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

The authors thank the reviewer for their additional thoughtful comments.

General comments

The revised manuscript is significantly improved, also including responses to all of this reviewer's comments/questions about the previously submitted (initial) draft.
The title is now more appropriate (operational AEP only), and numerous (formerly ambiguous or unclear) key aspects have been clarified.
Thank you for acknowledging the improvements in our manuscript.
We would like to point out that further major changes have been implemented in the latest version of the paper, following the comments by both reviewers.

The abstract is also better, though it is still lacking `in conclusion': since the stated purpose is to "examine the extent to which the assumption of uncorrelated uncertainties...is accurate and appropriate for operational AEP calculations", you should clearly state how large of an effect on AEP uncertainty estimation occurs, due to this assumption.
We have added the following sentence to the abstract: "We quantify that ignoring these correlations leads to an underestimation of total AEP uncertainty of, on average, 0.1%, and as large as 0.5% for specific sites. Although these are not large increases, these would still impact wind plant financing rates; further, we expect these values to increase for wind plants in complex terrain."

Further, it should be made clear that the results are for low-uncertainty sites, i.e. simple flow-regimes, where you have rejected all sites/data that do not correlate well (R<0.6) with the re-analysis products. This should perhaps also be included in the abstract.
It would be useful and honest to state how many sites were rejected based on the LTC R>0.6 criteria (the conclusions might be different if higher-uncertainty/more complex sites were included; low-uncertainty behaviors tend to be more easily linearized and correlated).
We have included the following additions in the revised manuscript to acknowledge the fair point the reviewer is raising:

- Abstract: "… operational AEP estimates for over 470 wind farms in the United States, mostly in simple terrain." and again: "we expect these values to increase for wind plants in complex terrain."
- Section 2.1.: "To lessen the impact of limited and/or poor-quality data on the results of our analysis, we filter for wind farms with a moderate-to-strong correlation with all three reanalysis products (R2 > 0.6). About 25% of the EIA wind farms are discarded with this filter."
- Section 3.1: "As already mentioned in Section 2, these results are obtained for wind plants in mostly simple terrain and with a moderate-to-strong correlation between reanalysis wind resource and wind energy production and, therefore, with an overall low operational AEP uncertainty. We acknowledge that the inclusion of wind plants with a weaker correlation with the reanalysis products would modify the relative contribution of the various uncertainty components (e.g., the importance of the regression uncertainty would increase)."

- Conclusions: "Moreover, our analysis excluded sites, mostly in complex terrain, with a weak correlation between reanalysis wind resource data and wind power production. Future work could explore the magnitude of operational AEP uncertainty and the correlation between its components for such complex flow regimes."

The addition of Figure 2 helps also; though it should be clear that the regression technique is usable in part because the speeds have been density-corrected (and normalized).
As per the reviewer's specific comments below, we have specified throughout the manuscript that the linear regression was performed using density-corrected wind speed data. The same specification has been added to the caption of Figure 2.

There is still some lack of clarity about several points, which are mentioned in the specific corrections below.

Specific corrections/suggestions

- line 13 (abstract): how is the Monte-Carlo approach more robust than simple sum-of-squares?
  We have rephrased as "Based on these results, we conclude that correlations between the identified uncertainty components should be considered when computing the total AEP uncertainty."

- line 52–53: perhaps there should also be a citation of the general engineering (measurement) uncertainty standard, GUM, which includes accounting for correlations between uncertainty components.
  We have rephrased the whole paragraph as "The uncertainty values from each component listed in Table 1 must be combined to produce a total estimate of AEP uncertainty. While general guidelines on how to combine (measurement) uncertainty components exists exists (ISO, IEC and OIML, BIPM, 1995), and can be applied to this task, we found no specific guidance in the literature for combining uncertainty components in an operational AEP estimate. On the other hand, considerable guidance exists for combining preconstruction AEP uncertainties (Lackner et al., 2007; Brower, 2012; Vaisala, 2014; Kalkan, 2015; Clifton et al., 2016)."

- Line 81: using M-O theory based on MERRA-2 heat and momentum fluxes?
  Correct, but please note that the product we used is provided in MERRA-2 directly, we did not apply any interpolation ourselves.

- line 95: reference the International Standard Atmosphere (ISO 2533:1975).
  Added.

- line 101-4: you should state how many sites were rejected due to poor correlation with the re-analysis products. Such site/data rejection limits the analysis and conclusions to sites with lower uncertainty, particularly regarding the long-term correction (windiness). Limiting to low-uncertainty sites can simplify various behaviors; e.g. the correlations may be stronger between uncertainty components.

We have added this information: “To lessen the impact of limited and/or poor-quality data on the results of our analysis, we filter for wind farms with a moderate-to-strong correlation with all three reanalysis products (R2 > 0.6). About 25% of the EIA wind farms are discarded with this filter. We also impose a threshold of eight months of wind plant data availability in order to investigate uncertainty as it relates to a low number of data points---but not so low as to make the use of a regression relationship questionable. A total of 472 wind plants are kept for the final analysis, and their locations are shown in Figure 1.”

- Line 109, 111,112: "wind speed" needs to be preceeded by _'density-corrected'_ in order to support the linear regression.
  We have added the specification.

- line 120: remove `instead'; perhaps italicize `operational' to emphasize this in comparison with non-operational (pre-construction) uncertainties.
  Done.

- l.121-122: How many consultants? The term "industry standard" is (likely) too strong for the characteristics you list, unless you can support the variety and number of conversations, and their representativeness for the wind industry across the world. (E.g. is this from consultants in the Americas, or Europe, or Asian markets?)
  We have rephrased as “we base our methodology on conversations with four major wind energy consultants which represent most of the operational market share in North America. These conversations overwhelmingly revealed the following characteristics for operational AEP analysis:”

- line 130, 131, 134: not just monthly average wind speed, but _density-corrected_ monthly-average speeds. Be clear about what is being 'operated upon'.
  We have added the specification.

- line 135: not just "gross" energy production, but _estimated_ gross energy production.
  Corrected.

- l.154-5: you don't sample meter data per se, you generated/synthesized using a Gaussian distribution.
  Correct, we have rephrased as “To incorporate this uncertainty component in the Monte Carlo simulation, we sample monthly revenue meter data from a synthesized normal distribution centered on the reported value and 0.5% imposed standard deviation.”

- l.156: "coherent" should be "consistent" (or is it equal to that in the IEC-60688?)
  Corrected.

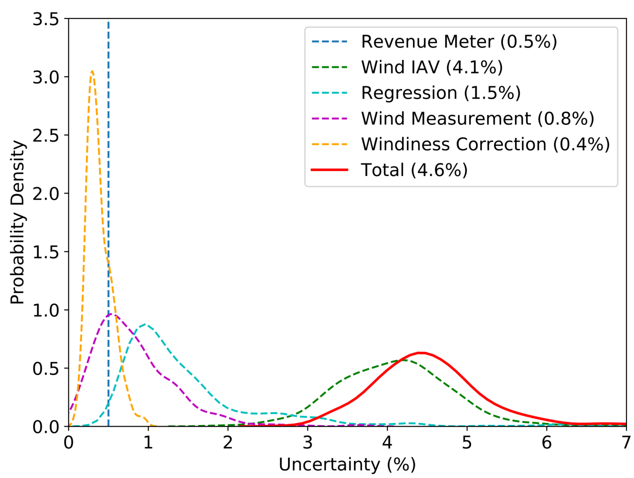
- lines 160-2: You are in effect using the variability between re-analysis datasets as a proxy for uncertainty; this should be stated, because it might be larger or smaller than the uncertainty in using a given re-analysis dataset. This is analogous to an _ensemble uncertainty_ measure. (perhaps include reference)

We have rephrased the paragraph as "Quantifying the uncertainty of the long-term wind resource data used in the operational AEP assessment is challenging because 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 adopt an ensemble uncertainty approach (Taylor et al., 2009; Zhang et al., 2015), and use as proxy the variability of the wind resource between different reanalysis products. Therefore, at each Monte Carlo iteration at each site, we randomly select wind resource data from one of the three considered reanalysis products."

- l.166-174: include reference, e.g. to the GUM (JCM100:2008).
  We have added the suggested reference.

- lines 184-7: do you mean that you randomly pick a number of years between 10 and 20? Or are you randomizing, or perhaps bootstrap-sampling, in another way? Please clarify.
  We have rephrased as "We incorporate this component by sampling the number of years (randomly picked between 10 and 20) to use as the long-term wind resource data …".

- Fig.5: can't see windiness; why not try a logarithmic scale on y-axis?
  We have tried using a log scale on y-axis, but the result did not look easy to read. We have increased the extension of the range shown on y-axis, and also increased the size of all labels and plot lines, to make this figure easier to read:



- Section 3.1 (l.216-...): The rejection of sites not well-correlated (R<0.6) with the RA datasets will affect the uncertainty in the linear regression rather significantly (increasing it), and possibly the reference-data uncertainty. As such, the value of 1.5% depends on the rejection threshold (what happens when e.g. R<0.5, or 0.8?).
  We have added the following discussion "As already mentioned in Section 2, these results are obtained for wind plants in mostly simple terrain and with a moderate-to-strong correlation between reanalysis wind resource and wind energy production and, therefore, with an overall low operational AEP uncertainty. We acknowledge that the inclusion of wind plants with a weaker correlation with the reanalysis products would modify the

relative contribution of the various uncertainty components (e.g., the importance of the regression uncertainty would increase)."

- l.297-8 / Fig.12 caption: not really "dependence", should be 'relationship between' or "mutual behavior of"
  Rephrased as "Relationship between IAV uncertainty and the total sum of squares …".

- l.300: not "direct", but a "positive" correlation emerges
  Corrected (also throughout the manuscript).

- l.305-7: this is not necessarily true -- the correlations are likely to be weaker, when the re-analysis data are less correlated with the site-specific data. As I noted above, some component uncertainties will also increase.
  In light of the additions to the manuscript on the topic (see previous answers on the topic), we have removed this sentence. We have also added the following comment to the Conclusions: "Moreover, our analysis excluded sites, mostly in complex terrain, with a weak correlation between reanalysis wind resource data and wind power production. Future work could explore the magnitude of operational AEP uncertainty and the correlation between its components for such complex flow regimes."

- l.319: 6% absolute, or relative to (percent of) %uncertainty?
  We have removed all references to relative percent of %uncertainty quantities throughout the manuscript. We have rephrased this specific sentence, according to the latest results, as: "Our results show that ignoring these correlations between uncertainty components causes an underestimation of the total operational AEP uncertainty of, on average, about 0.1%, with peak differences of 0.5% for specific sites.."

Technical Corrections

- Table 1: "measured or modeled" should occur before "long-term" in the reference-data description.
  Corrected.
- line 79: Remove "v2" and put "Version 2 of" at the beginning of the line; remove ")(" between "MERRA-2" and "Gelaro".
  Corrected.
- line 203: 10,000 times
  Corrected.
- Fig.6 caption: percent _difference_ between CoV
  Corrected.
- l.249: pluralize coefficient
  Done.
- l.296: dependence, not 'dependency'
  Corrected.
- l. 313: isn't it five, not six?
  Corrected.

- Line 379: The ISO reference appears to have been garbled a bit via BibTeX/reference manager.
  Corrected.

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

The authors thank the reviewer for their comments.

I appreciate the authors' responses to reviewer comments and updating of manuscript. The methods followed are much more clear now. Unfortunately, with that greater clarify in the method employed, I am less able to recommend publication than originally as the underlying central thesis of paper, exploration of input correlations, doesn't seem to be what's actually being revealed in the paper's results. My fundamental difficulty with the paper now is I think in-line with other reviewer's comments around seeming absence of a correlation matrix in the Monte Carlo procedure. If I understand correctly, the 5 input parameters have been sampled using an MC procedure completely independently drawing on non-correlated random number generators for each. This was done with individual per-parameter sampling, and then all-at-once sampling from all 5 parameters. Pearson coefficients were then used to examine correlation between input parameters.

If my understanding of the procedure presented is correct, then the results are unsurprising. For example, Revenue meter measurement error, a priori based on the definition of uncertainty included in the MC process could never be correlated with any of the other input parameters. There is no mathematical connection between that and the other 4 parameters. The statistical application of the MC process to establishing correlation between the inputs is therefore I think erroneous and the results are artefacts of the definitional form of the parameters. The main correlation found was wind resource IAV and long-term windiness correction; as the authors themselves state, both are driven definitionally by the same underlying data set. The MC method is independently randomly sampling from the input data sets, and so it's not clear to me that the statistical results obtained are actually representing the true correlation statistics between the input parameters.

Ultimately too, the connection from parameter correlated uncertainty back to operational AEP is not well articulated, but in any case, as per above comments I'm not convinced the MC method used is actually exploring parameter correlation.

We thank the reviewer for their thoughtful comments, which gave us an opportunity to revisit our analysis and address some weaknesses in the procedure we had originally applied.

We agree with the reviewer that the Monte Carlo approach itself does not reveal correlations between uncertainty components, nor it can be applied to obtain an assessment of the overall AEP uncertainty that takes into consideration these correlations, if all the parameters are sampled independently from each other. We have now made this point clear in many places throughout the paper. The differences in overall AEP uncertainty we showed in the previous version of the manuscript came from a discrepancy in the use of the reanalysis products between the two approaches we were comparing, and therefore were not meaningful. We apologize for that.

Following these lines, in the revised manuscript we use the Monte Carlo approach just to derive, for each wind farm, operational AEP distributions for each single uncertainty component (i.e. with individual per-parameter samplings). We have now emphasized in the manuscript how the main benefit of a Monte Carlo approach here is that it can be used to directly derive an estimate of AEP uncertainty by sampling the relevant parameters for each uncertainty component. For example, in section 2.3 we have added the following comment: *"Here, we apply this approach to derive a distribution of long-term operational AEP values from which its uncertainty can be calculated.*

Using a Monte Carlo approach provides a direct estimate of AEP uncertainty by sampling the relevant parameters connected to the various uncertainty components. By contrast, traditional approaches to assessing uncertainty are often less direct. For example, wind resource IAV is often calculated and then converted to AEP uncertainty through an "energy-velocity" (EV) ratio estimated from the wind and energy data. A Monte Carlo approach avoids this intermediate ratio and any uncertainty or error associated with it."

The analysis of the correlation between the various uncertainty components is a separate, a posteriori step, that we perform based on the Pearson's correlation coefficients between the results obtained for all 472 wind farms. While we agree with the reviewer that the definitional form of the uncertainty components is connected with the results we find, we would like to emphasize how these uncertainty components have been defined in terms of the relevant, physical parameters that control them. Therefore, while it might not be surprising that a correlation exists between wind IAV uncertainty and windiness adjustment uncertainty, this correlation is driven by the *physical* definition of the two, and it is currently neglected by most wind energy consultants.

To quantify the error introduced when these correlations are ignored in the computation of the overall operational AEP uncertainty, we have now followed and contrasted two approaches, described in the new Section 2.4:

2.4 Combination of Uncertainty Components

Once the contribution from each uncertainty component to the long-term operational AEP uncertainty has been quantified, the different components need to be combined to obtain the total AEP uncertainty. As stated in the Introduction, it is common practice for wind energy consultants to assume that all uncertainty components are uncorrelated, and combine them using Equation 1 to obtain $\sigma_{\text{tot,uncorr}}$. To test the validity of this assumption, we apply Equation 1, in which each of the five considered uncertainty components σ_i is quantified as the coefficient of variation of the corresponding operational AEP distribution obtained, by running the Monte Carlo simulation with a single sampling performed. We note that the same values of $\sigma_{\text{tot,uncorr}}$ would be obtained by running the Monte Carlo simulation with, at each iteration, all of the five samplings performed, independently from each other.

We contrast the total AEP uncertainty calculated assuming uncorrelated components with what we obtain by taking into account these correlations in the calculation. Following the guidance in ISO, IEC and OIML, BIPM (1995), we combine the various uncertainty components and calculate the total long-term operational AEP uncertainty for each wind plant as:

$$\sigma_{\text{tot,corr}} = \sqrt{\sum_{\text{i=1}}^{\text{N}} \sigma_{\text{i}}^2 + 2\sum_{\text{i=1}}^{\text{N-1}} \sum_{\text{j=i+1}}^{\text{N}} R_{\text{ij}}\sigma_{\text{i}}\sigma_{\text{j}}} \tag{7}$$

where, in our analysis, $N = 5$ and R_{ij} is the correlation coefficient between each pair of uncertainty components calculated from the results obtained from all 472 wind plants considered in the analysis.

The comparison between $\sigma_{\text{tot,uncorr}}$ and $\sigma_{\text{tot,corr}}$ will give insights into the error arising from ignoring the correlations existing between the various uncertainty components.

The results of the updated analysis are then shown and discussed in the rest of the paper.

Operational-Based Annual Energy Production Uncertainty: Are its Components Actually Uncorrelated?

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Abstract. Calculations of annual energy production (AEP) from a wind ~~farm—whether based on pre-construction~~ power plant—whether based on preconstruction or operational data—are critical for wind ~~farm~~ plant financial transactions. The uncertainty in the AEP calculation is especially important in quantifying risk and is a key factor in determining financing terms. A popular industry practice is to assume that different uncertainty components within an AEP calculation are uncorrelated ~~,~~ and can therefore be combined as the sum of their squares. We assess the practical validity of this assumption for operational-based uncertainty, ~~which is comprised of components associated with long-term correction and measurements,~~ by performing operational AEP estimates for ~~over~~ more than 470 wind ~~farms~~ plants in the United States~~. We contrast the uncorrelated sum-of-squares method with~~ , mostly in simple terrain. We apply a Monte Carlo approach ~~, in which no assumptions of correlation between uncertainty components are made. Results show that several component pairs exhibit weak to moderate correlations : inter-annual~~ to quantify uncertainty in five categories: revenue meter data, wind speed data, regression relationship, long-term correction, and future interannual variability. We identify correlations between categories by comparing the results across all 470 wind plants. We observe a positive correlation between interannual variability and the linearized long-term correction~~(positive correlation); wind resource inter-annual~~; a negative correlation between wind resource interannual variability and linear regression~~(negative); and~~; and a positive correlation between reference wind speed uncertainty and linear regression~~(positive). The sources of these correlations are described and illustrated in detail in this paper, and the effect on the~~. Then, we contrast total operational AEP uncertainty values calculated by omitting and considering the correlations between the uncertainty components. We quantify that ignoring these correlations leads to an underestimation of total AEP uncertainty ~~calculation is investigated.~~ of, on average, 0.1%, and as large as 0.5% for specific sites. Although these are not large increases, these would still impact wind plant financing rates; further, we expect these values to increase for wind plants in complex terrain. Based on these results, we conclude that ~~a Monte Carlo approach to operational AEP uncertainty quantification is more robust and accurate than the simple approach which neglects correlations between uncertainty components~~correlations between the identified uncertainty components should be considered when computing the total AEP uncertainty.

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1 Introduction

Calculations of wind ~~farm~~ plant annual energy production (AEP)—whether based on ~~pre-construction~~ preconstruction data before a wind power plant is built or on operational data after a wind ~~farm~~ plant has started its operations—are vital for wind ~~farm~~ plant financial transactions. ~~Pre-construction~~ Preconstruction estimates of AEP are needed to secure and set the terms for new project financing, whereas operational estimates of long-term AEP are required for important wind ~~farm~~ plant transactions, such as refinancing, purchasing/selling, and mergers/acquisitions. The need for AEP analyses of wind ~~farms is increasing , as~~ plants is increasing because global wind capacity increased to 539 GW in 2017, representing 11% and 91% increases over 1-year and 5-year periods, respectively; ~~and~~ capacity is expected to increase by another 56%, to 841 GW, by 2022 (Global Wind Energy Council, 2018). In the United States, wind ~~farms generated over~~ plants generated more than 300,000 GWh in 2019, about 7.5% of the total ~~US~~ U.S. electricity generation from utility-scale facilities that year, with a 50% increase over a 6-year period (Energy Information Administration, 2020).

This rapid growth of the wind energy industry is putting an increased spotlight on the accuracy and consistency of AEP calculations. For ~~pre-construction~~ preconstruction AEP estimates, there has been considerable movement ~~towards~~ toward standardization. The International Energy Commission (IEC) is currently developing a standard (IEC 61400-15:draft) ~~,~~ and there have long been guidance and best practices available (Brower, 2012). By contrast, long-term operational AEP estimates do not have such extensive guidance or standards. Only limited standards covering operational analyses exist; IEC 61400-12-1:2017 addresses turbine power curve testing, and IEC 61400-26-3:2016 addresses the derivation and categorization of availability loss metrics. ~~There are~~ However, to our knowledge, ~~however,~~ there are no standards and very limited published guidance on calculating long-term AEP from operational data. Rather, documentation seems to be limited to a consultant report (Lindvall et al., 2016), an academic thesis (Khatab, 2017), and limited conference proceedings (Cameron, 2012; Lunacek et al., 2018).

Documentation and standards for ~~pre-construction~~ preconstruction AEP methods are of limited use for operational-based AEP methods, given the many differences between the two approaches. In general, operational AEP calculations are simpler than ~~pre-construction~~ preconstruction estimates because actual measurements of wind ~~farm~~ plant power production at the revenue meter replace the complicated ~~pre-construction~~ preconstruction estimate process (e.g., meteorological measurements, wind and wake-flow modeling, turbine performance, estimates of wind ~~farm~~ plant losses). However, the two methods do share several similarities, including regression relationships between on-site measurements and a long-term wind speed reference, the associated long-term (windiness) correction applied to the on-site measurements, estimates of future interannual variability, and estimates of uncertainty in the resulting AEP calculation. The ~~uncertainty components for~~ shared components between operational AEP calculations ~~are simplified relative to those in a pre-construction estimate (IEC 61400-15:draft) ; shared components between the two methods~~ and preconstruction estimates (IEC 61400-15:draft) are listed in Table 1.

Uncertainty component	Description
On-site measurements	Measurement error in met mast wind speeds (~~pre-construction~~preconstruction) or power at the revenue meter (operational)
Reference wind speed data	Measurement or modeling error in ~~long-term reference~~ measured or modeled long-term reference 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~~ Interannual variability of resource	Sensitivity in future energy production because of resource variability

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

The uncertainty values from each component listed in Table 1 must be combined to produce a total estimate of AEP uncertainty. ~~We found no~~ While general guidelines on how to combine (measurement) uncertainty components exists (ISO, IEC and OIML, BIPM and can be applied to this task, we found no specific guidance in the literature for combining uncertainty components in an operational AEP estimate. ~~However~~On the other hand, considerable guidance exists for combining ~~pre-construction~~ preconstruction AEP uncertainties (Lackner et al., 2007; Brower, 2012; Vaisala, 2014; Kalkan, 2015; Clifton et al., 2016). In every case, recommended best practices assume that all uncertainties, $\cancel{\sigma_i}\sigma_{\mathrm{i}}$, are uncorrelated and can therefore be combined using a sum of squares approach to give the total AEP uncertainty, $\sigma_{\mathrm{tot,uncorr}}$:

$$\sigma_{\mathrm{tot,uncorr}} = \cancel{\sqrt{\sum_{i} \sigma_{\mathrm{i}}^2}}\sqrt{\sum_{\mathrm{i=1}}^{\mathrm{N}} \sigma_{\mathrm{i}}^2} \quad (1)$$

To better understand how uncertainties are combined in long-term operational AEP calculations, we reached out to several wind energy consultants who regularly perform these analyses. These conversations revealed that uncertainties in a long-term operational AEP calculation are also assumed uncorrelated and combined using Equation ~~1.~~ 1.

1.1 Goal of Study

The purpose of this study is to examine the extent to which the assumption of uncorrelated uncertainties—and~~therefore~~ , therefore, the combination of those uncertainties through a sum of squares approach—is accurate and appropriate for operational AEP calculations. Specifically, this study aims to identify potential correlations between AEP uncertainty components~~and propose a Monte Carlo approach to capture such correlations when combining individual uncertainty components.~~

~~Monte Carlo methods have been used in different applications for uncertainty quantification within the wind energy industry, ranging from the prediction of extreme wind speed events (Ishihara and Yamaguchi, 2015), to offshore fatigue design (Müller and Cheng, 20, to economic analysis of the benefits of wind energy projects (Williams et al., 2008). Here, the focus is on operational AEP uncertainty, using publicly available wind farm operational data~~ ~~.~~, using data for over 470 wind plants. While in the analysis we focus on operational AEP calculation, we expect that the results from this analysis—namely, the potential identification of correlated uncertainty components—can be equally relevant for informing and improving ~~pre-construction~~ preconstruction AEP methods.

In Section 2, we first describe the data sources used in this ~~analysis—namely wind farm~~ analysis (wind plant operational data and reanalysis ~~products—as well as~~ products), the Monte Carlo approach to ~~calculate operational AEPand quantify its uncertainty~~ quantify single uncertainty components in operational AEP, and the approaches used to combine these uncertainty components. Section 3 presents the main results of our analysis ~~,~~ in terms of uncertainty contributions and correlation among the different components. We conclude and suggest future work in Section 4.

2 Data and Methods

2.1 Wind ~~Farm~~ plant Operational Data and Reanalysis Products

Operational wind ~~farm~~ plant energy production data for this analysis are obtained from the publicly available Energy Information Administration (EIA) 923 database (EIA, 2018). This database provides reporting of monthly net energy production from all power plants in the United States, including wind ~~farms. A total of over~~ plants. More than 670 unique wind ~~farms~~ plants are available from this data set.

Long-term wind speed data (needed to perform the long-term or windiness correction in an AEP estimate) are used from three reanalysis products over the period of January 1997 through December 2017:

– ~~The~~ Version 2 of the Modern-Era Retrospective analysis for Research and Applications ~~v2~~ (MERRA-2~~) (Gelaro et al., 2017)~~, Gelaro et al. (2017)). We specifically use the M2T1NXSLV data product, which provides diagnostic wind speed at 50 m above ground level (AGL), interpolated from the lowest model level output (on average about 32 m AGL), using Monin Obukhov similarity theory. Data are provided at an hourly time resolution.

– The European Reanalysis Interim (~~ERA-interim~~ERA-Interim) data set (Dee et al., 2011). We specifically use output at the ~~58th~~ 58th model level, which on average corresponds to a height of about 72 m AGL. Data are provided at a 6-hourly time resolution.

– The National Centers for Environmental Prediction v2 (NCEP-2) data set (Saha et al., 2014). We specifically use diagnostic wind speed data at 10 m AGL. Data are provided at a 6-hourly time resolution.

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

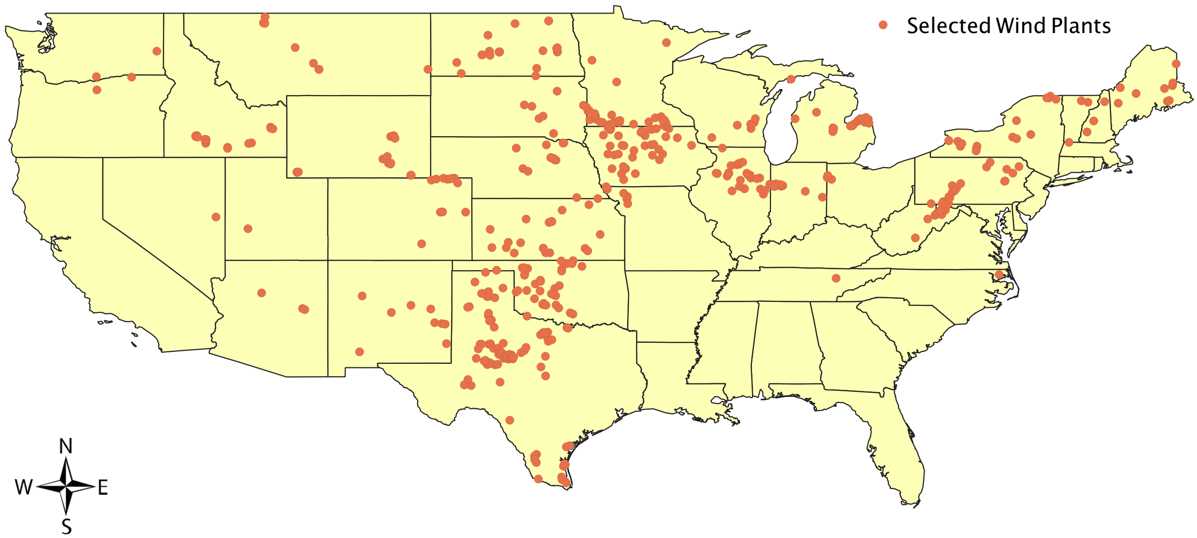

Figure 1. Map of the 472 wind ~~farms~~ plants that were considered in this study.

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 same height as wind speed, we first extrapolate the reported surface pressure to the wind speed measurement height, assuming hydrostatic equilibrium (ISO 2533:1975, 1975):

$$p = p_{\text{surf}} \exp\left[\frac{gz}{RT_{\text{avg}}} \right] \quad (3)$$

where p is the pressure at the wind speed measurement height, p_{surf} is the surface pressure, g is the acceleration caused by gravity, z is the wind speed measurement height, R is the gas constant, and T_{avg} is the average temperature between the reported value at 2 m AGL and at the wind speed measurement height.

To lessen the impact of limited and/or poor-quality data on the results of our analysis, we filter for wind ~~farms with at least 8 months of data and with~~ plants with a moderate-to-strong correlation with all three reanalysis products ($R^2 > 0.6$). ~~A threshold of 8 months is selected~~ About 25% of the EIA wind plants are discarded with this filter. We also impose a threshold of eight months of wind plant data availability in order to investigate uncertainty as it relates to a low number of data ~~points but~~ points—but not so low as to make the use of a regression relationship questionable. A total of 472 wind ~~farms~~ plants are kept for the final analysis, and their locations are shown in Figure 1. Because obtaining an accurate representation of wind data in

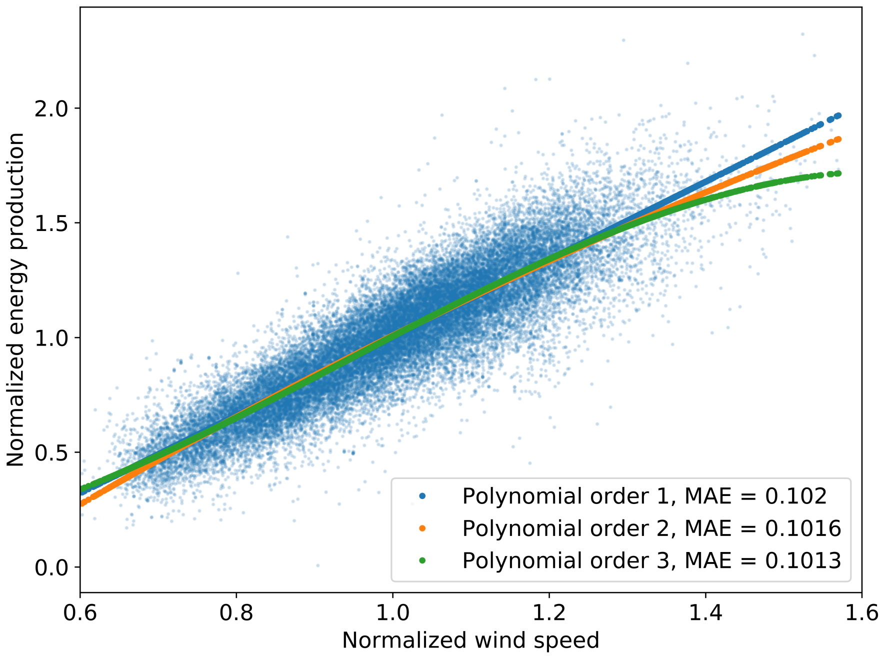

Figure 2. Scatterplot between normalized MERRA-2 density-corrected monthly wind speed and monthly energy production across all 472 selected sites, and linear, quadratic, and cubic best-fit lines.

complex terrain by reanalysis products is challenging (Shravan Kumar and Anandan, 2009), most of the selected wind plants are located in the Midwest and Southern Plains. Notably, no wind ~~farms~~ plants in California pass the filtering criteria ~~,~~ because they are predominately located in areas with thermally driven wind regimes, such as Tehachapi Pass, where coarse-resolution reanalysis products are poor predictors of wind energy production.

The fundamental step in an AEP calculation involves a regression between density-corrected wind speed (here, from the reanalysis products) and energy production (here, from the EIA 923 database). To investigate whether a simple linear function can be assumed to express the relationship between density-corrected wind speed and wind ~~farm~~ plant energy production when considering monthly data, we show a scatterplot between MERRA-2 density-corrected monthly wind speed and monthly energy production across all 472 sites in Figure 2. For each site, data have been normalized by the respective site mean. We show best-fits using a linear, quadratic, and cubic function, and calculate the mean absolute error (MAE) of each fit. We find that the difference between the normalized MAE values from the considered functions is less than 0.7%. Therefore, the uncertainty connected with the choice of using a linear regression in the operational AEP methodology at monthly time resolution appears minimal. Moreover, through conversations with wind industry professionals, we found that a linear regression based on monthly data is the standard industry approach when performing bankable[1] operational AEP analyses.

[1]Results are accepted by banks, investors, and so on for use in financing, buying/selling, and acquiring wind ~~farms~~plants.

2.2 Operational AEP Methodology

Given the lack of existing guidelines for a standard approach for ~~operational~~ *operational* AEP calculations, we ~~instead~~ base our methodology on conversations with ~~several~~ four major wind energy consultants who represent most of the operational market share in North America. These conversations overwhelmingly revealed the following characteristics ~~of an industry standard and bankable~~ for operational AEP analysis, and we follow the same approach in our analysis:

1. Wind speed data (measured or modeled) are density-corrected at their native time resolution, using ~~equation~~ Equation 2.

2. Monthly revenue meter data, monthly average availability and curtailment losses, and monthly average wind speeds from a long-term wind resource product are calculated.

3. Monthly revenue meter data are normalized to 30-day months (e.g., for January, the revenue meter values are multiplied by 30/31).

4. Monthly revenue meter data are corrected for monthly availability and curtailment (i.e., monthly gross energy data are calculated).

5. A linear regression between monthly gross energy production and concurrent density-corrected monthly average wind speeds is performed.

6. Long-term density-corrected 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, ~~...~~etc.).

7. Slope and intercept values from the regression relationship are then applied to the long-term density-corrected monthly average wind speed data ~~,~~ with the long-term or so-called windiness correction. A long-term data set of monthly (January, February, ~~...)~~ etc.) estimated gross energy production is obtained.

8. The resulting long-term monthly gross energy estimates, which are based on 30-day months, are then denormalized to the actual number of days in each calendar month (e.g., for January, the obtained value is multiplied by 31/30).

9. Long-term estimates of availability and curtailment losses are finally applied to the denormalized long-term monthly gross energy data, leading to a long-term calculation of operational AEP.

In the EIA-923 database, availability and curtailment data are not available. Therefore, in our analysis we omit steps 4 and 9 of the list, and only perform calculations on net energy data. ~~A diagram outlining the resulting general process of the operational AEP analysis adopted in our study is shown in Figure 3.~~

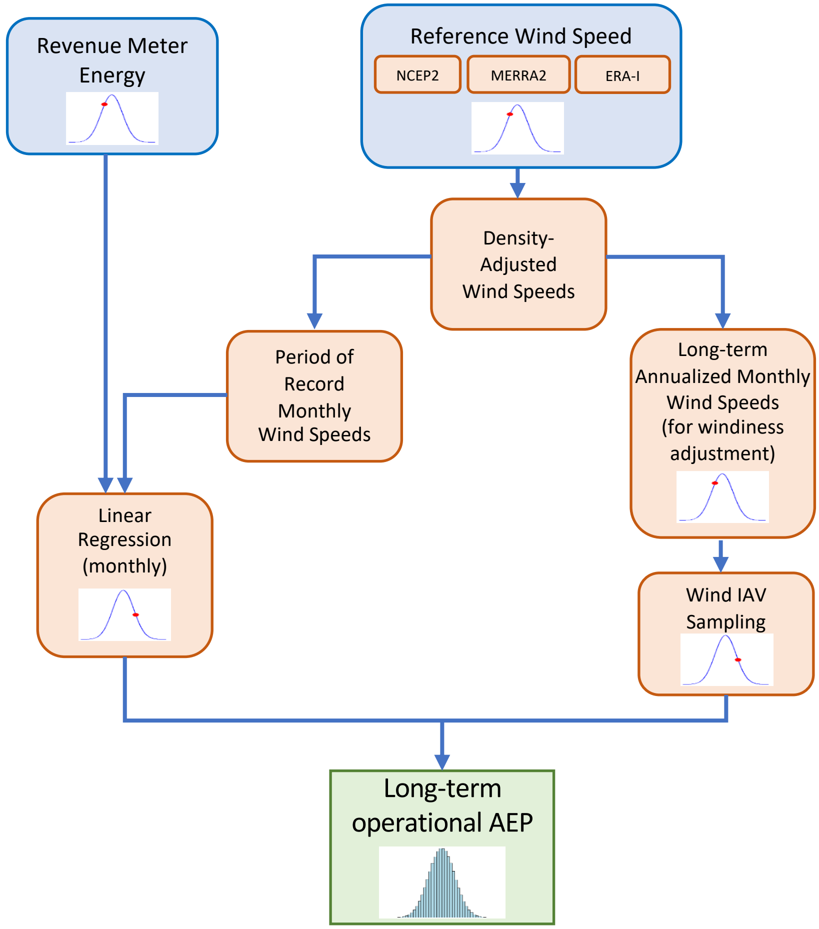

Figure 3. Long-term ~~annual energy production (~~AEP ~~)~~ estimation process using operational data under a Monte Carlo approach; sources of uncertainty and points of Monte Carlo sampling are denoted by probability distribution images. Note: IAV denotes ~~inter-annual~~ interannual variability.

2.3 Monte Carlo Analysis

To quantify the ~~uncertainty of the~~ impact of the single uncertainty components on 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~~, ~~. This is usually calculated as the standard deviation or the coefficient of variation (i.e. standard deviation normalized by mean) of the resulting distribution (ISO, IEC and OIML, BIPM, 1995; Dimitrov et al., 2018). Monte Carlo methods have been used in different applications for uncertainty quantification within the wind energy industry, ranging from the prediction of extreme wind speed events

(Ishihara and Yamaguchi, 2015), to offshore fatigue design (Müller and Cheng, 2018), to economic analysis of the benefits of wind energy projects (Williams et al., 2008). 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~~ Using a Monte Carlo approach provides a direct estimate of AEP uncertainty by sampling the relevant parameters connected to the various uncertainty components. By contrast, traditional approaches to assessing uncertainty are often less direct. For example, wind resource IAV is often calculated and then converted to AEP uncertainty through an "energy-velocity" (EV) ratio estimated from the wind and energy data. A Monte Carlo approach avoids this intermediate ratio and any uncertainty or error associated with it.

In our analysis, we separately consider five operational-based uncertainty components ~~, so that five different samplings are performed at~~ so that only the sampling of one parameter is performed in each Monte Carlo ~~iteration~~configuration. The following uncertainty components are included in our proposed Monte Carlo methodology for long-term operational AEP:

- Revenue meter measurement error. ~~We~~ To incorporate this uncertainty component in the Monte Carlo simulation~~by sampling~~ , we sample monthly revenue meter data from a synthesized normal distribution centered on the reported value ~~,~~ and 0.5% imposed standard deviation. In fact, a value of 0.5% is ~~coherent~~ consistent 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~~ because 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~~adopt an ensemble uncertainty approach (Taylor et al., 2009; Zhang et al., 2015) and use as proxy the variability of the wind resource between different reanalysis products. Therefore, at each Monte Carlo iteration at each site, we randomly select 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~~ We adopt a novel way, directly enabled by the use of Monte Carlo, to incorporate this uncertainty component in the operational AEP assessment. We sample 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~~ (ISO, IEC and OIML, BIPM, 1995) as:

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

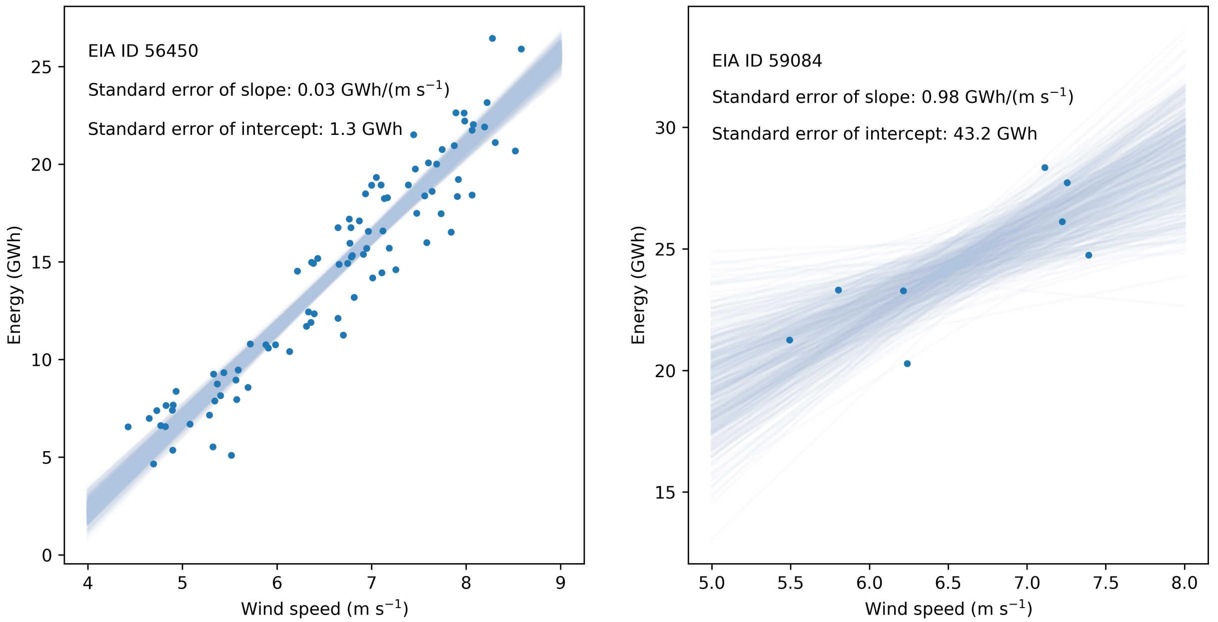

Figure 4. Sampling set of regression lines corresponding to the slope and intercept values derived from their standard errors in the Monte Carlo approach, for two stations in the EIA data set.

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 is:

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

and the standard error of the intercept is:

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

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 the covariance matrix derived from the standard errors of slope and intercept and their covariance. As shown in ~~the Figure~~ Figure 4, 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 (randomly picked 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~~ interannual 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.

~~For each wind farm, we estimate the total operational AEP uncertainty by running a~~ To calculate these uncertainty components at each wind plant, we run the Monte Carlo simulation ~~10,000 times. At each iteration, all five samplings, corresponding to the five considered uncertainty components (revenue meter, reference wind speed data, wind resource IAV, linear regression, and windiness correction), are simultaneously performed. The total uncertainty in long-term operational AEP is then estimated as the coefficient of variation of its resulting distribution. 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.~~

~~To understand the impact of the single uncertainty components and study their correlation, we also run, at each site, the Monte Carlo simulation with~~ under five different setups, each of them having only a single sampling performed (i.e., either revenue meter, reference wind speed data, IAV, linear regression, or windiness correction). ~~At each wind farm~~For each component, we run the Monte Carlo simulation 10,000 ~~time for each of the five single operational uncertainty components considered~~times. We quantify the impact of each single uncertainty component on the long-term 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.~~. 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 95% confidence.

The code used to perform the AEP calculations is published and documented in NREL's open-source operational assessment software, OpenOA.[2] Calculations were performed on Eagle, NREL's high-performance computing cluster. Specifically, each wind ~~farm~~ plant was assigned a different processor and run in parallel. Given the general simplicity of the AEP method used here, computational requirements were moderate despite the ~~60~~50,000 simulations (10,000 runs x ~~6~~ 5 uncertainty setups) required for each wind ~~farm~~plant.

[2]https://github.com/NREL/OpenOA

3 ~~Results~~

2.1 Combination of Uncertainty Components

2.2 ~~Operational-Based AEP Uncertainty Contributions~~

Once the contribution from each uncertainty component to the long-term operational AEP uncertainty has been quantified, the different components need to be combined to obtain the total AEP uncertainty. As stated in the Introduction, it is common practice for wind energy consultants to assume that all uncertainty components are uncorrelated, and combine them using Equation 1 to obtain $\sigma_{\text{tot,uncorr}}$. To test the validity of this assumption, we apply Equation 1, in which each of the five considered uncertainty components σ_i is quantified as the coefficient of variation of the corresponding operational AEP distribution obtained by running the Monte Carlo simulation with a single sampling performed. We note that the same values of $\sigma_{\text{tot,uncorr}}$ would be obtained by running the Monte Carlo simulation with, at each iteration, all of the five samplings performed, independently from each other.

~~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~~ We contrast the total AEP uncertainty calculated assuming uncorrelated components with what we obtain by taking into account these correlations in the calculation. Following the guidance in ISO, IEC and OIML, BIPM (199 , we combine the various uncertainty components and calculate the total long-term operational AEP uncertainty for each wind plant as:

$$\sigma_{\text{tot,corr}} = \sqrt{\sum_{\text{i=1}}^{\text{N}} \sigma_{\text{i}}^2 + 2\sum_{\text{i=1}}^{\text{N-1}} \sum_{\text{j=i+1}}^{\text{N}} R_{\text{ij}} \sigma_{\text{i}} \sigma_{\text{j}}} \tag{7}$$

where, in our analysis, $N = 5$ and ~~of its single components across the~~ R_{ij} is the correlation coefficient between each pair of uncertainty components calculated from the results obtained for all 472 wind ~~farms~~plants considered in the analysis.

The comparison between $\sigma_{\text{tot,uncorr}}$ and $\sigma_{\text{tot,corr}}$ will give insights into the error arising from ignoring the correlations existing between the various uncertainty components.

3 Results

3.1 Operational-Based AEP Uncertainty Contributions

Distributions of each uncertainty component, expressed in terms of the percent coefficient of variation of the resulting AEP distributions~~(Figure 5).~~ , across all 472 wind plants are shown in Figure 5. Uncertainty connected to wind resource IAV is found to contribute the most (average 4.1% across all wind ~~farms~~plants). The uncertainty in the linear regression model has the ~~second largest~~ second-largest contribution (1.5%), followed by the uncertainty of the reference wind speed data (0.8%; here, of the reanalysis products), and revenue meter data (here, imposed at 0.5%). The long-term windiness correction has the smallest uncertainty component (0.4%). Therefore, the number of years used for the long-term windiness correction does not

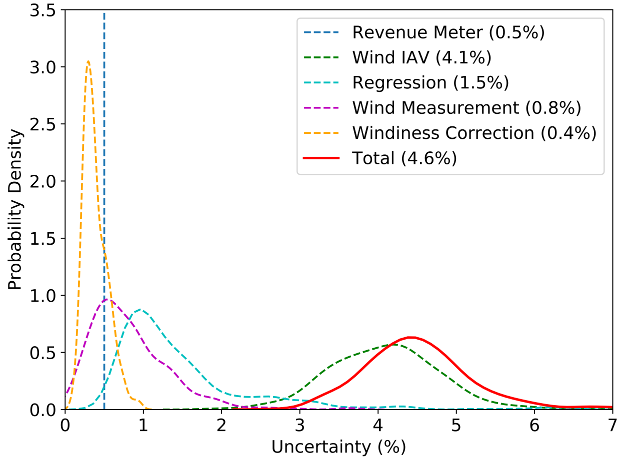

Figure 5. Operational-based AEP uncertainty distributions across projects for the different uncertainty components; mean values across projects are shown in the legend. Uncertainty values are quantified as the percent coefficient of variation of the long-term operational AEP distribution.~~Note that the sum of squares of the average values of the single components does not add up to the average of the total uncertainty.~~

have a large impact on the overall uncertainty in operational AEP, at least for the sampled range of 10–20 years. Using as few as 10 years seems sufficient to give stability to the long-term AEP estimate ~~,~~ and adding additional years does not provide a significant reduction in the uncertainty connected with the long-term estimate.

~~The proposed Monte Carlo approach does not require any assumption on the correlation between the different uncertainty components; on the other hand, the conventional sum of squares approach assumes the uncertainty components are all uncorrelated. Therefore, we compare the total operational AEP uncertainty from the Monte Carlo method with all the five simultaneous samplings ($CoV_{\text{Monte Carlo}}$) with the total uncertainty calculated using the conventional sum of squares approach ($CoV_{\text{uncorrelated}}$). For the latter approach, we quantify each of the five uncertainty components as the coefficient of variation of the corresponding operational AEP distribution obtained by running the Monte Carlo simulation with a single sampling performed. We then combine the five uncertainty components into the overall AEP uncertainty using Eq. 1. (a) Scatterplot of total operational AEP uncertainty values calculated with the proposed Monte Carlo approach and assuming uncorrelated uncertainty components for the 472 wind farms considered. Uncertainty is quantified as the percent coefficient of variation of the resulting long-term AEP distribution. (b) Histogram of percentage differences (Eq. **??**) between the AEP uncertainties calculated using the two different approaches. Figure 12 shows the results of this comparison for~~ As already mentioned in Section 2, these results are obtained for wind plants in mostly simple terrain and with a moderate-to-strong correlation between reanalysis wind resource and wind energy production and, therefore, with an overall low operational AEP uncertainty. We acknowledge that the inclusion of wind plants with a weaker correlation with the reanalysis products would modify the relative contribution of the various uncertainty components (e.g., the importance of the ~~472 wind farms considered, as a scatterplot and also as a histogram of the percentage~~

~~difference between the two versions of the total AEP uncertainty:~~

$$\Delta_{\text{CoV}} = \frac{\text{CoV}_{\text{Monte Carlo}} - \text{CoV}_{\text{uncorrelated}}}{0.5 \cdot (\text{CoV}_{\text{Monte Carlo}} + \text{CoV}_{\text{uncorrelated}})} \cdot 100$$

~~A weak bias can be observed, with a median value of -2% in uncertainty percentage difference (which corresponds to a -0.25% median difference in the actual total uncertainty value). In other words, if correlations between the different uncertainty components are allowed and taken into account in the calculation method, the whole AEP uncertaintyis then, on average, slightly reduced. This difference can be explained by considering that the two biggest sources of uncertainty (linear regression and IAV) are slightly negatively correlated (as will be shown in detail in the next section), thus making the Monte-Carlo-based total uncertainty lower, on average, than the one derived with the uncorrelated assumption. Moreover, assuming that all the uncertainty components are uncorrelated can introduce significant errors in the assessment of the AEP uncertainty for the single projects, with about 47% (16%) of the considered wind farms showing a $\pm 5\%$ (10%) uncertainty difference compared to the values from the Monte-Carlo-based approach.The mean absolute error of the distribution of uncertainty percentage differences is approximately 6% (Figure shown in the Supplement~~regression uncertainty would increase).

3.2 Correlation Between Operational-Based AEP Uncertainty Components

~~Because operational AEP uncertainty calculated by assuming a lack of correlation among its different components can greatly differ from the uncertainty values obtained when allowing for potential correlations , it is worth exploring the correlation~~ To be able to assess the validity of the uncorrelated assumption when combining different uncertainty components, we assess potential correlations between uncertainty components ~~which are responsible for this difference. We leverage the results of the Monte Carlo analysis at the 472 wind farms considered to reveal the correlation between the single operational~~ by analysing the Pearson's correlation coefficients R_{ij} (needed in Equation 7 to calculate $\sigma_{\text{tot,corr}}$) from each pair of AEP uncertainty components ~~, in terms of their Pearson correlation coefficient. As a result, we obtain the average~~ across the 472 wind plants, and we summarize the results in the correlation matrix in Figure 6. To assess which of the obtained correlations have statistical significance, we calculate the $p-$value (Westfall and Young, 1993) associated with the ten correlation coefficients. The test reveals that for three pairs of uncertainty components, the probability of finding the *observed* not-zero correlation coefficients if the *actual* correlation coefficient were~~in fact~~ , in fact, zero ($p-$value), is less than 10^{-5}. Therefore, the following three correlations have strong statistical significance:

- The wind resource IAV and the long-term windiness correction uncertainties are moderately correlated ($R = 0.49$, $p = 1.9 \cdot 10^{-29}$).
- The linear regression and reference wind speed data uncertainties are weakly correlated ($R = 0.35$, $p = 2.5 \cdot 10^{-15}$).
- The wind resource IAV and the linear regression uncertainties appear weakly negatively correlated ($R = -0.21$, $p = 2.6 \cdot 10^{-6}$).

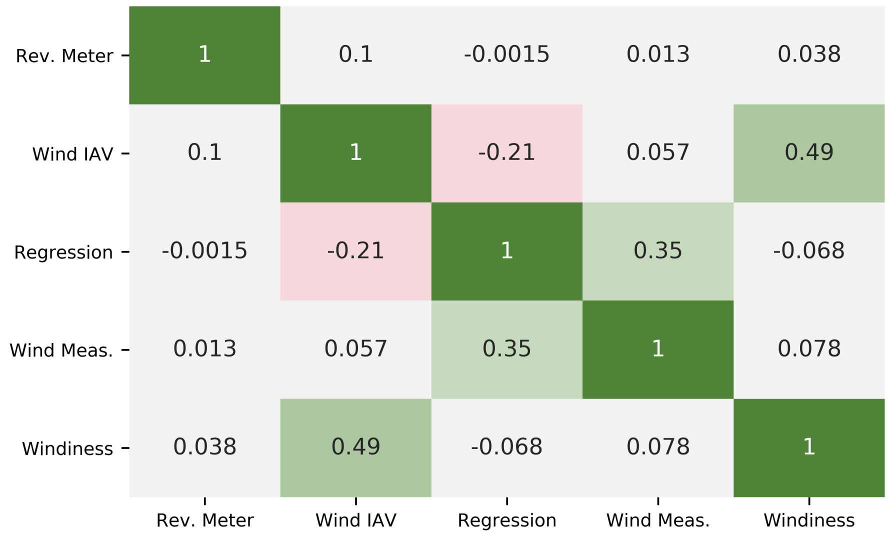

Figure 6. Correlation coefficient heat map between operational AEP uncertainty components, as calculated from the results of the Monte Carlo approach applied at the 472 wind ~~farms~~ plants considered in the analysis. Note: "Rev." denotes "Revenue~~"~~".

The first correlation noted earlier (wind resource IAV and long-term windiness correction) is explained simply by the fact that both uncertainty components are driven by wind resource variability. At a site with large wind variability, IAV will be large by definition ~~,~~ and so will the uncertainty introduced by different lengths of time series used for the long-term AEP calculation.

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 7).

Both the slope and intercept errors (Equations 5 and 6), from which the linear regression uncertainty depends (as described in Section 2.3), are inversely proportional to the number of data points ~~,~~ so that when a regression is performed on few data points, its uncertainty increases. This dependence is exemplified in Figure 4, where we have compared the sampling sets of regression lines for two stations in the EIA data set: for these two cases, the standard errors of regression slope and intercept for the station with 8 data points (on the right) are ~~30-50~~ 30–50 times larger than what is found for the station with 90 data points (on the left).

The number of data points used for the regression ~~has also~~ also has an impact on the reference wind speed data uncertainty. In fact, short periods of wind plant operation record can lead to different interpretations from the reference wind resource data sets used as to whether that short period of record was above, equal to, or below the long-term average resource. Over a longer period of record, these potential discrepancies between different wind resource data sets (in our case, reanalysis products) tend to average out~~, therefore~~; therefore, leading to a reduced uncertainty. We illustrate this phenomenon by exploring the long-term

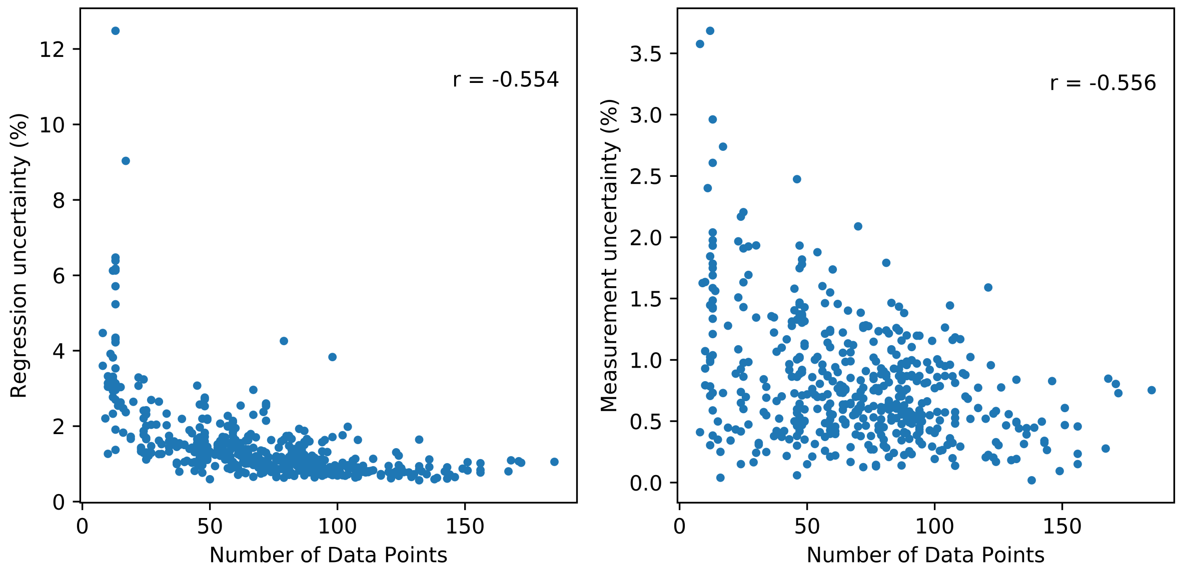

Figure 7. Dependence of linear regression uncertainty and reference wind speed data uncertainty on the number of data points in the period of record, for the ~~471~~ 472 projects considered in the analysis.

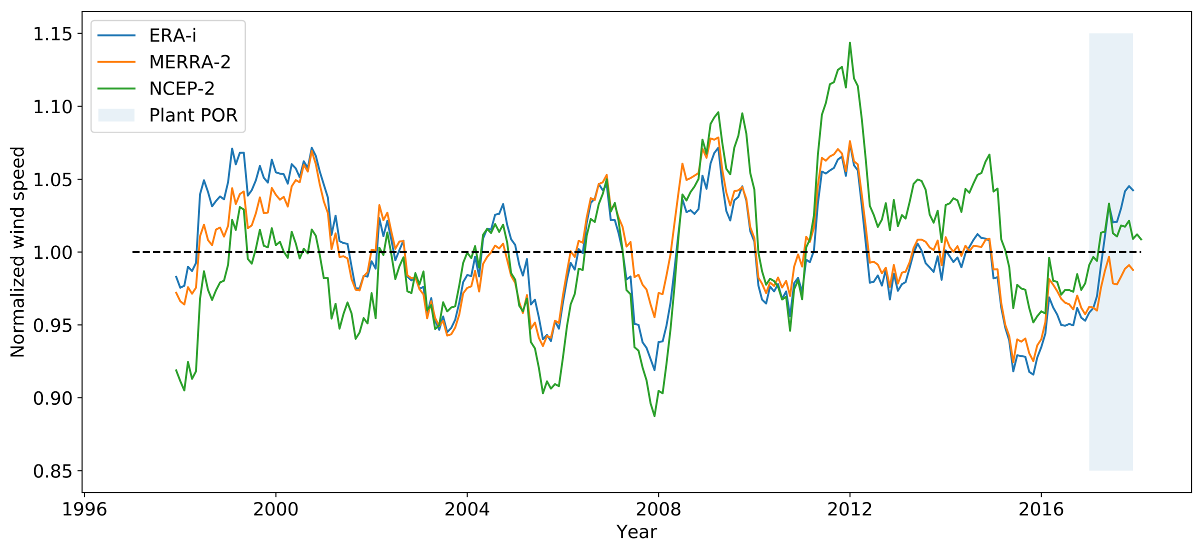

Figure 8. Long-term time series of normalized wind speed for EIA station ID 60502 from the three reanalysis products used in the study. The period of record (POR) for the wind ~~farm~~ plant is highlighted in light blue.

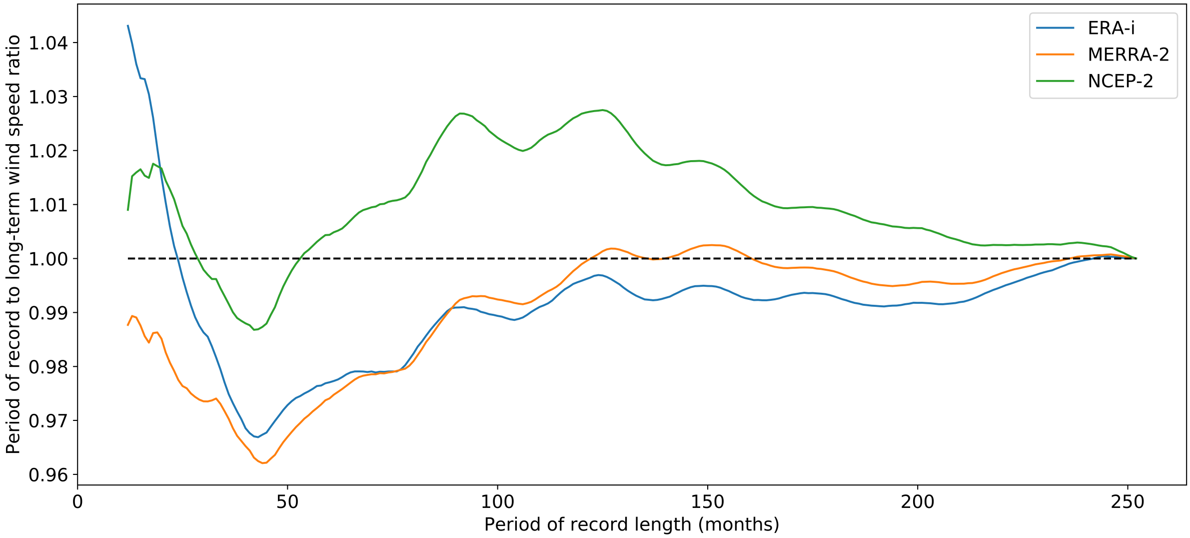

Figure 9. Ratio of wind speed to the long-term, 20-year average for periods of record of different lengths (all ending in December 2017), for EIA station ID 60502, using data from the three reanalysis products in the study.

trend of the reanalysis products for the wind ~~farm~~ plant with one of the highest reported reference wind speed data uncertainties (EIA ID 60502 ~~,~~ reported 3.7% reference wind speed data uncertainty). Figure 8 shows the result. The period of record for wind ~~farm~~ plant operation (shown by a shaded blue area in Figure 8) was only 12 months. As shown in the figure, the various reanalysis products have very different interpretations of the wind resource in the short period of record ~~,~~ relative to the long-term (~~ERA-i~~ERA-I: 4% above average~~,~~ ; MERRA-2: 1% below average; NCEP-2: 1% above average). Consequently, the use of each reanalysis product will lead to different magnitudes (both positive and negative) in the long-term windiness corrections, leading to high uncertainty in the resulting operational AEP calculation. By increasing the period of record (i.e., increasing the number of data points used in the regression), such discrepancies tend to average out. This is illustrated in Figure 9, where we show how the period of record to long-term wind speed ratio varies as we extend the period of record by increasing the number of months while keeping December 2017 as the fixed ending time. For short periods of record, there is considerable deviation of this ratio among the different reanalysis products (i.e., the reference wind speed data uncertainty is high). As the length of the period of record increases, this ratio tends to converge to 1.0, and the spread between the three reanalysis products decreases (i.e., the reference wind speed data uncertainty is low).

Finally, the (weak) negative correlation between linear regression and wind resource IAV uncertainties is linked to the fact that they respond differently to the R^2 coefficient between the reanalysis wind speed and the energy production data (Figure 10). Predictably, the linear regression uncertainty is inversely proportional to the coefficient of determination because a stronger correlation between winds and energy production will lead to a reduced uncertainty of the regression between the two variables.

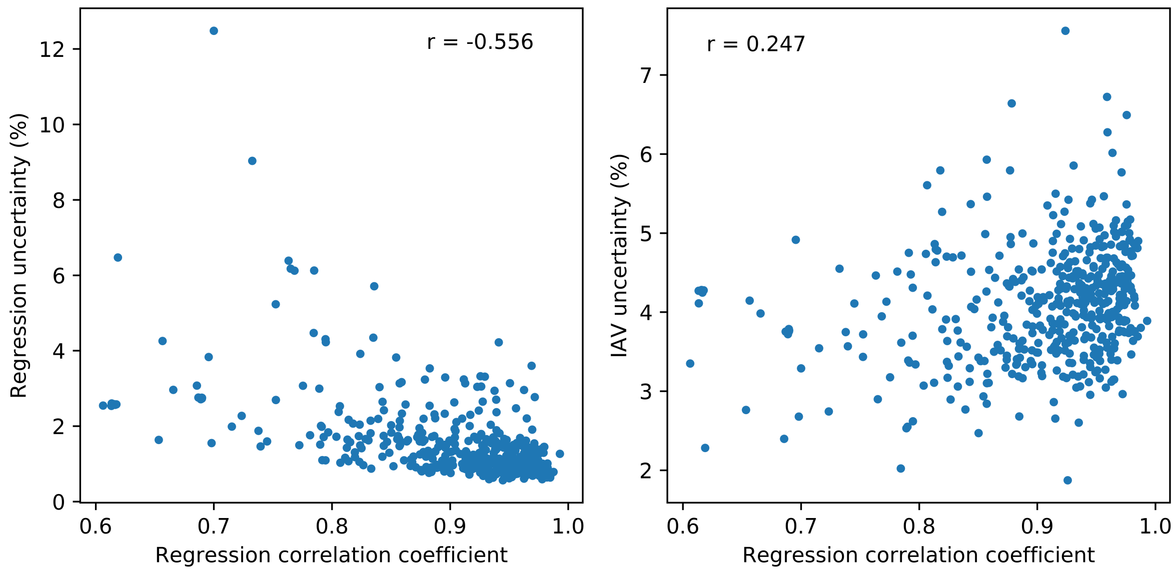

Figure 10. Dependence of linear regression uncertainty and IAV uncertainty on the R^2 of the regression between reanalysis wind speed and energy production data.

On the other hand, wind resource IAV uncertainty shows a ~~direct~~ positive correlation with the regression R^2 coefficient. This ~~dependency~~ dependence can be explained ~~as~~ because both quantities are ~~directly~~ positively correlated with the total variance of wind speed or, equivalently, produced energy. Figure 11 shows the relationship between IAV uncertainty and the total sum of squares $SS_{\text{tot, WS}}$ of reanalysis wind speed (here, using MERRA-2 monthly data), which is proportional to the variance of the data:

$$SS_{\text{tot, WS}} = \sum \cancel{{}_i(WS_i - \overline{WS})^2}\,{}_i(WS_i - \overline{WS})^2. \tag{8}$$

A ~~direct~~ positive correlation between IAV uncertainty and $SS_{\text{tot, WS}}$ emerges. At the same time, the linear regression R^2 coefficient also depends on the variance of the produced energy (and, equivalently, of wind speed) as it is defined as:

$$R^2 = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}} \tag{9}$$

where SS_{res} is the total sum of the residuals from the linear regression. Equation 9 shows that when the total sum of squares SS_{tot} increases, so does R^2, thus confirming the ~~direct~~ positive correlation between R^2 and the variance in the data.

~~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~~

3.3 Comparison Between Total Operational-Based AEP Uncertainty Under Different Assumptions

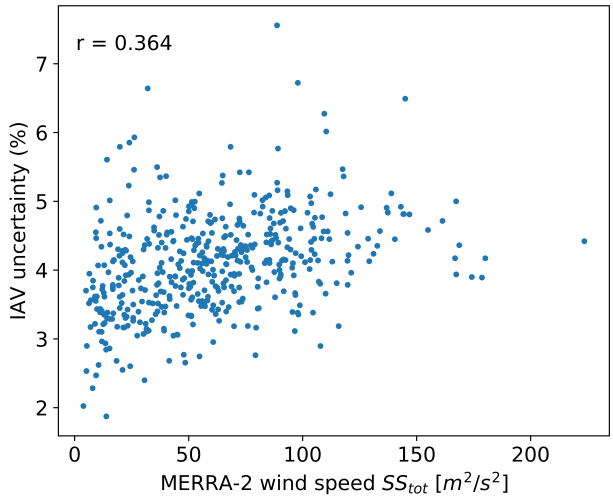

Figure 11. ~~Dependence of~~ Relationship between IAV uncertainty ~~on~~ and the total sum of squares $SS_{\mathrm{tot,\,WS}}$ of MERRA-2 wind speed data ~~,~~ for the 472 projects considered.

After having revealed the correlations existing between different AEP uncertainty components and explained their sources, we can compare the total operational AEP uncertainty calculated when allowing for these correlations (Equation 7) with the total uncertainty calculated with the uncorrelated assumption using the conventional sum of squares approach (Equation 1). Figure 12 shows the results of this comparison for the 472 wind plants considered as a scatterplot and also as a histogram of the difference $\sigma_{\mathrm{tot,corr}} - \sigma_{\mathrm{tot,uncorr}}$. A weak bias can be observed with a mean value of $+0.1\%$ in uncertainty difference (and differences up to 0.5% for specific wind plants). In other words, if correlations between the different uncertainty components are ignored in the calculation method, the whole operational AEP uncertainty is then, on average, slightly underestimated.

This difference can be explained by comparing the contributions $R_{\mathrm{ij}}\overline{\sigma_{\mathrm{i}}\sigma_{\mathrm{j}}}$ from the various uncertainty pairs in Equation 7 averaged over the 472 considered wind plants. Figure 13a shows the mean magnitude (across all wind plants) of these contributions for all of the considered uncertainty pairs. The negative correlation between IAV and linear regression has the largest single impact because this correlation involves the two largest uncertainty components (Figure 5). However, the sum of the contributions from all of the positive correlations exceeds the sum of the contribution from the negatively correlated components (Figure 13b), thus resulting in the overall average increase in total operational AEP uncertainty when the correlations are taken into account in the calculation.

4 Conclusions

Financial operations related to wind ~~farms~~ plants require accurate calculations of the annual energy production (AEP) and its uncertainty prior to the construction of the plant and, often, in the context of its operational analysis. As wind energy penetration increases globally, the need for techniques to accurately assess AEP uncertainty is a priority for the wind energy

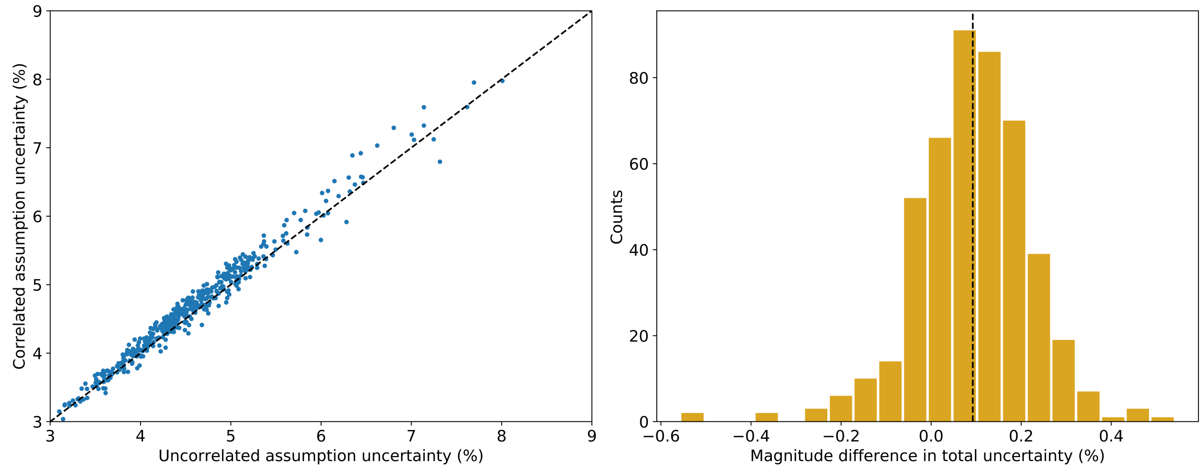

Figure 12. (left) Scatterplot of total operational AEP uncertainty values calculated with and without assuming uncorrelated uncertainty components for the 472 wind plants considered. Uncertainty is quantified as the percent coefficient of variation of the resulting long-term AEP distribution. (right) Histogram of difference $\sigma_{\text{tot,corr}} - \sigma_{\text{tot,uncorr}}$ between the total operational AEP uncertainty calculated considering and ignoring the correlation between its uncertainty components.

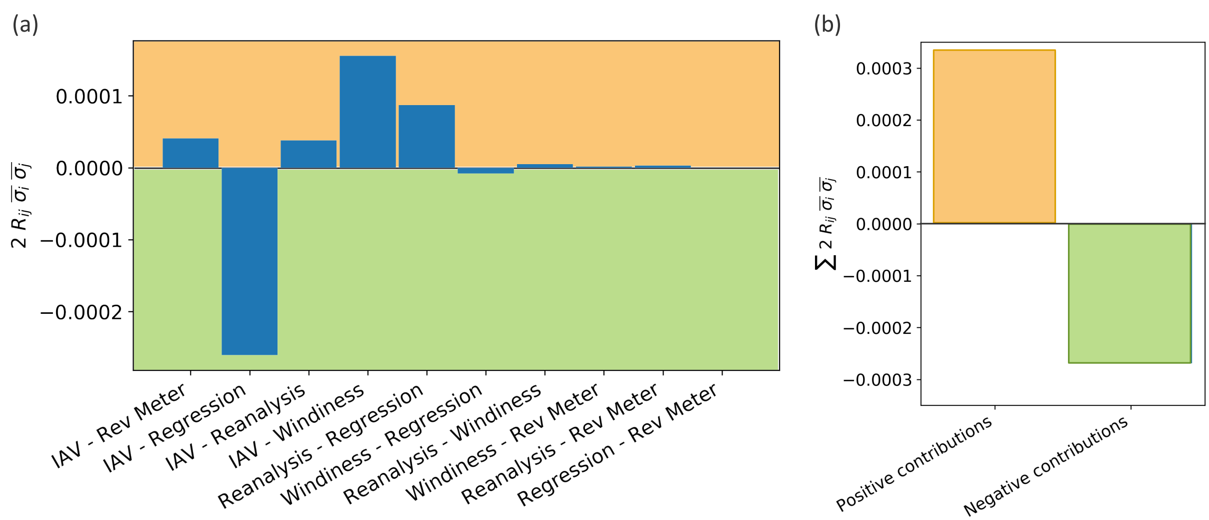

Figure 13. (a) Average (across 472 wind plants) contribution of the correlation between single uncertainty pairs to the total operational AEP uncertainty, according to Equation 7. (b) Comparison of the total contribution from positively and negatively correlated uncertainty pairs, computed by summing the contributions shown in panel (a).

industry. Typically, current industry practice assumes that uncertainty components in AEP estimates are uncorrelated. However, we have shown that this assumption is not valid for the ~~six components which~~ five components that comprise an operational-based uncertainty~~, using the EIA data set.~~

~~In this study we~~ . We used a Monte Carlo approach to assess ~~annual energy production; this not only accounts for correlations between uncertainty components, but also provides quantitative insight~~ AEP; this provides quantitative insights into aspects of the AEP calculation that drive its uncertainty. We have applied this approach using operational data from 472 wind ~~farms~~ plants, mostly in simple terrain, across the United States in the EIA-923 database~~.~~

~~Our results show that ignoring~~ , in order to study potential correlations between uncertainty components~~causes a mean absolute difference of 6% compared to the uncertainty calculated with the Monte-Carlo-based approach, with larger deviations (up to 20%) for specific sites. Moreover, three~~ . Three pairs of uncertainty components ~~reveal~~ revealed a statistically significant correlation: wind resource ~~inter-annual~~ interannual variability (IAV) and long-term windiness correction (positive correlation); wind resource IAV and linear regression (negative); and reference wind speed data and linear regression (positive). Wind resource IAV and long-term windiness correction uncertainties are correlated because they both depend on wind resource variability. Wind resource IAV uncertainty is correlated with linear regression uncertainty because they are both inversely proportional to the number of data points in the period of record. Finally, reference wind speed data uncertainty and linear regression uncertainty show a negative correlation because they respond oppositely to the R^2 coefficient between the (reanalysis) wind speed and energy production data. ~~Therefore, our results suggest that a Monte Carlo approach should be preferred to take into account~~

Our results show that ignoring these correlations between uncertainty components ~~to lead to more accurate results, compared to the current industry standard approach. For all the projects considered in this study, the Monte Carlo simulation reached convergence within 10,000 runs. To facilitate the transition towards this proposed new industry standard, NREL's open-source OpenOA software~~[3] ~~already supports the recommended Monte Carlo approach to assess AEP. In addition, the benefit of this technique will be further described in a guideline document in preparation for publication by the AWEA TR-1 working group~~causes an underestimation of the total operational AEP uncertainty of, on average, about 0.1%, with peak differences of 0.5% for specific sites. These differences, though not large, would still have a significant impact on increasing wind plant financing rates. Moreover, we expect differences would become even larger for sites characterized by a more complex wind flow. Therefore, our results suggest that correlations between uncertainty components should be taken into account when assessing the total operational AEP uncertainty.

Additional components of uncertainty in an operational AEP were not considered in our study because of limited reporting in the EIA-923 database. These components include reported availability, curtailment uncertainty, and various uncertainties introduced through analyst decision-making (e.g., filtering high-loss months from analysis and regression outlier detection). Future studies could include the impact of these additional sources of uncertainty on the operational AEP assessment. Moreover, our analysis excluded sites, mostly in complex terrain, with a weak correlation between reanalysis wind resource data and wind power production. Future work could explore the magnitude of operational AEP uncertainty and the correlation between its components for such complex flow regimes. Finally, this study focused on correlations between operational AEP uncer-

[3] ~~https://github.com/NREL/OpenOA~~

tainty components. Future work could explore correlations between ~~pre-construction~~ the numerous preconstruction AEP uncertainty components ~~. Given the numerous components~~ (e.g., wake loss, wind speed extrapolation, wind flow model)~~and their intercomplexities, a Monte Carlo approach could reveal correlations that are at present not considered~~.

Code and data availability. EIA data used in this study are accessible from https://www.eia.gov/electricity/data/eia923/. Geographical data of the EIA wind plants are available at https://www.eia.gov/maps/layer_info-m.php. Software used to assess operational AEP is available from https://github.com/NREL/OpenOA.

Author contributions. NB and MO are equal contributors to this work. MO performed the AEP estimates on the wind plants considered in the study. NB and MO analyzed the processed data. NB wrote the manuscript, with significant contributions by MO.

Competing interests. The authors declare that they have no conflicts of interest.

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