

RESEARCH ARTICLE

Exploiting *Aeolus* winds in a regional numerical weather prediction model

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Abstract

Aeolus was the first Doppler wind lidar (DWL) to measure wind profiles from space. *Aeolus* has proven to be beneficial for global models, used by meteorological centres around the world. Demonstrating added value for regional models has been less successful so far. Here, we continue with earlier impact assessments with the HARMONIE–AROME limited-area numerical weather prediction (NWP) model over the Nordic region. In this study, two limited-area domains are considered: one includes an Arctic region and the other a region covering part of the Atlantic and most of Western Europe. Statistically significant impact could be demonstrated best for the Atlantic domain and is overall neutral for winds determined from the Rayleigh backscattered signal to positive for winds determined from Mie backscatter. Results presented here demonstrate overall improved large-scale dynamics in the upper part of the atmosphere and improved temperature, which is related to the large-scale dynamics as well. Limitations of the existing data assimilation system were revealed, including the lack of an *Aeolus* bias-correction scheme and an imperfect implementation of the first-guess check, as part of observation quality control. The latter limits a correct assessment of the observation-error inflation technique. Recommendations for further improved usage of *Aeolus* winds in regional NWP are given to prepare NWP centres for a potential operational *Aeolus* follow-on mission.

KEYWORDS

Aeolus, Mie-cloudy winds, NWP impact assessment, observing-system experiments, Rayleigh-clear winds, regional limited-area model

1 | INTRODUCTION

Aeolus was launched in August 2018 by the European Space Agency (ESA) and is the first satellite mission to provide wind profiles from space using a Doppler wind lidar (DWL) instrument. As such, *Aeolus* partly filled the

wind-data gap of the current global observing system Straume *et al.* (2020). A spaceborne DWL has been considered for decades as the most promising technology to provide accurate wind profiles from space for weather and climate Baker *et al.* (1995). After a successful launch in 2018, *Aeolus* winds have been used operationally since January

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2020 at weather centres around the world, showing a substantial positive impact when used in their global NWP systems (Rennie *et al.*, 2021; Pourret *et al.*, 2022; Garrett *et al.*, 2022; Laroche & St-James, 2022; Rani *et al.*, 2022; Martin *et al.*, 2023). The mission ended in 2023, after exceeding its planned lifetime in orbit, with a successful first-of-its-kind assisted reentry into the Earth's atmosphere.

In contrast to global NWP, showing substantial beneficial impact for regional-scale NWP has been a challenge so far. For example, Hagelin *et al.* (2021) used the HARMONIE–Application of Research to Operations at Mesoscale (AROME) model in the Nordic region with large *Aeolus* data coverage and a three-dimensional variational (3DVar) data assimilation system and found an overall neutral impact. Adding *Aeolus* winds to the National Oceanic and Atmospheric Administration (NOAA) regional tropical cyclone (TC) model for tropical cyclone forecasting applications showed mixed results, with improved TC intensity and size forecasts in the Eastern Pacific basin, while the results for track forecasts and results from the Atlantic basin were mixed. Larger improvements in TC wind structures from assimilating *Aeolus* observations were found for altitudes above 400 hPa compared with the lower troposphere (Marinescu *et al.*, 2022). Also, statistically significant added value could not be demonstrated in the application of *Aeolus* for a single-case cyclone in the Mediterranean basin (Stathopoulos *et al.*, 2023).

In this study, we use the HARMONIE–AROME model applied to an Arctic region and a region covering a large part of the Atlantic. The next section discusses the HARMONIE–AROME model, followed by the details of *Aeolus* winds used in Section 3. Section 4 discusses the methodology for *Aeolus* impact assessment, followed by Section 5, which discusses the results mainly for the Atlantic domain. A summary and recommendations are provided in Section 6.

2 | HARMONIE–AROME LIMITED-AREA MODEL

The model used in this study is AROME (Applications of Research to Operations at Mesoscale) developed within the Aire Limitée Adaptation dynamique Développement InterNational (ALADIN) consortium and operated in the HIRLAM–ALADIN Research on Mesoscale Operational NWP in Euromed (HARMONIE) scripting environment, in the remainder shortly denoted as HARMONIE–AROME. The member countries of HIRLAM include Denmark, Estonia, Finland, Iceland, Ireland, Lithuania, Netherlands, Norway, Spain, and



FIGURE 1 Limited-area domains used in this study, with orange denoting the Arctic domain and red the Atlantic domain.

Sweden (with France as an associate member). The member countries of ALADIN include Algeria, Austria, Belgium, Bulgaria, Croatia, Czech Republic, France, Hungary, Morocco, Poland, Portugal, Romania, Slovakia, Slovenia, Tunisia, and Turkey. The model used has been described extensively in Bengtsson *et al.* (2017); the main characteristics are summarized here for completeness. We use HARMONIE–AROME cycle version 43 (cy43), which is the same model cycle as used in Hagelin *et al.* (2021). The three main components of this system are surface data assimilation, upper-air data assimilation, and the forecast model. Here we focus on the upper-air data assimilation that has been prepared for the assimilation of *Aeolus* horizontal line-of-sight (HLOS) wind observations. In NWP data assimilation, one aims to combine observational information optimally with prior information in a Bayesian context. The prior information comes from a short-term model forecast, also denoted as the background or first guess. The resulting analysis serves as the forecast initial state for the next cycle. In HARMONIE–AROME, a three-hour assimilation cycle is used. The experiments are carried out over the domains displayed in Figure 1 using a 2.5-km grid size and 65 vertical levels for the Arctic domain and a 2-km grid and 90 vertical levels for the Atlantic domain, with both domains having a model top at approximately 10 hPa. The lateral boundary conditions (LBCs) are provided by the deterministic forecast from the ECMWF model. These forecasts are launched every three hours with a one-hour output frequency. In contrast to Hagelin *et al.* (2021), no spectral large-scale mixing of the background-state fields with the lateral boundary

ECMWF model fields was applied, which results in less smoothed model fields and more clean observation impact assessment.

In the main part of this article we use the HARMONIE-AROME (cy43) standard data assimilation setup with a four-dimensional variational (4DVar) data assimilation with two outer loops at six and three times the model grid size of 2/2.5 km: 12/15 km and 6/7.5 km for the Arctic and Atlantic domains, respectively. The use of 4DVar has the advantage of using observations at their correct observation time rather than imposed at analysis time as in 3DVar and it makes the analysis increments flow-dependent. The data assimilation uses all available conventional observations in addition to microwave and infrared radiances from polar-orbiting satellites *NOAA-18*, *NOAA-19*, *MetOp-A*, and *MetOp-B* and ocean surface winds from the scatterometer on the *MetOp* satellites, as well as *Aeolus* winds. For the satellite radiance data, a variational bias correction (VarBC) based on Dee (2005) and Dee and Uppala (2009) is applied. Besides *Aeolus*, explicit wind-profile information comes only from radiosondes. Near airports, ascending and descending aircraft provide profile information as well. Atmospheric motion wind vectors (AMVs) obtained from tracking cloud features with geostationary satellites were not used in this study, because they were not in operations at that time. The data coverage of wind-profile information is low, in particular in the Arctic domain, where *Aeolus* may contribute substantially. The background-error statistics (**B** matrix) are calculated from downscaling (using the HARMONIE-AROME model) ensemble forecasts produced by ensemble data assimilation experiments at the European Centre for Medium-Range Weather Forecasts (ECMWF), as described in Hagelin *et al.* (2021). The **B** matrix itself is static as in 3DVar, but the 4DVar data assimilation time window makes the final increments flow-dependent (Thépaut *et al.*, 1996). Background and observation errors are assumed to have a Gaussian distribution as characterized by their error covariances. Observation errors are assumed to be uncorrelated and their Gaussian distribution within the minimization of the cost function is represented by the error variances. Assigned observation-error statistics for all types of observations, except *Aeolus* winds, are static and based on data assimilation studies. For *Aeolus* winds, the assigned observation error in the analysis step is discussed in Section 3. The observation-handling main components are the observation operators, which project the model state on the observed quantities, and the first-guess check, which rejects observations assumed to be affected by gross errors and identified by large observation minus background (in short, o-b) departures. In addition, a thinning is applied to some spatially dense data (such as satellite radiances

and aircraft observations) in order to alleviate effects of spatially correlated observation errors, which are not represented in the data assimilation.

3 | *AEOLUS* WIND CHARACTERISTICS

Aeolus was a polar-orbiting satellite, operated in space for almost five years during the period 2018–2023. The satellite carried a DWL instrument that is operated in the ultraviolet (UV) part of the electromagnetic spectrum at 354.8 nm wavelength, which enables measuring on both atmospheric molecules (from Rayleigh scattering) and aerosol particles, cloud droplets, and ice crystals (from Mie scattering). The atmosphere backscattered signal received from the emitted laser light is separated spectrally on board and processed further to yield so-called Mie and Rayleigh winds. *Aeolus* measures a single component of the horizontal wind, the so-called HLOS wind component, which is directed close to east–west for most of the orbit, except near the Poles. Mie and Rayleigh winds are the result of accumulating the received signal along the satellite track for 11–15 km and about 86 km, respectively. As a result, Mie winds are more densely spaced than Rayleigh winds, but only in the presence of clouds and/or dense aerosols. More details on the technical aspects of *Aeolus* are found in Straume *et al.* (2020) and references therein.

The *Aeolus* level-2B (L2B) dataset used in this study is from the second reprocessing activity (DISC, 2021). It is noted that winds from the fourth reprocessing activity, with quality improved further, were not yet available for this study. *Aeolus* provides three main products, denoted as

- (i) Mie-cloudy (HLOS winds obtained from the Mie signal in cloudy and dense aerosol conditions),
- (ii) Rayleigh-clear (HLOS winds obtained from the Rayleigh signal in clear-air conditions), and
- (iii) Rayleigh-cloudy (HLOS winds obtained from the Rayleigh signal in cloudy and dense aerosol conditions).

The quality of the latter has improved substantially in more recent reprocessing activities (Marseille *et al.*, 2023), but turned out to be of insufficient quality for use in this study. It was found that Mie winds from the second reprocessing (RP2) showed artifacts in the HLOS wind statistics, which could be solved in later reprocessing activities, following Marseille *et al.* (2022). To make use of this improvement already in the current study, similarly to Zuo *et al.* (2022), a new offline Mie-cloudy wind product, denoted RP2+, was generated for the 2020

experimental period and used in the experiments for the Atlantic domain.

Both Mie and Rayleigh winds complement each other, providing almost complete atmospheric coverage of *Aeolus* winds along a two-dimensional curtain, except below optically dense clouds, which cannot be penetrated by the instrument laser beam, as shown in Figures S1 and S2 in the supplementary material.

The quality of *Aeolus* L2B HLOS winds (denoted “o”) is generally assessed through the difference from their ECMWF model background counterparts (denoted “b”), that is, (o-b) statistics. Tuning of *Aeolus* winds as part of the L2B processing is based partly on minimizing the mean global bias with respect to ECMWF model winds; see Weiler *et al.* (2021a) for Rayleigh winds and Marseille *et al.* (2022) for Mie winds. As a result, on the global scale, the overall (o-b) bias of Mie-cloudy and Rayleigh-clear winds with respect to the ECMWF model is close to zero (Rennie *et al.*, 2022 and Supplementary Figure S3). In the remainder, when we speak of biases of Mie and Rayleigh winds and (o-b) biases, we mean the systematic difference between the observation and the corresponding model value, where it is noted that the latter may differ systematically as well, relative to the true atmosphere.

In this study we consider three experimental periods: November 25, 2019–December 15, 2019 (period 1), January 27, 2020–February 28, 2020 (period 2), and January 27, 2020–March 10, 2020 (period 3). The range bin setting, that is, *Aeolus* vertical sampling, was the same for all three periods, but did change along the orbit with different settings for the extratropical region above 30°N and 30°S, the extratropical region above 30°N, and a special setting for the polar region above 60°N. The extratropical setting reached a maximum altitude of 17.6 km, with bin sizes of 250/500/750 m in the lower troposphere, 500-m bins in the range 7.3–9.3 km, and 1 km aloft. The Northern Hemisphere polar setting reached a maximum altitude of 20 km and had 250-m, 500-m, and 1 km bins in the lowest 4 km, 750-m bins between 4 and 11 km altitude, and 1-km bins aloft. The range-bin settings are terrain-following, meaning that winds are obtained at altitudes exceeding the maximum range-bin settings, described above, in mountainous regions.

The focus of this study is on the domains displayed in Figure 1. The relatively small Arctic domain was used to address initial settings, provided by ECMWF, when applied to a limited-area model (LAM). These settings include quality control, to remove potential observation outliers, the weight that should be given to observations in the analysis in a LAM, and the identification of potential biases in Mie and Rayleigh winds. Lessons learned from the Arctic-domain experiments were next

applied to the experiments for the larger and much more computer-intensive Atlantic domain. It is noted that no statistically significant results can be expected from a three-week experimental period on the relatively small Arctic domain with limited coverage of upper-air observations from radiosondes and aircraft data, which are used for verification. In addition, studies have shown that forecast errors grow fast in mesoscale NWP models, already within the first couple of hours of the forecast, due to uncertainties in the lateral boundary conditions Zagar (2016), Zagar *et al.* (2016). The latter is detrimental for impact assessment, in particular for small model domains. For these reasons, we limit the statistical assessment in this article to the Atlantic domain and provide statistics for the Arctic domain in the supplementary material.

Figure 2 shows (o-b) statistics for the ECMWF model and *Aeolus* HLOS wind observations from the second reprocessing activity, limited to the Atlantic domain. Quality control (QC) was applied to remove erroneous winds from the statistics. This includes checking the validity flag of the *Aeolus* wind and applying threshold values on the estimate of the wind random error standard deviation, in the remainder also denoted briefly as “error estimate”, and the absolute difference between the observation and corresponding ECMWF model value, that is, |o-b|. All data needed for QC are available from the *Aeolus* L2B wind product. To stay as close as possible to the settings used in the experiments in Section 5, threshold values used for Mie winds to arrive at Figure 2a are ($4.5 \text{ m} \cdot \text{s}^{-1}$, $15 \text{ m} \cdot \text{s}^{-1}$), that is, $4.5 \text{ m} \cdot \text{s}^{-1}$ for the error estimate and $15 \text{ m} \cdot \text{s}^{-1}$ for |o-b|. For the Rayleigh winds, the QC setting used is ($8 \text{ m} \cdot \text{s}^{-1}$, $30 \text{ m} \cdot \text{s}^{-1}$), that is, as proposed earlier by ECMWF and confirmed in the Arctic experiments (not shown).¹

Mie winds from the RP2 product (blue curves) show substantial biases relative to their ECMWF counterpart in the lower and mid troposphere in Figure 2a, where most Mie winds are found. As mentioned above, Mie winds for period 3, used in this study, are not from the second reprocessing but from a patched version of the level-2 processor (RP2+) with reduced systematic biases (“wiggling” artifact removed: see Marseille *et al.* (2022)). Indeed, the overall (o-b) bias of this new product, that is, the dash-dotted magenta curve in Figure 2a, is much closer to $0 \text{ m} \cdot \text{s}^{-1}$ at most altitudes compared with the dash-dotted blue curve of the RP2 product. This is the result of more constant biases with altitude, and with opposite sign, of ascending and descending orbits of the RP2+ product (magenta curves). These statistics motivate the use of RP2+ for Mie winds for the Atlantic domain in the experiments discussed in the following sections. The Mie-wind random error of the RP2+ product is very close to the RP2 product, so only the latter is displayed in Figure 2a.

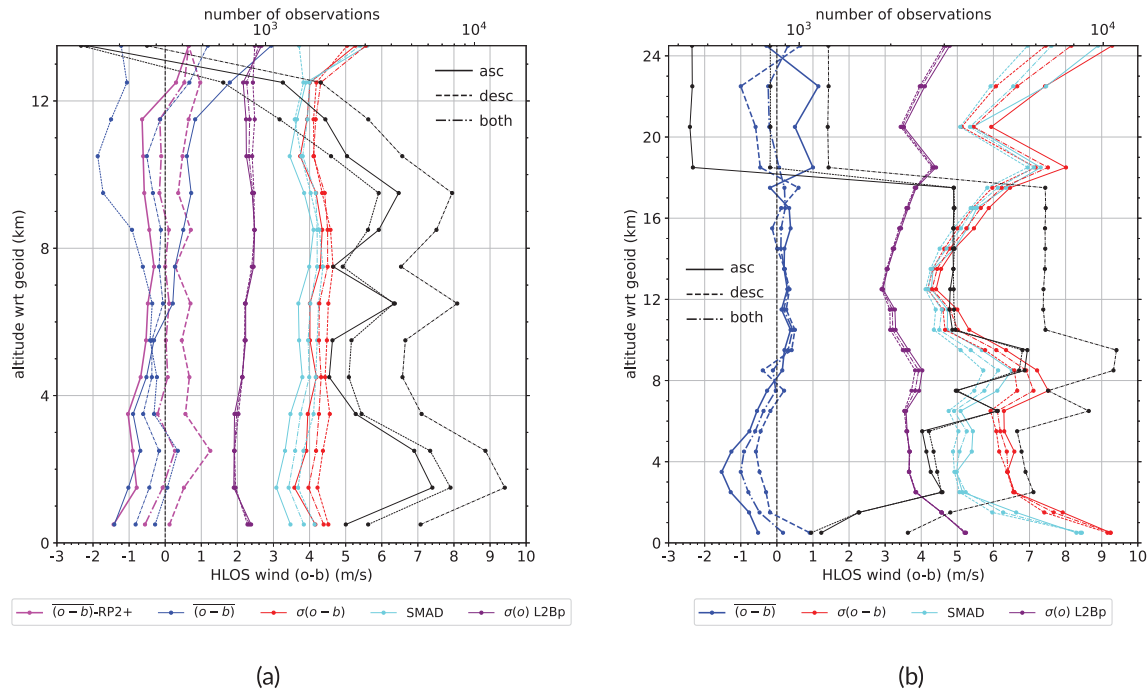


FIGURE 2 *Aeolus* second reprocessing (o–b) statistics for the Atlantic domain of (a) Mie-cloudy, for period 3, and (b) Rayleigh-clear, for period 2, HLOS winds (“o”) against ECMWF model data (“b”). See the text for details on the period definitions. Blue/magenta curves denote the mean value (bias), while red and cyan curves represent the random error, with red the standard deviation and cyan the scaled median absolute deviation (SMAD); see the text for details. The purple line denotes the observation-error estimate as calculated by the L2B processing. The black curves denote the number of observations used in the statistics on a logarithmic scale. Solid, dashed, and dash–dotted lines correspond to ascending, descending, and combined orbits, respectively. RP2+ refers to the improved Mie-cloudy wind product used in this study; see the text for details. The curves are plotted on a 1-km altitude grid at altitudes containing at least 100 observations.

The (o–b) profiles for Rayleigh winds in Figure 2b show a persistent altitude-varying bias with negative values in the lower troposphere increasing to positive values in the upper troposphere. The increasing bias of Rayleigh-clear winds is also observed on a global scale, and is approximately linear in the free troposphere (Supporting Information: Figure S3b). This is a persistent issue that still exists for the fourth reprocessing dataset.

The *Aeolus* product includes, for each wind observation, an error estimate, $\sigma(\epsilon_o)$. This value can be used in data assimilation to give weight to the observation in the analysis. The purple curves in Figure 2 show their mean value, which is smaller than the (o–b) standard deviation, $\sigma(o-b)$ (red curves), at all altitudes, as expected given that in theory $\sigma(\epsilon_o) \approx \sqrt{(\sigma^2(o-b) - \sigma^2(\epsilon_b) - \sigma^2(\epsilon_r))}$, with ϵ_b the background error, ϵ_r the representation error, which accounts for the difference between the effective model resolution and observation footprint (Janjić et al., 2017), and assuming that the covariance of observations and background errors is negligible. The typical range for $\sigma(\epsilon_b)$ is $1.5 - 2.5 \text{ m} \cdot \text{s}^{-1}$ Rennie et al. (2021), while $\sigma(\epsilon_r)$ is close to $0 \text{ m} \cdot \text{s}^{-1}$ for Rayleigh winds and estimated at about $1 \text{ m} \cdot \text{s}^{-1}$ for Mie winds, given their accumulation lengths. With these values it is concluded that $\sigma(\epsilon_o)$ from RP2 and

RP2+ is too low, that is, the purple curve is too far away from the red curve. Indeed, it has been confirmed that some noise contributors have not been taken into account in the observation-error estimate. This will be improved in upcoming *Aeolus* reprocessing activities. It is thus important that users realize such product changes between different *Aeolus* datasets when using the value of $\sigma(\epsilon_o)$ for giving weight to observations in their data assimilation system. We come back to this in Section 5.

For the Arctic region, the Mie wind (o–b) bias is close to zero except in the boundary layer. Rayleigh wind (o–b) biases for the Arctic region show the same linear increase as the global statistics (Supplementary Figures S3 and S4). Conclusions on the random error for the different regions cannot be drawn easily, given the different *Aeolus* range-bin settings used for the different regions.

Because *Aeolus* wind processing is tuned to the ECMWF model, there has been no urgency at ECMWF to implement a bias-correction scheme for *Aeolus* winds in their Integrated Forecasting System (IFS). Other meteorological centres did find the need to correct for *Aeolus* biases relative to their global model; see, for example, Laroche and St-James (2022). Based on the statistics presented, there was no urgent need to implement a bias-correction

scheme for *Aeolus* winds for use in HARMONIE-AROME. However, the biases found for the ascending and descending orbits for Mie winds relative to the ECMWF model, in particular for the Atlantic domain, suggest the need for bias correction in IFS before use of *Aeolus* winds in HARMONIE-AROME (and possibly for the ECMWF model). Initially it was decided to follow the ECMWF strategy for *Aeolus* data usage. Since HARMONIE-AROME is embedded in the IFS and noting that the overall (vertically averaged) wind biases for both Mie and Rayleigh winds, relative to the ECMWF model, for both the Atlantic and Arctic domains (see also Supplementary Table S1) are within the *Aeolus* mission requirement of $0.7 \text{ m} \cdot \text{s}^{-1}$, it was decided to not implement a bias-correction scheme for *Aeolus* winds in IFS at this stage.

It is noted that the mean $(o-b)$ for other wind profiling observing systems (radiosonde, aircraft) is very close to $0 \text{ m} \cdot \text{s}^{-1}$ at all altitudes (not shown), much closer than for *Aeolus*, suggesting that most of the *Aeolus* $(o-b)$ bias can be attributed to *Aeolus* winds, when assuming that the model is well tuned to show minimal bias to existing observing systems.

4 | METHODOLOGY OF IMPACT ASSESSMENT

The most common method to assess the impact of an additional observing system to the existing observing system is through an observing-system experiment (OSE) in which two experiments are conducted, one using the existing observing systems—the so-called control experiment (CTRL), and an experiment (EXP) using the same observing systems as in CTRL and in addition the new observing system under investigation.

The starting point of the *Aeolus* impact experiments with HARMONIE-AROME is to use the QC settings as proposed by ECMWF, that is, Mie and Rayleigh winds are rejected if the value of the error estimate exceeds the threshold values of 4.5 and $8 \text{ m} \cdot \text{s}^{-1}$ respectively. No Rayleigh winds for altitudes below 850 hPa have been used in the assimilation, because of their relatively low quality (large random error, see Figure 2b and Supplementary Figure S4b) at these altitudes. As discussed in the previous section, no bias correction is performed. *Aeolus* became operational at ECMWF on January 9, 2020, meaning that *Aeolus* information entered the Atlantic domain through the LBCs for periods 2 and 3 in 2020.

Additional error inflation and/or data thinning may be needed if the spacing of adjacent observations is smaller than the model effective resolution, which may potentially result in correlated errors exceeding the typical value of 0.2 reported in the literature (Liu & Rabier, 2003). This is

true in particular for Mie winds, given their typical low horizontal spacing of 11–15 km. To assess the impact of error inflation, first the value of the error estimate, $\sigma(\epsilon_o)$, is inflated. The threshold value of this parameter is kept unchanged. The result is that fewer wind observations pass this QC check. The winds that do pass enter the screening part of the data assimilation system, where they are subjected to the first-guess check to remove potential observation outliers (Hagelin *et al.*, 2021). The first-guess check reads: $(o - b)^2 < L(\sigma^2(\epsilon_o) + \sigma^2(\epsilon_b))$, with typical values $L = \{3, 4, 5\}$. Hence, inflating the value of $\sigma(\epsilon_o)$ in the equation relaxes the first-guess check, which has the undesired side effect of allowing more low-quality observations, that is, with larger $|o-b|$, in the analysis. We conclude that the current implementation of the first-guess check in IFS is not ideal for our purpose. In our case, the error inflation should have no impact on the selection of observations entering the analysis. Only their weight in the analysis should change.

The absolute impact of *Aeolus* winds in a limited-area model is twofold. It may come from the lateral boundary conditions of the hosting model, that is, the ECMWF global model for HARMONIE-AROME, and/or the direct assimilation inside the limited-area domain. The relative contribution of both cannot be derived from the results and would need two versions of the hosting model, one with the use of *Aeolus* and one without. This is however not available from the operational ECMWF archive. We therefore focus on the impact of the direct assimilation of *Aeolus*, given that both CTRL and EXP use the same boundary conditions.

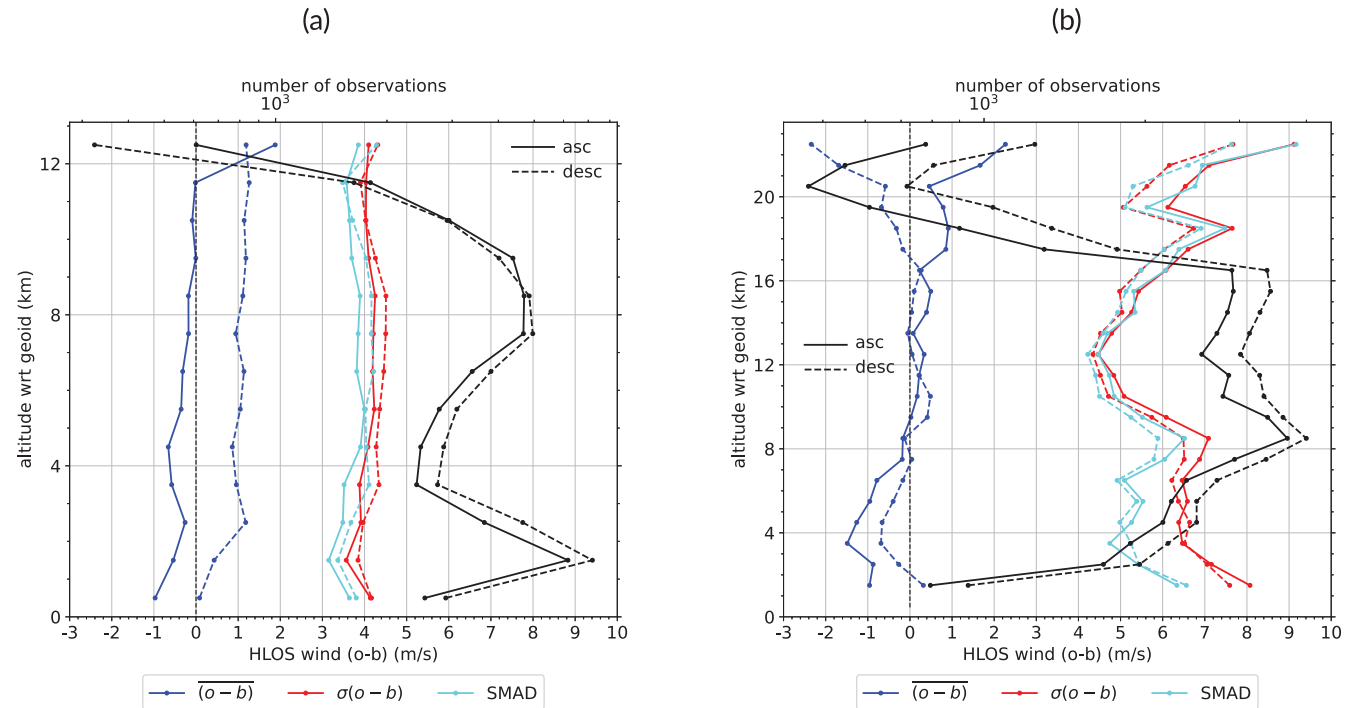
To quantify the impact, I , of an observing system with an OSE, we calculate the relative change of the $(o-b)$ root-mean-square error (RMSE) of the two experiments:

$$I = \frac{\langle o-b_{EXP} \rangle}{\langle o-b_{CTRL} \rangle} \times 100\%, \quad (1)$$

with $\langle . \rangle$ denoting RMSE, averaged over the experimental period for observations (o) from a reference observing system, which is used for verification of the model backgrounds (b) of the different experiments. The reference observing systems selected here are radiosondes and aircraft, from which temperature and wind observations are used, as well as humidity from radiosondes. For a clean impact assessment, it is mandatory that the dataset of observations used in the numerator and denominator of Equation (1) is identical, such that the difference can only come from the model background at the locations of the verifying observations. An impact value smaller than 100% implies that the model background error has reduced by adding the new observing system, hence demonstrating positive impact of the additional observing system (*Aeolus*

TABLE 1 HARMONIE–AROME Arome Atlantic experiment description for periods 2 and 3.

Experiment name	Information
AT_ref	Control experiment, period: January 20, 2020–March 10, 2020 (period 3)
AT_mie	Control + Mie winds only, period: see Control experiment
AT_mieinf	Control + Mie winds only, Mie error inflated with factor 2, period: see Control experiment
AT_rayleigh	Control + Rayleigh winds only, period: January 20, 2020–February 28, 2020 (period 2)

**FIGURE 3** (o–b) HLOS wind statistics, similar as Figure 2, for (a) Mie winds and (b) Rayleigh winds, but now ‘b’ comes from the HARMONIE–AROME model.

in our case). An impact value larger than 100% implies negative impact of the new observing system.

5 | EXPERIMENTAL RESULTS FOR THE ATLANTIC DOMAIN

For the Atlantic domain, three OSEs were conducted; the corresponding experiments are summarized in Table 1. All experiments started on January 20, 2020. The first seven days were used as the spin-up period.

The innovation statistics of *Aeolus* winds relative to the HARMONIE–AROME model have been derived from the observations used in the analyses of experiments AT_mie and AT_rayleigh. The statistics in Figure 3 compare well with Figure 2; however, the Mie wind (o–b) bias curves have shifted to the right, with overall (o–b) bias values for ascending and descending orbits of -0.29 and $0.92 \text{ m} \cdot \text{s}^{-1}$, respectively. Figures 4 and 5 show the impact scores, using

Equation (1), with experiment AT_ref used for “CTRL” and the other experiments in Table 1 used for “EXP” and taking radiosonde and aircraft observations for verification, respectively. The seven-day spin-up period has not been used in the calculation of the impact scores. Most of the positive impact is found in the mid and upper troposphere, while negative impacts are mainly limited to the lower troposphere. By construction, the green error bars, which represent all eight analysis times, are smallest. The relatively low number of aircraft flights around midnight explains the large error bars of the corresponding blue curves, which verify at 0000 UTC. For the wind components, there is a clear difference between the impact of ascending and descending orbit phases, overall more positive for the ascending (afternoon) orbits verifying at 0000 UTC (blue profiles). The slightly worse scores for descending (morning) orbits, verifying at 1200 UTC (red profiles), may be related to the positive (o–b) bias (see Figure 3a).

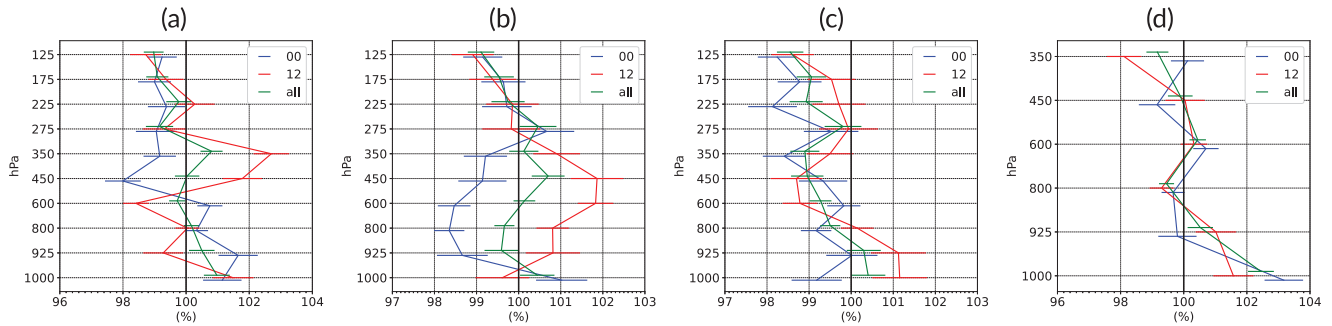


FIGURE 4 *Aeolus* Mie-cloudy HLOS wind impact scores for the six-week period 3 and the Atlantic domain when verified against the radiosonde (a) meridional wind component, (b) zonal wind, (c) temperature, and (d) humidity. Statistics are based on model background fields valid at 0000 UTC (blue), 1200 UTC (red), and all eight analysis times (green). Values smaller/larger than 100% denote positive/negative impact of adding *Aeolus* winds to the observing system. The error bars denote the 1σ uncertainty of the impact score.

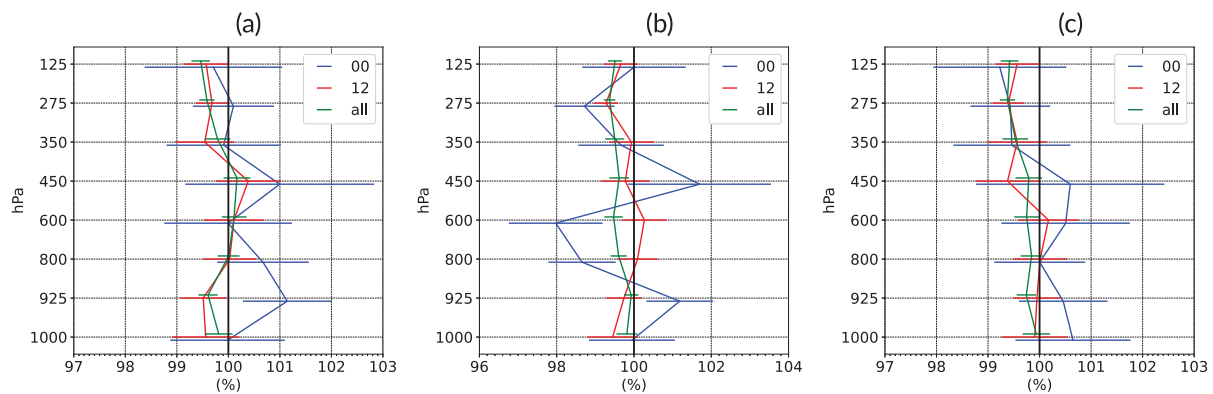


FIGURE 5 Same as Figure 4 but now for aircraft (a) meridional wind component, (b) zonal wind, and (c) temperature.

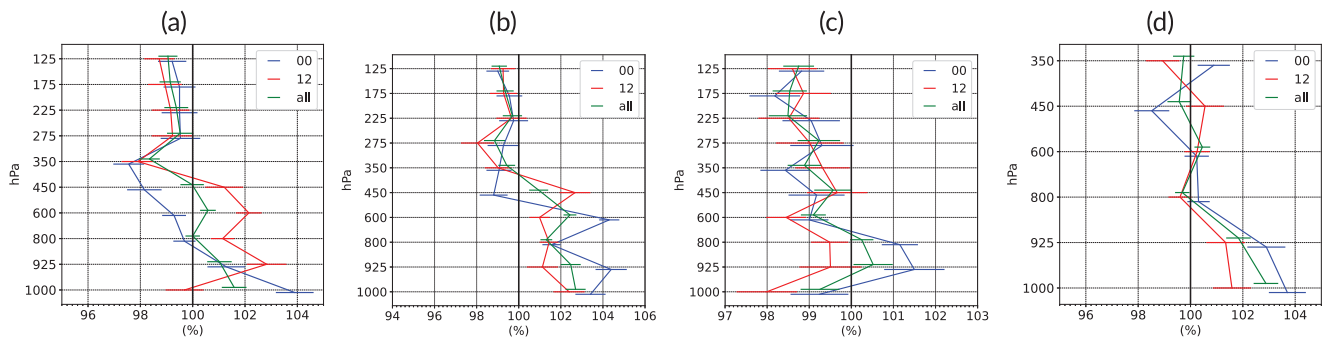


FIGURE 6 Same as Figure 4 but now for the *Aeolus* Rayleigh experiment and the 4.5-week period 2.

Similar impact scores for the *Aeolus* Rayleigh experiment are found in Figures 6 and 7. Also for Rayleigh winds, the most positive impact is obtained in the mid and upper troposphere and lower stratosphere, with negative impacts in the lower troposphere. It is noted that no Rayleigh winds were used in the data assimilation for altitudes below 850 hPa. Negative impacts at these altitudes are most probably due to the propagation of analysis increments at higher altitudes to lower altitudes through the background-error covariance structure

functions, which propagate observational information in model space, both horizontally and vertically.

Vertically integrating the profiles in Figures 4–7 shows that the overall impact of adding *Aeolus* is positive in Figure 8, that is, most of the bars are pointing to the left from the 100% line. The positive impact is largest on model temperature, from both Mie and Rayleigh winds, an indication that the largest impact of *Aeolus* is mostly on large atmospheric scales, which meets the main mission objective. Negative overall impacts are mainly due

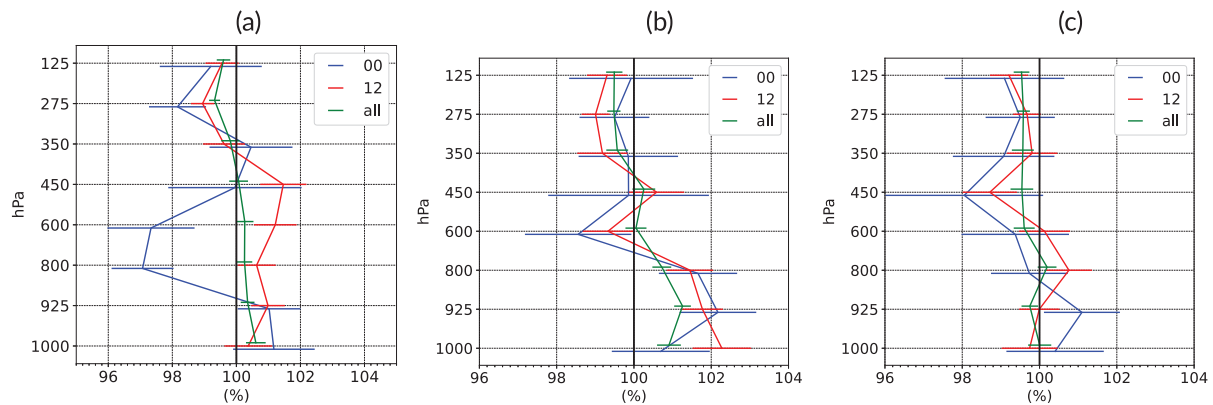


FIGURE 7 Same as Figure 5 but now for the *Aeolus* Rayleigh experiment and period 2.

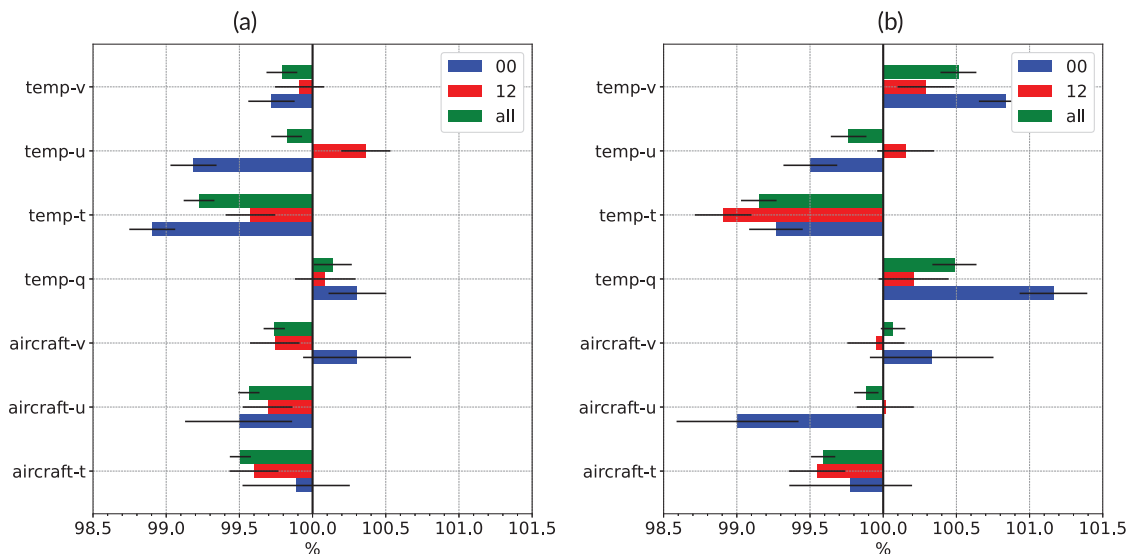


FIGURE 8 Atlantic domain vertically integrated HLOS wind impact scores for (a) Mie winds, averaged over the six-week period 3, and (b) Rayleigh winds, averaged over the four-week period 2. Verification was done against radiosonde (temp) and aircraft observations for the meridional wind component (*v*), zonal wind component (*u*), temperature (*t*), and humidity (*q*). The colours were defined in Figure 4. The error bars denote the 1σ uncertainty of the impact score.

to negative impacts in the lower part of the atmosphere, which is most prominent for humidity (temp-*q*). This is still unexplained and needs further investigation. A possible explanation may be an incorrect balance between the atmospheric parameters in the background-error covariance matrix for this particular period.

As can be inferred from Figure 2a, the error estimate in the *Aeolus* Mie-cloudy product of the second reprocessing is too low. The error estimate in the *Aeolus* products up to and including the fourth reprocessing dataset is based on the Poisson-distributed photon shot-noise random error only. Future products will also take into account corrections for the dark current signal and solar background, which contribute to the overall noise Weiler *et al.* (2021b), and will increase the error estimate to represent the actual wind-observation random

error better. To account for the too low-error estimate and hence potentially too-large weight given to *Aeolus* Mie winds in the analysis, experiment AT_mieinf with inflated Mie wind error was conducted; see Table 1. As discussed in Section 4, error inflation has the side effect of allowing more low-quality winds in the analysis. Indeed, the additional about 2% Mie-cloudy HLOS winds that passed the first-guess check were of very low quality, with an overall bias of $5.3 \text{ m} \cdot \text{s}^{-1}$ and standard deviation of $10.7 \text{ m} \cdot \text{s}^{-1}$. The additional low-quality observations may explain the overall negative impact (not shown) compared with the use of uninflated observation errors as in AT_mie. As discussed in Section 4, a decoupling of assigning errors to observations and quality control—for example, the first-guess check—is therefore recommended to allow for a correct implementation of error inflation.

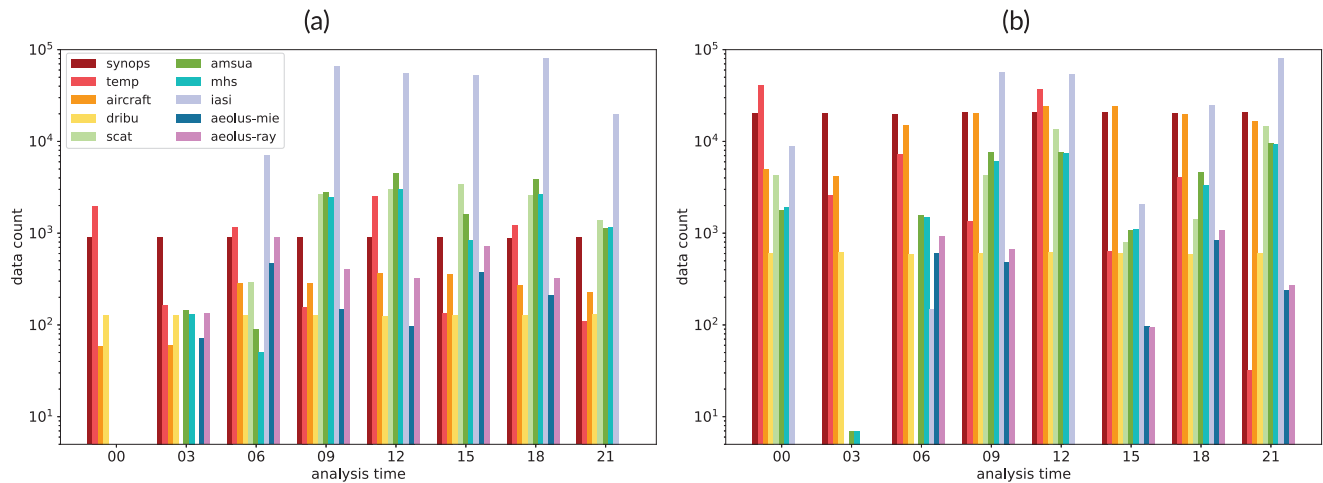


FIGURE 9 Typical observation data usage, on a logarithmic scale, for (a) the Arctic and (b) the Atlantic domain for the daily eight assimilation cycles, with analysis times along the x -axis. Observing systems used are from synop stations (synops), radiosondes (temp), both ascending and descending phase, AMDAR aircraft, drifting buoys (dribu), scatterometer (scat) on *MetOp-A/B/C*, microwave sounders (AMSU/MHS) on *MetOp-A/B/C* and *NOAA-15/18/19*, the infrared sounder (IASI) on *MetOp-B*, and Mie-cloudy and Rayleigh-clear winds from *Aeolus*.

The overall improvement found by adding *Aeolus* Mie winds in the Atlantic domain is $0.32\% \pm 0.28\%$, the first and second values denoting the mean and standard deviation respectively from all green bars in Figure 8a and similarly for *Aeolus* Rayleigh winds we find $0.07\% \pm 0.44\%$ from all green bars in Figure 8b. These numbers indicate that Mie winds have significant positive impact and Rayleigh winds marginally positive to neutral impact, with the remark that the impact of Rayleigh winds in the upper troposphere is largely positive and that in the lower troposphere is negative.

Similar statistics were produced for the Arctic domain (Supporting Information: Figures S6–S8 and Table S2). Given the caveats, discussed in Section 3, no statistically significant impact can be expected for such a relatively small domain, limited experimental period, and limited observations for verification, although there is an indication of a positive impact against radiosonde wind and humidity observations, with an overall score of $0.74\% \pm 1.12\%$, from the use of combined Mie and Rayleigh winds when inflating the Mie wind error with a factor of 2 and the application of a relaxed QC.

To put these numbers in context, Rennie *et al.* (2021) show typical improvements brought by *Aeolus* for the ECMWF model in the range of 0.2–0.5%, when globally averaged, for a number of observing systems taken for verification. Also, from fig. 14 of Rennie *et al.* (2021), *Aeolus* impact for the ECMWF model is smallest for the Northern Hemisphere extratropical region, which can be explained by the fact that this region is best observed by the existing observing system, leaving less room for *Aeolus* to have additional impact. In the context

of HARMONIE-AROME, Schönach *et al.* (2025) found improvements of generally less than 0.5% for the assimilation of Spinning Enhanced Visible and InfraRed Imager (SEVIRI) water-vapour radiances. Recent results show typical impact scores of assimilating radar winds and reflectivities and satellite infrared radiances from Cross-track Infrared Sounder in the HARMONIE-AROME model in the same range as those found for *Aeolus*, with the remark that the data coverage of these observing systems is substantially larger.

Another option is to look at the data count of *Aeolus* winds relative to other observing systems used in HARMONIE-AROME. Figure 9 shows the data count of observations used in each assimilating cycle for the different observing systems used in the experiments. Each day includes eight three-hour assimilation cycles, ranging from 1000–1300 UTC, 1300–1600 UTC, etc., that is, ranging from two hours before until one hour after analysis time. Only a very small fraction of the total data coverage is attributed to *Aeolus* winds (see the dark blue and pink coloured bars). Data from synop stations and drifting buoys are fairly constant during the day. Clearly, aircraft data are present more often during daytime than night-time. Radiosondes are launched mainly at 0000 and 1200 UTC. Polar satellite data generally dominate, but depending on their overpass time over the domain. It is noted that radiosonde observations are used at their actual location, hence taking into account drifting from the launch location during ascent and descent. In conclusion, given the relatively small number of *Aeolus* wind observations, their overall impact in the HARMONIE-AROME model is substantial and overall

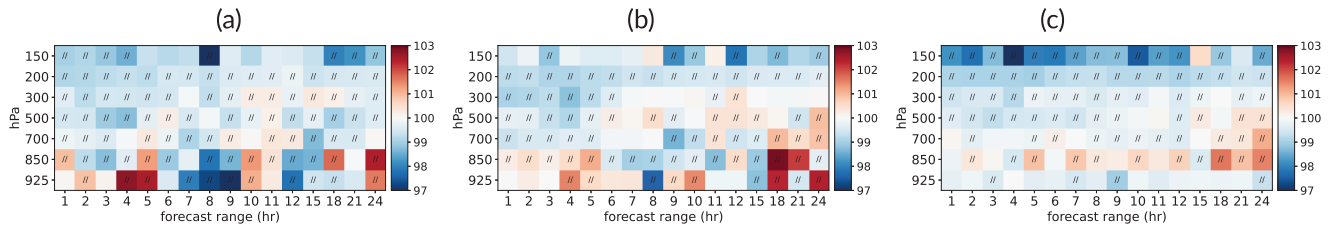


FIGURE 10 *Aeolus* Mie-cloudy wind impact on the HARMONIE-AROME model for period 3, as a function of forecast range and pressure level for (a) meridional wind, (b) zonal wind and (c) temperature, taking Mode-S data as a reference. Blue denotes positive impact, red negative impact, denotes significant at the 95% significance level.

positive and compares well with other, more densely sampling, observing systems and with *Aeolus* impact in the ECMWF model.

One may wonder why an experiment using both Mie and Rayleigh winds was not conducted for the Atlantic domain, given the visualized complementary impact in Supplementary Figure S9: that is, the impacts of Mie and Rayleigh winds do not counteract but largely show similar direction (positive and negative) and amplitude and would thus instead complement each other in the analysis. In our opinion, such an experiment would need the lessons learned from all experiments conducted, which include the following:

- (i) bias correction for observations from ascending and descending orbits,
- (ii) the Arctic experiments show indications of improved impact when applying error inflation, but, on the other hand,
- (iii) negative impact was found for Mie error inflation in the Atlantic domain, possibly due to allowing poor-quality data in the analysis.

To be valuable, a final experiment for the Atlantic domain, using both Mie and Rayleigh winds, would therefore need the implementation of a bias-correction scheme and a more sophisticated implementation of error inflation. These additional efforts include coding and testing in IFS, which was outside the scope of the current study, but is highly recommended for a follow-up study and in preparation for the use of observations from a potential operational *Aeolus* follow-on mission.

5.1 | Forecast impact

To assess the impact of *Aeolus* Mie and Rayleigh winds on the HARMONIE-AROME model forecasts, we used wind and temperature data from the European Meteorological Aircraft-Derived Data Centre (EMADDC) at

the Dutch weather service Koninklijk Nederlands Meteorologisch Instituut (KNMI) as an independent reference. These observations are inferred from a tracking and ranging radar used for air-traffic control, called Mode-S EHS because it is using the so-called Selective Enhanced Surveillance (EHS) mode of the radar (de Haan, 2011). The quality of the Mode-S EHS winds and high-altitude temperature is comparable with that of data collected using the Aircraft Meteorological Data Relay (AMDAR), and slightly less for temperature for altitudes below 850 hPa (de Haan *et al.*, 2025). The interrogation frequency between the aircraft and the traffic control radar is between 4 and 20 s, depending on the type of radar, meaning that profiles of wind and temperature can be inferred near airports during ascent and descent. At cruise level (approximately 10-km altitude), with a typical aircraft speed of $250 \text{ m}\cdot\text{s}^{-1}$, atmospheric wind and temperature observations are obtained with 1–5 km spacing along the flight path, which is much denser than for AMDAR. Also, it is noted that not all commercial aircraft are equipped with AMDAR, so more flight tracks are sampled by Mode-S EHS in the area covered by the air-traffic control radars. Outside these areas, no Mode-S observations can be obtained.

The number of observations from Mode-S over the Arctic domain is too limited, hence the forecast impact is limited to the Atlantic domain. Figure 10 shows the impact of *Aeolus* Mie winds from experiment AT_mie on the HARMONIE-AROME model for the forecast range up to 24 h. To arrive at these results, wind and temperature data from Mode-S EHS were used for *a* in Equation (1). Model forecasts interpolated to the observation locations were used for *b*. In general, the blue colours dominate the figure, meaning on average there is a positive impact on HARMONIE-AROME model forecasts when adding *Aeolus* to the observing system. The most positive impact is found in the upper part of the atmosphere and this reduces with increasing forecast range, as expected. The huge number of available Mode-S EHS data explains why many boxes in Figure 10 are marked as statistically significant. Figure 11 shows the impact of *Aeolus* Rayleigh winds from experiment AT_rayleigh. In general, the blue colours

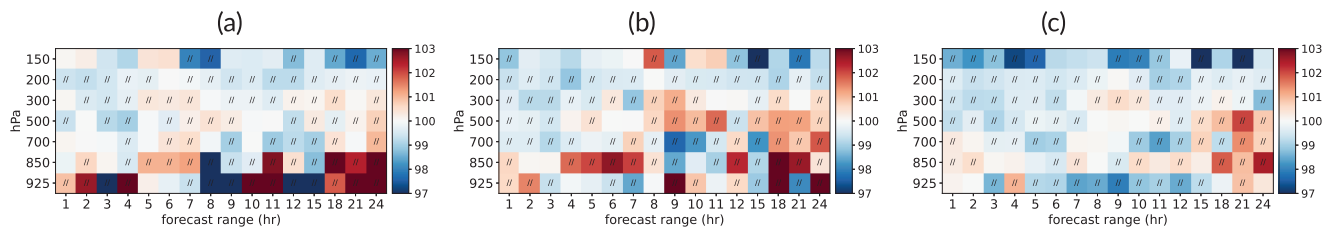


FIGURE 11 Same as Figure 10 but for Rayleigh-clear winds for period 2.

dominate the figure, in particular in the short-range and in the mid and upper troposphere and lower stratosphere. Negative impacts are found in the boundary layer (where no Rayleigh winds were assimilated) and in the 12–24 h range.

6 | SUMMARY AND RECOMMENDATIONS

It was demonstrated that the HARMONIE–AROME LAM, operated on an Atlantic domain, benefits from the use of *Aeolus* Doppler wind lidar winds. The impact scores compare well with the numbers presented by ECMWF on *Aeolus* impact for the Northern Hemisphere extratropics and with the numbers of other observing systems used in HARMONIE–AROME but with a much larger coverage. Impact experiments were conducted for two limited-area domains, an Arctic and an Atlantic domain. Statistically significant impact could be demonstrated best for the Atlantic domain, given the relatively dense network of radiosondes and aircraft that were used for verification, but which are insufficient for the Arctic domain. For the Atlantic domain, overall impact was neutral (Rayleigh winds) to positive (Mie winds). The latter is a nice result, given the very small extension of the number of *Aeolus* winds to the existing observing system used in LAM. The largest positive impact was found in the mid and upper troposphere and lower stratosphere and an overall negative impact was found in the lower troposphere. These conclusions are valid for both Mie and Rayleigh winds. Negative impacts for altitudes below 850 hPa cannot be attributed to Rayleigh winds measured at these altitudes, because they were excluded from data assimilation because of their generally low quality. Negative impacts of Mie winds in the lower troposphere may be explained by a possible overfitting of relatively densely sampled Mie winds in cloudy and aerosol-rich conditions. To check this hypothesis, additional experiments were conducted for both domains with error inflation through a doubling of the assigned Mie wind observation error. An undesired side effect of the current implementation of error inflation in the ECMWF IFS environment (in which

HARMONIE–AROME is embedded) was found, namely that quality control on the first-guess check is relaxed, which results in more low-quality winds entering the analysis. The overall impact of error inflation was negative in the Atlantic domain and neutral in the Arctic domain, but no conclusions could be drawn on whether this was the result of giving reduced weight to the observations or allowing low-quality winds in the analysis.

The spatial and temporal resolution of *Aeolus* is too coarse to sample and analyse small-scale weather phenomena such as polar lows well, although some indications of beneficial impact were found for the Arctic domain (Supplementary Figure S11). In general, the current observing system lacks high-resolution observations, in both space and time, to analyse and constrain the model's small spatial scales. Small-scale features, which the model is not capable of handling well, act as noise and should be avoided in the analysis to avoid forecast degradation (Stoffelen *et al.*, 2020). Indeed, the *Aeolus* mission's main objective was to improve the large-scale atmospheric dynamics of NWP models. The results presented demonstrate overall improved large-scale dynamics in the upper part of the atmosphere and improved temperature, which is related to the large-scale dynamics as well. The large-scale dynamics is best sampled by the Rayleigh channel and the resulting winds show substantial impact on the steering of synoptic storms (Supplementary Figure S10). Mie winds provide a more dense sampling, potentially higher than the model effective resolution (or background-error correlation length-scales) and with correlated errors. In general, then, it is better to reduce their weight in the analysis, for example, through data thinning and/or error inflation, to avoid overfitting and the introduction of small-scale observational information entering the analysis.

Aeolus Mie-cloudy winds from the second reprocessing (RP2) show substantial biases, relative to the ECMWF model background, for both ascending and descending orbits and the LAM model domains considered. Also, the biases are non-constant with altitude, but they largely compensate when taken together in the statistics, resulting in a close to constant small overall bias with altitude. *Aeolus* Rayleigh-clear wind biases, relative to the ECMWF

model, are varying with altitude, that is, with negative values in the lower troposphere and increasing about linearly to positive values in the upper troposphere. This applies to ascending and descending orbits and the combined dataset. The overall vertically averaged bias is close to zero. A patched version of the level-2B processor, which includes the technique described in Marseille *et al.* (2022), removed the artifacts in the (o–b) statistics. The resulting RP2+ Mie-cloudy product still shows biases for ascending and descending orbits, relative to the ECMWF model, for the Atlantic domain, but both are constant with altitude, with opposite sign and similar magnitude, giving an overall close-to-zero constant bias with altitude. The Mie winds of the RP2+ product were used in the experiments for the Atlantic domain. The resulting (o–b) Mie-wind statistics for the HARMONIE–AROME model show substantial biases, but mainly for the descending orbit node. The results confirm recommendations from users of global models to consider bias correction (Laroche & St-James, 2022) for both global and limited-area models to enhance *Aeolus* impact. It is expected that future *Aeolus* impact will benefit from the continuously improved quality of *Aeolus* winds from reprocessing activities in the framework of the *Aeolus* Data Innovation and Science Cluster (DISC) consortium.

For limited-area domains, the number of extreme weather events is too small to draw firm conclusions on *Aeolus* impact for extreme weather events, given also the relatively short mission period of less than 5 years. However, the results in the supplementary material indicate that *Aeolus* winds may have a substantial impact on the track and intensity of synoptic storms and polar lows and an extended lifetime follow-on mission may be more conclusive on the relative impact of Mie and Rayleigh winds on extreme weather events.

Based on the findings in this study, we recommend the following steps for *Aeolus* (and potentially future *Aeolus* follow-on) usage in limited-area (and global) models.

- The first step is to generate *Aeolus* (o–b) statistics for the LAM domain and to discriminate between ascending and descending orbits and apply quality control (QC). QC is applied on the estimate of the standard deviation of the wind random error, which is available from the L2B product, and on |o–b| as discussed in Section 3. As a starting point, threshold values for these QC parameters can be obtained from released verification reports, such as DISC (2021).
- The outcome of the above step serves as input to decide on the need for the implementation of a bias-correction scheme. As a rule of thumb, bias correction is needed if |o–b| biases exceed $1 \text{ m}\cdot\text{s}^{-1}$ systematically, to avoid negative impact in NWP (Horányi *et al.*, 2015).
- The L2B error estimate provides important input to give weight to *Aeolus* winds in data assimilation. The procedure to calculate this random error estimate has evolved in subsequent *Aeolus* reprocessing activities and is known to be an underestimate up to and including the fourth reprocessing dataset. The error estimate in future products will be improved by also taking into account noise contributors ignored so far (Weiler *et al.*, 2021b). The use of this parameter in QC and data assimilation should therefore be revisited with the release of new products. Comparing the error estimate, $\sigma(\epsilon_o)$, against the (o–b) random error standard deviation, $\sigma(o - b)$, as done in Section 3, provides an indication of the potential under- or overestimation of this parameter. A correction factor, f , may be needed when using this parameter in data assimilation. An initial guess may be $f = \sqrt{(\sigma^2(o - b) - \sigma^2(\epsilon_b))/\sigma(\epsilon_o)}$, for $\sigma(\epsilon_b)$ in the typical range of $1.5\text{--}2.5 \text{ m}\cdot\text{s}^{-1}$ (Rennie *et al.*, 2021).
- Observation usage strategy: additional error inflation and/or data thinning may be needed for Mie winds if the spacing of adjacent observations is smaller than the model effective resolution, which may potentially result in correlated errors exceeding the typical value of 0.2 reported in the literature (Liu & Rabier, 2003). The optimal observation usage strategy is model-dependent.
- The current implementation of error inflation has the side effect of allowing more low-quality data in the analysis, as discussed in Section 4. A more sophisticated implementation of error inflation is needed as part of the ECMWF IFS code by decoupling the assigned observation error from the first-guess check, which is part of quality control. This will allow more flexibility in controlling assignment of weights to observations in the analysis, which will become more important given the increasing number of observing systems providing high-density observations, such as for instance radar and Mode-S EHS, but also satellite data with footprints smaller than the effective model resolution.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

FUNDING INFORMATION

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DATA AVAILABILITY STATEMENT

The *Aeolus* data used were obtained from the ESA *Aeolus* Online Dissemination System, in particular the level-2 baseline 11 (2B11) product provided at https://aeolus-ds.eo.esa.int/oads/access/collection/L1B_L2_Products, which was used for the second reprocessing activity. The second reprocessing was based on level-1 and level-2 processor versions deployed in October 2020 (L1Bp 7.09.1, L2Ap 3.11.1, L2Bp 3.40.2), used for near-real-time generation of baseline 11 data products. The wind products were converted to the Binary Universal Form for the Representation of meteorological data (BUFR) format, which is the required input format for most NWP models. The Mie winds for the 2020 experimental period were obtained from a patched version of the level-2 processor, used for the second reprocessing. The resulting Mie-cloudy wind dataset is available from the author.

ENDNOTE

¹SMAD is the scaled median absolute deviation (MAD) and is less sensitive to wind-error outliers, and for wind errors following a Gaussian distribution the SMAD (with scaling factor 1.4826) and error standard deviation are identical (https://en.wikipedia.org/wiki/Median_absolute_deviation, accessed on 27, March 2026).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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