Response to Referee Comment #3 on

Correction of wind bias for the lidar on-board Aeolus using telescope temperatures

The authors thank Mr. Hui Liu for carefully reading the paper and providing useful feedback. In the following, referee comments are repeated in green and answers by the authors are provided directly below in black.

General comments:

This paper describes a correction of the bias in Aeolus winds related to the M1 temperature. This makes assimilation of Aeolus winds with NWP model much more successful and leads to improved impact on NWP. NWP users of Aeolus winds would benefit from the details of the bias correction as described in the paper. As such, this paper deserves published.

Specific comments:

1. abstract, line 28: "the approach of using ECMWF model-equivalent winds is justified by the fact that the global bias of models u-component winds w.r.t to radiosondes is smaller than 0.3 m/s", This statement may not be representative here since the majority of globe is not covered by radiosondes. Actually, over the large part of remote oceans and lands, NWP models still have large (on the order of several m/s) uncertainty including biases, e.g., in the upper troposphere and lower stratosphere of the Tropics. This comment also applies to line 236-239.
However, the regression of O-B to M1 temperatures globally and from all vertical layers makes the M1 correction less sensitive to the considerable latitudinal and vertical layer varying biases or uncertainty between NWP models. It might be helpful to make this point clearer in the paper.

It is correct that the statement about the low model bias is difficult to justify in regions with low radiosonde and pilots density. This point is addressed in lines 237 to 244. It is confirmed, for the M1 bias correction altitude varying model bias should not be an issue, because all O-B values of a profile are averaged before the fitting. Moreover, global model averages obtained from 24 hours of observations are used which should mitigate the effect of localized model errors.

The following information was added to Section 2.4 of the manuscript:

locations where radiosondes and pilots are available, which is mainly above northern hemisphere land surface. Thus, it is difficult to accurately assess the model bias in the southern hemisphere or above oceans. Nevertheless, Figure 4 shows that during all days the bias is clearly below 0.3 m/s, which is significantly smaller than the Aeolus M1 related bias (for the Rayleigh), justifying the choice of the ECMWF model as a reference for the bias correction. To mitigate the influence of model wind bias, 24 hours of global model winds averaged over all altitudes are used in the M1 bias correction. On the one hand, this makes sure that localized small-scaled model biases (e.g. in the tropics) appear only as noise source in the fit procedure. On the other hand, averaging over all altitudes ensures that any altitude varying model bias is not an issue.

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2. line 241: Potential wind background uncertainty may be explored by comparing winds from major NWP models, e.g., ECMWF vs. NOAA/GFS. In remote regions, current NWP models still have large uncertainty.

Yes, it is correct that in remote regions, especially in the tropics, model winds can be largely biased. Figure 1 below, for example, indicates the difference of the wind vector between the ECMWF and Met Office mean analysis over a 7-day period in 2015 at 100 hPa. Such analysis indeed helps to identify problem regions. As mentioned above, we try to mitigate the influence of localized model errors by using 24 h of vertically averaged global model winds. It is the preferred solution to use model-independent ground return winds to avoid model dependency. But results showed that the performance of this approach is not yet stable enough for the operational processing and analysis will continue.
For the comparison of different models, the Aeolus CalVal includes the different Met centers that can use in their analysis their own meteorological input data to further quantify the impact of the differences. This is an ongoing effort in a bigger framework.

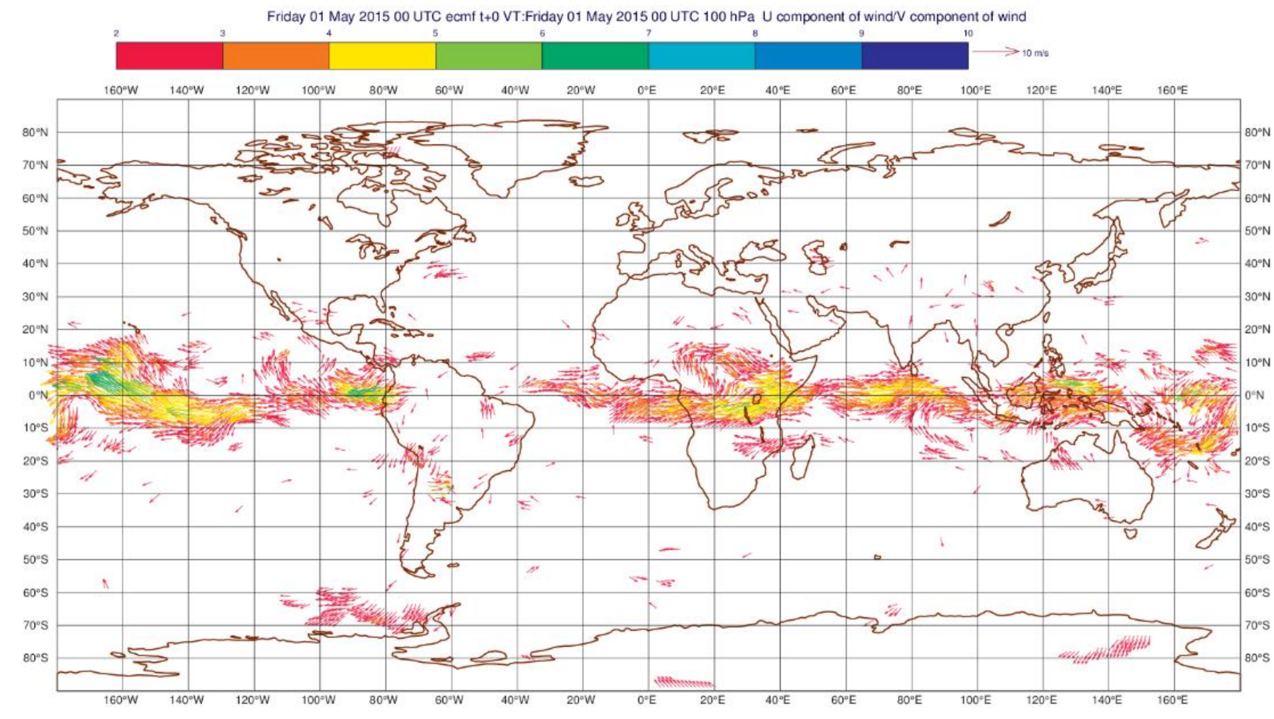

Figure 1: Mean(ECMWF analysis) – mean(Met Office analysis) from 1st to 7th May 2015 for vector wind at 100 hPa. Two analyses per day: 00 and 12 UTC. Only wind vectors > 2 m/s wind speed are plotted to highlight the problem areas. Produced by ECMWF (Michael Rennie) - from https://www.ecmwf.int/en/elibrary/18014-advanced-monitoring-aeolus-winds.

3. Figure 14 (bottom) is very interesting. I guess this is the O-B average over the entire vertical layer range (0-24km?). It will be helpful to provide this information in the figure caption. Also, it would be greater if the magnitudes and details of the remaining biases could be better visualized, e.g., some kind scatter plots with density distributions (vs. latitude and/or longitude).

Yes, the figure shows vertically averaged E(O-B) values at the L1B observation granularity. The determination of such is also explained in Section 2.4 of the manuscript. For the sake of clarity, further information was also added to the caption of Figure 14.
To better highlight the remaining bias, Figure 2 further below shows the residual bias as a function of the argument of latitude. The plot is based on the same data period as shown in Figure 14 of the manuscript. The plot reveals that the binned average (solid red line) is close to zero over the major part of the orbit. However, for the region with particular strong M1 temperature influence, i.e. at 230°

and 330° argument of latitude, remaining bias with a binned average of up to 1 m/s is visible. Despite the M1 bias correction being highly effective, the currently used regression approach still can be improved. However, testing more sophisticated regression models, such as random forests (Svetnik et al., 2003) or generalized additive models (Hastie and Tibshirani, 2014), is beyond the scope of this paper and could be considered for our future work. Thus, the following information was added to the summary of the manuscript:

return-based approach and use it for upcoming reprocessing campaigns or even in the near-real-time-processing of the Aeolus products. In addition, more sophisticated regression models, such as random forests (Svetnik et al., 2003) or generalized additive models (Hastie and Tibshirani, 2014), will be tested to further improve the performance of the M1 bias correction. With the knowledge obtained during this study, it will be possible in principle to improve both the thermal design of the telescope and the optical setup to reduce the bias contributions from the telescope temperature variation for a potential follow-on wind lidar mission. The goal would be to base the bias correction on measured ground-return speeds, as it was also initially foreseen also for Aeolus.

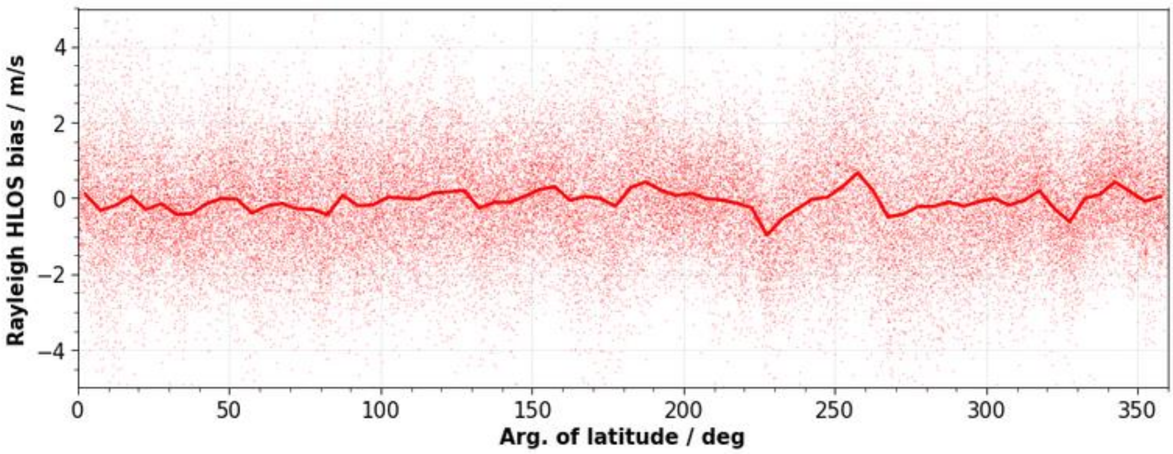

Figure 2: Rayleigh clear E(O-B) HLOS values (red points) after the M1 bias correction as a function of the argument of latitude. The solid red line indicates binned averages of the E(O-B) values using a bin size of 5° for the argument of latitude. One of week data from 15 to 22 August 2019 is shown.

4. It might be helpful to explicitly mention in the abstract and conclusion that the M1 correction has little impact on Mie winds.

It was decided to add this information to the summary:

and long-wave radiation of the Earth and the response of the telescope's thermal control system to that. The temperature changes affect the shape of the primary mirror which changes the focus of the telescope and it is assumed that this leads to a change of the angle of incidence of the incoming light at the spectrometers of the instrument and hence to a wind bias. Moreover, it was found that the sensitivity of the Mie bias on the M1 temperatures is ~10 times less than for the Rayleigh channel.

To correct for the~~is~~ M1 temperature effect a dedicated operational software was developed which describes the wind bias as a

References:

Hastie, T. and Tibshirani, R.: Generalized Additive Models, in: Wiley StatsRef: Statistics Reference Online, American Cancer Society, https://doi.org/10.1002/9781118445112.stat03141, 2014.

Svetnik, V., Liaw, A., Tong, C., Culberson, J. C., Sheridan, R. P., and Feuston, B. P.: Random Forest: A Classification and Regression Tool for Compound Classification and QSAR Modeling, J. Chem. Inf. Comput. Sci., 43, 1947–1958, https://doi.org/10.1021/ci034160g, 2003.