Reviewer's comments on "Evaluating the potential of short-term instrument deployment to improve distributed wind resource assessment" by Lindsay M. Sheridan, Dmitry Duplyakin, Caleb Phillips, Heidi Tinnesand, Raj K. Rai, Julia E. Flaherty, and Larry K. Berg

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.

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.

- 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.

- 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.

- 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.

- 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.

- 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.

- 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.

- 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'.

- 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.

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.

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

- 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.

- 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.

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

- 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.

- 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.

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.

[3] MEASNET. Evaluation of site-specific wind conditions, 2022.

[4] S. Liléo, E. Berge, O. Undheim, R. Klinkert, and R. E. Bredesen. Long-term correction of wind measurements-state-of-the-art, guidelines and future work. Technical Report Elforsk report 13:18, 2013.

[5] J. M. Wilczak, E. Akish, A. Capotondi, and G. P. Compo. Evaluation and bias correction of the era5 reanalysis over the united states for wind and solar energy applications. *Energies*, 17(7), 2024.