Authors' Response to Reviews of

Assessing the Accuracy of a Three-Year High-Resolution Mesoscale Wind Farm Wake Simulation with Lidar and Satellite Radar Data

Alexandros Palatos-Plexidas on behalf of all authors
Wind Energy Science (WES) Journal,

RC: ***Reviewers' Comment***, AR: Authors' Response, ☐ Manuscript Text

1. Reviewer #2

1.1. General comments

RC: ***This paper evaluates the long-term capability of the WRF–Fitch WFP modeling framework representing wake effects from an offshore wind farm cluster in the Belgium–Dutch cluster. About two years of profiling lidar observations at several coordinates and SAR data from four selected dates are used for comparison.***

There is indeed a literature gap on the evaluation of the cluster wakes simulated by WRF-WFP over more realistic meteorological conditions using observations. This is no easy task, as it is difficult to cover large areas for a long period of time with measurement devices. Thus, the research problem and gap are well stated. The text is very well written, and the figures are well made; some of them convey information very nicely and look great (Figs. 14 and 15). The methodological approach makes sense to me, with some reservations. First evaluate the error metrics in detail to support the subsequent analyses of the wake effects.

However, my main concerns are the superficial interpretation of results, the limited engagement with the literature, and consequently, very mild conclusions for a study with such strong potential. The paper often remains at a descriptive level ("the wake extends", "bias improves") without explaining why certain behaviors occur or how they compare to previous WRF–WFP, LES, or observational studies. If the authors strengthen the physical interpretation of their results and relate them more thoroughly to existing literature, the manuscript could make a significant contribution.

AR: Dear Reviewer,
We sincerely thank you for your time and for the detailed, insightful comments. We appreciate the recommended references. We have included them in the revised version of the manuscript, as they align well with our current study. All changes and additions in the revised manuscript are highlighted in blue and enclosed in boxes.

We should also highlight that we've corrected the interpolation at hub-height for the BSB-lidar cases, resulting in a more accurate representation of the metrics throughout the full manuscript. More specifically, in the first version of the manuscript, we unintentionally used the lidar-measured heights without adding the BSB platform height of 45 m. This led to an incorrect estimation of both wind speed and wind direction at the intended hub height of 107 m.

1.2. Specific comments

RC: ***1. Please provide details on the turbine types used, including hub height, rotor diameter, and ideally thrust/power coefficient curves. These curves can be placed in the Appendix. If some data are confidential, clarify which components are public and which are not.***

AR: A detailed table with types of turbines, hub-height, and rotor diameter has been added in the Appendix. Most of the power and thrust curves remain confidential.

RC: ***2. A more detailed characterization of the sources of model error needs to be made. The paper clearly shows that the simulations with the Fitch WFP lead to improved metrics of wind speed and wind direction based on the lidar observations. In Section 3.2.1, wind speed metrics for several lidar locations and models are shown. However, these error metrics are aggregated for all wind directions, and so they represent simultaneously the effect of the WF simulation representing the undisturbed wind and wake effects. This is a problem because wake effects can be misrepresented, both because of errors in the representation of the free wind and specificities to the WFP. This information is crucial to establishing what makes the model more or less accurate (inflow error, wake modeling error, spatial gradients errors). As we know, errors in the undisturbed wind speed propagate into errors in the wake effects. This piece of evidence will strengthen the discussions when a few selected cases are presented in the SAR evaluation (Fig. 15)***

AR: We have overall updated the revised manuscript considering this comment. More precisely:

- Regarding misrepresentation in errors in the free-stream, in Section 3.2.1 (lines 294-301):

> The bias score (Figure 5A) shows that both ERA5 and the NWF simulation exhibit a consistent negative bias at all sites except BSB, a consequence of the inherent ERA5 underestimation that propagates into WRF. The additional wind speed reduction introduced by the Fitch WFP leads to a slightly more negative bias in the WF run, although WRF generally aligns better with the lidar observations than ERA5. **Part of the improved bias in the NWF runs likely results from an error-cancellation effect with the negatively biased ERA5 input, whereas in the WF simulations, these errors become slightly amplified due to wake-induced deficits, but remain lower than those in ERA5.** At BSB, both ERA5 and the NWF runs show a positive bias, while the WF simulation produces a smaller negative bias, corresponding to an improvement of about 82% over NWF and 73% over ERA5 in the near-wake under the predominant southwesterly flow.

- Two extra figures on wind speed and wind directions bias per wind direction have been added, i.e., Figures 7 and 8, to better understand WRF performance at different wind sectors. Additionally, these paragraphs have been added in Section 3.2.1 (lines 324-340):

> In Figure 7, the wind speed bias for each wind direction at each location is depicted, allowing a clearer assessment of the bias sources. Colored lines represent NWF, WF, and ERA5 datasets, and the dashed lines indicate zero bias. At WHi, EPL, and LEG where wakes due to the existence of the Belgian-Dutch cluster are observed, the NWF and WF simulations generally show similar distributions, except along the principal wake directions, where NWF performs slightly better. More specifically, at WHi the dominant wake influence arrives from the northeast, and around 45^o the NWF bias is closer to zero. A similar pattern appears at EPL, and LEG, where NWF bias is closer to zero around 225^o and 255^o, respectively. Especially at EPL, the bias is close to zero between 190^o and 225^o in the NWF simulations. In all three cases, both WRF configurations reduce the negative bias found in the ERA5 data, highlighting that the Fitch scheme introduces

> an additional bias downstream of wind farm regions. Conversely, in the intra-farm region at BSB, the Fitch scheme provides a more accurate wind speed distribution across all wind directions, underscoring its importance in strongly waked environments. This behavior of the Fitch scheme, showing prolonged wakes and enhanced wind speed deficits at locations farther downstream and more accurate wind speed distributions closer to the turbines, has also been reported in previous studies [García-Santiago et al., 2024, Ali et al., 2023].
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> Similar to the wind speed bias per wind direction, Figure 8 presents the wind direction bias. Although the mean bias in Figure 6A suggests a closer agreement between the lidars and ERA5, WRF provides a better representation of the wind directions when the wind originates from the north to south-southeast(0 to 180^o). Conversely, for westerly wind directions between 180 and 360^o ERA5 performs better. At BSB, the mean bias is nearly identical between the WF runs and ERA5, but ERA5 shows a slightly closer agreement with the lidar measurements across all wind directions.

- Furthermore, in Section 3.2.3, regarding error metrics under different wind speed regimes for SW and NE wind directions, Tables 4, and 5 have been added. These Tables present bias and cRMSE for the NWF and WF wind speeds against the three analyzed lidars under different wind directions and wind speed classes. Please see the response to comment 4, where the updates in the manuscript are discussed.
- In addition, in response to comment 11, mean absolute error (MAE) and absolute error (AE) for the SAR-events are presented in Section 3.3 (please have a look at comment 11).

RC: ***3. Many more discussions are needed. For instance, Section 3.3 only describes the results without a single reference to the literature. That is unfortunate, because Figures 14 and 15 are the apex of the paper in my opinion. It is a missed opportunity to compare your evidence to the literature and describe the contrasts. Please cite papers that did WRF-WFP vs. lidar and/or SAR observations. Resort to the good references you already have and consider including Platis et al. (2018) and Cañadillas et al. (2020), which are great papers on the same scope. You cited Ali et al. (2023) in the Introduction, but their work is never mentioned again. The reader wants to know how the representation of the wake effects compares with other studies that use idealized LES or mesoscale simulations with observations near offshore wind farms.***

AR: We have updated the results sections throughout, incorporating additional literature and further details as requested. More precisely:

- Regarding Section 3.3, we have improved that part, linking the results and conclusions to existing literature. More precisely, we have included additional discussion on the stability stratification assessed in WRF simulations, and how it relates to the wake patterns, as well as with additional studies.

> Figure 16 presents the comparison of SAR and WRF wind fields at 10-meter height. The left column shows the SAR-derived wind speeds, denoted by the subscript 1. The middle column depicts the WF wind speeds, indicated by a subscript 2, and in the right column, the reference NWF wind speeds are illustrated, and denoted with a subscript 3, as a reference case. In case A, higher wind speeds are also related to stable-neutral conditions and a shallow boundary layer (see Table 7). The wake structure of the Belgian-Dutch wind farm cluster is well captured by the WF simulation. However, a slight deviation in wind direction is observed in WRF, exhibiting a positive bias toward more westerly flow. Similar bias has also been highlighted in the wind roses (Figure 4) and in the wind direction validation heatmap in Figure 6A. The prolonged wake extending more than 50km downstream under stable-neutral stratification agrees

with the findings of Cañadillas et al. [2020] and Platis et al. [2018], who also report that wake structures are more pronounced and longer during stable conditions. Furthermore, Siedersleben et al. [2020] examined a stable event simulated with the Fitch scheme in WRF (version 3.8.1), comparing the original formulation ($a = 1$) with a variant excluding the added TKE term, and showed that including the added TKE source under stable stratification results in a more realistic representation of the prolonged wake of a SAR-retrieved 10-meter wind speed pattern. In our study, although we use a finer grid spacing (1km instead of 1.67km) and a reduced TKE coefficient ($a = 0.25$), which limits the influence of the added TKE term, we observe a very good agreement between the SAR image and the WF simulations during stable conditions. Furthermore, Ali et al. [2023] evaluated several WFP schemes to characterize the wake of a specific event using 10 m SAR data. Their results show that, when comparing the Fitch model with $a = 1$ and $a = 0.25$, the latter produces a longer wake downstream of the wind farms, similar to the behavior observed in case A analyzed in the present study.

In case B, the wake is weaker, but still detectable both in SAR image and in the WF simulation. In this case, stability conditions are very unstable, and the PBLH is around 700 meters, explaining the attenuated wake pattern. Case C is characterized by higher wind speeds, L varies from -300 to -450 m, and PBLH is approximately 300 m across the three locations, resulting in a more unstable-neutral stratification profile, resulting in the observed downstream wake of about 40 to 50km. Similar wake patterns but slightly shorter, about 25 to 35km have been observed during neutral stratification in the study of Platis et al. [2018]. Last, in case D, very unstable ABL conditions prevail, and the PBLH varies between 250 meters upstream at the WHi location to 358 meters downstream at the EPL area. This is the only SAR image with clear wakes for SW wind conditions. Overall, the patterns of the wakes are accurately represented by the WF simulations, highlighting the importance of using the Fitch WFP scheme in WRF. Although SAR assumes neutral stability to compute the 10-meter wind speed, there are discrepancies with the WRF model, especially in cases B and D, where very unstable stratification dominates based on the values of Obukhov length. Uncertainty exists regarding the assumption of SAR image neutrality used to calculate wind fields, an issue that has also been reported in previous studies across different applications Hasager et al. [2011a], Ahsbahs et al. [2017]. Furthermore, there is uncertainty in the estimation of L within WRF, as it strongly depends on the PBL and surface schemes applied in each configuration.

In addition to the wind speed deficit maps, Figure 17 presents the transects that connect WHi, BSB, and EPL. The green line illustrates the 10-meter height SAR wind speeds, while the purple and orange lines correspond to the WF and NWF simulation outputs, respectively. Although a Hampel filter (see section 2.3.3) has been applied to the transect of the SAR data, we can still observe a few outlier values, especially in the intra-farm area. The wind turbines generate spikes in the wind fields due to strong radar reflection [Hasager et al., 2015, Ahsbahs et al., 2020]. Therefore, to further evaluate the performance of the WRF model, hub height-lidar measurements are incorporated when available, depicted as gray scatter points in Figure 17.

- Section 3.2.1 has also been updated, providing more details in the error-sources and links to literature (e.g., García-Santiago et al. [2024], Ali et al. [2023]), as described in the reply to comment 2.
- Section 3.2.3 has also been improved according to the next comment 4. Specifically, Tables 4, and 5 have been added, where wind speed bias and cRMSE metrics for the NWF and WF simulations are discussed (linked to comment 2 as well), and the discussion on Figures 12 and 13 has been updated and linked to existing literature (e.g., Ali et al. [2023], Fischereit et al. [2024a]. In the same Section, Figure

14 has been improved, including also a classification of averaged wind speed deficits under different wind speed magnitudes and stability conditions, for the analyzed SW, and NE wind directions, showing that an increase in the wake magnitude is observed when transitioning from unstable to neutral and stable conditions (see comment 7).

RC: ***4. Following on the aforementioned point, Figures 10 and 11 are not being discussed as well, which is another missed opportunity to communicate whether your results make sense with the literature or not.***

AR: The updated Figures 12, and 13 (i.e., Figures 10, and 11 in the first version of the manuscript) are now thoroughly analyzed and discussed. Fu, Tables 4, and 5 have been added, where wind speed bias and cRMSE metrics for the NWF and WF simulations are discussed. Therefore, we improved the clarity and the flow of this Section. Please find below the updates and changes in Section 3.2.3 in lines 398-433:

> Figures 12 and 13 depict the wind speeds along the transect connecting WHi, BSB, and EPL for the four different wind speed classes under SW and NE wind directions, respectively. The distributions at each location are clipped at the 1st and 99th percentiles solely for illustrative purposes, without affecting the presented statistics. Overall, the WF simulations slightly underestimate the wind speed, and this is corroborated by the bias scores in the full-period heatmaps presented in Figure 5A. More precisely, under SW winds, the model underestimates wind speeds at the upstream location of WHi across all the wind speed classes. Especially, when the wind speed is between [3, 5) m s^{-1} or above 8 m s^{-1}, the produced wind speed deficit of the Fitch model is overestimated. On the other hand, the model provides a more accurate wake pattern when wind speed belongs to [5, 8) m s^{-1} and [8, 11) m s^{-1} classes. These wind-speed ranges usually correspond to the power ramp-up region of a wind turbine, where power output exhibits strong sensitivity to wind-speed variations. Under northeasterly winds (see Figure 13), the model underestimates wind speeds in both the [3, 5) ranges across all locations, while performance improves markedly when wind speed varies from 5 to 11 m s^{-1}. In both wind direction cases, the WF simulations overestimate the intra-farm wind speed deficit when wind speed is above 11 m s^{-1}.
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> Table 4 summarizes the wind speed bias and cRMSE across the wind speed classes for the SW wind direction, highlighting how model performance varies in upstream, intra-farm, and downstream locations. Under SW winds, where the flow progresses from WHi (upstream) → BSB (intra-farm) → EPL (downstream), the largest errors occur upstream at WHi in the 3–5m s^{-1} class (bias=–1.09 m s^{-1}, and cRMSE=1.56 m s^{-1}, which are very similar to WF and NWF runs), reflecting that small inflow uncertainties propagate strongly before the flow encounters the farm. As the flow moves into and through the farm, the bias systematically decreases, reaching nearly zero at BSB and EPL in the 5–8 m s^{-1} class in the WF simulations. The cRMSE increases with the wind speed magnitude, indicating that although the mean wind speed is well captured, the variability associated with wake turbulence and flow transitions is still not well reproduced. Overall, the cRMSE in the WF simulations is comparable to, or slightly lower than, that in the NWF simulations across all locations and wind speed regimes.
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> Under NE winds, where the flow reverses (EPL → BSB → WHi), a similar pattern emerges as presented in Table 5. The upstream location (now EPL) shows a reduced bias at low wind speeds (about -0.50 m s^{-1} in both NWF and WF) but a higher cRMSE (1.8 to 1.95 m s^{-1}). Within the farm (BSB), bias remains modest across most wind speed classes, while cRMSE stays elevated. When wind speed is in the 8–11 m s^{-1} class, WF provides an almost negligible bias both at EPL and BSB. At higher wind speeds (above 11 m s^{-1}), both bias and cRMSE increase, especially at BSB. The improved bias in the NWF simulations and under specific wind speed magnitudes can be associated with error-cancellation

of the already biased ERA5 data (see section 3.2.1). The differences in bias and cRMSE scores between the NWF and WF simulations at the upstream locations (WHi under SW wind directions, and EPL when wind comes from NE) are related to the fact that the flow can already be slightly affected by the UK wind farms on the west and the Dutch cluster on the NE, as presented in Figure 1b.

Although Figures 12 and 13 present transects under different wind speed magnitudes for the SW and NE wind directions, transect-based analyses of instantaneous wake events have also been reported using flight measurements [Ali et al., 2023, Fischereit et al., 2024b]. Those studies showed that the Fitch WFP in WRF can reproduce the wake features and reduce wind speed biases along transects. The transects in Figures 13 and 14 extend this type of analysis but rely on lidar observations rather than flight data, allowing for a comparison of more events and analyzing upstream, intra-farm, and downstream wake characteristics.

RC: ***5. Figure 11: You state that "Notably, intra-cluster wake behavior differs under NE winds, with a continuous reduction in wind speed observed throughout the wind farm", and no explanation as to why this behavior takes place is provided. Why is it that the wind speed deficit is more flattened for the SW direction? As readers, we want these insights from you. Sometimes the most interesting aspects of the research appear in these details. What is the role of the different transects relative to the wake center? What is the role of the heterogeneous layout and density of the wind turbines?***

AR: There are two main reasons that we observe different wake structures on the SW and NE wind directions, and they are both related to the geometry of the Belgian Dutch cluster. First, in the SW case, the flow meets the Belgian cluster that extends perpendicular to the flow, and it has a dense wind turbine-layout. This results in a more rapid reduction of the wind speed, as well as the development of a blockage zone upstream of the Belgian cluster. The already reduced wind speed remains almost constant downstream of the Belgian cluster and when crossing the Borssele wind farm in the Netherlands. On the other hand, when the wind direction is NE, the reduction of the wind speed is smoother, as the Borssele wind farms cluster is less dense and has a greater area. When crossing the Belgian zone, an additional wind speed reduction is observed. This paragraph has been improved, including also the maximum wind speed deficits in the updated figures 12 and 13, and this statement has been included in the revised version of the manuscript in lines 434-452:

Notably, distinct intra-cluster wake patterns emerge under SW and NE wind conditions. Under SW winds, the strongest wind speed deficit originates within the Belgian wind farm cluster and remains nearly unchanged as the flow proceeds across the Borssele zone. In contrast, under NE winds, the wind speed decreases progressively throughout the entire wind farm region, beginning in the Borssele cluster and intensifying as the flow enters the denser Belgian wind farms. Furthermore, the wake recovery rate is less smooth at high wind speed magnitudes. These findings highlight the directional dependence of wake dynamics and underscore the need for improved model representation of low-speed flows and intra-cluster wake effects. More specifically, the maximum wind speed deficits increase with wind speed magnitude. At wind speeds above 11 m s^{-1}, the difference between SW and NE conditions becomes substantial: under SW winds, the maximum deficit reaches approximately 2.72 m s^{-1}, whereas under NE winds it increases to about 4.19 m s^{-1}. At lower wind speeds (below 8 m s^{-1}), the largest deficits in both SW and NE regimes occur near the center of the densely built Belgian wind farm zone. At higher wind speeds, however, the location of the maximum deficit shifts. Under SW winds, the strongest deficit moves toward the northeastern boundary of the Belgian zone, near the interface with the Dutch Borssele cluster. Conversely, under NE winds, the maximum deficit appears at the downstream exit of the Belgian wind farm cluster. These contrasting behaviors between the wake trends under SW and NE wind directions arise from the strong dependence of wake evolution on turbine spacing. The averaged density of the Belgian wind farms that the analyzed transect crosses is about 10 to 12 MW/km^2, while the Borssele cluster has a density of about 4 to 5 MW/km^2. Therefore, the dense Belgian cluster produces rapid wake merging and a deeper cumulative deficit, whereas the more widely spaced Borssele layout allows partial recovery before wakes redevelop downstream. As a result, SW winds encounter an already merged wake that weakens over the coarse Borssele area, while NE winds first traverse the coarse Borssele layout, where deficits remain modest, and then intensify sharply upon entering the dense Belgian cluster.

RC: ***6. L467–470: "Systematic biases in both wind speed and direction are evident, particularly in the wind speed metrics. However, it should be highlighted that the model is driven by ERA5 hourly data, which consistently introduce a negative bias, affecting the boundary conditions in WRF and propagating wind speed underestimations to the analyzed locations." And what is the effect of this modeling bias on the representation of the wake effects? This discussion is fundamental because sometimes you have a bias in the free wind speed that can actually improve, by accident, the validation metrics. This must be explained.***

AR: This has been partially addressed in comment 2. The negative bias in ERA5 can affect the wake assessment. It is shown in Section 3.2.1, in Figures 5 and 7, where NWF can provide lower biases compared to the WF runs (not at highly-waked locations like BSB). We consider that this can be due to an error-cancellation effect, as the ERA5 is already negatively biased.

This paragraph in Section 3.2.1 (lines 294-301) has been added:

The bias score (Figure 5A) shows that both ERA5 and the NWF simulation exhibit a consistent negative bias at all sites except BSB, a consequence of the inherent ERA5 underestimation that propagates into WRF. The additional wind speed reduction introduced by the Fitch WFP leads to a slightly more negative bias in the WF run, although WRF generally aligns better with the lidar observations than ERA5. **Part of the improved bias in the NWF runs likely results from an error-cancellation effect with the negatively biased ERA5 input, whereas in the WF simulations, these errors become slightly amplified due to wake-induced deficits, but remain lower than those in ERA5.** At BSB, both ERA5 and the NWF runs show a positive bias, while the WF simulation produces a smaller negative bias, corresponding to an improvement of about 82% over NWF and 73% over ERA5 in the near-wake under the predominant southwesterly flow.

In addition, in the analysis of SW, and NE wind direction in Section 3.2.3, in Figure 12, and Table 4, we observe that in the upstream location (WHi under SW wind conditions), there is always a negative bias, most likely propagated from ERA5 and the overall WRF performance. This under specific conditions, for example, in Table 4, under [3-5) m s^{-1} wind speeds, BSB provides a negligible bias in the NWF simulations that is higher in the WF. We consider that this can happen due to error cancellation. Similarly, under NE wind conditions in Table 5, when the wind speed is low, the bias at BSB is lower in NWF simulations compared to the WF.

In the conclusions, this paragraph (lines 593-605) has been updated as well:

Our findings demonstrate that the use of the Fitch WFP scheme, in combination with this particular WRF configuration, captures the wake effects and provides an improvement in model performance relative to a simulation without wind farms at the intra-farm region. First, focusing on the time-averaged wind speeds over the full analysis period, the WF simulations yield a substantial improvement in both bias and EMD, with reductions of approximately 82% and 73% compared with the NWF simulations, respectively, in the intra-cluster (BSB location). **Furthermore, when analyzing the wind speed bias under different wind directions, both NWF and WF configurations reduce the negative bias inherited from the ERA5 data, with the results indicating that the Fitch scheme introduces an additional deficit downstream of the Belgian-Dutch cluster.** However, within the intra-farm area, the Fitch scheme provides a more accurate wind speed distribution across all wind directions, underscoring its importance for representing strongly-waked environments. Beyond the improvements in bias and EMD, the WF simulations perform similarly to the NWF runs in terms of cRMSE and correlation, with only small and marginal differences. Similarly, wind direction metrics are also improved in the WF simulations, as bias is reduced by approximately 51% at BSB, while an analysis of wind direction biases by sector reveals that WF can perform better than ERA5 for wind directions from northeast to south.

RC: ***7. Many figures address modeling error metrics (Figs. 5–8), but none for the actual wake effects. I think we can increase the value of the paper if you use Figure 13 as a template and plot a wake-related metric (e.g. wind speed deficit). That template is great because it simultaneously separates the effects of wind speed classes and stability.***

AR: The manuscript has been updated to include wake-effects metrics in terms of wind speed deficit magnitude, as well as wake area and length. More precisely, Figure 14 has been moved to Section 3.2.3, and it has been updated, including also the average wind speed deficit magnitude per wind speed magnitude class for each ABL stability regime. Below in bold (lines 462-477) is presented the paragraph describing wind speed magnitudes under different stability regimes and wind speed conditions.

Figures 14A, and B present the frequency of the ABL stability conditions under the different wind speed ranges, for SW and NE wind directions, respectively. The ABL stability classification is based on Obukhov length, averaged across the three lidar probes in the NWF simulations. Under low wind speed conditions, very unstable and unstable events tend to dominate. Conversely, a transition toward near-neutral ABL stratification under high wind speeds is also evident. Previous studies [Rosencrans et al., 2024, Palatos-Plexidas et al., 2024, Porchetta et al., 2024] have demonstrated the dependence of wake propagation and wind speed losses on ABL stability, showing that transitioning from neutral to stable and very stable stratification, wakes tend to extend further downstream of wind farms. Similarly, we underscore the relation between wind speed magnitude, ABL stratification, and wake propagation, where during high wind speeds, the frequency of neutral events is enhanced and wakes propagate a few tens of kilometers downstream of the Belgian-Dutch cluster.

In addition to the frequency of the stability regimes, in Figures 14C and D, the magnitude of the average normalized wind speed deficit is presented under the different stability conditions. The wind speed deficits are estimated as the average across the three analyzed lidar locations. It is observed that under very unstable and unstable occurrences, the wake magnitude is relatively lower (varying from 4 to 8%). When ABL stratification is near neutral, higher wake magnitudes are also observed. Following the patterns presented in studies [Rosencrans et al., 2024, Palatos-Plexidas et al., 2024, Porchetta et al., 2024], moving from unstable to neutral and stable stratification results in higher wind speed deficits. However, this should be interpreted together with the frequency of events in each wind speed class, which shows that the number of very stable cases, where wake effects are relatively strong, is not particularly large. On the other hand, the wind speed deficits during very unstable and unstable events that occur more frequently (especially when wind speeds are below 8 m s^{-1}) are significantly lower. Near neutral conditions occur more frequently when wind speed is above 8 m s^{-1} in both SW and NE wind

direction, and the wake magnitude in those cases ranges from about 7 to 12%. Greater wind speed magnitudes are associated with more pronounced downstream wind speed deficits (see Figures 12 and 13), as higher wind speeds in this region occur more frequently under neutral to stable conditions. Under these regimes, particularly during stable conditions, reduced turbulent mixing limits wake recovery, leading to enhanced and more persistent wakes [Rosencrans et al., 2024, Ali et al., 2023, Siedersleben et al., 2020]. The transition toward neutral and stable ABL conditions with the increasing wind speed may contribute to the higher cRMSE values observed in Tables 4 and 5, as these regimes are associated with enhanced shear.

Furthermore, in Figure 15, Section 3.2.4, the 95% wake area is now depicted with purple solid lines. The maximum wake length of the wake recovery area per direction is shown in purple dashed lines. The wake length and wake area metrics are also presented in Table 6. Lines 481-501 have been updated as follows:

> The analysis presented in the previous section, based on SW and NE wind directions, supports the investigation of the two-dimensional wake characteristics and blockage effects within the Belgian-Dutch wind farm cluster. A reduction in wind speed upstream of the wind farms is evident both under SW and NE wind directions. In the transect under SW winds (Figure 12), a noticeable wind speed deficit begins approximately 8 km upstream of the wind farm. This reduction is present across the different wind speed magnitudes, but becomes more rapid around 4 to 5 km upstream, particularly when wind speeds exceed 5 m s^{-1}. For NE wind directions (Figure 13), the blockage effect is also visible, though it is confined to a smaller region, approximately 2 to 3 km upstream of the Borssele wind farm.
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> The wake maps in Figure 15 further confirm the presence of blockage effects under both SW and NE wind conditions. The solid purple lines indicate the 95% wake recovery area, while the dashed purple lines represent the maximum wake length within this area for each wind speed regime and wind direction. The wake structures become less coherent at wind speeds below 5 m s^{-1} while an induction zone defined by the 95% wake recovery area is observed in low wind speeds. More precisely, the maximum blockage distance from the front row of the wind turbines appears around 10 km under SW wind direction (Figure 15A_1), whereas around 5 km in the NE wind direction regime (Figure 15A_2). In addition, Table 6 presents the values of the 95% wake recovery area and the maximum wake length within this area. The largest coherent wake region is extracted using connected-component labeling. Its perimeter is obtained from the contour of the binary mask, and the maximum extent is computed as the convex-hull diameter of the perimeter points. The estimation of both the 95% wake recovery area and the maximum wake length near SW or NE wind directions is performed using the SciPy Python package[Virtanen et al., 2020]. The values under the different wind speed regimes in Table 6 are comparable for both SW and NE wind directions.
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> When the flow transitions to higher wind speeds (above 5 m s^{-1}), the wake structures become more coherent, with more pronounced wake recovery areas, leading to overall longer wake lengths (see Table 6). In the 5–8 m s^{-1} class, a blockage region forms upstream of the turbines, extending approximately 8 to 9 km from the first row under both SW and NE conditions. At higher wind speeds, this blockage pattern becomes negligible, and the flow tends to deflect around the cluster and propagate farther downstream.

RC: ***8. On the marine ABL being mostly unstable: "Similar conditions have been mentioned in the work of Rosencrans et al. (2024) analyzing the ABL stratification on the Rhode Island–Massachusetts area in a WRF execution from September 2019 to September 2020." Actually, Rosencrans et al. show that unstable vs. stable are almost 50-50, with a few occurrences of neutral cases. I think this statement needs an adjustment. Pointing out that your case is more unstable is actually interesting and adds to the discussion.***

AR: We have adjusted the text, as, although in the works of Archer et al. [2016], Porchetta et al. [2024], Palatos-Plexidas et al. [2024] there is a predominance of unstable events, in the study of Rosencrans et al. [2024], there is almost an equal number of unstable and stable events with a few neutral occurrences. Therefore, this paragraph has been changed in the manuscript as follows in lines 268-274

> Overall, the predominance of unstable to very unstable events has been highlighted in several studies over the past decade. For example, Archer et al. [2016] demonstrated that the marine ABL along the U.S. northeastern coast was mostly unstable during a 2003-2011 measurement campaign. Similar conclusions for the North Sea have been reported in recent WRF-based studies [Porchetta et al., 2024, Palatos-Plexidas et al., 2024]. However, it is important to note that ABL stability strongly depends on the region and period of interest. For instance, Rosencrans et al. [2024] found an almost equal mix of unstable and stable conditions, with relatively few neutral cases, in the Rhode Island-Massachusetts area based on WRF simulations from September 2019 to September 2020.

RC: ***9. You mention the Vollmer et al. correction in the introduction, but it was not used in the paper. Can you comment on what effect the Vollmer et al. correction would have on your simulations?***

AR: In the paper of Vollmer et al. [2024], the authors conclude that using the induction-correction method for multiple turbines within a computational cell (i.e., 5 22MW Turbines in that case, in the Fitch-mAIF model) can reproduce much better the power curve combined with the original Fitch implementation. On the other hand, they also highlight that downstream wind speeds applying the original Fitch scheme in WRF simulations have shown good agreement with measurements [Cañadillas et al., 2022, Fischereit et al., 2022], but this may occur partly because the Fitch scheme ignores induction effects and inner-grid wake interactions when multiple turbines occupy the same grid cell. Instead of neglecting these processes, the reduction in thrust and power from turbine clusters due to sub-grid wake effects should be estimated using an induction-corrected reference wind speed. The proposed correction is therefore only a first step toward a more physically consistent wind farm parameterization in mesoscale models. We should also highlight that in the work of Vollmer et al. [2024] a 2km grid resolution is used on a 5-day-long simulation.

Although we should take into account that the correction in the induction zone in the Fitch model proposed by Vollmer et al. [2024] has not been thoroughly studied yet, and further validation analysis is needed across longer periods, the proposed method is very promising and should be considered for future year-long WFP studies.

Considering that this three-year-long 1km study focuses only on the original Fitch WFP, coupled with the MYNN PBL scheme, we have included this in the conclusion for future studies: The part below has been added to the revised text, in the conclusions, in lines 635-639:

> The scope of this study is limited to using the Fitch WFP scheme combined with the MYNN 2.5 PBL scheme. Additional multi-year simulations using different WFP schemes, like the explicit wind farm (EWP) parametrization scheme [Volker et al., 2015, García-Santiago et al., 2024] applied with different PBL schemes or the induction correction to the original Fitch scheme [Vollmer et al., 2024], could also provide insights into the year-long effects of large wind-farm clusters.

RC: ***10. The SAR analysis looks great. But why have only 4 dates been selected over 2 years?***

AR: SAR images cannot easily capture wind farm wakes, as they primarily provide wind speeds at approximately 10m height. In addition, only about 8–10 SAR snapshots per month cover the area of interest, and only a few of these contain sufficiently clear wake signatures. Furthermore, we were specifically interested in SW and NE wind directions affecting the Belgian–Dutch cluster, as these can generate wakes that propagate toward the WHi (located SW the Belgian-Dutch cluster) and EPL (positioned NE the Belgian-Dutch cluster) lidar sites. As a result, the number of suitable SAR snapshots becomes even more limited. For this reason, we carefully selected the snapshots with clearly detectable long wake patterns (rather than short downstream deficits) to evaluate the WRF-WF performance during those cases. The snapshots are illustrative and may therefore reflect selection bias.

The overall text in Section 2.3.2, has been updated as follows (lines 191-201):

> The SAR data used in this study were retrieved by the Sentinel-1 European Space Agency mission. More specifically, there are two satellites, Sentinel-1A (2014-present) and Sentinel-1B (2016-2021), equipped with C-band Synthetic Aperture Radar (SAR) instruments operating at 5.405 GHz, and both satellites follow a sun-synchronous polar orbit at an altitude of 693 km [Hasager et al., 2024]. Focusing on the area of interest, including the Belgian-Dutch wind farms cluster in the Southern Bight of the North Sea, as well as additional upstream and downstream areas to study potential wake structures, the analyzed time instances occur approximately at 06:00 UTC every twelve days, and at 17:40 UTC every six days, respectively (Sentinel-1A, 2021-2023). The operation of Sentinel-1B during 2021 provided an additional set of overpasses at around 17:32 UTC every six days. This corresponds to approximately 8 to 10 SAR snapshots per month over the area of interest during the analyzed period. The wind speed at 10-meter height is then estimated by applying the CMOD5N geophysical model function [Hersbach et al., 2007], as explained also in the work of Siedersleben et al. [2020]. This indirect retrieval method assumes that radar backscatter from the sea surface, which reflects centimeter-scale waves generated by instantaneous wind stress, can be converted into wind speed at 10-meter height [Ahsbahs et al., 2017, 2018]. The wind fields are provided at a 500-meter pixel resolution through the Global Wind Atlas Science Portal of the Danish Technical University (DTU) Wind Energy Department (https://science.globalwindatlas.info/#/map/satwinds last access: 30 July 2025).

This has also been updated in Section 3.3., lines 504-510

> Four specific timestamps have been selected to analyze the wind speed patterns derived from SAR and WRF data, as well as to validate the model performance across the transect that connects the WHi, BSB, and EPL lidars (see Figure 2). These timestamps were selected manually based on the visual appearance of wind farm wakes in the SAR images. Although an average of 8 to 10 snapshots per month (see section 2.3.2) covers the analyzed region, the focus on wake events affecting the WHi, BSB, and EPL lidar sites under SW and NE wind directions resulted in a further reduction of the available snapshots. Therefore, an additional event from September 2020, outside the defined three-year simulation period, has been deliberately included for analysis.

RC: ***11. Are the biases of SAR observations fixed or vary in space and time? Can you estimate the SAR bias at 10 m for your case? The agreement does look very good in the wake region (errors of about 0.5 m/s or less at times), but more information on the reliability of these observations, preferably citing the literature, can strengthen your claims that the model works well.***

AR: We have assessed the mean absolute error between WRF and SAR at 10 meters height across the transects presented in the updated Figure 17 in the revised text. In addition, absolute error (AE) is provided between WRF and lidar measurements (when available). This has been added in the revised text in Section 2.3.4 (lines 242-245):

Last, for the SAR transects, we compute the mean absolute error, MAE $= \sum_1^n |U_{\mathrm{SAR}} - U_{\mathrm{WRF}}|$, where n is the number of points across the upstream, intra-farm, and downstream regions of each transect (70 points in total after interpolation of the SAR and WRF data). In addition, for the same time instances, we evaluate the point-wise absolute error, AE $= |U_{\mathrm{lidar}} - U_{\mathrm{WRF}}|$, using the lidar observations as reference.

The results of the evaluation for the SAR time instances are presented in Section 3.3., in Table 8. Furthermore, the overall text in Section 3.3., has been improved to include the metrics presented in Table 8, as well as a more detailed discussion on the SAR-detected wakes according to comment 3. More precisely, regarding the validation of WRF against the four SAR-retrieved occurrences, the first paragraph of Section 3.3., has been updated as follows (lines 512-517):

In this section, we focus on a one-by-one comparison of the WRF model output with SAR data. SAR images are retrieved from Sentinel 1A and 1B satellites as explained in section 2.3.2, and they provide wind speed fields at 10-meter height. Four specific timestamps have been selected to analyze the wind speed patterns derived from SAR and WRF data, as well as to validate the model performance across the transect that connects the WHi, BSB, and EPL lidars (see Figure 2). These timestamps were selected manually based on the visual appearance of wind farm wakes in the SAR images. Although an average of 8 to 10 snapshots per month (see section 2.3.2) covers the analyzed region, the focus on wake events affecting the WHi, BSB, and EPL lidar sites under SW and NE wind directions resulted in a further reduction of the available snapshots. Therefore, an additional event from September 2020, outside the defined three-year simulation period, has been deliberately included for analysis. The exact datetimes and the ABL stratification conditions derived from the NWF simulations, based on the Obukhov length and the planetary boundary layer height (PBLH), are provided in Table 7. Although this study uses only four specific SAR scenes and does not explicitly evaluate SAR data reliability, previous validation works provide strong evidence supporting the accuracy of SAR-retrieved winds. For example, Hasager et al. [2011b] compared SAR-derived wind speeds with meteorological mast measurements in the Baltic Sea and reported a small bias of -0.25m s^{-1} and a correlation coefficient of $R^2 = 0.783$ across 900 images. Similarly, de Montera et al. [2020] assessed 1544 SAR Level-2 Ocean product instances against four offshore buoys and three coastal weather stations around Ireland, finding an average bias of -0.4m s^{-1}.

In the same Section 3.3., Table 8 has been added, and the text has been revised accordingly in lines 554-585:

Therefore, to further evaluate the performance of the WRF model, hub height-lidar measurements are incorporated when available, depicted as gray scatter points in Figure 17. In addition to the qualitative assessment of the wind speeds in Figure 17, Table 8 presents the MAE across the upstream, intra-farm, and downstream transect regions, as well as the point-wise AE, when lidar measurements are available, and the evaluation methodology is described in section 2.3.4. In cases A, B, and C (NE wind flow), the transect follows the direction EPL (upstream) $\rightarrow$ BSB (intra-farm) $\rightarrow$ WHi (downstream), whereas case D corresponds to a SW flow event, where the sequence reverses.

Case A shows good agreement in the representation of the transect wake. Specifically, while the WF simulation tends to underestimate wind speeds upstream and within the Borssele zone, it accurately captures the wind speed deficit in the Belgian wind farms and downstream of the wind farm cluster. This is also reflected in Table 8, where only in the upstream region WF generates a slightly higher MAE

= 0.49 m s^{-1}, compared to MAE=0.37 m s^{-1} in the NWF simulation. However, the improvement between the WF against the NWF simulations in MAE in the intra-farm region and downstream is 81% and 85%, respectively. Similarly, in Case B, both the intra-farm and downstream wind speed patterns are well represented by the WF simulation. Although the overall trend is accurately reproduced, the WF simulation tends to overestimate the wind speeds upstream and downstream of the wind farms. Additionally, a flow acceleration is observed as the wind exits the Belgian-Dutch cluster. This pattern is consistent with the broader flow conditions downstream of the Belgian–Dutch cluster, since a similar acceleration is evident in the SAR observations and in both the WF and NWF simulations. Both the lidar measurements and the WF simulation effectively capture the intra-farm wind speed deficit and the downstream flow acceleration. Furthermore, in Table 8, MAE and AE are better in the WF than NWF simulation across the full transect regions.

Case C also features NE incoming wind conditions. Similar to the previous cases, the WF simulation successfully captures the wind speed deficit trends both within the intra-cluster zone and in the downstream wake recovery region. Both the NWF and WF simulations show noticeable discrepancies upstream at EPL compared to lidar observations with an AE reaching above 3 m s^{-1}. This is significantly improved both at BSB and downstream at WHi, where WF simulations outperform the NWF runs both in terms of MAE across the transect regions and AE against the lidar measurements. During this event, the Obukhov length at EPL is relatively high and negative, indicating unstable to near-neutral conditions. This may be attributed to less negligible shear, which can contribute to increased deviations from the lidar measurements. In the NWF simulation, an unrealistic and nearly linearly increasing pattern in wind speed of approximately 0.5 m s^{-1} between EPL and WHi is observed. Case D is the only selected timestamp with a SW wind direction. Although the SAR data exhibit considerable noise, particularly within the intra-farm region, the WF simulation is still able to reproduce the wind speed deficit and the downstream wake-recovery trend. In this case, only EPL lidar measurements are available, which show good agreement with the WF simulation, with a slightly improved AE compared to the NWF run. Furthermore, the MAE provides a more accurate matching with the 10-meter SAR wind speeds across the three transect regions in the WF simulations.

RC: ***12. In L367–368 you state that "greater wind speed magnitudes are associated with more pronounced downstream wind speed deficits". Why does the wind speed deficit increase with the wind speed in Figures 10–12?***

AR: The increase in wind speed deficit with increasing wind speed magnitude is primarily linked to the associated atmospheric stability conditions. As shown in Figures 14A, 14B, higher wind speeds (above 8 m s^{-1}) are more frequently associated with near-neutral stratification in both SW and NE flow regimes. Figures 14C and 14D further indicate that neutral and stable conditions correspond to larger normalized wind speed deficits. This behavior is consistent with previous studies, which show that neutral and stable atmospheric stratification promotes enhanced and more persistent wakes (e.g., Rosencrans et al. [2024], Palatos-Plexidas et al. [2024]). We have clarified this point in the revised manuscript in lines 472-477.

Greater wind speed magnitudes are associated with more pronounced downstream wind speed deficits (see Figures 12 and 13), as higher wind speeds in this region occur more frequently under neutral to stable conditions. Under these regimes, particularly during stable conditions, reduced turbulent mixing limits wake recovery, leading to enhanced and more persistent wakes [Rosencrans et al., 2024, Ali et al., 2023, Siedersleben et al., 2020]. The transition toward neutral and stable ABL conditions with the increasing wind speed may contribute to the higher cRMSE values observed in Tables 4 and 5, as these regimes are associated with enhanced shear.

RC: ***13. The Conclusions need an upgrade after the description and discussion of the results. As of now, it states that "Our findings demonstrate that the use of the Fitch WFP, in combination with this particular WRF configuration, is largely able to capture wake effects and improve the general accuracy over a simulation without wind farms included." Then, you proceed to describe that "The WF simulations accurately capture the wake structure when wind speeds range between 5 to 11 m/s." As you can see, in the Conclusions, you merely restate the results. In my view, this restatement of results occurs because of the insufficient description and discussion of the results, as I said before.***

AR: The analysis and the discussion in the results Sections, and the conclusions have been updated overall. For instance, lines 593-605 have been changed accordingly.

> Our findings demonstrate that the use of the Fitch WFP scheme, in combination with this particular WRF configuration, captures the wake effects and provides an improvement in model performance relative to a simulation without wind farms at the intra-farm region. First, focusing on the time-averaged wind speeds over the full analysis period, the WF simulations yield a substantial improvement in both bias and EMD, with reductions of approximately 82% and 73% compared with the NWF simulations, respectively, in the intra-cluster (BSB location). Furthermore, when analyzing the wind speed bias under different wind directions, both NWF and WF configurations reduce the negative bias inherited from the ERA5 data, with the results indicating that the Fitch scheme introduces an additional deficit downstream of the Belgian-Dutch cluster. However, within the intra-farm area, the Fitch scheme provides a more accurate wind speed distribution across all wind directions, underscoring its importance for representing strongly-waked environments. Beyond the improvements in bias and EMD, the WF simulations perform similarly to the NWF runs in terms of cRMSE and correlation, with only small and marginal differences. Similarly, wind direction metrics are also improved in the WF simulations, as bias is reduced by approximately 51% at BSB, while an analysis of wind direction biases by sector reveals that WF can perform better than ERA5 for wind directions from northeast to south.

In lines 611 to 617, there is an updated version in the conclusions:

> Extending the performance metrics to wake characteristics under different wind speed magnitudes, and focusing on SW and NE wind directions, the analysis revealed several consistent patterns. First, under SW wind direction, the WF simulations accurately capture the wake structure when wind speeds range between 5 to 8 m s^{-1}, providing an almost negligible bias at BSB and downstream at EPL. Under NE wind direction, the optimum performance of WF simulations occurs at wind speeds between 8 and 11 m s^{-1}. Although the model tends to overestimate intra-farm wind speed deficits at BSB under higher wind speed conditions, it shows comparable improvements in long-distance downwind wakes at EPL (for SW winds) and WHi (for NE winds), where smaller bias and cRMSE values are obtained.

And in lines 623 to 634:

> Furthermore, a comparison with SAR images at specific events shows that WF performs well in representing the wake structure generated by the Belgian-Dutch cluster. Both in the intra-farm and the wake recovery regions, WF provides a realistic wind speed deficit. To assess the performance of the model during these events, MAE and AE are computed. More specifically, MAE is estimated across the upstream, intra-farm, and downstream regions, while AE is calculated at each lidar location when

measurements are available. Building on the previously discussed improvements in the qualitative wake-pattern representation, the error metrics further confirm that the WF simulations provide a better alignment with observations than the NWF runs across all locations, with the most pronounced improvements occurring in the intra-farm and downstream regions.

This study can accurately evaluate the model performance by utilizing upwind, intra-farm, and downwind lidar measurements as well as SAR images at specific events. Systematic biases in both wind speed and direction are evident, particularly in the wind speed metrics. However, it should be highlighted that the model is driven by ERA5 hourly data, which consistently introduce biases, affecting the boundary conditions in WRF and propagating wind speed underestimations to the analyzed locations.

RC: ***14. In Table 2, you use a stability classification that includes classes such as "stable–neutral". Whereas this is valid, most commonly you will find a five-class system with "neutral", "weakly stable", and "very stable". Perhaps using the five-class system will make it easier to discuss your work with the literature and for other researchers to interpret your results. This is not criticism, just something to be aware of. Your work, your choice.***

AR: Thank you, in our study, we use an adapted classification based on the study of Sathe et al. [2011]. We will consider using the suggested ABL stability classification in future works.

Technical corrections

RC: ***1. Figure 1 needs domain dimensions in degrees or km.***

AR: We have updated Figure 1 in the revised text.

RC: ***2. The L parameter is just Obukhov length, not Monin-Obukhov length, even though it belongs to the Monin-Obukhov Similarity Theory. This requires changes in Tables and in the text e.g. when you write "MO length".***

AR: We have addressed this in the revised text.

RC: ***3. Please include a wind direction arrow in Fig. 15, as you did for Fig. 11.***

AR: Figure 17 (in the revised text) has been improved accordingly.

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