The authors are grateful to the two reviewers for the suggestions provided. In addition to responding to such suggestions in the latest version of the manuscript, the authors have also corrected a bug in the original scripts where the ERA5 wind speeds at 100 m were utilized twice as training variables instead of the intended ERA5 wind speeds at 10 m and 100 m.

Review #1

General comments

The authors investigated the impact of the MCP correction on the long-term wind resource assessment. They focused on the accuracy of the MCP corrections using the months-long observations to investigate the possibility of reducing the measurement period used for the training data for the MCP. They found that one month of onsite wind speed measurements improves the longterm wind estimate on average, although four months of onsite measurements is a better option to mitigate the errors. It was also reported that the summer months should be avoided, as these months tend to be the least representative of long-term wind speed means and standard deviations. The study is well conducted, and the methods used are appropriate. The data are clearly presented. This study has shown quantitatively that the MCP, using a data period of less than one year, is effective in improving the performance of long-term wind resource assessment based on a large data set.

Thank you for your time and your thoughtful review. We are very grateful for your feedback and support!

These findings will be of interest to wind energy developers working on the distributed wind resource assessment, as well as to researchers in the field. However, I have following concerns for the manuscript:

• Page 7, Line 131–136: Correlation coefficient, bias, and MAE were used as error metrics. In the case of bias and MAE, they would be associated with the magnitude of the values. Accordingly, the use of relative values would be more appropriate when comparing these results for different wind climates.

We appreciate this suggestion and have updated the results section to include relative error per your recommendation.

• Also, the accuracy of ERA 5 would depend on the measurement height as well as the region. I'm not so sure that the combined results can show the true performance of the ERA 5 dataset near the surface. If the accuracy is strongly dependent on the measurement height, it would be better to narrow the range of observations used for the analysis.

In response to your helpful question, we have added the error metrics according to measurement height to Figure 3. We have also added the accompanying text to Lines 155-158: “No consistent trends in ERA5 performance are noted according to height above ground (Figure 3d, e, f). The wind speed relative errors are greatest for measurement heights between 30 m and 40 m (median = 31%), while the median relative errors for measurement heights between 1) 20 m and 30 m and 2) 40 m and 50 m are 11% and 10%, respectively.”

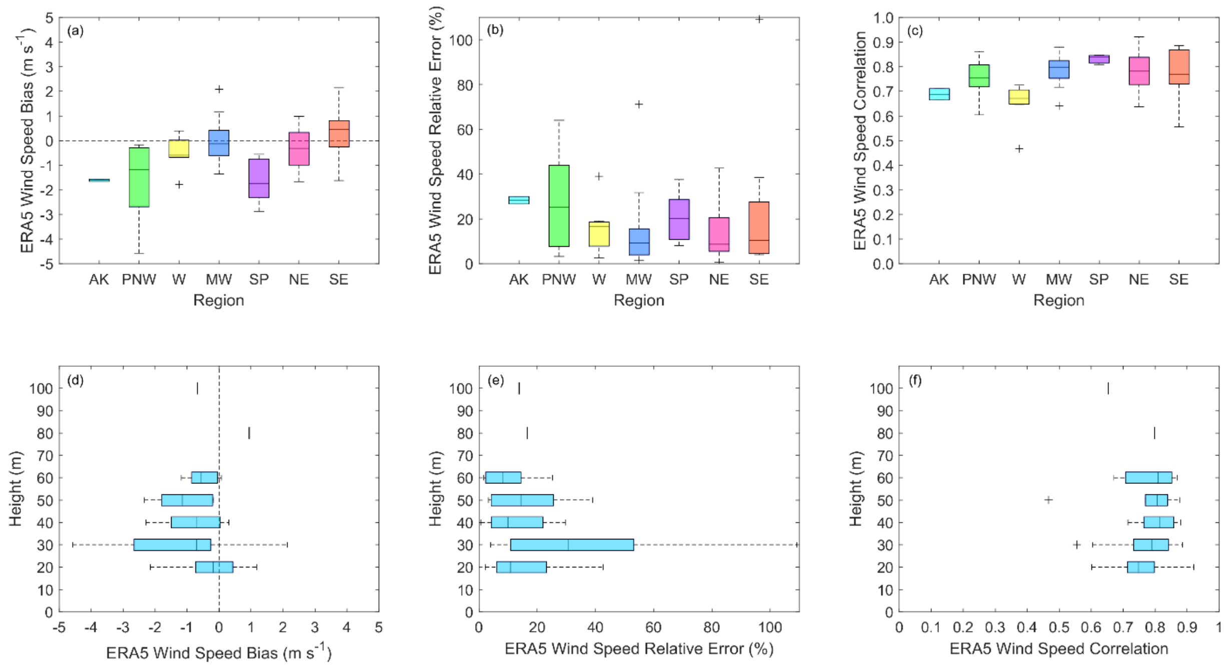


Figure 1. Long-term ERA5 wind speed (a), (d) bias (b), (e) relative error, and (c), (f) correlation across 66 measurement sites in the United States, grouped by region (top) and measurement height (bottom). AK = Alaska, PNW = Pacific Northwest, W = West, MW = Midwest, SP = Southern Plains, NE = Northeast, and SE = Southeast.

• Page 7, Lines 158–160: In addition to the three MCP algorithms used in this study, the other algorithms were also available. In fact, a commercial tool, such as WindPro provides methods using matrix and neutral network approaches. The reasons why these algorithms were chosen were briefly explained, but it is still unclear. Are there any reasons why they were chosen, e.g. because they gave better results than the other algorithms?

We agree that the three algorithms chosen are but a small subset of the techniques available for MCP exploration. Given the vast quantity of techniques available, we limited ourselves to three in order to optimize the effort we could spend analyzing their performance. In particular, we selected multiple linear regression and regression trees as they proved successful in our previous distributed wind-focused studies (Phillips et al., 2022) and added adaptive regression splines as a third method for comparison.

Phillips, C., Sheridan, L. M., Conry, P., Fytanidis, D. K., Duplyakin, D., Zisman, S., Duboc, N., Nelson, M., Kotamarthi, R., Linn, R., Broersma, M., Spijkerboer, T., and Tinnesand, H.: Evaluation of obstacle modelling approaches for resource assessment and small wind turbine siting: case study in the northern Netherlands, Wind Energ. Sci., 7, 1153–1169, https://doi.org/10.5194/wes-7-1153-2022, 2022.

• Page 11, Figure 4: The box plots for each month in the figures are based on the different numbers of samples. Is it possible to add the number of samples used for each box plot on the right axis? The authors would analyze a large dataset to derive the results. The information of the sample size would make it easier for readers to understand how much data was used in the analysis.

The box plots for each month are based on the average error metric for each site, so the boxes are composed of 66 values regardless of the number of months. But you are of course correct that different numbers of samples are going into the calculation of each of those averages according to number of training months. To help the readers understand how much data was used, we have added an additional box plot to Figure 5 that shows the number of samples per site incorporated according to the number of training months.

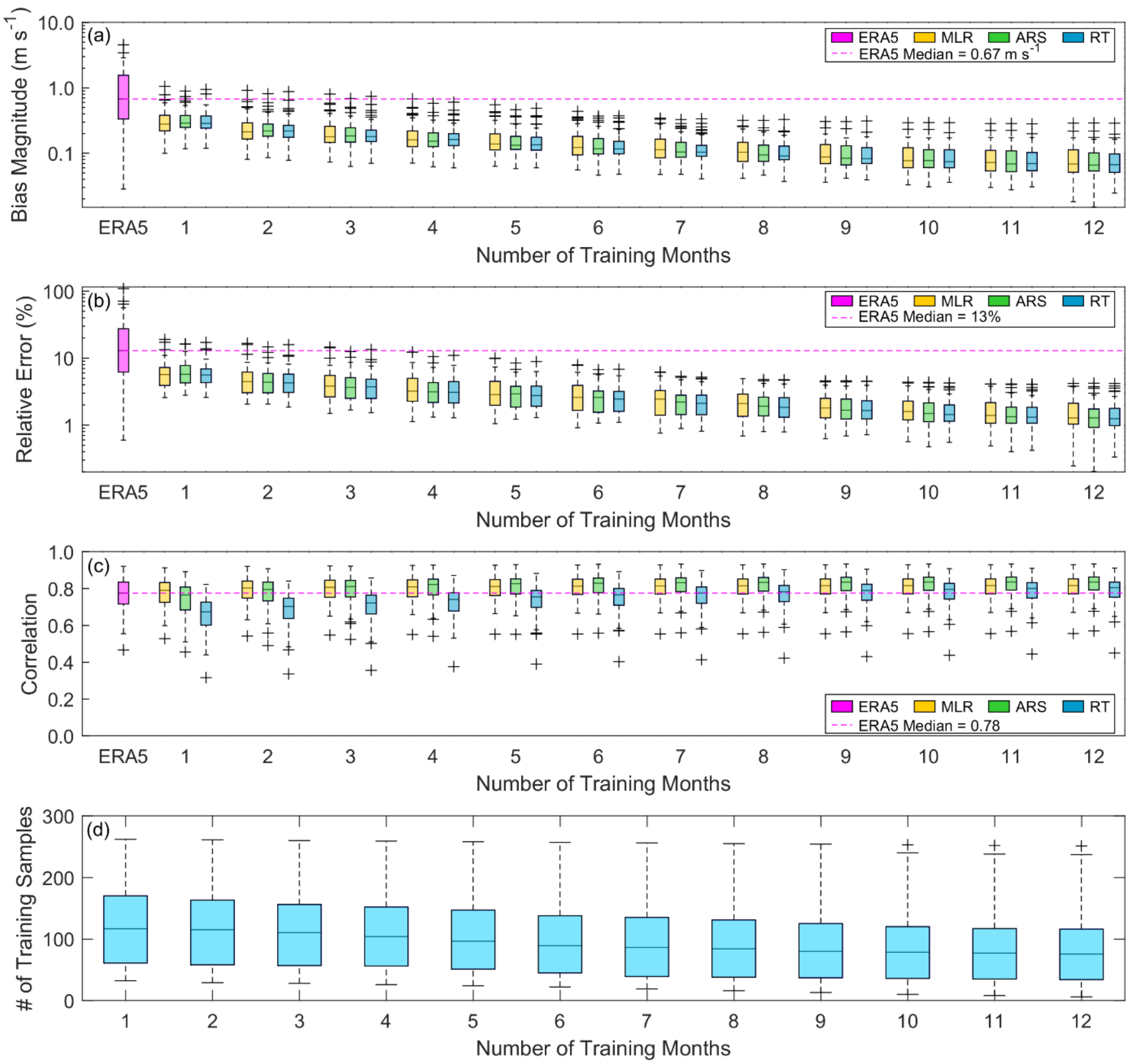


Figure 2. Average long-term (a) bias magnitude, (b) MAE, and (c) correlation for 66 sites comparing observations with ERA5 and MCP techniques using varying training period lengths, along with (d) the number of training samples per site and per number of training months.

• Page 22, Figure 12: Figure 12 (b) shows that the capacity factor errors appear to decrease when the training months reach four months. In the discussion, the authors concluded that four months is the preferred length of training months. If the aim of the investigation is to assess the capacity factor, is the MCP based the months-long observation an appropriate approach?

We stress in the discussion that four months is the minimum amount of time, as opposed to the preferred, that observations should be gathered in order to mitigate the errors that could occur if some of the wind speeds in the measurement period are misrepresentative of the longer-term trends (Lines 440-442): “While even one month of onsite wind speed measurements improves long-term wind speed estimates on average, incorporating at least four months of onsite measurements is a better option to mitigate the errors that could occur if some of the wind speeds in the measurement period are misrepresentative of the longer-term trends."

• The authors investigated the impact of observations using the error metrics with bias, MAE, and correlations. As shown in most of the figures in this study, the MCP methods would mainly affect the bias correction. Also, the improvement on the MAE scores would be due to the bias reduction, as discussed in Mattihas and Focken (2006). Is it necessary to use MAE and correlation coefficient for the KPIs as well as bias through the manuscript?

➢ Lange, Matthias, and Ulrich Focken. Physical approach to short-term wind power prediction. Vol. 208. Berlin: Springer, 2006.

We agree that some of our original choices of error metrics were redundant. We have removed MAE from the evaluation, but have kept correlation as we find it to be relevant for evaluating the performance of simulations in representing fluctuations in the wind, which is of interest when converting to power and assessing the implications of integration into a distribution network.

Minor comments

• Page 7, Figure 3: The error metrics were compared across seven regions. However, the number of sites used to drive the statistics would be different. One option would be to show the number of sites for each region in Figure 1.

We have updated Figure 1 with the number of observational sites in each region, per your helpful suggestion. Thank you!

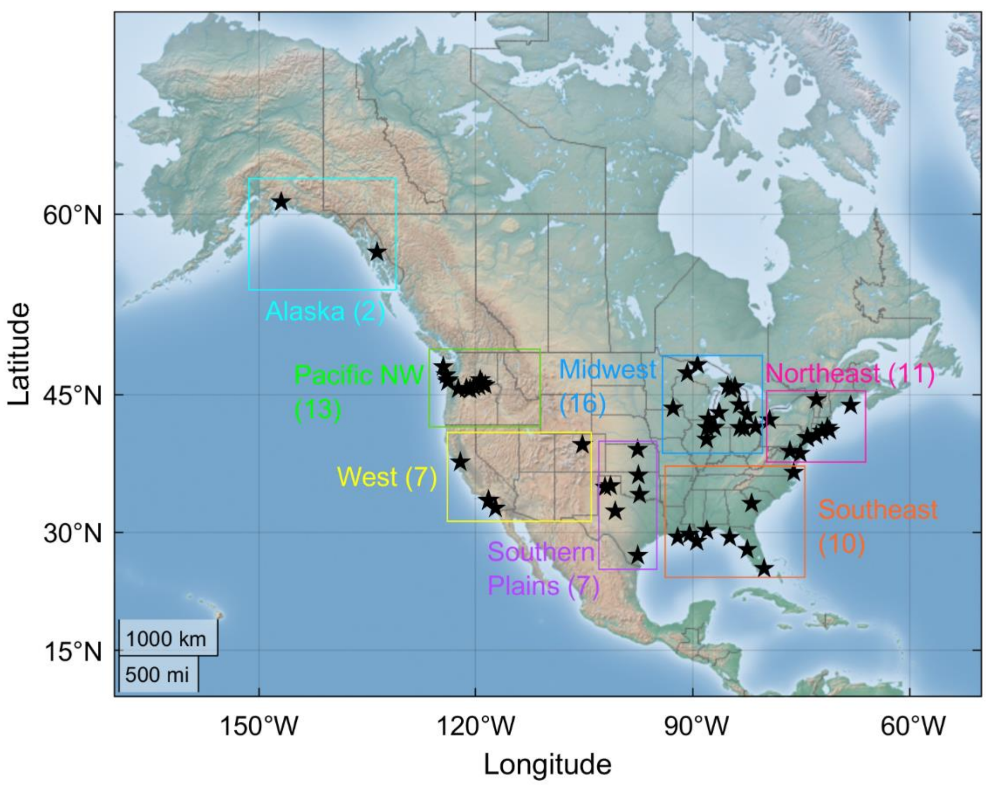


Figure 3. Locations of wind measurements assessed for establishing long-term performance based on months-long observations used in this study. The number of observational sites per region is included in parentheses.

• Page 7, Figure 3: The results of this study would be consistent with previous studies on the accuracy of the ERA5 dataset. The authors would be able to link the result to the previous study.

Thank you for this suggestion to link the ERA5 performance from our analysis to previous work. We have added the following on Lines 159-164: "The tendencies of ERA5 to underestimate the observed wind speeds in this analysis while exhibiting a relatively high degree of correlation with them aligns with the findings of Ramon et al. (2019), Murcia et al. (2022), Sheridan et al. (2022), and Wilczak et al. (2024) discussed in Section 2.2. The bias trends according to region (Figure 3a) also align with the findings of Wilczak et al. (2024) in that ERA5 underestimation is noted in the Pacific Northwest and Southern Plains, while a mix of overestimation and underestimated is noted for the Midwest."

• Page 8, Line 216–221: It's difficult to follow the numbers described in the main text. Please consider using more tables to show the numbers.

We agree and have added Table 2 and Table 3 to provide easier reference for the discussion.

Table 1. Median biases, bias magnitudes, relative errors, and correlations according to algorithm and number of training months.

		Number of Training Months											
Error Metric	**Algorithm**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Bias (m s^{-1})	MLR	-0.03	-0.02	-0.02	-0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01
	ARS	-0.04	-0.02	-0.02	-0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01
	RT	-0.08	-0.04	-0.03	-0.01	-0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00
Bias Magnitude (m s^{-1})	MLR	0.28	0.21	0.18	0.16	0.14	0.12	0.11	0.10	0.09	0.08	0.07	0.07
	ARS	0.29	0.22	0.18	0.15	0.13	0.12	0.10	0.09	0.08	0.08	0.07	0.07
	RT	0.29	0.22	0.18	0.16	0.13	0.12	0.10	0.09	0.08	0.07	0.07	0.07
Standard Dev. of Bias Magnitude (m s^{-1})	MLR	0.24	0.18	0.15	0.13	0.11	0.09	0.08	0.07	0.06	0.06	0.05	0.05
	ARS	0.28	0.19	0.15	0.12	0.10	0.08	0.07	0.07	0.06	0.05	0.05	0.05
	RT	0.24	0.18	0.14	0.12	0.10	0.08	0.07	0.06	0.06	0.05	0.05	0.05
Relative Error (%)	MLR	5.7	4.5	3.8	3.2	2.8	2.6	2.4	2.1	1.8	1.6	1.4	1.3
	ARS	5.7	4.4	3.6	3.1	2.9	2.6	2.2	1.9	1.7	1.5	1.3	1.3
	RT	5.6	4.3	3.7	3.1	2.8	2.4	2.1	1.8	1.6	1.4	1.3	1.2
Correlation	MLR	0.79	0.80	0.81	0.81	0.81	0.81	0.81	0.82	0.82	0.82	0.82	0.82
	ARS	0.77	0.80	0.81	0.82	0.83	0.83	0.83	0.83	0.83	0.84	0.84	0.84
	RT	0.67	0.70	0.72	0.74	0.76	0.77	0.78	0.78	0.79	0.80	0.80	0.80

Table 2. Median site-average capacity factor relative errors according to algorithm and number of training months.

		Number of Training Months											
Error Metric	**Algorithm**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
CF Relative Error (%)	MLR	9.7	8.5	7.6	6.8	6.2	5.6	4.9	4.3	4.1	3.7	3.5	3.5
	ARS	9.9	8.0	7.3	6.7	6.2	5.6	5.0	4.6	4.4	4.2	3.9	3.8
	RT	8.6	6.8	5.9	5.0	4.3	4.0	3.7	3.4	3.2	3.0	3.0	3.1

• Page 15, Figure 6: Studying the worst-case scenario is certainly an interesting approach to investigating the risk of the MCP with the months-long observation. On the other hand, the large errors for the data with fewer training months would be due to the outliers. I assume that there is a possibility to improve such errors by applying robust regression algorithms that are insensitive to the outliers.

Thank you for pointing out this consideration. We have added the following text to Lines 303-306:

“It is important to keep in mind that the worst-case scenario error analysis is a conservative approach that is not analogous to assessing algorithm uncertainty. Additionally, more robust algorithms than those studied in this work could reduce the sensitivity to the outliers in the shortest training timeseries that drive error in the long-term estimates.”

Review #2

The article investigates the errors associated with using wind measurements which are shorter than one year in measure correlate predict (MCP) methods to obtain representative long-term wind climates. The authors use a relatively large dataset comprising sites with a wide variation of wind conditions from different areas of the US. The results are presented in a clear manner and explained and discussed in detail. The findings highlight the value of using short-term measurements in combination with reanalysis data to improve wind resource estimations when compared to only relying on reanalysis data. The authors conclude that measurement data with durations as short as one month provide significant benefits but recommend using at least four months of measurement data.

The findings will be of interest for the wind energy community as mobile remote sensing devices like lidars have reduced the logistics associated with installing wind measurements (compared to mast-based measurements) and make short-term measurements much more viable. Moreover, short measurement periods are often used in the early stages of a measurement campaign to make intermediate assessments of the viability of wind energy projects.

Thank you very much for your helpful review! We appreciate and value your time and suggestions.

However, the following general points need to be addressed before I can recommend the manuscript for publication:

• Section 2.1: The analysis is based on quite a large dataset. While presenting lengths and heights of the individual datasets, information on the observed mean wind speeds is missing. I strongly recommend including a histogram of the mean wind speeds or at least some statistics characterizing the mean wind speeds over all stations – such as average mean wind speed, standard deviation, minimum and maximum.

A histogram of the mean wind speeds has been added to Figure 2 per your suggestion.

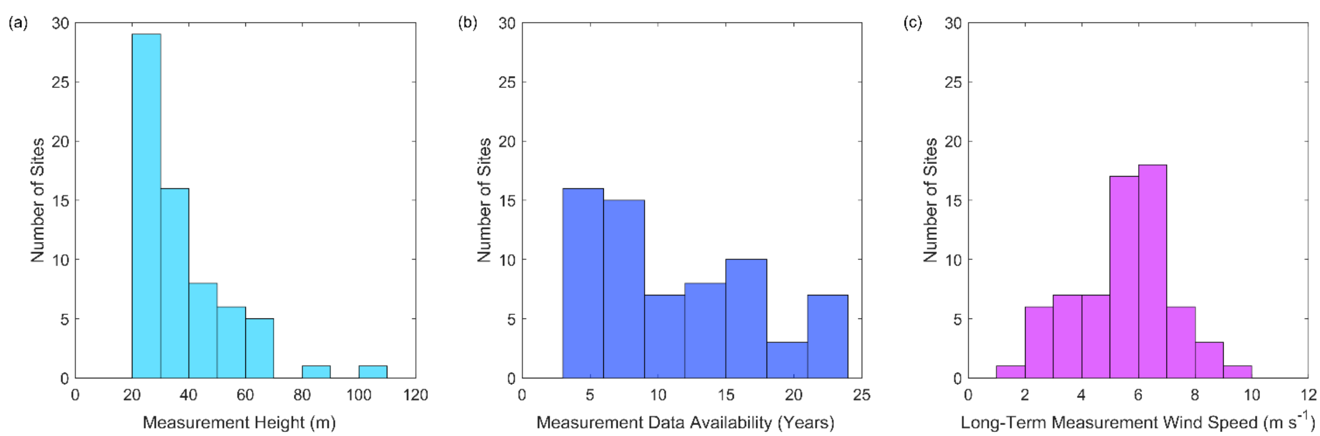


Figure 4. (a) Measurement heights, (b) long-term measurement availability, and (c) long-term measurement wind speeds for the sites evaluated for long-term performance based on months-long observations.

• Section 2.3: The authors use several different MCP methods. These include multiple linear regression, adaptive regression splines and regression trees. Linear regression but also other methods using a cost function optimizing the squared deviation between the model and the observations are well suited to perform bias corrections but have a strong tendency to create a negative bias in the variance. While the importance of errors in the variance of the long-term wind climate for resource estimation is usually smaller than the impact of errors in the mean wind speed it can be significant. For this reason, variance-conserving MCP methods have been developed [1, 2] and are now widely used in wind resource assessments. The authors should therefore clearly explain this limitation in the methods section and include the implications for estimations of annual energy production when discussing the results.

To document the limitations of the algorithms utilized in this work per your suggestions, the following has been added to Lines 184-188: "Numerous additional algorithms have been developed and tested for their ability to improve simulation accuracy, and it is important to note that each feature different approaches, computational investments, complexities, skills, and limitations. For example, Rogers et al. (2005) note that linear regression techniques are easily implemented and well suited for performing bias correction but have a tendency to create a bias in the variance that variance-conserving MCP techniques are better suited to resolve."

• Section 2.3: When introducing the MCP methods some important details remain unclear. The hyperparameters for the regression tree method are not specified. The authors should also explain how these hyperparameters were chosen. It remains unclear how the wind direction is used in the multiple linear regression approach. Due to its angular nature – i.e. 359° is next to 0° - the application of a linear regression approach including wind speed does not appear to be straightforward. In the industry, it is common to apply sectoral regression MCP [3] – i.e. binned by wind direction sectors. Authors should clearly explain why a different approach was chosen here and how their approach differs.

Thank you for your suggestion to add more information concerning the hyperparameters. We have supplemented Lines 177-184 as follows:

"Adaptive regression splines involve the construction of piecewise-cubic regression models based on the short-term target and reference datasets (Jekabsons, 2016). In this analysis, we utilise the default parameter configurations of Jekabsons (2016). The maximum number of basis functions follows the formula of Milborrow (2016): min(200, max(20, 2*the number of input variables)) + 1. The maximum degree of interactions between input variables is set to 1 for additive modelling, therefore the generalized cross-validation penalty per knot is set to 2 following the recommendation of Friedman (1991). Regression trees recursively partition and evaluate the concurrent short-term target and reference datasets into unique segments, which are subsequently used to predict long-term target behaviour. In this analysis, the ensemble aggregation method used is least-squares boosting with 100 learning cycles."

Friedman, J. H.: Multivariate Adaptive Regression Splines (with discussion), The Annals of Statistics, Vol. 19, No. 1, 1991.

Jekabsons, G.: Adaptive Regressions Splines toolbox for Matlab/Octave, version 1.13.0, http://www.cs.rtu.lv/jekabsons/Files/ARESLab.pdf, 2016.

Milborrow, S.: Earth: Multivariate Adaptive Regression Spline Models [code] (derived from code by Hastie, T. and Tibshriani, R.), https://cran.r-project.org/web/packages/earth/index.html, 2016.

We agree that using the wind direction was a misguided approach and have taken the opportunity to rework the analysis using the u and v components instead. Thank you for this helpful suggestion!

• Section 2.3 and section 3 and section 4: The presented analysis is mainly motivated by its relevance for resource assessments. However, out of the chosen error scores only the bias magnitude is of practical relevance for this application. While indicating the performance in reproducing temporal patterns, correlation and mean absolute errors are only of secondary importance in estimating AEP. This should be clearly addressed in section 2.3 and section 3 and section 4. While for other applications correlation and MAE might be more important, these applications are only briefly mentioned in lines 415ff. The provision of the standard deviation of the bias would be a useful additional performance measure as it corresponds to the uncertainty definition that is usually used in resource assessments.

Thank you for this suggestion. We have removed MAE as a featured error metric from the manuscript, though have kept correlation as we find it to be relevant for evaluating the performance of simulations in representing fluctuations in the wind, which is of interest when converting to power and assessing the implications of integration into a distribution network.

We have added the standard deviation to Figure 5 per your recommendation.

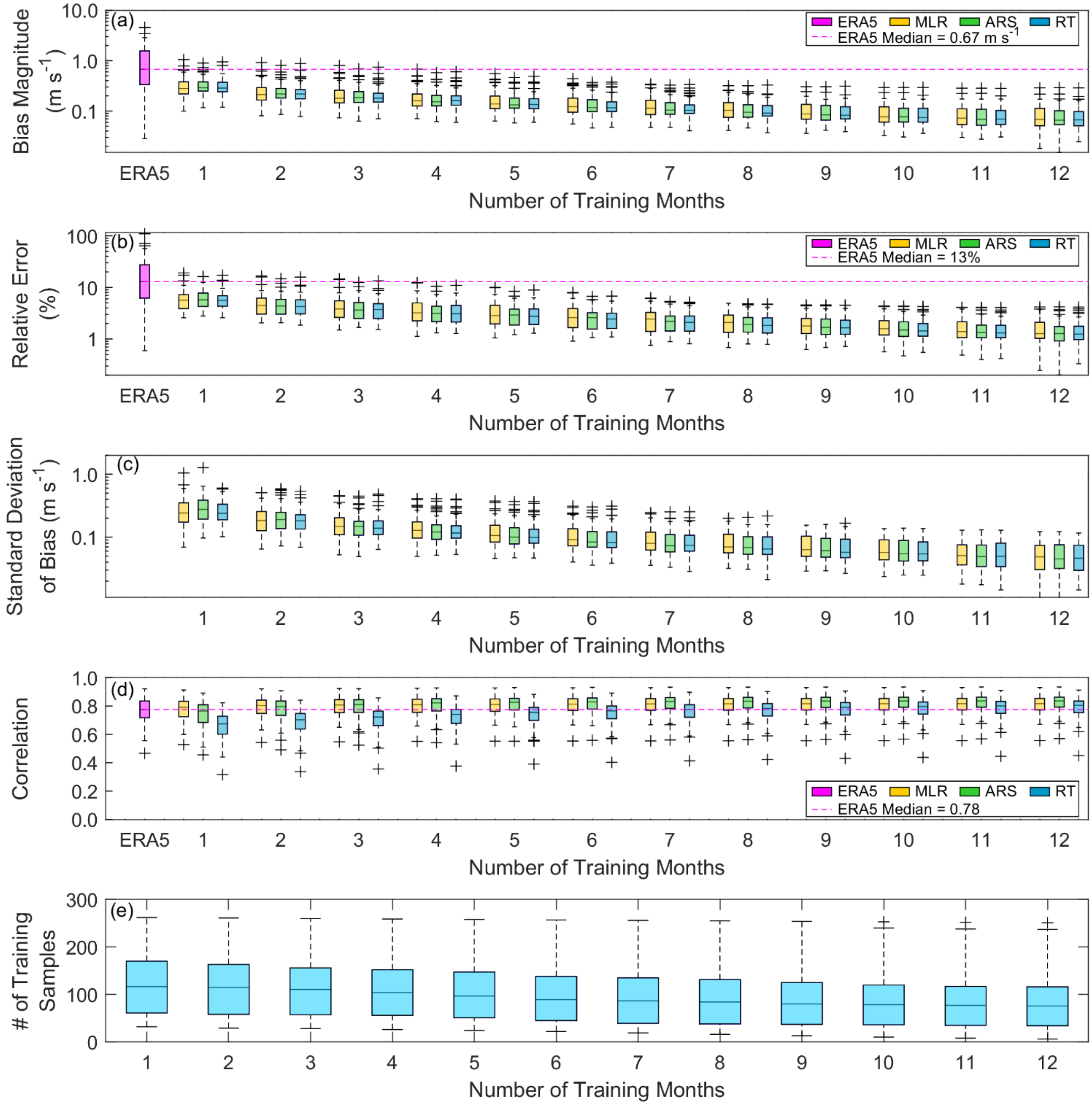


Figure 5. Average long-term (a) bias magnitude, (b) relative error, (c) standard deviation of bias magnitude, and (d) correlation for 66 sites comparing observations with ERA5 and MCP techniques using varying training period lengths, along with (e) the number of training samples per site and per number of training months.

• Section 2.3 and section 3: Wind conditions differ strongly between the different locations (cf. figure 7). The bias and MEA should therefore be presented in relative rather than absolute values or at least in relative values in addition to the absolute values currently given.

Per your helpful suggestion, we have added the relative error throughout the results section.

• Section 3.4: The approach chosen, and the conclusions drawn here are misleading for several reasons. Firstly, the analysis for all 6-months periods is performed for different sites. The different wind characteristics of these sites can cause differences in the performance of the MCP methods independently of the length of the long-term period. The observed differences might be caused by other reasons or just be coincidental. Instead of using different locations, locations with longer long-term period should be split-up artificially to obtain robust results. Secondly, increasing the length of the long-term period will result in more 6-months short-term periods in the analysis. This in turn will cause a worse performance in the worst-case scenario. This effect, however, is purely due to considerations in probability theory. A decline in the worst-case performance does not automatically relate to 'climate evolution' (line 362) as suggested. Comparing long-term periods with varying lengths directly will, thus, result in a distorted picture.

Thank you for pointing out the flaws in this analysis. We agree with your concerns and have removed Section 3.4 from the manuscript.

• Section 4: The conversion of the estimated long-term wind climates into energy provides significant added value for wind energy applications. However, the results should be presented using relative errors in the capacity factors rather than absolute values to make them more comparable. This is especially important since the reported capacity factors vary over more than one order of magnitude. Moreover, it is advisable to exclude locations with a very low wind resource, since these locations are not suitable for exploitation of the wind resource. In addition, the power production at these sites will be dominated by the tail end of the wind speed distribution and the skill of the MCP methods to reproduce the highest percentiles of wind speeds might differ significantly from their performance for a bias correction.

We appreciate your suggestion and have converted the capacity factor analysis to a study using relative errors and have removed the sites with very low wind resource using the threshold of capacity factors based on observed wind speeds that are < 10%.

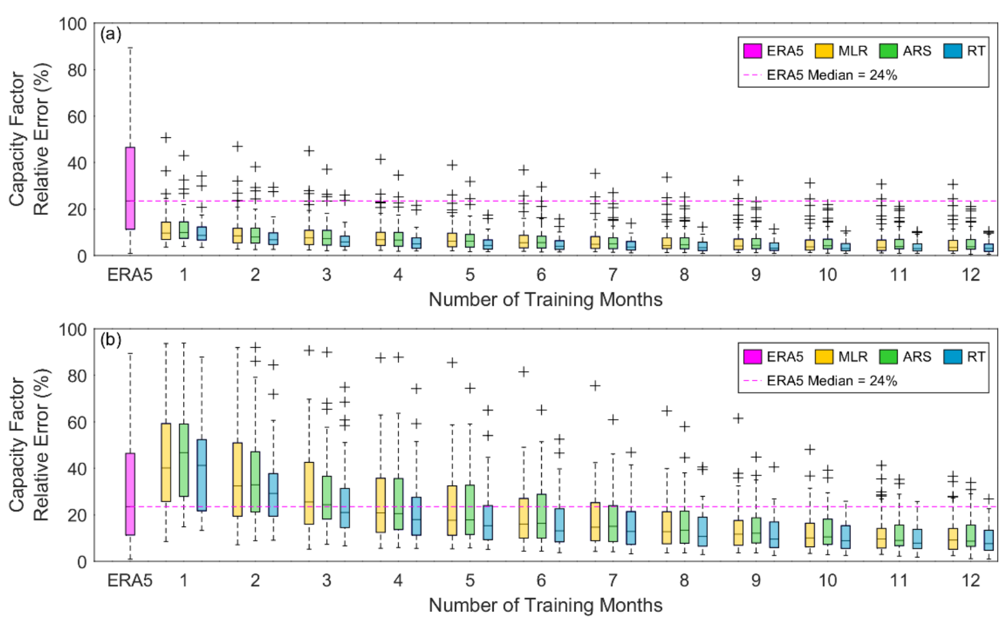


Figure 6. (a) Average and (b) worst-case scenario capacity factor relative error (|ERA5/MCP capacity factor – capacity factor based on observed wind speeds|/capacity factor based on observed wind speeds) according to number of training months for 58 sites with observation-simulated capacity factors of at least 10%.

• Section 4 has the heading ‘Discussion’. However, several new results are presented in this section. Moreover, several recommendations are drawn and observations are discussed in parts of section 3 (e.g., section 3.3 recommends that summer months should be avoided). I therefore recommend to integrate section 4 as a subsection into section 3 and rename Section 3 ‘Results and Discussion’.

Section 3 is now “Results and Discussion” with the former Section 4 integrated as Subsection 3.4, per your recommendation.

• L278: The authors state: ‘... it is imperative to consider the worst-case scenario errors ...’. While I agree that the worst-case scenario provides useful information, the current presentation and discussion of the results will overinflate the perceived uncertainties associated with using short-term measurements for MCP by looking at extreme cases and outliers. The authors should therefore either use e.g. the 90th percentile of the observed errors rather than the worst-case scenario or clearly explain that the worst-case scenario is a very conservative approach and cannot directly be interpreted as an uncertainty.

Thank you for your suggestion on how readers should interpret the worst-case scenario results. We have added the following text to Lines 303-306:

“It is important to keep in mind that the worst-case scenario error analysis is a conservative approach that is not analogous to assessing algorithm uncertainty. Additionally, more robust algorithms than those studied in this work could reduce the sensitivity to the outliers in the shortest training timeseries that drive error in the long-term estimates.”

Specific comments:

• L104f.: Many of the measurement heights are significantly lower than modern wind turbines. This should be highlighted and the limitations stemming from this point should be addressed in the discussion.

While the findings of the manuscript are hoped to be of interest to multiple wind energy sectors, the work was funded to be of primary benefit to the distributed wind sector. Hub heights for distributed wind turbines are wide ranging and, for small distributed wind turbines (≤ 100 kW capacity), often occur at those lower heights between 20 m and 40 m.

We have modified Lines 105-107 to improve the relevance as follows: “Many of the lowest observations, which align with small distributed wind turbine hub heights (between 20 m and 40 m), source from the National Data Buoy Center and are located along coastlines. The highest observations, which align with large distributed wind turbine hub heights (between 80 m and 100 m), are in Long Island, New York (85 m) and the San Francisco Bay Area, California (100 m).”

Additionally, per a suggestion from another reviewer, we have provided the ERA5 error metrics broken out by height ranges to Figure 3 to provide more insight into model performance at various heights. We have also added the accompanying text to Lines 155-158: “No consistent trends in ERA5 performance are noted according to height above ground (Figure 3d, e, f). The wind speed relative errors are greatest for measurement heights between 30 m and 40 m (median = 31%), while the median relative errors for measurement heights between 1) 20 m and 30 m and 2) 40 m and 50 m are 11% and 10%, respectively.”

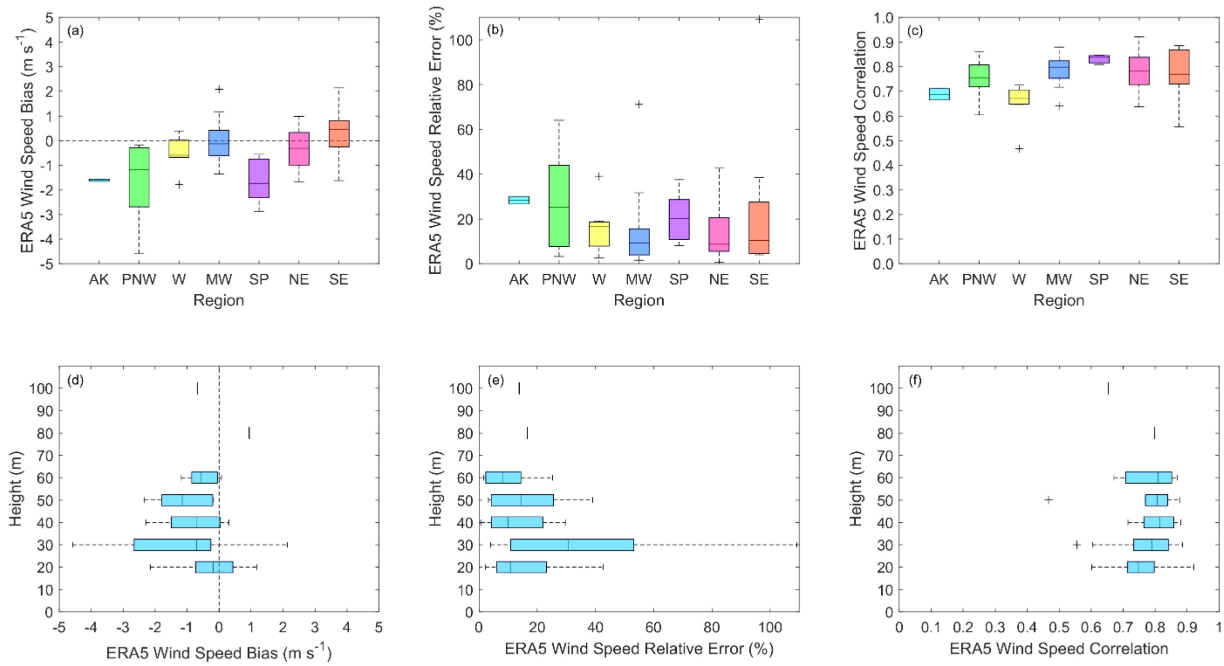


Figure 7. Long-term ERA5 wind speed (a), (d) bias (b), (e) relative error, and (c), (f) correlation across 66 measurement sites in the United States, grouped by region (top) and measurement height (bottom). AK = Alaska, PNW = Pacific Northwest, W = West, MW = Midwest, SP = Southern Plains, NE = Northeast, and SE = Southeast.

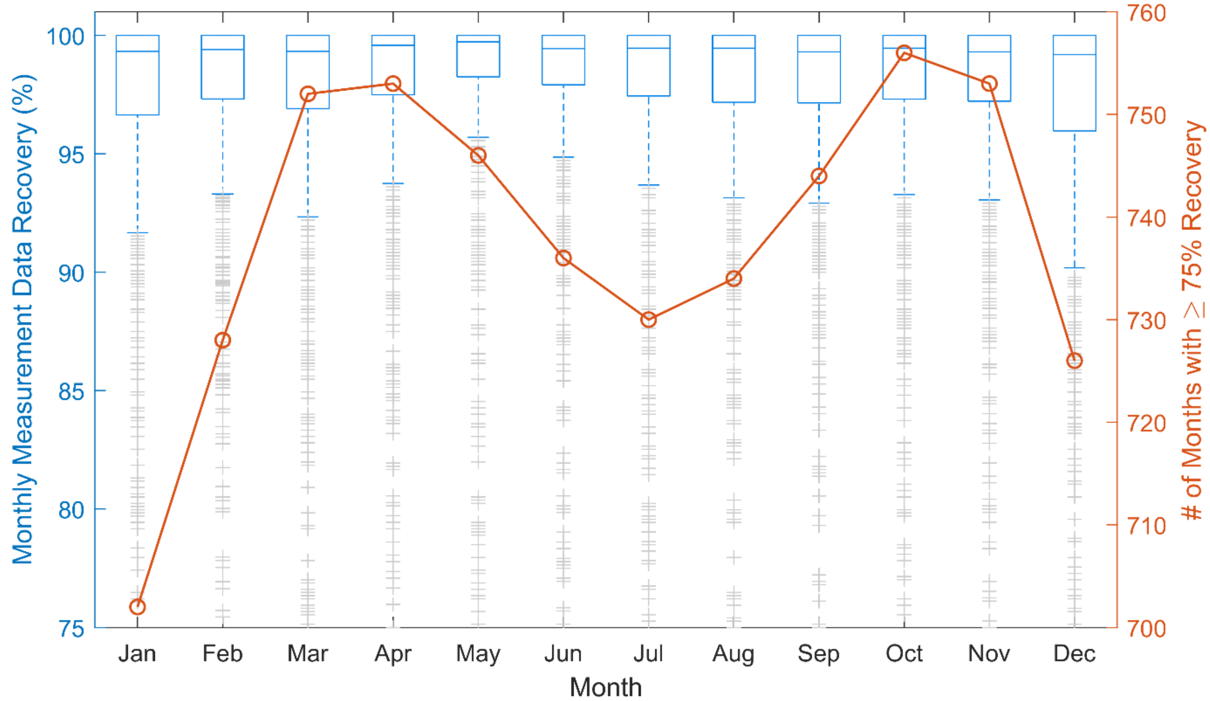
• L131ff.: This section is not related to the heading of the subsection (Reanalysis model for longterm correction). Consider moving it to a separate subsection.

Agreed. We have moved it to a separate subsection (2.3) entitled “Metrics for performance evaluation.”

• L206f.: ‘... provided each month in the training period meets the data recovery and quality threshold of 75%.’ Are there any seasonal patterns in data recovery i.e. caused by icing in winter? This could influence the results.

We appreciate this interesting suggestion, and have added a new figure and accompanying text to the manuscript in response (Lines 233-235):

“Across the measurement sites, calendar months in the spring and fall had the most single instances of ≥75% data recovery and quality, followed by summer, and lastly winter. Median measurement data recovery and quality percentages according to calendar month ranged from 99.2% (December) to 99.7% (May).”



• L442 states 'The results of this work highlight the benefits of anemometer or lidar loan programs'. The performed analysis, however, only highlights the benefits of short-term onsite measurements. Anemometer loan programs only provide one option to facilitate these.

The sentence has been rephrased as follows (Lines 450-452): "The results of this work highlight the potential for anemometer or lidar loan programs to affordably assist future distributed wind energy customers with more accurate long-term wind resource estimates while maximizing the number of customers that can be served by reducing the measurement time needed."

• L52ff.: Here the authors discuss previous research that was conducted on MCP methods. Lil´eo et al. [4] published a comprehensive report that should be included in the discussed literature and might also be useful when discussing the results.

Thank you for this reference. We have added it to the discussion on Lines 53-55: "The vast majority of wind resource assessment literature supports collecting at least one year of onsite measurements to represent a full seasonal wind cycle, including the analyses of Dinler (2013), Liléo et al. (2013), Mifsud et al. (2018), Zakaria et al. (2018), Tang et al. (2019), and Chen et al. (2022)."

• L116ff.: The characteristics and performance of the ERA5 dataset are discussed. Recently Wilczak et al. [5] published an evaluation of ERA5 evaluating regional biases in ERA5 for different regions in the US. This reference would provide value here and in the discussion in section 3.2.

We have added the results from this helpful paper to our manuscript as follows:

Lines 130-132: "Using measurements from more than 100 onshore and offshore lidars, sodars, and meteorological towers across the United States, Wilczak et al. (2024) determined that ERA5-derived wind power estimates were biased low by 20%."

Lines 159-162: "The tendencies of ERA5 to underestimate the observed wind speeds in this analysis while exhibiting a relatively high degree of correlation with them aligns with the findings of Ramon et al.

(2019), Murcia et al. (2022), Sheridan et al. (2022), and Wilczak et al. (2024) discussed in Section 2.2. The bias trends according to region (Figure 3a) also align with the findings of Wilczak et al. (2024) in that ERA5 underestimation is noted in the Pacific Northwest and Southern Plains, while a mix of overestimation and underestimated is noted for the Midwest."

• L238f.: 'Using one month of training, MLR provides higher correlations (median = 0.79) than ERA5 (median = 0.78)' This difference seems rather small and maybe not even statistically significant. Should be rephrased.

We agree and have rephrased the sentence as follows (Lines 263-265): "Using one month of training, MLR and ARS produce similar correlations (medians = 0.79 and 0.78, respectively) to ERA5 (median = 0.78), while the RT correlations are quite a bit worse (median = 0.68)."

References

[1] Anthony L. Rogers, John W. Rogers, and James F. Manwell. Comparison of the performance of four measure–correlate–predict algorithms. Journal of Wind Engineering and Industrial Aerodynamics, 93(3):243–264, 2005.

[2] S.M.Weekes and A.S. Tomlin. Data efficient measure-correlate-predict approaches to wind resource assessment for small-scale wind energy. Renewable Energy, 63:162–171, 2014.

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