

General Response to Referee #1

Original referee comments are in blue.

Our responses are in black with regular font format. Text from the updated manuscript:

Appears in italic and with ½ inch indentation and with the modified parts in red.

The manuscript for Pallotta et al. provides an overview of a processing chain which was developed for the South American lidar Network. The developments are based on open science and are all available on github, which is very honourable and I really appreciate the efforts and work the authors have made.

We are grateful for the encouraging comments. Although the scientific community is moving towards open science (see for instance NASA's TOPS program: [https:// science.nasa.gov /open-science/transform-to-open-science](https://science.nasa.gov/open-science/transform-to-open-science)), developing open-source code is still a hurdle, and the lidar community has not yet fully embraced the idea. As far as we know, our processing routines are the only publicly available lidar analysis routines meant to be distributed freely and to be applicable to any elastic lidar system.

However, I have strong doubts that the current manuscript fulfils the requirements for a research article and is thus appropriate for this journal. It is currently more a technical report, which, however, is not a valid manuscript type within this journal. The reasons are the following:

1. There is nothing scientifically new in this manuscript as the authors use existing approaches to homogenize the different hardware of the lidars in South America in terms of data analysis
2. Mostly, there are pure technical descriptions which are not relevant for a research article reader
3. On the other hand, the current manuscript is incomplete in terms of methodology description (e.g., how to determine the reference height and value, how does the feature mask really work.

The aim of this first paper is to (1) present the processing pipeline, as a publicly-available chain of lidar processing routines, (2) report on the development of a pipeline suitable for a heterogeneous network, and (3) discuss initial results based case studies. The algorithms behind the processing pipeline are not the main focus of this manuscript, instead, the focus is on giving a high-level view of our processing. Moreover, while we agree with the referee that the description of the pipeline is not a scientific novelty, the session on our initial results, now extended, corresponds to previously unpublished scientific data, both simulated and observed.

To emphasize these aspects of our manuscript, we have modified the **Introduction** and the fourth paragraph now reads:

*In recent years, the **LALINET** network has worked towards establishing routine quality-assurance tests and intercomparing the retrieval algorithms used by the different groups (Guerrero-Rascado et al., 2016; Barbosa et al., 2014). Here, **our first goal is to present a high-level overview of the Lidar Processing Pipeline (LPP), an ongoing and unfunded coordinated effort to homogenize the retrievals from different lidar instruments in Latin America. Our second goal is to introduce the tools developed to handle all the steps of a typical lidar analysis. We want to emphasize the modular framework that is generic***

enough to be applicable to any lidar instrument or network and, at the same time, also emphasize the open source character of the LPP development (see Code availability). Our third goal is to show how LPP performs, through quantitative and qualitative analyses of simulated and measured lidar signals. We will discuss case studies based on simulated and measured signals and analyze aerosol backscatter retrievals for elastic lidar signals and layer masking (clouds or aerosol), which are the focus of this first public release of LPP.

We also modified the **Abstract**:

Atmospheric lidars can simultaneously measure clouds and aerosols with high temporal and spatial resolution and hence help understand cloud-aerosol interactions, which are the source of the largest uncertainties in future climate projections. However, atmospheric lidars are typically custom-built, and there are significant differences between them. In this sense, lidar networks play a crucial role as they coordinate the efforts of different groups, providing guidelines for quality-assured routine measurements, opportunities for side-by-side instrument comparisons, and enforce algorithms validation, all aiming to homogenize the physical retrievals from heterogeneous instruments in a network. Here we provide a high-level overview of the Lidar Processing Pipeline (LPP), an ongoing, collaborative, and open-source coordinated effort in Latin America. The LPP is a collection of tools that have the ultimate goal of handling all the steps of a typical analysis of lidar measurements. The modular framework is generic enough to be applicable to any lidar instrument. The first publicly released version of LPP produces data files at levels 0 (raw and metadata), 1 (averaging and layer-mask), and 2 (aerosol optical properties). We assess the performance of LPP through quantitative and qualitative analyses of simulated and measured elastic lidar signals. For noiseless synthetic 532 nm signals with a constant LR, the root-mean-square error (RMSE) in aerosol extinction within the boundary layer is about 0.1 %. In contrast, retrievals of aerosol backscatter from noisy signals with a variable LR have an RMSE of 11 %, mostly due to assuming a constant LR in the inversion. The application of LPP for measurements in Sao Paulo, further constrained by co-located AERONET data, indicates a lidar ratio of 63.9 ± 6.7 sr at 532 nm, in agreement with reported values for urban aerosols. Over the Amazon, analysis of a 6-km thick multi-layer cirrus indicates a cloud optical depth of about 0.77, also in agreement with previous results. From this exercise, we identify the need for new features and discuss a roadmap to guide future development, accommodating the needs of our community.

We note that our approach is very similar to the one adopted by the European Lidar community, which developed the Single Calculus Chain (SCC). Their first paper on AMT just gives an overview of their pipeline and how it would be routinely used in the context of EARLINET:

<https://amt.copernicus.org/articles/8/4891/2015/>

Referee #3 wrote the following for this first SCC paper:

"In spite of the lack of technical information regarding the Earlinet algorithms and the general qualitative nature of the paper, I regard it as still being a useful submission. This paper does give the reader a good overview and appreciation of the issues surrounding the implementation of a standard processing chain complimented on top of a network which is heterogeneous in terms of hardware."

<https://amt.copernicus.org/preprints/8/C1647/2015/amtd-8-C1647-2015.pdf>

The methods behind SCC were only described in a pair of follow-up publications a year later:

Part 1 (pre-processing): <https://amt.copernicus.org/articles/9/491/2016/>

Part 2 (optical products): <https://amt.copernicus.org/articles/9/3009/2016/>

Finally, we would argue that this approach, and hence this type of manuscript, does indeed fit the scope of GI. According to the journal's website ([https://www. Geoscientific-instrumentation-methods-and-data-systems.net/about/aims_and_scope.html](https://www.Geoscientific-instrumentation-methods-and-data-systems.net/about/aims_and_scope.html)), their focus is not strictly on novel scientific findings, but:

"(...) A unique feature of the journal is the emphasis on the synergy between science and technology that facilitates advances in GI. These advances include but are not limited to the following:

- (...)
- *concepts, design, and description of data systems;*
- *major national and international field campaigns and observational research programmes;*
- *networking of instruments for enhancing high temporal and spatial resolution of observations;*
- *advanced data analytics and assimilation methods;*
- *citizen science data management;*
- (...)"

4. Most of this missing information might be available on github, BUT I have to judge the current manuscript and the information stored on github are not persistent. I.e., just today I went to the repository and see that the most recent changes are only some days back, while the manuscript was submitted weeks ago.

We apologize for that. We are indeed actively developing the code, and that is why you found these recent updates. However, we understand the need to reference a specific version in the paper and in the GIT repository, and we have now created a tag for version 1.1.0 which is exactly the version discussed in the paper.

This is now explained in the manuscript, in section *Code Availability*:

The Lidar Processing Pipeline Version 1.1.0 reported here can be obtained from the GitHub repository <https://github.com/juanpallotta/LPP/releases/tag/v.1.1.0> under a MIT license that enables reuse, redistribution, and reproduction of all methods.

5. Many of the action items listed in the outlook have also been already published by other groups for other processing chains but are not yet referenced. Thus, the paper lacks also a kind of more complete literature review.

We presented the action list (roadmap) to indicate the next steps in our algorithm development. A future paper that describes the algorithm in detail, including these new developments, will certainly cite all the relevant literature. However, we agree with the referee that mentioning other efforts even in this early stage could be useful. We have modified the *Future Roadmap* section as shown below. If there are other references the referee would recommend citing here, please let us know.

With the first release of LPP and its use by the different groups in LALINET, we have identified the necessary improvements and built a roadmap to guide future development. An initial consideration is that LPP processed data files must be FAIR (Findable, Accessible,

Interoperable, and Reusable) (Wilkinson et al., 2016) to be compatible with Open Science. In this sense, more information about the site, hardware, operation, files processed, and even the version of LPP used needs to be added as metadata in the output files. Moreover, the benefit of LPP's highly modular concept is the possibility of different groups modifying and testing different modules without interfering with the rest of the pipeline. To facilitate the customization of the pipeline to fulfill different needs and to allow more groups to contribute to LPP's development, future releases will include Python versions of all modules.

In terms of improvements in the physical retrievals, we have identified three priorities. First is to implement the Klett (1985) solution to the lidar equation with a range dependent LR. This would be useful, for instance, for the Sao Paulo station where the sea breeze frequently brings marine aerosols above the urban-polluted boundary layer (Rodrigues et al., 2013; Ribeiro et al., 2018). The second is to obtain the uncertainties in the extinction and backscatter coefficients by propagating the signal errors using a Monte Carlo approach (Press, 2007), following the work of Alvarez et al. (2006) and Mattis et al. (2016). Finally, we plan on implementing the Raman solution (Ansmann et al., 1992), but this might require an intercomparison effort of the existing algorithms in LALINET, as was done in EARLINET (Pappalardo et al., 2004). Moreover, in LALINET, the stations recording Raman return signals have photon-counting channels, which might be affected by dead-time effects (Johnson et al., 1966). Hence, we need to implement the known dead-time corrections for paralyzable and non-paralyzable systems (Whiteman et al., 1992; Knoll, 2010), which would also allow for 'gluing' the analog and photon-counting to extend the instrument dynamic range (Whiteman et al., 2006; Newsom et al., 2009).

Regarding the automation of the pipeline, a few updates are planned. For instance, we noticed that only a few lidar stations in Latin America have a nearby radio-sounding site, and it is only once or twice per day. To facilitate the processing of level 1 and level 2 data, an automatic "thermodynamic profile downloader" will be developed to obtain a co-located thermodynamic profile from a nearby radio-sounding, a forecast model, or a reanalysis. The MPLNET data processing, for example, automatically retrieves meteorological profiles from the Goddard Earth Observing System, version 5 (GEOS-5), atmospheric general circulation model for all molecular calculations (Lewis et al., 2016). We also plan to implement a method of re-scaling the standard atmosphere profiles based on co-located ground-based temperature and pressure measurements, which could also be retrieved automatically from meteorological databases.

Moreover, a well-known problem with the inversion of elastic lidar data is the need to assume an a priori lidar ratio. The typical solution is to choose a lidar ratio that brings the estimated AOD value closer to the reference value measured by AERONET, which can now be measured at day and nighttime (Perrone et al., 2022). This analysis can be made a-posteriori, as shown in Figure 4, but implementing an optimization routine would allow LPP to automatically identify the best LR for each profile, as has been done in previous studies (Cordoba-Jabonero et al., 2011; Roman et al., 2018), help reduce systematic errors (Welton and Campbell, 2002). The user could provide the reference AOD value, or it could be obtained by an "AOD data downloader" tool as part of the LPP framework.

Therefore, I propose the following: The authors should publish their Lidar Processing Chain Code and Description as it is on github via some platform which allow to issue DOI. For example, zenodo

can be used for this. Then, they either use this published code as publication only with the current draft manuscript as introductory comment and skip the publication of a manuscript in this journal

We thank the referee for the suggestion. However, as already mentioned, the goal of this paper is to give a high-level view of our processing pipeline and present initial results. According to our understanding, this initial overview paper would be a suitable type of manuscript for this journal. Regarding the suggestion to use Zenodo, we tried it but it is not a viable solution. The Zenodo DOI is linked to a GitHub release version, and it only includes as authors the code developers, i.e., the individuals with GitHub accounts who performed changes in the project's source code. This is unfair because important contributions to the development, like testing the code, discussing the methods, etc., are not accounted for. Some of the manuscript authors don't even have a GitHub account. In this sense, we think that a paper is the best way to publicize the LPP's software and get a DOI. Sharing the code can be done via the GitHub tagged version, which we explained before.

Or, after also having published the code and description with a DOI, they revise the current manuscript in a way, that it can be a research paper. For this, the scientific methods should be more intensively described, and differences to other processing chains (e.g. SCC, PollyNET, Ad-Net..) need to be highlighted.

We thank the referee for the suggestion.

Following the comments of both referees, we have improved the manuscript substantially, giving more details on the methodology, less on the computational aspects, and introducing a quantitative evaluation of the aerosol retrievals. However, very specific details on particular methods (e.g. feature mask) will be given in upcoming publications. These will cite the relevant literature and show analysis aimed at validating such new methods.

Having said that, we do not agree that highlighting "differences to other processing chains" would be relevant. First, we are not validating a new algorithm. Second, the algorithms used by SCC, MPLNet, and ADNet are not completely open and publicly available, and hence it would be complicated to perform a direct comparison. For SCC, for instance, we would have to create an account on their website, upload our data for remote processing, and then download the results. The only other publicly available algorithm, to our knowledge, is the one developed in Tropos/Germany for the PollyNet network:

https://github.com/PollyNET/Pollynet_Processing_Chain

However, it is designed for PollyXT systems, and we would have to investigate how much work it would be to adapt it for different systems.

We are now acknowledging this in the conclusions, where we added this as a final paragraph:

Although the scientific community is moving towards open science, developing open-source code is still a hurdle, and the atmospheric lidar community has not yet embraced the idea. Consolidated networks have long developed their own algorithms and pipelines, which unfortunately remain mostly inaccessible to the community, hampering faster scientific advancement. We hope open-source efforts, as the one presented here, become the rule rather than the exception in the near future.

We hope the updated manuscript will please the referee, and that all the changes implemented will make it clearer that our manuscript is a research paper.

Furthermore, the used methods need to be referenced or, if new, described. Of particular interest would be, e.g., how dead time correction is done (if done), how the reference value and height for the Fernald method is determined, how exactly the background subtraction is performed ...

Thanks for the suggestion.

We revised the methods section and expanded the description of the different steps, corrections, and analyses. The background subtraction was explained in the section about the Level-1 data, but we expanded it to read (see also our response to your minor comment on line 90):

The background noise can be found by averaging the signal in a high altitude range, defined in the configuration file, where the lidar signal is completely extinguished. Alternatively, it can be found by performing a so-called Rayleigh-Fit. In this case, it corresponds to the constant term in a linear least-square-fit between the lidar signal and the molecular signal, as in Grigorov et al. (2013) and Barbosa et al. (2014).

The current version of LPP does not yet include dead-time correction for the photon-counting channels. Most LALINET systems record the return signal only in Analog mode, hence the first LPP release focused on the analysis of the analog channels. This will be more important for the next release, when we plan to include the Raman inversion. By the way, we also do not glue the analog and photon-counting. We added the following new text in the *Future Roadmap* section to explain the future need for these corrections (the full Roadmap section appears in the response to your major comment #5):

Moreover, in LALINET, the stations recording Raman return signals have photon-counting channels, which might be affected by dead-time effects (Johnson et al., 1966). Hence, we need to implement the known dead-time corrections for paralyzable and non-paralyzable systems (Whiteman et al., 1992; Knoll, 2010), which would also allow for "gluing" the analog and photon-counting to extend the instrument dynamic range (Whiteman et al. 2006; Newsom et al., 2009).

About the Fernald reference: In this first version of LPP, the reference height (H_{ref}), is an input parameter, i.e., it is not computed automatically. The reference signal, $P(H_{ref})$, which we assume contains no aerosol contribution, can be calculated in two ways: (1) averaging the signal or (2) using the value of the molecular fit at the reference height. In both cases (average or molecular-fit), we consider an altitude range around the reference height, defined by the user. This is now explained in the section for the data level 2:

In this first release of LPP, the optical properties are obtained from the analog elastic channels using the Fernald method (Fernald, 1984). The value of the lidar ratio (LR), assumed to be constant, is set by the user in the configuration file. When multiple LR values are given, the inversion is performed for each value, producing a set of optical properties. The reference height, z_0 , is not determined automatically, and must be set by the user as well. The reference signal, $P(z_0)$, which we assume contains no aerosol contribution, can be calculated either by averaging the signal or by taking the value of the molecular fit at the reference height. In both cases, this is evaluated in an altitude range defined by the user. The

aerosol optical depth (AOD) is calculated assuming the extinction to be constant below a specific range (defined in the setting file), where the incomplete overlap precludes its calculation.

New References:

- Barbosa, H. M. J., Barja, B., Pauliquevis, T., Gouveia, D. A., Artaxo, P., Cirino, G. G., Santos, R. M. N., and Oliveira, A. B.: A permanent Raman lidar station in the Amazon: description, characterization, and first results, *Atmospheric Measurement Techniques*, 7, 1745–1762, 2014
- Grigorov, I. and Kolarov, G.: Rayleigh-fit approach applied to improve the removal of background noise from lidar data, in: 17th International School on Quantum Electronics: Laser Physics and Applications, edited by Dreischuh, T. N. and Daskalova, A. T., vol. 8770, p. 877010, International Society for Optics and Photonics, SPIE, 2013
- Johnson, F. A., Jones, R., McLean, T. P., and Pike, E. R.: Dead-Time Corrections to Photon Counting Distributions, *Physical Review Letters*, 16, 589–592, 1966
- Knoll, G. F.: Radiation detection and measurement, John Wiley, Hoboken, N.J, 4th ed edn., 2010
- Newsom, R. K., et al.: Simultaneous analog and photon counting detection for Raman lidar, *Applied Optics*, 48, 3903, 2009
- Whiteman, D. N., et al.: Raman Lidar Measurements during the International H₂O Project. Part I: Instrumentation and Analysis Techniques, *J. Atmos. & Oceanic Tech.*, 23, 157–169, 2006.
- Whiteman, D. N., Melfi, S. H., and Ferrare, R. A.: Raman lidar system for the measurement of water vapor and aerosols in the Earth's atmosphere, *Applied Optics*, 31, 3068, 1992.

Furthermore, in the introduction or an own section, the possible differences of different lidar systems should be more detailed described (e.g., analog detection vs. photon counting, pre-trigger vs. far-range background, scanning vs. stare mode etc.). Only by doing so, the reader which is not (yet) a complete Lidar expert can understand the need for this chain and why some variables might be needed and what they mean.

Thank you for the suggestion. While we agree that it is important to emphasize how heterogenous our network is, this manuscript is not about the measurement stations. Hence, providing a complete list of all the stations would be beyond its scope; moreover, such description is available on the LALINET website (always up-to-date) and in previous publications (e.g. Antuna 2017 and Landulfo 2020, which are now cited). Having said that, we included the following discussion and table, which highlights how different all the systems are:

There are currently 19 stations in 6 countries, most of which are equipped with tropospheric aerosol lidars measuring one or more elastic return signals; only a few systems can measure inelastic return signals, typically for N₂ and H₂O Raman scattering. Table 1 shows the wide distribution of emitted wavelengths and detection modes. Other important differences are found in the laser repetition rate (ranging from 10 to 30 Hz), beam expander factor (1 to 5x), mirror diameter (20 to 50 cm), telescope focal length (1 to 4 m), and width of the interference filters (0.25 to 1 nm). Finally, only a few stations have co-located or nearby measurements of the aerosol optical depth and the thermodynamic profile. More details about the network can be found in Landulfo et al. (2020).

Table 1. Number of stations in LALINET for each combination of emitted wavelength and detection modes.

	Emitted Wavelength		
Detection	355 nm	532 nm	1064 nm
Total Elastic	5	6	12
Cross Elastic	10	10	1
Parallel Elastic	10	10	1
HSRL	-	3	-
N2 Raman	7	4	-
H2O Raman	6	-	-

Beside this. some minor language editing would be needed.

Below you will find a point-by-point response to all your suggestions in the annotated manuscript. All the recommendations were accepted.

I again have to say, that I really appreciate the efforts and work the authors have done, but as a reviewer, I have to judge in this case a manuscript submitted as a research article which in my opinion the current manuscript is not.

We appreciate the acknowledgment of our efforts and understand the concern of the referee. However, we hope that all the modifications, including the new quantitative analysis, as well as our reasoning about the journal's policy and about the similar case of EARLINET's SCC convinced the referee about the validity and value of such an overview paper.

Point-by-point response

L14: Ref#1 Comment: ? authors?

We fixed the problem with this reference.

L17: Ref#1 Comment: t

Corrected: "no" instead of "to"

L18-19: Ref#1 Comment: reference for this statement? E.g; doi:10.5194/atm-9-1001-2016

Thank you for the suggestion. We added the reference.

L31: Ref#1 Comment: ?

Corrected "one more" to "one or more".

L31: Comment: phrasing. One cannot measure inelastic channels.

Fixed. The new text reads:

There are currently 19 stations in 6 countries, most of which are equipped with tropospheric aerosol lidars measuring one or more elastic return signals; only a few systems can measure inelastic return signals, typically for N₂ and H₂O inelastic Raman scattering.

L35: Ref#1 Comment: strikethrough

Corrected. The word *physical* was removed.

L40: Ref#1 Comment: what does it mean?

Corrected by removing “*molecular calibration*”.

L46: Ref#1 Comment: what is this? Please add a reference.

Corrected: reference was added.

L53: Comment: very technical

We agree that this part of the methodology was unnecessarily too technical. The three paragraphs in this session were shortened to:

The Lidar Processing Pipeline is being developed in a partnership between the lidar groups of the Latin American Lidar Network. The LPP reads a series of raw data files in the standard Licel format (Licel, 2023) and produces a NetCDF file containing its data levels products 0, 1, and 2. The processing pipeline has three main modules responsible for data processing at each level, all written in C/C++. These modules are independent, and the whole pipeline can be automated with a Linux shell script, or each module can be run directly in a Linux terminal.

The modules are driven by a single configuration file, and the input data for each module is the output file produced in the previous stage, as can be seen schematically in Figure 1. Moreover, the output file of a given level (e.g., 2) contains all the content of the previous level (e.g., 1) in addition to the new information generated in that level of data processing. In other words, all the information used to process the data to a given level is available in the corresponding file, thus allowing its reprocessing if needed. Figure 2 shows the content of a level 2 data file. The following sections explain the concept of each data level.

Figure 1: Ref#1 Comment: not understandable with the current description, nor in caption or text. EG. what is PDL2?

We agree this was confusing. Moreover, the figure was not matching the description in the paragraph on line 53, where the referee also asked for clarifications. We have modified the figure to match the revised section **2 PROCESSING PIPELINE** to avoid unnecessary technical details. This is the new figure and caption:

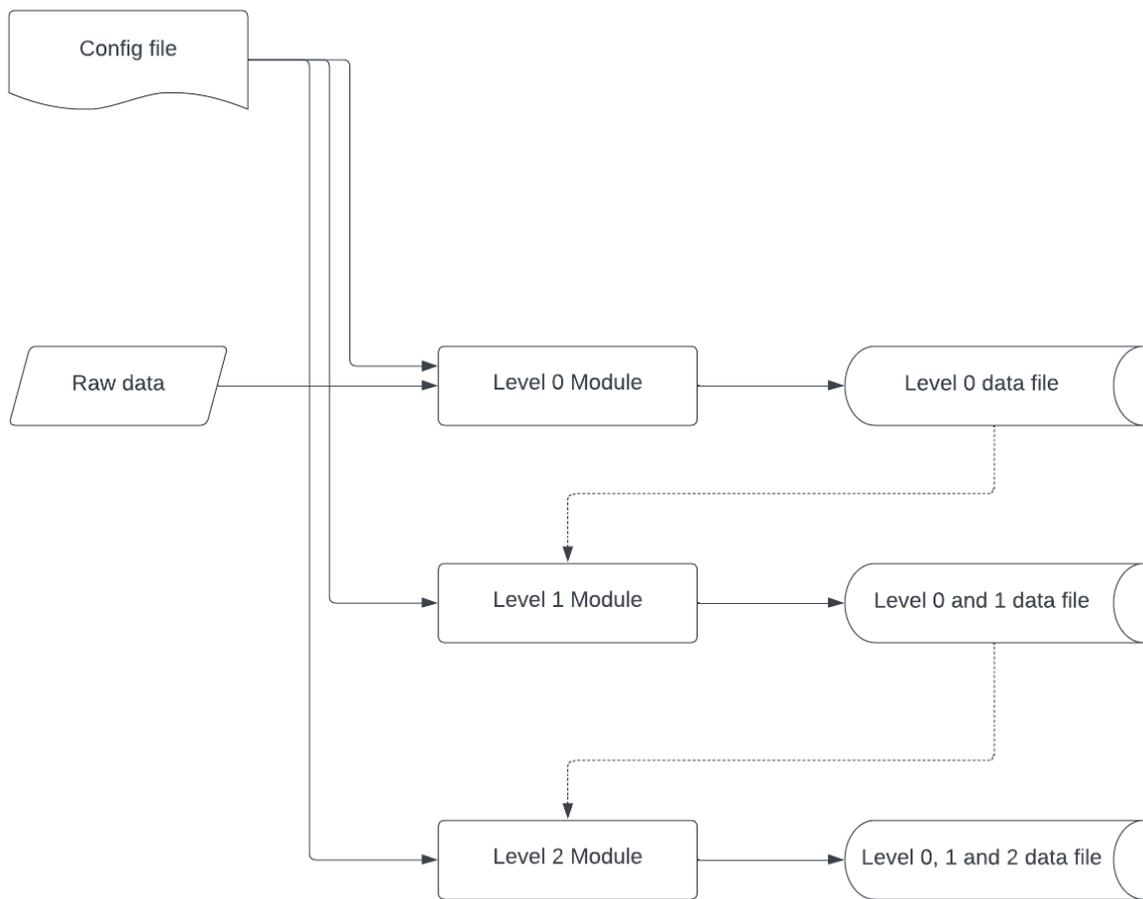


Figure 1. Flow diagram showing the structure of LPP version 1.1.0. **Each module receives as input the data file produced as output in the previous module. A single configuration file is used for all the modules.**

L55: Ref#1 Comment: very, very technical

Please see our response to your comment on L53 and Figure 1.

L60: Ref#1 Comment: as stated below, needs to be published so that it is available for many years. Best with a DOI, otherwise the whole publication is worthless.

We agree. Anyone looking at our paper in the future should be able to find and use the exact processing pipeline we are discussing. We have now created a GitHub release version, so the paper corresponds to v1.1.0 accessible here: <https://github.com/juanpallotta/LPP/releases/tag/v.1.1.0>

We modified the section about the code availability accordingly:

The Lidar Processing Pipeline Version 1.1.0 reported here can be obtained from the GitHub repository <https://github.com/juanpallotta/LPP/releases/tag/v.1.1.0> under a MIT license that enables reuse, redistribution, and reproduction of all methods.

L66-67: Comment: I know what you mean, but it might not be obvious for each user. Maybe add a table describing all these variables/attributes

We thank the referee for the suggestion. However, this is very specific information, taken directly from the header of the lidar files, and the referee suggested a few other changes to make the manuscript less technical. Therefore, instead of adding a table we included a reference for the Licel technical documentation and we modified this paragraph to read:

This includes all the information from the header of the raw files that describe the measurements, the instrument, and the site, such as filename, site name, start and stop time of the measurement, altitude, latitude, and longitude of the site, zenith and azimuth angles of the lidar signals (in case of scanning lidars), accumulated laser pulses, laser repetition rate, and the number of channels acquired. A description of these parameters is found in (Licel, 2023)

Refs.:

Licel GmbH: Licel Transient Recorder and Ethernet-Controller Programming Manual, Accessed: February 18, 2023, <https://licel.com/manuals/programmingManual.pdf>, 2023

L68: Ref#1 Comment: not explained

Corrected to “*photomultiplier*”.

L68: Ref#1 Comment: what is this?

Thank you for pointing out that this part was not clear enough.

What we mean here is the number of bits used in the conversion of the analog signal to digital, and the scale used for that conversion. Licel's hardware, used in all LALINET stations and most lidar instruments world-wide, has an *analog-to-digital converter (ADC)* that will convert the analog signal (a continuous value) into a digital signal (an integer number). This is computed as usual by:

$$\text{ADC count} = \text{round} \left((\text{analog signal}) / (\text{analogMaxRange} / (2^{\text{ADCbits}} - 1)) \right)$$

However, we believe this would be too much detail, as this is standard in lidar hardware and data. But we modified this line to read:

For analog channels, the number of bits and range of the analog-to-digital converter (ADC) are recorded, while for photon counting channels, the discriminator level is recorded.

L70-71: Comment: what does this mean? What is stored in the raw data?.

The "ADC readings" refers to the integer number computed by the ADC when it converts from the physical signals (analog or photoncount) into their digital (integer) counterpart. The following sentence (old Lines 71-73) explained that we do not convert those integer values into physical quantities, i.e., floating point numbers with units. Hence, our data level 0 contains the raw ADC counts.

To avoid any confusion, we changed the sentence as follows:

For each channel, the raw ADC counts are saved as 2-dimensional arrays indexed in height and time. Therefore, level 0 data consists of ADC counts for both analog and

photoncounting channels, i.e., the raw values are not converted to mV (analog) or MHz (photon counting).

L76: Ref#1 Comment: strikethrough

Corrected

L79: Ref#1 Comment: you never explained what this is

Agreed. We modified this line to give further explanation:

L1 data includes updated start and stop times for each averaged profile and time-averaged values for the lidar signals. For scanning lidars, zenith and azimuth pointing coordinates are also averaged and saved.

L84: Ref#1 Comment: phrasing

Thanks for pointing out this was confusing. We modified the explanation about the zero-bin and bin-shift tests as follows:

The first is the trigger delay correction. This accounts for the possible delay between the emission of the laser pulse and the start of the data acquisition, resulting in a vertical displacement of the measured signals, which affects both analog and photon-counting channels. The trigger delay can be measured by the so-called zero-bin (for the analog channels) and bin-shift (for the photon-counting channels) tests. Each channel has a different time delay, which is given in terms of an integer number of range bins and is informed in the configuration file. The correction consists of discarding these first few bins, so that all channels start in-sync with the laser pulse. The total length is also cropped so that all channels have the same length.

L90: Ref#1 Comment: That's what I don't understand. Any reference?

Background correction refers to subtracting the constant bias in the lidar signal. In the case of the analog channel, that could be due to electronic noise or the sun's light. For the photoncount channel, there is only the later effect. The standard way of finding this value is to average the final portion of the lidar signal in a range where the emitted pulse has been already completely attenuated. Typically the last ~500 or ~1000 bins (3.5 to 7 km) in the lidar profile.

There is an alternative approach which is using the so-called molecular fit. This involves doing a linear least-square fit between the lidar signal and the theoretical molecular signal in a region where there are no particles. The molecular signal is calculated from first principals (i.e. Rayleigh scattering from molecules) based on temperature and pressure profiles. This is the same fit that we have to do for calibrating the molecular reference before we perform the Klett inversion. However, if we allow for a free parameter B in this molecular fit, like:

$$\text{Lidar_signal}(z) = A * \text{molecular_lidar_signal}(z) + B$$

B will correspond to the constant bias in the lidar signal. This is discussed in detail by Grigorov and Kolarov (2013) and used in some lidar analysis (e.g. Barbosa et al., AMT 2014). To make this more clear, we modified this part of the text to give more details and point to these references as follows:

The background noise can be found by averaging the signal in a high altitude range, defined in the configuration file, where the lidar signal is completely extinguished. Alternatively, it can be found by performing a so-called Rayleigh-fit. In this case, it corresponds to the constant term in a linear least-square-fit between the lidar signal and the molecular signal, as in Grigorov et al. (2013) and Barbosa et al. (2014).

Refs.:

Grigorov and Kolarov (2013): <https://doi.org/10.1117/12.2012998>

Barbosa et al. (2014): <https://doi.org/10.5194/amt-7-1745-2014>

L91-92: Ref#1 Comment: where do they come from?

The user has to provide temperature and pressure profiles for the calculation of the molecular signal which is needed for the Klett inversion. These could come from near-by radiosondes, weather forecasts, reanalysis, etc. We are developing scripts for automatically retrieving this information for any location (i.e. lat, lon), but this is not yet ready, and hence it is only mentioned in the *Future Roadmap* section of our manuscript.

To make more clear, we modified this line as follows:

Besides the corrections and time averaging, L1 data also includes the temperature and pressure profiles provided by the user. The input thermodynamic profile can be obtained from any source, such as radiosondes, weather forecasts, or reanalysis. Alternatively, LPP includes and could use thermodynamic profiles from the US standard atmosphere (National Geophysical Data Center, 1992)."

Refs.:

National Geophysical Data Center, 1992: [http://doi.org/10.1016/0032-0633\(92\)90203-Z](http://doi.org/10.1016/0032-0633(92)90203-Z)

L92: Ref#1 Comment: what does this mean? Any reference? Especially, what do you mean with dynamic thresholds?

Our feature-mask algorithm is based on the ideas proposed by Vaughan et al (2004), who describe the algorithm used in the CALIPSO satellite. In their case, they use the ratio of the measured attenuated backscatter to the molecular attenuated backscatter. They compare this ratio with a threshold based on the signal noise, which they don't explain, but varies with altitude. They go searching for features from the top to the bottom of the atmosphere (because CALIPSO is in space), and they modify the threshold after each feature is found (i.e. below the feature, in terms of altitude).

In our case, we perform a molecular fit, as described in a previous response, but using the whole profile. The features (cloud or aerosol layers) are taken to be the pieces of the lidar signal where the measured signal is above the expected molecular signal (i.e. the molecular fit). We fine tune the location of the layer's base and top altitude by repeating this process, but starting from higher and higher initial ranges each time. In our case, we call this a dynamical threshold approach because the value above which the signal is considered to be a feature is calculated dynamically.

Because we use the molecular fit and the threshold based on the signal noise, this method can be applied to a heterogenous network, where the typical signal intensity and signal-to-noise ratio vary substantially.

We believe this explanation would be too much detail for this overview paper. Besides, we are working on a manuscript just about the feature-mask algorithm, and hence we would rather save a detailed description of the new algorithm for that publication. Nonetheless, we agree that we should provide more information at this point in the manuscript. Hence, we modified this paragraph as follows:

Finally, the L1 data processing creates a layer-mask to indicate the presence of aerosol and cloud layers. The method is based on the ideas proposed by Vaughan et al. (2004), where the return signal is compared to the expected molecular signal. The threshold for detecting a layer is calculated dynamically, based on signal noise, hence it can be applied to the wide range of instruments in the LALINET network. The time-averaged resolution for this product can be different than the used in data level 2.

Refs.:

Vaughan et al. (2004) <https://doi.org/10.1117/12.572024>

L93: Ref#1 Comment: ever explained?

The range-corrected lidar signal is a commonly used term in the lidar community, and that's why we did not explain it. However, given the more general audience of the GI journal, we have added additional explanation in the new *Validation* section, where RCLS is now mentioned for the first time. In the new manuscript, the original Figure 3 was removed and also the reference to the term range-corrected lidar signal.

The range-corrected lidar signal is the measured lidar signal multiplied by the square of the range. This is to account for the $1/R^2$ decay in the signal due to the spread of a light beam as it propagates. Correcting for this decay allows for better visualization of the lidar signal and its features from near-range (close to the ground, where the signal is large) all the way to the far range (away from the ground, where the signal is small).

Figure 4: Comment: how is the reference height determined? In this example, it looks like there is a negative bias in the free troposphere. Please comment!

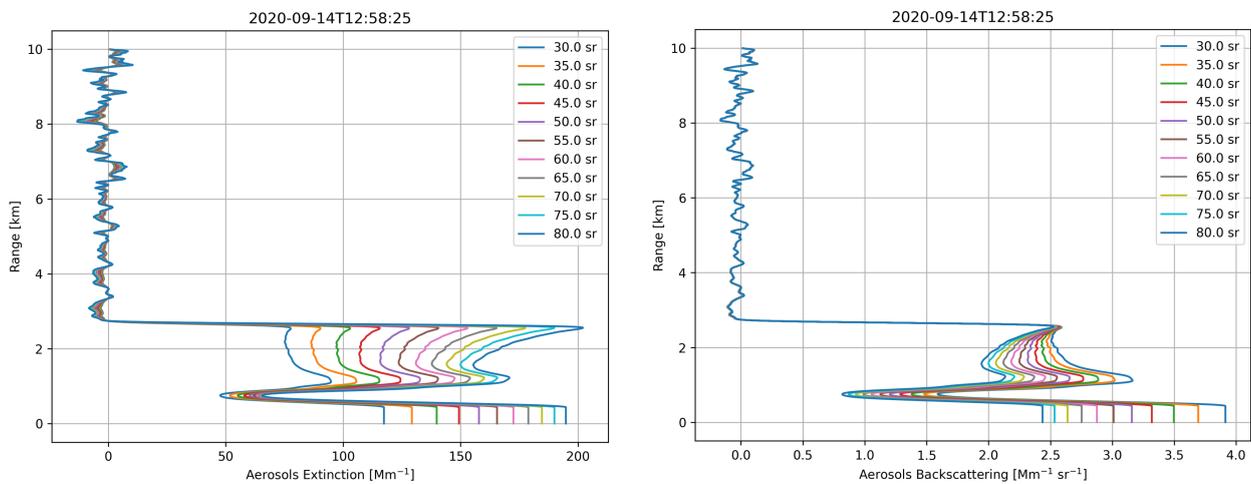
Automatic determination of the reference height is very challenging and, as far as we know, none of the lidar networks (Earlinet, ADnet, etc.) have developed that capability yet. In SCC, For instance, the user has to manually define a molecular range and the algorithm automatically chooses the reference height to be the point closest to the molecular fit, i.e., to minimize the difference between the reference value and the molecular value at the same altitude.

As we explained in a previous response, the reference height in LPP is an input parameter, i.e., it is set by the user in the configuration file. The reference signal can be calculated in two ways: (1) averaging the signal or (2) performing a molecular fit. In both cases, this is done around the reference height, in an altitude range that is also defined by the user. The 2nd method is more precise, as it considers the curvature of the lidar signal, and it can be performed over a large altitude range, which helps to reduce the uncertainty of the noisy lidar signal at these high altitudes. In fact, the larger the molecular range, the better. Moreover, because the reference signal is taken on the (calibrated) molecular signal, it doesn't really matter at which altitude we pick it (as

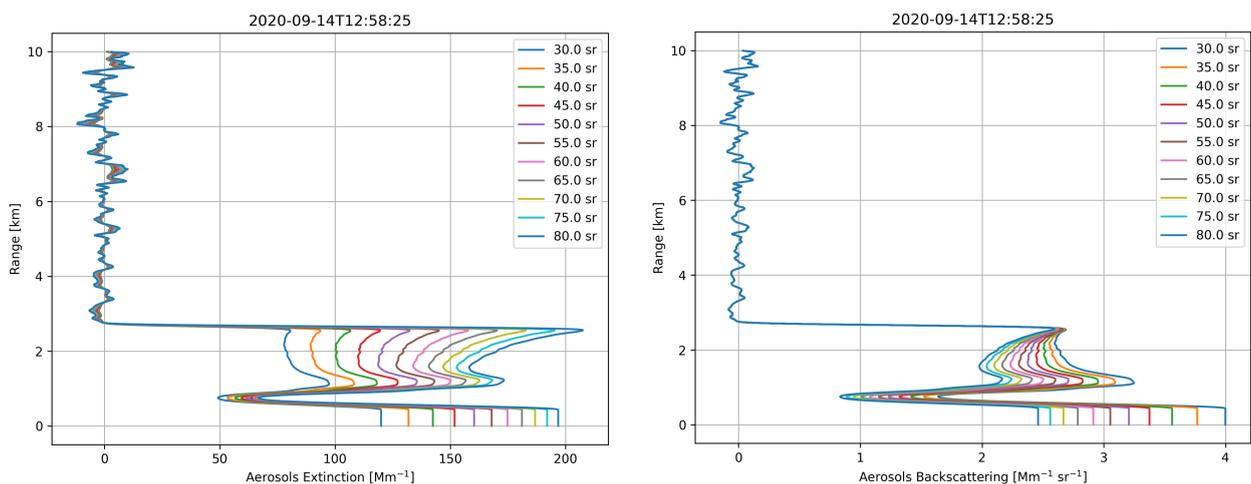
long as it is within the molecular range). In our case, we always pick the midpoint, i.e., the altitude in the middle of the molecular range.

Having said that, yes, we agree there was a negative bias from 4 to 6 km in figure 4, but we also note that the inversion was ok from 6 to 8 km. The issue was that we used a molecular reference region too small and too far away from the aerosol layer. We now increased the molecular reference region from 6-8 km to 4-10 km, and the new figure is shown below. We also found out a second issue. The old curve was showing the backscatter coefficient, while the x-axis label and the caption said it was the extinction. This is now fixed in the updated manuscript. For your convenience, we show below α and β for the two molecular ranges (old and new). There is no bias when using the reference from 4-10 km.

OLD - Fit 6-8 km



NEW - Fit 4-10 km



L96: Ref#1 Comment: phrasing

Rephrased as:

The main goal of level 2 data processing is obtaining the profiles of aerosol optical properties, namely backscatter and extinction coefficients.

L120: Ref#1 Comment: *formatting*

Corrected

L138: Ref#1 Comment: *ok, that sounds reasonable, but not only the LR, but also the reference height and value are important. How are these determined?*

Please see our response to your comments on the bias in Figure 4 (just above).

LPP can obtain the reference value in two ways: (1) averaging the signal or (2) performing a molecular fit. The 2nd method is more precise basically because it can be performed over a wide altitude range (typically > 4 km), which averages out the signal noise. Moreover, because the reference signal is taken on the (calibrated) molecular signal, it doesn't really matter at which altitude we pick it. That is as long as it is within the molecular range, and that there are enough points (i.e. how wide the molecular range is) to allow for a good precision of the molecular fit.

There are many authors who studied different problems related to the boundary condition in the inversion of the elastic lidar signal, including Klett, Fernald and Sazano. Rocadenbosch and Cameron (App. Opts. 1999) makes a good review of these papers, and presents an error analysis of the different methods. More recently, some authors have proposed methods based on minimizing the variance (e.g. Susnik et al., J. Atmos. Oce. Tech., 2014), segmenting the lidar signal (Mao et al., Optics Express 2015), or even parametrizing the backscatter ratio in a multi-wavelength lidar (Wang et al., Optics Comm., 2023). However, to investigate, or even discuss how the choice of the reference altitude and value may affect the retrieval would be beyond the scope of the current manuscript.

As for the Lidar Ratio value, the only way to determine LR with an elastic lidar is by calibrating retrieve extinction with an external instrument (like AOD provided by Aeronet or Modis). We have to iterate over possible LR values until we find the right extinction profile that matches the reference AOD value. That, of course, depends on the assumption you make for the extinction profile close to the ground, where the lidar cannot measure. While in this first release of LPP this iteration is set manually, future versions will do it automatically.

L142-143: Ref#1 Comment: *this is indeed very good, but I know two publications where such retrievals have been done and presented, so it is now new.*

We are not saying that this is a new idea, but a future feature of LPP. It is our effort to have a common, open, free, and highly configurable pipeline for processing elastic lidar data, which will be used for processing LALINET data, but which could also be used by anyone in the scientific community.

About the two publications mentioned by the referee: we could certainly cite these publications here if the referee let us know what these references are.

L145-156: Ref#1 Comment: *Here is much more detailed information compared to the Sao Paulo system - please homogenize.*

Thank you for the suggestion. We simplified the description of the Manaus-AM system. Following the suggestion from Referee #2, we have also created a new section to describe the case studies

(from simulations and observations) and the instruments. This is the updated paragraph describing the Manaus station:

The lidar deployed in Manaus (2.89° S, 59.97° W, 100 m altitude above sea level) is a UV Raman Lidar operated by the University of Sao Paulo (Barbosa et al., 2014). It is a bi-axial system pointed 5° from the zenith, which uses a commercial Quantel CFR-400 Nd-YAG laser at 355 nm with 95 mJ per pulse and a 10 Hz repetition rate. The receiving telescope has a 400 mm primary mirror, focal length of 4000 mm, and a field of view of about 1 mrad, reaching a complete overlap at 1.5 km. The detection box measures 3 wavelengths: elastic 355 nm and the corresponding Raman signals from nitrogen at 387 nm and water vapor at 408 nm. Data acquisition uses a Licel transient recorder model TR-20-160, with a raw resolution of 7.5 m.

L154: Ref#1 Comment: which lines? Please phrase correctly

We changed “lines” to “wavelengths”.

L161: Ref#1 Comment: the choice of the threshold and the overall methodology would be of particular interest, up to now, it is a “black box”

Please see our response to your comments on line 93.

Figure 8: Ref#1 Comment: location missing. Why is here the height axis suddenly horizontally? Please homogenize in the manuscript.

Thanks for pointing that out. We added the location (Manaus) and changed the plot axis. Figure 8 caption was rephrased as:

Extinction coefficient obtained using a constant lidar ratio for the Manaus lidar station, at 02:30 UTC on 15 August 2011. The extinction coefficient was assumed constant below 300 m.

Before “Conclusions”: Ref#1 Comment: the differences to the SCC and other processing chains should be highlighted, e.g. more flexibility by using config files.

Thank you for this suggestion.

The section before the conclusion is the *Future Roadmap*, where we present the future developments. Following your previous suggestions, we have already substantially improved the discussion there, making the proper reference to the existing literature about each of the aspects we plan on improving on LPP. Many of these references are papers describing the algorithm of more established lidar networks, like the SCC from Earlinet. Hence, we believe we already address this point.

L193: Ref#1 Comment: also this is already used in some other processing chains.

As previously mentioned, we are not saying we are the first ones to do or propose this. This paper aims to show (1) the Latin American effort to develop this platform, and (2) how this platform is meant to: (a) be used for any instrument, (b) be shared and built collaboratively, and (c) be freely available to our community.

Having said that, we did substantial changes to the *Future Roadmap* section, which can be find in our response to your major comment #5. And we also changed the *Conclusions* to make this message more clear:

Lidar networks are drivers of scientific advance as they coordinate the efforts of different groups, allowing for uniform quality-assurance procedures, as well as instrument comparison and algorithm validation. The development of LPP is a joint effort leveraging the expertise and manpower of different Latin-American lidar groups, part of the Latin American Lidar Network. The goal of LPP is to provide a set of open-source tools for each step of the typical lidar data analysis routine. Here, we provided a high-level overview of the first working version that is now released for the scientific community on our GitHub repository.

The performance of LPP was evaluated through an analysis of synthetic and measured elastic lidar signals. For noiseless synthetic signals with a constant LR, the mean relative error in the aerosol extinction within the boundary layer was quite small, ranging from -0.005% to -0.9%, depending on the wavelength. For noisy synthetic signals with a variable LR, the mean relative error in aerosol backscatter was larger, ranging from -0.63% to 4.5%, mostly due to assuming a constant LR in the inversion. For the case studies for urban aerosols in Sao Paulo and cirrus clouds in the Amazon, we found LR and COD values, respectively, in agreement with previous results. These analyses showed the capabilities of the current release but also highlighted the need for new features. Hence, we have built a roadmap to guide future development, which includes: (1) improvements in the physical retrievals (e.g. range dependent LR inversion of the elastic signal, or uncertainty propagation using Monte-Carlo), and (2) automation of the pipeline (e.g. optimizing the elastic LR by constraining the column AOD, or thermodynamic profile downloader tools). Future releases will bring these and other new features, accommodating the needs of our community.

Although the scientific community is moving towards open science, developing open-source code is still a hurdle, and the atmospheric lidar community has not yet embraced the idea. Consolidated networks have long developed their own algorithms and pipelines, which unfortunately remain mostly inaccessible to the community, hampering faster scientific advancement. We hope open-source efforts, as the one presented here, become the rule rather than the exception in the near future.

L95: Ref#1 Comment: Should be published with a DOI. Otherwise it might happen that the code is not longer available if, e.g., the user account is deactivated

Thank you for the suggestion.

However, as we previously mentioned, the Zenodo DOI is linked to a GitHub release version, and it only gives authorship to the code developers, i.e., the individuals with GitHub accounts who performed changes in the project's source code. This would be problematic because the Zenodo DOI could be cited instead of the paper DOI. This would not be fair with all authors contributing to LPP by other means, like testing the code, discussing the methods, writing this manuscript, etc.

Response to Referee #2

Original referee comments are in blue.

Our responses are in black in regular font format. Text from the updated manuscript:

Appears in italic and with ½ inch indentation and with the modified parts in red.

General comments

The authors illustrated a set of tools aimed to develop a Lidar Processing Pipeline in a collaborative way according to an open-science approach. The processing chain is described and two case studies are illustrated in the manuscript. The LPP approach has certainly a scientific interest for an operative workflow aimed to process Lidar data.

However, the research gaps the authors are willing to fill is not clear to me, and a description of novel aspects of the work is needed in the Introduction.

Thank you for pointing that out, and we agree this was not clear.

The aim of our manuscript is to (1) present the processing pipeline, as a publicly-available chain of lidar processing routines, (2) report on the development of a pipeline suitable for a heterogeneous network, and (3) discuss initial results based case studies. The algorithms behind the processing pipeline are not the main focus of this manuscript, instead, the focus is on giving a high-level picture. To emphasize these aspects of our manuscript, we have modified the 4th paragraph of the **Introduction**:

*In recent years, the **LALINET** network has worked towards establishing routine quality-assurance tests and intercomparing the retrieval algorithms used by the different groups (Guerrero-Rascado et al., 2016; Barbosa et al., 2014). Here, **our first goal is to present a high-level overview of the Lidar Processing Pipeline (LPP), an ongoing and unfunded coordinated effort to homogenize the retrievals from different lidar instruments in Latin America. Our second goal is to introduce the tools developed to handle all the steps of a typical lidar analysis. We want to emphasize the modular framework that is generic enough to be applicable to any lidar instrument or network and, at the same time, also emphasize the open source character of the LPP development (see Code availability). Our third goal is to show how LPP performs, through quantitative and qualitative analyses of simulated and measured lidar signals. We will discuss case studies based on simulated and measured signals and analyze aerosol backscatter retrievals for elastic lidar signals and layer masking (clouds or aerosol), which are the focus of this first public release of LPP.***

We note that our approach is very similar to the one adopted by the European Lidar community, who developed the Single Calculus Chain (SCC). Their first paper on AMT just gives an overview of their pipeline and how it would be routinely used in the context of EARLINET. The methods behind SCC were only described in a pair of follow-up publications a year later:

Initial description: <https://amt.copernicus.org/articles/8/4891/2015/>

Part 1 (pre-processing): <https://amt.copernicus.org/articles/9/491/2016/>

Part 2 (optical products): <https://amt.copernicus.org/articles/9/3009/2016/>

Moreover, the introduction should include a state of the art of the topic from scientific literature. E.g. see Reagan et al., 1989; Dang et al., 2019; Wang & Menenti, 2021.

Thank you for the suggestion. The introduction was substantially revised to include these and further references. Regarding *Dang et al (2019)*, this was not included because it is about using lidar to determine the atmospheric boundary layer height, which is something we do not currently do with LPP.

The first paragraph of the introduction was broken in these two:

Aerosols, clouds, and their interactions are the source of the largest uncertainties in current climate change estimates (IPCC, 2013; 2021). More frequent and higher quality measurements of aerosol, clouds, and the physical processes governing their link with climate are needed to reduce these uncertainties (Mather, 2021; National Academy of Sciences, 2018), and lidars are a powerful instrument to accomplish this task (Reagan et al., 1989). This instrument can provide information on the optical and microphysical properties of aerosol particles and hydrometeors, the concentration of trace gases, and, more recently, the 3D structure of the vegetation and urban canopies, allowing ecologists to accurately estimate biomass content and engineers to develop self-driving cars and drones (Wang and Mementi, 2021).

Atmospheric lidars, specifically, measure the atmosphere's constituents, from the troposphere to the mesosphere. However, they are developed by individual groups for particular applications; hence their hardware characteristics differ in essential aspects, such as receiving optics, emitted and detected wavelengths, polarization capability, and signal-to-noise ratio, to name a few. Even in the realm of single-wavelength elastic lidars, typical differences between custom-built lidar systems are large enough to require a careful, dedicated analysis of their return signals (Wandinger et al., 2016). In this sense, lidar networks play a crucial role as they coordinate the efforts of different groups, providing the guidelines for quality-assured routine measurements on a regional scale (Antuna et al., 2017). Moreover, the coordinated effort is of utmost importance to homogenize the physical retrievals from the highly non-uniform instruments in lidar networks, which typically involve comparing the retrievals based on the algorithms of different groups (Pappalardo et al., 2004) and the instruments themselves (Wandinger et al., 2016). This homogenization is only possible by developing a unified processing pipeline that accounts for the hardware heterogeneity in the pool of instruments, as it has been accomplished recently in the context of the European Aerosol Research Lidar Network (EARLINET) (D'Amico et al., 2015) and the Asian Dust and Aerosol Lidar Observation Network (AdNet) (Sugimoto et al., 2009). In contrast, homogeneous networks have the advantage of uniform calibration and data processing procedures, like those performed by the NASA Micro Pulse Lidar NETWORK (MPLNET) (Welton et al., 2001) or the Italian Automated Lidar-CEilometer network (ALICEnet) (Dionisi et al., 2018).

Finally, it is difficult to assess the quality of the results of the case studies without any comparison with different approaches or measurements. No quantitative or qualitative assessment has been done. I understand that is not easy to set up a quantitative comparative assessment, however, the authors should discuss this limitation and propose future actions to overcome it in the Future roadmap/Conclusion Section.

Thanks for the suggestion. Although the main purpose of the manuscript is to give a high-level overview of our processing pipeline, we agree that it would be worth showing a more quantitative comparison at this stage.

Hence, a new subsection was added in the *Results* section, where we show a quantitative analysis based on the inversion of synthetic lidar signals with aerosols in the boundary layer. First, we considered a case of an elastic lidar signal without noise and constant lidar ratio, which was provided by EARLINET colleagues (Holger Baars, Personal communication, 2014). Then we considered a more realistic case where the signal has noise and the LR varies in the profile (Pappalardo et al., 2004).

This is the content of these two new subsections:

4.1 Noiseless synthetic signals with constant LR

The range-corrected lidar signals (RCLS) from the first simulation are shown in Figure 3a for the three wavelengths. RCLS is suitable for plotting since it removes the inverse-squared range dependence in the raw-lidar signal, making it better for visualizations. The lack of noise in the signals makes finding the right reference value easier, reducing systematic errors related to this input parameter. Moreover, no vertical smoothing or time averaging was necessary. The inversions were performed using a reference altitude of 10 km and the true lidar ratio. Figure 4b shows the retrieved aerosol extinction coefficient and the input used for the simulation. There is an excellent visual agreement.

To quantify the small differences that might exist between the retrieval and the simulated profile, we computed the deviation as a function of altitude, and Table 2 reports the mean, maximum, minimum, and root-mean-square deviations in the boundary layer and in the free troposphere. There is a small negative bias within the boundary layer, where the relative deviations were always negative. The mean values are -0.045 %, -0.089 % and -0.901 % for 355, 532, and 1064 nm, respectively. Overall, the errors are greater for 1064 nm. In the free troposphere, where the aerosol loading is almost zero, there is a small positive bias. The mean deviations are 0.26, 0.092, and 0.003 Mm^{-1} for 355, 532, and 1064 nm, respectively.

Table 2 - Mean, maximum, minimum, and root-mean-square deviations in the retrievals of the extinction coefficient (Mm^{-1}) at 355 nm, 532 nm, and 1064 nm. Values in the PBL (250 to 2500 m) are expressed as relative deviations (in %), while values in the free troposphere (FT, above 2500 m) are given in Mm^{-1} .

		355 nm	532 nm	1064 nm
PBL	mean	-0.045 %	-0.089 %	-0.901 %
	max	-0.036 %	-0.020 %	-0.298 %
	min	-0.071 %	-0.194 %	-1.623 %
	RMS	0.046 %	0.106 %	1.001 %
FT	mean	0.263 Mm^{-1}	0.092 Mm^{-1}	-0.003 Mm^{-1}
	max	0.345 Mm^{-1}	0.119 Mm^{-1}	0.005 Mm^{-1}
	min	-0.094 Mm^{-1}	-0.305 Mm^{-1}	-1.623 Mm^{-1}
	RMS	0.271 Mm^{-1}	0.098 Mm^{-1}	0.094 Mm^{-1}

These errors are smaller than those reported by Bockmann et al. (2004) in a similar validation exercise in the context of EARLINET. Their case 2 considered an aerosol layer

extending up to 4 km altitude, with constant LR, and the synthetic signals did not include noise. For stage 3 of their intercomparison, all 18 groups used the same LR and reference value at the calibration height. The mean relative error within the aerosol layer was 1.87%, 1.48%, and 1.38% for 355, 532, and 1064 nm, respectively. While their synthetic profile was not the same as used here, this initial comparison gives confidence that LPP works well and can reproduce the simulations without biases if all input parameters are known.

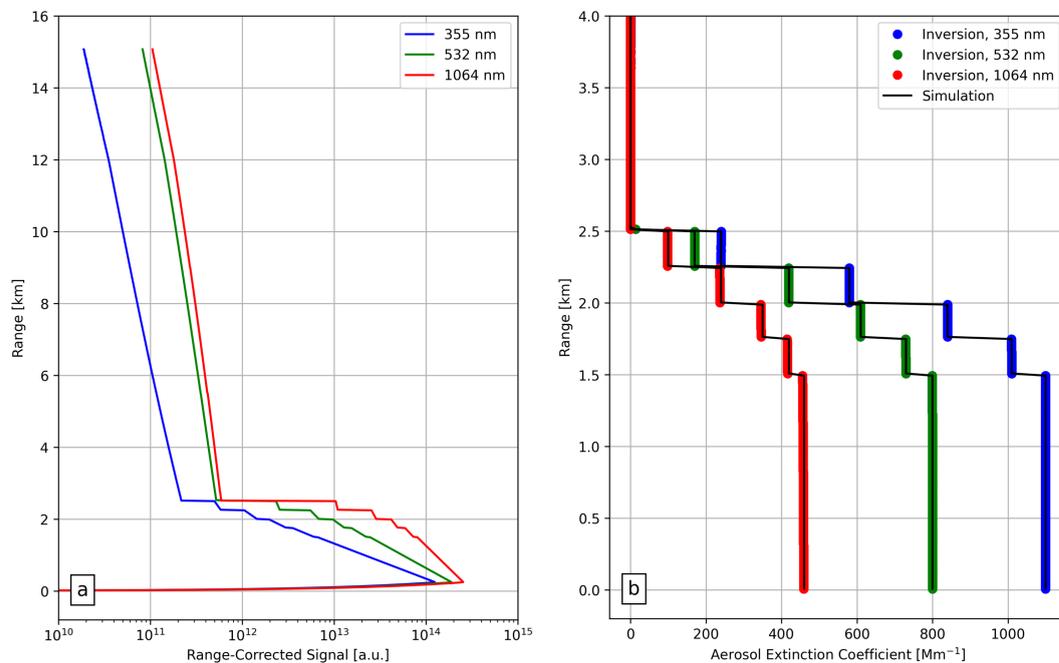


Figure 3 - (a) Synthetic Range-corrected signals (a.u.) and (b) aerosol extinction coefficients (Mm⁻¹) retrieved with LPP (bullets) and used as input for the simulation (black line) are shown for 355, 532 and 1064 nm.

4.2 Realistic synthetic signals with variable LR

The average signals from the set of realistic simulations, which includes signal noise and a variable LR, are shown in Figure 4. As this release of LPP considers a constant LR for the inversion of the elastic signals, we computed the mean of the LR profile below 7 km, where the simulated aerosols are. The values were 51 sr for 355 nm and 62 sr for 532 nm, which were the same constant values used by Mattis et al. (2016) to test the accuracy of SCC optical products. The reference height was set to 9 km for both wavelengths, with the molecular range between 7.5 to 10.5 km. Signals were vertically smoothed by applying a 5-point moving average, corresponding to an effective resolution of 75 m.

Figures 6a and 6b show the retrieved aerosol backscatter coefficients at both wavelengths. There is a very good agreement overall, despite our assumption of a constant LR. According to EARLINET requirements, relative errors in the optical retrievals at 355 and 532 nm should be below 20 % or 0.5 Mm⁻¹ sr⁻¹ (Mattis et al., 2016). The relatively higher values obtained with LPP occur for relatively lower values of the backscatter coefficient, which indicate this is related to the signal noise and hence could be minimized with stronger vertical smoothing. There are also large errors at the altitudes where the input LR makes a sudden change, which can only be resolved by implementing the range dependent LR solution for the elastic signal (Klett, 1985), or by implementing the Raman solution (Ansmann et al., 1992).

The mean errors for the three aerosol layers and the two wavelengths are shown in Table 3. The layer-mean relative errors are smaller than EARLINET's limits, with the largest values (about 15%) found in the free troposphere, where the true LR profiles deviate the most from our assumed constant values. Root-mean-square relative errors are larger, reaching up to 41% in the LL for 355 nm, however, these depend on the applied vertical smoothing as discussed above. Overall, the errors reported in table 3 are similar to those found for EARLINET's SCC (Mattis et al., 2016). This shows that LPP's retrievals do not have significant biases and can appropriately reproduce the realistic synthetic profiles.

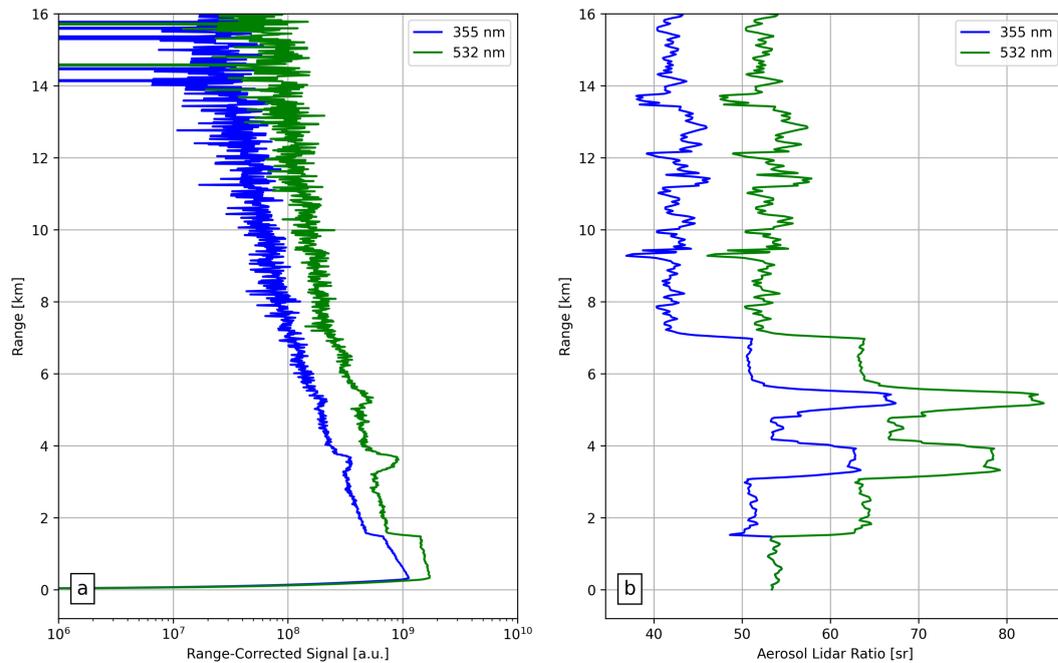
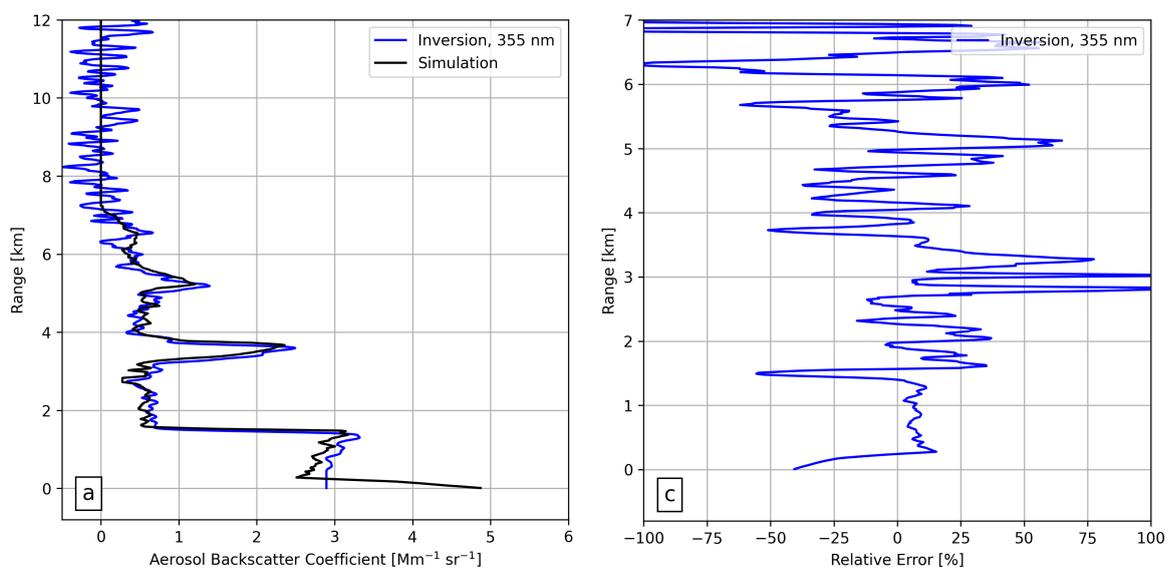


Figure 4 - (a) Synthetic Range-corrected signals (a.u.) with raw vertical resolution of 15 m and (b) aerosol lidar ratio (sr) used as input for the simulation are shown for 355 nm and 532 nm. The retrievals shown in Fig. 6 assumed constant lidar ratios of 51 sr and 62 sr, respectively.



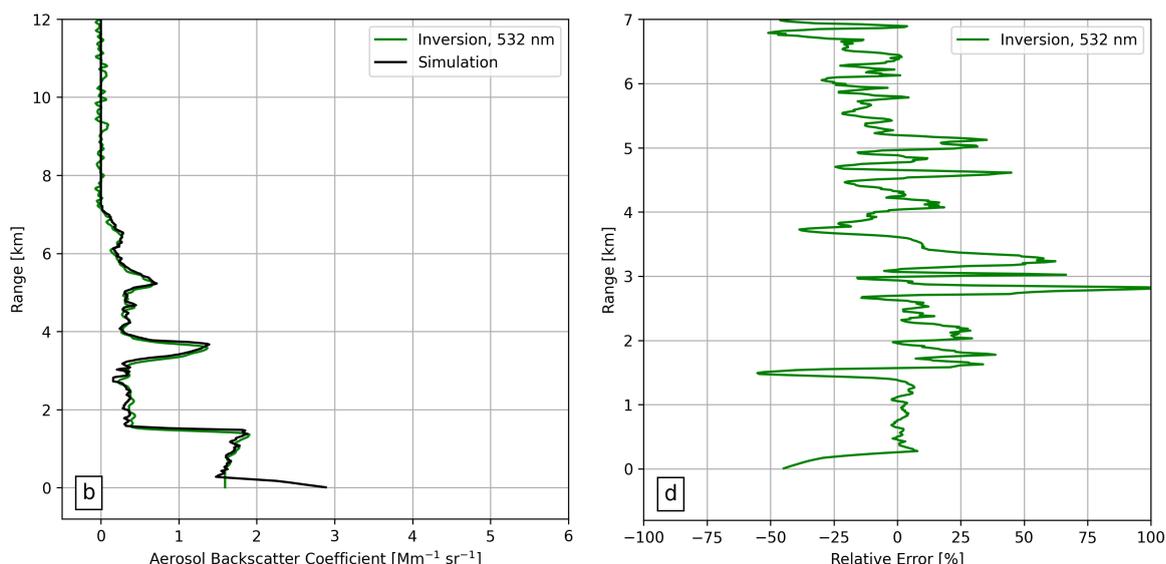


Figure 5 - Left panels show a comparison of the aerosol backscatter coefficient ($\text{Mm}^{-1} \text{sr}^{-1}$) retrieved at (a) 355 nm (blue) and (b) 532 nm (green) with those used as input for the simulation (black line). The right panels show the respective relative errors (%).

Table 3 - Mean, root-mean-square, and relative errors in the retrievals of the backscatter coefficient at 355 nm and 532 nm in the PBL (280 to 1500 m), free troposphere (FT, 1500 to 3000 m), and lofted layer (LL, 3000 to 7000 m). Values are reported in absolute ($\text{Mm}^{-1} \text{sr}^{-1}$) and relative (%) terms.

		355 nm		532 nm	
		$\text{Mm}^{-1} \text{sr}^{-1}$	%	$\text{Mm}^{-1} \text{sr}^{-1}$	%
PBL	mean	0.12	4.5	-0.013	-0.63
	rms	0.37	13.	0.19	11.
FT	mean	0.048	15.	0.030	15.
	rms	0.18	30.	0.10	29.
LL	mean	0.0026	-0.83	-0.0083	-3.3
	rms	0.25	41.	0.10	22.

Ref:

Papalardo et al, 2004: <https://doi.org/10.1364/AO.43.005370>
 Mattis et al., 2016: <https://doi.org/10.5194/amt-9-3009-2016>
 Bockman et al., 2004: <https://doi.org/10.1364/AO.43.000977>

Minor comments

Lidar technology can have multiple applications, but the authors focused their attention to clouds and aerosols measurements. Therefore, the Title of the manuscript should be more specific referring to the applications of their LPP approach.

The title has been changed to:

Collaborative development of the Lidar Processing Pipeline (LPP) for atmospheric retrievals of aerosol and cloud

Page 2, Lines 50-51. Page 4, lines 72-73. Page 7, lines 107-108. Page 8 Lines 143.145. Page 10, lines 167-169. Information on the future versions of the LPP should be moved to the Future Roadmaps section.

The lines pointed out were moved to the *Future Roadmap* section and edited for better reading. The new version of this section gives a much more comprehensive view of the changes we intend to do in the future:

With the first release of LPP and its use by the different groups in LALINET, we have identified the necessary improvements and built a roadmap to guide future development. An initial consideration is that LPP processed data files must be FAIR (Findable, Accessible, Interoperable, and Reusable) (Wilkinson et al., 2016) to be compatible with Open Science. In this sense, more information about the site, hardware, operation, files processed, and even the version of LPP used needs to be added as metadata in the output files. Moreover, the benefit of LPP's highly modular concept is the possibility of different groups modifying and testing different modules without interfering with the rest of the pipeline. To facilitate the customization of the pipeline to fulfill different needs and to allow more groups to contribute to LPP's development, future releases will include Python versions of all modules.

In terms of improvements in the physical retrievals, we have identified three priorities. First is to implement the Klett (1985) solution to the lidar equation with a range dependent LR. This would be useful, for instance, for the Sao Paulo station where the sea breeze frequently brings marine aerosols above the urban-polluted boundary layer (Rodrigues et al., 2013; Ribeiro et al., 2018). The second is to obtain the uncertainties in the extinction and backscatter coefficients by propagating the signal errors using a Monte Carlo approach (Press, 2007), following the work of Alvarez et al. (2006) and Mattis et al. (2016). Finally, we plan on implementing the Raman solution (Ansmann et al., 1992), but this might require an intercomparison effort of the existing algorithms in LALINET, as was done in EARLINET (Pappalardo et al., 2004). Moreover, in LALINET, the stations recording Raman return signals have photon-counting channels, which might be affected by dead-time effects (Johnson et al., 1966). Hence, we need to implement the known dead-time corrections for paralyzable and non-paralyzable systems (Whiteman et al., 1992; Knoll, 2010), which would also allow for 'gluing' the analog and photon-counting to extend the instrument dynamic range (Whiteman et al., 2006; Newsom et al., 2009).

Regarding the automation of the pipeline, a few updates are planned. For instance, we noticed that only a few lidar stations in Latin America have a nearby radio-sounding site, and it is only once or twice per day. To facilitate the processing of level 1 and level 2 data, an automatic "thermodynamic profile downloader" will be developed to obtain a co-located thermodynamic profile from a nearby radio-sounding, a forecast model, or a reanalysis. The MPLNET data processing, for example, automatically retrieves meteorological profiles from the Goddard Earth Observing System, version 5 (GEOS-5), atmospheric general circulation model for all molecular calculations (Lewis et al., 2016). We also plan to implement a method of re-scaling the standard atmosphere profiles based on co-located ground-based temperature and pressure measurements, which could also be retrieved automatically from meteorological databases.

Moreover, a well-known problem with the inversion of elastic lidar data is the need to assume an a priori lidar ratio. The typical solution is to choose a lidar ratio that brings the estimated AOD value closer to the reference value measured by AERONET, *which can now be measured at day and nighttime* (Perrone et al., 2022). This analysis can be made a-posteriori, *as shown in Figure 4*. Implementing an optimization routine would allow LPP to automatically identify the best LR for each profile, *as has been done in previous studies* (Cordoba-Jabonero et al., 2011; Roman et al., 2018), and help reduce systematic errors in the retrieved profiles (Welton and Campbell, 2002). The user could provide the reference AOD value, *or it could be obtained by an "AOD data downloader" tool as part of the LPP framework*.

Refs.

- Alvarez, J. M., et al: Calibration Technique for Polarization-Sensitive Lidars, *Journal of Atmospheric and Oceanic Technology*, 23, 683 – 699, 2006.
- Ansmann, A., et al: Independent measurement of extinction and backscatter profiles in cirrus clouds by using a combined Raman elastic-backscatter lidar, *Appl. Opt.*, 31, 7113–7131, 1992.
- Johnson, F. A., et al.: Dead-Time Corrections to Photon Counting Distributions, *Phys. Rev. Lett.*, 16, 589–592, 1966
- Knoll, G. F.: Radiation detection and measurement, John Wiley, Hoboken, N.J, 4th ed edn., 2010
- Mattis, I., et al.: EARLINET Single Calculus Chain – technical – Part 2: Calculation of optical products, *Atmospheric Measurement Techniques*, 9, 3009–3029, 2016.
- Newsom, R. K., et al.: Simultaneous analog and photon counting detection for Raman lidar, *App. Optics*, 48, 3903, 2009
- Press, W. H.: Numerical recipes: the art of scientific computing, Cambridge University Press, Cambridge, UK ; New York, 3rd ed edn., oCLC: ocn123285342, 2007.
- Ribeiro, F. N., et al.: Effect of sea breeze propagation on the urban boundary layer of the metropolitan region of Sao Paulo, Brazil, *Atmospheric Research*, 214, 174–188, 2018.
- Rodrigues, P. F., et al.: Assessment of aerosol hygroscopic growth using an elastic LIDAR and BRAMS simulation in urban metropolitan areas, *AIP Conference Proceedings*, 1531, 360–363, 2013.
- Whiteman, D. N., et al.: Raman Lidar Measurements during the International H2O Project. Part I: Instrumentation and Analysis Techniques, *J. Atmos. & Oceanic Tech.*, 23, 157–169, 2006.
- Whiteman, D. N., et al.: Raman lidar system for the measurement of water vapor and aerosols in the Earth's atmosphere, *Applied Optics*, 31, 3068, 1992.
- Wilkinson, M. D., et al.: The FAIR Guiding Principles for scientific data management and stewardship, *Scientific Data*, 3, 160 018, 2016.

Page 13 and following. The RESULTS AND DISCUSSION session includes the description of the case studies. A new Section called "Case studies" should be created before Section 3 in order to separate results from case studies description.

Thank you for this suggestion. We created a new section called "Validation". There we have a subsection describing the simulations used for the quantitative evaluation, and another subsection describing the observed data in Sao Paulo and Manaus.

3. VALIDATION

Analyses of synthetic and measured lidar signals are carried out to demonstrate the usage of LPP and to provide quantitative and qualitative validation of our initial results. These analyses are based on elastic signals, which are the focus of this first public release of LPP.

For a quantitative evaluation, we obtain the backscatter and extinction coefficients in the presence of aerosols or clouds and compare our results with either the input used for the simulations, AERONET retrievals of aerosol optical depth (Holben et al., 1998), or LR values reported in the literature. For a qualitative evaluation, we obtain the cloud-layer mask and compare it with the range-corrected signal by visual inspection. The subsections below give the details of the four cases considered for validation.

3.1 Synthetic Elastic Lidar Signals

We use two sets of synthetic lidar signals. The first is a simple case of an ideal lidar signal without noise and constant LR with altitude, provided by colleagues from Tropos, in Germany (Holger Baars, Personal communication, 2014). The aerosol profile has a constant extinction coefficient of 1100, 800, and 460 Mm^{-1} at 355, 532, and 1064 nm respectively, from the surface to the top of the boundary layer at 1.5 km. Above that height, it decreases every 250 m, reaching almost zero at 2.5 km. The residual aerosol in the free troposphere has an extinction of 0.014, 0.01, and 0.0058 Mm^{-1} at 355, 532, and 1064 nm, respectively. The LR is fixed at 28, 39, and 77 sr at these wavelengths.

The second set of simulations corresponds to a more realistic case where the signals have noise, and the LR varies with altitude. These are the synthetic signals described and analyzed by Pappalardo et al. (2004) in the context of EARLINET's intercomparison of aerosol Raman lidar algorithms. This same dataset, which includes elastic signals at 355, 532 and 1064 nm and inelastic Raman signals at 387 nm and 607 nm, was used later to test the accuracy of SCC's optical products (Mattis et al., 2016). Three layers are clearly identified in this simulated atmosphere, denoted as a planetary boundary layer (PBL, from 0 to 1500 m), the free troposphere (FT, from 1500 to 3000 m), and a lofted layer (LL, 3000 to 7000 m). The dataset has 30 profiles with 2-min resolution, corresponding to 2400 laser shots per profile (20-Hz laser), and a total acquisition time of 30 min. Spatial resolution is 15 m. For our analysis, we consider the average 355 and 532 nm elastic signals only.

Both sets of synthetic signals include the effect of incomplete overlap in the near-field to mimic a real measurement. We ignore this range for the inversions with LPP and analyze the profile only where the overlap is complete. Both simulations also include information on the thermodynamic profile, which we use for calculating the molecular signal.

3.2 Case Studies

To further validate LPP and demonstrate its application to real data, we analyze elastic return signals from the LALINET lidar stations in Sao Paulo and Manaus, both in Brazil. With over 21.5 million inhabitants, Sao Paulo is the largest metropolitan region in the Americas. One of the primary sources of air pollution there is vehicular emissions, and the city has struggled with high levels of traffic congestion for many years (Andrade et al., 2017). During the winter (June to September), this can be exacerbated by temperature inversions, which inhibit mixing between the planetary boundary layer and the free atmosphere above. This well-stratified atmosphere shows high aerosol particle number concentrations within the boundary layer and a mostly clean atmosphere above it. While the air quality can vary depending on a number of factors, including weather patterns and traffic, we will evaluate measurements by the Sao Paulo lidar station on a typical winter day, 14 September 2020.

The lidar deployed at Sao Paulo (23° 56' S, 46° 74' W, 740 m above sea level) is a multiwavelength Raman LIDAR operated by the Lasers Environmental Applications Research Group at the Center for Lasers and Applications (CLA), Nuclear and Energy Research Institute (IPEN) (Landulfo et al., 2020). It is a monostatic coaxial system, vertically pointed to the zenith and using a commercial Nd:YAG laser by Quantel, model Brilliant B at a repetition rate of 10 Hz. The output energy per pulse is 850 mJ for 1064 nm, 400 mJ for 532 nm, and 230 mJ for 355 nm. A 300 mm diameter telescope with a 1.5 m focal distance and 1 mrad field-of-view (FOV) is used as a collection system, reaching a full overlap at 300 m above ground level. The detection box collects six different wavelengths: elastic 355 and 532 nm with the corresponding shifted Raman signals from nitrogen: 387 and 530 nm respectively. Also, the water vapor line at 408 nm and the elastic from 1064 nm. The electronic acquisition system is a Licel transient recorder model TR-20-160.

The second set of measurements is taken from the Manaus lidar station in the Amazon rainforest. The site is located about 20 km up-wind from the city, hence it is not affected by the significant urban emissions (Nascimento et al., 2022). Therefore, the atmosphere is mostly pristine throughout the year, with the exception being the dry season (June to October), when long-range transport of biomass burning affect the whole basin (Artaxo et al., 2013), and aerosols can be found up to 5 to 6 km (Baars et al., 2012). There is a marked diurnal cycle of convection, even during the dry season, with a peak in the late afternoon (Tanaka et al., 2014). Cirrus produced from the outflow of deep convective clouds are omni-present, with a frequency of occurrence much higher than other tropical regions (Gouveia et al., 2017). Here, we will analyze a case of multi-layered cirrus clouds measured during the dry season, on 21 September 2011.

The lidar deployed in Manaus (2.89° S, 59.97° W, 100 m altitude above sea level) is a UV Raman Lidar operated by the University of Sao Paulo (Barbosa et al., 2014). It is a bi-axial system pointed 5° from the zenith, which uses a commercial Quantel CFR-400 Nd-YAG laser at 355 nm with 95 mJ per pulse and a 10 Hz repetition rate. The receiving telescope has a 400 mm primary mirror, focal length of 4000 mm, and a field of view of about 1 mrad, reaching a complete overlap at 1.5 km. The detection box measures 3 wavelengths: elastic 355 nm and the corresponding Raman signals from nitrogen at 387 nm and water vapor at 408 nm. Data acquisition uses a Licel transient recorder model TR-20-160, with a raw resolution of 7.5 m.