RE-REVIEW OF 'JOINT RETRIEVAL OF SURFACE REFLECTANCE AND AEROSOL PROPERTIES WITH CONTINUOUS VARIATIONS OF THE STATE VARIABLES IN THE SOLUTION SPACE: PART 2: APPLICATION TO GEOSTATIONARY AND POLAR-ORBITING SATELLITE OBSERVATIONS'

My primary comments concern your response our opinions of Fig. 14.

- *"The bias between the CISAR retrieval and the AERONET data is shown in Fig. 2, which shows different performances for SEVIRI and PROBA-V. These differences show that the bias does not only depend on the CISAR algorithm itself, but also on the quality of the processed data."*

Your SEVIRI and PROBA-V implementations use a different number of channels, so it is entirely reasonable for them to exhibit different bias profiles. This does not excuse the fact that your algorithm exhibits biases of around 50% in your own validation (and an independent validation would be expected to find worse comparisons). I appreciate that the two satellites you use don't exhibit the radiometric quality of MODIS or AATSR. That is expressed (as I would expect) through the large uncertainty in your products relative to MODIS.

The PV-LAC validation report (https://earth.esa.int/documents/700255/2632405/PV-LAC_ATMO_VR_v2.2.pdf/4c46403b-bfe5-4208-bfdf-2d42585d6589), prepared by Erwin Wolters from VITO (De Vlaamse Instelling voor Technologisch Onderzoek) through an independent verification, does not show much worse results, keeping in mind that the algorithm improved since then.

However, Fig. 2 of your response only worsens my opinion of your results. A calibration offset should result in a retrieval bias that is (roughly) independent of optical depth. Lower quality detectors should give a wider scatter (which, admittedly, you appear to have). Cloud contamination should result in a positive bias. Yes, your results for SEVIRI are within the GCOS requirements for a particular range but your biases for AOD < 0.2 are almost 100%. As AOD is log-normally distributed, this region carries significant weight.

We recognize the limitations of CISAR retrieval for low AODs when applied on SEVIRI and PROBA-V data. However, the bias for AOD = 0.1 is 54% for SEVIRI and 48% for PROBA-V. For AOD=0.15 the bias decreases to 18% for SEVIRI and 27% for PROBA-V.

I think we see Fig. 2 very differently. I expect you see the SEVIRI bias as a straight line around zero, that drops off above 0.7 due to the small volume of data and cloud contamination. I look that that line and, neglecting the last point, see a linear downwards trend. PROBA-V does the same, but with a different gradient. I can live with data with a large RMS—average could reduce it. I can live with data that has a bias — one can subtract it. Your data has a slope. I'd need both coefficients of ax+b to bias correct your data and that's difficult. To my mind, an algorithm that sruggles to retrieve both small and large AOD provides little of use.

So what do I think should be done? It would be inhuman to ask you to rubbish your own data in your own paper. Your revisions do better represent the quality of this data, but

you primarily blame the instruments and cloud. If those were the only problem, you should resubmit the paper after applying it to a better instrument.

I continue to believe that your algorithm is conceptually interesting. What I need is a discussion of what you intend to do next. What aspects of the algorithm are you working on? Where do you think the problem lies?

The sentence "The cloud mask omission errors impact on the AOT overestimation at low optical thickness deserve additional work." has been moved at line 516 and the following lines have been added afterwards:
"In order to reduce the impact of cloud contamination in the AOT retrieval, a new version of the CISAR algorithm is under development in the framework of the ESA-SEOM ConsIstent Retrieval of Cloud Aerosol Surface (CIRCAS) project (www.circas.eu). The new version of CISAR aims to retrieve both the AOT and the Cloud Optical Thickness (COT), overcoming the need of an external cloud mask. Within the CIRCAS project CISAR will be applied to observations acquired by the Sea and Land Surface Temperature Radiometer (SLSTR) on-board Sentinel-3."

- *It can be seen there only few points correspond to AOT È 0.8 (less than 5% of the total number of observations), affecting the reliability of the statistics for high values of AOT. The histograms have been added in Fig. 14.*

Though I agree that large AOD events are rare, they can be very important. Large dust plumes seed the equatorial ocean, large fires impact air quality over entire continents, and volcanic eruptions affect international air travel. Most algorithms have trouble with high AOD, where the fundamental assumptions of such retrievals begin to break down, but they are an area of active development.

As stated in the manuscript, we believe that the processing of more data would be necessary to increase the confidence in the results for high AOT values.

- *The overestimation rapidly decreases as the AOT approaches values of about 0.2.*
This is unimportant as the line has to cross the axis somewhere.

It is not clear to me what the reviewer means by this.

- *We are not aware of any algorithm capable of delivering a good AOT product from PROBA-V over land surfaces.*
I'm not aware of anyone having tried as I'd never heard of the instrument before reading this paper.

The operational product includes an atmospheric correction method. However, when compared with CISAR retrieval during the PV-LAC project, it did not show promising results.

- With regard to my own point 33, your Fig. 14 shows the comparison of CISAR to AERONET through boxplots. In the supplement, you show a comparison of CISAR to MODIS through 2D histograms. I vastly prefer the later form of plot and was requesting a second version of Fig. 14 in the style of Fig. S1.

  During the Aerosol-CCI project, it was strongly advised to show boxplots for the AOD retrieval, hence our choice.

A few other thoughts:
- I'm not overly happy with the assumptions you make in §2.4 but they're rational. I will note, though, that on L148 you state you set the uncertainty to a 'high arbitrary value'. Unity is not high. When I wish to avoid setting a prior for a variable, I use a prior uncertainty of 10^8.

  Reviewer#1 seemed to believe the opposite. From his annotate pdf "2.0 for the coarse mode is unreasonably high". An uncertainty of 1.0 associated with values < 0.2 (this is the cases for the AOD climatology values) can be considered as a high value.

- You reference an unusual number of reports and conference presentations. I know private companies struggle to justify publication costs but I'm slightly concerned that many background details for this algorithm haven't been peer reviewed.

  We will be happy, in the future, to cite this paper and its companion.

- I think I now understand §5. I'm not fond of this manner of qualitative quality filtering, but it is commonly used so I'll not comment further.

- Is Fig. 12 actually binned (i.e. showing the average correlation for all retrievals with QI in a certain range)? If so, it would be useful to represent those ranges on the plot (e.g. the step histograms of matplotlib).

  The final QI is rounded to one decimal place; therefore no binning is performed in Fig. 12.

All the reviewer's suggestions in the pdf were implemented, with the exception of:
- "CISAR has been applied to SEVIRI and PROBA-V observations acquired over 20 AERONET stations". The reviewer suggestions was to replace "over" with "from". However, the satellite observations are not acquired from AERONET, but over an area surrounding the AERONET station.
- "PROBA-V satellite mission is intended to ensure the continuation of the Satellite Pour l'Observation de la Terre 5 (SPOT5) VEGETATION products since May 2014". The reviewer suggestion was to replace "since" with "begun in". However, it was preferred to replace "since" with "starting from".
- "FASTRE uncertainty is in the range of 1% - 3% (Table 6), which is smaller or equal to the instrument radiometric noise." The reviewer suggestion was to replace "smaller

or equal" with "equivalent". However, this would change the meaning of the sentence.

- The reviewer suggests eliminating the word "however" at L406. Nonetheless, it is needed to relate to the previous sentence and explaining why, despite the poor radiometric performances, the AOT retrieval from the two instruments is meaningful.

Joint retrieval of surface reflectance and aerosol properties with continuous variation of the state variables in the solution space: Part 2: Application to geostationary and polar-orbiting satellite observations

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Abstract. This paper presents the simultaneous retrieval of Aerosol Optical Thickness and surface properties from the CISAR algorithm applied both to geostationary and polar orbiting satellite observations. The theoretical concepts of the CISAR algorithm have been described in Govaerts and Luffarelli (2017). CISAR has been applied to SEVIRI and PROBA-V observations acquired over

5   20 AERONET stations during the year 2015. The CISAR retrieval from the two sets of observations is evaluated against independent datasets such as the MODIS land product and AERONET data. The performance differences resulting from the two types of orbit are discussed, analysing and comparing the information content of SEVIRI and PROBA-V observations.

1   Introduction

10   ~~Aerosol properties retrieval~~ The retrieval of aerosol properties over land surfaces from space ~~observation~~ observations is a challenging problem due to the strong radiative coupling between atmospheric and surface radiative processes. Different approaches are usually exploited to retrieve different Earth system components (e.g. Hsu et al. (2013), Mei et al. (2017)), leading to inconsistent and less accurate datasets. The joint retrieval of surface reflectance and aerosol properties, as

15   originally proposed by Pinty et al. (2000), presents many advantages, such as the possibility to perform the retrieval over any type of surface and assure the radiative consistency among the retrieved variables.

Govaerts and Luffarelli (2017) (hereafter referred to as Part I) describes the theoretical aspects of the Combined Inversion of Surface and AeRosols (CISAR) algorithm, designed for the joint re-

20   trieval of surface reflectance and aerosol properties. This new generic retrieval method specifically

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addresses issues related to the continuous variation of the state variables in the solution space within an Optimal Estimation (OE) framework. Through a set of experiments, the capability of CISAR of retrieving surface reflectance and aerosol properties within the solution space was illustrated. Nonetheless, these experiments only represent ideal simulated observation conditions, *i.e.* ~~noise free~~ noise-free data acquired in narrow spectral bands placed in the principal plane, assuming unbiased surface prior information. This second part aims to demonstrate CISAR's applicability to actual satellite observations, with less favourable geometrical conditions than the principal plane and accounting for the radiometric noise. For this purpose, the algorithm has been applied to two radiometers with similar spectral properties but different orbits (geostationary and polar). Radiometers ~~on board of~~ on-board geostationary platforms deliver observations with a revisit time of tens of minutes but with a limited ~~field of view~~ field-of-view so that many instruments are needed to cover the entire Earth. The poles cannot be observed. Conversely, a polar orbit, combined with an adequate swath, could offer a daily revisit time of the entire globe. The selected radiometers are the Spinning Enhanced Visible and Infrared Imager (SEVIRI), flying on board of the Meteosat Second Generation (MSG) geostationary platform, and the PRoject for On-Board Autonomy - Vegetation (PROBA-V). These two instruments have similar radiometric performances and both have acquired more than 15 years of observations thanks to the launch of a succession of radiometers with very similar characteristics. Applying the same algorithm on similar instruments flying in different orbits represents a meaningful way to analyse the CISAR generic algorithm performance.

This paper is organised as follows. Section 2 describes the observation system considered in the OE framework: the satellite observation, the ancillary information, the prior information and the forward model. The uncertainty characterisation of the observation system is also described in Sect. 2. The algorithm implementation is described in Sect. 3. Section 4 analyses the information content of the satellite observations, comparing the differences between the geostationary and polar orbiting instruments, and discusses the challenges encountered when little or no information about the retrieved variables is carried by the observation. Given these difficulties in the retrieval, a Quality Indicator (QI) is implemented and presented in Sect. 5, characterising the reliability of the solution. Finally, the performance of CISAR is discussed in detail in Sect. 6. The CISAR retrieved Aerosol Optical Thickness (AOT) and Bidirectional Hemispherical Reflectance (BHR) will be compared against those derived from the Aerosol Robotic Network (AERONET) (Giles et al., 2017) and the Moderate Resolution Imaging Spectroradiometer (MODIS) Land product data (DAAC, 2017), respectively. The performance differences between the retrieved datasets obtained from SEVIRI and PROBA-V observations will be further investigated through statistics on the quality of the retrieval and through the information content of the satellite observations.
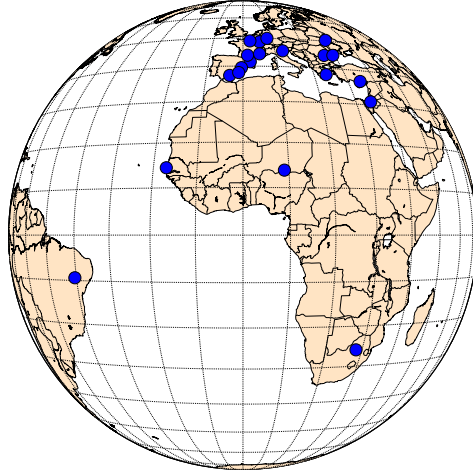
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Fig. 1: Selected AERONET stations location. All stations are located within the SEVIRI field of view.

2 Observation system characterisation

2.1 Observation system definition

The fundamental principle of ~~the~~ OE is to maximise the probability $P = P(\mathbf{x}|\mathbf{y}_{\Omega\tilde{\Lambda}},\mathbf{x_b},\mathbf{b})$ with respect to the values of the state vector $\mathbf{x}$, conditional to the value of the measurements and any prior information (Rodgers, 2000). The ensemble of measurements, prior information, ancillary data and the forward model constitutes the observation system. This section describes each component of this system for the two satellite datasets processed in the framework of this study.

In order to evaluate the CISAR algorithm performance when applied to observations acquired from different orbits, 20 AERONET stations located within the SEVIRI field of view have been selected (Fig. 1, Table 1). These targets span different geometries and land cover types (vegetation, urban, bare areas, water, mixed). The observations pertain year 2015.

For each of these stations, satellite data have been acquired, together with ancillary information, such as the cloud mask and the model parameters, which are ~~all~~ the parameters that are not retrieved by the algorithm but that influence the observation. Satellite data and ancillary information are accumulated in time to form a multi-angular observation vector $\mathbf{y}_{\Omega\tilde{\Lambda}}$, in order to correctly characterise the surface reflectance anisotropy. Nevertheless, retrieving surface and aerosol properties from satellite observations is an ill posed problem (Wang, 2012). Consequently, assumptions on the magnitude and on the temporal/spectral variability of the state variables are made. The ensemble of these assumptions and their associated uncertainties constitutes the prior information.

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Table 1: AERONET targets

Name	Latitude	Longitude	Land Cover Type
Athens_NOA	37.99	23.77	Urban
Barcelona	41.39	2.12	Urban
Bucharest_Inoe	44.35	26.03	Mixed
Bure_OPE	48.56	5.50	Vegetation
Burjassot	39.51	-0.42	Urban
Carpentras	44.08	5.06	Vegetation
Dakar	14.39	-16.96	Costal
Gloria	44.60	29.36	Water
Granada	37.16	-3.60	Urban
IMS-METU-ERDERMLI	36.56	34.25	Costal
Kyiv	50.36	30.50	Vegetation
Mainz	49.50	8.30	Mixed
Murcia	38.01	-1.17	Vegetation
Paris	48.87	2.33	Urban
Petrolina_SONDA	-9.38	-40.50	Urban
Pretoria_CSIR-DPSS	-25.76	28.28	Mixed
Sede_Boker	30.85	34.78	Bare Areas
Toulouse_MF	43.57	1.37	Urban
Venise	45.31	12.51	Water
Zinder_Airport	13.78	8.99	Bare Areas

The observation uncertainty σ_o characterisation is one of the most critical aspect of the CISAR algorithm as it directly determines the likelihood of the solution. In fact, σ_o determines the observation term of the cost function (Eq. 17 of Part I). The observation uncertainty is composed of the radiometric uncertainty , (directly related to the radiometer characteristics), the forward model uncertainty and the uncertainty related to the model parameters.

2.2 Satellite data

MSG nominal position is $0°$ over the equator in a geostationary orbit. SEVIRI is the main instrument of the MSG mission, which has as primary objective the observation in the near real-time of the Earth's full disk, shown in Fig. 1. SEVIRI achieves this with 12 channels, ranging from 0.6 μm to 13 μm, three of which are located in the solar spectrum and centred at 0.64 μm, 0.81 μm and 1.64 μm and are used within this study. SEVIRI observes the Earth's full disk with a 15 minute repeat cycle. The sampling distance between two adjacent pixels at the sub-satellite point is 3 km for the visible bands. As there is no on-board device for the calibration of the solar channels, the calibration within this study has been performed with the method proposed by Govaerts et al. (2013).

The PROBA-V satellite mission is intended to ensure the continuation of the Satellite Pour l'Observation de la Terre 5 (SPOT5) VEGETATION products since starting from May 2014 (Ster-
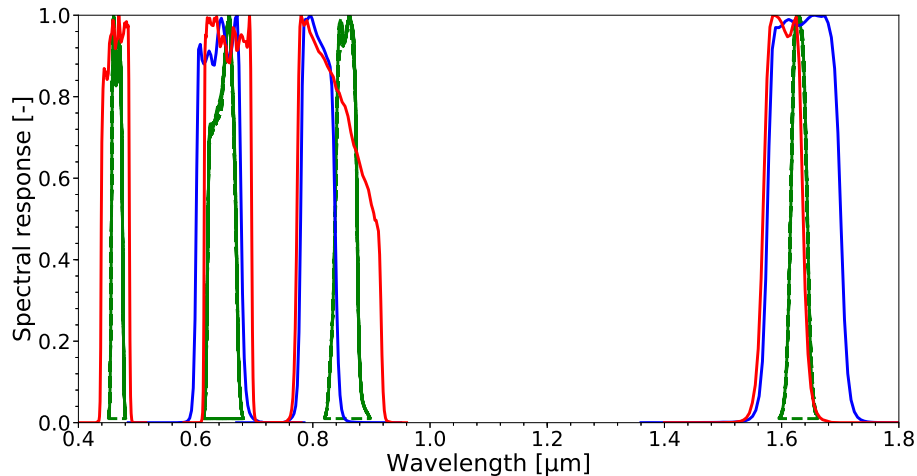
Fig. 2: SEVIRI (in blue), PROBA-V (in red) and MODIS (in green) spectral responses.

90   ckx et al., 2014). The microsatellite offers global coverage of land surface with daily revisit for latitude from 75°N to 56°S in four spectral bands, centred at 0.46 μm, 0.66 μm, 0.83 μm and 1.61 μm. The PROBA-V products are provided at a spatial resolution of 1/3 km and 1 km, the latter being used in the framework of this study. To cover the wide angular field of view (101°) in a small-sized platform, the optical design of PROBA-V is made up of three cameras (identical three-mirror

95   anastigmatic telescopes). The three cameras have an equal field of view. The down-pointing central camera covers a swath 500 km wide, while the swath of the right and left cameras is 875 km wide. Although the three cameras have different responses, a mean Spectral Response Functions (SRF) is considered within this study, accounting for the radiometric uncertainty associated with this approximation. Each camera has two focal planes, one for the short wave infrared (SWIR) band and one for

100   the visible and near-infrared (VNIR) bands. Despite the different viewing angles in the SWIR band, CISAR assumes the observations are acquired with the same geometry in all bands. This assumption leads to an additional term in the observation uncertainty. Because of the omission of on-board calibration devices, the PROBA-V in-flight calibration relies only on vicarious methods (Sterckx et al., 2013).

105   The similarities between the three SEVIRI solar bands and the red, NIR and SWIR PROBA-V bands permit the evaluation and comparison of the CISAR performances when applied to the two instruments, whose spectral responses are shown in Fig. 2. The satellite observations have been acquired from the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Earth Observation Portal and from the Flemish Institute for Technological Research

110   (VITO) for SEVIRI and PROBA-V respectively. The Top Of Atmosphere (TOA) Bidirectional Reflectance Factor (BRF) is computed directly from the digital count value in case of SEVIRI, whereas for PROBA-V the Level 2-A TOA BRF is provided by VITO (Wolters et al., 2018). The satellite

Table 2: PROBA-V instrument noise [%]

Band	Left camera	Center Camera	Right Camera
BLUE	4	4	4
RED	3	3	3
NIR	3	3	3
SWIR	5	4	5

observation uncertainty is derived from the radiometric noise σ_i and the geolocation uncertainty σ_r. For PROBA-V two additional terms are calculated: the uncertainty σ_c associated ~~to~~ with the approximation of a mean SRF of the cameras and the one deriving from considering the same viewing geometry in the SWIR and in the VNIR bands, σ_Ω.

PROBA-V radiometric noise has been delivered by VITO (Sindy Sterckx, personal communication, September 2017) per camera and per band (Table 2). For SEVIRI, this term is computed considering (*i*) the instrument noise due to the dark current, (*ii*) the difference between the detectors gain and (*iii*) the number of digitalization levels (Govaerts and Lattanzio, 2007). The geolocation uncertainty σ_r, arising from the assumption of the satellite data being correctly mapped to the surface of the Earth, is estimated for each pixel **p** as follows (Govaerts et al., 2010):

$$\sigma_r^2(t,\tilde{\lambda},\mathbf{p}) = \left(\frac{\partial \mathbf{y}_0(t,\tilde{\lambda},p_x,p_y)}{\partial p_x} \sigma_x(t,\tilde{\lambda}) \right)^2 + \left(\frac{\partial \mathbf{y}_0(t,\tilde{\lambda},p_x,p_y)}{\partial p_y} \sigma_y(t,\tilde{\lambda}) \right)^2 \tag{1}$$

where $\sigma_{x,y}$ is the geolocation/coregistration standard deviation and $\mathbf{y}_0(t,\tilde{\lambda},p_x,p_y)$ is the TOA BRF in the channel $\tilde{\lambda}$ acquired at the time t.

The uncertainty σ_c, originating from the usage of a mean SRF for the three PROBA-V cameras, has been estimated by simulating the TOA BRF considering both the mean and actual SRF for a wide range of observation conditions. The assessed σ_c is lower than 0.2% in all bands and for all cameras. Finally, the assumption of having the same viewing geometry for the three PROBA-V bands is associated ~~to~~ with the uncertainty σ_Ω, computed as follows:

$$\sigma_\Omega^2(t,\tilde{\lambda},\Omega,\mathbf{p}) = \left(\frac{\partial \mathbf{y}_0(t,\tilde{\lambda},\theta)}{\partial \theta} \sigma_\theta^2(t,\tilde{\lambda}) \right)^2 \tag{2}$$

Table 3: Total radiometric uncertainty median values [%]

	0.4 μm	0.6 μm	0.8 μm	1.6 μm
SEVIRI		3	2	3
PROBA-V	4	3	3	4

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The total relative radiometric uncertainty median values are shown in Table 3.

2.3 Ancillary data

In addition to satellite observations, a cloud mask and the model parameters ~~information~~ are required. For SEVIRI observations, the nowcasting Satellite Application Facility (SAF) cloud mask (Meteo France, 2013), provided at the radiometer's native temporal and spatial resolution, is used; for PROBA-V the cloud mask is provided by VITO (Wolters et al., 2018). The model parameters, *i.e.* Total Column Water Vapour (TCWV), Total Column Ozone (TCO3) and surface pressure are taken from the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis (Dee et al., 2011).

The uncertainties of the model parameters $\mathbf{b}$ are converted into an equivalent noise σ_B, calculated as ~~follow (Govaerts et al., 2010):~~ follows (Govaerts et al., 2010):

$$\sigma_B^2(\mathbf{b},\tilde{\lambda},\Omega_0,\Omega_v) = \left(\frac{\partial y(\mathbf{x},U_{oz};\Omega,\tilde{\lambda})}{\partial U_{oz}} \frac{\partial \mathbf{y}(\mathbf{x},U_{oz};\Omega,\tilde{\lambda})}{\partial U_{oz}} \sigma_{U_{oz}} \right)^2 + \left(\frac{\partial y(\mathbf{x},U_{wv};\Omega,\tilde{\lambda})}{\partial U_{wv}} \frac{\partial \mathbf{y}(\mathbf{x},U_{wv};\Omega,\tilde{\lambda})}{\partial U_{wv}} \sigma_{U_{wv}} \right)^2$$
$$+ \left(\frac{\partial y(\mathbf{x},U_{sp};\Omega,\tilde{\lambda})}{\partial U_{sp}} \frac{\partial \mathbf{y}(\mathbf{x},U_{sp};\Omega,\tilde{\lambda})}{\partial U_{sp}} \sigma_{U_{sp}} \right)^2$$

$$(3)$$

where U_{oz}, U_{wv} are the ozone and water vapour total column concentration, U_{sp} is the surface pressure and $\sigma_{U_{oz}}$, $\sigma_{U_{wv}}$ and $\sigma_{U_{sp}}$ are their associated uncertainties. The surface pressure contribution to the signal is about 10 times smaller than the contribution of the water vapour concentration. The TCWV is distributed among the two atmospheric layers in the forward radiative transfer model assuming a US76 water vapour vertical profile (Sissenwine et al., 1976). The fraction of TCWV in the scattering layer interacts with the aerosol particles and thus strongly affects the CISAR retrieval. Unlike the ozone which is mainly present in the stratosphere, the water vapour is dominant in the lower part of the atmosphere, severely impacting the aerosol retrieval in SEVIRI and PROBA-V band 0.8 μm (Table 4). Hence, only the uncertainty related to the TCWV is considered and Eq. **??** is approximated to:

Table 4: Water Vapour transmittance in the SEVIRI, PROBA-V and MODIS bands

	0.4 μm	0.6 μm	0.8 μm	1.6 μm
SEVIRI		0.993	0.915	0.988
PROBA-V	1.000	0.990	0.926	0.995
MODIS	1.000	0.990	0.985	0.996

Table 5: Total EQMPN median values [%]

	0.4 μm	0.6 μm	0.8 μm	1.6 μm
SEVIRI		0.28	2.02	0.38
PROBA-V	0.01	0.37	1.49	0.14

$$\sigma_B^2(\mathbf{b}, \tilde{\lambda}, \Omega_0, \Omega_v) \approx \left(\frac{\partial y(\mathbf{x}, U_{wv}; \Omega, \tilde{\lambda})}{\partial U_{wv}} \sigma_{U_{wv}} \right)^2 \tag{4}$$

The median values of the Equivalent Model Parameter Noise (EQMPN), computed as in Eq. 4, are shown in Table 5.

2.4 Prior information

Within an OE framework, the definition of the prior information and its uncertainty plays a fundamental role. In CISAR four different sources of prior information are considered:

1. Surface parameters magnitude. The surface reflectance, represented by the RPV (Rahman-Pinty-Verstraete) model (Rahman et al., 1993), is not expected to undergo rapid variations on a short temporal scale, hence the retrieval in the previous accumulation period can be used as prior information for the next inversion (Govaerts et al., 2010). The prior information on the RPV parameters at the time t_d is built by computing a running mean over the N_r previously-converged accumulation periods.

$$\mathbf{x}_b(t_d) = \frac{\Sigma_{t_i=0}^{t_d-1} \hat{\mathbf{x}}(t_i)}{N_r} \tag{5}$$

The corresponding prior uncertainty is defined as half of the variability range of the solution $\hat{\mathbf{x}}(t_i)$ retrieved during the considered N_r accumulation periods.

$$\sigma_{\mathbf{x}_b}(t_d) = \frac{\max_{t \in N_r} \hat{\mathbf{x}}(t_i) - \min_{t \in N_r} \hat{\mathbf{x}}(t_i)}{2} \tag{6}$$

When N_r is smaller than a certain minimum threshold N_{min} (Table 7), the prior information on the magnitude of the RPV parameters is taken from the last successful retrieval and its uncertainty is computed as in Eq. 7, where N_d is the number of days since the last successful retrieval (Govaerts et al., 2017).

$$\sigma_{\mathbf{x}_b}(t_d) = \sigma_{\mathbf{x}_b}(t_d - 1) 1.05^{N_d} \tag{7}$$

2. AOT magnitude. This information is taken from an annual mean climatology dataset (Kinne

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et al., 2013). From this dataset, the prior information on the AOT magnitude for the coarse
and fine mode (absorbing and non absorbing distinctly) is taken. The uncertainty is set to a
high arbitrary value $\sigma_{\mathbf{x}_b}$ for all the wavelengths (Table 7).

3. Constraints on the AOT temporal variability. These constraints result from the assumption that
   the AOT is not changing rapidly on a very short temporal scale, therefore a maximum temporal
   variation is defined through a sigmoid function. The temporal constraints are described by the
   matrix $\mathbf{H}_a$ in Eq. 13 of Part I.

4. Constraints on the AOT spectral variability. The AOT is expected to decrease with the wavelength, proportionally to the ratio of the extinction coefficient (see Eq. 15 of Part I). The
   applied constraints define the matrix $\mathbf{H}_l$ (Eq. 14 of Part I).

2.5 Forward model

FASTRE, the CISAR forward Radiative Transfer Model (RTM), and its uncertainty σ_F are described
in Sect. 4.4 of Part I. FASTRE uncertainty in the SEVIRI and PROBA-V processed bands has been
estimated as in Eq. 10 of Part I, comparing the outcome of FASTRE with a more elaborated RTM,
where 50 atmospheric layers are considered. The results of this evaluation are shown in Table 6. The
forward model uncertainty is lower than 3% in all processed bands, presenting its largest value in the
SEVIRI VIS0.8 band, the most affected by water vapour absorption (Table 4). The FASTRE two-
layer approximation of the atmosphere does not allow a correct discretisation of the water vapour
vertical profile and, thus, a correct characterisation of its interaction with the scattering particles.
Moreover, the two-layer approximation assumes that the scattering particles are only present in the
lower layer. Given the spectral behaviour of the AOT, this assumption leads to a higher uncertainty
at wavelengths shorter than 0.4 μm (Seidel et al., 2010). Despite the limitations associated ~~to~~ with
the two-layer approximation, FASTRE uncertainty is in the range of 1% - 3% (Table 6), which is
smaller or equal to the instrument radiometric noise.

Table 6: FASTRE relative uncertainty in the SEVIRI and PROBA-V processed bands [%]

	0.4 μm	0.6 μm	0.8 μm	1.6 μm
SEVIRI		1.88	2.75	0.96
PROBA-V	2.38	1.31	2.20	0.75

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3 Data processing

3.1 General setup

175 In order to perform the inversion on actual satellite data, the observations are accumulated in time and the corresponding uncertainty is computed as described in Sect. 2. This temporal accumulation is performed in order to build a multi-angular observation vector $\mathbf{y}_{\Omega\tilde{\Lambda}}$ to characterise the surface reflectance anisotropy. The surface optical properties are considered invariant during the accumulation period, and therefore a trade-off between having enough ~~cloud free~~ cloud-free observations to

180 build the observation vector and allowing the algorithm to catch surface variations is introduced; the high-repeat temporal coverage of geostationary satellites allows a shorter accumulation periods with respect to polar orbiting instruments. For SEVIRI acquisitions, although the angular sampling does not vary much from one day to the next, the length of the accumulation period is set to 5 days in order to maximise the occurrence of ~~cloud free~~ cloud-free observations. For polar orbiting satellites,

185 the length of the temporal accumulation is normally driven by the repeat cycle, as it is the case for MODIS (DAAC, 2018). In the case of PROBA-V, the satellite orbit is not maintained and there is no repeat cycle. Hence, the choice of the length of the time window during which the satellite observations are accumulated results from empirical studies~~aims at balancing~~, aiming to balance the trade-off previously described. Consequently, the length of the accumulation is set to 16 days and the

190 successive accumulation periods are shifted by 8 days. An example of the angular sampling during this accumulation period is shown in Fig. 3 for SEVIRI and PROBA-V. During the accumulation period, observations acquired with a sun or viewing angle larger than θ_{max} (defined in Table 7) are discarded.

The definition of the first guess is an important aspect of the inversion process and it is defined in order to minimise the possibility of finding local minima. When a minimum value is found, an investigation of the cost function in the vicinity of the solution should be made in order to determine whether or not it is a local minimum. However, this exploration could be computationally expensive. In order to minimise the possibility of local minima without degrading the computational performances, the AOT first guess is assigned to successive observations alternating between a low value τ_{low} and a larger one τ_{high} (see Table 7). As CISAR retrieves ~~one~~ a single set of RPV parameters over the entire accumulation period in each processed band, only one set of first guesses $\mathbf{x}_0$ is defined:

$$\mathbf{x}_0(t_d) = \mathbf{x}_b(t_d) + (-1)^{i_{t_d}} * \sigma_{\mathbf{x}_b}(t_d) \tag{8}$$

where i_{t_d} is the index of the current accumulation period and $\mathbf{x}_b$ is the prior information at the

195 accumulation period t_d.

From the retrieved set of RPV parameters the BHR is calculated, assuming perfectly diffuse illumination conditions, and the AOT is extrapolated at 0.55 μm through the extinction coefficient
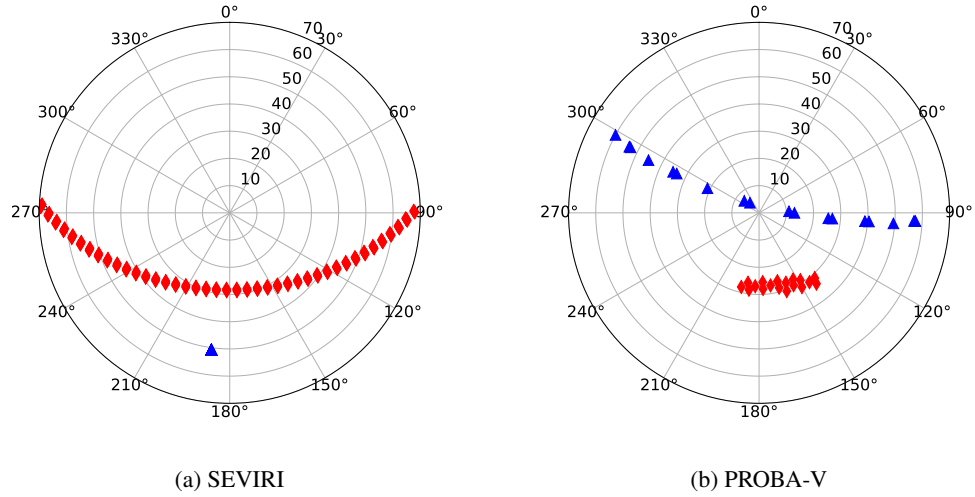
(a) SEVIRI

(b) PROBA-V

Fig. 3: Polar plot of the angular sampling during 5 days (2015/05/01-2015/05/05) of SEVIRI observations (left panel) and during 16 days (2015/05/01-2015/05/16) of PROBA-V observations (right panel) over Carpentras, France. The blue triangles represent the satellite viewing angles, the red diamonds the illumination one. Circles represent the zenith angle and polar angles represent azimuth angles with zero azimuth pointing to the North.

Table 7: CISAR setup parameters

		SEVIRI	PROBA-V
N_d	Length of the accumulation period	5	16
N_s	Shift between the accumulation period	5	8
N_{min}	Minimum converged retrievals to compute the mean on the RPV parameters	5	5
-	Maximum number of iterations	20	20
θ_{max}	Maximum processed sun and viewing zenith angles [°]	70	70
τ_{low}	Minimum AOT first guess value	0.001	0.001
τ_{high}	Maximum AOT first guess value	0.100	0.100
σ_{x_b,τ_F}	Fine mode prior uncertainty for the AOT	1.0	1.0
σ_{x_b,τ_C}	Coarse mode prior uncertainty for the AOT	2.0	2.0
$\sigma_{x_b,RPV}$	Default prior uncertainty for the RPV parameters	1.0	1.0

α:

$$\tau_{0.55,v} = \tau_{\lambda,v} \left(\frac{\alpha_{0.55,v}}{\alpha_{\lambda},v} \right) \quad (9)$$

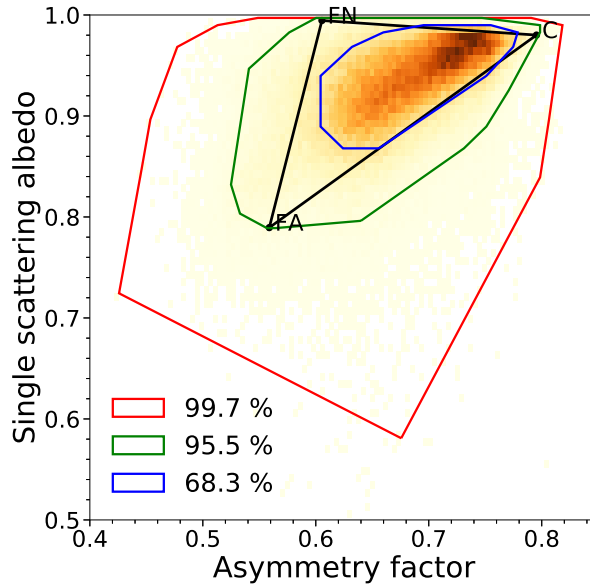where v is the considered aerosol vertex and λ is the wavelength from which the AOT at 0.55 μm is extrapolated.

Fig. 4: Solution space (black triangle) for the wavelength 0.6 μm defined by the non absorbing fine mode (FN), the absorbing fine mode (FA) and the coarse mode (C) vertices. The red, green and blue lines show the 99.7%, 95.5% and 68.3% probability regions respectively, as derived from AERONET inversion product for all the observations available over all the AERONET stations.

3.2 Aerosol vertices

The choice of the aerosol vertices subsamples the entire solution space to a region where the aerosol properties can be retrieved. The relationship between the particle size and the single scattering properties has been discussed in Part I. As recommended, three vertices are selected, defined by the asymmetry factor g and the Single Scattering Albedo (SSA) ω_0: two fine mode vertices, absorbing and non-absorbing, and one coarse mode vertex, defining a triangle in the $[g,\omega_0]$ space in each processed band. The three vertices are chosen analysing the single scattering properties derived from the AERONET inversion product on all available observations since 1993 (Dubovik et al., 2006), similarly to the approach proposed by Govaerts et al. (2010). The aerosol single scattering properties distribution in the $[g,\omega_0]$ space, as derived from AERONET inversion product, is shown in Fig. 4 for $\lambda = 0.6$ μm. The aerosol properties are clustered in the region defined by $0.60 < g < 0.80$ and $0.85 < \omega_0 < 0.98$, containing 68.3% of the data (blue line). The selected CISAR vertices defining the solution space cover about the 80% of possible solutions (black triangle).

4 Information content

The analysis of the information content relies on a two-fold approach. First, the Jacobians are used as an indicator of the TOA BRF sensitivity to state variable changes under different observation conditions. Next, the entropy is used as a rigorous metric to determine the information content of
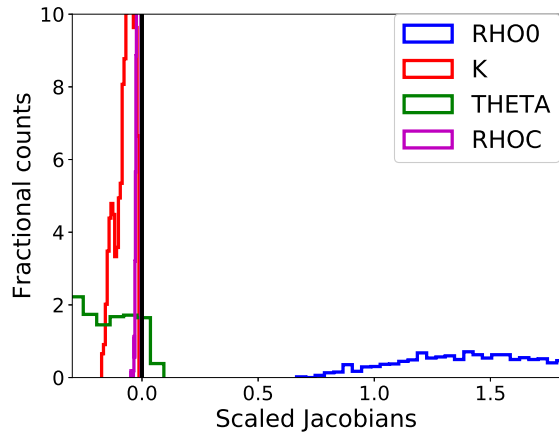
12

Fig. 5: Histograms of the distribution of the Jacobians related to the RPV parameters (x-axis), scaled by the variability range of each variable. These distributions are obtained from PROBA-V observations (RED band) over Carpentras, France (vegetated target). Positive (negative) values of the Jacobian show that the TOA BRF is positively (negatively) correlated to the considered state variable.

215 the observation system for each radiometer. The Jacobians, *i.e.* the partial derivatives of the forward model with respect to the state variables, are affected by the changes in illumination and viewing geometry both in terms of sign and magnitude (Luffarelli et al., 2016). The minimisation of the cost function relies on an iterative approach where the direction of steepest descent is determined by the Jacobians (Marquardt, 1963). An analysis of the Jacobians gives information about the amount

220 of information carried by the observation and ~~the challenges associated to its sign and magnitude~~ ~~variations~~ highlights variations in sensitivity throughout the year. The larger the magnitude of the Jacobians, the higher the sensitivity of the signal ~~on~~ to the selected state variable. The Jacobians have been scaled by the variability range of each state variable to compare their dimensionless magnitude.

An illustrative example of the distributions of the Jacobians relative to the RPV parameters is

225 shown in Fig. 5. The Jacobians are dominated by the ρ_0 parameter (controlling the magnitude of the surface BRF), followed by θ, k and ρ_c (characterising the surface reflectance anisotropy). Consequently, the retrieval of the surface reflectance shape is more challenging than the retrieval of its mean magnitude; nevertheless, its accurate retrieval is necessary to correctly account for the coupling between the surface and the atmosphere (Govaerts et al., 2008).

230 The aerosol contribution to the TOA BRF differs according to the brightness of the surface. Figure 6 shows the ~~AOT scaled~~ AOT-scaled Jacobians distribution over Carpentras (dark surface) and Zinder Airport (bright surface). The Jacobians over Carpentras reach higher values with respect to the Jacobians related to Zinder Airport, because the signal at Zinder is dominated by the bright surface (Sun et al., 2016). When the magnitude of the AOT Jacobian is close to 0, the observed TOA BRF

235 is not sensitive to changes in the aerosol concentration in the atmosphere. It is worth noticing that the ~~AOT scaled~~ AOT-scaled Jacobians can be both negative and positive, meaning that the aerosols

13

Table 8: Median and standard deviation of the scaled Jacobians. The table refers to all processed targets during 2015. The values are shown for the SEVIRI and PROBA-V bands centred at 0.6 μm.

	Median value	Standard deviation
ρ_0	1.316	0.385
κ	-0.008	0.038
θ	-0.250	0.265
ρ_c	-0.023	0.023
τ_F	0.017	0.014
τ_C	0.007	0.008

can increase or decrease the TOA BRF depending on the season and the viewing and illumination geometry. This variability of the sign of the Jacobians, occurring also over dark ~~target~~ targets (Fig. 6a), represents one limitation in the MODIS Dense Dark Vegetatation (DDV) algorithm (Kaufman et al., 1997), which assumes that an increase in the AOT results in an increased signal at the satellite.

240

Table 8 shows the median value and the standard deviation of the scaled Jacobians for all the state variables at SEVIRI and PROBA-V bands centred at 0.6 μm, over all selected AERONET stations. This table confirms the previous findings on the Jacobians magnitude shown in Fig. 5 and 6 over Carpentras and Zinder Airport. The ~~AOT scaled~~ AOT-scaled Jacobian is about 2 orders of magnitude

245 smaller than ~~the one of the magnitude of the~~ tthat for the surface reflectance. The variability of the Jacobian sign and magnitude along the year is illustrated in Fig. 7, where it can be seen that the effect of the aerosols on the reflectance can vary with the geometry for the same land cover type. The Jacobian variations in Fig. 7 essentially depend on the viewing and illumination geometry. Aerosol particles mostly scatter in the forward direction, given the positive sign of the asymmetry

250 factor g (controlled, among other factors, by the aerosol size distribution) (Andrews et al., 2006).

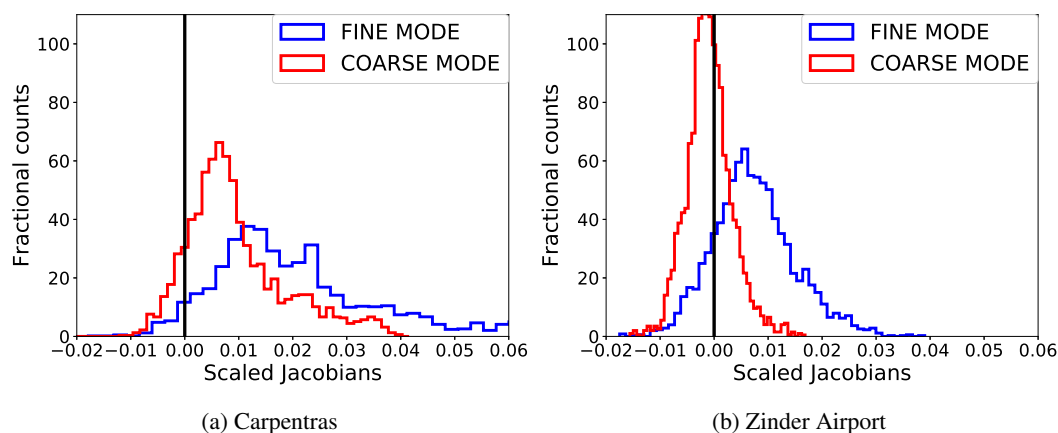(a) Carpentras

(b) Zinder Airport

Fig. 6: Distribution of the ~~AOT scaled~~ AOT-scaled Jacobian over Carpentras (dark surface) and Zinder Airport (bright surface). The histograms are obtained from PROBA-V observations (RED band) over year 2015.
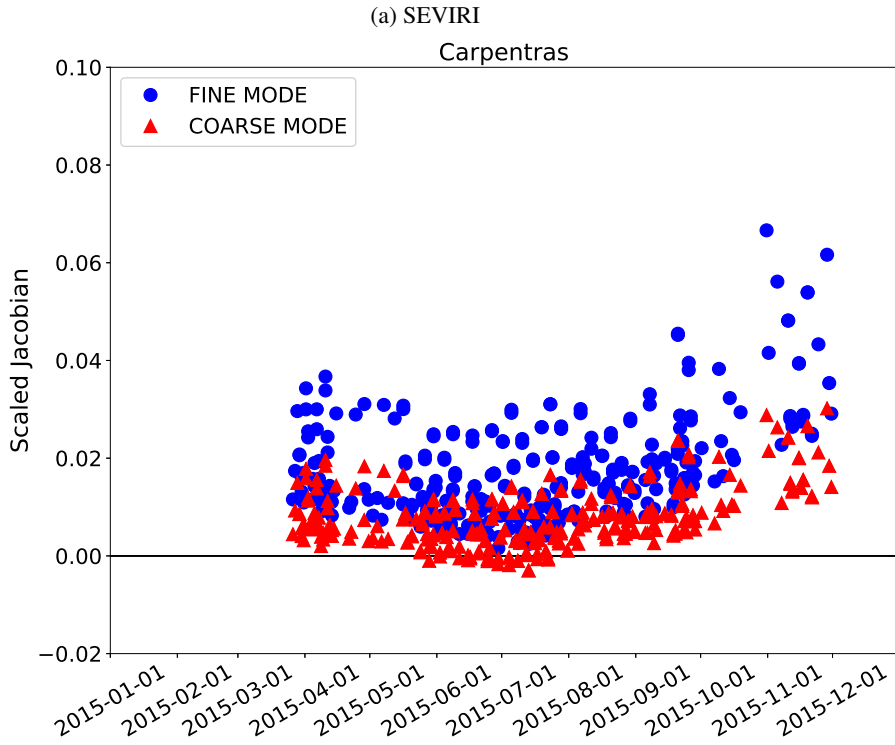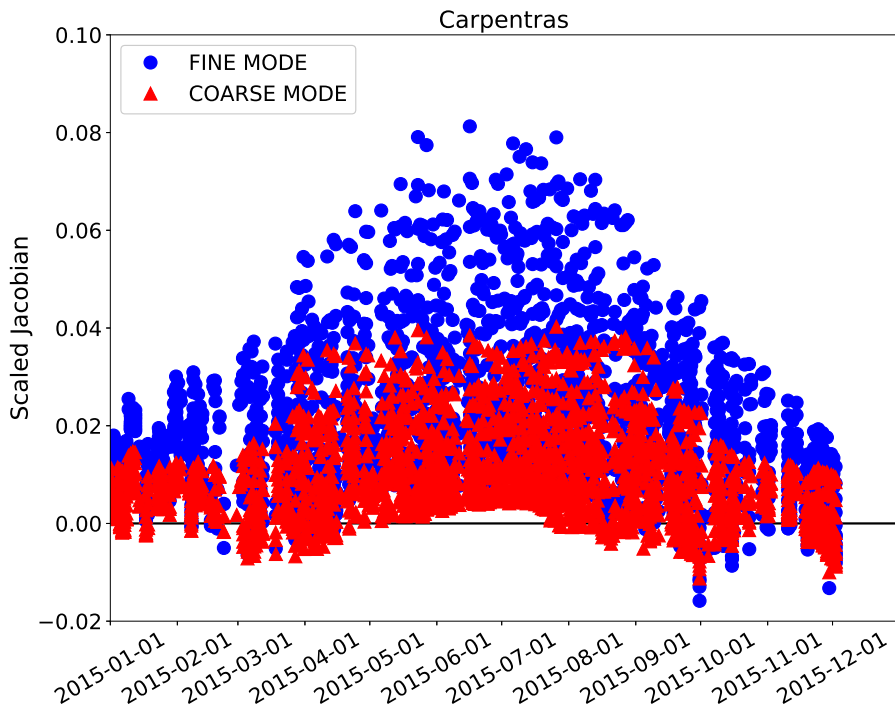
(a) SEVIRI

(b) PROBA-V

Fig. 7: Scaled AOT Jacobians timeseries over Carpentras, France (vegetated target) related to SEVIRI VIS0.6 band (top panel) and PROBA-V RED band (bottom panel) observations. The blue dots represent the fine mode, the red triangles the coarse mode.
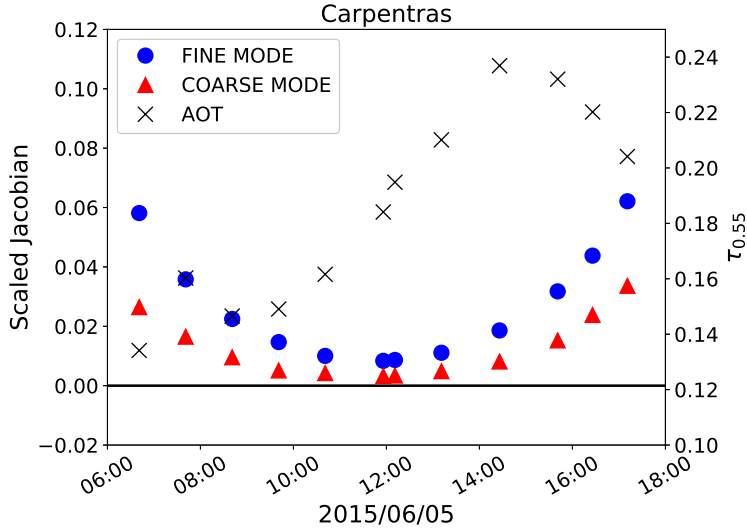
15

Fig. 8: Scaled AOT Jacobians (left y-axis) associated ~~to~~ with SEVIRI observation in the VIS0.6 band over Carpentras, France, for 2015/6/5. The blue dots represent the fine mode, the red triangles the coarse mode. The black crosses represent the retrieved AOT at 0.55 μm (right y-axis).

For this reason, the maximum information on the aerosols is located in the forward direction, while it decreases when approaching the backscattering direction. Additionally, a longer atmospheric path increases the aerosol effects on the reflectance, given the higher probability of interactions between the reflected sunlight and the atmospheric particles. The impact of the length of the atmospheric path is highlighted in Fig. 8, showing the Jacobian daily cycle over Carpentras. The sensitivity of the TOA BRF with respect to the AOT almost disappears at noon, when the atmospheric path is shortest and the effect of the aerosols on the signal is minimised. A more detailed analysis of the AOT Jacobians and their relation with the AOT magnitude is performed by Luffarelli et al. (2016). Given the seasonal variations of the Jacobians, shown in Fig. 7 and 8, it is not expected to get the same accuracy of the retrieval throughout the day and throughout the year.

A more rigorous analysis of the information content can be made through the entropy, which measures the uncertainty reduction (Rodgers, 2000). In an OE framework, the prior information and its uncertainty represent ~~an~~ a hypothesis on the expected value of the state variables. It is envisaged that the inversion process provides a posterior uncertainty on the state variables which is smaller than the prior one; the entropy quantifies this uncertainty reduction. When there is no information coming from the satellite observations, the entropy will be close to 0 as the observation does not add any additional knowledge on the system. Formally, the entropy is computed as follows:

$$H = -\frac{1}{2} ln \left(\frac{|\mathbf{S}_{\hat{x}}|}{|\mathbf{S}_x|} \right) \tag{10}$$

where $\mathbf{S}_{\hat{x}}$ (Eq. 21 of Part I) and $\mathbf{S}_x$ are the uncertainties of the posterior and the prior information

16
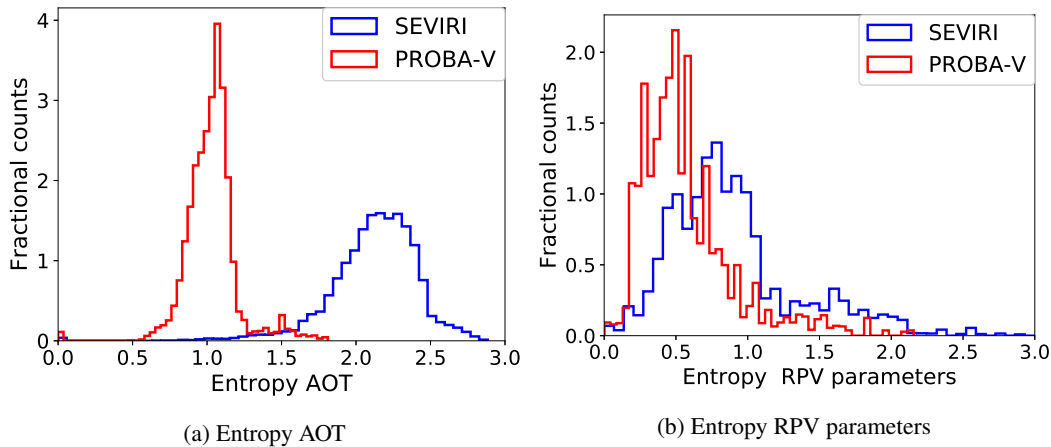
(a) Entropy AOT (b) Entropy RPV parameters

Fig. 9: Distribution of the entropy related to the AOT (left panel) and to the RPV parameters (right panel).

respectively.

In CISAR, the entropy is calculated considering the surface and atmospheric state variables and their associated prior and posterior uncertainty separately; the entropy distribution is shown in Fig. 9. The distribution of the surface and AOT entropy related to SEVIRI observations exhibits higher values compared to the one related to PROBA-V observations, given the larger radiometric uncertainty associated to the observations acquired by the polar orbiting satellite. The entropy depends not only on the information carried by the satellite observation, but also on the uncertainty associated to the prior information. As the prior information on the surface is updated (Sect. 2.4), the associated uncertainty decreases in time, whereas the prior information on the AOT remains weakly constrained, as the uncertainty is kept to the default high value. For this reason the entropy associated to the RPV parameters exhibits smaller value than the one associated to the AOT (Fig. 9a).

5 Quality indicator

5.1 Review of existing methods

Section 2.5 discussed the limitations of the forward model FASTRE. Furthermore, in Sect. 4 it has been shown how the AOT Jacobian magnitude is subject to temporal variations, depending on the viewing and illumination geometries. These issues compromise the reliability of the retrieved solution, which can ~~however~~ be assessed using different methods. Dubovik et al. (2011) use the relative fitting measurement residual, to filter the retrieval outliers. Such an approach presents some limitations as the number of degrees of freedom can vary depending on the availability of ~~cloud free~~ cloud-free observations. The requirement on the quality of the fit should be stricter when only a limited number of observations is available (Govaerts et al., 2010). ~~To address this specific issue~~

17

, ~~Govaerts and Lattanzio (2007)~~ This specific issue was addressed in Govaerts and Lattanzio (2007), who developed an approach which also takes into account the number of ~~cloud free~~ cloud-free

285 observations. The authors observed that the cost function is proportional to the quadratic sum of the mismatch between the simulation and the observation for each acquisition, weighted by the observation uncertainty. As the cost function is strongly dependent on the number of observations, it is not possible to define a universal range of acceptable values for its residual without performing additional operations on the cost function. Both methods do not correctly identify situations in

290 which a good fit is reached but the retrieval of the state variables is not reliable, due to limited or no dependency of the TOA BRF on the state variables (the Jacobians are close to 0). A more elaborate QI has been developed for the MODIS Aerosol Product Collection 6 (Hubanks, 2017), which is composed of different tests accounting for the fitting residual, the magnitude of the retrieved AOT, the possible presence of cirrus, the brightness of the scene and information on the number of pixels

295 and the percentage of water pixels present in the processed area. Despite taking into account different factors in addition to fitting residuals, this approach does not consider the actual information content of the satellite observation. Moreover, as CISAR processes each pixel independently, the information on the number and type of pixels over which the retrieval is performed, as used in the MODIS product, is not applicable within this method.

300 ## 5.2 Overview

A new approach is proposed for the CISAR algorithm, which combines a series of individual tests j with an associated value p_j in the range $[0,1]$, defining a $QI(t_i)$ associated ~~to~~ with the solution
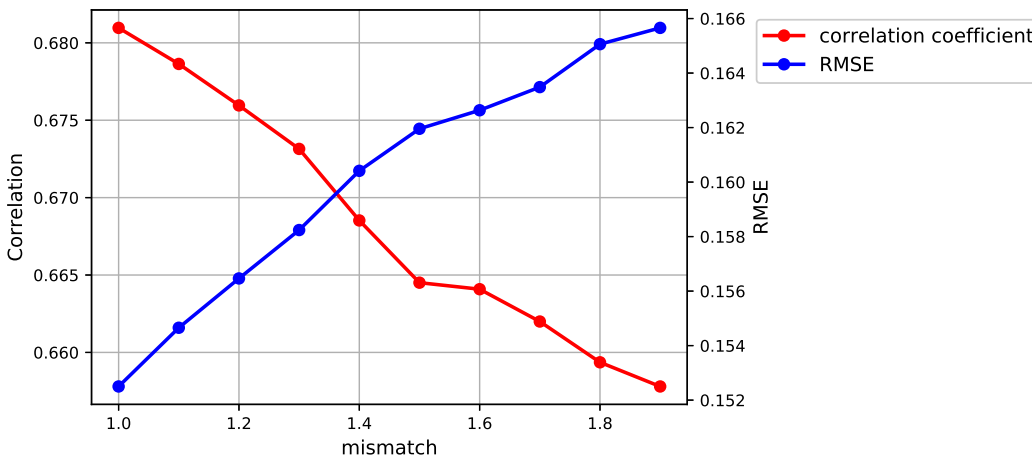

Fig. 10: Correlation (in red) and RMSE (in blue) variations in function of the mismatch between the satellite observation and the simulated signal (test 3). The figure refers to the CISAR AOT retrieval evaluation against AERONET data. These results are obtain from CISAR applied to SEVIRI observations.

retrieved at the time t_i. These tests ~~are performed~~ evaluate on the convergence of the inversion to a solution after a given number of iterations (0), on the validity range of the total AOT (1) and surface albedo (2), on the mismatch between observations and simulations (3) and on the information content of the satellite acquisition through the Jacobians (4) and the entropy, as discussed in Sect. 4. The entropy is computed separately for the AOT (5) and RPV parameters (6). These tests have been defined through an analysis of their impact on the CISAR performance when evaluated against independent reference datasets. The value p_j associated ~~to~~ with each test can assume values between 0 (bad quality) and 1 (good quality). Figure 10 shows an example of the evaluation of the retrieved AOT against the AERONET data for the mismatch test (3). As the mismatch increases, the correlation decreases, while the Root Mean Square Error (RMSE) shows opposite behaviour.

5.3 Quality indicator tests

5.3.1 Convergence

The first test to be performed is on the convergence of the inversion. When the maximum number of iteration is reached p_0 is equal to 0, otherwise $p_0 = 1$.

5.3.2 State variable validity range

The validity of the retrieved total AOT and of the surface BHR is examined in the tests 1 and 2. In CISAR, a validity range for each state variable is defined, based on physical boundaries and empirical observations. When the value of retrieved AOT (BHR) falls on the extremes of this range, p_1 (p_2) is equal to 0. The acceptable values for the BHR range from 0 to 1, while the AOT can only assume positive values smaller than 5. The values p_1 and p_2 are equal to 1 when $0 < BHR < 1$ and $0 < AOT < 5$ respectively.

5.3.3 Mismatch between observation and simulation

As discussed in Sect. 5.1, the fitting residual between the observation and the simulation is normally used to assess the reliability of the solution, as it describes how well the signal simulated with the forward model $\mathbf{y}_\mathrm{m}(t_i,\lambda)$ fits the satellite observations $\mathbf{y}_0(t_i,\lambda)$. The mismatch between the observed and simulated TOA BRF is weighted by the ~~observations~~ observation's uncertainty $\boldsymbol{\sigma}_0(t_i,\lambda)$. For this test, the largest mismatch among the processed bands is considered. Two thresholds T_1 and T_2 are defined to identify good ($p_3 = 1$) and bad ($p_3 = 0$) quality retrievals. The difference between the simulated signal and the satellite observation should have the same magnitude as the observation uncertainty $\boldsymbol{\sigma}_0(t_i,\lambda)$, therefore the T_1 is set to 1. Conversely, the maximum acceptable mismatch value $T_2 = 2$ has been chosen ~~observing the relation~~ by observing the relationship between the mismatch and the performances of CISAR when evaluated against the independent datasets used as reference. Fig. 10 represents an example of this analysis. When the mismatch assumes values within the range
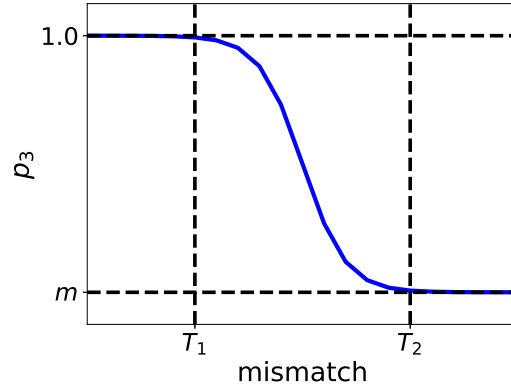
Fig. 11: Non linear p_3 definition between the minimum value m and 1 which applies when the mismatch is larger than T_1 and smaller than T_2.

defined by T_1 and T_2, thresholds included, a value between a minimum m and 1 is assigned to p_3 through a sigmoid function with width equal to $10/(T_2 - T_1)$ (Fig. 11). A different coefficient m is defined for each test j in order to give different weights to the tests, according to the magnitude of their impact on the retrieved solution and its evaluation against the reference dataset. The outcome
340 of the test 3 is thus defined as follows:

$$
\begin{cases}
p_3(t_i) = 0 & \text{if} \quad \max_\lambda \left\{ \dfrac{|y_{\mathrm{m}}(t_i,\lambda) - y_0(t_i,\lambda)|}{\sigma_0(t_i,\lambda)} \right\} > T_2 \\[2ex]
p_3(t_i) = 1 & \text{if} \quad \max_\lambda \left\{ \dfrac{|y_{\mathrm{m}}(t_i,\lambda) - y_0(t_i,\lambda)|}{\sigma_0(t_i,\lambda)} \right\} < T_1 \\[2ex]
m < p_3(t_i) < 1 & \text{if} \quad T_1 \leq \max_\lambda \left\{ \dfrac{|y_{\mathrm{m}}(t_i,\lambda) - y_0(t_i,\lambda)|}{\sigma_0(t_i,\lambda)} \right\} \leq T_2
\end{cases}
\tag{11}
$$

with $\lambda = 1, \ldots,$ number of wavelengths.

5.3.4   Jacobians

The magnitude of the Jacobians gives information on the sensitivity of the TOA BRF ~~on~~ to the state variables. Performing a test on the Jacobians related to each state variable can be computationally
345 expensive. In order to reduce the computational effort, only the Jacobian of the AOT is taken into account. The spectral constraints applied to the AOT variability as in Sect. 2.4 impose a correlation between the AOT retrieved in the different spectral bands. Consequently, it is desirable to have large absolute Jacobians in at least one band. To have a good retrieval of the total AOT, the AOT associated ~~to~~ with each aerosol vertex has to be correctly retrieved. The quantity $\hat{K}_x(t_i)$ analysed in the test 4
350 is thus the following:

$$
\hat{K}_x(t_i) = \max_\lambda \left\{ \min_v \left\{ |K_{x_{\lambda,v}}(t_i)| \right\} \right\}
\tag{12}
$$

20

with $\lambda=1,\dots$,number of wavelengths and $\upsilon=1,\dots$, number of aerosol vertices.

The aim of this test is to discard observations with little or no sensitivity to the AOT, identifying those situations where the test on the miss-fit is successful because of the prior information and/or the temporal and spectral constraints (Sect. 2.1) rather than actual information coming from the observations. The thresholds T_1 and T_2 are set to 0.01 and 0.02 respectively. The values of p_4 are defined similarly to p_3:

$$
\begin{cases}
\quad p_4(t_i) = 0 & \text{if} \quad \hat{K}_x(t_i) < T_1 \\
\quad p_4(t_i) = 1 & \text{if} \quad \hat{K}_x(t_i) > T_2 \\
m < p_4(t_i) < 1 & \text{if} \quad T_1 \le \hat{K}_x(t_i) \le T_2
\end{cases}
\tag{13}
$$

5.3.5 Entropy

Section 4 discusses how the entropy, ~~quantifying~~ which quantifies the uncertainty reduction from the prior knowledge on the system to the posterior uncertainty, represents a rigorous analysis of the information content. Tests 5 and 6 analyse the entropy associated ~~to~~ with the AOT and the one associated ~~to~~ with the RPV parameters, computed as follows:

$$
\begin{aligned}
H_{AOT}(t_i) &= -\frac{1}{2N_\lambda} ln\left(\frac{\prod_\lambda \prod_\upsilon \sigma_{post}(t_i,\lambda,\upsilon)}{\prod_\lambda \prod_\upsilon \sigma_{prior}(t_i,\lambda,\upsilon)} \right) \\
H_{RPV}(t_i) &= -\frac{1}{2N_\lambda} ln\left(\frac{\prod_\lambda \prod_p \sigma_{post}(t_i,\lambda,p)}{\prod_\lambda \prod_p \sigma_{prior}(t_i,\lambda,p)} \right)
\end{aligned}
\tag{14}
$$

where N_λ is the number of processed wavelengths, $\lambda=1,\dots,N_\lambda$, $p=1,\dots$,number of RPV parameters and $\upsilon=1,\dots$,number of aerosol vertices. The normalization to N_λ assures consistency in the entropy evaluation when different number of bands are analysed, as for SEVIRI and PROBA-V cases. The entropy computation is strongly dependent on the magnitude of the prior uncertainty as explained in Sect. 4. Low entropy might be due to reliable prior information, with a low associated uncertainty. Similarly, the uncertainty reduction would be very large in case of little prior information on the state variable. For these reasons, tests 5 and 6 are only performed when the prior uncertainty is smaller than the validity range of the AOT and RPV respectively and larger than 1/6 of it. The thresholds associated ~~to~~ with the two tests on the entropy are $T_1 = 0.1$ and $T_2 = 0.6$ that correspond to a 20% and 70% uncertainty reduction respectively. The values $p_5(t_i)$ and $p_6(t_i)$ are computed as in Eq. 15.

$$
\begin{cases}
\quad p_{5,6}(t_i) = 0 & \text{if} \quad H_{AOT}(t_i), H_{RPV}(t_i) < T_1 \\
\quad p_{5,6}(t_i) = 1 & \text{if} \quad H_{AOT}(t_i), H_{RPV}(t_i) > T_2 \\
m < p_{5,6}(t_i) < 1 & \text{if} \quad T_1 \le H_{AOT}(t_i), H_{RPV}(t_i) \le T_2
\end{cases}
\tag{15}
$$

5.4 Quality indicator computation

The final QI is computed by combining the results of the tests performed on the retrieved solution:
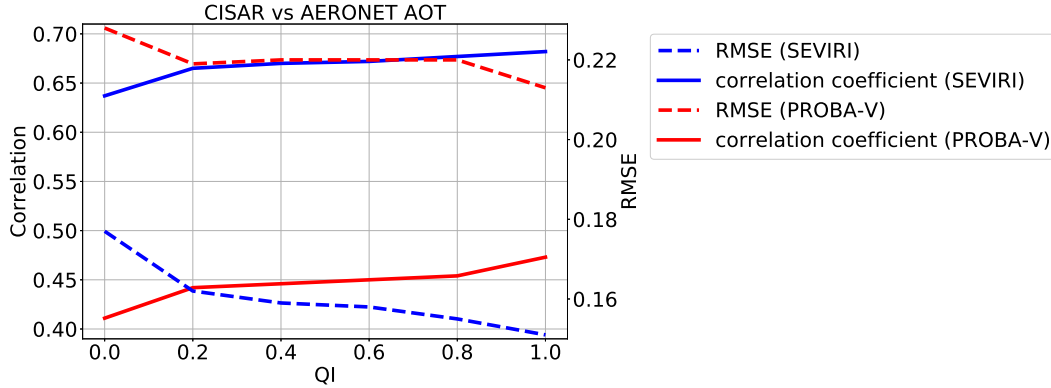
21

Fig. 12: Correlation (straight lines) and RMSE (dashed lines) variations in function of the QI. The figure refers to the CISAR AOT retrieval from SEVIRI (in blue) and PROBA-V (in red) observations evaluated against AERONET data.

$$QI(t_i) = p_0(t_i)p_1(t_i)p_2(t_i)\max\left\{1 - \sum_{j=3}^{6}(1 - p_j(t_i)), 0\right\} \tag{16}$$

The final $QI(t_i)$ ranges from 0 to 1, where 0 designate a poor quality retrieval and 1 indicates a
375 reliable solution. Figure 12 shows the variations of the correlation and the RMSE between CISAR retrieved AOT and AERONET data as a function of the QI. Correlation increases as QI is taking larger values, while the RMSE decreases. This behaviour is observed with CISAR AOT retrieved from both SEVIRI and PROBA-V observations (Fig. 12). This correlation increase (RMSE decrease) is particularly visible when QI is taking values between 0.0 and 0.2. For this reason, only
380 retrievals with $QI \geq 0.2$ are considered in Sect.6.

Table 9: CISAR retrieved BHR from actual observations comparison with MODIS in all the processed bands.

	SEVIRI			PROBA-V			
	0.6 μm	0.8 μm	1.6 μm	0.4 μm	0.6 μm	0.8 μm	1.6 μm
Number of points		7409			744		
Correlation	0.917	0.779	0.854	0.743	0.864	0.618	0.841
Root Mean Square Error	0.045	0.067	0.079	0.029	0.052	0.098	0.091
Mean Absolute Bias	0.039	0.067	0.067	0.025	0.045	0.070	0.077

22

6 Performance evaluation

6.1 BHR

The CISAR BHR, computed from the RPV parameters, is compared with the MODIS Land product (Schaaf and Wang, 2015). To account for the different spatial sampling, the MODIS data have been averaged on 5x5 km and 1x1 km for the comparison with the retrievals from SEVIRI and PROBA-V respectively. The results of this comparison are shown in Table 9 in terms of correlation, RMSE, and Mean Absolute Error (MAE). The CISAR results show a high correlation with the MODIS product, higher than 0.7 in all the processed spectral bands, except the PROBA-V NIR band, which shows a correlation ~~equal to~~ of 0.618. The density plots of the CISAR BHR retrievals against MODIS data are included in the Supplement for all the processed bands, for both satellites. Despite the instrument differences discussed in Sect. 2.5, the CISAR retrievals and the MODIS Land Product ~~dataset~~ show similar seasonal trends. Figure 13 shows the BHR timeseries over Zinder Airport (Niger, Africa), as retrieved from the CISAR algorithm applied to SEVIRI and PROBA-V observations and from the MODIS Land Product. The rainy season, going from May 20 to October 5 (Weatherspark.com, 2018), is distinguishable through the decrease of the surface BHR in both the MODIS and CISAR datasets, although CISAR retrieves a larger seasonal variation with respect to MODIS product. The effect of the updating mechanism on the surface prior described in Sect. 2.4 is also visible as the retrieval uncertainty decreases in time, given that the prior information on the surface is better defined.

6.2 Aerosol Optical Thickness

The CISAR AOT retrieval, extrapolated at 0.55 μm, has been evaluated against the AERONET data over the selected targets listed in Sect. 2. The CISAR AOT retrieval is evaluated in terms of correlation, RMSE, MAE with respect to AERONET values. Additionally, the percentage of points falling within the Global Climate Observation System (GCOS) requirements (Systematic Observation Requirements for Satellite-Based Data Products for Climate, 2011 Update), defined as $\max\{0.03, 10\%\}$, is also accounted for. The GCOS requirements are a useful tool to compare different algorithms' performances. However, both the SEVIRI and PROBA-V missions were not originally designed for AOT retrieval. The GCOS requirement of 0.03 for low optical thickness translates into a radiometric noise requirement much better than 2 (1)% at 0.4 (0.6) μm, ~~way~~ well below the radiometric performance of the SEVIRI and PROBA-V instruments (Table 3). The duration of the corresponding missions provides however a decisive advantage for the generation of AOT datasets from these instruments. In the following, the GCOS requirements are evaluated in terms of percentage of retrievals satisfying them.

Figure 14 shows the evaluation of the retrieved AOT against AERONET data for both SEVIRI (left panel) and PROBA-V (right panel). The CISAR retrievals from SEVIRI observations shows a
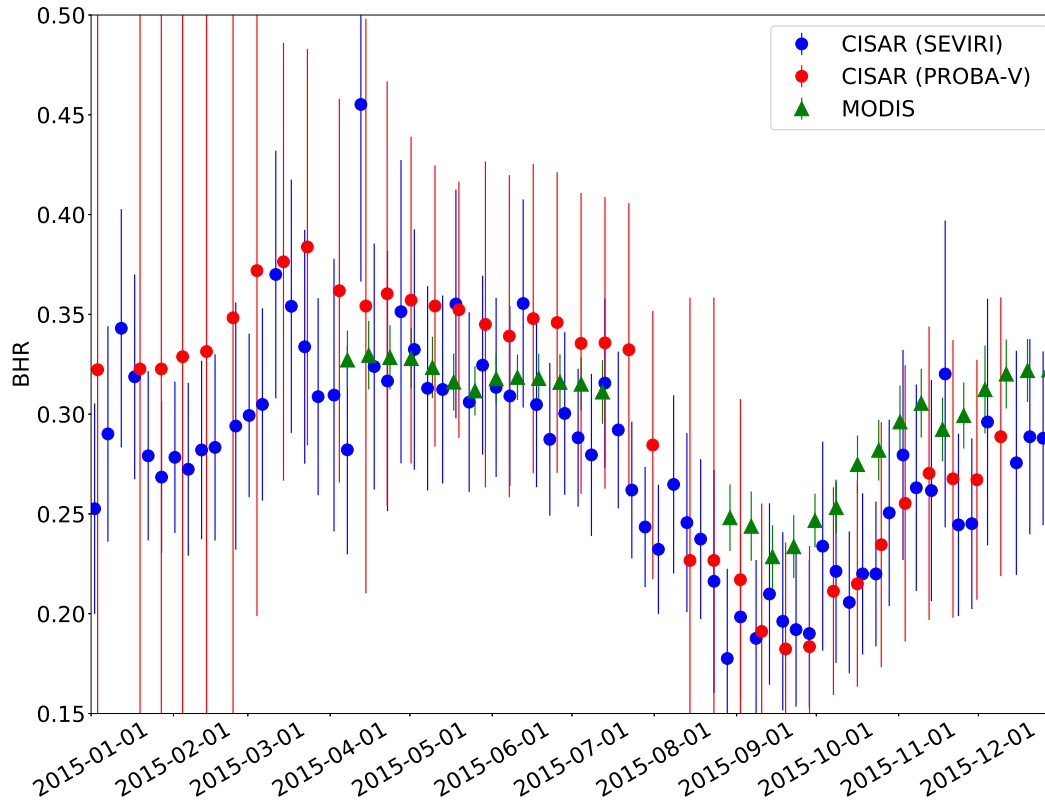
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Fig. 13: CISAR retrieved BHR from SEVIRI (blue dots) and PROBA-V (red dots) and MODIS Land Product (green triangle) over Zinder Airport (Niger, Africa). The results are shown for ~~the sensors~~ each sensor's band centred at 0.6 μm, for year 2015. The vertical bars represent the retrieval uncertainty for SEVIRI and PROBA-V and standard deviation over the selected area for MODIS.

better agreement with the AERONET data compared to the retrievals from PROBA-V observations. This is in accordance with the poor radiometric performances of the polar orbiting instrument and with the outcome of the information content analysis performed in Sect. 4.

The boxplots in Fig. 14 show an overestimation of the retrieval for low AOT and an underesti-

420   mation for large AOT. A similar behaviour is also observed in Wagner et al. (2010). The underestimation for large values might be partially due to the temporal constraints described in Sect. 2.4, as they might prevent the algorithm ~~to fit~~ from fitting rapidly evolving aerosol events associated with large AOT values. However, the applied temporal constraints are intended to optimise the retrieval of low aerosol concentration, given the global distribution of AOT which is normally smaller than

425   0.2 (Kokhanovsky et al., 2007). Additionally, very high AOT normally correspond to local events, especially in Europe (e.g. plume, fire), therefore the AOT obtained by the retrieval from the satellite pixel containing the AERONET station will be lower than the one measured by the AERONET tower (Jiang et al., 2007). The histograms in Fig. 14 show that AOT values larger than 0.8 represent less than 5% of the total number AERONET observations, affecting the reliability of the statistics

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430 for high values of AOT. The processing of more data would be necessary to increase the confidence in the results for high AOT values. Some examples of CISAR's ability to detect high AOT are shown in the Supplement.

The overestimation of low AOT might originate from the different spatial scale between the satellite observations and the ground measurements. Most of the selected AERONET stations are located

435 in Europe (Fig. 1), where the SEVIRI pixel resolution is about 5x8 km (as opposed to 3x3 km at the subsatellite point), which is compared to AERONET point measurement. The probability of residual cloud contamination at this scale might thus explain part of the overestimation (Henderson and Chylek (2005), Chand et al. (2012)). Furthermore, the shortest SEVIRI spectral band is centred at 0.67 μm, where the sensitivity to low optical thickness is about 2 times smaller than in the blue

440 spectral region. Consequently, the retrieval in these cases essentially relies on the prior information regardless of the very large associated uncertainty. Despite the presence of a blue band and a better spatial resolution (1 km), the retrievals from PROBA-V observations still show overestimation at low AOT, due to the poor radiometric performances which decrease the importance of the information derived from the observations and to the lack of a thermal channel that leads to an unreliable cloud

445 mask.

The CISAR potential to discriminate between the fine and coarse mode is analysed next. Figure 15 shows the fine ~~and~~ to coarse mode ratio distribution related to AERONET data (in green) and
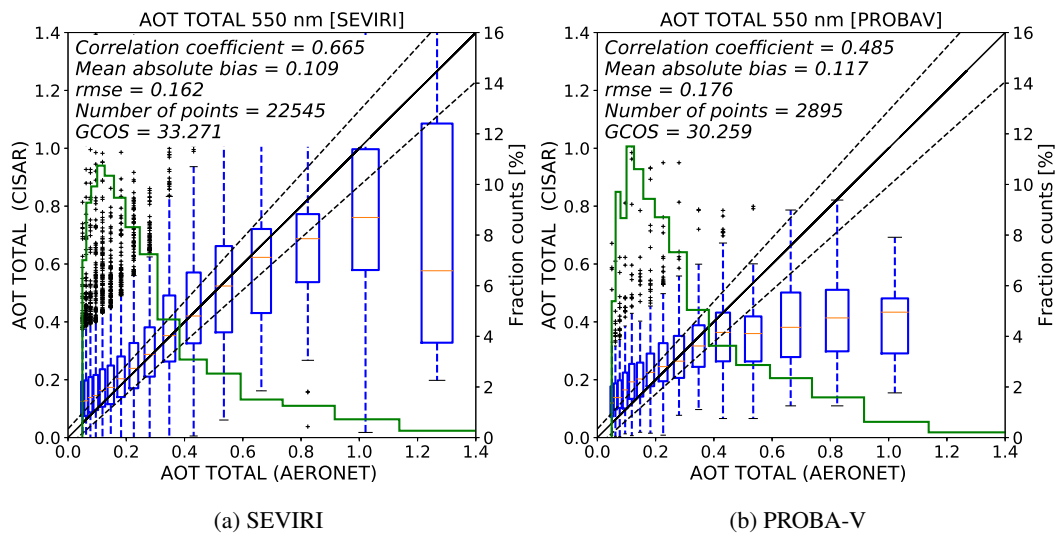

(a) SEVIRI   (b) PROBA-V

Fig. 14: Boxplots showing the CISAR AOT retrieval extrapolated at 0.55 μm (left y-axis) against the AERONET data (x-axis) for SEVIRI (left panel) and PROBA-V (right panel) over all the selected stations. Only retrievals with $QI \geq 0.2$ are considered. The blue boxes represent the interquartile range (IQR), the red horizontal line represents the median value, the vertical dashed bars represent the $1.5 \times IQR$ range and the black crosses represent the outliers. Boxes with less than 10 points are not displayed. The green histograms represent the AERONET AOT distribution. The right y-axis shows the percentage of points contained in each bin.

CISAR retrieval for SEVIRI (in blue) and PROBA-V (in red). It can been seen that the distribution related to CISAR retrievals from SEVIRI and PROBA-V observations ~~seem to~~ underestimate the fine mode concentration for $\tau_F/\tau_C > 3$. The percentage of cases where CISAR succeeds in retrieving a ~~predominant~~ <u>predominantly</u> fine mode contribution to the total AOT ($\tau_F/\tau_C > 1$), is equal to 80% when the retrieval is performed on SEVIRI acquisition and 62% when CISAR is applied to PROBA-V data. This represents an improvement with respect to the Land Daily Aerosol (LDA) algorithm (Wagner et al. (2010), Table 4) where particles retrieved by AERONET as spherical were correctly characterised by the algorithm only in ~~the~~ 12% of cases. This represents a decisive advantage of the proposed approach with a continuous variations of the aerosol properties in the solution space, as opposed to the use of a limited number of aerosol classes, as in Wagner et al. (2010). The coarse particle retrieval appears to be more challenging for both satellites. The percentage of cases where the coarse mode is correctly retrieved as predominant is 43% and 30% for the retrieval from SEVIRI and PROBA-V observations respectively. The less accurate retrieval of the coarse mode compared to the fine mode is expected, as the considered wavelengths are less sensitive to the radii in the range of the coarse particles than to those of fine ones (Torres et al., 2017). This can also be observed in Table 8 where the median magnitude of the coarse mode Jacobian is less than an half of the fine mode Jacobian.

6.3 Single scattering albedo and asymmetry factor

In Sect. 3.2 the solution space defined by the aerosol classes vertices has been described. CISAR retrieves the averaged SSA and asymmetry factor within this solution space as linear combinations
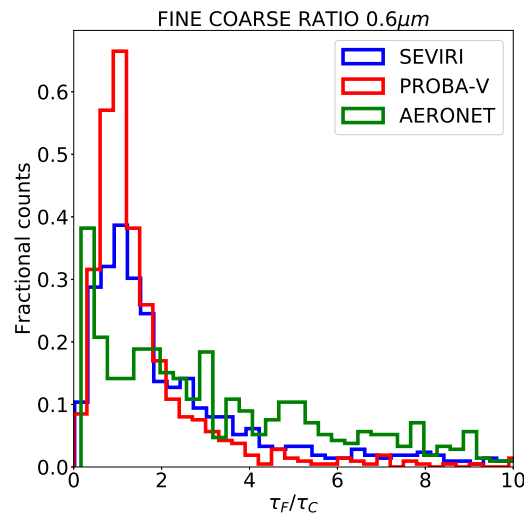

Fig. 15: Fine-coarse mode ratio distribution at 0.6 μm from AERONET (green) and from CISAR applied to SEVIRI (blue) and PROBA-V (red) observations.

of the single scattering properties of each selected aerosol vertex (Eq. 8 and 9 of Part I). Figures 16 and 17 show the SSA and asymmetry factor distributions related to the AERONET inversion product and CISAR retrievals. All the AERONET inversions are considered, without applying the quality test as in Holben et al. (2006). The three datasets show similar distributions, although spikes can be observed at the extremes of the CISAR retrievals distributions. When the AERONET solution is located outside the solution space, CISAR cannot converge to it and the retrievals falls on the solution space boundaries, causing the spikes. The aerosol vertices selection as in Fig. 4 is conceived to limit the number of occurrences of these spikes. Figure 17 shows that the g parameter distributions obtained from PROBA-V observations is much narrower than the same distribution related to AERONET and CISAR applied to SEVIRI observations. This is in line with what has been discussed in Sect. 6.2 on the poorer CISAR performances in retrieving the predominant mode when applied to PROBA-V observations rather than the SEVIRI ones. In fact, as in computing g the aerosol size distribution is the most important parameter to measure (Andrews et al., 2006), an inexact estimate of the dominant mode (fine or coarse) leads to an erroneous measurement of the asymmetry parameter.

7 Discussion and conclusion

This paper describes and evaluates the application of the CISAR algorithm to satellite observations acquired from geostationary and polar orbiting instruments. The theoretical aspects of CISAR, a new generic algorithm for the joint retrieval of surface reflectance and aerosol properties, with continuous
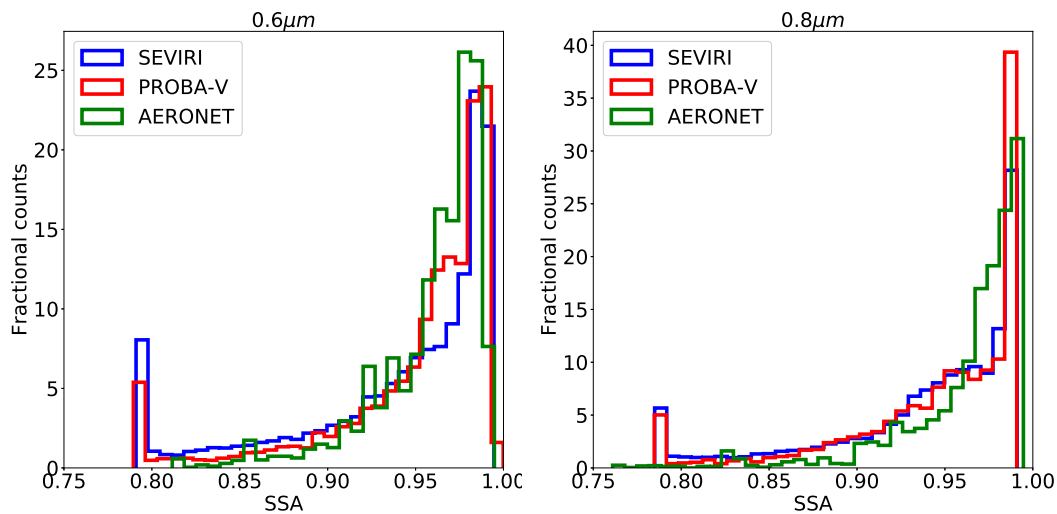

Fig. 16: SSA distributions at 0.6 μm (left panel) and 0.8 μm (right panel) for AERONET (green), CISAR applied to SEVIRI (blue) and to PROBA-V (red).
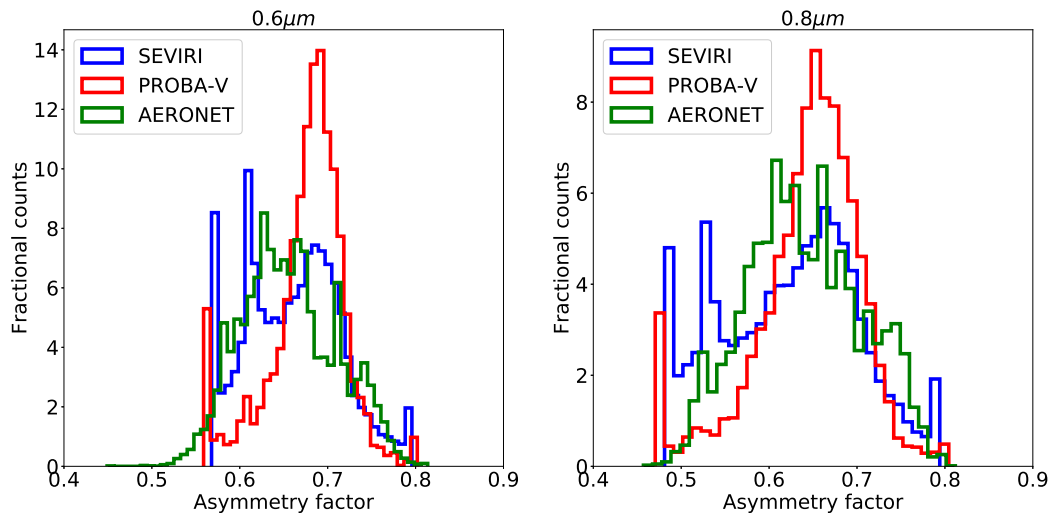
Fig. 17: Same as Figure 16 but for the asymmetry factor.

variation of all the state variables in the solution space, are described in Part I. In the latter, CISAR is applied to simulated ~~noise free~~ noise-free observations in the principal plane. This paper provides an evaluation of the algorithm in non ideal situations, *i.e.* actual satellite observations acquired from both geostationary and polar orbiting satellites, namely SEVIRI and PROBA-V.

The proposed retrieval method relies on an OE approach which consists of the inversion of FASTRE, a simple radiative transfer model composed of two horizontal layers. The FASTRE model is evaluated in Sect. 2.5 showing an accuracy within 3% when compared to a complex 1D radiative transfer model. Higher uncertainties are observed in spectral bands affected by water vapour as a result of the limited vertical discretisation.

The analysis of the information content of the satellite observations is performed in Sect. 4. Though the PROBA-V instrument has one blue channel which is not present in SEVIRI, the better radiometric performances of the geostationary satellite provide more information for the retrieval of surface reflectance and aerosol properties than the polar orbiting instrument.

The CISAR retrieval is evaluated against independent datasets. The retrieved AOT is compared to AERONET data. A specific QI has been developed to disregard suspicious retrievals. With a RMSE of 0.162 for SEVIRI and 0.176 for PROBA-V, CISAR shows better performances when applied to the geostationary satellite. CISAR retrieves the single scattering aerosol properties assuming a linear behaviour of g and ω_0 in the solution space; although this assumption is not exactly true when far from pure single mode situations, CISAR retrieved aerosol properties distributions are in good agreement with the AERONET inversion products, especially when the algorithm is applied to geostationary observations, as discussed in Sect. 6.3. These differences are explained by the different information content associated ~~to~~ with the observations acquired by the two satellites. For

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both satellites, CISAR discrimination between fine and coarse mode is improved with respect to the
LDA algorithm (Wagner et al., 2010), as the continuous variation of the aerosol properties in the
solution space allows more accurate retrievals of the single scattering properties with respect to that
LUT-based approachesapproach. The CISAR surface albedo is compared with the MODIS product,
showing a correlation higher than 0.74 in all processed bands (to with the exception of the NIR
PROBA-V band). The better performances of CISAR in retrieving the surface reflectance rather
than the AOT are explained by the larger contribution to the TOA BRF at the satellite of the surface.
The little variance of the small variance of surface reflectance on a short time scale allows a good
prior definition based on the previous CISAR retrievals.

Several aspects of the new CISAR algorithm would still require additional efforts to improve its
performance. The cloud mask omission errors impact on the AOT overestimation at low optical
thickness would also deserve additional work. The analysis of the Jacobian median values has
revealed the very small magnitude of the fine and coarse mode AOT Jacobians. The spectral and
temporal constraints of the AOT variability play therefore a critical role in supporting the assessment
of aerosol properties. However, these constraints might lead to an underestimation of the AOT for
large values. The cloud mask omission errors impact on the AOT overestimation at low optical
thickness deserve additional work. In order to reduce the impact of cloud contamination in the
AOT retrieval, a new version of the CISAR algorithm is under development in the framework of the
ESA-SEOM ConsIstent Retrieval of Cloud Aerosol Surface (CIRCAS) project. The new version
of CISAR aims to retrieve both the AOT and the Cloud Optical Thickness (COT), overcoming the
need of an external cloud mask. Within the CIRCAS project CISAR will be applied to observations
acquired by the Sea and Land Surface Temperature Radiometer (SLSTR) on-board Sentinel-3.

As pointed out in Part I, the limited number of state variables retrieved by CISAR allows the
same algorithm to be applied to sensors which have not been originally designed for aerosol or
surface albedo retrieval. The possibility to apply the same algorithm to data acquired by different
instruments for the retrieval of several ECVs presents a decisive advantage as it provides radiatively
consistent ECVs derived from different sensors. Conversely, the use of separate methods for the
retrieval of different variables might lead to a radiance bias, which has to be corrected preliminary to
before the assimilation of these variables (Thépaut, 2003). The effort for the assimilation of surface
and atmospheric products could be reduced if the different ECVs are were consistently derived with
one single algorithm. The consistent retrieval of the state variables and the algorithm applicability
to different sensors represent an important advantage for the Numerical Weather Prediction (NWP)
community, whose main future challenges are related to a more consistent retrieval of Earth's system
components and to the availability of more satellite data.

8 Supplement

Included are the scatterplots of the BHR retrieved by CISAR versus the BHR delivered by MODIS
545 (Fig. S1, S2), and a few examples of the CISAR high-AOT retrievals compared with AERONET
data.

9 Acknowledgements

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