In this document, the reviewer's comments are in black, the authors' responses are in red.

The authors thank the reviewer for their thoughtful and productive comments.

General comments

The authors have worked to propose a more statistically accurate method for operational AEP wind farm estimates through correlations with various sources of uncertainty. The topic is certainly worthwhile, as large projects involve huge financial contributions and associated risk. Overall the paper is well laid and out and written. As per the comments, there are a number of places where wording and figure captions need improvement for clarity. Similarly, some specific details of the method and metric equations need better definition.
Thank you for finding our manuscript interesting and well written. We have addressed your specific comments to add clarity to our paper.

My main challenge with the paper is the use of the word 'uncertainty' in a non-precise manner. Uncertainty accrues from various sources including measurement errors (epistemic) and underlying stochastic processes (aleatoric). Moreover, the statistical quantification of that uncertainty has to be careful, whether it's a uniform, normal, or other distribution that describes the range of uncertain values (PDF of values). The paper is a bit too loose in using the term uncertainty, and also in the numerical MC sampling of those variables assumed uncertain. Tightening up the presentation in this respect would really help statistical validity and understanding of the method and results.
We have addressed your specific comments on the theme, to add more rigor to the description of our analysis.

Specific Comments

1. ln 25; I wonder given the emphasis of the paper on AEP if better figures to quote would be GWh produced vs. (or in addition to) GW installed capacity?
   We have added the following sentence to the paragraph: "In the United States, wind farms generated over 300,000 GWh in 2019, about 7.5 % of the total US electricity generation from utility-scale facilities that year, with a 50% increase over a 6-year period (Energy Information Administration, 2020).".

2. Around Table 1: Need to define windiness correction factor (formula, etc). The word 'accuracy' used throughout table; is that true? or is it really combination of epistemic and aleatoric uncertainties? Really need to discuss more on sources of uncertainty in terms of measurement errors and underlying stochastic processes involved.
   We have aligned the terminology used in Table 1:

Uncertainty component	Description
On-site measurements	Measurement error in met mast wind speeds (pre-construction) or power at the revenue meter (operational)
Reference wind speed data	Measurement or modeling error in long-term reference measured or modeled wind speed data
Losses	Error in estimated or reported availability and curtailment losses
Regression	Sensitivity in the regression relationship between on-site measurements and reference wind speeds
Long-term (windiness) correction	Sensitivity in the long-term correction applied to the regression relationship between on-site measurements and reference wind speeds
Inter-annual variability of resource	Sensitivity in future energy production because of resource variability

Table 1. Main Sources of Uncertainty in a Long-Term Operational AEP Estimate.

3. In the intro discussion on operational AEP estimates, the wording seems a little counterintuitive, in that AEP can be calculated exactly (in terms of delivered energy) given the data (and just whatever error in the power meter itself). I think a little rewording here talking more about the purpose of operational AEP for e.g. future year operations, etc. would help reveal the intent and importance of the work.
   We have now referred to operational AEP as "long-term operational AEP" in many places throughout the introduction. Moreover, we think the following sentence in the introduction will clarify the point to the reader: "operational estimates of long-term AEP are required for important wind farm transactions, such as refinancing, purchasing/selling, and mergers/acquisitions."

4. Would be nice to explicitly relate eqn 2 back to CP equation for readers to understand exponential weighting.
   We have rephrased this part as:

   The wind speed data are density-corrected at their native time resolutions to correlate more strongly with wind farm power production (i.e., higher density air in winter produces more power than lower density air in summer, wind speed being the same):

   $$U_{\text{dens,corr}} = U\left(\frac{\rho}{\rho_{\text{mean}}}\right)^{1/3} \quad (2)$$

   where $U_{\text{dens,corr}}$ is the density-corrected wind speed, U is the wind speed, ρ is air density (calculated at the same height as wind speed), ρ_{mean} is the mean density over the entire period of record of the reanalysis product, and the exponent $1/3$ is derived from the basic relationship between wind power and wind speed cubed (Manwell et al., 2010). To calculate air density at the

5. ln 95; the data exclusions that end up being geographically driven suggest the need for some more discussion here (or later) on the ramifications for the correlations uncovered; i.e. are there physical reasons the correlations would be different for more complex terrain locations?
   We have added the following sentence at the end of Section 3.2: "Finally, we note that although the sites selected for this analysis are primarily in simple terrain (Figure 1), we do not expect more complex topography to impact the correlations revealed from the Monte

Carlo analysis, as all the underlying relationships would also be applicable to more complex sites.”.

6. list in lns 105-115; not clear what ’regression’ in item 5. Also 10-20 years of hindcast (vs. forward prediction) right?
   We have rephrased this part to make more explicit which regression is performed: “A linear regression between monthly gross energy production and concurrent monthly average wind speeds is performed.”
   We have also added details to the description of the long-term data used to clarify that these are past data, i.e. a hindcast approach: “Long-term monthly average wind speed is then calculated for each calendar month (i.e., average January wind speed, average February wind speed, and so forth) with a hindcast approach, using 10--20 years of the available long-term reference monthly wind resource data (reanalysis products, long-term reference measurements, ...).”

7. Fig 2 ‘Wind IAV’ not defined.
   The caption of the Figure now states: “Note: IAV denotes inter-annual variability.”

8. Did you consider more efficient Monte Carlo sampling methods, and/or convergence of statistics at 10000 samples?
   We have tested the convergence of the Monte Carlo AEP distribution at 10,000 samples, and added the following sentence to the paragraph: “Convergence of the AEP distribution within 0.5% of the true mean after the 10,000 Monte Carlo runs was verified for all projects, with a 95% confidence.”

9. Table 2; need to define pdf type for each uncertain variable (uniform, normal, etc.) Would also be nice to see more justification for e.g. 0.5% uncertainty values assumed.
   We have greatly improved the description of the single uncertainty components considered in our analysis. We have added information on the pdf type used, and justified the choice of 0.5% for the revenue meter uncertainty. The paragraphs now read:

2.3 Monte Carlo Analysis

To quantify the uncertainty of the long-term operational AEP estimate obtained using the methodology described in the previous section, we implement a Monte Carlo approach. In general, a Monte Carlo method involves the randomized sampling of inputs to or calculations within a method which, when repeated many times, results in a distribution of possible outcomes from which uncertainty can be deduced, usually calculated as the standard deviation or the coefficient of variation of the resulting distribution (ISO and OIML, 1995; Dimitrov et al., 2018). Here, we apply this approach to derive a distribution of long-term operational AEP values, from which its uncertainty can be calculated. To do so, we consider and include in the Monte Carlo approach five operational-based uncertainty components, so that five different samplings are performed at each Monte Carlo iteration. The following uncertainty components are included in our proposed Monte Carlo methodology for long-term operational AEP:

– Revenue meter measurement error. We incorporate this uncertainty component in the Monte Carlo simulation by sampling monthly revenue meter data from a normal distribution centered on the reported value, and 0.5% standard deviation. In fact, a value of 0.5% is coherent with what is typically assumed in the wind energy community as revenue meter uncertainty (IEC 60688:2012; ANSI C12.1-2014).

– Reference wind speed data modeling error. Quantifying the uncertainty of the long-term wind resource data used in the operational AEP assessment is challenging, as it can vary based on the location, long-term wind speed product used, or instrument from which reference observations are taken. To include this uncertainty component in a systematic way across the 472 locations considered in our analysis, we incorporate it in the Monte Carlo simulation by randomly selecting, at each iteration at each site, wind resource data from one of the three considered reanalysis products.

– Linear regression model uncertainty. This component is incorporated in the Monte Carlo method by sampling the regression slope and intercept values from a multivariate normal distribution centered on their best-fit values and covariance matrix equal to the one of the best-fit parameters. The diagonal terms in the covariance matrix are given by the square of the slope and intercept standard errors. For a regression model between an independent variable x and a dependent variable y the standard error of the regression is defined as

$$e_y = \sqrt{\frac{\sum (y_i - \hat{y_i})^2}{n-2}}, \tag{4}$$

where $\hat{y_i}$ is the regression-predicted value for y_i, and n is the number of data points used in the regression. The standard error of the regression slope:

$$e_a = \frac{e_y}{\sum (x_i - \overline{x_i})^2}, \tag{5}$$

and the standard error of the intercept:

$$e_b = e_y \, e_a \sqrt{\frac{\sum x_i^2}{n}}. \tag{6}$$

e_a^2 and e_b^2 are the diagonal terms in the covariance matrix of the multivariate normal distribution of regression slope and intercept, from which Monte Carlo values are drawn. Slope and intercept values are strongly negatively correlated, which is captured by their covariance when performing the linear regression. The off-diagonal terms in the covariance matrix of the multivariate normal distribution constrain the random sampling of slope and intercept values, to avoid sampling unrealistic combinations. An example of this sampling is shown in Figure 4 for two projects of different regression strengths. We sample 500 slope and intercept values from a multivariate normal distribution centered around the best-fit parameters, and with covariance matrix derived from the standard errors of slope and intercept and their covariance. As shown in the Figure, the low standard errors found for the leftmost regression relationship constrain the possible slope and intercept values that can be sampled while the high standard errors in the rightmost regression relationship allow for a much wider sampling.

– Long-term (windiness) correction uncertainty. We incorporate this component by sampling the number of years (between 10 and 20) to use as the long-term wind resource data to which the regression coefficients are applied to derive long-term energy production data (the so-called windiness correction).

– Wind resource inter-annual variability (IAV) uncertainty. We incorporate this uncertainty component in the Monte Carlo method by sampling the long-term (reanalysis) average calendar monthly wind speeds (i.e., average January, average February) used to calculate long-term monthly energy production data. The sampling distribution is normal, centered on the calculated long-term average calendar monthly wind speed, and with a standard deviation equal to the 20-year standard deviation of the long-term average monthly wind speed for each calendar month.

Each of the listed sources of uncertainty corresponds to a Monte Carlo sampling, and is highlighted by a probability distribution in the flowchart in Figure 3. Note that uncertainty components related to availability and curtailment losses are not considered in our approach because the EIA 923 database does not include measurements of these losses.

10. Fully linking Table 2 variables explicitly in Fig 2 would help to understand the method.
The last part of the paragraph copied above connects the detailed explanation of the uncertainty components with what shown in Figure 2. We have also changed the diagram to have it better match the description in the test:

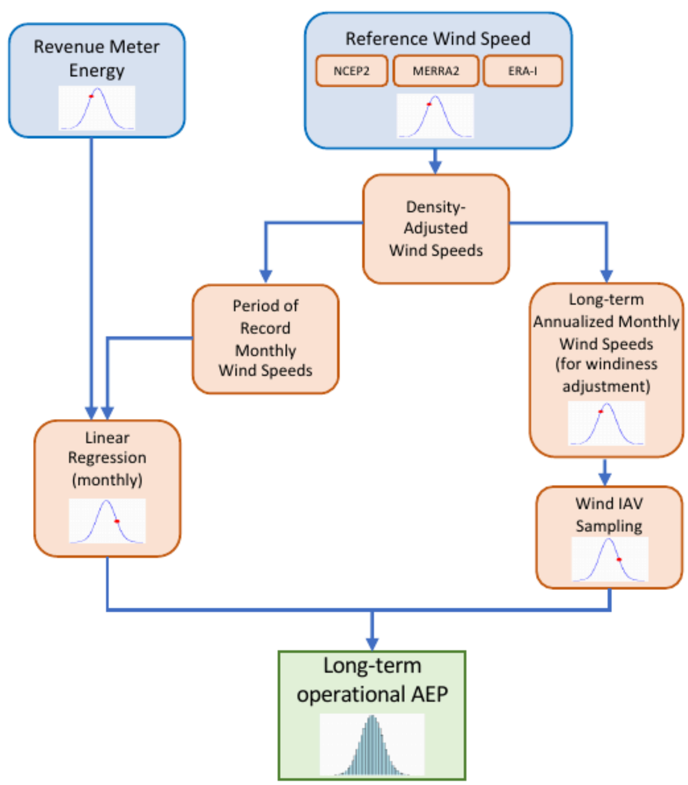

Figure 3. Long-term annual energy production (AEP) estimation process using operational data under a Monte Carlo approach; sources of uncertainty and points of Monte Carlo sampling are denoted by probability distribution images. Note: IAV denotes inter-annual variability.

11. Around ln 140; define how covariance defined, and numerical procedure in MC for ensuring the covariance is respected.
    We have added more details to the description of the technique used, as can be seen in the linear regression model uncertainty paragraph shown in the answer to specific comment #9.

12. Throughout the word uncertainty is used; I think you're always meaning standard deviation, but need to explicitly define as numerical results are presented
    We have clarified in many parts throughout the manuscript that we quantify uncertainty in terms of the coefficient of variation of the AEP distribution.
    In Section 2.3, we have added the following sentences to make clear how we calculate the total AEP uncertainty and its components: "The total uncertainty in operational AEP is then estimated as the coefficient of variation of the resulting distribution." And also "We quantify the impact of each single uncertainty component on the operational AEP in terms of the coefficient of variation of the distribution of operational AEP resulting from the Monte Carlo simulation run when sampling only that single uncertainty component."
    In Section 3.1 we now have: "The application of the different setups of the Monte Carlo approach first allows for an assessment of the distributions of the total operational-based AEP uncertainty and of its single components across the 472 wind farms, expressed as percent coefficient of variation (Figure 5)."
    Caption of Figure 5 now includes: "Uncertainty values are quantified as the percent coefficient of variation of the AEP distribution."
    Caption of Figure 6 now explicitly states: "Uncertainty is quantified as the percent coefficient of variation of the resulting AEP distribution."
    We have also decided to use CoV instead of σ in equation 7.

13. It's not clear to me what's been plotted in Fig 4? How is uncertainty defined in % terms? How is computed across your results sets? Is that eqn 7?
    We have clarified this point - see our answer to previous comment.

14. Define which data used to make Fig 7.
    We have rephrased the paragraph as "The correlation between linear regression and reference wind speed data uncertainties can be justified given the dependence of both these uncertainty components on the number of data points used in the regression between energy production data and concurrent wind speed data (Figure 8)".
    We have also changed the caption as "Dependence of linear regression uncertainty and reference wind speed data uncertainty on the number of data points in the period of record, for the 471 projects considered in the analysis."

15. In conclusions, towards a universal method, should explore MC sampling convergence requirement. Also, the assumed distribution type (as defined presumably by the 'uncertainty') is undefined, so not clear how to implement and assumptions there.
    We have added the following sentence: "For all the projects considered in this study, the Monte Carlo simulation reached convergence within 10,000 runs." Regarding the distribution type of the various uncertainty components, since each component involves

different ways to be incorporated in the Monte Carlo approach, we have the details of the methods in Section 2.3.