Land Cover Classifications of Clear-cut Deforestation Using Deep Learning

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Abstract. *Using Deep Learning Neural Networks, we made supervised classifications of a small region of the Brazilian Amazon in order to map clear-cut deforestation. We organized Landsat 8 Surface Reflectance images into time series and we classify the images using the bands ad a Linear Mixture Model. We obtained similar accuracies using both data sets when compared to the data reported by the Brazilian Amazon Deforestation Monitoring Program (PRODES). These results suggest the possibilities of using automatic supervised techniques to extend the coverage of forest monitoring programs to those excluded areas by lack of human resources.*

1. Introduction

Monitoring the tropical forest through remote sensing helps reducing deforestation [SEYMOUR and HARRIS 2019]. Usually, monitoring efforts focus on either accounting, alerting, or following land use after deforestation. In the Brazilian Amazon, each of these aims stands for three projects: (i) Brazilian Amazon Deforestation Monitoring Program (PRODES), whose reports accurately estimates clear-cut of pristine forest, (ii) the near real-time deforestation detection system (DETER), that produces fast alerts of change in forest areas for law enforcement authorities, and (iii) TERRACLASS, which tracks land use and cover after clear-cut deforestation [SHIMABUKURO et al. 2012].

To achieve high accuracies (e.g. TERRACLASS accuracy is above 77% [ALMEIDA et al. 2016]), these monitoring projects rely on expert visual classifications, which are costly and time-consuming. For example, PRODES consolidated forest loss rates are published months after deforestation happened. In the other hand, DETER reports deforestation faster than PRODES but with lower confidence levels regarding the deforested areas. The accuracy-speed tradeoff between PRODES and DETER shapes not only their accuracy, but also the interpretation of their results. These differences make the data prone to misunderstandings by the public with daring consequences for the academia [ESCOBAR 2019].

We believe that PRODES must continue being the reference regarding deforestation in the Amazon for both historical and statistical reasons. We also believe science should explore and provide new and better answers. This brings up to the question of how to close the accuracy-speed gap by finding a cheaper and reproducible way to monitor clear-cut deforestation. An alternative is to train machine how to spot deforestation, given that they are good for boring repetitive tasks. Teaching machines is a current challenge to science and the possibility of improving forest monitoring systems with the available techniques is worth it.

In this work, we automatically classify deforestation using Neural Networks on a study area of the Amazon rainforest. The aim of this study is to evaluate a cutting-edge classification process on deforestation detection that uses Deep Learning and satellite image time series. By comparing the raw classification maps without applying on it any post-processing algorithms, we are able to assess the bottom-line accuracy of our classification process. Our findings give us an idea on how far we are from reach the same accuracies of non-automatic visual classification systems such as PRODES. In what follows, we present the material and methods used generate the maps.

2. Material and Methods

Our area of interest is located in the Brazilian Amazon forest, in the state of *Pará*, between the municipalities of *Altamira* and *São Félix de Xingu*. This area is characterized by large amounts of deforestation and a long rainy season (Figure 1). We obtained Landsat-8 images of the Path-Row 226/064 from National Aeronautics and Space Administration (NASA) through the Geological Service of the United States of America [WULDER et al. 2019]. These images are geometrically aligned and radiometrically consistent to the conditions of the surface of the Earth, including atmospheric correction and cloud identification, as shown in Figure 2.

Figure 1. Area of interest. Path Row 226 064 in Landsat World Reference System 2.

To train the classification algorithm, we collected sample points of forest and deforestation from the PRODES project. PRODES provides public access to deforestation data including where and when deforestation was detected. These samples were carefully selected to be representative of each class along each PRODES year (Figure 3).

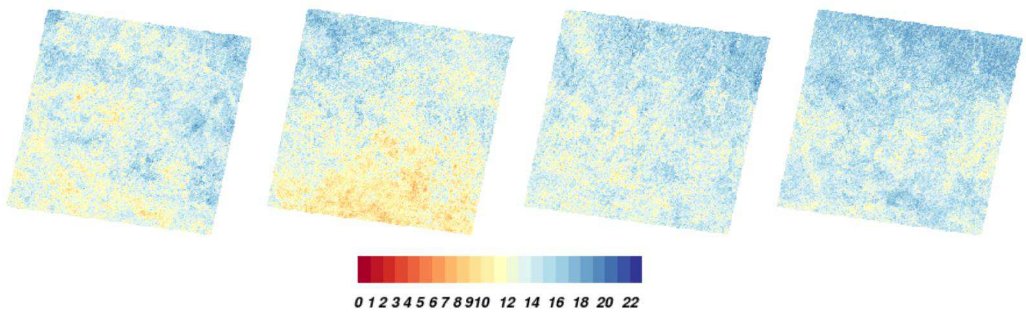

Figure 2. Number of clouded pixels by PRODES year from 2013 (leftmost image) to 2016 (rightmost image).

To prepare the data for classification, we stacked Landsat-8 images into one-year time series. We organized our data into PRODES years, which range from August to July, in order to match the seasonality of the dry and wet seasons. Each yearly dataset was stored in TIFF files, one for each variable.

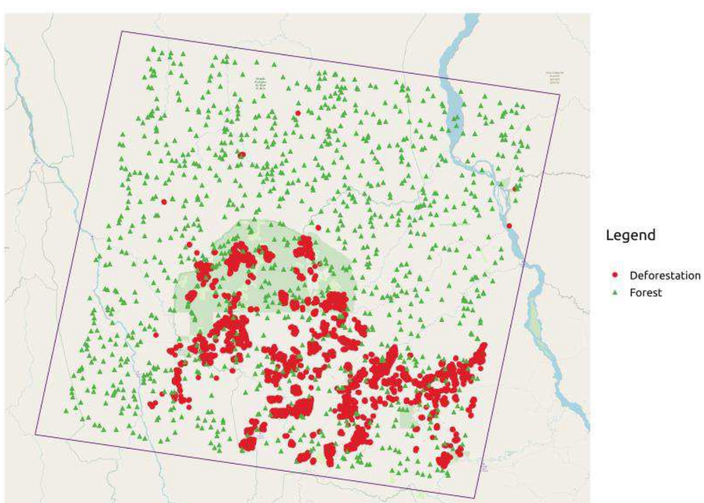

Figure 3. Sample distribution across the area of interest.

For the sake of comparison, we arranged Landsat data in three groups. The first includes Landsat bands and a vegetation index. The second includes the End Members of the global calibrated Spectral Mixture Model as described in [SOUSA and SMALL 2017]. The last one is the combination of the other two (Table 1).

Table 1. Data included in each classification.

Classification Id	Description	Variables in the classification
Bands	Landsat Bands and vegetation index.	nir, red, swir2, ndvi
MM	Spectral mixture model.	Vegetation, substrate, dark
Bands_MM	Landsat bands and mixture model.	nir, red, swir2, vegetation, ndvi, substrate, dark

We ran a supervised classification using Deep Learning technique. Deep Learning is concerned to statistically estimate complicated functions out of generalizable patterns in training data. This technique corresponds to supervised learning because, given a set of samples, the computer learns how to identify new (unknown) instances as forest or deforestation. As we increase the number of samples, the computer improves its classificatory capabilities [GOODFELLOW, BENGIO and COURVILLE 2016].

We trained a Deep Learning Neural Network using the yearly time series in our samples. The training process is about finding the right parameters (weight and bias) and hyperparameters of the Neural Network. The network hyperparameters are concerned with finding the best parameters while the parameters are directly concerned in classifying the data [BENGIO 2012]. In order to maximize our chances of finding the best hyperparameters, we explored the solution space (the combinatory of all the possible hyperparameter values) by a successive process of randomization and pruning, as shown in Table 2.

Table 2. Hyperparameter used while training our Deep Learning neural networks. All the trainings used the same optimizer (Adam), number of Layers (5), validation split (20%), and learning rate of 0.001.

Experiment Id	Activation	Batch size	Dropout rates	Epochs	Units
Bands	selu	64	0.4	200	700
MM	selu	64	0.4	300	600
Bands_MM	sigmoid	64	0.5	300	1000

We validate our results by asking remote sensing experts to classify a set of random points, which were compared to our resulting maps. Regarding software and hardware, we used QGIS and R to prepare the samples, and a combination of R, Keras, and TensorFlow to train our neural network and to classify the images. To achieve parallelism during computations, we relied on GNU Parallel along the tools provided by operating systems based on the Linux kernel [ABADI et al. 2016; CHOLLET 2015; R CORE TEAM 2018; SIMOES et al. 2018; TANGE 2011]. The machine has 32 64-bit INTEL processors with 128 GB RAM running Ubuntu 14.04 with Linux kernel 4.4.

3. Results

Once we were done training our Network, we classify the time series derived from Landsat-8 images. We did not apply any postprocessing because we are interested in finding how far we can we reach by using only Deep Learning.

The classification results are shown in Figure 4. The areas painted as white are deforestation in other years, water bodies, or non-forest areas, which are ignored in the comparison. Remarkably, the classifications display small roads in the forest which are missing from the PRODES (Figure 4, PRODES year 2017, to the South of each map). Regarding noise, these classification presents two types: one is salt and pepper noise which is product from random errors in the classification, while the other type is elongated and clustered, resembling north-west to south-east clouds (Figure 4, year 2014, to the North-West and to the South-East).

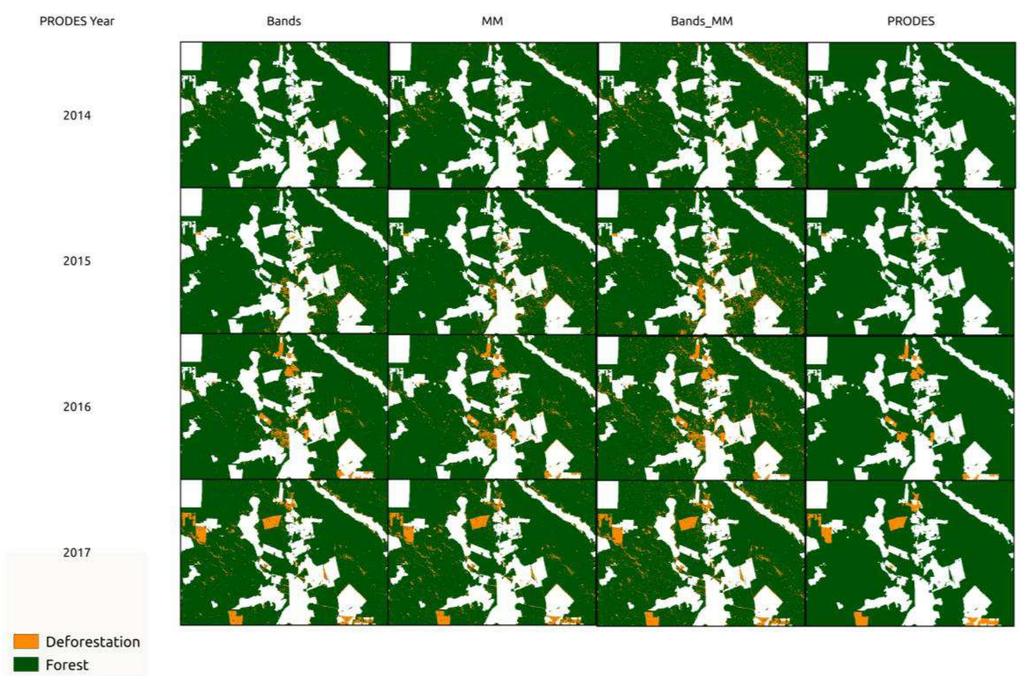

Figure 4. Classification results and PRODES map (right most column) from 2014 to 2017.

To validate our classification, we selected a set of 150 random points and then we asked experts in remote sensing to perform a visual classification. The user and producer accuracies of the classification (Figure 5) are above 50% with few exceptions. In general, for the forest, the producer accuracy is larger than the user and the opposite holds true for the deforestation on each PRODES year.

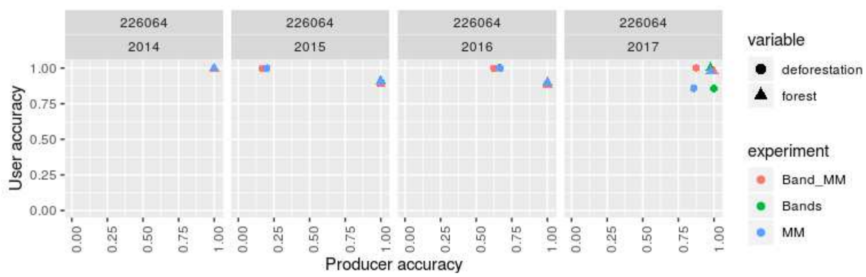

Figure 5. Classification validation using samples classified by experts.

The forest validation points tend to have a producer greater than the user accuracies while the opposite holds true for the deforestation class. For the forest, this means that more often the reference data was rightly tagged. The classifier accuracy is higher for the deforestation than for the forest areas.

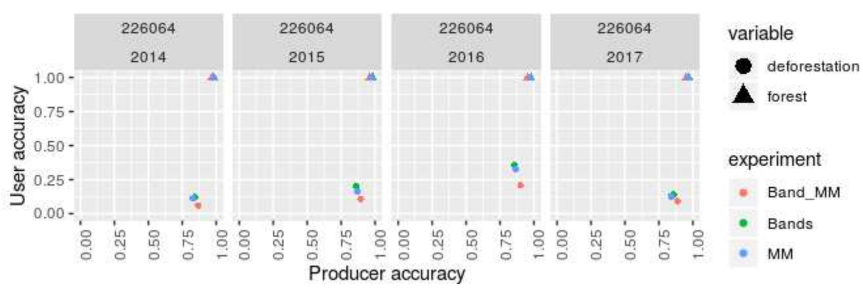

Figure 6. Comparison of the classification to PRODES.

We also estimated how similar are our results if compared to PRODES. The similarity is reported in Figure 6 in the form of user and producer accuracies. While our results present large similarity regarding the forest class, for the deforestation class the user accuracy is low. As a reference, we ran the same comparison between MAPBIOMAS (see https://mapbiomas.org/) and PRODES and we observed high accuracies for the forest class and lower for deforestation (Figure 7). These results are consistent to those of [MAURANO and ESCADA 2019].

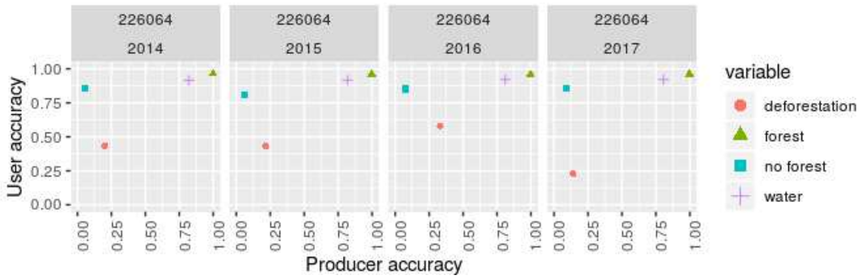

Figure 7. Comparison of the MAPBIOMAS to PRODES.

4. Discussion

We used annual time series of Landsat-8 data to classify a scene for the years from 2014 to 2017. Despite obtaining good classification accuracies, they are still far from those obtained by visual classification used in forest monitoring projects such as PRODES. We ran our classification using Deep Learning Neural Networks with three sets of data: Landsat bands plus NDVI, Linear Mixture Model, and their combination. However, we did not observe much difference among them in the accuracy. This is favorable for using the Linear Mixture Model giving its smaller data size and its corresponding reduction in processing time.

However, this study was constrained to a small region of the Amazon forest for short period of time. Besides, the amount of clouds in the area of interest is a limitation. Another limiting factor on the accuracy of the classifications is the relative proportions of pixels, which can induce artifacts (e.g. ratio of forest to deforestation pixels is approximately 60 to 1).

5. Conclusion

Monitoring the Amazon forest is hard, mainly due to its extent and almost constant cloud cover. We acknowledge this fact and at the same time reinforce the scientific need of proposing, adapting, and testing new approaches to improve classifications and/or to reduce financial costs to produce such classifications. In this work, we used Deep Learning Neural Networks over time series to identify deforestation in Landsat images. We believe that our method can support the monitoring systems because the use of time series reduces the gap between the time of deforestation and its detection.

In the results, we also found that some areas classified by us as deforestation were later found as deforestation in PRODES. We would like to quantify to which extent this corresponds to the identification of forest degradation. This is possible because PRODES only reports clear cuts. Our classifications could identify early signs of deforestation, which could improve monitoring systems as DETER.

Although the accuracies of our automatic classifications are inferior to those of visual monitoring systems such as PRODES, the approach has great potential to be improved with post-processing procedures such as spatial and temporal filters. Another possibility is to increase the temporal resolution of the images to create longer time series. A better temporal resolution might reduce the negative effects of cloudiness in our classification. To achieve this, we are planning to use products of the Harmonized Landsat Sentinel-2 project [CLAVERIE et al. 2018]. Another next step in our research is to increase the area of interest to cover the whole state of Pará.

Finally, automatic classification results have the potential to help decision makers to design policies and enforce laws such as the Forest Code (Brazilian Law 12.651 of 2012). Instead of being a concurrent of visual interpretation, they can work in a complementary way. For instance, they could be used as a first step to identify deforestation using less resources if it could be possible to guarantee that false negative deforestation spots would be minimum. The errors in the automatic classifications identified visually can then be used as input to further improve the classification model.

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