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DETECTING CLEARCUT DEFORESTATION EMPLOYING DEEP LEARNING METHODS AND SAR TIME SERIES

Evandro C. Taquary[1], *Leila G. M. Fonseca*[1], *Raian V. Maretto*[2], *Hugo N. Bendini*[1]
Bruno M. Matosak[1], Sidnei J. S. Sant'Anna[1], José C. Mura[1]
{evandro.taquary, leila.fonseca, hugo.bendini, bruno.matosak, sidnei.santanna, jose.mura}@inpe.br
r.v.maretto@utwente.nl

[1]National Institute for Space Research, Brazil
[2]Faculty ITC, University of Twente, The Netherlands

ABSTRACT

Automating the systematic monitoring of deforestation in the Brazilian biomes has become imperative. In this sense, a promising research field lies upon the exploitation of orbital imaging based on Synthetic Aperture Radar (SAR) sensors, since this technology is less affected by cloud cover, allowing systematic data acquisitions. In addition, the growing availability of with no charge SAR data products enables investigations on the use of time series extracted from this category of instruments, paving the way for more sophisticated temporal analyzes. This work presents the results of a SAR time series classification model designed to identify clearcut deforestation patterns in time, through an Artificial Intelligence approach known as Recurrent Neural Networks. The classification was performed using 5216 samples of Sentinel-1 time series within the Amazon basin, reaching an overall accuracy of 96.74%.

Index Terms— Deep Learning, Deforestation, Time Series, Sentinel-1, SAR

1. INTRODUCTION

Despite the issues concerning cloud cover, the majority of forest monitoring systems are based on orbital imagery captured by optical sensors. Examples of such systems are the Global Forest Watch (GFW) [1], the Program to Calculate Deforestation in the Amazon (PRODES) and the Near Real Time Deforestation Detection System (DETER) [2]. This prevalence is but a practical constraint, once raw SAR imagery are historically less prone to easily get transformed into an Analysis Ready Data product. Nevertheless, in the wake of the ESA's Sentinel-1 mission, great advances have been made to increase the availability of SAR Analisys Ready Data (SARD) and, since 2015, researchers can rely upon medium resolutions SARD products. Beyond that, more freely available SAR orbital instruments with varying operation bands, are to come [3].

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Even though Sentinel-1 derived products have being made available at no cost, those still pose some important SAR specific challenges that need to be addressed. With regard forest monitoring, [4] performed a set of successful preprocessing steps in order to tackle two spurious effects that directly affect the forest backscatter response, namely, speckle noise and vegetation moisture. The main drawback is, however, the lack of a classification model capable of taking the temporal dependencies of time series' observations into account.

Much of the real world data has a sequential nature in which the order the records are collected is relevant. In other words, the optimal decision made by a predictive model, given an input, may depend on the past inputs that have already been presented to the model. Recurrent Neural Networks (RNR) [5] are a family of Artificial Neural Networks endowed with the ability to take those dependencies into account. This is possible thanks to a feedback mechanism that occurs by the means of a recurrence: a connection between the network output and its input during the processing step of the next observation.

This work presents a Deep Learning approach that, given a stabilized SAR Time Series (TS), is able to recognize temporal patterns within it, considering the underlying statistical dependencies between the TS observations. An experiment has been conducted towards discovering of clearcut deforestation patterns occurred in the Amazon basin, throughout the year of 2019, by analysing TS extracted from a Sentinel-1 SARD product hosted in Google Earth Engine (GEE) platform [6]. In the next session the database used in this study is going to be explained, as well as a brief description of a deep RNR known as Long Short Term Memory (LSTM) [7] and how this network has been trained. Then, the outcomes are going to be explained, followed by a brief discussion. Finally, the final remarks and the proposed future works will be exposed.

2. MATERIALS AND METHODS

The current work used a subset of a larger database created in [4] as part of an endeavor whose goal is to develop a new Early Warning System (EWS), intended to monitor Amazon deforestation in near real time. To this end, [4] randomly selected points inside two sample spaces within the whole Amazon basin, tapping into a reliable and refined source of clearcutting information provided by the projects DETER [8] and MapBiomas Alertas [9]. For the TS extraction to take place, 3000 points were sorted inside the "forest disturbances" sample space, all occurred in 2019, and another 3000 points inside the "forest invariant" areas. Following, the Sentinel-1A VH and VV backscatter intensity values of the corresponding locations were collected and stored as multivariate TS. Out of all possible combinations of the pre-processing routines undertaken in [4], the present work made use of the TS that suffered only the following transformations: (i) Local Incidence Angle correction; (ii) Seasonal stabilization; (iii) Speckle noise filtering.

All the 6000 selected TS cover approximately 3 years (2017 to 2019) of regularly spaced registries of the Sentinel-1A with a 12-days gap between them, giving a maximum length of 92 observations per TS. However, the chosen database shows inconsistencies between some data points, what could compromise the proposed temporal analysis. For instance, many TS show several "nodata" values throughout the considered span of time, leading those with less than 80 valid entries to be cutted off. Also, all TS samples that haven't values for the two polarization modes (VH+VV) were also discarded, once the proposed approach depends on bivariate TS. Finally, TS whose length of not null values diverge between polarization modes were also discarded in an attempt to guarantee the temporal alignment between them. After running these steps, only 5216 (out of the initial 6000) have remained, but also maintaining the 50% proportion of each class.

The LSTM, a deep RNR architecture, was employed to classify the TS samples. It is capable of handling long sequences, therefore being able to recognize temporal-polarimetric patterns into long Remote Sensing TS. In this sense, a LSTM model was fitted to accomplish the task of recognizing the presence of a deforestation event in the last third of a 3-year long Sentinel-1 TS. The idea is that the first two-third portion will provide the model the information it needs to discriminate between real clearcutting backscatter response and sources of noise which can get confused with clearcutting, such as the speckle noise and variations in the forest moisture due to seasonality or rain cells.

Figure 1 shows a general flowchart that comprises the steps followed to devise the model that yielded the reported results. There are three main phases:

1. **Further Filtering**: After fetching the 6000 TS out of chosen database, execute the aforementioned filtering processes to remove the ineligible TS.

2. **Sensitivity Analysis**: a critical set of procedures conducted in order to get a meaningful Deep Learning model. Here, the proper network topology must be found as well as an hyperparameters optimization, seeking the minimization of the loss function.

3. **Performance Evaluation**: in this phase, proper evaluation metrics are computed, needed to asses the classification performance. If metrics meet the project goals, save the assessed model; else, return to the Sensitivity Analysis phase to once again fine-tune hyperparameters and try to improve the overall model performance.

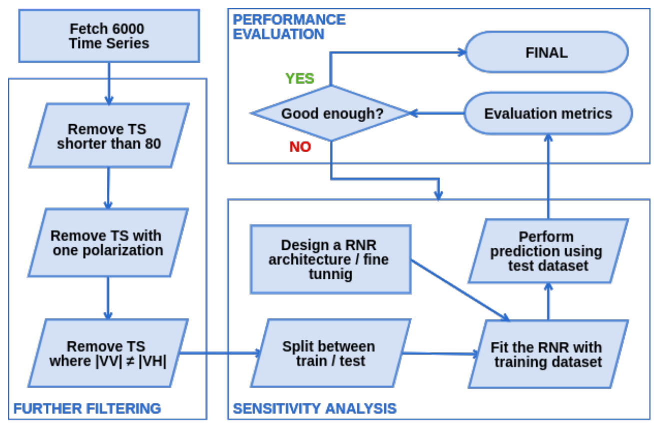

Figure 1: The general workflow accomplished.

After several loops between Sensitivity Analysis and Performance Evaluation phases, the reported network has the following topology structure and hyperparameters:

- Architectural layers:
  - One LSTM cell with 256 hidden units.
  - A fully connected layer with 128 neurons and ReLU activation function.
  - A fully connected layer with 16 neurons and ReLU activation function.
  - A fully connected layer with 2 neurons and Softmax activation function.
- Loss function: Categorical Cross Entropy.
- Optimizer: Adaptive Moment Estimation (Adam) [10].
- Learning rate: 0.000013.
- Batch size: 32.
- Epochs: 2000.

3. RESULTS AND DISCUSSION

The experiments were carried out into an Ubuntu 20.04 environment equipped with a quad-core Intel® Core™ i5-3570 3.40 GHz CPU, 16GB RAM and a 6GB/s Sata SSD drive with 1TB. The 2000 training epochs were done without the support of GPUs, using the Keras framework with Tensorflow 1.14 as backend. The entire training took 8 hours and 21 minutes to get finished, even though an early stopping were used to select the model's parameters configuration that showed the higher global accuracy in the validation dataset.

As shown in the diagram (Fig. 1), the train/test dataset splitting strategy also influences the model's outcome, and should be carefully done. The final model were obtained by shuffling and splitting the 5216 remaining data points into 4694 (90%) for the training set while 522 (10%) were reserved for the final model testing after the training process. Once properly fitted, a inference was performed over the 522 testing TS for the evaluation metrics to be computed and for the model generalization to be assessed. The chosen evaluation metrics are the following:

1. **Global accuracy**: 0.9674
2. **Precision**: 0.9588
3. **Recall**: 0.9708
4. **F1-Score**: 0.9648

Beyond the good global accuracy, the metrics exhibits a good balance between commission (approx. 3%) and omission (approx. 4%) errors, a characteristic that can also be inferred by the F1-Score index. A good F1-Score index indicates the model's vocation to perform a classification whose main objective is to accurately estimate the total area of the deforested regions, given that the total amount of false-positive regions are offset by the false-negative ones, whose total area is similar.

The maximum global accuracy of 95.91% reported in [4] cannot be directly compared with the same metric reported by the present study. As the two approaches have different purposes, there are some important differences between the way the dataset is analysed. For example, the current approach classify the entire 3-year TS at once while [4] undertake a single analysis for each observation that falls inside a 4-month window of the same TS.

The exposed classification approach can be used, for example, to generate annual deforestation reporting. The mappings produced by such models could help official government forest monitoring programs like PRODES to increase efficiency and reduce costs of operation.

4. CONCLUDING REMARKS

The approach developed is still very incipient and needs further investigation regarding operational viability. However, the good initial results motivate the development of future works in the same direction. For example, the implementation of the RNR used in this experiment makes a prediction only at the end of the entire TS analysis. In other words, the "day" within the TS where the deforestation detection occurred is not informed by the model. However, it is possible to adapt the LSTM architecture and training procedures to be able to produce an inference for each time step of the input sequence. This adaptation would make the approach a good candidate to be incorporated into an EWS.

Another improvement is to pipe the LSTM output to the input of a Convolutional Neural Network, as done in [11]. In this manner, the spatial coherence could be dramatically improved, diminishing the salt and peeper effect and making the deforested areas more semantically meaningful. Yet, it is also possible to combine the SARD products with optical ones in order to leverage the best of the two worlds.

5. REFERENCES

[1] M. C. Hansen, P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend, "High-resolution global maps of 21st-century forest cover change," *Science*, vol. 342, no. 6160, pp. 850–853, 2013.

[2] Y.E. Shimabukuro, João Santos, Antonio Formaggio, V. Duarte, and Bernardo Rudorff, "The brazilian amazon monitoring program: Prodes and deter projects," *Global Forest Monitoring from Earth Observation*, pp. 153–169, 01 2012.

[3] Africa Flores, K. Herndon, Rajesh Thapa, and Emil Cherrington, *The SAR Handbook: Comprehensive Methodologies for Forest Monitoring and Biomass Estimation*, 04 2019.

[4] Juan Doblas, Yosio Shimabukuro, Sidnei Sant'Anna, Arian Carneiro, Luiz Aragão, and Claudio Almeida, "Optimizing near real-time detection of deforestation on tropical rainforests using sentinel-1 data," *Remote Sensing*, vol. 12, no. 23, pp. 3922, Nov. 2020.

[5] Jordan M.I, "Serial order: a parallel distributed processing approach. technical report, june 1985-march 1986," *Institute for Cognitive Science, California University: San Diego, CA, USA*, 1986.

[6] Noel Gorelick, Matt Hancher, Mike Dixon, Simon Ilyushchenko, David Thau, and Rebecca Moore, "Google earth engine: Planetary-scale geospatial analysis for everyone," *Remote Sensing of Environment*, vol. 202, pp. 18 – 27, 2017, Big Remotely Sensed Data: tools, applications and experiences.

[7] Sepp Hochreiter and Jürgen Schmidhuber, "Long short-term memory," *Neural computation*, vol. 9, pp. 1735–80, 12 1997.

[8] Dalton Valeriano, Yosio Shimabukuro, Valdete Duarte, Liana Anderson, Fernando Espírito-Santo, Egidio Arai, Luis Maurano, Ricardo Souza, Ramon Freitas, and Luigi Aulicino, "Detecção do desflorestamento da amazônia legal em tempo real -projeto deter," 01 2005.

[9] Carlos M. Souza, Julia Z. Shimbo, Marcos R. Rosa, Leandro L. Parente, Ane A. Alencar, Bernardo F. T. Rudorff, Heinrich Hasenack, Marcelo Matsumoto, Laerte G. Ferreira, Pedro W. M. Souza-Filho, Sergio W. de Oliveira, Washington F. Rocha, Antônio V. Fonseca, Camila B. Marques, Cesar G. Diniz, Diego Costa, Dyeden Monteiro, Eduardo R. Rosa, Eduardo Vélez-Martin, Eliseu J. Weber, Felipe E. B. Lenti, Fernando F. Paternost, Frans G. C. Pareyn, João V. Siqueira, José L. Viera, Luiz C. Ferreira Neto, Marciano M. Saraiva, Marcio H. Sales, Moises P. G. Salgado, Rodrigo Vasconcelos, Soltan Galano, Vinicius V. Mesquita, and Tasso Azevedo, "Reconstructing three decades of land use and land cover changes in brazilian biomes with landsat archive and earth engine," *Remote Sensing*, vol. 12, no. 17, pp. 2735, Aug. 2020.

[10] Diederik Kingma and Jimmy Ba, "Adam: A method for stochastic optimization," *International Conference on Learning Representations*, 12 2014.

[11] Evandro Carrijo Taquary, "Deep learning for accurately identifying deforestation through the use of high resolution satellite imagery," M.S. thesis, Federal University of Goiás, Institute of Informatics, Goiânia, 2019-09-24 2019.