Near-real time deforestation detection in the Brazilian Amazon with Sentinel-1 and neural networks

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ABSTRACT

Optical-based near-real time deforestation alert systems in the Brazilian Amazon are ineffective in the rainy season. This study identify clear-cut deforested areas through Neural Network (NN) algorithm based on C-band, VV- and VH-polarized, Sentinel-1 images. Statistical parameters of backscatter coefficients (mean, standard deviation, and the difference between maximum and minimum values – MMD) were computed from 30 Sentinel-1 images, from 2019, used as input parameters of the NN classifier. The samples were manually selected, including forested and deforested areas. After deforestation, mean backscatter signals decreased on the average of 2 dB for VV and 2.3 dB for VH from May to September–October. A Multi-Layer Perceptron (MLP) network was used for detecting near-real time forest disturbances larger than 2 ha. Case studies were performed for both polarizations considering the following input sets to the MLP: mean; mean and standard deviation; mean and MMD; and mean, standard deviation, and MMD. For the 2019 dataset, the latter showed the best performance of the NN algorithm with accuracy and F1 score of 99%. Automatic extraction using 2018 Sentinel-1 images reached accuracy and F1 score of 89% with the MapBiomas reference data and accuracy of 81% and F1 score of 79% with the PRODES reference data.

Introduction

The Brazilian Amazon covers an area of approximately 5.2 million km², about 60% of the Brazilian territory, encompassing the following states: Acre (AC), Amapá (AP), Amazonas (AM), Mato Grosso (MT), Pará (PA), Rondônia (RO), Roraima (RR), Tocantins (TO), and part of Maranhão (MA; Figure 1). Satellite-based monitoring of such a large territory is a complex task because of its continental size and long rainy seasons. Forest disturbance in the Brazilian Amazon by human occupation is mostly concentrated in a large region named deforestation arch. The arch has about 1.7 million km² (33% of the Brazilian Amazon), extends from northeast of Maranhão State to southeast of Acre State, and concentrates most of the monitoring efforts conducted by the Brazilian environmental organizations (Cochrane, 2003; Davidson et al., 2012; Farias et al., 2018; D. Nepstad et al., 2001; Souza et al., 2020; Yanai et al., 2017).

Clear-cut deforestation larger than 200 hectares was commonly observed in the region between 2000 and 2018 (Davis et al., 2020). In the last five years (2016–2020), the Brazilian Amazon has lost about 43,300 km² of forest cover. Deforestation, which is frequently associated with fire occurrences and illegal selective logging (Silva Júnior et al., 2018; Van Marle et al., 2017), exceeded 10,000 km² in 2019 and 10,800 km² in 2020. The Brazilian Amazon has also been degraded by intensive selective logging activities, causing a significant loss of forest diversity (Bezerra et al., 2021; Matricardi et al., 2020). Silva et al. (2021) recently addressed the dynamics of occupation and greenhouse gas emissions in this region. Pará is the state presenting the highest levels of deforestation since 2006, mostly driven by the rural settlement, beef production, crop plantation, and large reservoirs of hydropower plants (D. C. Nepstad et al., 1999; Farias et al., 2018; Kastens et al., 2017; Yanai et al., 2020).

The National Institute for Space Research (INPE) is the Brazilian institution responsible for monitoring annual deforestation in the Brazilian Amazon through the Project of the Deforestation Monitoring by Satellite (PRODES). The program relies on optical sensors onboard the Landsat 8, Sentinel-2, and China–Brazil Earth Resources Satellite (CBERS-4 and CBERS-4A) satellites. In this project, deforestation is defined as the conversion of primary forest into clear-cut areas (Diniz et al., 2015; Terrabrasilis – Geographic Data Platform, n.d.). Reports and deforestation data about the Brazilian Amazon can also be obtained from the Brazilian Annual Land Use and Land Cover Mapping Project (MapBiomas initiative). It is a non-governmental organization that generates annual land use and land cover (LULC) time series of the entire country through the Landsat satellite data processing and analysis in the Google Earth Engine platform (Davis et al., 2020; MapBiomas Brasil, n.d.).
Figure 1. Location of the Brazilian Legal Amazon and the deforestation arch in Brazil. State identification: AC = Acre; AM = Amazonas; AP = Amapá; MA = Maranhão; MT = Mato Grosso; PA = Pará; RO = Rondônia; RR = Roraima; and TO = Tocantins.

During the rainy season, when the forest monitoring based on optical satellites is impaired, the Management and Operational Center for the Amazon Protection System (Censipam), from the Ministry of Defense, is the organization responsible for processing the X-band, synthetic aperture radar (SAR) images over critical areas. Regrettably, the reports issued by the institution are used basically for environmental law enforcement procedures. Figure 2 shows the deforestation process and weather conditions throughout the year in the Brazilian Amazon.

Currently, in terms of Brazilian satellites, the Brazilian Amazon is imaged by the joint Brazil–China, CBERS-4A optical satellite along with the Amazonia-1 satellite. The latter carries a wide-view optical imager with three visible (VIS) bands and one near-infrared (NIR) band with a swath of 850 km and 60 m of spatial resolution. The Ministry of Defense and INPE are currently conducting the zero-phase analysis of the national SAR mission. The integration of optical and SAR imageries can improve forest monitoring in tropical regions. Reiche et al. (2015) fused Landsat normalized difference vegetation index (NDVI) and L-band ALOS PALSAR backscatter time series in the Viti Levu Island, Fiji. They found a strong correlation between the backscatter multi-temporal HV/HH ratio and NDVI, while the accuracy using only NDVI decreased significantly.

Monitoring the Brazilian rainforest through remote sensing claims for some level of automation because of its large territorial extent. Neural networks (NNs) are one of the most advanced technological frontiers to increase the automation level in satellite image processing. A NN is a massively parallel distributed processor made up of simple processing units using cumulative empirical knowledge (Haykin, 2009). It has been successfully applied in different cases. Del Frate and Wang (2001) analysed the C- and L-band backscatter coefficients for retrieving sunflower biomass using NN algorithm to perform the inversion modelling. NN has been also applied to map the evolution of human settlements and urban land using C-band SAR images (Del Frate et al., 2008), to characterize the seismic source of an earthquake and its geometric parameters (Stramondo et al., 2011), to classify different crops by multi-polarized and multi-temporal backscattering coefficients (Del Frate et al., 2003), to detect land cover changes in urban areas.
using X-band SAR images (Pratola et al., 2013), and to detect vegetation burnt areas to monitor regrowth of maquis vegetation with X-band data (Laurin et al., 2018).

Del Frate and Solimini (2004) proposed a NN algorithm to estimate soil moisture, leaf area index (LAI), and biomass in wheat fields. The algorithm was tested with experimental data collected at X-, C-, and S-bands. The model was based on the radiative transfer theory and a combination of scattering contributions. These authors obtained good results of moisture retrieval over bare soil and moderate results under vegetation cover. Even though the saturation effects reduced the absolute accuracy, the algorithm could reproduce the biomass trend with a reasonable agreement. Laurin et al. (2013) used the NN classifier to map areas of tropical forests in West Africa. In this study, the authors applied Landsat, ALOS AVNIR-2, and ALOS PALSAR data. The classification results were evaluated using optical data alone, SAR data alone, Landsat and PALSAR, AVNIR-2 and PALSAR, and a combination of three sensors. The integration of the three sensors reached the best results.

Few works have been conducted using machine learning algorithms or SAR images to detect deforestation in the Amazon rainforest. Bem et al. (2020) proposed a method based on convolutional neural networks (CNNs) applied to Landsat optical images from the Brazilian Amazon. They investigated different CNN architectures to predict annual changes in vegetation cover, comparing the results with two other machine learning algorithms, the Random Forest and the Multi-Layer Perceptron (MLP). They obtained good results employing CNNs, with the F1 score of 94–95%. However, CNNs are not widely accessible since they require a large number of samples and specific hardware for training, unlike other machine learning algorithms.

Doblas et al. (2020) suggested a procedure based on Sentinel-1 data, maximum likelihood classification (MLC), and adaptive thresholding (AT) for deforestation detection. They used SAR images acquired over 4 years (from November 2016 to December 2019) and studied the time series of the backscatter coefficients to identify deforested areas in the Brazilian Amazon. They obtained 94% of accuracy with MLC and 96% with AT. However, a comprehensive performance analysis comparing training and validation data was not addressed in that procedure. In our approach, the aim is to assess the classification capability of the NN algorithm to detect deforested areas based on different spatial statistical characteristics of the backscatter coefficient trend. In addition, machine learning algorithms have been proved more appropriate than traditional statistical algorithms for the classification of
remote sensing data (Benediktsson et al., 1990). This work, therefore, presents a method to discriminate deforested areas over the Brazilian Amazon based on NN and Sentinel-1 SAR images. To our best knowledge, the scientific community has not explored this approach to detect near real-time deforestation over the Brazilian Amazon. This paper is organized as follows: Section 2 provides details of the data set and the chosen NN. Section 3 presents the main results obtained, while the results are discussed in Section 4. The concluding remarks are presented in Section 5.

Material and methods

Study area

The study area encompasses part of the municipalities of Altamira, Itaituba, and Novo Progresso, southwest of Pará State, a region with the highest deforestation rates in this state (Figure 3). This region is considered a hotspot in terms of human occupation and is one of the main frontiers of deforestation in the deforestation arch.

Sentinel-1 data set

For this research, we selected Sentinel-1A, Single Look Complex (SLC) images acquired in the Interferometric Wide (IW) swath mode from the European Copernicus program with a free and open data distribution policy (Open Access Hub, n.d.; Potin et al., 2019). The Sentinel-1A operates at a C-band (5.3 cm wavelength) and a swath width of 250 km (Torres et al., 2012). We selected one image every 12 days, dual-polarization (VV and VH), descendent mode, from the years 2019 to 2018, i.e. a total of 30 images per year (Table 1). The incidence angle ranged from about 29º to 46º and the resolution was about 5 m in range and 20 m in azimuth (ESA, 2021).

The SAR images were pre-processed by means of Sentinel Application Platform (SNAP), an open-source software developed by the European Space Agency (ESA; SNAP Download, n.d.). The pre-processing operations included orbit file correction, thermal noise removal, radiometric calibration (Sigma0), de-burst, and speckle filtering by the Gamma-Map filter. For terrain correction, we used external data of 30-m spatial resolution, obtained from AW3D digital elevation model (DEM) (“ALOS Global Digital Surface Model ‘ALOS World 3D – 30 m’ (AW3D30)” n.d.). As a result, we obtained images with an approximate spatial resolution of 14.05 m (WGS84, UTM) converted into backscattering coefficients (σ°, units in dB).

Forested and deforested sampling

Table 2 shows the selected Sentinel-2 overpasses from May to October of 2019 that were used to visually select areas without deforestation (FF) and areas with
deforestation (FD). We collected samples over homogeneous areas (at least 90%) in terms of primary forest and clear-cut deforestation, located in flat topography. The presence of forest was guaranteed by evaluating Sentinel-2 images from 2018 to 2020 (25 August 2018 image and 20 June 2020). The 98 FF samples presented an average size of 95 pixels, while the 199 FD samples presented an average size of 66 pixels (Figure 4).

For each FF and FD sample, the mean, standard deviation, and maximum-minimum difference (MMD), that is the difference between the maximum and minimum value of the backscatter coefficient, were calculated for both VH and VV polarizations. The metrics were computed over the polygons for each acquisition in the year 2019. Figure 5 shows an example of each statistical parameter for FF and FD areas in the VH and VV polarizations. For every acquisition, shown on the horizontal axis, the related statistical value is reported on the y-axis. In this way, the variation of the statistical parameter throughout the year can be obtained and used to discriminate the forested area from the deforested area.

**Table 1.** Sentinel-1A interferometric wide (IW), single look complex (Level 1) overpasses from 2019 to 2018 considered in this study.

| Overpass 2019 | Scene Identification 2019 | Overpass 2018 | Scene Identification 2018 |
|---------------|---------------------------|---------------|---------------------------|
| Jan-03        | S1A_IW_SLC_1SDV_20190103T092340 | Jan-08        | S1A_IW_SLC_1SDV_20180108T092333 |
| Jan-15        | S1A_IW_SLC_1SDV_20190115T092340 | Jan-20        | S1A_IW_SLC_1SDV_20180210T092333 |
| Feb-08        | S1A_IW_SLC_1SDV_20190208T092339 | Feb-01        | S1A_IW_SLC_1SDV_20180210T092333 |
| Feb-20        | S1A_IW_SLC_1SDV_20190220T092339 | Feb-13        | S1A_IW_SLC_1SDV_20180213T092332 |
| Mar-04        | S1A_IW_SLC_1SDV_20190304T092339 | Feb-25        | S1A_IW_SLC_1SDV_20180225T092332 |
| Mar –16       | S1A_IW_SLC_1SDV_20190316T092339 | Mar-09        | S1A_IW_SLC_1SDV_20180309T092332 |
| Mar –28       | S1A_IW_SLC_1SDV_20190328T092339 | Mar-21        | S1A_IW_SLC_1SDV_20180321T092332 |
| Apr-09        | S1A_IW_SLC_1SDV_20190409T092339 | Apr-02        | S1A_IW_SLC_1SDV_20180402T092333 |
| Apr-21        | S1A_IW_SLC_1SDV_20190421T092340 | Apr-14        | S1A_IW_SLC_1SDV_20180414T092333 |
| May-03        | S1A_IW_SLC_1SDV_20190503T092340 | Apr-26        | S1A_IW_SLC_1SDV_20180426T092334 |
| May-15        | S1A_IW_SLC_1SDV_20190515T092341 | May-08        | S1A_IW_SLC_1SDV_20180508T092334 |
| May-27        | S1A_IW_SLC_1SDV_20190527T092341 | May-20        | S1A_IW_SLC_1SDV_20180520T092335 |
| Jun-08        | S1A_IW_SLC_1SDV_20190608T092342 | Jun-01        | S1A_IW_SLC_1SDV_20180601T092336 |
| Jun-20        | S1A_IW_SLC_1SDV_20190620T092343 | Jun-13        | S1A_IW_SLC_1SDV_20180613T092337 |
| Jul-02        | S1A_IW_SLC_1SDV_20190702T092344 | Jun-25        | S1A_IW_SLC_1SDV_20180625T092337 |
| Jul-14        | S1A_IW_SLC_1SDV_20190714T092344 | Jul-07        | S1A_IW_SLC_1SDV_20180707T092338 |
| Jul-26        | S1A_IW_SLC_1SDV_20190726T092345 | Jul-19        | S1A_IW_SLC_1SDV_20180719T092339 |
| Aug-07        | S1A_IW_SLC_1SDV_20190807T092346 | Jul-31        | S1A_IW_SLC_1SDV_20180731T092339 |
| Aug-19        | S1A_IW_SLC_1SDV_20190819T092347 | Aug-12        | S1A_IW_SLC_1SDV_20180812T092340 |
| Aug-31        | S1A_IW_SLC_1SDV_20190831T092347 | Aug-24        | S1A_IW_SLC_1SDV_20180824T092340 |
| Sep-12        | S1A_IW_SLC_1SDV_20190912T092348 | Sep-05        | S1A_IW_SLC_1SDV_20180905T092341 |
| Sep-24        | S1A_IW_SLC_1SDV_20190924T092348 | Sep-17        | S1A_IW_SLC_1SDV_20180917T092342 |
| Oct-06        | S1A_IW_SLC_1SDV_20191006T092349 | Sep-29        | S1A_IW_SLC_1SDV_20180929T092342 |
| Oct-18        | S1A_IW_SLC_1SDV_20191018T092348 | Oct-11        | S1A_IW_SLC_1SDV_20181011T092342 |
| Oct-30        | S1A_IW_SLC_1SDV_20191030T092349 | Oct-23        | S1A_IW_SLC_1SDV_20181023T092342 |
| Nov-11        | S1A_IW_SLC_1SDV_20191111T092349 | Nov-04        | S1A_IW_SLC_1SDV_20181104T092342 |
| Nov-23        | S1A_IW_SLC_1SDV_20191123T092348 | Nov-16        | S1A_IW_SLC_1SDV_20181116T092342 |
| Dec-05        | S1A_IW_SLC_1SDV_20191205T092348 | Nov-28        | S1A_IW_SLC_1SDV_20181128T092341 |
| Dec-17        | S1A_IW_SLC_1SDV_20191217T092347 | Dec-10        | S1A_IW_SLC_1SDV_20181210T092341 |
| Dec-29        | S1A_IW_SLC_1SDV_20191229T092347 | Dec-22        | S1A_IW_SLC_1SDV_20181222T092341 |

**Table 2.** Forest–Deforested and Forest–Forest samples (FD) manually collected based on Sentinel-2 images acquired in 2019.

| Time interval      | Number of samples FD | Number of samples FF |
|--------------------|----------------------|----------------------|
| May 7–June 16      | 58                   |                      |
| Jun 16–June 21     | 1                    |                      |
| Jun 21–June 26     | 8                    |                      |
| Jun 26–July 16     | 35                   |                      |
| Jul 16–Jul 21      | 15                   |                      |
| Jul 21–Jul 31      | 21                   |                      |
| Jul 31–Aug 30      | 16                   |                      |
| Aug 10–Aug 20      | 10                   |                      |
| Aug 20–Aug 30      | 14                   |                      |
| Aug 30–Sep 9       | 8                    |                      |
| Sep 9–Sep 19       | 13                   |                      |
| Sep 19–Oct 9       | 1                    |                      |
| Total              | 199                  | 99                   |
NNs can be distinguished by their architectures or structures. In this study, we considered the MLP. MLP is a feedforward NN, i.e. the input is projected unidirectionally to the output, which is distinguished by the presence of one or more hidden layers between the input and output layers. MLPs are applied in classification and regression problems in many fields, including remote sensing (Ramchoun et al., 2016). Since we implemented a binary classifier, a sigmoid activation function was used for the final layer. It outputs a value between 0 and 1 that can be treated as a probability that the given input belongs to a particular class (Sharma et al., 2020).

The number of hidden layers and units depends on the specific problem and cannot be determined a priori (Ramchoun et al., 2016). In this study, we applied two hidden layers of units between the input vector with the measured features and the output vector with the classification response (Del Frate & Solimini, 2004). The initial number of units was estimated following the study conducted by Del Frate and collaborators and was defined for each specific case. The MLP topology consists of four layers (Figure 6). As discussed in detail in Section 2.5, four case studies with different input configurations were analysed. Therefore, we designed four MLP topologies with the number of input and hidden units varying depending on the case study.

**Data set preparation**

The statistical features extracted from the FD and FF sample areas were inputs to the NN, trained to automatically detect the probability that an area was deforested. Different case studies were considered to form the input vectors. First, the statistical parameters were involved individually, and then a combination of them was considered. Specifically, four different sets of inputs were chosen:

1. mean $\sigma^\circ$ values of both VV and VH polarizations;
2. mean $\sigma^\circ$ values and corresponding standard deviation of both VV and VH polarizations;
3. mean $\sigma^\circ$ values and corresponding MMD values of both VV and VH polarizations; and
4. mean $\sigma^\circ$ values and corresponding standard deviation and MMD of both VV and VH polarizations.

![Figure 4. Example of Forested–Forest (FF) and Forested–Deforested (FD) samples manually collected in different overpasses of Sentinel-2 satellite, overlaid on the RGB color composite of bands 4, 3, and 2 of Sentinel-2 satellite image obtained in 1 July 2019.](image-url)
Standard deviation and MMD were not considered individually as they did not exhibit good performances. Similarly, preliminary results obtained with single polarization configurations suggested disregarding such an option. Figure 7 shows the processing procedure, which is the same for the four case studies.

As a first step in the data set construction, the number of samples related to the FF condition was equalized to the FD ones by increasing the former through a data augmentation process. More specifically, synthetic data (noisy data) was generated from the original data (seeds) by adding slightly modified copies of them.

Figure 5. Mean, standard deviation, and MMD (maximum-minimum difference) example of the backscatter coefficient in VH and VV polarizations.
Random noise vectors of the same size as the seeds vectors were created according to a Gaussian distribution with specific mean and variance. These two parameters were chosen due to the required similarity between the noisy vector and the original one. For the first case study, where only the mean $\sigma^e$ values are considered, an example of a noise vector is shown in Figure 8(a). It consists of 30 elements, as the number of features in case study (1) in the VH polarization only. The noise values range approximately from $-0.3$ to $0.3$.

The sum of the noise vector and the original seed vector is shown in Figure 8(b) for the average value of the backscatter. The original vector is shown in orange, while the noisy one in blue.

To have a data set of sufficient size to train the NN, the whole number of input samples (both FD and FF samples) was increased in a similar way. The data set generation results for the case study (1) (average value of the backscatter coefficient) are shown in Table 3. In this case, the data set was enlarged five-fold to obtain
a total number of samples equal to 1194 + 1194 = 2388. Since the statistical features differ significantly, each sample was normalized between 0 and 1 before being input to the NN.

Each sample in the data set is described by features related to the backscatter coefficient in the VH and VV polarizations. The number of features for each sample depends on the case study: for the case study (1), the features are 60 (30 VH + 30 VV features); for the case studies (2) and (3), they are 120 (60 VH + 60 VV features); and for the case study (4), they are 180 (90 VH + 90 VV features). Table 4 provides a summary of this split. Thus, the input of the NN is a vector with the number of entries that is equal to the number of features. Since the features differ significantly, each sample was normalized between 0 and 1.

**Training phase (2019 data set)**

Generally, in machine learning models, the data set is divided into three distinct parts: training, validation, and test data sets split into the proportion of 75%, 15%, and 10%, respectively. These proportions are a typical choice in machine learning data separation (Haykin, 2009). The training and validation sets are used during the training process, while the test set is used to evaluate the performance achieved. Indeed, the test set is used separately from the previous ones and is not involved in the learning procedure. In this paper, these proportions were considered for all case studies. The sample division for the first case study is reported in Table 5.

During the supervised learning process, the connection weights are optimized to minimize the error, namely the difference between the desired response and the actual response, according to a loss function. This error is evaluated both on the training and validation sets, which consists of examples not belonging to the training one. To avoid overfitting problems, i.e. to make the NN able to generalize over new patterns, the training of the network is stopped when the error on the validation data set reaches its minimum, according to the early stopping algorithm (Prechelt, 1998).

The number of units in the hidden layer was optimized for each input configuration, in terms of classification accuracy and generalization capability. Several attempts were made to select the proper number of units in the hidden layers which finally led to the topologies summarized in Table 6.

### Evaluation of the 2018 data set

The NN capability achieved during the training phase is applied to novel input data. The trained model is used for the automatic recognition of areas deforested during the year 2018. The properties of the data set used in this phase are similar to those of the training data set: it was composed of 30 pre-processed Sentinel-1 images acquired over the same area with the same spatial resolution, which shows the $\sigma^0$ values for the VH and VV polarizations.

Each image of the time series was automatically divided into sub-images with a size of $10 \times 10$ pixels, resulting in 223,725 patches for each acquisition. Considering the pixel resolution of the S1 images of 14.05 m, 10 pixels $\times$ 10 pixels makes an area of approximately 2 ha. Table 7 shows an overview of the data set dimension. The statistical parameters were calculated for each patch for both polarizations, as described in Section 2.5, and the same four case studies were considered. Therefore, the input of the trained NN is a vector with a number of entries depending on the examined case study.
Table 7. Data set description of selected Sentinel-1 images from 2018.

| Parameter                          | Specification |
|------------------------------------|---------------|
| Number of acquisitions per year    | 30            |
| Number of patches (for each acquisition) | 223,725      |
| Polarizations                      | VH and VV     |

Results evaluation

The sigmoid activation function in the NN output layer returns a class probability in the interval \([0, 1]\). A predicted value equal to or close to 0 means that the model identifies an area as forested (FF); conversely, a prediction equal to or close to 1 indicates a deforested area (FD). To evaluate the results, the confusion matrix was computed, and accuracy, precision, recall, and F1 score were derived. They are defined as (Equations 1–4):

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}
\]

\[
\text{Precision} = \frac{TP}{TP + FP} \tag{2}
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \tag{3}
\]

\[
F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}
\]

Where:

- \(TP\) = True positives, i.e. the number of deforested areas classified as deforested.
- \(TN\) = True negatives, i.e. the number of forested areas classified as forested.
- \(FP\) = False positives, i.e. the number of forested areas classified as deforested.
- \(FN\) = False negatives, i.e. the number of deforested areas classified as forested.

Results

Figure 9 shows an example of the multitemporal backscattering coefficients from an area that faced clear-cut deforestation between 7 May 2019 (a) and 16 June 2019 (c) for both VH (b) and VV (d) polarizations. The backscatter signal of deforestation presents a short increase followed by a sharply decreased in both polarizations until approximately 3 months (roughly, 31 August 2019). Then, the signals tended to increase after September.

From all FD samples collected in 2019, an average decrease of the mean backscatter coefficients of approximately 2 dB for VV polarization and 2.3 dB for VH polarization can be observed after deforestation. This decrease in the backscatter signal remains evident for the next 3–4 months approximately. After this period, we observed an irregular increase in both polarizations.

2019 data set

Table 8 reports the results achieved for the four case studies for the data sets obtained in 2019. The mean, standard deviation, and MMD input set showed accuracy and F1 score of 99%. The other case studies also achieved promising results: the accuracy obtained using mean and MMD slightly decreased to 98%. Lastly, mean and standard deviation, as well as mean, only showed an accuracy of 97%. False positives and false negatives were also very low. They were evaluated through the F1 metric, which is the harmonic mean of precision and recall. This means that the algorithm avoids, to a great extent, false alarms and, in most cases, does not miss the deforested areas.

2018 data set

To assess the NN performance, the 2018 results were validated using two ground truth images provided by the MapBiomas and PRODES projects. MapBiomas produces annual LULC maps by applying Random Forest classification overall Landsat scenes acquired in a specific year. The LULC maps are pixel-based, with a minimum mapping area of 1 ha. PRODES provides the annual rates of clear-cut deforestation with a minimum mapping area of 6.25 ha. PRODES makes use of moderate spatial resolution from Landsat-8, CBERS-4, and Sentinel-2 with 30 m, 20 m, and 10 m of spatial resolutions, respectively.

The data from MapBiomas and PRODES considered only deforested areas from 2018 found in the same region of the Sentinel-1 data set. The ground truth images were clipped into patches with the size of 10 pixels × 10 pixels, following the image division used for the SAR data set obtained in 2018. Each patch in the ground truth image is geographically related to the patch in the Sentinel-1 imagery in the data set. Out of the total, the ground truth patches reporting areas deforested in 2018 represent approximately 0.3% in MapBiomas while in PRODES they represent 0.6%.

The predictions related to 2018 deforested patches were collected, and the same number of predictions related to forested patches is selected randomly from the total to create a well-balanced data set. Table 9 shows the results achieved for the 2018 images for the four case studies.

Compared with the results obtained in 2019, all evaluation parameters decreased for the data sets obtained in 2018, especially for the recall, due to the relatively high number of false negatives. The recall decreased for the PRODES data. For both reference
The best-case scenario corresponded to the case study that considered mean, standard deviation, and MMD as input. In this case, the model achieved accuracy and F1 score of 89%, with a low number of false positives and false negatives, validating with the MapBiomas ground truth image and accuracy and F1 score of 81% and 79%, respectively, with the PRODES ground truth. The second best case was obtained for the mean backscatter coefficient as input parameter. The model performance declined when mean and standard deviation and mean and MMD were considered.

**Discussion**

In this study, we proposed a method based on NNs that detects deforested areas by analysing the annual trend of specific statistical parameters related to the backscatter coefficients obtained from Sentinel-1 images. Different statistical parameters, i.e., different case studies including mean, standard deviation, and MMD of the backscatter coefficient in VH and VV polarizations were considered. This method analysed 2 years of data sets: 2019 and 2018. Areas deforested in 2019 were manually selected, labelled, and used to train and test the algorithm, while the trained NN automatically identified areas deforested in 2018.

Figures 10, 11, 12, and 13 represent samples extracted from the 2019 data set. Figures 10 and 11 report two FF areas, while Figures 12 and 13 report FD areas. On the left, the figures illustrate the RGB colour composites (a, c) obtained from Sentinel-2 2019 images. The right shows the related mean backscatter trend in both VH (b) and VV (d) polarizations.

**Table 8.** Statistical results for the data sets obtained in 2019.

| Statistical parameters | Accuracy | Precision | Recall | F1  |
|------------------------|----------|-----------|--------|-----|
| Mean                   | 0.97     | 0.98      | 0.97   | 0.97|
| Mean + standard deviation | 0.97    | 0.99      | 0.94   | 0.97|
| Mean + MMD             | 0.98     | 0.96      | 0.99   | 0.98|
| Mean + standard deviation + MMD | 0.99 | 0.99      | 0.98   | 0.99|

MMD = maximum-minimum difference.
The VV and VH signals from the Forested–Forested samples (depicted in Figures 10 and 11) show regularity of the signal for both polarizations with the mean backscatter signal values from −14.2 dB for VH and −7.7 dB for VV polarizations. When deforestation occurs, the VV and VH backscatter signals are perturbed. After deforestation, it was observed a short increase of the backscatter signal before a more pronounced decrease. From all samples collected, we observed an average decrease of 2.3 dB for VH and 2 dB for VV polarizations. The decrease was evident and lasted from about 3 to 4 months. Some authors have observed the increase and decrease of the backscatter signal after deforestation (Bouvet et al., 2018; Doblas et al., 2020; Hoekman et al., 2020; Joshi et al., 2015; Kellndorfer, 2019; Reiche et al., 2018a, 2018b).

Reiche et al. (2018a) found a decrease of 2.0 dB in VH after deforestation in the province of Riau, Indonesia, through Sentinel-1 C-band SAR data time-series. Reiche et al. (2018b) observed a decrease of 2.5 dB, using VV time-series of Sentinel-1, from deforestation studies in the province of Santa Cruz, Bolivia.

Bouvet et al. (2018) stated that the C-band SAR backscatter signal over cleared or burned areas presents a lower backscatter signal of ~2.5 dB in the Amazon rainforest in Peru. Decrease backscattering was also observed for the majority of our deforested areas collected in 2019.

Hoekman et al. (2020) reported that, in general, undisturbed forests have a relatively high and stable backscatter level; therefore, a significant decrease in backscatter level would indicate deforestation. The backscatter of clear-cut areas, in both polarizations, is

Table 9. Statistical results for the ground truth data sets obtained in 2018. SD = standard deviation. MMD = maximum-minimum difference.

| Parameter            | MapBiomas |            | PRODES |            |
|----------------------|-----------|------------|--------|------------|
|                      | Accuracy  | Precision  | Recall | F1         | Accuracy | Precision | Recall | F1         |
| Mean                 | 0.85      | 0.88       | 0.81   | 0.85       | 0.79     | 0.87      | 0.67   | 0.76       |
| Mean + SD            | 0.88      | 0.96       | 0.79   | 0.87       | 0.78     | 0.95      | 0.58   | 0.72       |
| Mean + MMD           | 0.85      | 0.87       | 0.82   | 0.85       | 0.76     | 0.84      | 0.64   | 0.73       |
| Mean + SD + MMD      | 0.89      | 0.90       | 0.89   | 0.89       | 0.81     | 0.88      | 0.73   | 0.79       |

Figure 10. Sentinel-2 RGB colour composite (a, c) acquired on 21 July 2019 of a Forested–Forested sample (highlighted in red), and backscatter mean trend in VH (b) and VV (d) polarizations. The red line highlights the backscatter position coincident with the data of the optical image.
usually 2.0 dB lower than the original forest cover. However, remaining debris and undergrowth, terrain slopes, soil roughness, and soil moisture may intensify the decrease. The rainforest site in the Indonesian province of Central Kalimantan and in the Pará State, Brazil, Hoekman et al. (2020) observed that VH and VV signals go up and down, and deforestation was characterized at the first moment the signal goes down.

Joshi et al. (2015) revealed an L-band backscatter decrease of 1.1 dB in VH after clearing full forest cover events in the region of Madre de Dios in Peru.

Doblas et al. (2020), in a study in the Amazon rainforest, determined the mean backscattering values of the forest as −12.4 and −6.25 dB for VH and VV polarizations, respectively, while the mean backscattering values of the deforested series are consistently lower, reaching −13.1 and −7.6 dB for VH and VV polarizations.

For the 2019 test data set, the NN model achieved high performance in all case studies. This was due to the manual selection and labelling of the test areas employing the RGB composition of Sentinel-2 images. For the 2018 data set, the performance decreased, as shown in Figure 14 that reports the trend of the F1 metric for the four case studies from 2019 to 2018 images.

To investigate the 2018 results, three deforested areas among the largest ones in the ground truth images were analysed. Figures 15, 16, and 17 show the three areas. Each RGB color composition shows the areas captured by the Sentinel-2 satellite from April to July of 2018. These figures highlight the differences in land cover changes due to the clear-cutting process. At the bottom, the figures represent the ground truth images and the classification made by the MLP for the MapBiomas (b), (c), and PRODES (d), (e) ground truths. In the ground truth images (b) and (d), the areas deforested in 2018 are shown in white, areas forested are shown in black, and areas deforested before 2018 are in grey. The classification images (c) and (e) show the patches as they were classified overlapped to the ground truth image.

The F1 score differences between the PRODES and MapBiomas ground truth images may be related to the resolution employed by the two projects. The coarser PRODES resolution does not capture small deforested areas that are considered in the MapBiomas ground truth. Indeed, PRODES does not capture small forested areas inside a deforested polygon. This can explain the difference in Recall, due to the number of false negatives...
between the two ground truth images. A large number of false negatives are localized in the small areas detected by the MapBiomas. Moreover, the misclassification may be caused by the deforestation method. After clear-cutting, the trees are left on the ground for drying before being burned. Since the amount of biomass remains the same, the result is somehow similar in backscatter values compared with intact forest areas. Bouvet et al. (2018), Kellndorfer (2019), and Hoekman et al. (2020) observed these trends.

Bouvet et al. (2018) reported that large branches remaining in the ground can cause a double-bounce scattering mechanism and mask the decrease of the backscatter signal. The authors also stated that, after rainfall events, the backscatter signals can exhibit the same values as intact forests.

Kellndorfer (2019) stated that if deforestation results in rough soil conditions (e.g. slash) backscatter can be significantly enhanced until logs are removed. The authors declared yet that, after deforestation, there is a dominant change from volumetric scattering to surface scattering, with an expected decrease in the cross-polarized (VH, HV) signal.

Hoekman et al. (2020) reported that deforestation in Brazil often is the slash-and-burn type of small scale, and in most instances, the deforestation is preceded by severe degradation.

Figure 18 shows examples of test sites from the Amazon forest, with slashed trees after 3 months of drying (A). As it can be seen, the site conserves all the previously standing biomass but with dried leaves and trunks. The green leaves are from liana vines that grew along with the slashed biomass (Soares Neto et al., 2009). Figure 18 also shows how a clear-cut site appears after the cleaning fire (B). Small branches and leaves are combusted to completion, while large trunks are only partially consumed (Christian et al., 2007). Long ash trails indicate trunks, mostly palm trees that were completely consumed through smouldering. However, misclassification may be associated with the deforestation method.

In this study, we implemented a new methodological flow based on Sentinel-1 data and MLP classifier capable of detecting deforestation automatically in the Amazon rainforest. The accuracy was in the range of 81% to 89%, depending on the considered
In hand-picked areas used for training the NN, the accuracy reached 99%, comparable to those achieved by Bem et al. (2020), whose accuracy reached 94%. Bem et al. (2020) combined optical images and NN for detecting deforestation. The method, however, could only be applied in the dry season of the Amazon rainforest, which lasts for about 6 months. Methods based on radar data can be used throughout the year.

Doblas et al. (2020), which research is based on radar data, reached maximum accuracy of 96% in detecting deforestation. Our results are 2% higher than those of Doblas et al. (2020).

Figure 13. Sentinel-2 RGB colour composite acquired on 21 July 2019 (a) and 31 July 2019 (c) of a Forested–Deforested sample (highlighted in blue), and backscatter mean trend in VH (b) and VV (d) polarizations. The red line highlights the backscatter position coincident with the first data of the optical image before deforestation.

Figure 14. F1 variation for the 2019 test set and 2018 data set for both ground truth images.
than the data set of 2019 and 7% lower for the 2018 images, which were obtained automatically by the algorithm.

The MLP does not require high computer processing capability compared with other NN algorithms, such as the CNNs (Bouguettaya et al., 2019). The algorithm

Figure 15. First example of an area with deforestation (highlighted in red), shown by the Sentinel-2 RGB color composites acquired in April, May, June, and July 2018 (a), MaBiomas ground truth (b), classification output with MapBiomas ground truth (c), PRODES ground truth (d), and classification output with PRODES ground truth (e). FP = False positives (number of forested areas classified as deforested), TN = True negatives (number of forested areas classified as forested), FN = False negatives (number of deforested areas classified as forested), and TP = True positives (number of deforested areas classified as deforested).
used in this work was performed on a personal computer with the following configuration: NVIDIA® GeForce® GTX 1650 Max Q GPU with 4GB RAM. Once the network is trained, the time required to make predictions is quite short. During the test phase with the data from 2018, the time necessary to open the images and complete the whole processing was around 1 minute (Table 10).

Figure 16. Second example of an area with deforestation (highlighted in red), shown by the Sentinel-2 RGB color composites acquired in April, May, June, and July 2018 (a). MapBiomas ground truth (b), classification output with MapBiomas ground truth (c), PRODES ground truth (d), and classification output with PRODES ground truth (e). FP = False positives (number of forested areas classified as deforested), TN = True negatives (number of forested areas classified as forested), FN = False negatives (number of deforested areas classified as forested), and TP = True positives (number of deforested areas classified as deforested).
Further research should involve strategies to detect deforested areas smaller than 2 ha and use the algorithm as an alert system essential for deforestations related to illegal mining activities in the Brazilian Amazon. In addition, the algorithm could be refined to detect recently deforested areas (slashed areas) and to disregard areas under vegetation regrowth. In this latter case, vegetation...
indices proposed in literature such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), or Normalized Difference Water Index (NDWI) can be used to identify the plant growth status and correlate it with forest regrowth (Silva et al., 2019). The method proposed in this study could also be integrated with textural analysis, which exploits correlation among neighbouring pixels, such as those based on the computation of the Gray-Level Co-Occurrence Matrix (GLCM; Del Frate et al., 2008) or geostatistical measures of spatial variability, as suggested by Zawadzki et al. (2005).

Conclusions

In this work, we investigate deforestation in the Amazon rainforest using Sentinel-1 data, and three statistical parameters related to the backscatter coefficient were analysed (mean, standard deviation, and MMD (maximum-minimum difference)). It was observed a backscatter decrease in the average signal of C-band SAR images, approximately 2 dB for VV polarization and 2.3 dB for VH polarization, immediately after deforestation. The decrease is evident for approximately 3–4 months after the deforestation.

The MLP (Multi-Layer Perceptron) was used to detect near real-time forest disturbances larger than 2 hectares. The algorithm analysed SAR images from 2019 for training and 2018 to identify deforest areas automatically. A set of data from 2019 were used to test the performance of the NN (Neural networks) algorithm. Considering the mean, standard deviation, and MMD of the backscatter coefficient as input parameters, the NN was able to classify forested and deforested areas with accuracy and F1 score of 99% for the 2019 data set. For the 2018 data set, the results showed accuracy and F1 score of 89% with MapBiomas ground truth and accuracy and F1 score of 81% and 79%, respectively, with the PRODES ground truth.

The proposed method may be suitable for monitoring forest events in the Amazon at low cost and short processing times and for assisting Brazilian environmental law enforcement agencies in combating illegal deforestation.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

These data were derived from the following resources available in the public domain: [Copernicus at https://scihub.copernicus.eu/]; [MapBiomas Brasil at https://mapbiomas.org/en]; [Terrabrasilis at http://terrabrasilis.dpi.inpe.br/en/home-page/]

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