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► To cite this version:

Xiaojun Li, Jean-Pierre Wigneron, Frédéric Frappart, Lei Fan, Philippe Ciais, et al.. Global-scale assessment and inter-comparison of recently developed/reprocessed microwave satellite vegetation optical depth products. *Remote Sensing of Environment*, 2021, 253, pp.1-19. 10.1016/j.rse.2020.112208 . hal-03121281

HAL Id: hal-03121281

<https://hal.inrae.fr/hal-03121281>

Submitted on 2 Jan 2023

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1 **Global-scale assessment and inter-comparison of recently developed / reprocessed**
2 **microwave satellite vegetation optical depth products**

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30 **Abstract**

31 The vegetation optical depth (VOD), a vegetation index retrieved from passive or active microwave
32 remote sensing systems, is related to the intensity of microwave extinction effects within the
33 vegetation canopy layer. This index is only marginally impacted by effects from atmosphere, clouds
34 and sun illumination, and thus increasingly used for ecological applications at large scales. Newly
35 released VOD products show different abilities in monitoring vegetation features, depending on the
36 algorithm used and the satellite frequency. VOD is increasingly sensitive to the upper vegetation layer
37 as the frequency increases (from L-, C- to X-band), offering different capacities to monitor seasonal
38 changes of the leafy and/or woody vegetation components, vegetation water status and aboveground
39 biomass. This study evaluated nine recently developed/reprocessed VOD products from the AMSR2,
40 SMOS and SMAP space-borne instruments for monitoring structural vegetation features related to
41 phenology, height and aboveground biomass.

42 For monitoring the seasonality of green vegetation (herbaceous and woody foliage), we found that X-
43 VOD products, particularly from the LPDR-retrieval algorithm, outperformed the other VOD products
44 in regions that are not densely vegetated, where they showed higher temporal correlation values with
45 optical vegetation indices (VIs). However, LPDR X-VOD time series failed to detect changes in VOD
46 after rainfall events whereas most other VOD products could do so, and overall daily variations are
47 less pronounced in LPDR X-VOD. Results show that the reprocessed VODCA C- and X-VOD have
48 almost comparable performance and VODCA C-VOD correlates better with VIs than other C-VOD
49 products. Low frequency L-VOD, particularly the new version (V2) of SMOS-IC, show a higher
50 temporal correlation with VIs, similar to C-VOD, in medium-densely vegetated biomes such as
51 savannas ($R \sim 0.70$) than for other short vegetation types. Because the L-VOD indices are more sensitive
52 to the non-green vegetation components (trunks and branches) than higher frequency products, they
53 are well-correlated with aboveground biomass: ($R \sim 0.91$) across space between predicted and
54 observed values for both SMOS-IC V2 and SMAP MT-DCA. However, when compared with forest
55 canopy height, results at L-band are not systematically better than C- and X-VOD products. This
56 revealed specific VOD retrieval issues for some ecosystems, e.g., boreal regions. It is expected that
57 these findings can contribute to algorithm refinements, product enhancements and further developing
58 the use of VOD for monitoring above-ground vegetation biomass, vegetation dynamics and phenology.

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61 **Key words: Vegetation optical depth, SMOS-IC, SMAP MT-DCA, LPDR, LPRM, VODCA,**
62 **biomass, phenology, height of vegetation, vegetation cycle**

63

64 **1. Introduction**

65 Microwave vegetation optical depth (VOD), as a promising ecological indicator, is directly
66 proportional to the vegetation water content (VWC) of the aboveground canopy biomass (Brandt et
67 al., 2018; Jackson and Schmugge, 1991; Mo et al., 1982; Wigneron et al., 2017). Different VOD
68 indices (referred to as VODs in the following) derived from microwave observations at relatively
69 "high" frequencies such as Ku- (18.7 GHz), X- (10.7 GHz) or C- (6.9 GHz) band have been used to
70 monitor phenology (Jones et al., 2011), vegetation fractional cover (Guan et al., 2012), the impact of
71 El Niño events on vegetation in Australia (Liu, et al., 2007), isohydrlicity patterns (Konings and
72 Gentine, 2017) and aboveground biomass (AGB) dynamics (Liu, et al., 2015). In recent years, VOD
73 at L-band (1.4 GHz) has been established as a useful indicator for estimating the dynamics in AGB in
74 tropical forests. This was made possible because of the lower extinction of low frequency radiations
75 within the canopy layer, making L-band arguably more efficient for monitoring biomass in dense
76 vegetation canopies (Brandt et al., 2018; Fan et al., 2019; Tian et al., 2018; Wigneron et al., 2020). In
77 comparison to optical-near infrared vegetation indices such as the Normalized Difference Vegetation
78 Index (NDVI) and the Enhanced Vegetation Index (EVI), currently available VODs have a coarse
79 spatial resolution, but are largely insensitive to effects from the atmosphere, clouds and sun
80 illumination, in particular at low frequencies (L-, C- and X-bands).

81 Several VOD datasets used in the above-mentioned studies are derived from multiple spaceborne
82 microwave sensors operating at different frequencies (Fernandez-Moran et al., 2017a; Li et al., 2020a;
83 Liu et al., 2011). Among these sensors (satellites), the Advanced Microwave Scanning Radiometer 2
84 (AMSR2; Imaoka et al., 2012) is the successor of the Advanced Microwave Scanning Radiometer for
85 EOS (AMSR-E; Koike et al., 2004), which enabled the fusion of the first long-term (1987-2008)
86 global microwave - based VOD product (Liu et al., 2011). The ESA's Soil Moisture and Ocean
87 Salinity (SMOS) and NASA's Soil Moisture Active Passive (SMAP) are two L-band sensors
88 (Entekhabi et al., 2010; Kerr et al., 2010) which are designed for monitoring surface soil moisture (SM)
89 in moderately and densely vegetated areas (Wigneron et al., 2017). While the main objective of these
90 satellite missions was to monitor SM at global scale, the accurate retrieval of SM using radiative
91 transfer models requires the consideration of the extinction effects of the vegetation layer, which are
92 parameterized by the VOD index (Mo et al., 1982; Wigneron et al., 2007). In particular, the SMOS
93 satellite has multi-angular capabilities, allowing simultaneous retrievals of SM and VOD (Wigneron et
94 al., 2000), while multi-temporal VOD retrieval approaches have been developed for SMAP (Konings
95 et al., 2016; 2017). Thus, both the SMOS and SMAP missions support the development of a separate
96 VOD product in addition to the original SM product. Note that some specific satellite products focus
97 only on SM, as the Japan Aerospace Exploration Agency (JAXA) standard SM products (Njoku et al.,

98 2003). Recently, VOD products have been combined to long-term time series by blending multiple
99 microwave sensors, such as the new global land parameter data record (LPDR) X-band VOD derived
100 from AMSR-E and AMSR2 (Du et al., 2017b), and the global long-term microwave VOD Climate
101 Archive (VODCA; Moesinger et al., 2020) produced by the Vienna University of Technology (TU
102 Wien) including Ku-, X- and C-band VOD.

103 Assessing the performance of these remotely sensed VOD retrievals is crucial to improve their
104 quality and evaluate their potential applications in many fields such as monitoring AGB, vegetation
105 dynamics and phenology. However, VOD, like NDVI, is a radiometric variable rather than a well-
106 defined and “easily validated” geophysical parameter (Liu et al., 2011). Evaluation based on field data
107 of different vegetation components is rare (Brandt et al., 2019) and most evaluations of VOD datasets
108 are based on a side-by-side comparison with proxies of the vegetation greenness based on optical
109 vegetation indices (Du et al., 2017b; Grant et al., 2016; Jones et al., 2011; Karthikeyan et al., 2019;
110 Lawrence et al., 2014; Li et al., 2020a; Liu et al., 2011; Moesinger et al., 2020; Tian et al., 2016; Tong
111 et al., 2019), including NDVI, EVI and Leaf Area Index (LAI). These previous comparisons revealed
112 that VOD can generally capture vegetation seasonal cycles and interannual variations in a similar
113 fashion as NDVI (Li et al., 2020a; Liu et al., 2011) and LAI (Moesinger et al., 2020; Cui et al., 2020).
114 However, unlike NDVI, which is restricted to the upper green canopy layer, microwave-based VOD is
115 able to sense the entire vegetation deeper within the canopy, with different layers and depths
116 depending on the penetration capability of the observation frequency. Hence, NDVI saturates quickly
117 as vegetation density increases and the green canopy closes, while VOD is sensitive to both the leaf
118 and woody component of vegetation and not restricted to the upper canopy. Moreover, VOD is related
119 to the water content of the vegetation canopy (i.e., VWC) that cannot be observed by optical indices.
120 Lower frequencies (L-band) observations are sensitive to the water content present in the whole
121 vegetation layer including the woody components of the vegetation, while higher frequencies (C- and
122 X-band) observations are more sensitive to the water content of the upper layer of the vegetation
123 canopy and, consequently, to the green vegetation components (leaves and stems for herbaceous
124 vegetation, crown and leafy part of trees in forests). Therefore, evaluating VOD against optical indices
125 should be limited to relatively low-density vegetation canopies. In particular, the optical indices are
126 not a good reference for evaluating the capabilities of low frequency VODs (such as L-band VOD) for
127 monitoring biomass, in particular over moderate to highly dense forests, especially in tropical regions.

128 As VWC is determined by the quantity of vegetation (parameterized by biomass) and the
129 vegetation water status (parameterized by vegetation moisture content (M_g (kg/kg), the ratio between
130 wet biomass and total (wet + dry) biomass, i.e., $M_g = VWC / (VWC + B_s)$, where B_s represents vegetation
131 dry biomass)), VOD can thus provide information on AGB and the vegetation water status and stress
132 of the vegetation canopy (Frappart et al., 2020; Togliatti et al., 2019). By assuming that the yearly

133 average of Mg is relatively constant from year to year, which can be confirmed in intact forest regions
134 and non - affected by severe drought/mortality events (Frappart et al., 2020), the yearly average of
135 VOD can be considered as a good proxy of AGB (Liu et al., 2015; Brandt et al., 2018). Moreover, the
136 function relating VOD to AGB has been established from a spatial calibration in several studies (see
137 Frappart et al., 2020 for a review and more details on that topic). As the yearly averaged VOD
138 computed at different frequencies is strongly correlated with the woody vegetation (Brandt et al.,
139 2018; Brandt et al., 2019; Wigneron et al., 2017), the evaluation of VOD retrievals can be based on
140 comparisons with AGB products. With the ongoing development of VOD retrieval
141 algorithms/products at different frequencies, efforts have been made to compare the sensitivity of
142 different VODs to forest carbon stocks. In the following, we will use L-VOD, C-VOD and X-VOD to
143 denote the VOD products at L-, C- and X-bands, and so forth. Liu et al. (2015) computed a non-linear
144 relationship between a reference map of AGB (Saatchi et al., 2011) and Ku/X/C-VOD products, and
145 used this relationship to study the VOD-derived global biomass dynamics. Following this global
146 analysis, Tian et al. (2016) confirmed the good relationship between AGB and Ku/C-VOD over the
147 West African Sahel dryland ecosystems using temporal *in-situ* biomass measurements. Rodríguez-
148 Fernández et al. (2018) conducted an inter-comparison of the spatial patterns of SMOS L-VOD
149 products against four AGB benchmark maps over the African continent and revealed a high
150 performance of the SMOS-INRA-CESBIO or SMOS-IC V105 L-VOD product relative to other
151 SMOS products. More recently, Chaparro et al. (2019) compared the sensitivity of different VOD
152 products at X-, C- and L-bands to AGB over tropical forests of Peru, southern Colombia and Panama.

153 However, very few studies have inter-compared VODs retrieved from different satellites and at
154 different frequencies. For instance, inter-comparisons of VODs at L-band were limited to either the
155 SMOS (Rodríguez-Fernández et al., 2018) or SMAP products (Chaparro et al., 2019), but to our
156 knowledge the two products have rarely been inter-compared. Moreover, most inter-comparisons were
157 conducted over limited study areas for specific biomes or on a limited time scale. For example,
158 Rodríguez-Fernández et al. (2018) and Chaparro et al. (2019) mostly focused on the yearly averaged
159 VOD without considering the seasonal variations. For a better understanding of remotely sensed
160 VODs and to facilitate improvements of the retrieval algorithms for future space-borne missions, the
161 evaluation/inter-comparison of VOD products from different sensors and frequencies for a variety of
162 spatio-temporal conditions is essential. Furthermore, new VOD algorithms and new versions of VOD
163 products, such as the SMOS-IC version 2 (V2) L-VOD recently designed by INRAE Bordeaux (Li et
164 al., 2020b; Wigneron et al., Submitted), are not yet comprehensively evaluated and inter-compared.

165 This study fills this gap by assessing and inter-comparing globally nine VOD products at three
166 frequencies (X-, C- and L-bands; See Table 1). This evaluation considered the ability of VOD
167 products to monitor both the seasonal vegetation cycle and the spatial distribution of AGB.

168 Consequently, the objectives of this study are: (1) to assess and inter-compare the sensitivity of VODs
 169 (at L-, C- and X-bands) to AGB, as well as to compare those products with optical vegetation indices
 170 from Moderate Resolution Imaging Spectroradiometer (MODIS) considering both seasonal and annual
 171 spatial variations at the global scale; and (2) to examine the performance of the nine VODs in various
 172 biomes reflecting different environmental conditions. The second objective provides insight in how
 173 satellite-based VOD retrievals may be impacted by land cover features (vegetation structure,
 174 phenology, etc.) and heterogeneity.

175 2. Datasets

176 2.1 Remotely sensed VOD products

177 Table 1 presents an overview of the VOD datasets included in this study, mainly from SMOS,
 178 SMAP and AMSR2. More details about these satellite-based VOD products are provided in Appendix
 179 A.

180 **Table 1.** Overview of the VOD datasets used in this study. Our study period is 04/2015-12/2017 as this
 181 period was sufficient to analyze seasonal variations in VOD.

Variable name	Dataset/ Sensor	Frequency	Metadata Period	Sampling	Method/Algorithm	Reference
SMAP L-VOD	SMAP	1.4GHz	04/2015-09/2020	Daily, 9 km	MT-DCA	Konings et al. (2017)
IC V105 L-VOD	SMOS	1.4GHz	01/2010-09/2020	Daily, 25 km	SMOS-IC V105	Fernandez-Moran et al. (2017a) Wigneron et al. (Submitted)
IC V2 L-VOD					SMOS-IC V2	
AMSRU X-VOD	AMSR-E and AMSR2	10.7GHz	01/2002-12/2019	Daily, 25 km	LPDR V2	Du et al. (2017a)
AMSR2 X-VOD	AMSR2	10.7GHz	07/2012-01/2020	Daily, 25 km	LPRM V5	Owe et al. (2008)
AMSR2 C1-VOD		6.9 GHz				
AMSR2 C2-VOD		7.3 GHz				
VODCA X-VOD	WindSat, AMSR-E, AMSR2 and TMI	10.65 GHz, 10.7 GHz	12/1997-12/2018	Daily, 0.25°	LPRM V6	Moesinger et al. (2020)
VODCA C-VOD	WindSat, AMSR-E and AMSR2	6.93 GHz, 7.3 GHz, 6.8GHz	06/2002-12/2018			

182 MT-DCA = multi-temporal dual-channel algorithm; LPRM = Land Parameter Retrieval Model.

183 To get an overview of the various approaches used in the VOD retrievals, we summarized the
 184 main differences in the algorithms used (Table 2). The brightness temperature (TB) measured by the
 185 passive microwave radiometers measures the natural microwave emission from the land surfaces. All
 186 these algorithms use a simple 0th-order Tau-Omega (τ - ω) radiative transfer model as the starting point
 187 to simulate the TB ([Mo et al., 1982](#), [Wigneron et al., 2017 for a review](#)). As summarized in Table 2,
 188 the main differences in the VOD retrieval algorithms can be distributed in different categories,
 189 considering the parameterizations of the physical temperature including the effective soil and
 190 vegetation temperatures, surface roughness, effective scattering albedo, and dielectric mixing models.
 191 For example, unlike the other algorithms, where the roughness effects are estimated from a separate
 192 roughness correction step, the LPDR algorithm assumes a constant dry soil emissivity to facilitate the
 193 VOD retrieval process, thus its VOD incorporate the soil roughness effects ([Jones et al., 2010](#);

194 Mladenova et al., 2014). VODCA is a fusion of VOD retrieval results from multiple sensors after co-
 195 calibration via cumulative distribution function matching using AMSR-E as the scaling reference
 196 (Moesinger et al., 2020). We did not list the VODCA retrieval algorithm separately as it is an updated
 197 version of LPRM V5, not yet available to the public. Readers are referred to Table 2 in Scanlon et al.
 198 (2020) for more details about this algorithm.

199 **Table 2.** Summary of key differences among the SMOS-IC, MT-DCA, LPDR V2 and LPRM V5
 200 retrieval algorithms.

Algorithm	SMOS-IC	MT-DCA	LPDR V2	LPRM V5
Observation	Multi-angular and dual polarization SMOS L3 T_B	Enhanced SMAP dual polarization T_B at a fixed incidence angle of 40°	Calibrated T_B retrieval records from both AMSR-E and AMSR2	AMSR2 spatial-resolution-matched T_B (L1SGRTBR)
Effective soil temperature	<ul style="list-style-type: none"> $T_G = f(T_{soil_surf}, T_{soil_depth})$ $T_{soil_surf}, T_{soil_depth}$ from Layer 1 & 3 of ECMWF $C_T = \min\left(\left(\frac{SM}{W_0}\right)^{b_0}, 1\right), W_0 = 0.3 \text{ m}^3/\text{m}^3; b_0=0.3$ 	<ul style="list-style-type: none"> $T_G = f(T_{soil_surf}, T_{soil_depth})$ $T_{soil_surf}, T_{soil_depth}$ from Layer 1 & 2 of GEOS-5 $C_T = 0.246$ 	<ul style="list-style-type: none"> $T_G = f(T_{BP(18.7GHz)}, T_{BP(23.8GHz)})$ (P = H, V) using an iterative algorithm approach (Jones et al., 2010) 	<ul style="list-style-type: none"> $T_G = LST = f(T_{Bv(37GHz)})$ LST derived from the method of Holmes et al. (2009)
Vegetation temperature	$T_C = \text{ECMWF skin temperature}$	$T_C = T_G$	$T_C = T_G$	$T_C = T_G$
Vegetation modelling	τ - ω model (Mo et al., 1982)	τ - ω model (Mo et al., 1982)	τ - ω model (Mo et al., 1982)	τ - ω model (Mo et al., 1982)
Soil roughness modelling	<ul style="list-style-type: none"> H-Q-N modelling (Wang and Choudhury, 1981) H_R values from Parrens et al. (2016) $N_{RP} = -1$ (P = H, V) over short vegetation $N_{RV} = -1, N_{RH} = 1$ over forests $Q_R = 0$ 	<ul style="list-style-type: none"> H-Q-N modelling (Wang and Choudhury, 1981) Assuming a constant roughness root-mean-square height of 0.13 (being the basis for formulations of H_R) $N_{RP} = 0$ (P = H, V) $Q_R = 0$ 	<ul style="list-style-type: none"> dry bare soil emissivity $H_R = -, Q_R = -$ 	<ul style="list-style-type: none"> H-Q-N modelling (Wang and Choudhury, 1981) $N_{RP} = 1$ (P = H, V) $H_{R(10.7GHz)} = 0.18;$ $H_{R(7.3GHz)} = 0.09;$ $H_{R(6.9GHz)} = 0.09;$ $Q_{R(10.7GHz)} = 0.127;$ $Q_{R(7.3GHz)} = 0.115;$ $Q_{R(6.9GHz)} = 0.115;$
Effective scattering albedo	ω calibrated based on IGBP classifications	ω is retrieved simultaneously with SM and VOD	ω is prescribed as a constant value of 0.06	<ul style="list-style-type: none"> $\omega_{10.7GHz} = 0.06$ $\omega_{7.3GHz} = 0.05$ $\omega_{6.9GHz} = 0.05$
Dielectric mixing model	Mironov et al. (2004)	Mironov et al. (2004)	Dobson et al. (1985)	Wang and Schmugge (1980)

201 T_B = brightness temperature; T_G = effective soil temperature; T_C = vegetation canopy temperature; LST = land surface temperature; T_{soil_surf} = surface
 202 soil temperature; T_{soil_depth} = deep soil temperature; C_T = parameters (Choudhury effective temperature scheme); W_0, b_0 = fitting parameters (Wigner
 203 effective temperature scheme); ECMWF: European Centre for Medium-Range Weather Forecasts; GEOS-5: Goddard Earth Observing System Model,
 204 Version 5; H_R = roughness parameter; N_{RP} = roughness parameter accounting for polarization dependency; Q_R = polarization mixing coefficient; ω =
 205 effective scattering albedo; In LPDR, the Dobson dielectric model is only used for the retrieval of SM as the VOD retrieval considers a constant dry soil
 206 emissivity (Mladenova et al., 2014).

207 2.2 Evaluation datasets

208 2.2.1 MODIS vegetation indices

209 Two optical vegetation indices (VIs), NDVI and EVI, were compared with each VOD product.
 210 These two VIs were chosen as both are regarded as proxy for green vegetation cover (Weber et al.,
 211 2020). In particular, NDVI climatology is also used to estimate VOD in the inversion algorithm of the
 212 official NASA SMAP soil moisture products (Chan et al., 2013; Dong et al., 2017). Compared to
 213 NDVI, EVI is designed to decouple the canopy background signals and reduce atmospheric influences
 214 and it is designed to be less susceptible to saturation over forest areas (Huete et al., 2002). More
 215 information on NDVI and EVI are summarized in Table S1. In this study, the 16-day MODIS product
 216 (MOD13A2 Collection 6) was used to obtain the NDVI and EVI. Global MOD13A2 data is provided

217 as a gridded level-3 product projected on the Sinusoidal projection with a spatial resolution of 1 km.
218 To retain high-quality observations, we filtered out pixels not flagged as ‘good quality’ and pixels with
219 snow/ice, cloud cover, and non-land as done by [Grant et al. \(2016\)](#). NDVI and EVI were subsequently
220 aggregated to 25 km using nearest-neighbor interpolation.

221 *2.2.2 Lidar tree height*

222 The global tree height dataset from [Simard et al. \(2011\)](#) was used to assess the dependency of
223 VOD on vegetation density. This height dataset was produced at 1 km resolution using lidar data
224 collected in 2005 by the Geoscience Laser Altimeter System (GLAS) sensor. In addition, estimates
225 over the areas not directly covered by the lidar footprint are made by combining relevant auxiliary data
226 with Random Forest models. The lidar-derived data were chosen here not only because the total
227 amount of vegetation is related to canopy height ([Asner et al., 2013](#)), but GLAS is also widely used as
228 a primary source of information for carbon stock databases, reflecting the ability of tree height data for
229 comparison purposes. Further details about this product and algorithm are described in [Simard et al.](#)
230 [\(2011\)](#), and data can be freely downloaded at https://webmap.ornl.gov/ogc/dataset-.jsp?ds_id=10023.
231 The dataset was aggregated (using linear averaging) to the VOD resolution (i.e. 25 km).

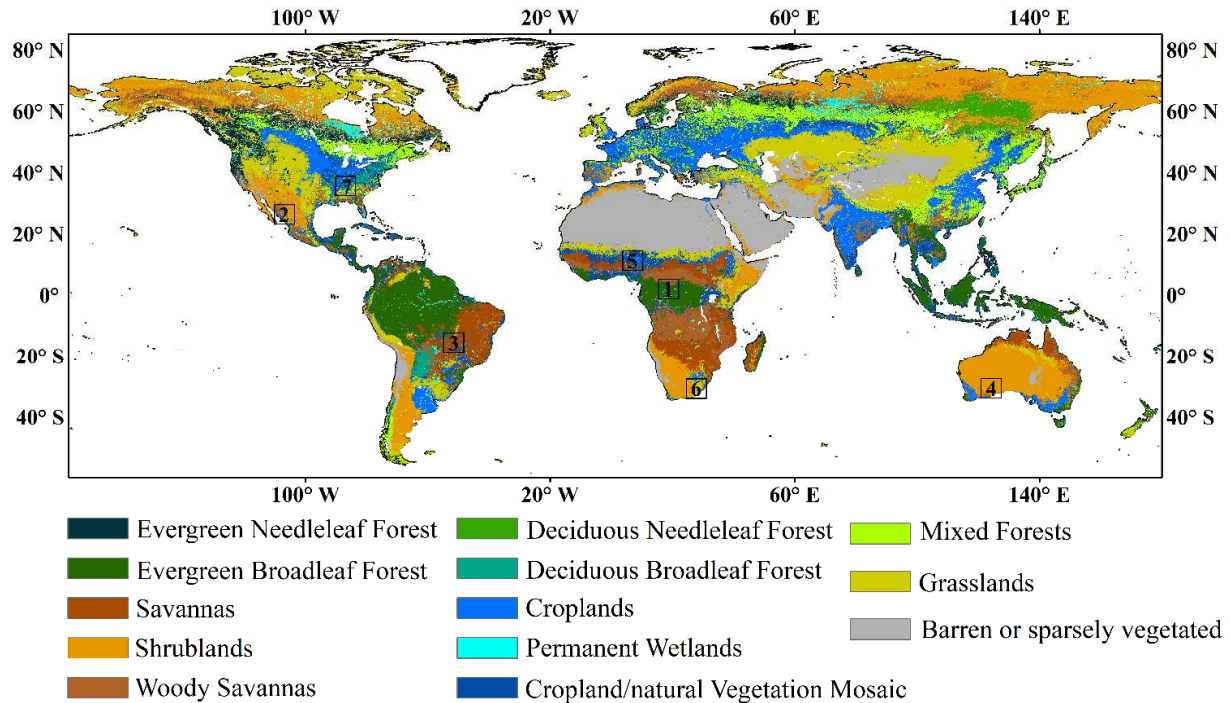
232 *2.2.3 Aboveground biomass*

233 We compared VOD with AGB provided by the global map updated from [Saatchi et al. \(2011\)](#)
234 ([Saatchi et al.](#), unpublished results) to assess the relationships of different VOD products to the spatial
235 variations in aboveground vegetation carbon stocks. The 1-km resolution Saatchi AGB map is
236 produced from a variety of datasets (e.g., *in-situ* inventory plots, MODIS and Quick Scatterometer
237 (QuikSCAT) products). The detailed methodology for generating this dataset is described in [Saatchi et](#)
238 [al. \(2011\)](#). The map obtained in this study (referred as to Saatchi AGB) represents AGB circa 2015
239 ([Carreiras et al., 2017](#)). We selected this dataset as an AGB benchmark map because it has been
240 widely used as a reference map to obtain calibration coefficients for converting L-VOD to carbon
241 density ([Tong et al., 2019](#); [Fan et al., 2019](#); [Wigneron et al., 2020](#)). In these studies, best correlation
242 scores between VOD and AGB were generally obtained using Saatchi AGB, confirming the accuracy
243 of the [Saatchi et al. \(2011\)](#) datasets. In our study, the static Saatchi AGB dataset was aggregated (using
244 averaging) to 25 km scale to match the spatial resolution of the other datasets.

245 *2.2.4 Ancillary datasets*

246 Several additional datasets resampled to 25 km were also used to interpret the results. The
247 MODIS-based global land cover climatology map (Fig. 1) was applied to analyze the VOD inter-
248 comparison results as a function of land cover types. This land cover map is generated by combining

249 the 0.5 km MODIS product (MCD12Q1) in the International Geosphere-Biosphere Programme (IGBP)
 250 scheme, as described in Broxton et al. (2014). In addition, daily precipitation from NASA's Global
 251 Precipitation Measurement (GPM) IMERG Late Precipitation L3 1 day 0.1°×0.1° (version 06) was
 252 used to identify the influence of precipitation events on the temporal dynamics of VOD (Liu et al.,
 253 2011).



254
 255 **Fig. 1.** Distribution of the IGBP land cover types. The boxes on the map indicate the selected sites
 256 (pixels) to illustrate the main features of the nine VOD products for a variety of vegetation conditions.

257 3. Methodology

258 3.1 VOD dataset pre-processing

259 The accuracy of the retrieved VOD data is generally highly variable depending on topography,
 260 presence of frozen land surface conditions (e.g., ice, snow), radio frequency interference (RFI), and
 261 pixel heterogeneity (e.g., water or urban fractions) (Fernandez-Moran et al., 2017a). Filtering out
 262 potentially spurious observations was an important step for the reliability of this study. Hence, the
 263 following data pre-processing strategies were applied: i) to guarantee a fair inter-comparison, the
 264 assessment of the VOD products was conducted for the same dates for all products, which covers the
 265 period from April, 2015 to December, 2017. This time period of about 2 years and a half was
 266 sufficient to analyze seasonal variations in VOD; ii) the assessment was performed only over pixels
 267 considering statistical error indicators (for example, the p-value to estimate the robustness of the
 268 information provided by correlation coefficients), which will be introduced in the following Section
 269 3.2; iii) applying the following data filtering for all VOD retrievals:

- 270 - RFI. Microwaves emitted by artificial devices on the Earth's surface distort signals received by
271 satellite sensors, resulting in unreliable VOD retrievals. RFI intensity varies with frequency and
272 location and its impact varies with the sensor. For instance, at L-band, the SMAP sensor, which is
273 more recent than SMOS, is equipped with improved RFI filtering techniques; SMOS is more
274 affected by RFI in Asia and Europe than elsewhere (Al-Yaari et al., 2019). Daily observations
275 affected by RFI are partly filtered out in this study by using corresponding flags in each dataset as
276 recommended by the data producers.
- 277
- 278 - Frozen soil. Due to the differences in the dielectric properties of water and ice, VOD retrievals are
279 generally unreliable when the ground is frozen (Moesinger et al., 2020). Hence, we removed
280 observations where the surface temperature was below 273.15 K. This was done with the available
281 flags for those VOD datasets, e.g., SMOS-IC provides a flag corresponding to frozen conditions
282 (Fernandez-Moran et al., 2017a).
- 283
- 284 - Other potentially uncertain observations. In this study, we directly used land classification data to
285 eliminate static water bodies. We also masked all pixels being “heterogeneous” or with a strong
286 topography. Heterogeneity was determined when the summed fraction of urban, wetland, open
287 water, and ice was greater than 10% (Fernandez-Moran et al., 2017a). Finally, negative VOD
288 values, which are physically impossible, were removed.

289 The above filtering rules were applied independently to all daily-scale VOD retrievals. We then
290 adopted bilinear interpolation to resample SMAP MT-DCA, AMSR2 and VODCA VOD to the same
291 projection with a spatial resolution of 25 km. The same method has been utilized in other studies
292 involving VOD processing (Brandt et al., 2018; Chaparro et al., 2019; Fan et al., 2019; Liu et al.,
293 2018). Finally, the resulting daily VOD data were averaged per pixel to 16-day mean values to match
294 the temporal resolution of the optical vegetation indices.

295 3.2 Methods for inter-comparison

296 A direct validation of the VODs at the global scale is not possible as there is a lack of consensus on
297 the reference values from *in-situ* measurements or models to use (Li et al., 2020a). Several studies
298 have shown that at the global scale, VOD values not only have a high spatio-temporal consistency with
299 optical vegetation indices (Du et al., 2017b; Lawrence et al., 2014), but also have a fairly consistent
300 spatial distribution with vegetation biomass and forest canopy height (Liu et al., 2011; Tian et al.,
301 2016). Hence, comparing VOD values with related variables and proxies is an alternative method to
302 evaluate the VOD performance which has often been used (Fernandez-Moran et al., 2017a; Li et al.,
303 2020a; Rodríguez-Fernández et al., 2018). In this study, the temporal and spatial correlation between
304 different VOD products and evaluation (vegetation-related) datasets were assessed using the Pearson

305 correlation coefficient (R) (Grant et al., 2016; Lawrence et al., 2014; Li et al., 2020a). We also
306 considered the probability value (p) as a measure of statistical significance; a level of $p < 0.05$ was used
307 here.

308 To evaluate the ability of VOD to monitor AGB, we directly compared the spatial correlation
309 between VOD and aboveground carbon density. We used a logistic function to fit the relationship
310 between VOD and AGB following the method used by Rodríguez-Fernández et al. (2018):

$$311 \quad AGB = \frac{a}{1+e^{-b(VOD-c)}} + d \quad (1)$$

312 where AGB and VOD represent aboveground carbon density and vegetation optical depth at each
313 frequency, respectively, and a , b , c and d are best-fit parameters. The fitted curve gives AGB (Mg ha^{-1})
314 as a function of VOD (dimensionless). Thus, the units of a and d are Mg ha^{-1} , while b and c are
315 dimensionless quantities. Spatial correlation computed between predicted (using the AGB – VOD fit
316 given in Eq. (1)) and observed AGB is also presented to evaluate the accuracy of the AGB predictions
317 based on different VOD products.

318 In addition to the above metric, we adopted the Hovmöller diagram to compare the spatio-temporal
319 patterns of VOD for the nine products. This diagram is a two-dimensional plot that shows the time–
320 latitude variations of a longitudinally averaged variable (Hovmöller, 1949), highlighting consistency
321 and differences between the nine VOD products. Moreover, an analysis at the pixel-scale was
322 conducted to compare the nine VOD datasets for a variety of biomes: seven pixels taking into
323 consideration relatively homogeneous land cover conditions (measured using the Gini–Simpson index;
324 Simpson, 1949) and contrasting vegetation types (see Fig. 1 and Table 3) were selected to compare the
325 VOD time series from different products. Although this comparison was limited to seven locations that
326 cannot cover the full range of climatic, vegetation, and soil conditions at a global scale, the comparison
327 at the pixel-scale allowed us to analyze and illustrate some of the main characteristics of the nine VOD
328 datasets (Al-Yaari et al., 2014; Karthikeyan et al., 2019).

329 All the above defined statistical indicators were only calculated on common pixels that contained
330 observations for all nine VOD products. For example, to obtain the spatial R values between VOD and
331 the evaluation datasets, we used the time averaged values computed only when each of the nine 16-day
332 mean VOD data were available from the different datasets. However, in a second step, to ensure a good
333 overview of all datasets in the analysis of the spatial patterns and of the Hovmöller diagram, all
334 available data has been kept for the different VOD products.

335 **Table 3.** Location and type of biome of the seven sites (pixels) selected to compare the different VOD
336 time series.

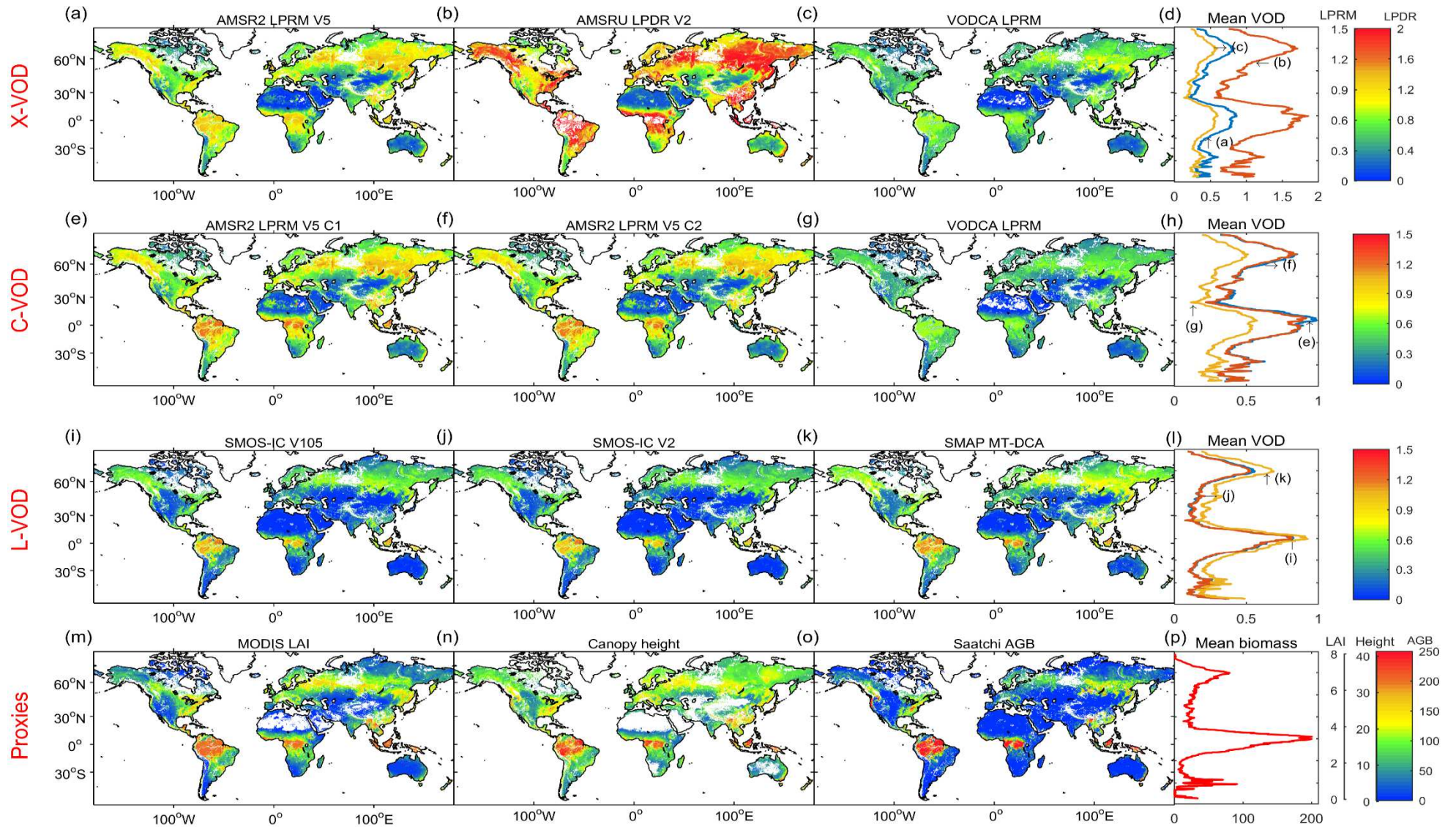
	Location	Latitude	Longitude	Land Cover
1	Congo	2.060° N	18.545° E	Evergreen broadleaf forest

2	Mexico	25.641° N	106.988° W	Mixed forests
3	Brazil	15.993° S	51.484° W	Savannas
4	South Australia	30.747° S	124.106° E	Open shrublands
5	Nigeria	11.551° N	7.133° E	Croplands
6	South Africa	31.432° S	27.882° E	Grasslands
7	South East US	35.173° N	86.758° W	Cropland/natural vegetation mosaic

337 4. Results

338 4.1 Spatial patterns and temporal dynamics at global scale

339 At a global scale, all VODs show a similar spatial pattern, matching MODIS LAI and canopy
340 height, with highest VOD values in tropical (e.g., Amazon and Congo basins) and boreal (e.g., Canada,
341 Northern Russia) forests and low VOD values in sparsely vegetated and dry areas (e.g., Sahara in
342 northern Africa, desert areas in Australia and central Asia) (Fig. 2a-l). The same patterns can be found
343 in the AGB map (Fig. 2o). There are a few exceptions and notably the AGB values are much higher in
344 the tropical and eastern Russia forests than in western Russia, Canada and Alaska forests, while VOD is
345 about equally high in each of these areas. In terms of absolute VOD values, it can be seen that there are
346 large differences even for a given frequency. For instance, considering X-band, LPDR V2 VOD is
347 obviously larger than LPRM V5 and VODCA VOD (by a factor of about 2 in some densely vegetated
348 regions). Considering C-band, the harmonized VODCA C-VOD value is generally lower than the value
349 of LPRM V5 C1- and C2-VOD, while the latter two are very similar. As for L-VOD, both versions of
350 SMOS-IC have lower values than SMAP MT-DCA, especially in eastern Brazil, southern China, and
351 boreal forests. According to the theoretical principle that propagation of the microwave radiations
352 decreases with frequency due to increasing extinction effects, the VOD values in the high frequency
353 band should theoretically be larger than those in the lower frequency bands (Moesinger et al., 2020).
354 However, the VOD values obtained from the LPRM algorithm do not seem to support this theory; in
355 particular, over southern Mexico, Amazon and Congo basins LPRM V5 X-VOD has lower values than
356 LPRM V5 C-VOD (Fig. 2a, e-f). A deeper analysis of this signature is discussed in Section 5.1. Zonal
357 VOD averages (side plots of Fig. 2) confirm the results presented above. It can be seen that the zonal
358 averaged distribution of X-, C-, L-VOD and AGB is similar, that is, two obvious high VOD and AGB
359 peaks can be noted around latitudes of $\sim 0^\circ$ N and $\sim 60^\circ$ N corresponding to regions of dense tropical
360 and boreal forests. The sharp peak presented by L-VOD for the SMOS and SMAP products correspond
361 better to the AGB peaks (Fig. 2p) as compared to the X- and C-VOD products which show more gentle
362 and flat peaks (Fig. 2d and h). These results are in line with the fact L-VOD is more sensitive to the
363 whole biomass, including stems, while higher frequency VODs are more sensitive to the top of canopy
364 and to leaf biomass, as found over Africa (Brandt et al., 2018).

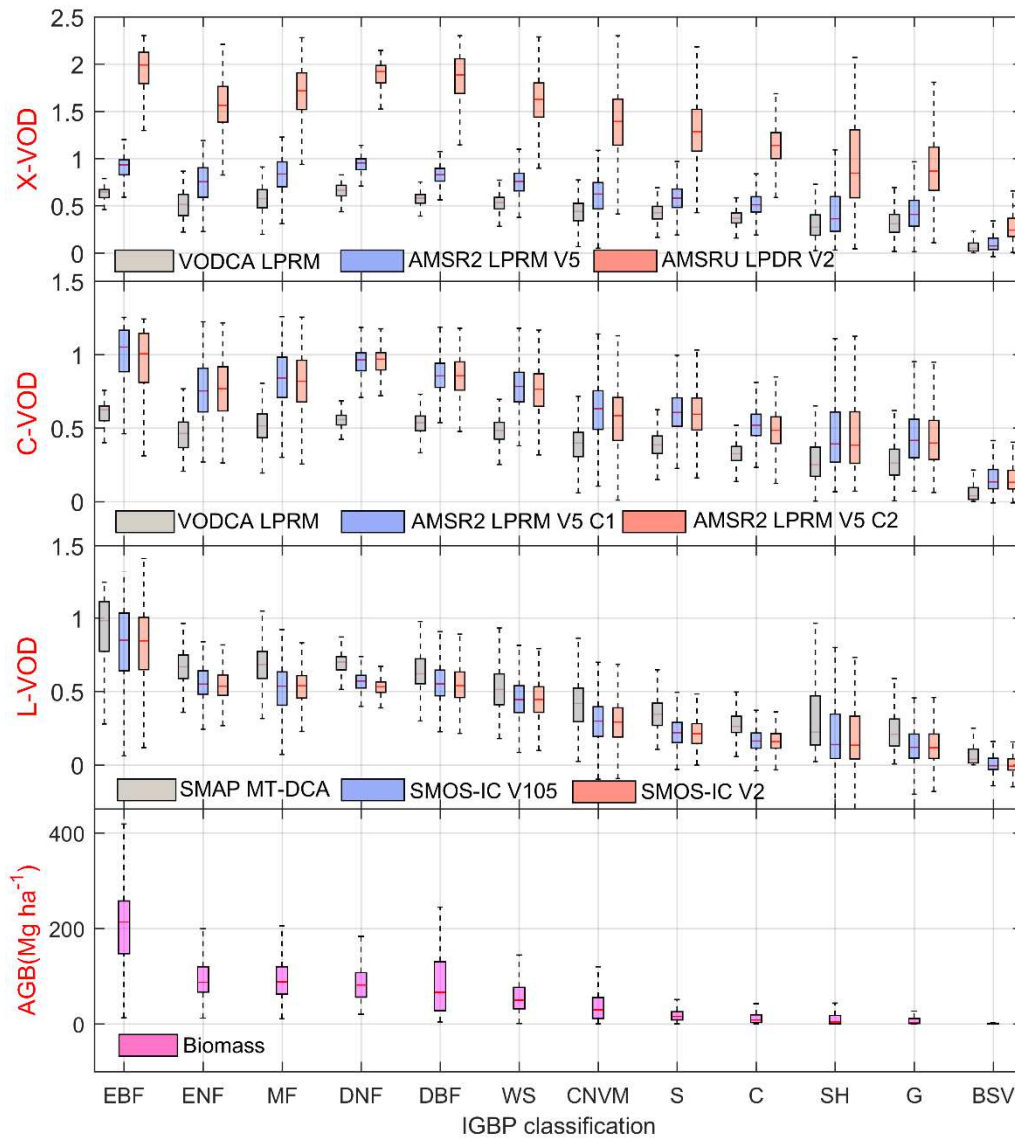


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Fig. 2. Time averaged global maps of VOD from April, 2015 to December, 2017 for a) AMSR2 LPRM V5 X-VOD, b) AMSRU LPDR V2 X-VOD, c) VODCA LPRM X-VOD, e) AMSR2 LPRM V5 C1-VOD, f) AMSR2 LPRM V5 C2-VOD, g) VODCA LPRM C-VOD, i) SMOS-IC V105 L-VOD, j) SMOS-IC V2 L-VOD, k) SMAP MT-DCA L-VOD and of m) MODIS LAI (m^2/m^2), n) lidar vegetation height (m) and o) Saatchi AGB (Mg ha^{-1}). Side plots show zonal averages for d) X-VOD, h) C-VOD, l) L-VOD and p) biomass. Note: to ensure a good overview of all datasets after quality control, no inter-mask is applied here.

371 Boxplots of the average VOD values per land cover class show that grasslands and shrublands as
372 well as croplands have the lowest VOD values, followed by savannas (Fig. 3). In contrast, forests and
373 biomes with more woody vegetation such as deciduous broadleaf, deciduous needleleaf, and mixed
374 forests show higher VOD values, which is consistent with previous findings using *in-situ* biomass data
375 and AMSR-E VODs over Sahel drylands (Tian et al., 2016). All VODs consistently show that
376 evergreen broadleaf forest, mainly distributed in the wet tropics, has the highest VOD values.
377 Interestingly, VODs from different algorithms/products were found to have a wide range of quantile
378 values over shrublands and grasslands, but a narrow range over croplands despite the fact that planting
379 density, crop types, and growing season vary across regions, and despite the fact that biomass and
380 hydraulic behavior varies depending on crop types (Konings et al., 2017). As noted before, for a given
381 IGBP class, the VOD values should theoretically increase with frequency. However, even if we exclude
382 the reprocessed VODCA VOD and only compare the VODs obtained from the same algorithm and for
383 the same mission, this theory is not fully supported. For example, for evergreen broadleaf forest, the
384 median X-VOD value (~0.93) obtained from AMSR2 LPRM V5 is lower than the values of C1-VOD
385 and C2-VOD (both ~1.05). There are also variations for observations in the same frequency range: at
386 L-band, VOD values derived from SMAP MT-DCA are higher than those derived from both versions
387 of SMOS-IC for all IGBP categories. As observed from the spatial patterns shown in Fig. 2, the average
388 VOD values of the two versions of SMOS-IC are very similar. It can also be seen that L-VOD values
389 generally follow the decreasing trend in the AGB values from left to right in the plot, which is not clear
390 in other VOD products.

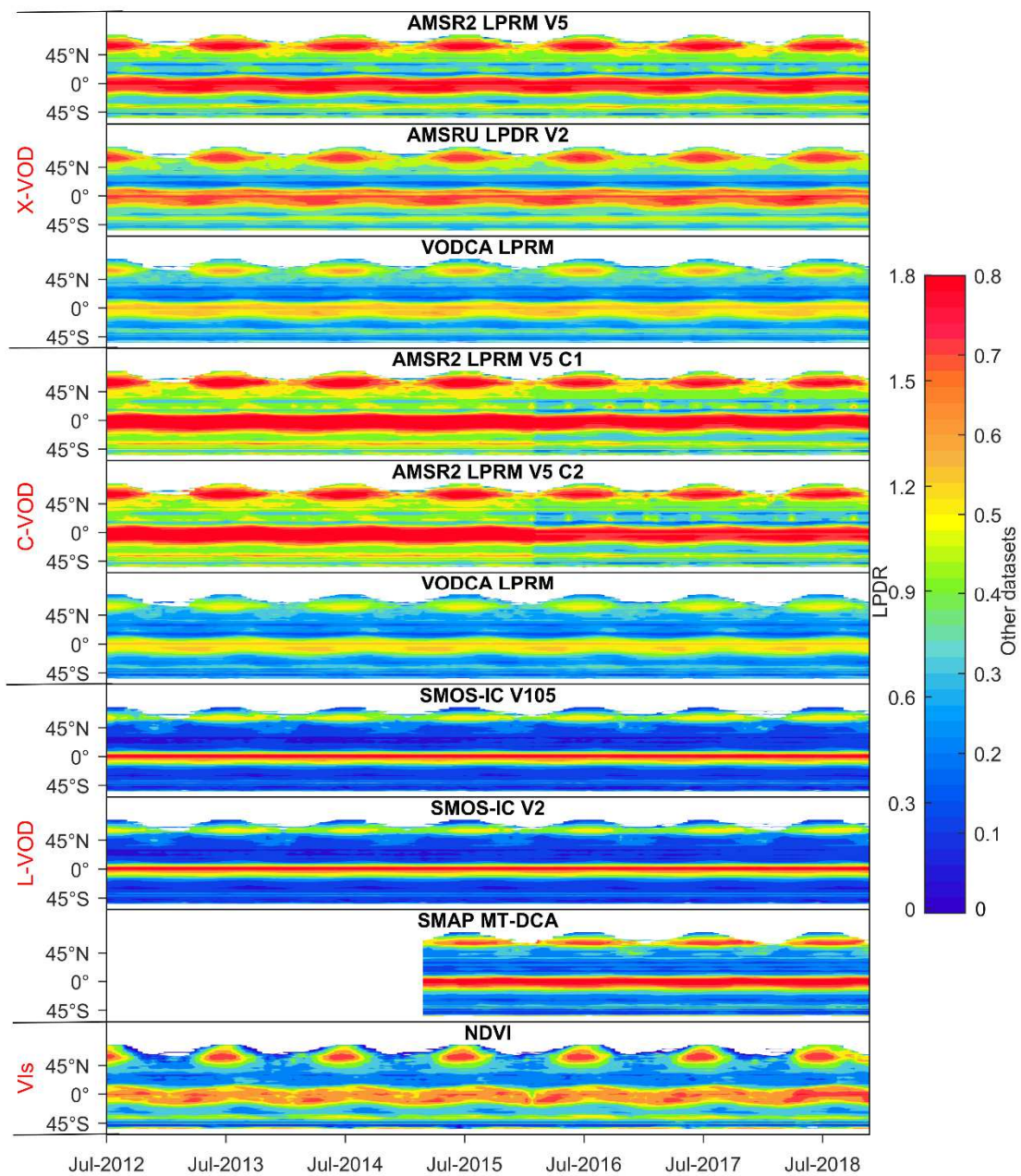
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 393 **Fig. 3.** Boxplots of VOD at three frequencies (X-, C- and L-band) and of biomass for different IGBP
 394 land cover classes. The vegetation IGBP classes are sorted by decreasing median values of the AGB
 395 values. The central mark within each box shows the median value, and the bottom and top edges mark
 396 the extent of the 25th and 75th percentiles. Whiskers include 99.3% of all data. EBF = evergreen
 397 broadleaf forest, ENF = evergreen needleleaf forest, MF = mixed forests, DNF = deciduous needleleaf
 398 forest, DBF = deciduous broadleaf forest, WS = woody savannas, CNVM = cropland/natural
 399 vegetation mosaic, S = savannas, C = croplands, SH = shrublands, G = grasslands, BSV = barren or
 400 sparsely vegetated.

401 VOD varies temporally and spatially, and this variability depends mainly on the season and
 402 latitude (Tian et al., 2018). We also evaluated the ability of all VODs to detect the spatio-temporal
 403 variations in the vegetation cycle, e.g., growth and senescence (Fig. 4). All nine VODs have some
 404 common periodical features. For instance, similarly to NDVI, a distinct seasonal pattern for all products
 405 can be seen in the Northern Hemisphere ($> 35^{\circ}\text{N}$) with higher VOD values during the summer months
 406 corresponding to the period of maximum vegetation growth and leaf production (as expected).
 407 However, the amplitude (maximum – minimum) of the VODs in response to seasonal changes in
 408 vegetation structure and production differs. Specifically, the order of this amplitude is X-VOD >
 409 VOD > L-VOD. In the high latitudes of the Northern Hemisphere (between 45°N and 60°N), all X-

410 VODs show a clear seasonality comparable to that of NDVI, followed by all C-VODs while all L-
 411 VODs present weaker seasonal dynamics. This can be related to the fact that VOD contains more
 412 information on the non-green woody component (e.g. woody stems and branches which are vegetation
 413 components with less seasonal changes than leaves) with decreasing frequency (Grant et al., 2016; Tian
 414 et al., 2016). So, even during leaf development in deciduous forests, L-VOD values are almost
 415 insensitive to leaf density, in agreement with tower-based experiments (Guglielmetti et al., 2007). This
 416 phenomenon is even more pronounced in tropical regions, where all L-VODs are almost constant.
 417 Surprisingly, since June 2015, the C1-VOD and C2-VOD values obtained by AMSR2 LPRM V5 are
 418 globally systematically lower than before and we did not find related literature to point out the specific
 419 reason for this discontinuity, nor if there a reason to think the raw AMSR2 observations changed in that
 420 time period.



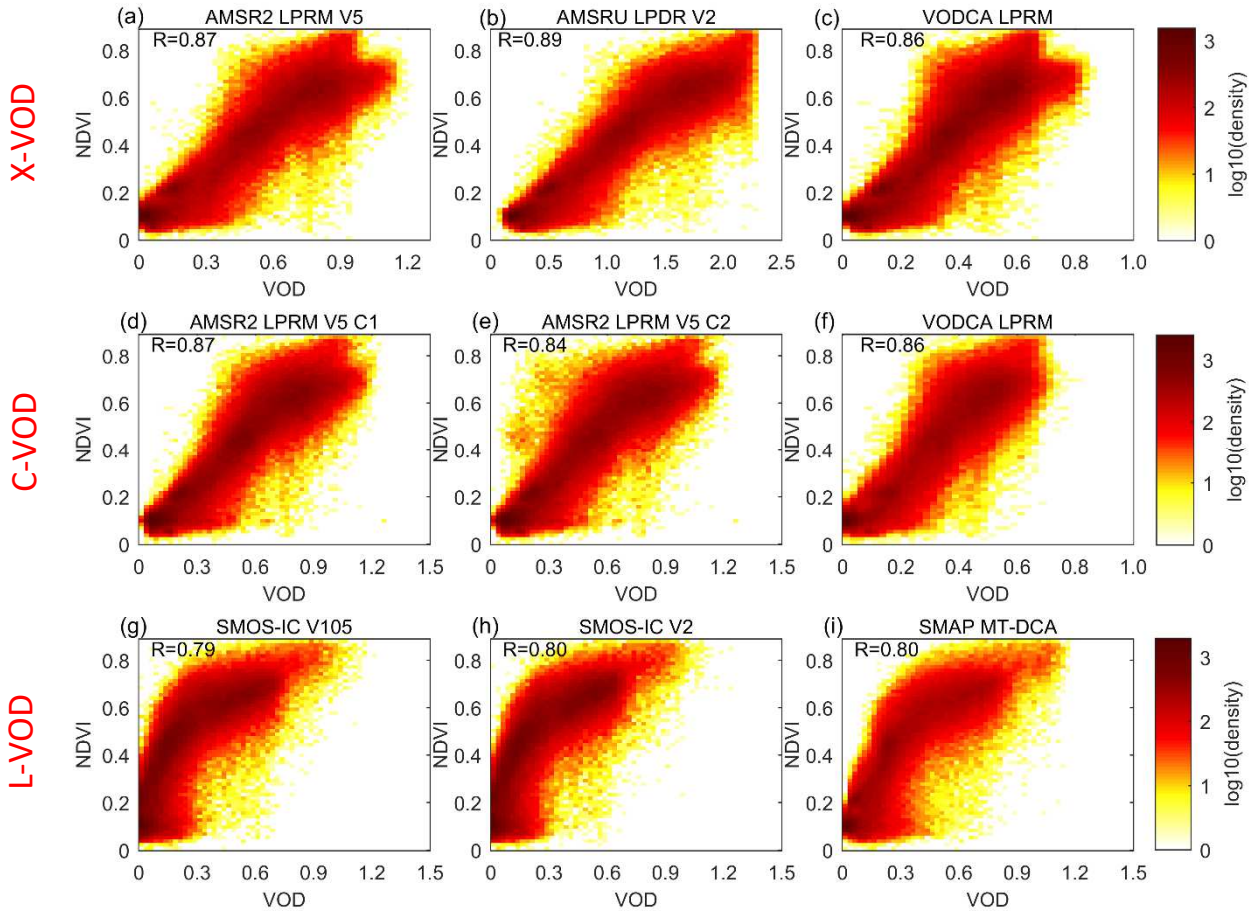
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422 **Fig. 4.** Hovmöller diagrams showing the 16-day mean values per latitude for the nine VOD products
423 at X-, C- and L-bands and for NDVI. Note that frozen soil conditions were removed during the data
424 pre-processing (Section 3.1), so that there is no-data at higher latitudes in winter.

425 4.2 Evaluating VOD against MODIS NDVI & EVI

426 4.2.1 *Spatial correlation*

427 The spatial correlation (R) of the nine VODs with mean NDVI and EVI is presented in Table 4,
428 while the corresponding density plots are shown in Fig. 5 and Fig. S3 (with EVI). When considering
429 the IGBP vegetation types altogether, all VODs were found to have a slightly higher correlation with
430 NDVI (Bold items in Table 4; $R=0.79-0.89$) than with EVI ($R=0.73-0.84$). This could be related to the
431 fact EVI is more sensitive to forest cover than to AGB as suggested by [Chaparro et al. 2019](#). The
432 highest correlation values were obtained between LPDR V2 X-VOD and NDVI/EVI, while SMOS-IC
433 V105 L-VOD had the lowest correlation with NDVI/EVI, although its value is very close to the other
434 L-VODs. We found that the slope between VOD and NDVI varies with VODs. The correlation
435 between VOD and NDVI or EVI is found to be generally higher for higher frequencies (L-VOD < C-
436 VOD < X-VOD), which is related to the fact that high-frequency VOD is sensitive to green vegetation
437 which is not the case for low frequency VOD ([Jones et al., 2013](#)). Moreover, both NDVI and EVI
438 saturate at moderate L-VOD values (~ 0.5) (Fig. 5 and Fig. S3). Therefore, as we mentioned in the
439 introduction, only comparing with optical vegetation indices is not enough to evaluate low frequency
440 VODs (such as L-VOD) that are relatively insensitive to green vegetation and more sensitive to non-
441 green vegetation components.



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Fig. 5. Density scatter plots showing the spatial relationship between time averaged VOD values for the nine products at X-, C- and L-bands and NDVI at the global scale.

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As the optical vegetation indices saturate over densely vegetated areas (Fig. 5) we listed only the spatial correlation between VODs and optical indices for relatively short vegetation IGBP types (i.e., non-forest and non-bare land types) in Table 4. The highest spatial correlation between VOD and vegetation indices can generally be found within shrublands, while the lowest correlation is for woody savannas followed by croplands, regardless of frequency or product (or algorithm). For X-VOD, the same R value ranking (AMSRU LPDR V2 > AMSR2 LPRM V5 > VODCA LPRM) was found over all short vegetation IGBP land cover types, except for woody savannas where VODCA LPRM has a higher correlation value than AMSR2 LPRM V5 compared to EVI. AMSR2 C1-band (6.9 GHz) VOD is generally found to have higher (or comparable) correlations with optical indices than the C2-band (7.3 GHz) VOD for these IGBP vegetation types. Considering low frequency L-VOD, SMOS-IC V2 has higher or comparable spatial correlation values with NDVI or EVI for all vegetation types than V105 and SMAP MT-DCA. The spatial correlation (R) values between the three L-VODs and NDVI (or EVI) were found to be lower than those of C-VOD and X-VOD over grasslands and croplands, while the R values are comparable over the other IGBP types. SMOS-IC V2 L-VOD presents even higher correlation values than C-band VODs for savannas, woody savannas and cropland/natural vegetation mosaic.

461 **Table 4.** Spatial correlation between the nine VOD products at X-, C- and L-bands and NDVI/EVI for
 462 different short vegetation IGBP types.

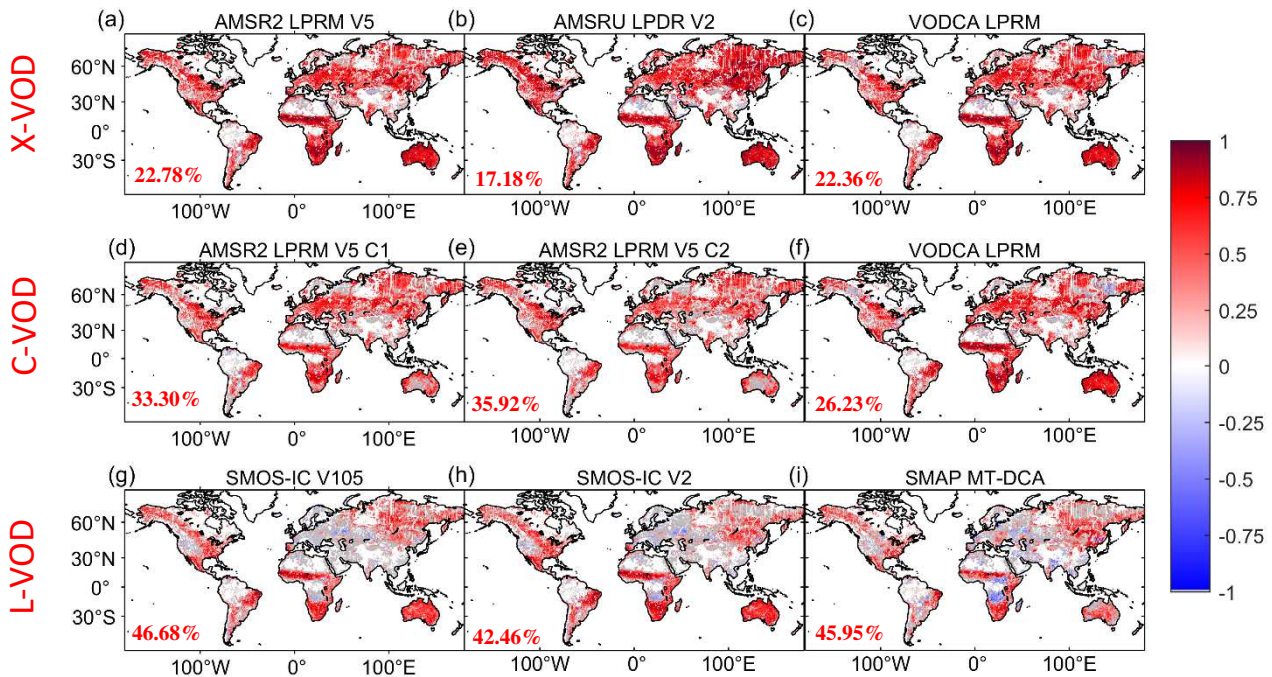
Frequency	Product	NDVI							EVI						
		SH	WS	S	G	C	CNVM	R_{total}	SH	WS	S	G	C	CNVM	R_{total}
X-VOD	AMSR2 LPRM V5	0.81	0.38	0.72	0.72	0.60	0.73	0.87	0.77	0.23	0.71	0.64	0.53	0.65	0.80
	AMSRU LPDR V2	0.83	0.43	0.75	0.74	0.62	0.74	0.89	0.78	0.41	0.76	0.65	0.59	0.74	0.84
	VODCA LPRM	0.79	0.34	0.69	0.71	0.57	0.70	0.86	0.75	0.27	0.69	0.63	0.51	0.63	0.79
C-VOD	AMSR2 LPRM V5 C1	0.81	0.36	0.68	0.73	0.59	0.71	0.87	0.77	0.26	0.68	0.64	0.53	0.65	0.80
	AMSR2 LPRM V5 C2	0.82	0.33	0.63	0.71	0.48	0.65	0.84	0.78	0.15	0.62	0.63	0.49	0.56	0.76
	VODCA LPRM C	0.79	0.30	0.56	0.70	0.58	0.71	0.86	0.76	0.27	0.57	0.62	0.52	0.63	0.80
L-VOD	SMOS-IC V105	0.78	0.42	0.68	0.55	0.47	0.72	0.79	0.73	0.23	0.67	0.46	0.43	0.70	0.73
	SMOS-IC V2	0.78	0.41	0.69	0.57	0.48	0.72	0.80	0.74	0.27	0.68	0.48	0.44	0.71	0.75
	SMAP MT-DCA	0.77	0.33	0.64	0.52	0.44	0.69	0.80	0.74	0.18	0.65	0.44	0.41	0.69	0.75

463 Note: all the correlation coefficients are significant considering the criteria $p < 0.05$.

464 Note that optical indices (i.e., NDVI or EVI) saturate when the vegetation cover is dense, so their
 465 applicability for a proper evaluation is limited to high frequency VOD. For a complementary
 466 comparison of VODs considering separately sparse and dense forest areas (i.e., evaluating VOD against
 467 forest canopy height), we refer to the supplementary material.

468 4.2.2 Temporal correlation

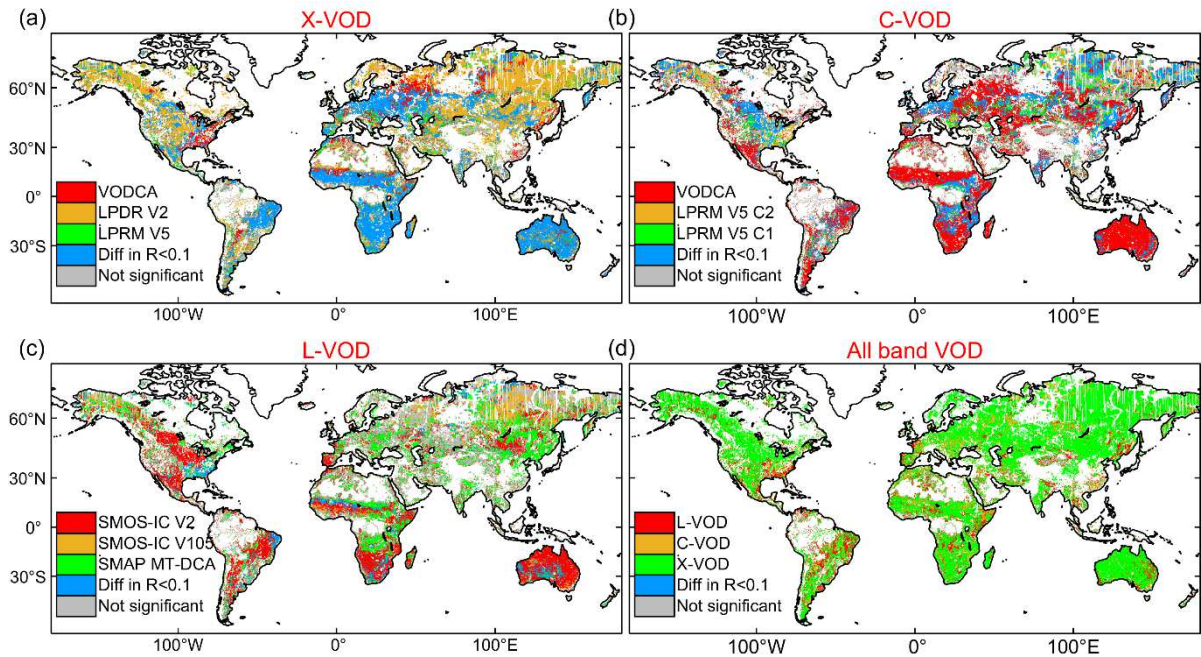
469 We found that the spatial patterns of the temporal correlation (R) values between VODs and NDVI
 470 or EVI are generally similar for all VOD products, whether they are obtained at the same frequency or
 471 not (Fig. 6 and Fig. S4). LPDR V2 X-VOD presents the highest temporal R values with NDVI or EVI
 472 among the nine VOD products over most of the globe, especially in central and eastern Russia
 473 ($R > 0.75$, Fig. 6) where most other products show relatively low correlations. More generally, all X-
 474 VODs are better correlated with NDVI than C- and L-VODs over most regions of the globe, in
 475 particular in areas where annual rainfall controls vegetation production, e.g., over Australia, southern
 476 Africa, Sahel, eastern Brazil, Mexico, and also in eastern Canada, and eastern Russia. All VODs were
 477 found to have non-significant R values ($p > 0.05$) over desert areas in central Asia and northern Africa
 478 and in most tropical areas (e.g., Congo and Amazon basins) with a low inter-annual green vegetation
 479 dynamic. The temporal R values between VOD and NDVI (or EVI) increase with frequency (L-VOD <
 480 C-VOD < X-VOD) over most regions of the globe, e.g., eastern Canada, Russia, India, central and
 481 eastern Europe; another fact is that the proportion of pixels with non-significant correlation values is
 482 also decreasing. However, there are some exceptions. For instance, reprocessed VODCA C- and X-
 483 VOD have almost comparable performance and both versions of SMOS-IC L-VOD still have higher
 484 temporal R values than AMSR2 LPRM V5 C1- and C2-VOD over eastern Brazil, western Sahel, south
 485 Africa and Australia. Interestingly, all L-VODs show a negative temporal correlation with NDVI or
 486 EVI (Fig. 6 and Fig. S4) in the dry tropical woodlands around the rain forests in the Congo Basin, in
 487 line with previous findings of the decoupling between seasonal changes in L-VOD (stem water content)
 488 and leaf phenology estimated from LAI (Tian et al., 2018, regions (i) and (ii) in their Fig. 3).



489 **Fig. 6.** Per-pixel temporal correlation (R) for the relationship between 16-day average values of the
 490 nine VODs at X-, C- and L-bands and MODIS NDVI from April, 2015 to December, 2017. Grey areas
 491 correspond to pixels where correlation is not significant ($p > 0.05$; their percentages are also given in
 492 the figure). White areas denote “no valid data”.
 493

494 To get an easier overview of the comparison considering the observation frequency, a map
 495 showing which VOD product has the strongest per-pixel correlation with NDVI (and by a difference in
 496 correlation R of 0.1 at least in absolute terms) is provided for each frequency separately in Fig. 7 (and
 497 in Fig. S5 for EVI). Note that the relationship to NDVI can be negative especially for L-VOD in dry
 498 tropical woodlands, as discussed above (Fig. 6g-i). At X-band, the strongest correlations are generally
 499 found for AMSRU LPDR V2 (over 36.24% of the pixels without considering non-significant
 500 relationships), while VODCA VOD shows highest R values over the eastern US and western Russia,
 501 and has a comparable performance with AMSR2 LPRM V5 X-VOD for other regions (Fig. 6). At C-
 502 band, VODCA C-VOD presents the highest correlation values over 53.92% of the pixels (Fig. 7b); in
 503 the eastern US AMSR2 LPRM V5 C2 generally shows the highest correlation values. For L-VOD,
 504 SMOS-IC V2 shows generally the highest correlation values (42.44% of the pixels), except in some
 505 Northern Siberian regions, eastern Sahel, Kenya and Miombo woodlands in Tanzania, where stronger
 506 correlation values are obtained with SMAP MT-DCA (32.44% of the pixels). It is worth to note that the
 507 temporal correlation between SMOS-IC V2 and NDVI is generally better than that obtained using
 508 V105 in most regions of the globe, especially over Mexico, eastern Brazil, southern Africa and
 509 Australia (Fig. 6 and Fig. 7). When considering frequencies rather than products (Fig. 7d), it is also
 510 interesting to note that, although X-VOD presents stronger correlation values with NDVI over most of
 511 the globe, L-VOD correlates better with NDVI than X-VOD in some regions (e.g., eastern US, mid-
 512 west Brazil and Miombo woodlands (Fig. S5)). This may be caused by the different time lags between
 513 NDVI and VOD at different frequencies. So, more generally, a higher correlation value between NDVI

514 and VOD cannot be directly interpreted as the ability of the VOD product to better capture the seasonal
 515 changes of vegetation. More details about the effects of time lags are discussed in 5.2. Similar plots
 516 using MODIS EVI confirm the results presented above for NDVI (Fig. S5) and, as for spatial
 517 correlation, lower temporal correlation values were obtained for the VOD / EVI relationship as
 518 compared to the VOD / NDVI relationship over most of the globe except in some eastern Europe and
 519 Northern Siberian regions (Fig. S6).



520
 521 **Fig. 7.** Maps of VOD products showing the strongest correlation (R) values with MODIS NDVI for a)
 522 X-VOD; b) C-VOD; c) L-VOD; d) All-band VOD for each pixel. The pixels for which the difference
 523 in R is lower than 0.1 in absolute terms are indicated by a blue color. Grey areas correspond to pixels
 524 where the correlation is not significant ($p > 0.05$). White areas denote “no valid data”.

525 The highest temporal correlation with NDVI or EVI per IGBP vegetation type (Table S4) is found
 526 for savannas regardless of frequency or product; this case is illustrated by the time series of VOD and
 527 NDVI at the savannas site (Fig. 8c). In general, the VODCA C-VOD has temporal correlation values
 528 comparable (or relatively closer than the other C-VODs) to X-VOD for the listed vegetation types
 529 (Table 4). Excluding this reprocessed product, the temporal correlations between L- and C- VODs and
 530 NDVI (or EVI) were found to be lower than those obtained with X-VOD for these short vegetation
 531 types (including considering the IGBP types altogether), while both versions of SMOS-IC L-VOD and
 532 C-VOD have comparable correlations over most IGBP types except woody savannas and croplands.
 533 Among the three L-band VOD products, SMAP MT-DCA L-VOD shows relatively low temporal
 534 correlations with NDVI and EVI for these short vegetation types, which is reflected in Fig. 8 where the
 535 SMAP L-VOD time series remain relatively stable, even when NDVI has strong dynamics. A deeper
 536 analysis of this is discussed in Section 5.1. SMOS-IC (V2) shows higher temporal correlations than C-
 537 band VODs (e.g., AMSR2 LPRM V5 C1- and C2-VOD) for shrublands and savannas (Table S4),

538 which is surprising. This may be due to the fact that L- and C-bands can both penetrate the canopy of
539 medium-densely vegetated biomes well.

540 4.2.3 *VOD Time series*

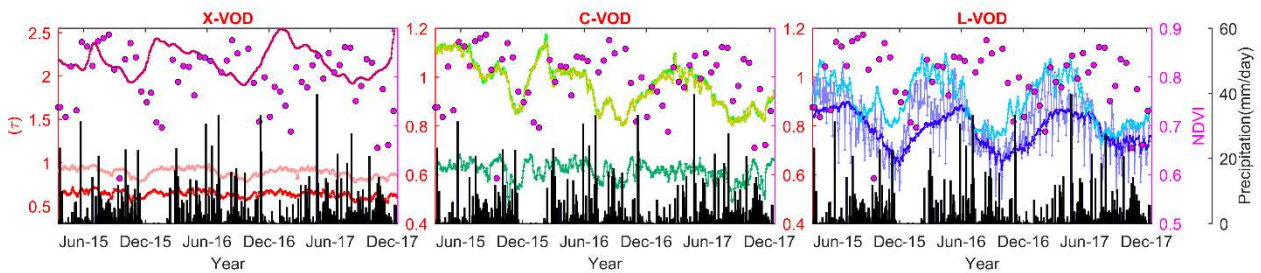
541 An analysis of the seasonal dynamics in the different VODs is here conducted based on daily time
542 series of the nine VOD products along with precipitation and NDVI at seven selected sites (Fig. 8,
543 Table 3). In general, LPDR V2 X-VOD was found to show smoother daily variations than the other
544 VOD products over all sites. It is also observed that SMOS-IC V2 VOD has a strongly reduced high
545 frequency variability compared to its previous version (V105), especially in dense vegetation, for
546 example over the evergreen broadleaf forest site in the Congo basin (Fig. 8a) and the mixed forests site
547 over Mexico (Fig. 8b). This is because SMOS-IC adopted in V2 a new constraint method accounting
548 for the fact that L-VOD has relatively low variations over short time periods (Wigneron et al., 2000).
549 Consistent temporal patterns were found between most VOD products and NDVI at sites with low
550 vegetation density, e.g. the savannas site over Brazil (Fig. 8c), the open shrublands site over south
551 Australia (Fig. 8d) and the croplands site over Nigeria (Fig. 8e). An interesting feature of the time series
552 is that some relatively small but distinct fluctuations in most VODs can be visually related to rainfall
553 events; some examples are the December 2015 rainfall event at the savannas site, the November 2015
554 rainfall event at the open shrublands site, the January 2017 rainfall event for the grasslands site. These
555 rainfall-related VOD variations could be a result from canopy-intercepted water and/or from changes in
556 the vegetation water status due to the increase in the soil moisture availability (Feldman et al., 2018;
557 Saleh et al. 2006).

558 Generally, for all sites, all VOD products and NDVI show a clear seasonality, i.e. increases during
559 the vegetation growing season and decreases in the senescence period. However, this pattern is more or
560 less pronounced depending on the sites and products, and some interesting features over the different
561 sites are described below: At the evergreen broadleaf forest site, all L-VOD products, LPRM V5 C1-
562 and C2-VOD, and LPDR V2 X-VOD show more dynamic variations in comparison with the LPRM V5
563 X-VOD, VODCA X- and C-VOD, and NDVI time series. However, even so, it seems that the seasonal
564 change in VOD for LPRM V5 C1- and C2-band, and LPDR V2 X-band is less stable than that of the L-
565 VOD products. Such a result was also found over the mixed forests site. These signatures may result
566 from the saturation effects in the high frequency VOD values (see Section 4.3) in densely vegetated
567 regions, which in turn lead to increased uncertainty in the retrievals. Over the savannas site in Brazil,
568 the seasonal dynamics in all VODs and NDVI are very consistent and highly correlated (e.g. R values
569 between 16-day averaged VOD of SMOS-IC V2 and NDVI is 0.94).

570 At the open shrublands site, a sudden decrease of AMSR2 LPRM V5 C1- and C2- VOD is
571 observed at the end of February 2016, which is abnormal (seen as well in the Hovmöller diagrams Fig.

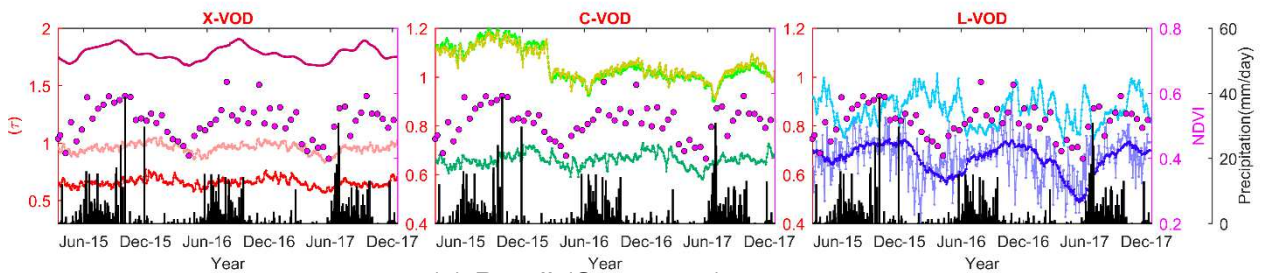
572 4). Ignoring this period, over that site, we found that most products could detect the relatively small but
 573 distinct fluctuations of VOD due to increased precipitation, whereas the LPDR V2 X-VOD time series
 574 failed to do so; for instance this can be noted for rainfall events that occurred in December 2016,
 575 January 2017, and March 2017. In the case of the croplands site, all VODs were found to lag with
 576 NDVI by ~ 16 days for LPDR V2 X-VOD and both versions of SMOS-IC L-VODs, and of ~ 30 days
 577 for the other VODs. A similar behaviour is also observed, at the grasslands site, although less
 578 pronounced. All these results are consistent with Lawrence et al. (2014), who found that the SMOS L-
 579 VOD values (which are more related to the whole vegetation canopy including leaves, stems and
 580 fruits/grains) generally peaked later than the MODIS LAI values (more related to the vegetation green
 581 fraction) with an estimated time difference of about 19 days over crop zones of the USA.

582



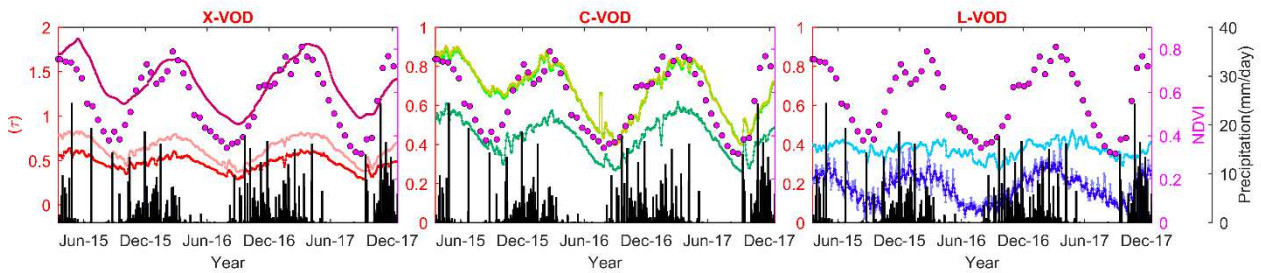
(b) Mexico (Mixed Forests)

583



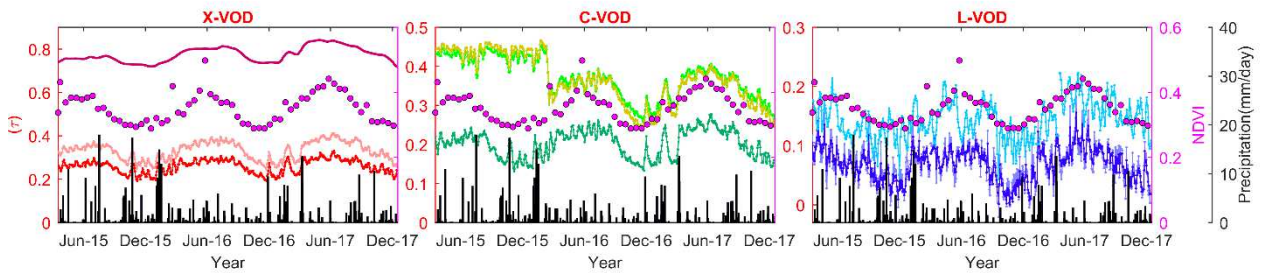
(c) Brazil (Savannas)

584

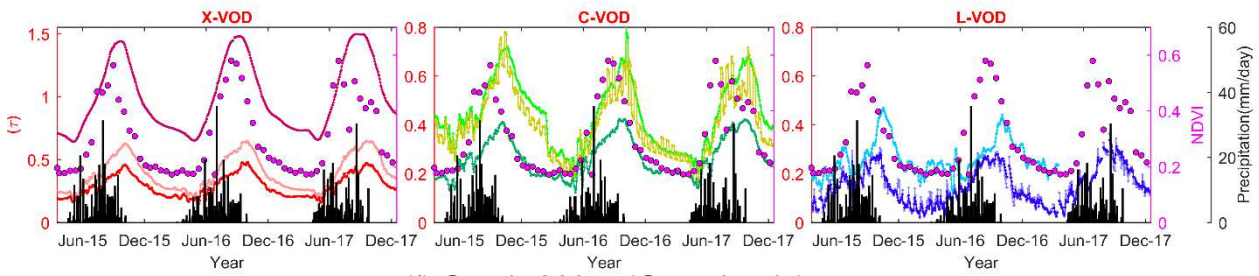


(d) South Australia (Open Shrublands)

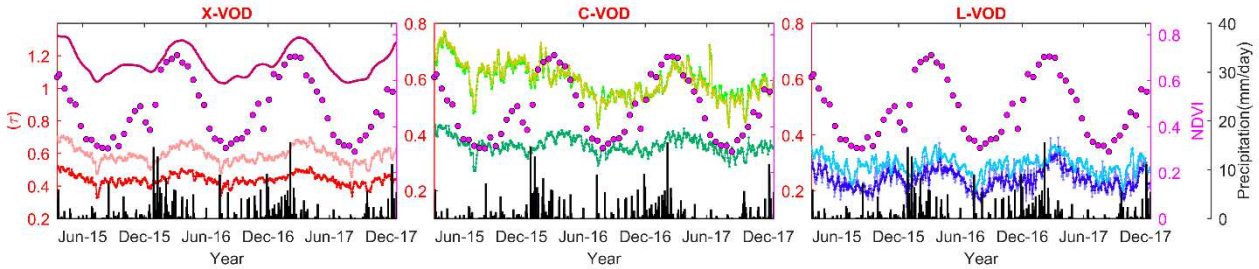
585



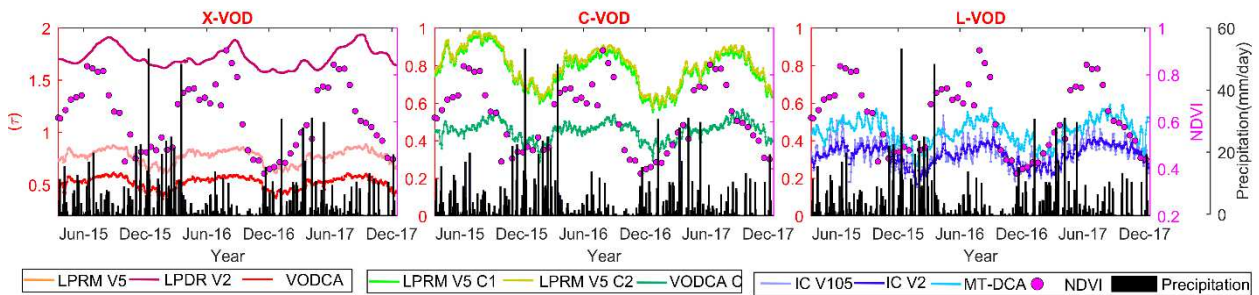
(e) Nigeria (Croplands)



(f) South Africa (Grasslands)



(g) South East US (Cropland/natural Vegetation Mosaic)



586

587

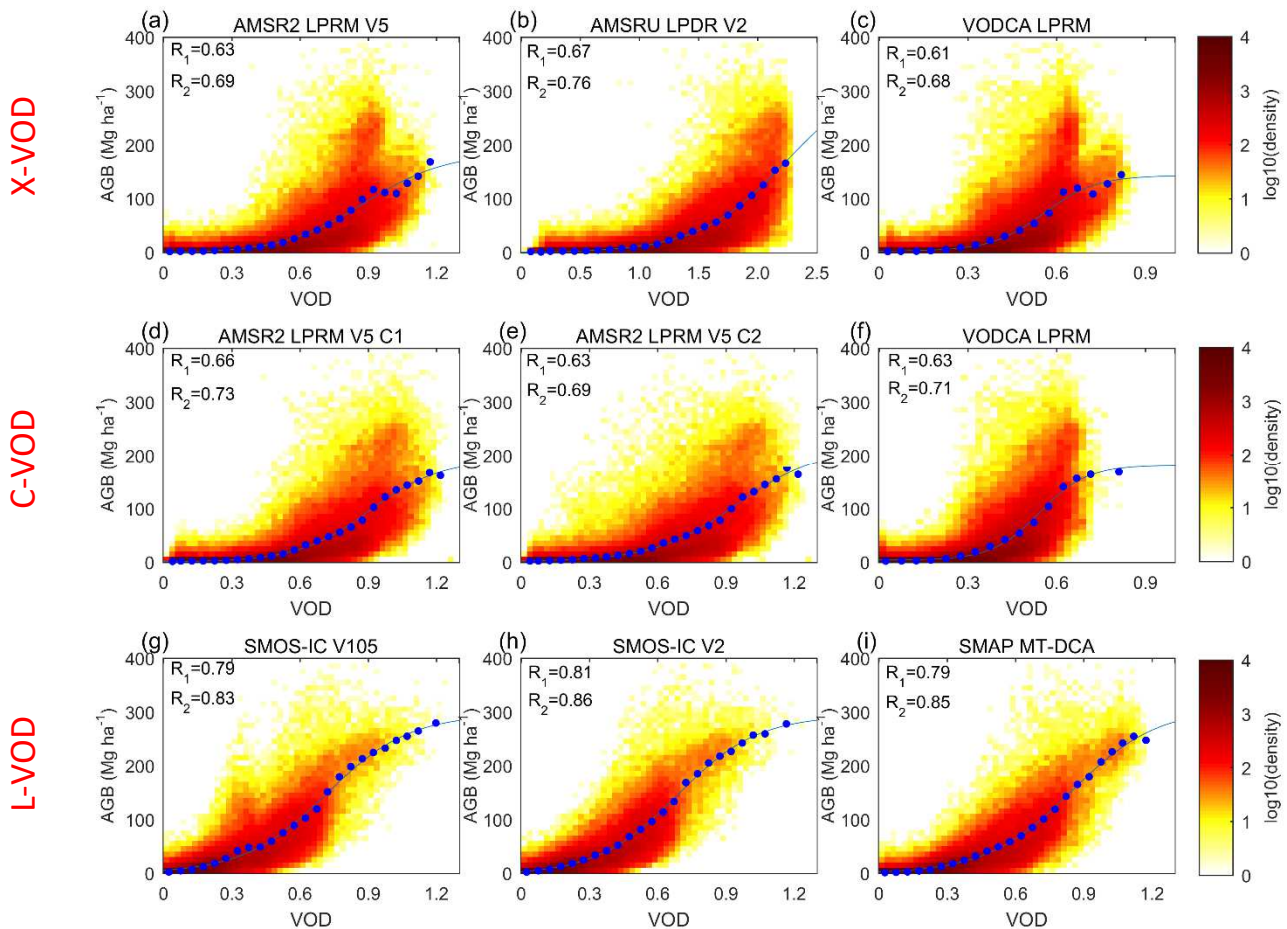
588

589 **Fig. 8.** Time series of the nine VOD products (smoothed with a moving window filter of seven days) at
 590 X-, C- and L-bands at selected sites from April 2015 to December 2017. Each plot also includes NDVI
 591 (shown in magenta dots; axis on the right) and daily precipitation (mm/day, shown in black; axis on
 592 the rightmost side) observed during the same period. Note: for completeness, Fig. 8a used data without
 593 quality control for LPDR VOD.

594 4.3 Evaluating VOD against aboveground biomass

595 Density scatter plots of VOD-AGB relationships for the nine VOD products at the global scale
 596 reveal (1) an obvious non-linear saturating relationship between VOD and AGB, and (2) less
 597 pronounced saturation for L-VOD (Fig. 9). The spatial correlation of the relationship between VOD
 598 and AGB is ~ 0.80 for the L-VODs and between 0.61 and 0.67 for X-VODs and C-VODs, respectively.
 599 At X-band, VOD obtained from reprocessed VODCA and AMSR2 LPRM V5 showed a similar
 600 dispersion and distribution shape, and the correlation values with AGB are lower than that obtained
 601 with LPDR V2 (Fig. 9a-c). At C-band, unlike LPRM V5 C1-band and C2-band which have a gradually
 602 smooth slope transition, the reprocessed VODCA VOD has a steep increase near $AGB \sim 50 \text{ Mg ha}^{-1}$
 603 ($VOD \sim 0.3$) (Fig. 9d-f). At L-band, the shape of the density distribution obtained with SMOS-IC V2
 604 has less distortion around $VOD \sim 0.3$ and $AGB \sim 120 \text{ Mg ha}^{-1}$ compared to V105, similar as SMAP
 605 MT-DCA (Fig. 9g-i). Notably, low-frequency L-VODs exhibit a high sensitivity to AGB, with a
 606 smooth relationship and without strong signs of saturation, which is not the case for high-frequency X-
 607 VODs and C-VODs.

608 Using the logistic function fitting (Section 3.2), both SMOS-IC V2 and SMAP MT-DCA L-VODs
609 predict surface AGB very well, with a correlation (R) of ~ 0.85 computed between predicted and
610 observed AGB (Fig. 9). Best results were obtained from L-VODs followed by X-band LPDR V2
611 ($R=0.76$), which performed better than the other X-band products (i.e., AMSR2 LPRM V5 and
612 VODCA LPRM X-VOD) and the C-band products. To achieve a fair comparison, we used identical
613 pixels for the nine products at X-, C- and L-bands, filtering out many pixels corresponding to
614 evergreen broadleaf forest (EBF) in tropical regions. This filtering was particularly due to the LPDR
615 V2 X-VOD product, which includes many regions with no data in the tropical area after quality
616 control (Fig. 2b) (such data gaps do not appear in the other VODs). This filtering leads to an
617 underestimation in the ability of the other products (e.g., L-VOD) to estimate AGB. So, in a second
618 step, we removed LPDR V2 from the comparison (the number of pixels increased by 8446 (6.02%) for
619 the remaining comparisons), and the spatial correlation and prediction ability of the reprocessed
620 VODCA was found to be slightly lower than LPRM V5 at both X-band and C-band when compared
621 with AGB (results in parentheses in Table 5 and in Fig. S7). In summary, the sensitivity of all the
622 VODs to AGB follows the order L-VOD > C-VOD > X-VOD and the correlation between predicted
623 AGB and observed AGB decreases from $R \sim 0.92$ to ~ 0.73 as the frequency increases.



624 **Fig. 9.** Density scatter plots showing the spatial relationship between time averaged VOD at X-, C-
625 and L-bands with AGB values. The mean AGB distribution in bins of VOD are displayed as blue
626 circles, while solid blue lines are the fits obtained using a logistic function (Eq. 1). R_1 represents the
627

628 spatial correlation between VOD and AGB, while R_2 represents the relationship between predicted
 629 AGB and reference AGB. All regressions are significant (p -value < 0.001, the best-fit parameters are
 630 shown in Table S5).

631 All nine VOD products were found to have the highest spatial R values with AGB for shrublands
 632 (Table 5). However, after removing LPDR V2 which has more data gaps, a comparably high R value
 633 for evergreen broadleaf forest was obtained for L-VODs (Table S6). Lower R values for X-VODs and
 634 C-VODs were generally found over forest biomes. At X-band, both LPRM V5 and VODCA showed a
 635 higher R value with AGB than LPDR V2 for evergreen needleleaf forest and grasslands, while it was
 636 the opposite for the other IGBP types. At C-band, LPRM V5 C1-VOD (or VODCA C-VOD) was
 637 found to have the lowest (or non-significant) R value over deciduous broadleaf forest. Interestingly,
 638 the correlation obtained by LPRM V5 C2-band (7.3 GHz) was higher than that obtained by C1-band
 639 (6.9 GHz) over most forest types, while the opposite result was found over the short vegetation types
 640 (Table 5). More generally, for most vegetation types, VODCA VOD shows slightly lower R values
 641 than LPRM V5. For low frequency L-VOD, higher R values were obtained for SMOS-IC V2 vs V105
 642 over most vegetation types, while the R values obtained by both versions of SMOS-IC were lower
 643 than those of SMAP MT-DCA over mixed forests. As expected, due to the improved propagation
 644 capabilities of the microwave radiations as the frequency decreases, the spatial correlation between
 645 VOD and AGB increased with decreasing frequency, and this feature is more obvious in dense forests,
 646 even from X-band to C-band (except VODCA VOD). However, for short vegetation, although the L-
 647 band still has the leading edge, results obtained at X-bands are very good and almost comparable to
 648 those obtained with C-VODs, in particular over woody savannas, savannas and cropland/natural
 649 vegetation mosaic.

650 **Table 5.** Spatial correlation of the nine VOD products at X-, C- and L-bands with AGB for different
 651 IGBP land cover classes.

Frequency	Product	ENF	EBF	DNF	DBF	MF	SH	WS	S	G	C	CNVM	B	R_{total}	$R_{estimate}$
X-VOD	AMSR2 LPRM V5	0.28	0.22	0.36	0.26	0.38	0.66	0.34	0.48	0.56	0.49	0.57	0.34	0.63(0.66)	0.69(0.75)
	AMSRU LPDR V2	0.14	0.19	0.40	0.25	0.41	0.68	0.44	0.52	0.54	0.51	0.63	0.37	0.67 (×)	0.76 (×)
	VODCA LPRM	0.24	0.16	0.38	-	0.38	0.66	0.33	0.46	0.55	0.45	0.54	0.36	0.61(0.64)	0.68(0.73)
C-VOD	AMSR2 LPRM V5 C1	0.31	0.32	0.42	0.28	0.40	0.68	0.40	0.51	0.58	0.51	0.58	0.28	0.66(0.73)	0.73(0.84)
	AMSR2 LPRM V5 C2	0.34	0.36	0.42	0.42	0.44	0.67	0.34	0.46	0.58	0.44	0.52	0.26	0.63(0.71)	0.69(0.81)
	VODCA LPRM C	0.32	0.28	0.34	-	0.35	0.64	0.34	0.39	0.56	0.47	0.54	0.35	0.63(0.68)	0.71(0.78)
L-VOD	SMOS-IC V105	0.37	0.59	0.66	0.54	0.18	0.73	0.53	0.63	0.63	0.61	0.73	0.39	0.79(0.86)	0.83(0.90)
	SMOS-IC V2	0.41	0.61	0.63	0.57	0.34	0.72	0.59	0.63	0.64	0.67	0.74	0.39	0.81(0.88)	0.86(0.92)
	SMAP MT-DCA	0.47	0.61	0.66	0.55	0.50	0.73	0.59	0.59	0.65	0.68	0.69	0.41	0.79(0.85)	0.85(0.91)

652 Note: [-] indicates that correlation is not significant (p -value>0.05). The number in brackets indicates the comparison result after removing LPDR V2 (the
 653 number of pixels increased from 140302 to 148748 (6.02%).)

654 5. Discussion

655 The results presented in this study have implications in two main fields. First, we revealed
 656 specific features and deficiencies in the VOD products that may provide useful hints for the remote

657 sensing community dedicated to VOD retrieval improvements. Second, our results may be useful for
658 the research community more dedicated to the use of the VOD products for vegetation monitoring.
659 These two main types of implications are discussed in the following sections.

660 5.1 Possible ways to improve the VOD retrievals

661 The analysis of the different results obtained in this study revealed specific features or
662 deficiencies of some products:

663 (i) For LPRM V5 products, the magnitude of X-VOD < C-VOD over some dense forests (Fig. 2
664 and Fig. 3) does not meet the theoretical principle that the penetration of microwave radiations within
665 the vegetation canopy should decrease with frequency due to increasing extinction effects;

666 (ii) LPDR V2 X-VOD time series failed to detect changes in VOD after rainfall events (Fig. 8)
667 whereas most VOD products could do so, and overall LPDR V2 X-VOD has smoother daily variations;

668 (iii) The MT-DCA approach for SMAP has lower correlation with optical datasets (NDVI, EVI)
669 than SMOS-based L-band products (Fig. 8 and Table S4);

670 (iv) The spatial correlations between L-VODs and MODIS VIs were found to be lower than those
671 of C- and X-VODs particularly over grasslands and croplands (Table 4), while all VODs have
672 comparable performances over the other relatively short vegetation IGBP types.

673 (v) C- and X-VODs have a comparable or even higher spatial correlation with respect to canopy
674 height than L-VODs over evergreen needleleaf forest and mixed forests (Table S2). This relative
675 deficiency of the L-VODs was noted particularly in boreal regions.

676 All these findings indicate that there is some margin to improve the current VOD products or
677 algorithms, but also keeping in mind their field of application. Concerning deficiencies (i), the
678 evaluation/calibration of the model parameters (e.g., roughness (H_R) and effective scattering albedo
679 (ω)) may need to be reconsidered to develop improved products. Considering the calibration of ω ,
680 divergences could be noted in different studies. For instance, [Baur et al. \(2019\)](#) found that ω decreased
681 slightly with frequency or showed highest values at C-band when retrieving simultaneously VOD and
682 ω at X-, C-, and L-bands. However, the setting of ω in the LPRM V5 algorithm is reversed (the
683 calibrated value of ω is increasing with frequency) (Table 2). Uncertainties associated with the
684 roughness and ω parameters affect all VOD products, not just those from LPRM - there is still no
685 consensus on how the roughness parameters change with frequency (even though [Wigneron et al.](#)
686 [\(2017\)](#) found these changes are relatively low), and how these changes affect the VOD retrievals at
687 different frequencies. Indeed, differing assumptions for the values of these ancillary parameters may
688 also explain the very different magnitudes of the X-VOD values between the LPDR and LPRM

689 datasets (although these could also be caused by differing corrections for the effects of open water
690 bodies and land surface temperature between the datasets). In addition, the H_R roughness parameter
691 may also have a considerable effect on the retrieved values of VOD, SM and ω (Fernandez Moran et
692 al., 2017a, 2017b; Karthikeyan et al., 2019). For instance, at L-band, changes in roughness can be
693 partially accounted for by changes in L-VOD, leading to a low impact on the SM retrievals but a
694 strong impact on L-VOD (Hornbuckle et al., 2017; Parrens et al., 2016).

695 Issues (ii) and (iii) are both related to assumptions made in the algorithm development. For
696 instance, the LPDR algorithm assumes a constant dry bare soil emissivity in the VOD retrievals (Table
697 2), which may balance/ignore the impact of rainfall on the simulated TB in the original τ - ω equation
698 (Du et al., 2017). Another possible reason is that a 30-day moving median filter is applied to its daily
699 VOD values (Jones et al., 2011), which also makes its time series smoother than for the other products
700 in Fig. 8. As for SMAP, to solve the under-determined retrieval problem of the dual-channel
701 algorithm (DCA) from its single-angle TB, MT-DCA was developed assuming that VOD is constant
702 over a time window. However, this assumption is likely to be violated especially over grasslands and
703 croplands where vegetation growth can be very fast, e.g., the VOD value can increase by ~ 0.2 [-] per
704 10 days in a cornfield (Jackson et al., 2004), or right after a rain storm, when the relative vegetation
705 water content increases quickly. Besides, the temporal changes of emissivity are not evenly distributed
706 across the globe, which may also affect the performance of MT-DCA (Gao et al., 2020b). One
707 possible way to improve the weak assumption in MT-DCA is to take into account the slow changes of
708 VOD using a smooth-regularization technique (Gao et al., 2020a).

709 Issues (iv) and (v) could be partly related to the fact the IGBP classification used here does not
710 match the study period, and pure biomes are also very rare in the 25 km land classification: in reality
711 all pixels are more or less heterogeneous and include a variety of IGBP land vegetation types. On the
712 other hand, it is likely issues (iv) and (v) revealed specific retrieval issues for some ecosystems, e.g.,
713 grasslands, croplands and boreal regions. Possible reasons are briefly discussed in the following.
714 Grasslands exhibit complex microwave signatures at L-band, due to the presence of a thatched litter
715 layer of dead grass under the green vegetation in non-plowed areas (Grant et al., 2016; Saleh et al.,
716 2007). Such a thatched litter layer, particularly when it is wet, can have a large effect on the L-band
717 emission and/or may lead to complex coherent scattering effects within the vegetation layer, for
718 specific moisture status of the vegetation, litter and soil layers (Grant et al., 2009). These effects may
719 be lower for high-frequency observations as the latter are more sensitive to the top-of-the-canopy layer.
720 For croplands, changes in surface roughness due to farming practices may impact the VOD retrievals
721 (Fernández-Morán et al., 2015; Patton and Hornbuckle, 2012) and this impact may be more
722 pronounced at L-band than at X- and C-bands for some specific soil/vegetation conditions (Montpetit
723 et al., 2015).

724 In boreal regions, the VOD retrievals may be intricate due to specific features (e.g., open water
725 bodies and frozen conditions) of the ecosystems in the northern regions. In the latter regions, large
726 climatic variations support the existence of diverse conifer forests types, with very different tree
727 densities with specific phenological behaviors, in particular for deciduous needleleaf forest (DNF)
728 which are prevalent in east Siberia (Crowther et al., 2015). Moreover, both broadleaf and needleleaf
729 species coexist in most boreal forests, making VOD temporal averaging delicate and temporal
730 averaging can be only calculated over a limited period, since the data in winter are often affected by
731 frozen/snow conditions. Furthermore, soils in the boreal regions are characterized by a high content of
732 organic matter leading to distinct dielectric behaviors, as organic materials differ from the mineral
733 ones by their complex structure, large specific surface area, high porosity and small bulk density
734 (Wigneron, et al., 2017). Such an effect is not considered in VOD retrieval algorithms (Table 2) and
735 particularly in the two L-VOD retrieval algorithms (SMOS-IC and SMAP MT-DCA) which currently
736 use the Mironov dielectric mixing model (Mironov et al., 2004) based only on the clay fraction. Thus,
737 adopting a new dielectric model applicable to organic soils in boreal regions may be considered in
738 future generations of the VOD retrieval algorithms (Mironov et al., 2019). Finally, the RFI impact is
739 also very important in the boreal regions, especially at L-band (Al-Yaari et al., 2019).

740 5.2 Limitations of the evaluation approach

741 It should be noted that there are some limitations in the VOD evaluation made here that should be
742 considered for a better interpretation of the results in VOD application studies. First, temporal
743 correlation between VOD and optical VIs (Fig. 6 and Fig. 7) cannot be used as an "absolute" criterion
744 for judging the quality of the different products as low or even negative temporal R values can be
745 explained by a temporal lag between different climate and vegetation variables (SM, X/C/L-VOD,
746 LAI, EVI) in some ecosystems (Jones et al., 2011). For instance, Jones et al. (2014) found that the
747 period of canopy biomass growth (indicated by X-VOD), maximum water availability and net leaf
748 flush in the Amazon forests are asynchronous and follow a gradient from west to east, which reveals
749 the adaptability of the Amazon forests to water and light availability. Similarly, Tian et al. (2018)
750 found that SMOS L-VOD lags the leaf development by up to ~180 days in dry tropical woodlands,
751 explaining that L-VOD vs optical VIs showed a negative correlation in some regions such as the large
752 Miombo woodlands south of the Congo basin (Fig. 6g-i). A time lag of ~19 days between L-VOD and
753 LAI was also found for crops in the USA (Lawrence et al., 2014), similarly to the site analysis
754 presented in this study (Fig. 8e) (a time lag was found here for all the X-, C- and L-band VODs).

755 Additionally, the proxies we chose, MODIS VIs, Lidar tree height and AGB, although widely
756 used in VOD evaluation studies (Fan et al., 2019; Liu et al., 2011; Rodríguez-Fernández et al., 2018),
757 cannot be considered as "truth" (Li et al., 2020a). Moreover, the impact of daily or seasonal changes in

758 the vegetation water status as considered in other fields of research by [Konings et al. \(2019\)](#) and [Tian](#)
759 [et al. \(2018\)](#), were not evaluated/removed here when evaluating VOD against annual AGB maps.
760 Similarly, averaging VOD retrievals to 16-day to analyze its ability to monitor the vegetation
761 dynamics may also ignore some information observed by daily-scale VOD, e.g., pulse-reserve
762 paradigm ([Feldman et al., 2018](#)). This latter topic would require a specific analysis based on other
763 proxies of the vegetation water status and water stress ([Konings et al., 2019](#)) and will be considered in
764 more focused future studies. Nevertheless, in spite of their limitations, we think the chosen proxies are
765 relatively complementary in this study to evaluate VOD retrievals as (i) correlation with MODIS VIs
766 could be regarded as a criterion more pertinent for short vegetation canopies. We noted too that higher
767 correlation values in both temporal and spatial terms and for most vegetation types were generally
768 found between VOD and NDVI as compared to VOD and EVI; (ii) correlations with global tree height
769 and biomass is considered relevant for woody vegetation types. In the future, triple collocation (TC) or
770 TC-related methods may also be used to estimate the correlation metric of satellite vegetation optical
771 products relative to unknown ground truth ([Dong et al., 2019](#); [Gruber et al., 2016](#)), once an
772 independent vegetation optical product is available (e.g., ASCAT active VOD; [Liu et al., 2020](#)).

773 **6. Concluding remarks and outlook**

774 In this study, the performance of nine recently developed/reprocessed microwave satellite VOD
775 products at L-, C- and X- bands for monitoring vegetation features, were assessed and inter-compared
776 in relation to seasonal change and of sensitivity to biomass at the global scale. The nine VODs were
777 evaluated against MODIS VIs (i.e., NDVI and EVI), tree height, and AGB across different IGBP
778 vegetation types. We found that:

- 779 (i) X-VODs, particularly in the LPDR version, have a stronger ability than C- and L- VODs to
780 monitor seasonal changes in the green vegetation components in regions which are not densely
781 vegetated, and they show higher temporal correlation values (R) with MODIS VIs (median R
782 values of 0.74 at the global scale). More surprisingly, low frequency L-VOD, particularly the new
783 SMOS-IC V2 version also shows high temporal correlation values with VIs similar to C-VODs in
784 some biomes such as savannas (R~0.70).
- 785 (ii) L-VODs which have stronger penetration capabilities within the vegetation canopies than high-
786 frequency products, show a high spatial correlation with canopy height, with SMOS-IC V2 and
787 SMAP MT-DCA showing similar scores at global scale (R ~ 0.90). Moreover, we reveal a good
788 linear relationship with a low dispersion with respect to tree height, even in tall forests.
- 789 (iii) L-VODs are more sensitive to the non-green vegetation components (trunks and branches) than
790 the higher frequency (i.e., X- and C-VOD) products, thus showing a high correlation with

791 aboveground biomass. Logistic fitting function provided a correlation between predicted AGB
792 and observed AGB of $R \sim 0.91$ for SMOS-IC V2 and SMAP MT-DCA L-VOD at a global scale.

793 Our results suggest that it may be very interesting to analyze the time lags of VODs computed at
794 different frequencies and vegetation or climate variables, as it may help us to better understand the
795 adaptability of the vegetation ecosystems to water and light availability and temperature conditions, as
796 done by [Jones et al., \(2014\)](#) in the Amazon forests. Further studies can now be made, considering the
797 availability of long-term and improved sequences of L-VODs, that can provide information on forest
798 dynamics for deeper layers of the canopy, e.g., SMOS-IC L-VOD is now available for 10 years (Table
799 1). Moreover, VODs can be particularly useful in regions where the optical observations are affected
800 by atmospheric and aerosol effects and by cloud cover, as VODs are retrieved independently of the
801 optical-near infrared remote sensing-based VIs and are relatively insensitive to signal perturbation
802 from sun-sensor illumination conditions and atmospheric effects. Conversely, optical VIs have a
803 relatively higher spatial resolution and VOD and optical VIs may thus be used complementary. Their
804 synergistic use could provide a more comprehensive assessment of dynamic vegetation features such
805 as phenology ([Jones et al., 2011](#)) and carbon stocks ([Chaparro et al., 2019](#)).

806 We expect that our findings can contribute to improve the satellite vegetation optical depth
807 retrieval algorithms by reporting on strengths and weaknesses of current VODs depending on the
808 vegetation features (leaf development, structure, height and biomass). Our findings could also help
809 selecting best suited VOD product depending on the applications and contribute to promote the use of
810 VODs for vegetation monitoring on the subjects of carbon stocks, vegetation dynamics and phenology.

811 **Appendix A. remotely sensed VOD products**

812 *A.1 SMOS-IC (V105&V2)*

813 The ESA's SMOS mission, which was launched on November 2, 2009, was the first L-band
814 space-borne mission dedicated to monitoring global land soil moisture ([Kerr et al., 2010](#)). It is
815 equipped with a microwave synthetic aperture radiometer (1.4 GHz) which can provide multi-angle
816 and dual-polarized brightness temperature (TB) observations over a range of incidence angles (~ 0 –
817 60°). This observational feature allows to robustly infer properties of the soil and vegetation (i.e.,
818 retrieving SM and VOD) simultaneously from the SMOS data ([Wigneron et al., 2017](#)). In this context,
819 to make efficient use of the TB observations (that is, to be as much as possible independent from
820 auxiliary datasets), an alternative SMOS SM and VOD product (initially called SMOS-INRA-
821 CESBIO or SMOS-IC) was developed and the first publicly released version was V105 ([Fernandez-
822 Moran et al., 2017a, 2017b](#)). SMOS-IC has the main following features:

- 823 i) independent of auxiliary data: contrary to the official algorithms no ECMWF modelled SM data or
824 MODIS LAI products are used in SMOS-IC; only ECMWF temperature is used currently
825 (Fernandez-Moran et al., 2017a; Li et al., 2020a);
- 826 ii) relative to the baseline SMOS algorithms, it is simpler and avoids uncertainties and errors
827 associated with inconsistent auxiliary datasets and decision trees which are adopted to characterize
828 the pixel heterogeneity in the other SMOS algorithms (Wigneron et al., 2018);
- 829 iii) it is based on new maps of model parameters for soil roughness and vegetation scattering effects
830 (Fernandez-Moran et al., 2017a; Parrens et al., 2016).

831 All the above features make SMOS-IC products very performant compared to other products
832 for both SM (Al-Yaari et al., 2019; Dong et al., 2020; Ma et al., 2019; Sadeghi et al., 2020) and VOD
833 (Rodríguez-Fernández et al., 2018). For instance, in terms of SM, recent inter-comparison studies have
834 shown that the SMOS-IC SM product is very accurate and close to the performances of SMAP (Al-
835 Yaari et al., 2019), and possibly reaching best performances over dense vegetation canopies (Ma et al.,
836 2019). In terms of VOD, the SMOS-IC VOD products have been found to provide more accurate
837 relationships than the CATDS (Centre Aval de Traitements des Données SMOS) official SMOS
838 products to estimate above ground biomass (Rodríguez-Fernández et al., 2018). The SMOS-IC VOD
839 products have been increasingly used over the very recent years in a number of applications, such as
840 monitoring vegetation seasonality (Tian et al., 2018), crop modelling (Chaparro et al., 2018), and
841 carbon cycle (Bastos et al., 2020; Brandt et al., 2018; Fan et al., 2019; Wigneron et al., 2020), etc.

842 Since the release of the first version V105, several improvements have been applied to the SMOS-
843 IC algorithm, leading to the production of the version 2 (V2), based on a collaboration between
844 INRAE and China Scholarship Council. A major improvement concept is that VOD has low time
845 variations over short time periods (Tian et al., 2018; Wigneron et al., 2007), which was not properly
846 considered in V105. To implement this concept, the optimization processing of the *a priori* information
847 on VOD to constrain the retrievals has been modified in SMOS-IC V2: to retrieve VOD at a date t ,
848 previously retrieved VOD values (over a period of 10 days before date t) are used to initialize the first
849 guess value of VOD (VOD^{ini}) in the cost function. Readers are referred to Wigneron et al. (Submitted)
850 for more detailed description of the SMOS-IC V2 retrieval algorithm. It should be noted that the
851 improvements in SMOS-IC V2 are obvious for both SM and VOD. As the focus of this study is VOD,
852 the assessment of SM is not presented here (Li et al., 2020b; Wigneron et al., Submitted).

853 Both versions of SMOS-IC products are projected on a global Equal Area Scalable Earth Grid
854 version 2 (EASE-Grid 2.0), and the SM datasets of V105 are available in the Network Common Data
855 Form (NetCDF) format through CATDS for both ascending (6:00 am) and descending (6:00 pm)
856 orbits with a spatial resolution of 25 km. In this study, we used both versions of SMOS-IC VOD

857 retrieved using observations acquired from the ascending orbits, at early morning, which are less
858 sensitive to the vegetation water status than observations acquired in the afternoon from the
859 descending orbits.

860 *A.2 SMAP MT-DCA*

861 The NASA's SMAP mission, which was launched on January 31, 2015, is the most recent L-band
862 space-borne satellite for global soil moisture and landscape freeze/thaw state mapping (Entekhabi et
863 al., 2010). Since the radar instrument (1.26 GHz) failed after about 11 weeks of operation, SMAP has
864 only relied on the passive radiometer (1.41 GHz) to collect fully-polarized TB operating at a single
865 incidence angle of 40°. This single-angle configuration limits the robustness of retrievals of both SM
866 and VOD from a dual-channel algorithm (DCA) as the Horizontal (H-) and Vertical (V-) polarized TB
867 observations contain some shared information (O'Neill et al., 2015; Konings et al., 2016). After
868 comparing several algorithms, the driving SM inversion algorithm of the SMAP mission is a single-
869 channel algorithm (Jackson, 1993) based on V polarization (SCA-V), which NDVI data is used as
870 ancillary information to estimate VOD in the retrieval process (Chan et al., 2013). In contrast, by
871 considering multi-temporal (MT-) observation information in the DCA approach, a new algorithm
872 called MT-DCA was developed for simultaneously retrievals of SM, VOD and effective scattering
873 albedo without using ancillary datasets on vegetation (Konings et al., 2016; 2017). One of the main
874 assumptions of MT-DCA is that the temporal variations of VOD is slower than that of SM and the
875 values of VOD are assumed to be almost constant for two consecutive overpasses. Readers are
876 referred to Konings et al. (2016, 2017) for more information about this algorithm.

877 The latest SMAP MT-DCA (V4) L-VOD including 9 km and 36 km is available in a binary
878 format (.mat) on a global EASE-Grid 2.0 through <http://afeldman.mit.edu/mt-dca-data>. In this study,
879 we used the 9 km SMAP MT-DCA L-VOD covering about 2 years and a half (see Section 3.1). This
880 dataset was retrieved from the SMAP Level 1C Enhanced Brightness Temperature Product
881 (L1C_TB_E) with the descending orbit (6:00 AM) as input.

882 *A.3 AMSR2 (LPRM&LPDR)*

883 The AMSR2, which was launched by JAXA on May 17, 2012, is an improved successor of
884 AMSR-E onboard GCOM-W1. AMSR2 has similar orbits, bands and local overpass times (1:30 am
885 for descending orbit and 1:30 pm for ascending orbit) as AMSR-E (Imaoka et al., 2012). In addition, it
886 also includes a second C-band channel (C2-band, 7.3 GHz), which can be applied to cover areas where
887 RFI exists in the main C1-band channel (6.9 GHz). In this study we used AMSR2 VOD products for
888 the descending orbits computed from two reference algorithms (i) LPRM (Land Parameter Retrieval
889 Model; Owe et al., 2008) and (ii) LPDR (Land Parameter Data Record; Du et al., 2017b). These

890 AMSR2 VOD products have the same sample resolution of 25 km and are briefly described in the
891 following.

892 In the LPRM algorithm, based on the 0th-order Tau-Omega emission model (Mo et al., 1982),
893 both SM and VOD are obtained simultaneously from the Microwave Polarization Difference Index
894 (MPDI) with the use of an analytical retrieval methodology (Meesters et al., 2005). In the present
895 study, we used the AMSR2 VOD product retrieved from LPRM V5 (Owe et al., 2008), as the latest
896 version (V6) is not publicly available (van der Schalie et al., 2017). The LPRM V5 retrieval process
897 used AMSR2 spatial-resolution-matched TB (L1SGRTBR) as input TB data, and the input land
898 surface temperature was retrieved separately from the AMSR2 Ka-band (36.5 GHz; Holmes et al.,
899 2009). Here, we used the descending VOD products from AMSR2 C1-, C2-, X-band (Vrije
900 Universiteit Amsterdam and NASA GSFC, 2014).

901 The LPDR version 2 (V2) is an enhanced data record over prior (V1) LPDR, in which X-band
902 VOD is obtained by inverting the land-water microwave emissivity slope index (Du et al., 2017b). In
903 comparison to the previous version (Jones et al., 2010), V2 has advantages in both temporal coverage
904 and retrieval accuracy, and the main refinements and updates include: i) extended time period from
905 AMSR-E (June 19, 2002) to AMSR2 (December 31, 2018) by empirically calibrating the AMSR2
906 multi-frequency TB retrieval algorithm on the same channel as AMSR-E; ii) refined AMSR2
907 estimation of the daily maximum and minimum surface air temperature by considering terrain and
908 latitude effects (Du et al., 2015); iii) improved SM retrieval by using a dynamic selection of
909 vegetation-scattering albedos (Du et al., 2016). We refer readers to Du et al. (2017b) for further
910 detailed information on this algorithm. The LPDR V2 X-VOD is projected on global EASE-Grid (V1)
911 with a GeoTIFF format and is freely available via (<https://nsidc.org/data/nsidc-0451>).

912 *A.4 VOD Climate Archive (VODCA)*

913 The TU Wien's VODCA product, which combined multiple single-sensor VOD retrievals derived
914 using LPRM algorithm, is a global daily VOD product with a sampling resolution of 0.25 degrees
915 (Moesinger et al., 2020). This product was inspired by Liu's long-term (1987–2008) harmonized multi-
916 sensor VOD dataset (Liu et al., 2011) and ESA's first long-term satellite-based climate data record of
917 soil moisture within the Climate Change Initiative (ESA CCI SM; Gruber et al., 2019). It is based on a
918 similar core methodology as Liu et al. (2011) but incorporates new insights into VOD and the
919 strategies in the production of ESA CCI SM climate data records in recent years (Moesinger et al.,
920 2020). Specifically, unlike Liu et al. (2011), which harmonized all observations to AMSR-E's high-
921 quality C-VOD, this product is a frequency-specific VOD dataset as different frequencies carry
922 valuable specific information suitable for various applications (Teubner et al., 2019). VODCA
923 combined VOD observations from AMSR2, WindSat, AMSR-E, Tropical Rainfall Measuring Mission

924 (TMI), and Special Sensor Microwave/Imager (SSM/I) into long-term VOD datasets at C-band (period
925 2002–2018), X-band (1997–2018), and Ku-band (1987–2017). The biases between the VOD values
926 retrieved from different sensors were eliminated by scaling them to AMSR-E VOD using a new
927 implementation of the cumulative distribution function matching technique; further detailed
928 information about the retrieval algorithm are given in [Moesinger et al. \(2020\)](#). In this study, we only
929 used VODCA X- and C-VOD, as the Ku-VOD products were incomplete in 2017 (no data from
930 August to December).

931 Acknowledgments

932 This work is conducted under the support by both CNES, France (Centre National d'Etudes
933 Spatiales) and the China Scholarship Council (201804910838). Lei Fan acknowledges additional
934 support from the National Natural Science Foundation of China (Grant No. 41801247) and Natural
935 Science Foundation of Jiangsu Province (Grant No. BK20180806). Alexandra G. Konings was
936 supported by the NASA Terrestrial Ecology (award 80NSSC18K0715) through the New Investigator
937 Program. We would like to thank Dr. Robin van der Schalie from Transmissivity B.V./VanderSat for
938 spending his precious time to check the parameters of LPRM V5 in Table 2.

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