Image Data Mining and Digital Processing applied to land cover change assessment in Brazilian Amazon

André Augusto Gavlak, Raian Vargas Maretto

Abstract— **The study of degraded areas dynamics in the Amazon may help to clarify the potential impact of current patterns of land use on the Amazon rainforest and its competence to recover over time and also on how these phenomena are related to regional social and environmental dynamic [6]. This study aims to use change detection techniques to identify changes in land cover and a structural classifier to characterize patterns of human occupation in a region of the municipality of Novo Progresso (Pará State/Brazil) from multitemporal Landsat TM data and ETM + data (scene 22765) and deforestation data from Prodes (Brazilian monitoring program of the Amazon). Were used accumulated deforestation data from PRODES and the Geographical Data Mining Analyst (GeoDMA) classifier [27][28] (KORTING et al., 2007, SILVA et al, 2007) to classify land cover patterns at 2001, 2005 and 2007, using cellular representation, and obtaining, beyond the land cover patterns, the trajectories of it. Were also generated maps of land cover change using Spectral Linear Mixture Model [25] in order to know how and when the major changes occurred. The interest classes are: 1) Deforestation; 2) Regrowth; 3) no change.**

Index Terms— **Image data mining; Spectral Linear Mixture Model; land cover patterns; Brazilian Amazon**

I. Introduction

Remote sensing images are the primary means of assessment of land change around the world, and currently most noteworthy source of new data about our planet. From these satellites, is possible to know that the planet Earth has undergone major changes in recent decades, especially in areas of rainforest [14].

In the last years has been observed an increase in the process of deforestation of the Amazon region often as a result of a disorderly process of human occupation and the possibility of association this type of occupation with certain patterns of deforestation is great value for the planning and use of socio-environmental policies.

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The Brazilian National Institute for Space Research (INPE) has two important projects interrelated to Amazon deforestation monitoring, known as DETER (Deforestation Detection in Real Time alert system) and PRODES (Deforestation Monitoring Project). DETER uses sensor images with lower spatial resolution (250m) while PRODES estimates the deforested areas with images of higher spatial resolution (30m). These projects use change detection techniques based on spectral mixture models of remote sensing images [24].

Though, one of the most important challenges in our time is tracking patterns of land use change. Patterns of land use will change over time. Small settlements tend to grow over the forest, increasing the cultivated areas. In these and other similar cases, the use of remote sensing data and techniques of digital image processing make possible, based on their shapes and their spatial arrangement, to relate each pattern of land cover with his agent, thus enabling to analyze the role and spatial organization of the actors involved.

The study of the dynamics of degraded areas in the Amazon may help to clarify the possible impacts of present patterns of land use on the Amazon rainforest and its competence to recover over time and also in how these phenomena are related to social and environmental dynamics of the region [6].

Therefore, this study is aimed to use techniques to detect changes in land cover and a structural classifier to characterize patterns of human occupation in a region of the municipality of Novo Progresso / PA from LANDSAT 5 multitemporal data and PRODES deforestation data.

II. Literature review

A. Deforestation patterns in the Amazon

The Brazilian Amazon has experienced different stages and economic activities that most often develop at the same time, such as rubber tapping, farms, roads and expansion of companies interested in farming, mechanized farming, logging and mining.

These ways of occupation and economic activities are associated with different social actors present in the Amazon. Several studies have been performed seeking associate the occupation patterns with deforestation patterns observed in remote sensing images.

[8] proposed the following types of patterns of deforestation: geometric, corridor, fishbone, diffuse, fragments

and island. [7] used the hypothesis that different practices of land use result in small and large clearings. Small farmers grow in small areas and irregular while the large farmers produce large gaps and more regular.

[18] tested if sudden changes could be detected by landscape structure indices in real and simulated landscapes. The authors compared three different deforestation patterns in the Brazilian Amazon: small properties regularly extend along roads (fishbone), irregularly dotted small properties and large properties. The center of attention of their work was in habitat loss and conservation biology.

[7] used the hypothesis that different practices of land use result in small and large clearings. The small farmers cultivate in small areas and irregular while the large farmers produce large gaps and more regular.

The analysis of spatial patterns of deforestation should consider their temporal evolution. A particular spatial deforestation pattern is consequence from the land use strategies of different actors. The assessment of spatial deforestation patterns using remote sensing images from a single date does not reveal the whole deforestation process. So, the spatial patterns detected are the result of a combination of different actions from different actors and their land use strategies.

B. *Spectral Linear Mixing Model*

In remote sensing images, the radiance detected by the sensor is caused by a mixture of many different materials, plus the atmospheric contribution [25]. So, each pixel can include more than one type of ground cover [1].

Thus, the spectral linear mixing model (SLMM) aims to estimate the proportion of image components, such as soil, shade and vegetation for each pixel, from the spectral response in the various bands of the sensor. This model generates the images fraction soil, shade and vegetation [25]. The linear relation is used to represent the spectral mixture of the components within the resolution element of the sensor. The response of each pixel, in any spectral band of the sensor, can be defined as a linear combination of the responses of each component [24].

The SLMM can be represented as:

$$r_i = a \times vege_i + b \times soil_i + c \times shade_i + e_i \qquad (1)$$

where r_i is the spectral response of the pixel in the band i; a, b and c are the proportions of *vegetation*, soil and shade (or water), respectively; $vege_i$, $soil_i$, and $shade_i$ are the spectral response of the components vegetation, soil and shadow (or water), respectively; e_i is the the error in the band i; and i indicates the band of the sensor [24].

[22] used RGB shade fraction images derived from multitemporal Landsat-TM data for studying the deforestation in the Brazilian Amazon. For tropical forested areas, these images have a medium amount of shade, while for deforested areas have a low proportion of shade. So, shade fraction image is a viable alternative to map deforested areas in tropical forested regions using digital techniques.

[23] segmented and classified the shade fraction image in order to identify deforestation areas in Brazilian Amazon. They used the growing regions segmentation method followed by the *isoseg* classification method.

[5] propose the segmentation (by the growing regions method) and the classification (by regions) of the shade fraction image to map the extent of deforested areas in Brazilian Amazon through digital processing of Landsat-TM images.

In this work, we execute the SLMM using the spectral bands 3, 4 and 5 from the Landsat-5-TM sensor (to 2005 and 2007) and from the Landsat-ETM+ (to 2001). Later, we use the soil fraction and shade fraction images from each year to identify the land cover changes.

III. METHODOLOGY

Accumulated deforestation data from PRODES and the structural classifier GeoDMA [27][28] were used to classify patterns of occupation of 2000, 2004 and 2007, using the cellular representation and getting, in addition to patterns of occupation, the trajectories of the standards for the time period analyzed.

The GeoDMA is a system for mining spatial data developed by [13] based on the method proposed by [27]. This system works as a plug-in for TerraView, which manipulates and displays data stored in geographic databases. The system was developed in C + + Language, based on TerraLib [13].

Change maps in land cover for three periods (2001-2005, 2005-2007 and 2001-2007) were produced from the segmentation and classification of the soil and shade fraction images of the SLMM. Each SLMM was made using one of the multitemporal images acquired by the Thematic Mapper Sensor (TM) and the Enhanced Thematic Mapper Plus sensor (ETM+), of 30 meters spatial resolution (scene 227/65), on board of the Lansat-5 and Landsat-7 satellites, respectively. These images, shown in Figure 1, are available in the image catalog of DGI (Image Generation Division) / INPE (2009 - http://www.dgi.inpe.br/CDSR/). This mapping was made in order to know how and when major changes have occurred. The classes of interest are: 1) conversion from forests to deforestation, which we called Forest to deforestation 2) Conversion from deforestation to regrowth (Deforestation to regrowth); 3) Kept Deforestation (Kept deforestation); 4) Water; and 5) Kept Forest (Kept forest).

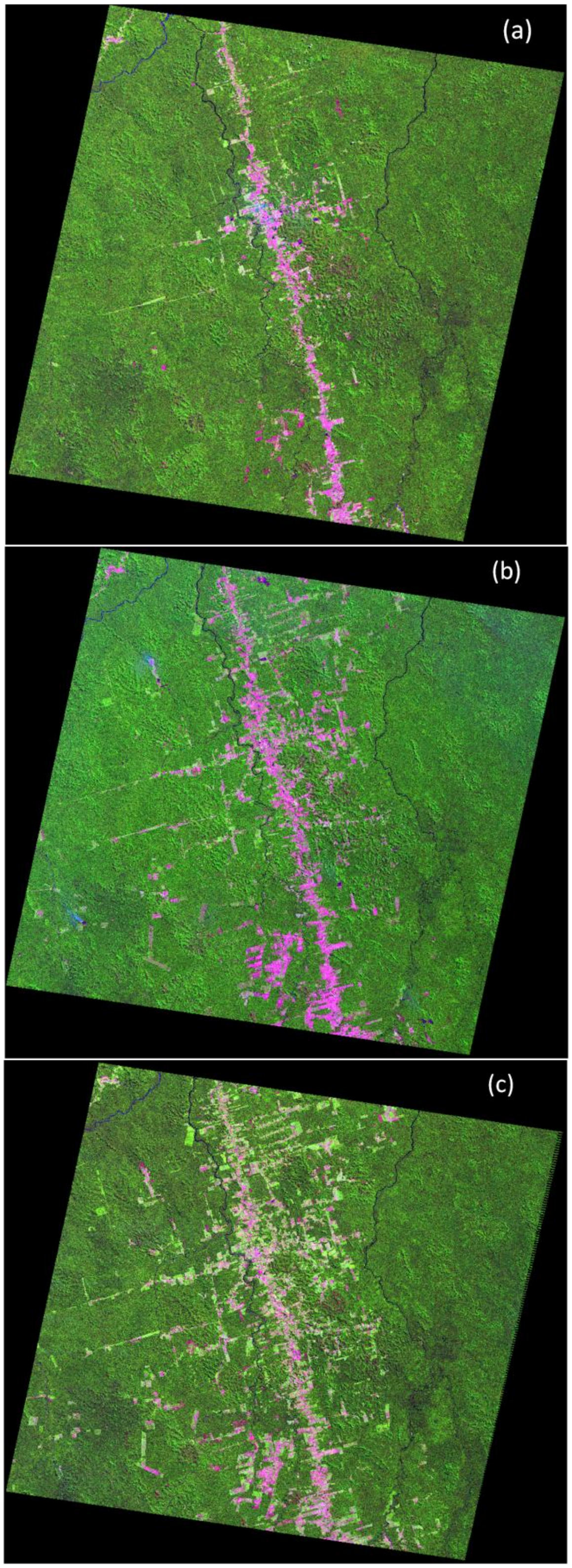


Fig. 1. (a) R(5) G(4) B(3) composition of the ETM+ image used, from 14/07/2001; (b) R(5) G(4) B(3) composition of the TM image used, from 17/07/2005; (c) R(5) G(4) B(3) composition of the TM image used, from 21/06/2007.

A. *Study Area*

The municipality of Novo Progresso is located in Para State, northern Brazil, with a vast area of Amazon forest in its territory. The formation of the town began between 1978 and 1979, when the first people arrived at the settlement called Quilometro 1085 (Kilometer 1085). With the expansion of the village in 1992, the city was emancipated, creating the municipality of Novo Progresso (Figure 2).

Fig. 2. Legal Amazon and Study Area

With the perspective of the paving of the BR-163, and consequent economic growth, many loggers settled in the area between late 1990 and 2004, warming the illegal land market and causing the local population increase.

Census data shows that Novo Progresso had a population of 24,948 inhabitants in 2000. However, in 2007 there was a decline in population to 21,598. It is believed that this decrease is related to federal intervention in the region in 2004 that established the BR-163 Sustainable Forest District (Distrito Florestal Sustentável da BR-163), with the aim of curbing the predatory exploitation of natural resources and start a process of land consolidation.

The main economic activity currently carried out in Novo Progresso is livestock. In 2006, had about 91,810 head of cattle [9]. Until 2007 the city had accumulated 4707.4 km2 deforested [11], representing 12% of the total area of the municipality.

The case of the municipality of Novo Progresso seems paradigmatic. The high participation of the agricultural sector in GDP of the city, associated with decreased power of migratory attraction and population attachment in the years 2000 to 2007 indicate a process of concentration of land ownership.

These characteristics would place the town of Novo Progresso as an agricultural area of circumvention, due to a factor of expulsion by the process of change in productive structure [29]. However, the Ecological-Economic Zoning of the BR-163 (2007), conducted by the ADA (Agency for the Development of Amazonia) and Embrapa (Brazilian Agropecuary Research Corporation), indicates that the more intense process of mechanization of agriculture has been concentrated in the municipality of Santarém region.

The deforestation intensification in the area can be observed in Figure 3:

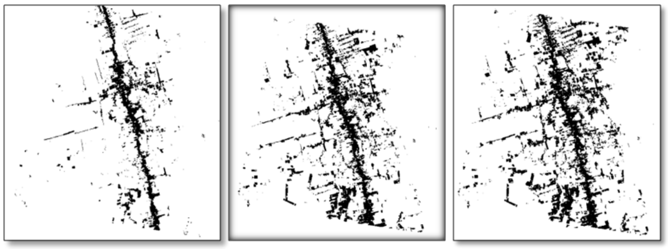


Fig. 3. Deforestation evolution at Novo Progresso

Such considerations point to the hypothesis that evasion observed in the agricultural town of Novo Progresso is the result mainly of a process of land concentration, led by the expansion of livestock operations and activities not linked to the crop yield.

B. *First phase: Making the SLMM*

The first phase to map the changes was to make the SLMM for each of the three images. Figure 4 shows a flowchart illustrating the steps followed in this phase.

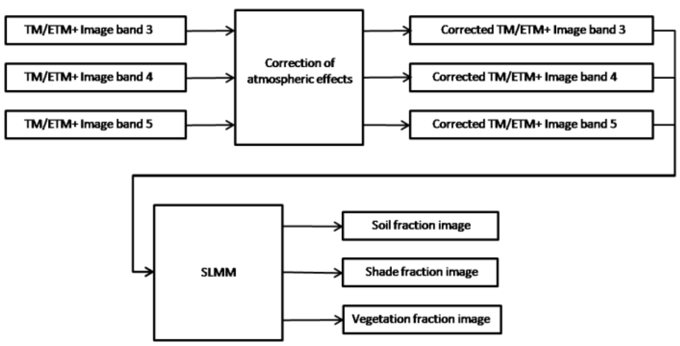


Fig. 4. Flowchart illustrating the steps followed to make the SLMM.

In the way between the earth surface and the sensor, the radiation may be modified by scattering and absorption by gases and aerosols in the atmosphere [30]. When we are working with changes detection, this possible modification may generate differences among the images. These differences can be interpreted by the classifier as changes in the land cover, when in fact, there are no changes in that place. In order to reduce these possible mistakes, we correct the atmospheric effects using the second simulation of the satellite signal in the solar spectrum (6s) [33]. This is a multiple-stream simulation of atmospheric absorption and scattering based on inputs of optical depth and aerosol composition [31].

After correct the atmospheric effects, we have started to produce the SLMM, using the corrected images. As we made the SLMM to make a comparison between the three years, we have used the same endmembers for all SLMM. They were collected in the 2007 TM image. Figure 5 shows the spectral behavior of the endmembers in the three bands considered (Bands 3, 4 and 5 of TM).

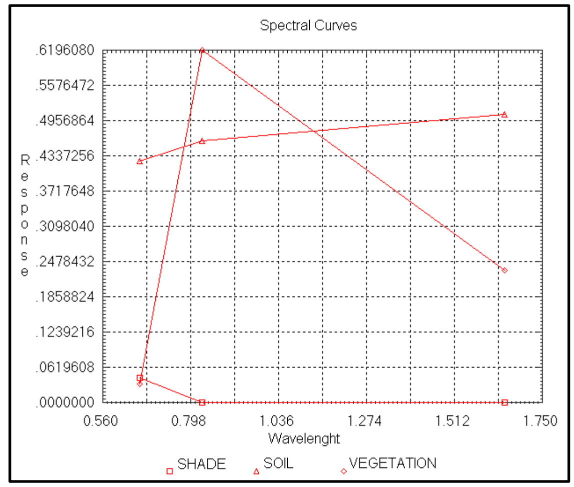
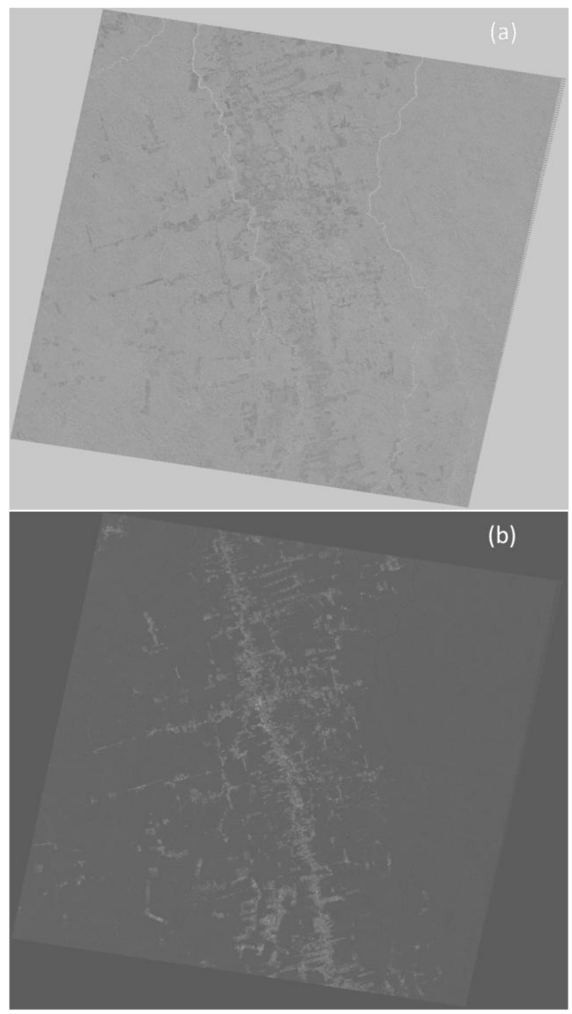


Fig. 5. Spectral behavior of the endmembers used to make the SLMM.

Using these endmembers, we generate the SLMM for each image. Figure 6 shows the fraction images generated by the SLMM for the 2007 image.



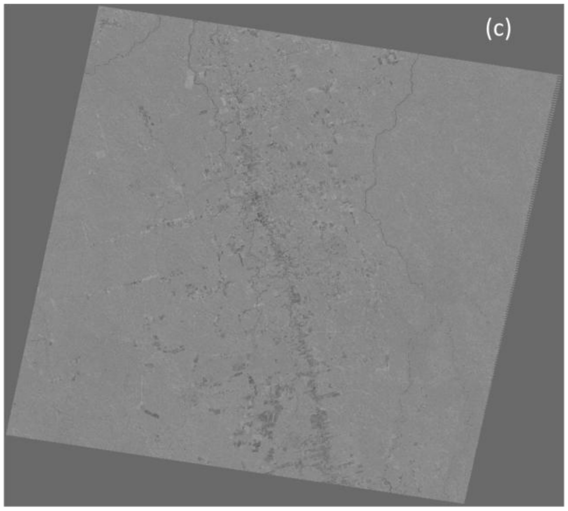


Fig. 6. Fraction images from SLMM made from 2007 image. (a)Shade fraction image; (b) Soil fraction image; (c) Vegetation fraction image.

C. Second phase: Generating the map changes

After making the SLMM, we have to segment and classify the fraction images to generate the change maps. The Figure 7 shows a flowchart illustrating the steps followed in this phase.

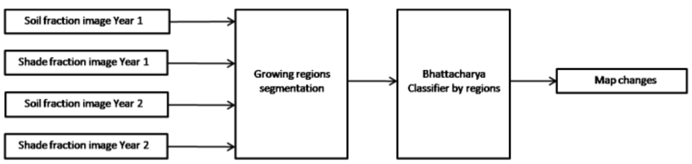


Fig. 7. Flowchart illustrating the steps followed to generate the change maps.

To make these change maps, we have been based in a part of the idea presented by [22] that in a RGB composition of multitemporal shade fraction images we have highlights the changes occurred between the times considered. Figure 8 (a) shows a composition RGB of an area of 2005 and 2007 shade fraction images used in this work. The red areas are the areas that were deforested between 2005 and 2007. Figure 8 (b) shows a composition RGB of the soil fraction image of the same area. As we can see, the soil fraction images highlight the exposed soil. In the red areas, the soil was more exposed in 2005 than in 2007, and in the cyan areas the soil was more exposed in 2007 than in 2005. This information can help identify, for example, the regrowth areas, which not have as much shade as the forest canopy and not have as much exposed soil as the deforested areas.

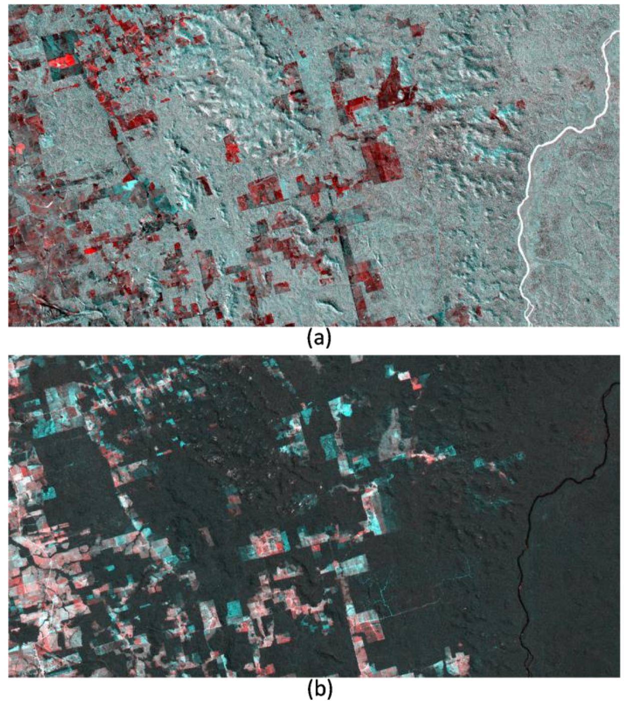


Fig. 8. RGB composition of an area of 2005 and 2007 (a) shade fraction images; and (b) soil fraction images; (Red = 2005; Green and blue = 2007).

One of the purposes of this work is to identify not only the areas that were deforested, but the regrowth areas too. So, if we use only the shade fraction, we have confusion in some areas. Thus, were used as parameter to the segmenter algorithm and to the classifier algorithm the shade fraction and the soil fraction images together.

The procedure used to the image segmentation was based on the “region growing” algorithm, where a region is a set of homogeneous pixels connected according their properties [34]. A detailed description of this algorithm can be found in [2]. This algorithm was applied to the shade and soil fractions images of the two years when making each map (2001-2005, 2005-2007 and 2001-2007), and the proportion, spatial and contextual attributes of the segments were acquired to be used in the classification procedure. We have to insert two parameter values to the segmentation algorithm:

(1) *Similarity*: the Euclidean distance between the mean digital numbers in the attributes space of two regions under which two regions are grouped together [24]; in this case, we consider a 4-Dimentional space, because we have 4 images used in the segmentation process. Thus, the similarity is the minimum distance between two regions in the attributes space of these formed by these four images. In this work, we used the value of similarity as 8, as proposed by [23].
(2) *Area*: minimum area to be considered as region, defined in number of pixels [24].

In this work, we used the values of similarity and area as 8 and 16, as used in the PRODES methodology (available in http://www.obt.inpe.br/prodes/metodologia.pdf).

After the segmentation procedure, we have chosen some samples of each interest class, which were used to training the supervised region-based classifier algorithm. This algorithm, which is based on the Bhattacharya distance, uses the training samples to estimate the probability density function of the classes pointed in the training process. After this, evaluates, for each region, the Bhattacharya distance between the classes [17], as shown in the equation 2 [16],

$$B(p_i, p_j) = \frac{1}{2}(m_1, m_2)^T \sum(m_i, m_j) + \frac{1}{2}\ln\frac{|\sum(m_i, m_j)|}{|\sum i|^{\frac{1}{2}}|\sum j|^{\frac{1}{2}}} \quad (2)$$

where B is the Bhattacharya distance; p_i and p_j are the pixels in the classes i and j; m_i and m_j are the means of the classes i and j; T is the transposed matrix; and i and j are the classes within the context. The Bhattacharya algorithm needs to receive a threshold similarity value, which in this work we used as 90%. This value was defined through some empirical tests.

D. *Third Phase: Image data mining*

The deforestation regions are represented by objects that are called landscape objects, according to [26]. A landscape object is a structure detected in remote sensing image using an image segmentation algorithm. We characterize the landscape objects by spatial patterns[1] in cells of analysis, using several landscape metrics.

The cells containing the landscape objects are trained using the specialist expertise. This set is used to generate a classification model which can be used to classify the cells in the map.

One of the objectives of this work is to evaluate the stability of the geometric landscape metrics to characterize the objects when considering different spatial resolution and different deforestation patterns in the Amazon. Then, an initial concern was to define the size of the cell size of the landscape to be studied, hoping to avoid patterns confusion. Were generated scenarios with a resolution of 2km and 10km (Figure 9) but only the second one was selected.

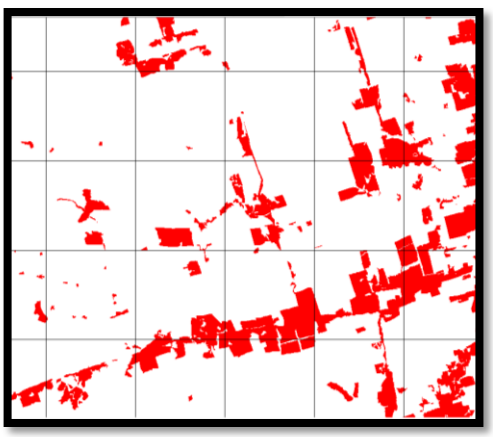


Fig. 9. Landscape objects and the Cellular grid

[1] Spatial Patterns – the geometric structures extracted from the images using techniques for feature extraction, segmentation, and image classification. They are identified and labeled according to a typology that expresses their semantics. Examples of such patterns include corridor-like regions and regular-shaped polygons representing patterns of the mined data [26].

To see where changes have occurred and characterize the occupation patterns according to the dynamics and trajectories, the changing maps obtained by SMM were associated with the patterns map using cellular representation and Cells Filling plug-in2 for TerraView. At the end were obtained maps of land cover changing (2000, 2004 and 2007), the trajectories of occupation patterns (2000, 2004 and 2007) and analysis of change in land cover for the mapped patterns to the same periods.

E. *Landscape Metrics*

Patch metrics from landscape ecology were used to select the attributes that discriminate the different types of land change patches. Landscape ecology theory defines a landscape as an area of terrain containing a mosaic of patches [32]. It considers that land patterns strongly control ecological processes and proposes metrics for the geometrical and spatial properties of patches [4]. Landscape objects can be described by many landscape metrics, from a simple perimeter to a complex calculation of a contiguity index.

Table I describes eight geometric landscape metrics used. To make possible the landscape metrics extraction, were used as input the set of geometric representation, obtained from PRODES deforestation thematic maps.

[2] Plugin for filling the attributes of cellular layers created by TerraView application, based on vectorial and matricial input data. Additional information can be found in <http://www.dpi.inpe.br/~anapaula/plugin_celulas/>.

TABLE I
DEFINED TOPOLOGY

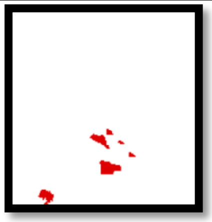
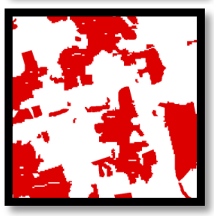
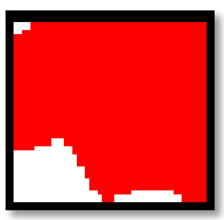
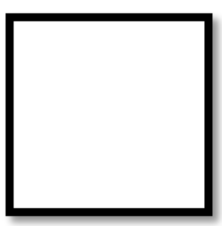
Metric	Type	Description	Semantic	Actors
	Diffuse	- Small patches - Isolated patches -Low to medium density -Uniform distribution	- Primary occupation - Spontaneous occupation -Smallholders (Unplanned) - Riverside occupation (next to rivers)	- Small farmers and/or family household
	Linear	- Elongated and continuous spots - Sparsely -Unidirectional	- Beginning of occupation along the road - spontaneous Occupation (rarely planned) - Smallholders	- Small household
	Geometric	- Regular geometric shape - Low to medium density - Medium and large isolated patches	- Initial stages of occupation - Medium and Large Farmers	- Large farmers
	Multidirectional	- Small to medium spots that have joined - diversified shape (irregular, geometric, linear) - Medium to high density - Multidirectional	- Occupation expanding, initially spontaneous - There is the possibility of land concentration - Small and medium farmers	- Small settlers
	Consolidated	- Large and continuous spots - Low density and small areas of remaining forest - compact and continuous spots	- Advanced stages of occupation - Land concentration, small, medium and large farmers - Exhaustion forest - Occupation consolidated	- Large farmers - Urban Sites
	Forest	no deforestation polygons	There are no records of human occupation	- No actors

TABLE II
LANDSCAPE METRICS USED

Metric	Purpose
Class Area (CA)	Calculates the total area of deforestation patches of a landscape cell.
Percent LAND (%LAND)	Calculates the percentage of area currently deforested landscape cell.
Patch Density (PD)	Number of deforestation patches within the cell per landscape km ².
Mean Patch Size (MPS)	Calculates the average size of deforestation patches of the landscape.
Landscape Shape Index (LSI)	Calculates the complexity of the deforestation patches form within the cell based on their areas and perimeters
Mean Shape Index (MSI)	Calculates the average complexity of the deforestation patches form within the cell based on their areas and perimeters
Area Weighted Mean Shape Index (AWMSI)	Calculates the average complexity of the deforestation patches form weighted by their own areas.
Mean Patch Fractal Dimension (MPFD)	Calculate the average complexity of the deforestation patches form using logarithms.

F. Training and Classification

During the training process, the specialist associates some samples to their equivalent classes. As any training process, the number of samples of each class and its quality will determine the classification success or fail. The GeoDMA training module creates classification models by using landscape metrics extracted in landscape metrics extraction section. There is also an alternative to perform the training stage by selecting only some landscape metrics. To select only the more representative attributes, scatter plots are generated with the all extracted attributes. So the analyst is able to choose the more representative ones at the final classification.

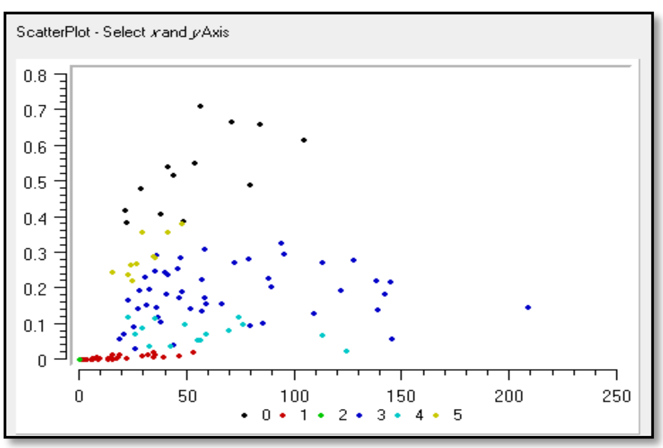


Fig. 10. Scatter plot showing the separability of each attribute

Using the classification model defined in the last step, each landscape cell is associated to only one class by a decision tree [28]. Figure 11 exemplifies how the decision tree is built by the structural classifier.

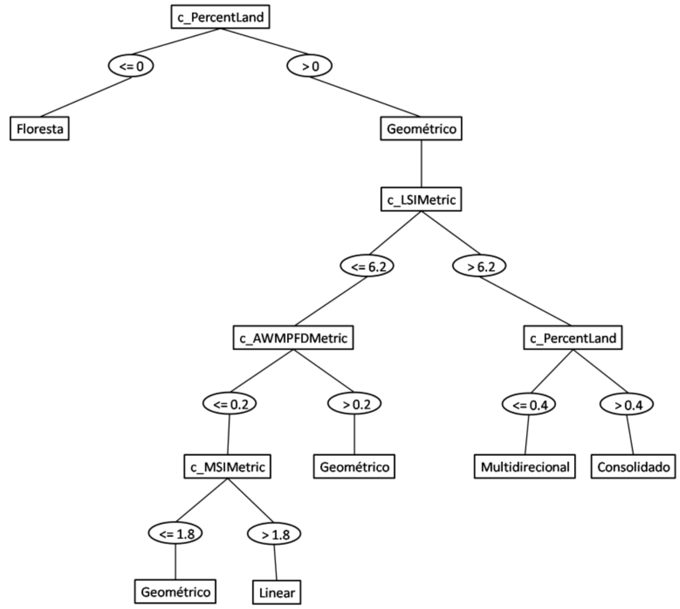


Fig. 11. Decision tree generated for the year 2007

All the methodological process of classifying the landscape cells is describe at the following flow (Figure 12)

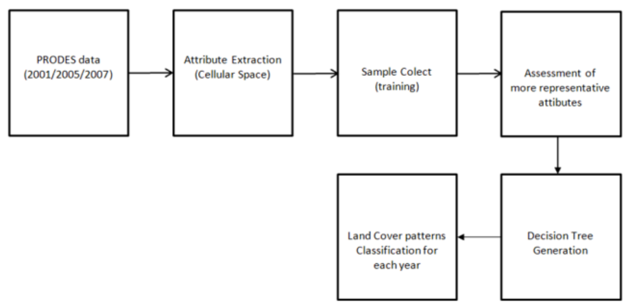


Fig. 12. Flowchart illustrating the steps followed to generate the land cover patterns maps

IV. Results

In an overview of the situation during the years studied, 44.4% of the cells showed some degree of change in land cove (Figure 13). This is a high value, considering the short period of time analyzed.

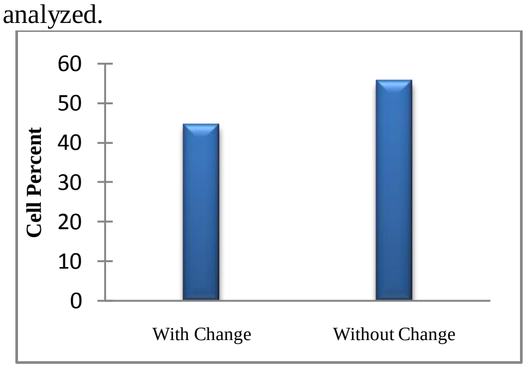


Fig. 13. Percentage of cells with land cover change between 2001 and 2007

During the period of analysis, the dominant pattern of deforestation was the diffuse, corresponding to small areas, characteristics of initial occupation (Table III and Figure 14). It is also observed an equal distribution in the percentage of cells with the other patterns.

TABLE III
EVOLUTION OF EACH LAND COVER PATTERN

Land Cover Pattern	2001	2005	2007
Forest	55.526	39.474	38.421
Diffuse	24.737	25.526	20.263
Consolidated	0.526	2.368	2.368
Geometric	6.842	18.684	20.263
Linear	6.053	6.316	3.684
Multidirectional	6.316	7.632	15.000

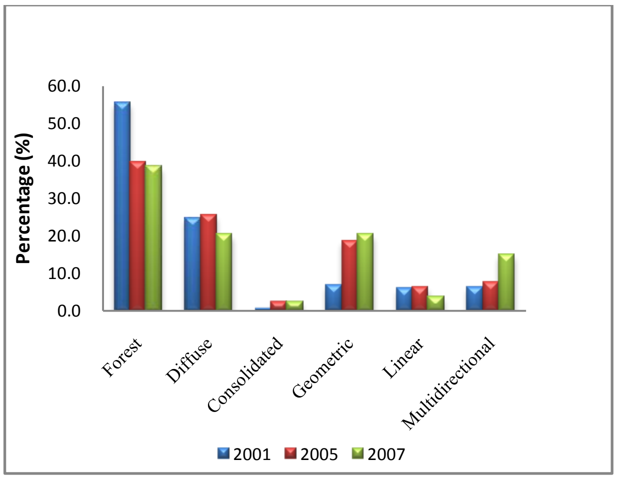


Fig. 14. Percentage of cells with each land cover pattern between the years 2001 and 2007

The consolidated pattern, related to advanced stages of occupation, has the minimum values, even with a progressive increase over the years. This is due to intense recent occupation of the study area, which does not yet allow the ideal conditions to identify these patterns in cells with 10 kilometers away.

In general, as expected, the percentage of the landscape of forest decreases significantly with the largest decrease between 2001 and 2005 as shown in Figure 15. During the years 2005 to 2007, the impetus of deforestation has somewhat stabilized, compared with previous years.

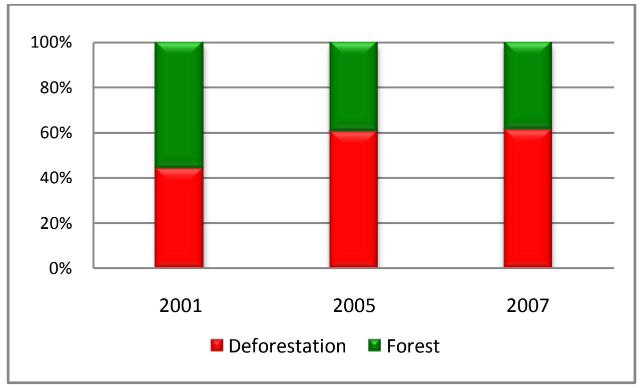


Fig. 15. Percentage of cells with deforestation presence

The geometric pattern grew more than three times between 2001 and 2007, which means an increase in the existence of large farms, coming from the merging of smaller properties. The main paths for the emergence of geometric patterns can be seen in Table IV:

TABLE IV
GEOMETRIC PATTERN MAIN TRAJECTORIES

Classes 2001	Classes 2005	Classes 2007
Diffuse	Geometric	Geometric
Forest	Diffuse	Geometric
Forest	Geometric	Geometric
Diffuse	Linear	Geometric
Diffuse	Geometric	Geometric
Forest	Linear	Geometric

The increased amount of cells with multidirectional pattern is mainly the result of the increase in diffuse patterns in the cell. However, the union of geometric patterns with other geometric and diffuse with geometrical also plays a part in this phenomenon.

Linear patterns were higher at 2005 had a decrease during the 2005-2007 period and are associated to secondary road construction and roadside farm clearings.

The deforestation patterns show a trend towards land concentration, where large farms dominate over small settlements It shows that the resulting spatial arrangement has small farms and family households concentrated along roads, and large and medium farms arranged near secondary roads and in remote places.

All these analyses are based on Figure 16, that shows the results of the cells classification for each year. Were collected about 100 samples for each year, with 94.4% of sample accuracy average on classification, what represents a high precision in classification.

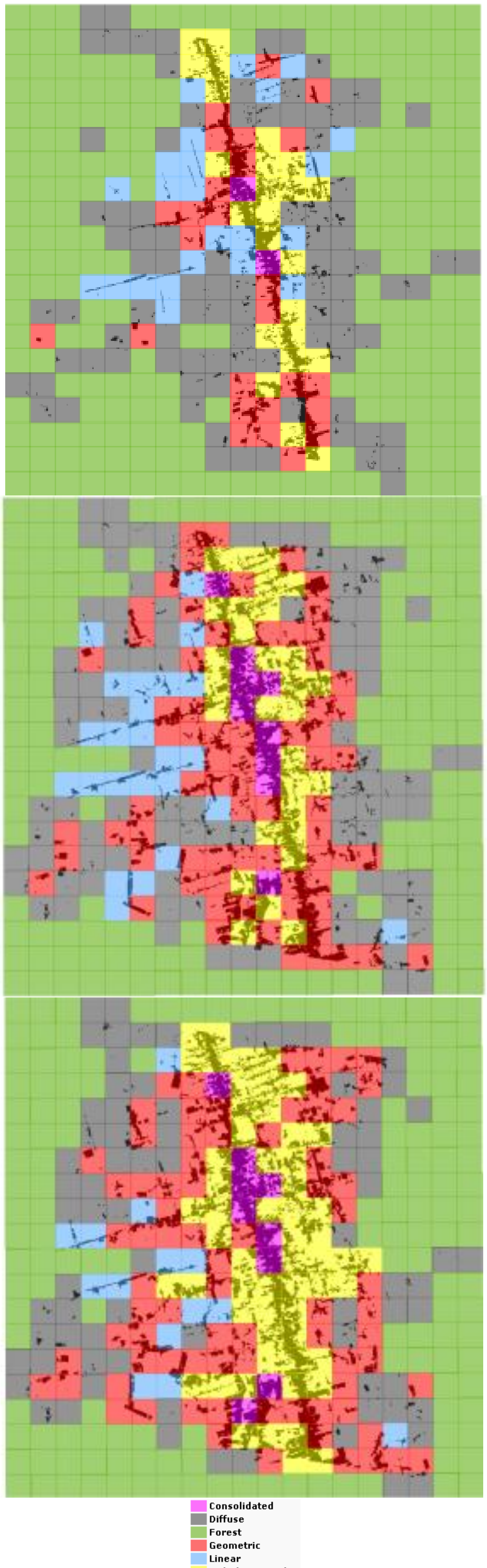


Fig. 16. Deforestation Patterns Evolution by year (2001, 2005 and 2007)

Figure 17 shows the change maps produced through the segmentation and classification of the synthetic bands produced by the SLMM.

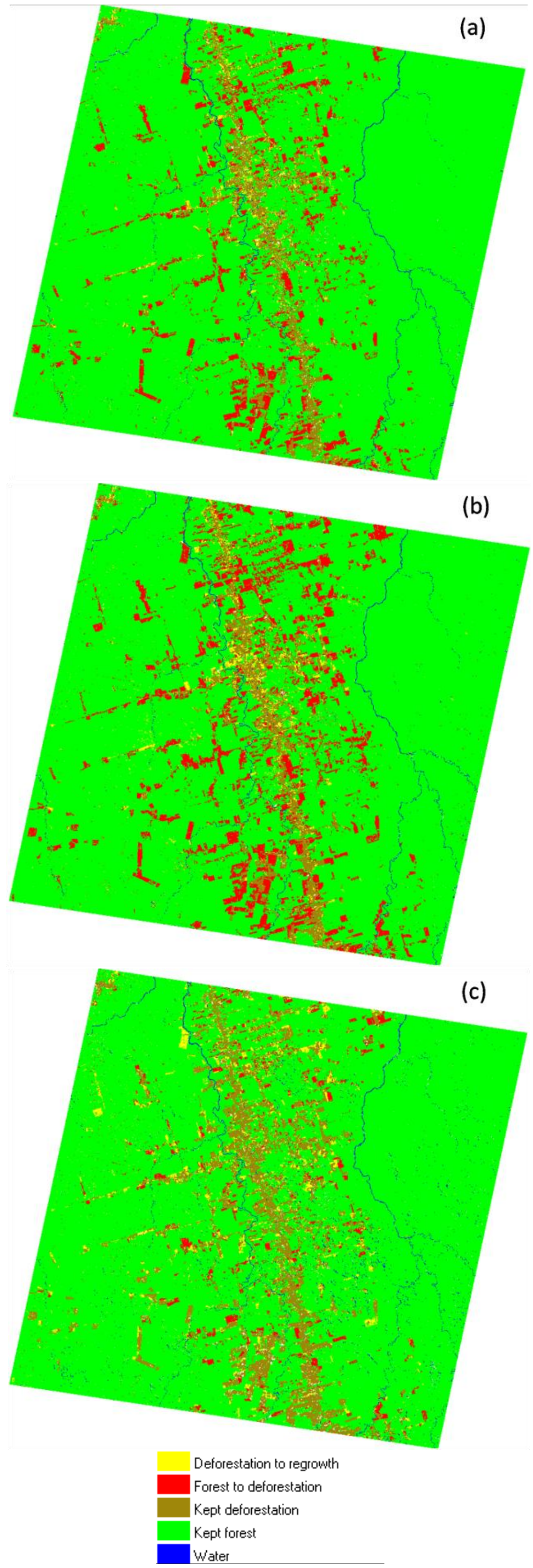


Fig. 17. Change maps generated through the segmentation and classification of the soil and shade fractions images. (a) 2001-2005 map; (b) 2001-2007 map; (c) 2005-2007 map.

As we can see in these maps and in the graphic presented in the Figure 18, the deforested area grew more between 2001 and 2005 than between 2005 and 2007, when we had a growth of the regrowth areas. These results show that the human actions in the region had a fast growth between 2001 and 2005, with a break in this growth after 2005. Such braking, after 2005, can be seen through the large amount of regrowth areas that appears between 2005 and 2007, that shows the growth of the abandon in this period.

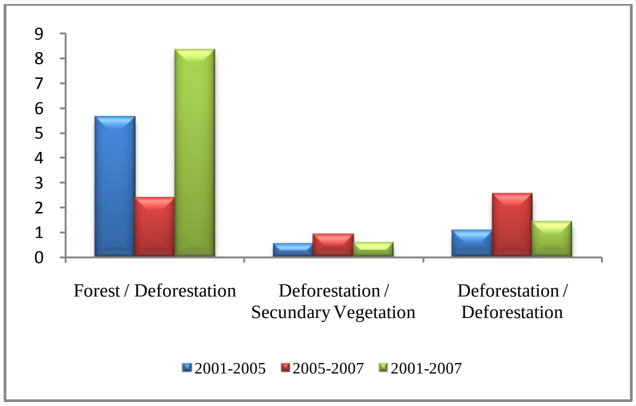


Fig. 18. Percentage of area of each class

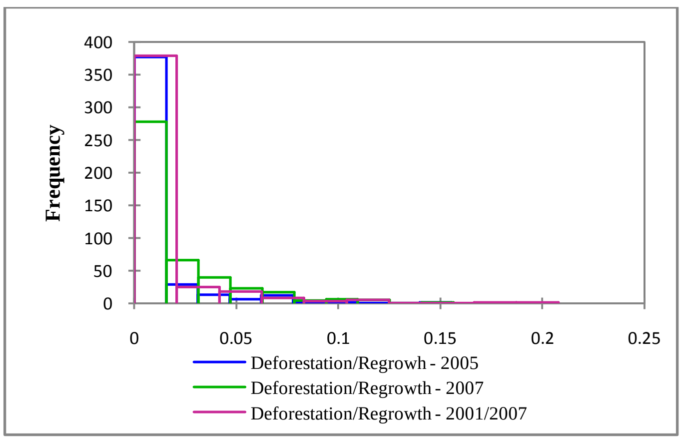


Fig. 19. Histogram – Percentage of "Deforestation to Regrowth" class within each cell (All years)

The histogram of the Figure 19 shows percentege of "deforastation to regrowth" class inside the cells. Its possible to observe that at the year 2005, great part of the cells contains less than 2% of this class. The scenario changes at the next period (2007), when the frequency of higher percentage values inscrease, what indicates tha a great number of deforested areas have been abandoned. The Table V demonstrates the variation of the average percentege of deforestation within the cells.

TABLE V
AVERAGE PERCENTAGE OF "DEFORESTATION TO REGROWTH" CLASS WITHIN EACH CELL

Class	Average
Deforestation to Regrowh - 2005	0.007
Deforestation to Regrowth - 2007	0.018
Deforestation to Regrowth - 2001/2007	0.010

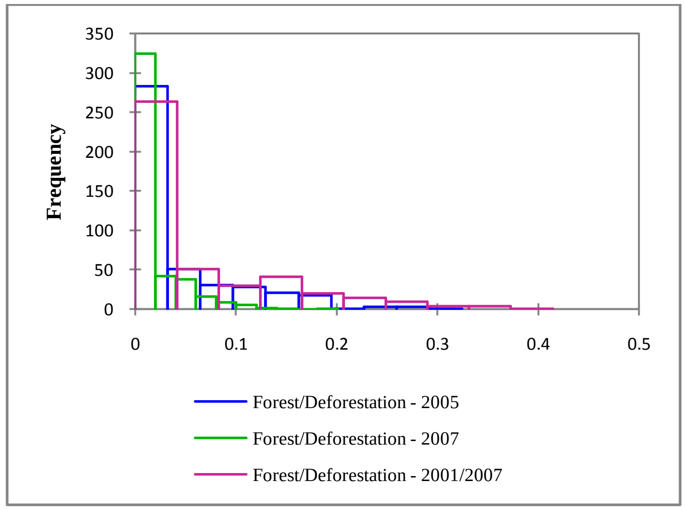


Fig. 20. Histogram – Percentage of "Forest to deforestation" class within cells (All years)

By the same way, the percentage of Forest/Deforestation within the cells has a huge increase during the first period of analyse (Figure 20 and Table VI), followed by a decrease at the rate of deforestation in the site at the next period.

TABLE VI
AVERAGE PERCENTAGE OF "FOREST TO DEFORESTATION" CLASS WITHIN EACH CELL

Class	Average
Forest to Deforestation - 2005	0.039
Forest to Deforestation - 2007	0.017
Forest to Deforestation - 2001/2007	0.058

Its important to measure the relationship between the land cover change and the evolution of the land cover patterns. Table VII shows the percentage of cells with presence of Deforestation/Regrowth. Most of Deforestation/Regrowth is present in cells classified as Geometric, Diffuse and Multidirectional.

TABLE VII
PERCENTAGE OF CELLS WITH "DEFORESTATION TO REGROWTH BY LAND PATTERNS

Class	2001 - 2005	2005 - 2007	2001 - 2007
Consolidated	7.48	4.86	7.02
Diffuse	26.17	25.41	20.18
Geometric	35.51	33.51	29.82
Linear	7.48	5.41	3.51
Multidirectional	23.36	30.81	39.47

About the average percentage of "Deforestation to Regrowth" within the cell (Figure 21), the higher values are present at Consolidated, Geometric and Multidirectional. The percentege os this class is lower in diffuse cells.

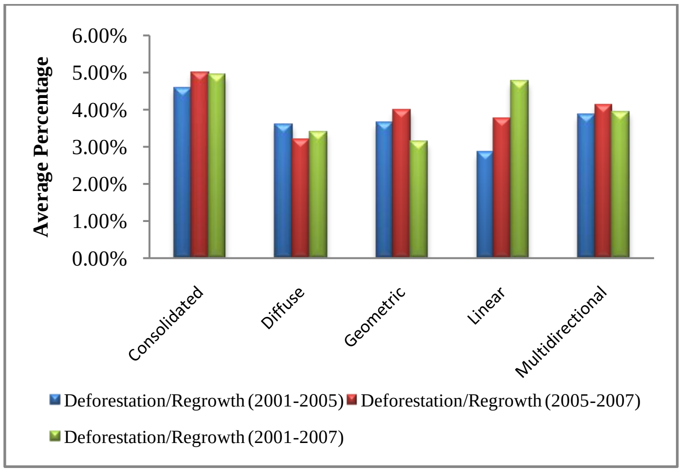


Fig. 21. Average percentage of "Deforestation to regrowth" class within the cells

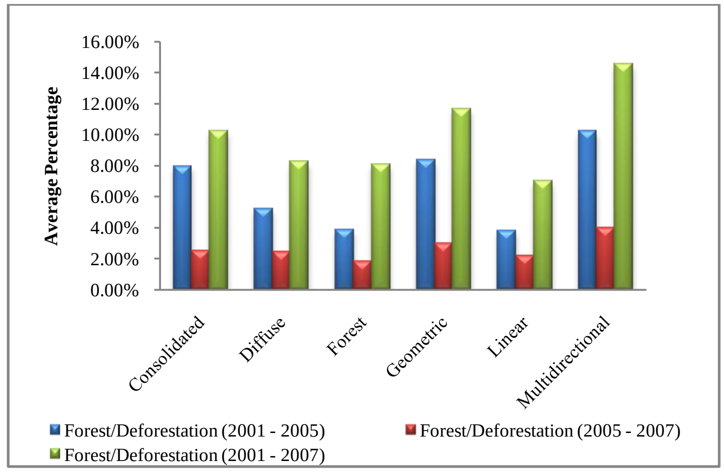


Fig. 22. Average percentage of Forest/Deforastation class within cell

All these data indicates an increase of regrowht areas during the period of 2005-2007. Regrowth dynamics are closely correlated to factors such as the way the forest was cut and burnt; land used in diferent crops and/or pasture; the government policies applied in the area; the length of use, the tecnology used; the presence or absence of surround forest vegetation, the size and shape of the area; the soil´s fertility; and the presence or absence of species whose dispersion patterns realies on wind and/or animals that frequent fallows [15][19]. Also, a long-run implication of a dominant emphasis on annual crops is that a larger area is deforested quickly and a secondary vegetation may cover a much larger area of the farm property [15].

As already noted throughout this work, Novo Progresso experienced a high level of deforestation during the period. The expansion of more rapacious deforestation occurred between 2001 and 2005, with a considerable drop between 2005 and 2007.

The more voracious deforestation expansion occurred between 2001 and 2005, with a significant fall between 2005 and 2007. The higher values of average percentage of Forest/Deforestation that occurred until 2005 were present mainly inside Multidirectional but also in Consolidated and Geometric cells. After the year 2005, we observed a decrease of deforestation, with similar numbers for all land use patterns (Figure 22).

Its interesting that during the first period, as revealed the data, we have a intensive level of deforestation, and a low presence of regrowth. At the second period (2005-2007), the deforestation impetuosity decrease, and the regrowth raises.

V. Conclusions

One important aspect to be considered in the analysis of patterns of deforestation and relate them to processes of change in land use is the fact that the processes are dynamic and evolve over time. If patterns of deforestation are analyzed using data from a single date, the observation of the process is severely compromised, because the patterns tend to be the result of a combination of processes of different periods, actors and/or strategies to use the soil.

One limitation with the structural classification refers to the amount and quality of landscape objects used to generate the model, because if the number of samples or its descriptive ability to distinguish these different patterns is not appropriate, the decision tree generated will classify incorrectly many cells.

Some questions if answered in future work, can greatly contribute to the understanding of the dynamics of deforestation and regrowth in the area. They are: might the increase in secondary vegetation succession represent a cyclical fallow management strategy of the farmers? Is this observed process a secular trend possibly reflecting length-of-time trajectories of land use associated with the development of family farms?

This methodology can greatly increase the chances to detect, assess and reduce the high deforestation rate of Amazon, and can also contribute for a better understanding of processes of frontier expansion/consolidation and the dynamics of use and occupation of this territory.

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