Manuscript: AMV Error Characterization and Bias Correction by Leveraging Independent Lidar Data: a Simulation using OSSE and Optical Flow AMVs

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1 Responses to Reviewer 2

The manuscript explores the application of machine learning techniques to assess bias and uncertainty in the assimilation of atmospheric motion vectors (AMVs). The authors frame the problem by treating independent LIDAR wind observations as a dependent variable in a supervised learning machine model. The study utilizes an Observing System Simulation Experiment (OSSE) framework, with reference geophysical state data derived from high-resolution Weather Research and Forecasting (WRF) simulations.

The literature review is comprehensive, providing a strong foundation for the study. The motivation for the research is clearly articulated. However, it's crucial to note that the paper primarily serves as a proof-of-concept, a fact that becomes evident through the text. While the title implies a broader scope, the content remains focused on the proposed machine learning approach for bias correction in wind field assimilation.

The approach presented is sound, addressing and resolving issues identified in previous methodologies. The paper is well-structured, and the visual aids effectively support the discussion. However, there are opportunities to better depict certain concepts, as outlined below.

We would like to thank the reviewer for the kind comments, and for providing constructive input which helped improve our manuscript. Please see our detailed responses below.

1. **The authors should provide a more detailed explanation of their efforts to obtain accurate AMVs. Although they refer readers to another publication for details, as that reference is still "submitted for publication," a general explanation or summary is important for proper understanding.**

We apologize for the lack of clarity. Our AMV approach relies on tracking water vapor using a method called optical flow. More detail of the algorithm is described in the updated Section 2.2, which is now much expanded compared to the previous draft.

2. **Clarity regarding the connection between the proof-of-concept and the utilization of Lidar data is essential. It seems that certain errors associated with Lidar wind profiles were not considered, impacting the comprehensiveness of the study. Clarifying this aspect would strengthen the paper.**

To address this concern, we opted to add a random zero-mean Gaussian error to the WRF u-wind when simulating lidar data. The standard deviation for this Gaussian error depends on the pressure levels: 2 m/s for 850 hPa, 3 m/s for 500 hPa, and 5 m/s for 300 hPa. These are rather conservative numbers since in practice quality filtering can typically reduce the magnitudes of the errors below what are assumed here. However, these somewhat large measurement errors do not adversely affect the conclusions that we have seen in the previous draft.

After we have added these random errors to the simulated lidar winds, we found that

- The bias-correction performance (Table 4 and 5) did not change significantly. This is likely because random noise is Gaussian, and their impact is greatly reduced since we are only estimating the first moment (the mean value) in the bias-correction exercise.
- The coverage percentage in Figure 5 tends to be increased compared to the last draft. This is because we added a constant error (2 m/s for 850 hPa, 3 m/s for 500 hPa, and 5 m/s for 300 hPa), which is added to both the numerator and the denominator of the coverage probability calculation in Figure 5.
- The increased variability introduced by the lidar simulated error weakens the linear relationship between the predicted error and the empirical error in Figure 6 (i.e., the R^2 value is decreased). However, the monotonically increasing relationship is still evident.
- The relationship between the predicted error and Root-Mean-Squared-Vector-Difference (RMSVD) is no longer clear, since the magnitude of the error we introduced (2 m/s for 850 hPa, 3 m/s for 500 hPa, and 5 m/s for 300 hPa for *both* the u and v winds) is too large compared to the magnitude of the typical bias variability ($\tilde{1}$-2 m/s). Therefore, we have opted to remove the subsection on the comparison of the predicted error to RMSVD.

We have updated the corresponding Tables and Figures to reflect the added error for lidar simulated values. Overall, although the strength of some of the relationships have weakened, the conclusions from before (with no error added) are still valid.

3. **The presentation of optical flow could be improved for better interpretation.**

   Thank you for the comment. We are addressing this by expanding the section on optical flow in Section 2.2. Please see the answer in #1 for detail of the changes.

4. **The right column in Figure 1, in particular, may benefit from replacing arrows indicating differences with a color-coded scale. Additionally, consider addressing potential confusion related to the arrows' direction by emphasizing differences in magnitude rather than implying directional changes.**

   Upon careful consideration of the comment, we found that we can make Figure 1 more informative by keeping all the arrows (i.e., optical flow, NatureRun, and difference plots), on the *same* scale. This way, the difference plots will be able to highlight *both* the changes in direction and magnitudes of the windspeed difference.

   We have also included a legend key (in red) on the top of each plot that should help readers decipher the speed in m/s of each arrow.

   Thank you for the comment.

5. **While the paper is technically sound, providing a more explicit link between the proposed methodology and Lidar data considerations would enhance the manuscript's overall coherence and contribute to a more comprehensive understanding for readers.**

   Thank for the comment. Our goal here is to present a preliminary look at how AMVs could be improved if we knew the wind values for pixels in a lidar orbit curtain that crosses the AMV retrieval area. In particular, we wanted to assess what sort of information we would be able to get from the combination of colocated AMVs and lidar winds.

   To this end, we made some simplification in the way we simulated the lidar winds. For instance, we assumed that the simulated lidar wind can only observe the u-wind component, and that we can observe the u-wind with perfect accuracy.

   To make it clearer that we are using simulated lidar data in this analysis, we have changed some of the wording in the paper to make it clearer. For instance, in the Introduction, we have modified the description of the experiment as follows:

> “We use as our reference (truth, or NatureRun) datasets output from the Weather Research and Forecasting (WRF) Model run for three different weather events (Posselt et al., 2019). The water vapor fields from these WRF model runs are processed through an Optical Flow algorithm (Yanovsky et al., 2024) to provide AMVs, and we similarly simulate lidar observations from the same WRF model data. Finally, we assess the ability of a bias-correction algorithm to model and correct biases (relative to the simulated lidar winds) that arise from the optical flow AMV retrieval.“

We also addressed the assumption of using the u-wind component in the simulated lidar wind in Section 3.1:

> “It’s important to highlight that our results primarily focus on errors related to a single wind component, as lidar systems typically only observe winds along the line-of-sight. In this OSSE study, we simplified the line-of-sight direction to align with the u-wind direction, and we have shown that the uncertainty in the u-wind bias has a positive linear correlation with the validation error. We anticipate that these findings will generalize to the relationship between the HLOS wind and the full-vector wind in other regions, as this is essentially a change of basis for the (u, v) wind components.“

The lack of measurement error on the simulated lidar wind (as was in the previous draft) makes it difficult to judge how much the conclusions therein would apply to real world operations. Therefore, we have modified this assumption and added simulated measurement error to the lidar wind as suggested in Comment #2. We believe this modification has strengthened the paper. Thank you for the valuable suggestion!

6. **The first abbreviation of Observing System Simulation Experiments should appear in Line 49.**

   We added the abbreviation (OSSE) on this line. Thank you!

7. **Line 52: Use the abbreviation of Observing System Simulation Experiment.**

   We used the abbreviation here instead of the full name as suggested. Thank you.

8. **Line 58: Use the abbreviation of Atmospheric Motion Vectors.**

   It is fixed as suggested. Thank you.

9. **Line 427: No need to repeat almost the exact same sentence as in Lines 43-45.**

   This sentence ("...NASA's MERRA and MERRA-2 AMVs tend to overestimate wind output by 50% in northwest Europe...") is now removed. Thanks.

Again, we would like to thank the reviewer for insightful comments about adding measurement errors to lidar data, changing Figure 1, and elaborating on the description of Optical Flow. The paper has improved significantly after incorporating your feedback!

References

Posselt, D. J., Wu, L., Mueller, K., Huang, L., Irion, F. W., Brown, S., Su, H., Santek, D., and Velden, C. S. (2019). Quantitative assessment of state-dependent atmospheric motion vector uncertainties. *Journal of Applied Meteorology and Climatology*, 58(11):2479–2495.

Yanovsky, I., Posselt, D., Wu, L., and Hristova-Veleva, S. (2024). Quantifying uncertainty in atmospheric winds retrieved from optical flow: Dependence on weather regime. Submitted for publication to *Journal of Applied Meteorology and Climatology.*