

## Comparison between accuracy measures of images classified by Maximum likelihood and Artificial Neural Networks

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### Abstract

*This work presents a comparison between the performances of the supervised classification with maximum likelihood algorithm and neural networks in the classification of three LANDSAT/TM sensor scenes in the south of the Amazonas State through Envi 4.6. The maxver classifier obtained better results with the parameters default of the computer system not adopting values for the control of the sample standard deviation. The best results obtained followed the contribution of the internal weight with 0.9 level of activation for the point Training Threshold Contribution and 0.2 for the Training Rate. The experimental results show that the maxver algorithm presented better performance with accuracy over 88% in all the scenes.*

**Keywords:** Neural Networks, Maxver, kappa, accuracy.

### 1. Introduction

The precision of land cover maps is of major importance for remote sensing users and researchers. Several ways of precision measuring are available, but the best one is not yet in common sense. Satellite image data is available for these mappings performance any time it is valid and coherent with reality (Oliveira, 2010). According to (Neponuceno, 2000) the automatic classification of images is essential when time/dependency operations are carried out for the mapping of wide regions such as the Amazonian. For such researches, (Gonçalves, 1998), (Ribeiro and Centeno, 2001), (Rodrigues et al., 2003) and (Oliveira, 2010) have been using techniques of artificial neural networks (RNA) and Maximum likelihood for the recognition of patterns and classification of orbital images.

Moreover, one of these mappings' validation ways is the utilization of confusion matrix and kappa index. It has already been published classification works showing the excellent performance through the use of kappa and global accuracy in the separation of several land uses (Limet et al., 2007).

Therefore, it is observed the need to analyze, develop and validate new architectures and methodologies destined to the classification of remote sensing images. The present work aimed at testing the applicability of RNA in the classification of a

TM/LANDSAT scene comparing its performance with that of a Maximum Likelihood classifier measured through kappa and global accuracy indices.

### 1.1. Study Area

The present study was carried out in the region of medium Purus river, south of the Amazonas State, between the geographic coordinates 08° 47' 21", 07° 40' 33" latitudes South and 68°44' 48" e 65° 36' 14" longitudes, West of Greenwich, comprising areas under jurisdiction of the municipalities of Boca do Acre, Lábrea and Pauini-AM (Figure 1), accounting for an area near 400,000 ha (RADAMBRASIL, 1976).

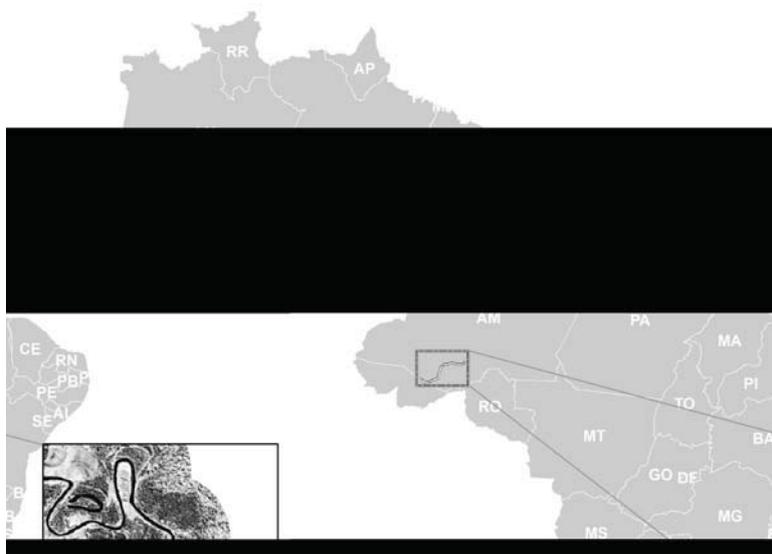


Figure 1: Study area localization, south region of the Amazonas State.

### 1.2. Work Methodology

For this work it was used Landsat/TM5 images (bands 1, 2, 3, 4 and 5), corresponding to orbit points 01/65, 02/65 and 02/66 from July 20088, obtained in the web site of the National Institute for Space Research – INPE ([www.dgi.inpe.br/cdsr](http://www.dgi.inpe.br/cdsr)). After the bands composition, it was performed a filtering of atmospheric correction and geometric correction (utilization of Geocover images), in Envi 4.7 environment, as recommended by (Ponzoni and Rezende, 2004).

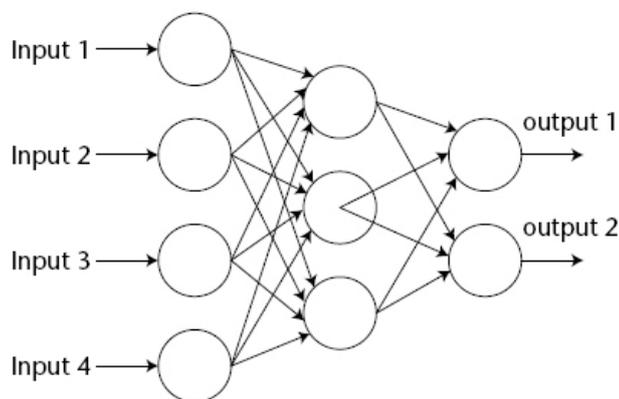
### 1.3. Classification

In order to fulfill processing mechanisms and to optimize the period of images classification, the scenes were cut in seven non-uniform rectangles, maintaining the irregular draw of Purus river, Amazonas, centralized. The classifications were supervised whereas the Maximum likelihood algorithm (MAXVER) likelihood log was given by (Equation 1).

$$l(x|\theta) = \log[L] = \log \left[ \prod_{i=1}^n f(x_i) \right] = \sum_{i=1}^n \log [f(x_i)] \quad (1)$$

Where: The likelihood measure is the conjunct distribution, which in the case of observations i.d ( $X_1; \dots ; X_n$ ).

The Neural Networks Simulator searched for alternatives for the low performance of the Backpropagation pattern algorithm, whereas it is usually pointed as the main obstacle for a wider utilization in the images classification, the neural architecture (Figure 2). Further details about the algorithm may be found in (Gonçalves et al., 1998), (Ribeiro and Centeno, 2001) and (Kavzoglu and Mather, 2003)

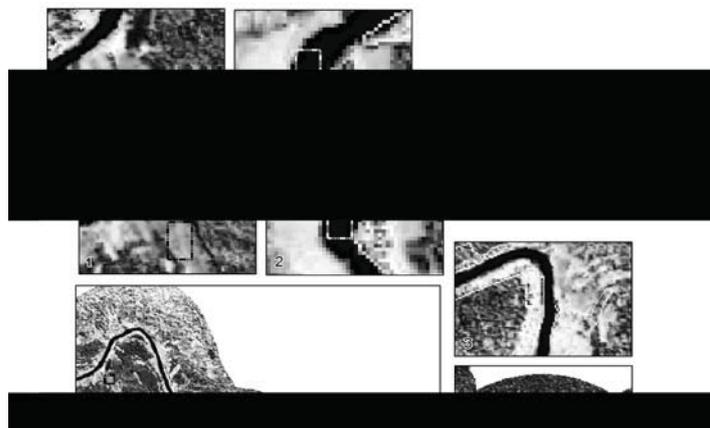


**Figure 2:** Neural networks simulator.

The process consisted on training and classification of samples of the groups of similar variables for both classification methods, Maxver and Neural Networks, where the program classified the samples by one method and, then, by the other. In the classification by Maxver the samples collected by pixels are samples in which the numeric values of the sampled pixels are the data that compound the training file, using the Imagethreshold tool; these values enabled the control and the probability of the classification parameters.

#### **1.4. Accuracy of the classified images**

The recognition of the patterns was carried out from 90 control points obtained with a global positioning system (GPS) in field, digitalized on the compound image. Likewise (Nepomuceno, 2000), the accuracy was carried out using the cross tabulation method, which consists on crossing the patterns of the classified images with the samples of the field verification classes. The main types of regions of interest selected from the land cover were: exposed land, presence of cocoa, water bodies, open forest, dense forest (Figure 3).



**Figure 3:** Group of data and training for the maximum likelihood classifier.

It was used the same sample group of field verification classes, for both classifiers, enabling to identify and combine the patterns with respect to classes, and another to perform the global accuracy analysis. The patterns present in the classified images were related to the classes through the amount of pixels of each pattern compared to the amount of pixels. This way, we may identify which patterns were more representative compared to each class, and from this analysis, combine the most representative patterns for a certain class.

The accuracy validation of a classification is the last step of the classification process. The most used way, according to (Novo, 2008), and here used, is the comparison of the map derived from the image with the reference map from an error matrix, also known as confusion matrix.

The confusion matrix analysis is considered the most indicated method to evaluate the classification accuracy of remote sensors' data. (Congalton and Green, 1999) cite that the classification accuracy depends on other factors, such as: the amount of effort, level of detail (classification) and the variability of categories to be mapped. Thereunto, the index of classification accuracy considered excellent for a classifier may not be so effective for the other. We observe in it the error of commission and omission, kappa coefficient and the global accuracy. The global accuracy represents the classification agreement for the whole map overall. (Equation 2).

$$P_o = \frac{\sum_{i=1}^m n_{ii}}{N} (2)$$

Where:  $P_o$ = global accuracy;  $N$ = total number of sample unities comprehended by the matrix;  $n_{ii}$ = the elements of the main diagonal;  $m$  = number of matrix classes.

### 1.5. Processing

For each group of variables it was acquired the same number of samples for training and for the classification validation. As (Novo, 2008), the number of samples was representative of all pixels of that class, being adjusted to the theoretical presuppositions of the decision rule adopted.

In the classification by Maxver, the samples collected by pixels are samples in which the numeric values of the pixels sampled are the data that compound the training file being used for such Imagethreshold tool, enabling the control and the probability of the classification parameters. It follows the classes and the number of the respective training samples collected for all the regions.

## 2. Results

(Figure 4) shows the summary of the classifiers average by sample class. The soil class was the best classified in both classifiers, confirming 100% of the pixels. Forest was the most confusing class for the classifiers, obtaining error over 44%.

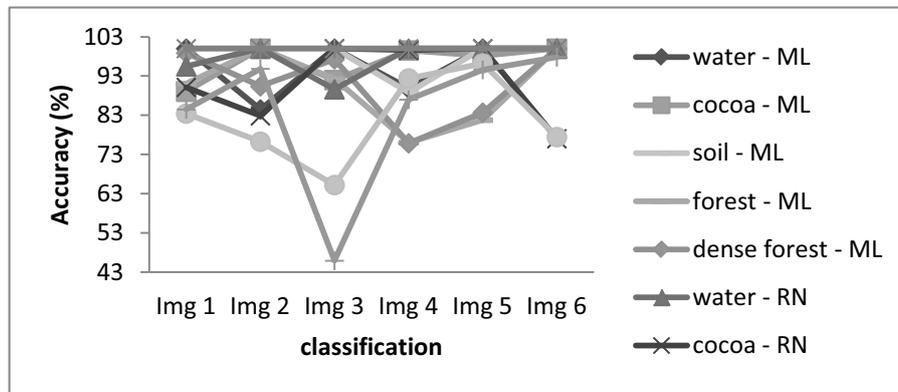


Figure 4: Global statistical measures resultant from the seven classified images.

After reaching a number of patterns equal to the number of field verification classes, it was again generated a confusion matrix, according to (Table 1), observing the values of the field verification classes samples, in conjunction with the accuracies by classes, Kappa index the global accuracy of the classifier.

Table 1: Mean kappa indices of the RNA (Neural Networks) and ML (Maxver) classified images.

Class	water (%)		cocoa(%)		soil (%)		forest (%)		dense f. (%)	
	RNA	ML	RNA	ML	RNA	ML	RNA	ML	RNA	ML
mean	95.50	100.00	90.15	89.02	100.00	100.00	83.47	91.09	84.50	98.90
Img1	95.50	100.00	90.15	89.02	100.00	100.00	83.47	91.09	84.50	98.90
Img2	100.00	84.50	82.87	100.00	100.00	100.00	76.30	100.00	94.86	90.40
Img3	89.66	100.00	100.00	92.00	100.00	100.00	65.25	92.30	45.95	97.30
Img4	100.00	89.85	99.60	99.55	100.00	88.80	92.43	76.06	87.00	75.89
Img5	100.00	100.00	100.00	98.14	100.00	100.00	96.25	81.79	94.60	83.70
Img6	100.00	100.00	77.05	100.00	100.00	100.00	77.48	100.00	97.85	100.00
Img7	100.00	100.00	93.21	100.00	99.30	100.00	89.46	100.00	95.37	100.00

### 3. Conclusion

Overall, the global measures and the kappa index presented superior behavior in the maximum likelihood algorithm.

### Acknowledgments

The authors thank the financial aid of the Post-Graduation Department of UnB.

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