



Median-filter quality control for the recovery of Aeolus Mie-cloudy wind observations under low-signal conditions

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Abstract. The Aeolus mission demonstrated the significant value of global Doppler wind lidar observations for numerical weather prediction (NWP) and atmospheric research by providing the first spaceborne measurements of wind profiles on a global scale. In particular, Aeolus Mie-cloudy winds showed a strong positive impact on weather forecasting despite their comparatively limited spatial coverage. However, the operational Level-2B processing was deliberately optimized for robust retrievals from strong cloud returns, resulting in the rejection of many potentially useful wind observations under weak backscatter conditions such as aerosol layers, optically thin cirrus clouds, and polar stratospheric clouds. Recovering additional winds in these regions is scientifically important because they are closely linked to aerosol transport and upper-tropospheric and lower-stratospheric dynamics.

To address this limitation, a median-filter-based quality-control scheme was developed to identify physically meaningful wind observations among the large fraction of Mie-cloudy winds flagged as invalid by the operational processing. The method compares each wind result with neighbouring observations in along-track distance and altitude space using a computationally efficient k-d tree approach. Invalid winds are recovered only if they are dynamically consistent with the surrounding wind field and satisfy additional plausibility criteria designed to suppress gross retrieval artefacts.

The performance of the algorithm was evaluated for representative Aeolus orbits throughout the mission and for month-long periods in September 2022 and April 2023. The method substantially increases the number of useful Mie-cloudy wind observations while maintaining acceptable error characteristics. Depending on the selected filter configuration, the number of retrieved winds increases typically by 25–60%, whereas the associated increase in random error remains below 1 m s^{-1} . Particularly strong improvements are achieved in the upper troposphere and lower stratosphere, including during measurements of the 2022 Hunga Tonga stratospheric volcanic aerosol plume, when the coverage of wind observations with departures from the model background of less than 2.5 m s^{-1} increased by up to a factor of six in the lower stratosphere. The developed approach therefore significantly enhances the scientific and meteorological value of the Aeolus dataset and provides a promising approach for future spaceborne Doppler wind lidar missions such as Aeolus-2.



1 Introduction

The Aeolus mission (2018–2023) marked a major milestone in atmospheric remote sensing as the first spaceborne Doppler
25 wind lidar system capable of providing global wind-profile observations ([European Space Agency \(ESA\), 2008](#); [Reitebuch, 2012](#); [Reitebuch et al., 2020](#); [Straume et al., 2020](#); [Reitebuch, 2025](#); [The Aeolus Data Innovation and Science Cluster \(DISC\), 2024](#)). Launched by the European Space Agency (ESA) in 2018 and operated until 2023, Aeolus delivered unprecedented observations of one component of the horizontal wind vector throughout large parts of the troposphere and lower stratosphere. The mission demonstrated the substantial benefit of direct wind-profile measurements for numerical weather prediction (NWP),
30 leading to measurable forecast improvements in operational forecasting systems worldwide ([Rennie et al., 2021](#); [Pourret et al., 2022](#); [Garrett et al., 2022](#); [Halloran and Forsythe, 2024](#); [Rennie and Isaksen, 2024](#); [Shenolikar et al., 2025](#)). Beyond its meteorological impact, Aeolus also enabled a broad range of scientific applications related to atmospheric circulation, gravity waves, aerosol transport, and climate-relevant processes ([Wright et al., 2021](#); [Lukens et al., 2022](#); [Sun et al., 2024](#); [Banyard et al., 2024](#); [Wang et al., 2024](#); [Žagar et al., 2025](#); [Trajon et al., 2025](#)). Building on these achievements, ongoing activities now focus
35 on both maximizing the scientific exploitation of the existing Aeolus dataset and preparing the next generation of operational Doppler wind lidar missions. In particular, the planned operational follow-on mission EPS-Aeolus/Aeolus-2 incorporates several technological and processing advancements intended to further improve data quality, coverage, and operational capability ([Helie et al., 2023](#); [EUMETSAT, 2023](#); [Knobloch et al., 2025](#); [Marksteiner et al., 2025](#); [Porciani, 2025](#); [Berceau et al., 2025](#); [Flament et al., 2026](#); [Ciapponi et al., 2026](#)). Simultaneously, extensive simulation and processor-development efforts are being
40 conducted to optimize instrument performance and retrieval strategies for future spaceborne wind lidar observations.

As part of the Aeolus post-mission activities from 2024 to 2028 (so-called phase F), the Aeolus Data Innovation and Science Cluster (DISC) is undertaking a comprehensive reprocessing effort to generate a uniformly processed dataset covering the complete mission lifetime. The objective of these activities is to further enhance the scientific usability of the Aeolus observations, improve their impact on weather forecasting, and support the development of Aeolus-2. To this end, refinements of the Level-1
45 and Level-2 processors are being implemented and tested in dedicated reprocessing campaigns ([Knobloch, 2026](#)), resulting in the forthcoming Baseline 17 dataset planned for release by the end of 2027. One important aspect of these developments is the enhancement of the data coverage of Mie-cloudy winds.

Operational Aeolus Mie-cloudy winds were primarily retrieved from liquid clouds providing sufficiently strong particle backscatter to satisfy the operational quality-control (QC) criteria. Consequently, the global coverage of valid Mie-cloudy
50 winds is comparatively low, typically only about 7–12%, whereas Rayleigh-clear winds achieve coverage exceeding 90% ([Lux et al., 2026](#)). Despite this limited spatial coverage, Mie-cloudy winds contributed significantly to forecast-error reduction in NWP systems, especially in polar regions and tropics up to day 3 ([Rennie and Isaksen, 2024](#)). However, the operational Level-2B (L2B) processing was optimized for robust wind retrievals from strong cloud returns by balancing signal-to-noise ratio (SNR) and spatial resolution, resulting in only sparse wind retrievals from aerosols, optically thin cirrus clouds, and polar
55 stratospheric clouds (PSCs). This likely excludes a substantial fraction of potentially useful wind observations under weak backscatter conditions.



Recovering additional winds in such conditions is scientifically important because aerosol and thin-cloud layers frequently act as tracers of dynamical and transport processes in the upper troposphere and lower stratosphere (UTLS). Cirrus clouds, for example, strongly influence the Earth's radiation budget and remain among the largest uncertainties in climate studies because of their complex interactions with atmospheric dynamics and aerosols (Lee, 2012; Kärcher, 2018; De La Torre Castro et al., 2026). Similarly, PSCs are closely linked to polar ozone depletion through heterogeneous chemical processes and are strongly modulated by stratospheric transport and gravity-wave activity (Koutsogiannis et al., 2023). Enhanced wind coverage in these regions would therefore provide additional observational constraints for studies of cloud dynamics (Titus et al., 2026), cloud microphysics, aerosol transport, and atmospheric composition. A particularly illustrative example was provided by the 2022 Hunga Tonga eruption, which injected large amounts of aerosol into the stratosphere (Khaykin et al., 2022). While these aerosol layers initially produced sufficiently strong backscatter for Mie wind retrievals, the signal weakened over time and eventually became too faint to satisfy the QC thresholds for wind retrievals, despite still containing potentially valuable dynamical information.

Atmospheric remote sensing observations from satellites are inherently affected by measurement noise, sampling uncertainty, and sporadic outliers arising from both instrumental and geophysical processes. In lidar-based retrievals, random noise may originate from photon-counting statistics, detector noise, signal attenuation, and low-SNR conditions, while gross outliers can result from cloud contamination, hard-target reflections, precipitation, retrieval failures or high-energy cosmic particles. Such artifacts can substantially degrade the accuracy and representativeness of atmospheric products and therefore require robust denoising and QC procedures prior to scientific analysis or data assimilation into numerical models. A central challenge in atmospheric data processing is that filtering methods must suppress noise while simultaneously preserving physically meaningful structures such as sharp gradients, wave signatures, and boundary-layer transitions. Conventional linear smoothing approaches, including moving-average or Gaussian filters, efficiently reduce high-frequency random noise but tend to blur localized structures and remain sensitive to isolated extreme values. Consequently, robust statistical filtering techniques have become increasingly important in atmospheric remote sensing. Among these, median filtering represents one of the simplest and most widely used approaches for outlier-resistant denoising. Unlike mean-based methods, the median estimator is minimally affected by isolated spikes and therefore efficiently suppresses impulsive noise while preserving discontinuities and edges in geophysical fields.

Median and related robust filters have been widely applied in lidar and remote-sensing QC, including aerosol backscatter denoising (Wang et al., 2020), lidar signal enhancement (Wu et al., 2006; Jiao et al., 2015), airborne lidar point-cloud cleaning (Matkan et al., 2014; Carrilho et al., 2018), ceilometer preprocessing and boundary-layer retrievals (Schween et al., 2014), and filtering of Doppler wind lidar and radar data (Weber et al., 1993; Beck and Kühn, 2017; Gryning and Floors, 2019; Päsche and Detring, 2024; Erdmann and Gasch, 2026). More advanced approaches, including Hampel filters (Roos-Hoefgeest Toribio et al., 2025), bilateral filters (Lu et al., 2025), wavelet denoising, and Kalman filtering (Lange et al., 2014), can provide improved adaptability or multi-scale noise suppression, but often require stronger assumptions regarding noise statistics or increased computational complexity. In comparison, median filtering provides a computationally efficient and assumption-light solution that is particularly suitable for QC of atmospheric wind observations, where isolated retrieval artifacts coexist



with highly variable dynamical structures. Its robustness against impulsive noise and isolated outliers makes it especially attractive for lidar observations obtained under weak backscatter conditions, where conventional QC procedures often reject measurements because of increased uncertainty despite the presence of physically meaningful wind information.

95 In the context of Aeolus Mie-cloudy winds, this is particularly relevant for observations originating from aerosols, optically thin cirrus clouds, and PSCs, for which the operational L2B processing was deliberately configured in a conservative manner, prioritising the delivery of high-confidence wind estimates from optically thicker cloud returns to ensure robustness for NWP assimilation (Rennie et al., 2020). Robust median-based filtering therefore offers the possibility to identify coherent wind structures within noisy retrieval populations and to recover additional valid wind observations while maintaining acceptable random error characteristics. Enhancing the recovery of Aeolus Mie-cloudy winds in regions with weak particle backscatter
100 can thus increase the scientific value of the dataset.

In this study, a median-filter algorithm is proposed that takes all Aeolus L2B Mie-cloudy wind results as input, irrespective of their operational validity flag. Approximately 90% of these observations are currently classified as invalid because they do not pass the operational L2B QC criteria (Lux et al., 2026), although a significant fraction still contains useful wind information.
105 The proposed median-filter approach identifies and recovers these observations, thereby substantially increasing the Mie wind data coverage while maintaining low random-error characteristics. This approach is neither necessary nor applicable to the Rayleigh channel, where valid wind results in the L2B product already cover more than 90% of the sampled atmosphere. Invalid Rayleigh-clear winds are primarily located beneath optically dense clouds, where the laser beam is strongly attenuated, making the retrieval of useful wind information impossible.

110 The article is organised as follows. Section 2 introduces the methods and datasets used in this study, including a description of the Aeolus Mie wind data (Sect. 2.1 and the associated L2B validity flags (Sect. 2.2). The general concept of the median-filter approach is then illustrated using a single Aeolus orbit as an example (Sect. 2.3), followed by a description of the k-d tree method employed for nearest-neighbour identification (Sect. 2.4). The complete median-filter algorithm is subsequently presented in Sect. 2.5. Its capability to recover invalid Mie-cloudy winds under weak backscatter conditions is demonstrated in
115 Sect. 2.6 for the case of stratospheric aerosols following the Hunga Tonga eruption. Section 3 focuses on the optimisation of the adjustable median-filter parameters in order to balance data yield and random error characteristics (Sect. 3.1). Two different filter configurations are identified, one minimising the increase in random error and the other maximising the recovery of additional Mie-cloudy winds. These configurations are subsequently evaluated with respect to the variability of the median-filter output (Sect. 3.2), the resulting data coverage (Sect. 3.3), and their influence on the estimated error characteristics (Sect. 3.4).
120 Finally, the article concludes with a summary in Sect. 4.

2 Methods and Datasets

The Atmospheric Laser Doppler Instrument (ALADIN) was the sole instrument onboard the Aeolus satellite, delivering vertical profiles of one wind vector component along the instrument's line-of-sight (LOS) direction from the ground up to about 30 km in the stratosphere. The payload comprised a pulsed, frequency-stabilised ultraviolet (UV) laser transmitter, transmit-receive



optics, a Cassegrain telescope, and a dual-channel receiver designed to measure atmospheric backscatter from both molecular (Rayleigh) and particulate (Mie) backscatter (European Space Agency (ESA), 2008; Reitebuch, 2012). Detailed analyses of the performance of the laser (The Pierre Auger Collaboration et al., 2024; Lux et al., 2020, 2024a), the Rayleigh and Mie spectrometer channels (Witschas et al., 2022; Vaughan et al., 2025), and the detector characteristics (Weiler et al., 2021a; Lux et al., 2024b, 2025) have been presented in recent studies.

2.1 Aeolus Mie wind data

The Mie channel retrieved Doppler shifts from narrowband backscatter originating from clouds and aerosols (Vaughan et al., 2025). To this end, the instrument employed a Fizeau interferometer based on the fringe-imaging technique (McKay, 2002), in which the Doppler-induced spectral shift was inferred from the spatial displacement of an interference pattern (fringe) imaged onto the detector.

In the Level-1B (L1B) processing, the measured fringe signals are processed to characterise the Mie spectrum. For each measurement, the fringe signal is fitted with a Lorentzian or Voigt line shape (Baseline 16 and Baseline 17, respectively) using a Downhill-Simplex nonlinear optimisation method. This fit provides the spectral centroid together with additional parameters, including the peak width (for the Lorentzian fit), peak amplitude, and Rayleigh background offset. These parameters are used for the determination of quantities such as the scattering ratio and SNR, as well as for the generation of QC flags.

A measurement refers to an on-chip accumulation of backscattered signals over a defined number of laser pulses. During most of the mission, the nominal accumulation length corresponded to approximately 2.8 km. To improve signal quality and reduce the relative contribution of readout noise, the accumulation configuration was changed in December 2021 and April 2022, increasing the effective measurement length first to approximately 5.7 km and subsequently to approximately 17.2 km (Lux et al., 2024b). Multiple measurements are then combined to form an observation spanning approximately 86 km along track, corresponding to the 12 s repeat cycle of the instrument's data acquisition represented in the L1B product.

The L2B processor uses the Mie signal levels provided in the L1B product as input to the wind retrieval. It performs its own Lorentzian fit to these signal levels to determine the Mie spectral centroid and thereby derive the Doppler shift and horizontal line-of-sight (HLOS) wind speed. The retrieval subsequently applies a comprehensive set of bias corrections and error-characterisation procedures. In particular, Mie and Rayleigh winds are corrected for orbitally induced variations in the spectrometer incidence angle associated with thermal deformations of the primary telescope mirror (Weiler et al., 2021b; Rennie et al., 2021). L1B-derived parameters are also used for scene classification, which separates clear and cloudy conditions and thereby enables the generation of Rayleigh-clear and Mie-cloudy wind products. These wind estimates are finally formed through a configurable grouping procedure that balances horizontal resolution against measurement noise. A detailed description of the L2B processing chain is provided in Rennie et al. (2020), with a concise overview given in Lux et al. (2026).

The resulting L2B wind products are distributed as one-dimensional arrays containing geolocation, error estimates, and quality flags. This representation differs from the two-dimensional L1B structure defined by measurement number and range bin. The horizontal extent of each L2B wind result depends on the number of grouped L1B measurements and typically ranges between 10 and 20 km in Baseline 16 for Mie-cloudy winds.



2.2 Level-2B validity flag

160 In the L2B product, each wind result is assigned an overall validity flag with a binary value of “0” (invalid) or “1” (valid). The overall validity is determined by a large number of QC flags, each comprising 8 bits that indicate the outcome of individual checks for potential causes of degraded wind-data quality. Among these, several checks are designed to identify and exclude wind results derived from measurements potentially contaminated by ground echoes. These checks compare the measurement altitudes with a Digital Elevation Model (DEM). In this study, the ACE2 (Altimeter Corrected Elevations, version 2) information provided in the L1B product was combined with auxiliary meteorological data from ECMWF and used as a proxy for orography. For the Mie channel, numerous QC checks relate to the fitting procedure used to derive the Doppler shift, and hence the wind speed, from the fringe centroid position. For example, the full width at half maximum (FWHM) of the fitted fringe peak is required to lie within the range of 1.0 to 2.2 detector pixels. If this condition is not met, the corresponding bits of the QC flag indicating a violation of the lower or upper FWHM limit are set to “True”, and the overall validity flag is set to “0”.

165 For Mie-cloudy wind results, the vast majority (approximately 90%) are flagged as invalid. Of these, typically more than 95% fail one or more of the fringe-fitting quality criteria, with the fit residual error, peak FWHM, peak height, or peak position falling outside their predefined ranges. The remaining approximately 5% of invalid results are either affected by ground-echo contamination or rejected by a climatological screening criterion, which excludes unrealistically high wind speeds exceeding 130 m s^{-1} .

170 It should be noted that not all QC checks contribute to the determination of the overall validity flag. For example, a check indicating insufficient Mie-signal SNR is set to “True” for the majority of Mie-cloudy wind results, but does not directly affect the overall validity. Nevertheless, this condition may occur in combination with other QC flags that do affect the overall validity, such as those associated with the fringe-fitting parameters described above.

For some orbits, an additional flag is activated when a large mean wind bias ($> 5 \text{ m s}^{-1}$) relative to the ECMWF model background is detected for an individual orbit and vertical range bin. The most likely trigger for this flag is the presence of a hot pixel on the detector whose dark-current offset is not properly corrected. This typically occurs when the dark current rate of a hot pixel changes sporadically. In such cases, the applied Dark Current in Memory Zone (DCMZ) correction is no longer suitable for the affected pixel and is only updated after a new DCMZ calibration has been performed. The frequency of such calibrations was increased from one to eight per day over the course of the mission, as the growing number of hot pixels increasingly affected the wind data quality (Weiler et al., 2021a; Lux et al., 2025).

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In addition to the L2B QC flags acting on individual wind results, several validity screenings based on the Level-1B input are performed on measurement scale. One important check concerns moon blinding of the star tracker used for satellite attitude control. In the case of moon blinding, i.e., when the Moon approaches the star tracker’s field of view and overwhelms the sensor with reflected sunlight, the star tracker is temporarily replaced by gyroscopes for attitude propagation. This may lead to lidar LOS mispointing and, consequently, to large wind biases of several metres per second.

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Therefore, a moon-blinding flag on measurement scale is provided in the L1B product and used in the L2B processor QC to flag all Rayleigh and Mie winds within the moon-blinding period as invalid. This results in a loss of wind data in the tropics



(between 30° N and 30° S) over several consecutive days each month. However, not all moon-blinding events are associated with large wind biases. Therefore, for Baseline 17, it is foreseen to include an additional check based on the mean ($O - B$) wind speed difference relative to the ECMWF model background in order to discard only those winds that are actually affected by large biases during moon-blinding events.

2.3 Median-filter algorithm

The median-filter application is demonstrated using six representative orbits spanning the nearly five-year Aeolus mission, as summarised in Table 1. The selected orbits correspond to days analysed with respect to data coverage and error characteristics in Lux et al. (2026). They were chosen to represent different phases of the mission, including changes in the active laser transmitter, atmospheric backscatter conditions, and signal accumulation settings.

Table 1 lists the Normalised Atmospheric Signal (NAS), measured by the Rayleigh channel under clear-sky conditions ($SR < 1.3$) at an altitude of approximately 10 km. The NAS is normalised relative to late July 2019, when the atmospheric backscatter signal reached its highest level during the mission. The table also provides the number of valid Mie-cloudy wind observations, the corresponding random error, and the fraction of gross errors. The random error is defined as the scaled median absolute deviation (MAD) of the observation-minus-background ($O - B$) differences, where the background is provided by short-range (up to 12 h) ECMWF forecasts (Rennie and Isaksen, 2024). Gross errors are identified as observations for which the ($O - B$) wind speed difference exceeds a modified Z-score threshold of 3.5.

The modified Z-score Z_m is a robust outlier metric particularly suited to non-Gaussian and small-sample datasets, and has been previously applied to Aeolus wind validation (Lux et al., 2022). It measures the deviation of each observation from the median, normalised by the scaled MAD, which provides a more outlier-resistant dispersion estimate than the standard deviation. Following Iglewicz and Hoaglin (1993), values with $|Z_m| > 3.5$ are classified as gross errors.

Table 1. Aeolus orbits used in this study, including the Normalised Atmospheric Signal (NAS) relative to 26 July 2019, the number of valid Mie-cloudy wind results, the Mie-cloudy wind random error based on ($O - B$) statistics, the percentage of gross errors in terms of the modified Z-score.

Dataset	Day	Orbit number	NAS	Number of valid Mie-cloudy wind results	Mie-cloudy wind random error	Percentage of gross errors
1	08/04/2019	03618	0.61	7488	3.5 m s ⁻¹	1.5%
2	20/07/2019	05254	1.00	7997	3.7 m s ⁻¹	2.0%
3	21/08/2020	11574	0.61	7072	3.7 m s ⁻¹	2.1%
4	18/12/2021	19249	0.43	6233	3.8 m s ⁻¹	2.1%
5	15/09/2022	23546	0.33	4902	3.8 m s ⁻¹	2.5%
6	25/04/2023	27064	0.72	5328	3.7 m s ⁻¹	2.4%



The validity checks, particularly the QC thresholds related to the Mie fringe fit parameters, were carefully optimized during the development of the L2B processor to achieve a balance between high data yield and low error in the Mie-cloudy wind results. The wind results with validity flag “1” for orbit 27064 on 25 April 2023 are shown in Fig. 1(a). The data gap between 15:18 and 15:23 UTC was caused by a DCMZ calibration performed to measure the dark current rates on all pixels of the detector memory zone, which are then corrected for in the following orbits.

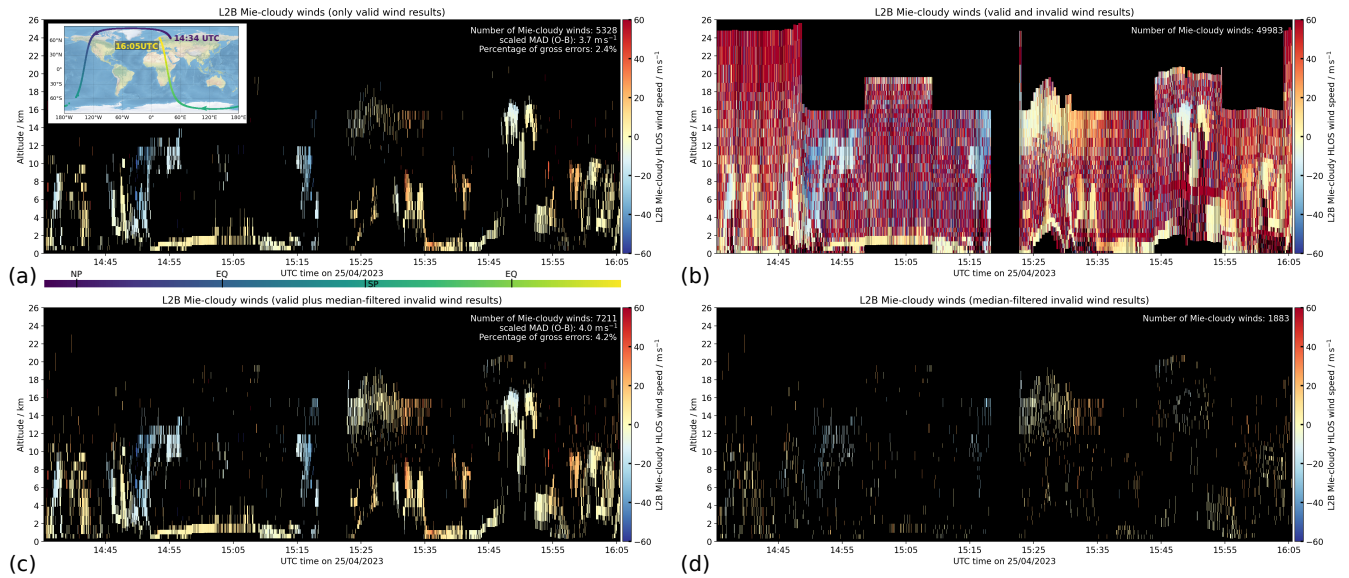


Figure 1. Mie-cloudy wind results from orbit 27064 on 25 April 2023 between 14:34 and 16:05 UTC: (a) Mie-cloudy wind results flagged as valid in the L2B product; (b) all Mie-cloudy wind results, regardless of validity flag; (c) Mie-cloudy wind results after application of the median-filter algorithm, i.e., valid winds together with median-filtered invalid winds using the parameters $N = 15$, $v_{thr} = 4 \text{ m s}^{-1}$, $w_{thr} = 30 \text{ m s}^{-1}$; and (d) the winds added by the median-filter algorithm. The inset in panel (a) shows the measurement track along the orbit, with the colour scale indicating the timeline plotted below the x-axis of panel (a) (NP: North Pole; EQ: equator; SP: South Pole).

Out of a total of 49,983 Mie-cloudy wind results, only 5328 ($\approx 11\%$) are flagged as valid, while the remaining results are flagged as invalid. However, when looking at all L2B bins irrespective of validity flag (Fig. 1(b)), a substantial number of wind results that are absent in panel (a), i.e., flagged as invalid, appear to exhibit reasonable wind speeds. This is particularly evident for the profiles measured during the first ten minutes after the data gap in the altitude range between 12 and 18 km, which are likely attributed to stratospheric aerosols and possibly PSCs over Antarctica (Jandreau et al., 2026).

Attempts to adjust the QC thresholds in order to retain these winds in the dataset were unsuccessful, as they also led to the inclusion of numerous wind results with large errors. Therefore, an alternative method was developed to identify bins containing useful wind data despite being flagged as invalid for the reasons discussed in the previous section. The approach compares the wind speed of each bin with those of the surrounding bins. If the wind speed of an individual bin is close to the



median wind speed of its neighbouring bins, it is considered plausible and flagged as useful. Conversely, if the wind speed deviates from the median by more than a predefined threshold, it is discarded.

The outcome of the developed median-filter algorithm for orbit 27064 is shown in Fig. 1(c), which contains 7211 Mie-cloudy
230 wind results, i.e., 1883 ($\approx 35\%$) more than obtained using the validity flag alone. The exact procedure used to identify these additional wind results, which are shown in panel (d), is explained in the following sections using orbit 27064 as an example.

2.4 Identification of nearest neighbours using a k-d tree

An important component of the median-filter algorithm is the identification of the nearest neighbours for each wind result. This task is not straightforward because the individual parameters in the L2B product are provided as one-dimensional arrays
235 containing, e.g., timestamps, geolocations, altitudes, and HLOS wind speed. This differs from the wind data in the L1B product, where the data are organised as bins on a two-dimensional grid spanned by measurement number and range bin. Within the L2B processor, these bins are combined by a grouping algorithm to generate the L2B wind results (Rennie et al., 2020).

Each wind result has a horizontal extent that varies according to the L2B processor settings, thereby providing flexibility in the definition of the horizontal resolution by balancing spatial detail and SNR. Consequently, identifying nearest neighbours
240 in the L2B wind data cannot simply be achieved by searching for wind results with adjacent latitudes in the horizontal domain or adjacent altitudes in the vertical domain. This is particularly true for neighbouring wind results originating from different observations, since the altitudes of all range bins within a profile are shifted according to a look-up table of the onboard DEM. As a result, the vertical bin centres of the wind results vary with the DEM from one observation to the next. This effect is also visible in the wind curtains shown in Fig. 1.

245 Determining the nearest neighbours of every L2B bin by explicitly calculating the distances between all individual bin centres is computationally too expensive, given that a single orbit typically contains approximately 50,000 Mie-cloudy wind results. Instead, a k -dimensional tree (k -d tree) provides an efficient solution for this task. The principle is described in Bentley (1975) and involves recursively partitioning a dataset along one of the k coordinate dimensions. At each level, the median point in the selected dimension is chosen as the splitting point, dividing the dataset into two subsets. This process is repeated
250 recursively for each subset until the tree is fully constructed. For the L2B Mie-cloudy wind data, the partitioning is performed in $k = 2$ dimensions using the along-track distance in the horizontal dimension (x) and the altitude in the vertical dimension (y), as illustrated in Fig. 2(a).

For simplicity, only a small subset of wind bins was selected to visualise the construction of the corresponding k -d tree shown in Fig. 2(b). Starting from wind result A with coordinates (x_A, y_A) , the dataset is first split along the x -direction, yielding points
255 B and C as the medians of the two subsets. These two points form the next level of the tree, from which a subsequent split in the vertical direction produces the sub-branches leading to points D, E, and F. These alternating splits continue recursively until every data point is represented within the k -d tree. Based on this structure, the nearest neighbours of a given wind result can be identified efficiently without explicitly calculating distances to all other data points.

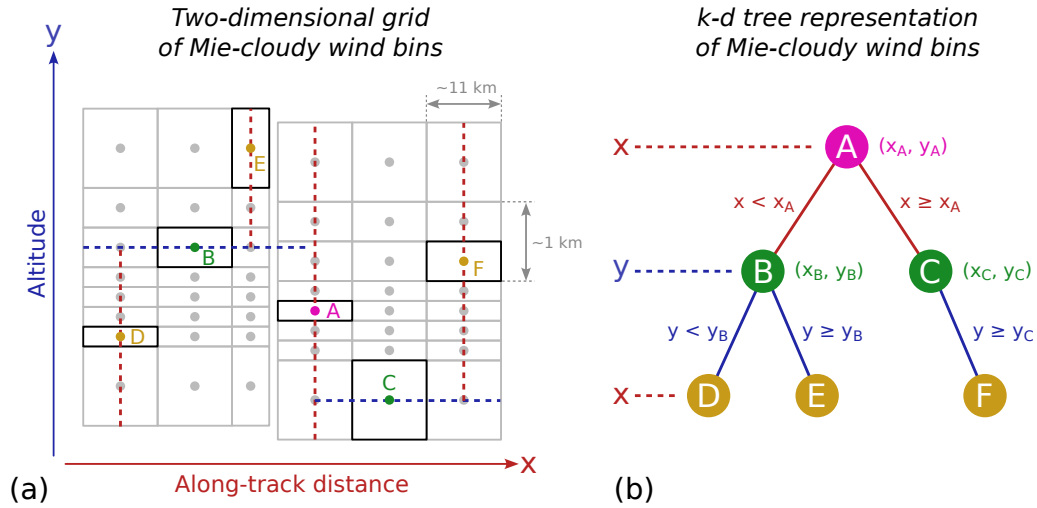


Figure 2. (a) Schematic of the Level-2B Mie-cloudy wind results represented on a two-dimensional grid spanned by along-track distance x and altitude y . Each wind bin is defined by the coordinates (x_i, y_i) . Note that this grid does not reflect how the data are organized in the L2B product. Instead, each parameter is provided as a one-dimensional array. (b) Corresponding k-d tree representation of the Mie-cloudy wind bins, constructed by recursively partitioning the dataset with alternating splits along the x - and y -dimensions. At each tree level, the median point in the selected dimension is used to divide the remaining bins into left/right or lower/upper subspaces.

For the actual implementation of the median-filter algorithm, the varying horizontal and vertical extents of the wind bins must also be considered. During most of the mission, the horizontal length of the Mie-cloudy wind bins ranged between 10 and 20 km, depending on the L2B processor settings. While the bin length was close to 10 km during the first phase of the mission, the grouping of L1B measurements into L2B wind results was modified in December 2021 together with changes to the detector accumulation settings, resulting in horizontal bin lengths of approximately 17 km. For Baseline 17, a consistent horizontal bin length of 17 km for the whole mission is planned. The vertical bin extent varied with altitude and was typically set to 250 m or 500 m in the troposphere and to 1000 m in the stratosphere.

To account for the differing horizontal and vertical bin dimensions when constructing the k-d tree, the along-track distance was divided by a factor of 25. This reduces the along-track distance between neighbouring bins to 0.4–0.8 km, making it comparable to the typical vertical bin spacing of 0.5 km or 1.0 km. Such balancing is important when comparing the wind speed of a bin with those of the surrounding bins, since strong vertical wind shear would otherwise lead to large wind speed differences from the median and, consequently, to the rejection of a bin even when its wind speed is physically plausible. Optimization of the used scaling factor is discussed in Sect. 3.

The implementation of the median-filter QC in the Aeolus L2B processor is currently being tested. To this end, instead of using a k-d tree, nearest neighbours were identified based on auxiliary parameters used in the L2B grouping algorithm (de Kloe et al., 2023). The results of this implementation will be part of the final reprocessing for Baseline 17, which is planned for publication by the end of 2027.

2.5 Median-filter algorithm

The median-filter algorithm is illustrated in the flowchart shown in Fig. 3. The algorithm is applied to the L2B Mie-cloudy wind product using all wind results, irrespective of validity status, as input. Its underlying principle is to combine the mask of valid wind results (overall validity flag = 1; path 1 in the figure) with a mask of median-filtered invalid wind results. The latter is constructed from the three conditions indicated by the green diamonds in paths 2–4, which are described in detail below.

The purple ellipses in Fig. 3 denote input parameters from the L2B product, whereas the yellow ellipses represent the three configurable filter parameters: N , the number of nearest neighbours; v_{thr} , the median-filter deviation threshold; and w_{thr} , the absolute wind speed threshold.

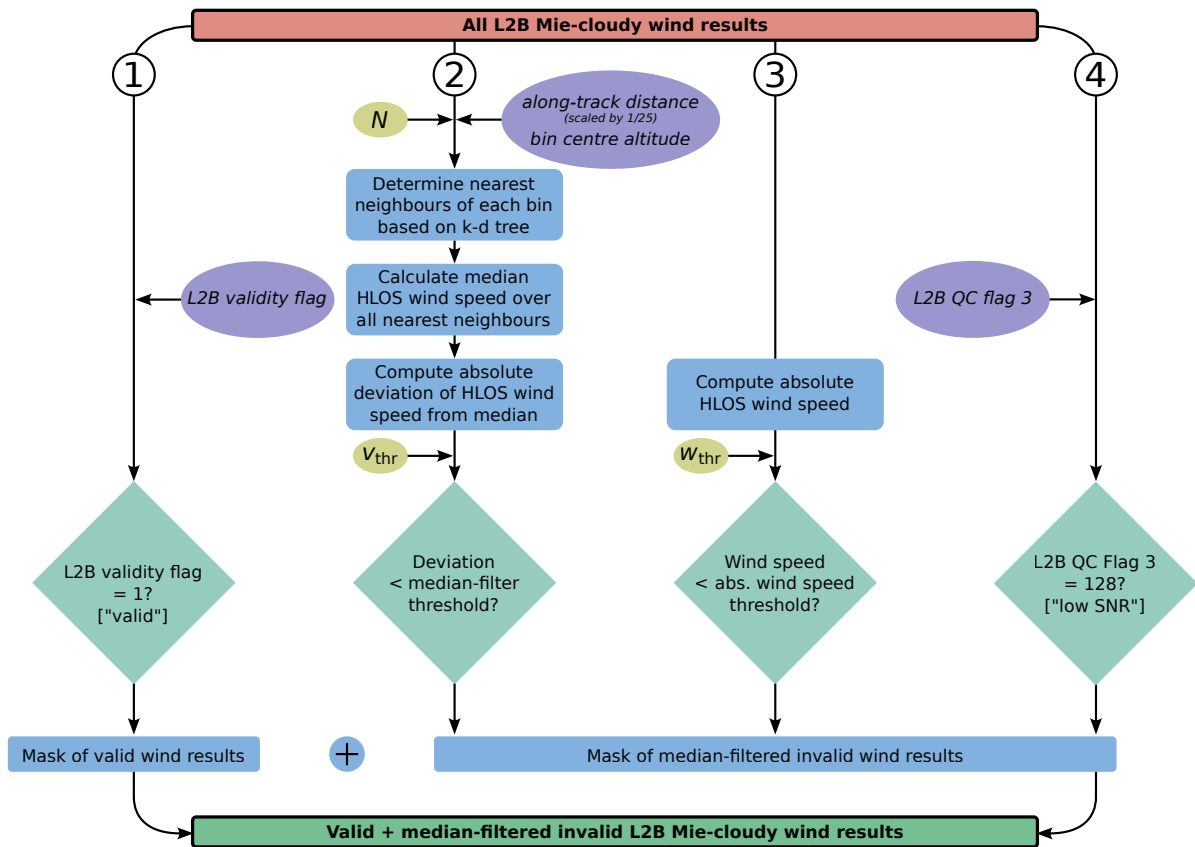


Figure 3. Flowchart of the median-filter-based quality control algorithm applied to Aeolus L2B Mie-cloudy wind results. For each wind result, the N nearest neighbours are identified in along-track and altitude space using a k-d tree, and a local median wind speed is computed. Wind results are flagged as outliers if their deviation from the local median exceeds a threshold v_{thr} or if their absolute wind speed exceeds w_{thr} . From the remaining subset, only winds previously flagged as invalid by the L2B processor due to low SNR are retained and combined with valid wind results to form the final dataset of valid and median-filtered Mie-cloudy winds.



In the first step of path 2, the N nearest neighbours of each wind result are identified using a k-d tree based on along-track distance and bin centre altitude, as explained in Sect. 2.4. The along-track distance is not directly available in the L2B product and is therefore calculated as the cumulative geodetic distance between consecutive ground-track coordinates (latitude and longitude) provided in the L2B product. After identification of the neighbouring bins, the median HLOS wind speed is computed over all N neighbours, and the absolute deviation from the HLOS wind speed of the considered bin is determined. Finally, it is checked whether this deviation is smaller than the median-filter threshold v_{thr} .

This condition alone is insufficient to ensure that only physically plausible winds are recovered from bins flagged as invalid. In particular, groups of neighbouring bins with similarly unrealistic wind speeds would still satisfy the median-filter criterion. This occurs especially when the L2B fit routine fails to converge, in which case a placeholder HLOS wind speed of 327.67 m s^{-1} is assigned as a missing-value indicator. In orbit 27064, for example, this behaviour is observed at the beginning of the orbit above approximately 18 km, where the SNR is too low for successful convergence of the fit routine. Additionally, there are cases where neighbouring bins exhibit a broad range of positive and negative wind speeds with absolute values exceeding 50 m s^{-1} , resulting in a median wind speed with a realistic magnitude that, by chance, does not deviate substantially from that of the bin under consideration, even though the wind speed in this bin does not represent the actual wind field. To prevent such bins from being retained, the additional threshold parameter w_{thr} is introduced (path 3). Only bins with absolute HLOS wind speeds below this threshold are eligible for inclusion in the mask of median-filtered invalid winds.

The final condition is linked to one of the L2B QC flags (path 4). As discussed in Sect. 2.2, bins may be classified as invalid for several reasons. To avoid recovering bins contaminated by ground echoes, only bins for which the “too low SNR” check is set to “True” are considered for inclusion in the mask. This condition corresponds to QC flag 3 with a binary value of 10000000 ($= 128$). Although this particular check does not directly influence the overall validity flag, the low-SNR condition applies to the vast majority of invalid bins ($> 90\%$), including nearly all bins flagged as invalid for reasons unrelated to ground contamination, most notably those with fringe-fitting parameters outside their valid ranges. Consequently, this criterion provides a sufficiently effective means of excluding ground-contaminated bins while still allowing other potentially useful invalid bins to be recovered.

Invalid bins satisfying all three conditions in paths 2–4 are combined into a mask that is added to the mask of valid bins, resulting in the final set of valid and median-filtered L2B Mie-cloudy wind results. The individual steps of the algorithm are illustrated using orbit 27064 as an example. Figure 4(a) shows a zoomed-in section of the wind curtain depicted in Fig. 1(b), spanning three observations with five wind results per range bin (17 km horizontal length each) over an altitude range of 8 km. While the plot displays all Mie-cloudy wind results, both valid and invalid, the valid bins are indicated by black frames. One bin, marked by a pink dot, represents a selected wind result for which the N nearest neighbours are determined using the k-d tree. The identified nearest neighbours are indicated by green dots. For the present example, a value of $N = 15$ was chosen to include surrounding wind results over a range of approximately $\pm 1 \text{ km}$ vertically and $\pm 17 \text{ km}$ horizontally. Several of these bins, including the selected bin itself, are flagged as invalid although their wind speeds are similar to those of the valid bins.

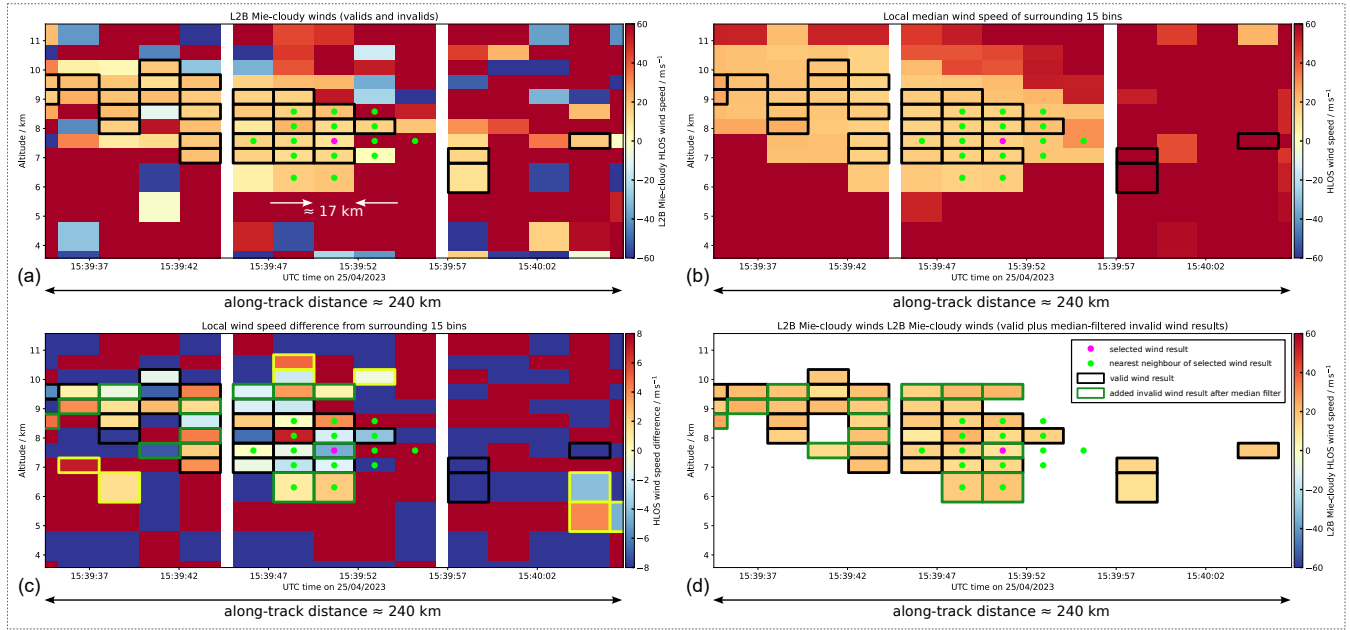


Figure 4. Application of the median filter to Mie-cloudy wind results. For each bin (example bin indicated by pink dot), the $N = 15$ nearest neighbours (green dots) are identified from all wind results using a k-d tree (panel (a)), and their median HLOS wind speed is computed (panel (b)). Bins whose HLOS wind speed differs from the median by more than $v_{thr} = 8 \text{ m s}^{-1}$ are rejected (panel (c)). The remaining bins (green frames) are combined with the bins flagged as valid in the L2B product (black frames) to obtain the wind field in panel (d). Bins satisfying the median-filter criterion but exceeding $w_{thr} = 30 \text{ m s}^{-1}$ are not recovered (yellow frames).

In the next step, the median HLOS wind speed of the nearest neighbours is calculated. The resulting median wind speed field is shown in Fig. 4(b). The difference between the HLOS wind speed in panel (a) and the median wind speed in panel (b) yields the plot shown in Fig. 4(c). The colour scale ranges from -8 to $+8 \text{ m s}^{-1}$, corresponding to the chosen median-filter deviation threshold v_{thr} , which determines whether an invalid bin is added to the valid ones. Consequently, only bins that are neither dark blue (wind speed difference $< -8 \text{ m s}^{-1}$) nor dark red (wind speed difference $> +8 \text{ m s}^{-1}$) are added, according to path 2 in Fig. 3. Another condition (path 3) requires that the absolute HLOS wind speed of the bin remains below the threshold w_{thr} , which is set to 30 m s^{-1} in the present example. This condition prevents the isolated bins at the beginning and at the end of the zoomed-in section around 6 km (yellow frames in panel (c)) from being recovered, although their wind speeds differ by no more than 8 m s^{-1} from the median of their respective neighbours, whose wind speeds range from -72 m s^{-1} to more than 100 m s^{-1} . This example demonstrates that the median filter performs well only in contiguous regions with a narrow range of wind speeds extending over several tens of kilometres horizontally and a few kilometres vertically. Such regions predominantly exhibit absolute HLOS wind speeds below 30 m s^{-1} , while higher wind speeds are relatively rare (typically 10–15% of all valid wind observations), making them more difficult to recover. Hence, w_{thr} is set to a relatively low value to prevent gross errors, at the expense of preventing the recovery of strong winds.



It should be emphasized that the absolute wind speed threshold w_{thr} applies only to the additionally recovered invalid bins and not to the valid ones. All valid winds are retained in the final output of the median-filter algorithm. This particularly ensures that isolated wind results, such as those at the end of the zoomed-in section, remain included in the final output although they would not pass the median filter because they are surrounded by outliers. The bins fulfilling the three conditions (paths 2–4) are indicated by green frames. The final masked wind curtain, including all valid bins and the median-filtered invalid bins, is presented in Fig. 4(d), demonstrating how the developed algorithm closes many gaps of the measured wind field.

2.6 Recovery of Hunga Tonga stratospheric aerosols

Before justifying the selected median-filter parameters used in the previous example, another orbit is presented that demonstrates the capability of the developed algorithm to increase Mie-cloudy wind data coverage, particularly in atmospheric regions of high relevance for both NWP and scientific studies.

The 2022 Hunga Tonga–Hunga Ha’apai eruption was one of the most powerful volcanic events ever observed in the satellite era. It occurred on 15 January 2022 at an underwater volcano in the South Pacific near Tonga. The explosion generated massive shock waves, tsunamis across the Pacific, intense volcanic lightning, and a plume that rose into the mesosphere to an altitude of approximately 58 km. What made this eruption exceptional was that it injected an unprecedented amount of water vapour directly into the stratosphere (Khaykin et al., 2022; Chen et al., 2025). This led to a rapid conversion of SO_2 into sulfate aerosols and induced a descent of the plume to altitudes of 24–26 km, where volcanic sulfates and water vapour persisted until late 2022, mainly confined between 35°S and 20°N (Legras et al., 2022).

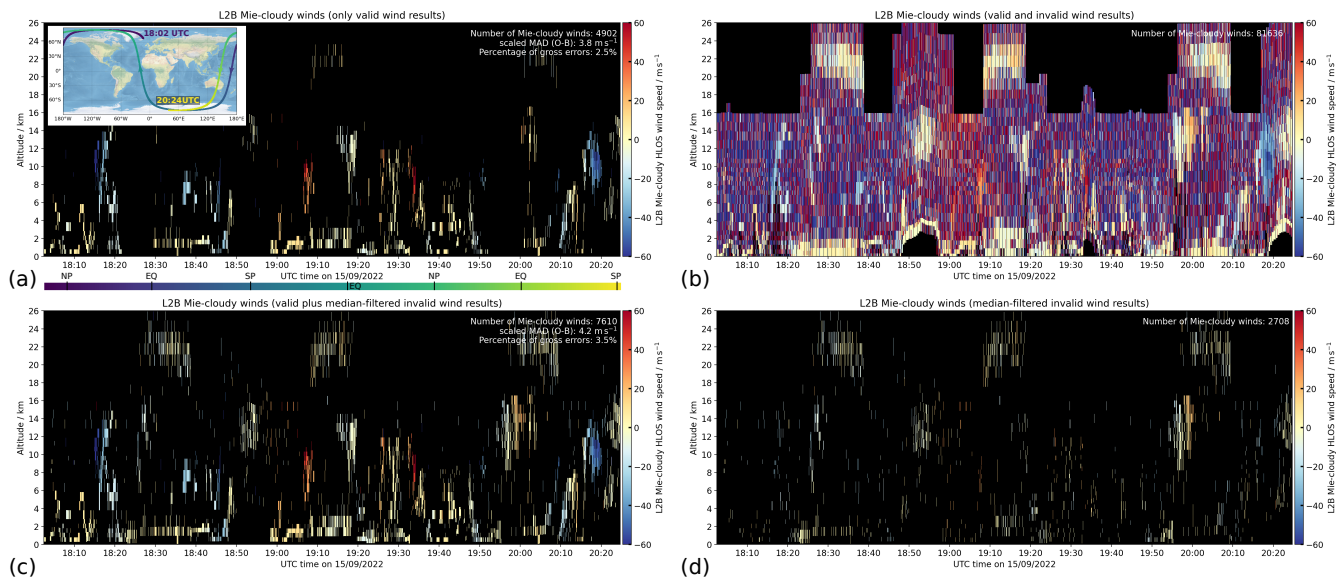


Figure 5. Same as Fig. 1, but for orbit 23546 on 15 September 2022 between 18:02 UTC and 20:24 UTC.



The enhanced stratospheric aerosol load led to a noticeable increase in Mie-cloudy winds in 2022 (Rennie and Isaksen, 2024), especially after the Aeolus range bin settings were adapted in late January to capture the plume in the tropical stratosphere. Within this region, the plume gradually descended from approximately 23 km to below 20 km altitude during summer 2022 (Legras et al., 2022; Duchamp et al., 2023; Trapon et al., 2026). By autumn 2022, however, the aerosol backscatter of the plume had become tenuous (scattering ratios < 1.2), and the Mie-cloudy winds retrieved from the stratospheric aerosols became increasingly noisy. Consequently, a growing fraction of these winds was rejected by the QC, leading to low data counts.

This situation highlights the potential of the median-filter algorithm to recover Mie-cloudy winds that were rejected because of low SNR but are nevertheless of sufficient quality to be useful for scientific analyses. In analogy to Fig. 1, the valid Mie-cloudy winds from orbit 23546 on 15 September 2022 are shown in Fig. 5(a). Of the total 4902 valid Mie winds, only a small fraction (2.6%) is obtained at altitudes above 18 km, where the Hunga Tonga aerosols resided. Figure 5(b), showing all Mie-cloudy winds (valid and invalid), however, reveals a much larger coverage of winds with plausible wind speeds at these altitudes. Consequently, when applying the median-filter algorithm to this orbit using the filter parameters $N = 15$, $v_{thr} = 4 \text{ m s}^{-1}$, and $w_{thr} = 30 \text{ m s}^{-1}$, the number of winds above 18 km increases from 128 to 736. This corresponds to 9.7% of all Mie-cloudy winds after application of the algorithm (Fig. 5(c)). The overall gain in Mie winds is 55%, while the increase in random error is moderate, from 3.8 to 4.2 m s^{-1} . However, it should be noted that the overall gain is particularly large because a significant number of invalid winds were recovered during the periods 18:21:41–18:29:39 UTC and 19:51:05–20:00:17 UTC, during which the moon-blinding QC flag was active (Sect. 2.2). For Baseline 17, a bias check will be implemented to determine whether the wind results from these periods should be flagged as invalid.

The example underscores the effectiveness of the algorithm to retrieve Mie wind data in low-SNR regions that would otherwise be lost. The retrieval of winds in the stratosphere and tropics is especially important because these are the regions where Aeolus observations showed the largest impact on NWP (Rennie et al., 2021; Rennie and Isaksen, 2024). Moreover, winds retrieved from aerosols are also the subject of aerosol transport research and related studies (Sun et al., 2024; Amiridis et al., 2023; Wang et al., 2024).

3 Optimization of the median-filter parameters

The performance of the median-filter algorithm as a function of the filter parameters N , v_{thr} , and w_{thr} is evaluated using three metrics:

1. the gain in Mie-cloudy winds, defined as the relative increase in the number of retrieved wind results with respect to the number of originally valid wind results;
2. the change in the random error of Mie-cloudy winds, O , quantified by the scaled MAD of the $(O - B)$ wind speed difference relative to the ECMWF model background, B , without consideration of the model background error; and
3. the change in the percentage of gross errors, defined as the fraction of wind results for which the modified Z-score of the $(O - B)$ wind speed difference exceeds 3.5.



380 These quantities, which are also listed in the upper-right corner of the wind-curtain plots in panels (a) and (c) of Figs. 1 and 5, were evaluated for six representative orbits spanning the mission period. Two of these orbits, from 15 September 2022 and 25 April 2023, were already discussed in the previous sections. The corresponding performance metrics obtained when considering only valid Mie-cloudy winds are summarized in Table 1. To determine optimal filter settings, the parameters were varied over the following ranges: N from 4 to 40, v_{thr} from 2 to 12 m s^{-1} , and w_{thr} from 20 to 60 m s^{-1} .

385 3.1 Balancing data yield and error characteristics

The resulting performance metrics are shown in Figs. 6 and 7. The top, middle, and bottom rows correspond to the three metrics listed above, while the left, middle, and right columns show their dependence on the three filter parameters. In each panel, two parameters are held fixed while the third is varied.

Orbit 3618 from 8 April 2019 represents a notable outlier, exhibiting only very small changes in all three metrics across the
390 full ranges of the filter parameters. This behaviour is explained by the fact that the B16 dataset covering the period before 28 June 2019 contains very few invalid Mie-cloudy wind results. Instead, most bins that failed the QC tests were omitted entirely from the product, making their recovery by the median-filter algorithm impossible. Although the L2B processing chain used for the full-mission reprocessing is otherwise consistent, the handling of the validity flag differed during the period up to the end of June 2019, corresponding to the operational phase of the first laser transmitter flight model (FM-A) (Lux et al., 2024a).
395 Following the switch to the second laser (FM-B) on 28 June 2019, the sampled atmosphere is fully populated with valid and invalid Mie-cloudy wind results, enabling the recovery of invalid winds through application of the median filter. In Baseline B17, a consistent handling of the L2B validity flag will also make it possible to recover Mie-cloudy winds from the FM-A period in 2018/2019.

The results in Fig. 6 indicate that all three performance metrics depend only weakly on the number of nearest neighbours N .
400 The gain in Mie-cloudy winds increases slightly as N is raised from 2 to approximately 15, beyond which it remains nearly constant. Likewise, both the random error and the percentage of gross errors show only minor sensitivity to N .

A stronger dependence is observed for the absolute wind speed threshold w_{thr} , particularly for the percentage of gross errors, which increases from about 2–3% at $w_{\text{thr}} = 20 \text{ m s}^{-1}$ to approximately 5–8% at $w_{\text{thr}} = 60 \text{ m s}^{-1}$ depending on the values of the other filter parameters. This behaviour indicates that w_{thr} must remain sufficiently low to prevent the inclusion
405 of gross errors arising from neighbouring bins that either have similarly unrealistic wind speeds or exhibit a broad range of positive and negative wind speeds, such that the median by chance is close to the wind speed of the bin itself. Conversely, a threshold that is too low would exclude plausible invalid wind results with physically realistic but large wind speeds. A value of $w_{\text{thr}} = 30 \text{ m s}^{-1}$ therefore represents a suitable compromise, given that only 10–15% of all valid Aeolus wind observations have absolute HLOS wind speeds exceeding this value.

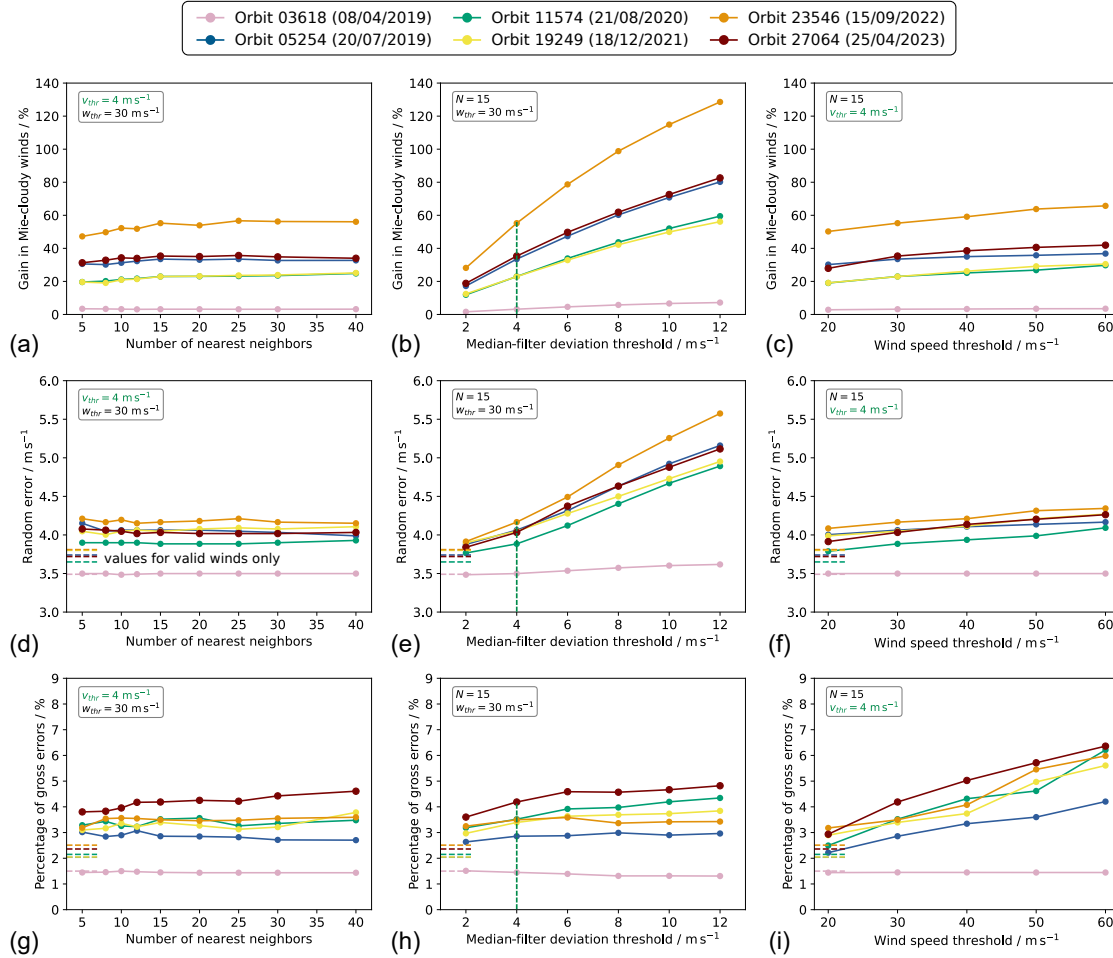


Figure 6. Gain in Mie-cloudy winds (panels (a)–(c)), random error ((d)–(f)), and percentage of gross errors ((g)–(i)) as a function of the QC parameters (number of nearest neighbours N , median-filter deviation threshold v_{thr} , and wind speed threshold w_{thr}) for six selected orbits throughout the mission. Two of the three QC parameters are fixed along the columns, as indicated in the inset box, while the third parameter is varied. The combination of QC parameters ($N = 15$, $v_{thr} = 4$ m s⁻¹, $w_{thr} = 30$ m s⁻¹) discussed in the text is highlighted by vertical dashed lines. The horizontal dashed lines in panels (d)–(i) indicate the random error and percentage of gross errors obtained when only valid winds are considered. Orbit 3618 stands out because of the low number of invalid wind results in the B16 dataset from the period before 28 June 2019 (see text).

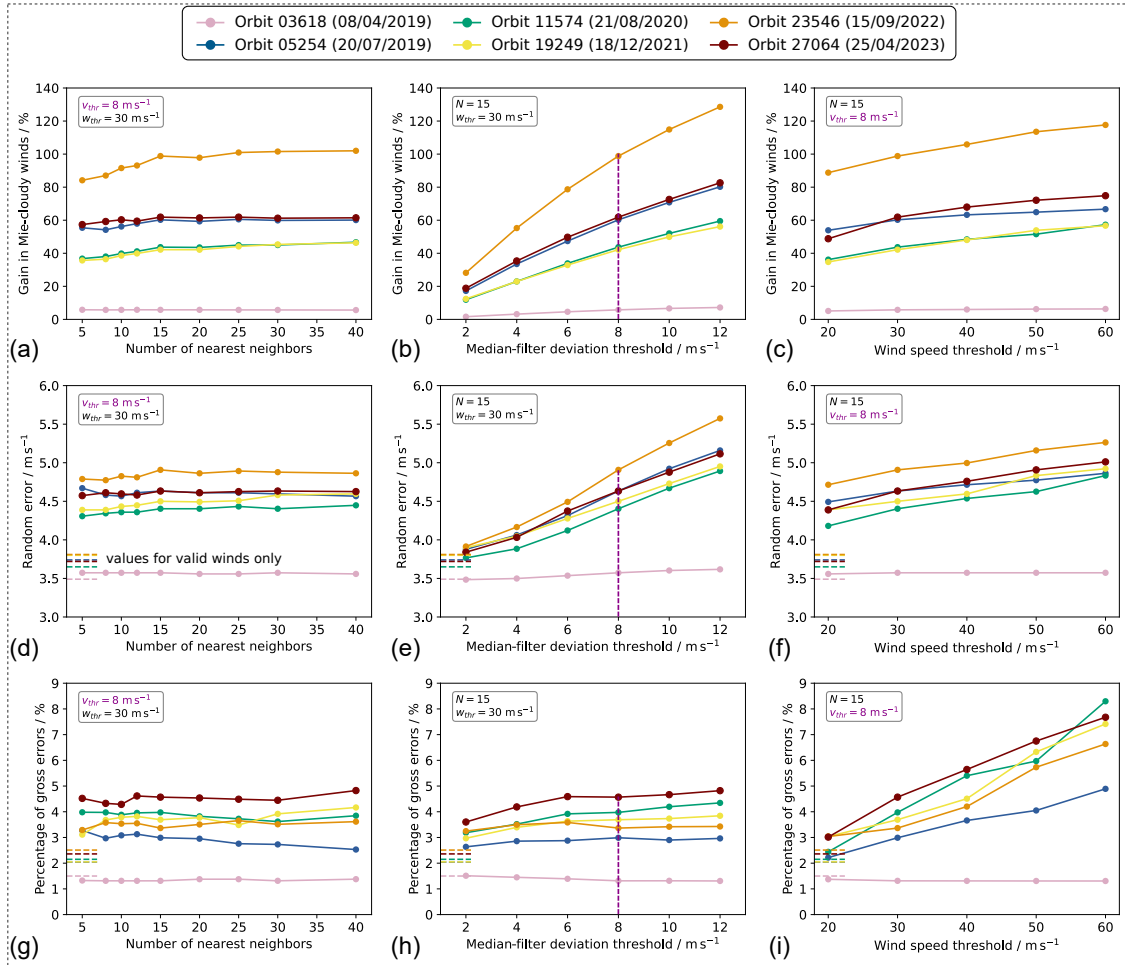


Figure 7. Same as Fig. 6, but for a median-filter deviation threshold of $v_{thr} = 8 \text{ m s}^{-1}$.

410 The strongest sensitivity of the performance metrics is found for the median-filter deviation threshold v_{thr} . The gain in
Mie-cloudy winds increases from less than 20% at $v_{thr} = 2 \text{ m s}^{-1}$ to approximately 40–60% at $v_{thr} = 12 \text{ m s}^{-1}$ (excluding
the exceptional 2022 case). Over the same range, however, the random error increases from about 3.8 m s^{-1} —close to the
value obtained for valid winds only—to nearly 5 m s^{-1} . In contrast, the percentage of gross errors increases only slightly and
remains between 3 and 5% across the full range of v_{thr} values. Selecting an appropriate deviation threshold therefore requires
415 balancing the gain in retrieved winds against the increase in random error.

To accommodate different application priorities, two parameter settings are proposed. A "low-error" configuration employs
 $v_{thr} = 4 \text{ m s}^{-1}$ to minimize the increase in random error, whereas a "high-gain" configuration uses $v_{thr} = 8 \text{ m s}^{-1}$ to maximize
the recovery of additional wind results. In the following sections, both configurations are investigated in parallel while keeping
the remaining filter parameters fixed at $N = 15$ and $w_{thr} = 30 \text{ m s}^{-1}$.



420 The performance metrics obtained for the two configurations are summarized in Table 2. The values given in parentheses indicate the change relative to the results obtained using only valid Mie-cloudy winds, as listed in Table 1. Excluding the exceptional orbits from April 2019 (very few invalid winds) and September 2022 (moon blinding periods and Hunga Tonga aerosols), the gain in Mie-cloudy winds ranges from 23% to 35% for the low-error configuration and from 42% to 62% for the high-gain configuration. These gains are accompanied by increases in random error of only 0.2–0.4 m s⁻¹ and 0.7–1.1 m s⁻¹,
 425 respectively. The increase in the percentage of gross errors is comparable for both configurations and remains limited to approximately 1–2%.

Table 2. Key output parameters after application of the median-filter algorithm when using QC parameters $N = 15$, $w_{\text{thr}} = 30 \text{ m s}^{-1}$ and two different deviation thresholds $v_{\text{thr}} = 4 \text{ m s}^{-1}$ and $v_{\text{thr}} = 8 \text{ m s}^{-1}$. The values in parentheses denote the change compared to valid Mie-cloudy wind results only, as listed in Table 1.

Dataset	Day	Orbit number	v_{thr}	Number of Mie-cloudy wind results	Mie-cloudy wind random error	Percentage of gross errors
1	08/04/2019	03618	4 m s ⁻¹	7726 (+3%)	3.5 m s ⁻¹ (+0 m s ⁻¹)	1.4% (-0.1%)
			8 m s ⁻¹	7920 (+6%)	3.6 m s ⁻¹ (+0.1 m s ⁻¹)	1.3% (-0.2%)
2	20/07/2019	05254	4 m s ⁻¹	10676 (+34%)	4.1 m s ⁻¹ (+0.4 m s ⁻¹)	2.9% (+0.9%)
			8 m s ⁻¹	12814 (+60%)	4.6 m s ⁻¹ (+0.9 m s ⁻¹)	3.0% (+1.0%)
3	21/08/2020	11574	4 m s ⁻¹	8696 (+23%)	3.9 m s ⁻¹ (+0.2 m s ⁻¹)	3.5% (+1.4%)
			8 m s ⁻¹	10163 (+44%)	4.4 m s ⁻¹ (+0.7 m s ⁻¹)	4.0% (+1.9%)
4	18/12/2021	19249	4 m s ⁻¹	7662 (+23%)	4.0 m s ⁻¹ (+0.2 m s ⁻¹)	3.4% (+1.3%)
			8 m s ⁻¹	8862 (+42%)	4.5 m s ⁻¹ (+0.7 m s ⁻¹)	3.7% (+1.6%)
5	15/09/2022	23546	4 m s ⁻¹	7610 (+55%)	4.2 m s ⁻¹ (+0.4 m s ⁻¹)	3.5% (+1.0%)
			8 m s ⁻¹	9746 (+99%)	4.9 m s ⁻¹ (+1.1 m s ⁻¹)	3.4% (+0.9%)
6	25/04/2023	27064	4 m s ⁻¹	7211 (+35%)	4.0 m s ⁻¹ (+0.3 m s ⁻¹)	4.2% (+1.8%)
			8 m s ⁻¹	8624 (+62%)	4.6 m s ⁻¹ (+0.9 m s ⁻¹)	4.6% (+2.2%)

It should be noted that, in addition to the three filter parameters N , v_{thr} , and w_{thr} , the scaling factor applied to the along-track distance in the construction of the k-d tree—and thus in the identification of the nearest neighbours for each bin (see Sect. 2.4)—can also be optimized. The choice of scaling factor determines whether the neighbouring bins are distributed
 430 predominantly horizontally or vertically around the selected bin. For a scaling factor of 25, the along-track distance between neighbouring bins is reduced from 10–20 km to 0.4–0.8 km, making it comparable to the typical vertical bin spacing of 0.5 km or 1.0 km. As a result, the 15 nearest neighbours identified by the k-d tree are distributed nearly uniformly around the selected bin and span a vertical range of approximately ± 1 km, as illustrated in Fig. 4.

For smaller scaling factors, the neighbouring bins become more vertically aligned, covering altitude ranges of several kilo-
 435 metres. In the presence of vertical wind gradients, this is problematic because the median wind speed derived from the neigh-



bouring bins no longer accurately represents the local wind field of the selected bin. Consequently, the potential increase in useful Mie-cloudy wind results is reduced, while the likelihood of introducing gross errors increases. Conversely, excessively large scaling factors lead to a predominantly horizontal distribution of neighbouring bins extending over several tens of kilometres, resulting in similar issues. A comparison of the resulting output parameters for different scaling factors identified an optimum value of 25.

3.2 Temporal variability of performance

The key performance metrics of the median-filter algorithm summarized in Table 2 demonstrate its capability to substantially increase the number of Mie-cloudy wind observations, albeit at the expense of a moderate increase in random error and in the fraction of gross errors for selected orbits across the mission. To assess the temporal variability of these metrics, the analysis was extended to two one-month periods: September 2022 (including orbit 23546) and April 2023 (including orbit 27064). The algorithm was applied using the two filter configurations introduced above: the low-error configuration with $N = 15$, $w_{\text{thr}} = 30 \text{ m s}^{-1}$, and $v_{\text{thr}} = 4 \text{ m s}^{-1}$; and the high-gain configuration with $N = 15$, $w_{\text{thr}} = 30 \text{ m s}^{-1}$, and $v_{\text{thr}} = 8 \text{ m s}^{-1}$.

The resulting time series of the number of Mie-cloudy winds, the random error, and the percentage of gross errors before and after inclusion of the median-filtered invalid winds are shown in Fig. 8. Results obtained with the low-error and high-gain configurations are indicated in green and purple, respectively.

A comparison of the two months reveals that the number of valid Mie-cloudy winds was already substantially higher in April 2023 (approximately 6000 winds per orbit) than in September 2022 (approximately 4000 winds per orbit). This increase is primarily attributed to the improved instrument performance following the switch from the redundant laser transmitter (flight model B) to the nominal transmitter (flight model A) in November 2022, which resulted in significantly enhanced atmospheric backscatter signal levels (Lux et al., 2024a, 2026). Despite this difference in the absolute number of winds, the relative increase achieved by the median-filter algorithm is remarkably consistent between both periods. For the low-error configuration, the gain in Mie-cloudy winds amounts to $(39 \pm 6)\%$ in September 2022 and $(40 \pm 7)\%$ in April 2023, whereas the high-gain configuration yields increases of $(71 \pm 11)\%$ and $(72 \pm 13)\%$, respectively. Here, the values in parentheses denote the temporal mean and standard deviation over the corresponding month.

The associated increase in random error is likewise relatively stable, amounting to $(0.33 \pm 0.17) \text{ m s}^{-1}$ in September 2022 and $(0.38 \pm 0.08) \text{ m s}^{-1}$ in April 2023 for the low-error configuration, and to $(0.9 \pm 0.2) \text{ m s}^{-1}$ and $(1.02 \pm 0.13) \text{ m s}^{-1}$ for the high-gain configuration. The percentage of gross errors exhibits a somewhat stronger increase in April 2023, with values of approximately $(1.6 \pm 0.5)\%$ for both configurations, compared to only $(1.0 \pm 0.6)\%$ in September 2022.

One notable feature in the September 2022 time series is the pronounced spike in both random error and percentage of gross errors on 28 September 2022. This degradation was caused by a hot pixel on the Mie-channel accumulation charge-coupled device (ACCD) detector (Lux et al., 2025). Among the 41 hot pixels identified on the detector, pixel [02,10] — where the indices denote the row and column within the 25×16 ACCD memory-zone array — proved particularly detrimental to the quality of the Mie-cloudy wind data for two main reasons. First, the pixel exhibited sporadic transitions between multiple dark-current levels, referred to as random telegraph signals (RTS), with comparatively large dark-current rates of several tens



470 of electrons per second. More importantly, because the pixel was located close to the maximum of the Mie fringe in one of the central ACCD columns (column 10 of 16), the enhanced dark current led to falsely detected Mie fringes in situations without particulate backscatter, i.e., in the absence of a real narrowband-signal image on the Mie detector.

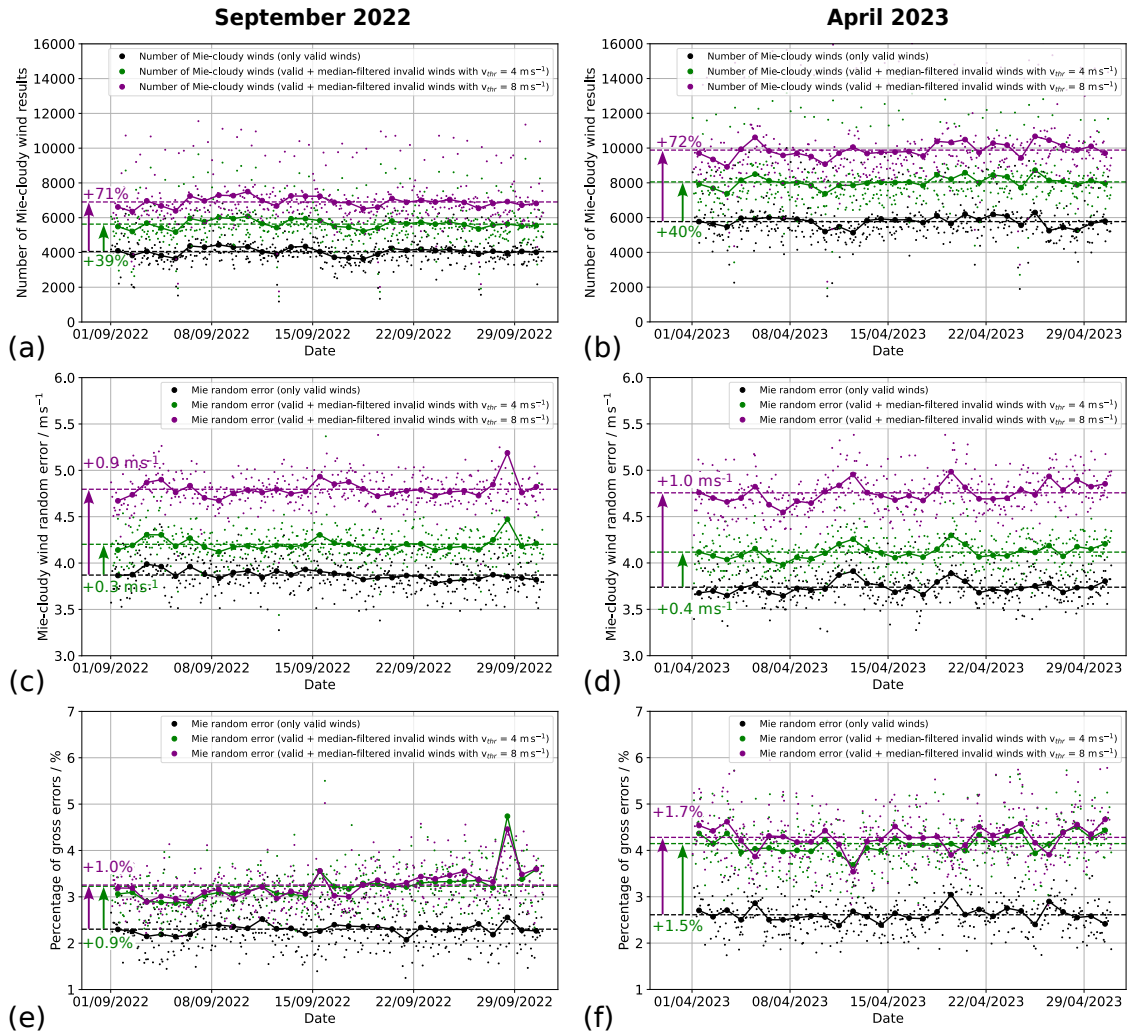


Figure 8. Timelines of the key output parameters for valid wind results only (black), and after adding median-filtered invalid wind results using filter parameters $N = 15$, $w_{thr} = 30 \text{ m s}^{-1}$, and $v_{thr} = 4 \text{ m s}^{-1}$ (green) or $v_{thr} = 8 \text{ m s}^{-1}$ (purple). The top panels ((a), (b)) present the number of Mie-cloudy winds, the middle panels ((c), (d)) the Mie-cloudy random error derived from (O–B) statistics relative to the ECMWF model background, and the bottom panels ((e), (f)) the percentage of gross errors based on the modified Z-score ($Z_m > 3.5$). Small dots represent data from individual orbits, while large dots denote daily averages. The left column (panels (a), (c), (e)) corresponds to September 2022, whereas the right column (panels (b), (d), (f)) corresponds to April 2023.



Consequently, during orbit 23753 (28/09/2022, 20:45 UTC), in which an RTS transition occurred for this pixel, the corresponding range bin 2 (the second uppermost range bin of the Mie wind profile) exhibited a large number of Mie wind retrievals with apparently reasonable wind speeds. Although these winds were flagged as invalid by the L2B processor because the fringe-fitting parameters were outside predefined ranges (see Sect. 2.2), the median-filter algorithm did not identify them as hot-pixel affected wind results, particularly because the associated wind speeds remained within the absolute wind speed threshold of $w_{\text{thr}} = 30 \text{ m s}^{-1}$.

As a result, a substantial number of these hot-pixel affected wind results passed through the median-filter algorithm, causing a considerable increase in both the random error derived from $(O - B)$ statistics and the percentage of gross errors. Following DCMZ calibration (Weiler et al., 2021a) at 23:18 UTC, the enhanced dark current of pixel [02,10] was properly corrected during subsequent orbits, leading to a reduction in both the random error and the fraction of gross errors to typical values. An investigation of several longer time series did not reveal frequent occurrences of such hot-pixel-induced degradation of the median-filter performance. For instance, despite the larger number of hot pixels in April 2023, no comparable spikes are visible in the time series shown in Fig. 8((d), (f)).

3.3 Enhancement of aerial data coverage

The inclusion of median-filtered wind results is not uniformly distributed across all altitudes. To better understand where additional Mie-cloudy winds are recovered within the vertical profiles, the altitude dependence of the Mie wind data coverage is investigated for the two one-month periods of September 2022 and April 2023. In this context, it is important to account for the variable horizontal and vertical bin sizes of the wind observations; in particular, the vertical extent of the bins generally increases with altitude. Consequently, data coverage is not evaluated by simply counting wind results within fixed altitude intervals, but rather by considering the fraction of the atmospheric area containing useful wind information relative to a reference area. This reference area, corresponding to full coverage, is defined as the total area spanned by all Mie-cloudy wind results—independent of their validity flag—from the surface up to the upper boundary of the highest range bin in the L2B wind product. Useful wind observations are defined as those L2B wind results flagged as valid and whose wind departure relative to the ECMWF background model does not exceed a modified Z-score of 3.5 (see Sect. 2.3).

The area coverage is evaluated for 1 km altitude intervals as the ratio of the area containing useful wind observations to the total area spanned within the respective altitude layer, following the methodology described in Lux et al. (2026). In addition, the wind observations are classified according to their HLOS wind speed departures from the ECMWF model background using the parameter

$$\varepsilon = \sqrt{(v_O - v_B)^2 - \sigma_B^2}, \quad (1)$$

where σ_B denotes the short-range forecast background error. A constant value of $\sigma_B = 2.5 \text{ m s}^{-1}$ is assumed as a simplified best-case estimate that neglects the scene dependence of forecast and representativeness errors. Wind observations with $\varepsilon < 2.5 \text{ m s}^{-1}$ are classified as high-quality, those with $2.5 < \varepsilon < 5.0 \text{ m s}^{-1}$ as medium-quality, and those with $\varepsilon > 5.0 \text{ m s}^{-1}$ as



low-quality, consistent with the Aeolus mission requirements (European Space Agency (ESA), 2016) and the WMO OSCAR criteria (WMO, 2025). The uncertainty range associated with assumed model background errors between 1.5 and 2.5 m s⁻¹, as well as the influence of representativeness errors, is discussed in Lux et al. (2026).

The altitude-dependent area coverage of the Mie-cloudy wind observations, separated into the three error categories, is shown in Fig. 9 for September 2022 (top row) and April 2023 (bottom row). The left panels ((a), (d)) show the coverage obtained using only valid winds, whereas the middle ((b), (e)) and right panels ((c), (f)) correspond to the low-error and high-gain configurations, respectively. As in the previous figures, green and purple colours indicate the two filter configurations. The coloured shaded regions denote the three quality classes defined by the ε thresholds above. For the high-quality wind observations, horizontal error bars indicate the 1 σ standard deviation over all orbits within the respective month. In the middle and right panels, the black dashed line marks the high-quality data coverage obtained from valid winds only.

For both months, the coverage generally increases from the lower stratosphere towards the lower troposphere, reflecting the vertical distribution of clouds that largely determines the regions from which Mie-cloudy winds are retrieved. The coverage reaches its maximum between 1 and 2 km altitude, where more than 20% of the atmospheric area is covered by Mie winds. This pronounced low-level maximum is mainly associated with extensive marine stratocumulus decks, which represent a major source of low-level Mie-cloudy wind observations. Across most of the remaining atmospheric column, the coverage of Mie-cloudy winds typically does not exceed approximately 7–12%, as discussed in more detail in Lux et al. (2026).

Application of the median-filter algorithm substantially enhances the area coverage in the UTLS region between 8 and 18 km altitude by recovering Mie-cloudy winds from cirrus clouds. This effect is especially pronounced in April 2023, where the coverage of high-quality winds near 15 km approximately doubles from about 3% to 6% for the low-error configuration (panel (e)) and nearly triples for the high-gain configuration (panel (f)). When all additionally recovered wind observations are considered irrespective of their quality category, the total area coverage around the tropopause increases from less than 10% to approximately 15% for the low-error configuration and to nearly 20% for the high-gain configuration, although with a larger contribution from low-quality winds.

For September 2022, the enhancement of Mie-cloudy wind coverage in the UTLS is somewhat less pronounced, increasing from approximately 5% to around 8% for the low-error configuration and to about 10% for the high-gain configuration. However, a particularly strong increase is evident between 20 and 24 km altitude, associated with the enhanced stratospheric aerosol load following the Hunga Tonga volcanic eruption. In this region, the peak area coverage near 22 km altitude increases from only about 5% for valid winds alone to approximately 17% for the low-error configuration and up to nearly 28% for the high-gain configuration. Restricting the analysis to high-quality wind observations only, the coverage still increases substantially, from about 2% to 8% and 12%, respectively. These results demonstrate the considerable gain in wind information achieved by the median-filter algorithm, particularly in aerosol-rich and optically thin atmospheric layers that are highly relevant for studies of UTLS dynamics, cirrus clouds, and stratospheric transport.

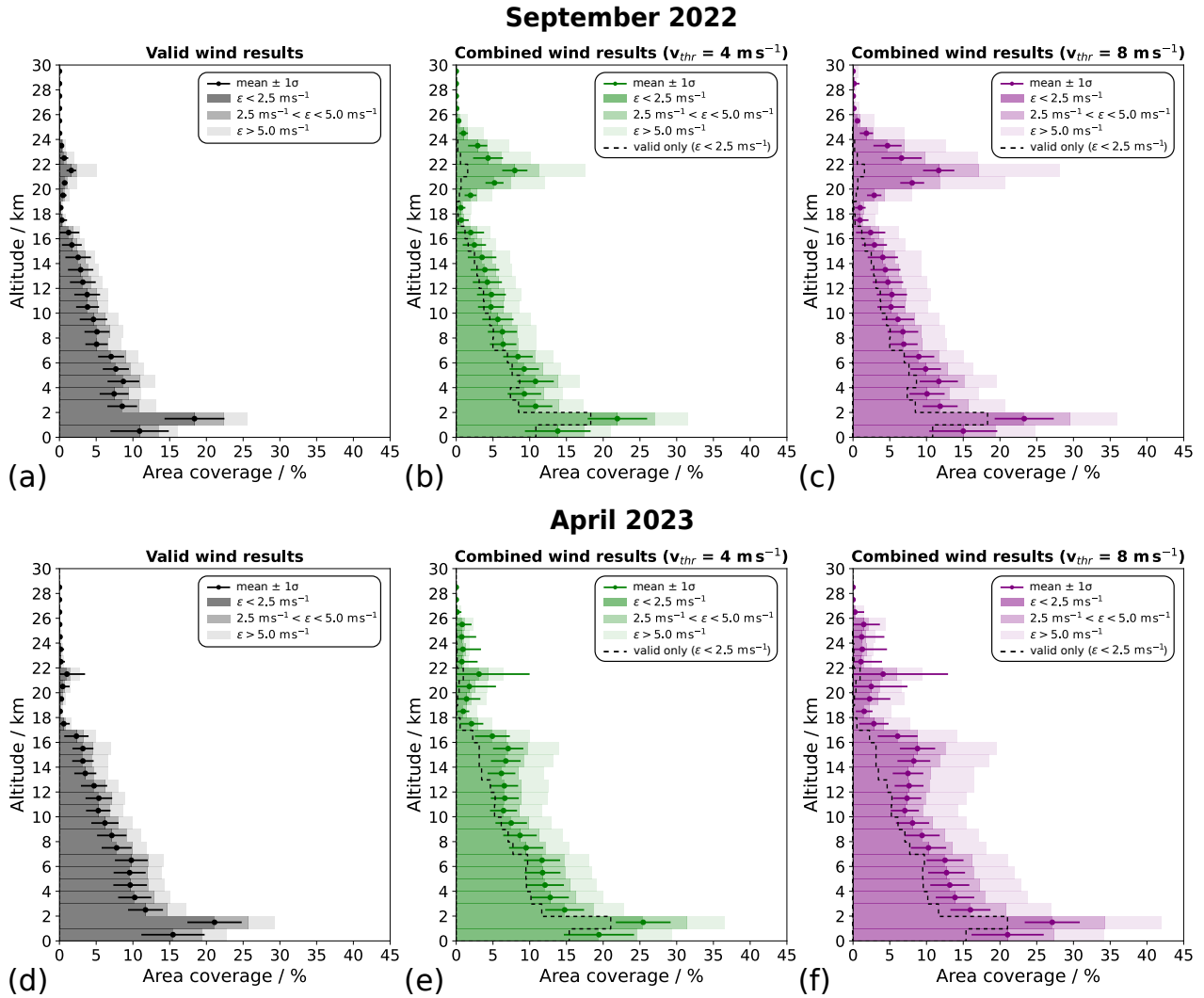


Figure 9. Mie-cloudy global wind data coverage for valid wind results only (grey shading; panels (a), (d)), and after adding median-filtered invalid wind results using filter parameters $N = 15$, $w_{thr} = 30 \text{ m s}^{-1}$, and $v_{thr} = 4 \text{ m s}^{-1}$ (green shading; panels (b), (e)) or $v_{thr} = 8 \text{ m s}^{-1}$ (purple shading; panels (c), (f)). The colour shading indicates the proportion of data within specific intervals of the (O-B) wind speed difference ε relative to the ECMWF model background, assuming a background error of 2.5 m s^{-1} . Data points and error bars represent the mean and standard deviation of the high-quality wind data coverage (wind speed difference $\varepsilon < 2.5 \text{ m s}^{-1}$) over all orbits during the respective period. Dashed lines in panels (b), (c), (e), and (f) denote the high-quality data coverage for valid winds only. The top panels ((a)–(c)) correspond to September 2022, whereas the bottom panels ((d)–(f)) correspond to April 2023.

3.4 Estimated error characteristics and quality control

In the L2B product, each Mie-cloudy wind result is associated with an estimated error (EE). The EE represents the 1σ standard uncertainty of the HLOS wind speed derived through error propagation and may therefore be interpreted as a confidence



540 interval for the retrieved wind observation. For the Mie channel, the EE is obtained from the error covariance matrix of the fitting algorithm used to determine the peak position of the interference fringe imaged onto the detector, from which the Doppler shift is derived. The covariance matrix itself is calculated from the partial derivatives of the Lorentzian line shape with respect to four fit parameters: peak position, peak height, line width, and offset. A detailed description of the EE calculation is provided in the Aeolus L2B Algorithm Theoretical Basis Document (Rennie et al., 2020), while a concise overview is given in
545 Lux et al. (2022). Previous analyses of the EE and its relationship to $(O - B)$ error statistics showed generally good agreement, particularly in the low-SNR regime corresponding to EE values larger than about 3 m s^{-1} . At lower EE values, however, the EE no longer closely follows the random error derived from $(O - B)$ statistics. This discrepancy is mainly attributed to representativeness errors, which become increasingly dominant in the high-SNR regime due to the coarser horizontal resolution of the ECMWF model background (40–80 km) compared to that of the Mie-cloudy wind observations (10–20 km) (Rennie
550 et al., 2021).

The impact of including median-filtered invalid wind results on the EE distribution was analysed for the month of April 2023 and is illustrated in Fig. 10. The left panels show the EE distributions for valid Mie-cloudy winds only (black), together with the corresponding distributions obtained after inclusion of the median-filtered invalid winds using the low-error configuration (green, panel (a)) and the high-gain configuration (purple, panel (c)). The dashed lines indicate the distributions of the additionally
555 recovered wind results alone. The inclusion of the recovered winds broadens the EE distribution substantially and extends it towards larger EE values of up to approximately 20 m s^{-1} . This behaviour is expected, as many of the additionally recovered winds originate from low-SNR regions associated with weak particle backscatter from optically thin clouds or aerosol layers. Nevertheless, a considerable number of the recovered winds also exhibit relatively small EE values below 5 m s^{-1} , thereby contributing significantly to the peak of the overall EE distribution.

560 The right panels of Fig. 10 show the $(O - B)$ wind speed differences as a function of EE, again distinguishing between valid winds only (black) and the additionally recovered winds obtained with the low-error (green, panel (b)) and high-gain (purple, panel (d)) configurations. As expected, the variance, or equivalently the scaled MAD, of the $(O - B)$ wind speed differences generally increases with increasing EE and can be interpreted as the wind random error. For the valid winds alone, the random error (black solid line, right-hand y-axis) approximately follows a 1:1 relationship with the EE. In contrast, the recovered winds
565 exhibit a substantially flatter dependence of random error on EE (green and purple solid lines). This behaviour demonstrates that the additionally recovered winds are associated with comparatively large EE values because they predominantly originate from low-SNR conditions, while at the same time exhibiting considerably smaller random errors than valid winds retrieved under similar low-SNR conditions. This highlights the capability of the median-filter algorithm to identify physically meaningful wind observations in situations where the operational L2B processor and its QC procedures reject the measurements. The
570 lower random error of the recovered winds at comparable EE values can be interpreted as a narrowing of the $(O - B)$ wind speed difference distribution. By rejecting large wind speed differences, the median filter effectively removes the tails of the distribution, resulting in a reduced variance and, consequently, a lower random error.

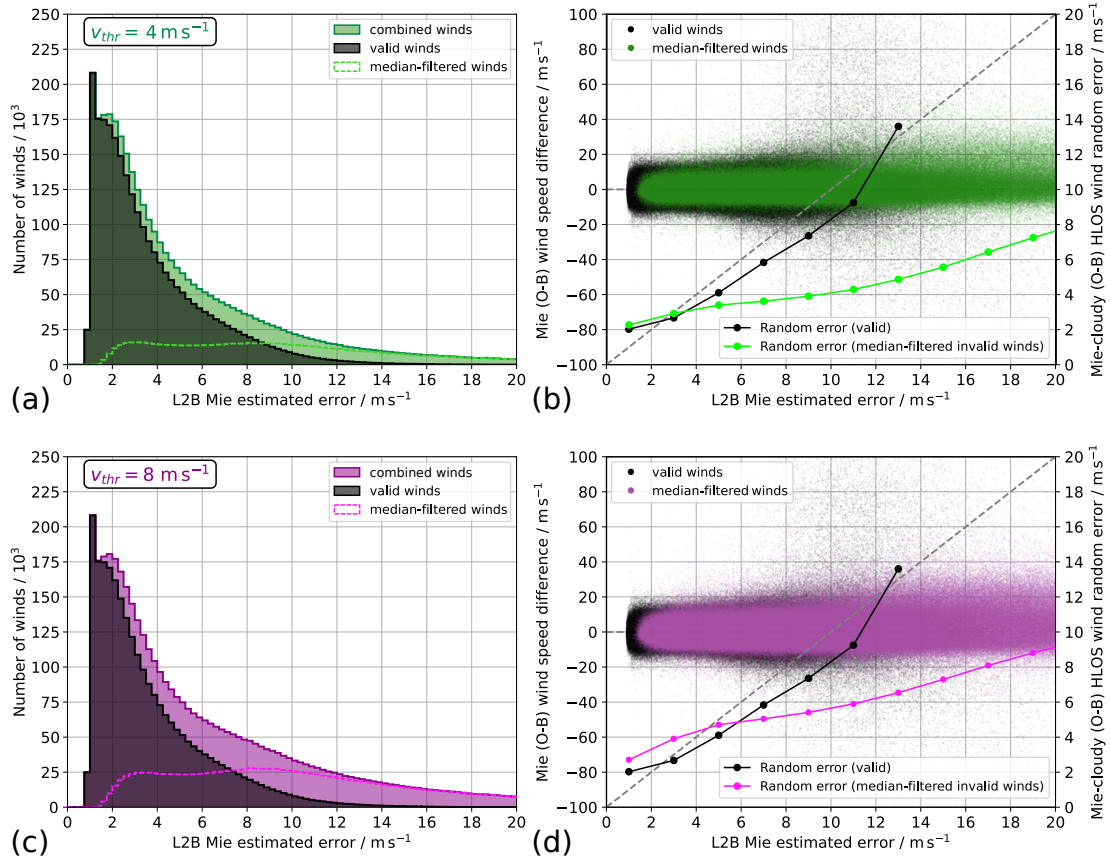


Figure 10. (a) Distribution of the L2B estimated error for April 2023 considering valid Mie-cloudy wind results only (black) and after inclusion of additionally recovered, median-filtered invalid wind results (green), using the filter parameters $N = 15$, $w_{thr} = 30 \text{ m s}^{-1}$, and $v_{thr} = 4 \text{ m s}^{-1}$. The dashed green line represents the distribution of the additionally recovered wind results only. (b) Mie-cloudy (O–B) wind-speed differences relative to the ECMWF model background as a function of the L2B estimated error for the valid wind results (black) and the additionally recovered, median-filtered invalid wind results (green). The random error of the Mie-cloudy winds is derived from these differences as the scaled MAD calculated for all winds within estimated-error bins of width 2 m s^{-1} and is shown as a solid lime line (right-hand y-axis). Panels (c) and (d) show the corresponding results for the relaxed deviation threshold $v_{thr} = 8 \text{ m s}^{-1}$, with the additionally recovered winds indicated in purple instead of green.

The balance between the gain in Mie-cloudy wind results and the associated random error can be further optimized by applying an additional QC step based on the EE after the median-filter algorithm. By discarding wind results that exceed a specified EE threshold, the quality of the resulting dataset can be improved at the expense of data coverage. This trade-off is illustrated in Fig. 11, which shows the gain in Mie-cloudy wind results and the corresponding wind random error, as defined above, as functions of the EE threshold for the two median-filter configurations. The horizontal solid and dashed lines indicate the respective values obtained without applying an additional EE-based QC. The random error for the valid winds only, corresponding to a gain of 0%, is represented by the black dashed line.



580 For EE thresholds larger than approximately 10 m s^{-1} , i.e. in the regime where the majority of the median-filter output consists of additionally recovered invalid winds, the gain increases rapidly for both configurations before gradually converging towards the values obtained without EE filtering. A similar behaviour is observed for the random error, although its increase begins already at somewhat lower EE thresholds. The EE thresholds at which the random error of the filtered winds matches that of the valid winds only ($\approx 3.6 \text{ m s}^{-1}$) are approximately 7 m s^{-1} for the high-gain configuration (point t_1 in Fig. 11) and
 585 10 m s^{-1} for the low-error configuration (point t_2). The corresponding gains in Mie-cloudy wind results relative to the valid winds only are 10% and 17%, respectively. Thus, combining the median-filter algorithm with a subsequent EE filter provides Mie-cloudy wind results in addition to the valid ones even without degrading wind precision. This is due to the fact that also some of the lower-quality valid wind results are filtered out based on the EE.

It is also instructive to determine the EE threshold at which the high-gain configuration achieves the same gain ($\approx 39\%$)
 590 as the low-error configuration without additional EE filtering. This occurs at approximately 12 m s^{-1} (point t_3). However, the random error of the EE-filtered high-gain configuration is then slightly larger by approximately 0.1 m s^{-1} . Therefore, the low-error configuration alone is preferable for achieving an approximately 40% increase in wind results while incurring only a minor degradation in random error.

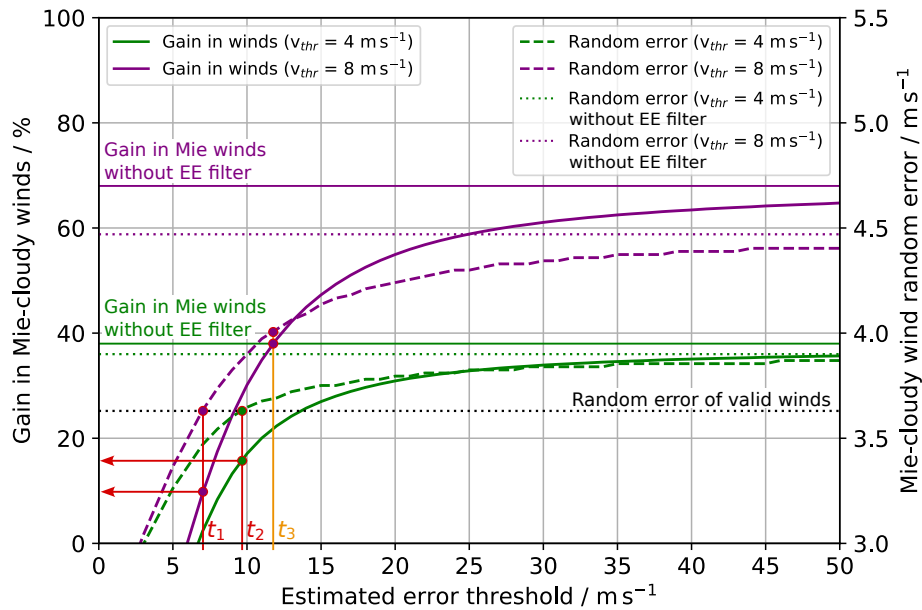


Figure 11. Gain in Mie-cloudy wind results (solid lines, left-hand y-axis) and wind random error (dashed lines, right-hand y-axis) as a function of the EE threshold applied in the subsequent QC of the median-filter algorithm output, obtained for the low-error (green) and high-gain (purple) configurations. The horizontal solid and dotted lines indicate the corresponding values without application of the EE filter, while the black horizontal dotted line represents the random error for the valid winds only. The points (t_1 , t_2 , t_3) mark specific EE thresholds that are discussed in the text.



4 Summary and conclusions

595 The Aeolus mission represented a major milestone in atmospheric remote sensing as the first spaceborne Doppler wind lidar providing global wind-profile observations from orbit. The mission demonstrated the substantial value of direct wind-profile measurements for NWP, atmospheric dynamics, and aerosol-transport research, while also revealing important limitations in the operational retrieval of Mie-cloudy winds under weak backscatter conditions. Because the L2B processing was deliberately optimized for robust retrievals from strong cloud returns, many potentially useful winds from tropospheric and stratospheric
 600 aerosols, optically thin cirrus clouds, and PSCs were rejected by the operational QC, despite often containing physically meaningful dynamical information.

To address this limitation, a median-filter-based QC algorithm was developed to recover additional valid wind observations from the population of invalid Aeolus Mie-cloudy winds. The method was specifically designed to identify useful low-SNR wind results while avoiding the inclusion of erroneous retrievals. In the operational L2B product, typically only about 10%
 605 of all retrieved Mie-cloudy winds are flagged as valid, whereas the majority are rejected because one or more fit parameters fall outside predefined QC thresholds. Nevertheless, inspection of the complete dataset revealed that many invalid observations still exhibit coherent wind structures consistent with the surrounding atmospheric flow.

The developed algorithm compares each wind result with the median wind speed of neighbouring bins identified using a two-dimensional k-d tree in along-track distance and altitude space. Invalid winds are recovered only if their deviation from
 610 the local median remains below a configurable threshold v_{thr} , if their absolute wind speed remains below w_{thr} , and if they were originally rejected solely because of low-SNR-related QC criteria. This approach efficiently suppresses isolated retrieval artefacts while preserving dynamically coherent atmospheric structures and sharp gradients.

The capability of the algorithm was demonstrated using Aeolus observations of the Hunga Tonga stratospheric volcanic aerosol plume in September 2022. As the aerosol backscatter weakened over time, many otherwise plausible stratospheric Mie
 615 winds failed the operational QC. Application of the median filter increased the number of winds above 18 km altitude from 128 to 736 for a representative orbit, while increasing the random error only moderately from 3.8 to 4.2 m s^{-1} . This example highlights the potential of the method to recover scientifically valuable wind observations in weak-backscatter regions such as aerosol layers, thin cirrus, and PSCs.

A systematic optimization of the filter parameters showed that the number of nearest neighbours N has only minor influence
 620 on the performance, whereas the median-deviation threshold v_{thr} governs the main trade-off between data yield and random error. The absolute wind speed threshold w_{thr} avoids the inclusion of gross errors from regions where rare or even unphysical high wind speeds by chance meet the median-filter condition. Two configurations were therefore proposed: a low-error configuration ($N = 15$, $v_{thr} = 4 \text{ m s}^{-1}$, $w_{thr} = 30 \text{ m s}^{-1}$) and a high-gain configuration using $v_{thr} = 8 \text{ m s}^{-1}$. Across selected orbits throughout the mission, the low-error configuration increased the number of Mie-cloudy winds typically by 23–35% while
 625 increasing the random error by only 0.2–0.4 m s^{-1} . The high-gain configuration achieved increases of 42–62%, accompanied by moderate random-error increases of 0.7–1.1 m s^{-1} . In both cases, the increase in gross-error fraction remained comparatively small at approximately 1–2%. For the early mission period until the switch to the second laser FM-B in late June 2019,



the lack of invalid Mie-cloudy winds in the L2B product largely prevents the recovery of wind results. This limitation will be addressed in the upcoming Baseline B17, for which a median-filter QC similar to that presented in this work will be implemented. An additional validity flag will be added to the L2B product, allowing users to select Mie-cloudy wind results that pass the median-filter QC. The details of the implementation are currently being tested.

The robustness of the algorithm was further confirmed using analyses for the whole months of September 2022 and April 2023. Despite substantial differences in instrument performance between the two periods, the relative increase in recovered winds remained remarkably stable, reaching approximately 40% for the low-error configuration and more than 70% for the high-gain configuration. The largest gains were obtained in the UTLS, where high-quality wind coverage approximately doubled or tripled depending on the chosen configuration. Particularly strong improvements were found near 22 km altitude in September 2022 because of the Hunga Tonga aerosol plume, where the coverage of high-quality winds increased from about 2% to as much as 12%.

While the substantial increase in the number of available Mie-cloudy wind observations may benefit NWP, the corresponding forecast impact cannot be inferred directly from the increase in data volume. The additional winds are predominantly recovered in regions where valid observations are already present, implying that part of the atmospheric information may already be represented by neighbouring measurements. Consequently, the impact per additional observation is not necessarily expected to match that of the operationally valid winds, and the overall forecast benefit is unlikely to scale linearly with the increase in observation count. Quantifying the actual contribution of the recovered winds to NWP therefore requires dedicated observing system experiments or data assimilation impact studies, which are beyond the scope of the present work.

The inclusion of median-filtered invalid winds broadens the EE distribution towards larger values, reflecting the recovery of observations from low-SNR conditions. However, the recovered winds exhibit considerably smaller random errors than expected for valid winds with comparable EE values. This demonstrates that the median-filter algorithm can successfully identify physically meaningful wind observations that are conservatively rejected by the operational L2B QC procedures. Applying an additional EE-based QC threshold after the median filter provides an additional means to balance increased wind coverage against wind precision, allowing gains of about 10–20% in wind results without degrading the random error relative to the valid Mie-cloudy winds only.

Overall, the developed median-filter approach substantially enhances Aeolus Mie-cloudy wind coverage in dynamically important atmospheric regions while maintaining acceptable error characteristics. The method therefore increases the scientific and meteorological value of the Aeolus dataset for studies of atmospheric circulation, aerosol transport, cloud processes, and UTLS dynamics. Moreover, the approach provides a promising blueprint for future Doppler wind lidar missions such as Aeolus-2, currently under development by ESA and the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT). With its substantially increased number of vertical range bins (66 instead of 24) and extended altitude coverage up to 40 km (Porciani, 2025), Aeolus-2 will face similar challenges in retrieving winds from low-SNR aerosol and thin-cloud conditions. Robust median-filter-based QC approaches such as the one presented here therefore offer considerable potential for maximizing future wind-data coverage while preserving high data quality.



Code availability. The Python code implementing the median filter is not publicly available as it is being developed for integration into the ESA Aeolus Level-2B processor and is therefore confidential; it is available on request to the corresponding author. The filtering approach and its parameters are fully described in the Methods and Datasets section.

665 *Data availability.* The presented work includes data of the Aeolus mission which is part of the European Space Agency (ESA) Earth Explorer Programme. This includes the reprocessed L2B wind product (Baseline 16; de Kloe et al. (2023); <https://earth.esa.int/eogateway/documents/20142/37627/Aeolus-L2B-2C-Input-Output-DD-ICD.pdf>, last access: 16 September 2025) that is publicly available and can be accessed via the ESA Aeolus Online Dissemination System (https://aeolus-ds.eo.esa.int/oads/access/collection/L2B_Wind_Products_Reprocessed, last access: 26 January 2025; European Space Agency, 2025). The processor development, improvement, and product reprocessing preparation
670 have been performed by the Aeolus DISC (Data, Innovation and Science Cluster), which involves DLR, DoRIT, TROPOS, ECMWF, KNMI, CNRS, S&T, ABB, and Serco, in close cooperation with the Aeolus PDGS (Payload Data Ground Segment) from ESA.

Author contributions. OL developed the median-filter algorithm for the Aeolus L2B product, performed the data analysis and wrote the manuscript. MR developed the L2B processor, remains responsible for its ongoing development, and contributed to the manuscript. OR supported the interpretation of the results and assisted with manuscript preparation.

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