OPEN ACCESS

1st World Sustainability Forum
1-30 November 2011

www. wsforum.org

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# Amazonian Forest Deforestation Detection Tool in Real Time Using Artificial Neural Networks and Satellite Images

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*Received: / Accepted: / Published:*

**Abstract:** The main purpose of this work was the development of a tool to detect in real time (daily) deforestation in the Amazon rainforest, using satellite images from the MODIS/TERRA sensor and Artificial Neural Networks. The developed tool provides the parameterization of the configuration for the neural network training to enable finding the best neural architecture to address the problem and makes use of confusion matrixes to determine the degree of success of the network. Part of the city of Porto Velho, in Rondônia state, makes up the tile H11V 09 of the MODIS/TERRA sensor, which was used as the study area. A spectrum-temporal analysis of this area was made on 57 images from 20 of May to 15 of July 2003 using the trained neural network. This analysis allowed verifying the quality of the implemented neural network classification as well as helped the understanding of the dynamics of deforestation in the Amazon rainforest. The great potential of neural networks for image classification was perceived with this work. However, the generation of consistent alarms, in other words, detecting predatory actions at the beginning; instead of firing false alarms is a complex task that is not yet solved. Therefore, the major contribution of this paper is to provide a theoretical basis and practical use of neural networks and satellite images to combat illegal deforestation.

**Keywords:** Artificial Neural Networks, satellite images classification, deforestation detection.

## 1. Introduction

The Brazilian Rainforest in the Amazon was nearly intact until 1970, when the construction of Trans-Amazonian Highway triggered the high level of deforestation rates. Since then, such rate of deforestation in Legal Amazon has oscillated. However, the numbers have always been elevated [1]. According to Instituto Nacional de Pesquisas Espaciais – INPE (National Institute for Space Research), approximately 16% of the Forest has been destroyed, that is, out of its 3, 5 million Km² , over 550 thousand Km² have been deforested. In 1978, INPE carried out a survey of the Forest for the first time using a satellite. And found out that as much as 140.000Km² had been cleared. In the following years, no other survey was done, because the agenda of the government did not prioritized environmental preservation issues. Only in 1988, INPE started to carry out annual surveys, due to international concern regarding the way the Amazon Forest was being taken care of [2].

Considering the elevated rates of deforestation, it becomes clear that some action to help monitoring the region is necessary, which would increase the control of authorities over the area.

Some tools have been developed, aiming monitoring improvement, nevertheless, none of them in real time (daily). As an example of the main projects that have been developed and used by INPE, we can name Prodes and Deter.

Prodes Methodology targets to produce estimates of deforestation levels of annual close cut in Legal Amazon, through digital classification of images. Such methodology was described by [3]. It is an important tool for obtaing estimates. However, it is inefficient as fiscalization is regarded, once the estimates are produced annually.

Deter Project creates maps with the location of the areas that are being cleared, using photo interpretation of images detected by MODIS sensor (Moderate Resolution Imaging Spectrodiometer) aboard Terra satellite and images of WFI sensor aboard CBERS satellite. Those maps have information about the dynamics of the deforestation in Legal Amazon. Such information is sent to entities and departments like IBAMA (Instituto Brasileiro do Meio Ambiente e Recursos Naturais Renováveis) [4] fortnightly and supports the surveillance and control of deforestation.

Ideally, as far as fiscalization is regarded, there should be a detection system running daily, which would make possible to forecast any changes in the Forest, increasing the surveillance and reducing loss in the areas surrounding the deforested location. Within this framework, an artificial intelligence technique that seems to present great potential for fast classification of satellite images is Rede Neural Artificial (Artificial Neural Network), which is applied to the images of MODIS/TERRA sensor and might contribute to the daily detection of deforestation zones [5]. According [6], an Artificial Neural Network (ANN) can be seen as a group of artificial neurons that have capacity to process data locally. A connection topology defines how these neurons are connected and a learning rule as well. [7] adds that an ANN is a processor distributed parallelly through simple processing units (neurons), which have capacity to store knowledge and use it to solve complex problems. In this sense, we propose the creation of a tool for the training and use of artificial neural networks, so that a faster classification of images from MODIS/TERRA sensor can be achieved.

## 2. Data and Methodology

Images of *tile* H11V09 of MODIS/TERRA sensor from May 20th –July 15th 2003 were used for the testing and training of this tool. The images used amount 57, and were numbered 140 to 196, according to the Julian calendar. The images were chosen because they present a terrestrial truth and have been used in previous works, as in [8] and in [9]. This *tile* corresponds to the area of study in the

State of Rondônia, according to the following geographic coordinates:: 64º 16' 24.19" and 62º 26' 59.41" of longitude W and 9º 30' 27.69" and 7º 50' 28.62" of latitude S (see Figure 1) [8]. To the pre-processing of the images, a tool called SPRING (Sistema de Processamento de Informações Georeferenciadas- Georeferenced Information Processing System) version 5.1.5, was used and was developed by INPE.

To the application of this work Java programming was used in addition to AWT (*Abstract Windowing Toolkit*) and *Swing* components for the elaboration of graphical interface. *Framework Encog* [10] was incorporated for the development of the neural network module, as well as the database management system *MySQL Server* for the storage of data related to the processed images.

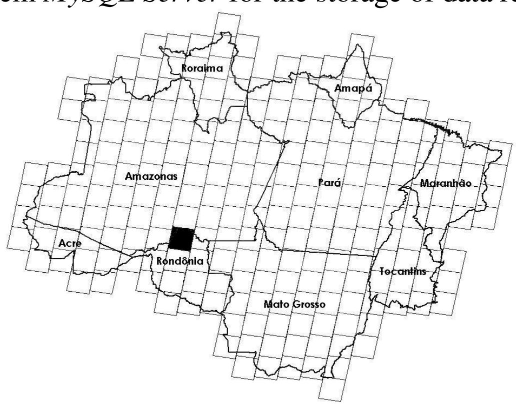


**Figure 1.** Legal Amazon , outlined in bold *tile* H11V09 used as area of study.
Source: Adapted from [4].

The neural tool for deforestation detection was developed according the methodology shown by [8], aiming to detect daily degradation based on Terra Satellite sensor data. Firstly, SPRING program produced images divided into soil, vegetation and shade fractions of the 57 available images using the Linear Mixture Model . The fraction images were then turned into GeoTIFF [11] format, which characterized the database used in this research.

With the georeferenced fraction images in GeoTIFF format, it became possible to develop a neural module and test it. The neural module takes in the same *pixel* xy of each one of the fraction images: soil, shade and vegetation. And the outcome is expected to be one of the following five results: water/shade, savanna, deforestation, vegetation or clouds.

When the neural network classifies the area as deforestation, a visual alarm is fired, showing the geographic coordinates that the *pixel* represents. In order to avoid processing areas that have already been completely cleared out or areas that are known to be out of vegetation, a digital mask was created. *Pixels* that can be identified as savanna or completely cleared out are removed from this mask. It is, then, possible to analyze the *pixels* which are expected to show vegetation.

Due to the neural networks' difficulty in determining the best architecture for solving the problem in question, freedom of parameterization was considered the best option found. That is, it is possible to adjust the number of intermediate layers, through graphical interface, as well as the number of neurons in each layers, the number of epochs, expected mistakes, and training algorithm.

The Multilayer neural network received two training algorithms: Perceptron: the algorithm of Back-Propagation) and a variation of it, the Resilient Back-Propagation [12].

In order to find the best architecture for the problem in question, in each training program there was a different number of neurons in the intermediate layer. In addition, the number of epochs and the number of intermediate layers were also altered. As there is a possibility of there being performance differences between the two networks, even if the same training parameters are applied, all the networks were double-trained and the best result was used.

An automatic generator of confusion matrix was applied in order to determine the quality of the neural response. The confusion matrix shows the extent to which the image classifier mixes up each mapped class.

The data used for training were obtained randomly out of 240 *pixels* of the images dating May 20th and July 14th, first and last images of the data collection, which have the best quality among the available images. The data are divided into:

- 30 points of vegetation
- 60 points of savanna
- 60 points of deforestation
- 30 points of shade/water
- 60 points of clouds

The test data collection, used to certify neural response correction, is made up of 30 samples of each class, which totalize 150. It is necessary to mention that the selection of points for training and testing were collected randomly, in distinct times and are two disjoint sets.

## 3. Results and Discussion

According to what was previously explained in section 2, various training sections were conducted, in order to obtain the best architecture for a problem. It should be pointed out, however, that it is impossible to guarantee that an artificial neural network is totally reliable for solving the given problem. During the training processes that were conducted, the Mean Squared Error (MSE) set was 1%. However, it was not possible to achieve this number in any of the training sections. The fact that the network has not achieved the expected MSE percentage does not mean that the training has been faulty. The hit rates in Table 1 - whose value is as much as or over 90% for all training processes - show that the Network is responding correctly, although the stipulated MSE has not been achieved. The hit rates are calculated by Equation 1:

$$\text{Hit}_{\text{Rate}} = (n_{\text{hits}} / n_{\text{sum}}) * 100 \qquad (1)$$

In which $n_{hits}$ is the number of points that the Network has associated to correct categories and $n_{sum}$ is the total amount of samples used for the test with the trained Neural Network.

**Table 1**. Set of Training Procedures and Parameters for the Neural Network

| Training | Neurons | Epochs | Achieved MSE | Hit Rates |
|---|---|---|---|---|
| 1 | 5 | 1.000 | 29,47% | 92,67% |
| 2 | 5 | 2.000 | 29,63% | 94,00% |
| 3 | 6 | 1.000 | 29,60% | 92,67% |
| 4 | 6 | 2.000 | 28,81% | 93,33% |
| 5 | 7 | 1.000 | 30,90% | 93,33% |
| 6 | 7 | 2.000 | 29,60% | 93,33% |
| 7 | 8 | 1.000 | 30,83% | 92,67% |
| 8 | 8 | 2.000 | 26,41% | 93,33% |
| 9 | 9 | 1.000 | 27,78% | 92,67% |
| 10 | 9 | 2.000 | 27,48% | 94,67% |
| 11 | 9 | 3.000 | 26,44% | 94,00% |
| 12 | 9 | 10.000 | 25,07% | 92,67% |
| 13 | 9 | 20.000 | 20,58% | 92,00% |
| 14 | 10 | 1.000 | 27,74% | 94,00% |
| 15 | 10 | 2.000 | 27,65% | 92,67% |
| 16 | 11 | 1.000 | 29,63% | 93,33% |
| 17 | 11 | 2.000 | 27,00% | 93,33% |
| 18 | 15 | 1.000 | 27,93% | 94,67% |
| 19 | 15 | 2.000 | 28,49% | 92,00% |
| 20 | 30 | 1.000 | 24,72% | 93,33% |
| 21 | 30 | 2.000 | 22,43% | 90,00% |
| 22 | 50 | 1.000 | 23,95% | 92,67% |
| 23 | 50 | 2.000 | 19,31% | 92,00% |
| 24 | 50 | 20.000 | 14,95% | 90,67% |

The Artificial Neural Network which has classified the set of samples with highest number of hits was represented by training process number 10 on the table. Training process number 18 obtained the same rate, but it shows a more complex structure. According to [6] the complexity of the neural model defines the scope for possible solutions for a determined problem, to which the use of a greater number of neurons than necessary affects its power of generalization. For that reason, the least complex neural network, which also solves the problem satisfactorily, is considered the best. In order to evaluate Neural Network 10, a confusion matrix was produced (Table 2). Confusion matrixes make it possible to verify confusion mapped classes. Another category - Undefined - was added to cases in which there was excitation of more than one neuron or the inhibition of all of them, allowing to define a particular mapped category.

**Table 2.** Confusion Matrix for a Neural Network Training Process to Class Savanna.

| Class | Water | Cloud | Savanna | Deforestation | Vegetation | Undefined | Sum |
|---|---|---|---|---|---|---|---|
| Water | 30 | 0 | 0 | 0 | 0 | 0 | 30 |
| Cloud | 0 | 30 | 0 | 0 | 0 | 0 | 30 |
| Savanna | 0 | 0 | 27 | 3 | 0 | 0 | 30 |
| Deforestation | 0 | 0 | 5 | 25 | 0 | 0 | 30 |
| Vegetation | 0 | 0 | 0 | 0 | 30 | 0 | 30 |
| Sum | 30 | 30 | 32 | 28 | 30 | 0 | 94.67% |

The confusion matrix shows that the neural network successfully classified 142 *pixels* out of the 150. When there was confusion, only on *pixels* of deforestation and savanna. Out of a total of 30 deforestation samples, 25 were correctly classified by the network and 5 were confused with Savanna.

It is believed that confusion is due to the fact that savanna and deforestation have similar spectral signature, which makes the classification process harder. Difficulty in category sorting similar spectral signature categories was also observed by [5] and by [13] as well. The latter conducted a comparative study between statistics technique and Artificial Intelligence Networks, and found that both methods show difficulties in classification.

In order to demonstrate the difficulty in sorting out two categories with similar spectral signature, the same network was trained with exactly the same parameter, without, however, the points related to savanna. Three training sections were conducted and in all of them the network converged to the expected MSE before iteration number 500, due to the extinction of the confusion between categories.

It is important to emphasize that due to fast convergence, the Mean Square Error stipulated was 0.1%, and not 1% as in previous training processes.

The confusion matrix for that neuron network, produced with the same training data set, except for the savanna points, allows infer that Savanna category causes the confusion in the classification process. In that case, the hit rate of the artificial neural network was 100%, and there was no confusion in association with any other categories. It should be highlighted that this neural network was able to classify the 5 pixels which had previously been wrongly classified as savanna. Notwithstanding, a neural network containing only savanna and deforestation samples was trained. It was observed, then, that the MSE found was similar to those achieved in the training processes of Table 1. The tests show that savanna and deforestation are two categories spectrally similar, which interferes with the neural process of classification by the neural network. It is possible to point out that, in addition to architecture, the sets of data and the ones the of mapped categories affect the good performance of the neural network.

**Table 3.** Confusion Matrix for the Neural Network being trained for Savanna.

| Category | Water | Cloud | Savanna | Deforestation | Vegetation | Undefined | Sum |
|---|---|---|---|---|---|---|---|
| Water | 30 | 0 | 0 | 0 | 0 | 0 | 30 |
| Cloud | 0 | 30 | 0 | 0 | 0 | 0 | 30 |
| Savanna | 0 | 0 | 30 | 0 | 0 | 0 | 30 |
| Deforestation | 0 | 0 | 0 | 30 | 0 | 0 | 30 |
| Vegetation | 0 | 0 | 0 | 0 | 30 | 0 | 30 |
| Sum | 30 | 30 | 30 | 30 | 30 | 0 | 100% |

The capacity of generalization of the neural network was, firstly, determined with the application of a set of tests and construction of the confusion matrix. However, it is necessary to determine the capacity that the neural network has to completely identify an image of MODIS/TERRA sensor. This image was chosen due to the absence of clouds in it, which is considered appropriate for the comparison of the produced maps. On the whole, the classification obtained was satisfactory, and all the categories and water were distinguished in the whole image.

Deforestation, however, was mistaken as savanna in some points, due to their spectral similarity. Analyzing the thematic maps, it is also possible to identify some areas of savanna which were classified as vegetation, possibly, due to the lack of training samples to those areas.

Some *pixels* were categorized as undefined when there was the excitation of more than one neuron of the network or none of them was activated. In case there is no activation of a neuron, the use of that *pixel* becomes impossible for the triggering of alarms to the processed scene. Nevertheless, if there is more than one active neuron, it is still possible to use the estimates for calculation of alarm triggering. It should be emphasized that, as far as producing a thematic map for the scene is regarded, the use of some filter is possible, in order to determine the category to the undefined pixels. An option for that could be considering the undefined category point according to the majority of points around it.

## 4. Conclusions

According to the results obtained, it is possible to conclude that Neural Networks have great potential in categorizing orbital images. In such way, the developed tool emerges as as classifier of satellite images, as much as a general purpose tool, including teaching purposes, for the creation and test of neural networks applicable in many areas. Therefore, although MODIS/TERRA sensor has been used in this work for the development of a tool for daily detection of deforestation, due to its flexibility, it can be used for a variety of purposes.

In view of the inherent difficulty of the process of efficient deforestation alarms production, that is, when false alarms are not fired and all areas are considered deforestation points, more studies are necessary. The developed tool was able to detect deforestation points. However, it is still instable, and produces false alarms. Potentially, better results might be found if the data used are obtained by remote sensing specialists for the training of neural networks. All the same, the *software* must be enhanced in order to standardize the alarm triggering.

## References and Notes

1. Fearnside, P. M. **Deforestation in Brazilian Amazonia: History, rates and consequences. Conservation Biology**, v. 19, n. 3, p. 680–688, Junho 2005.

2. INPE. **Projeto PRODES Monitoramento da Floresta Amazônica Brasileira por satélite**. 2010a. Disponível em: <http://www.obt.inpe.br/prodes/index.html>. Acesso em: 20 Novembro 2010.

3. Câmara, G.; Valeriano, D. de M.; Soares, J. V. **Metodologia para o Cálculo da Taxa Anual de Desmatamento na Amazônia Legal.** São José dos Campos, Set. 2006.

4. INPE. **Sistema DETER Detecção de Desmatamentos em Tempo Real.** 2010b. Disponível em: <http://www.obt.inpe.br/deter/metodologia_v2.pdf>. Acesso em: 20 Novembro 2010.

5. Todt, V.; Formaggio, A. R.; Shimabukuro, Y. **Identificação de áreas desflorestadas na Amazônia através de uma rede neural artificial utilizando imagens fração derivadas dos dados do IR-MSS/CBERS.** In: XI Simpósio Brasileiro de Sensoriamento Remoto,. Belo Horizonte: INPE, 2003. p. 2697–2704.

6. Braga, A. de P.; Carvalho, A. P. de Leon F. de; Ludermir, T. B. **Redes Neurais Artificiais: Teoria e Aplicações**. 2. ed. [S.l.]: LTC, 2007. 226 p.

7. Haykin, S. **Neural networks: a comprehensive foundation.** 2. ed. New Jersey: Prentice Hall, 1999. 842 p. ISBN 0-13-273350-1.

8. Todt, V. **Detecção em tempo real de desflorestamentos na Amazônia com uso de dados MODIS/TERRA e Redes Neurais.** Tese (Doutorado) — Instituto Nacional de Pesquisas Espaciais, São José dos Campos, São Paulo, 2007.

9. Deckmann, R. O. **SOS Amazônia: Utilização de Redes Neurais Arificiais para a detecção de desmatamentos.** São Leopoldo, Rio Grande do Sul, 2009.

10. Heaton, J. **Introduction to Encog 2.3 for Java**. 2010. Disponível em: <http://www.heatonresearch.com/dload/ebook/IntroductionToEncogJava.pdf>. Acesso: 20 Novembro 2010.

11. Vasconcellos, R. M. **GeoTIFF uma abordagem resumida do formato.** Rio de Janeiro, 2002.

CPRM Serviço Geológico do Brasil. Disponível em: <www.cprm.gov.br/publique/media/geotiff.pdf>. Acesso em: 20 Novembro 2010.
12. Riedmiller, M.; Braun, H. **A direct adaptive method for faster backpropagation learning: The RPROP algorithm.** In: Proceedings of the IEEE International Conference on Neural Networks. San Francisco, California: [s.n.], 1993. v. 1, p. 586–591.
13. Queiroz, R. B.; Rodrigues, A. G.; Gomez, A. T. **Estudo comparativo entre as técnicas máxima verossimilhança gaussiana e redes neurais na classificação de imagens IR-MSS CBERS 1**. In: I WorkComp Sul. Palhoça: [s.n.], 2004.