General Comments:

The paper reports on a well-reasoned and performed piece of work related to wind speed and wind energy assessment for small, distributed wind turbines. The approach taken, data used, and results presented are useful and needed, and the work represents a step forward. Identification of the source data is useful, especially for any that would like to use the wind simulation data from the sources listed. Typical proposed small wind turbine installations do not have good met tower or weather data from nearby sources, so the use of simulation data is very practical, and thus the some understanding of its ultimate accuracy in predicting AEP is critical.

Thank you, Dr. Acker, for your time, positive feedback, and suggestions for improvement of our article. We are very grateful and have addressed your comments in the revised draft as outlined below. Thank you again!

Specific Comments:

The wind speed bias errors are only positive for the smallest wind speed bin plotted in Fig. 5 (0-5 m/s), yet the wind turbine capacity factors are almost all overpredicted (Fig. 7). This seems to imply that the wind speed spends most of its time in the lowest wind speed bin. However, most of the wind power curves shown in Fig. 2 show little production in this wind speed range. Would it be possible to add to Fig. 5 the percent of time that the wind speed was in each wind speed bin? That could help in interpreting the results. Moreover, if they possess sufficient time resolution in the wind turbine production data, it would be helpful if the authors provided an explanation for the overestimate of capacity factor… at which wind speeds (or wind speed bins) does the overestimate of energy occur?

We appreciate the suggestion to add the percentage of time spent in each wind speed bin, and have transformed Fig. 5 into Fig. 5a, which shows the frequency of occurrence for each wind speed bin, and Fig. 5b, which depicts the wind speed bias according to each wind speed bin. The frequency analysis reveals that the wind speed does spend most of its time in the lowest wind speed bin. Model wind speed overestimation of observed wind speeds in the 0 – 5 m $s^{-1}$ range can lead to significant production overestimation, given the transition from zero power to the steep portion of the power curve around cut-in speeds.

While a subset of the turbines do possess high-resolution (10-second) production data, a lack of on-site hub height wind speed measurements presented the first hurdle to directly correlating wind speed to simulated energy production under/overestimation. The authors considered using bias-corrected reanalysis wind speeds, based on the results of Sect. 3.1, in conjunction with the production data rolled up to an hourly resolution, but encountered a final hurdle with the lack of similar temporal resolution and overlap within the tools. For example, the APRS World collection began outputting 10-second production data within the last few years (monthly kWh total production values are available prior to that), while the latest year that SAM provides hourly production simulations for is 2013. We wish that we could incorporate this analysis for this collection of turbines and tools, and hope to revisit the concept as tools increase temporal coverage and resolution.

The (simulated – actual) capacity factors for 55 turbines are presented in Fig. 7, split up by region of the country. Another interesting categorization would be by "surface roughness" or something similar that provides an indication of whether the area in the vicinity of the turbine is forest, fields, etc. It would also be nice to sort by complex terrain vs non-complex, and to provide some suggestion of how to distinguish between the two. Have the authors considered looking at the data in these ways?

We are thankful for the excellent suggestions on different ways to visualize the capacity factors errors. Fig.7 now includes Fig. 7d, which examines the capacity factor errors according to the land cover categories provided by the Copernicus Global Land Cover dataset (https://lcviewer.vito.be/). The turbines in this collection fall into the following categories: herbaceous vegetation/shrubland, cropland, forests, and built up. By including this analysis, we learned that the highest energy production overestimation occurs in forested locations. We appreciate the suggestion, and the discussion can be found on lines 375-384 of the revised draft.

We also created Fig. 7e, which estimates terrain complexity by considering the difference in maximum and minimum elevation within a 2 km radius of each turbine using the ASTER Global Digital Elevation Model V003 (https://cmr.earthdata.nasa.gov/search/concepts/C1575731655-LPDAAC_ECS.html). One of the tools (MyWindTurbine.com) showed an average trend of increasing error with increasing terrain complexity. The remaining tools exhibited no such average trends in capacity factor error according to terrain complexity, however, extreme tool underestimation outliers were found in accordance with complex terrain. The discussion can be found on lines 385-393 of the revised draft.

Fig. 10 shows availability statistics for 9 turbines of varying ages. Why were only nine turbines used? Also, did the authors sort the availably by turbine age?

The nine turbines were originally selected to provide a geographically-diverse overview of availability. Your question encouraged us to present the entire suite of turbines with availability information (36 of the 55 turbines), the discussion of which can be found on lines 457-485 of the revised draft. Additionally, Fig. 10 was reimagined to sort the availability data according to turbine age, per your suggestion.

Thanks to your encouragement to further develop this section, we learned that the annual *average* percent of time missing or spent in a stopped/fault state ranged from 14% to 30%, and only SAM's loss assumption falls within this range (18%). The annual *median* percent of time missing or spent in a stopped/fault state ranged from 4% to 18%, and the loss assumptions from all the tools falls within this range.

For the conclusions: Do the authors have any recommendation about how a person whose job is estimating small wind turbine AEP/capacity factor should account for interannual variability, given its significant influence on capacity factor?

We are grateful for this suggestion to tie the findings together and provide recommendations for the small wind community. We have added the following text to lines 522-528 in the conclusions:

"Given the significance of interannual variability on turbine production estimates, the authors recommend that small wind turbine production estimators utilize a tool that provides a range of annual production possibilities in order to set expectations for average, high, and low wind resource years. For currently deployed small wind turbines, an owner can estimate whether the wind resource during the current or near future time period will be above or below average by considering climate oscillations, such as the El Niño-Southern Oscillation. Hamlington et al. (2015) correlates La Niña events with faster wind speeds and El Niño events with suppressed wind speeds across the U.S. Great Plains."

Hamlington, B. D., Hamlington, P. E., Collins, S. G., Alexander, S. R., and Kim, K-Y., Effects of climate oscillations on wind resource variability in the United States, Geophysical Research Letters, 42, 145-152, doi:10.1002/2014GL062370, 2015.

Technical Corrections:

Page 6 Line 148: Should read "2.1 kW to 56 kW" NOT "8.9 kW to 56 kW"

Thank you for catching this error! We have made the change to "2.1 kW."

I believe the Southwest WindPower Skystream is now owned by Xzeres. Perhaps some mention should be made of this when introducing the turbine?

A footnote has been added to Table 2, stating that "Southwest Windpower closed in 2013 and the remaining Skystream assets were acquired by the now-defunct XZERES Corporation. The Skystream turbine models included in this analysis were installed in 2008 through 2012." Thank you for the suggestion!