INFLUENCE OF SURFACE WATER VARIATIONS ON VOD AND BIOMASS ESTIMATES FROM PASSIVE MICROWAVE SENSORS

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ABSTRACT

Vegetation optical depth (VOD) is a remotely sensed indicator characterizing the opacity of the vegetation layer. This study focuses on the behaviour of L-band VOD (L-VOD) retrieval algorithm over seasonally inundated areas, as previous observations have shown an unexpected decline in VOD during floods. The signal emitted by a mixed scene composed of soil and standing water was simulated, leading to an overestimation of the retrieved soil moisture (SM) and an underestimation of the retrieved L-VOD, typically by ~10% over flooded forests and up to 100% over flooded grasslands. We evaluated the induced underestimation of aboveground biomass (AGB) by 15/20 Mg ha⁻¹ in the largest seasonal wetlands, which can represent more than 50% of the actual AGB of the savanna wetland, and up to higher values during exceptional years. Surface water seasonality needs to be taken into account in passive microwave retrieval algorithms to better estimate the global biomass.

Index Terms— biomass, water fraction, passive microwaves, SMOS, L-band, VOD, retrievals

1. INTRODUCTION

Passive microwaves have recently been arousing greater interest to infer biomass. A strong synergy was found between K-band vegetation optical depth (K-VOD) from AMSR-E satellite and other vegetation indices (NDVI, EVI, LAI) time series [1]. AMSR-E C- and X-VOD were used to monitor the evolution of aboveground biomass carbon [2]. L-VOD measured with SMOS satellite was also proven to be highly sensitive to aboveground biomass (AGB) in Africa, with less saturation over dense forests than optical indices and than C- or X-VOD [3].

VOD is related to vegetation structure and to vegetation water content (VWC). Therefore, VOD seasonality is predominantly linked to soil moisture (SM) [4, 5], following the pulse-reserve paradigm [6]. Nevertheless, over seasonally inundated regions, an asynchronism was reported between VOD, water fraction, EVI and GPP [1, 7], with no plausible phenological explanation. Jones et al. (2011) [1] suggested that the strong decline in VOD during flooding could be an artefact due to the presence of vertically-oriented vegetation over a highly reflective water surface. Floods can also induce an overestimation of SM [8]. Temporary flooding affect 4% of the Earth's land surface [9] and may impact substantially passive microwave estimates.

The aim of this work is to investigate the retrieval of L-VOD over flooded areas, in order to improve passive microwave biomass estimates.

2. DATA

2.1. SMOS data

Launched by ESA in 2009, the Soil Moisture and Ocean Salinity (SMOS) satellite [10] performs passive microwave observations at L-band (1.4 GHz). Its full-polarization and multi-angular capabilities allow the simultaneous retrieval of soil moisture content and vegetation optical depth. SM and L-VOD are derived from SMOS brightness temperatures (Tb) using the L-MEB (L-band Microwave Emission of the Biosphere) radiative transfer model [11], based on the τ − ω parameterization [12]. The vegetation attenuation is taken into account in the τ parameter, also known as L-VOD. SM and L-VOD used here were derived from SMOS-INRA-CESBIO (SMOS-IC) retrieval algorithm [13] version 105. SMOS-IC considers the footprint homogeneous in terms of land cover. Footprints permanently covered with more than 20% of open water according to MODIS land cover [14] are excluded, but smaller water bodies and surface water dynamics are currently not taken into account by SMOS-IC algorithm. SMOS-IC dataset is computed on EASE-Grid version 2 (~25 km). Monthly averages from June 2010 to December 2019 were computed with both ascending and descending overpasses, and radio frequency interferences (RFI) areas were excluded.
Fig. 1. Pearson correlation coefficient $R$ between SMOS-IC L-VOD and SM anomalies, 2010-2019. RFI areas were filtered out, as well as regions covered with snow in winter, and barren, urban, snow and ice land cover classes.

2.2. GIEMS-2 dataset

Seasonally inundated areas were located with GIEMS-2 dataset [9], a new version of the Global Inundation Estimate from Multiple Satellites. It provides a long-term global map of surface water extent by merging passive, active, visible and near-infrared data (SSM/I, ERS, AVHRR). The water fraction $f_w$ is delivered at a monthly time-scale from 1992 to 2015, on an equal area grid at ~25 km resolution. Though current GIEMS-2 estimates were only available until 2015, we considered the seasonal evolution of water fractions to be representative of the studied period (2010-2019) at the 25 km scale.

3. METHODS

3.1. Satellite data processing

The study was conducted at the global scale with the exception of areas covered with snow or ice, which can interfere with L-band observations. The Interactive Multisensor Snow and Ice Mapping System (IMS) database [15] was used to filter out areas covered with snow or ice for at least one month per year. Regions affected by RFI were also excluded, as well as barren, urban, snow and ice land cover [14]. The study was conducted from June 2010 to December 2019, at a monthly time scale in order to remove daily variability and to focus on seasonal patterns. All datasets were resampled to SMOS EASE-Grid 2 (~25 km). A representative year was computed for each dataset in order to analyse its average seasonality.

The Pearson correlation coefficient map between SMOS-IC L-VOD and SM anomalies was computed in order to highlight areas where a significant increase (resp. decrease) in SM is linked to a decrease (resp. increase) in L-VOD, such that $R \sim -1$.

3.2. Modelling experiment

SMOS-IC algorithm considers the scene homogeneous in terms of land cover and proceeds the retrieval without removing the contribution of open water. We evaluated the uncertainties introduced by this assumption in the derived SM and L-VOD with a modelling experiment, conducted as follows:

1) Simulation of a brightness temperature ($T_{\text{mix}}$) for a scene under heterogeneous land cover conditions, i.e. with an open water fraction ($f_w$). The soil moisture value on the soil fraction ($f_s$) is called SM$_s$. A vegetation layer is considered above soil ($\tau_v$), and possibly above water ($\tau_w$). The radiative model used to simulate $T_{\text{mix}}$ is the L-MEB model [11]. The brightness temperatures $T_{\text{mix}} (K)$ were simulated for incidence angles ranging from 0 to 55 deg following Eq. (1):

$$T_{\text{mix}} = f_w \times T_{BW}(\tau_w) + (1 - f_w) \times T_{Bw}(\text{SM}_s, \tau_v)$$

where $T_{BW}$ and $T_{Bw}$ stand for the brightness temperatures of the soil and of the water respectively.

2) Retrieval of SM ($\text{SM}_s$) and L-VOD ($\tau_v$) using $T_{\text{mix}}$ computed in step 1 and SMOS-IC algorithm, which assumes the scene to be homogeneous. SM$_s$/\tau$_v$ retrieval was performed assuming that the pixel was homogeneous and only composed of soil, with a brightness temperature $T_{Bw}$:

$$T_{\text{mix}} = T_{Bw}(\text{SM}_s, \tau_v)$$

The retrieval was computed with a minimization of the cost function computed from the quadratic differences between modelled brightness temperatures $T_{\text{mix}}$ and $T_{Bw}$ for different incidence angles ($\theta$):

$$CF = \frac{\sum (T_{\text{mix}}(\theta) - T_{Bw}(\theta))^2}{\sigma(T_{Bw})^2} + \sum \frac{(P_i - P'_i)^2}{\sigma(P)^2}$$

(3)

In which both polarizations and all available angles were used. $\sigma(T_{Bw})$ is the radiometric accuracy associated with the brightness temperature measurements, set to 3 K at 300 K; $P'$ ($i \in \{1;2\}$) is the value of the retrieved parameters ($\text{SM}_s$, $\tau_v$); $P_{\text{iini}}$ ($i \in \{1;2\}$) is the initial value of the free parameters; and $\sigma(P)$ is the uncertainty associated with these free parameters, fixed to 0.3 on SM and $\tau$.

3) Evaluation of the differences between the retrieved couple ($\text{SM}_s$, $\tau_v$) and the initial couple ($\text{SM}_{\text{iini}}$, $\tau_{\text{iini}}$).

3.3. Impact on AGB estimates

The modelling experiment was then computed for a representative year at the global scale. The water fraction $f_w$ was the sum of GIEMS-2 seasonality and permanent water bodies from MODIS land cover [14]. SM$_s$ was from SMOS-IC SM seasonality and $\tau_v$ from the maximum value of SMOS-IC L-VOD seasonality, which is supposed to be its value without floods. The vegetation amount above water $\tau_w$ was adapted to the land cover. We considered high values of 0.8 × $\tau$ for forest classes; 0.4 × $\tau$ for intermediate vegetation; and 0 for low vegetation and permanent water bodies. These considerations are highly simplified and only aim to provide an order of magnitude of the global impact of surface water.
Fig. 2. Impact of increasing water fraction \( f_w \) (colorbar) on the retrieved couple \((\text{SM}_r, \tau_r)\). The red circles represent the initial conditions \((\text{SM}_r, \tau_r)\) when \( f_w = 0 \). Each curve represents the evolution of \((\text{SM}_r, \tau_r)\) when \( f_w \) increases from 0 to 1. Three cases were considered for \( \tau_r \): no vegetation above water \((\tau_r = 0, \text{left})\), sparse vegetation above water \((\tau_r = \tau_s/2, \text{centre})\), and same amount of vegetation above water as above soil \((\tau_r = \tau_s, \text{right})\).

The obtained yearly average error on L-VOD was then converted into an AGB error, using Eq. (4) and \( a, b, c, d \) parameters determined with Baccini AGB dataset [3]:

\[
\text{AGB} = \frac{a}{1 + e^{-b(\text{VOD}-c)}} + d
\]  

(4)

4. RESULTS

4.1. Satellite observations

The Pearson correlation coefficient between SMOS-IC L-VOD and SM anomalies is shown at the global scale in Fig. 1. A strong anti-correlation (R close to -1, red areas) appears over most seasonally inundated areas: the Mississippi River alluvial plain, the Orinoco’s drainage basin, Rio Branco and Bolivian floodplains, the Pantanal, the Rio de la Plata basin, Liuwa plains, Western India and South-East Asia. These results support previous observations of a strong decline in K-VOD during flooding [1]. L-VOD and SM anomalies are well correlated over most dry regions (R close to 1, blue areas), following the pulse-reserve paradigm [6].

4.2. Modelling experiment

The retrieved \((\text{SM}_r, \tau_r)\) for various initial conditions \((\text{SM}_r, \tau_r)\) and \( \tau_r \) cases are presented in Fig. 2. When \( f_w = 0 \), \((\text{SM}_s, \tau_s)\) is equal to \((\text{SM}_r, \tau_r)\) for all cases. As expected, \( \text{SM}_r \) increases with the water fraction and tends toward 1 when the whole scene is covered with water. \( \text{SM}_r \) is overestimated by 0.24 m³ m⁻³ in average when \( f_w = 0.5 \). The retrieved L-VOD \((\tau_r)\) slightly increases for low water fractions and low \( \text{SM}_r \) (+10% in average), then decreases for increasing water fractions. It is particularly significant when the vegetation is submerged underwater \((\tau_r = 0, \text{left})\), especially since the total amount of visible vegetation decreases. \( \tau_r \) decreases by 74% in average when \( f_w = 0.5 \), and drops to 0 when \( f_w = 1 \) (full inundation). For the intermediate case of \( \tau_r \) (central panel), \( \tau_r \) decreases by 30% when \( f_w = 0.5 \). When the vegetation is not submerged \((\tau_r = \tau_s, \text{right panel})\), \( \tau_r \) values barely decrease, meaning a negligible impact of standing water, except for dense vegetation covers \((\tau_r \geq 0.8, 8\% \text{ decrease when } f_w = 1)\).

4.3 Impact on AGB estimates

The yearly average L-VOD error was computed at the global scale and derived to estimate the AGB error (Fig. 3) using Eq. (4). At the global scale, errors linked with surface water have little impact on AGB estimates (-0.6 Mg ha⁻¹). AGB errors are predominantly negative, and can reach -15/-20 Mg ha⁻¹ in the largest wetlands. Lower positive errors (+3 Mg ha⁻¹) are found in North-West America and Australia, linked with low water fractions. These values were obtained for a representative year, but can be higher during exceptional meteorological years.

5. CONCLUSION

This study highlighted the anomalous decrease of SMOS-IC L-VOD during flooding; and showed with a modelling experiment that this phenomenon was linked to the influence of the water fraction temporal variations. Most operational algorithms take the major water bodies into account with a static map, but this study showed the importance of considering the temporal dynamics of water extent. Indeed, it induces an overestimation of SM and an underestimation of L-VOD, particularly significant over submerged vegetation areas (low vegetation). L-VOD tends towards 0 when the inundation is total, leading to an asynchronous seasonal cycle with respect to other vegetation indices. Though less impacted, flooded forests are also affected.

The underestimation of L-VOD in areas affected by inundations can lead to a noticeable underestimation of the biomass amount (-15/-20 Mg ha⁻¹ in the largest wetlands). This impact is limited over forests, characterized by AGB values of 150-300 Mg ha⁻¹, but can be significant over
herbaceous wetlands with a typical AGB of ~30 Mg ha⁻¹. It is thus important to better account for the open water extent and dynamics in SM/t retrieval algorithm.

Fig. 3. AGB error at the global scale (Mg ha⁻¹), computed with the yearly average L-VOD error and Eq. (4) fitted with the mean curve of Baccini AGB distribution [3]. Regions covered with snow in winter, barren, urban, snow and ice land cover classes were excluded.

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