TROPICAL FORESTS MAPPING WITH TANDEM-X AND DEEP LEARNING METHODS

Jose-Luis Bueso-Bello[1], *Daniel Carcereri*[1], *Michele Martone*[1], *Carolina González*[1], *and Paola Rizzoli*[1]

[1]German Aerospace Center (DLR), Microwaves and Radar Institute

ABSTRACT

The TanDEM-X Forest/Non-Forest Map, derived from the volume decorrelation factor using a supervised fuzzy clustering algorithm, represents the baseline approach for forest mapping with TanDEM-X data at large/global-scale. Deep learning methods have been demonstrated to be also suitable for mapping forests with TanDEM-X interferometric data, e.g. by utilizing a U-Net convolutional neural network (CNN) on full-resolution images. In this work, we investigate the capabilities of using a U-Net-like architecture with TanDEM-X interferometric data for forest and water mapping on a large scale. An ad-hoc training strategy has been developed to detect forest and water on TanDEM-X images acquired with different acquisition geometries over the Amazon rainforest. In this case, a significant performance improvement with respect to the clustering approach, with a mean f1-score increase of 0.13 on test images has been measured with respect to the baseline clustering technique. The trained U-Net over the Amazon rainforest has been used to extend the forest and water mapping to other tropical forests over Africa and Asia. The classification improvements applying CNN methods on TanDEM-X data allow for the generation of time-tagged mosaics over the tropical forests by utilizing the nominal TanDEM-X acquisitions between 2011 and 2017, skipping the weighted mosaicking of overlapping images used in the clustering approach for achieving a good final accuracy, as well as avoiding the use of external layers to filter out water surfaces. The explotation of such mosaics over extended areas is a key aspect for the detection and monitoring of deforested areas worldwide.

Index Terms— Synthetic Aperture Radar, TanDEM-X, rainforest, tropical forest, forest mapping, deforestation monitoring, deep learning, convolutional neural network, U-Net

1. INTRODUCTION

The TanDEM-X (TerraSAR-X add-on for Digital Elevation Measurement) mission, as other actual SAR missions, maps the Earth's surface providing single images at high resolution from the recorded backscattered signal. The advantage of flying two satellites in close formation, constituting a single-pass interferometric SAR (InSAR) system, adds valuable information to the amplitude data, such as the the interferometric phase and coherence. The global acquired data set has been exploited for the generation of the global Digital Elevation Model (DEM) at a spatial resolution of 12 m x 12 m [1].

The interferometric coherence, defined as the normalized complex correlation coefficient between the two InSAR acquisitions, gives information about the amount of noise in the interferograms and is sensitive to different decorrelation sources such as signal-to-noise ratio losses and volume scattering mechanisms. This last aspect is quantified by the volume decorrelation factor (γ_{Vol}), which was the main input feature for the generation of the global TanDEM-X Forest/Non-Forest (FNF) map using a fuzzy clustering algorithm [2]. Moreover, the total interferometric coherence was exploited for the generation of the global TanDEM-X Water Body Layer (WBL) as well, based on a watershed segmentation algorithm [3].

For information extraction and forest mapping in the context of TanDEM-X SAR images, the potential of deep learning has been demonstrated in [4], where three state-of-the-art CNN architectures were compared, showing very promising performance. The U-Net [5] solution demonstrated to be the most effective one. This previous study investigated different combinations of TanDEM-X SAR input features and was performed on single images at full-resolution on a temperate forest area where very high-resolution reference data from lidar and optical data where available.

Since our focus lies on the generation of large/global scale land cover classification maps with TanDEM-X data, we have extended the input features of the previous work to consider the different acquisitions geometries from the TanDEM-X InSAR system and to generate as output images with three land cover classes: forest, non-forest and water. For training the U-Net, we have considered the unique environment provided by the Amazon rainforest. As in [2], the TanDEM-X quicklook dataset at a resolution of 50 m x 50 m has been used during the present investigations to generate in a reasonable time large scale maps over the Amazon rainforest, as well as over the tropical regions in Africa and Asia. The generated mosaics have been compared with other available maps showing a good accuracy.

The paper is organized as follows: In Section 2 the baseline approaches for water bodies detection and forest mapping with TanDEM-X , including previous investigations with deep learning methods, are summarized. The further developments done in the present analysis to extend the land classification of TanDEM-X images on a large scale are presented in Section 3. The obtained results over the tropical forests, including some comparisons with other contemporary land classification maps, are resumed in Section 4. Finally, in Section 5 conclusions are drawn.

2. BASELINE CLASSIFICATION APPROACHES

2.1. Water mapping with TanDEM-X

In the framework of TanDEM-X products, a correct detection of water bodies is of key importance for the editing of DEMs [6]. The global TanDEM-X Water Body Layer (WBL) [3] is based on the TanDEM-X interferometric coherence as main input, and relies on a watershed algorithm to generate accurate water bodies classification results on single images. A two-step mosaicking strategy of overlapping images is followed to improve the final product accuracy.

2.2. Forest mapping with TanDEM-X

In a bistatic SAR system such as TanDEM-X , with the absence of temporal decorrelation, the γ_{Vol} adds valuable information for discriminating between forested and non-forested areas, due to its sensitivity to vegetated areas. The γ_{Vol} was selected as main feature for the generation of the global TanDEM-X FNF map, based on a supervised geometry-dependent fuzzy clustering classification approach as explained in [2]. This approach represents the baseline approach for forest mapping with TanDEM-X .

In the generation of the global TanDEM-X FNF map, only acquisitions with a height of ambiguity ($\mathrm{h_{amb}} < 100$m) were classified. On images acquired with higher $\mathrm{h_{amb}}$, the forest classification was too ambiguous due to the acquisition geometry characterized by smaller perpendicular baselines between the satellites, which reduce the sensitivity of the γ_{Vol} to vegetated areas. The classified images were mosaicked in a final single forest map following a weighted mosaicking process. Mosaicking of the overlapping images were necessary to improve the accuracy of the generated TanDEM-X global FNF. On this map, external references were necessary to filter out water bodies as well as cities [2].

The potentials of deep learning for forest mapping in the context of TanDEM-X bistatic SAR images, were demonstrated in [4], where three different state-of-the-art CNN architectures were utilized, namely ResNet, DenseNet and U-Net, while training and testing were performed on a limited data set of TanDEM-X full resolution images acquired over the state of Pennsylvania, USA. Overall, the U-Net [5] solution demonstrated to be the most effective one for such a task, achieving the best performance among all investigated architectures. It constitutes the starting point of the investigations presented in this paper.

3. DEEP LEARNING METHODS FOR FOREST AND WATER MAPPING WITH TANDEM-X

The U-Net presented in [4], uses as activation function in the output layer a sigmoid, allowing just to a binary classification. We have kept for the present study the same activation layer. Taking advantage of the unique environment presented by the Amazon rainforest, we have used two different training datasets to train the U-Net to distinguish between forest/non-forest areas or water/non-water bodies, separately. Both outputs have been combined to classify TanDEM-X images in forest, non-forest and water.

An ad-hoc training strategy for model generalization on all different acquisition geometries have been developed. The number of considered input features of the U-Net has been extended. The acquisition incidence angle (θ_{i}) and the $\mathrm{h_{amb}}$ have been added to the backscattering coefficient, the total interferometric coherence, the volume decorrelation factor and the local incidence angle - used in previous studies - as major descriptors of the variability in the TanDEM-X acquisition geometries. The θ_{i} angles have been divided in three main ranges ($\theta_{\mathrm{i}} \in [0° - 35°, 35° - 45°, 45° - 90°]$), as for the TanDEM-X FNF map [2]. The $\mathrm{h_{amb}}$, showing typical values between 20 m and 12 m, has been divided in ranges with an step of 2 m. Mainly acquisitions acquired in 2011 and 2012 have been considered for the training, in order to assure a good classification agreement with the considered reference map of 2010 for training: a forest map based on Landsat imagery from 2010 [7]. Up to 5 images per range (both $\mathrm{h_{amb}}$ and θ_{i}) have been selected, where possible.

Overall, 455 TanDEM-X quicklook images, with a forest content between 30% and 70% according to the reference map, have been selected for training of the forest mapping U-Net architecture. A separated set of 376 TanDEM-X images, representative of the different types of water bodies, such as open water, lakes and rivers, have been used to train the U-Net for water detection.

The trained CNN has been firstly tested on a separate set of 976 images with at least 10% forest content and representative for the considered ranges of $\mathrm{h_{amb}}$ values and θ_{i} angles. A mean f1-score of 0.88 has been obtained for the new maps generated with the U-Net, improving the f1-score of 0.75 obtained with the clustering approach used for the generation of the global TanDEM-X FNF map. Figure 1 depicts the performance obtained by comparing the forest classification with the CNN and the clustering approach [2] as a function of the percentage of forest in the image according to the Landsat map used as reference. An improvement of the classification of the forest with the U-Net CNN is overall observable, but specially noticeable over dense forested areas (percentage of forest samples > 70%). Figure 2 shows the results obtained for a test image acquired with a $\mathrm{h_{amb}} = 86$ m in 2013 over the Amazon rainforest. The reference map (Landsat), TanDEM-X baseline approaches (FNF+WBL) and the U-Net CNN ap-

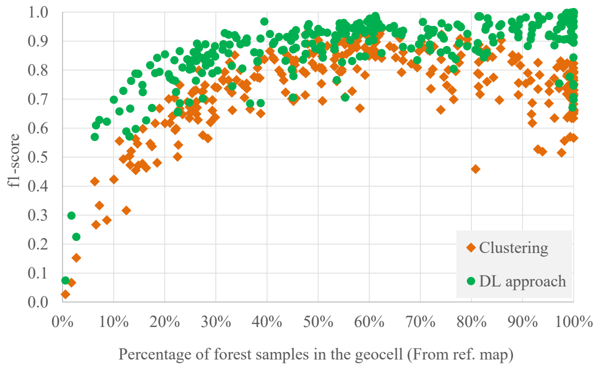

Fig. 1. F1-score for the forest class as a function of the forest density. Results obtained with the U-Net are compared with the clustering ones. Forest samples estimated from Landsat reference data.

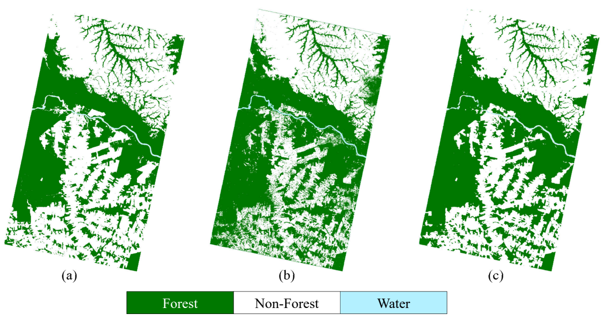

Fig. 2. Land cover classification of an image north of Macadinho d'Oeste, Rondônia state, Brazil. (a) Reference map based on Landsat, (b) Classification obtained with both baseline approaches for forest and water mapping with TanDEM-X . (c) Classification reached with TanDEM-X and DL methods.

proach are depicted. The f1-score for all three classes with the clustering approach is around 84%. In the case of the CNN approach it is improved to a 91%. In general, thanks to its capabilities in understnding two-dimesional patterns, the CNN performs better, it is able to generate forest maps with closed forested areas and non-forest regions less noisier. Moreover, the water classification looks reliable as well.

4. RESULTS OVER THE TROPICAL FOREST

More than 50,000 TanDEM-X images acquired over the tropical forests between end of 2010 and middle of 2017 have been classified with the proposed methodology. After combination of the binary outputs of the U-Net with forest/non-forest and water/non-water, a final classification map is available for each TanDEM-X image. The improvement in the classification accuracy of the TanDEM-X images allows for skipping the weighted mosaicking process of overlapping acquisitions used in the clustering approach, as well as for avoiding the use of external reference maps to filter out water bodies. Up to three time-tagged mosaics over the Amazonas rainforest have been generated and two over the other tropical forest areas locaded in Africa and South-East Asia, respectively. Figure 3 shows the three obtained mosaics over the tropical forests using TanDEM-X images acquired during the second global coverage (from March 2012 up to the end of 2013) [1].

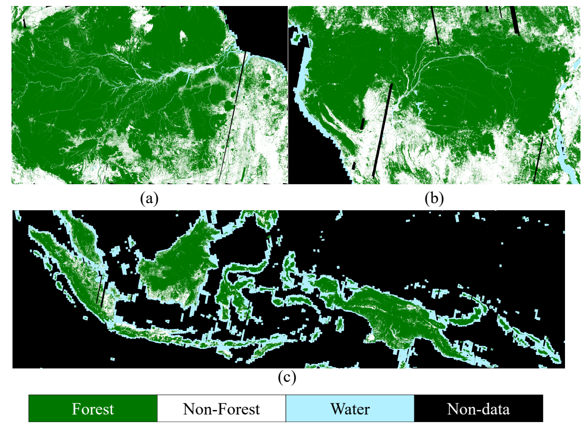

Fig. 3. Large scale maps over the Tropical forest areas obtained with TanDEM-X data from the second global coverage, March 2012 - December 2013. (a) Amazon rainforest, (b) African tropical forest, (c) Asia-Pacific tropical forest.

For validating the results obtained with the U-Net, the generated TanDEM-X mosaics of 2013 and 2016 have been compared with a global land cover map, based on optical imagery, the FROM-GLC (Finer Resolution Observation and Monitoring - Global Land Cover) [8]. This map has a resolution of 10 m x 10 m and is based on Landsat imagery up to 2015 and was updated to 2017 with Sentinel-2 images. The deforestation in the tropical forests accounts for a certain variability and differences on the classification maps acquired at different epochs should be considered. Nevertheless, a good agreement is observed for the generated TanDEM-X large scale mosaics, as summarized in Table 1, with an overall accuracy $> 85\%$. Note that for the evaluation of the f1-score, only tiles with a class content $> 5\%$ (according to the reference data) have been considered. The forest classification achieves overall a f1-score mostly $> 80\%$, showing the high capabilities for forest mapping using the presented approach. The U-Net suffers from the spatial resolution of the used images at 50 m x 50 m when detecting narrow rivers. Coastal areas, as in the case of the Asia-Pacific mosaic are well mapped. For the non-forest class, an f1-score in the range 72-79% has been obtained. Specially in areas close to the rivers, where the vegetation presents different character-

Table 1. Classification accuracy of different mosaics over the tropical forests generated with TanDEM-X and DL techniques. FROM-GLC used as comparison map. Number of evaluated geocells (1° x 1° in latitude and longitude) specified between braquets.

	Overall	F1-score		
	accuracy	Forest	Non-forest	Water
Africa'13	85.56 (303)	79.78 (295)	71.73 (206)	96.54 (36)
Asia'13	90.41 (634)	83.35 (469)	72.58 (284)	98.19 (567)
America'13	90.61 (589)	87.28 (577)	78.79 (332)	85.7 (60)
America'16	87.58 (296)	87.38 (289)	75.64 (206)	66.36 (56)

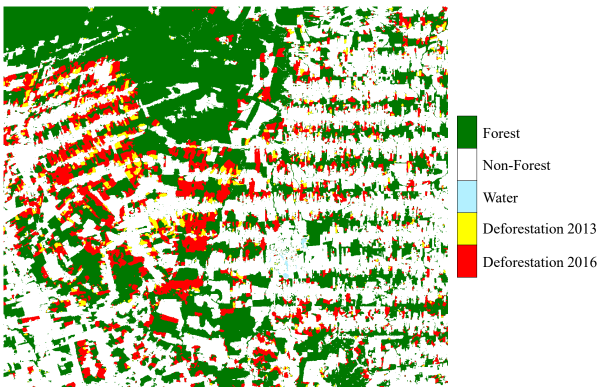

Fig. 4. Deforested areas detected with TanDEM-X and the generated mosaics with DL approaches for 2011, 2013, and 2016.

istics as a dense forest, as well as areas with secondary forest, are seen at X band as non-forest areas. TanDEM-X images acquired over these areas show a low classification accuracy with respect to the reference data but a high agreement between the U-Net forest/non-forest classification and the TanDEM-X FNF map obtained with the baseline clustering approach.

The high accuracy shown by the obtained mosaics represents a good starting point to estimate the deforestation occured over the tropical areas in the last decade. Figure 4 shows an examplary area located over the Amazon rainforest, south of Porto Velho in the Rondônia state, Brazil. From the initial 220,000 ha covered by forests at the end of 2011, 9,200 ha were deforested in 2012/13 and 48,200 ha between 2014 and 2016.

5. CONCLUSIONS AND OUTLOOK

In this paper we present the possible improvements using deep learning methods with TanDEM-X imagery for performing forest and water mapping in tropical forested areas. Previous works have been extended by considering new input features and extending the output of the CNN to classify forest/non-forest, as well as water bodies on large scale maps. On single TanDEM-X images acquired over the Amazon rainforest, the f1-score shows an improvement of 0.13 with respect to the clustering approach used for the generation of the global TanDEM-X FNF map. Different time-tagged mosaics of the whole tropical forest areas have been produced as well, just by averaging the single image maps classified by the ad-hoc trained CNN. No mosaicking weights were necessary, thanks to the increased accuracy of the classification obtained with the CNN. Moreover, no external references are necessary either to filter out water bodies, as done for the global TanDEM-X FNF map. By comparing the forest detect on the different mosaics deforestation areas can be quantized, showing the capabilities of TanDEM-X for forest mapping and monitoring based on CNN approaches.

6. REFERENCES

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