A COMPARISON OF VISUAL INTERPRETATION AND OBJECT BASED IMAGE ANALYSIS FOR DERIVING LANDSCAPE METRICS

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KEYWORDS: Landscape Ecology, Land cover, Accuracy, SPOTMaps, fused image, FRAGSTATS, SPRING, eCognition.

ABSTRACT:

Remote sensing systems have been widely used for several ecological applications. Great part of research in landscape ecology uses visual interpretation because it is flexible and efficient at extracting spatial information. But this method demands more time to be accomplished. Semi-automatic classification provided very high automaticity and needs less time, but it is not suitable for accurately classifying all classes of interest. Geographic object-based image analysis – GEOBIA has been used to achieve better results regarding classification quality. Thus, in this study we aim to verify if landscape metrics derived from visual interpretation differ significantly from the ones derived using GEOBIA. We used a 2.5 m resolution HCR SPOTMaps product to perform two different classifications: visual interpretation (VI) and object-based classification (OBC), using SPRING 5.1.5 and eCognition 8, respectively. Landscape metrics were calculated using FRAGSTATS 3.1, and compared using Pearson's chi-squared (χ^2) statistics ($p<0.05$). We found that VI demanded more processing time when compared to OBC. Nevertheless, VI showed higher accuracy (kappa=0.92; Figure 1) than the OBC (kappa=0.74; Figure 2). There were significant difference between some landscape metrics derived from VI and OBC. Different mapping strategies based on satellite imagery can affect the measurement of landscape metrics, compromising their ecological meaning. It is important to consider the classification method when performing landscape ecology studies, in order to avoid misinterpretations and induce decision makers to develop erroneous conservation actions. This study allowed us to visualize the importance of choosing higher accuracy mapping, providing a better understanding of landscape metrics.

1. INTRODUCTION

Remote sensing systems have been widely used in many areas of science, especially for environmental studies. Due to its ability to collect multispectral data at different scales and various points in time, this tool offers the opportunity to synoptically analyze a number of processes occurring on the Earth surface (Brown et al., 2000). Remote sensing is commonly used to derive land cover maps and to monitor land cover changes (Purkis and Klemas, 2011).

For ecologists, satellite imagery presents great potential to obtain more accurate data for studying ecosystem dynamics (Kerr and Ostrovsky, 2003, Turner et al. 2003). Remote sensing is an ideal tool to investigate the Earth surface with low cost (Newton, 2009), providing essential data to characterize landscape patterns and processes (Groom et al., 2006, Newton, 2009).

Vegetation and land cover mapping using remote sensing data is currently of standard use for deriving landscape metrics, in spite of the inadequate spatial accuracy of conventional methods (Lobo, 1997). Other complicating factors are the fragmentation of tropical areas caused by deforestation, as well as the diversity of land cover, which affect the selection of good training areas for digital image classification (Puig et al., 2002). Moreover, ecological applications require land cover classes that sometimes cannot be discriminated using conventional classification methods.

Newton et al. (2009) analyzed the use of remote sensing in support of mapping activities, especially for mapping landscape pattern and spatial structure. They observed that most studies employed image analysis, but did not provide enough details concerning methods and uncertainty.

Great part of research in landscape ecology use visual interpretation to derive landscape metrics. Interactive visual interpretation can make full use of the interpreter's experience and knowledge. Visual image interpretation of remote sensing imagery offers an efficient method to classify complex and heterogeneous landscapes and spatial units with image pattern characteristics (Antrop and Van-Eetvelde, 2000). This method is flexible and efficient at extracting spatial information, but demands more time to be accomplished with different interpreters producing different results (Wang, 2008).

Puig et al., 2002 compared digital classification and visual interpretation of Landsat TM satellite image scenes. They concluded that both methodologies presented similar precision and processing time, but even giving better spatial detail, computer assisted classification demanded more time for editing and post-processing to reduce errors. So, they recommended the use of a combination of automatic processing and visual interpretation. The authors also highlighted that an increase in spatial resolution could demand more time for visual analyses.

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Ribeiro et al. (2009) working at continental scales performed visual interpretation of TM/Landsat-5 (TM) and CCD/CBERS-2 (CCD) imagery to map Atlantic Forest remnants in Brazil. Overall accuracy ranged between 76% and 97%, considered acceptable by the authors for maps at the considered geographical scale.

Antrop and Van-Eetvelde (2000) also showed in that the spatial resolution when dealing with heterogeneous landscapes is a limiting factor in satellite imagery, which results in a large proportion of mixed pixels and consequent poor classification accuracy.

Wang et al. (2008) used a 0.2 meter resolution aerial image to compared supervised classification and visual interpretation. They concluded that, although computer assisted classification provided very high automaticity and needs less time, it is not suitable for accurately classifying all classes of interest.

Because of the different results provided by different kinds of image classification, it is very important to understand that remote sensing-based classifications are subject to different kinds of errors, which will be propagated to the calculation of landscape metrics (Shao and Wu, 2008).

Another factor that could also influence classification accuracy and subsequently landscape metrics is the type of the satellite image. Nowadays, several image providers perform data fusion to enhance spatial resolution. Image fusion is a methodology concerned with the integration of multiple images, e.g. derived from different sensors, into a composite image that is more suitable for the purposes of human visual perception or computer-processing tasks (Piella and Heijmans, 2003). But not always the quality of fusion is suitable, and it compromises the classification accuracy (Colditz et al., 2007).

For these reasons, we notice that there is a need for a closer integration between landscape ecology and remote sensing disciplines because data quality of digital map layers is crucial for spatial analysis (Antrop and Van-Eetvelde, 2000).

One alternative is to use geographic object-based image analysis - GEOBIA (Hay and Castilla, 2008; Dungan, 2006; Zhan et al., 2005). It has been regarded as a promising approach assembling characteristics from visual interpretation and providing better information extraction from remote sensing data (Hay et al., 2005, Wulder et al., 2008, Barrile and Bilotta, 2008).

The purpose of this paper is to compare different approaches of producing land cover maps for ecological studies at the landscape level. We intended to evaluate landscape metrics from both a visually classified map and a map derived digitally using GEOBIA. This will allow us to verify if the latter can be a better alternative considering cost benefit and processing time needed for achieving the results.

More specifically, we want to answer the following question: does landscape metrics derived from visual interpretation differ significantly from the ones derived using GEOBIA?

2. MATERIAL AND METHODS

2.1 Study area

The study area is located in Carmo de Minas, Serra da Mantiqueira region, southern Minas Gerais. The region's climate is classified as subtropical highlands according to Köppen's system (Martins, 2000). It presents vegetion types of the Atlantic Forest domain: dense broadleaf upper montane forest, mixed broadleaf upper montane forest, rocky outcrops, and high-altitude fields (Veloso et al., 1991). Historical fragmentation occurred mainly due to timber exploitation and agricultural development (Silva, 2005). These activities were critical to the economic development of the region, but caused major changes to the original landscape.

2.2 Data processing

A SPOTMaps product with 2.5 m resolution HCR SPOT mosaic acquired in 2008, was used in this study to perform two different classifications: visual interpretation (VI) and object-based classification (OBC). This product is orthorectified and radiometrically corrected, with three bands in the visible part of the electromagnetic spectrum and one panchromatic band. We used a color composite RGB-12Pan.

VI was performed by on-screen digitizing using SPRING 5.1.5 (Câmara et al., 1996). We mapped eight land cover classes: (*i*) annual agriculture, (*ii*) coffee, (*iii*) natural vegetation, (*iv*) other uses, (v) pasture, (vi) secondary forest, (vii) silviculture, and (viii) watercourses.

OBC was performed with eCognition 8 (Definiens, 2008). After a number of trials to achieve a good segmentation, the scale parameter was set to 30, smoothness to 0.4, and compactness to 0.4 (Baatz and Schape, 1999). We collected sample objects of each class described above and used nearest neighbour classification including both spectral and textural attributes.

2.3 Accuracy assessment

Field survey was carried out to evaluate classification accuracy. For each class of land cover we sampled 50 points (georeferenced with a Garmin 76CSx GPSMAP). The statistical accuracy was evaluated using confusion matrices and Kappa statistics (Lillesand and Kiefer, 2000).

2.4 Landscape analysis

The raster files were resampled to 5m and then converted to ASCII format. Landscape metrics included: (*i*) percentage of forest cover (PLAND); (*ii*), number of patches (NP); (*iii*), mean patch size area (AREA_MN) (hectares); (*iv*), larger patch index (LPI) (%); and (*v*), mean nearest-neighbour distance (ENN_MN) (meters). All metrics were calculated using FRAGSTATS 3.1 (McGarigal and Marks, 1995).

2.5 Data Analysis

To compare the landscape metrics derived from both classification approaches we used Pearson chi-squared (χ^2) test ($p<0.05$).

3. RESULTS

3.1 Classification accuracy

We found that VI demanded more processing time when compared to OBC. This procedure required a long time for interpreting the image. The interpreter worked eight hours a day, during 40 days in order to finalize image classification (about 350 hours). On the other hand, OBC took 104 hours (during 5 days). Nevertheless, VI showed higher accuracy (kappa=0.92; Figure 1) than the OBC (kappa=0.74; Figure 2). Confusion among categories occurred in the OBC mainly between forest and coffee, as well as between secondary forest and pasture.

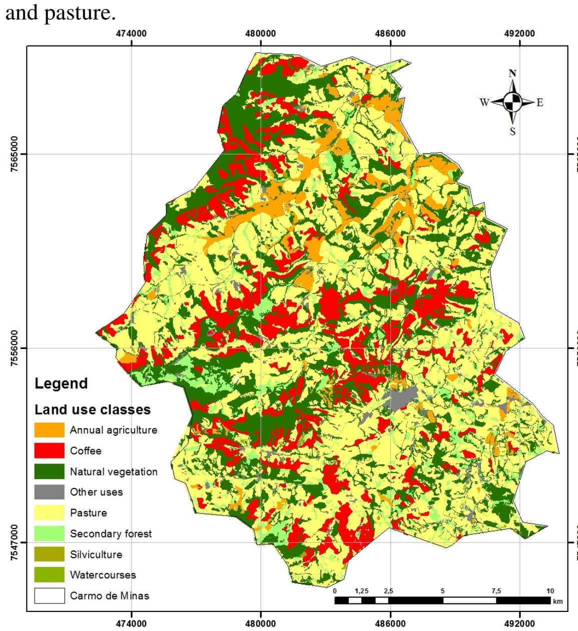

Figure 1. Visual interpretation (VI) mapping of Carmo de Minas, MG, Brazil, 2010, using a SPOTMaps product with 2.5 m resolution HCR SPOT mosaic acquired in 2008.

3.2 Analysis of the landscape structure

As VI presented higher accuracy, we considered that the landscape metrics calculated using this image classification presented the more realistic values. In this regard, OBC provided significantly different values of landscape metrics, especially for NP, considering all land cover classes.

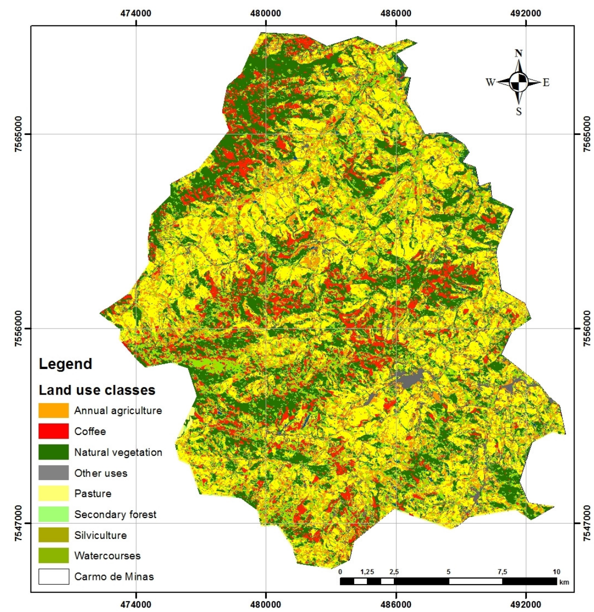

Figure 2. Object-based classification (OBC) of Carmo de Minas, MG, Brazil, using a SPOTMaps product with 2.5 m resolution HCR SPOT mosaic acquired in 2008.

The number of patches increased for all land cover classes. Annual agriculture and watercourses classified using OBC presented the higher increases for NP (Table 3; Figure 4), while silviculture and other uses showed the lower increase for this metric.

Variables	Annual agriculture	Coffee	Natural vegetation	Other uses	Pasture	Secondary forest	Silviculture	Watercourses
NP_VI	110	238	829	432	564	924	61	130
NP_OBC	636	841	3230	2059	1668	3034	292	190
PLAND_VI	5.67	14.90	26.50	2.50	43.60	6.35	0.25	0.23
PLAND_OBC	6.90	10.60	25.05	3.10	42.34	9.43	1.31	1.27
LPI_VI	0.00	0.00	2.84	0.00	2.67	0.00	0.00	0.00
LPI_OBC	0.00	0.00	1.95	0.00	2.91	0.00	0.00	0.00
AREA_MN_VI	16.80	20.18	12.79	1.87	24.95	2.23	1.31	0.01
AREA_MN_OBC	15.47	18.85	11.46	0.54	23.62	0.90	1.02	0.34
ENN_MN_VI	315.31	129.26	55.31	190.56	31.85	110.37	943.51	542.39
ENN_MN_OBC	118.32	78.45	26.73	64.41	24.56	53.29	456.34	512.66

Table 3. Values of metric parameters obtained from visual interpretation (VI) and object-based classification (OBC), used for analyzing the landscape structure of Carmo de Minas, MG, Brazil, in 2010. PLAND, or the percentage of forest cover (%); NP, or number of patches; AREA_MN, or the mean patch size area (hectares); LPI, or larger patch index (%); and ENN_MN, or the mean nearest-neighbor distance (meters).

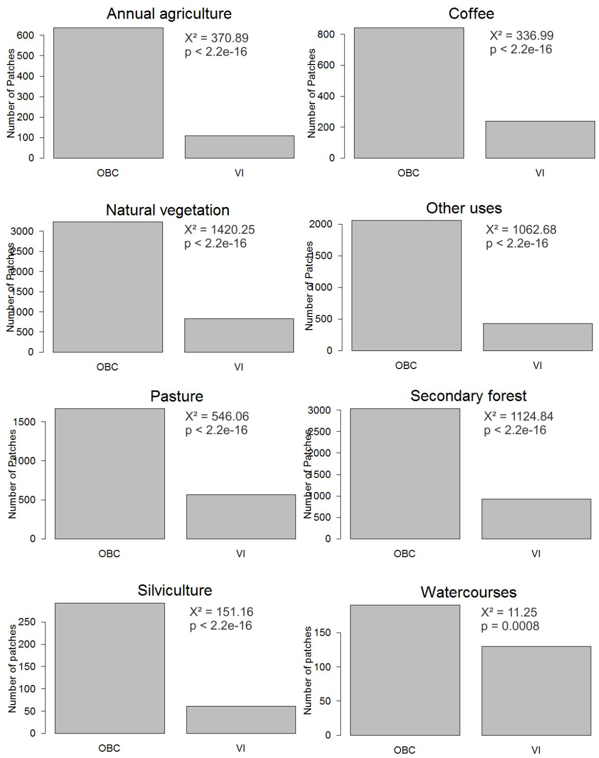

Figure 4. Number of patches (NP) for each land cover classes derived from visual interpretation (VI) and object-based classification (OBC).

ENN_MN presented significant difference for almost all land cover classes, excluding pasture and watercourses. Other uses and annual agriculture presented low values of ENN_MN, followed by secondary forest, natural vegetation and silviculture. All the other land cover also reduced their ENN, but this reduction was not so imperative (Table 3; Figure 5).

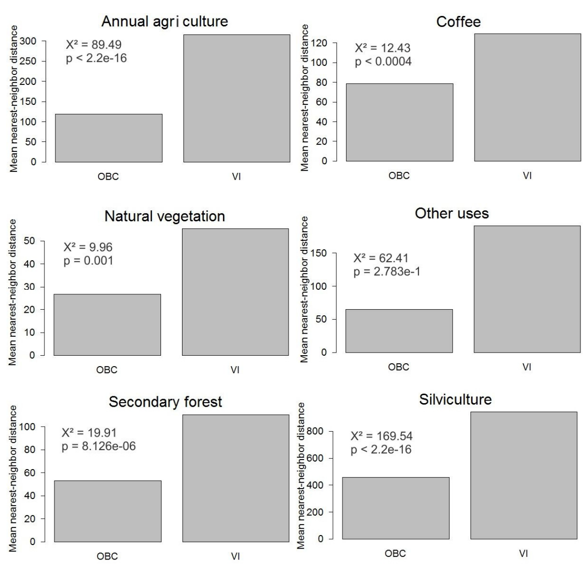

Figure 5. Mean nearest-neighbour distance (ENN_MN) for each land cover classes derived from visual interpretation (VI) and object-based classification (OBC).

Differences in PLAND, LPI and AREA_MN are not significant for all land cover classes (Table 3).

4. DISCUSSION

4.1 Classification accuracy

Some studies have reported that the classification of satellite imagery for landscape analysis can be considered difficult, since spectral data alone are insufficient to discriminate key classification categories (Cayuela et al., 2006) and this will certainly affect the calculation of landscape scale metrics (Newton et al., 2009).

Comparing time processing for both classification approaches, OBC showed a better time performance than VI. Nevertheless, it is worth noting that more processing time would be needed to increase the accuracy of the OBC approach. In this sense, cost benefit for both classifications can be almost the same.

Another factor that influenced classifications results was the kind of image used in this study. We believe the HCR SPOT image did not provide the spectral data necessary for a higher quality OBC approach, as this image is fused and presents information only from the bands in the visible portion of the electromagnetic spectrum. It was not a problem for VI approach. If the image had more spectral data regarding to other portions of the electromagnetic spectrum, OBC could present higher accuracy. Thus, OBC could present a higher cost benefit in relation to VI.

4.2 Analysis of the landscape structure

The analyses of landscape structure allowed us to verify that the classification approaches used in this study provided significantly different values for some landscape metrics. Main differences possibly occurred because of the increase in the number of patches that affects patch isolation. Nonetheless, these differences are not reliable because of the OBC accuracy.

Even though some metrics did not present significant differences, the different classifications considered in this work influenced the derived landscape metrics, compromising their ecological meaning. This information is important to take into account when performing landscape ecology studies because it can generate misinterpretation of landscape metrics and induce decision makers to develop erroneous conservation actions.

5. CONCLUSION

Different mapping strategies based on satellite imagery can affect the measurement of landscape metrics, since the approaches used in this study produced considerably different land cover maps. We believe it is important to consider the classification method when performing landscape ecology studies, in order to avoid misinterpretations of landscape metrics.

Depending on the type of satellite image OBC can provide higher cost benefit compared to VI. More studies are necessary to test this hypothesis.

This study allowed us to visualize the importance of choosing higher quality accuracy mapping with the purpose of obtaining a better understanding of landscape metrics.

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AKNOWLEDGMENT

We are very grateful to the staff of EPAMIG, to Professor Flávio Meira Borém, to FAPEMIG and CAPES for providing financial support and the scholarship.