DISCRIMINATING MIXED OMBROPHILOUS FOREST SUB-TYPOLOGIES USING OBJECT-BASED IMAGE ANALYSIS AND DECISION TREES

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ABSTRACT:

A dramatic area reduction on original Mixed Ombrophyllus Forest occurrence has been observed since early 20th Century. Nowadays this ecosystem forest remnants occupy 2 to 4% of its original cover area and primary or even advanced forests represent less than 0,7%. The Embrapa/Epagri Forest Reserve, located at Caçador County, Santa Catarina State, encompasses one of the most important and last forest remnants representing this ecosystem. In order to actions such as conservation planning and sustainable forest management to take place, techniques aiming this particular type of forest mapping and monitoring are needed. The present work intends to provide Ikonos-II data information extraction methodology, allowing higher quality forest pattern classification as means to subsidize Mixed Ombrophyllus Forest monitoring. As so, advanced and promising techniques such as multi-resolution segmentation and decision tree classification algorithms were adopted. Additionally, a quantitative segmentation evaluation methodology was adopted allowing segmentation parameters selection in a way that image objects resemble the visually defined reference map. Spectral, textural and shape attributes were calculated for segmentation polygons, allowing generation of 405 auxiliary image for classification. Using attribute selection methods such as decision tree induction and Student's T-test indulged dataset dimensionality reduction to 6 to 18%. Decision tree algorithms *RandomTree*, *RepTree*, *SimpleCART*, *CART* and *J48* were used. The results obtained indicate that the proposed methodology presents great potential for Mixed Ombrophyllus Forest discrimination. Compared to previous results, a 30% increase on Land Cover Land Use Map quality was accomplished. *SimpleCART* decision tree algorithm applied to 155 scale parameter and 0,1 shape factor image segmentation generated the highest overall accuracy, equals to 83,36%.

1. INTRODUCTION

Mixed Ombrophyllus Forest (MOF) occurrence area in southern Brazil has suffered a drastic reduction since the beginning of the Twentieth Century (Medeiros *et al.*, 2005). Currently reduced to 2-4% (Guerra *et al.*, 2002; Castella and Britez, 2004), remaining populations are senescent and forests in primary or even advanced stages do not represent more than 0.7% of its original area (MMA 2002).

For these reasons the MOF is among the most threatened typologies within Atlantic Forest Biome, which is considered one of the most threatened ecosystems and a world conservation priority (Myers *et al.*, 2000; MMA 2000).

One of the largest continuous forest remnants with characteristic vegetation of MOF phytogeographic region, part of the Atlantic Forest domain (Rosot *et al.*, 2007a), is the Embrapa / Epagri Forest Reserve (EEFR) at Caçador County, Santa Catarina state (SC). The area has served to numerous studies aimed at developing strategies for MOF biodiversity preservation and conservation (Kurasz, 2005; Dlugosz, 2005; Lingner *et al.*, 2007; Rivera, 2007; Rosot *et al.* 2007a; Rosot *et al.*, 2007c; Mattos *et al.* 2007; Mattos *et al.*, 2010).

Multiple use forest management, landscape planning, preservation and environmental restoration are some of the strategies to reverse MOF fragmentation and degradation trend and conserve its biodiversity. (Castella and Britez, 2004, Medeiros *et al.*, 2005; Rosot, 2007; Britez, 2007). These strategies are drawn from the knowledge of spatial distribution pattern, ecology information and species spatial structure (Anjos, 1998; Anjos *et al.*, 2004). Field survey and remote sensing play a key role in information acquisition, providing the basis for any of these strategies. Despite the need for detailed information, there are still only few studies in which MOF sub-typologies classification is contemplated. The work of Dlugosz (2005) can be considered one of the first to attempt MOF sub-typologies identification through high spatial resolution Ikonos-II images.

According to the author, some challenges to be faced in the production of quality maps are related to forest characteristics, such as the intricate species composition, successional stages and anthropogenic intervention levels on forests. Other challenges are related to the image and classification algorithms. High spatial resolution images have higher gray levels pixel variability representing the objects. Traditional classifiers, which adopt a pixel-by-pixel approach, have poor performance reflected in low accuracy classification values (Hay *et al.*, 2005; Hay and Castilla, 2006). Franklin (2001) places the development of alternatives for high spatial image resolution processing as the biggest challenge in remote sensing contribution to sustainable forest management. Among these

alternatives is object-based image analysis (OBIA), term established in 2006 by Hay and Castilla. This approach allows the use of color, shape, texture and context attributes to classify image objects, favoring forest patterns and information extraction (Syed *et al.*, 2005; Ju *et al.*, 2005; Chubey *et al.*, 2006; Mallinis *et al.*, 2008; Wulder *et al.*, 2009; Ke *et al.*, 2010; Kovacsova and Antolova, 2010). Another approach that has shown potential for forest pattern classification are decision-tree algorithms (Murthy, 1995; Lim *et al.*, 1997; Hand, 1997, Martens *et al.*, 1998, Lim *et al.*, 2000, McIver and Friedl, 2002). However, object-based image analysis and decision-tree algorithms applied to MOF patterns classification are still incipient (Dlugosz, 2005; Luz, 2005; Albergoni, 2011). The combined use of these techniques is recent and has shown great potential for forest patterns discrimination (Luz, 2005; Chubey *et al.*, 2006; Ke *et al*, 2010).
This study aims to discriminate sub-typologies of MOF in Ikonos-II images through integration of object-based image analysis techniques and decision-tree algorithms.

2. METHODS

2.1 Study Area

The EMBRAPA/EPAGRI Forest Reserve (EEFR), focus of this study, is located in Caçador County, central-west area of Santa Catarina State, Southern Brazil. The EEFR comprises an area of 1157.48 hectares and is located between the geographic coordinates 26°50'32,69"S, 26°52'36,73"S, 50°54'51, 69"N and 51°58'40.36"N, as shown in Figure 1.

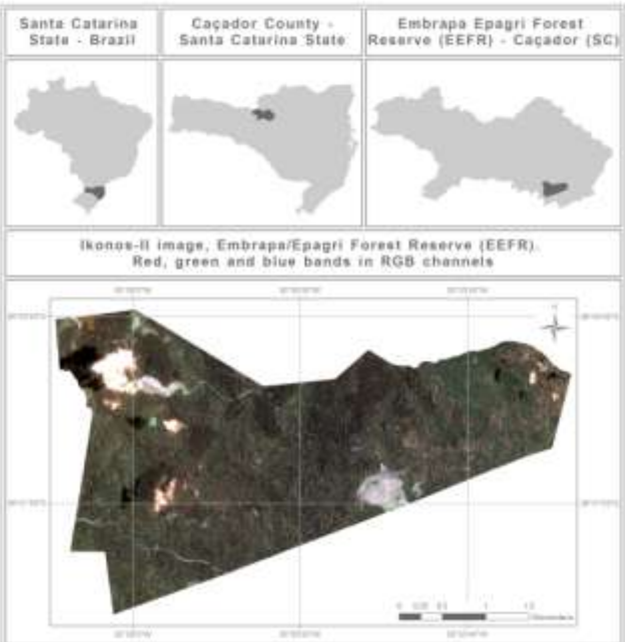

Figure 1. Study area in Caçador County, Santa Catarina State, Southern Brazil

The relief is softly wavy with altitudes ranging from 920 and 1060 a.s.l. The EEFR is one of the largest and also one of the last remaining continuous remnants with characteristic vegetation of MOF phytogeographic region. Recipient of major ecological, economic and scenic importance, EEFR contains specimens of flora and fauna threatened with extinction. Examples are the small mammal *Leopardus tigrinus* and a large population of the *Araucaria angustifolia* trees (ROSOT *et al*, 2007a).

2.2 Image pre-processing

Ikonos-II satellite images were acquired on February 17, 2004 at 13 hours and 43 minutes Greenwich Mean Time (10:43a.m. local time). Panchromatic and multi-spectral bands were purchased, but only multi-spectral bands were used in image processing steps. The original images were submitted to geometric correction, based on field control points collected with a DGPS. The survey, conducted by Dlugosz (2005) and collaborators, relative static method was adopted and some criteria, like a minimum of 20 minutes at each point and PDOP $\leq$ 6.0 were adopted. Control points (25 totals) collected presented 1.33m average horizontal accuracy. Since there is a need for comparison with the reference-image and the main goal is a thematic map, it was not possible to perform image orthorectification. The Universal Transverse Mercator (UTM) projection system and South American Datum horizontal datum of 1969 (SAD-69) were adopted in this study.

2.3 Image Processing

Image processing workflow is shown in Figure 2. It starts with segmentation of pre-processed images, using software eCognition 4.0 Fractal Net Evolution Approach algorithm. Several combinations of scale and shape factor were applied, followed by segmentation results quantitative and qualitative evaluation. Attribute selection techniques indicated most important polygon features for image classification, performed with decision-tree algorithms.

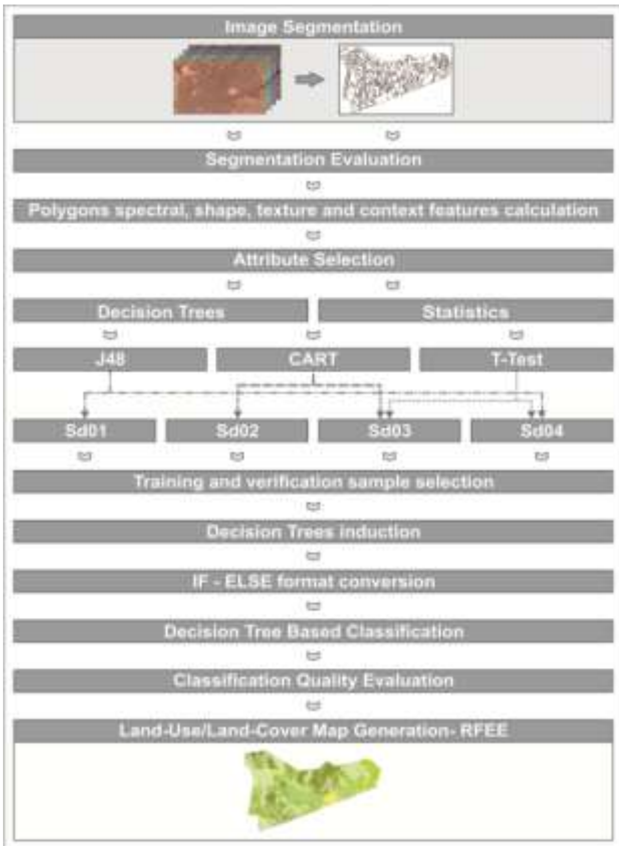

Figure 2. Image processing workflow.

2.3.1 Segmentation evaluation: Qualitative evaluation included visual comparison against a reference image, polygons Obtained through delineation and several field campaigns. The segmentation quantitative evaluation methodology adopted was described by Oliveira (2003) and is based on the empirical method of discrepancies that uses the principle of *Relative Ultimate Measurement Accuracy* (RUMA) system, developed by Zhang and Gerbrands (1994). Discrepancy measures that compose the Index for Evaluation of Digital Imagery Segmentation (Iavas) are: number of polygons, the total length of lines, variance of the polygons area, closest mass center and coincidence buffer. Four successive approximation steps were used to search for the optimal solution. Search space was defined by existing values of shape factor (SF) (which varies from 0 to 1) and scale parameter (SP) from 0 to 550. The compactness/smoothness relation (CS) of the polygon shape was held constant at 0.5, preventing its influence on other segmentation parameters.

2.3.2 Attribute selection: Features describing spectral, shape, texture and context of image objects available in eCognition sotware were calculated, generating 405 attributes for each polygon. Attribute selection techniques based on pairwise t-test and decision-tree algorithms (CART and J48, available in WEKA software) were performed. Four sub-datasets were originated. The first one contained attributes selected by the induction of decision tree generated by *J48* algorithm (SD01), the second resulted from application of the *CART* decision tree algorithm induction (SD02), the third formed by Test-T selected attributes (SD03) and fourth combined all attributes selected on first three sub-datasets (called C04). These data sets were used as input data in image classification.

2.3.3 Image Classification: Land-use/land-cover classes were defined in accordance with the reference-map, aiming compatibility and results comparison. The reference-map was prepared by Dlugosz (2005), EMBRAPA researchers and technicians, through polygon delineation and several field campaigns performed over a year investigation. Non-forest classes defined were "lake", "bare soil", "road", "agriculture/horticulture" and "bamboo". MOF sub-typologies included: "*Araucaria angustifolia* dominance", " *Araucaria angustifolia* low density", "*Ocotea porosa* dominance", "*Mimosa scabrella* and *Ocotea puberula* dominance", "*Piptocarpha* sp. dominance", "*Baccharis* sp. dominance", "pioneer formation of fluvial influence" and "floodplain". According to ROSOT *et al.* (2007b) sub-typologies have a particular composition of species, stage of development and number of layers, allowing silvicultural treatments to be applied in accordance with each of them.
Image classification was performed using different decision-tree algorithms. The sub-datasets of image-object attributes were subjected to *J48*, *SimpleCART*, *RandomTree* and *RepTree* decision-trees algorithms. The four algorithms were applied to each of the four sub-datasets, generating sixteen resulting classifications. Another sixteen classifications were performed for the same sub-datasets obtained from image segmentation with qualitative evaluation parameters selection.
Rules generated by decision-tree induction in WEKA software were implemented in MATLAB software language format, using IF-ELSE commands. A routine for rules conversion into IF-ELSE Matlab language was developed in C ++ BUILDER6.0 by Santos (2010).

2.3.4 Accuracy checking: Classification results obtained in MATLAB software were exported to ENVI software and land-use/land-cover map accuracy was evaluated. For this purpose, independent samples of those used for training image classification algorithms were collected. The verification samples were obtained by overlaying a grid of points over the reference-map. Over 200.000 points containing land-use/land-cover class attribute composed verification samples file, exported from ArcGIS to ENVI. Points imported into ENVI were then used to evaluate the map accuracy, through confusion matrices and Kappa index calculation

3. RESULTS

3.1 Segmentation evaluation

Qualitative evaluation lead to the choice of SP-335 and SF-0, 1. These values were chosen in an attempt to reduce image over-segmentation. The visual analysis carried out before quantitative evaluation showed that visual comparison alone is not sufficient to determine good segmentation parameters, even when a reference-map is available.
For qualitative evaluation, the four steps of approximation search over the optimization space, minimum error Index IAVAS pointed out SP-155 and SF-0, 1 as the optimal solution (Figure 3).

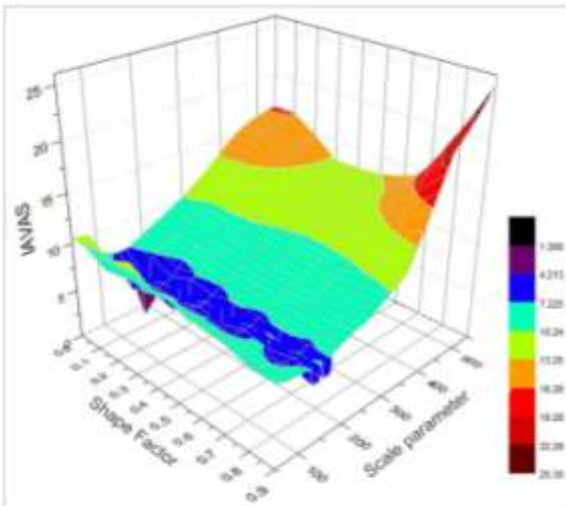

Figura 3. Optimal segmentation parameters search space.

Local minimums can be perceived for two regions, characterized by depressions that occur around the SP-150 and SP-200. Local minimums remained constant over the entire range of SF (0.0 to 0.9). Maximum SP and SF adopted can be considered sufficient for the quantitative evaluation analysis, since higher SP and SF values lead to higher IAVAS results (Figure 3).

3.2 Attribute selection

Overall, 70 attributes were selected for the previously described attribute selection tools. This represents approximately 17% of the initial dataset of image-object features calculated (equals to 405). Only Brightness and Maximum Pixel Value (calculated for the blue band) were selected by the three feature selection methods adopted. The sub-dataset selected by the induction of *J48* decision-tree algorithm (SD01) contains 42 layers of information. Sub-dataset selected by the *CART* decision tree algorithm induction contains 33 attributes. The Sub-dataset selected by the T-test (SD03) comprises 26 layers of information. The set 70 SD04 is formed by layers of information selected by all three methods.

3.3 Image Classification

Results obtained through accuracy evaluation of image classification using polygons generated by application of qualitative segmentation parameters evaluation (SP-325 and SF-0, 1) are shown in Table 1.

DT algorithm	Sub-dataset	Accuracy	Kappa Coefficient
SimpleCART	SD04	80,16%	0,7741
J48	SD02	79,92%	0,771
SimpleCART	SD03	79,83%	0,7703
J48	SD01	79,74%	0,7692
RepTree	SD02	79,56%	0,7674
SimpleCART	SD02	78,03%	0,7502
RandomTree	SD02	77,14%	0,7402
J48	SD04	76,83%	0,7351
J48	SD03	73,02%	0,6949
RepTree	SD03	72,13%	0,6828
SimpleCART	SD01	63,12%	0,5932
RandomTree	SD03	62,63%	0,5781
RandomTree	SD01	62,15%	0,5851
RepTree	SD01	48,98%	0,4461
RandomTree	SD04	38,60%	0,3527
RepTree	SD04	31,91%	0,2569

Table 1. Accuracy values for segmentated image classification using qualitative segmentation evaluation selected parameters (SP-325; SF-0.1).

According to values presented in Table 1, one can observe great variability in the accuracy obtained when different decision tree algorithms and data sets are adopted. The minimum accuracy obtained was 31.91%, with application RepTree algorithm and the largest sub-dataset, C04. The more accurate classification resulted in 80.16% when SimpleCART algorithm was used with the same set of input sub-dataset.

A similar result was obtained when the J48 algorithm was applied to SD02, with 79.92% classification accuracy. Similar results, with values greater than 79% classification accuracy was obtained by the application of algorithms SimpleCART, J48 and Rep tree to the sub-datasets SD03, SD01 and SD02.

However, best results were obtained for classification accuracy when the image was segmented with SP-155 and SF-0.1 as shown in Table 2. The single best result was achieved by classification of SD01 classified by SimpleCART algorithm, resulting in map accuracy of 83.36% (Table 2).

DT algorithm	Sub-dataset	Accuracy	Kappa Coefficient
SimpleCART	SD01	83,36%	0,8106
RandomTree	SD02	83,09%	0,8071
SimpleCART	SD02	82,99%	0,8061
J48	SD02	82,40%	0,7994
J48	SD04	81,43%	0,7881
RepTree	SD02	80,92%	0,7828
RepTree	SD01	78,57%	0,7556
RandomTree	SD04	78,01%	0,7497
RandomTree	SD03	78,01%	0,7497
RepTree	SD04	77,88%	0,7479
J48	SD01	65,57%	0,6146
RepTree	SD03	62,28%	0,5445
RandomTree	SD01	60,90%	0,564
SimpleCART	SD03	31,97%	0,2592
J48	SD03	25,06%	0,1792

Table 2. Accuracy values for segmentated image classification using quantitative segmentation evaluation selected parameters (SP-155; SF-0,1).

Approximate results were obtained when *Random Tree* algorithm and *SimpleCART* were applied to the input sub-dataset selected by *CART* algorithm (C02), resulting in 83.09% and 82.99% respectively.

The results of accuracy and Kappa coefficient suggest that lower segmentation parameters, especially scale parameter, can produce more accurate land-use/land-cover maps. This effect can be linked to over generalization generated by higher segmentation parameter values. It can be said that it is preferable to select segmentation parameters leading to over-segmentation and then perform image classification, followed by adjacent same class polygons grouping than using parameters that under-segment an image. The excessive segmentation divides objects represented in the image into more than one polygon, which can be further merged into same class adjacent polygons. The opposed situation, insufficient segmentation, can be considered undesirable, since polygons representing a same object cannot be correctly classified for both classes.

The best classification result shows great confusion among forest classes, probably due to reduced spectral separability between some types of forest cover, as shown in Table 3.

Although a class called “*Araucaria angustifolia* dominance” provided 80.84% accuracy, some confusion (4.84%) with the class that also features *Araucaria angustifolia* in its canopy in lower density (class 2, “*Araucaria angustifolia* low density”), as expected. The separability of these classes is evident in the field, given the density of occurrence of dominant species, but this division is not as clear in terms of spectral response. Slightly lower error occurred between this class and “*Ocotea porosa* dominance” class (class 3), 4.5%.

“*Araucaria angustifolia* low density” (class 2) showed highest confusion rates among other forest classes and second worst among all classes. There was great confusion (13.57%) between this and class 3 (“*Ocotea porosa*”), as with “*Araucaria angustifolia* dominance” (7.79%). Class 2 was also confused with classes 4 (error 6.66%) and 5 (5.70% error) ("*Mimosa scabrella*" and "bamboo", respectively).

Classes*	1	2	3	4	5	6	7	8	9	10	11	12	13
1	**80,83**	7,79	2,73	2,54	0,06		0,03	0,06	0,02		1,59		0,69
2	4,84	**54,72**	7,52	2,66	0,28		0,32	0,06	0,08		0,81		0,19
3	4,50	13,57	**63,08**	7,21	0,81		1,24	0,44	0,62	0,07	0,45		0,19
4	1,73	6,66	10,45	**69,32**	3,02		0,20	1,37	0,18	0,04	1,10		
5	0,68	5,70	6,37	7,69	**93,01**		4,59	0,01	0,04		0,24		
6		0,03		0,02		**98,59**		0,66					
7			2,85	2,79	2,49		**92,66**		0,01				
8	0,92	2,01	1,73	3,00	0,16		0,23	**95,96**	2,19	0,04	1,42		0,50
9	0,62	0,47	0,45	0,54	0,04		0,06	1,11	**96,06**	0,03	1,14	0,43	0,06
10	0,75	0,03	0,35	0,11			0,01	0,01	0,17	**97,25**	1,34		
11	4,08	6,64	2,65	2,32	0,05		0,33	0,14	0,62	2,58	**90,60**	59,15	0,19
12	1,05	2,38	1,83	1,80	0,06	1,41	0,33	0,19	0,02		1,14	**40,43**	0,44
13											0,16		**97,75**

Table 3. Confusion matrix of image classification obtained with *SimpleCart* decision-tree algorithm. Missing values equals zero.

*Numbers in first colum and first line refer to the following land-use/land-cover classes: Os números na primeira linha e primeira coluna da tabela referem-se às classes contidas na legenda do Mapa de Uso e Cobertura da terra, conforme a seguinte codificação: 1 - *Araucaria angustifolia* dominance; 2 - *Araucaria angustifolia* low density; 3 - *Ocotea porosa* dominance; 4 - *Mimosa scabrella* and *Ocotea puberula* dominance; 5 - bamboo; 6 - *Baccharis* sp. dominance; 7 - *Piptocarpha* sp. dominance; 8 - pioneer formation of fluvial influence; 9 - floodplain; 10 - agriculture/horticulture; 11 - road; 12 - bare soil; 13 - lake.

The class "*Ocotea porosa* dominance" presented confusion with the class "*Araucaria angustifolia* low density" (7.52%) and also mess with the class 4 "*Mimosa scabrella*" (10.45%). Despite the similarity reduced spectral pixels of this class were also misclassified as "bamboo" (class 5).
Class 4 ("*Mimosa scabrella*") was confused with the class "*Ocotea porosa* dominance" (class 3) at 7.21% and with "bamboo", with an error of 7.69%. The class of "bamboo" was classified into their correct locations of occurrence in EEFR, since few of its pixels were confused with other classes, considered 93.01% accuracy. The high percentage accuracy attributed to the class called "*Baccharis* sp. dominance" (98.59%) is probably related to the occurrence its characteristic spectral signature. Class 7, "*Piptocarpha* sp. dominance" was also classified with high class accuracy, equals to 92.66%.

4. CONCLUSIONS

The results of classification can be considered satisfactory, being close to the stated value of 85% as satisfactory by Anderson *et al.* (1976) as cited by Dlugosz (2005). Dlugosz (2005) carried out research work with image segmentation and classification of Ikonos-II in the same study area. The author used segmentation algorithm available on *software* SPRING and performed supervised classification using *Bhattacharya* algorithm, obtaining an overall accuracy of 51.73%.
In the case of EEFR, where information field are available and are frequently updated, it is believed that future new scenes processed could be obtained by adopting this approach, which would reduce the time and cost of creating an upgraded map.
The adoption this methodology allowed sufficiently accurate discrimination of MOF sub-typologies, although application in other areas would depend, in theory, on selection of new parameters for optimal segmentation and adjustment of classification rules. A new decision tree must be generated for each image, especially if images from other satellites are used. Therefore, it is believed that the methodology has potential application for discrimination of these and other vegetation types.
The classification of images using decision-tree algorithms has proven to be a robust and easy to use methodology, allowing the user to understand information extraction from generated decision-rules. The results can be considered satisfactory, especially if taken into account the characteristics of forest cover classes, which have high spectral similarity.

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