Replies to referee comment 2

We want to thank the referee for carefully reading our submission, valuable hints and a discussion based on deep knowledge in Doppler lidar evaluation.

This paper describes a wind profile retrieval software called AtmoProKIT to retrieve wind profiles from Doppler Lidar measurements. This open-source retrieval code is modular with standardized data formats and configurable module chains to handle complexity related to different types of Doppler Lidars, and different types of scans (PPI, RHIs, step-stare) in order to ensure quality controlled, standardized wind profiles with traceable uncertainties. While availability of an open-source, standardized wind profile retrieval code for Doppler lidar would benefit the scientific community, I am not sure the paper fits the scope of Geoscientific Model Development journal. It is primarily focused on describing the publicly available code to retrieve wind profiles from measurements, and nothing to do with model development or validation. One could argue that adaptation of this code could result in uniform wind profiles for data assimilation and model validation.

Producing an open-source, standardized wind profile retrieval code is exactly the purpose of this submission, with data assimilation and model validation being the inherent drivers of this development. The processing of the Swabian MOSES campaign wind profiles was indeed carried out for data assimilation. We highlight this purpose in the revised version and added a reference [Handwerker et al., 2025].

Developing a toolbox to bring measurements into models fits the scope of GMD from our understanding, as GMD is not limited to complete models and comprises also utility tools like toolboxes according to `https://www.geoscientific-model-development.net/about/manuscript_types.html`. Before submission, we also studied other publications doing so within GMD (e.g. `https://doi.org/10.5194/gmd-18-101-2025`, `https://doi.org/10.5194/gmd-15-8983-2022`, `https://doi.org/10.5194/gmd-15-7557-2022`, `https://doi.org/10.5194/gmd-13-6111-2020`).

We applied for the joint GMD/AMT Special issue 'Profiling the atmospheric boundary layer at a European scale' `https://gmd.copernicus.org/articles/special_issue400_1209.html`. We think our purpose of processing unified and traceable wind profiles from heterogeneous measurements for use in models fits the scope of GMD and this special issue in particular, since the focus of this work is code-development based rather than measurement technique based. As noted, obtaining wind profiles from Doppler lidar is a widely used technique in general, however, few generalized and open-source algorithms to do so exist.

To ensure the paper fits the scope of GMD, we declare it as a software toolbox with a geoscientific application with paper type *model description paper* according to the link above. Hence, we added the name and the version of the software to the title as required for such model description papers. We hope highlighting the algorithm development for easier, more traceable and reproducible measurement processing for usage in modeling and data assimilation, and the clear indication of a software toolbox according to the GMD scope, makes this contribution acceptable for consideration in the GMD special issue.

We reworded the manuscript to clarify the relevance for modelling and data assimilation. We now reference the name and version of the software in the title of the manuscript as required by GMD.

The following comments need to be addressed before the paper is accepted for publication.
Major Comments:

Wind profile retrievals from heterogeneous Doppler lidar data: Heterogeneous Doppler lidar data from different scans have been used to retrieve wind profiles on a different vertical retrieval grid before (e.g. [Tucker et al., 2009, Bonin et al., 2017, Pichugina et al., 2019]). [Pichugina et al., 2019] used wind profiles retrieved at high vertical resolution near the surface from multiple PPIs, including very shallow elevation angles, to evaluate NWP for wind energy applications. Thus, the use of heterogeneous Doppler lidar data and the concept of retrieval volume is not novel.

It is correct that height binning is not a novelty. In the original submission we mentioned that this binning concept is common for Doppler lidars operated on airplanes and ships. In the revised version, we clarified that this concept is an established concept to overcome the issue of range gate based retrievals and added the references you mentioned. We think the concept is useful and therefore utilize it to enable flexibility for retrieving wind profiles from arbitrary scans. However, the focus of the manuscript is on the open-source code development, ensuring standardization and reproducibility of procedures, not on the the development of new retrieval techniques.

We modified the discussion to clarify the scope and novelty of this study and included the references provided to give appropriate credit to previous studies developing the concepts used by us.

Choice of CNR Threshold and Confidence Interval: The choice of upper CNR thresholds of -25 dB for WLS200s seem arbitrary, and very conservative. Based on Figure E1, the CNR threshold should be closer to the lower

CNR threshold i.e. -30 dB. By arbitrarily setting the upper threshold at -25 dB, a lot of data is categorized as potentially bad, and exaggerates the benefit of the confidence background method presented in the paper. I suggest the authors characterize the noise floor for one of the WLS200s presented in the paper and then assess the benefit of the confidence background method. If a proper noise floor (e.g. -29 dB) had been considered, I think all the gains made during the first iteration shown in Figurer 11a would have been included in the retrieval in the first place. In such a case, the gains from using the confidence interval method would be minimal and could even argued as not worth the effort.

We agree that -25 dB used for the WLS200s is a conservative threshold. Similarly, the -22 dB for the StreamLine XR+ and -5 dB for the WTX are conservative thresholds for these systems. The purpose of the conservative thresholds is to retain only reliable wind profiles, since the background is used to guide wind profile retrievals at lower CNR levels. Therefore, we placed the threshold at a level for which the presence of noise in the spectrum is very low. For us, this threshold is indicated by the broadening of the radial velocity distribution in the previous Fig. D3, which we now place and discuss more prominently in the manuscript (Fig. 8 in the revised manuscript).

Note that we also present the results of a direct non-iterative retrieval using a -30 dB CNR threshold in Fig. E1, as suggested by you. Fig. E1 shows that the number of retrieved wind profile points is reduced when using a direct CNR thresholded retrieval, compared to our suggested standard module chain using an iterative retrieval. Additionally, individual outliers are present in the edge regions of the retrieval.

For your reference, we also conducted the retrieval for CNR thresholds -25 dB, -26 dB, -27 dB, -28 dB, -29 dB, -30 dB. You can find the results at the end of this document (Fig. 1 - 6). The number of retrieved wind vectors is 4945 for -25 dB, 5380 for -29 dB, and 5451 for -30 dB. In comparison, the proposed standard module chain yields 5556 wind vectors, i.e. more points than the directly thresholded retrieval variants. In addition, the outliers present in the directly thresholded retrievals are avoided.

The determination of a complete 'noise floor' within the retrieval itself is non-trivial and beyond the scope of this study. Noise characteristics depend on the lidar system, laser characteristics (e.g. pulse length/energy, pulse repetition frequency), data acquisition settings (e.g. detection bandwidth, detection algorithm, number of averaged laser pulses, noise level and noise compensation quality), which may vary between different users, systems and measurements. The difficulties, as well as possible solutions, are discussed in [Päschke and Detring, 2024], to whom we now refer in the manuscript.

The conservative thresholds used in the iterative retrieval are only suggested for use in our so-called 'standard module chain'. The standard module chain is not advertised as the most efficient or best possible processing chain, but as an easy to use solution for users with little Doppler lidar processing experience. The processing and retrieval requirements may differ depending on the user and field of application. Our software gives the user the opportunity to set the thresholds individually and/or modify the retrieval chain. We also present and discuss results from a more simple, single iteration, direct CNR threshold, based module chain.

We now state the used thresholds more clearly, label them as conservative and indicate them in the Figure mentioned in the referee comment. Further, an extended discussion on user choices on CNR thresholds and their potential impact is now included. Additionally, the potential gains of the iterative retrieval are put into context.

For your reference, we here include retrieval quality evaluations with different CNR thresholds applied (Fig. 1 - 6.)

Note that depending upon the definition of the CNR used by manufacturers, and measurement bandwidth, usable CNR threshold for a Doppler lidar will be different. Thus, noise floor for each lidar needs to be characterized independently so that all good data are used in the retrieval.

What CNR thresholds were used from the WLS200s at Payerne, WTX at VS and StreamLine XR+ at Neumayer Station? Based on figure D3, the CNR threshold for WLS200s, WTX and StreamLine XR+ should be very different.

We agree on the importance of varying parameters between systems and apologize for the previously unclear presentation of the used values. Noise characteristics depend on the lidar system, laser characteristics (e.g. pulse length/energy, pulse repetition frequency), data acquisition settings (e.g. detection bandwidth, number of averaged laser pulses, noise level and noise compensation quality), which may vary between different users, systems and measurements. The difficulties, as well as possible solutions, are discussed in [Päschke and Detring, 2024], to which we now refer in the manuscript. For our calculations we used as a conservative threshold for reliable measurements -25 dB for WLS200s, -22 dB for the StreamLine XR+, and -5 dB for the WTX. The second-pass thresholds were set to -30 dB for WLS200s, -30 dB for the StreamLine XR+, and -12 dB for the WTX (Table A2 now). We now state the parameters and values used in our standard module chain in Tab. A2. An advantage and purpose of our software is that different threshold levels can be applied by every user depending on the system and operation characteristics. Since the used module chain and configuration parameters (not limited to the CNR thresholds) are stored in the output metadata, the applied retrieval remains reproducible

and modifiable by others.
We now state the CNR thresholds used for the systems more clearly, placed former Fig. D3 in the main manuscript part and extended the discussion on the selection of the CNR thresholds.

Some peak detection algorithms used by Doppler Lidars to determine line of sight velocity (LOSV) follow the strongest peak from the high CNR region to lower CNR region. This could potentially result in wrong LOSV determination in presence of wind shear. This could be the case with StreamLine XR+ at Neumayer Station. The confidence background method would potentially double down on determining these erroneous LOSV data points as good data points. So, one needs to be cautious when applying methods such as confidence interval to determine reliable data points in the low CNR regions.
We obtained the measurements from Neumayer Station from the ACTRIS Cloudnet data portal where no raw spectral data is available, such that we cannot verify this hypothesis. Since we are not the operators of the StreamLine XR+ at Neumayer station, and also don't have experience in operating these systems, we cannot determine the reasons for the observed behavior. Its cause may be software or hardware issues, or interference with other electronic systems (see appendix D). The operators of the system have been informed on our observations and thankfully acknowledged the information. We agree, judging the reliability of measurements at low CNR is challenging. This difficulty is the reason why we conduct an iterative retrieval starting from the above discussed conservative CNR thresholds to construct the confidence background. The proposed algorithm includes an iterative removal of radial velocity measurements which deviate by more than a user determined value from the acceptable background (3 m/s in the standard module chain). Since unreliable measurements at low CNR typically resemble white noise, we do not see an effect of erroneous modification of the conservative confidence background by weak CNR measurements. To validate the appropriate application of the confidence background, we validate the retrieval with independent radiosonde measurements under a variety of conditions, showing high data availability and reliable retrievals also in weak CNR conditions. We have now included an analysis of retrieval errors as a function of CNR, which also does not show an impact of low CNR on retrieval quality (Sect. 5.3 and Fig. 16). The influence of CNR on retrieval quality are discussed in detail in our answer below ('Comparison with radiosondes').
Added impact of CNR in Sect. 5.3 and Fig. 16, see below changes in 'Comparison with radiosondes' answer.

Uncertainty Analysis: There is no description of the uncertainty in the paper. How is it calculated? How is it impacted by having different types of scans? Depending upon the scans and retrieval grid used, some grids will have more data points than others, how does this impact the uncertainties? Please add how uncertainty is calculated in Appendix C.
We are not sure to which aspect of uncertainty you are pointing on. Different aspects of uncertainty require consideration in wind profile retrievals:

- Uncertainty due to random errors in the measured radial velocities, related to the CNR discussion above: As discussed, measurement conditions, laser and data acquisition settings impact the amount of random error present in the radial velocities. In the wind profile retrievals, such random errors contribute to the residuals between the wind vector estimated from all measurements and the individual radial velocity measurements. Typically, levels or random radial velocity noise are low (i.e. below 0.5 m/s) and thereby present a smaller source of error compared to turbulent fluctuations in the retrieval volume. Additionally, random errors should present white noise and hence average out overall, if a sufficient number of measurements are used in the retrieval (note that gross outliers are prevented through the iterative removal of radial velocity deviations beyond a user defined threshold, in our case 3 m/s). To reduce the impact of random radial velocity noise, a longer integration time or more measurements within one bin can be considered.
- Numerical uncertainty in the wind profile retrieval process: In Section 2.1, we address the issue of insufficient beam dispersion in the measurements used for wind profile retrieval. To avoid a high impact of error propagation, wind vectors with an insufficient dispersion of the underlying measurements are rejected by the user-specified condition number (CN) threshold (CN $>$ 8 threshold in the standard module chain).
- Lidar representativeness error: The wind at the locations measured by the lidar beam may not correspond to the average wind present within the retrieval volume spanned by the lidar beams during the retrieval time. Unfortunately, this error can only be assessed in LES-based virtual lidar studies where the 3D wind vector is known everywhere in the retrieval volume (see e.g. [Gasch et al., 2020, Gasch et al., 2023, Rahlves et al., 2022, Robey and Lundquist, 2022]).
- Retrieval error due wind field inhomogeneity (e.g. due to turbulence) within the retrieval volume (see e.g. [Gasch et al., 2020, Gasch et al., 2023, Rahlves et al., 2022, Robey and Lundquist, 2022]): Turbu-

lence in the volume probed by the lidar beam causes deviations of the wind retrieval, assumed to be homogeneous in the retrieval process. Fluctuations below the (temporal and spatial) size of the retrieval volume are detectable as deviations of the retrieved, projected wind vector from the measured radial velocities, i.e. residuals similar to the random radial velocity errors. Fluctuations beyond the (temporal and spatial) size of the retrieval volume are *not* detectable as deviations, but cause erroneous mapping of wind components instead. Unfortunately, this error can only be assessed in LES-based virtual lidar studies where the 3D wind vector is known everywhere along the path of the lidar scan (see e.g. [Gasch et al., 2020, Gasch et al., 2023, Rahlves et al., 2022, Robey and Lundquist, 2022]).

- Representativeness error in measurement intercomparison: Differences between the Doppler lidar retrieved wind and reference measurements may arise from differences in the probe volume, besides measurement errors of the reference measurement. See below comment on the radiosonde intercomparison.

Due to the superposition of the above factors influencing retrieval accuracy, an overall uncertainty associated with each individual wind profile is difficult to establish and beyond the scope of this study. For this reason, we chose the validation through intercomparison with radiosondes as a verification method. Especially the lidar representativeness, retrieval, and measurement intercomparison errors, driven by turbulence, are often the largest, but difficult to estimate in real measurements. Estimation of these errors typically requires application of LES-based models where the 3D wind vector at the point of the lidar measurements and within the retrieval volume is known (e.g. [Gasch et al., 2020, Gasch et al., 2023, Rahlves et al., 2022, Robey and Lundquist, 2022]).
The software provides the variance of the residuals as an indicator of the agreement of radial velocities measurements within each bin. This metric enables the user to identify the radial velocity variance level within each retrieval bin, which is often related to random radial velocity error and/or turbulence. However, the metric can only be used for a comparative uncertainty/turbulence assessment since the scan pattern can change within and between retrieval bins.
Having the variance/standard deviation for the single wind components is desirable but not easy to implement. The precision estimation introduced by [Newsom et al., 2017] uses the variance of the residuals for the estimation of the uncertainty in u and v direction (see equations (7) and (1) there). Similarly, the standard module chain provides the variance of the residuals as an indicator (that needs to be used carefully). Using highly frequent measurements for a reliable determination of the uncertainty, e.g. carried out by Steinheuer et al. [Steinheuer et al., 2022], has special requirements for the scan pattern (very short scans with fast scanner rotation). For the proposed standard module chain the intention is to keep the scan pattern as flexible as possible. The modular architecture enables specialized modules, e.g. for evaluations based on special scans. The scope of the present contribution is, however, the introduction of this flexible architecture and a retrieval algorithm (module chain) with a broad applicability, high availability and quality suitable for data assimilation. In case your question addresses another topic or focuses on one of the aspects, please provide additional details.
We have now included a more extended discussion of the aspects contributing to uncertainties in the retrieved wind vector in the radiosonde comparison section (Sect. 5.2) of the revised manuscript.

Comparison with radiosondes do not provide retrieval error for individual wind profiles. Depending upon the atmospheric conditions, some wind profiles will have larger uncertainty than others. How is this calculated and is the calculated uncertainty representative? This is especially important for low CNR regimes. Bulk comparison as shown in the paper usually hides the larger bias and uncertainty likely present in the low CNR regimes. For example, all three stations show a bias in v at higher altitudes (Figure 13, 14 and 15). How does this comparison look if only the low CNR regime data are included? I suggest the authors characterize performance/uncertainty as function of CNR.
We use radiosondes for validation, since there are no other wind measurements available above the surface. We agree, determining an intercomparison error for each individual wind profile is possible but not meaningful due to the potential retrieval errors listed above ('Uncertainty Analysis'). For this reason we only provide standard statistical error metrics for the bulk intercomparison or individual altitude bins. To ensure representativeness of the intercomparison overall 17 months of data and more than 500 radiosonde profiles at three different sites are used in the intercomparison. As pointed out in Section 5.2 and our above answer, radiosondes are not an ideal reference measurement. As an in-situ measurement they produce reliable measurements for a specific time and specific location. The retrieved Doppler lidar profiles represent a vertical profile of the wind within a time span (in our case 10 minutes) and retrieval volume (depending on the used scan directions and elevations). Hence, the representativeness error cannot be avoided in real-world intercomparisons. However, the added representativeness error means that the underlying deviations between radiosonde and wind lidar are on average smaller than observed in the bulk intercomparison.
To analyze and validate the retrieval error as a function of CNR, we have now included the intercomparison statistics as a function of lidar CNR. Overall, little effect of decreasing lidar CNR on retrieval error is discernible.

Additionally, one has to keep in mind cross-correlations with additional variables. Lower CNR are typically measured above the boundary layer, i.e. at higher altitudes. There the distance between lidar and radiosondes is larger on average, leading to an increased representativeness error.
Providing an uncertainty estimate for each wind profile solely based on Doppler lidar measurement data is non-trivial and beyond the scope of this study, as discussed above ('Uncertainty Analysis'). Previous LES-based studies haven shown that the retrieval errors due to turbulence can overwhelm those due to typical random radial velocity error (see e.g. [Gasch et al., 2020, Gasch et al., 2023, Rahlves et al., 2022, Robey and Lundquist, 2022]), but are difficult to quantify based on the lidar measurements alone.
To enable insight in the single profile intercomparisons, we added plots of all radiosonde-lidar comparisons to the radiosonde comparison dataset (see data availability statement).
We have now included this discussion Sect. 5.3 and Fig. 16 to characterize the performance as a function of CNR. We added plots of all single radiosonde comparisons to the provided dataset.

Minor Comments:

First Guess: It is not appropriate to call the results of the initial VAD fit as first guess. It is a result of the full VAD retrieval, and not a guess. I suggest the authors replace it with initial result or first result.
We changed it into *initial retrieval/initially retrieved wind profiles* as suggested by reviewer.

Line 126: "CNR is not a completely reliable indicator". This is a misleading statement. One could argue no variable is a completely reliable indicator. One could always filter out very high CNR data to remove contamination from hard targets or moving objects. I suggest the authors revise this statement to "CNR for each lidar needs to be carefully characterized to determine the appropriate thresholds for reliable data".
We agree. The revised version is: *"The CNR is system and measurement setup dependent and needs to be carefully characterized to determine the appropriate thresholds for reliable measurement".*
We revised this sentence.

Line 182: How and why does time coordinate differ between level 0 and level 1 data? It seems level 1 data is just standardizing the data format for different types of lidars?
This is correct. Level 1 is a standardized data format to homogenize data from different lidar types. The time coordinate between level 0 and level does not differ. An exception is if the timestamp indicated in the level 0 dataset does not represent the centre of the measurement interval and the difference is not negligible. In that case the coordinate of the level 1 dataset could be shifted.
We clarified the meaning of level 0 and level 1 in the revised text.

Line 188: It is not clear why anyone would want to change the range gate settings for different scans. It seems less practical and adds to complexity to lidar operation, data analysis, and in case of this paper, complexity of description. For simplicity, I suggest the authors use same settings for all scans so that the number of range gates is limited by the pulse repetition frequency (PRF), and all scans use same number of range gates. In that case, Figure 2 will look same as Figure 3 with all the block filled in.
For DBS scans on the WLS200s system, available from the factory settings, the vertical beam utilizes different range gate lengths than the tilted one. Such a setup enables ordinary retrievals to calculate wind vectors based on range gates, while ensuring availability of a vertical beam measurement within every retrieval volume. Since we operate multiple WLS200s and the DBS scan is a factory setting we have the requirement of dealing with changing range gate numbers within a single scan. Thereby, the software is required to consider different range gate settings even within one scan.
We highlighted in the introduction that users with no influence on the measurement setup (e.g. using the default WLS200s DBS scan), as well as Doppler lidar operators with opportunity for individual settings, are addressed.

Line 188: I would assume level 0 data is in range gate index, and you add range information in level 1? For example, the StreamLine level 0 data used to include range gate index and not range. Maybe this has changed with newer versions?
Yes, StreamLine hpl files include range gate indices, but WLS200s include ranges, WLS7 defines vertical altitudes. To standardize and enable homogenized retrieval, we propose the suggested data format.
No changes.

Line 446: The lower number of retrieved bins in simple -30 dB CNR threshold retrieval due to +/-3 m/s

filtering?
Yes.
We clarified this in the text.

Figure 7 & 8: It would be better to include Figure 8 as the 4th panel in Figure 7. Figure 8 caption: The data gap is at 21:40 UTC.
This is a good suggestion. We thank you for the careful reading and corrected this mistake.
We included the figure as a subpanel and corrected the mistake.

Figure 12: Is the omitted radiosonde profile shown as x?
Yes.
We added a note in the Figure caption.

Supplementing figures

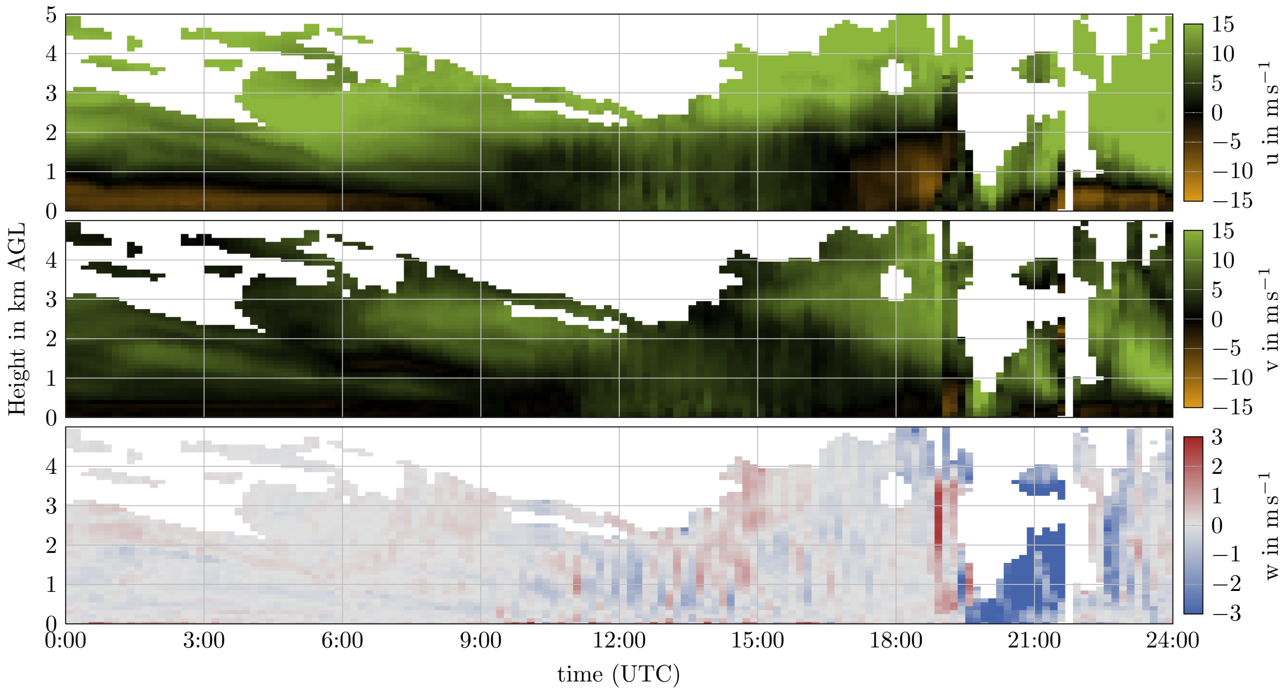

Figure 1: Result of modules (1) to (6) with a CNR threshold of −25 dB in module (4). In sum, 4945 wind vectors are retrieved (compared to 5556 vectors when using the proposed standard module chain).

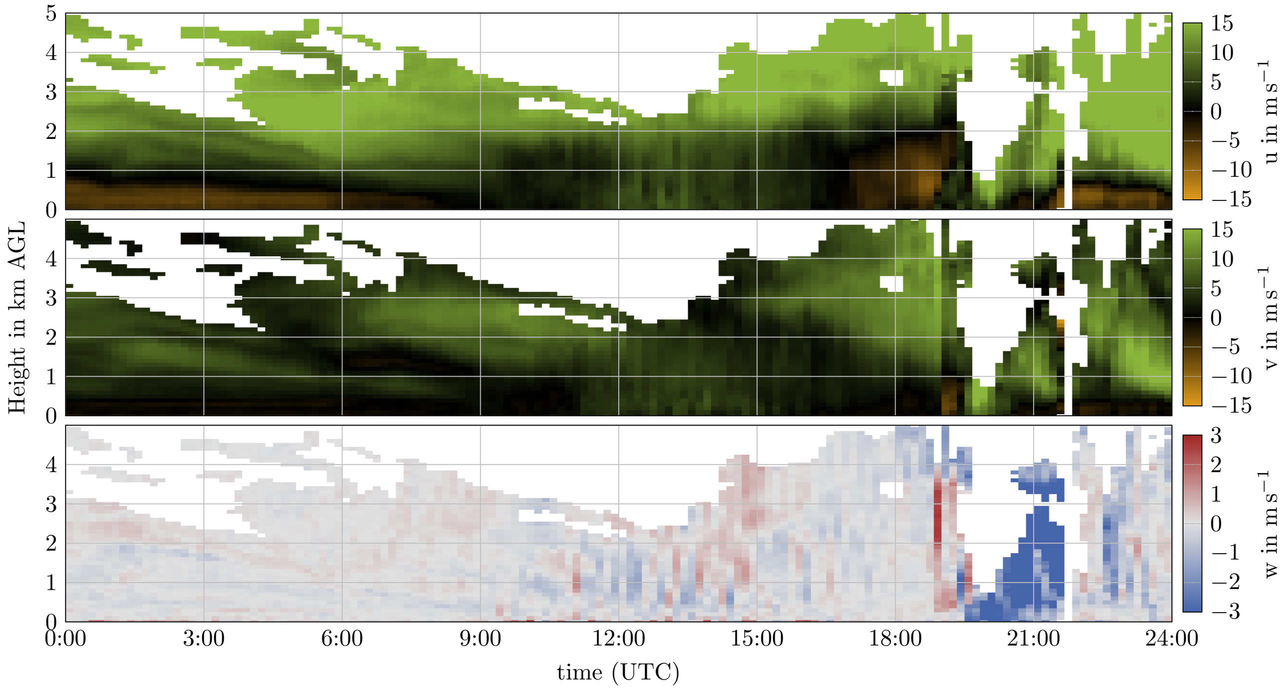

Figure 2: Result of modules (1) to (6) with a CNR threshold of −26 dB in module (4). In sum, 5091 wind vectors are retrieved (compared to 5556 vectors when using the proposed standard module chain).

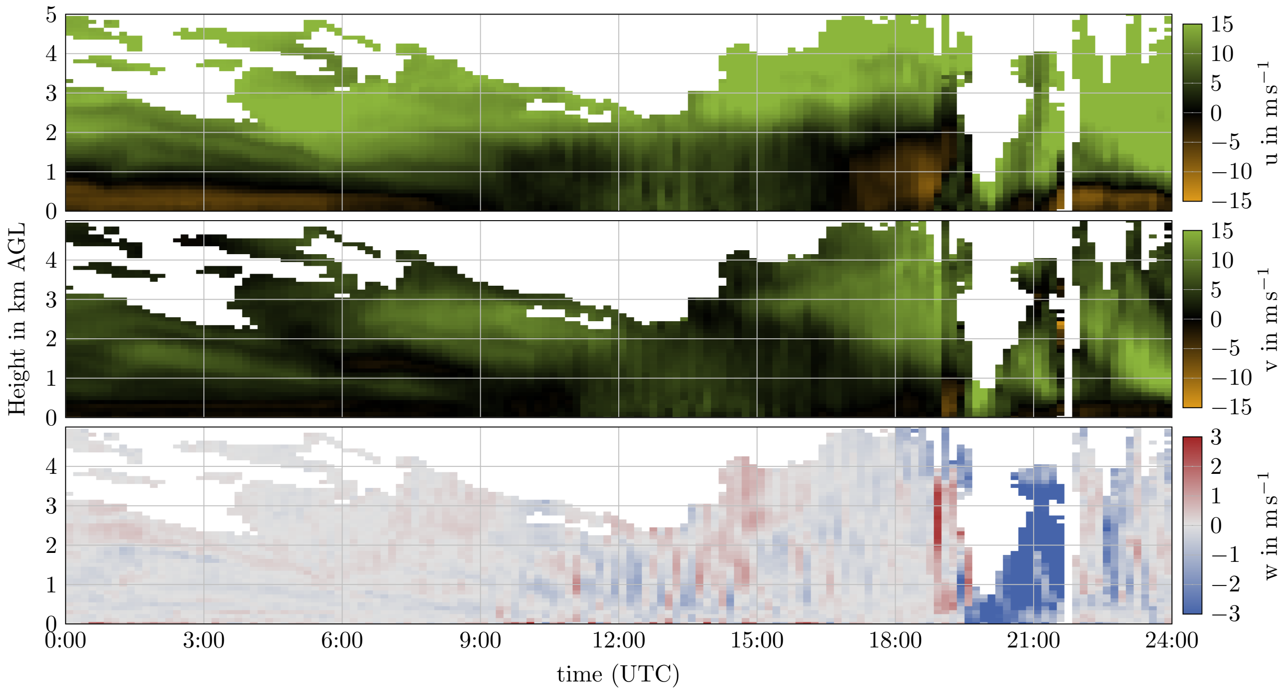

Figure 3: Result of modules (1) to (6) with a CNR threshold of −27 dB in module (4). In sum, 5193 wind vectors are retrieved (compared to 5556 vectors when using the proposed standard module chain).

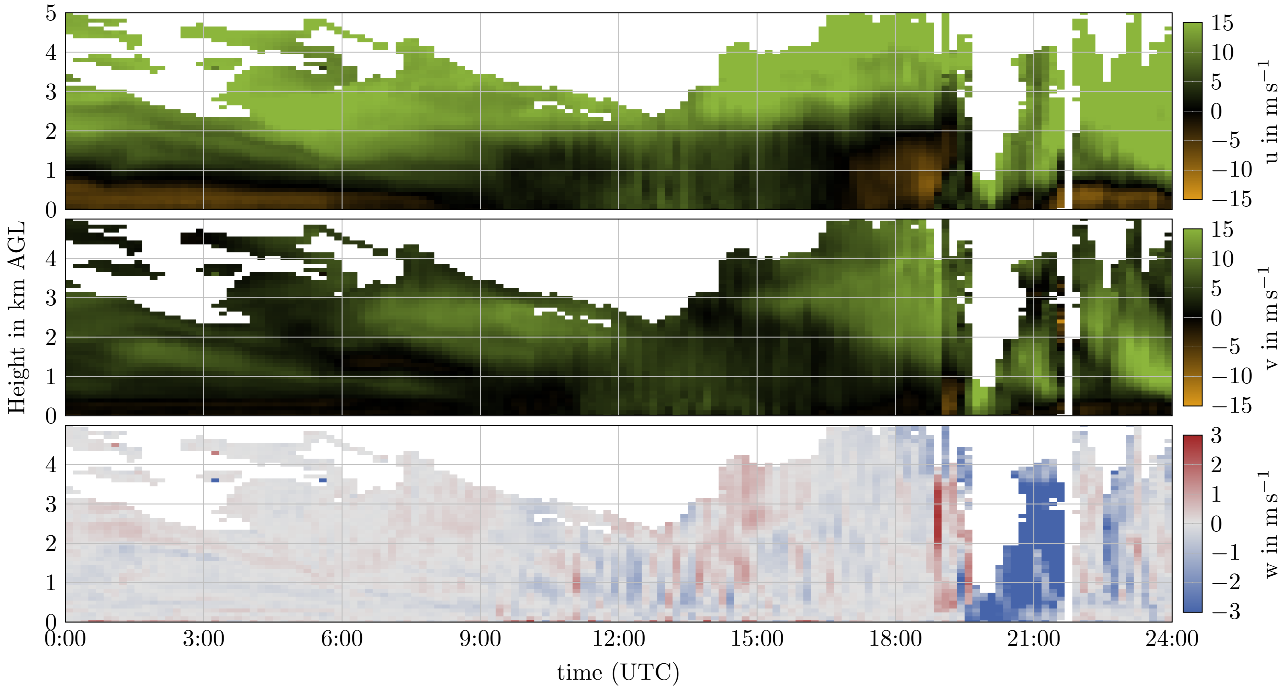

Figure 4: Result of modules (1) to (6) with a CNR threshold of −28 dB in module (4). In sum, 5293 wind vectors are retrieved (compared to 5556 vectors when using the proposed standard module chain).

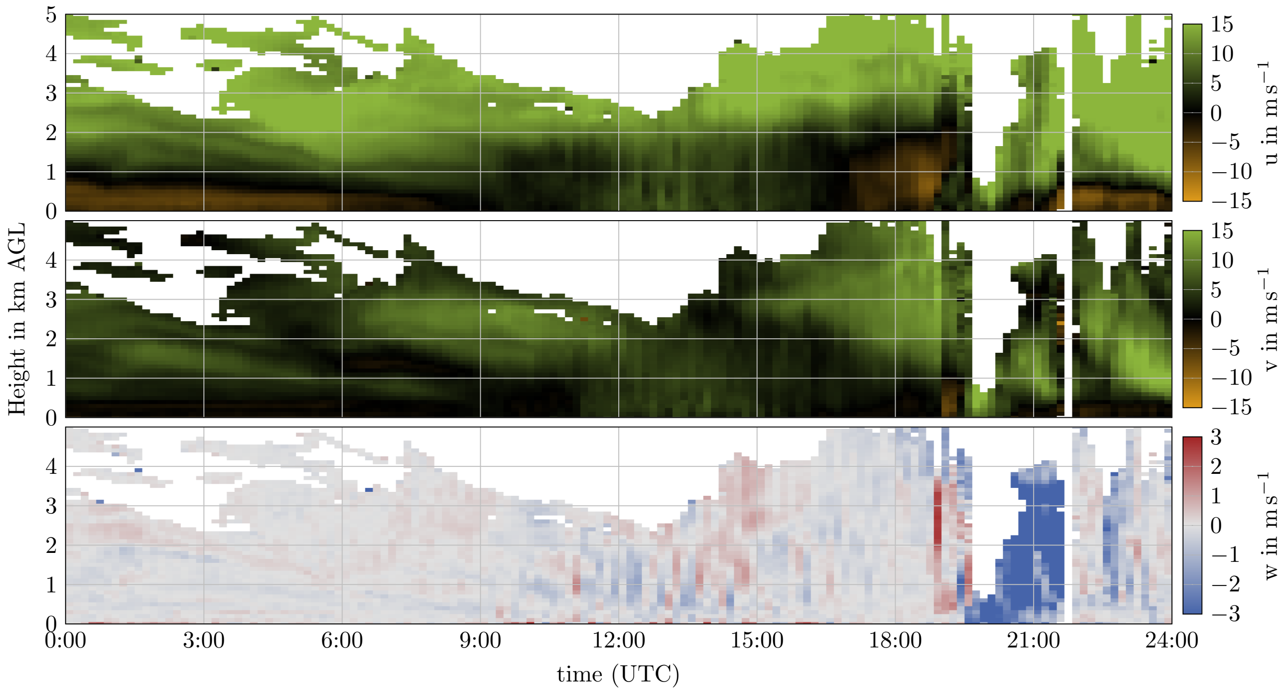

Figure 5: Result of modules (1) to (6) with a CNR threshold of −29 dB in module (4). In sum, 5380 wind vectors are retrieved (compared to 5556 vectors when using the proposed standard module chain).

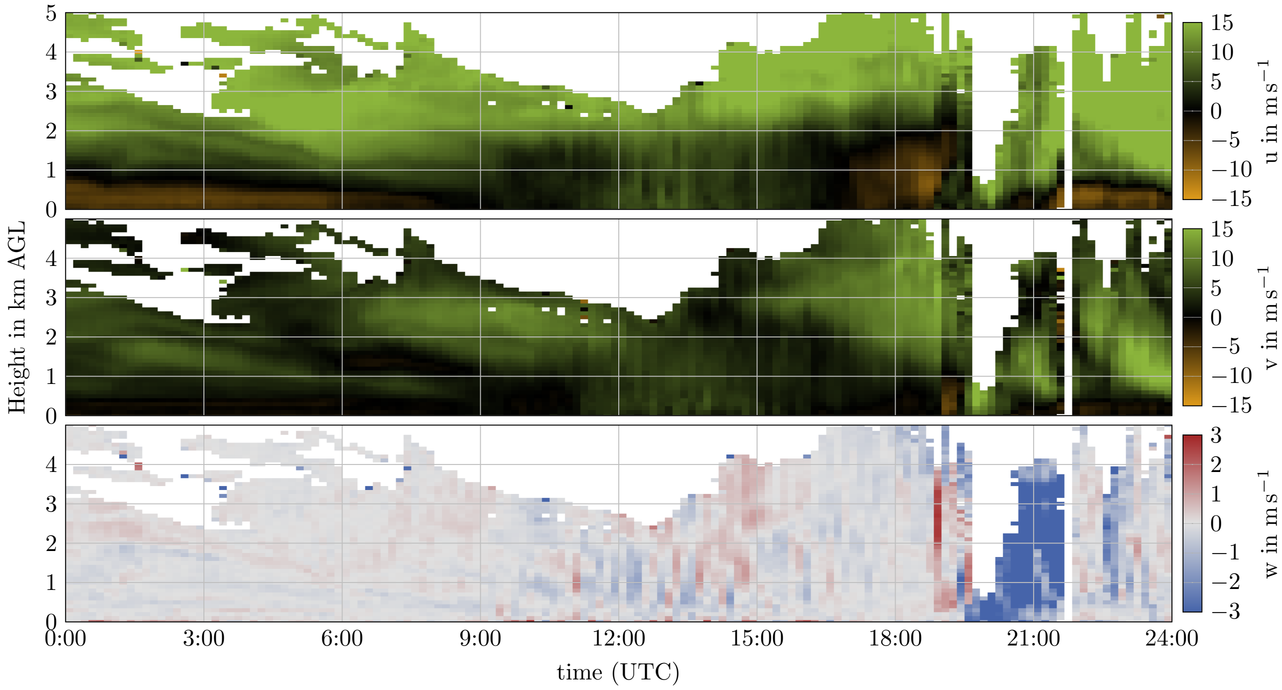

Figure 6: Result of modules (1) to (6) with a CNR threshold of −30 dB in module (4). In sum, 5451 wind vectors are retrieved (compared to 5556 vectors when using the proposed standard module chain).

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