

**STUDY OF THE VEGETAL COVERING AND LAND USE DYNAMICS IN THE REGION OF JI-PARANÁ/RO USING CLASSIFICATION TECHNICIS**

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**ABSTRACT**

The Brazilian Amazon has been object of anthropic activities (agronomic and cattle raising) that have been changing areas of forests into areas destined to the agriculture and pasture, contributing to the alteration of the environment. The evaluation of the vegetal covering and the land use is therefore indispensable for a rational planning that will overcome problems of uncontrolled development and deterioration of the environmental quality. However, high costs and difficulties of obtaining data in a short period characterize the conventional techniques used for that end. In this context, the analysis process and interpretation of images is an effective technique for the evaluation of that dynamics. The aim of this paper is to present the results obtained by the visual analysis and interpretation of Landsat Thematic Mapper (TM) imagery (Path/Row = 231/067) for years 1995 and 1997 using remote sensing techniques for mapping the classes of vegetal covering and land use in the study area, as well as the quantification of the area deforested in that period. It is also showed the results obtained with supervised and unsupervised classifiers. The major change occurred in the area was the mature (primary) and secondary forest that became bare soil and pasture, representing 69.79 Km<sup>2</sup> (6.35%) of the study area. The second more representative alteration was the bare soil that became pasture, representing 33.47 Km<sup>2</sup> or 3.05% of the total area.

**1. INTRODUCTION**

Since the 70's, optical remotely sensed data has been used for monitoring of natural areas. These data have been used for land cover/land change mapping, allowing the identification of several cover classes like crop fields, bare soil, pasture, secondary forest and mature forest.

This work presents a simplified analysis of landscape changes in an area of high deforestation rates in the state of Rondônia. The aim of these analyses is to contribute to a better understanding of the results that can be obtained using image classification techniques - visual, supervised and unsupervised.

The study was split into two parts. In the first part, the images were visually analyzed by using interpretation keys, and allowed the determination of six classes: mature forest, secondary forest, regrowth, pasture, bare soil e burned areas, as well as the quantification of the area and percentage of class modification in the 1995-1997 period.

During the second part, a region of the images were analyzed using the supervised and non-supervised classification techniques and the results were then compared with the results obtained during the visual analysis. The values obtained with this comparison will be presented in this work.

**2. STUDY SITE**

The study area is located at Rondônia State, western Brazilian Amazon, with the boundary coordinates: from 09° 41' to 09° 54' of latitude South and from 62° 16' to 62° 41' of longitude west, representing a total area of 1.099,30 Km<sup>2</sup>.

The region presents a slightly undulated terrain, with an average annual rainfall of about 2,200mm, mean annual temperature of 23,6° C (H. Schimitz, unpublished data), and a dry season from late April to late August. After the 70's decade the settlement of small farmers began along the BR-364 highway. As a consequence forest has been clear cut to

allow crop fields and pasture establishment. Deforested land is used for some years and when soil loses its fertility the areas are sometimes abandoned, leading to forest regeneration.

Human occupation in the study area has considerably increased during the last three decades, following the building of federal road BR-364 and the development of some of the oldest and largest settlement projects in the state of Rondônia. The deforestation process continues to be intense in the region (Alves *et al.* 1998a), arousing the interest in monitoring it. The BR-364 road bisects the area of study and served as the way of penetration in the region at the time of its colonization. To the present, the road constitutes the basic link by land between Rondônia and the more populated south of Brazil, serving as the major way to export the region's production, and to bring goods in. The region includes several of the largest settlements projects organised in the state of Rondônia under the programs of Amazon colonization during the 1970's, including: Projeto Integrado de Colonização (PIC) Ouro Preto (created in 1970), Projeto de Assentamento Dirigido (PAD) Burareiro (1974), PIC Padre Adolpho Rohl (1975), PAD Marechal Dutra (1978) and PAD Machadinho (1982) (Instituto Nacional de Colonização e Reforma Agrária (INCRA) 1996). These projects occupied more than 2 million ha in the region, where more than 24,000 families were settled from 1970 till 1995 (INCRA 1996). The majority of the properties in these settlements is relatively small (25 to 100 ha, INCRA 1996) and is scattered along secondary roads that emerge from the major arteries, creating the typical Rondônia "fish-bone" pattern. The area also includes mid-size (1000 ha) and large (10,000 ha or more) properties. The native vegetation in the region consists of dense tropical forests with mild seasonal characteristics (RADAMBRASIL 1978), a 4 to 6-month dry season and elevations ranging from 100 to 600m. The region also presents several areas covered by non-forest vegetation, associated to the presence of rocky soils.

### 3. DATA AND METHODS

For this study, two TM images (Path/Row = 231/067), acquired in August 03, 1995 and July 07, 1997 were used. Both TM images were geocoded using coordinates acquired on the field by differential GPS equipment. After the geocoding the images had their radiometric characteristics enhanced. All these previous steps, as well as the classifications were performed using the ENVI (Environmental for Visualizing Images) software, version 3.2.

When image data is available in digital form, spatially quantised into pixels and radiometrically quantised into discrete brightness levels, there are two approaches that may be adopted in endeavouring to extract information. One involves the use of a computer to examine each pixel in the image individually with a view to making judgements about pixels specifically based upon their attributes. This is referred to as quantitative analysis since pixels with like attributes are often counted to give area estimates. The other approach involves a human analyst/interpreter extracting information by visual inspection of an image composed from the image data. In this he or she notes generally large scale features and is often unaware of the spatial and radiometric digitisations of the data. This is referred to as photointerpretation or sometimes image interpretation; its success depends upon the analyst exploiting effectively the spatial, spectral and temporal elements present in the composed image product. Because of this, to perform a visual analysis, the analyst/interpreter needs to elaborate the interpretation keys. These interpretation keys consist of the description of elements that characterize a specific feature of the terrain. In this study the characteristics used for composing the interpretation keys were size, shape, color and texture.

This technique consists of the acquisition of information about a given target on the surface, through the analysis of its response either in different individual channels or combined channels under the form of color compositions, considering the spectral and temporal aspect of these images, see Pereira *et al.* (1989), Donzeli *et al.* (1992), Watrin (1994) and Valério Filho and Pinto (1996).

The visual analysis was then accomplished using the mentioned aspects (size, shape, color and texture), and the following classes were obtained: **Mature forest**: area dominated by the Open Tropical Forest, without the effect of anthropic activities. The mature tropical forests are formed by a great number of species and high variability, presenting in the image with a tonality of green dark. **Secondary forest**: resultant of the abandonment of areas previously occupied by the tropical forest (mature or secondary), allowing the regeneration of the vegetation, or secondary succession. In the image is represented by a clearer green coloration than the one of the mature forest. **Regrowth**: defines the areas of secondary succession with age below 5 years. These are characterized by a tonality of green clearer than the one of the secondary forest. **Pasture**: areas under agronomic and cattle-raising activities with various shapes and sizes presenting clear magenta coloration. **Bare soil**: areas characterized by various shapes and sizes with coloration dark magenta. **Burned areas**: areas without defined form and characterized by a dark purple coloration.

The objective of the second part of this study was to compare the results obtained with the supervised and unsupervised classifiers with the visual analysis result and verify how suitable they are.

Unsupervised classification is a means by which pixels in an image are assigned to spectral classes without the user having foreknowledge of the existence or names of those classes. It is performed most often using clustering methods. These procedures can be used to determine the number and location of the spectral classes into which the data falls and to determine the spectral class of each pixel. The analyst then identifies those classes *a posteriori*, by associating a sample of pixels in each class with available reference data, which could include maps and information from ground

visits. While the information classes for a particular exercise are known, the analyst is usually totally unaware of the spectral classes, or sub-classes as they are sometimes called. Unsupervised classification is therefore useful for determining the spectral class composition of the data prior to detailed analysis by the methods of supervised classification.

The unsupervised classifier used was the K-Means. K-Means unsupervised classification calculates initial class means evenly distributed in the data space and then iteratively clusters the pixels into the nearest class using a minimum distance technique. Each iteration recalculates class means and reclassifies pixels with respect to the new means. All pixels are classified to the nearest class unless a standard deviation or distance threshold is specified; in which case some pixels may be unclassified if they do not meet the selected criteria. This process continues until the number of pixels in each class changes by less than the selected pixel change threshold or the maximum number of iterations is reached (Tou and Gonzalez, 1974). For this study the number of iterations selected was 100; the number of classes was 5 and change threshold was 5.00.

Supervised classification procedures are the essential analytical tools used for the extraction of quantitative information from remotely sensed image data. An important assumption in supervised classification usually adopted in remote sensing is that each spectral class can be described by a probability distribution in multispectral space: this will be a multivariable distribution with as many variables as dimensions of the space. Such a distribution describes the chance of finding a pixel belonging to that class at any given location in multispectral space. This is not unreasonable since it would be imagined that most pixels in a distinct cluster or spectral class would lie towards the centre and would decrease in density for positions away from the class centre, thereby resembling a probability distribution. The distribution found to be of most value is the normal or Gaussian distribution. It gives rise to tractable mathematical descriptions of the supervised classification process, and is robust in the sense that classification accuracy is not overly sensitive to violations of the assumptions that the classes are normal.

The supervised classifier used was the Maximum Likelihood. Maximum likelihood classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Unless a probability threshold is selected all pixels are classified. Each pixel is assigned to the class that has the highest probability (i.e., the "maximum likelihood"). For this study no probability threshold was selected.

#### 4. RESULTS AND DISCUSSION

Regions of Interest were created for each situation (changes in land use and cover) to be analyzed in the images and the colors chosen for each one are presented in the Table 1.

1995 SITUATION	1997 SITUATION	COLOR
Mature and secondary forest	Bare soil	Red
Mature and secondary forest	Pasture	White
Bare soil	Pasture	Blue
Pasture	Bare soil	Yellow
Regrowth	Pasture	Cyan
Burned areas	Bare soil	Black
Burned areas	Pasture	Brown

Table 1 – Table of colors used for the visual analysis of the Landsat Images.

The Figures 1 and 2 depicts the 1995 and 1997 TM images respectively, after the process of radiometric enhancement. These images were visually analyzed and a color mask representing the changes in land use/cover obtained. This mask was superimposed to the image acquired in 1997 as is shown in Figure 3. Parts of the region's landscape can be appraised on Figure 4.

After the analysis and interpretation of the images it was performed the calculation of the area corresponding to each and every one of the changes identified. The total area of each change was calculated multiplying the area of each pixel (0.9 Km<sup>2</sup>) by the number of pixels present in the Region of Interest (ROI). Percent of change is the modified area relative to the total study area. The results can be seen in Table 2.

1995 SITUATION	1997 SITUATION	CHANGED AREA	PERCENT OF CHANGE
Mature and secondary forest	Bare soil	29.79 km <sup>2</sup>	2.71%
Mature and secondary forest	Pasture	40.00 km <sup>2</sup>	3.64%
Bare soil	Pasture	33.47 km <sup>2</sup>	3.05%
Pasture	Bare soil	4.58 km <sup>2</sup>	0.42%
Regrowth	Pasture	1.26 km <sup>2</sup>	0.12%
Burned areas	Bare soil	1.73 km <sup>2</sup>	0.16%
Burned areas	Pasture	0.16 km <sup>2</sup>	0.02%

Table 2 –Evolution of changes in Land use/cover.

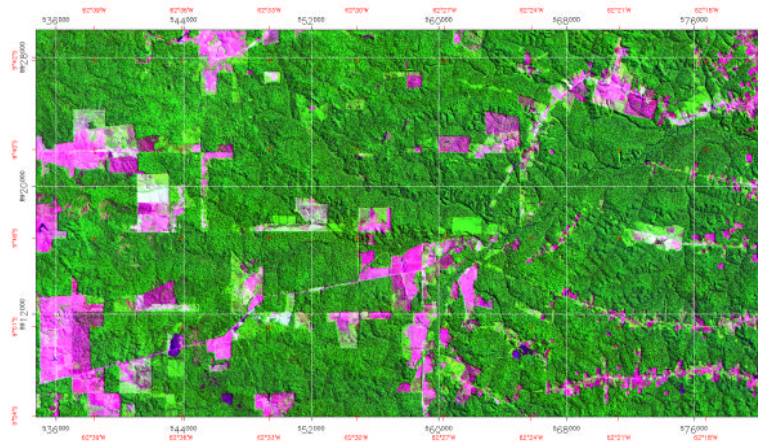


Figure 1. 1995 TM Image. Color composite (TM5-red; TM4-green; TM3-blue). Projection UTM.

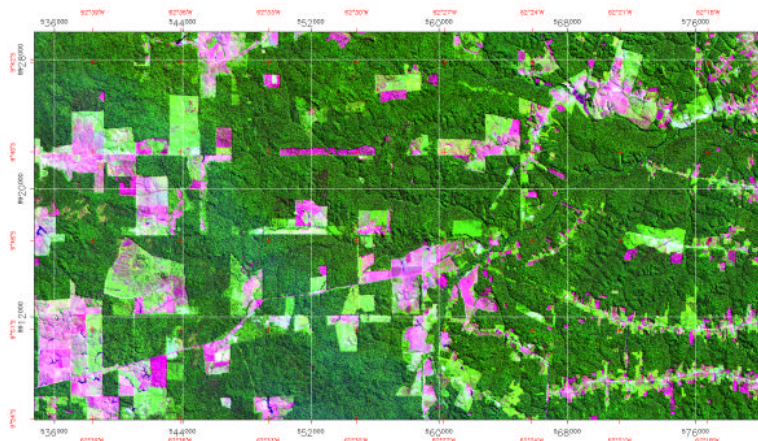


Figure 2. 1997 TM Image. Color composite (TM5-red; TM4-green; TM3-blue). Projection UTM.

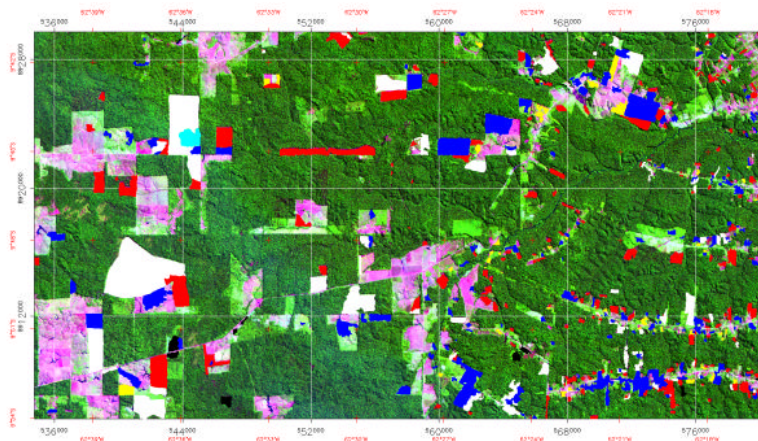


Figure 3. 1997 TM Image with the color mask representing the results obtained with the visual interpretation superimposed. Projection UTM.



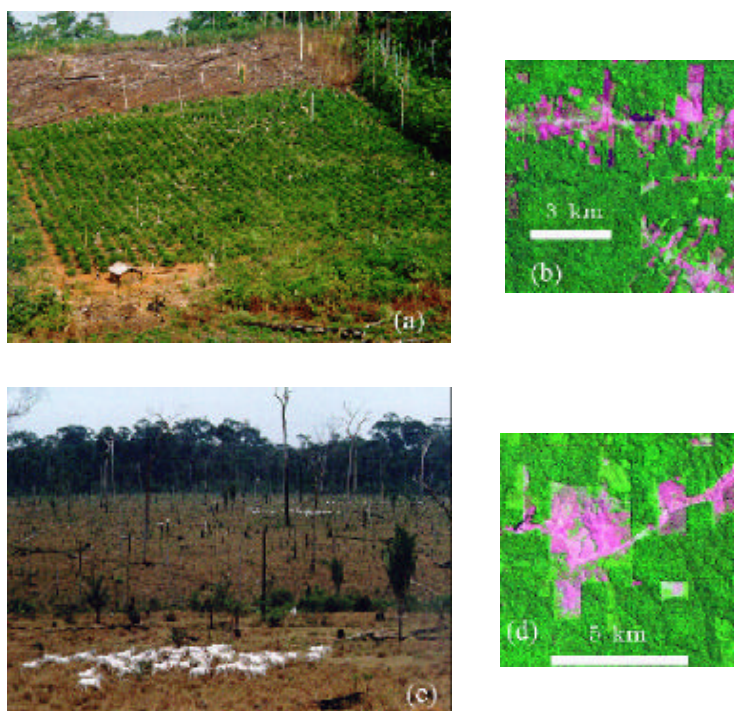


Figure 4. Views of the land use patterns in the region: coffee plantation in a new settlement project (a) and pastures (c), and corresponding patterns on TM color composites (respectively (b) and (d)). FONTE: Adapted from Alves et al., (1998b).

As can be observed from the analysis of the changes occurred in the study area, it is noticed that a considerable area of the mature forest was substituted by pasture and bare soil areas (that will probably be used as pasture areas in the future), corresponding to an area of 69.79 Km<sup>2</sup>, what represents 6.35% of the study area.

Another significant change observed in the study area was the bare soil that became pasture, corresponding to an area of 33.47 Km<sup>2</sup> or 3.05% of the total area. The percentages corresponding to the other alterations can be verified in Table 2 and are not quite representative.

From these results one can observe that the main changes occurred in areas actually or previously occupied by forest (as is the case of bare soil that became a pasture), this bare soil was previously a forest. In other words, these changes represent the deforestation that characterizes this region.

After this analysis, it was selected (from inside the study area) a region of 541.35 Km<sup>2</sup> (49% of the total area), to be tested with the supervised and unsupervised classifiers and the results are showed in Tables 3,4 and 5. The Figures 4, 5 and 6 depicts the color mask build for the changes detected with the visual analysis as well as with the supervised and unsupervised classification, respectively.

1995 SITUATION	1997 SITUATION	COLOR	CHANGED AREA	PERCENT OF CHANGE
Mature and secondary forest	Bare soil	Red	14.17 Km <sup>2</sup>	2.62%
Mature and secondary forest	Pasture	White	28.36 Km <sup>2</sup>	5.24%
Bare soil	Pasture	Blue	7.74 Km <sup>2</sup>	1.43%
Pasture	Bare soil	Yellow	0.88 Km <sup>2</sup>	0.16%
Regrowth	Pasture	Cyan	1.26 Km <sup>2</sup>	0.23%
Burned areas	Bare soil	Black	1.30 Km <sup>2</sup>	0.24%
Burned areas	Pasture	Brown	0.00Km <sup>2</sup>	0.00%

Table 3 –Evolution of changes obtained with the visual analysis.

1995 SITUATION	1997 SITUATION	COLOR	CHANGED AREA	PERCENT OF CHANGE
Mature and secondary forest	Bare soil	Red	12.54 Km <sup>2</sup>	2.32%
Mature and secondary forest	Pasture	White	25.84 Km <sup>2</sup>	4.77%
Bare soil	Pasture	Blue	5.98 Km <sup>2</sup>	1.11%
Pasture	Bare soil	Yellow	9.27 Km <sup>2</sup>	1.71%
Regrowth	Pasture	Cyan	0.00 Km <sup>2</sup>	0.00%
Burned areas	Bare soil	Black	0.42 Km <sup>2</sup>	0.08%
Burned areas	Pasture	Brown	0.41 Km <sup>2</sup>	0.08%

Table 4 –Evolution of changes obtained with the unsupervised classification (K-means).

1995 SITUATION	1997 SITUATION	COLOR	CHANGED AREA	PERCENT OF CHANGE
Mature and secondary forest	Bare soil	Red	12.53 Km <sup>2</sup>	2.32%
Mature and secondary forest	Pasture	White	28.00 Km <sup>2</sup>	5.17%
Bare soil	Pasture	Blue	6.36 Km <sup>2</sup>	1.18%
Pasture	Bare soil	Yellow	0.84 Km <sup>2</sup>	0.16%
Regrowth	Pasture	Cyan	1.74 Km <sup>2</sup>	0.32%
Burned areas	Bare soil	Black	0.28 Km <sup>2</sup>	0.05%
Burned areas	Pasture	Brown	0.78 Km <sup>2</sup>	0.15%

Table 5 –Evolution of changes obtained with the supervised classification (Maximum Likelihood).



Figure 4. Regions of Interest (Land use and cover changes) obtained with the visual analysis.

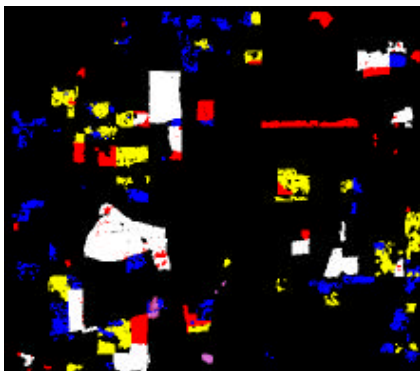


Figure 5. Regions of Interest (Land use and cover changes) obtained with unsupervised classification.

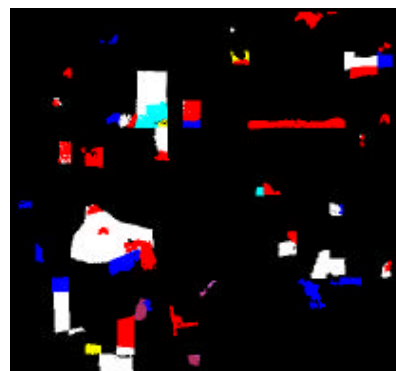


Figure 6. Regions of Interest (Land use and cover changes) obtained with supervised classification.

In this part of the study the values presented in Table 3 and the Regions of Interest shown in Figure 3 are used as ground truth. It can be noticed that the results presented in Table 3 (ground truth), Table 4 (K-means) and Table 5 (maximum likelihood) are quite similar. But, when we analyze the regions of interest (showed in Figures 4, 5 and 6), detected from the visual analysis of TM images, unsupervised and supervised classification, respectively, that the unsupervised classification presents a lot of misclassification areas, mainly for the region of pasture in 1995 that became bare soil in 1997 (yellow color).

The results obtained with the supervised classification is quite reasonable when compared with the ground truth results, and represent an easy and fast way to classify images with the purpose of monitoring changes in natural areas. The

results of the analyses can also be seen in Figure 7. It must be noticed that the effectiveness of the supervised classification is dependent of the number of pixels included in the training samples. These pixels will be used to estimate the mean vector ( $m$ ) and the covariance matrix ( $S$ ) of the whole spectral class. Considering  $x$  the vector correspondent to a pixel in the  $N$  classes involved, the mean vector of the pixels belonging to a class is given by:

$$m = E(x) = \frac{1}{K} \sum_{j=1}^k x_j \quad (1)$$

Where  $K$  is the number of pixels in the class and  $E(x)$  is the expectancy of  $x$ .

and the covariance matrix is given by:

$$S_x = E\{(x-m)(x-m)^t\} = \frac{1}{K-1} \sum_{j=1}^k (x-m)(x-m)^t \quad (2)$$

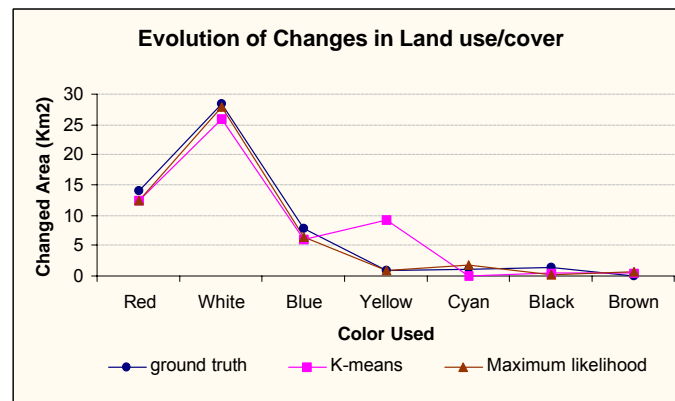


Figure 7. Results obtained with the visual analysis of the TM images, as well as with the supervised and unsupervised classifications.

## 5. CONCLUSION

This study reported data on landscape changes between 1995 and 1997 for a region that has undergone important alterations during the last three decades. Results were based on a relatively simplified approach that nevertheless showed how these changes are causing the continuous forest depletion in this region.

This continued process of forest removal is possibly happening in other areas of the Amazon and the use of remote sensing and spatial techniques can help the identification of such a process and contribute to a better understanding of the processes occurring in the Amazonian region. The supervised classification showed to be a good tool for this purpose.

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