DEEP LEARNING FOR MAPPING THE AMAZON RAINFOREST WITH TANDEM-X

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ABSTRACT

The TanDEM-X Synthetic Aperture Radar (SAR) system allows for the recording of the bistatic interferometric coherence, which adds additional information to the common amplitude images acquired by monostatic SAR systems. More concretely, the volume decorrelation factor, which influences the interferometric coherence, has been proved to be a reliable indicator of vegetated areas and was exploited in [1] to generate the global TanDEM-X Forest/Non-Forest Map, based on a supervised clustering algorithm. In this work, we investigate ad-hoc training strategies to extent the Convolutional Neural Network (CNN) presented in [2] for mapping forests and monitoring the extend of the Amazonas using TanDEM-X. By applying the proposed method on single TanDEM-X images, we achieved a significant performance improvement with respect to the clustering approach, with an f-score increase of 0.13, using as reference a forest map of 2010 based on Landsat data. The improvement in the forest classification makes it possible to skip the weighted mosaicking of overlapping images used in the clustering approach for achieving a good final accuracy. In this way, we were able to generate three time-tagged mosaics over the Amazon rainforest, by utilizing the nominal TanDEM-X acquisitions between 2011 and 2017. In the final paper, we will present more consolidated results, including the validation and comparison of the generated mosaics, as well as change detection investigations, aimed at showing the capabilities of Deep Learning approaches for forest mapping and monitoring with bistatic TanDEM-X images.

***Index Terms*—** Synthetic Aperture Radar, TanDEM-X, Amazon, forest mapping, deforestation monitoring, deep learning, convolutional neural network

1. INTRODUCTION

The Amazon rainforest plays a key role in environmental processes on the Earth, such as carbon and climate regulation, water cycle, as well as hosting about 30% of the world's species of plants and animals. The Amazon rainforest covers around 5.5 million km^2 in the North of South America and represents the largest moist broadleaf tropical forest on the planet. In the past years, illegal deforestation and devastating fires, set to clear acreage for mining and agriculture activities, have contributed to a severe degradation of this unique environment.

Spaceborne synthetic aperture radar (SAR) missions are able to acquire images at a global scale, independently on weather conditions and solar light and represent therefore an ideal source of data for forest mapping over the Amazon rainforest, which is almost completely hidden from view for optical sensors during the entire wet season. TanDEM-X is the first spaceborne SAR mission capable of providing single-pass interferometric data at a global scale using two separate spacecrafts. Its data has already been exploited to generate global products such as the TanDEM-X digital elevation model (DEM), with a ground resolution of 12 m x 12 m [3], and the TanDEM-X Forest/Non-Forest (FNF) map, with a resolution of 50 m x 50 m [1]. Both products rely on the mosaicking of the acquired data from 2011 up to 2016.

In this paper we present an approach to enhance forest mapping with TanDEM-X using deep learning and, in particular, convolutional neural networks. Using TanDEM-X data acquired between 2011 and 2017 and extending the work done in [2], we are now able to generate up to three forest maps at a resolution of 50 m x 50 m, one for each one of the two global acquisitions and one for dedicated regions with on-going deforestation activities, subsequently acquired during 2016 and 2017. In this draft paper we introduce the methodology and present preliminary results. In the final paper we will present more consistent results, including large-scale maps, validation and inter-comparison with other forest maps, as well as a more detailed quantification of forest loss in the last decade.

2. CONVOLUTIONAL NEURAL NETWORK FOR TANDEM-X FOREST MAPPING

For information extraction and forest mapping in the context of TanDEM-X SAR images, the potentials of deep learning have been demonstrated in [2], where three state-of-the-art CNN architectures were compared, showing very promising performance. The U-Net [4] solution demonstrated to be the most effective one. The specific implementation of the U-Net for TanDEM-X works on four scale levels, with two chained convolutional layers located on both encoder and decoder sides at each level. The network head has an additional 1×1 convolution, used to map 64 features in a single probability channel. The U-Net has been trained from scratch to avoid any type of transfer learning.

In the actual study for forest mapping over the Amazon rainforest, the U-Net presented in [2] has been improved by including as input feature the height of ambiguity as well. Moreover, given the special environment presented by the Amazon region, with the presence of many river beds, the U-Net has also been extended to provide three classes: forest, non-forest, and water. The selected input features for the U-Net are:

- The absolutely calibrated amplitude, identifying the backscatter in SAR systems and broadly used for land classification purposes.

- The interferometric coherence γ_{Tot} and its volume correlation factor γ_{Vol}. γ_{Tot} is defined as the normalized cross-correlation coefficient between the interferometric images pair. It represents the main indicator for assessing the quality of an interferogram and can be factorized as [5]

$$\gamma_{\text{Tot}} = \gamma_{\text{SNR}} \gamma_{\text{amb}} \gamma_{\text{quant}} \gamma_{\text{az}} \gamma_{\text{rg}} \gamma_{\text{Vol}} \gamma_{\text{Temp}}, \quad (1)$$

  where γ_{SNR} refers to decorrelation due to a limited signal-to-noise ratio, γ_{amb} represents range and azimuth ambiguities, γ_{quant} accounts for the quantization noise, γ_{az} and γ_{rg} relate to processing issues, such as the relative shift of the Doppler spectra and baseline differences, respectively. For a bistatic system such as TanDEM-X, there is no temporal decorrelation ($\gamma_{\text{Temp}} = 1$) and γ_{Vol} is the volume correlation factor, which represents the decorrelation effects caused by the presence of multiple scattering in a volume, such as snow packs and forests. This term is a reliable indicator of the presence of vegetation on ground and it was therefore selected in [1] as main feature for forest mapping with TanDEM-X data at global scale.

- The height of ambiguity, which is a good descriptor of the acquisition geometry. It represents the height difference corresponding to a complete 2π cycle of the interferometric phase and informs about the phase-to-height sensitivity in the interferogram. For bistatic systems such as TanDEM-X is defined as

$$h_{\text{amb}} = \frac{\lambda R \sin \theta_{\text{i}}}{B_{\perp}}, \quad (2)$$

  where λ is the wavelength, R the slant range distance, θ_{i} refers to the local incidence angle, and $B_{\perp}$ is the baseline perpendicular to the line of sight. The lower the height of ambiguity, the lower the γ_{Vol} and thus the interferometric coherence [5].

- θ_{i} is the local incidence angle and relates the line-of-sight of the satellite with the height and slope of a point on the Earth. SAR amplitude strongly depends on its value.

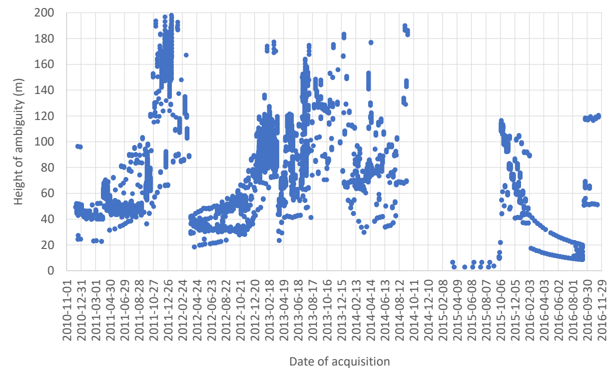


Fig. 1. Height of ambiguity values for TanDEM-X acquisitions over the Amazon rainforest acquired between 2011 and 2016.

All input images have been divided into patches of 128 × 128 pixels and fed to the U-Net for training, validation, and test purposes.

3. TANDEM-X DATA SET AND CNN TRAINING STRATEGY

The multi-looked TanDEM-X quicklook images, generated at an independent pixel spacing of 50 m × 50 m are the basis of the TanDEM-X global Forest/Non-Forest (FNF) map [1] and are used in this work as well. More than 500,000 quicklook images have been acquired between 2011 and 2016, covering twice the complete Earth's landmasses. In the case of the Amazon rainforest, we have extracted and processed the TanDEM-X quicklook data acquired during 2017, too. Figure 1 depicts the height of ambiguity for the considered data takes. A typical value for the height of ambiguity of 45 m is observed during the first TanDEM-X global coverage, from the end of 2010 up to March 2012. The second TanDEM-X global coverage, ranging from April 2012 up to March 2013, was acquired with a typical height of ambiguity around 35 m, to improve the DEM performance [3]. From the available TanDEM-X acquisitions over the Amazon rainforest, typical values from 20 m up to 120 m height of ambiguity are observed in Figure 1. The training set for the CNN has been defined accordingly, by dividing the h_{amb} range into steps of 2 m. Moreover, The incidence angles θ_{i} have also been divided in three main ranges, as for the TanDEM-X FNF map, : a) $\theta_{\text{i}} < 30°$, b) $\theta_{\text{i}} \in< [30°, 45°]$, and c) $\theta_{\text{i}} > 45°$. Up to 5 images per range (both h_{amb} and θ_{i}) have been selected, where possible. Such images have been chosen with a forest content between $30^{\%}$ and $70^{\%}$, in order to mitigate class imbalance. As external reference to estimate the forest content in each TanDEM-X image, a forest map from 2010 based on Landsat imagery has been used [6]. A total of 455 images, mainly acquired during the first

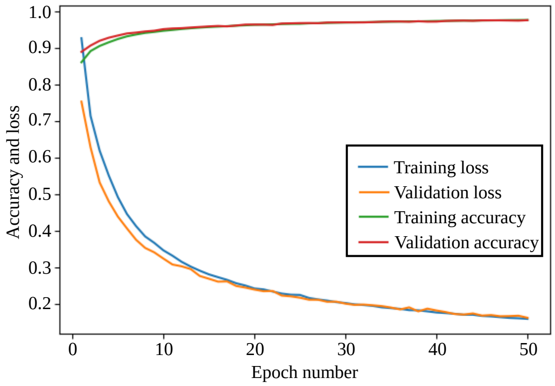


Fig. 2. Loss and accuracy obtained after training the TanDEM-X U-Net for forest mapping.

TanDEM-X global coverage have been selected for training the U-Net. 5% of these images have been reserved for validation during the training process. Figure 2 depicts the loss function and the accuracy trends obtained after training the U-Net for 50 epochs. A good agreement between both data set, as well as a convergence during the training process is observed.

4. RESULTS

The trained CNN has been tested on a set of 320 images with at least 10% forest content and representative for the considered ranges of height of ambiguity values and incidence angles. The test data set was not used during the training phase. Figure 3 depicts the performance obtained by comparing the forest classification with the CNN and the reference Landsat map as a function of the forest content in each image. Moreover, the same analysis has been made using the clustering approach described in [1], as baseline algorithm.

The accuracy evaluation is based on the f-score, which is mainly used to evaluate binary classifications and it is specially useful when dealing with imbalanced data sets. The f-score is defined as the harmonic mean of precision and recall of a model and ranges between 0 and 1. It can be expressed as

$$f_{\text{score}} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}, \tag{3}$$

where precision and recall represent the trade-off between the need of catching the target class whenever it occurs (Recall = 1) and that of reducing false alarms (Precision = 1). They relate with the classical and widespread measures used for detection such as the true/false positives/negatives rates as

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}), \tag{4}$$

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}), \tag{5}$$

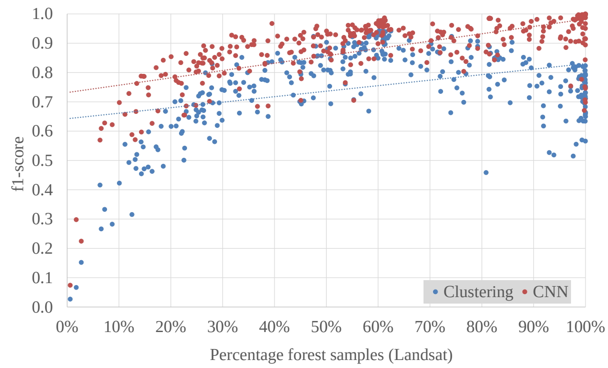


Fig. 3. F-score values obtained by comparing the forest classification with the CNN, the clustering approach described in [1] (as baseline algorithm), and the reference Landsat as a function of the forest content in each image.

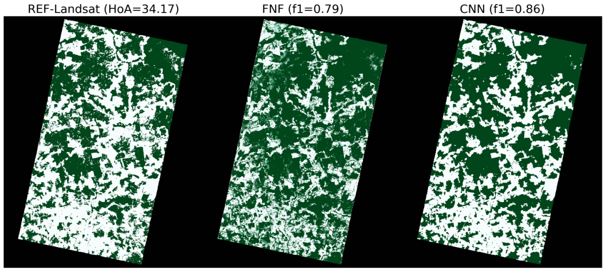
where TP (true positives) represents the pixels classified as forest in both maps, FP (false positives) accounts for the pixels classified as forest in the TanDEM-X CNN and as non-forest in the reference map, and FN (false negative) means pixels classified as non-forest by the TanDEM-X CNN and as forest in the reference map.

Moreover, in Figure 3 a linear fitting has been superimposed to both data sets. A mean-improvement of around 0.13 in the f-score is observed, which further increases towards more dense forests. The mean f-score over the test data set of 320 TanDEM-X for the CNN forest map is 0.88 and for the FNF map is 0.75. Figure 4 shows two examples of the reference map (Landsat), the FNF clustering approach, and the actual CNN approach, for two images with different height of ambiguity values. The detected forest is shown in green, non-forest areas are depicted in white, water is represented in light blue and no-data in black. The f-score (f1) is indicated over each image as well. The improvement in the classification accuracy is clearly visible, in particular when considering high height of ambiguity values, typically characterized by lower volume decorrelation. In general, thanks to its two-dimesional capabilities, the CNN is able to generate forest maps with closed forest areas and cleaner clear-cuts regions. Moreover, the water classification looks reliable, too.

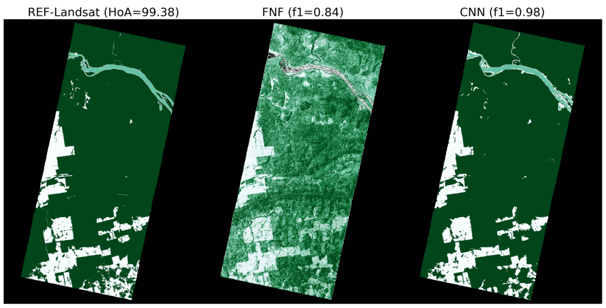
All available TanDEM-X acquisitions over the Amazon rainforest have then been classified with the CNN, allowing for the generation of three time-tagged mosaics. As example, Figure 5 shows the forest map from the TanDEM-X images acquired during the second global coverage (from March 2012 up to the end of 2013).

5. CONCLUSIONS AND OUTLOOK

In this paper we present the developed approach for performing forest mapping in the Amazon rainforest, by combining



(a) Forest maps for an image with a low height of ambiguity



(b) Forest maps for an image with higher height of ambiguity

Fig. 4. Forest classification maps for two TanDEM-X images. Landsat forest map used as reference and depicted together with TanDEM-X forest maps obtained with both approaches, clustering and CNN. (a) Image with a low height of ambiguity (34.17 m) acquired in April 2012. (b) Image with higher height of ambiguity (99.38 m) acquired in May 2013, where water bodies are detected in the TanDEM-X CNN image, too.

TanDEM-X acquisitions and convolutional neural networks. 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 single TanDEM-X images acquired over the Amazon rainforest, the f-score shows an improvement of 0.13 with respect to the clustering approach used for the generation of the global TanDEM-X FNF map. Moreover, three time-tagged mosaics of the whole Amazon basin 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 waterbodies, as done for the FNF map. In the final paper, we will present more consolidated results, including the validation and comparison of the generated mosaics with other existing forest maps. Change detection investigations will be conducted as well, aimed at showing the capabilities of TanDEM-X for forest mapping and monitoring based on CNN approaches.

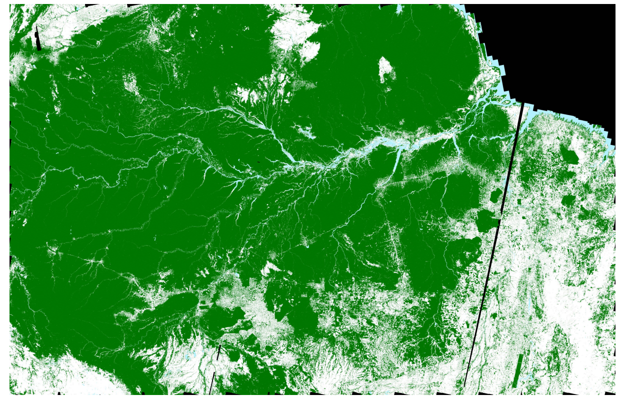


Fig. 5. Forest mosaic obtained for the second global coverage (2013) with TanDEM-X quicklook data and the purposed CNN.

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