The paper presents an interesting modification to the DWM model, that moves away from the assumption that the wake is transported as passive scalar and instead is akin to momentum transport, which is less efficient. The authors are using lidar wake measurements to motivate their modification. Overall the paper is clear, well structured and written, but fails to make full use of the measurements available.

Whilst the paper is sufficiently detailed with respect to the modelling choices and underlying procedures the validation approach remains somewhat unclear and is completely lacking any uncertainty quantification (measuring the lateral component with a lidar for instance should have large uncertainty). Spatially and temporal varying measurements of the wake need more rigorous treatment than stationary data if they are meant to be useful in the context of validating a dynamic wake model. There is temporal and spatial variation in the reference data and the measurement uncertainties need to be propagated to the derived quantities like the wake centre location. They should also propagate the input uncertainties through the DWM model and then compare with the observations. The authors need to perform validation under uncertainty to clearly demonstrate that their is statistically significant improvement from their modification of the DWM model. The linear regression lines shown throughout the submission are not sufficient. There are plenty of previously published studies using complex lidar measurements for model validation the authors could refer to for inspiration. The scientific impact of the submission will be much greater once all uncertainties are accounted for.

We are grateful to Referee #2 for the provided feedback and for reviewing the manuscript. We acknowledge that we have not treated the measurement uncertainty with the needed scientific rigor, which we addressed in the revised manuscript. Briefly summarized, we estimated the uncertainty of our measurement data and propagated it to the model predictions and the derived wake quantities. We detail this and the changes to the manuscript in the following. Also, please note that we implemented extensive changes to section 3.2 of the manuscript due to the feedback of Referee #1.

We make the following assumptions for the initial measurement uncertainty:

- The wake-scanning lidar used a signal-to-noise ratio (SNR) threshold of -14 dB, 3000 averaged pulses per estimate, and six points per range gate. For those settings, we estimate the uncertainty of the radial velocity as 0.3 m/s (Pearson et al. 2009, Eq. (2) therein). This uncertainty applies to the SNR threshold, but our data points have a better SNR than -14 dB and therefore this is an upper bound for the uncertainty. We previously used a SNR threshold of -17 dB, but we increased it for the revised manuscript. A technical report by Newsom and Krishnamurthy (2022) shows uncertainties of 0.1-0.2 m/s for six different Halo Photonics Stream lidars at an SNR of -14 dB experimentally, which is in line with our estimate for the uncertainty.
- For the spatial uncertainty of the wake-scanning lidar, we assume that it is equal to the azimuth distance travelled by the scanner head during a measurement. The assumed uncertainty of the azimuth is therefore 2° for our PPI scans. For spatial errors due to tower bending, see the last part of our reply.
- The measurements of the lateral velocity from the forward-mounted lidar have a much higher SNR than the -14dB threshold due to short measurement distance. Using Eq. (2) of Pearson et al. 2009 and the recorded SNR values leads to a theoretical uncertainty that is always smaller than 0.02 m/s across the data set, which is lower than the velocity resolution of instrument (0.038 m/s). Therefore, we use the velocity resolution as the uncertainty for the lateral velocity.

• We found a root-mean-square error (RMSE) of 0.45 m/s between the mean wind speed from the SCADA data and the mean wind speed from upstream stares parallel to the rotor axis of the front-mounted Doppler lidar. The upstream stares were mentioned in the manuscript, but their data had not been used so far. The RMSE includes errors resulting from the spatial separation of those measurements, different time periods averaged, and a bias that likely originates from the induction zone. If we remove the bias before computing the RMSE it reduces to 0.25 m/s, which is used as uncertainty of the mean wind speed for the error propagation.

Based on the above uncertainties, we employed a Monte Carlo method to estimate the propagated uncertainty. We created 100 resamples of the measurement data of a given case by adding random fluctuations drawn from a normal distribution with a standard deviation equal to the above estimated uncertainties. In case of the azimuth uncertainty, we used a uniform distribution across an interval equal to the uncertainty. This procedure was applied to the measurement values of the lidar radial velocities, the lidar azimuth readings, and the SCADA wind speed. We then recomputed the wake quantities and the DWM model predictions for each resample. Lastly, the propagated uncertainty was quantified as the RMSE between the original result and the results of the 100 resamples. This procedure was applied to each of the 43 cases of our data set. If results are normalized in a figure, we apply the error propagation rules for a division as a last step.

In case of the DWMM, the Monte Carlo approach was implemented in two stages. First, we estimated the uncertainty of  $y_{pre}$  with the Monte Carlo approach based on the uncertainties of v and  $\bar{u}_{hub}$ . Then, we estimated the uncertainty of the mean velocity deficit and the added turbulence intensity with a second Monte Carlo approach based on the uncertainties of  $y_{pre}$  and  $\bar{u}_{hub}$ .

To present the uncertainty in the manuscript, we made the following additions:

- The measurement uncertainties of the instruments are stated in the methods sections, when we introduce the measurement setup (lines 161-165, 176-179, and 189-190).
- Subsection 3.2.2 was added that introduces the method of error propagation (lines 237-247).
- The propagated measurement uncertainty is displayed as error bars of the data points in Fig. 5, 10, 11, and 12. We split Fig. 10 into two panels for clearer visibility with the error bars and swapped x-axis and y-axis to be more intuitive.
- Additionally, we provide for those figures the confidence interval of the linear regression to show its statistical uncertainty due the scatter of the data.
- We did not include the measurement uncertainty in Fig. 6 and 8, because the existing error bars in those figures show the variation due changes of the environment conditions that we deem more important here (Fig. 6 and 8 show the same quantities as Fig. 5 and 10 and the propagated measurement uncertainty can be seen there).

Let us now focus on the reviewer's comment on the uncertainty of lateral velocity measurements with a Doppler lidar. Even when we assume a higher uncertainty for the lateral velocity, the low-pass filter applied to the data leads to substantial temporal averaging, which reduces the propagated uncertainty for the DWM model predictions (we tested an uncertainty of 0.2 m/s and the errors of the DWM model were acceptable). For the predictions of the DWM model, the uncertainty of the mean wind speed proved to be a more substantial error source.

Overall, the results of the uncertainty propagation are consistent with the behavior of the data points. The error bars in Fig. 10-12 are not large enough to explain a strong scattering of the

data points, which is consistent with the high correlation coefficients reported ( $r \ge 0.8$ ). Figure 5 has a lower correlation, which is consistent with comparatively larger error bars there.

Further, the error analysis shows that the errors of the DWM and the observed wake quantities are not large enough to invalidate the results in our opinion. The modification of the DWM model led to a significant improvement, which can be seen from the confidence bounds of the linear fit in Fig. 10a that do not cover the identity, while they do in Fig. 10b.

We want to close by discussing tower bending. Even though the instrument was leveled before the campaign, a tilting of the instrument due to tower bending (a "nodding" like fore-aft movement of the tower) cannot be excluded. We do not have adequate support measurements to quantify this properly (the lidar's internal pitch and roll sensors seem very noisy even if the instrument is on solid ground).

However, based on maximum tower top displacements for above rated wind speeds found in the literature, we can estimate an upper bound for a tilting of the lidar beams. A maximum tower top displacement ( $\Delta x$ ) of 0.2 m was given in Bossanyi (2003). Two further estimates found in the grey literature provided similar values ( $\Delta x = 0.2$  m in a technical report by Hooft et al. (2003) for a turbine with a hub height of 92 m and  $\Delta x = 0.12$  m by Mate Jelavic et al. (2007) in conference proceedings). To estimate the effect on the lidar beam, we assume that the tower is stiff and compute the beam misalignment with  $tan^{-1} (\Delta x/z_{hub})$ , which results in a maximum beam misalignment of  $0.15^{\circ}$  for  $\Delta x = 0.2$  m. The corresponding vertical displacement of the lidar beam is  $\Delta z = 0.72$  m at x = 3D and  $\Delta z = 1.94$  m at x = 8D.

We expect the effect on the wake center position to be small assuming a regular shape of the wake (i.e. no branching). The effect on the mean velocity deficit should be small as well, because the wind shear over this height range should be small compared to the velocity deficit of the wake.

## References

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