Responses to Review #1

The author would like to thank the reviewer for his valuable comments which helped in improving the quality of the manuscript. My point-by-point responses to the reviewer's comments appear in bold below.

General Comments

1. I found the article quite difficult to read, with numerous errors (some but not all highlighted below). I found the introduction in particular lacked coherence, and this needs a significant rewrite to ensure that the context and novelty of the research is clearer to the reader. The author should go through the full article to improve readability.

   Clarifications have been made throughout the article, particularly in response to the reviewer's comments. The introduction was indeed rather too general and did not focus sufficiently on the article's objective. I have therefore revised and simplified it to make this clearer.

   Section 2 now contains a more detailed description of the FENNEC field campaign, partly based on the original introduction. Mentioning FENEC in such detail in the old introduction somewhat detracted from the article's focus.

   New introduction:

   Modelling is essential for characterising aerosol types and providing the most accurate possible assessment of their impacts on climate (Giorgi and Lionello, 2008; IPCC, 2022; Nabat et al., 2015; Flamant et al., 2015), as well as on meteorology and air quality (Wang et al., 2013, 2014a; Benedetti et al., 2009; Huneeus et al., 2012; Fourrié et al., 2019). This process relies on the validation of model-derived estimates against relevant observations. However, identifying aerosol types from observations remains a challenging and active area of research. In particular, the ability to characterise aerosols as a function of altitude and time is crucial not only for the validation of chemistry transport models but also for the interpretation and validation of spaceborne observations.

   Significant progress on aerosol typing has been achieved with the advent of satellite missions carrying lidar instruments, such as the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) (Winker et al., 2009). Dedicated field campaigns were conducted both to support the development of the mission and to validate its products. These efforts notably relied on polarised and multispectral lidar measurements to discriminate between different aerosol types and their potential mixtures (Burton et al., 2012). The recent launch of the Earth Cloud, Aerosol and Radiation Explorer (EarthCARE) satellite mission (Wehr et al., 2023) has underscored the need for robust validation methods to accurately identify the different aerosol types. This need is particularly critical given that the mission relies solely on polarised channels at 355 nm in order to optimise the performance of the high-spectral-resolution atmospheric lidar (ATLID). Consequently, aerosol typing must primarily rely on the lidar ratio (LR) and the linear particle depolarisation ratio (PDR). Although the operational algorithm

accounts for a range of aerosol types, significant overlaps between classes may still occur.

This study presents an approach based on a straightforward N_2–Raman lidar technique for retrieving aerosol optical properties at 355 nm with high spatial resolution in the troposphere, for the purpose of performing aerosol classification. The study examines the temporal evolution of these properties during the FENNEC (https://africanclimateoxford.net/projects/fennec/: last access 4 April 2026) ground-based field campaign conducted from mid-June to the end of August 2011. The focus is on identifying different types of aerosols (e.g. dust, carbonaceous, and soluble particles). The resulting optical apportionment (i.e. the classification of aerosols using optical measurements) is then compared with mesoscale simulations of the chemical composition of aerosols from the Copernicus Atmosphere Monitoring Service (CAMS; https://atmosphere.copernicus.eu/: last access: 8 February 2026) (Inness et al., 2019). This is performed alongside a study comparing the optical properties of aerosols (i.e. aerosol optical thickness and vertical profiles of the aerosol extinction coefficient) retrieved from Raman lidar measurements with those derived from numerical simulations. Unlike spaceborne lidar observations, for which few coincidences are available due to satellite revisits, this method provides a substantial amount of statistical overlap during the field campaign. Consequently, the reliability of the CAMS reanalysis of aerosols can be examined to enhance our understanding of the impact of aerosols on climate and air quality. However, this is also part of the long-term vision to use modelling data alongside ATLID products.

Subsection 2.1

The FENNEC airborne component took place from June to July 2011 (Ryder et al., 2015; Marsham et al., 2013), and was extended to include ground-based measurements from 25 June to 23 August. These measurements primarily focused on the contribution of Saharan dust to the atmospheric particle load. During this extended summer period, the vertical distribution of aerosols was monitored from a ground-based remote sensing station located in San Pedro Alcántara, southern Spain (36°29′11″ N, 4°59′33″ W), between Gibraltar and Marbella in Andalusia (Figure 1a). The complex topography of the Mediterranean coastline at this site gives rise to contrasting air masses in the lower and middle troposphere (Rodríguez et al., 2001). These air masses transport a variety of aerosol types, whose physicochemical and optical properties are closely linked to their source regions (e.g. the Sahara area).

The FENNEC ground-based experiment follows the Mediterranean Dust Experiment (MEDUSE) (Hamonou et al., 1999; Dulac and Chazette, 2003) and predates the Chemistry-Aerosol Mediterranean Experiment (ChArMEx), which was conducted between 2013 and 2014 (Chazette et al., 2016b; Di Girolamo et al., 2020; Chazette et al., 2019; Mallet et al., 2015). The latter notably included contributions from the European Aerosol Research Lidar Network (EARLINET) (Barragan et al., 2017; Navas-Guzmán et al., 2013). Compared with these

campaigns, FENNEC provided an exceptionally long and continuous lidar sampling of the troposphere in cloud-free troposphere.

2. The calculation of vertical profiles of aerosol extinction for the reanalysis may be overly simplistic and the author only verifies that the calculation reproduces the model AOT. In particular, using a single value for the specific cross section for each aerosol type neglects any dependence on humidity or the aerosol species within the type that is included in the reanalysis. Indeed neglecting the impact of increasing humidity near the surface could explain the underestimate of the extinction. More recent versions of the model used for the reanalysis do output aerosol extinction, so I would suggest checking that the method works well for extinction at the same location for a more recent period when the extinction is available.

Indeed, this section of the article requires further discussion. In the model, aerosol optical thicknesses (AOT) take relative humidity (RH) into account, but this is based on several assumptions. The main assumptions are that aerosols do not change bin during growth with RH, and that for highly hydrophilic sea salt aerosols, only RH = 80% is considered for both the AOT and mixing ratio (see https://www.ecmwf.int/sites/default/files/elibrary/112024/81630-ifs-documentation-cy49r1-part-viii-atmospheric-composition.pdf). Therefore, the impact of RH on the modelling is based on strong assumptions.

Therefore, I would say that the hypotheses put forward in this article are fairly well supported for sea salts (which are highly hydrophilic) and dust particles (which are slightly hydrophilic). Furthermore, the model accounts for dependence on RH via the AOTs.

Normally, the wet AOT should be calculated more accurately using an equation of the form:

$$AOT_W(z) = \int_{ground}^{z} \overbrace{\underbrace{M_D(z') \cdot \left(1 + \mu(z') \cdot \frac{RH(z')}{(1 - RH(z'))}\right) \cdot \sigma_W(z')}_{C}}^{\alpha_{CAMS}} \cdot dz'$$

In the article, I assumed that *C* is constant in order to derive Eq. 11.

- **μ is the aerosol mass increase coefficient (e.g. Hänel, 1976)**
- M_D **is the dry matter mass, and** $M_W = M_D \cdot \left(1 + \mu \cdot \frac{RH}{(1-RH)}\right)$ **is the wet matter mass (e.g. Hänel, 1976)**
- σ_W **is the wet specific cross-section**

It turns out that, when hydrophilic aerosols are present in high concentrations in the model (below 1 km), the relative humidity (RH) remains stable at altitude with a certain degree of repetition from one night to the next in the lower layers. Values between 50% and 80% are observed (see the figure 4 below). This therefore minimises the impact of RH on calculations. It could be said that the cross-section retrieved here is a pseudo-wet cross-section. Please note that the model's hypothesis

also involved the use of a pseudo-wet cross-section, and that below the deliquescence point (RH between 50% and 70%, 76.8% for sea salt), the hygroscopicity effect is low (see McMurry and Stolzenburg, 1989; Randriamiarisoa et al., 2006).

Table 2 provides a comparison of the AOT from the model with those recalculated based on my assumptions. The bias in the total AOT is very small (5.65 × 10^3), particularly when dust is present. I have updated this table to present the same type of results for the three types of aerosols considered. There is an excellent match for dust and carbonaceous aerosols. The correlation is slightly weaker for soluble aerosols but still shows a correlation of 0.82 with a very small bias.

Therefore, I think that the AOTs recalculated using the hypothesis set out in the article are in very good agreement with the ones provided directly by CAMS. This suggests that we are not far off the extinction profiles we are looking for, particularly given that the soluble and carbonaceous components are primarily found in the lower part of the profiles, below ~1 km. Therefore, the loss of significant correlation in the lower layers (see Table 4) does not necessarily indicate that hygroscopicity was not adequately considered in my calculations. It should be noted that the model is primarily validated using AOTs, which it also assimilates. The vertical profiles derived from the model are therefore adjusted accordingly.

A more precise comparison of the model's reliability can be made once all the hygroscopicity information is available in the database. In particular, the mass increase coefficients and wet densities of the aerosols would be useful to know. Unfortunately, the aerosol extinction coefficient profiles are not available. I have looked for recent data, but cannot find any. If these profiles are calculated, they should be included for all products, enabling users to assess the consistency of the dataset.

I propose including all these explanations in subsection 3.2 of the article. Therefore, the following changes have been made to subsection 3.2:

3.2 CAMS-derived Aerosol optical properties

3.2.1 CAMS-derive aerosol extinction coefficient

The AEC at 550 nm can be assessed based on the mixing ratios, with the CAMS-derived AOT serving as a constraint. In the reanalysis, the AOTs take relative humidity (RH) into account, but this is based on several assumptions. The main assumptions are that aerosols do not change bin during growth with RH, and that for highly hydrophilic sea salt aerosols, only RH = 80% is considered for both the AOT and mixing ratio (see https://www.ecmwf.int/sites/default/files/elibrary/112024/81630-ifs-documentation-cy49r1-part-viii-atmospheric-composition.pdf).
The wet AOT (AOT_W) should be calculated against the AEC (α_{CAMS}) at each altitude z using an equation of the form:

$$AOT_W(z) = \int_{ground}^{z} \alpha_{CAMS}(z') \cdot dz' \quad (10)$$

where considering each compound i:

$$\alpha_{CAMS}(z) = \sum_{i=1}^{3} M_{wi}(z) \cdot \sigma_{Wi}(z) \quad (11)$$

M_{Wi} and σ_{Wi} are the wet matter mass and the wet specific cross-section, respectively. Following Hänel (1976), M_{Wi} is a function of the dry matter mass, the mass increase coefficient μ_i and RH:

$$M_{Wi}(z) = M_{Di}(z) \cdot \left(1 + \mu_i(z) \cdot \frac{RH(z)}{(1 - RH(z))}\right) \quad (12)$$

When hydrophilic aerosols are present in high concentrations in the model (below ~1 km a.m.s.l.), the relative humidity (RH) remains stable at altitude with a certain degree of repetition from one night to the next in the lower layers. Values between 50% and 80% are observed (Figure 4). This therefore minimises the impact of RH on calculations. Please note that below the deliquescence point, for RH between 50% and 70%, even 76.8% for sea salt (McMurry and Stolzenburg, 1989; Randriamiarisoa et al., 2006), the hygroscopicity effect is low. It is therefore assumed here that product $\sigma_{Wi}(z) \cdot \left(1 + \mu_i(z) \cdot \frac{RH(z)}{(1-RH(z))}\right)$ remains constant for each type of aerosol. Therefore, the specific cross sections and the AEC can be evaluated using the mixture ratios r_i of each compound i (i.e. dust, carbonaceous matter and soluble matter) provided by CAMS, with the AOTs at 550 nm serving as a constraint. It should be noted that the model assimilated spaceborne-derived AOTs and is validated using ground-based AOTs. The vertical profiles derived from the model are therefore adjusted accordingly. The AEC is expressed according to the relationship:

$$\alpha_{CAMS}(z) = \frac{M_a}{\mathcal{N}} \cdot n_a(z) \cdot \sum_{i=1}^{3} r_i(z) \cdot \sigma_{Wi} \quad (13)$$

where M_a is the molar mass of dry air (28.94 g), $\mathcal{N}$ is Avogadro's number (6.022 10^{23}) and n_a is the atmospheric density. The values determined for the specific cross sections are given in Table 2.

The matching between the AOTs provided by CAMS and those recalculated from the AEC profiles in Eq. 13 is evaluated using statistical parameters defined in Appendix A. Their values are also given in Table 2 for each aerosol type. There is very good agreement, as shown by the mean bias (MB) and root mean square error (RMSE). The correlation coefficient (COR) between CAMS AOTs and AOTs recalculated from mixing ratios is very significant with a value of 0.97. There is an excellent match for dust (not very hydrophilic) and carbonaceous aerosols. The correlation is slightly weaker for soluble aerosols but still shows a COR of 0.82 with a very small bias.

Table 2: Specific cross sections σ_W assessed for each aerosol compound using the CAMS data. The statistical parameters of the comparison between the AOTs provided by CAMS and those recalculated are also given: Mean bias (MB), root mean square error (RMSE) and corelation coefficient (COR).

	Dust	Carbonaceous	Soluble	Total
σ_W at 550 nm	0.93	4.16	2.25	-

(m^2 g^{-1})				
Statistical parameters on AOT at 550 nm				
MB	**+5.06 10^{-3}**	**-8.10 10^{-5}**	**+6.73 10^{-4}**	**+5.65 10^{-3}**
RMSE	**1.47 10^{-2}**	**6.51 10^{-3}**	**1.61 10^{-2}**	**2.41 10^{-2}**
COR	**0.98**	**0.95**	**0.82**	**0.97**

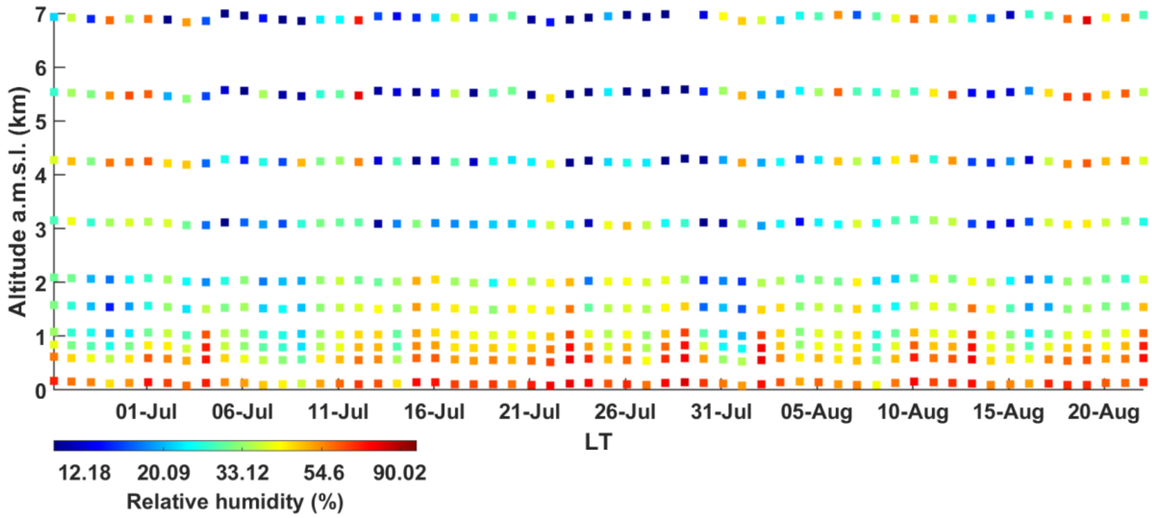


Figure 4: Temporal evolution of the mean values of the CAMS-derived relative humidity displayed for the period between 23:00 and 05:00 UTC on a nightly basis.

3.2.2 Optical properties at the lidar wavelength of 355 nm

CAMS products contain AOTs for the different classes of aerosol compounds. These AOTs are provided at different wavelengths. The wavelengths closest to the lidar wavelength are used, i.e. 469 and 550 nm. This allows the Ångström exponent (A) predicted by the model to be derived. It is then used to convert the AOT at 550 nm (AOT_{550}) to the AOT at 355 nm (AOT_{355}) using the relationship (Ångström, 1964):

$$AOT_{355} = AOT_{550} \cdot \left(\frac{355}{550}\right)^{-A} \tag{14}$$

A similar relationship to that in Eq. 10 exists for the AEC. However, as the Ångström exponent is calculated based on the total AOT, it may vary between different aerosol species. It is not possible to fully separate the contributions using the available EAC4 data. Therefore, the Ångström exponent for dust-like particles has been assumed to be the smallest value found in photometric measurements (see Erreur ! Source du renvoi introuvable.) **and in the CAMS data, i.e. $A_D \approx 0.3$. With the total spectral dependency, it is therefore possible to calculate the Ångström exponent (A_{CS}) for the carbonaceous and soluble components in a coupled system using the following equation:**

$$A_{CS} = -\frac{log\left(\frac{AOT_{355} - \left(\frac{355}{550}\right)^{-A_D} \cdot AOT_{550}^{Dust}}{AOT_{550}^{Carbonaceaous} + AOT_{550}^{Soluble}}\right)}{log\left(\frac{355}{550}\right)} \tag{15}$$

In practice, taking this relationship or the Ångström exponent for the total AOT has a negligible effect on the statistical results presented below.

3. The "RMSE" used in this article is more typically called the centred root mean square error (e.g. Taylor, 2001) I appreciate that the terminology used in this article is used by some authors, but I think RMSE is more widely understood to mean the error including the bias (i.e. what is called RMSD in this article). I think it would be better to adopt the more widely used terminology, which is less likely to cause confusion. In addition, while the appendix was useful for highlighting that a non-standard definition of the RMSE is used, I think it is unnecessary if the more widely used terminology is used.

   Ultimately, it comes down to definitions. The key point is that they are clearly stated. We have consistently used these definitions when comparing measurements and models, and they are also found in numerous publications. While I am not certain which definitions are the most widely used, I do not believe that this is particularly important. Maintaining consistency with our previous work seems more valuable.

   Note that RMS is calculated on a centred variable and reflects statistical noise. I believe the appendix is helpful for readers who may be less familiar with this type of calculation, as it can provide additional clarity.

4. I appreciate that there may be non-scientific reasons, but am puzzled by the long delay between collection of the data and the submission of this paper. I expect other readers will be too. It would be good to highlight how this older dataset remains relevant and important given the availability of more recent observations and more sophisticated instruments.

   Although the dataset is old, it remains entirely relevant. It is the longest continuous dataset available from our lidars. Furthermore, I can confidently state that lidar technology has not changed significantly since 2011. LAASURS is a French lidar system that remains operational and uses proven technology employed in recent developments and field campaigns (Laly et al., 2024). The FENNEC dataset has the additional advantage of having been collected during a period of low cloud cover in southern Spain. This provided sufficient nights for meaningful statistical analysis, following a robust inversion process.

   I explained this in subsection 2.2.2.

   "LAASURS (Figure 1b) itself is described in detail and validated in Royer et al. (2011a) and Chazette et al. (2019b). It has been used in numerous field campaigns, such as the journey from Paris to Lake Baikal (Dieudonné et al., 2015). LAASURS is a French lidar system that remains operational and uses proven technology that has also been employed in recent research activities (Laly et al., 2024). "

Another important point is the need to create databases to preserve records of observations for reuse years after they were collected, both in Europe and elsewhere. The same applies to model outputs. These datasets will remain relevant in the decades to come and must be used. It is better to focus on the relevance of the data than on its age.

Specific Comments

P1, L10: Expand FENNEC acronym.

This is not an acronym; it is the name of the project.

P2, L32: This should be *after* the Mediterannean dust experiment?

Yes, this paragraph has been moved to section 2.1.

P5, L20: This is incorrect. Aeronet observations are not assimilated into the model

Yes, the reviewer is correct. AERONET data are used for validation. The correction has been made.

"In particular, AOTs derived from satellite observations, such as those of the Moderate Resolution Imaging Spectroradiometer (MODIS) (Remer et al., 2005), are directly assimilated into the model. Ground-based measurements from permanent AERONET stations are also used as a validation dataset. However, vertical aerosol profiles are not assimilated and are rarely considered for validation purposes."

P13, L9: During *the* day…

The correction has been done.

P16, L10: No need for upper case The.

The correction has been done.

Fig. 9: Can you add ticks to the axis with the same orientation as the lines that show constant values for that aerosol to make it clear which lines correspond to which aerosol?

I have used different colours to mark the projections for the three types of aerosols because it was unclear when adding the ticks. This makes the ternary diagram easier to read.

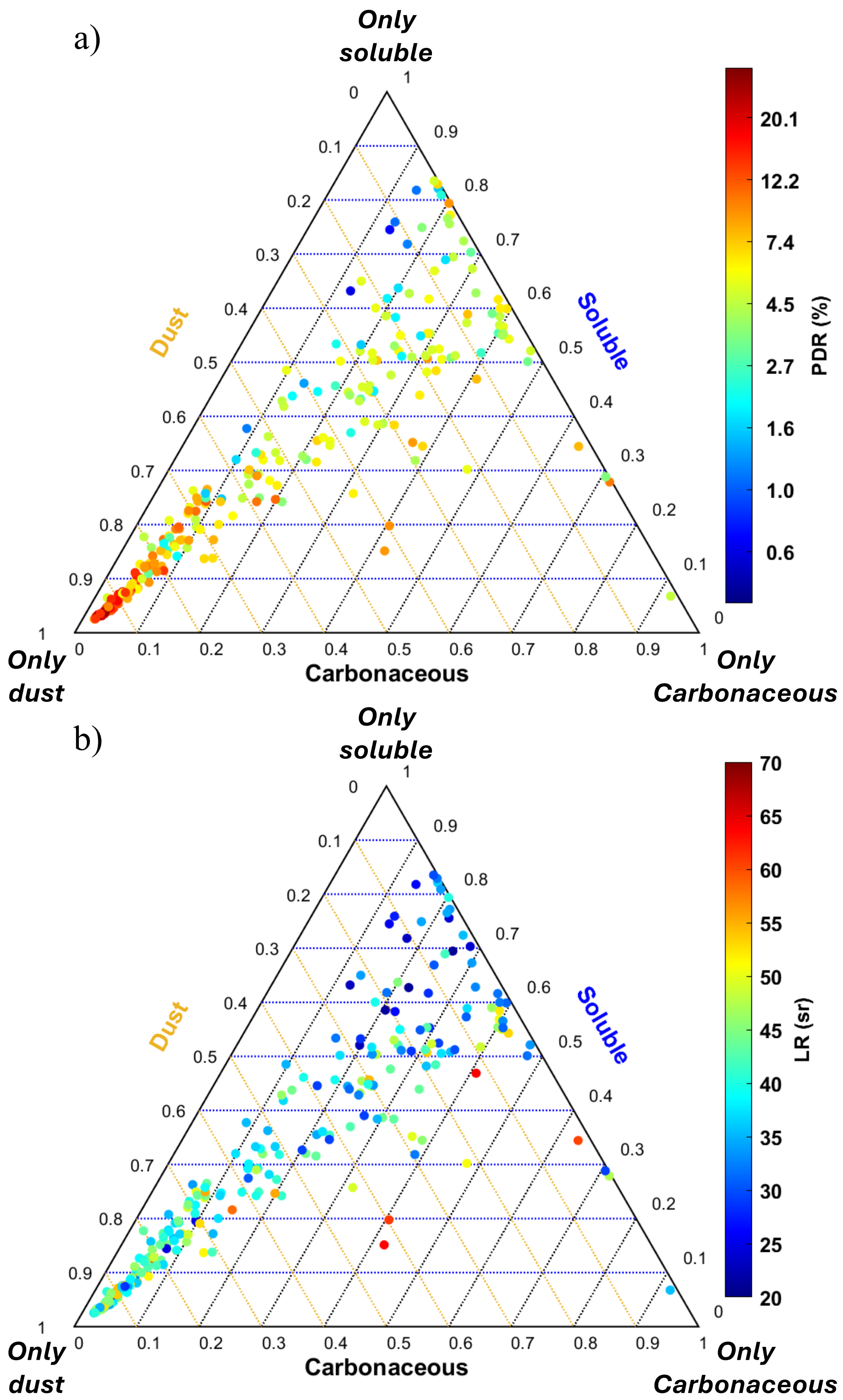


Figure 1. Ternary diagram established from the aerosol compounds derived from CAMS: dust, carbonaceous and soluble compounds. Each colour dot corresponds to lidar-derived optical properties: a) particulate depolarization ratio (PDR) and b) lidar ratio (LR). The projections onto the sides of the equilateral triangle are colour-coded as follows: orange for dust aerosols, blue for soluble aerosols, and black for carbonaceous aerosols.

P19 L 23: expends should be extent?

The correction has been done.

Responses to Review #2

The author would like to thank the reviewer for his valuable comments which helped in improving the quality of the manuscript. My point-by-point responses to the reviewer's comments appear in bold below.

Major comments

Robustness and uncertainty of aerosol classification

The aerosol classification is based on the joint use of LR and PDR (Section 4.2, Table 3). While this approach is well established, it relies on predefined ranges of LR and PDR for different aerosol types.

However:

- The ranges assigned to different aerosol classes (e.g. dust vs pollution) partly overlap.
- The classification is applied deterministically without providing any estimate of uncertainty or confidence.

Given the frequent occurrence of mixed aerosol layers (as acknowledged in the manuscript), this may lead to ambiguous classification.

Suggestion:

Provide a discussion on the uncertainty and potential misclassification of aerosol types.

If possible, include a probabilistic interpretation or at least comment on the sensitivity of the classification to the assumed LR/PDR ranges.

The LR and PDR classes in Table 3 were estimated using data from various lidar observation campaigns. These campaigns reveal considerable variability in the values for the different aerosol types. This also depends on whether mixing occurred during the measurements. I have expanded the justification for considering the LR and PDR values for the three aerosol classes. These values are highlighted in independent measurement campaigns.

The text in Section 4.2 has therefore been updated as follows:

"…

4.2.1 Parameterisation and assumptions

Dust aerosols over the western Mediterranean Sea are attributable to the long-range transport of Saharan dust. These aerosols are typically associated with LRs between 30 and 80 sr (Papayannis et al., 2008), specifically for high PDRs, above 10% and up to ~30%. This variability is explained by the level of mixing with other aerosol types and the nature of soils in uplift areas. In the overview by Mallet et al. (2022), the reported LR values at 355 nm are predominantly between 32 and 84 sr, including polluted dust aerosols. In Groß et al. (2015), however, they are closer to 55±20 sr, and for the same authors, the PDRs are of the order of 25±15%. These values include those provided by Chazette and Totems (2023), which range from 45 to 70 sr for the LR and from 20±15% for the PDR.

Marine aerosols have been found to have low LRs, ranging from 20 to 30 sr (Flamant et al., 1998), which corresponds to a very low PDR. However, these particles are often mixed with polluted aerosols or dust, which increases their LR and PDR. Mallet et al. (2022) reported LR of ~25±6 sr, which is very close to the values given in Groß et al. (~25±10 sr). The PDR remains low due to the spherical characteristics of these highly hydrophilic aerosols, with values of ~3±3% (e.g. Chazette et al., 2019; Groß et al., 2015).

The LR of pollution and biomass fire aerosols is highly variable depending on the combustion source, with values of ~60±20 sr (Chazette et al., 2019; Groß et al., 2015). Mallet et al. (2022) also report smoke-like aerosols with an LR between 42 and 73 sr. It should be noted that the combustion temperature influences the LR by affecting the chemical composition of the aerosols. It also influences the PDR, mainly in the event of strong thermal convection, whereby terrigenous particles can be lifted from the surface, leading to PDRs of the order of 8% (Chazette et al., 2016a). By contrast, the PDRs typically range from 2 to 3% for young aerosols, rising to over 6% after long-range transport and potential mixing with other air masses. Groß et al. (2015) reported PDRs of ~3±3% for smoke-like aerosols. These values are similar to those provided by Chazette and Totems (2023).

All of these values are obtained from short-term campaigns in very specific locations and are few in numbers. Significant variation can clearly occur depending on the degree of particle mixing and potential ageing during transport.

Figure 5 also allows us to determine the range of variation for the LR and PDR. For dust-like aerosols, LR varies from approximately 30 to 70 sr, whereas PDR is around 20%±10%. This is broadly consistent with previous reports. Similarly, the LR for marine-like (soluble) aerosols tends to be between 20 and 40 sr, with PDRs ranging from ~0 to 8%. Pollution-like (carbonaceous) aerosols, on the other hand, are associated with LR values between 40 and 80 sr and PDRs of up to 10%.

…"

I have also added the following after Eq. 10:

"…as presented previously. The exponential form clarifies potential mixtures by assigning lower weights to extreme values, while still taking the large variability associated with each type of aerosol into account…"

I believe all this provides a clearer picture of the variability of each type of aerosol, and consequently of the potential uncertainties in the classification. It also demonstrates how these factors were considered when selecting the parameters for the Gaussian distributions.

Lack of uncertainty propagation

Although uncertainties are provided for individual retrieved quantities (AEC, LR, PDR), there is no propagation of these uncertainties into: aerosol classification, comparison with CAMS, or the final conclusions. Given that the study draws quantitative conclusions based on correlation, bias, and RMSE, this is an important limitation.

Suggestion:

Include a discussion on how measurement uncertainties may impact: classification results, and the evaluation of CAMS performance. A full propagation may not be necessary, but a quantitative or semi-quantitative assessment would be valuable.

The AEC is not a factor in aerosol classification. As previously mentioned, only LR and PDR are used. A Monte Carlo approach can be used to assess how the classification changes based on the determined LR and PDR values and by increasing the relative errors to 5% for LR and the absolute errors to 2% for PDR. I carried out this study on two profiles where the three aerosol types that reached the highest altitudes were present. For clarity, subsection 4.2 has been divided into three parts:

4.2.1 Parameterisation and assumptions

4.2.2 Classification results

4.2.3 Sensitivity study

The following elements have been added to subsection 4.2.3:

"A sensitivity analysis using a Monte Carlo approach was performed to assess the reliability of this optical apportionment based on lidar measurements, as described by Royer et al. (2011a). Uncertainties in LR and PDR were assumed to be up to 5% (relative) for LR and 2% (absolute) for PDR. Figure 7 presents the results for the three particle types. As can be seen, the influence of the uncertainties on lidar-derived optical parameters is small, remaining below 5% for each aerosol type. This demonstrates the robustness of the classification with respect to realistic uncertainties associated with lidar measurements."

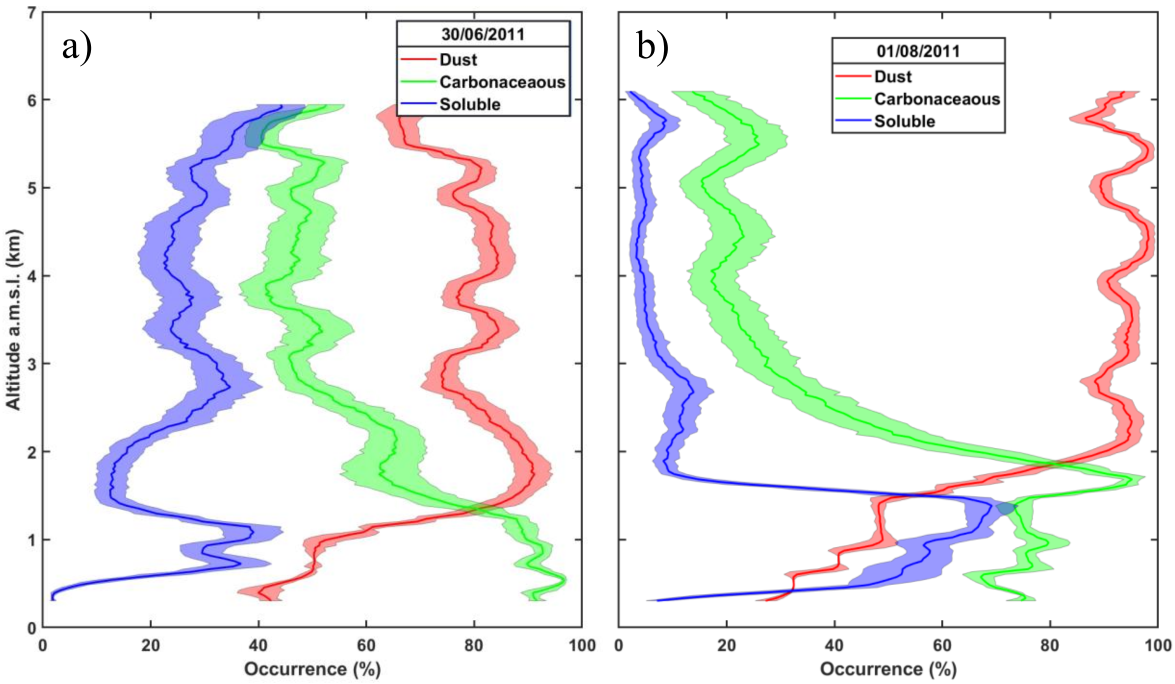
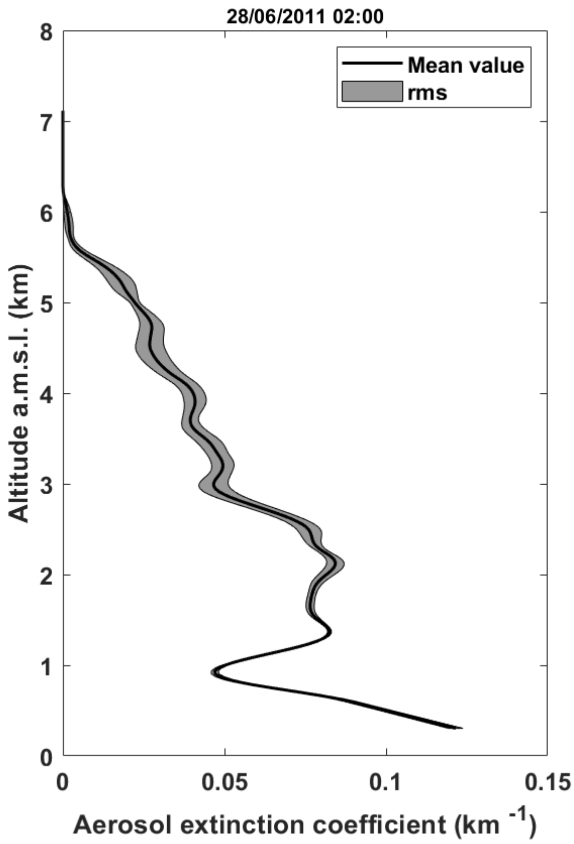


Figure 7. Uncertainty on the occurrences of each aerosol type due to statistical error on both the lidar ratio (LR, 5% in relative) and linear particle depolarization ratio (PDR, 2% in absolute) on 30 June 2011 and 1 August 2011. The mean value is given by the continuous lines and the standard deviation by the shaded area.

When comparing AEC profiles, uncertainties in the lidar measurements (RMS<0.01 km^{-1} for the average profiles) have little impact on the model's performance (see the figure below for an example). Furthermore, these uncertainties are accounted for by the variability of the profiles and, consequently, in the statistical results. This is even more evident for AOTs, which integrate AEC profiles. For example, a vertical profile of the AEC with its uncertainty (gray area) is given below:



Vertical representativeness mismatch between lidar and CAMS

The comparison between lidar profiles and CAMS data (Section 5.2) does not explicitly account for differences in vertical resolution and representativeness, as Lidar profiles have high vertical resolution (~100 m), while CAMS profiles are much coarser and model-based.

The observed discrepancies, particularly in the boundary layer (low correlation and positive bias), are attributed mainly to model deficiencies. However, part of these differences may arise from scale mismatch and representativeness errors, especially in a coastal environment.

Suggestion:

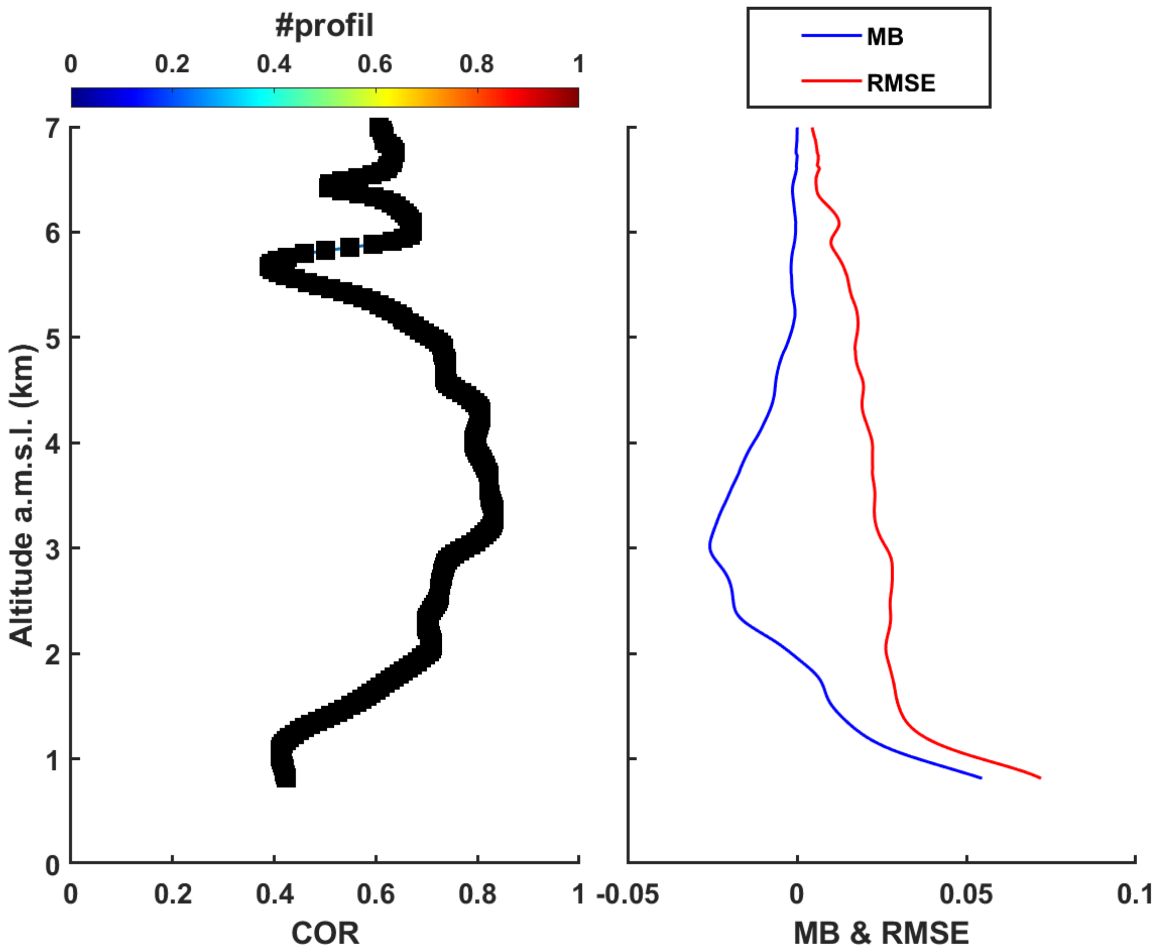
- Discuss the impact of vertical resolution mismatch.

- If possible, consider smoothing lidar profiles to the CAMS vertical grid, or explicitly acknowledge this limitation.

There is indeed a significant difference in vertical resolution between the lidar measurements and the CAMS data. This is one of the challenges involved in comparing vertical profiles. In this article, this challenge was overcome by down sampling the lidar data to match the resolution of the CAMS profiles using spline interpolation. I verified that similar results could be obtained using the lidar's vertical resolution, again via spline interpolation applied to model data. The result is shown below, but I have not included it in the article as it adds nothing further. I have added the following text to subsection 5.2:

"The significant difference in resolution between the CAMS and LiDAR data requires the application of spline interpolation (Perperoglou et al., 2019). The results presented here are at the model resolution. Similar results are obtained when the vertical resolution of the lidar is used with spline interpolation applied to the model data. It is worth noting that the model's resolution is higher for the lower layers, meaning they are estimated more accurately. However, for the upper layers, the thickness of the desert dust clouds limits the effectiveness of the model's vertical resolution."

Perperoglou, A., Sauerbrei, W., Abrahamowicz, M., and Schmid, M.: A review of spline function procedures in R, https://doi.org/10.1186/s12874-019-0666-3, 6 March 2019.



Interpretation of CAMS performance

The manuscript concludes that CAMS shows "excellent agreement" with lidar observations. While this is valid for the free troposphere, the results clearly show significantly lower correlation in the boundary layer (~0.5) and systematic bias near the surface. Therefore, the conclusions appear somewhat over-generalized.

Suggestion:

Refine the conclusions to clearly distinguish between:

- good performance in the free troposphere,
- and more limited performance in the boundary layer.

I have separated the two layers and strengthened the conclusion:

"…In the free troposphere, the CAMS reanalyses (EAC4) were found to be in agreement with the geophysical products derived from optical lidar measurements for dust layers. This is particularly notable for the AOTs. The reanalyses accurately reproduce dust events in terms of both time and vertical extends with COR ~0.85. However, there is an overestimation of the AOT at 355 nm (-0.04 or 39%) compared to the Raman lidar products.
In the lower troposphere, below 2 km a.m.s.l., the mixing of pollution (characterised by the carbonaceous component) with marine (characterised by the soluble component) and dust contributions is also accurately reproduced throughout the two-month experiment. Nevertheless, the correlation between lidar measurements and CAMS reanalyses is significantly lower (0.55). It is associated with an underestimation of the AOT contribution of this layer of around +0.04 (+29%) at 355 nm, which may be due to an incorrect representation of emission processes. However, it should be noted that the neglect of aerosol hygroscopicity may also affect this result. Such an omission may be present in the model itself, given that a number of assumptions have been made. Alternatively, it may arise from the calculation of aerosol extinction coefficients performed in this study. Note that, conversely, lidar measurements account for the hydrophilic nature of aerosols.
In the entire atmospheric column, good agreement is observed in the temporal evolution of total AOT derived from CAMS and lidar. This is associated with a small mean bias (+0.01 or 3%) and a significant correlation coefficient (0.83). This is primarily due to the fact that dust aerosols dominated the aerosol load during the FENNEC field campaign, and the reanalyses better represent them in terms of total AOT. There is a compensation effect between the upper and lower layers: the reanalyses do not distribute dust particles perfectly across these two layers, with an overestimation in the upper layer and an underestimation in the lower layer…"

Assumptions in CAMS extinction reconstruction

The method used to reconstruct extinction profiles from CAMS mixing ratios (Section 3.2) assumes constant specific cross-sections for each aerosol type. This simplification neglects hygroscopic growth (especially relevant near the surface), variability in aerosol composition within each class, and size distribution changes. These factors may contribute significantly to the discrepancies observed in the lower troposphere.

Suggestion:

- Expand the discussion of these assumptions and their impact.
- If possible, comment on the sensitivity of the results to these choices.

The answer was provided in detail in the replies to reviewer #1, so I will not repeat it here. A discussion was indeed lacking. It should be noted that the calculation based on the model data is justified not only by the meteorological conditions, but also by an understanding of the model's underlying assumptions. For instance, bin size does not change due to growth with humidity, and it is assumed that sea salt has 80% relative humidity (RH). Table 2 of the article now illustrates the impact of the calculation assumptions on the AOTs for each type of aerosol. The effect remains small, though it is slightly higher for soluble aerosols in terms of correlation (0.82).

When comparing with lidar data, it is important to bear in mind that the measurement considers the aerosol as a whole and therefore includes potential mixtures. No assumptions are made during inversion of the profiles. The statistical results therefore provide an incomplete representation of the model's estimation of the effect of relative humidity (RH). Nevertheless, according to the RH values derived from ERA5, it should be noted that the deliquescence points are not necessarily reached. Having compared ERA5 profiles with radiosonde and lidar observations, I have considerable confidence in these reanalyses.

Temporal averaging strategy

The lidar profiles are averaged over relatively long nighttime periods. While this is necessary for signal-to-noise reasons, it may smooth out short-term variability, and potentially improve apparent agreement with model data.

Suggestion:

- Include a discussion of the implications of this temporal averaging.
- Optionally, illustrate one case with higher temporal resolution.

Novelty and relevance of the dataset

The dataset dates from 2011, and the manuscript does not sufficiently justify its relevance in the context of more recent observations and advances in instrumentation and modelling.

This point was also raised by Referee #1.

Suggestion:

- Clearly state the added value of this dataset

The relevance of the dataset has been clarified.

Although the dataset is old, it remains entirely relevant. It is the longest continuous dataset available from our lidars. Furthermore, I can confidently state that lidar technology has not changed significantly since 2011. LAASURS is a French lidar system that remains operational and uses proven technology employed in recent developments and field campaigns (Laly et al., 2024). The FENNEC dataset has the additional advantage of having been collected during a period of low cloud cover in southern Spain. This provided sufficient nights for meaningful statistical analysis, following a robust inversion process.

I explained this in subsection 2.1 and 2.2.2.

"It is worth noting that the FENNEC ground-based experiment follows the Mediterranean Dust Experiment (MEDUSE) (Hamonou et al., 1999; Dulac and Chazette, 2003) and predates the Chemistry-Aerosol Mediterranean Experiment (ChArMEx), conducted between 2013 and 2014 (Chazette et al., 2016; Di Girolamo et al., 2020; Chazette et al., 2019; Mallet et al., 2015). The latter notably included contributions from the European Aerosol Research Lidar Network (EARLINET) (Barragan et al., 2017; Navas-Guzmán et al., 2013). Compared with these campaigns, FENNEC provided an exceptionally long and continuous lidar sampling of the troposphere in cloud-free conditions. "

"LAASURS (Figure1b) itself is described in detail and validated in Royer et al. (2011a) and Chazette et al. (2019b) and it has been used in numerous field campaigns, such as the journey from Paris to Lake Baikal (Dieudonné et al., 2015). LAASURS is a French lidar system that remains operational and uses proven technology that has been employed in recent developments and field campaigns (Laly et al., 2024). "

Link to radiative implications

The introduction emphasizes aerosol radiative effects and climate relevance, but the study does not directly quantify radiative forcing.

Suggestion:

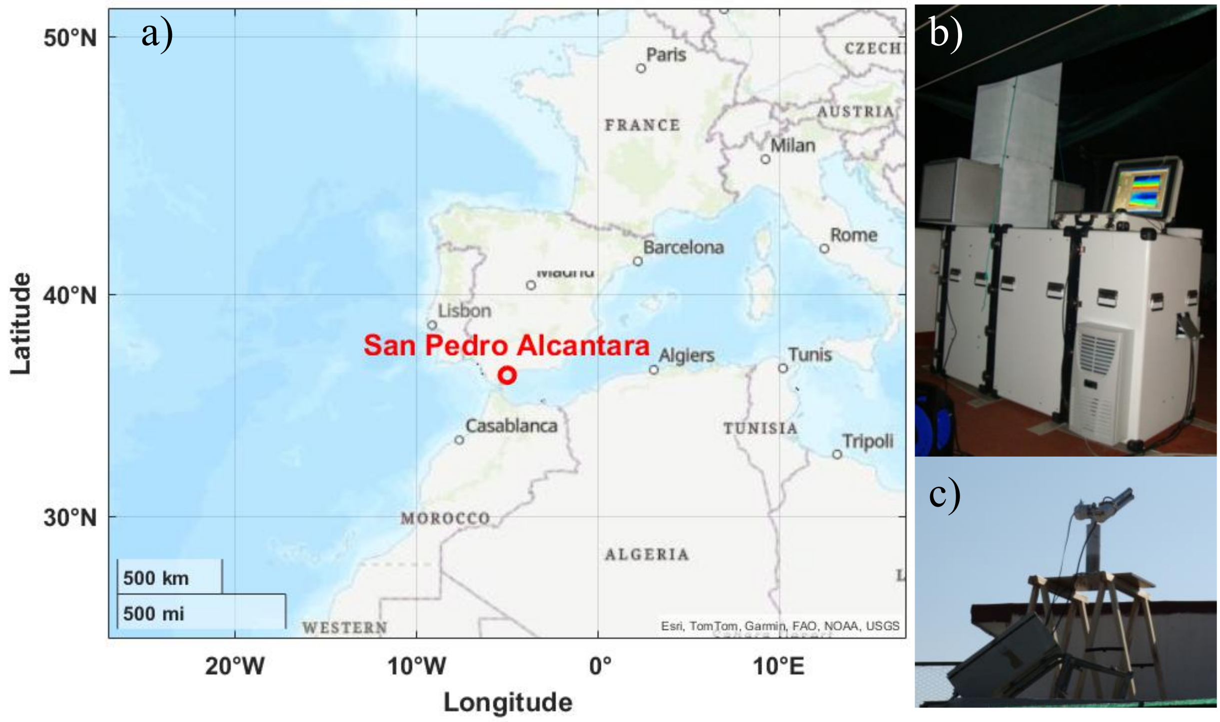
- Either briefly discuss the radiative implications of the observed aerosol properties or moderate the claims in the introduction

The introduction was too general and exceeded the scope of the article. It has now been revised to be more focused (see the responses to Review_RC1).

Minor comments

- Figure 1- the map is blurry; please improve the quality in the final uploaded file

  I think it is related to the conversion to PDF. I hope that Figure 1 below is not blurry.



- Figure 4 and 5- consider improving readability (the graphs are blurry).

  Unfortunately, it seems that converting the figures to PDF has lowered their quality. My apologies for this. Please note that the figures are provided in JPG format for the final publication.

- Terminology such as "optical apportionment" should be clearly defined when first introduced.

  It has now been defined in the introduction: (i.e. classification of aerosols using optical measurements)

- Ensure consistency in terminology for statistical metrics (RMSE vs RMSD), in line with Referee #1.

  As I wrote in my reply to Referee #1, this mainly stems from the conventions within each scientific field. These definitions are widely used and have been employed several times in our publications. For the sake of consistency with previous works, I would prefer not to change them. Moreover, since they are clearly defined in the Annex, I do not believe it will impair comprehension.

- page 12 Lines 11 and 12 "may lead to LRs of the order of 8%"; LR is measured in sr, not %. Please clarify in here what 8% (and 2-3% on the next line) mean

  Yes, the correction has been done.

- page 16 Line 10: "Qualitatively, The altitude and time locations…"; "The" should be lowercase.

  The correction has been done.

- page 18 Line 2 and 3 "rectangle" Should be corrected with " triangle"

The correction has been done.

General language issues

The manuscript would benefit from a careful language revision, as it contains a number of minor grammatical errors, typographical issues, and occasional imprecise phrasing. While these do not affect the scientific content, improving readability would significantly enhance the clarity of the paper.

Some long sentences could be split for clarity.

The manuscript has been proofread and the errors corrected.