# Author response to reviewer 2

The authors response is shown in red

We thank the reviewer for the valuable comments and suggestions, which we consider very important and help us to sharpen and improve the manuscript. Here our response to each comment.

This manuscript proposes two methods for evaluating rotor loads under wake conditions. The work is primarily based on synthetic data generated through Mann's model and imposing modeled wake velocity deficits for different incoming wind speed and turbulence intensity:

I struggled to read through the entire manuscript and complete my review due to the cumbersome writing, lack of rigor of some statements and, sometimes, excessive technical details and jargons making more difficult the text comprehension. These are my main comments:

- In my opinion, this manuscript requires a major rewriting to sharpen its focus, remove jargons, and increase rigor in the description of the work.

  A substantial update of the manuscript is carried out to clarify and sharpen the explanations. Further, an improved motivation of the study, a better description of the load validation procedure, and an improved description of the assumptions of the DWM model are provided to increase rigor in the description of the work.

- Many statements are not precise or incorrect, which makes the presentation of the work very cumbersome.

  The cumbersome statements highlighted by the reviewer have been improved or removed.

- This work uses a statistical approach to inject lidar data (here only simulated) in an existing velocity field through a technique proposed by the same authors in Dimitrov and Natarajan (2017). As shown in Figs. 4 and 12, this can produce reasonable characteristics of variance and spectra; however, it is far to be considered a data-assimilation technique (see more comments below). Maybe this method can be useful for wind energy applications, but it is highly below current standards for the turbulence/fluid mechanics community.

  The scope of the work (which has now been updated in the manuscript) is to verify that incorporating nacelle lidars measurements in the wake field reconstruction methods improve the accuracy of power and load predictions when compared to wake field reconstruction methods that are based on engineering wake models alone (e.g., the DWM model). The introduction section now motivates in detail the need for this study. From the improved manuscript, it should be now clear that the scope of this study is not to outperform data-assimilation techniques developed in the turbulence/fluid mechanics community, but to propose and demonstrate lidar-based techniques that are suitable and practical for engineering purposes such as power and load assessments under wake conditions at a given site, which require hundreds to thousands of aeroelastic simulations.

Comments:
1. The abstract should be sharpened to clarify the contribution of this manuscript and highlight the results achieved. There are too many details that result to be confusing without reading first the text in detail, see e.g., the "target observations", the baseline, etc.

The abstract has been sharpened by clarifying the main contributions and leaving details of the work outside.

2. L20, "The wake-induced velocity deficit and its spatial displacement…", just call it meandering.

This has been corrected.

3. L28, "For the purpose of load validation, the IEC 61400-1 standard (IEC, 2019) recommends engineering wake models, which ensures low computational effort and an acceptable level of accuracy." This sentence can be rephrased. It sounds in contradiction with the previous paragraph. Maybe you can say that detailed predictions of wake-generated turbulence can be achieved with LES; however, the required computational cost makes engineering wake models a practical alternative.

The sentence has been rephrased by emphasizing that as current state-of-the-art, LES can simulate wake flow fields accurately; however, they are still impractical in a design or site-specific power load assessment analysis.

4. L29, spell out DWM the first time in the text, even though you already mentioned it in the abstract.

This is now done.

5. L 54, "wake deficit characteristics and their motions": the motion of the wake deficit characteristics has no sense to me. Please clarify what you are trying to explain.

The sentence in L54 is unclear and has been corrected as: 'The second approach reconstructs wake deficit characteristics including wake meandering by fitting...'

6. L56-59. Again, the description of the work is very confusing. If I am not mistaken, you compare the load predictions obtained with the two proposed models against those obtained by injecting to the aeroelastic code more classical predictions obtained through the DWM model. Then, at L62 it is stated "the load prediction obtained using lidar-reconstructed wake flow fields is as accurate or superior than that obtained with the DWM model". How can you get better accuracy of your benchmark dataset? At the very best, you can match those data with your new models.

We have replaced that sentence with 'The main objective of this study is to verify that nacelle-mounted lidar measurements incorporated into wake field reconstruction methods improve the accuracy of power and load predictions when compared to wake field reconstruction using engineering wake models alone.'

The sharpened introduction section clarifies better the limitations of the IEC-recommended engineering wake models for load calculations, and how lidar-based wake field reconstruction techniques can potentially tackle these limitations.

We have also improved Section 2 'Problem formulation', which provides a better description of the load validation procedure and how lidar-based wake field reconstruction methods can potentially outperform the DWM model by reducing the statistical uncertainty in power and load predictions. So, at very best the lidar-based wake field reconstruction approaches can fulfill the Criteria I and II described in Ln 101-104.

7. L60, "two sets of independent turbulence seed realizations", the meaning of this is not clear.

We have replaced the wording 'seed' with 'turbulence field'. A stochastic turbulence field generated with the Mann turbulence model or the Kaimal model (both are recommended in the IEC 61400-1 standard) is defined as a zero-mean homogeneous Gaussian turbulence field. Two random turbulence field realizations will produce two zero-mean homogeneous turbulence fields that are Gaussian, independent and uncorrelated (the realization of one turbulence field does not affect the probability distribution of the other).

8. L80-82. I disagree that you can quantify the statistical uncertainty of a turbulent process only by comparing two simulations. Furthermore, differences between the two simulations can be ascribed to both turbulence and wake meandering. How did you quantify the statistical distribution of your samples? How do you define the error between the two simulations? What statistical tests did you use to quantify the uncertainty?

The purpose of Section 2 'Problem formulation' is to formulate the load validation procedure and criteria used along the study. The exact details with regards to the questions: 'How did you quantify the statistical distribution of your samples? How do you define the error between the two simulations? What statistical tests did you use to quantify the uncertainty?' are defined and described in detail in 'Sect. 4.2 Load validation'. We provide a short description in here to answer the reviewer's comments:

We run a load validation analysis following the guidelines of the IEC 61400-13, which consists of applying a one-to-one comparison between predicted and measured (in our case *target*) power and load statistics (on a 10-min basis). This one-to-one load validation procedure is typically conducted in the design phase of a wind turbine to verify that the aeroelastic model predict loads accurately (see also IEC61400-13). Here, we extend this one-to-one load validation procedure under wake conditions in order to evaluate whether lidar-reconstructed wake fields, which are input to aeroelastic simulations, can predict power and loads accurately (e.g., with respect to the *target* results).

The IEC 61400-1 standard recommends using either the Mann model or the Kaimal model for generating random turbulence field realizations for aeroelastic simulations. Since these turbulence fields are stochastic, the resulting power and load predictions are affected by statistical uncertainty (e.g., load scatter). To overcome this issue, the IEC 61400-1 standard recommends performing aeroelastic simulations with at least 6 random turbulence field realizations for each 10-min realization of the inflow wind conditions, so to compute a more representative value of the loads. As described in Sect. 4.2, we use 18 turbulence field realizations (a factor of 3 higher than the recommendations of the IEC standard) for each 10-min realization of the inflow wind and quantify the statistical uncertainty in power and load predictions accordingly.

For example, given a wind speed of 6 m/s and $TI_{amb} = 6\%$, we generate 18 random turbulence field realizations that are input to the DWM model, run 18 aeroelastic simulations, and calculate the corresponding 18 values of the power and load statistics. We denote as bias the ratio between the simulated and *targeted* statistic for a single realization, and compute the uncertainty estimates on the statistical distribution of this bias variable over multiple realizations. Therefore, we calculate the mean bias ($\Delta_R$ out of 18 simulations) and the standard deviation from all the 18 biases ($X_R$). In our study, the statistical uncertainty in power and load predictions presented in Figures 10 and 12 are computed out of 162 simulations and not only by comparing two simulations.

We agree that this procedure does not describe all the statistical uncertainty of a turbulent process; however, this is not our goal. The goal is to describe the statistical uncertainty due to the differences between the simulated and targeted power and load predictions inherent to traditional load validation procedures (i.e., the realization-to-realization uncertainty).

'Differences between the two simulations can be ascribed to both turbulence and wake meandering'. This is correct, and we have discussed this point in the introduction (Ln 34–40). Indeed, this study's primary purpose is to verify that incorporating nacelle lidar measurements in the wake field reconstruction methods improves the accuracy and decrease the uncertainty in wake field representations (and consequently that of power and load fluctuations). How? As one can reduce the statistical uncertainty occurring due to the stochastic nature of the turbulence fields and the wake meandering time series (among others) that are inherent to conventional engineering wake models (such as the DWM model).

'How did you quantify the statistical distribution of your samples?' See Ln 372. According to the IEC recommendations at least 6 random turbulence field realizations should be used to account for statistical uncertainty in power and load predictions; here we use 18 turbulence field realizations to ensure we can accurately estimate the statistical uncertainty.

'How do you define the error between the two simulations?' See Ln. 351-356 and the whole Sect. 4.2, i.e., using $\Delta_R$ and $X_R$ indicators.

'What statistical tests did you use to quantify the uncertainty?' See answers to comment nr. 10 below.

9. L83-84, "we use a virtual lidar simulator that scans the target wake fields, and, through a field reconstruction technique, incorporates these samples in a random turbulence seed from set B". This is quite an obscure description of your research! What field reconstruction technique? How do you incorporate samples from one simulation in the other one?

This sentence belongs to a section (Sect. 2 'Problem formulation') that explains what field reconstruction techniques are used in the study. We have corrected the sentence with 'and through our proposed wake field reconstruction techniques,...'. The proposed approaches are explained few lines below (Ln. 90-95) as well as in the abstract (Ln. 1-6) and introduction (Ln. 51-56). Further, Sects. 3.4.1 and 3.4.2. describe how we incorporate lidar samples into the wake field reconstruction methods.

10. L 103, The statistical uncertainty (i.e., standard deviation of the bias) ? I have never seen this definition of uncertainty. Provide references, if any.

We have rephrased it with 'The statistical uncertainty (here defined as the standard deviation computed from all biases (Dimitrov et al. (2017) and Conti et al. (2020)) ...'. We show an illustrative example in Fig. 1 and then provide a detailed description.

Our study defines two uncertainty indicators to assess the power and load predictions accuracy: $\Delta_R$ and $X_R$ (see also Fig. 1-right), which are defined mathematically in Sect. '4.2 Load validation' Ln. 350-352 together with a detailed description of the performed aeroelastic simulations. Indeed, for each 10-min realization of the inflow wind conditions (e.g., given a wind speed of 6 m/s

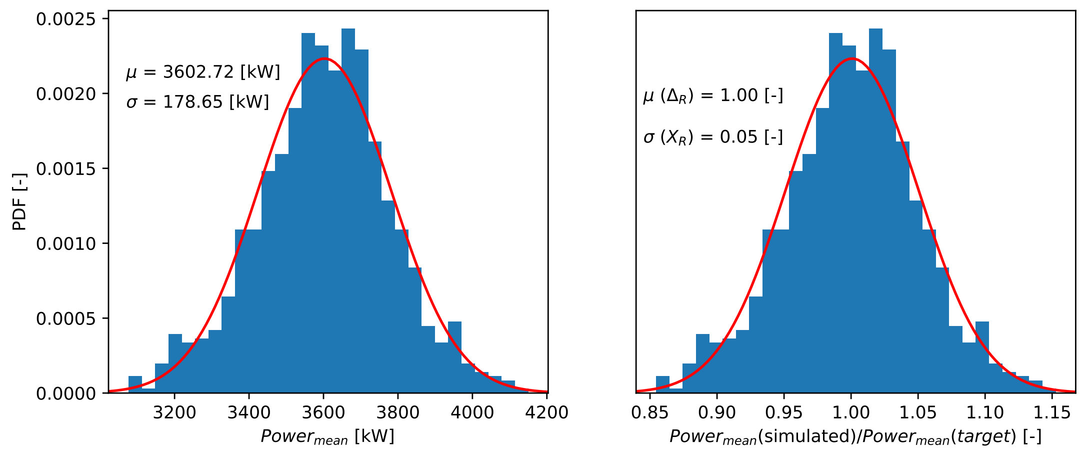


Figure 1: Left: Probability distribution function (PDF) of the mean power productions ($Power_{mean}$) obtained from 100 aeroelastic simulations (thus 100 random turbulence field realizations) with an inflow wind speed of 6 m/s and $\text{TI}_{amb} = 6\%$. Right: The $Power_{mean}$ results are normalized with respect to the *target* results. The mean and standard deviation values (i.e., $\mu$ and $\sigma$ that corresponds to $\Delta_R$ and $X_R$ when normalized with the *target* results) are reported in the figure.

and $TI_{amb}$=6%), we run aeroelastic simulations with 18 random turbulence field realizations, and quantify the mean bias between predicted and *target* load statistics ($\Delta_R$), and a measure of the standard deviation of these biases (out of 18 values) that is $X_R$ (i.e., the load's scatter dispersion).

Since the standard deviation is typically used as a measure of uncertainty in model predictions, here we use $X_R$ that is mathematically defined as the standard deviation of the bias. (Figure 1 should clarify this, and we show results from 100 simulations for illustrative purpose only).

We use $\Delta_R$ and $X_R$ as we aim to verify the load validation criteria described in 'Sect. 2 Problem formulation': (I) evaluating that lidar-reconstructed wake field provides unbiased power and load predictions. (II) verifying that the statistical uncertainty (which is here quantified using $X_R$ that is the standard deviation of the biases computed out of all the simulations) is lower when using lidar-based wake fields than conventional DWM model-based fields.

11. L 117, "wave vector with the wavenumbers in" at least remove wave.

This has been removed.

12. Sect 3.2 is a single paragraph with 20 lines, a great exercise for diving apnea training!

This section has been divided into smaller paragraphs. Further, we have rephrased the text to clarify the underlying flow modeling assumptions of the DWM model.

13. L144-L148 and Fig. 1. You are presenting the results of simulations without providing any sort of basic description or references. For instance, how did you get the Ct of the turbine as a function of incoming wind speed, what incoming velocity did you use for the simulations with different turbulence intensity? What spatial resolution do you have in your data?

We agree that this figure lacks essential information. This figure's purpose was to provide a qualitative illustration of how the wake deficit recovers for increasing ambient turbulence and wind speeds. As we improved the description of the DWM model in Sect. 3.2, we have also replaced this figure.

14. Eq. 4, How did you select the standard deviation of the Gaussian weighting function? Why did you choose a Gaussian function to simulate the spatial averaging? Can you provide references? More realistic functions have been proposed in the past, see e.g., work by Mann.

The weighting function of a continuous-wake lidar is often approximated by a Lorentzian form [1]. However, the Gaussian weighting approximation may also be used [2, 3]. Dimitrov et al. (2019) [3] quantified a difference in the $u$-velocity variance of less than 3% when using a Gaussian weighting function compared to the Lorentzian form.

For the data sets used in the present study, the difference between using a Gaussian and a Lorentzian weighting function was negligible. Figure 2 shows a comparison between the Gaussian- and Lorentzian-like weighting functions. As shown, using a Gaussian function has negligible effects when reconstructing the $U$-velocity component (longitudinal velocity component that is the primary driver to power and load predictions). The procedure to derive the $U$-velocity component is provided below.

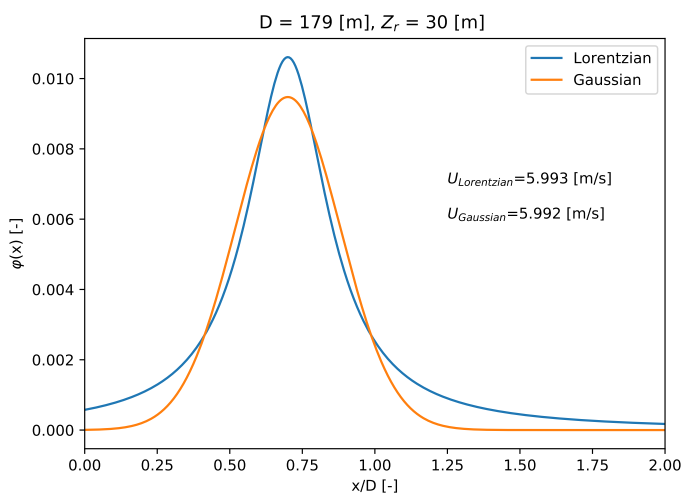


Figure 2: Lidar's weighting functions (i.e., Lorentzian and Gaussian shape). $D$ denotes the rotor diameter of the DTU 10 MW wind turbine, $Z_r$ is the probe volume length defined as the standard deviation of the Gaussian function or as the half-width-half-maximum for the Lorentzian function. $U$ defines the reconstructed velocity component accounting for the weighting function as described in the text below. An estimate of the resulting $U$ velocity is provided in the plot accounting for both the Lorentzian and Gaussian weighting functions.

The procedure to derive the $U$-velocity component: as the lidar simulator scans numerical wind fields, the sampled data points are discrete, and therefore the velocity estimates represent the weighted sum of a distribution of velocity measurements along the line-of-sight ($v_{los}$) as:

$$\tilde{v}_{los} = \frac{\sum_{i=1}^{n_p} \varphi(s_i) v_{los}(s_i)}{\sum_{i=1}^{n_p} \varphi(s_i)}, \tag{1}$$

where $n_p$ indicates the number of discrete points along the measurement volume. The weighting function ($\varphi(s_i)$) is approximated by a Gaussian function. The line-of-sight velocity is then expressed as function of the wind speed components and the geometrical angle ($\phi, \theta$), where $\phi$ is the elevation and $\theta$ the azimuth angle:

$$\tilde{v}_{los}(\phi, \theta) = u \cos\phi \cos\theta + v \cos\phi \sin\theta + w \sin\phi. \tag{2}$$

Yet the wind field at a given location cannot be fully characterized using a single lidar, instead a retrieval assumption is required to characterize the longitudinal velocity component, which is the major driver to power and load calculations. Considering that $u \gg v, w$, the measured radial wind speed is typically presumed to be due to the $u$ component alone with $v$=$w$=0. Thus Eq. (2) becomes:

$$\tilde{v}_{los}(\phi, \theta) = U \cos(\phi) \cos(\theta). \tag{3}$$

Equation (3) allows the virtual lidar simulator to reconstruct the horizontal wind velocity at each individual scanned point within the scanning configuration.

15. L156, this sentence "The u-velocity is computed from the projection of VLOS,eq onto the longitudinal axis, i.e., the v- and w-velocity components are neglected in the field reconstruction" is not correct unless you mention the constraints used in the angle difference between the velocity vector and the LOS vector. I guess we all agree that if the LOS vector is perpendicular to u, the LOS velocity is zero, but u is not.

This is correct; however, the maximum opening angles relative to the scanning configurations analyzed in this work reach a maximum of 35°. Further, for large opening angles (e.g., larger than $\approx 25°$), the lidar is actually measuring an area that is outside of the rotor area. Thus, the uncertainty introduced by the flow assumptions ($v$ and $w$=0) is marginal, and it is anyway discussed as one of the sources of uncertainty that affect the accuracy in power and load predictions.

16. L 164, "8192×32×32 (x,y,z)" What is the corresponding spatial domain with respect to the used reference frame?

As described in Ln. 165: 'A spatial resolution of 6.5 m is used for the grid in the rotor plane, which leads to a turbulence box with dimension 208 m × 208 m in both lateral and vertical directions ($y, z$).'.

Note that the turbulence fields used in aeroelastic simulations (and in the DWM model) are vector fields, where each grid point represents the local speed of the flow. In the generation of these fields, we use Taylor's assumption of frozen turbulence. Therefore, the large turbulence structures do not really change with time but are simply transported with the mean wind speed of the ambient wind field. As we run simulations with different ambient wind speeds, but the dimension of the turbulence box is fixed in the longitudinal axis to 8192 'points', the spatial resolution is function of $dx = (U_{amb} T_{sim})/8192$, where $T_{sim}$ is the simulation time in seconds (e.g., 600 s for a 10-min simulation). We have added this to the paper.

17. L 166, "These dimensions ensure an adequate turbulence field for a 10 min wind field simulation over a large rotor" How did you assess this statement through the simulation data? Please add these details.

A turbulence field with 32x32 points is considered sufficient because the field is internally downsampled to approximately 15 points per blade when running the Blade Element Momentum (BEM) code in the HAWC2 software [4]. Larger turbulence boxes can be used, but they will not affect the result's accuracy but only increase the storage required to generate larger turbulence boxes. As we generate over 1000 simulations, we opted to keep the computational and storage requirements low without compromising the results' accuracy.

We also added a reference to Dimitrov and Natarajan (2017), who used the DTU 10 MW for load validation analysis and found these dimensions to be suitable for load calculations.

18. L 171, maybe continuous wave (CW).

This has been corrected.

19. L 170-188. This review of different lidars is not needed because this work is mainly numerical. Please remove this part and only describe the scanning strategy considered.

This part has been removed.

20. L 196, what is a scan radius? Please define it.

We added a definition as: 'we use scan radii (defined as the radius between hub height and the location of the scanned points)...'

21. In Eq. 5 and 6, I guess you need to add time as an independent variable.

The DWM model assumes Taylor's frozen turbulence hypothesis; therefore, the wind field is described by the spatial vector solely. We have added a line in the text to describe this. Further, 'Sect. 3.2 Dynamic Wake Meandering model' has been improved to describe better the DWM model's assumptions.

22. L 219, "in Eq. (19) in Madsen et al. (2010)" I suggest to add this equation in the manuscript.

This has been added

23. L 223, The meaning of point 2 is unclear.

We have slightly rephrased point 2 as: 'The lidar-based wake fields are reconstructed by incorporating lidar observations (e.g., in the form of constraints or lidar-fitted velocity deficits) into a zero-mean, homogeneous, and random Gaussian turbulence field generated by the Mann spectral tensor model.'

We state this assumption as the lidar-based wake field reconstruction methods are similar to the wake field reconstruction methods inherent in engineering wake models. Indeed, the wake features are either pre-computed using a physical-based model (e.g., the DWM model) or fitted through lidar data (e.g., the CS and WDS algorithms of the present work). Successively, these lidar-based or physical-based wake features are superposed on stochastic homogeneous turbulence fields generated by the Mann model. By doing so, we keep the computational time as that for engineering wake models; thus, the lidar-based techniques are practical for power and load validation analyses, which require many aeroelastic simulations.

As described in a previous comment (see 13.), we have now rephrased 'Sect. 3.2 Dynamic Wake Meandering model' to emphasize the underlying assumptions of the DWM model, so Point 2 becomes more evident to the reader.

24. L 224, What velocity fluctuations with reference to Eq. 5?

If this comment refers to what velocity fluctuations are reconstructed by the lidar-based wind field reconstruction procedures, then Sect. 3.4.1 and 3.4.2 should clarify this. We have also added an equation that relates the LOS velocity to the u-velocity component.

25. L 226. Can you please define what are these turbulence seeds for set A and set B. To the best of my knowledge, turbulence seed is not mentioned in any turbulence book.

We agree that 'seed' is not appropriate here. We have replaced the term 'seed' with 'turbulence field realization' throughout the whole paper. The seed method is used to initialize the random number generator to create a random turbulence field realization from the Mann turbulence model.

26. L 245 "that maintains the covariance and coherence properties of the unconstrained field $\tilde{g}(r)$ What about fulfilling the Navier-Stokes equations? Is this a real turbulent flow or only a collection of random numbers? Looking at Eqs. 7 and 8, I guess this is true for a random timeseries. However, you cannot call these signals "turbulence". Other constraints and more sophisticated data-assimilation techniques should be considered to generate a turbulence field (see e.g., P. Bauweraerts, J. Meyers, J. Fluid Mech., Reconstruction of turbulent flow fields from lidar measurements using large-eddy simulation, 906, A17, 2020).

The Mann model is used in this work because it describes the atmospheric-turbulence velocity spectra for different surface, wind, and atmospheric-stability conditions (see i.a., [5, 6]). Further, the Mann model is recommended in the IEC 61400-1 and -3 standards for modeling three-dimensional turbulence fields required as input to aeroelastic simulations, and is widely used in load validation analysis (see i.a., [3, 7])

We agree that more sophisticated data-assimilation techniques exist (e.g., the work of P. Bauweraerts, J. Meyers, J. Fluid Mech., Reconstruction of turbulent flow fields from lidar measurements using large-eddy simulation, 906, A17, 2020). We have cited and discussed it in this paper's discussion section (Ln. 545-551). However, these high-fidelity techniques are yet not practical for power and load assessments that require many aeroelastic simulations (i.e., hundreds to thousands).

We have also sharpened the work scope to clarify that we are not aiming at outperforming LES-based data-assimilation techniques but providing a practical alternative to engineering wake model-based power and load assessment procedures commonly used in the wind energy industry today.

27. There might be an inconsistency between Eq. 10 and Eq. 11., i.e., $U_{lidar} = U_{WDS}$? Furthermore, Eq. 11, states that Kdef,lidar is not only the imposed velocity deficit kdef, WDS with a random perturbation added u'B. If that the case, then Eq. 11 is trivial and a simpler description can be provided.

This has been corrected and a simpler description is now provided.

28. L 298, "explained variance"? This might be only acceptable as jargon among lab mates not for a scientific publication.

The explained variance is actually used as a statistical term, e.g. [Achen, C. (1982) Interpreting and Using Regression, Sage Publications] [8]. In its classical use it is defined as the proportion of the variance in the dependent variables which can be accounted for by a mathematical model. For a regression model this is equivalent to the coefficient of determination (the square of the Pearson's correlation coefficient). Since in this work we use the definition in the broader sense, we prefer to retain the term explained variance. We have rephrased this in the text, so to clarify that we did not self-defined it.

29. L 373, what does is the list 8, 7, 7, 6,6,6 ,,,etc mean?

The list indicates the corresponding turbulence intensity values for each analyzed wind speed ranging from 6 to 22 m/s with a 2 m/s step. We have rephrased the text so it is clearer.

## References


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