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1 **A new global C-band vegetation optical depth product**  
2 **from ASCAT: description, evaluation, and inter-**  
3 **comparison**

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28

29 **Abstract:**

30 Active microwave measurements have the potential to estimate vegetation optical depth  
31 (VOD), an indicator related to vegetation water content and biomass. The Advanced  
32 SCATterometer (ASCAT) provides long-term C-band backscatter data at vertical-vertical  
33 (VV) polarization from 2007. So far, very few studies have considered retrieving VOD from  
34 this active sensor. This study presents a new publicly released global long-term and  
35 continuous (2007-2020) C-band VOD dataset retrieved from the ASCAT observations, named  
36 the ASCAT INRAE-BORDEAUX or ASCAT IB VOD product. The retrieval algorithm is  
37 based on the Water Cloud Model (WCM) including the Ulaby bare soil model. The algorithm  
38 takes advantage of a multi-temporal (MT) retrieval method relying on a cost function where  
39 constraints to the retrieved parameters are implemented and a reanalysis soil moisture (SM)  
40 dataset from ERA5-Land is used as an input. The performance of ASCAT IB VOD was  
41 evaluated by inter-comparing it with ASCAT Technische Universität Wien (TUW), the  
42 Advanced Microwave Scanning Radiometer 2 (AMSR2), and VOD Climate Archive  
43 (VODCA) VOD products (the last two products are estimated from passive microwave  
44 observations). Results showed that ASCAT IB VOD presented the highest spatial correlation  
45 with aboveground biomass ( $R \sim 0.83$ ) and with the Global Ecosystem Dynamics Investigation  
46 (GED) canopy height ( $R \sim 0.84-0.85$ ). In terms of temporal performance, ASCAT IB VOD  
47 had the highest correlation R values with leaf area index (LAI) and Normalized Difference

48 Water Index (NDWI) in most parts of the globe from 2013 to 2018. This contrasts with  
49 AMSR2 VODs which correlated better with Normalized Difference Vegetation Index (NDVI).  
50 The new ASCAT-based VOD product on a global scale highlighted the potential benefit of  
51 combining active (namely ASCAT) and passive (namely AMSR2) VOD products for  
52 vegetation studies.

53 Keywords: VOD; biomass; vegetation phenology; ASCAT; Active microwave; multi-  
54 temporal (MT); AMSR2

## 55 **1. Introduction:**

56 Microwave vegetation optical depth (VOD) has proven to be a useful indicator for the study  
57 of terrestrial ecosystems based on its sensitivity to vegetation biomass as well as water  
58 content of vegetation (Chaparro et al., 2019; Frappart et al., 2020; Rodríguez-Fernández et al.,  
59 2018a; Vittucci et al., 2019; Wigneron et al., 2021). To date, long-term VOD retrieved from  
60 K-, X-, C- and L-band passive microwave brightness temperatures (Kerr et al., 2012; Konings  
61 et al., 2017; Liu et al., 2011; Moesinger et al., 2020; Wang et al., 2021a; Wigneron et al.,  
62 2017) have been used to monitor the global vegetation biomass changes (Liu et al., 2013), the  
63 carbon dynamics in tropical and Siberian regions (Fan et al., 2022; Fan et al., 2019; Wigneron  
64 et al., 2020), resilience of the Amazon rainforest (Boulton et al., 2022), vegetation dynamics  
65 in drylands over West African Sahel (Tian et al., 2016) and vegetation phenology over the  
66 mid- and high-latitude Northern Hemisphere (Li et al., 2023). However, some deficiencies,  
67 including the discontinuity in time series between observations from satellites and their  
68 successor (the Advanced Microwave Scanning Radiometer for EOS, AMSR-E, and the  
69 Advanced Microwave Scanning Radiometer 2, AMSR2), as well as data quality issues related  
70 to radio frequency interference (Li et al., 2021; Wang et al., 2021b), affect the quality of the  
71 above-mentioned passive long-term VOD datasets. Most importantly, a long-term freely  
72 available global active VOD product is still lacking and very few studies have focused on this

73 topic. The development of a new active global product could be very interesting as it could  
74 provide useful data to monitor the vegetation characteristics, in a way complementary to  
75 passive VODs (Liu et al., 2021b).

76 The active microwave observations show a different sensitivity to vegetation and soil  
77 compared with the passive ones (Link et al., 2021; Prigent et al., 2022). Using a discrete  
78 radiative transfer model to simulate the relationship between active and passive signals in  
79 three vegetation types (wheat, corn, and forest), Link et al. (2021) found the coupling between  
80 active and passive signals decreases with increasing vegetation water content because of the  
81 decreasing sensitivities of the radar (active) and radiometer (passive) observations to soil  
82 moisture. The sensitivity of the radar systems to SM over vegetation areas decreases more  
83 quickly than that of the radiometers due to the two-way vegetation attenuation (forward and  
84 backward) (Piles et al., 2015) and active systems are more sensitive to the effects of the  
85 vegetation structure (Ferrazzoli et al., 1989; Fung and Eom, 1985; Wigneron et al., 1999).  
86 Prigent et al. (2022) found the diurnal and seasonal cycles of backscatter and emissivity  
87 collected from Global Precipitation Mission (GPM) at a  $1^\circ \times 1^\circ$  resolution tend to be in phase  
88 opposition in the tropical forest region, while backscatter and emissivity vary more in phase  
89 during the dry season in the less densely forested regions of southeast Amazon. The dissimilar  
90 information obtained from active and passive microwave signals motivates us to explore the  
91 retrieval of VOD from active microwave observations.

92 Active microwave data provide complementary observations to passive observations because  
93 1) they are sensitive to specific vegetation characteristics, 2) are less affected by radio  
94 interference than passive observations (Liu et al., 2021b) and 3) can also provide long-term  
95 records, such as observations from three series of Advanced SCATterometer (ASCAT)  
96 Meteorological Operational (MetOp -A/B/C) satellites which start in 2007 and can be  
97 extended to the 2020s (Srivastava et al., 2016). Radar observations have been used in many

98 studies for vegetation monitoring (phenology, structure, or productivity) (Canisius et al., 2018;  
99 Chang et al., 2022; Hosseini et al., 2015; Meroni et al., 2021; Neumann et al., 2010; Wagner  
100 et al., 1999), while studies on active VOD retrievals are scarce and only conducted at the site  
101 scale or over small regions (El Hajj et al., 2019a; Grippa and Woodhouse, 2003; Magagi and  
102 Kerr, 1997; Quast et al., 2019; Zhou et al., 2022). The first active VOD research at a  
103 continental scale (Vreugdenhil et al., 2016) was conducted for assessing the vegetation  
104 correction in the Technische Universität Wien (TUW) method of the C-band ASCAT soil  
105 moisture retrieval (Wagner et al., 2013). The TUW VOD is retrieved by the change detection  
106 method using the Water Cloud Model (WCM) (Attema and Ulaby, 1978). The TUW VOD  
107 value is mainly dependent on two parameters (slope and curvature) which are the coefficients  
108 of a second-order Taylor expansion function established to describe the angular ASCAT  
109 backscatter dependency (Hahn et al., 2017). The preliminary TUW VOD data set did not  
110 consider inter-annual variability as the climatology of slope and curvature are computed in the  
111 algorithm (Vreugdenhil et al., 2016; Vreugdenhil et al., 2017). With a novel calculation of  
112 slope and curvature, the updated TUW VOD can capture vegetation dynamics in Australia  
113 (Vreugdenhil et al., 2017). However, it is not yet public and there are few studies on the  
114 global assessment of TUW VOD (Teubner et al., 2018; Vreugdenhil et al., 2016).

115 Recently, INRAE-BORDEAUX (IB) developed a new active VOD product from ASCAT in  
116 Africa (hereafter ASCAT IB V1 VOD) (Liu et al., 2021b). The algorithm is based on the  
117 WCM integrated with the Ulaby bare soil scattering model (Ulaby et al., 1978) as these  
118 simple models can be used efficiently to simulate the ASCAT backscattering signals (Lievens  
119 et al., 2021; Santoro et al., 2022; Shamambo et al., 2019). To retrieve VOD from the VV  
120 polarization and mono-angular (incidence angle at  $40^\circ$ ) normalized ASCAT observations, the  
121 ERA5-Land soil moisture (SM) dataset was used as an input to the algorithm. The evaluation  
122 of ASCAT IB V1 VOD showed a high spatial correlation with Climate Change Initiative

123 (CCI) and Saatchi above-ground biomass (AGB) (Carreiras et al., 2017; Saatchi et al., 2011;  
124 Santoro and Cartus, 2019), with R values generally higher than for ASCAT TUW VOD and  
125 C-band passive VOD, namely the Advanced Microwave Scanning Radiometer 2 (AMSR2)  
126 and VOD Climate Archive (VODCA) VOD. ASCAT IB V1 VOD was also found to be  
127 highly temporally correlated to Moderate Resolution Imaging Spectroradiometer (MODIS)  
128 Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and leaf  
129 area index (LAI). However, the algorithm used in ASCAT IB V1 VOD has been applied  
130 globally with imperfect results (Liu et al., 2021a), mainly because the hypothesis that the  
131 vegetation scattering parameter ( $\omega$ ) consists globally of two constant values (distinguishing  
132 very densely vegetated regions from the other vegetated regions) did not hold.

133 In the present study, to improve the quality of the global ASCAT IB VOD product, we  
134 evaluated the possibility of retrieving VOD and  $\omega$  simultaneously from the ASCAT  
135 normalized backscatter at  $40^\circ$  by adding constraints in the retrieval process. The first  
136 constraint was applying a multi-temporal (MT) method which is generally based on the  
137 assumption that VOD varies relatively slowly in time as was first developed by Wigneron et  
138 al. (2000) for the SM and VOD retrieval algorithm of the Soil Moisture and Ocean Salinity  
139 (SMOS) mission (Kerr et al., 2010). This assumption is now widely used in the development  
140 of passive VOD retrievals. For instance, in the multi-temporal dual channel retrieval  
141 algorithm (MT-DCA), VOD was assumed to be nearly constant between every two  
142 consecutive overpasses (Konings et al., 2016). Based on MT-DCA, (Konings et al., 2017;  
143 2016) successfully retrieved VOD and SM from L-band Aquarius (with a seven-day revisit  
144 time) and SMAP (with a three-day revisit time). This assumption was also adopted in the  
145 different operational VOD and SM retrieval algorithms of the SMOS observations (Al Bitar et  
146 al., 2017; Wigneron et al., 2021). Similarly in the active domain, El Hajj et al. (2019a)  
147 assumed that VOD remains stable during four consecutive overpasses (18 days) of Sentinel-1

148 and hence obtained the very first retrievals of VOD from Sentinel-1 images in southern  
149 France.

150 Incorporating a *priori* information into the algorithm is another interesting way to constrain  
151 the retrieved parameters. A key feature of the widely used L-band microwave emission of the  
152 biosphere (L-MEB) inversion method is integrating a *priori* information into the retrieval  
153 (Wigneron et al., 2021; Wigneron et al., 2017). In the SMOS-IC Version 2 algorithm  
154 (Wigneron et al., 2021), by using the mean value of VOD retrieved in the previous ten days as  
155 a first guess value of VOD for subsequent SM and VOD retrievals, results showed a  
156 considerable improvement compared with the preceding versions. In the SMAP official SM  
157 baseline algorithm (O'Neill et al., 2015), the MODIS NDVI was converted to vegetation water  
158 content and then multiplied by a factor to represent VOD. Based on the optimization of the *a*  
159 *priori* information, Li et al. (2022) developed a new SMAP SM and VOD product (called  
160 SMAP-IB) using the L-MEB algorithm. In addition, Wang et al. (2021a) calibrated a  
161 relationship between VOD and the Microwave Polarization Difference Index (MPDI) and  
162 then used the VOD based on MPDI as the initial value to retrieve X-band VOD from the  
163 AMSR2.

164 In this context, the main objective of this study is to retrieve simultaneously a global ASCAT  
165 product including VOD and the vegetation scattering parameter ( $\omega$ ). The retrieval algorithm  
166 used the model-based soil moisture (SM) data from the ERA5-Land product as it offers long-  
167 term data at a time close to the ASCAT satellite observations owing to its hourly availability.  
168 The use of SM data from satellite missions (*e.g.* SMOS, SMAP and AMSR2) is more difficult:  
169 observation time is not concurrent to the ASCAT observations; the time period is not long  
170 enough; and accuracy may be limited for some satellite products in some areas (Liu et al.,  
171 2021b; Xing et al., 2021). To overcome the challenge of retrieving two parameters from a  
172 single-angle and polarization ASCAT observation, the concept of “slow VOD time variations”



173 introduced previously and the *a priori* information obtained from ASCAT IB V1 VOD  
174 retrievals over Africa were incorporated into the algorithm. Similar to previous VOD  
175 assessment studies (Chaparro et al., 2019; Li et al., 2021; Liu et al., 2021b), thirteen years of  
176 global ASCAT IB VOD (2007-2020) were retrieved and evaluated using different AGB, tree  
177 height and optical vegetation index products. The key characteristics of the global ASCAT IB  
178 VOD product are illustrated by performing comparisons with ASCAT TUV VOD and two  
179 other passive C-band VOD products from the AMSR2 satellite, namely AMSR2 VOD and  
180 VODCA VOD.

## 181 **2. Data description**

### 182 **2.1 ASCAT backscatter**

183 The ASCAT sensors are equipped with fan-beam (mid, fore, and aft) antennas which conduct  
184 VV backscatter observations with incidence angles varying from 25 to 65 degrees at a carrier  
185 frequency of 5.255 GHz (C-band) covering two 550 km wide swaths separated by a gap of  
186 about 360 km with a 30–50 km spatial resolution and twice a day temporal resolution (Figa-  
187 Saldaña et al., 2014). In the present study, we used the backscatter measurements normalized  
188 at the standard reference angle (40°) and the historically wettest measurements (referred to as  
189 wet reference), which were extracted from the ASCAT Soil Moisture near-real time (NRT)  
190 product at 12.5 km Swath Grid. This product provides 15 scene acquisitions per day and  
191 covers the globe approximately every two days. The stack of the ASCAT backscatter data  
192 used in this study consisted of all data acquired by MetOp-A descending orbits (9:30 am)  
193 from 2007 to 2020. We used data measured at morning because vegetation water stress is  
194 typically lower in the morning making “morning” VOD better suited for monitoring biomass  
195 (Frappart et al., 2020; Liu et al., 2021b). The data with good quality (probability flags for  
196 frozen soil and snow equal to zero, topographic complexity flags and wetland probability  
197 flags lower than 30% and 10%, respectively) were resampled to a 0.25° grid (~ 25 km × 25

198 km) by the inverse distance weighting algorithm (Lievens et al., 2017). The ASCAT data is  
199 freely available at <https://archive.eumetsat.int/>.

## 200 **2.2 ERA5-land data**

201 In this study, we used the 0–7 cm SM and soil temperature (ST) datasets of ERA5-Land  
202 (Muñoz-Sabater et al., 2021). This dataset is on a 0.1-degree grid with hourly time steps. The  
203 new surface model (Carbon Hydrology-Tiled ECMWF Scheme for Surface Exchanges over  
204 Land) used in ERA5-Land is able to better simulate the SM dynamics than the older scheme  
205 (Wagner et al., 2022). The evaluation of ERA5-Land SM also shows good performance on the  
206 global scale (Beck et al., 2020; Chen et al., 2021; Lal et al., 2022; Muñoz-Sabater et al.,  
207 2021). More importantly, as the ERA5-Land does not assimilate land surface observations  
208 (whereas ERA5 assimilates the ASCAT SM), ERA5-Land SM and the ASCAT backscatter  
209 measurements can be treated as quasi-independent variables (Wagner et al., 2022). In the  
210 present study, ERA5-Land SM is used as an input to the WCM model to retrieve ASCAT IB  
211 VOD, and ERA5-Land ST is used for simulating the Ulaby bare soil model parameters.  
212 ERA5-Land SM and ST were aggregated to the 0.25° grid using area-weighted averaging, and  
213 then temporally matched with the ASCAT descending (~9:30 local time) observations.

## 214 **2.3 Vegetation variables for evaluating VOD**

215 Three kinds of vegetation variables widely used in VOD evaluation (Grant et al., 2016; Li et  
216 al., 2021; Rodríguez-Fernández et al., 2018b; Tian et al., 2016) were used to evaluate the  
217 retrieved ASCAT IB VOD: AGB, canopy height, and optical vegetation indices. The rationale  
218 for using those parameters is that 1) there is no consensus on *in-situ* VOD reference values, so  
219 proxies of VOD as vegetation height and vegetation biomass are often used to evaluate the  
220 performance of the VOD retrieval algorithms (Li et al., 2022; Li et al., 2021); 2) VOD can  
221 provide information on AGB at the inter-annual scale and on the vegetation water status at the

222 seasonal scale (Lyons et al., 2021; Wang et al., 2023). Since total vegetation biomass (AGB)  
223 is generally well related to vegetation height (Asner et al., 2012), utilizing canopy height may  
224 confirm the anticipated relationship between VOD and AGB. We also refer the reader to the  
225 inter-comparison study of nine commonly used VOD for more details (Li et al., 2021).

### 226 **2.3.1 AGB datasets**

227 Three AGB products, the Saatchi AGB in 2015 (Carreiras et al., 2017; Saatchi et al., 2011),  
228 the Climate Change Initiative (CCI) AGB dataset version 1 in 2017 (Santoro and Cartus,  
229 2019) and the Global Ecosystem Dynamics Investigation (GEDI) L4B AGB in 2020  
230 (Dubayah et al., 2022), were used to evaluate the ability of ASCAT IB VOD to monitor AGB.  
231 Those three datasets are all at 1-km spatial resolution and were resampled to the  $0.25^\circ$  grid by  
232 spatial averaging.

### 233 **2.3.2 Canopy height datasets**

234 Two canopy height products (Lang et al., 2022; Potapov et al., 2020) used in this study were  
235 derived from the GEDI LIDAR measurement. The product developed by Potapov et al. (2020)  
236 is produced by extrapolating the GEDI footprint-level forest canopy height to a 30 m spatial  
237 resolution map using a regression tree algorithm and Landsat analysis-ready data for the year  
238 2019. Lang et al. (2022) used the GEDI Level 1B waveforms and Bayesian deep learning  
239 algorithm to develop a global  $0.5^\circ$  resolution canopy height map, which has a lower root mean  
240 square error (RMSE = 2.7m) than the product (RMSE = 6.6m) from Potapov et al. (2020).

### 241 **2.3.3 Optical vegetation indices datasets**

242 Three vegetation indices (VIs) products, the 10-day NDVI and LAI data from Copernicus  
243 Global Land Service (CGLS) (<https://land.copernicus.eu/global/>) and 8-day Normalized  
244 Difference Water Index (NDWI) calculated from the MODIS MOD09A1 product (Gu et al.,  
245 2008), were used to assess the temporal variations in ASCAT IB VOD. LAI and NDVI are

246 good proxies of phenology and vegetation greenness. NDWI represents the vegetation water  
247 dynamics which is expected to be important in terms of temporal changes. Therefore, those  
248 three VIs can be used to test the ability of ASCAT IB VOD to monitor the seasonal and  
249 interannual variations of vegetation phenology and vegetation water status. After quality  
250 control, the dataset was resampled to a spatial resolution of a  $0.25^\circ$  grid (Fuster et al., 2020).

#### 251 **2.4 Other C-band VOD products**

252 To better illustrate the performance of the ASCAT IB VOD product, we inter-compared it  
253 with three other C-band VOD products, namely ASCAT TUV, AMSR2 and VODCA VOD.  
254 ASCAT TUV VOD was provided by Vreugdenhil et al. (2016). TUV VOD is calculated  
255 from the loss in sensitivity to soil moisture (i.e., attenuation of the bare soil backscatter). The  
256 sensitivity is calculated as the difference between the wet and dry reference, and more details  
257 on the product are given in (Vreugdenhil et al., 2016; Vreugdenhil et al., 2017). AMSR2 and  
258 VODCA VOD can be freely downloaded at the Goddard Earth Sciences Data and Information  
259 Services Center (GES DISC) website and the Zenodo repository (Moesinger et al., 2020).  
260 These two products are retrieved from the passive sensor AMSR2 (providing data from July  
261 2012) but with different algorithms. The AMSR2 VOD retrieval algorithm is based on the  
262 Land Parameter Retrieval Model (LPRM) version 5 (Owe et al., 2008), while VODCA VOD  
263 is retrieved via the LPRM version 6 and then a cumulative distribution function (CDF)  
264 matching technique is used to scale VOD to the AMSR-E VOD (Moesinger et al., 2020). The  
265 key differences between those three products and ASCAT IB VOD are presented in the  
266 discussion section.

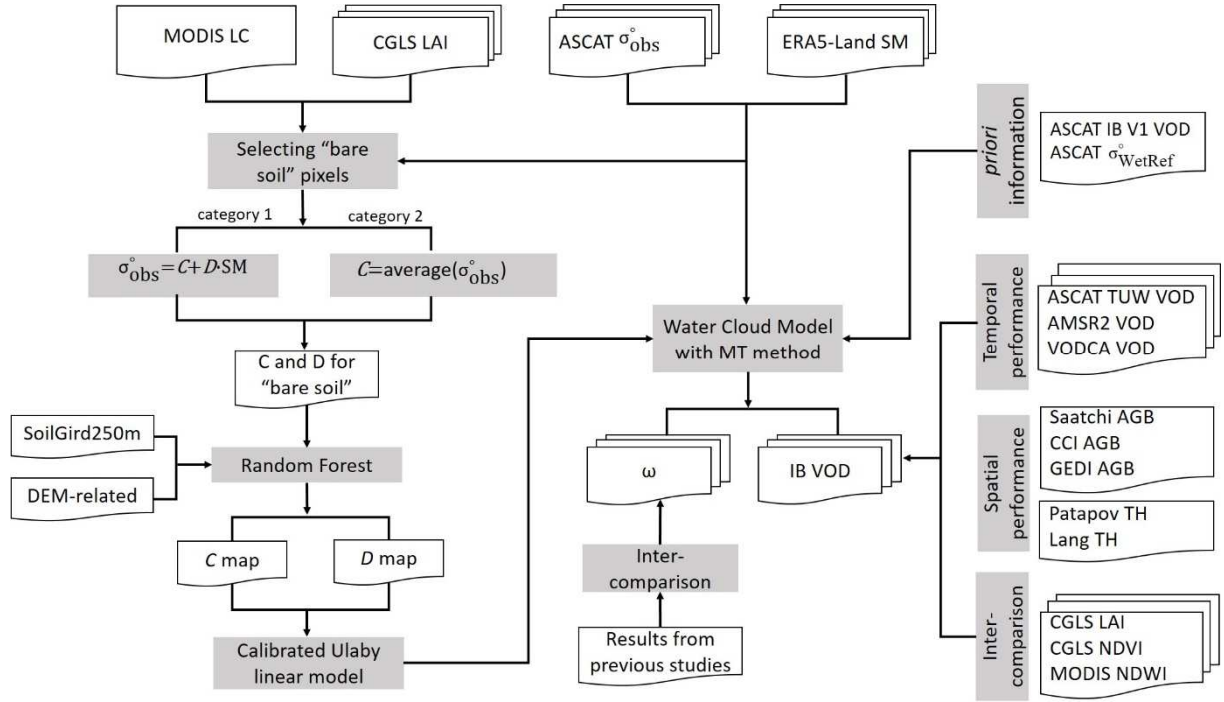
#### 267 **2.5 Ancillary datasets**

268 This study also utilized several ancillary datasets, including ISRIC SoilGrids250m data  
269 (Hengl et al., 2017), Digital Elevation Model (DEM)-related data (Danielson and Gesch,

270 2011), and MODIS land cover map (Sulla-Menashe et al., 2019). The SoilGrids250m dataset  
271 provides global standard numeric soil properties at seven standard depths with a 250 m spatial  
272 resolution. DEM-related data were calculated from the 1km Global Multi-resolution Terrain  
273 Elevation Data 2010 by using the System for Automated Geoscientific Analyses (SAGA) GIS  
274 software (Conrad et al., 2015). The SoilGrids250m (15 types, in Table S1), and DEM-related  
275 (9 types, in Table S2) data were used in the estimation of the soil parameters of the Ulaby  
276 linear model (see Section 3.1). As several previous studies showed that VOD varies as a  
277 function of the land cover (Li et al., 2021; Vreugdenhil et al., 2016), the land cover map  
278 extracted from the MODIS MCD12Q1 product based on the International Geosphere-  
279 Biosphere Programme (IGBP) scheme was used to analyze the different VOD products.

### 280 **3. Methodology**

281 The ASCAT IB retrieval approach is illustrated in the flowchart of Fig.1. The retrieval model  
282 is based on a vegetation backscatter model (Water Cloud Model) integrated with the Ulaby  
283 bare soil model (Section 3.1). Instead of the common procedure in which VOD and SM are  
284 retrieved simultaneously, which may lead to an ill-posed problem (Wigneron et al., 2000), we  
285 focused on retrieving the two vegetation parameters, VOD and vegetation scattering  
286 parameter ( $\omega$ ), which can be assumed to be relatively constant over a short time-window,  
287 while model-based dynamic SM data is used as an input in the retrieval algorithm. One  
288 prototype study undertaken to retrieve VOD from AMSR2 in Africa supports the validity of  
289 this idea (Wang et al., 2021a). The estimation of the Ulaby linear model parameters is  
290 described in Section 3.2. The retrieval of the VOD and  $\omega$  from the integrated retrieval model  
291 is presented in Section 3.3. The methods implemented to quantify the performance of ASCAT  
292 IB VOD and to qualify the  $\omega$  parameter are described in Section 3.4.



293

294 **Fig. 1.** Flowchart presenting the development and assessment of global ASCAT IB VOD.

295 **3.1. Vegetation backscatter model**

296 The radar backscatter from vegetation was described by the Water Cloud Model (WCM)  
 297 (Attema and Ulaby, 1978). The sensor-received backscattering coefficient ( $\sigma_{\text{obs}}^{\circ}$ , in  $\text{m}^2/\text{m}^2$ ) at  
 298 the incidence angle  $\theta$  ( $40^{\circ}$  in this study) can be denoted as a combination of two components:  
 299 the direct vegetation backscatter signal ( $\sigma_{\text{veg}}^{\circ}$ , in  $\text{m}^2/\text{m}^2$ ) and the backscatter from the soil  
 300 surface ( $\sigma_{\text{soil}}^{\circ}$ , in  $\text{m}^2/\text{m}^2$ ) attenuated by the vegetation canopy ( $\gamma^2$ , called the two-way  
 301 vegetation attenuation factor). This leads to the following equations:

302 
$$\sigma_{\text{obs}}^{\circ} = \sigma_{\text{veg}}^{\circ} + \gamma^2 \sigma_{\text{soil}}^{\circ} \quad (1)$$

303 
$$\sigma_{\text{veg}}^{\circ} = \omega \cdot \cos \theta \cdot (1 - \gamma^2) \quad (2)$$

304 
$$\gamma^2 = \exp(-2 \cdot \tau / \cos \theta) \quad (3)$$

305 where  $\omega$  is the vegetation scattering parameter related to the single scattering albedo, and  $\tau$  is  
 306 the vegetation optical depth (VOD).

307 A simple linear approach (Eq. (4)) (Ulaby et al., 1978) was used to model the bare soil  
 308 backscatter ( $\sigma_{\text{soil}}^{\circ}$ , in dB) as a function of soil moisture (SM, in  $\text{m}^3/\text{m}^3$ ):

309 
$$\sigma_{\text{soil(dB)}}^{\circ}=10 \cdot \log_{10} \sigma_{\text{soil(m}^2/\text{m}^2)}^{\circ}=C+D \cdot \text{SM} \quad (4)$$

310 where  $C$  is the radar backscatter of the very dry bare soil,  $D$  represents the radar backscatter  
 311 sensitivity to soil moisture changes, and SM comes from the ERA5-land SM product.

312 The Eqs. (2)- (4) were finally inserted into Eq. (1) to express  $\sigma_{\text{obs}}^{\circ}$  as a function of vegetation  
 313 optical depth ( $\tau$ ):

314 
$$\sigma_{\text{obs}}^{\circ}=\omega \cdot \cos \theta \cdot (1 - \exp(-2 \cdot \tau / \cos \theta))+\exp(-2 \cdot \tau / \cos \theta) \cdot 10^{0.1 \cdot (C+D \cdot \text{SM})} \quad (5)$$

### 315 **3.2 Calibration of the model parameters**

316 The soil-vegetation radar model in Eq. (5) contains three parameters ( $\omega$ ,  $C$  and  $D$ ) that needed  
 317 to be calibrated on each pixel in space and time. As there are no “true” VOD samples, the  
 318 three parameters cannot be calibrated at the same time. In this study, we calibrated the bare  
 319 soil parameters ( $C$  and  $D$ ) and then retrieved  $\omega$  and VOD simultaneously.

320 The soil parameter calibration consisted of three steps (1) selecting so-called “bare soil”  
 321 pixels globally where vegetation effects can be neglected during a specific period (which  
 322 varies over each pixel) (2) computing the  $C$  and  $D$  parameters over the “bare soil” pixels  
 323 during that specific period (3) training machine learning models by using the retrieved  $C$  and  
 324  $D$  values over “bare soil” pixels obtained in the step (2) and then estimating the two  
 325 parameters ( $C$  and  $D$ ) globally. These three steps are detailed below:

326 **Step1:** Globally selecting the “bare soil” pixels based on LAI and land cover data. Two kinds  
 327 of “bare soil” pixels can be identified: i) vegetation-free pixels during the entire year (desert  
 328 area), and ii) pixels with sparse vegetation ( $\text{LAI}<0.5$ ) seasonally. Some “bare soil” pixels  
 329 have very low moisture condition ( $< 0.05 \text{ m}^3/\text{m}^3$ ) and almost stable  $\sigma_{\text{obs}}^{\circ}$ . In those pixels, only  
 330  $C$  can be calculated. Therefore, we divided the “bare soil” pixels into two categories, namely  
 331 category 1: where soil moisture and  $\sigma_{\text{obs}}^{\circ}$  show a significant correlation; category 2: where  
 332 soil moisture is very low and there are very low time variations in  $\sigma_{\text{obs}}^{\circ}$ .

333 **Step2:** calculating the parameters  $C$  and  $D$  over the “bare soil” pixels. For the pixels in  
 334 category 1, the  $C$  and  $D$  values were obtained with linear fitting on Eq. (4). For the pixels in  
 335 category 2, only the  $C$  value can be computed, and it was estimated from the averaged  $\sigma_{\text{obs}}^{\circ}$ .  
 336 At the same time, the corresponding soil properties (Table S1) and DEM-related (Table S2)  
 337 data were extracted.

338 **Step3:** estimating  $C$  and  $D$  globally. The pixels in step 2 were used to train two random forest  
 339 (RF) regression models, in which the parameters  $C$  and  $D$  computed over the “bare soil”  
 340 pixels were treated as the target and the soil properties (Table S1) and DEM-related (Table S2)  
 341 data were selected as the predictors. More details about the implementation of the RF model  
 342 are presented in Appendix A. Then, the selected global predictors were used as input to the  
 343 trained RF models to estimate  $C$  and  $D$  globally.

344 Two years (2015-2016) of ASCAT  $\sigma_{\text{obs}}^{\circ}$  and ERA5-Land SM were used to select the “bare  
 345 soil” pixels. For more details about each step, readers can refer to the same calibration work  
 346 done in Africa (Liu et al., 2021b).

### 347 **3.3 Retrieval of VOD and $\omega$**

348 The simultaneous retrieval process of two variables, VOD and  $\omega$ , was performed by using a  
 349 cost function ( $CF$ ) (Eq. (6)).  $CF$  integrates the squared weighted differences between the  
 350 backscatter simulations ( $\sigma_{\text{sim}}^{\circ}$ ) and the observations ( $\sigma_{\text{obs}}^{\circ}$ ), taking into account the constraint  
 351 information on the retrieved model parameters (Wigneron et al., 2007). This strategy was also  
 352 implemented in the development of SMOS IC V2 and SMAP IB (Li et al., 2022; Wigneron et  
 353 al., 2021).

$$354 \quad CF = \frac{\sum (\sigma_{\text{obs}}^{\circ} - \sigma_{\text{sim}}^{\circ})^2}{\text{StdDev}(\sigma^{\circ})^2} + \sum_{i=1}^2 \frac{(P_i^{\text{ini}} - P_i^*)^2}{\text{StdDev}(P_i)^2} \quad (6)$$



355 where the sum of the differences between observed ( $\sigma_{\text{obs}}^{\circ}$ ) and simulated ( $\sigma_{\text{sim}}^{\circ}$ ) backscattering  
356 coefficient is computed from VV polarization observations over a  $w$ -day window. In this  
357 window, the value of retrieved  $P_i^*$  ( $VOD^*$  and  $\omega^*$ , respectively for  $i = 1, 2$ ) are time-invariant.  
358  $\text{StdDev}(\sigma^{\circ})$  is the standard deviation associated with  $\sigma_{\text{obs}}^{\circ}$ .  $P_i^{\text{ini}}$  ( $VOD^{\text{ini}}$  and  $\omega^{\text{ini}}$ , respectively  
359 for  $i = 1, 2$ ) is the initial value of VOD or  $\omega$  in the retrieval process and corresponds to a  
360 constraint information (or “*priori* information”) estimate;  $\text{StdDev}(P_i)$  is the standard deviation  
361 associated with this estimate.

362 Two sources of constraint information were used in the retrieval algorithm: (1) the ASCAT IB  
363 V1 VOD developed in Africa (Liu et al., 2021b) was used to estimate the *a priori* information  
364 on VOD, and (2) the wet reference of the ASCAT observations was used to estimate the *a*  
365 *priori* information on  $\omega$ . Specifically, due to the diversity of the vegetation conditions in  
366 Africa, the  $VOD^{\text{ini}}$  and  $\text{StdDev}(VOD)$  parameters used in Eq. (6) were simply estimated for  
367 the forest and non-forest regions in Africa. In this study,  $VOD^{\text{ini}}$  was set to 0.87 and 0.16 for  
368 forest and no-forest pixels, respectively.  $\text{StdDev}(VOD)$  was set to 0.40 for forest pixels and  
369 0.15 for no-forest pixels. According to the definition of  $\omega$ , the  $\omega^{\text{ini}}$  and  $\text{StdDev}(\omega)$  parameters  
370 were calculated from the ASCAT wet reference ( $\sigma_{\text{WetRef}}^{\circ}$ ) data which is computed from the  
371 maximum backscattering coefficient for each pixel during the peak growth season (Fig. 1 in  
372 Steele-Dunne et al. (2019) and Fig. 2 in Vreugdenhil et al. (2016)) or during times with high  
373 values of ERA5-Land SM (Fig. S1).  $\sigma_{\text{WetRef}}^{\circ}$  is provided over each pixel and is almost constant  
374 on a daily basis. The yearly mean value of  $\sigma_{\text{WetRef}}^{\circ}$  in each pixel was used to estimate  $\omega^{\text{ini}}$ . Like  
375 the calculation of  $\text{StdDev}(VOD)$ ,  $\text{StdDev}(\omega)$  was estimated from the yearly mean value of  
376  $\sigma_{\text{WetRef}}^{\circ}$  over the forested and non-forested areas. It was set to 0.01 for the forested areas and  
377 0.03 for the non-forested areas.

378 In order to ensure a good quality of  $P_i^*$  (VOD and  $\omega$ ) and to consider that  $P_i^*$  did not change  
379 much over the period of  $w$ -days, the  $w$  value cannot be too small or too large (Wigneron et al.,

2021). An 18-day window was used in this study. This window size allows for robust results with more than three consecutive observations and it corresponds to the time-period used for Sentinel-1 VOD (El Hajj et al., 2019a). We also checked that this window size led to the best results when evaluating the performance of ASCAT IB VOD against AGB (Table S3).

### 3.4. Evaluation metrics for ASCAT IB retrievals assessments

Evaluating the ASCAT IB retrievals, we mainly focused on the VOD parameter as there are few studies evaluating the  $\omega$  parameter at a large scale (Du et al., 2016; Fernandez-Moran et al., 2016; Konings et al., 2017; Vittucci et al., 2017). As in (Li et al., 2021), the global ASCAT IB VOD retrievals were evaluated in time and space. For the temporal performance, the Pearson correlation coefficient (R) between optical vegetation indices (i.e., LAI, NDVI and NDWI) and ASCAT IB VOD was calculated. To evaluate ASCAT IB VOD in terms of spatial performance, we estimated the spatial correlation between ASCAT IB VOD and different AGB products (Eq. (7)). Meanwhile, the spatial correlation between VOD-predicted-AGB and AGB was also computed: the aim is to evaluate the performance of ASCAT IB VOD and other VOD in estimating AGB. To compute the VOD-predicted AGB as a function of ASCAT IB VOD, two functions (Eq. (8)-(9)) were chosen to fit the relationship between VOD and AGB (Li et al., 2021; Wang et al., 2021a). The root mean square deviation (RMSE) between VOD-predicted-AGB and AGB was also calculated (Eq. (10)). The same calculation was also done for ASCAT IB VOD and different canopy height products.

$$R = \frac{\sum_{i=1}^n (VOD_i - \overline{VOD})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (VOD_i - \overline{VOD})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (7)$$

$$Y = \frac{a}{1 + \exp(-b * (VOD - c))} + d \quad (8)$$

$$Y = a * \exp(b * VOD) + d \quad (9)$$

402 
$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (y_i - Y_i)^2}{n}} \quad (10)$$

403 where  $Y$  is AGB or canopy height,  $a$ ,  $b$ , and  $c$  are best-fit parameters,  $y$  is the predicted AGB  
 404 or predicted canopy height,  $n$  is the valid number of pixels.

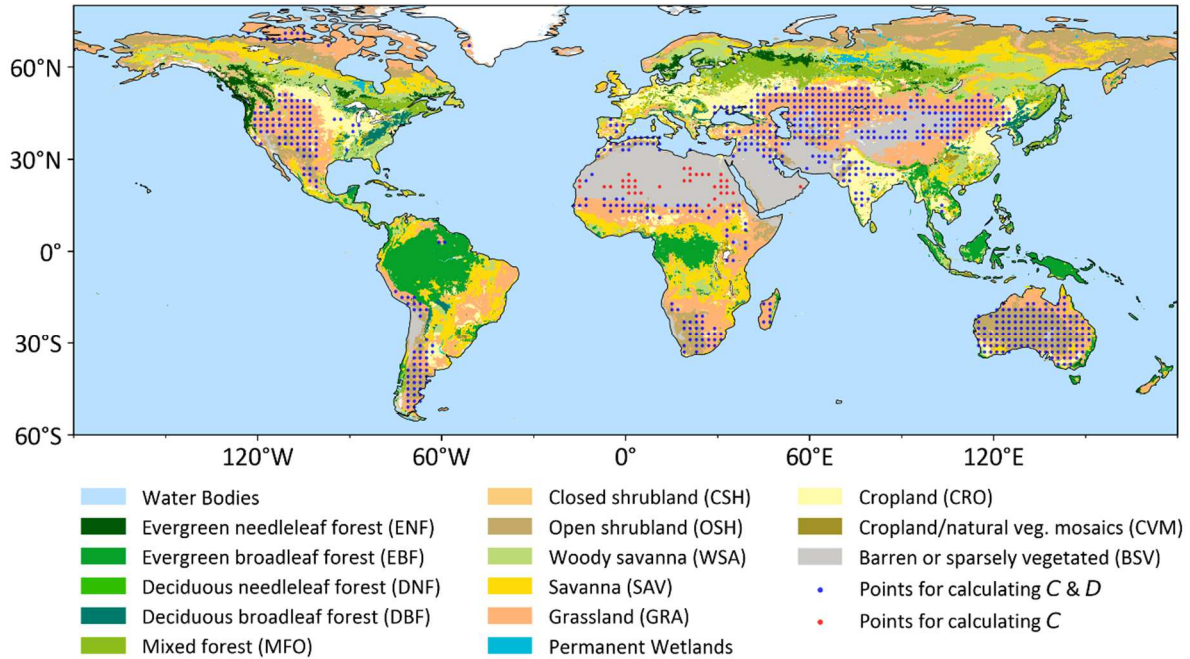
405 The spatial and temporal performance of three other C-VOD products were also evaluated for  
 406 inter-comparing with ASCAT IB VOD. In order to keep consistency for each product, the  
 407 following criteria were used: 1) for each product, we used VOD data from the same year (or  
 408 close in time) as the vegetation-related proxies; 2) since the VODCA data set is only available  
 409 until 2018 and AMSR2 provides data from July 2012, the temporal evaluation was made from  
 410 2013 to 2018; and 3) over each pixel and each year, the number of VOD data should be larger  
 411 than 60 per year to avoid statistical under-representation. The retrievals of the VOD and  $\omega$   
 412 parameters were also analysed considering different classes of vegetation types defined by the  
 413 MODIS IGBP classification scheme.

## 414 **4. Results**

### 415 **4.1 Calibration results of the $C$ and $D$ parameters**

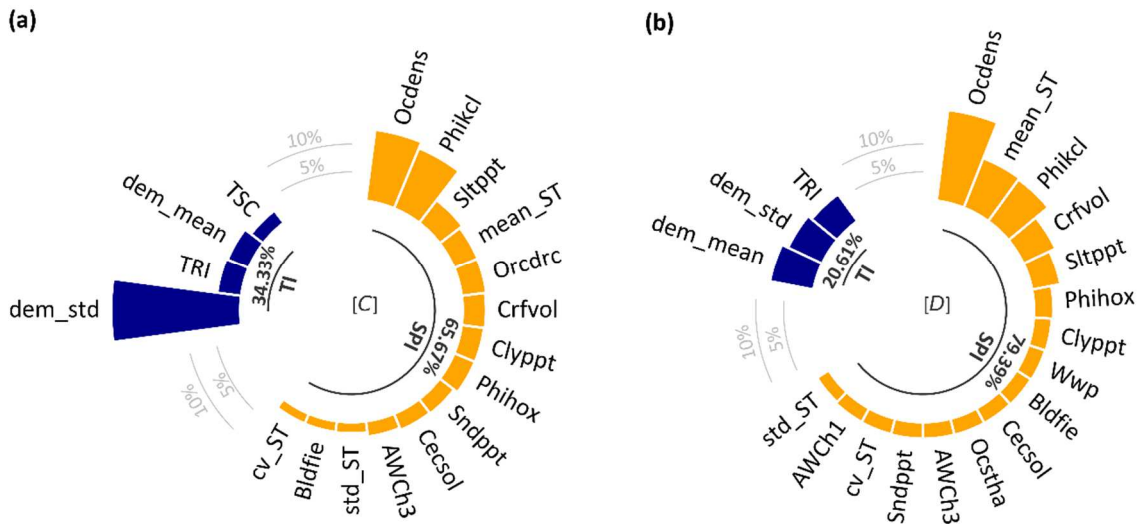
416 The “bare soil” pixels used for the computation of the  $C$  and  $D$  parameters of the Ulaby bare  
 417 soil scattering model (Eq. (4)) are presented in Fig. 2. The red pixels, corresponding to the  
 418 “bare soil” regions where the backscatter signals were observed in a prolonged state of  
 419 dryness, are in the desert area. For the blue pixels in non-desert regions, the  $C$  and  $D$  values  
 420 were computed from Eq. (4), keeping only pixels where the correlation coefficient ( $R$ ) is  
 421 larger than 0.25. Those pixels are mainly distributed in the north, center, and south of Africa,  
 422 the south of Australia, south of Southern America, Central Asia, and the western regions of  
 423 the United States. The main land cover types associated with the blue pixels are grassland,  
 424 cropland, and open shrubland which have a clear seasonality. As a result, the  $C$  value could be

425 estimated over 23,482 pixels and the  $D$  value over 24,205 pixels. The corresponding soil  
 426 properties (18 types) and terrain-related indexes (9 types) of these pixels were extracted, and  
 427 then they were used as predictors to train two random forest models (referred to as the  $C$  and  
 428  $D$  models, respectively) for simulating, separately, the  $C$  and  $D$  parameters at the global scale.



429  
 430 **Fig.2.** Spatial distribution of the “bare soil” pixels (represented by points) and MODIS IGBP  
 431 land cover map. The “bare soil” pixels are shown in a  $2^\circ \times 2^\circ$  grid if the total number of  $C$  or  
 432  $D$  pixels is larger than six.

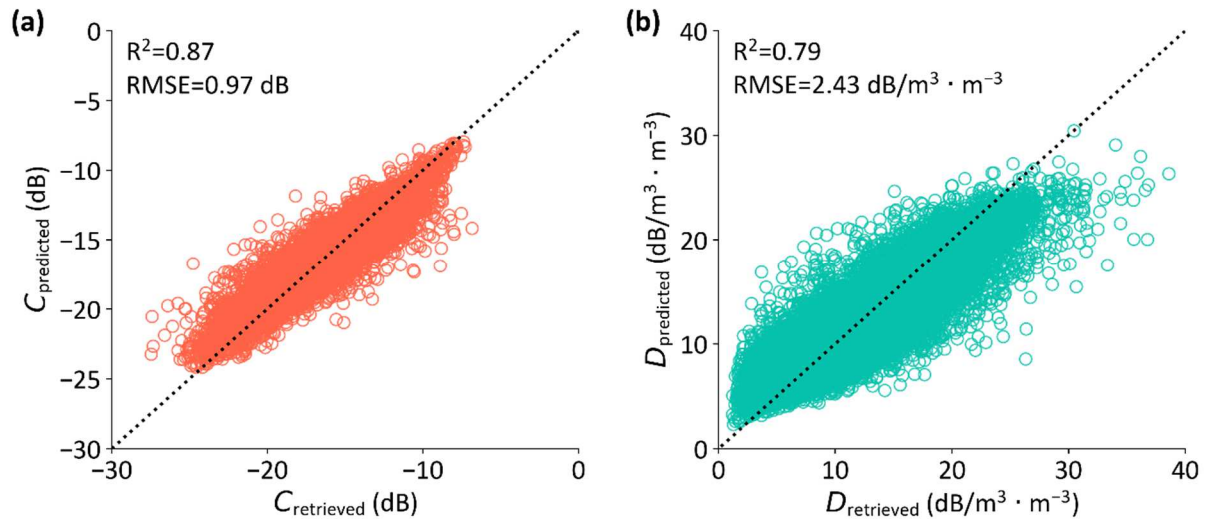
433 In total, 18 predictor variables were selected to train the  $C$  model and 19 predictor variables  
 434 were selected to train the  $D$  model after applying the recursive feature elimination (RFE)  
 435 method. Fig. 3 (a-b) shows the variable importance of each  $C$  and  $D$  model. Soil property  
 436 indices (group SPI) played a key role in estimating the target variables in both the  $C$  and  $D$   
 437 models, with a total importance of 79.39 % and 65.67 %, respectively. The soil organic  
 438 carbon density (Ocdens) ranked first in SPI for both models. The terrain-related features  
 439 (group TI) contributed more in the  $C$  model than in the  $D$  model, which is consistent with the  
 440 results obtained in Africa (Liu et al., 2021b).



441

442 **Fig.3.** Predictive variable importance of the *C* (a) and *D* (b) model values. SPI and TI mean  
 443 soil property indices (in orange) and terrain-related feature variables (in dark blue),  
 444 respectively. The definition of each variable is given in Table S1 and S2.

445 The results of the 10-fold cross-validation of two RF models trained by the selected indices  
 446 (Fig. 4) are better than those obtained in Africa (Liu et al., 2021b). For the *C* model,  $R^2$   
 447 increased from 0.85 to 0.87, and RMSE decreased from 1.31 dB to 0.97 dB. The  $R^2$  metric of  
 448 the *D* model improved from 0.61 to 0.79, but the RMSE showed a slight increase (from  
 449 2.37 dB/  $m^3 \cdot m^{-3}$  to 2.43 dB/  $m^3 \cdot m^{-3}$  ). The overestimation of the lower values and  
 450 underestimation of the higher values obtained in Africa still occurred for the two models  
 451 calibrated here at the global scale. This is likely due to the limitation of the RF regression  
 452 model that cannot be extrapolated; namely when the range of the test fold is not included in  
 453 the training fold, values beyond the range of the training data set will be overestimated or  
 454 underestimated.

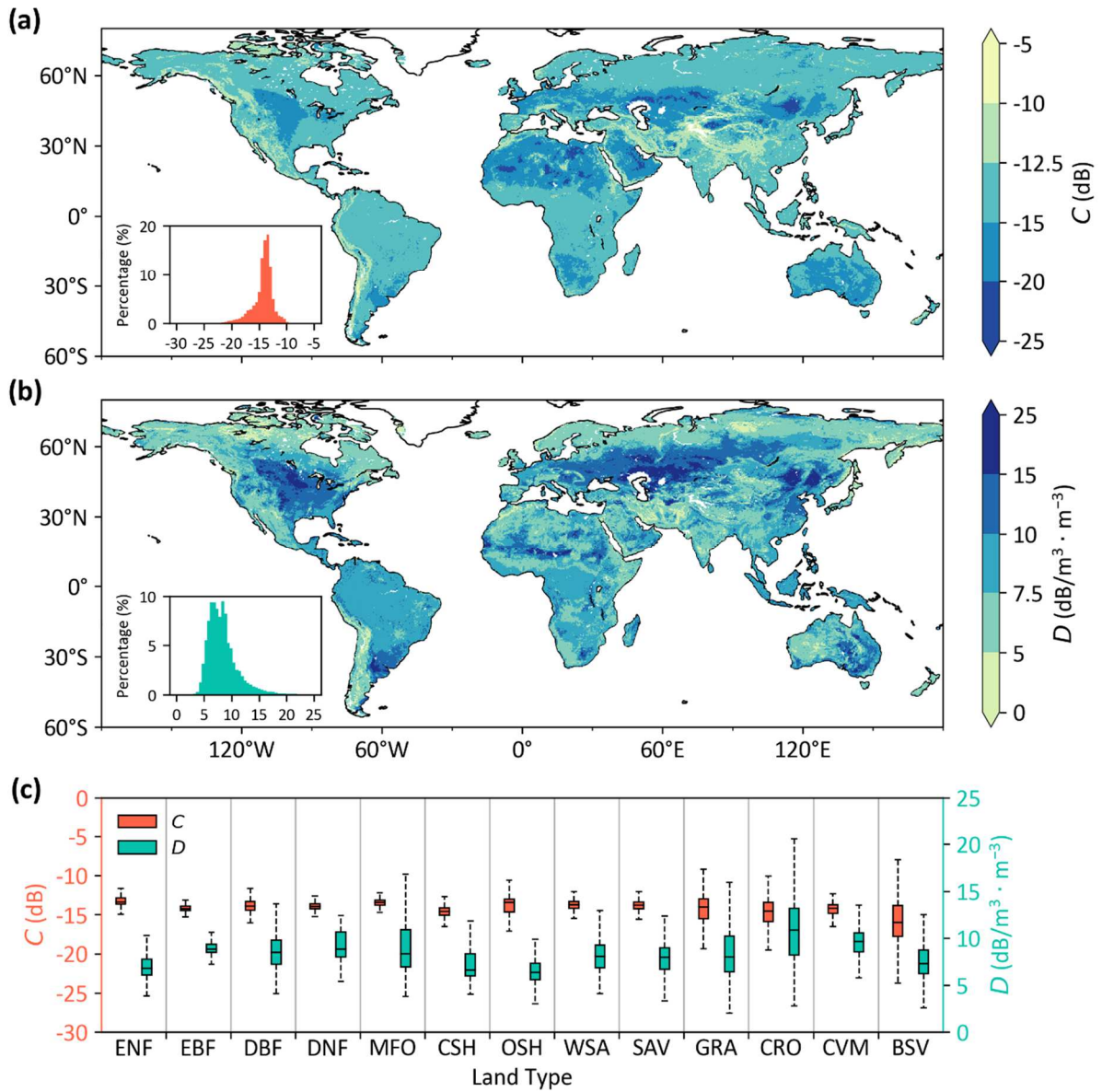


455

456 **Fig. 4.** Performance of the  $C$  (a) and  $D$  (b) soil model based on the 10-fold cross-validation.

457 The spatial patterns of the global predicted  $C$  and  $D$  parameters are illustrated in Fig. 5. The  
 458 5<sup>th</sup>–95<sup>th</sup> percentiles of the  $C$  and  $D$  values among all pixels varied from -18.05 dB to -11.82  
 459 dB, and from 5.12 dB/ m<sup>3</sup>·m<sup>-3</sup> to 13.97 dB/ m<sup>3</sup>·m<sup>-3</sup>, respectively. These values are in the  
 460 usual range for C-band SAR observations (Baghdadi et al., 2008; Baghdadi et al., 2016;  
 461 Verhoest et al., 2008). The distribution of the  $D$  values is more discrete than that of the  $C$   
 462 values. The pixels with a value ranging from -15 dB to -10 dB account for 76.20 % of the  
 463 pixels in the  $C$  map, while 66.62 % of them are concentrated in the range of -15 dB to -12.5  
 464 dB. Comparatively, 75.26 % of the pixels have a  $D$  value in the 5-10 dB/ m<sup>3</sup>·m<sup>-3</sup> range and  
 465 are evenly distributed in 5-7.5 dB/ m<sup>3</sup>·m<sup>-3</sup> (accounting for 38.79 %) and 7.5-10 dB/  
 466 m<sup>3</sup>·m<sup>-3</sup> (accounting for 36.46 %). In addition, the distribution of the pixels with a  $C$  value  
 467 lower than -15 dB in the  $C$  map matches well with the distribution of pixels with a  $D$  value  
 468 larger than 10 dB/ m<sup>3</sup>·m<sup>-3</sup> in the  $D$  map, especially in South and North America, Eastern  
 469 Europe, and Central Asia. Considering each IGBP landcover (Fig. 5 (c)), we can see that the  
 470  $C$  and  $D$  parameters have a wide range of values in the low vegetation areas. A wide range of  
 471  $C$  values can also be found in mixed forest (MFO). The median  $C$  values were similar across

472 all vegetation types, while the median  $D$  values varied across the different land cover types.  
 473 More details about the statistical description of  $C$  and  $D$  are given in Appendix Table 1-3.



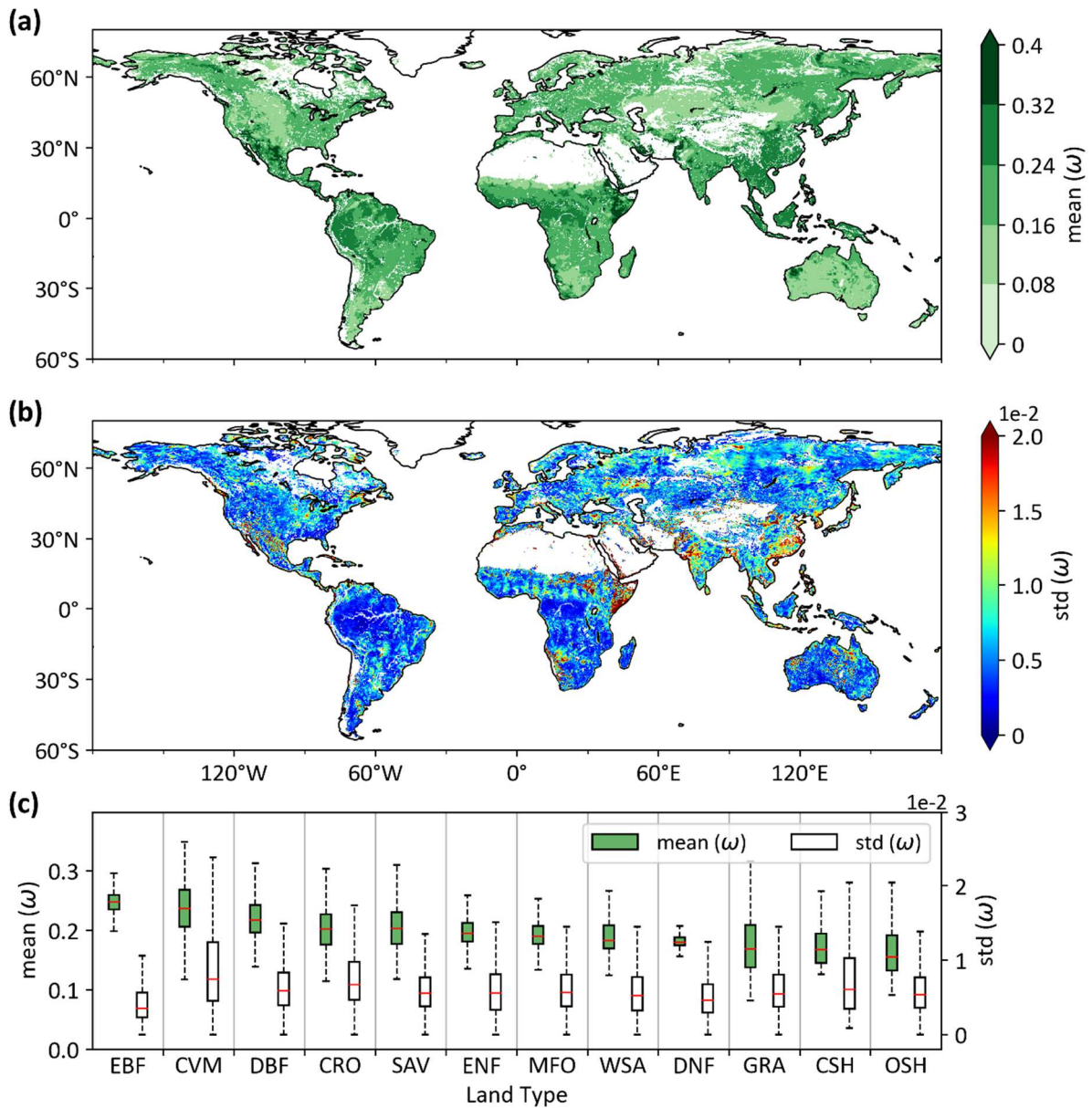
474  
 475 **Fig. 5.** Global maps of the  $C$  (a) and  $D$  (b) soil model parameters estimated from the RF  
 476 models and (c) their boxplots for different IGBP land types.

477 **4.2 Vegetation scattering parameter ( $\omega$ ) retrieval**

478 A global map of the thirteen-year time-average retrieved  $\omega$  (based on  $w=18$  days) is shown in  
 479 Fig. 6 (a). The highest values ( $\omega > 0.32$ ) were obtained in Western Australia, northern  
 480 Mexico, northwest Canada, eastern Lena River in Russia, southern Somalia, western Arabian

481 Peninsula, southwest Iran, and northern Pakistan. Those regions are in areas with complex  
482 terrain of hills and gullies. High values of  $\omega$  were also retrieved in most pixels of the tropical  
483 regions. A clear gradient of increasing average  $\omega$  value from north to south can be seen across  
484 the Sahel. The maximum values of  $\omega$  reach up to 0.97, and the pixels with values in the range  
485 of 0.08-0.32 account for 97.36 % of all pixels. A boxplot of  $\omega$  for each land cover type sorted  
486 by decreasing median values are shown in Fig 6 (c). Evergreen broadleaf forests (EBF) have  
487 the highest  $\omega$  values, which is consistent with previous results from a calibration of the  $\omega$   
488 values over southern France (Shamambo et al., 2019). Interestingly, high  $\omega$  values were  
489 obtained in the Cropland/Natural vegetation mosaics (CVM) where roughly half of the pixels  
490 (53.48%) have a value greater than 0.24. The standard deviation of the  $\omega$  value in low  
491 vegetation is larger than that in the forest and woody savannas areas.





492

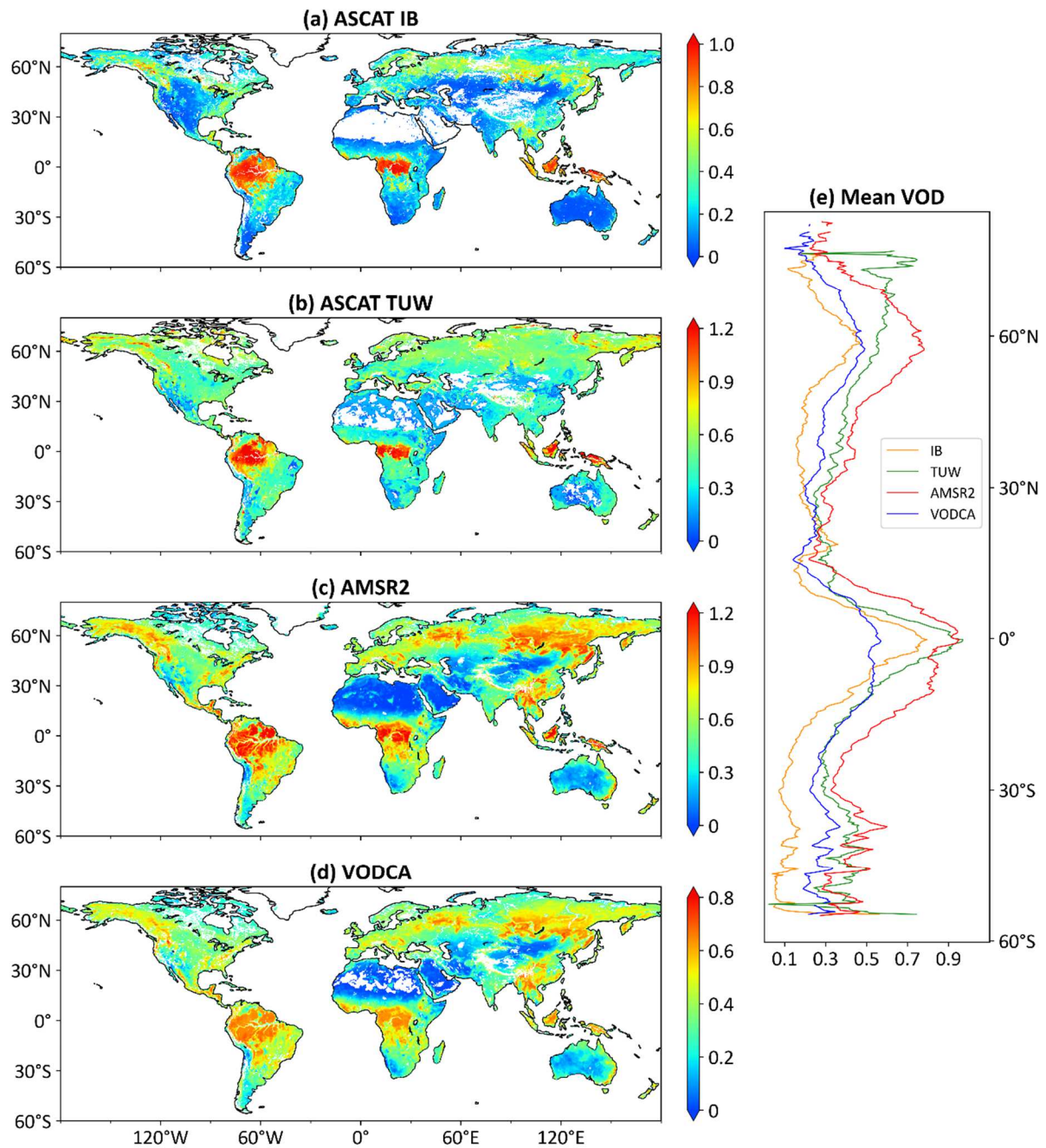
493 **Fig. 6.** Global distribution of (a) temporal average and (b) standard deviation of the retrieved  
 494  $\omega$  parameter from 2008 to 2020, and (c) the mean value per vegetation type ordered by  
 495 decreasing values and the corresponding standard deviation.

496 **4.3 ASCAT IB VOD evaluation**

497 **4.3.1 Global spatial patterns**

498 The spatial distribution of the four VODs (Fig. 7) shows that the passive VOD products  
 499 (AMSR2 VOD and VODCA VOD) have a larger coverage as the active VOD products  
 500 (ASCAT IB VOD and ASCAT TUW VOD) failed to obtain values in some areas (algorithm

501 failure). In the ASCAT IB VOD retrieval algorithm, we did not perform VOD retrievals in  
502 bare soil areas when the bare soil fraction is greater than 99 % and in pixels where we failed  
503 to simulate the bare soil backscatter (*i.e.* when the simulated bare soil backscatter value is  
504 larger than the observed backscatter value). The retrieval of TUV VOD was not performed  
505 when the difference between the wet and dry reference exceeds the maximum range in the  
506 backscatter signal over bare soils (Vreugdenhil et al., 2016). The maximum values of all the  
507 four VODs were retrieved in the tropics with VOD  $\sim 1.2$  for AMSR2 and ASCAT TUV  
508 VOD,  $\sim 1.0$  for ASCAT IB VOD, and  $\sim 0.75$  for VODCA VOD. The two passive VOD  
509 products (AMSR2 and VODCA) have a similar spatial distribution, with higher values in the  
510 boreal forests similar to those in the tropical region because they are retrieved from the same  
511 sensor (AMSR2) but with a different version of the algorithm. The zonal averaged VOD per  
512 latitude (Fig. 7 (e)) shows two peaks at the latitudes of  $\sim 0^\circ\text{N}$  and  $\sim 60^\circ\text{N}$  for all three VODs,  
513 except for ASCAT TUV VOD. At the latitude of  $\sim 0^\circ\text{N}$  corresponding to regions of dense  
514 tropical forests, both ASCAT VODs decrease rapidly from north to south, while both AMSR2  
515 VODs show a plateau at  $\sim 0^\circ\text{N}$  and decrease from a latitude of about  $13^\circ\text{S}$ .

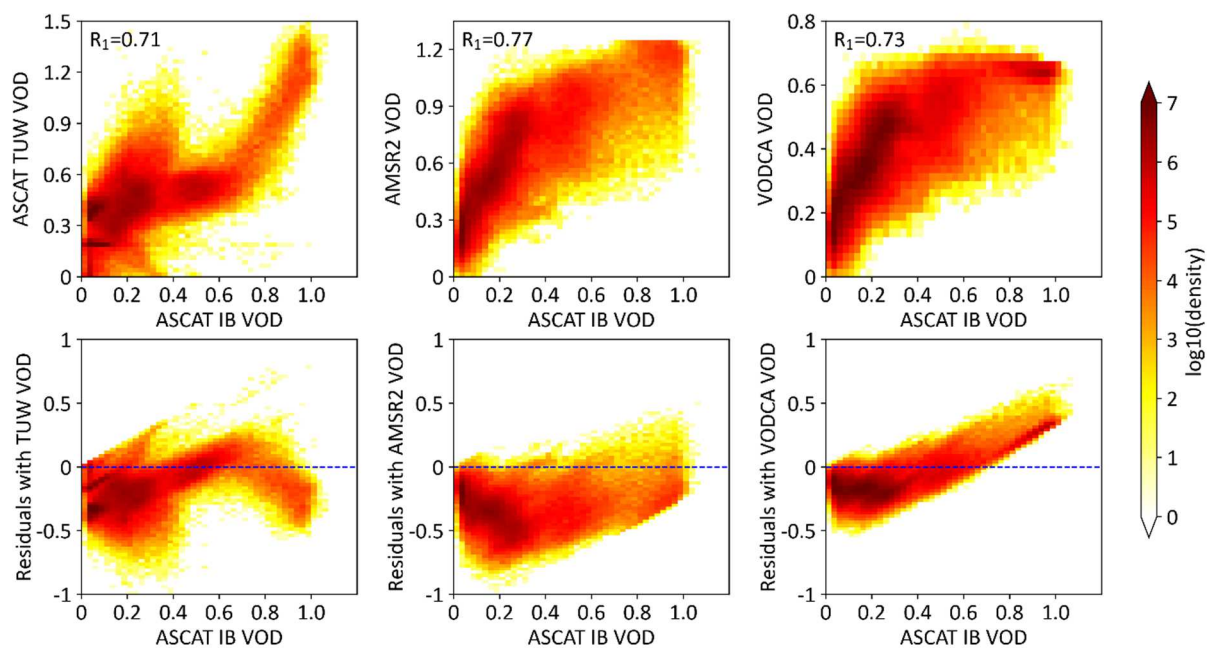


516

517 **Fig. 7.** Global distribution of time-averaged VOD maps over the period from years 2013-  
 518 2018, (a) ASCAT IB, (b) ASCAT TUW, (c) AMSR2, (d) VODCA and (e) corresponding  
 519 zonal average.

520 In order to quantitatively describe the differences among the four VODs, we computed the  
 521 spatial correlation and residuals of the relationship between ASCAT VOD IB and the three  
 522 other VOD products (Fig 8). ASCAT IB VOD has the highest correlation with AMSR2 VOD,

523 followed by VODCA VOD and ASCAT TUV VOD. AMSR2 and VODCA VOD show a  
 524 piecewise linear correlation with ASCAT IB VOD, while the correlation between TUV VOD  
 525 and ASCAT IB VOD is quite low when the ASCAT IB VOD value is lower than 0.6. The  
 526 residual plots show that the value of ASCAT IB VOD is lower than that of AMSR2 VOD in  
 527 almost all pixels. Compared with VODCA VOD, ASCAT IB VOD values are larger when  
 528 their values exceed 0.8. ASCAT IB VOD values are lower than the ASCAT TUV VOD  
 529 values except for values in the range of 0.7-0.8.



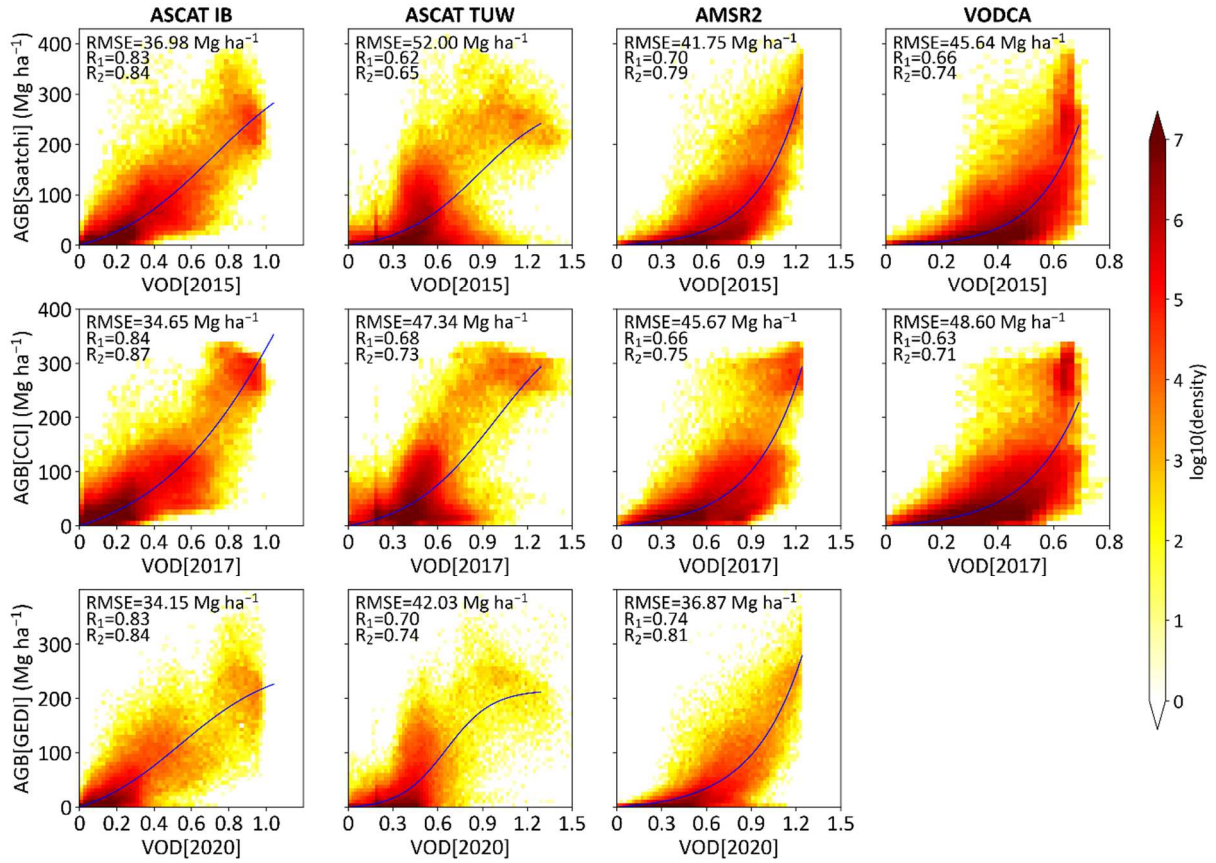
530

531 **Fig. 8.** Density scatter plots and residuals of the spatial relationship between ASCAT VOD  
 532 IB and the three other VOD products. VOD is time-averaged over 2013-2018, with residuals  
 533 calculated as ASCAT IB VOD minus the three other VODs.

#### 534 *4.3.2 Spatial correlation with aboveground biomass and canopy height*

535 Fig. 9 shows the density scatter plots of the four VODs with the three aboveground biomass  
 536 (AGB) products. The density of points in the scatter plots of GEDI AGB is lower than that of  
 537 the two other AGB products because the range of GEDI biomass did not include areas with  
 538 latitudes above 53.99°N. The distribution density plot of VOD versus AGB differs between

539 the ASCAT and AMSR2 VOD products. The shape of the density distribution of ASCAT  
540 VOD shows a gradual slope rise, while that of AMSR2 VOD presents first a slow slope  
541 increase and then a steep increase for AGB greater than  $\sim 100 \text{ Mg ha}^{-1}$ . Therefore, two  
542 different parameterization functions (Eq. (8) for ASCAT VOD; Eq. (9) for AMSR2 VOD)  
543 were used to fit the relationship between VOD and AGB. The results show that ASCAT IB  
544 VOD exhibits the best performance to predict all three AGB products, with a correlation of  
545 0.83-0.87 and RMSE values (34.62-36.86  $\text{Mg ha}^{-1}$ ) computed between reference and  
546 predicted AGB. AMSR2 VOD achieved the second-best performance in predicting the  
547 Saatchi and GEDI AGB. Similarly, ASCAT TUV VOD achieved the second-best  
548 performance in predicting CCI AGB. ASCAT TUV with Saatchi and GEDI AGB and  
549 VODCA with CCI AGB presented the lowest correlation values (0.63-0.66). Note that there  
550 is some scatter in these relationships and at low height levels, it cannot be concluded that the  
551 C-band VOD product will be a good proxy of the vegetation biomass. In particular, further  
552 studies based on specific data sets will be necessary to better evaluate the potential  
553 capabilities of ASCAT IB VOD in low vegetation canopies as croplands and grasslands.

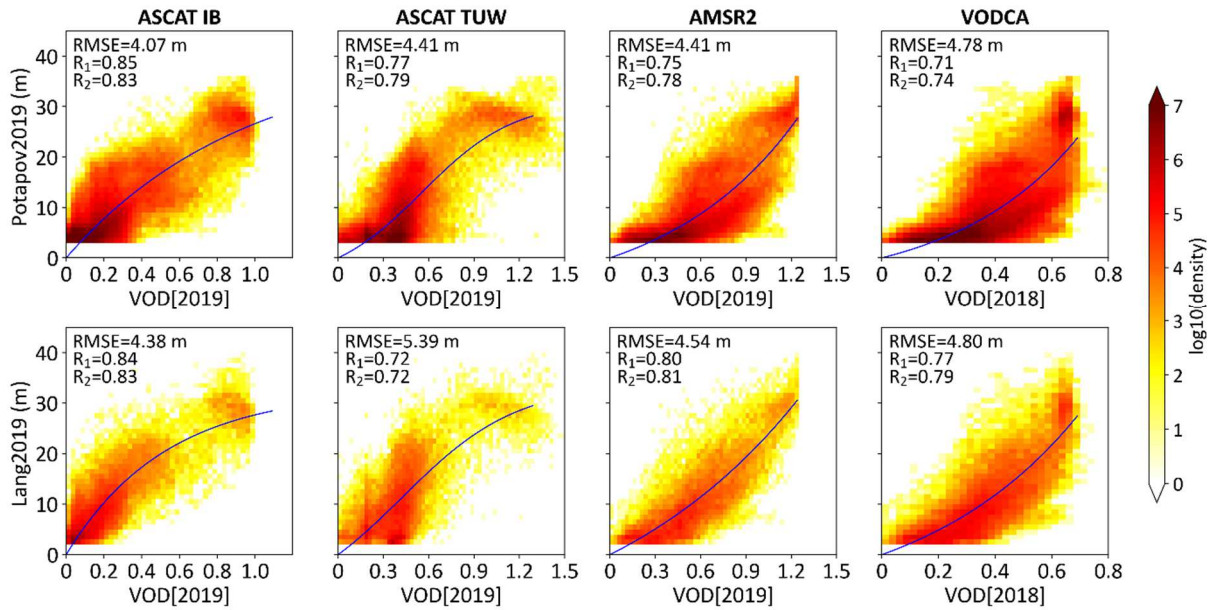


554

555 **Fig. 9.** Density scatter plots of the four global C-VOD (yearly averaged value) vs Saatchi  
 556 AGB (first row), CCI AGB (second row) and GEDI AGB (third row) datasets. R<sub>1</sub> is the  
 557 spatial Pearson correlation coefficient calculated between C-VOD and AGB (Eq. (7)), while  
 558 R<sub>2</sub> is calculated between VOD-predicted AGB and AGB. The solid blue lines are the  
 559 predictive fits obtained using Eqs. (8) or (9).

560 Considering the density scatter plot (Fig. 10) between VOD and the two GEDI canopy height  
 561 (CH) (Lang and Potapov) products, ASCAT IB VOD obtained the best correlation (R = 0.84-  
 562 0.85). The saturation of VOD to CH is more serious for AMSR2 and VODCA VOD than for  
 563 ASCAT IB and TUW VOD. AMSR2 and VODCA VOD saturate at a value of CH exceeding  
 564 15 m, while ASCAT IB and TUW VOD saturate at a higher value (> 20 m). Regarding the  
 565 potential to predict canopy height, ASCAT IB VOD presents again the best results with the  
 566 two canopy height (CH) products at different spatial resolutions (Potapov: from 30 m  
 567 resampled to 0.25 degrees, Lang: 0.5 degrees). The lowest RMSE values were obtained in the

568 ASCAT IB VOD predictions of CH: RMSE = 4.07 m for Potapov’s CH and RMSE = 4.38 m  
 569 for Lang’s CH. The  $R_2$  value (computed using a predictive fit) is lower than the  $R_1$  value for  
 570 the ASCAT IB VOD. This is mainly because we forced the predictive fitted line to start from  
 571 (0, 0). The quality of the relationship between VOD and CH is slightly weaker for the Lang  
 572 product (Fig. 10) probably due to the coarse resolution of the latter product.



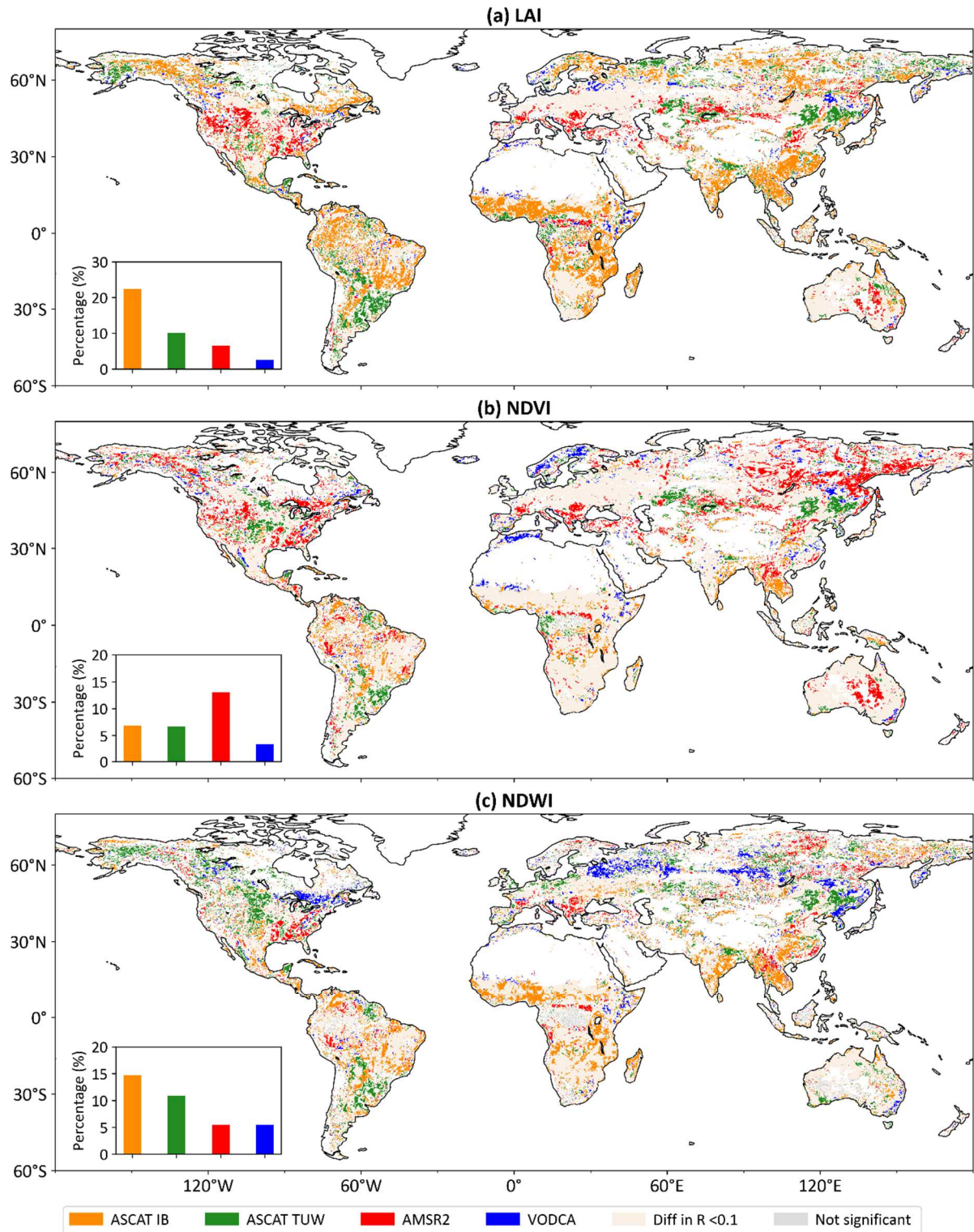
573  
 574 **Fig. 10.** Density scatter plots of the four global C-VOD (yearly value) vs the Potapov et al.  
 575 canopy height (first row), and Lang et al. canopy height (second row) datasets.  $R_1$  is the  
 576 spatial Pearson correlation coefficient calculated between C-VOD and canopy height (CH)  
 577 (Eq. (7)), while  $R_2$  is calculated between VOD-predicted CH and CH. The solid blue lines are  
 578 the fits obtained using Eq. (8) or (9).

### 579 4.3.3 Temporal correlation with vegetation indices

580 The regions where the four VODs products presented the highest absolute temporal  
 581 correlation with VIs are shown in Fig. 11. The two ASCAT VODs had more pixels with a  
 582 higher correlation with LAI and NDWI, with ASCAT IB VOD showing the highest  
 583 percentage. Passive VODs have a higher correlation with NDVI over more pixels, with  
 584 AMSR2 VOD having the highest percentage. Similar features can be seen in Fig. 11 (a)-(c)

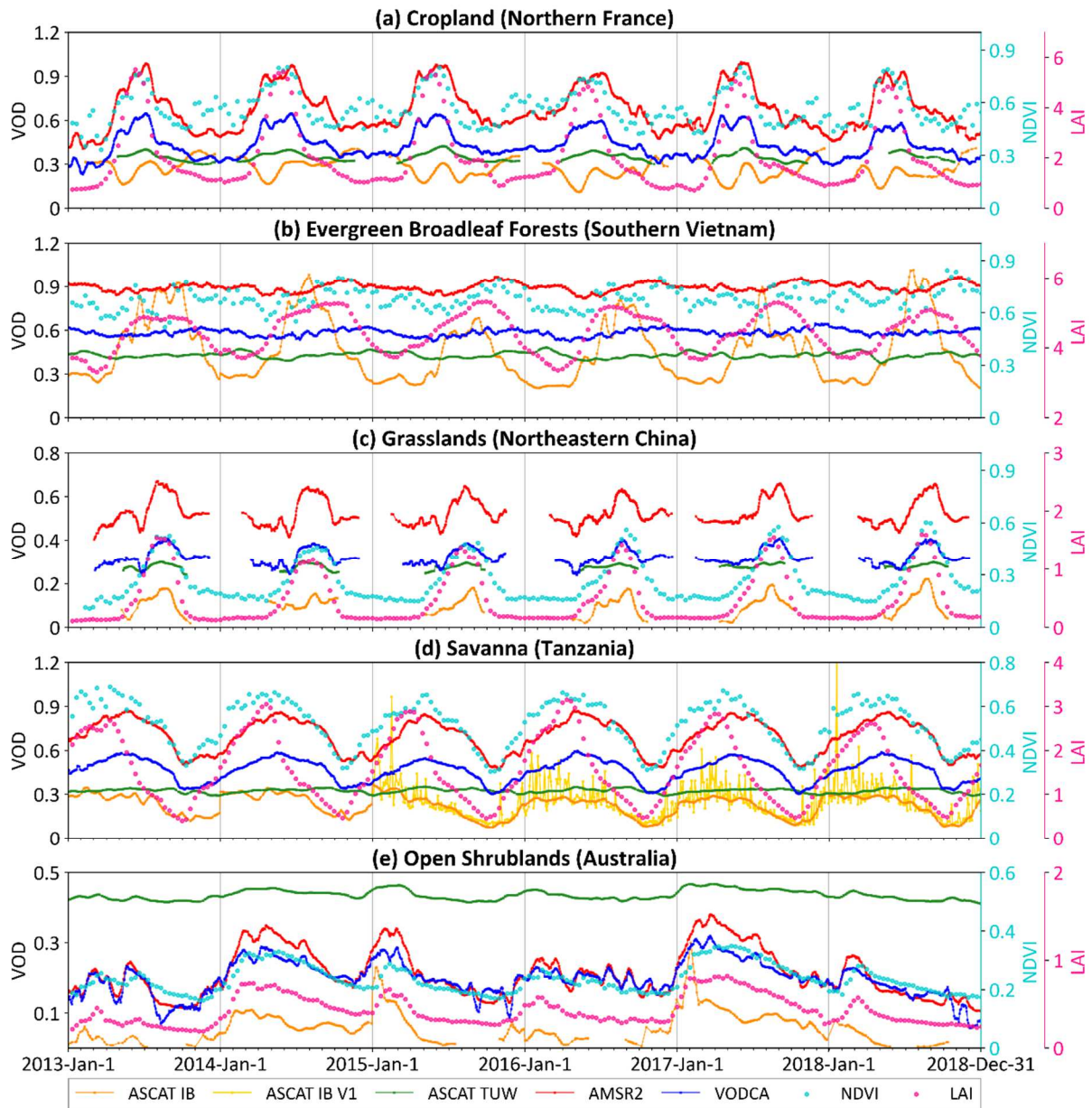
585 for the three vegetation indices, with ASCAT IB VOD obtaining the highest correlation  
586 values over more pixels in the subtropics regions, same for TUV VOD in the eastern United  
587 States, and same for the two AMSR2 VODs in Europe and Australia. The main differences  
588 were found in Alaska and central and eastern Russia where ASCAT IB VOD vs. LAI (Fig. 11  
589 (a)) and TUV VOD vs. NDWI (Fig. 11 (c)) showed the highest correlation values, while the  
590 two AMSR2 VODs showed highest correlation values with NDVI (Fig. 11 (b)). In central  
591 Russia, the two AMSR2 VODs (Fig. 11 (b)-(c)) achieved the highest correlation values with  
592 NDWI and NDVI, while the two ASCAT VODs showed the highest correlation values with  
593 LAI (Fig. 11 (a)). The pixel-wise temporal correlations between the four VODs and the three  
594 VIs are shown in Fig S2. Overall, AMSR2 VODs obtained significant correlations with VIs in  
595 more pixels than ASCAT VODs. Specifically, more significant correlations were obtained (i)  
596 between AMSR2 VODs and NDVI, and (ii) between ASCAT VODs and LAI. Both the  
597 ASCAT VOD and AMSR2 VOD have the lowest number of values significantly associated  
598 with NDWI. The spatial distribution of correlation values between the two AMSR2 VODs  
599 and the three different VIs is very similar, but the results for the active VODs are significantly  
600 different. The correlation values between the two active VODs and the VIs are in opposite  
601 directions in some specific regions. In the Amazon and Congo forest regions, ASCAT IB  
602 VOD shows negative correlations with the three different VIs, while ASCAT TUV VOD  
603 shows positive correlations. In the Central African Republic, northern Argentina and southern  
604 Bolivia, ASCAT IB VOD correlates positively with the three different VIs, while ASCAT  
605 TUV VOD correlates negatively with the same VIs. For further details, see Fig. S2





606  
 607 **Fig. 11.** Maps of the highest absolute temporal correlation (R) values between four VOD  
 608 datasets and three VIs based on six-year datasets (2013-2018) and corresponding percentage  
 609 of coverage (bottom left). “Not significant,” represented by shaded areas, means the P-value  
 610 of the correlation is larger than 0.05. White areas mean “no valid data.”

611 To illustrate the seasonal dynamics of the active and passive VODs, the time series of VOD  
612 and NDVI (LAI) are plotted over five pixels with relatively homogeneous land cover  
613 conditions but different vegetation types (Fig. 12). The fractional coverage of the land cover  
614 class and location information of each pixel is presented in Table S4. In the cropland site over  
615 northern France, ASCAT IB VOD showed a negative correlation with NDVI and LAI, while  
616 the three other VOD products showed the same seasonal dynamics as NDVI and LAI (the  
617 ASCAT IB VOD changes were similar to the three other VODs and VIs only from May to  
618 July). Fig. 12 (a) illustrates the negative temporal correlations obtained by ASCAT IB VOD  
619 with all three VIs in Eastern Europe (Fig. S2). The soil moisture and backscattering  
620 coefficient data for both periods (Feb.-May and Aug.-Nov.) were checked (Fig. S3). The  
621 backscattering coefficient changes are in phase with the time changes in soil moisture.  
622 However, the backscattering coefficient has a high value at the beginning of the vegetation  
623 development and the end of senescence, even larger than the value at the time when the LAI  
624 was at its peak. Shan et al. (2022) have also identified the same phenomenon that they  
625 attributed to human activity before and after sowing and to vegetation senescence in  
626 agricultural fields that increased soil roughness resulting in the high value of the observed  
627 backscatter signals. In addition, previous studies have observed a decrease in the backscatter  
628 signals as LAI increased in narrow-leaved crops (Fontanelli et al., 2013; Macelloni et al.,  
629 2001).



630  
 631 **Fig. 12.** Time series of the five VOD products (including the old ASCAT IB V1 version in  
 632 (d)), NDVI, and LAI over five types of vegetation cover in the period from January 2013 to  
 633 December 2018 (AMSR2 and VODCA VOD were smoothed by an 18-day moving window).

634 Interestingly, over the evergreen broadleaf forest site in southern Vietnam, ASCAT IB VOD  
 635 presents large seasonal variations similar to those of LAI, while the three other VODs and  
 636 NDVI showed slight time variations. In the high latitude grasslands site (Fig. 12 (c)), the  
 637 temporal availability of ASCAT IB VOD is shorter than that of the passive VODs, but  
 638 ASCAT IB VOD still monitored well the vegetation growth. The AMSR2 VODs have a

639 longer temporal availability than the active VODs in the high latitude regions, which is clearly  
640 shown in the Hovmöller diagrams (Fig. S4). In the savanna site in Africa (Fig. 12 (d)), the  
641 peak of ASCAT IB VOD is well synchronized with that of LAI, while the AMSR2 VODs and  
642 NDVI are more synchronized. Compared to the ASCAT IB V1 VOD version (only available  
643 in Africa) (Liu et al., 2021b), it can be clearly seen that the new global ASCAT IB VOD  
644 product is smoother and solves the noise issue mentioned in the previous study in Africa. In  
645 the open shrublands site (Fig. 12 (e)), the values of LAI and NDVI were higher in 2017 than  
646 in the other three years, and ASCAT IB VOD also captured well this inter-annual variation in  
647 the vegetation cycle. ASCAT TUW VOD presents weak temporal variations over all the  
648 different vegetation types, because a time window ranging from 2 to 12 weeks were used to  
649 calculate VOD (Vreugdenhil et al., 2016).

## 650 **5. Discussion**

### 651 **5.1 Uncertainty in the VOD retrieval**

652 There are three main uncertainties associated with ASCAT IB VOD. The first one is the  
653 simplified scattering process considered in the retrieval algorithms, and the other two are the  
654 soil parameters estimated from the random forest models and the ERA5-Land SM input. The  
655 water cloud model that is used to simulate the backscattering coefficient in the present study  
656 neglected the multiple scattering effects as it is hard to quantify this part in the model. Some  
657 studies showed that the multiple scattering effects can be generally ignored for low levels of  
658 the vegetation cover at the C- and L-bands (El Hajj et al., 2019b; Hosseini et al., 2015; Zribi  
659 et al., 2019). One study (Li et al., 2020) confirmed also this conclusion by comparing the  
660 VOD and SM parameters retrieved from L-band SMOS TB based on Tau-Omega and a  
661 higher order radiative transfer model, named the Two-Stream emission model (Schwank et  
662 al., 2018), which holds a stronger physical background with consideration of multiple  
663 scattering and reflection. However, the VOD values retrieved from the two models vary over

664 dense vegetation areas and boreal regions. A study that explored the contribution of double-  
665 bounce to the total signal of the P-, L- and C-bands in forest regions showed that the double-  
666 bounce component at C-band is lower than that at the L- and P-bands and accounts for a small  
667 contribution (1%) to the total signal in forests (Freeman and Durden, 1993). Quast et al.  
668 (2019) used a generalization of the WCM that incorporates an estimate of first-order (i.e.,  
669 double-bounce) interaction-effects to simulate the ASCAT backscattering signals. The results  
670 also showed the interaction-contributions are very small. In the passive domain, (it is likely it  
671 is the same in the active domain), several studies showed that multiple scattering effects can  
672 be well accounted for by zero-order radiative transfer models that neglect multiple scattering  
673 effects, provided that the model parameters (VOD and scattering parameter) are considered as  
674 effective parameters (Kurum, 2013; Li et al., 2020). Here, we roughly simulated the effect of  
675 neglecting multiple scattering, by accounting for the impact of a 0 to 5 % change in the total  
676 signal (the value of 0 to 5 % was estimated from Freeman and Durden (1993) and Quast et al.  
677 (2019)), on VOD retrievals for the three vegetation types (Fig. S5). Assuming multiple  
678 scattering accounts for 5 % of the total signal (worst-case scenario), the results showed that  
679 the relative variation of VOD in the evergreen broadleaf forest reached 19 % when ignoring  
680 multiple scattering. The relative change of VOD in grasslands also showed a higher value (17  
681 %) than in savannah (12 %) even though their VOD value changed little (~ 0.02). These  
682 results show that neglecting multiple scattering effects in ASCAT VOD retrievals has a non-  
683 negligible effect, potentially leading to a change in VOD values by around 10-20 % in the  
684 worst case and that better consideration of multiple scattering effects should be considered in  
685 future improvements to our retrieval approach. However, the relative change in VOD caused  
686 by neglecting multiple scattering is relatively small compared to the large uncertainties  
687 associated with global AGB datasets: AGB values can vary by up to 50 % in some forest  
688 regions for different AGB data sets (Araza et al., 2022; Urbazaev et al., 2018). Considering

689 that there is no simple equation to quantitatively describe the multiple scattering effects in  
690 WCM, the traditional WCM equations were used in this study. Although there are some  
691 discrete models (Bracaglia et al., 1995; Ulaby et al., 1990) that considered the multiple  
692 scattering effects, it is difficult to apply these models over large regions as they need too  
693 many input parameters for a rigorous retrieval (Bai et al., 2018; Bai et al., 2022).

694 Another possible uncertainty associated with ASCAT IB VOD is related to the fact we  
695 ignored the subsurface scattering in the simplified Ulaby soil model. Wagner et al. (2022)  
696 showed that the backscattering coefficient negatively correlates with SM when subsurface  
697 scattering is the main contribution of the soil backscatter and positively correlates with SM  
698 when the surface scattering effects dominate. When both types of scattering are present, the  
699 backscattering coefficient will exhibit a negative correlation with SM in dry conditions and a  
700 positive correlation as SM gradually increases, showing a U-shape (Liu et al., 2016; Wagner  
701 et al., 2022). Based on the correlation with AGB, the ASCAT IB VOD retrieved using the soil  
702 parameters predicted by different models trained with different positive correlation thresholds  
703 were evaluated, with the threshold  $R > 0.25$  achieving the best results (Table S5). When a  
704 higher threshold value is selected, pixels with mixed scattering that may be U-shaped with a  
705 lower R-value are excluded from the model training, resulting in more errors in the soil  
706 parameters prediction and finally causing errors in the ASCAT IB VOD retrieval. Although  
707 some studies have showed that the subsurface scattering effects usually happen in dry desert  
708 areas (McColl et al., 2014), the correlation values between the ASCAT backscatter  
709 measurements and ERA5-land SM revealed that pixels with negative correlation values are  
710 also located in some sparsely vegetated areas (Fig. 1 in (Wagner et al., 2022)). Because of the  
711 negative correlation, the  $\sigma_{\text{WetRef}}^{\circ}$  parameter fails to represent the time period when SM values  
712 are high (Fig. S1). Therefore, neglecting subsurface scattering in soil scattering modeling and  
713 in estimating initial values of the vegetation parameter from  $\sigma_{\text{WetRef}}^{\circ}$  will introduce

714 uncertainty to the ASCAT IB VOD retrievals, especially when the subsurface effects are  
715 dominant.

716 Random forest models were used in this study to simulate the global  $C$  and  $D$  soil model  
717 parameters. The underestimation of the high values and overestimation of the low values of  
718 the soil parameters ( $C$  and  $D$ ) can be noted in the 10-fold cross-validation (Fig. 4 (a)-(b)).  
719 This is caused by the limitations of the tree-based (e.g. random forest) models to perform  
720 extrapolations (Hengl et al., 2018). The predictions for test data outside the range of training  
721 data are often underestimated or overestimated. During the 10-fold cross-validation, the data  
722 are divided into ten groups with 9 groups used for training and 1 group for testing, and each  
723 group is tested once for the model. The range of data in the training and testing folds may be  
724 similar if the data has a normal distribution, where the mean is equal to the median value. In  
725 the histogram of the  $C$  and  $D$  values extracted in “bare soil” pixels (Fig. S6), there is a larger  
726 difference between the averaged and median value of the  $D$  values than for the  $C$  values. As a  
727 result, the underestimation and overestimation of the  $D$  model are more severe than that of the  
728  $C$  model (Fig. 4 (a)-(b)). The effect of the uncertainty associated with the parameters  $C$  and  $D$   
729 on the VOD retrievals was evaluated on three vegetation types based on RMSE in Fig. 4. The  
730 results (Fig. S7) show that the most significant impact is on grasslands, followed by savannas  
731 and evergreen broadleaf forests. Following the method of Liu et al. (2021b), the uncertainty  
732 associated with ERA5-Land’s SM on the VOD retrievals was analyzed by examining changes  
733 in SM values in relation to relative changes in VOD values over three vegetation types. The  
734 selected change in SM value, derived from an estimate of ERA5-Land’s ubRMSE, is  $0.05$   
735  $\text{m}^3/\text{m}^3$ . The results (Fig. S8) show that the relative change in VOD values is  $\pm 17\%$  on  
736 grassland,  $\pm 8\%$  on savannah and  $\pm 3\%$  on evergreen broadleaf forest when SM values vary  
737 by  $\pm 0.05 \text{ m}^3/\text{m}^3$ . As expected, the impact of errors on SM is weaker as VOD values increase.

738 These results are similar to the sensitivity analysis of the uncertainty associated with ERA5-  
739 Land SM on ASCAT IB V1 VOD retrievals (Liu et al., 2021b).

## 740 **5.2 Inter-comparison of the active and passive VOD**

741 The assessment and comparison results indicate that there are some discrepancies between  
742 ASCAT IB VOD and AMSR2 VODs. Regarding spatial relationships, ASCAT IB VOD  
743 showed the highest correlation with AGB and canopy height (Fig. 9-10). It was also found  
744 that ASCAT IB VOD had the best temporal correlation with LAI and NDWI for most of the  
745 pixels at the global scale, while AMSR2 VODs showed best correlation with NDVI (Fig. 11  
746 (b)). The statistics of the temporal correlation between VODs and VIs in each land cover type  
747 show similar results (Table S6), especially for short vegetation. Physical radiative transfer  
748 mechanisms may help to understand why LAI and NDWI have a better spatial and temporal  
749 correlation with active ASCAT IB VOD than passive AMSR2 VODs. As active microwave  
750 sensors emit energy, the observed backscattering coefficient is a measurement of the  
751 microwave radiation scattered in a single backward direction, while the passive microwaves  
752 sensors detect the naturally emitted microwave energy which corresponds to the integration of  
753 the bi-static coefficient considering the incident radiations over the whole hemisphere  
754 (Ferrazzoli et al., 1989; Wigneron et al., 1999). Therefore, compared to passive observations,  
755 active observations are more sensitive to volume scattering within the canopy. This is because  
756 passive microwave remote sensing integrates over all of the possible directions of incident  
757 radiation, while active microwave remote sensing only samples a single direction, resulting in  
758 less averaging of coherent effects. Consequently, active microwave remote sensing is more  
759 sensitive to vegetation canopy structure and specifically temporal changes in leaf water and  
760 orientation than passive microwave remote sensing.

761 Even though ASCAT IB VOD performed well in space and time when compared with the  
762 three other C-band VOD products, we should be aware that the algorithms and input datasets



763 of those four products differ and also make the VOD values and ranges different (Fig. 8). We  
764 summarized these main differences in Table 1. For the two active VOD products, the retrieval  
765 algorithms are both based on the water cloud model, but the inputs are different. TUV VOD  
766 was retrieved by using the ASCAT dry and wet references which are the mean value of the 10%  
767 highest and lowest normalized backscatter data at 25° and 40° (Pfeil et al., 2018), while the  
768 ASCAT normalized backscatter data at 40° was used to retrieve ASCAT IB VOD. The  
769 hypotheses made in the two active VOD retrieval algorithms are also very different. In the  
770 ASCAT IB VOD retrieval algorithm, the vegetation scattering ( $\omega$ ) and VOD parameters were  
771 assumed to be constant within a period of 18 days and retrieved together using a model-based  
772 SM as input to the algorithm. In contrast, the TUV VOD retrieval algorithm assumes that the  
773 maximum range of backscatter values (- 6.68 dB) over bare soil is the same around the world,  
774 excluding desert areas. The auxiliary data used by both algorithms mainly concern the  
775 modelling of soil scattering. The ASCAT IB VOD retrieval algorithm employed many  
776 ancillary data sets (*e.g.* SoilGrids250m and DEM-related datasets) for calibrating the  
777 parameters of the soil model and used a modelled reanalysis SM product from ERA5-land as  
778 input to the soil model. Conversely, the TUV VOD retrieval algorithm utilized only the  
779 Koppen–Geiger climate classification data to model the bare soil scattering. The different  
780 ancillary data used in the two algorithms will affect the VOD retrievals. The most obvious  
781 difference is that the two active VODs are retrieved using ancillary information for soil  
782 moisture, while VOD and SM are simultaneously retrieved in the passive domain (Owe et al.,  
783 2008; Wigneron et al., 2017). The two passive VOD are retrieved from AMSR2 brightness  
784 temperature measurements at 55° (Imaoka et al., 2012) but with different versions of the  
785 LPRM algorithm. VODCA VOD was retrieved based on LPRM version 6 (van der Schalie et  
786 al., 2017) which update the setting of the effective scattering albedo and of the soil roughness  
787 parameter, compared with LPRM version 5 used in the AMSR2 VOD retrievals. Those

788 discrepancies among the four VOD products may make the interpretation of the inter-  
 789 comparison more challenging.

790 **Table 1.** Summary of the key differences in the retrieval algorithms of the active ASCAT  
 791 VODs (ASCAT IB, TUW) and the passive VODs (AMSR2 and VODCA).

Algorithm	ASCAT IB	ASCAT TUW ( <a href="#">Vreugdenhil et al., 2016</a> )	LPRM version 5 (AMSR2 VOD) ( <a href="#">Owe et al., 2008</a> )	LPRM version 6 (VODCA VOD) ( <a href="#">Moesinger et al., 2020</a> ; <a href="#">van der Schalie et al., 2017</a> )
Observations	ASCAT $\sigma_{\text{obs}}^{\circ}$ at VV polarization	ASCAT $\sigma_{\text{WetRef}}^{\circ}$ and $\sigma_{\text{DryRef}}^{\circ}$ at VV polarization	AMSR2 $T_B$ at dual (V, H) polarization	AMSR2 at dual (V, H) polarization
Vegetation scattering modelling	Water cloud model ( <a href="#">Attema and Ulaby, 1978</a> )	Water cloud model ( <a href="#">Attema and Ulaby, 1978</a> )	$\tau$ - $\omega_p$ model ( <a href="#">Mo et al., 1982</a> ) $\omega_p = 0.05$	$\tau$ - $\omega_p$ model ( <a href="#">Mo et al., 1982</a> ) $\omega_p = 0.075$
Soil scattering modelling	Ulaby linear model ( <a href="#">Ulaby et al., 1978</a> )	$\Delta\sigma_s^{\circ}$ : maximum range in backscatter values over bare soils	H-Q-N modelling ( <a href="#">Wang and Choudhury, 1981</a> ) $H_R = 0.09$	H-Q-N modelling ( <a href="#">Wang and Choudhury, 1981</a> ) $H_R = 1.2*(1-2*SM)$
Hypothesis	VOD is the same over a short time window (18 days)	$\Delta\sigma_s^{\circ}$ is the same everywhere in the world, except in desert areas.	VOD is the same at H and V polarizations	VOD is the same at H and V polarizations
Ancillary data	SoilGrids250m ( <a href="#">Hengl et al., 2017</a> ) and DEM-related data ( <a href="#">Danielson and Gesch, 2011</a> ) are used to estimate the soil parameters of the Ulaby linear model;  ERA5-Land SM ( <a href="#">Muñoz-Sabater et al., 2021</a> ) is used as input to simulate the bare soil backscatter coefficient	Koppen–Geiger climate classification was used to set the $\Delta\sigma_s^{\circ}$ parameter	Vertically polarized Ka-band (36.5 GHz) observations from AMSR2 are used to derive the effective temperature ( <a href="#">Holmes et al., 2009</a> );  Soil texture (clay, silt and sand) from FAO is used to estimate the soil dielectric constant ( <a href="#">Wang and Choudhury, 1981</a> )	Same with LPRM version 5
VOD retrieval	VOD is retrieved simultaneously with the vegetation scattering parameter ( $\omega$ )	Only VOD is retrieved	VOD is retrieved simultaneously with SM	VOD is retrieved simultaneously with SM, VOD is re-scaled to AMSR-E VOD by a CDF matching technique

Limitations	The multi-temporal method may result in VOD not being sensitive to dry-down periods (Li et al., 2021) and has larger uncertainties over grasslands and croplands where vegetation growth can be very fast (Jackson et al., 2004).	The use of a kernel smoother with a half-width window of 21 days (Vreugdenhil et al., 2020) when calculating $\sigma_{WetRef}^{\circ}$ and $\sigma_{DryRef}^{\circ}$ decrease the seasonal amplitude of VOD; $\sigma_{WetRef}^{\circ}$ and $\sigma_{DryRef}^{\circ}$ are not optimized for regional conditions (Pfeil et al., 2018).	The global constant value of $\omega_p$ and $H_R$ may cause uncertainties in VOD retrieval (Baur et al., 2019).	Same with LPRM version 5
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792  $T_B$  = brightness temperature;  $\omega_p$  = Effective scattering albedo;  $H_R$  = roughness parameter

## 793 6. Conclusion and Outlook

794 The objective of this work was to retrieve the first global ASCAT IB VOD product and the  
795 vegetation scattering parameter ( $\omega$ ) from the single-channel (VV) active microwave  
796 observations of ASCAT. The spatial distribution of the retrieved  $\omega$  map matches well  
797 vegetation distribution, which is in line with the previous findings of the literature. When  
798 compared to the other C-VOD products, ASCAT IB VOD had a competitive advantage. In  
799 spatial terms, ASCAT IB VOD presented the highest correlation values with AGB and tree  
800 height, with R values of  $\sim 0.83$  and  $\sim 0.84$ , respectively. In comparison with the previous  
801 ASCAT IB V1 VOD developed only over Africa, the global ASCAT IB VOD has shown  
802 strong improvement in terms of temporal evolution which are much less noisy pixel-based  
803 time-series than those of the previous version. Some interesting discrepancies were also  
804 observed between ASCAT and AMSR2 VODs. The non-linear density distribution presented  
805 by ASCAT VOD and AGBs is different from that presented by AMSR2 VOD. ASCAT  
806 VODs have a linear spatial relationship with LAI and a non-linear one with NDWI and NDVI,  
807 while AMSR2 VODs presented opposite results (Fig. S9). Similar results were obtained in  
808 terms of temporal variations: ASCAT VODs show greater synchronization with LAI and  
809 NDWI, while AMSR2 VODs are more closely aligned with NDVI. So, the different  
810 characteristics of the two ASCAT VODs (more closely related to changes in LAI) and the two  
811 AMSR2 VODs (more closely related to changes in NDVI and NDWI) showed appealing  
812 complementarity for conducting joint vegetation studies.

813 The strong ability of ASCAT observations to predict AGB as found in this work and Santoro  
814 et al. (2022) encourages us to apply this long-term VOD to investigate the time changes in  
815 aboveground biomass at continental scales since 2007. Recently, Tao et al. (2022) developed  
816 the first global C-band scatterometer dataset which dates back to 1992. Applying the new  
817 ASCAT IB algorithm to this dataset would allow obtaining a 30-year data set of the VOD  
818 parameter which is very promising for studies of vegetation resilience (Forzieri et al., 2022).  
819 Considering that global ASCAT IB VOD showed a good sensitivity to NDWI, some  
820 applications (like wildfire prediction or post-fire recovery) related to vegetation water content  
821 can be explored in the future (Bousquet et al., 2022; Fan et al., 2018). Furthermore, a specific  
822 version of our algorithm could be developed for Sentinel-1 (S1): less uncertainty in the  
823 retrievals could be obtained by combining the S1 observations at the two VV and VH  
824 polarisations, instead of using only one (VV) for ASCAT. In addition, improved bare soil  
825 models and the use of machine learning methods that can be extrapolated (e.g. ensemble RF,  
826 Cubist) (Lin et al., 2017; Pouladi et al., 2019) could lead to a decrease in the uncertainty  
827 associated with the simulation of the bare soil backscattering.

## 828 **Data availability**

829 Global ASCAT IB VOD and vegetation scattering parameter ( $\omega$ ) can be downloaded from the  
830 INRAE Bordeaux remote sensing lab website (<https://ib.remote-sensing.inrae.fr>) after  
831 registration.

## 832 **Appendix A**

### 833 **A.1 Random forest model**

834 In this study, the random forest (RF) regression model was used to simulate the global soil  
835 parameters ( $C$  and  $D$ ) of the Ulaby bare soil model. RF is a tree-based machine learning

836 method and has been widely adopted in many geographic-related studies (Liao et al., 2022;  
 837 Wang et al., 2022). RF works by training many regression trees and reporting the mean  
 838 response over all the trees. In each tree, approximately two-thirds of the samples in the dataset  
 839 are used for training and the remaining third (called the out-of-bag data (OOB)) are used for  
 840 internal validation of the model. The r-square values ( $R^2$ ) and RMSE calculated from the  
 841 OOB samples are used to assess the model performance. The python sklearn package  
 842 (Pedregosa et al., 2011) was used for the implementation of RF, including the establishment  
 843 of the model, the selection of the predictor of the model, and the validation of the model.

844 The ‘*RandomForestRegressor*’ was used as the estimator and its two parameters  
 845 (`n_estimators` and `max_features`) were optimized by the ‘*GridSearchCV*’ function. The  
 846 ‘`random_state`’ has been defined to guarantee the reproducibility of the model. The predictor  
 847 variables of the model were selected using a recursive feature elimination (RFE) method  
 848 (Guyon et al., 2002). We first fitted the model with all the predictors and then removed the  
 849 least important predictor from the model. This process was iterated until only one predictor  
 850 variable was left. The selected predictors are those that lead to the highest  $R^2$  and lowest  
 851 RMSE. Finally, the 10-fold cross-validation (CV) (Stone, 1974) was used as an independent  
 852 validation to assess the accuracy of the selected model. The mean value of the  $R^2$  and RMSE  
 853 of 10-fold CV and the importance of each predictor were reported.

#### 854 **Appendix Table 1**

855 Statistics of *C* and *D* at the global scale.

Parameter	Max	95th percentiles	Min	5th percentiles	Mean	Median
C(dB)	-7.60	-11.82	-26.01	-18.05	-14.27	-13.92
D (dB/ m <sup>3</sup> ·m <sup>-3</sup> )	34.12	13.97	1.75	5.12	8.46	9.76

#### 856 **Appendix Table 2**

857 Statistics of *C* and *D* over different ranges of values.

Parameter	Range [Min, Max]	Percentage	Mean	Median
C (dB)	[-25,-20]	1.51 %	-21.05	-20.78

	[-20,-15]	21.98 %	-16.64	-16.38
	[-15,-12.5]	66.62 %	-13.73	-13.72
	[-12.5,-10]	9.58 %	-11.65	-11.85
	[-10,-5]	0.31 %	-9.53	-9.70
D (dB/ m <sup>3</sup> ·m <sup>-3</sup> )	[0,5]	3.96 %	4.57	4.67
	[5,7.5]	38.79 %	6.38	6.43
	[7.5,10]	36.47 %	8.63	8.59
	[10,15]	17.31 %	11.74	11.47
	[15,25]	3.39 %	17.67	16.95
	[25,35]	0.08 %	26.92	26.32

### 858 Appendix Table 3

859 Statistics of *C* and *D* for different IGBP land cover classes.

IGBP land cover	Min		Max		Mean		Median		Percentage
	C	D	C	D	C	D	C	D	
ENF	-16.48	3.88	-9.83	12.88	-13.12	7.12	-13.34	6.83	2.17 %
EBF	-16.81	4.52	-9.79	16.14	-14.02	8.86	-14.21	8.84	7.32 %
DBF	-17.28	4.10	-10.09	18.00	-13.80	8.59	-13.90	8.51	1.80 %
DNF	-15.34	5.42	-12.35	12.42	-13.90	9.11	-13.92	8.86	0.11 %
MFO	-16.53	3.83	-9.91	16.82	-13.42	8.82	-13.43	8.34	4.84 %
CSH	-17.39	4.08	-10.76	13.19	-14.51	7.22	-14.55	6.64	0.23 %
OSH	-21.04	1.75	-9.17	30.59	-13.85	6.76	-13.44	6.38	13.15 %
WSA	-20.09	4.13	-9.90	16.91	-13.69	8.21	-13.69	8.07	10.03 %
SAV	-19.61	3.05	-10.25	17.46	-13.82	8.04	-13.78	7.95	13.44 %
GRA	-26.01	2.06	-8.72	34.12	-14.43	9.02	-14.01	8.00	23.48 %
CRO	-22.01	2.81	-1.08	26.35	-14.67	10.88	-14.53	10.86	9.64 %
CVM	-18.40	4.63	-12.31	22.20	-14.34	9.84	-14.17	9.65	0.61 %
BSV	-20.43	2.23	-7.60	24.42	-15.76	7.81	-15.99	7.31	13.18 %

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