

Incorporation of aerosol into the COSPv2 satellite lidar simulator for climate model evaluation

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Abstract The atmospheric aerosol has substantial impacts on climate, air quality, and biogeochemical cycles, and its concentrations are highly variable in space and time. A key variability to evaluate within models that simulate aerosol is the vertical distribution, this influencing atmospheric heating profiles, and aerosol-cloud interactions, to help constrain aerosol residence time, to better represent the magnitude of simulated impacts. To ensure a consistent comparison between modeled and observed vertical distribution of aerosol, we implemented an aerosol lidar simulator within the Cloud Feedback Model Intercomparison Project (*CFMIP*) Observation Simulator Package version 2 (*COSPv2*). We assessed the attenuated total backscattered (ATB) signal and the backscatter ratios (SR) at 532 nm in the U.S. Department of Energy’s Energy Exascale Earth System Model version 1 (*E3SMv1*). The simulator performs the computations at the same vertical resolution as the Cloud-Aerosol Lidar with Orthogonal Polarization (*CALIOP*), making use of aerosol optics from the *E3SMv1* model as inputs, and assuming that aerosol is uniformly distributed horizontally within each model grid-box. The simulator applies a cloud masking and an aerosol detection threshold, to obtain the ATB and SR profiles that would be observed above clouds by *CALIOP* with its aerosol detection capability. Our analysis shows that the aerosol distribution simulated at a seasonal timescale is generally in good agreement with observations. Over the Southern Ocean, however, the model does not produce the SR maximum as observed in the real world. Comparison between clear-sky and all-sky SRs shows little differences, indicating that the cloud screening by potentially incorrect model clouds does not affect the mean aerosol signal averaged over a season. This indicates that the differences between observed and simulated SR values are due not to sampling errors, but to deficiencies in the representation of aerosol in models. Finally, we highlight the need for future applications of lidar observations at multiple wavelengths to provide insights into aerosol properties and distribution and their representation in Earth system models.

1. Motivation

The role of aerosol in the Earth system has been recognized as a major source of uncertainty for decades. Aerosol has significant impacts on the climate system, as well as on weather and air quality, and Earth’s biogeochemical cycles (Szopa et al., 2021). They modulate the Earth’s energy budget via

1 aerosol-radiation and aerosol-cloud interactions, exerting radiative forcings to the climate system
2 (Forster et al., 2021). They also affect the Earth's water cycle by changing clouds and precipitation
3 characteristics (Douville et al., 2021). Due to its short lifetime (up to several days in the troposphere)
4 compared to long-lived greenhouse gases, aerosol is highly variable in space and time. Obtaining ap-
5 appropriate information about the spatiotemporal distribution of aerosol from satellite measurements re-
6 mains a key challenge (Constantino and Bréon, 2013).

7
8 Passive satellite measurements have been used to study column-integrated properties of aerosol, but
9 they are not suited for the vertical distribution of aerosol. Nevertheless, aerosol vertical distribution is
10 critical when it comes to aerosol-radiation interactions (Zarzycki and Bond, 2010). This in particular
11 applies to the adjustments to aerosol-radiation interactions or semi-direct effect, where the vertical
12 alignment of clouds and aerosol is crucial (Koch and Del Genio, 2010). Aerosol vertical distribution
13 also affects aerosol lifetime (e.g. Keating and Zuber, 2007) and aerosol-cloud interactions (e.g. Waquet
14 et al. 2009; Stier, 2016; Quaas et al., 2020).

15
16 Space-borne lidars fill this gap by providing detailed information about the vertical distribution of
17 aerosol. This is particularly useful for studying long-range transport of smoke or dust in the free tro-
18 posphere and stratosphere, and for studying the interactions between aerosol and ice clouds in the up-
19 per troposphere, because the vertically integrated aerosol quantities retrieved from passive sensors are
20 mostly about aerosol in the planetary boundary layer. Furthermore, space lidars can retrieve aerosol in
21 regions where the surface is reflective, such as the polar regions and desert, while passive satellite in-
22 struments only have limited capabilities retrieving aerosol in those conditions. Over the last decade, the
23 aerosol profiles collected by space lidars (Winker et al. 2013) have contributed to progress on a variety
24 of aerosol research questions (Koffi et al., 2012, 2016; Tian et al., 2017; Ratnam et al., 2021). More
25 advanced comparisons between model and lidar observations have demonstrated the value of using a
26 lidar aerosol simulator to ensure consistent comparisons between the modeled aerosol and the observed
26 aerosol (Ma et al. 2018, Hodzic et al. 2004, Watson-Parris et al. 2018). In parallel, the cloud communi-
28 ty has developed satellite simulators to establish a closer bridge between observed and modeled clouds
29 and facilitate the use of space-based data by the model community for a variety of topics such as evalu-
30 ating the model physics, studying climate feedbacks, inter-comparing several models in a consistent
31 way over short-term and long-term simulations (Konsta et al. 2016, Chepfer et al. 2018). In particular,
32 the active sensor satellite simulators developed for lidars and radars have been proven to be useful tools
33 to properly take into account the limits of observations (eg. cloud masking, signal-to-noise ratio, sub-
34 gridding) when comparing observations and models (e.g. Ma et al. 2018).

35
36 These studies point to the potential for satellite lidars to provide important constraints for the aerosol
37 distributions in climate models, of benefit to a range of different configurations. There is now a 15
38 year-record of the space-borne CALIOP lidar on the Cloud-Aerosol Lidar and Infrared Pathfinder
39 Satellite Observations (CALIPSO) satellite (2006-2020). In evaluating the simulated vertical aerosol
40 distribution in nudged simulations where e.g. winds are relaxed towards reanalyses, these measure-
41 ments can provide important observational constraints to improve transport and removal processes in
42 models. On the other hand, using observational constraints together with a climatology statistic ap-
43 proach of simulations with prescribed SST can be beneficial to account for circulation feedbacks to

1 aerosol forcing. Indeed, while the transport by large-scale circulation determines the geographical pat-
2 terns of aerosol forcing, this aerosol forcing also impacts large-scale circulation (Kim et al. 2007).
3 These mechanisms can be studied by making use of aerosol optical depths (AOD) retrieved by MOD-
4 erate resolution Imaging Spectroradiometer (MODIS) or VIvisible Infrared Imaging Radiometer Suite
5 (VIIRS). Finally, long-term (100 years) simulations of the coupled ocean-atmosphere system (control
6 and RCP8.5 type simulations) can help to understand the role of aerosol in the context of climate
7 change.

8
9 The lidar simulator translates the vertical profiles of aerosol extinction and backscatter coefficients
10 computed by a model into vertical profiles of the two key variables retrieved by a lidar : the attenuated
11 total backscatter (ATB), and the backscatter ratio (SR). These two lidar variables are derived online
12 within the model, to account for the 2-way attenuation within the light’s transmittance along its path
13 from the laser to the scattering object, and the return-path back to the detector. The calculations also
14 account for the molecular backscatter (i.e. Rayleigh backscatter), calculated from the model’s air tem-
15 perature and pressure profiles. Furthermore the model is sampled on the satellite orbital path, the fully
16 overcast cases are masked out to take account of the impossibility for a space lidar to observe aerosol
17 below optically thick clouds, and only the signal above the instrumental noise is retained.

18
19 We incorporate modules included in previously developed simulators (Ma et al. 2018, Vuolo et al.
20 2009, Hodzic et al. 2004) into the community tool Cloud Feedback Model Intercomparison Project
21 (CFMIP) Observation Simulator Package version 2 (COSPV2) to create a simple base on which each
22 group can build up its own analysis. The goal is to facilitate the comparison between GCMs and space
23 lidar aerosol data. Besides CALIPSO operating at 532 nm and 1064 nm, the ATmospheric LIDar
24 (ATLID) instrument of the EarthCARE mission is expected to become operational in 2023. In synergy
25 with other instruments, it will provide vertical profiles of aerosol and thin clouds, operating at 355 nm
26 with a high-spectral resolution (HSR) receiver and depolarization channel. Moreover another HSR Li-
27 dar operating at 532 nm and 1064 nm is expected to be launched in the future. The COSPV2 lidar simu-
28 lator will thus be a useful tool for the exploitation of these new datasets and the comparison with Gen-
29 eral Circulation Models (GCMs) of several modeling groups.

30
31 We have chosen to implement the lidar aerosol simulator within the COSPV2 software package to
32 leverage all the simulator capabilities available in COSPV2. Moreover, COSPV2 is already implement-
33 ed in several GCMs (Webb et al. 2019) so the addition of the aerosol lidar simulator module should
34 only require a small amount of effort for the modeling groups.

35 **2. Concept and Design**

36
37 The aerosol simulator described in this section mimics the aerosol observations that would be observed
38 by a space lidar overflying the atmosphere simulated by the model (Fig. 1). Hereafter we first define
39 the usual aerosol variables (specifically, the attenuated total backscattered signal ATB and the
40 backscatter ratio SR). Then we describe the procedure of the lidar aerosol simulator. Finally we discuss
41 its implementation and its main differences with the cloud lidar simulator.
42

2.1 Definitions

As defined by Stromatas et al. (2012), the attenuated total backscattered signal (in $\text{m}^{-1} \text{sr}^{-1}$) represents the signal backscattered towards the lidar by aerosol and molecules, and attenuated along its path by aerosol and molecules in a cloud-free atmosphere. The ATB is integrated vertically from the surface to the top of the atmosphere (TOA) :

$$ATB = (\beta_m(\lambda, z) + \beta_a(\lambda, z)) \cdot \exp[-2 \int_z^{TOA} (\alpha_m(\lambda, z') + \alpha_a(\lambda, z')) dz'], \quad \text{where } \beta_m \text{ and } \beta_a \text{ are the}$$

molecule and aerosol 180° backscatter profiles (in $\text{m}^{-1} \text{sr}^{-1}$), respectively ; α_m and α_a are the extinction coefficients for molecules and aerosol (in m^{-1}), respectively. The 180° Rayleigh/molecular backscatter coefficient depends on temperature (in K), pressure (in Pa) and on the wavelength λ (in μm) :

$$\beta_m = \frac{P}{kT} (5.45 \times 10^{-32}) \left(\frac{\lambda}{0.55}\right)^{-4.09}, \quad \text{where } k \text{ is the Boltzmann constant } (k=1.38 \times 10^{-23} \text{JK}^{-1}). \text{ The}$$

extinction coefficient by molecules can be simply expressed as : $\alpha_m = \frac{\beta_m}{0.119}$ (Stromatas et al. 2012).

The 180° backscatter and extinction coefficients for aerosol depend on the microphysical properties (size distribution) and chemical composition of the particles, the latter determining its refraction index. To highlight aerosol in an atmospheric layer versus molecular background, one often uses the backscatter ratio (SR). The definition of SR used in CALIPSO products (e.g. Chepfer et al. 2008, 2013)

is : $SR(\lambda, z) = \frac{ATB}{AMB}$, where AMB is the attenuated molecular backscattered signal in the absence of

aerosol : $AMB(\lambda, z) = \beta_m(\lambda, z) \cdot \exp[-2 \int_z^{TOA} \alpha_m(\lambda, z') dz']$. Therefore $SR = 1$ indicates the

absence of aerosol, where the backscatter signal is from gaseous molecules only.

2.2 Concept

The GCM provides pressure, temperature and cloud fraction at each level and for each latitude-longitude grid cell. When the GCM includes an interactive aerosol module, it also provides on this 3D-grid the optical properties of aerosol at a given wavelength. The simulated aerosol optical properties and distribution depend on the aerosol parameterization in the GCM. The aerosol optics diagnostics in GCMs vary, with some models computing single-wavelength extinction and 180° backscatter, whilst others calculate only the waveband-integrated aerosol optical properties (i.e. extinction, absorption and phase function). In the latter case, the modeling centers will need to implement additional aerosol optics diagnostics to convert these optical properties into the aerosol extinction and 180° backscatter coefficients in order to use the lidar simulator. These coefficients must be defined monochromatically (i.e. at specific wavelengths) : 532 and 1064 nm for CALIPSO/CALIOP, these being standard wavelengths for most GCMs. Coefficients defined at other wavelengths, such as 355nm for EarthCare/ATLID, could also be added as additional diagnostics.

1 In the steps listed below, it is assumed that the process applies to a vertical profile, and that it is
2 repeated for all longitude-latitude grid cells and for each instantaneous model output. In this study, the
3 model writes out at 1:30 am and 1:30 pm local time, corresponding to the CALIPSO overpass time.
4

- 5 1) Construct subgrids : The ACTSIM procedure already implemented in COSP calculates the
6 $\alpha_M(z)$, $\beta_m(z)$ and $AMB(z)$ vertical profiles using the GCM pressure and temperature profiles,
7 according to the equations of Section 2.1. The GCM vertical profile of cloud fraction is also passed
8 to the Subgrid Cloud Overlap Profile Sampler (SCOP) (Klein and Jakob, 1999) procedure in
9 COSPv2, to generate subgrid columns within a grid cell in accordance with the simulated cloud
10 fraction and the vertical overlap assumption.
11
- 12 2) Compute ATB and SR : The ATB and SR profiles are computed at model levels. These variables are
13 calculated according to the equations of Section 2.1, using the input variables α_a and β_a and the
14 variables α_m , β_m and AMB calculated in Step 1. Because the GCM does not consider subgrid
15 variability of aerosols, we compute the ATB and SR for each grid cell.
16
17
- 18 3) Vertical regridding : The total extinction ($\alpha_a + \alpha_m$), ATB and SR profiles are vertically re-gridded
19 over a standard vertical grid having N equidistant levels to obtain profiles of total extinction
20 (EXT_initial), attenuated total backscatter (ATB_initial) and backscatter ratio (SR_initial) at the
21 vertical resolution of the space lidar observations that would be observed in absence of instrumental
22 noise. For consistent comparison with CALIPSO observations, N is set to 320 levels so that each
23 level is 60m thick from the surface to 19,14 km of altitude. We design the code to allow N to be set
24 by users so that it can be easily adapted for other lidars. For example, the vertical resolution of
25 ATLID/EarthCare is 100 m , so N will need to be set to 192 for the simulator to operate between the
26 surface and 19.1 km above ground level.
27
28
- 29 4) Apply aerosol detection thresholds : The aerosol detection thresholds, based on the actual space lidar
30 capability (above instrumental noise) are applied to the EXT_initial, ATB_initial and SR_initial
31 profiles, in order to get the profiles of total extinction (EXT_detectable), attenuated total
32 backscatter (ATB_detectable) and backscatter ratio (SR_detectable) that would be observed by a
33 space lidar overflying the atmosphere simulated by the model in absence of clouds. This takes into
34 account the limited capability to detect aerosol when the signal-to-noise ratio (SNR) is too low for
35 CALIPSO. The aerosol detection threshold considered in this study is SR=1.2, which is different
36 from the previous study that considered the detection threshold as a function of height (Ma et al.,
37 2018), but we designed the code to be flexible so that it can be easily adapted for sensitivity studies
38 or for future space lidars that have a different SNR.
39
- 40 5) Apply cloud masking : The cloud masking is applied to the initial profiles EXT_initial, ATB_initial
41 and SR_initial to get the total extinction (EXT_masked), attenuated total backscatter (ATB_
42 masked), and backscatter ratio (SR_masked) profiles that would be observed above clouds by a
43 space lidar with a perfect aerosol detection capability (no instrumental noise). This takes into ac-

1 count the fact that a space lidar is unable to observe aerosol below optically thick clouds (with opti-
2 cal depth larger than 3-5) where the laser beam is fully attenuated. To simulate this cloud masking
3 effect, the cloud masking in the simulator is built from the modeled clouds (not the actual clouds)
4 as it would be seen by a space lidar. We take the cloud lidar simulator output called Cloud Fraction
5 profiles (CF3D). When scanning each grid point from the TOA to the surface, the first altitude level
6 where CF3D=1 is called “z_bottom” and all aerosol-related output values at that altitude and below
7 are set to Fill_value.

- 8
- 9 6) Combine all factors : The cloud masking (step 5) and aerosol detection thresholds (step 4) are ap-
10 plied to the initial profiles (EXT_initial, ATB_initial and SR_initial) to get the total extinction (EX-
11 T_observable), the attenuated total backscatter (ATB_observable), and backscatter ratio (SR_ob-
12 servable) profiles that would be observed above clouds by a space lidar with actual aerosol detec-
13 tion capability.

14

15 Note that in the code, the variables have different names than in this paper. Table 1 establishes the cor-
16 respondence between the names of the variables in this text and in the code.

17

18

19 **2.3 Differences between the CALIPSO Aerosol and Cloud Simulators**

20 The aerosol lidar simulator is implemented within the COSPv2 infrastructure, which has been opti-
21 mized for computational performance so that it can be used for long climate simulations when needed.
22 COSPv2 already contains a cloud lidar simulator from which several routines are used within the
23 aerosol lidar simulator (Chepfer et al. 2008, Cesana and Chepfer, 2012, 2013, Guzman et al. 2017,
24 Reverdy et al. 2015) from which several routines are used by the aerosol lidar simulator. The main dif-
25 ferences between the aerosol lidar simulator presented in this paper and the cloud lidar simulator are
26 described below:

- 27
- 28
- 29 1) The aerosol lidar simulator needs aerosol optics from the models as inputs (α_a and β_a profiles in each
30 model grid box) because those optical properties are strongly dependent on aerosol size distribution
31 and chemical composition. They depend on the aerosol parameterization in the GCM and the size of
32 aerosol is close to the lidar wavelength. By contrast, because cloud droplets are much larger than the
33 lidar wavelength, cloud optical properties can be parameterized in a simpler way than aerosol, so
34 COSPv2 can easily compute cloud optical properties from cloud microphysical properties.
- 35
- 36 2) Within the aerosol lidar simulator, the computations are performed in each grid-box (with a typical
37 grid spacing of 1°), while the cloud simulator computations are performed at a sub-grid scale (typically
38 50 sub-grid boxes in a grid box). This is consistent with the assumptions in GCMs. While GCMs
39 represent the subgrid variability of clouds, aerosol is assumed to be homogeneous within a grid box.
40 Therefore, the aerosol lidar simulator assumes that aerosol is uniformly distributed horizontally within
41 a grid-box while cloud simulators assume subgrid variability according to SCOP.
- 42

1 3) The aerosol lidar simulator uses a higher-resolution vertical grid than the cloud simulator : eg. 320
2 vertical levels (typically 60m) instead of 40 (typically 480m). This is because the detailed vertical
3 structure of aerosol is important for understanding aerosol mixing, transport and other physical
4 processes especially in the atmospheric boundary layer. To be consistent with the CALIOP aerosol data
5 product, we use the same vertical resolution. Note that, for clouds the vertical resolution used in
6 CFMIP experiments (dz=480m) results from a compromise between the wish to keep high horizontal
7 resolution for sparse shallow clouds, the SNR of CALIOP data in day time and the vertical resolution
8 of CloudSat.

9
10 Users can choose to run the new aerosol simulator alone, the standard cloud simulators alone (default),
11 or both aerosol and cloud simulators. These new features are controlled by two new keys in the user's
12 configuration file in COSPv2 code. Users can set "lidar_aerosols" and "use_vgrid_aerosols" to true to
13 invoke the aerosol simulator. The logical variable "use_obs_for_aerosols" must be set to "false" for
14 now as it is reserved for future feature development. Lastly, users need to set the number of vertical
15 levels for aerosol "nlvgrid_aerosols", which is set to 320 by default as recommended by this study.

16 17 18 **3. Observations**

19
20 To facilitate fair comparisons between models and observations, we have created an observation-
21 al dataset that is consistent with the simulator approach described in the previous section. The
22 simulator outputs SR_observable and ATB_observable can be directly compared with the SR and ATB
23 profiles above clouds observed by CALIOP. However, it should be noted that the total extinction pro-
24 file (EXT_observable) cannot be observed directly by CALIOP, it is an output from the simulator that
25 can only be used to interpret the difference between the observation and the model+simulator outputs.

26
27 We use the CALIOP L1.5 orbit file (NASA/LARC/SD/ASDC, 2019) dataset that contains cloud
28 screened ATB profiles at 532nm with 60m vertical resolution and 20km along-track and 90m cross-
29 track horizontal resolution. The CALIOP L1.5 data is built from the native L1 CALIOP data (1/3km
30 horizontal resolution along-track, 90m cross-track horizontal resolution and 30m vertical resolution),
31 but a cloud-screening procedure is applied so that the L1.5 data only contains above-cloud measure-
32 ments. The cloud screening is applied iteratively at different horizontal resolutions from 1/3km up to
33 80km. When clouds are detected at a vertical level, all the data below the cloudy level is marked as
34 Fill_Value and all the cloud-free and above-cloud profiles are retained below the altitude of 8 km.
35 Then, these cloud-free and above-cloud profiles are averaged horizontally over the along-track 20km
36 grid. Since each L1.5 20km profile represents an averaged signal over the cloud-free profiles over
37 20km, this dataset cannot be used to study the horizontal heterogeneity of aerosol with a spatial scale
38 smaller than 20km. Nevertheless, this dataset has the advantage of a much higher SNR than the origi-
39 nal L1 profile (1/3km) which permits the use of a lower aerosol detection threshold in both observa-
40 tions and simulations, then able to detect optically thin aerosol layers at the 20 km spatial scale (Ma et
41 al. 2018).

1 In this study, we created an example gridded data product from CALIPSO that is consistent with the
2 GCM grid, so that the translation from the model to the simulator results can be more easily understood
3 by the reader, in relation to how it can affect the interpretation of a comparison to the CALIOP obser-
4 vation profile. This dataset was created by averaging all the L1.5 ATB cloud-screened profiles over
5 $1^\circ \times 1^\circ$ latitude-longitude grid at a given date. It is worth noting that since CALIPSO is a polar-orbiting
6 satellite with a relatively narrow swath, the number of profiles at high latitudes is larger than that in the
7 tropics, and that not all the grid boxes contain a satellite observation in any single day.

8
9 Similarly, we build the gridded product for SR from the orbit L1.5 ATB dataset. We first compute the
10 AMB profiles - the signal that would be measured by the lidar in a cloud-free and aerosol-free at-
11 mosphere - at the resolution of 20km along-track resolution and 60m in the vertical, from the pressure

12
13 and temperature profiles from NASA Global Modeling and Assimilation Office (GMAO) that are in-
14 cluded in the L1.5 data. We compute the SR profiles by dividing the L1.5 ATB with AMB. Finally we
15 average all the 20km-SR profiles over $1^\circ \times 1^\circ$ grid boxes. Because the model SR profile is normalized
16 against the model pressure and temperature profiles and the observed SR profile is normalized against
17 the pressure and temperature from the GMAO reanalysis, comparing SR profiles between observations
18 and models is more informative regarding aerosol distributions than ATB profiles which are subject to
19 differences in atmospheric temperature and pressure as well.

20
21 In the upper troposphere where AMB and ATB values are low, the ATB profiles measured along the
22 orbit have low signal-to-noise ratios which leads to high values of SR, even at $1^\circ \times 1^\circ$ resolution. To ad-
23 dress this issue, we set $ATB=AMB$ when $ATB-AMB$ is lower than $1e-4 \text{ km}^{-1} \text{ sr}^{-1}$ and $SR=1$ when SR is
24 lower than 1.2. The threshold on AMB typically applies above 8 km. While this procedure removes the
25 noise, it can also remove the signal from tenuous aerosol layer (e.g. Watson-Parris et al. 2018). Both
26 threshold values are relevant for night profiles, that are less noisy than daily ones. We thus focus in this
27 study on profiles observed at night only, before and after the application of the AMB/SR thresholds.
28 Note that the threshold on SR is parameterized in the aerosol simulator and can be easily adjusted to
29 other values for various research and application purposes.

30
31 Finally, we generate daily and monthly average of the gridded data. This enables users to perform
32 comparisons at three different spatiotemporal scales : 1) the instantaneous SR profiles at the resolution
33 of 1° along-track and 60m in the vertical, 2) the 3D daily $1^\circ \times 1^\circ$ gridded SR data with a 60m vertical
34 resolution, and 3) the 3D monthly $1^\circ \times 1^\circ$ gridded SR data with a 60m vertical resolution.

35 36 **4. Examples of outputs of the COSPv2/Lidar-Aerosol simulator**

37 38 **4.1 Orbit files**

39 We consider the attenuated total backscatter profiles observed by CALIPSO at 532 nm along its trajec-
40 tory on 20 March 2008 as an example to demonstrate the comparison using the aerosol simulator and
41 show the impacts of the AMB/SR thresholds. These profiles, characterized by their latitude in Figures
42
43

1 2a and 2c, show missing values below the clouds with sufficient optical thickness to fully attenuate the
2 laser beam. Such clouds occur at very high altitudes within the tropics, making it impossible to retrieve
3 significant signals below 17 km at some locations. In dry regions (e.g., between 10°N and 30°N, 20°S
4 and 40°S) however, the absence of clouds allows the lidar to retrieve entire ATB profiles down to the
5 surface. The attenuated total backscatter signal, that contains the molecular backscatter signal, shows a
6 maximum near the surface, with a monotonic decrease as altitude increases. The SR profiles (Figures
7 2b and 2d), being normalized by the molecular signal, filter out the contribution by air molecules and
8 are thus more appropriate to retrieve aerosol concentrations. A large amount of SR values that were
9 initially lower than 1 because of the instrument noise (Figure 2b) are set to 1 by the application of the
10 AMB/SR thresholds (Figure 2d). In this particular orbit, two dense aerosol layers can be identified.
11 One is in the polar region in the Northern Hemisphere between 10 km and 12 km, another one is in the
12 lower troposphere at 30°S. CALIPSO also shows signals of thinner aerosol layers that are generally
13 below 4 km.

14
15 In Figure 3, we show the results of the U.S. Department of Energy's Energy Exascale Earth System
16 Model version 1 (E3SMv1) (Golaz et al. 2019) with improved calibration of cloud and subgrid effects
17 (Ma et al. 2022). The model is configured to run with prescribed SST and sea ice extent. The E3SM
18 atmosphere model version 1 (EAMv1) (Rash et al. 2019) model outputs are used to compute the ATB
19 and SR profiles that would be seen by the lidar along its trajectory on the same date (20 March 2008).
20 The model horizontal winds are nudged towards Modern-Era Retrospective analysis for Research and
21 Applications version 2 (MERRA-2) (Gelaro et al. 2017) reanalysis with a relaxation time scale of 6
22 hours (Zhang et al., 2014 ; Ma et al., 2015). The simulated cloud vertical profiles (Figure 3a) agree
23 very well with the observations (Figure 2), as high cloud fractions along the satellite trajectory coincide
24 with the horizontal locations and altitudes of missing data in the observations.

25
26 The vertical profiles of cloud fractions of Figure 3a are then defined at the horizontal sub-grid scale
27 (with about 50 profiles being produced in each grid box), with values of cloud fraction being equal to 0
28 or 1 in each subgrid box. Vertically, the cloud fractions are interpolated on 40 levels, defined by their
29 altitude. The resulting sub-profiles are shown in Figure 3b and are consistent with the model outputs of
30 cloud cover of Figure 3a.

31
32 Finally, the aerosol optical properties α_a and β_a calculated by the E3SMv1 model at 532 nm along the
33 satellite trajectory are used as inputs to the COSPv2 simulator. These quantities are calculated by the
34 E3SM model at a very high vertical resolution, where the layer thickness is about 25 m at the surface,
35 about 90 m in the first 1.5 km above the ground level, and about 600 m between 1.5 km and 10 km
36 (Rasch et al. 2019 ; Xie et al. 2018). The aerosol extinction and backscatter profiles show a very high
37 correlation, with largest values below 800 hPa (Figures 3c and 3d).

38
39 The α_a profiles are then interpolated vertically on the 320 altitude levels to produce the EXT_initial
40 variable (Figure 4a). The differences between the EXT_initial and EXT_detectable fields (Figure 4b)
41 illustrate the effect of applying the instrument aerosol detection threshold. In the EXT_detectable field,
42 the values of the extinction coefficients that are lower than that threshold are set to zero. The extinction
43

1 profiles thus appear less noisy in the middle troposphere (for example around 6 km at 20°S), whereas
2 they remain similar in the lower troposphere. Finally the EXT_masked field (Figure 4c), shows the
3 extinction profiles when the cloud screening is applied ; and the EXT_observable field (Figure 4d) both
4 combines the cloud screening and the aerosol detection threshold.

5
6 The resulting SR profiles computed by the COSPv2 simulator are shown in Figure 5. The obtained SR
7 values, going up to 3 in maximum regions, agree well with the observations. South of 20°N, the signal
8 above the detection threshold (Figure 5b) is found below the altitude of 4 km, but north of 20°N, the
9 aerosol plume extends vertically and a significant signal is found at altitudes as high as 12 km, in good
10 agreement with the observations (Figure 2b).

11 Figure 6 shows the impacts of the AMB/SR thresholds on the comparison between the simulated and
12 observed SR profiles. In Figure 6a, we show the differences between the SR_masked field (with cloud
13 screening only) and CALIOP profiles before applying the AMB/SR thresholds. In the upper tropos-
14 phere, the instrument noise induces differences in absolute value that sometimes exceed 0.4. In Figure
15 6b, the differences between the SR_observable field (with cloud screening and aerosol detection
16 threshold) and the CALIOP profiles after applying the AMB/SR thresholds, become close to zero in the
17 upper troposphere. In this comparison, we find that the E3SMv1 model underestimates the aerosol con-
18 centrations near the surface around 30°S, but overestimates the concentrations in the aerosol plume
19 north of 20°N between 1km and 9 km.

20 21 **4.2 Global statistics**

22
23 To have an overview of the aerosol distribution at the seasonal timescale, we average the observed and
24 simulated ATB and SR profiles over three months: March, April and May (MAM) 2008. As
25 aforementioned, the thresholds on AMB and SR are applied to observations. The profiles are further
26 averaged over all longitudes for each 1° latitude bin and are represented in Figure 7. The attenuated
27 total backscatter signal, as the molecular backscatter signal (not shown), shows a decrease with altitude
28 in the lower troposphere. The SR ratio, directly depending on aerosol concentrations, shows maxima
29 reaching the value of 3 in the 2 km - layer above the surface, indicating a very dense aerosol layer in
30 the boundary layer. The ratios are especially large at 10°N and between 40°S and 60°S, which can be
31 attributed to the presence of dust and sea-spray aerosol. At 10°N, dust is the predominant component of
32 aerosol over Northern Africa, the Arabian Peninsula and the Western China (Yu et al. 2010). Between
33 40°S and 60°S, the main aerosol contribution during the MAM season is sea spray, as biomass burning
34 over Southern America and Southern Africa occurs mainly between June and November. The
35 maximum between 40°S and 60°S also appears within the first kilometer above the surface on zonal
36 mean 532 nm aerosol extinction profiles retrieved from CALIOP over the whole year during nighttime
37 by Winker et al. (2013). The vertical extension of the aerosol plume seems to be largest in the Northern
38 Hemisphere, where convection is the most active in MAM, whereas it is limited to the top of the
39 boundary layer in the Southern Hemisphere, consistently with the scale heights retrieved by Yu et al.
40 2010.

41
42 The simulated SR_observable profiles computed for the same period by the COSPv2 simulator are
43 shown in Figure 8d. The maximum at 10°N is well reproduced, but the maximum in the Southern

1 Hemisphere does not appear, which might be due to an inaccurate simulation of sea spray aerosol in the
2 model at this time and location. As in the observations, the aerosol plume shows a larger vertical
3 extension in the Northern Hemisphere than in the Southern Hemisphere, which validates the convective
4 transport of aerosol in the model. Yu et al. (2010) raised the issue that the convective transport of
5 aerosol could not be well observed by CALIOP because it is not possible to retrieve aerosol in the
6 presence of thick convective clouds. However, the comparison between the SR_initial (Figure 8a) and
7 SR_masked fields (Figure 8c) shows little differences, indicating that at least in this particular model
8 simulation, cloud screening does not affect dramatically the mean aerosol concentrations and does not
9 modify significantly the amount of aerosol transported upward.

10
11 Finally, we compare the simulated and observed SR values to identify model biases. Figure 9 shows the
12 differences between the SR_observable profiles and the CALIOP SR profiles after the application of
13 the AMB/SR thresholds (see Section 3) in the first 4 km above the surface. The SR maxima are
14 underestimated by 1 to 1.5 in the model from the surface to 500-800 m, and are slightly overestimated
15 above this level up to 1.5-1.8 km. The underestimation of SR in the surface layer corresponds to a
16 relative model error on the aerosol optical depth of approximately 50%. This vertical distribution bias
17 revealed by the simulator could have several causes that need to be investigated further, as overly
18 efficient vertical mixing or incorrect wet scavenging in the E3SMv1 model.

20 21 **4.3 Validity of the comparison between CALIOP data and simulator outputs**

22 A cause of the discrepancy between simulated SR_observable fields and SR fields retrieved from
23 CALIOP observations can be due to the differences between model and observed clouds. For those two
24 fields corresponding to cloud-free conditions only, the differences in the occurrences of cloud-free
25 scenes in the model and observations can affect the sampling of aerosol concentrations. If those aerosol
26 plumes show a large spatiotemporal variability, differences in sampling can induce differences in the
27 seasonal or zonal mean concentrations, and thus in the mean SR.

28
29 To compare the sampling induced by the cloud-screening in E3SMv1 and in CALIOP, we consider the
30 probability of having cloud-free conditions during the night at a daily scale in $1^\circ \times 1^\circ$ horizontal grid
31 cells at a given latitude, during the MAM period (Figure 10a). In the observations, the total cloud cover
32 CLT is estimated in the 532 nm channel of CALIOP. The probability for cloud-free conditions
33 (CLT=0%) at nighttime is extremely low in CALIOP for all latitudes, except for polar regions that are
34 dry and less cloudy than the rest of the globe (especially over land). The cloud-free probability is much
35 higher in E3SMv1, with a maximum value of 70% in the Southern Hemisphere polar region, and about
36 40% and 50% at 25°S and 25°N, respectively.

37
38 However the cloud-free grid cells are not the only ones to be sampled for the estimation of the mean
39 SR. SR can still be obtained in grid cells with partial cloud cover ($0 < \text{CLT} < 100\%$), as the SR will be
40 computed in the clear-sky sub-columns of the considered grid cell in E3SMv1, and retrieved in the
41 cloud-free pixels belonging to the grid cell by CALIOP. Making the reasonable assumption that aerosol
42

1 concentrations are homogeneous within the $1^\circ \times 1^\circ$ grid, this local estimation of SR can be considered to
2 be representative of the whole grid cell.

3
4 The probability of partially covered grid cells (shown in Figure 10b) is generally higher in CALIOP
5 observations than in the E3SMv1 model. In CALIOP, the probability shows two maxima of about 70%
6 in the subtropical regions, while it is not above 50% in E3SMv1 at these latitudes.

7
8 If the probability of $CLT < 100\%$ was equal to 100% both in model and observations (i.e., no overcast
9 grid-boxes in both model and observations), then the sampling would be perfect, with the totality of the
10 grid cells equally contributing to the estimations of the observed and modeled mean SR values for the
11 MAM period. However, we find that the sum of the cloud-free probability (Figure 10a) and the partial
12 cloud cover probability (Figure 10b) is lower than 100%, in both E3SMv1 and CALIOP. Figure 10c
13 shows the probability of fully overcast grid cells ($CLT = 100\%$) as a function of latitude. Aerosol in
14 these grid cells is totally filtered out and thus does not contribute to the mean SR. The overcast proba-
15 bility is highest at 60°S in both E3SMv1 (80%) and CALIOP observations (65%) during the MAM
16 period. Maxima of lower amplitude are also found in the equatorial region and in middle and high lati-
17 tudes in the Northern Hemisphere. The model overestimates the overcast probability almost every-
18 where in the globe, producing either cloud-free or fully overcast conditions most of the time, which is
19 not found in observations.

20
21 The large occurrences of overcast cases at 60°S suggest that the SR values estimated in both simula-
22 tions and in the real world might not be representative of the true aerosol distribution due to the cloud-
23 screening procedure. Large sampling errors can then be introduced to the mean SR at 60°S . Similarly,
24 sampling errors might also exist in the Equatorial region and in the Northern Hemisphere mid-latitudes,
25 where the occurrence of fully overcast cases is high, or in the Northern polar region, where occurrence
26 of fully overcast cases in the model is significantly different from that in observations.

27
28 The occurrence of overcast cases depends on the size of the horizontal grid cells, and decreases with a
29 coarser resolution. For example, the probability of having $CLT = 100\%$ does not exceed 5% at 60°S
30 for $10^\circ \times 10^\circ$ horizontal grid cells (not shown). Choosing a coarser resolution might then ensure a better
31 temporal sampling, but on the other hand, taking account of the partially covered $10^\circ \times 10^\circ$ grid cells for
32 the mean SR estimation would be based on the implicit assumption that the aerosol concentrations are
33 homogeneous over these grid cells of large horizontal surfaces, which is probably not realistic in the
34 vicinity of the source regions.

35
36 To assess the impact of the cloud screening on the mean SR values in E3SMv1 simulations, we com-
37 pute the relative difference between the $SR_{\text{observable}}$ field (with both aerosol detection threshold and
38 cloud screening applied) and the $SR_{\text{detectable}}$ field (with the detection threshold applied and no
39 cloud-screening). This relative difference, shown in Figure 11 as a function of altitude and latitude, is
40 lower than 10% everywhere. In regions where cloud screening is large in the model (e.g. near 60°S and
41 in the Equatorial region) $SR_{\text{observable}}$ values tend to be larger than $SR_{\text{detectable}}$ values, probably
42 because most of the $SR_{\text{detectable}}$ profiles coincide with cloud and rainfall conditions, while $SR_{\text{ob-}}$
43 $SR_{\text{observable}}$ profiles contain dry cases only, and thus cloud-screened aerosol concentrations are higher be-

1 cause wet scavenging does not occur. Furthermore the low absolute values of relative differences in
2 Figure 11 imply that the intra-seasonal variability of aerosol emissions might be low in the model. This
3 variability depends on the emissions of anthropogenic aerosol, that are monthly mean averaged, consis-
4 tently across all CMIP6 models (Hoesly et al (2018) and van Marle et al (2017)). It also depends on the
5 variability of sea spray aerosol emissions, that somewhat follows the variability of surface winds and
6 sea surface temperature (SST).

7
8 Overall, the sampling bias introduced by the cloud-screening procedure does not significantly affect the
9 mean SR values in E3SMv1. Therefore, errors in E3SMv1 clouds is not likely the primary reason for
10 the differences in the aerosol seasonal comparison between E3SMv1 and CALIOP observations. In
11 particular, the large difference observed at 60°S between the observed and simulated mean SR values
12 cannot be explained by the large cloud-screening in E3SMv1 at this latitude.

13
14 Nevertheless, cloud-screening might have a larger impact on the mean aerosol CALIOP retrievals.
15 Winker et al. (2013) found a lack of correlation between high semi-transparent cloud and aerosol in the
16 lower troposphere in most regions in CALIOP data, implying that the screening of thin clouds does not
17 significantly impact the retrieved values of aerosol optical depth or aerosol extinction coefficients.
18 However this result has to be extended to opaque cloud screening and has to be examined over a three-
19 month period at the specific locations that exhibit large cloud covers. To get an insight into the repre-
20 sentativeness of our SR values retrieved from CALIOP, we computed the zonal mean SR values over
21 the MAM period, by only considering one third of the CALIOP data. We find that the relative differ-
22 ence between these SR values and those obtained by using the full CALIOP data is highest in covered
23 regions, but it never exceeds 15% (not shown). This gives us confidence about the robustness of our
24 results retrieved by CALIOP over a three-month period. An alternative approach would be to extend
25 the analysis to cover multiple years, but the results would then be affected by the inter annual variabili-
26 ty of aerosol.

27
28 We can thus conclude that :

- 29 1) The SR maxima retrieved by CALIOP over three months are robust, and
- 30 2) The method of comparing modeled and retrieved SR is robust, although the modeled and observed
31 clouds show large differences.

32 Therefore, the differences between observed and simulated SR values should be attributed to the repre-
33 sentation of aerosol in the model.

34 35 **5. Discussion**

36
37 Aerosol modeling basically consists of the representation of aerosol sources, optics, chemistry, micro-
38 physics, aerosol-cloud interactions and transport. In the E3SMv1 model, aerosol optics is parameter-
39 ized in terms of wet refractive index and wet surface mode radius of each mode (Ghan and Zaveri,
40 2007). It assumes volume mixing to compute the wet refractive index for mixtures of insoluble and
41 soluble particles. The parameterization provides the aerosol extinction α_a . We apply the same Ghan and
42 Zaveri (2007) methodology and add the diagnostic variable of the 180° backscatter β_a , as the aerosol
43 lidar simulator requires these two input variables. Most GCMs compute the aerosol extinction, but not

1 many of them routinely compute the aerosol 180° backscatter β_a . Hence, more work has to be done so
2 that other GCMs also diagnose their aerosol 180° backscatter β_a in a way that is consistent with their
3 aerosol optics parameterization. For future comparisons between CALIOP data and other GCMs, or for
4 model-to-model comparisons, one might find useful to use one single optics module, to eliminate
5 aerosol optics as a potential source of discrepancy in the comparisons. This is beyond the scope of this
6 study and requires future investigation.

7
8 To evaluate the representation of aerosol composition in the model, the NASA product providing
9 aerosol types from CALIPSO data is of particular interest. Indeed CALIOP level 2 data include seven
10 aerosol classes: clean marine, dust, polluted continental, clean continental, polluted dust, smoke, other.
11 This classification utilizes depolarization ratio, integrated attenuated backscatter coefficient, altitude,
12 and land vs ocean (Kim et al., 2018). The aerosol subtypes of CALIOP measurements have been shown
13 to be in good agreement with the daily aerosol types derived from AERONET level 2.0 inversion data
14 (Mielonen et al., 2009).

15
16 The CALIOP classification might be useful to provide insights into the model deficiency in represent-
17 ing aerosol composition in the model. According to this classification, the aerosol observed at 60°S
18 during MAM is mostly clean marine aerosol. The large differences observed between CALIOP and
19 E3SMv1 at this latitude may then be due to model biases in simulating marine aerosol in this region.
20 Fig 9 in Rasch et al (2019) and Fig 11 in Wang et al (2020) also show an aerosol bias over the Southern
21 Ocean. There are certainly many possible reasons. The E3SMv1 model has both sea salt and marine
22 organics as marine aerosol. Their “emissions” are function of surface winds and SST, based on
23 Martensson et al. (2003). If the model has significant surface wind bias, that may thus impact the ma-
24 rine aerosol sources. Furthermore, McCoy et al (2021) shows that new particle formation (NPF) might
25 be important in that region when they contrast SOCRATES field campaign measurements and Com-
26 munity Atmosphere Model version 6 (CAM6) simulations. This process is not well represented in the
27 CAM6 model or in the E3SM model. We demonstrate here that the aerosol lidar simulator can be very
28 useful in revealing these model biases, providing insights into future model development directions.

29 **6. Perspectives**

30
31 The validation of aerosol simulated by GCMs with space lidar data will be expanded to other lidars and
32 to other GCMs. We plan to perform studies with the Laboratoire de Météorologie Dynamique Zoom
33 (LMDZ) model, the European Center - Hamburg (ECHAM) model and the ICOSahedral Non-hydro-
34 static (ICON) model. The modal aerosol module “HAM” that employs seven log-normal aerosol modes
35 has been used interactively in the ECHAM model since almost two decades (Zhang et al. 2012 ; Tegen
36 et al. 2019). Recently it is also implemented in the successor of ECHAM, the ICON model (Salzmann
37 et al. 2022). The two models with profoundly different dynamical cores share the same physics pack-
38 age. It will be interesting to evaluate the differences induced by the two numerical representations of
39 the atmospheric dynamics with the satellite retrievals.

40
41 Note that for a multi-model comparison, it is necessary to use a standard vertical grid with a coarser
42 vertical resolution than N=320 levels and $\Delta z = 60\text{m}$, as traditional climate models do not reach such a
43

1 fine resolution. For the comparison of these models with CALIOP observations, data interpolation is
2 needed on the same vertical coarser grid. Vertically averaging the CALIOP data would enhance the
3 SNR, and consequently would allow to lower the aerosol detection threshold and make use of the more
4 noisy CALIOP daily data. For each model it is important to check that the errors in the model clouds
5 do not significantly impact the model-observation aerosol comparison over the considered period.

6
7 Since 2018, the ADM-Aeolus mission has been operating the first High-Spectral Resolution Lidar
8 (HSRL) in space. Although primarily dedicated to wind measurements, the HSRL capability in the UV
9 allows the separation of the molecular and particulate contributions and enables the measurements of
10 the particulate backscatter and extinction coefficients. These measurements provide new insight into
11 very thin aerosol layers and can be very useful for the validation of models that directly compute these
12 quantities. Later in 2023, the EarthCare mission will also provide data from the HSRL lidar ATLID at
13 355 nm. The COSPv2 simulator can be easily adapted to other wavelengths, which opens the way to
14 the determination of new diagnostics for cloud susceptibility, aerosol typing and aerosol-cloud proxim-
15 ity metrics.

16 **7. Code and data availability**

17
18
19 *Code availability:* The aerosol lidar simulator presented in this paper is available at <https://doi.org/10.5281/zenodo.7418199> and is incorporated in the COSPv2 infrastructure at <https://github.com/CFMIP/COSPv2.0>
20
21
22

23
24 *Data availability:* the CALIPSO L1.5 data is available at https://asdc.larc.nasa.gov/project/CALIPSO/CAL_LID_L15-Standard-V1-01_V1-01 (NASA/LARC/SD/ASDC (2019)). The processed gridded
25 CALIOP ATB and SR data files used in this study are available at <https://doi.org/10.5281/zenodo.7107232> and <https://doi.org/10.5281/zenodo.7107162>.
26
27
28

29 *Competing interests:* Po-Lun Ma is a Topical Editor of Geoscientific Model Development. Other
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31

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Variable subscript in article	Description of variable	EXT	ATB	SR
initial	Profiles computed with aerosols + gas molecules	EXT0	ATB0	SR0
masked	As above but masking the highest cloud and all layers below	EXT1	ATB1	SR1
detectable	Removing SR<1.2 from initial profiles	EXT2	ATB2	SR2
observable	Removing SR<1.2 from initial profiles and masking the highest cloud and all layers below	EXT3	ATB3	SR3

Table 1 : Translations between the name of the variables in the text and in the code. For example, EXT_initial in the paper corresponds to EXT0 in the code.

Figure 1 : Schematic of the lidar aerosol COSPv2 simulator. See Table 1 for the correspondence between the names of the variables in the code and in the present paper.

Figure 2 : Attenuated total backscatter profiles ($\text{km}^{-1}\text{sr}^{-1}$) before noise filtering (a) and after noise filtering (c); backscatter ratio profiles before noise filtering (b) and after noise filtering (d); observed by CALIOP at 532 nm along the satellite orbit on the 20-03-2008

Figure 3 : (a) Vertical profiles of cloud fraction simulated by the E3SMv1 model along the satellite orbit on the 20-03-2008; (b) Same vertical profiles, defined by the COSPv2 simulator at the sub-grid scale and interpolated on 40 vertical levels; (c) Aerosol extinction profiles (in m^{-1}) and (d) Aerosol backscatter coefficient profiles (in $\text{m}^{-1} \text{sr}^{-1}$) calculated by E3SMv1 along the satellite orbit

Figure 4 : Total extinction vertical profiles (m^{-1}) defined on 320 levels and calculated by the COSPv2 simulator along the satellite orbit on the 20-03-2008 : (a) Initial profiles ; (b) Profiles with the instrument aerosol detection threshold ; (c) Cloud screened profiles ; (d) Cloud screened profiles with aerosol detection threshold applied.

Figure 5 : Backscatter ratio vertical profiles defined on 320 levels and calculated by the COSPv2 simulator along the satellite orbit on the 20-03-2008 : (a) Initial profiles ; (b) Profiles with the instrument

1 aerosol detection threshold ; (c) Cloud screened profiles ; (d) Cloud screened profiles with aerosol de-
2 tection threshold applied.

3 Figure 6 : (left) Difference between model SR_masked and CALIOP data before data processing ;
4 (right) Difference between model SR_observable and CALIOP data after data processing (see text for
5 details) along the satellite orbit on the 20-03-2008.

6 Figure 7 : (a) Attenuated total backscatter profiles ($\text{km}^{-1}\text{sr}^{-1}$) and backscatter ratio profiles (b) observed
7 by CALIOP at 532 nm at night and averaged over longitudes and time during MAM 2008.

8 Figure 8 : SR profiles simulated by E3SMv1 at 532 nm and averaged over longitudes and time during
9 MAM 2008 : (a) initial profiles ; (b) with the aerosol detection threshold applied ; (c) cloud screened
10 profiles ; (d) cloud screened profiles, with aerosol detection threshold applied.

11 Figure 9 : Up left : CALIOP SR after data processing (see text for details) ; Up right : Model SR_ob-
12 servable ; Bottom : Difference between model SR_observable and CALIOP SR. All fields are shown
13 between 0 and 4 km and are averaged over all longitudes and time during MAM 2008.

14 Figure 10 : (a) Probabilities of (a) cloudy-free; (b) partially cloud covered; (c) totally cloud covered
15 $1^\circ \times 1^\circ$ horizontal grid cells as a function of latitude, during the MAM period (nighttime), in CALIOP
16 and E3SMv1.

17 Figure 11 : Relative difference (in %) between the SR_observable field and the SR_detectable field
18 both computed by E3SMv1, as a function of latitude and altitude.

