The global forest/non-forest map from TanDEM-X interferometric SAR data

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ABSTRACT

In this paper we present the activities performed at the Microwaves and Radar Institute of the German Aerospace Center (DLR) to derive global forest/non-forest classification mosaics from interferometric synthetic aperture radar (InSAR) data acquired by the TanDEM-X mission. The data have been collected between 2011 and 2016 in bistatic stripmap single polarization (HH) mode, with the main goal of generating a consistent, timely, and highly accurate 3D representation of the global terrain’s surface (digital elevation model, DEM). The global data set of quicklook images, which represent a spatially averaged version of the original full resolution data at a ground independent pixel spacing of 50 m × 50 m, was used as input, in order to limit the computational burden. For classification purposes, several observables, systematically provided by the TanDEM-X system, can be exploited, such as the calibrated amplitude, the digital elevation model (DEM), and the interferometric coherence. Among the several factors contributing to a coherence degradation in InSAR data, the so-called volume correlation factor quantifies the coherence loss due to volume scattering phenomena, which typically occur in presence of vegetation. This quantity is directly derived from the interferometric coherence and used as main indicator for the identification of vegetated areas. For this purpose, a fuzzy multi-clustering classification approach, which takes into account the geometry and acquisition configuration, is applied to each acquired scene separately. A certain variability of the interferometric coherence at X band was observed among different forest types, mainly due to changes in forest structure, density, and tree height, which led to an adjustment of the algorithm settings depending on the considered type of forest. The identification of additional information layers, such as urban settlements or water areas, is also discussed, and the procedure for mosaicking of overlapping acquisitions (two at global scale, up to ten over mountainous terrain, forests, and desert regions) to improve the classification accuracy is detailed. The resulting global forest/non-forest map was validated using external reference information as well as with other existing classification maps and an overall agreement was observed that often exceeds 90%. Finally, examples for high-resolution (at 12 m × 12 m) forest maps and potentials for deforestation monitoring over selected regions are presented as well, demonstrating the unique capabilities offered by the TanDEM-X bistatic system for a broad range of geoinformation services and scientific applications. The global TanDEM-X forest/non-forest map presented in this paper will be made available to the scientific community for free download and usage.

1. Introduction

Covering about 30% of the Earth’s landmasses, forests represent the dominant terrestrial ecosystem and are of extreme importance for all living being on our planet. Indeed, forests act as Earth’s lung, by continuously absorbing, storing, and converting carbon dioxide (CO₂) into oxygen which helps to reduce the concentration of atmospheric greenhouse gases and, ultimately, to control climate change. Plants and trees in forested areas catch rainwater and are natural watersheds preventing from flood events. Moreover, they mitigate soil erosion, which naturally happens due to the action of water and/or wind, or artificially because of irresponsible farming practices. They are an essential source of energy (such as biomass), food, jobs and livelihoods in general for a many populations on Earth and serve as natural habitat to a large variety of animal species, preserving the existence of biodiversities and healthy ecosystems.

However, this delicate balance is put in danger by the loss and degradation of forests, which is nowadays occurring at an alarming...
rate. Deforestation is a process which dates back to the dawn of human civilization. Over the past 10,000 years, more than 50% of the world’s forests have been lost due to anthropogenic activities, such as the demand of energy (e.g., timber) and food (e.g., agriculture), and the realization of living spaces and of transportation infrastructure for a constantly increasing population. Such an age-old deforestation process was severely accelerated in the mid-twentieth century, and more sensitive environments have been irreversibly damaged, leading to a permanent loss of plants and animal habitats, a reduction in forest carbon stocks, and an accelerated soil erosion (Solomon et al., 2007).

For all these reasons, an up-to-date assessment and monitoring of forest resources becomes of crucial importance and, in this scenario, spaceborne remote sensing represents a unique instrument for providing consistent, timely, and high-resolution data at a global scale. In the last decades global forest classification maps have been produced by mainly optical and near-optical systems such as the Advanced Very High Resolution Radiometer (AVHRR) (Hansen et al., 2000; Hansen and De Fries, 2004), at 1 km spatial resolution, the Moderate Resolution Imaging Spectroradiometer (MODIS) (Hansen et al., 2003), 500 m resolution, or ENVISAT MERIS (CCI Land Cover (Hansen et al., 2003; Kirches et al., 2015), 300 m resolution) and its follow-on instrument on Sentinel-3. In 2013 a global forest tree cover map was produced from mosaics of Landsat sensor data at a spatial resolution of 30 m, including annual forest gain and loss (Hansen et al., 2013). In this frame, SAR sensors represent a very attractive solution for reliable mapping and monitoring of forest areas, thanks to their weather and daylight independence. The first global forest/non-forest classification map derived from SAR data, exploiting backscatter in HV polarization, has been provided by the L-band sensor ALOS PALSAR at a posting of 25 m (Shimada et al., 2014).

In this paper we present the first global forest/non-forest classification map from TanDEM-X interferometric SAR data at X band, based on the exploitation of the coherence-derived volume correlation factor, which quantifies the amount of interferometric decorrelation caused by volume scattering phenomena. The TanDEM-X mission comprises the two twin satellites TerraSAR-X and TanDEM-X, with the main goal of producing a global and consistent digital elevation model (DEM) with an unprecedented accuracy by exploiting single-pass SAR interferometry (Krieger et al., 2007). The potentials of TanDEM-X interferometric data for forest mapping have been successfully demonstrated e.g. in Schlund et al. (2014) and Martone et al. (2015a, 2016a).

The paper is organized as follows: the main aspects of the TanDEM-X mission and the available data set are summarized in Section 2, where the suitability of different observables for forest mapping at X band is also discussed. In Section 3 the volume correlation factor is introduced as main parameter used for the present classification approach, and a theoretical background for existing volume scattering models is shortly recalled. Section 4 introduces the set of external data sources that were used as support for the generation of the global forest/non-forest product. The developed method for forest/non-forest classification, based on fuzzy clustering, is introduced in Section 5, and in Section 6 the method for properly mosaicking all overlapping available observations is described. The procedure for the definition of a binary classification threshold as well as additional post-processing filtering is presented in Section 7. Section 8 focuses on the identification of additional information layers (such as areas affected by geometrical distortions, urban settlements, and water bodies) derived from TanDEM-X data as well as from the external data sources listed in Section 4. The resulting global forest/non-forest classification map at 50 m × 50 m spatial resolution is presented in Section 9, while the product validation with external reference data and comparisons with existing land cover maps is discussed in Section 10. Examples for high-resolution forest mapping (at a spatial resolution of 12 m or below), and the potentials for forest change monitoring are shown in Section 11, and in Section 12, conclusions are drawn.

2. The TanDEM-X mission and data set

TanDEM-X (TerraSAR-X add-on for Digital Elevation Measurement) is the first operational spaceborne bistatic SAR system comprising the two twin satellites TerraSAR-X (launched in 2007) and TanDEM-X (launched in June 2010). After a first period of commissioning phase, the mission officially started in December 2010. Since then, the two satellites have been operationally acquiring interferometric SAR images in bistatic configuration, stripmap mode (HH polarization), with a typical resolution (azimuth and range) of about 3 m. Both satellites fly in a closely controlled orbit formation with the opportunity for flexible along- and across-track baseline selection with the primary objective of generating a global, consistent and high-precision digital elevation model (DEM) (Krieger et al., 2007) at a final independent posting of 12 m × 12 m. The global TanDEM-X DEM has been finalized and delivered in September 2016 (Rizzoli et al., 2017a). Such a high-demanding goal has been achieved by performing at least two global mappings of the Earth’s land masses and multiple acquisitions over selected regions (such as mountainous terrain, forested areas, or sandy desert regions) to improve the overall product accuracy. Since the beginning of the mission, more than half a million high-resolution scenes have been acquired and processed, with incidence angles ranging between 30° and about 50°, and interferometric baselines Ḃ in the range between 80 m and 500 m, which have been considered for the present work.

A fundamental acquisition parameter for the current investigation is the height of ambiguity hamb, which represents the height difference corresponding to a complete 2π cycle of the interferometric phase, and gives information about the phase-to-height sensitivity in the interferogram. For the bistatic case, it is defined as

\[ h_{amb} = \frac{\lambda r \sin(\theta_i)}{B_\perp}, \]  

being λ the radar wavelength, r the slant range, and θi the incidence angle. For the first DEM global acquisition of TanDEM-X, the height of ambiguity was typically between 45 m and 60 m, ensuring good unwrapping quality over most land types. For the second one, larger baselines were considered (hamb around 35 m), in order to increase the final DEM accuracy. The combination of at least two acquisitions by means of multi-baseline phase unwrapping algorithms allowed then to fully meet the mission requirements (Lachaise et al., 2012). A single bistatic scene typically extends over an area of about 30 km in range by 50 km in azimuth. From this, quicklook images, representing several SAR and InSAR quantities (like backscatter and coherence maps, or the roughly calibrated DEM (RawDEM)), are generated at a ground resolution of 50 m × 50 m by applying a spatial averaging process to the corresponding operational TanDEM-X interferometric data at full resolution. Working with such quicklook data allows for the exploitation of the TanDEM-X dataset on a global scale with a limited computational load: Indeed, a nominal TanDEM-X stripmap bistatic scene at full resolution comprises two raster images (master and slave), each with a size up to 2 GB, while the corresponding quicklook data have a size of only 1–2 MB each. Moreover, together with a reduction of about three orders of magnitude in terms of data volume, one should also point out that, when dealing with the original products at full resolution, the complete interferometric processing chain needs to be applied to generate, e.g., the coherence map or the DEM, which are used as input to the classification algorithm. This step requires additional processing time (and an increase in the memory usage), which becomes a critical bottleneck due to the large number of bistatic scenes (about half a million) used for the generation of the global classification product presented in this paper. On the other hand, the corresponding quicklook images are generated as a by-product of the full resolution data by the Integrated TanDEM-X Processor (Fritz et al., 2012), hence requiring no additional processing effort. Global mosaics from TanDEM-X quicklook data have already been produced in the last years (Rizzoli et al., 2014, Rizzoli et al., 2017a).
and have been exploited during the whole mission duration as a helpful tool for performance monitoring and acquisition planning optimization. Thus, the global product presented in this paper has a final resolution of 50 m, which represents a good compromise between spatial level of detail and the resulting computational burden. Further examples of full resolution maps are shown at local/regional scale, which demonstrate the opportunity and benefits of deriving, as a next step, a high resolution product at global scale.

3. Decorrelation in vegetated areas

The X-band radar signal, backscattered from the Earth’s surface, depends on the particular land cover type under illumination. However, due to the influence of soil moisture variation, roughness, and other dielectric and geometric characteristics, the discrimination of the particular land type may become difficult, as verified in Martone et al. (2016a) and Schlund et al. (2014).

On the other hand, the interferometric coherence $\gamma$ is considered as the main parameter for forest/non-forest classification. It represents the normalized complex correlation coefficient between master and slave acquisition and gives information about the amount of noise in the interferogram (Bamler and Hartl, 1998). Several contributions cause a coherence degradation in TanDEM-X interferometric data (Martone et al., 2012), which, assuming statistical independence, can be factorized as follows:

$$\gamma = \gamma_{\text{SNR}} \gamma_{\text{Quant}} \gamma_{\text{Range}} \gamma_{\text{Azimuth}} \gamma_{\text{Temp}} \gamma_{\text{Vol}}$$

The terms on the right-hand side describe the error contributions due to limited signal-to-noise ratio ($\gamma_{\text{SNR}}$), quantization errors ($\gamma_{\text{Quant}}$), ambiguities ($\gamma_{\text{Amb}}$), baseline decorrelation ($\gamma_{\text{Range}}$), errors due to relative shift of Doppler spectra ($\gamma_{\text{Azimuth}}$), and temporal decorrelation ($\gamma_{\text{Temp}}$). The last term ($\gamma_{\text{Vol}}$) is called volume correlation factor and describes the coherence loss caused by volume scattering. It represents the contribution which is predominantly affected by the presence of vegetation, and can therefore be exploited for forest mapping purposes. Given a coherence estimate $\gamma$, it is straightforward to quantify $\gamma_{\text{Vol}}$ as

$$\gamma_{\text{Vol}} = \frac{\gamma}{\gamma_{\text{SNR}} \gamma_{\text{Quant}} \gamma_{\text{Range}} \gamma_{\text{Azimuth}} \gamma_{\text{Temp}}}$$

For this purpose, several quantities, such as the radar backscatter, the noise equivalent sigma zero (NESZ), a precise local incidence angle map derived from orbit data and the calibrated RawDEM (Rossi et al., 2012), need to be considered as well. The impact and the evaluation procedure of each decorrelation contribution from TanDEM-X data is discussed in detail in Martone et al. (2015a) and Rizzoli et al. (2017b) and, for the sake of completeness, it is shortly presented in the following:

- $\gamma_{\text{SNR}}$: it describes the coherence loss due to the finite sensitivity of the radar system. For TanDEM-X, the signal-to-noise ratio (SNR) is estimated from the measured backscatter coefficient and the noise equivalent sigma zero (NESZ). Assuming the same performance for master and slave channels, $\gamma_{\text{SNR}}$ is derived as

$$\gamma_{\text{SNR}} = \frac{1}{1 + \text{SNR}}$$

For TanDEM-X nominal acquisitions, $\gamma_{\text{SNR}} > 0.8$ can be expected for most types of land cover (Martone et al., 2012).
- $\gamma_{\text{Quant}}$: it represents the errors due to the quantization of the recorded raw data signals. On the TerraSAR-X and TanDEM-X satellites, block adaptive quantization (BAQ) is employed for raw data compression and, for the generation of the global DEM, BAQ rates of 2, 2.5, and 3 bits/sample have been selected. For typical image performance, decorrelation smaller than 10% (for the lowest BAQ rates) can be reasonably expected (Martone et al., 2015a,b).
- $\gamma_{\text{Range}}$: possible baseline decorrelation effects (due to presence of, e.g., rugged topography) are estimated by deriving a local slope map from orbit and elevation information. However, for the baselines range employed in the TanDEM-X mission (typically smaller than 500 m) and flat to moderate terrain, a decorrelation in the order of 2% or less can be expected.
- $\gamma_{\text{Temp}}$: TanDEM-X operates in single-pass bistatic mode, which means that the backscattered signal is simultaneously recorded from the Earth’s surface by both the TerraSAR-X and TanDEM-X satellites. For single-pass bistatic acquisitions, the along-track baseline of the TanDEM-X formation is typically smaller than 600 m, so that the time lag between master and slave acquisitions is less than 40 ms. In this scenario, the temporal decorrelation contribution can be reasonably neglected, i.e. $\gamma_{\text{Temp}} \approx 1$.
- Regarding the remaining error contributions $\gamma_{\text{Amb}}$ and $\gamma_{\text{Azimuth}}$, adaptive selection of the azimuth processing bandwidth as well as total independent zero Doppler steering are employed in TanDEM-X, and an additional coherence loss in the order of about 2% can be assumed (Krieger et al., 2007; Martone et al., 2012).

A global mosaic of the volume correlation factor from TanDEM-X data is presented in Martone et al. (2017). As an example, for a TanDEM-X acquisition over the Amazon rainforest (with center coordinates [9°S, 56.5°W]), Brazil, the map for the normalized backscatter coefficient $\gamma^B$ (Small, 2011) is presented in Fig. 1 (a), while in Fig. 1 (b) and (c) the interferometric coherence $\gamma$ and the estimated volume correlation factor $\gamma_{\text{Vol}}$ are depicted, respectively, overlaid to a GoogleEarth optical image. The mean height of ambiguity is of about 40 m and the mean incidence angle of 43°. As reference, the corresponding optical GoogleEarth image alone is shown in Fig. 1 (d):

![Fig. 1. Quicklook images derived from a TanDEM-X bistatic acquisition over the Amazon rainforest, Brazil (with center coordinates [9°S, 56.5°W]), with a height of ambiguity of 40 m (corresponding to a baseline of about 180 m): (a) normalized backscatter coefficient $\gamma^B$, (b) interferometric coherence $\gamma$, (c) volume correlation factor $\gamma_{\text{Vol}}$, (d) the optical image available from GoogleEarth is depicted. The considered area is delimited by the red rectangle and extends by about 50 km x 30 km. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)](image-url)
the area of interest is delimited by the red rectangle and extends by about 30 km in range by 50 km in azimuth (the satellites fly in descending orbit - from top to bottom of the image - in right-looking geometry).

The area is characterized by densely forested areas and clear-cuts and, from a first visual inspection, it can already be noticed that the coherence and the volume correlation factor are actually more suitable for forest discrimination purposes if compared to SAR backscatter, for which a higher confusion between the two land cover types is observed.

For the generation of the global forest/non-forest map, external reference data have been used for discrimination of land cover types which, for different reasons, degrade the quality of the TanDEM-X data, leading ultimately to the occurrence of classification errors. These include, e.g., water areas, urban settlements, and sandy deserts, and are further detailed in Section 8. Finally, highly accurate reference data are required in the validation process, to assess the accuracy of the final

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Based on the promising results shown in this section, the volume correlation factor only is exploited for the forest/non-forest discrimination purposes from TanDEM-X data. More in general, due to its short wavelength, X-band waves have a quite low penetration capability through the tree canopy, and the ability of discriminating between woody and herbaceous forest may be limited, if compared to longer wavelengths.

From a theoretical formulation, a vegetation canopy can be modeled as the superposition of multiple scatterers located at different heights $z$. Each of these scatterers contributes with a phase term $\varphi = 2\pi h/\lambda_{amb}$, being $\lambda_{amb}$ the height of ambiguity, defined in Eq. (1). The resulting correlation factor $\gamma_{\text{Vol}, \text{th}}$ is obtained from the ensemble average over all scatterers within the canopy layer (Treuhaft et al., 1996)

$$
\gamma_{\text{Vol}, \text{th}} = \frac{\int_{0}^{h} \sigma^0(z) \exp\left(\frac{1}{2\pi z \lambda_{amb}^2}\right) dz}{\int_{0}^{h} \sigma^0(z) dz},
$$

where $h_{\text{vol}}$ is the height of the volume layer and $\sigma^0(z)$ represents the vertical scattering profile. Assuming the extinction through a homogeneous medium, $\sigma^0(z)$ can be modeled as

$$
\sigma^0(z) = \exp\left(-2\beta h_{\text{vol}} - \frac{z}{\cos(\theta)}\right),
$$

being $\theta$ the incidence angle and $\beta$ the one-way extinction coefficient. Simulations of the coherence loss $\gamma_{\text{Vol}, \text{th}}$ for different volume heights and typical extinction coefficients are carried out in Krieger et al. (2007), and a good agreement between the model in Eqs. (5) and (6) and the volume correlation factor estimated as in Eq. (3) for time series of TanDEM-X bistatic acquisitions over forested areas is verified in Martone et al. (2015a, 2017).

One has to point out, however, that the inversion of the described theoretical model would require the estimation of two unknowns, i.e., the volume height $h_{\text{vol}}$ and the extinction coefficient $\beta$, both strongly varying depending on the specific forest type and characteristics. For this reason, the model in Eq. (5) cannot be applied for the implementation of a classification procedure from a single TanDEM-X scene, unless additional information is available (such as, e.g., a digital terrain model, DTM), or further assumptions on the unknowns are made. Moreover, it has been shown that the TanDEM-X system is actually sensitive to horizontal inhomogeneities in the vegetation canopy and a more elaborated model structure consisting of clouds of scatterers with gaps and extinction has been suggested as more suitable to characterize the spectral properties of interferograms over forests (De Zan et al., 2013). A tomographic approach could in this sense reveal interesting potentials for better understanding forest structure at X band (Nannini et al., 2017), and will be further investigated in the future.

Hence, in the present approach we use the volume correlation factor estimated from TanDEM-X data as in Eq. (3). For this, statistical information is derived by using external reference for training, which is then exploited for the proposed classification method, as discussed in Section 5.

4. External reference data

For the generation of the global forest/non-forest map, external reference data have been used for different reasons. They are required, first of all, for the training of the input data for classification. Moreover, external information is exploited for the identification of land cover types which, for different reasons, degrade the quality of the TanDEM-X data, leading ultimately to the occurrence of classification errors. These include, e.g., water areas, urban settlements, and sandy deserts, and are further detailed in Section 8. Finally, highly accurate reference data are required in the validation process, to assess the accuracy of the final...
classification product. Hence, for the sake of clarity, the complete set of external reference data that was used throughout the entire work is presented in the following:

- **Landsat Tree Cover Map** (Hansen et al., 2013; Sexton et al., 2013): freely available, 30 m × 30 m resolution, global vegetation continuous fields tree cover data provided by the Landsat multispectral sensors constellation, with data acquired until 2015. The map provides the estimates of the percentage of horizontal ground in each 30-m pixel covered by woody vegetation greater than 5 m in height.

- **Pennsylvania Forest Map** (University of Maryland and University of Vermont Spatial Analysis Laboratory, 2015): This data set was provided by a joint collaboration between University of Maryland and University of Vermont, and was originally used for the validation of the Landsat forest map. Optical and lidar data are combined to generate a forest/non-forest classification map (binary information) for vegetation higher than 2 m, with a ground resolution of 1 m × 1 m. The methodology used for the generation of this map is described (O’Neill-Dunne et al., 2014), and an accuracy of about 98% or above is typically obtained. For our purposes, we scaled the original resolution down to the one of the TanDEM-X quicklooks by counting the input pixels within a cell of 50 m × 50 m which are classified as forest obtaining then a density map (e.g. if half of the input pixels within a cell of 50 m × 50 m is classified as forest, the corresponding output value is set to 50%).

- **Copernicus High Resolution Layers (HRL) Forest Density** (Langanke et al., 2016): It is a semi-automatic classification and computer aided visual refinement, based on high-resolution satellite imagery provided by the European Space Agency (ESA). It has a 20 m × 20 m resolution and is available over Europe.

- **CCI Land Cover** (Kirches et al., 2015): Global land cover maps using as input observations from the 300 m MERIS sensor on board the ENVISAT satellite mission between 2008 and 2012 (the MERIS follow-on is on board the Sentinel-3 instrument). The product is made available by the ESA. From the same project, a map of water bodies at 150 m spatial resolution is also available.

- **MODIS Snow/Ice Map** (Pagano and Durham, 1993): global map generated at a monthly rate using the spectroradiometer MODIS calibrated radiance data products with a resolution up to 500 m.

However, one should note that resolutions and projections of the external maps listed above are different from each other. As reference, we took the native resolution and projection of the TanDEM-X data, which are sampled on a uniform grid in latitude/longitude coordinates, referred to the WGS84 ellipsoid, and then re-projected and rescaled the external maps, to match with the TanDEM-X data grid.

5. Single scene forest/non-forest classification algorithm

For the generation of the global forest/non-forest map from TanDEM-X interferometric data, a classification method based on a fuzzy clustering algorithm has been developed. For each input scene, it is applied to the volume correlation factor and the algorithm settings are adapted to the specific acquisition geometry.

5.1. The fuzzy clustering approach

Fuzzy clustering represents a powerful and effective approach for data classification. It is widely used in numerous contexts and applications, such as data mining or pattern recognition. Typically, one refers to clustering as the task of grouping together a set of $N$ input observations $Y = \{y_k\} (k = 1, ..., N)$ into $c$ non-empty partitions, depending on how similar they are to each other. In the following, the term partition and cluster will be used indifferently. Each observation is characterized by $P$ features. If a hard clustering approach is applied, each observation can be associated to a single cluster only. The concept of fuzzy clustering has been then introduced to allow a certain amount of overlap among different clusters, which means that an observation can be associated to each existing partition with a certain probability. A well established fuzzy clustering algorithm is the so-called c-means fuzzy clustering (Bezdek et al., 1984), which has already been applied to remote sensing data in several other works. For example, its potentials have been demonstrated for classifying the Greenland ice sheet snow facies by using TanDEM-X interferometric data (Rizzoli et al., 2017b) or ENVISAT active and passive observations (Tran et al., 2008).

According to that, each cluster is identified by its cluster center, which is defined as a $P$-dimensional vector $v_i$ (being $i$ the $i$-th cluster center). The elements of $v_i$ represent, therefore, the values of the corresponding feature set which describe $i$-th cluster center. A so-called membership function $\mu = \{u_k\} \in [0, 1]$ is associated to the $k$-th input observation, and describes the probability of an observation to belong to each cluster and, for each $k$, it satisfies the relation

$$\sum_{i=1}^{c} u_{ik} = 1, \forall k.$$  

(7)

In the above equation, $c$ is the total number of fuzzy partitions of the input observation data set, each one containing observations characterized by a high intracluster similarity (intended in terms of affinity of the values assumed by the feature set $P$) and a low extraclass overlap. For the derivation of the cluster centers, in the present work a dedicated training of the data by means of an external reference is carried out. From the c-means clustering algorithm, we took the concept of membership, but we modified its formulation by introducing quality weights, which increase the reliability of the estimation, as explained in Section 5.3. The number of cluster centers is set a priori $c = 2$, to discriminate forest (F) from non-forest (NF) pixels. As already discussed, we exploit as feature the volume correlation factor only (i.e. $P = 1$). The center of each cluster $v = \{v_F, v_{NF}\}$ is therefore identified as a function of its own feature $\{V_{vol,F}, V_{vol,NF}\}$.

5.2. Cluster centers definition

In this subsection the method implemented for the definition of the cluster centers is presented. The method consists of different steps, summarized by the flowchart in Fig. 3. The output is a complete set of cluster centers, which takes into account the dependency of $V_{vol}$ on the acquisition geometry. The classification procedure will afterwards assign a different set of cluster centers to each $V_{vol}$ Value to be classified, depending on the input height of ambiguity $h_{amb}$ and local incidence angle $\theta_{loc}$. This is the reason why we refer to a multi-clustering classification algorithm for the generation of forest/non-forest maps. Each single step of the method is explained in the following paragraphs.

![Flowchart of the developed method for the determination of a complete set of cluster centers.](image-url)
5.2.1. Geometry-dependent data grouping

Together with the specific characteristics of the forest under illumination, such as tree height and density, the volume correlation factor $\gamma_{\text{Vol}}$ strongly depends on the employed imaging geometry as well. Indeed, in Martone et al. (2017) it is shown that the coherence loss at X band over forest is sensitively influenced by the local incidence angle $\theta_{\text{loc}}$. A larger decorrelation is expected for steeper incidence angles, since the radar microwaves can penetrate deeper into the canopy, resulting in a significant amount of volume scattering. On the other hand, for shallow incidence angles, the surface scattering component of the canopy becomes dominant, resulting in a higher coherence. Moreover, it is well known that the interferometric performance over forests is strongly influenced by the specific interferometric baseline $B_1$ (or, equivalently, by the height of ambiguity $h_{\text{amb}}$, according to Eq. (1)). This is due to the ensemble average of all backscattered returns from the same resolution cell, which increases the interferometric phase uncertainty, as described in Section 3. As an example, the mean value of the interferometric coherence for a set of repeated acquisitions, and for two test areas characterized by different land cover types, is shown as a function of $h_{\text{amb}}$ in Fig. 4. The two test sites have been repeatedly acquired for long-term monitoring of the interferometric performance since the TanDEM-X mission start, by exploiting the change over time of the Helix close formation (the Helix formation combines an out-of-plane - i.e. horizontal - orbital displacement by different ascending nodes with a radial - i.e. vertical - separation by different eccentricity vectors resulting in a helix-like relative movement of the satellites along the orbit (Krieger et al., 2007; Moreira et al., 2002). For the "Amazon Rainforest" test area (blue dots), the specific height of ambiguity strongly impacts the resulting volume decorrelation effects, and the coherence varies between about 0.4 for $h_{\text{amb}} = 30$ m and 0.8 for $h_{\text{amb}} = 80$ m. On the other hand, the "Death Valley" test site (red dots) is characterized by a non-vegetated, rocky land cover, and shows a substantial stability of the coherence over $h_{\text{amb}}$ (and over time as well).

For this test site, the main source of coherence loss ($\gamma$ constantly around 0.8) is caused by the limited SNR, which is principally influenced by the local incidence angle $\theta_{\text{loc}}$ (for this time series a mean incidence angle of about 30° has been used) and by the antenna pattern. It is worth highlighting that, during the whole TanDEM-X mission, dedicated re-acquisition phases have been carried out over vegetated regions with smaller orthogonal baselines (corresponding to $h_{\text{amb}}$ typically larger than 60 m), to improve the global DEM performance (Martone et al., 2012, 2013). For the present approach, such large heights of ambiguity are of course non-optimal for forest discrimination, due to smaller volume decorrelation effects which reduce the possibility to distinguish between non-forested and forested areas, as also shown in Fig. 4.

On the other hand, if a completely different approach for the identification of forested areas is considered, by exploiting, e.g., the digital elevation information (or, equivalently, the interferometric phase layer), even larger heights of ambiguity (in the order of 100 m or more) can be successfully exploited for classification purposes as well as for the estimation of the above ground biomass (ABG), provided that a digital terrain model or external references (Askne et al., 2017; Solberg, 2014; Treuhaft et al., 2015) or data stacks (i.e. time series) (Treuhaft et al., 2017) are available for the same area.

It is therefore evident that the strong impact of the acquisition geometry on the volume correlation factor $\gamma_{\text{Vol}}$ needs to be taken into account to accurately detect forested areas from interferometric SAR data acquired with different imaging geometries: for TanDEM-X, the nominal incidence angle range (i.e. taking into account the relative inclination of the antenna beam and a flat topography) varies between 30° and about 50°, and $h_{\text{amb}}$ may achieve values up to 100 m. For this reason, we subjectively partitioned the original input $\gamma_{\text{Vol}}$ data set into $S$ subsets, covering the entire ranges of both $h_{\text{amb}}$ and $\theta_{\text{loc}}$ as follows:

1. The complete ranges of available $h_{\text{amb}}$ and $\theta_{\text{loc}}$ are divided into $N_{h_{\text{amb}}}$ and $N_{\theta_{\text{loc}}}$ intervals, respectively. $S$ is consequently given by $S = N_{h_{\text{amb}}} \cdot N_{\theta_{\text{loc}}}$.

2. The k-th input $\gamma_{\text{Vol},k}$ observation (pixel) is associated to the $(l,m)$-th subset if

$$ h_{\text{amb},k} \in \left[ h_{\text{amb},l,\text{min}}, h_{\text{amb},l,\text{max}} \right], \quad l = 1, \ldots, N_{h_{\text{amb}}} \tag{8} $$

and

$$ \theta_{\text{loc},k} \in \left[ \theta_{\text{loc},m,\text{min}}, \theta_{\text{loc},m,\text{max}} \right], \quad m = 1, \ldots, N_{\theta_{\text{loc}}} \tag{9} $$

being $h_{\text{amb},l,\text{min}}$, $h_{\text{amb},l,\text{max}}$, the minimum and maximum heights of ambiguity for the $l$-th subset, and $\theta_{\text{loc},m,\text{min}}$, $\theta_{\text{loc},m,\text{max}}$ the minimum and maximum incidence angles for the $m$-th corresponding subset.

The number of partitions $N_{h_{\text{amb}}}$ and $N_{\theta_{\text{loc}}}$ was chosen as a compromise, on the one hand, to guarantee a sufficiently large and well-balanced number of input $\gamma_{\text{Vol}}$ observations for each combination of $\theta_{\text{loc}}$ and $h_{\text{amb}}$ intervals, and, on the other hand, to preserve the information contained in the data, opportunely sampling the classification space described by the possible combinations of $(h_{\text{amb},k}, \theta_{\text{loc},k})$.

Using the notation in Eqs. (8) and (9), we ended up with the following classification set-up:

$$ N_{h_{\text{amb}}} = 10; \quad h_{\text{amb},l} = [0 \text{ m}, 30 \text{ m}, 35 \text{ m}, 40 \text{ m}, 45 \text{ m}, 50 \text{ m}, 55 \text{ m}, 60 \text{ m}, 70 \text{ m}, 80 \text{ m}, 100 \text{ m}]; \quad \theta_{\text{loc},m} = [0°, 35°, 45°, 90°]. \tag{10} $$

In the above relations, $h_{\text{amb},l}$ and $\theta_{\text{loc},m}$ indicate the thresholds (subscript $t$) used to discriminate between the different intervals, that is, each partition is identified by a pair of consecutive values of $h_{\text{amb},l}$ and $\theta_{\text{loc},m}$, respectively.

5.2.2. Cluster centers derivation

Cluster centers are evaluated by means of opportunity training of the input data. As external reference data we used the Landsat tree cover map generated from data acquisition until 2015, which has been described in Section 4. For the discrimination between forest and non-forest from such a map, pixels having a tree cover density smaller than 5% are taken as reference for non-vegetated areas. On the other hand, values of tree cover density larger than 60% are identified as forested ones. Both thresholds were selected from visual inspection in a way that only those areas which are actually bare soil and densely forested ones are considered within the data training (i.e. fragmented forests, which
may increase the risk of wrong training, are excluded).

Hence, for each \( \{Lm\} \) subset of input observations, derived as discussed in the previous paragraph, the corresponding cluster centers are finally taken as

\[
v_{\ell,m} = \{\gamma_{\text{Vol},F}, \gamma_{\text{Vol},NF}\} = \left[\mathbb{E}\left[\gamma_{\text{Vol},F} \in \{h_{\text{amb}}, \delta_{\text{loc},m}\}\right]\right],
\]

\[
\mathbb{E}\left[\gamma_{\text{Vol},NF} \in \{h_{\text{amb}}, \delta_{\text{loc},m}\}\right]
\]

(11)

In the above equation \( \mathbb{E}\{\cdot\} \) indicates the expectation operator (from probability theory). In practice, the cluster center is obtained as the sample expectations (mean value) of the corresponding \( \gamma_{\text{Vol}} \) distributions for forested and non-forested areas, respectively. Finally, a second-order polynomial fitting is separately performed for each incidence angle interval, in order to obtain a look-up-table of cluster centers function which can be sampled at different \( h_{\text{amb}} \) steps.

5.2.3. Forest type dependence

In order to take into account the different characteristics of forests (e.g. the tree type, density), we have categorized them into three macro-classes: tropical, temperate, and boreal forest, according to the division suggested by the National Science Foundation (NSF) (National Science Foundation, 2008) which is depicted in Fig. 5. Hence, the data training has been carried out for each of the above mentioned classes, using the regions highlighted in red in Fig. 5. The resulting cluster centers are shown in Fig. 6, for tropical, temperate, and boreal forests, respectively. The curves are evaluated for different heights of ambiguity and local incidence angle ranges, according to Eq. (10).

Over bare areas it was verified in Martone et al. (2016a) that, as expected, the volume correlation factor does not depend on the particular combination of incidence angles and baselines. For our classification algorithm, a constant value \( \gamma_{\text{NF}} = 0.98 \) has been selected (represented by the brown horizontal line (non-forest)). The choice was made to avoid considering possible remaining uncompensated decorrelation contributions, due to e.g. ambiguities or terrain-induced spectral shifts.

As discussed in Martone et al. (2017), depending on the particular forest type, described by, e.g., its canopy characteristics and tree density, X-band radar waves are differently affected. Indeed, values of volume correlation factor observed during the data training procedure for the rain forest in Brazil (Fig. 6 (a)) are larger than the ones obtained for the boreal forest in Russia (Fig. 6 (c)), which is due to the generally sparser canopy density shown by the boreal forest, if compared to the Amazon rainforest. This consideration has been verified by looking at the typical values of vegetation density provided by the Landsat tree cover map, which range between 50% and 60% for the boreal Russian forest, going then up to around 100% for the tropical forests in the Amazon. These values can be qualitatively related to the sparsity (or, alternatively, to the presence of gaps) of the corresponding canopy density. Thus, the sparser the forest, the deeper the penetration of the X-band waves through the vegetation structure, implying the reflections coming not only from the canopy layer but also from the ground itself. Such different height contributions interfere with each other within the coherence estimation window, resulting ultimately in a larger decorrelation.

Furthermore, we have also refined the cluster definition by introducing additional forest classes for smaller geographical areas (which are not shown in Fig. 5), such as e.g., the Chaco Boreal region, which is divided among western Bolivia, Paraguay, and a portion of the Brazilian state of Mato Grosso, and characterized by a very dry, sparse and open, savanna-like vegetation (Spichiger and Ramella, 1989). This allowed to further improve the final classification accuracy.

5.3. Multi-clustering classification method

Once the entire set of cluster centers has been defined, for a given set of input volume correlation factors, a fuzzy clustering algorithm is independently run on each subset of input observations, depending on the specific combination of \( \{h_{\text{amb}}, \delta_{\text{loc}}\} \) (as in Section 5.2). For this purpose, starting from the concept of membership from the c-means fuzzy clustering algorithm, which is based on the computation of the distances between the cluster centers and the observations (Bezdek et al., 1984), we define a weighted membership, computed as
Fig. 6. Cluster centers of the volume correlation factor $\gamma_{Vol}$ for tropical (a), temperate (b), and boreal (c) forests, respectively, as a function of the height of ambiguity $h_{amb}$, for the three different of local incidence angle intervals (depicted in different colors), defined as in Eq. (10). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

\[
\alpha_{i,k} = \left\{ \begin{array}{ll}
\frac{1}{p(c = i|y_k)}, & 1 \leq k \leq N.
\end{array} \right.
\]

(13)

In the above equation, $c = 2$ is the number of clusters ("forest", "non-forest"), $y_k$ indicates the $k$-th input observation (volume correlation factor), $v_i$ is the $i$-th cluster center ($v_F$ or $v_N$), and the parameter $m$ controls the fuzziness of the algorithm. In our case $m = 2$, which represents a good compromise in terms of resulting cluster compactness and classification performance (Bezdekm et al., 1984). Indeed, in order to properly exploit the a priori information available from the data training, the Euclidean distances between the $k$-th observation and the $i$-th cluster center is now weighted by

\[
w_{i,k} = \frac{1}{p(c = i|y_k)}.
\]

(13)

where $p(c = i|y_k)$ represents the likelihood of a given observation ($y_k$) of belonging to the $i$-th cluster. This probability is estimated from the distribution of the training data set of the corresponding ($h_{amb}, \theta_{loc}$). As an example, in Fig. 7, the distribution of the volume decorrelation estimated from the training data in the Amazon, for forest (red) and non-forest (blue) areas is depicted, for $h_{amb} \in [35 \, m, 40 \, m]$ and $\theta_{loc} \in [35°, 45°]$.

In order to provide binary forest/non-forest information, a decision threshold on the derived weighted membership needs to be set. This step is normally not performed on each single scene, but on the mosaicked products, as discussed in the next sections.

5.4. Single-scene classification: examples

We present here some examples of the obtained results for the classification of single TanDEM-X scenes.

First, the TanDEM-X acquisition over the Brazilian Amazon forest, already considered in Figs. 1 and 2, is shown in Fig. 8. Dense forest (dark green in the map on the right-hand side) and non-forest (in white) areas are clearly distinguishable and match quite well with the optical image, which is given on the left-hand side of the figure for comparison. For each pixel, the binary decision threshold is set according to the largest value of the corresponding weighted membership function (i.e. threshold at 50%).

A further example over temperate forest in Germany is depicted in Fig. 9. Again, one can observe that the two different land cover types are overall correctly discriminated, and that even single lines of trees around agricultural fields are detected (zooms in subfigures (c) to (f)).

It is worth pointing out that the computational load required for the execution of the present method is very limited. Indeed, the classification algorithm consists basically of a comparison, at pixel basis, of the estimated volume correlation map $\gamma_{Vol}$ to a variable set of thresholds, which are derived offline and only once from the data training process (see Fig. 6). Moreover, as already introduced in Section 4, the use of quicklook images allows to reduce the total volume of data to be managed to a few tens of megabytes per scene.

6. Mosaicking of multiple coverages

Once the weighted membership has been derived for each bistatic scene, the next step for generating a global product consists in properly combining and mosaicking the large amount of acquisitions available from the TanDEM-X global data set. Overall, more than 500,000 scenes have been acquired since 2011 until 2016, which have been considered for the current work.

6.1. Mosaicking algorithm

The global TanDEM-X data set is composed by scenes acquired with different acquisition geometries. At least two global coverages are available. Some regions, such as forests, sandy deserts, and
mountainous areas, have been acquired up to 10 times (Borla-Tridon et al., 2013).

For each scene, its weighted membership, derived as in Section 5, is used as input data for the mosaicking process. Moreover, other available information at scene level, such as layover and shadow layers or the local incidence angle and the height of ambiguity maps are used in the mosaicking process, too.

For each pixel on ground, given \( N \) input overlapping scenes, \( N \) independent weighted membership values are combined together in a weighted average process to compute a combined weighted membership \( u_{\text{comb}} \) as follows. Normalized mosaicking quality weights \( \alpha_i \) (for \( i = [1, \ldots, N] \)) are defined as

\[
\alpha_i = \Delta M_i^{-1} \left( \sum_{i=1}^{N} \Delta M_i^{-2} \right)^{-1},
\]

where

\[
\Delta M_i = \frac{1}{\Delta \gamma_{\text{Vol}}} \frac{1}{\gamma_{\text{SNR}}} - 1.
\]

\( \Delta \gamma_{\text{Vol}} = \| v_{\text{ff}} - v_{\text{nf}} \| \) represents the difference between the corresponding cluster centers of the forest \( (v_f) \) and non-forest classes \( (v_{nf}) \), as shown in Fig. 10.

The mosaicking weights give an idea about the reliability in the classification of each input weighted membership. The role of \( \Delta \gamma_{\text{Vol}} \) is to give a higher importance to those input acquisitions which were acquired with a \( h_{\text{amb}} \) that can provide a good cluster centers separability (typically lower heights of ambiguity). \( \gamma_{\text{SNR}} \) is instead responsible for giving a higher weight to those input observations located towards the beam center, which is characterized by a lower noise floor (NESZ) with respect to the beam’s borders, and in general to discard low backscatter values (in case of, e.g., a temporal change in the scene between two bistatic acquisitions).

For each pixel, the combined membership \( u_{\text{comb}} \) is then obtained from all the available membership values \( \hat{u}_i \) as

\[
u_{\text{comb}} = \sum_{i=1}^{N} \alpha_i \hat{u}_i.
\]

Moreover, the following additional rules are taken into account:

- Input observations affected by geometric distortions, such as shadow or layover (identified by exploiting backscatter as well as coherence information), are excluded in the process;
- Scenes affected by snow coverage receive a lower mosaicking weight. Snow coverage information is obtained from the global snow cover maps provided by MODIS (Pagano and Durham, 1993);
- In order to reduce misclassification due to, e.g., vegetation growth, an artificially increased \( \alpha \) weight is associated to those pixels which are characterized by a high probability of belonging to the non-forest class (according to the value of the weighted membership) and, at the same time, are identified as “reliable” according to specific criteria, which include minimum thresholds on the local SNR and on the separation between the corresponding forest/non-forest cluster centers \( \Delta \gamma_{\text{Vol}} \) in Fig. 10). Such pixels are referred to as super pixels, since the information that they carry dominates in the averaging process.

According to the above considerations, possible seasonal effects are mitigated in order to further improve the classification accuracy. As an example, the combined weighted membership for an area extending by \( 4' \times 2' \) in latitude/longitude coordinates over the state of Pennsylvania (USA) is given in Fig. 11. The mosaic is composed by 8 geocells (or tiles), each one of \( 1' \times 1' \) in latitude and longitude, delimited by the red lines. Forested and non-forested areas are indicated in green and white, respectively, and no particular discontinuities are visible within each geocell and among different tiles, which proves the effectiveness of the proposed mosaicking algorithm.

7. Binary threshold setting and post-processing filtering

Once the classification and the mosaicking algorithms are defined, a decision threshold on the output combined weighted membership needs to be selected to finally generate the binary TanDEM-X forest/non-forest map. For this purpose, a dedicated procedure has been developed to calibrate the threshold value which maximizes the output forest/non-forest map performances.

Since each considered forest type (tropical, temperate, and boreal forest) behaves differently, it is necessary to define a proper threshold for each of them separately; a process which is accomplished by
exploiting once more the available external reference data (Section 4).
In this section, we consider the temperate forest as sample test case; for the other forest types, the same procedure is applied.

7.1. Threshold setting procedure

In order to find the optimal classification threshold to be applied to the weighted membership, the accurate reference map available for the state of Pennsylvania (USA) has been considered. On the left-hand side of Fig. 12 the weighted membership provided by TanDEM-X is shown, and on the right-hand side the corresponding reference map (Lidar-Optic), resampled and rescaled as a density map to match the weighted membership, is depicted. As this tile is also part of the validation area only 1% of the area of this 1° by 1° tile is considered for the threshold calculation.

To properly evaluate the thresholds, the correlation between two binary variables has to be evaluated. For this purpose, the $\phi$ coefficient (also called mean square contingency coefficient or Pearson correlation coefficient) has been selected. It represents a measure of statistically significant linear relationship for discrete variables. In the case of two binary variables it is derived by combining the different elements of the contingency table which, in our case, corresponds to the confusion matrix.
(since both variables correspond to the same classification) as follows:

\[
\phi = \frac{TP - TN - FP - FN}{\sqrt{P - RP - RN - N}}.
\]

(17)

where \(TP, TN, FP, FN, P, RP, RN,\) and \(N\) are defined in Table 1. Hence, the \(\phi\) coefficient has been calculated by varying the thresholds on the mosaicked membership value and on the reference lidar-optic data, to get binary variables. The resulting contour plot of the \(\phi\) coefficient is given in Fig. 13. The maximum value of \(\phi\) coefficient is of about 0.72 (values of \(\phi > 0.7\) verify strong correlation), in correspondence of a membership value of 60% for TanDEM-X and 25% for the reference lidar-optic forest density map, as highlighted by the white lines. This result can be helpful to define the binary “forest” within the global product: at least one fourth of the area of one pixel (50 m × 50 m) with vegetation taller than 2 m.

We have carried out the same procedure to derive the proper membership threshold for the tropical and boreal forest classes. For this purpose, the globally available Landsat forest tree cover was employed as reference. The calculated membership threshold are 61% and 64% for tropical and boreal forest class, respectively. This values are very similar to the threshold calculated for the temperate forest class, which proves a good consistency of the overall procedure. Hence, considering possible inaccuracies of the reference data used for boreal and tropical forest classes, as well as possible changes in the forest state between the two acquisition dates, we decided to set a limit membership value of 60% for all types of forests for the generation of the binary forest/non-forest map.

7.2. Final post-processing filtering

The presence of isolated outliers after the classification process may be caused by uncompensated contributions for the estimation of the volume correlation factor (due, in turn, to e.g. possible geometrical distortions). To reduce such effects we applied a simple post-processing filter which substitutes an isolated pixel outlier with the value of the surrounding ones, if they are all in accordance with each others. The principle is explained in Fig. 14, where an input forest pixel (F), surrounded by non-forest (NF) pixels only, is substituted by a non-forest one (NF) and vice-versa.

In this way, we operate on a pixel basis only, avoiding an overall deterioration of the output resolution (as by applying, e.g., a median filter, typically used in standard image processing for salt and pepper noise removal). Of course, one should be aware that the application of such a filter may lead, in some rare case, to gaps closure and introduce additional errors.

8. External information layers

In order to improve the final classification accuracy, additional information layers are applied to the mosaicked membership, by exploiting external classification maps (as in Section 4) in a final post-processing step. They are presented in the following:

- **Urban Areas**: Over urban areas InSAR performance is typically degraded due to the presence of additional geometrical distortions,
such as layover and multiple reflections, which, similarly to what occurs over vegetated areas, lead to a loss in the volume correlation factor. For this reason, by applying the present algorithm, urban areas are often misclassified as forest. They are therefore filtered out by applying the Global Urban Footprint (GUF) derived from full-resolution TanDEM-X data backscatter information (Esch et al., 2012, 2013). The GUF is a binary classification map (city/non-city) and is freely available at a resolution of 2.8 arcsec (75 m–85 m). As an example, Fig. 15 shows the GUF over Europe.

- **Water Bodies**: Very low backscatter values (in the range of the system sensitivity) are typically observed over calm water areas due to almost specular reflection of the radar signal. This may lead to incorrect estimation of the corresponding SNR, ultimately resulting in a bias in the volume correlation factor. Moreover, temporal decorrelation due to the short along-track baseline can additionally affect the coherence estimation. To avoid possible misclassification, we used the freely available global map of open permanent water bodies obtained from the Land Cover (LC) project of the Climate Change Initiative (CCI), provided by the European Space Agency (ESA) (Kirches et al., 2015). The product has a 150 m × 150 m spatial resolution and is based on data acquired by the Envisat ASAR, SRTM, and MERIS sensors.
- **Tree Line**: The tree line can be a virtual altitude line that sets the edge of the regions at which trees can grow. Its location changes depending on, e.g., temperature, moisture conditions, and tree species. In the literature, it is described in terms of altitude as a function of latitude (Körner, 2007). The estimation of a global tree line is very useful to correctly filter out mountainous areas where forest growth is not possible at all, avoiding possible classification errors due to geometrical distortions, such as shadow and layover effects. For this purpose, we derived a global tree line mask at a resolution of 0.5° × 0.5° in latitude/longitude, by combining information coming from the final global TanDEM-X DEM and the ESA CCI Land Cover map (Kirches et al., 2015). The following procedure has been implemented, for each 0.5° by 0.5° geocell:
  - The distribution of forested and non-forested areas, made available by the CCI Land Cover map (Kirches et al., 2015), is derived as a function of the height information provided by the TanDEM-X DEM.
  - A cumulative distribution of the forested and non-forested classes is then calculated as a function of the altitude.
  - A first threshold on the TanDEM-X DEM height is set at the height that includes 98% of the classes corresponding to non-forested areas (equivalent to 2% of the forested ones). In order to filter out

![Table 1](image1)

<table>
<thead>
<tr>
<th>TDX Forest = 0</th>
<th>TDX Forest = 1</th>
<th>Total ref. Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ref. Forest = 1</td>
<td>FN</td>
<td>TP</td>
</tr>
<tr>
<td>Ref. Forest = 0</td>
<td>TN</td>
<td>FP</td>
</tr>
<tr>
<td>Total TDX Forest</td>
<td>N</td>
<td>P</td>
</tr>
</tbody>
</table>

![Fig. 12](image2)

(Left) TanDEM-X weighted membership. (Right) Pennsylvania Lidar-optic forest density map (originally at 1 m × 1 m resolution) re-projected, rescaled and resampled to match the TanDEM-X membership map (50 m × 50 m).

![Fig. 13](image3)

Contour plot for the $\phi$ coefficient as a function of the lidar-optic vegetation density (x-axis) and of the TanDEM-X membership value (y-axis).

![Fig. 14](image4)

Working principle of the post-processing filter applied to the binary forest/non-forest map to reduce classification errors. Each cell represents a classified pixel ($F = \text{forest}, NF = \text{non-forest}$). Inputs and corresponding outputs are displayed on the left-hand and right-hand sides, respectively.
possible outliers, a further margin of 100 m is added. In this sense, since the actual statistics of the land cover distribution are exploited, the resulting tree line map is indeed sensitive to possible local variations (i.e. comparable with the reference geocell size, which corresponds to about 55 km × 55 km at the equator) in terms of temperature, moisture and wind conditions, and/or trees species. However, in the case uneven distributions of forested and non-forested areas are obtained for a given geocell, a reliable and consistent estimation of the tree line through this approach is not possible. In this (however infrequent) case, we consider the tree line value provided in the literature (Körner, 2007), depending on the latitude of the corresponding 0.5° by 0.5° geocell only.

Fig. 16 shows the distributions of forested (green line) and non-forested (orange) areas for an exemplary geocell. The blue line indicates the tree line as in Körner (2007). The red line indicates the altitude above which 98% of the pixels are classified as non-forest. We add a further margin of 100 m, which results in the final tree line for that geocell, indicated by the violet line. The resulting global tree line mask is shown in Fig. 17. Areas above the tree line (i.e. where no trees grow) are depicted in red. Fig. 18 shows a detail of the tree line mask over the Austrian Alps overlaid on a GoogleEarth optical image, and confirms the potentials of such a product to further improve the final classification accuracy.

Fig. 17. Global tree line mask (in red), estimated from the global TanDEM-X DEM height and the GlobCover classification map. This map is applied in the final TanDEM-X forest map. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
• **Deserts:** Sandy desert regions are characterized by low levels of signal-to-noise ratio (SNR), due to poor backscatter returns, which result in a strongly degraded interferometric coherence. To fulfill the TanDEM-X mission specifications, such regions were reacquired using steeper incidence angles during a dedicated reacquisition phase (Martone et al., 2016b). The backscatter values over sandy regions are often close to the system sensitivity, which can lead to an incorrect estimation of the volume correlation factor, and explains the higher “noisiness” over those areas, as shown in Martone et al. (2017). For this reason, desert regions are separately filtered out by using the GlobCover classification map (Arino et al., 2007).

9. The TanDEM-X global forest/non-forest map

In this section we present the global forest/non-forest product, together with additional information layers, made available after the mosaicking processing.

9.1. The global forest/non-forest classification map

The final TanDEM-X global binary forest/non-forest map is shown in Fig. 19. It was generated by processing and mosaicking more than 500,000 TanDEM-X bistatic scenes acquired from 2011 until 2016. The map has a spatial resolution of 50 m × 50 m and is divided into geo-cells of 1° by 1° in latitude and longitude, as done for the production of the TanDEM-X global DEM (Rizzoli et al., 2017a). Forested and non-forested areas are depicted in green and white, respectively. All those pixels which have been flagged after applying the external layers (such as urban areas, invalid pixels, which are detailed in the previous section) are classified as “non-forest”. The global product is planned to become available for free for scientific purposes by end of 2017. As a further example, Fig. 20 shows the TanDEM-X forest/non-forest map over Europe, overlaid on GoogleEarth.

9.2. Additional information layers

Together with the global forest/non-forest binary classification map, from the input data and after the mosaicking process additional information layers are provided, which are detailed in the following:

- **Coverage Map:** A map indicating the number of mosaicked acquisitions for a specific ground area. An example is provided in Fig. 21, where the coverage map associated to the mosaic of Pennsylvania in Fig. 11 is depicted. As one can see, up to ten overlapping acquisitions were acquired over this area, in both ascending and descending orbit mode.
- **Super Pixels Count and Date Maps:** The first layer provides, for each output cell, the number of reliable super pixels in input. An example is presented in Fig. 22 (a) for an area located in Southern Germany, extending by about 75 km × 55 km. As explained in Section 6, super pixels are introduced in order to classify as non-forest those areas in which a vegetation regrowth occurs because of, e.g., deforestation or farming activities. Then, the information to assess how reliable and “up-to-date” the detection of non-forest is, is given by the acquisition date of the most recent super pixel, as shown by the date map in Fig. 22 (b). The idea is that the more recent the detection of a super pixel is, the more reasonable it is to exclude the occurrence of a possible vegetation regrowth.
- **Reliability Map:** an additional layer provides information about the reliability of the classification results. Depicted in Fig. 23, this map gives information about the difference between the combined membership and the applied binary threshold, used to discriminate between forest and non-forest. Membership values closer to the cluster centers are far away from the threshold and indicate clearly forested and non-forested areas (in dark blue and red), respectively. The areas where the classification is not so reliable are the ones in which the combined membership approaches the threshold, and are depicted in green to light blue (the solid light blue regions correspond in the image to three lakes, which are anyway filtered out at a second processing stage).

10. Validation and comparisons

In this section the forest/non-forest map derived from TanDEM-X data is validated with external references, and compared with other available classification maps. In this context we are going to distinguish between the term validation and comparison. The first one should be employed only in the case ground truth measurements or highly-accurate data are available. Such data are typically accessible at local scale only (single state or delimited regions). On the other hand, classification maps available at global or continental scale typically show a limited accuracy (in the order of 90% or below). Hence, they can not be considered as a actual reference and it is therefore more correct to refer to them as a comparison. Accordingly, in the following, we employ the term accuracy or agreement, whether a validation or a comparison between the TanDEM-X forest map and the above mentioned classification
maps, respectively, is considered. In both cases, however, the quality measure $A$ for performance assessment is calculated as follows:

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

(18)

and represents the fraction of pixels that have been correctly detected with respect to the amount of total pixels in the geocell. All contributions in Eq. (18) are defined in Table 1 and described in Section 7.1.

10.1. Forest/non-forest map validation

For the validation of the temperate forest we have used the lidar-optic forest map as reference, available for the state of Pennsylvania (USA) (O’Neil-Dunne et al., 2014). For this, eight geocells have been considered in an area extending from 40°N to 42°N in latitude and from 77°W to 81°W in longitude.

Fig. 24 shows the binary comparison of three geocell maps between the TanDEM-X forest/non-forest map and the Pennsylvania tree density map, from which the elements of the confusion matrix in Table 1 are

![Fig. 19. Global TanDEM-X forest/non-forest map at 50 m × 50 m sampling. Forested regions are depicted in green, non-forested ones in white, water bodies/invalid areas in black. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)](image)

![Fig. 20. TanDEM-X forest/non-forest map obtained over Europe. The red rectangle delimits the region considered for comparison with the Copernicus High Resolution Layer (HRL) forest density map (Langanke et al., 2016), which is shown in Figs. 26 and 27. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)](image)
calculated. It can be noticed that the classification errors are highly clustered. In particular, false positives (in red) mainly occur in correspondence of densely to sparse built-up areas, whereas false negatives (in blue) are concentrated over narrow rivers, small lakes and ponds, or rugged terrain, such as slopes and valleys, which cause the occurrence of geometric distortions. Such remaining error sources would be further mitigated by employing a urban and a water mask at higher resolution, as well as by means of a larger stack of available acquisitions with higher resolution.
different viewing geometry. For the three geocells shown in Fig. 24, the resulting accuracy is of 91%, 92%, and 93%, respectively, and for all validation geocells the accuracy, for each geocell, is in the range between 85% and 93%. Fig. 25 depicts the forest/non-forest classification map for the validation test area in Pennsylvania, showing the distribution of forested (depicted in green) and non-forested areas (white), as well as of some rugged terrain (visible in the central part of the image, corresponding to the area in Fig. 21 covered by a larger number of acquisitions, both in ascending and descending orbits). Finally, urban settlements and water bodies are highlighted in black.

Ground truth data for the other forest classes were not available at the time of publication. A dedicated validation process for the tropical and boreal forests is the main goal of several collaborations with external partners and will be carried out in the near future.

10.2. Comparisons to other forest maps

We have additionally compared the TanDEM-X forest/non-forest map to other available forest maps, such as the ones provided by Landsat (Sexton et al., 2013) and by the Copernicus HRL forest density map (Langanke et al., 2016). Differently from the reference map exploited for validation, all these classification maps are characterized by an accuracy often comparable to the one of our classification product. Hence, they can not be considered as a valid reference and, for this reason, it is more correct to refer to a comparison between different sources. From this, we estimated a certain agreement (in percentage unit), which is derived as in Eq. (18).

- **Copernicus HRL Forest Density:** About 150 geocells have been compared to the Copernicus HRL Forest density, including the areas of Germany and Eastern Europe, highlighted by the red rectangle in Fig. 20. Fig. 26 shows the agreement, calculated as in Eq. (18), for all the compared geocells. The horizontal light blue line indicates the mean value of agreement, which is of about 86%. By considering mountainous regions only (i.e. the Alps and Southern Germany), a mean agreement of 84% is obtained (red line). Over flat regions (yellow line), the agreement is of about 90%. Fig. 27 shows the agreement distribution, in percentage unit, for the considered region. For each 1° × 1° geocell one value is depicted.
Landsat: The Amazon rainforest is on the one hand one of the most extensively and densely vegetated areas in the world, but also, on the other hand, it is one of the regions which is mostly affected by deforestation activities, as further discussed in Section 11.2. This unique ecosystem is therefore of particular interest to monitor it and assess possible forest losses and gains. As an example, Fig. 28 shows the TanDEM-X forest/non-forest map over the Amazonas, for a region extending from 3°S to 11°S in latitude and from 50°W to 65°W in longitude. A comparison to the Landsat tree cover map for about 70 geocells has been carried out, and the resulting agreement between both maps is shown in Fig. 29. The mean agreement of 90% (solid line) is partially affected by forest changes observed between the two maps, which explains the large deviation (dashed lines), and in particular the lower values (around 80%) obtained in few cases. It is worth highlighting that additional data takes over these regions are being planned with optimized acquisition geometry to further improve the final classification accuracy of the TanDEM-X forest/

11. Outlook

In this section the potentials of high-resolution TanDEM-X data for forest mapping and monitoring are discussed, some promising examples are shown, and opportunities for land classification products in consideration of next-generation SAR missions are discussed.

11.1. High-resolution classification maps

High-resolution forest classification maps from TanDEM-X data are produced at an independent posting of 12 m × 12 m. This corresponds also to the resolution provided by the final TanDEM-X DEM, in order to allow a sufficient multilooking and denoising for phase estimation. They can be exploited on a local scale to further improve the classification detail and accuracy, opening new scenarios for the monitoring of forested areas. As an example, Fig. 30 (a) and (b) shows the forest/non-forest maps for an area located in Germany (extending by 65 km × 40 km) obtained from quicklook and full-resolution data, respectively. The high-resolution map has been obtained by using the experimental TanDEM-X processor (TAXI), developed at DLR (Prats-Iraola et al., 2010). Fig. 30 (c) and (d) shows the quicklook- and full-resolution maps, respectively, for the zoomed area delimited by the red

![Agreement distribution between TanDEM-X and Copernicus HRL forest density over Germany and east Europe. For each geocell one value is considered.](image1)

Fig. 27. Agreement distribution between TanDEM-X and Copernicus HRL forest density over Germany and east Europe. For each geocell one value is considered.

![TanDEM-X forest/non-forest map for a region in the Amazon rainforest which extends from 3°S to 11°S in latitude and from 50°W to 65°W in longitude. About 75% of the total region area (125 out of 165 million hectares) is classified as forest.](image2)

Fig. 28. TanDEM-X forest/non-forest map for a region in the Amazon rainforest which extends from 3°S to 11°S in latitude and from 50°W to 65°W in longitude. About 75% of the total region area (125 out of 165 million hectares) is classified as forest.

![Agreement between TanDEM-X and Landsat for about 70 geocells located in the Amazon rainforest, Brazil. The solid and the dashed horizontal lines indicate the mean and the standard deviation of the agreement distribution, respectively.](image3)

Fig. 29. Agreement between TanDEM-X and Landsat for about 70 geocells located in the Amazon rainforest, Brazil. The solid and the dashed horizontal lines indicate the mean and the standard deviation of the agreement distribution, respectively.
rectangle in Fig. 30 (b). A clear improvement in terms of edge and detail preservation can be achieved by exploiting high-resolution data. Finally, Fig. 30 (e) and (f) shows the optical GoogleEarth image and the confusion map obtained by comparing TanDEM-X and Copernicus HRL forest density data for the zoom of the area delimited by the red rectangle in Fig. 30 (d). The areas in red in (f), corresponding to single tree lines at the border of the agricultural fields, are “seen” by TanDEM-X only, and verify the improvement in details and in classification accuracy. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

**11.2. Change detection**

The high accuracy and reliability offered by the TanDEM-X forest classification map can be exploited for the monitoring of forest changes. This goal is accomplished by using stacks of repeated acquisitions (time series), especially over areas characterized by highly uncontrolled deforestation activities. As an example, in Fig. 31 (a) the vegetation map provided by Landsat is shown for a region located in the state of Rondonia, in Brazil, extending by 28 km × 18 km. This map was generated using data acquired in 2009, i.e. before the launch of the TanDEM-X mission. Fig. 31 (b) shows the forest map over the same area generated using TanDEM-X data acquired in 2011, and first logging activities (the narrow “tracks” in the middle of the scene) are already noticeable. In Fig. 31 (c) the same map is obtained from TanDEM-X data acquired in 2013, and the increase of deforested areas is clearly visible. Fig. 31 (d) shows in red the forest losses that occurred between the two TanDEM-X acquisitions (corresponding to an area of about 20 km²), and verifies the great potentials to exploit TanDEM-X acquisitions for monitoring of forested areas. Finally, Fig. 31 (e) shows the confusion matrix between
11.3. Potentials of forest monitoring for future SAR missions

The assessment and monitoring of the forest resource state is a central task for present and next-generation SAR missions as well. As an example, in the MirrorSAR mission proposal from DLR, a multistatic single-pass satellite interferometer with two simultaneous baselines (corresponding to heights of ambiguity of, e.g., 15 m and 75 m) is considered (Krieger et al., 2017), which shows great potentials for the implementation of updated and improved high-resolution forest/non-forest maps. In particular, the intended ground resolution of the acquired SAR images is in the order of 1 m–1.5 m, allowing for the generation of coherence maps with a resolution of about 10 m. Moreover, the global repeat cycle of 4–6 months would provide unique opportunities for systematic forest change monitoring, as well as for the generation of advanced land classification products.

The proposed approach can be extended to future interferometric SAR missions in C band (e.g. SESAME (Lopez-Dekker et al., 2017)) and L band, such as Tandem-L (Moreira et al., 2015). In particular, Tandem-L offers a potential for the generation of global forest/non-forest maps on a weekly basis thanks to its novel imaging techniques and vast recording capacity. Further possibilities arise if the orbit of the upcoming satellites Sentinel-1C and 1D are adjusted to allow a mission phase with a close formation flight. For example, global forest/non-forest maps could be generated with high temporal and spatial resolution. This would lead to an enhancement of the product family obtained by the Sentinel-1 satellites in the scope of the ESA/EU Copernicus program without additional costs for implementing a dedicated space segment.
12. Conclusions

Remote sensing data represent a highly valuable source for land classification purposes. The identification and monitoring of vegetated areas is crucial for a large variety of applications, such as agriculture, forestry, global change research, as well as for regional planning. In this paper, we have presented the first global forest/non-forest classification map generated from the TanDEM-X single-pass interferometric SAR (InSAR) data set. Among the error sources which affect the quality of TanDEM-X InSAR data, the coherence loss caused by volume scattering represents the contribution which is predominantly influenced by the presence of vegetation on ground. The volume correlation factor has therefore been exploited as input information for a multi-clustering classification algorithm based on fuzzy logic. Since the beginning of the TanDEM-X mission, about half a million of single polarization (HH) bistatic scenes covering all the Earth’s land masses have been acquired and processed. For global classification purposes, we have used an averaged and downsampled version of the original full resolution data at a ground independent pixel size of 50 m × 50 m (so-called quicklooks), which represents a good compromise between final product resolution and resulting computational burden. The proposed classification approach and the mosaicking strategy, which aimed at an optimum combination of the multi-temporal and multi-baseline TanDEM-X data set, have been presented as well.

The final product has been compared and validated with existing vegetation maps and by means of external land cover classification data, and an accuracy/agreement typically above 90% has been obtained for a variety of forest types and terrain.

Potentials for further applications, such as, e.g., high-resolution mapping as well as forest change detection have been demonstrated as well, proving the unique capabilities offered by the TanDEM-X mission for a broad range of commercial and scientific applications. The global TanDEM-X classification mosaics presented in this paper will be opened to the scientific community for free download and usage.

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