ASSESSMENT OF BIOPHYSICAL STRUCTURE OF RIPARIAN ZONES BASED ON SEGMENTATION METHOD, SPATIAL KNOWLEDGE AND TEXTURE ANALYSIS

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ABSTRACT:

Riparian forests play an important role in the ecological balance of river ecosystems. Given the narrow nature of these environments, medium resolution sensors such as Landsat have limited use. Conversely, products obtained from high-resolution images, such as Ikonos-2, have wide applications in riparian forest studies. The objective of this article is to describe a methodology for delineating riparian areas and extracting their biophysical parameters from an Ikonos scene. The methodology is divided into two stages. Firstly, the image is segmented into a riparian forest class and non-riparian classes using a segmentation algorithm and a river-based buffer. The segmentation package MAGIC (Map Guide Image Classification) was used to separate the riparian forest zones from the rest. In the second phase, texture features derived the co-occurrence matrix were used to estimate the biophysical parameters of the riparian forest. Allometric measurements were made in 70 plots of riparian area from both sides of the Pandeiros River, located in Northern Minas Gerais, Brazil. These plots were used to calibrate and validate our models based on texture parameters. The forest structure variables included height, diameter at breast height, basal area, stem density, volume, canopy openness and leaf area index which were acquired by direct measurements in the field. The results show that MAGIC segmented the riparian environment with an accuracy of more than 85% when compared with the map obtained by visual image interpretation. The best results for modeling riparian structure were obtained respectively for volume and basal area (R^2=0.66 and R^2=0.61) using Angular Second Moment, Entropy, Infrared band, distance analysis of four pixels and a window of 11×11 pixels.

RÉSUMÉ:

Les forêts riveraines jouent un rôle important dans l'équilibre écologique des écosystèmes fluviaux. Compte tenu de l'étroitesse de ces milieux, les capteurs à résolution moyenne comme LANDSAT ont un usage limité. Par compte, les produits obtenus à partir d'images haute résolution, comme Ikonos-2, ont d’amples applications pour l’études des forêts riveraines. L'objectif de cet article consiste à décrire une méthodologie pour la délimitation des zones riveraines et l'extraction de leurs paramètres biophysiques à partir d'une image Ikonos. La méthodologie est divisée en deux étapes. Tout d'abord l'image est segmentée en classe de forêt riveraine et le reste des classe non-riveraines en utilisant un algorithme de segmentation et une zone tamponée basée sur la rivière. Le programme de segmentation MAGIC (*Map Guide Image Classification*) a été utilisé pour séparer les zones de forêt riveraines du reste. Dans la deuxième phase, des images de texture dérivées de la matrice de cooccurrence ont été utilisés pour estimer les paramètres biophysiques de la forêt riveraine. Des mesures allométriques ont été effectuées dans 70 parcelles de la zone riveraine sur les deux rives de la rivière Pandeiros, situé dans le nord de Minas Gerais, au Brésil. Ces parcelles ont été utilisées pour créer et valider les modèles en fonction des paramètres de texture. Les variables structurelles de la forêt inclus la hauteur, le diamètre à hauteur de poitrine, la surface basale, le volume, la densité des troncs, l'indice de surface foliaire et l’ouverture de la canopée, qui ont été acquis par des mesures directes sur le terrain. Les résultats montrent que MAGIC a segmenté le milieu riverain avec une précision de plus de 85% par rapport à la carte obtenue par interprétation visuelle. Les meilleurs résultats pour la modélisation de la structure de la forêt riveraine ont été obtenus respectivement pour le volume et la surface basale (R^2 = 0,66 et R^2 = 0,61) en utilisant le Second Moment Angulaire, l’Entropie, l’infra-rouge, une distance d’analyse de quatre pixels et une fenêtre de 11×11 pixels.

1. INTRODUCTION

Riparian zones can be defined as the interface between aquatic and terrestrial ecosystems that occurs along rivers and creeks (Johansen and Phinn, 2006a). Riparian zones can extend to the limit of river margin when flooded, and its vegetation plays an important role in the ecological balance of river ecosystems (Muller, 1997).

The ecological functions of riparian forest include: nutrients supply from litter fall, river bank stability, shade to stabilize water temperature, natural filtering of water pollutants, and large woody debris for stream channel development (LWRRDC, 1999a; Congalton *et al.*, 2002). In addition to these functions, riparian vegetation acts as ecological corridors allowing the flow of fauna communities, especially in fragmented landscapes (Congalton *et al.*, 2002).

In Brazil, most of riparian zones are impacted by logging to make charcoal, agriculture at the margins, livestock and others predatory human activities. The effective inventory of these ecosystems stands as an important tool for making public policy. In this context, remote sensing and image processing techniques allow the rapid and low-cost production of maps (Jensen, 2007).

However, making riparian zones inventories using remote sensing are not an easy task given its narrow extends (Muller,

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1997). Mapping these areas and their biophysical parameters is a challenge that has motivated many authors in remote sensing (Nagler *et al.*, 2001; CSIRO, 2003; Johansen and Phinn, 2006b). Previous studies have showed that images with medium spatial resolution (Landsat-TM and ETM) suffer shortcomings for mapping narrow environments (< 30m), such as riparian zones (Congalton *et al.*, 2002; Johansen and Phinn, 2006a). Moreover, the alternative to use high-resolution image (Ikonos, Quickbird), has become affordable in recent years. The most commonly applied approach to map riparian areas using high spatial resolution is image classification. Studies by Davis *et al.* (2002) and Johansen and Phinn (2006a) showed a significant gain of accuracy in classification of riparian zones when using texture parameters in the process.

Taking advantage of the spatial knowledge that the riparian vegetation accompanies the river, buffer zones can be used as a way of optimizing the image processing. This procedure was carried out successfully to map palm swamps (Maillard *et. al.*, 2008). Even though high resolution image data proved valuable for delineating riparian zones, traditional information extraction methods like threshold and classification (e.g. maximum likelihood, minimum distance) offer low accuracy. Conversely, image segmentation using Markov random fields (MRF) has produced promising results in a variety of applications, such as image segmentation and restoration (Tso and Mather, 2001). But to assess the ecological values of riparian forests, the mere classification is insufficient and biophysical parameters are often needed.

The objective of this article is to describe a methodology for delineating riparian areas and extract their biophysical parameters from an Ikonos scene. The proposed methodology includes the following stages: (i) classification of the image in two classes: riparian zone and non-riparian zone using 50 meters buffer, (ii) acquisition of texture features from riparian zones segments, and (iii) auto-correlation of visible, near-infrared and texture bands with allometric measurements data from 70 field plots. The correlation aims at elaborating explanatory models of vegetation structure.

1.1 Mapping Riparian Forest from Remote Sensing Data

A study using Landsat-5 and photo interpretation, for mapping riparian forest in the Yaquina River - Oregon/USA, showed a success ratio of only 30% between satellite images and photo interpretations (Congalton *et al.*, 2002). In another study, Johansen and Phinn (2006a) showed that the width of riparian zones is a limiting factor for their identification through products of medium spatial resolution, such as Landsat series. They pointed out that only riparian area upper than 50m could be accurately identified by Landsat-7 ETM+. Muller (1997) emphasizes the importance to develop new remote sensing methods for mapping riparian vegetation along rivers.

In a study by Davis *et al.* (2002), the analysis of high-resolution aerial photographs (resolution between 11 and 100 cm) obtained overall accuracy of 75% to classify riparian areas using maximum likelihood classification and image texture. Texture features increased the accuracy by 20-30% in almost every case. Johansen and Phinn (2006b) used an Ikonos image to classify not only the riparian zone, but also the biophysical parameters and species of a riparian savannah forest in Australia. The authors highlighted the need to use high-resolution imagery and texture parameters for mapping riparian vegetation structures. They used the following forest parameters: canopy percentage foliage cover, leaf area index, tree crown size, tree height, stem diameter at breast height, tree species, and riparian zone width. In addition to the four bands of the Ikonos image (blue, green, red and near-infrared), eight vegetation index and measurements of texture (contrast, dissimilarity, entropy, homogeneity and variance) were used. Results showed an overall accuracy of 55% for species classification and a determination of 86% for the canopy percentage foliage using 19x19 pixels texture analysis window in the NDVI band.

Alencar-Silva and Maillard (2009) compared two different methods of classification for palm swamps in an Ikonos image: traditional per-pixel classification and region-based segmentation and classification using MAGIC (a program based on Markov Random Fields). Results have shown that MAGIC obtained better results when compared with tradition classification. MAGIC was especially good in removing the salt and pepper effect on the classified image.

1.2 Study Area

The study area is situated in the margins of the Pandeiros River in Northern Minas Gerais, Brazil, an environmental protection area (Figure 2).

The Pandeiros River is an affluent of São Francisco River, the third largest watershed of Brazil. The total area of the Pandeiros' watershed is 3921.00 km^2 and its elevation varies from 450 m to 850 m. The study site is 1.2 km^2 along a slightly meandering stretch of river (Figure 3). The marginally climate is semiarid with about 900 mm of precipitation and an average temperature of over 25˚C. Precipitation varies from 124 mm per month between October and April to less than 2 mm between May and September. A land use map of the region was produce from a single Landsat-7 scene acquired in August 2009. The classes and their respective area are presented in Table 1.

Class	% of catchment
Open Water	0.33
Dry Forest	1.08
Savannah	48.85
Wetland	3.09
Plantation / Savannah Regeneration	43.61
Rock	0.12
Bare Soil	2.92

Table 1: Land-use table area of Pandeiros River

With about 44% of plantation or degraded areas, the Pandeiros watershed has been strongly impacted by human activities. The Pandeiros also hosts the largest wetland complex of the State of Minas Gerais where several species of fish bird species reproduce, some of which are rare, endemic and threatened (Biodiversitas, 2005).

Figure 3 shows the Ikonos scene of the entire study site in true-colour composition. The green areas located along the river and on the bottom right of the figure correspond to riparian forest and savannah formations, respectively. The zones in brown represent herbaceous areas. Palm swamps, characterised by a specific texture, can be seen on the left hand side of the image. The others light tone areas are bare soil. On the Ikonos scene riparian forest often appears similar to wooded savannah formation. To avoid confusion, a river buffer of 50 m was applied to the image to eliminate savannah from the segmentation process. Figure 4 shows details of the riparian formations.

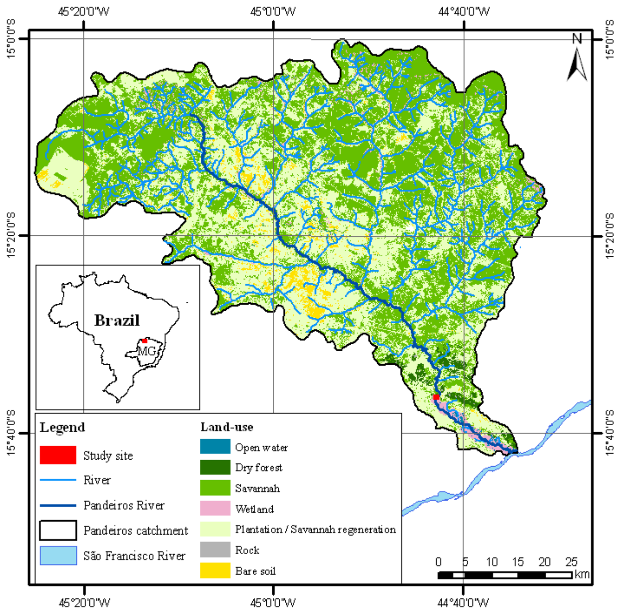

Figure 2: Land-use map and location of study area.

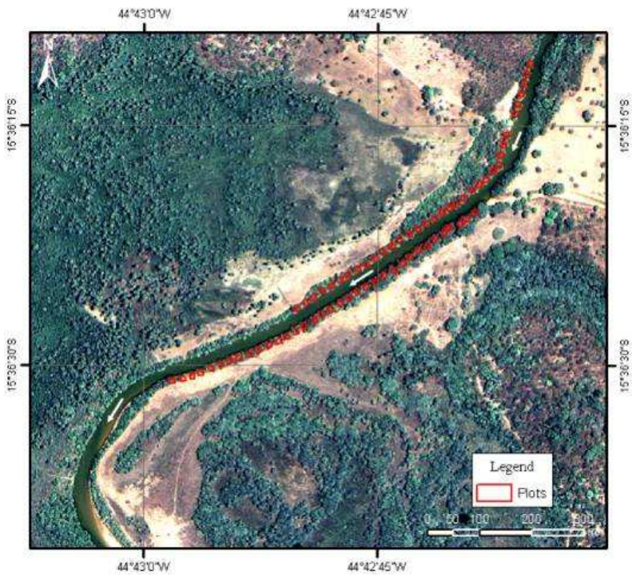

Figure 3: Location of entire study site with the 70 plots, 35 on each side.

(a) (b)

Figure 4: Riparian forest of study site: (a) aerial view and (b) ground view (photos by Thais Amaral and Ivan Seixas – 04/2010).

2. MATERIAL AND METHODS

2.1 Fieldwork

The first field campaign (February 2008) was carried out to locate and collect allometric data. The group from the “Ecology and Plant Propagation Laboratory” (UNIMONTES University) demarcated 70 ten by ten meter plots, along both banks of the Pandeiros River. The plots were at a distance of 3 meters from the Pandeiros River and are always oriented parallel to the Pandeiros River. A 10 m gap is always left between each plot except when the area was too degraded to be considered as riparian forest. Plots 1-35 are located on the left bank while plots 36-70 on the right bank. A total of 7000 m^2 was surveyed.

The allometric measurements of tree height and stem circumference at breast height (CBH) were taken for all trees within each plot. Shrubs and grasses were not considered. Hemispherical photographs were taken in each plot for later computation of canopy openness and leaf area index. Altogether seven allometric measurements were produced: (i) tree height, (ii) stem diameter at breast height (DBH), (iii) basal area, (iv) volume, (v) plot density, (vi) canopy openness and (vii) leaf area index (LAI).

The second and third fieldworks were conducted in January 2009 and April 2010, respectively, to obtain ground control points (GCPs). A L1 geodetic GPS was employed to acquire GCPs, which were used for rectifying the Ikonos scene and precisely locating each plot.

2.2 Image Acquisition and Pre-processing

The Ikonos image used in this study was provided by the Forestry Institute of Minas Gerais. It was obtained with their multispectral bands (red, green and blue = 4m) and panchromatic (1m) already fused to a spatial resolution of 1 m. The data, acquired in September 2007 during the dry season showed a good visibility with no cloud cover (Figure 3). The image was registered to a UTM grid coordinate by bilinear interpolation with a root mean square error (RMSE) less than 1 meter. No atmospheric correction was applied to the image.

2.3 Data Processing

Data processing involved four steps: 1) cartographic modelling, 2) image segmentation, 3) texture feature calculation and 4) statistical modelling.

2.3.1 Cartographic Modelling

The cartographic modelling consisted in using spatial knowledge to “limit” the search to areas having a strong probability of belonging to riparian vegetation (Maillard *et. al.*, 2008). This method avoids confusion between vegetation classes present in the study area, such as: palm swamps and savannah. To do so, the hydrographic network was digitized, overlaid on the image and used to build a buffer of 50 m (knowing the riparian vegetation width in the study site is well below that value). The buffer was used to mask parts of the image that fell outside of it. The Ikonos image and the mask are then fed to the segmentation algorithm which is instructed to find two classes: riparian vegetation e non-riparian vegetation.

2.3.2 Image Segmentation

The riparian vegetation was first visually interpreted in order to validate the results of the segmentation. The MAGIC program (Clausi *et al.*, 2009) was chosen to segment the image due to its excellent results reported in several studies (Maillard *et. al.*, 2008; Barbosa *et al.*, 2009; Alencar-Silva and Maillard, 2009). MAGIC is an acronym that means "Map Guided Ice Classification" because it was originally developed as a tool for classification of ice sea types. The segmentation of MAGIC is unique in its implementation and the principles it embodies. It is an hybrid segmentation approaches that uses two different approaches to segmentation: "watershed" and Markov Random Field (MRF). The segmentation is started by applying a "watershed" algorithm that produces a preliminary segmentation and generates segments (areas) of 10-30 pixels depending on the noise level in the image. The smaller segments are then arranged topologically, so all contiguous segments can be determined through an adjacency graph or RAG (Region Adjacency Graph). The second step is based on the MRFs that will join or not contiguous segments if the union produces a decrease in the total energy of the neighbourhood defined by Equation 1.

$$E = E_f + \alpha E_r \tag{1}$$

where: E_f is the global spectral energy, E_r is the local spatial energy, α is normally a floating constant.

The advantage of the MRF model is its inherent ability to describe both the spatial context location (the local spatial interaction between neighboring segments) and the overall distribution in each segment (based on parameters of distribution of spectral values for example). That new approach was entitled "Iterative Region Growing Using Semantics" or IRGS and is described in Yu and Clausi (2008).

MAGIC is able to segment each band image individually or as a multivariate data. In this study, the spectral bands were used both as a multivariate dataset and individually. Three parameters have to be specified for the segmentations to take place: (i) the number of classes, (ii) β1, and (iii) β2. The number of classes varies depending on how the user wants to segment the image.

For our study two categories were desired: riparian and non-riparian. However, because there are several different elements in the non-riparian group (*i.e.* water, herbaceous, bare soil, grass, etc), tests were performed with 3, 4, 5, 6, 7 and 8 classes. The best result obtained by the MAGIC was to be used as a mask in the texture calculations.

2.3.3 Image Texture Calculations

The texture of an image can be defined as changes in spatial patterns of gray levels in a set distance (Tso and Mather, 2001). An approach widely used in texture parameters calculation is the Gray Level Co-occurrence Matrix (GLCM) (Lillesand and Kiefer, 2000). This method proposes that each element of the matrix is a probability measure of occurrence between two gray levels separated by a certain distance and direction (Haralick, 1979). In this paper five features were considered: contrast (CON), angular second moment (ASM), entropy (ENT), inverse difference moment (IDM) and correlation (COR). The Ikono's red and infra-red bands were chosen in order to calculate the five texture features. The blue and green bands were not used because they have strong correlation with the red band. Analysis window sizes of 11x11, 15x15, 20x20, 25x25 and 30x30 pixels were used. The distances between analysis pixels vary between 3 and 7 and the four directions: 0°, 45°, 90° and 315°.

A special program was created to compute the texture feature to account for the use of a mask. MACOOC (Philippe Maillard ©2010) takes an image and a binary mask as input to compute all five texture measurements in all four directions. Because the mask can adopt just about any shape, regular texture extraction programs would have to discard the texture computation for many riparian pixel when the analysis window overlaps the zeros areas of the mask. MACOOC compensates the "incomplete" windows by adjusting the number of co-occurrences in order to compute comparable probabilities. The probabilities values are then rescaled between 0 and 10000.

Finally, the 70 plots were overlaid in the image. The average values of the four spectral channels (blue, green, red and infrared) and 20 texture bands were computed for each plot and organized in a matrix along with the allometric data. *Multiple Regression* using *Stepwise* feature selection was used to analyze the data.

3. RESULTS AND DISCUSSIONS

The results of this study are presented in two blocks: image segmentation and biophysical riparian forest modelling.

3.1 Image Segmentation Results

The best MAGIC segmentation was obtained using the image as a multivariate dataset with all four Ikonos' bands (Table 5).

Spectral Band	Riparian %	Non-Riparian %	Total %
1 (blue)	89.19	80.71	84.16
2 (green)	-	-	-
3 (red)	88.82	75.14	80.71
4 (infrared)	-	-	-
1, 2 and 3	91.28	85.01	87.56
1, 2, 3 and 4	**88.31**	**90.61**	**89.68**

Table 5: MAGIC overall segmentation success (average user's and producer's) result for riparian and non-riparian vegetation.

The best results were obtained with five classes and an overall accuracy of 89.68% when compared with the visual interpretation. This result takes into account both omission and commission errors (Figure 4). Results obtained with the green and infrared bands had very low correlation with the interpreted image.

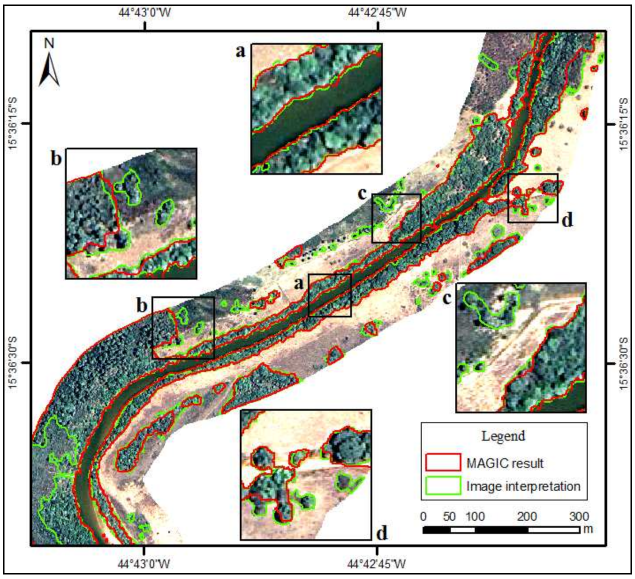

Figure 6: Segmentation result. The best finding was acquired using all Ikonos' bands.

Figure 6 shows the 50m buffered Ikonos scene. The riparian forest consists of all trees within this buffer. The polygons in green are validation data and those in red were obtained with MAGIC.

The MAGIC segmentation result points to a high visual correspondence with the validation data like in zoom window (a). The MAGIC was able to segment some features like individual trees (zoom window (d)). However, some individual features or narrow areas were not segmented properly (zoom windows (c) and (b)).

3.2 Biophysical Riparian Forest Modelling Results

From the initial 70 plots, only 62 were used to obtain the average spectral and texture values. The remaining eight plots were partially located outside the riparian mask and had to be withdrawn.

The statistical correlations results (adjusted R^2) between spectral data, textural data and the allometric and structural measurements of the plots are presented in Table 7: band 3 indicates that the texture features were computed from the red spectral band and band 4 the infrared band. The red band is much more related with allometric parameters than the infrared band for which only the LAI had some success. Basal area and volume obtained the best overall results with R^2=0.61 and R^2=0.66, respectively. The results show better correlations when using an 11x11 pixel window for the parameters DBH, Basal Area and Volume. The most successful distance between pixels is d=4, which showed better results with Basal Area, Volume, DBH and LAI. The best mathematical model for each allometric parameter is presented in Equation 2 to 8.

	Band 3						
Parameters	**Height**	**DBH**	**Basal Area**	**Volume**	**Density**	**Canopy Openness**	**LAI**
w11/d3	0.34	**0.52**	0.50	0.64	0.07	0.32	0.45
w11/d4	0.44	0.24	**0.61**	**0.66**	0.13	0.33	0.41
w15/d3	0.39	0.30	0.36	0.42	0.20	**0.44**	0.46
w15/d7	**0.52**	0.29	0.49	0.63	0.04*	0.34	0.40
w20/d4	0.49	**0.34**	0.52	0.48	0.16	0.20	0.40
w30/d3	0.25	0.19	0.21	0.27	**0.45**	0.39	0.45
	Band 4						
w30/d4	0.16	0.20	0.19	0.09	0.05	0.41	**0.54**

Table 7: The correlations results for band 3 and 4 (adjusted R^2 with p test value < 0.05). The left column shows the window size (w) and the lag distance between pixels (d). Boxed values are significant at p>0.05.

$$\textbf{\textit{Height}} = 64.6 - 0.001\,\mathbf{con_{90}} - 0.00574\,\mathbf{ent_{135}} - 0.0055\,\mathbf{asm_0} - 0.0065\,\mathbf{ent_{90}} + 0.00128\,\mathbf{idm_{135}} + 0.00064\,\mathbf{con_{135}} \quad (2)$$

$$\textbf{\textit{DBH}} = 184 - 0.0397\,\mathbf{ent_{90}} + 0.0584\,\mathbf{B} - 0.0662\,\mathbf{R} + 0.126\,\mathbf{cor_0} - 0.0786\,\mathbf{cor_{135}} - 0.0103\,\mathbf{asm_{90}} + 0.0037\,\mathbf{idm_{135}} - 0.005\,\mathbf{idm_0} - 0.00246\,\mathbf{con_{45}} \quad (3)$$

$$\textbf{\textit{Basal Area}} = 0.0569 + 0.000002\,\mathbf{asm_{135}} + 0.000001\,\mathbf{IR} - 0.000004\,\mathbf{asm_{45}} - 0.000013\,\mathbf{ent_{45}} \quad (4)$$

$$\textbf{\textit{Volume}} = 80.7 + 0.00304\,\mathbf{asm_{135}} - 0.00555\,\mathbf{asm_{45}} - 0.0187\,\mathbf{ent_{45}} \quad (5)$$

$$\textbf{\textit{Density}} = 0.018 - 0.000287\,\mathbf{con_{90}} + 0.000137\,\mathbf{con_{45}} - 0.000190\,\mathbf{cor_{135}} + 0.000081\,\mathbf{idm_0} - 0.000531\,\mathbf{ent_{135}} + 0.000094\,\mathbf{con_{135}} + 0.000547\,\mathbf{ent_{45}} \quad (6)$$

$$\textbf{\textit{Canopy Openness}} = -\,1129 + 0.214\,\mathbf{ent_{90}} + 0.136\,\mathbf{R} - 0.0865\,\mathbf{cor_{135}} + 0.0137\,\mathbf{con_{135}} + 0.143\,\mathbf{asm_{90}} - 0.101\,\mathbf{G} \quad (7)$$

$$\textbf{\textit{LAI}} = 0.556 - 0.00203\,\mathbf{R} + 0.000573\,\mathbf{con_0} - 0.00337\,\mathbf{cor_0} + 0.000695\,\mathbf{idm_0} - 0.000119\,\mathbf{asm_{90}} + 0.00354\,\mathbf{cor_{45}} \quad (8)$$

The direction is not a determining factor in the models and none appear to occur predominantly. It is also difficult to pinpoint a single co-occurrence measurement that stands out. In models with few parameters, the ASM seem to be reoccurring (Eq. 4 and 5). Entropy seems to come in second place. It is likely that the diversity of measurements is the best asset of these models and accounts for their strength. When all texture features are analyzed together, it can be verified that Second Angular Moment and Entropy are predominant for the best results (basal area and volume). These models are but indicative of the condition of the riparian forest and are probably not directly applicable in another region. However, but they can be used regionally to orientate the riparian restoration efforts that are currently being undertaken in various watersheds of Northern Minas Gerais by the Forest Institute of MG.

4. CONCLUSIONS AND FUTURE WORKS

In this article two methodological approaches were used to map and model the structure of riparian vegetation in a Brazilian savanna region. For this, combining a high resolution image, the MAGIC segmentation/classification software and the use of texture measurements was evaluated. The results demonstrate a great capacity of the MAGIC program to identify regions of riparian forest without the need of field data. For this step, the best results were obtained by using all four spectral bands of the Ikonos image and a sufficient number of classes to account for the wide variety of land cover within the non-riparian class.

Statistical analysis between the parameters obtained in the field and image processing results permitted the creation of explanatory vegetation structure models applicable regionally. The best models were obtained for the allometric variables basal area and volume (0.61 and 0.66), using window size of 11x11 pixels and distance analysis of four pixels. The direction did not appear to be critical but some texture parameters (ASM and Entropy) are more frequently chosen by the stepwise feature selection. Moreover, it is the diversity of measurements that appear to be most effective.

Future work will include a much broader range of plots in different segments of the river in the hope of creating a more robust set of models. Texture feature will also be made direction-invariant. The approach taken here is comparable to an object-oriented approach that is much more appropriate for high resolution images. It will eventually be integrated into a single package.

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