Retrieval of growing stock volume in boreal forest using hyper-temporal series of Envisat ASAR ScanSAR backscatter measurements

Maurizio Santoro a,⁎, Christian Beer b, Oliver Cartus c, Christiane Schmullius c, Anatoly Shvidenko d, Ian McCallum d, Urs Wegmüller a, Andreas Wiesmann a

⁎ Gamma Remote Sensing, CH-3073 Gämlik, Switzerland
b Max-Planck Institute for Biogeochemistry, D-07745 Jena, Germany
c Department of Earth Observation, Friedrich-Schiller University, D-07743 Jena, Germany
d International Institute of Applied Systems Analysis, A-2361 Laxenburg, Austria

ABSTRACT

Methods for the estimation of forest growing stock volume (GSV) are a major topic of investigation in the remote sensing community. The boreal zone contains almost 30% of global forest by area but measurements of forest resources are often outdated. Although past and current spaceborne synthetic aperture radar (SAR) backscatter data are not optimal for forest-related studies, a multi-temporal combination of individual GSV estimates can improve the retrieval as compared to the single-image case. This feature has been included in a novel GSV retrieval approach, hereafter referred to as the BIOMASAR algorithm. One innovative aspect of the algorithm is its independence from in situ measurements for model training. Model parameter estimates are obtained from central tendency statistics of the backscatter measurements for unvegetated and dense forest areas, which can be selected by means of a continuous tree canopy cover product, such as the MODIS Vegetation Continuous Fields product. In this paper, the performance of the algorithm has been evaluated using hyper-temporal series of C-band Envisat Advanced SAR (ASAR) images acquired in ScanSAR mode at 100 m and 1 km pixel size. To assess the robustness of the retrieval approach, study areas in Central Siberia (Russia), Sweden and Québec (Canada) have been considered. The algorithm validation activities demonstrated that the automatic approach implemented in the BIOMASAR algorithm performed similarly to traditional approaches based on in situ data. The retrieved GSV showed no saturation up to 300 m3/ha, which represented almost the entire range of GSV at the study areas. The relative root mean square error (RMSE) was between 34.2% and 48.1% at 1 km pixel size. Larger errors were obtained at 100 m because of local errors in the reference datasets. Averaging GSV estimates over neighboring pixels improved the retrieval statistics substantially. For an aggregation factor of 10 × 10 pixels, the relative RMSE was below 25%, regardless of the original resolution of the SAR data.

1. Introduction

The forest growing stock volume, GSV, is a key parameter in the context of forest resource management and global change issues. The GSV, also referred to as stem volume or bole volume of living trees, represents the volume of the tree stems for all living species per unit area, including bark but excluding branches and stumps. The GSV is a major predictor for assessing the above-ground biomass (Häme et al., 1992; Shvidenko et al., 2007) and is central for estimating compartment (Jenkins et al., 2003) or total above-ground biomass (Somogyi 1992; Shvidenko et al., 2007) and is central for estimating compartment...
according to the Forest Inventory and Planning (FIP) system in areas of intensively managed forests and aerial survey for remote unmanaged forests. Approximately 70% of Russian forests are inventoried by FIP, which should be completed every 10 to 20 years. The high costs associated with local surveys, the scarcity of resources and the large extent of the areas to be mapped hinder accurate inventory of forest resources and frequent update. In the absence of other reliable sources of information, the GSV derived from inventoried measurements end up being the reference dataset for resources assessments and carbon budget calculations well beyond the time for which they can be considered reliable. As a consequence, figures on total GSV and trends of carbon accumulation can suffer in the long run from biases and large uncertainties. Kindermann et al. (2008) showed that downsampling national estimates of GSV reported in the 2005 Forest Resources Assessment to 0.5° resulted in unrealistic GSV estimates in several regions due to errors or omissions in the input datasets.

Earth Observation (EO) using satellite data has the potential to overcome such limitations because of the synoptic view and the repeated acquisitions. In addition, EO data are generally much cheaper, particularly when coarser resolution data sets are used. The advantage of synthetic aperture radar, SAR, is the all-weather acquisition capability, which guarantees the generation of temporally dense image data sets over short time periods. Furthermore, the intensity of the signal backscattered from forests depends on the number, shape and orientation of the scattering objects, thus being directly related to forest structural parameters, such as growing stock volume.

Despite the large archives of C-band (5.3 GHz carrier frequency, 5.6 cm wavelength) data acquired by the European Remote Sensing Satellites (ERS-1 and -2), the Environmental Satellite (Envisat) and the Radarsat SAR instruments during the last 20 years, C-band is commonly neglected when deciding which remote sensing observable shall be used for the estimation of forest GSV, or the like parameter above-ground biomass. The reason is the weak sensitivity of the C-band backscatter to these variables (Dobson et al., 1992; Fransson & Israelsson, 1999; Imhoff, 1999; Pulliainen et al., 1994; Rignot et al., 1994b; Wang et al., 1995). The retrieval of GSV from a single C-band backscatter measurement is generally poor. In addition, the strong effect of the environmental conditions further limits the use of the backscatter. As an example, the relationship of SAR backscatter with respect to forest biophysical parameters was shown to change from slightly increasing to decreasing for increasing soil moisture (Prosio et al., 2000; Pulliainen et al., 1996, 1999; Wang et al., 1994, 1995). The strongest increase of backscatter for increasing GSV or biomass was between 2 dB and 3 dB, primarily under frozen conditions or dry unfrozen conditions (Baker & Luckman, 1999; Balzter et al., 2002a; Harrell et al., 1995, 1997; Pulliainen et al., 1994, 1996; Ranson & Sun, 2000; Rignot et al., 1994a). Table 1 presents a summary of retrieval statistics reported in the literature, expressed as relative root mean square error (RMSE), i.e., the RMSE divided by the mean GSV. For the single-date cases, the lowest relative RMSE is reported. Somewhat better results were obtained using winter-time data acquired under frozen conditions. The retrieval accuracy improved when several estimates of GSV were combined in a multi-temporal approach. Agreement between in situ and retrieved GSV up to 300 m$^3$/ha (Pulliainen et al., 1996) and relative RMSE below 30% (Kuronen et al., 1999) were obtained when considering forest stands larger than 20 ha.

The scope of this paper is to demonstrate that, with a straightforward approach hereafter referred to as the BIOMASAR algorithm, it is possible to retrieve forest GSV from hyper-temporal series of C-band SAR backscatter observations. Hyper-temporal datasets are available from Envisat Advanced SAR (ASAR) operating in ScanSAR mode. The 400 km wide swath of the ScanSAR mode on Envisat ASAR implies strong overlap of images acquired along adjacent satellite tracks, although at coarse resolution (at least 100 m). The wide swath of the ScanSAR mode also implies that large areas can be covered at once; thus, it is possible to assess the capability of C-band backscatter data to derive regional estimates of GSV.

To assess applicability, robustness and performance of the BIOMASAR algorithm, the investigations were carried out at several study areas located in Central Siberia (Russia), Sweden and Québec (Canada). The algorithm has been validated for forests in the boreal zone since this is characterized by long periods of suitable environmental conditions for the retrieval using C-band data and because of the somewhat opener canopy structure compared to other forest types, which implies sensing major elements of the forest canopy. GSV has been chosen as the forest parameter to be retrieved since it is (i) commonly used in forest inventory within the boreal zone and (ii) a parameter related to forest structure and thus to SAR backscatter.

The study areas and the datasets of reference measurements used for algorithm validation are presented in Section 2. The Envisat ASAR datasets are described in Section 3. Section 4 provides a description of the BIOMASAR algorithm. The algorithm validation and the retrieval performance are presented and discussed in Sections 5 and 6 respectively. The retrieval of GSV using the validated algorithm is presented in Section 7. Section 8 includes a brief summary of the main findings and a discussion on the exploitation potential of the GSV retrieved with the BIOMASAR algorithm.

### 2. Study areas

The objective behind the development of the BIOMASAR algorithm has been to set up a robust GSV retrieval methodology that would be general enough for mapping large areas, such as continents. For this reason, the algorithm has been developed and applied simultaneously at different study areas located in Central Siberia, Sweden and Québec. The study areas are shown in Fig. 1 and presented in Table 2. They were chosen on the basis of the availability of extensive datasets of forest GSV to be used as reference for validating the results and large data stacks of Envisat ASAR backscatter measurements. It is here remarked that in the boreal zone, accurate in situ measurements of forest GSV are practically unavailable for large areas. Hence, in some cases, it was necessary to consider a fall back on equivalent datasets obtained from Earth Observation (EO) data. The implications are discussed in Sections 6 and 7, which deal with the interpretation of the modeled backscatter and the GSV retrieval respectively.

Other in situ data consisted of daily observations of temperature, wind speed, precipitation and snow depth collected at weather stations within and nearby the study areas (79 in Sweden, 50 in Central Siberia and 10 in Québec). In this context, the weather data were used essentially to understand the performance of the algorithm with respect to seasonal conditions.

<table>
<thead>
<tr>
<th>Area and sensor</th>
<th>Relative root mean square error (RMSE)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Finland, ERS-1</td>
<td>49.6% (frozen), 77.1% (unfrozen)</td>
<td>Kuronen et al. (1999)</td>
</tr>
<tr>
<td>Sweden, ERS-1</td>
<td>62% (winter), 80% (other seasons)</td>
<td>Fransson and Israelsson (1999)</td>
</tr>
<tr>
<td>Finland, ERS-1</td>
<td>65%</td>
<td>Hyppäälä et al. (2000)</td>
</tr>
<tr>
<td>Finland, EMISAR</td>
<td>56% (frozen) and 65% (thaw)</td>
<td>Balzter et al. (2002a)</td>
</tr>
<tr>
<td>Finland, ERS-1</td>
<td>58% (multi-temporal, 12 images), 78%</td>
<td>Pulliainen et al. (1996)</td>
</tr>
<tr>
<td>Sweden, ERS-1/2</td>
<td>53% (multi-temporal, 18 images), 61%</td>
<td>Santoro et al. (2002)</td>
</tr>
</tbody>
</table>
2.1. Central Siberia, Russia

The study area in Central Siberia included four forest enterprises (Bolshe-Murtinsky, Chunsky, Irbeisky and Mansky), located in the southern taiga sub-zone of the boreal forest domain (Schmullius et al., 2001). In this sub-zone, vegetation is represented by typical boreal forests. Conifers are predominant in mature forests whereas soft deciduous species are typical of young regrowing forest. The four forest enterprises were located within a 400×400 km² large area and covered approximately 6300 km² (Fig. 1). Each forest enterprise comprised between three and five forest compartments, each being between 200 and 500 km² in area. The compartments are here referred to in terms of their geographical location within the forest enterprise (e.g., Chunsky North).

For each forest compartment, the database of forest inventory measurements consisted of forest stand boundary maps in digital form and field measurements of GSV at the stand level. A forest stand or polygon is defined in terms of homogeneous forest cover and forest properties; nonetheless, it could also encompass different type of forest cover with significant differences in GSV. Forest stand boundaries are based on human interpretation, usually of aerial photos. For each stand, a value of GSV was reported. GSV ranged between 0 and 470 m³/ha, with prevalence of mature and overmature forest stands. The GSV measurements originated from regular forest surveys carried out according to the Russian Forest Inventory Manual (FFSR, 1995) and were updated in 1998. After 1998, the database was updated to take into account recently clear-felled and damaged areas. Vastness and, in some cases, remoteness of the areas implied that the accuracy of the inventoried data was spatially variable. GSV for forests close to roads or fluvial connections were characterized by higher accuracy of the order of 10–15%. Errors up to 25–30% were typical for more remote forested areas (Balzter et al., 2002b; Santoro et al., 2007). In addition, the in situ data in mature forests underestimated the GSV by about 10% (Shvidenko et al., 2008a).

2.2. Västerbotten and Västra Götaland, Sweden

In Sweden, the study areas coincided with the counties of Västerbotten in the north and Västra Götaland in the south. While in Västerbotten, the forest is typically boreal with somewhat sparse forest cover, low productivity and gaps between trees, Västra Götaland is located along the border between boreal and hemi-boreal forest conditions, thus being characterized by higher forest productivity, dense forest cover and higher GSV. A large proportion of forests consist of coniferous tree species (Norway spruce and Scotch pine); of the deciduous species, birch is most prominent.

For the purpose of this study, the country-wide dataset on forest GSV obtained with the k-nearest neighboring (kNN) algorithm (Reese et al., 2003) for the year 2000 was found to be better suited than the few in situ measurements from two small forest sites (Santoro et al., 2009). The kNN GSV estimates were obtained from a combination of National Forest Inventory (NFI) plot measurements, satellite optical data and map data. The kNN product was validated against in situ measurements locally (Fazakas et al., 1999; Reese et al., 2003). At the pixel level (25 m), the GSV estimates presented inherent errors and the relative RMSE was above 40%. When aggregating kNN GSV estimates to lower spatial resolutions, the accuracy improved with the size of the averaging window. At the kilometric scale, the relative RMSE was below 25%, thus being comparable to the accuracy of the aggregated estimates based on in situ measurement (Fazakas et al.,

### Table 2

<table>
<thead>
<tr>
<th>Study area</th>
<th>Area (km²)</th>
<th>Dataset of reference GSV</th>
<th>Mean GSV (m³/ha)</th>
<th>Std GSV (m³/ha)</th>
<th>Range GSV (m³/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central Siberia, Russia</td>
<td>6300</td>
<td>Inventory</td>
<td>167.2</td>
<td>76.9</td>
<td>0–470</td>
</tr>
<tr>
<td>Västerbotten, Sweden</td>
<td>59,300</td>
<td>Inventory (local)</td>
<td>95</td>
<td>N/A</td>
<td>0–184</td>
</tr>
<tr>
<td>Västra Götaland, Sweden</td>
<td>25,400</td>
<td>NFI statistics</td>
<td>173.0</td>
<td>N/A</td>
<td>0–386</td>
</tr>
<tr>
<td>Lac Mistassini, Québec, Canada</td>
<td>240,000</td>
<td>BioSF product</td>
<td>103.2</td>
<td>38.6</td>
<td>0–271</td>
</tr>
</tbody>
</table>

Fig. 1. Location of the study areas.
Hence, the kNN dataset could be considered reliable for cross-comparing with the retrieved GSV at the kilometric scale. A certain margin of uncertainty had to be taken into account at the 100 m scale.

2.3. Québec, Canada

The study area was located nearby Lac Mistassini and covered approximately 240,000 km². The terrain was mostly flat, characterized by forests, some shrubland/grassland and a large number of lakes. The study area belonged to two sub-arctic ecosystems: the eastern taiga shield and the boreal shield. The dominant tree species in the region is Black Spruce with only minor occurrence of Jack Pine and a few other species. Due to the lack of extensive measurements of inventory data, only EO-products could serve as reference (Table 2). As a consequence, this study area was considered only for assessing the retrieval accuracy of the validated BIOMASAR algorithm.

The first product is referred to as BioSF GSV. Maps of total stem volume with 30 m pixel size were derived for two small test sites from high resolution Quickbird imagery for the year 2006 using a shadow fraction method called BioSF (Leboeuf et al., 2007). The accuracy of the BioSF biomass maps was reported with an \( R^2 \) of 82%, a RMSE of 15.3 tons/ha and a bias of 4.2 tons/ha. The other product was a kNN map of GSV produced using 11 Landsat images from the year 2005 (Guindon et al., 2005). It consisted of pixel-wise (25 m pixels) estimates of total stem volume, including stump, stem top and small trees. The kNN algorithm was driven by the BioSF estimates. The RMSE of the kNN biomass maps for the two BioSF test sites was 13.3 tons/ha and 9.1 tons/ha. The bias was negligible. The accuracy was found to increase when aggregating the maps to coarser pixel sizes.

3. SAR dataset

The SAR dataset consisted of large stacks of detected Envisat ASAR ScanSAR images (ground range geometry, level 1P) acquired in Wide Swath Mode (WSM) and Global Monitoring Mode (GMM). WSM SAR images have 150 m spatial resolution and high radiometric accuracy because of the large number of looks being used during the SAR processing (~100). GMM SAR images are acquired with a lower bit rate compared to the WSM data, which implies coarser spatial resolution (500 m) and lower radiometric accuracy (7 looks). Both modes acquire only single polarization, co-polarized data (HH or VV). The ScanSAR mode has an extended swath capability compared to the traditional Stripmap imaging mode (400 vs. 100 km). This observing configuration implies a wider range of incidence angles (18 to 45°) and a much higher degree of overlap of adjacent orbital tracks. Therefore, it is possible to build up a hyper-temporal dataset of SAR backscatter measurements in a short time period.

All SAR images were acquired during 2004 and 2005 in order to minimize the time difference with the reference datasets of GSV measurements. Prior to this, no systematic acquisitions of Envisat ASAR in ScanSAR mode were performed. One year of SAR data was sufficient to obtain a dense stack of backscatter measurements, except for the WSM dataset covering Central Siberia for which two years of data had to be considered. It was ensured that within this period, forests were not affected by large-scale changes, which might have an impact on the modeling and thus on the retrieval. A stack of data spanning at least one year also allowed evaluating the effects of seasonal conditions on the retrieval. Fig. 2 shows the number of backscatter observations per pixel for each study area. Typically, the amount of data acquired by Envisat ASAR in GMM is larger than in WSM since the European Space Agency (ESA) has implemented the GM mode as background mission acquisition strategy. This is clearly shown by the histogram for Central Siberia, where some areas were imaged more frequently than others. For Lac Mistassini, only 10 images were acquired during 2005 in WSM, whereas in GMM the dataset was by far denser compared to the other study areas. Over Scandinavia, Envisat ASAR acquires primarily in WSM and higher resolution modes, thus explaining the denser dataset of WSM for the two Swedish study areas.

4. BIOMASAR algorithm

The BIOMASAR algorithm is outlined in Fig. 3 and consists of two major blocks:

• Generation of a stack of calibrated, geocoded and co-registered SAR backscatter images;
• Inversion of individual backscatter measurements by means of a Water–Cloud type of model to estimate GSV and multi-temporal combination of individual estimates of GSV.

SAR processing, SAR backscatter modeling, model inversion to estimate GSV and multi-temporal combination of individual GSV estimates will be presented hereafter in related Sections. The algorithm requires a number of additional datasets. More details on the latter aspect are provided in Section 4.2.
4.1. SAR data processing

The SAR processing block produces a stack of calibrated and terrain-corrected geocoded images, which are co-registered at sub-pixel level and present high radiometric quality (i.e., limited speckle noise). Considering the extensive number of images that need to be processed, it was preferred to use established and robust processing algorithms rather than developing area- or dataset-specific procedures. The latter approach might improve image quality in single cases while the overall performance might be poorer. In the remainder of this Section, it is assumed that the SAR dataset is in the form of calibrated SAR intensity images and in the radar acquisition geometry (i.e., range-Doppler coordinate system), as it is in the case of Envisat ASAR ScanSAR data.

For this analysis, three types of SAR datasets were considered. The images were obtained from ESA in ground-range geometry with a pixel spacing of 150 and 500 m for the WS and the GM modes respectively. Besides the original WSM and GMM imagery, a GMM-like version of the WSM images was computed by multi-looking, i.e., spatial averaging, to obtain almost the same pixel size of a GMM image. In this way, the km-scale SAR datasets could be populated with more images. Table 3 provides an overview of the SAR datasets and the processing applied to each type of data.

4.1.1. Speckle filtering

The radiometric quality of a SAR image can be improved by means of speckle filtering in the spatial and temporal domain. The original WSM and GMM images were first multi-looked with factors 2 and 2 in range and azimuth to slightly improve the radiometric quality of the data without significantly degrading the spatial resolution. To obtain the GMM-like dataset from the original WSM images, a 14×14 multi-looking was applied instead. The availability of a large number of uncorrelated observations suggested the use of the multi-channel filter for an effective suppression of speckle (Quegan & Yu, 2001). Over textured terrain, however, spatially adaptive filters allow better estimates of the radar cross section; hence, it was chosen to drive the multi-channel filter by means of data that was filtered with the texture-based GAMMA MAP filter (Lopes et al., 1993). Since the multi-channel filter required that all images in a data stack are co-registered, terrain geocoding had to be performed before applying the filter. Spatial filtering was instead applied to the images in the radar

Table 3

<table>
<thead>
<tr>
<th>ScanSAR mode</th>
<th>Pixel size (original, radar geometry)</th>
<th>Pixel size (after multi-looking, radar geometry)</th>
<th>Pixel size (map geometry)</th>
<th>Processing steps</th>
</tr>
</thead>
<tbody>
<tr>
<td>WSM</td>
<td>75 m</td>
<td>150 m</td>
<td>100 m</td>
<td>2×2 multi-look GAMMA MAP filter</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Terrain geocoding</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Multi-channel filter</td>
</tr>
<tr>
<td>GMM</td>
<td>500 m</td>
<td>1000 m</td>
<td>1000 m</td>
<td>2×2 multi-look GAMMA MAP filter</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Terrain geocoding</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Multi-channel filter</td>
</tr>
<tr>
<td>WSM (aggregated)</td>
<td>75 m</td>
<td>1050 m</td>
<td>1000 m</td>
<td>14×14 multi-look GAMMA MAP filter</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Terrain geocoding</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Multi-channel filter</td>
</tr>
</tbody>
</table>
geometry, prior to geocoding. The Equivalent Number of Looks (ENL) (Oliver & Quegan, 1998) after speckle filtering was ≥60. The corresponding residual speckle noise was therefore less than 0.6 dB.

4.1.2. Image geocoding

The main requirement for image geocoding is to obtain images that present geolocation error of a fraction of the pixel size. The BIOMASAR algorithm implements the automated approach described in (Wegmüller, 1999; Wegmüller et al., 2002), which is particularly suited for processing large data stacks. A look-up table describing the transformation between the radar and the map geometry is generated based on orbital parameters and a Digital Elevation Model (DEM). Refinement of the look-up table is achieved by estimating the offsets between the SAR backscatter image to be geocoded and a similar image assumed to be in the true map geometry, e.g., a simulated SAR image from the DEM. For the Envisat ASAR ScanSAR datasets considered, the requirement of co-registration at sub-pixel level was fulfilled since the standard deviation of the offsets after refinement of the look-up table was below one third of the pixel size. The geocoded images are then tiled in order to obtain stacks of co-registered imagettes of reasonable size. In this way, disk space resources are managed in an optimal way and direct access to a specific area for detailed analysis is facilitated.

4.1.3. Compensation of SAR backscatter for topographic effects

The radar backscatter is significantly affected by slope-induced distortions, which can have a direct impact on the GSV retrieval if not accounted for. For effective compensation of radiometric distortions, the spatial resolution of the DEM used for geocoding needs to be comparable to the resolution of the SAR dataset and the elevation accuracy must be sufficiently large for correct slope representation. For the boreal zone, the SRTM-3 DEM (Rabus et al., 2003) below 60° N and 3–arcseconds digitized Russian topographic maps above 60° N (http://www.viewfinderpanoramas.org/dem3.html) were found to be a reliable solution (Santoro & Cartus, 2010). The original elevation data were used to geocode and normalize the backscatter of the WSM images. Aggregated versions at 30 arcsecond were used for the GMM and the aggregated WSM images.

The correction of the SAR backscatter for topography-induced distortions consists of a compensation for the area pixel size and the local incidence angle (Castel et al., 2001; Ulander, 1996): 

\[
\gamma^0 = \frac{\gamma_{\text{flat}}}{\cos \theta_{\text{loc}}} \left( \frac{\cos \theta_{\text{loc}}}{\cos \theta_{\text{ref}}} \right)^n
\]  

In (1) \( \theta_{\text{loc}} \) and \( \theta_{\text{ref}} \) represent the local incidence angle and a reference incidence angle (e.g., the incidence angle at mid-swath) respectively. \( \gamma_{\text{flat}} \) and \( \gamma_{\text{slope}} \) represent the true pixel area and the local pixel area for theoretically flat terrain respectively. The images of the area normalization factor (\( \gamma_{\text{flat}}/\gamma_{\text{slope}} \)) and of the local incidence angle can be obtained from the DEM and orbital information (Wegmüller, 1999). For bare surfaces, the exponent \( n \) is equal to 1. For vegetated surfaces, \( n \) expresses the variation of the scattering mechanism due to the presence of a volume on the sloped terrain, thus being related to the optical depth of the vegetation. For C-band co-polarized data, it can be assumed to be equal to 1 (Castel et al., 2001; Ulander, 1996).

The topographic normalization performed well in case of slopes tilted away from the sensor. Concerning slopes facing the sensor, the high sensitivity of the pixel area estimates to errors in the estimates for the local incidence angle from the DEM entailed residual topography-induced distortions in the normalized backscatter images. Therefore, steep slopes facing the sensor should be masked to avoid topographic distortions affecting the GSV retrieval. An area ratio \( \gamma_{\text{flat}}/\gamma_{\text{slope}} \) less than 0.85 proved to be sufficiently robust to identify sloped terrain to be excluded from the retrieval (Santoro & Cartus, 2010).

4.2. Backscatter modeling as a function of GSV

The retrieval of GSV from the SAR backscatter data is most robust if a physically based model is used rather than a linear or non-linear empirical regression model derived using a set of in situ measurements. At C-band, spatial and temporal variability of the SAR backscatter are issues that make empirical modelling practically useless. To achieve robustness and flexibility in the SAR backscatter model, a sensible approach is to rely on a formulation that expresses the SAR backscatter in terms of the main scattering mechanisms in as general a manner as possible.

The Water–Cloud model with gaps (Askne et al., 1997) satisfies this requirement. The model in Eq. (2) expresses the total forest backscatter as the sum of direct scattering from the ground through the canopy gaps, ground scattering attenuated by the tree canopy and direct scattering from the vegetation.

\[
\sigma^0_{\text{fl}} = (1-\eta)\sigma^0_{\text{gr}} + \gamma \sigma^0_{\text{tree}} + \gamma_{\text{reg1}}\sigma^0_{\text{reg}}(1-T_{\text{tree}})
\]  

In Eq. (2), the forest backscatter, \( \sigma^0_{\text{fl}} \), is expressed as a function of the so-called area-fill factor, \( \eta \), which represents a measure of the percentage of forest floor covered by vegetation (0 meaning no canopy cover, 1 meaning completely closed canopy cover). The model includes three parameters: the backscatter coefficient of the forest floor, \( \sigma^0_{\text{fl}} \), the backscatter coefficient of the vegetation layer, \( \sigma^0_{\text{reg}} \), and the two-way tree transmissivity, \( T_{\text{tree}} \). This term can be expressed as \( e^{-\alpha h} \), where \( \alpha \) is the two-way attenuation per meter through the tree canopy and \( h \) is thickness of the attenuating layer.

In practice, Eq. (2) is not useful since the area-fill factor is not widely used in forestry. For retrieval purposes, it is more convenient to use the expression where the forest backscatter is described as a function of the growing stock volume, \( V \), (Pulliainen et al., 1994):

\[
\sigma^0_{\text{fl}} = \sigma^0_{\text{fl}0} e^{\gamma_{\text{fl}} V} + \gamma_{\text{reg}}\sigma^0_{\text{reg}}(1-e^{-\beta V})
\]  

In Eq. (3), \( \beta \) is an empirically defined coefficient expressed in ha/m\(^3\). The link between the parameters \( \eta, \alpha, \) and \( \beta \) is expressed in Eq. (4) (Santoro et al., 2002):

\[
\eta = \frac{1-e^{-\beta V}}{1-e^{-\alpha h}}
\]  

The backscatter model in Eq. (3) contains three unknowns that need to be estimated: \( \sigma^0_{\text{fl}0}, \sigma^0_{\text{reg}} \) and \( \beta \). These can be estimated by means of least-squares regression, using a dataset of reference forest GSV measurements (Fransson & Israelsson, 1999; Pulliainen et al., 1994; Santoro et al., 2002). This approach is, however, unreasonable when aiming at covering large areas because it would imply having a dense network of training sites to capture possible spatial variations of the SAR backscatter caused by different forest structures and/or environmental conditions. In this paper, we overcome this shortcoming by means of an approach for model training that does not rely on in situ measurements. It will be hereafter assumed that the estimation and the retrieval are described at the pixel level.

The parameter \( \sigma^0_{\text{fl}0} \) represents the backscatter in the case of an unvegetated land surface. Hence, it can be assumed that a reasonable estimate corresponds to the average (or a like central statistics measure) of the backscatter for pixels that can be labeled as unvegetated within a window of finite size centered in the pixel of interest. The selected pixels will be referred to as “ground” pixels. For details on the statistical measure used, it is referred to Section 5. Similarly, an estimate of the parameter \( \sigma^0_{\text{reg}} \) can be obtained from a measurement of central tendency of the backscatter of dense forest within a finite-size window. Rigorously speaking, \( \sigma^0_{\text{fl}0} \) represents the backscatter in the case of a completely opaque forest canopy. Because
of gaps, even in the densest forest a fraction of the measured backscatter contains a certain contribution from the forest floor. Hence, in order to obtain an estimate for $\sigma_{0_{\text{veg}}}^b$, compensation of the measured backscatter over dense forests for the residual backscatter component from the ground seen through the gaps in the canopy is necessary. Since $\sigma_{0_{\text{veg}}}^b$ is known at this stage, Eq. (3) can be inverted to obtain $\sigma_{0_{\text{veg}}}^b$ from the backscatter of the pixels forming a so-called “dense forest” class.

$$\sigma_{0_{\text{veg}}}^b = \frac{\sigma_{0_{\text{veg}}}^g - \sigma_{0_{\text{veg}}}^{\text{fl}} e^{-\beta_{\text{df}} g_{\text{veg}}}}{1 - e^{-\beta_{\text{df}} g_{\text{veg}}}} \quad (5)$$

In Eq. (5) $\sigma_{0_{\text{veg}}}^g$ represents a measurement of the backscatter for the “dense forest” class. The estimation of $\sigma_{0_{\text{veg}}}^b$ requires knowledge of the parameters $\beta$ and $V_{df}$, the latter representing a GSV value representative for the “dense forest” class. More details are provided towards the end of this Section.

The estimation of the parameters $\sigma_{0_{\text{veg}}}^b$ and $\sigma_{0_{\text{veg}}}^b$ can profit from continuous tree canopy cover products. For low resolution data, an effective solution is represented by the MODIS Vegetation Continuous Fields (VCF) tree cover product. The MODIS VCF product represents continuous estimates of percentages of tree cover with a 500 m pixel size (Hansen et al., 2003), thus being a well-suited image product for automatic selection of SAR backscatter values to be included in the “ground” and the “dense forest” class. Since this product has been only partially validated (Hansen et al., 2002), an in-depth analysis on the VCF product had to be performed in order to assure that inaccuracies on the tree cover percentage estimates would not affect the performance of the BIOMASAR algorithm. In (Santoro & Cartus, 2010), it has been concluded that the use of the VCF product simultaneous to the SAR dataset minimizes the impact of uncertain VCF values on the model parameter estimates. It is here remarked that the VCF product is used solely as mask to select pixels to be labeled as “ground” and “dense forest”; the actual values of tree cover percentage are not used by the BIOMASAR algorithm.

The parameter $\beta$ is related to dielectric properties of the vegetation (e.g., frozen/unfrozen conditions) and forest structural properties. An analysis of the VCF parameterized by means of Eq. (4) as a function of GSV showed that $\beta$ is mostly confined within a narrow interval of values, between 0.004 and 0.008 ha/m$^3$. These results were in line with estimates from ERS backscatter and coherence data (Santoro et al., 2002). Higher values up to 0.016 ha/m$^3$ were obtained locally; with estimates from ERS backscatter and coherence data (Santoro et al., 2002). Nonetheless it was unclear whether this was a consequence of specific forest or environmental conditions. To test the sensitivity of the GSV retrieval to the range of potential $\beta$ values at the study areas, the model in Eq. (3) was trained with different values of $\beta$ and then inverted. The resulting GSV estimates differed by less than 10%, regardless of the study area, thus indicating weak dependence of the retrieval upon the exact value of this model parameter. A trade-off between computational efficiency and retrieval performance, it was decided to set $\beta$ equal to 0.006 ha/m$^3$, regardless of seasonal conditions and forest type. This assumption considers that fine tuning of the model parameter to local environmental conditions and forest type characteristics is unrealistic due to the paucity, if not lack, of detailed weather information and forest structural properties when aiming at large-scale retrieval of GSV with coarse resolution EO data.

The GSV for the “dense forest” class, $V_{df}$, represents the GSV level typical for dense forests within the area to which the pixel belongs to. The definition of this parameter requires some a priori knowledge on the spatial distribution of GSV. This is generally available at the level of an administrative region or eco-region from nation-wide inventory data. Attaching one value of $V_{df}$ to an area of the size of a region, i.e., of several thousands of km$^2$, is reasonable considering that the variability of GSV for the densest forests is small at kilometic resolution. For example, the GSV for the densest forests in Central Siberia decreases from approximately 300 m$^3$/ha (dark taiga) to 150 m$^3$/ha (light taiga) over a latitudinal gradient of 15°. More details on this parameter can be found in Section 5.

Besides the MODIS VCF product, the BIOMASAR algorithm also requires additional datasets, which are used to mask out pixels belonging to a land-cover class not strictly related to vegetation (namely water bodies, urban and suburban areas and exposed rocks). These objects generally present either very low or very high backscatter, which can therefore distort the distribution of the backscatter of the “ground” pixels, thus leading to mis-estimation of $\sigma_{0_{\text{veg}}}^b$. The choice of the image products used for de-selecting pixels is of minor importance in the context of this article. Further details can be found in (Santoro & Cartus, 2010).

4.3. Retrieval of GSV

Once the model parameters have been estimated, the model in Eq. (3) can be inverted to derive an estimate of GSV from a measurement of the SAR backscatter.

$$\hat{V} = \frac{1}{\beta} \ln \left( \frac{\sigma_{0_{\text{veg}}}^b - \sigma_{0_{\text{veg}}}^{\text{fl}}}{\sigma_{0_{\text{veg}}}^b - \sigma_{0_{\text{veg}}}^{\text{fl}}} \right) \quad (6)$$

In Eq. (6), $\hat{V}$ represents the retrieved GSV corresponding to a backscatter measurement, $\sigma_{0_{\text{veg}}}^b$. At C-band, it is likely that the measured SAR backscatter is not within the range of modeled backscatter values, especially in areas with high GSV where the backscatter typically saturates. This issue requires the modeling and the inversion to be constrained to certain ranges of backscatter values and GSV. This concept can be explained by means of the plot in Fig. 4. The curve represents a realization of the model in Eq. (3) and corresponds to the general behavior of the C-band backscatter to forest GSV. If the backscatter measurement to be inverted is within the interval of modeled backscatter (i.e., between −10 and −8 dB for the example in Fig. 4), a GSV estimate is obtained from Eq. (6). Otherwise, a distinction is made depending on how far off the measurement is with respect to the interval of modeled backscatter. A measurement within the buffer zones is considered to be potentially containing forest information. The width of the buffer zone is assumed to be equal to the residual speckle noise component, which can be estimated from the ENL. The retrieved GSV is equal either to 0 or to the maximum retrievable GSV depending whether the backscatter measurement is closer to the modeled value for GSV = 0 or the

![Fig. 4. Modeled backscatter as a function of GSV and definition of the intervals of backscatter for which retrieval takes place with corresponding retrieval rules.](image-url)
maximum retrievable GSV, i.e., below or above the model curve in Fig. 4 respectively. As for the definition of the GSV for the “dense forest” class, the maximum retrievable GSV implies that certain knowledge on the range of GSV for the area of interest is known a priori. The sensitivity of the inversion to the actual value of the maximum retrievable GSV will be discussed in Section 6. Finally, a measurement falling in the outlier zone is likely to be strongly affected by environmental conditions; hence, no GSV is retrieved.

At C-band, the estimate of the GSV for individual images is affected by residual speckle, a temporally random component due to the environmental conditions and a more systematic type of error component due to the weak sensitivity of C-band backscatter to GSV. To decrease the amount of noise, a multi-temporal combination is used (Kurvonen et al., 1999; Santoro et al., 2002, 2006):

\[
\hat{\tilde{V}}_{me} = \frac{\sum_{i=1}^{N} w_i \tilde{V}_i}{\sum_{i=1}^{N} w_i}.
\]

In Eq. (7) \( \tilde{V}_i \) represents the ith estimate of GSV and \( w_i = (\sigma_{gr}^0 - \sigma_{veg}^0)_{i} \) is the corresponding weight based on the difference between the two model parameters representing the backscatter of vegetation and ground. It is assumed that backscatter measurements characterized by stronger sensitivity of the backscatter to GSV should weight more. \( N \) is the number of measurements for which an estimate of GSV has been obtained. The coefficient \( w_{\text{max}} \) corresponds to the largest of the \( w_i \) weights.

5. Validation of the backscatter modeling approach

The model in Eq. (3) has been validated with in situ data at selected test sites using least-squares techniques (Pulliainen et al., 1994; Santoro et al., 2002). This model training approach is however unfeasible when targeting large areas because it requires a dense network of in situ measurements. To overcome this shortcoming, we propose a novel approach for estimating the two unknown model parameters \( \sigma_{gr}^0 \) and \( \sigma_{veg}^0 \) based on a number of plausible approximations. In this Section, performance and robustness of each single procedure are presented and discussed.

5.1. Estimation of \( \sigma_{gr}^0 \)

The estimation of the parameter \( \sigma_{gr}^0 \) requires the definition of a window of finite size, centered in the pixel of interest, in which pixels corresponding to a low value of the MODIS VCF product are selected. A measure of central tendency (mean value, median or mode) for the corresponding to a low value of the MODIS VCF product are selected. A measure of central tendency was used to determine the model parameter estimate. The histogram of the backscatter for the “ground” pixels can present different shapes depending on the soil moisture characteristics within the estimation window and the presence of sparse vegetation. Moreover, often the proportion of pixels with low VCF close to zero is minimal. Therefore, pixels with a small percentage of trees also need to be selected. As a consequence, the estimate of \( \sigma_{gr}^0 \) can vary significantly depending on the statistical parameter used to define the central tendency of the backscatter distribution. Since the BIOMASAR algorithm aims at automatic model parameter estimation, criteria had to be defined in terms of window size, range of VCF values and central tendency measure that guarantee a robust estimate of \( \sigma_{gr}^0 \).

Concerning the measure of central tendency, the estimates of \( \sigma_{gr}^0 \) were practically identical when the distribution of the backscatter for the “ground” pixels was unimodal and peaked. The largest difference between estimates was about 0.2 dB. For fuzzier distributions, significant differences occurred. Since the median was the least affected by the distribution of the backscatter and was found to correctly represent the central tendency in most cases, it was decided to adopt it as statistical measure for the estimation of \( \sigma_{gr}^0 \).

The robustness of the procedure for estimating \( \sigma_{gr}^0 \) was tested by checking the sensitivity to different combinations of window size and threshold on the VCF percentage. The VCF threshold was varied between 15 and 25%. The radius of the estimation window was varied between 50 and 200 pixels. With smaller thresholds and/or radii, hardly ever more than a few pixels were labelled as “ground”. The VCF threshold was limited to 25% to avoid that the backscatter from sparsely vegetated areas affected the histogram. VCF of 30–40% generally corresponds to shrubland in global land-cover datasets. A radius of the estimation window larger than 200 pixels did not affect the estimation of \( \sigma_{gr}^0 \).

The set of \( \sigma_{gr}^0 \) estimates for the different combinations were compared to the value obtained using the traditional model training approach based on reference GSV. Fig. 5 shows a representative example for this analysis. Crosses and circles represent the estimates for the different combinations of VCF threshold and window size. The filled circle and the vertical bars represent the estimate obtained with the traditional approach and the backscatter range for GSV < 10 m^3/ha. The estimates obtained with the BIOMASAR algorithm were always within the error bars of the measurements for combinations characterized by at least 1% of “ground” pixels (circles). Otherwise, the estimate of \( \sigma_{gr}^0 \) was often too low or not within the range of the measurements (crosses). More details on the estimation are provided at the end of this Section.

A further analysis focused on relating the percentage of “ground” pixels to the shape of the distribution of the backscatter. For this purpose, the Hartigan’s dip test on unimodality (Hartigan & Hartigan, 1985) was used. The analysis revealed that (i) for a percentage of “ground” pixels below 1%, the dip test always stated the lack of unimodality and (ii) for at least 2% “ground” pixels, the dip test always stated unimodality.

Based on such results, the estimation procedure was set up as described in the flowchart in Fig. 6. Starting from a minimum VCF threshold and radius of the estimation window, the percentage of “ground” pixels is computed. The estimation window is then enlarged until at least 2% of the pixels within the estimation window are labeled as “ground”. The size of the estimation window is limited by an upper bound, which depends on the proportion of unvegetated areas within the study region. If still the percentage of “ground” pixels is below 2%, the VCF threshold is increased while the window size is reset to the minimum radius. Also the range of VCF threshold is limited by an upper bound. The 2% level was reached for most pixels when the threshold on the VCF was 30–35%. Higher threshold values should be avoided to prevent that the backscatter from partially vegetated areas distorts the histogram of the “ground” pixels. If the percentage of “ground” pixels is below 2% for all combinations of window radius and VCF threshold, the approach is repeated setting the minimum percentage of “ground” pixels to 1%. If the percentage of the “ground” pixels does not reach the 1% level either, \( \sigma_{gr}^0 \) is set equal to not-a-number, which in turn means that no GSV is retrieved for the specific backscatter measurement.

Fig. 5 shows that, for unfrozen conditions (June to October), the agreement between the estimates using the BIOMASAR algorithm (filled grey circle) and the traditional model training approach (filled black circle) was reasonable. For images acquired during winter-time (January–beginning of May), the estimates obtained with the BIOMASAR algorithm were somewhat lower than the values predicted by the traditional modeling approach. The frozen conditions decreased the backscatter from bare soil significantly. In the case of layered snow, absorption of the radar wave can also decrease the backscatter substantially.

5.2. Estimation of \( \sigma_{veg}^0 \)

The estimation of the parameter \( \sigma_{veg}^0 \) also relies on the definition of an estimation window and selection of pixels, which in this case are...
labeled as “dense forest”. Pixels labeled as “dense forest” are characterized by a canopy cover percentage above a certain threshold. The central tendency of the backscatter distribution for dense forests, $\sigma_{df}^0$, needs then to be corrected for residual contributions from the forest floor as shown in Eq. (5). Therefore, a sensitivity analysis aiming at defining rules for a robust estimation of $\sigma_{veg}^0$ had to consider (i) the sensitivity of $\sigma_{df}^0$ to the size of the estimation window and to the VCF threshold, and (ii) the sensitivity of $\sigma_{veg}^0$ to the GSV for dense forests, $V_{df}$. In principle, the sensitivity analyses should have taken into account the propagation of errors due to an incorrect estimate of $\sigma_{gr}^0$ and/or $\beta$ as well. This aspect was however considered of minor importance since, at C-band, the compensation of the backscatter...

**Fig. 5.** Comparison of $\sigma_{gr}^0$ estimates for a pixel in the Västerbotten study area for ASAR WSM data acquired during 2005. For each image date, the set of estimates of $\sigma_{gr}^0$ corresponding to different combinations of VCF threshold and size of the estimation window is shown. Circles and crosses represent combinations for which the percentage of “ground” pixels was above and below 1%, respectively. The grey-filled circle corresponds to the estimate for a window with a 50 pixels radius and a VCF threshold of 20% (percentage of “ground” pixels: 1.5%). The filled black circles represent the estimates using the traditional model training approach based on GSV reference data. The vertical bars represent the range of backscatter for GSV $< 10$ m$^3$/ha (5th and 95th percentile).

**Fig. 6.** Flowchart illustrating the procedure for the estimation of the model parameter $\sigma_{gr}^0$ by the BIOMASAR algorithm.
from dense forests to obtain the estimate of \( \sigma_{\text{veg}}^0 \) is of marginal relevance.

The percentage of dense forest pixels was found to be sufficiently large at all study areas to obtain a clearly peaked backscatter distribution. The estimates of \( \sigma_{\text{veg}}^0 \) using the mean, the median or the mode did not show particular differences. In the following, results will be shown using a median-based estimation of \( \sigma_{\text{veg}}^0 \).

The sensitivity analysis of \( \sigma_{\text{veg}}^0 \) considered the simultaneous effect of the estimation window size, the VCF threshold for dense forest and the GSV for dense forest. To start with, plausible intervals for each of the variables were defined. The VCF threshold was constrained between 70 and 80% of the maximum VCF value in order to include only dense forests in the “dense forest” class and label at least 2% of the pixels within the estimation window as “dense forest”. Similarly, the radius of the window was allowed to vary between 50 and 100 pixels. Larger estimation windows always included more than 2% of pixels labeled as “dense forest” and the estimate of the model parameter did not differ compared to the case of 100 pixels radius. For \( V_{df} \), values between the 80th and the 95th percentile of the GSV histograms obtained from the reference data were considered.

Because of the weak sensitivity of the backscatter to GSV in dense forest, practically all combinations produced a model realization that followed the trend between the backscatter measurements and the reference GSV values. Nonetheless, some model realizations were closer to the average backscatter trend in a least squares sense than others. Therefore, to gain insight on the parameter estimation sensitivity, the mean difference of the backscatter measurements with respect to the specific model realization, MD, was computed:

\[
MD = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( \sigma_{\text{meas},i}^0 - \sigma_{\text{model},i}^0 \right)^2}
\]  

In Eq. (8), \( \sigma_{\text{meas},i}^0 \) and \( \sigma_{\text{model},i}^0 \) represent the measured and the modeled backscatter for the ith pixel and \( V_{i} \) represents the corresponding GSV. \( N \) represents the number of pixels considered within the study area (or part of it). Since the evaluation of the MD is of interest for the dense forest, Eq. (8) was computed only for pixels with VCF above 70%, corresponding to GSV above 150 or 200 m³/ha depending on the study area. Taking into account that at C-band the sensitivity of the backscatter to GSV is much reduced at high GSV, the choice of the range of GSV for the computation of the mean difference was not a relevant issue.

For each combination of (i) VCF threshold for dense forest, (ii) estimation window size and (iii) GSV for dense forest, the MD was computed on an image-by-image basis and the statistics for the entire data stack were analyzed. The performance of the estimation was quantified by means of three criteria: i) the mean value of MD over the stack must be low, ii) the standard deviation of the MD over the stack must be small and iii) the span of MD values must be limited. The distribution of the MD for 27 possible combinations is shown in Fig. 7 by means of box-plots. For the specific example illustrated in Fig. 7, the best combination corresponded to the smallest window (radius of 50 pixels). The effect of the other variables was negligible. Nonetheless, the distribution of the MD was different depending on the study area. A closer look at the box-plots from the study areas used for validation of the algorithm revealed that combination 14 (see Fig. 7) was always characterized by the one of the lowest overall and mean MD, and small spread. The analysis also indicated that the sensitivity of the estimation was weakest with respect to the latter variable, i.e., combinations 13 and 15 performed similar to 14. In this way, the estimation of \( \sigma_{\text{veg}}^0 \) is simplified because it postulates the knowledge of the highest GSV in the area of interest. This information can be easily obtained from records of regional and national forest inventory statistics.

Based on these results, the following rules were set for the estimation of \( \sigma_{\text{veg}}^0 \):

1) radius of estimation window equal to 100 pixels;
2) VCF threshold to select “dense forest” pixels equal to 75% of maximum VCF within the estimation window;
3) \( V_{df} \) equal to the maximum GSV for the area of interest.

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**Fig. 7.** Box-plots of MD for 27 combinations of VCF threshold/window size/GSV of dense forest for the Bolshe-Murtinsky Northeast (Bolshe-NE) forest compartment in the case of WSM data.
5.3. Backscatter modeling with the BIOMASAR algorithm

The approach for the model parameters estimation implemented in the BIOMASAR algorithm is summarized in Fig. 8. The output of the model training block consists of per pixel estimates of $\sigma_{gr}^0$ and $\sigma_{veg}^0$. A comparison between modeled and measured backscatter values for a pixel randomly selected in the Chunsky forest compartment is illustrated in Fig. 9. The upper plot shows that (i) the modeled backscatter at this pixel is close to the measured backscatter (filled circle) and (ii) the modeled realization using the BIOMASAR algorithm (solid curve) follows the trend of the backscatter measurements. The backscatter measurements were relative to the area covered by the forest compartment. The histograms show that the distribution of the backscatter for "ground" pixels and "dense forest" pixels is peaked and unimodal. Despite the rather small percentage of "ground" pixels, the median of the histogram returned a plausible estimate of $\sigma_{gr}^0$, as shown by the asterisk on the y-axis of the upper plot for 0 m$^3$/ha. The histogram for the "dense forest" class was slightly skewed. Nonetheless, the estimate of $\sigma_{df}^0$ was in line with the trend in the measurements (approximately $-9.5$ dB) and the model realization based on the corresponding estimate of $\sigma_{veg}^0$ followed the trend between the measured backscatter and the in situ GSV.

The analysis of several hundreds of such plots confirmed the robustness of the method proposed for modeling. Only in a few cases the model realization did not reflect the backscatter at the lowest GSV because of soil moisture effects, producing an over-estimation. This is physiological when considering that the backscatter is modeled several hundred times per pixel. The over-estimation of $\sigma_{gr}^0$ implied that the BIOMASAR algorithm predicted very week sensitivity of the backscatter to GSV. This error did not have any impact on the retrieval since the multi-temporal combination has been implemented in order to reject GSV estimates with a very difference between $\sigma_{gr}^0$ and $\sigma_{veg}^0$.

6. Analysis of the GSV retrieval approach

6.1. Estimation of GSV from a single measurement

The only factor that plays a significant role on the performance of the retrieval from a single backscatter measurement is the maximum retrievable GSV, see Eq. (6). Because of the weak sensitivity of the C-band backscatter to GSV, the occurrence of estimates of the GSV equal to the maximum retrievable value is likely to be substantial. An increase or decrease of the maximum retrievable GSV would result in a consequent increase or decrease of the retrieved GSV for a number of observations, which in turn affects the multi-temporal estimate of GSV using Eq. (7) in the form of an offset. For the sensitivity analysis, several model inversions and multi-temporal combinations were carried out, each time with a different value of the maximum retrievable GSV. As starting point, we considered the value selected for the GSV of dense forest, $V_{df}$. The maximum retrievable GSV was increased each time by 10 m$^3$/ha. The largest offset was 100 m$^3$/ha. This ensured that also the highest GSV in the area of interest were considered within the range of retrievable GSVs. To avoid point-wise noise affecting the interpretation of the results, average values from the retrieved and the reference datasets were compared. The aggregated GSV retrieved from the ASAR data was always closest to the average reference GSV for an offset between 40 and 50 m$^3$/ha. Based on this analysis, it was decided to define the maximum retrievable GSV, $V_{max}$, simply as:

$$V_{max} = V_{df} + 50$$  \(9\)

6.2. Multi-temporal combination

The multi-temporal combination described in Eq. (7) assumes that the individual GSV estimates derived from a stack of backscatter measurements are weighted according to the sensitivity of the backscatter to the GSV. Fig. 10 shows that this approach is not only plausible but also produces an estimate in line with the reference GSV. The estimates of GSV for observations characterized by large weights, i.e., strong sensitivity to the backscatter, were closer to the reference value shown by the horizontal line in Fig. 10. The estimates of GSV for observations characterized by lower weights presented a much larger spread.

![Fig. 8. Model training and retrieval approach implemented in the BIOMASAR algorithm.](image)
Fig. 9. The plot on top shows the measured backscatter (filled circle) for a pixel randomly selected within the forest compartment of Chunsky East, the modeled backscatter (solid curve) and the trend in the measurements for the area surrounding the pixel (dashed line). The Envisat ASAR image was acquired on 2005-02-06 in GM mode. The vertical bars represent the standard deviation of the backscatter measurements grouped into 50 m$^3$/ha wide classes, centered at the points indicated by the crosses (mean values). The asterisk at 0 m$^3$/ha represents the estimate of $\sigma_{gr}$ with the BIOMASAR algorithm. The two plots at the bottom show the distribution of the backscatter for the “ground” pixels (left) and the “dense forest” pixels (right). For each histogram, information on radius of the estimation window (in pixels), VCF threshold (in %), and percentage of pixels selected within the estimation window (in %) has been provided.

Fig. 10. Retrieved GSV from individual backscatter observations with respect to the weight $w$, for two pixels representative of a mature forest (left) and a young regrowing forest (right). Study area: forest compartment of Chunsky East, Central Siberia. Each point represents an ASAR observation. Circles and dots indicate GSV estimates for which the weight is above and below 0.5 dB respectively. Circles have been colored according to three main types of environmental conditions at the time of image acquisition (white-fill = frozen, grey-fill = unfrozen, black-fill = freeze/thaw). The dashed horizontal lines represent the multi-temporal GSV estimate and the reference GSV value.
Fig. 10 also shows that observations characterized by small or negative weights often showed large discrepancy and extreme GSV estimates. Such cases corresponded to images severely affected by the environmental conditions at the time of image acquisition, since the backscatter from the ground is greater or equal than the backscatter from the vegetation. To avoid that observations characterized by a dominant contribution related to the environmental conditions distort the retrieval, it was decided that the algorithm discards GSV estimates characterized by a weight below a given threshold. The 0.5 dB level was found to represent a reasonable compromise between keeping a large number of observations while discarding those characterized by a strong noise component. Fig. 10 shows that practically all observations with a weight below 0.5 dB were characterized by either 0 m$^3$/ha or the maximum retrievable GSV. Higher thresholds had the effect that a large number of observations potentially containing forest information were rejected.

Fig. 10 gives a first insight on the effect of the seasonal conditions on the retrieval. The larger weights and the stronger agreement between the retrieved and the reference GSV were often obtained under frozen conditions ($T < -3 \, ^\circ C$). This can be explained as a consequence of the increased penetration of the microwaves into the forest canopy, which implies that larger elements of the trees are sensed. Unfrozen conditions ($T > 5 \, ^\circ C$) were characterized by lower weights and larger discrepancies between the retrieved and the reference GSV. This could be explained in terms of the weak penetration of the microwaves into the canopy and the significant soil moisture effects on the backscatter. Under freeze/thaw conditions ($-3 \, ^\circ C \leq T \leq 5 \, ^\circ C$), the retrieval was rather unpredictable since the total forest backscatter is strongly affected by external factors such as snow wetness and structure. The asymmetry of the temperature interval for the freeze/thaw conditions ensured that, in case of unfrozen conditions, these had been unfrozen during several hours before image acquisition.

The effect of the seasonal conditions is shown in more general terms in Fig. 11 for the forest compartment of Mansky, Central Siberia. The relative RMSE for each image covering the forest compartment has been plotted with respect to the average weight, i.e., the average value of the pixel-wise values of $\left( \alpha_{\text{veg}} - \alpha_{\text{gr}} \right) / T$ for a given image. The relative RMSE decreased with increasing weight. The retrieval performed better mostly under frozen conditions. Nonetheless, some images acquired under frozen conditions were characterized by large errors too. The sensitivity of the backscatter to GSV was mostly between 2 and 4 dB for frozen conditions, below 3 dB for unfrozen conditions and mostly below 2 dB for freeze/thaw conditions. The results were consistent for all study areas.

To verify whether the multi-temporal combination can be restricted to GSV estimates characterized by the largest weights, individual GSV estimates were sorted for decreasing average weight and each time a new observation was included in the hyper-temporal stack. Fig. 12 illustrates the performance of the multi-temporal retrieval for decreasing weight for the same dataset shown in Fig. 11. The relative RMSE decreased significantly when combining the first few images with the largest weights. The retrieval continued improving, even if marginally, when further including estimates characterized by smaller weights. Such results were obtained for all study area, indicating that an a priori selection of images based on environmental conditions does not imply obtaining the best result in terms of retrieval accuracy. Our analysis revealed that at least 20 observations satisfying the criterion of a weight above 0.5 dB are necessary for optimal performance of the multi-temporal combination. A dataset consisting of 60–100 backscatter measurements seemed sufficient to reach the critical mass of data, under the assumption that repeated acquisitions were collected during all seasons.

7. Retrieval of forest GSV

The retrieval performance of the BIOMASAR algorithm was tested at 100 m using the WSM images and at 1 km using the combined dataset of GMM and aggregated WSM images. To quantify the performance of the retrieval, the following statistical measures were used:

- the relative RMSE;
- the estimation bias defined as the difference between the mean values of the retrieved and the reference GSV for the specific study area;
- the Pearson’s coefficient of correlation.

Since the GSV produced by the BIOMASAR algorithm had to be compared against datasets of GSV of different origin and accuracy (see Section 2), the interpretation of the retrieval required caution. In principle, we can speak of an accuracy assessment of the retrieval only for the study area in Central Siberia, for which inventory data were available. For the remaining study areas, it is more correct to speak of an inter-comparison between retrieved and reference data. For this reason, we will primarily focus on the results obtained in Central Siberia. Results from the remaining study areas are reported in order to provide a more general perspective on the retrieval performance of the BIOMASAR algorithm.
The time lag between the ASAR datasets and the year of compilation of the reference datasets was another issue that had to be taken into account. Correction factors for yearly growth were applied. Annual productivity rate reported for Central Siberia in (Shvidenko et al., 2008b) and for Sweden in (Loman, 2008) were used. The Lac Mistassini dataset did not need correction. Furthermore, forest cover changes due to disturbances implied that part of the data used as reference was obsolete. To get insight on the reason for the discrepancy, Landsat images acquired after the date of the reference material but before the acquisition of the ASAR data were overlaid on the GSV maps. While the Landsat images could clarify most cases of disagreement between reference and retrieved GSV, we preferred computing the retrieval statistics using the original reference GSV to avoid biasing the retrieval statistics with subjective interpretation.

7.1. GSV retrieval at 100 m

At 100 m, the retrieval of GSV was possible for the forest compartments of Bolshe-Murtinsky and Chunksy in Central Siberia, and for Västerbotten and Västra Götaland in Sweden. Table 4 shows that the retrieval statistics were rather poor and differed significantly depending on the study area. This was partly a consequence of the quality of the reference datasets at 100-m pixel size (see Section 3).

For the Siberian study areas, Fig. 13 shows a scatterplot of the GSV retrieved with the BIOMASAR algorithm against the corresponding GSV from the inventory. For clarity reasons, only forest polygons larger than 100 ha have been considered. The majority of the polygons clustered along the 1:1 line up to almost 300 m³/ha. Polygons showing substantial differences between retrieved and in situ data could be grouped into two major clusters. Polygons within the ellipse on the right hand-side of the scatterplot showed up as almost entirely unvegetated in the Landsat imagery, thus supporting the validity of the estimate from the BIOMASAR algorithm. Polygons within the ellipse on the left hand-side of the scatterplot appeared in the Landsat image as a mixture of patches of unvegetated areas and densely vegetated areas. The BIOMASAR GSV estimates seemed in line with this condition since the vertical bars spanned over a large range of GSV values and the mean GSV was located in the middle of the distribution, at a level that plausibly represented the mean GSV in case of polygons with patchy forest cover. The proportion of polygons characterized by some sort of anomaly was not negligible, thus explaining the rather high retrieval error reported in Table 4. Hence, interpretation of the retrieval statistics should be handled with care.

For the study area in Sweden, the inter-comparison between the retrieved GSV and the reference GSV from the kNN dataset revealed moderate agreement. Considering that the uncertainty level of the kNN dataset at 100 m pixel size was not negligible (see Section 2), we prefer avoiding further considerations on the retrieval.

7.2. GSV retrieval at 1 km

The statistical analysis of the retrieval consisted of a comparison between the GSV estimates from the BIOMASAR algorithm using the ASAR data at 1-km spatial resolution (GMM and aggregated WSM) against the values obtained by spatial aggregation of the reference datasets to the same pixel size. Table 5 shows the retrieval statistics for each of the study areas. Compared to the 100 m case (Table 4), the statistics for 1 km pixel size were more homogeneous because spatial aggregation significantly reduced local noise and errors in the reference datasets. For the study area of Lac Mistassini, the retrieval statistics have been reported separately for the northern, the central and the southern part because different trends between retrieved and reference GSV were observed. Furthermore, the trend was again different when comparing against the BioSF GSV, as shown by the estimation bias values in Table 5. Because of these inherent differences between the different GSV datasets used as reference, the results from Lac Mistassini are not further discussed in this paper.

The retrieved and the reference GSV for all four forest enterprises in Central Siberia are shown in Fig. 14. The plot shows reasonable agreement between the two datasets, without apparent sign of saturation up to 300 m³/ha. For GSV greater than 300 m³/ha, the

### Table 4

<table>
<thead>
<tr>
<th>Area</th>
<th>Relative RMSE (%)</th>
<th>Correlation coefficient</th>
<th>Estimation bias (m³/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bolshe-Murtinsky NE, Central Siberia</td>
<td>70.9</td>
<td>0.27</td>
<td>~62.3</td>
</tr>
<tr>
<td>Chunksy North, Central Siberia</td>
<td>96.2</td>
<td>0.56</td>
<td>~23.1</td>
</tr>
<tr>
<td>Chunksy East, Central Siberia</td>
<td>78.3</td>
<td>0.76</td>
<td>~36.5</td>
</tr>
<tr>
<td>Västra Götaland, Sweden</td>
<td>47.7</td>
<td>0.36</td>
<td>7.4</td>
</tr>
<tr>
<td>Västerbotten, Sweden</td>
<td>60.4</td>
<td>0.53</td>
<td>~0.8</td>
</tr>
</tbody>
</table>

### Table 5

<table>
<thead>
<tr>
<th>Area</th>
<th>Relative RMSE (%)</th>
<th>Correlation coefficient</th>
<th>Estimation bias (m³/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central Siberia</td>
<td>34.2</td>
<td>0.65</td>
<td>~8.3</td>
</tr>
<tr>
<td>Västra Götaland</td>
<td>37.5</td>
<td>0.26</td>
<td>~0.7</td>
</tr>
<tr>
<td>Västerbotten</td>
<td>47.7</td>
<td>0.34</td>
<td>4.7</td>
</tr>
<tr>
<td>Lac Mistassini (kNN, North)</td>
<td>44.6</td>
<td>0.33</td>
<td>10.7</td>
</tr>
<tr>
<td>Lac Mistassini (kNN, Center)</td>
<td>48.1</td>
<td>0.49</td>
<td>32.1</td>
</tr>
<tr>
<td>Lac Mistassini (kNN, South)</td>
<td>46.2</td>
<td>0.36</td>
<td>8.2</td>
</tr>
<tr>
<td>Lac Mistassini (kNN, BioSF)</td>
<td>44.5</td>
<td>0.38</td>
<td>~19.8</td>
</tr>
</tbody>
</table>
7.3. Aggregated GSV estimates

The weak sensitivity of C-band backscatter to GSV implies that aggregation of GSV estimates to lower spatial resolution should reduce noise. Aggregation has also the advantage that random errors in the reference datasets can be filtered out so that the accuracy assessment of aggregated GSV products should be characterized by statistics which are less affected by residual noise or local errors.

Fig. 15 illustrates the trends of the correlation coefficient and the relative RMSE as a function of aggregated pixel size in the case of 1 km pixel size SAR data. The agreement between the retrieved and the reference GSV increased with increasing aggregation level. For small aggregation factors (up to approximately 5 × 5), the correlation coefficient increased substantially. Similarly, the relative RMSE decreased steadily. For larger aggregation windows, the retrieval improved only marginally. The correlation coefficient for 10 km pixel size, i.e., for an averaging window of 10 × 10 pixels, was between 0.62 and 0.82. The relative RMSE was between 15% and 25%.

Fig. 16 shows the scatterplot between the aggregated values from the retrieved and the reference GSV datasets for 10 km pixel size, for the study area in Central Siberia. The agreement is remarkable, without apparent signs of saturation for the entire range of GSV within the study area, i.e., 0–300 m³/ha. Similar patterns were observed for the aggregated estimates at the two study areas in Sweden as well (see the plot on the right-hand side of Fig. 17).

The availability of ASAR datasets at 100 m and 1 km over some of the study areas allowed us to verify scaling issues on the retrieval accuracy. As for the 1-km case, the relative RMSE and the correlation coefficient for the aggregated 100-m GSV datasets improved more rapidly for small aggregation factors. For 1 km², i.e., a 10 × 10 aggregation factor, the relative RMSE was approximately 25%. This was less than the error obtained for the 1-km dataset (see Table 5). Comparison of retrieval statistics for the different aggregation levels showed that the retrieved GSV was more accurate when starting from the higher resolution, i.e., 100 m, estimates. Fig. 17 shows an example of aggregated GSV at 10 km for the 100 m case (left) and the 1 km (right). The aggregated GSV obtained from the SAR dataset with higher resolution presented stronger agreement with the reference data. The result can be explained in terms of the stronger averaging applied to the 100 m GSV estimates, as well as in terms of the more detailed information about the distribution of the GSV within the aggregation window compared to the 1-km case.

8. Conclusions

The scope of this paper has been to present a straightforward algorithm for the estimation of forest growing stock volume (GSV) using hyper-temporal stacks of SAR backscatter data and test its performance in the case of Envisat ASAR ScanSAR C-band data. The formulation of the algorithm is general enough to be applied to other SAR datasets as well as other forest types, as long as the physical description of the forest backscatter as a function of the forest GSV holds true. The methodology, referred to as the BIOMASAR algorithm, couples standard SAR processing steps to obtain co-registered stacks of SAR backscatter images, a Water–Cloud type model relating the SAR backscatter to the GSV and a multi-temporal combination of individual estimates of GSV from corresponding backscatter measurements. One novel aspect consists of the independence of the method from in situ data used for tuning the forest backscatter model, making it applicable at large scales from continents to entire biomes. The unknown model parameters are estimated by determining the central tendency (e.g., median value) for the distribution of measured backscatter for two categories of pixels: unvegetated and dense forest pixels. These can be identified by means of remotely sensed forest cover information (e.g., the MODIS Vegetation Continuous Field tree cover product). The multi-temporal combination of individual GSV estimates consists of a weighted average. Weights are defined as the difference of the modeled backscatter for unvegetated areas and completely dense forest. In this way, it is ensured that the information provided by the temporally consistent component of the backscatter signal related to the forest structure is enhanced whereas the temporally variable signal related to environmental conditions is filtered out.

Performance and robustness of the retrieval algorithm were assessed by means of sensitivity analyses with respect to factors that influence modeling and retrieval, and considered simultaneously several study areas. These were located in the boreal zone because of the urgent need of up-to-date information on forest conditions and because of the simple structure of forest, which implies a certain potential for short wavelength radar data to provide the required information. The outcome of the sensitivity analyses consisted of a set of rules for the estimation of the model parameters and for the retrieval. The model parameters estimated with the BIOMASAR algorithm were mostly in line with the values obtained using the traditional model training methods that potentially bear a certain uncertainty component (fi, σf0, Vdf, fi, β, and Vdf) have been perturbed with a zero-mean Gaussian noise term. The standard deviation for each term was derived from the statistical distribution of “ground” and “dense forest” histograms (f0,σ0 and Vdf), from the estimate of residual speckle (σf0,σ0) and considering the range of plausible values (β and Vdf). The GSV was retrieved with the BIOMASAR algorithm 200 times to ensure statistical significance to the uncertainty analysis. The uncertainty of the retrieval due to the algorithm was found to be on average 10%, with a standard deviation: 3.2%. The uncertainty has been defined as the ratio between the standard deviation and the mean value of the 200 GSV estimates.
approach based on in situ data. The rules for the retrieval proved to be plausible when comparing retrieved and reference GSV values.

The agreement between retrieved and reference GSV was well beyond the level expected from C-band SAR backscatter. The retrieved GSV did not show saturation up to 300 m$^3$/ha, which corresponded to 99.99% of the GSV at all study areas. The key to such results was the optimal weighting of the GSV from individual observations based on the forest/non-forest backscatter sensitivity. Images acquired under frozen conditions and, to a certain extent, under dry unfrozen conditions contributed mostly to the final estimate of GSV. Under such conditions, the increased transparency of the canopy implies that the backscatter originates at the level of the main elements of the tree (large branches and possibly the stem) while the backscatter from the forest floor is small because of the negligible soil moisture contribution.

The BIOMASAR algorithm has been developed and tested at 100 m and 1 km pixel size. Local errors in the reference data implied that, at 100 m, the retrieval statistics differed depending on the study area. Significant bias was observed in a few cases. The relative root mean square error (RMSE) was between 47.7 and 96.2%. The correlation coefficient was between 0.27 and 0.76. At 1 km, the retrieval statistics were more homogeneous because of the smaller error component in the reference datasets. The relative RMSE was between 34.2 and 48.1%. The correlation coefficient was between 0.26 and 0.65. Perturbation of the BIOMASAR algorithm by means of random noise showed that the retrieval of GSV with the BIOMASAR algorithm is robust. The retrieval uncertainty introduced by the algorithm was approximately 10%.

Aggregation of GSV retrieved with the BIOMASAR algorithm to lower resolution helped to remove uncertainty associated with, for example, residual speckle noise and local errors in the reference data. The relative RMSE decreased for increasing size of the averaging window. Starting from the 1 km dataset, the relative RMSE at 10 km pixel size was between 15 and 25%. The correlation coefficient was between 0.62 and 0.82. Higher accuracy was obtained when starting from the 100 m estimates. At 10 km pixel size, the relative RMSE was 16.8% and 23.6% for the aggregated 100 m and 1 km datasets respectively, whereas the correlation coefficients were equal to 0.87 and 0.68 respectively. Overall, the GSV estimates from the BIOMASAR algorithm presented strong agreement with the reference GSV for aggregation factors of 10 × 10 pixels or more.

This study has demonstrated that the use of available tools implemented in a straightforward approach allows estimates of forest GSV from Envisat ASAR C-band backscatter data for practically the full range of GSV in the boreal zone. Having proven the performance and the robustness of the proposed approach, possibilities open up to exploit the extensive archive of Envisat ASAR ScanSAR data to generate forest GSV maps for the boreal zone at kilometric scale. Although the level of detail is limited, such mapping would represent a substantial step in updating forest information, which in large part of the boreal zone are outdated or not even assessed yet. In addition, such large-scale information on GSV with such detailed spatial resolution will allow a much more rigorous calibration and validation of process-based terrestrial biosphere models operating as land-surface boundary conditions for the atmosphere in climate models than ever before. In particular, the estimation of model parameters using a multiple-constraint approach (Carvalhais et al., 2010; Williams et al., 2005) requires such information.

Future investigations will deal with the temporal consistency of the GSV estimates obtained with the BIOMASAR algorithm. This topic will therefore address the generation of GSV maps on a periodical basis, which could allow tracking forest cover changes. In this study, it was concluded that the optimal dataset, at C-band, consist of at least 20 measurements of backscatter characterized by a forest/non-forest backscatter contrast above 0.5 dB. This critical mass can be obtained
with archived Envisat ASAR ScanSAR data practically globally, on a yearly basis. Hence, it is reasonable to assume that yearly maps of GSV for the boreal zone could be generated. In a similar manner, it can be reasonably assumed that the GSV for other forest environments characterized by dry periods (e.g., savanna) might be mapped with a level of uncertainty comparable to the level obtained in the boreal zone.

Finally, it is believed that the multi-temporal approach devised in this paper can play a substantial role in mapping GSV thanks to ScanSAR data currently acquired by the Advanced Land Observing Satellite (ALOS) Phased Array-type L-band Synthetic Aperture Radar (PALSAR) and planned for the forthcoming Sentinel-1 SAR mission. With respect to the results obtained with Envisat ASAR, improved estimates of GSV are likely because of the higher sensitivity of L-band to forest parameters and the higher spatial resolution of the ScanSAR mode on Sentinel-1.

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References


Fig. 17. Scatterplots of retrieved GSV with respect to reference GSV for aggregation to 10 km pixel size starting from the 100 m (left) and the 1 km (right) GSV estimates. Study area: Västerbotten, Sweden.


