Uncertainties in Results of Measure-Correlate-Predict Analyses

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Summary

This paper explores the uncertainties in measure-correlate-predict (MCP) predictions. Prediction uncertainties as a function of concurrent data length are determined using 12 pairs of reference and target sites for which long term concurrent data sets exist. The data are then used to test methods for estimating uncertainties of MCP results when long-term data are not available. Uncertainties resulting from a linear regression analysis significantly underestimate the uncertainties due to the serial correlation of wind data. The jackknife estimate of variance, which estimates variance using MCP results based on multiple estimates, each with a segment of the original data missing, are also considered. The jackknife estimate of variance is an improvement, as shown by estimates of the uncertainty of predicted mean wind speed and Weibull parameters at the 12 paired sites. The jackknife estimate of variance appears to correctly estimate the uncertainty based on the concurrent data but still often underestimates the overall uncertainty in the relationship between the two sites because of the unknown variability at time scales longer than the concurrent data length. An MCP model with monthly terms and the use of an empirical correction factor are considered to remedy this situation. The empirical correction factor shows promise, but may not be applicable to all sites. An alternate approach, the relationship between MCP prediction uncertainty and the correlation coefficient of the data sets, does not provide any better results than the jackknife estimate.

Introduction

Measure-correlate-predict (MCP) algorithms are used to predict the wind resource at target sites for wind power development. MCP methods model the relationship between wind data (speed and direction) measured at the target site, usually over a period of up to a year, and concurrent data at a nearby reference site. The model is then used with long-term data from the reference site to predict the long-term wind speed and direction distributions at the target site. In order to be most useful for wind power development, the uncertainties in the predictions need to be understood.

This paper explores possible approaches to estimating the uncertainties in MCP predictions. Prediction uncertainties as a function of concurrent data length are explored using reference and target sites for which long term concurrent data sets exist. Statistical models that estimate the uncertainties in an MCP prediction when only short-term concurrent data exist are then investigated. The first of these uses the variances and covariance of the slope and offset of a linear regression MCP model. An alternate approach, using the jackknife estimate of variance, is then introduced. The jackknife estimates are determined for the predicted mean wind speed and Weibull shape parameters. The results of using these statistical models on long-term data sets are then used to illuminate important issues and suggest possible approaches to the solution of estimating the uncertainties in MCP predictions. Empirical corrections to the jackknife estimate are discussed, as well as other approaches.

MCP Models

A variety of MCP algorithms or models have been proposed in the literature [1-17] for modeling the relationship between the concurrent wind data at the two sites. The authors [17] investigated four of these and the methods of Mortimer [10] and one proposed by the authors, the “Variance” method, were shown to reliably predict a variety of site characteristics important to wind power applications. The two methods that used linear regression did not predict the wind speed distributions as well as the Variance or Mortimer’s method. In this study, the Variance method will be used almost exclusively to model the relationship between the data from the two sites. Linear regression will be used when the applicability of using the uncertainties of the slope and offset for estimating the standard deviation of the results is being explored.

Data Used For Analysis

Twelve sets of data have been used in this analysis. Six pairs of sites are offshore buoy or tower sites. Six are inland pairs of sites. The details of the data are included in Table 1. Each data set consists of numerous years of long term concurrent data from two sites. These sites are often more distant from each other than desirable for an MCP analysis, but they are just as useful as nearby sites for testing the acceptability of statistical techniques. No long-term data is complete. As implemented, the MCP method only uses data for which both of the pairs of data exist. Any gap in either data set reduces the number of useful pairs of data.

Table 1. Details of sites used for analysis. Reference sites are designated by an asterisk (*).

Data Set	Site Pair Code	Site Pairs	Location	Distance km	Data Length yrs	Percent Good Pairs	Correlation Coefficient
Inland							
1	KG	Kennewick - Goodnoe*	Oregon	112	17.00	67.8%	0.597
2	ROC	Red Oak - Cedar*	Iowa	219	4.85	93.4%	0.620
3	EF	Estherville - Forest City*	Iowa	100	4.85	87.3%	0.843
4	IS	Inwood - Sibley*	Iowa	66	4.95	87.4%	0.850
5	RS	Radcliffe - Sutherland*	Iowa	186	4.00	78.8%	0.748
6	US	US176x1 - US127x07*	Indiana	9	11.11	90.1%	0.760
Offshore							
7	57	44005 - 44007*	New England	87	14.79	69.1%	0.732
8	B44	44013 - 44008*	New England	231	19.39	69.5%	0.646
9	BUZ	BUZM3 - IOSN3*	New England	178	19.22	74.6%	0.640
10	MDR	MDRM1 - MISM1*	New England	62	20.11	83.1%	0.880
11	13	51001 - 51003*	Hawaii	497	19.01	71.0%	0.497
12	24	51002 - 51004*	Hawaii	566	19.14	71.8%	0.744

Measuring Uncertainties in MCP Predictions

The uncertainties of the MCP prediction can be explored by using data from sites for which concurrent long-term data sets exist. When long-term target site data exist, multiple lengths of non-overlapping, shorter concurrent data sets from the longer set can be used, with the long-term reference site data to predict the characteristics of the long-term target site data set. The standard deviation of the estimates for different concurrent data sets can then be used to estimate the uncertainty of the predictions. This analysis was performed using eight 45-degree direction sectors and also using only one 360-degree direction sector. The results using one 360-degree direction sector are shown below.

The results for the mean wind speed predictions for the 6 inland and 6 offshore data sets are illustrated in Figure 1. The graphs show the standard deviation of the separate MCP estimates for each site, normalized by the site mean wind speed. Results using eight 45-degree direction sectors are very similar. The inland pairs of sites have a wider range of variability of the MCP estimates than do the offshore sites, although the uncertainty of some of the inland sites is less than any of the offshore sites.

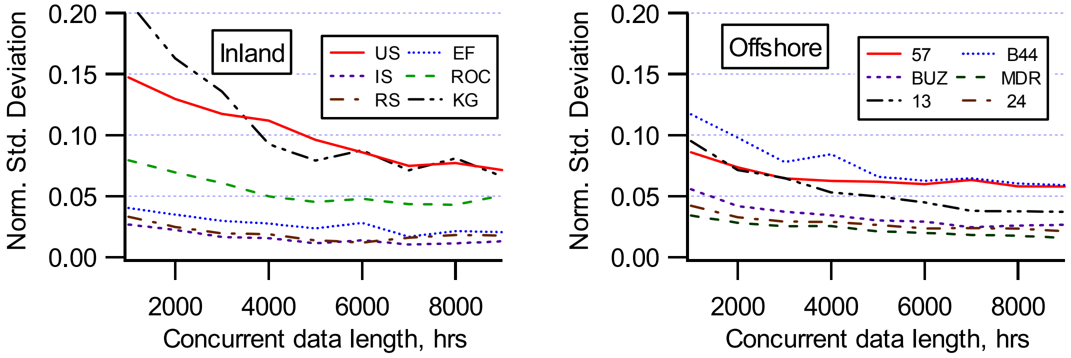

Figure 1. Measured normalized standard deviation (standard deviation / mean wind speed) of mean wind speed for six inland and six offshore pairs of data.

These initial results indicate that:

- The uncertainty of the MCP estimates of long-term wind speed typically decreases as the length of the concurrent data increases, over the range of concurrent data lengths tested. It would be expected that the standard deviation should decrease as the square root of the concurrent data length, if the MCP model that is used correctly models the relationship between the two data sets. However, un-modeled seasonal and long-term changes may affect the results.
- The normalized standard deviation of MCP estimates, when using 1000 hours of concurrent data, are often about 3% to 4% of the mean wind speed, but may be as high as 20% of the mean wind speed.
- The normalized standard deviation of MCP estimates, for 9000 hours of concurrent data, are usually between 3% and 6% of the mean wind speed for the offshore sites, but between 2% an 8 % for the inland sites.

A similar analysis was done with the uncertainty of the Weibull parameters derived from the predicted wind speeds. The following graphs illustrate the results for the Weibull shape parameter, k. The results of the Weibull scale parameter, c, are very similar to those for the mean wind speed and are not shown. Figure 2 shows the results for the standard deviation of the Weibull scale parameter, k, normalized by the site Weibull k estimate. The results using eight 45-degree direction sectors are very similar. The uncertainty of the Weibull k estimate tends to be lower at the inland sites than at the offshore sites.

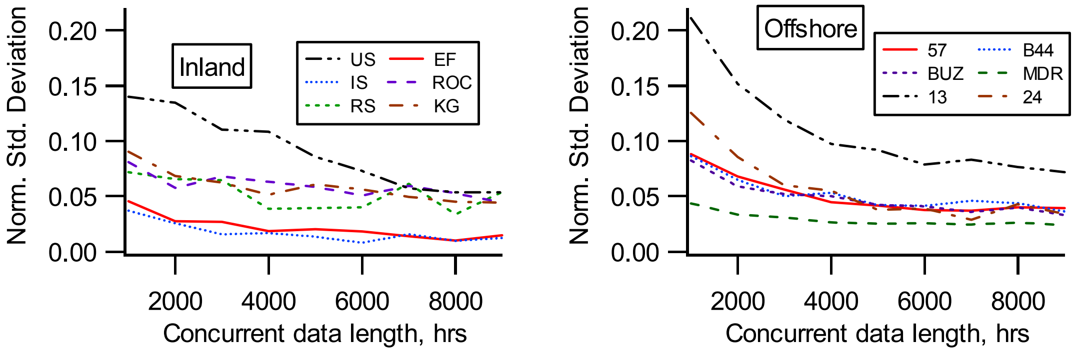

Figure 2. Mean of measured MCP uncertainties of Weibull k estimates for six inland and six offshore pairs of data.

Estimating Uncertainties in MCP Predictions

Users of an MCP algorithm do not have long-term data at each site with which to estimate the uncertainty of the results. Thus, the question arises how the uncertainties in the MCP predictions can be estimated, with only the long-term reference site data and the shorter term concurrent data from the target site.

When linear regression is used to model the relationship between the reference and target sites, the uncertainty of the slope and offset are often used to determine the uncertainty of the results. For example, Derrick [1, 2] has detailed the approach for estimating the standard deviation of the estimate of the predicted wind speed, using the variances and covariance of the slope and offset, when the analysis is performed for different direction bins.

The use of linear regression assumes that the data are not serially correlated, i.e. that the correlation coefficient of the two sites is zero at and beyond a lag of one data point. In contrast, wind data at two nearby sites are indeed serially correlated and this turns out to affect the results significantly. For example, Figure 3 illustrates the result of using a linear regression fit for the MCP analysis and for calculating the estimate of the standard deviation of the predicted mean wind speed. In this example, the approach is applied to two different sets of data. One data set is the original Red Oak – Cedar data set. The other is the same data but with the paired data points randomly ordered to remove the serial correlation. When the randomized data is used, the linear regression approach correctly estimates the measured uncertainty of the MCP predictions. When applied to the original data, the linear regression estimate approximates that of the random data set, but this significantly underestimates the uncertainties of the original data set.

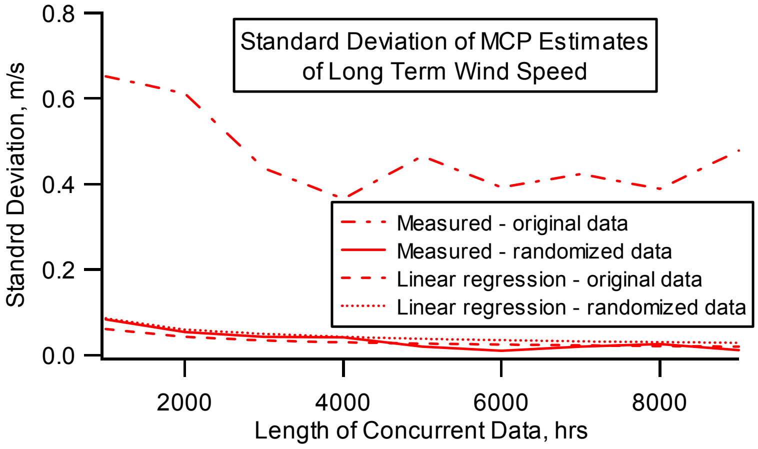

Figure 3. Comparison of linear regression estimates of uncertainty with measured uncertainty using original and randomly sorted Red Oak – Cedar data.

The approach of using the uncertainty of the slope and offset from the linear regression fit to estimate the uncertainty of the mean wind speed works for data that are independent, but not for serially correlated data. The approach has additional drawbacks. It can only be used with a linear regression MCP model. It can also not be used to predict the uncertainty of other values of interest, for example Weibull parameters or capacity factors that one might derive from an MCP analysis. Finally, when used on serially correlated data, underestimation of the MCP prediction uncertainties leads to unjustified confidence in the results.

An alternate statistical approach, the jackknife estimate of variance [18], is investigated in the rest of this paper to evaluate MCP predictions for mean wind speed and Weibull parameters of the wind speed distribution. The jackknife estimate of variance assesses the prediction uncertainty using the variability of the MCP predictions made by dropping out subsets of the concurrent data as described below. The use of the jackknife method to estimate the uncertainty will then be explored.

Both the use of linear regression and the jackknife method attempt to estimate the MCP prediction uncertainty based on the variability in the relationship between the concurrent data from the two sites. This assumes that the variability of the relationship between the two sites, as exhibited in the concurrent data set, reflects the long-term variability between the two sites. This is not necessarily the case. The validity of this assumption will be discussed later in this paper.

Jackknife Estimate of Variance

The jackknife estimate of variance estimates the uncertainty of the MCP predictions by considering the variability of MCP estimates resulting from dropping out subsets of the concurrent data. It can be used to estimate the uncertainty of the results of any MCP model and can be used to estimate the uncertainty of values derived from the MCP wind speed results such as Weibull parameters or wind turbine capacity factors. The method is described below.

If Y^* is an estimate of mean wind speed or a Weibull parameter based on one set of concurrent data and if Y_i^* are *n* estimates using the same concurrent data sets that have each a different, non-overlapping 1/*n*th of the data file missing, then an asymptotically unbiased estimate of the variance of the estimate of Y^*, based on the complete concurrent data set, can be expressed as:

$$\sigma^2\left(Y^*\right)=\frac{(n-1)}{n}\sum_{i=1}^{n}\left(Y^*-Y_i^*\right)^2 \tag{1}$$

The approach assumes that the *n* subsets that are removed are independent. This may not be true if the *n* subsets are of such short duration that they are correlated. In that case, the serial correlation of the data will affect this method. It can be shown that, if the data are independent (not correlated), then the jackknife variance estimate converges to the regression estimate as sample sizes increase. The following steps are used to determine the measured standard deviation of the MCP estimates and the jackknife estimate:

1. Using sets of long term data from each site, the measured standard deviation of the predicted MCP results is determined by repeating the MCP analysis with *m* separate lengths of concurrent data. This estimate has (*m*-1) degrees of freedom.
2. Within each separate length of concurrent data, *n* jackknife sub-sets are used to estimate the uncertainty in the predicted results. The *n* estimates of the predicted results are obtained by dropping out of each jackknife subset 1/*n*th of the data file and determining the predicted results. The estimated prediction variance is then determined, using the Equation (1). This results in *m* estimates of variance of the prediction, one for each *m* lengths of concurrent data. From the *m* variance estimates, a pooled estimate of the predicted standard deviation, $\sigma^*\left(Y^*\right)$, is obtained, using Equation (2). This estimate has *m*(*n*-1) degrees of freedom.

$$\sigma^*\left(Y^*\right)=\sqrt{\frac{\sum_{k=1}^{m}\sigma_k{}^2\left(Y^*\right)}{m}} \tag{2}$$

Number of Jackknife Subsets

As mentioned above, the length of the jackknife subsets may have some effect on the results. The best choice of number of jackknife subsets may depend on the length of concurrent data and the serial correlation characteristics of the data. To determine the most useful number of jackknife subsets, jackknife estimates of the standard deviation of the MCP estimates of mean wind speed were made, using a variety of numbers of jackknife subsets and concurrent data lengths and using each of the 12 data sets. The root-mean-square prediction error (RMSE) of the estimate of the standard deviation of the mean wind speed for each site was used to determine the best number of jackknife subsets. If $\sigma_M\left(Y^*\right)$ is the measured standard deviation of the predicted MCP estimates and $\sigma_k^*\left(Y^*\right)$ is the *k*th estimate of the predicted standard deviation, then the RMSE for a given site pair is defined as:

$$RMSE=\sqrt{\frac{1}{m}\sum_{k=1}^{m}\left(\sigma_M\left(Y^*\right)-\sigma_k^*\left(Y^*\right)\right)^2} \tag{3}$$

The RMSE is fairly insensitive to the choice of *n*. For each concurrent data length, the optimum number of jackknife subsets was chosen to be the median of the best performing (least RMSE) number of jackknife subsets among the 12 data sets. The results are illustrated in Figure 4. This selection of number of jackknife subsets was used in the rest of the analysis described in the paper. The fact that the choice of *n* does not affect the results suggests that serial correlation is not affecting the jackknife results.

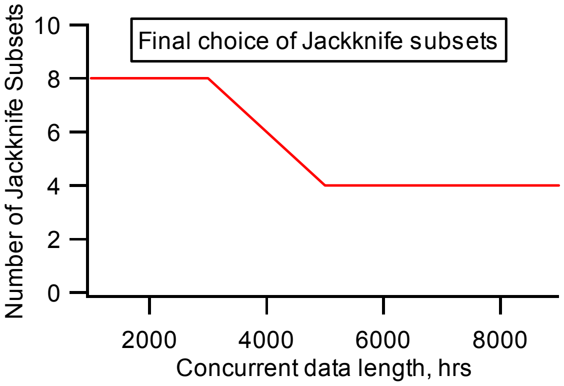

Figure 4. Optimum number of jackknife subsets as a function of concurrent data length.

Results of Jackknife Estimates of Variance

The jackknife estimate of variance, with the numbers of jackknife subsets fixed as in Figure 4, was then used to estimate the uncertainty in estimates of long-term mean wind speed and Weibull parameters. In the following sections the results for mean wind speed and the Weibull shape parameter, k, are explained and illustrated. The results for the Weibull scale parameter, c, are very similar to those of the mean wind speed and are not shown. This analysis was performed using eight 45-degree direction sectors and also using only one 360-degree direction sector. The results using one 360-degree direction sector are shown below.

Jackknife Estimates of Uncertainties for Mean Wind Speed Predictions

The analysis of the results of the use of the jackknife estimate of variance on all of the 12 data sets is presented below. In general, the jackknife method showed a vast improvement over using the results of linear regression, but is not perfect. The graphs in Figure 5 show the measured standard deviation and jackknife estimates for each of the inland sites. The graphs in Figure 6 show the results for each of the offshore sites. The jackknife method often does better with longer lengths of concurrent data. Finally, there are no distinct differences in the results between the inland and offshore sites.

Figure 7 shows the normalized RMSE of the jackknife estimates of mean wind speed prediction uncertainty as a function of concurrent data length. The data are normalized by dividing the RMSE by the measured standard deviation of the MCP predictions. The results show that, at both the inland and the offshore sites, the typical RMSE of the jackknife estimates is on the order of 40% to 60% of the standard deviation being estimated. The RMSE using eight 45-degree direction sectors are similar, but results for any given site may be slightly different due to the directional characteristics of the data.

Figure 8 shows the ratios of the measured standard deviation of the mean wind speed prediction to the jackknife estimate at each site. The ratio of the measured uncertainty of the MCP prediction to the estimated uncertainty typically decreases at the inland sites as the concurrent data length increases. This ratio is fairly constant for the offshore data sets over different concurrent data lengths. The overall mean of the ratios across these 12 sites and lengths of concurrent data is about 1.6. The ratios using eight 45-degree direction sectors are very similar.

Jackknife Estimates of Uncertainties for Weibull Shape Parameters

A similar analysis was performed for the estimates of Weibull shape parameter uncertainty. The Weibull scale parameter results are very similar to those of the mean wind speed and are not shown here. Figure 9 shows the measured and estimated standard deviation of Weibull k parameter of the wind speed for the inland data sets. Figure 10 shows the same for the offshore data sets. The jackknife method does a somewhat better job of estimating the standard deviation of the Weibull k estimates, even with short lengths of concurrent data, than of estimating the standard deviation of the mean wind speed estimates, especially at the offshore sites.

Figure 11 shows the normalized RMSE of the jackknife estimate as a function of length of concurrent data. The results are normalized by dividing by the measured uncertainty of the Weibull k estimates. At both the inland and the offshore sites, the RMSE of the jackknife estimates is usually on the order of 40% to 50% of the measured standard deviation. Again, the RMSE using eight 45-degree direction sectors are similar, but results for any given site may be slightly different due to the directional characteristics of the data.

Finally, Figure 12 illustrates the ratio of the measured standard deviation of Weibull k to the jackknife estimate of the standard deviation. The ratios at the offshore sites average between 1 and 1.5, indicating that the jackknife estimate of the Weibull shape parameter tends to slightly underestimate the Weibull shape factor. In general, the results for the offshore sites are much less variable, as a function of concurrent data length, than for the inland sites. The ratios using eight 45-degree direction sectors are very similar.

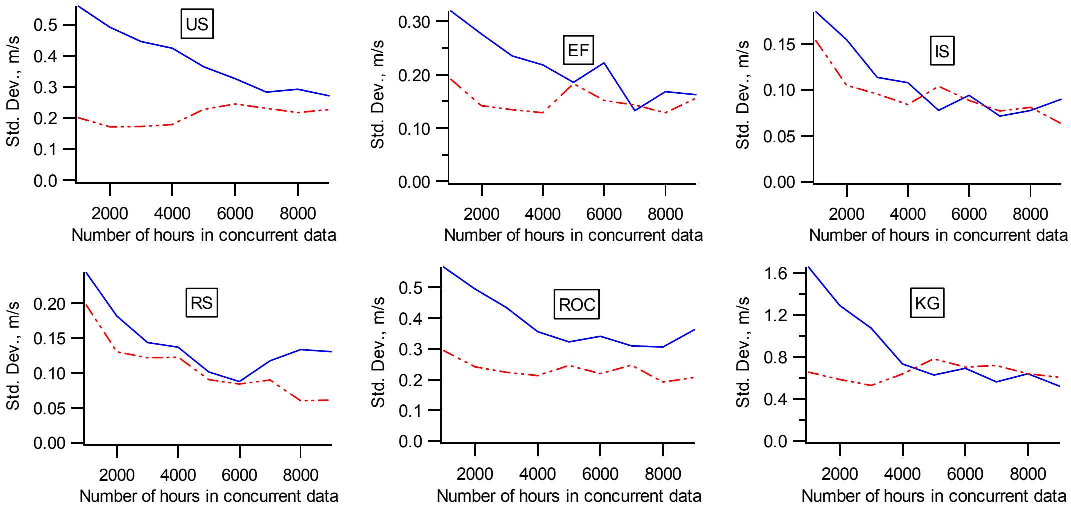

Figure 5. Measured and estimated standard deviation of the mean wind speed estimates at the inland sites. The solid line is the measured uncertainty of the MCP estimates. The broken line is the jackknife estimate.

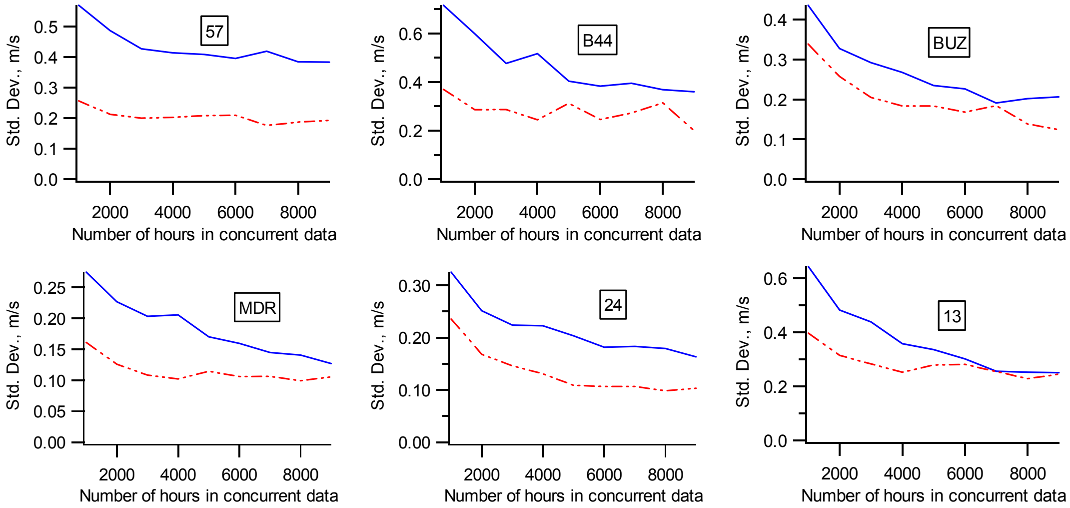

Figure 6. Measured and estimated standard deviation of the mean wind speed estimates at the offshore sites. The solid line is the measured uncertainty of the MCP estimates. The broken line is the jackknife estimate.

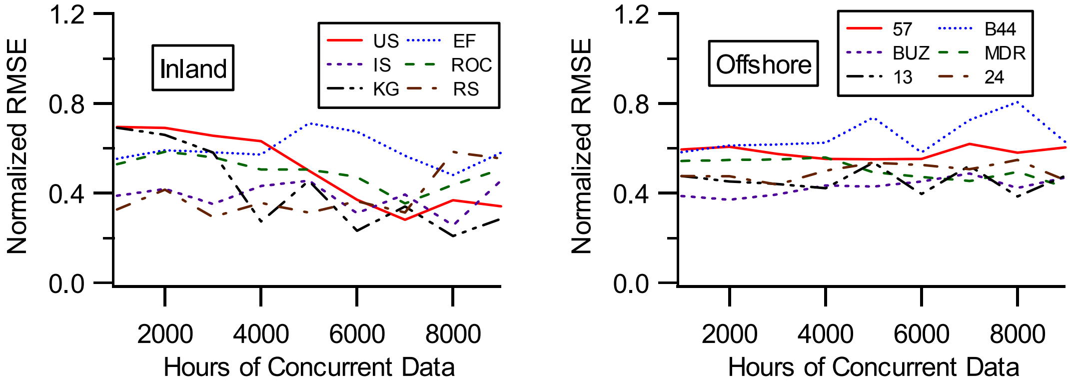

Figure 7. Normalized RMSE of jackknife estimates of mean wind speed. Different lines are from different sites.

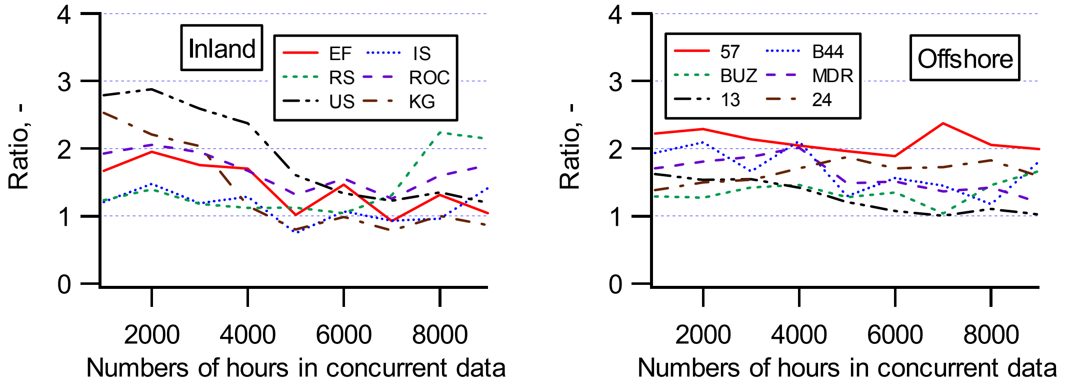

Figure 8. Ratio of measured to estimated standard deviations of mean wind speed. Different lines are from different sites.

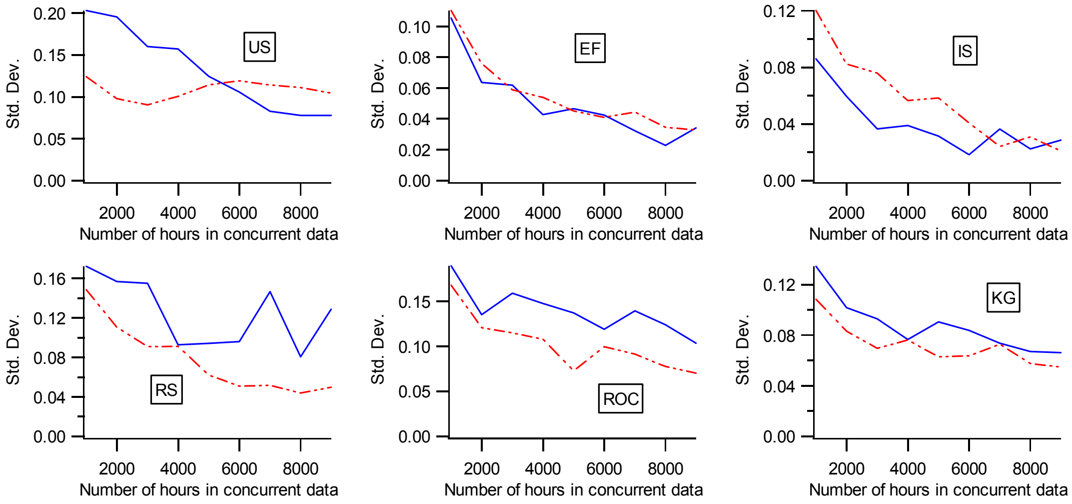

Figure 9. Measured and estimated standard deviation of the Weibull K estimates for the inland sites. The solid line is the measured uncertainty of the MCP estimates. The broken line is the jackknife estimate.

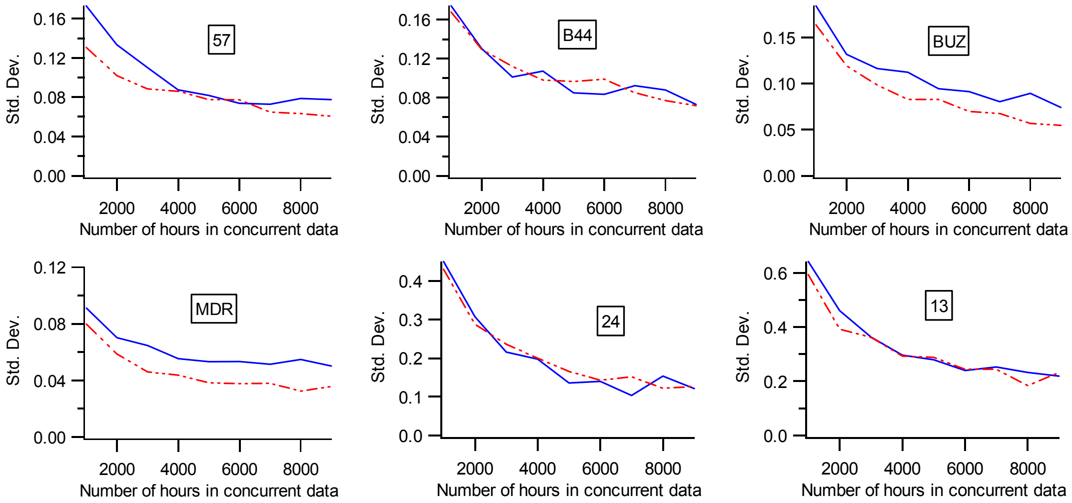

Figure 10. Measured and estimated standard deviation of the Weibull k estimates for the offshore sites. The solid line is the measured uncertainty of the MCP estimates. The broken line is the jackknife estimate.

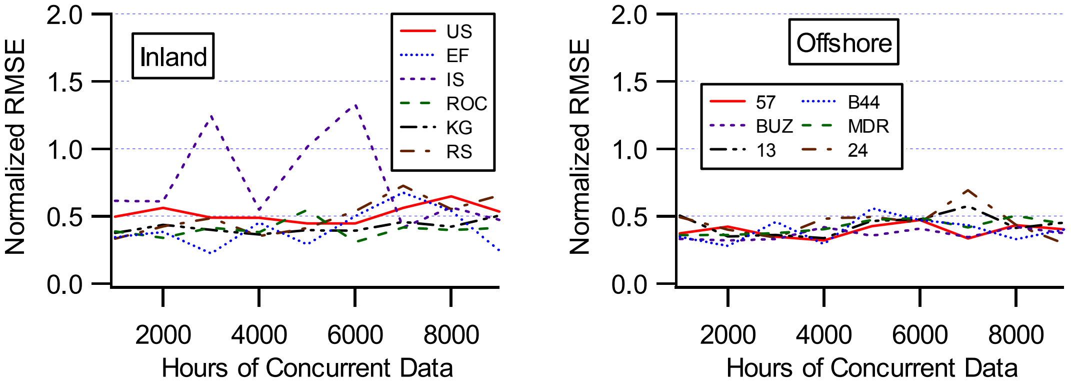

Figure 11. Normalized RMSE of jackknife estimate of Weibull k. Different lines are from different sites.

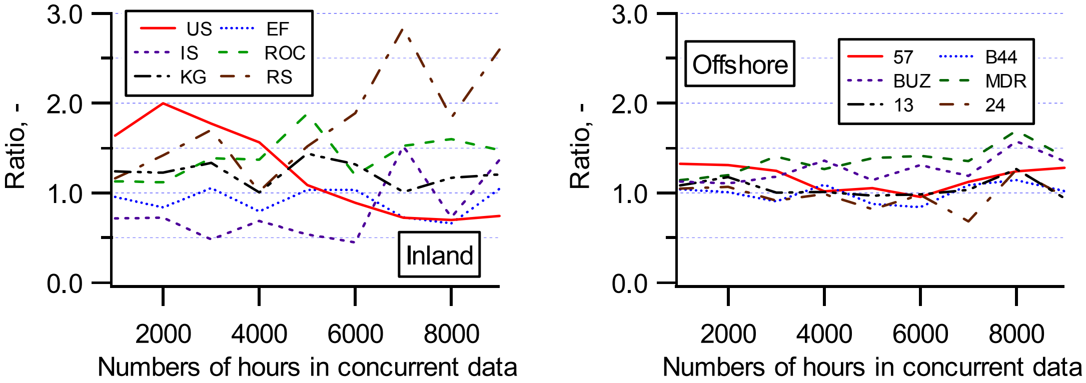

Figure 12. Ratio of measured to estimated standard deviation of Weibull k. Different lines are from different sites.

Discussion

The analysis shows that the jackknife method does a much better job than linear regression. Nevertheless, it tends to underestimate the uncertainty of the mean wind speed prediction by about 38% and that of the Weibull k prediction by about 18%, on average. Additionally, the RMSE of individual uncertainty estimates is relatively high, compared to the value being estimated. A closer look at the nature of the jackknife estimate and the behavior of the data is useful for considering how to improve the estimates.

Figure 13 shows the MCP estimates of mean long-term wind speed for successive concurrent data segments for the two Indiana sites, US176x14 and US127x07. These sites are inland and 9 km distant from each other. The jackknife estimate of uncertainty for the concurrent data segments is indicated by the error bars. The graph shows a thin solid line for successive lengths of 1000 data points and a thicker dotted line for lengths of 9000 points. The data for 1000 points shows a clear seasonal variability. The jackknife estimates of uncertainty for each 1000 point segment usually significantly underestimate the standard deviation of all of the 1000 point segments. In this case the variability within the 1000 point segments is significantly less than the variability among 1000 point segments and the jackknife estimate is lower than the measured standard deviation. The jackknife estimate of the variability of the 9000 point segments, based on the variability within each 9000 point segment, is within the range of the actual variability of the 9000 point predictions. Thus, the jackknife prediction for 9000 points is reasonably good. Figure 13 shows the measured standard deviation and jackknife estimate for this data.

The uncertainty of the predicted results can be divided into three parts: 1) the uncertainty related to the ability of the chosen MCP model to correctly model the relationship between the two data sets, 2) the variability of the relationship between the data during the period of the concurrent data set and 3) the variability at time scales greater than the concurrent data length. Approaches, including the jackknife estimate, that use the concurrent data to estimate the overall uncertainty cannot take the uncertainty at time scales longer than the concurrent data into account.

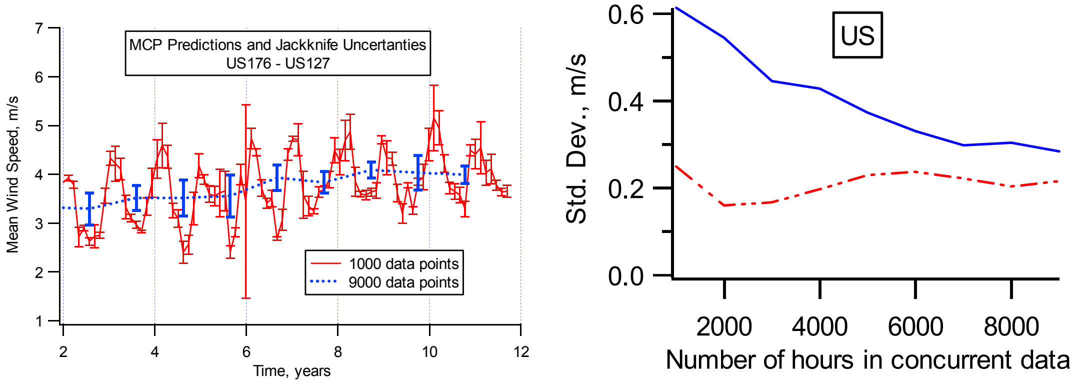

Figure 13. Left: MCP predictions of mean wind speed and jackknife uncertainties (error bars) for data lengths of 1000 and 9000 hours (US data set). Right: Measured and estimated standard deviation of the mean wind speed estimates for the same site.

Alternate Approaches and Modifications to the Jackknife Estimate

Modifications to the MCP model and to the jackknife estimate, designed to improve the uncertainty estimation, have been considered. An alternate empirical approach has also been investigated. The preliminary results of these investigations are presented here.

One modification to the jackknife estimate is the use of an empirical correction factor to account for the systematic underestimation of the uncertainty of the mean wind speed. For example, when the jackknife estimate of the mean wind speed prediction uncertainty is multiplied by a factor of 1.6, the resulting uncertainties are closer to the measured uncertainties. The RMSE of any given estimate is also usually reduced. This approach improves the results overall, but its applicability to other sites has not been demonstrated and it may not improve the results at a particular site.

An alternate approach has been investigated, in which the MCP model is fit to monthly data. For example, if the concurrent data set covers 6 months from January to June, separate model fits are determined for each month. In addition, a fit to the complete data set is determined. When applied to the long-term data set, the monthly relationships are used, where possible. For reference site data collected during months for which no concurrent data and therefore no fit exists (e.g. October), the MCP relationship for the overall data set is used. Figure 14 illustrates the average resulting ratios of measured to estimated uncertainty. The graphs show that this approach provides a slight, but not significant, improvement.

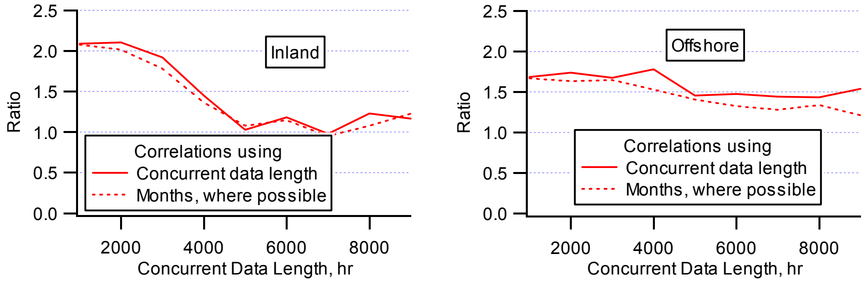

Figure 14. Average ratios, across the data sets, of measured to estimated uncertainties. The solid line shows results from when using all of the concurrent data for the MCP relationship. The dotted lines show results using monthly relationships, when possible.

Finally, the relationship between the correlation coefficients of concurrent data sets and the measured uncertainty is considered as a model for estimating uncertainty. Figure 15 shows the relationships between correlations coefficients and uncertainty for 9000 hours of concurrent data and linear fits for the inland and offshore data. The graph shows that the uncertainties are only weakly correlated with the correlation coefficients and that the concurrent data correlation coefficients at any given site may vary over a wide range. The RMS prediction error, based on a given concurrent data set is on the order of the RMSE using the jackknife approach. Thus, using the correlation coefficient does not appear to be an improvement.

Conclusions

In conclusion:

- The use of linear regression statistics seriously underestimates uncertainty estimates due to serial correlation of data.
- The jackknife estimate of variance appears to correctly estimate the uncertainty due to the application of the MCP model to the concurrent data and is a great improvement for estimating uncertainty of MCP

predictions of mean wind speed and Weibull parameters of the wind speed distribution. Nevertheless, issues related to seasonal and long-term variability remain.

- The performance of jackknife estimate of variance is limited by a lack of knowledge of the variability at time scales longer than the concurrent data length.
- The use of an empirical correction factor to the jackknife estimate, the use of monthly terms and the use of correlation coefficients may prove to be useful, but need to be explored further.

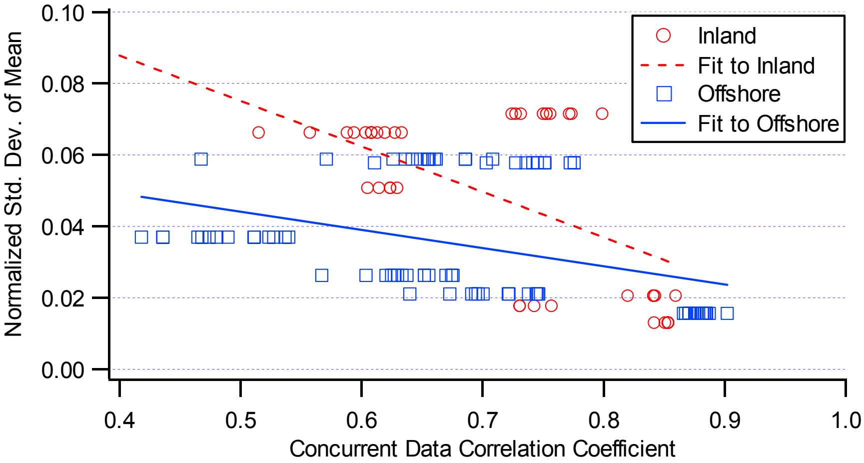

Figure 15. Normalized standard deviation of MCP prediction of mean wind speed vs. correlation coefficient of concurrent data sets.

Acknowledgements
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