAR results indicate a roughly 40% increase in RMS errors over the SVM regression.
- IGRA radiosonde linear regression produced RMS error of 0.87 m/s. The error distribution for the radiosonde-based linear regression is noticeably broader than that for the other techniques, with an RMS error roughly 85% larger than that for the SVM-based results.

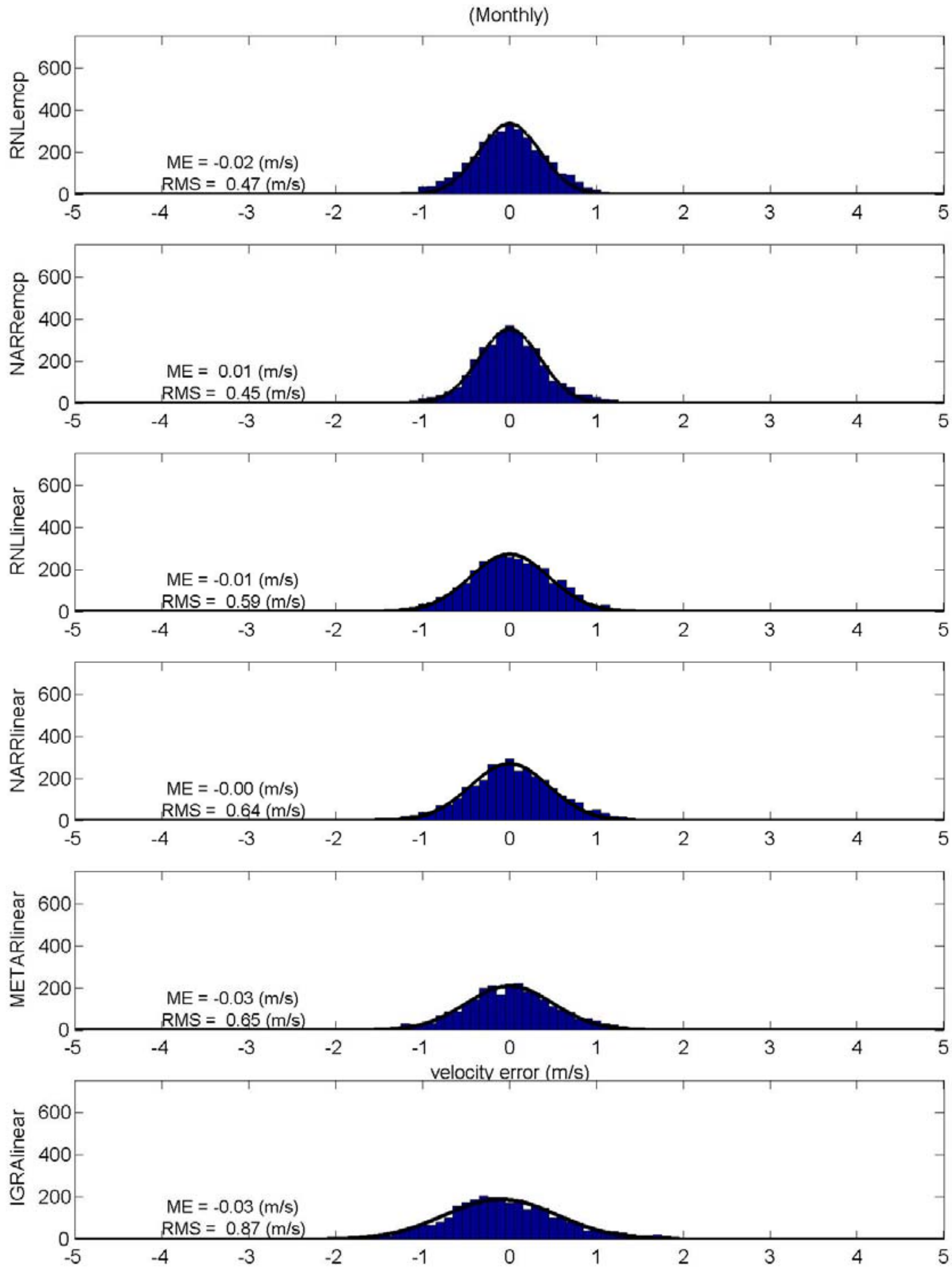

Figure 1. Monthly speed estimate error histograms for various reference sources and methods. NARR and RNL SVM based regression correspond to the top two panels labeled "RNLemcp" and "NARRemcp" respectively.

Testing SVM Regression for Real Wind Energy Sites

WindLogics has extensive experience using RNL-based SVM regression for wind energy customers as part of its patent-pending *Enhanced Measure-Correlate-Predict* (E-MCP) product family. An E-MCP report involves application of the SVM regression technique using customer-supplied met tower data (typically 50 to 60 m) as the training data. The number of months of met tower data used in an E-MCP project typically ranges between 7 and 40 months.

Using customer data from twenty-three wind projects locations throughout North America, we did a detailed comparison between RNL-based SVM regression and RNL-based linear regression methods. Many of these E-MCP studies involve challenging sites in the western US with significant mesoscale flow components.

The SVM process involves a monthly round-robin training procedure, in which data for a given month are withheld from the training dataset used to estimate the conditions for that month. For comparison, an unconstrained linear fit of all the speed data is also performed using the best-correlated RNL grid point and used to estimate the time series for each month. For both the E-MCP and linear MCP, the coefficient of determination (R^2) is calculated based on matching up the estimated monthly-average speeds with those measured at the tall tower.

Figure 2 summarizes the results all twenty-three E-MCP studies. The average R^2 value when using linear regression is 0.44. This low value is primarily a reflection of the degree to which local speed variability is not directly accounted for in the RNL data due to mesoscale effects in complex terrain. By using the SVM regression technique to relate the onsite conditions to patterns in the regional RNL data, the ability to estimate the tower conditions is greatly improved and the average R^2 value is 0.83.

Even for sites where the linear-based R^2 is essentially zero, the SVM-based R^2 is in the 0.7 – 0.8 range. In other words, appropriate application of the SVM regression method works very well even at locations where linear regression cannot find *any* correlation.

These results point out the danger of looking at a single point from long-term data. Such an approach can lead to very misleading conclusions. The use of regional and three-dimensional data with multivariate, non-linear pattern detection methods proves to be a much more powerful approach.

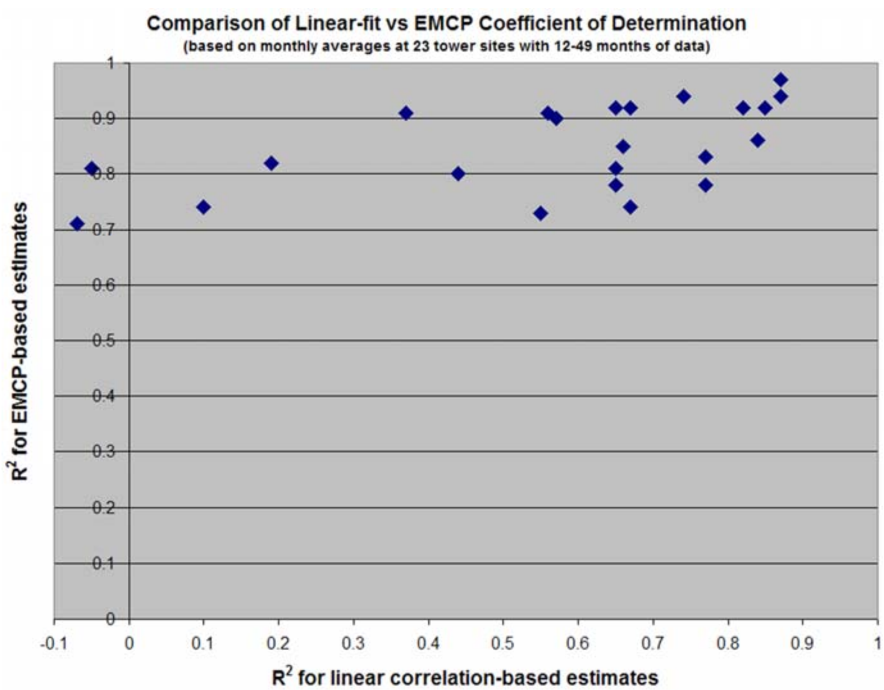

Figure 2. Summary of R^2 for E-MCP studies.

But what does this mean for wind energy production? Using the measured and estimated wind speed data from the twenty-three sites, we used a turbine power curve to calculate the monthly-accumulated energy. Figure 3 shows the Mean Absolute Error (MAE) for monthly energy at each site from the linear and E-MCP methods.

For several of the sites with weaker correlation, the linear monthly energy errors are in the 20-25% range while the E-MCP-based energy errors never exceed 10%. The average MAE is 13.5% for the linear technique and 7.1% for the E-MCP method, an improvement of almost a factor of two.

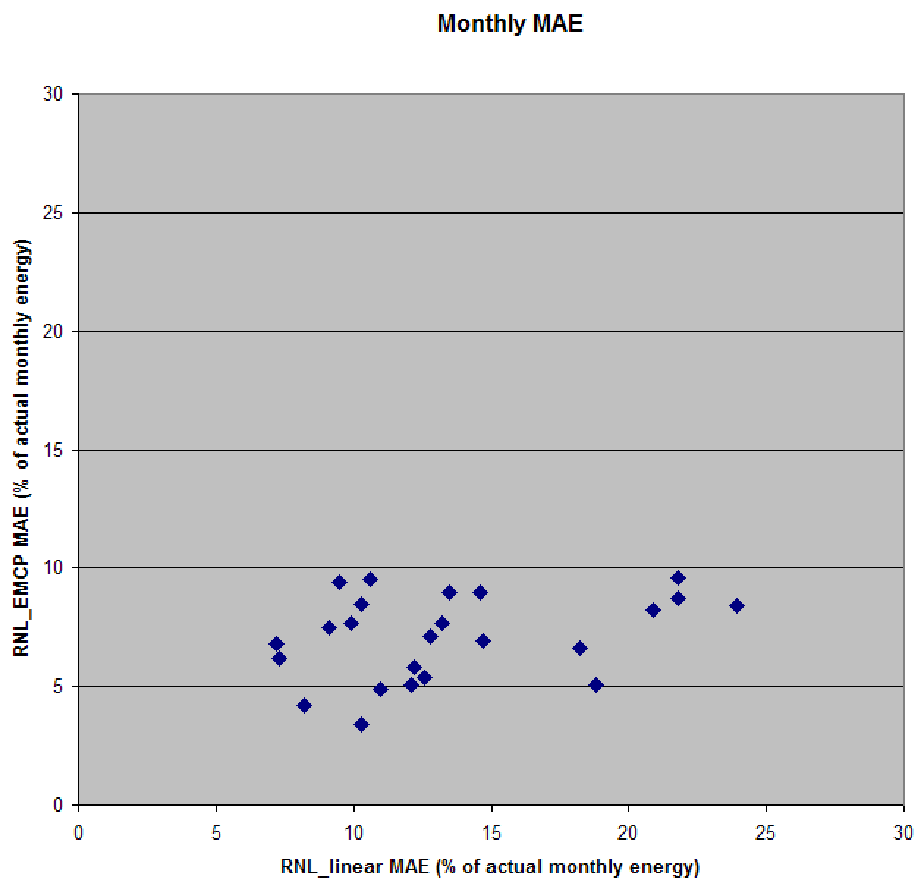

Figure 3. Summary of monthly energy estimation errors for E-MCP sites.

A closer look at the actual and estimated wind speed (on an every six hour basis) reveals insight as to the improved performance of the E-MCP approach. Figure 4 shows a histogram of estimated and actual wind speeds for a site in a mountainous area in the west for a period of 18 months. This is one of the cases where the linear regression showed a negative R^2 of -0.07 and E-MCP showed a value of 0.71.

The E-MCP estimated winds show a much better match to the speed distribution measured at the tower. In particular, the distribution generated by linear regression is compressed into the middle values and does not do a good job of matching tower measurements. Even for more highly correlated sites, the improvement of E-MCP over linear methods is often most evident in the speed and power distributions.

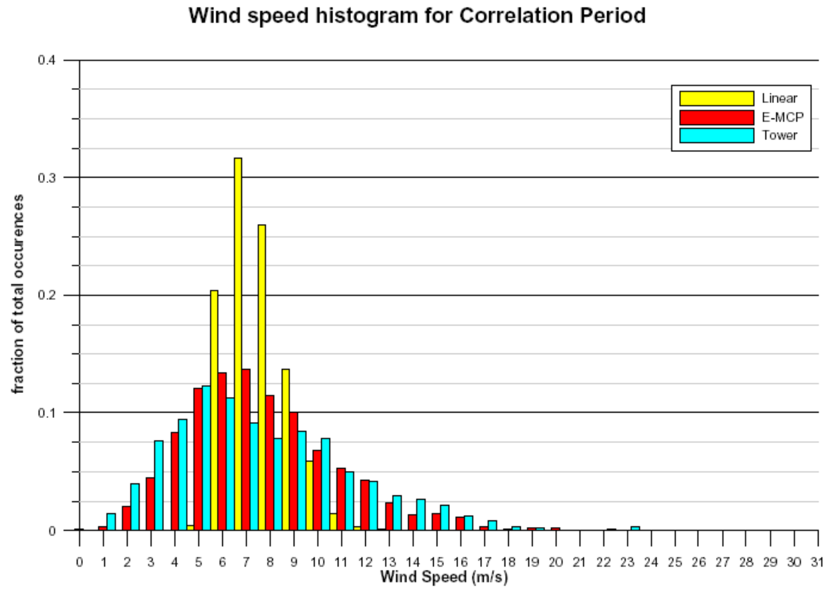

Figure 4. Estimated and actual wind speed distributions.

A similar distribution of energy production is shown in Figure 5 for a site in the southern central plains. The tower measurements and estimated speeds were passed through a power curve to generate the energy production on an every six hour basis. The E-MCP estimated energy distribution does a much better job of matching the measured distribution.

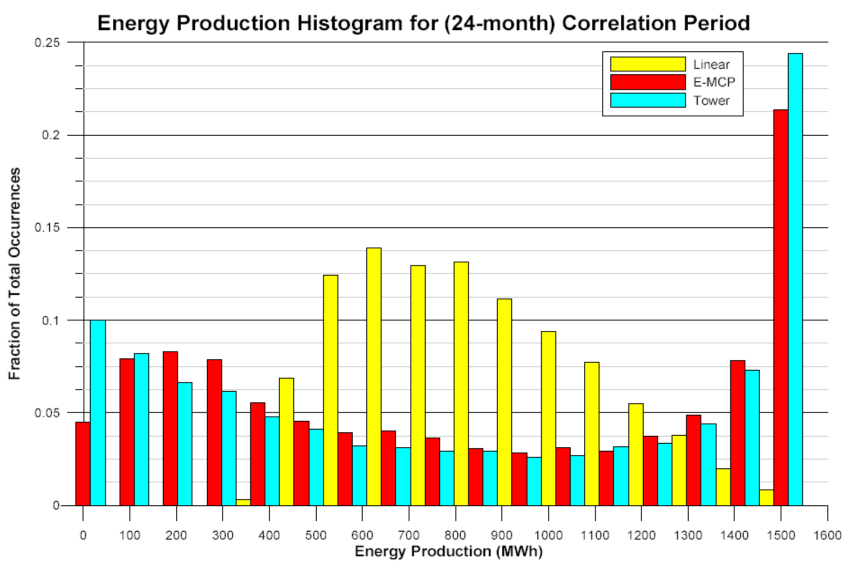

Figure 5. Estimated and actual energy production distributions.

Conclusions

Significant climatic variability occurs on timescales spanning decades. Because of this, it is critical to base estimates of wind plant energy production and variability on thirty or more years of long-term data.

Several sources of long-term reference data and correlation techniques were investigated. While all of the data sources must be applied with care and can be susceptible to false trends due to changes in the instrument system, several conclusions are evident.

- The two global reanalysis datasets exhibit generally good agreement. The agreement is somewhat weaker in mountainous areas where localized flows can have a large impact. This weaker level of agreement in mountainous areas is not indicative of the quality of the datasets as a whole.
- Linear correlation tests against multi-year tower data show that the RNL and NARR datasets exhibit, on average, the best correlation. The METAR data lags slightly behind, while the radiosonde data typically show the weakest correlation.
- The downscaling method is just as important as the dataset used. Advances in the climatic research community on the problem of downscaling coarse resolution datasets stress the use of relating weather patterns to the onsite conditions rather than relying on single-point linear methods. Our work validates this concept. Estimates of multi-year tower data based on multi-point SVM regression, using either the RNL or NARR data, show significantly smaller error rates than any of the datasets when using linear regression. In comparison, estimates based on the METAR data show RMS error rates about 40% larger, while the RMS errors based on the radiosonde data are roughly 85% larger.
- When looking at the actual wind speed and energy time series results, the SVM regression-based estimates show much higher correlation with tower data than linear regression estimates. The errors in monthly energy estimates using SVM regression were roughly half of those using the linear technique.
- The E-MCP technique shows an excellent ability to derive relationships between the weather patterns and onsite conditions, even at sites with very poor linear correlation. Indeed, even for sites with a linear-based R^2 near zero, the E-MCP approach demonstrated R^2 values in the 0.7 to 0.8 (highly correlated) range.
- The wind speed and power distributions are a particularly sensitive indicator of the ability of the EMCP system to generate the realistic time series of on-site conditions.

Implications

Understanding the long-term wind resource is critical to wind energy projects, and a growing body of research shows the need for longer data sets (30 or more years of data) and the value of using the various reanalysis data sets.

Resistance to change is always an issue, but some recent criticism of reanalysis datasets is rather ironic. For example, the NCAR/NCEP Global Reanalysis dataset has been a primary data source for most wind maps, including those produced for the Wind Powering America program and United Nations Environment Programme. These wind maps are typically created with 366 days of data that are randomly sampled from fifteen years of the RNL reanalysis dataset, thereby implicitly using the reanalysis data for long-term normalization. This sampling/modeling approach makes direct validation against anemometer measurements rather difficult, but fundamentally, this is a downscaling method based on reanalysis data.

Proper use of a reanalysis dataset requires techniques that exploit the regional patterns in the data. For wind mapping, this is done by using mesoscale weather models to generate higher local resolution. For site-specific long-term normalization, comparable techniques that use the regional data and convert it to higher-fidelity local understanding are similarly required.

Extracting a single point from reanalysis data and using traditional linear methods to compare it with other data sources can appear to identify inconsistencies in the data. This is simply because appropriate methods of downscaling reanalysis data and weather pattern analysis must be used when inferring site-specific results from the data. Those who are skilled in the use of reanalysis data know this to be the case and can apply it appropriately.

As we have validated against actual tower measurements, appropriate methods that exploit the regional nature of reanalysis data provide results that are superior to single-point methods or traditional linear approaches. While all datasets must be examined and used with care, reanalysis data with SVM regression methods shows dramatic improvements over other long-term datasets, including ground-based measurements and radiosonde data.

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