An assessment of the sensitivity of landscape pattern metrics to classification approaches

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Abstract. In landscape ecological studies, the use of landscape pattern metrics computed from spectrally classified digital images is becoming increasingly common. Recently, object-orientated image classification is being seen as an alternative and is tending to replace pixel-based approaches. However, object-based methods are likely to influence and produce biases in the results of these spatial analyses. In this study, the sensitivity of 85 landscape metrics to different classification methods (pixel-based versus object-based) are analyzed. A Landsat image of a complex mountainous forest region of Mexico was classified using pixel-based and object-based approaches. Nine object-based classified images were obtained using a region-growing algorithm based upon different segmentation parameters. Pixel-based classified images were smoothed using different methods (majority filtering, sieving and clumping). Accuracy assessment was carried such that classified images with similar accuracy were compared. Landscape metrics were then derived from the different classified images and compared through a coefficient of variation computing. Almost all the metrics showed variability due to classification and post-processing methods, particularly core area metrics and some proximity and contagion/interspersion indices. Caution must be observed when comparing values of metrics derived from images with slight differences in their characteristics or in the way they have been processed as, for example, in landscape monitoring studies based upon multidate imagery.

Palavras-chave: landscape patterns metrics, fragmentation indices, object-oriented classification, pixel-oriented classification.

1. Introduction

Identifying and characterizing spatial patterns of landscape are often necessary in landscape ecological studies. Over the last decades, such studies have benefited from a proliferation of metrics for characterising landscapes (Frohn, 1998; Gustafson, 1998; McGarigal and Cushman, 2002; Vogt et al., 2007). Typically, remote sensing images are classified using algorithms that utilise the spectral values of individual pixels without making use of spatial information in the image such as the spectral response of the neighbouring pixels. Alternative approaches, such as object-oriented classification, which use neighbouring pixel information, are increasingly used by the remote sensing community. In object-oriented classification, homogeneous image objects are first extracted and subsequently classified. The mapping results thus represent real-world objects and lack the salt-and-pepper appearance of pixel-based classified images.

The characteristics of the remotely sensed images and the methodologies applied for their processing and classification may strongly influence the spatial characteristics of the land cover data from which spatial metrics are calculated. Recently, object-orientated image classification is tending to replace pixel-based approaches. Pixel-based and object-based oriented approaches produce classified images with different spatial patterns. However, there is no study aimed at assessing the effects of these classification approaches in landscape pattern evaluation. This paper aims at assessing the effects of the classification method (pixel-based versus object-based) and of the parameters used to carry out object-oriented classifications on landscape metrics.

2. Study area and data

The study area is located in the State of Michoacán, central west Mexico, and covers an area of approximately 58 x 60 km^2 (Figure 1). It is a mountainous region, with elevation ranging from 220 to 3830 m. The area is a complex mosaic of several land cover types including temperate pine and oak forest, dry tropical forest, orchard, bare soil, crops and pasture lands. This spatially complex area was chosen to highlight the differences between the image processing approaches.

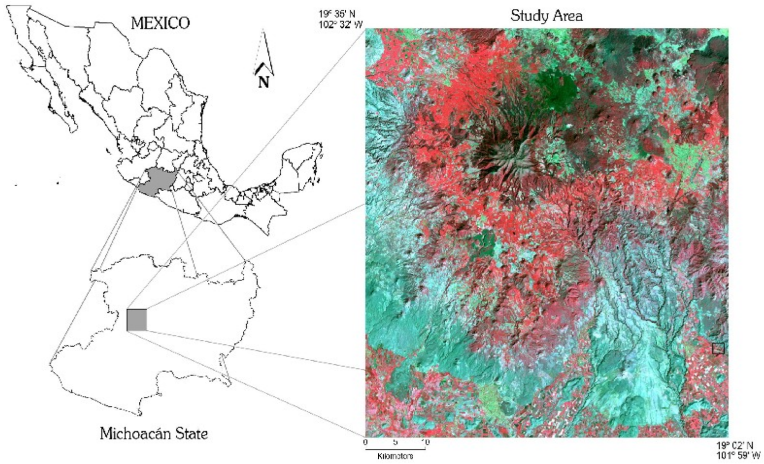

Figure 1. Location of the study area. Left side of the figure are two sketch maps indicating Mexico and Michoacán state where the study area is located; right side is the false colour composite of Landsat image.

3. Methods

The available data comprise a geometrically corrected Landsat ETM+ image obtained on 16/Feb/2003; ortho-corrected air photographs and a land cover map from the National Forest Inventory 2000 (Mas et al., 2002). Image segmentation was performed using the image processing package SPRING (Câmara et al., 1996). The landscape metrics were generated using the FRAGSTATS program version 3.3 (McGarigal and Cushman, 2002; McGarigal et al., 2002).

The research had several major components: i) land use / cover classification; ii) accuracy assessment of classified images iii) computation of landscape metrics; (iv) sensitivity measurement; and (v) interpretation and analysis. This section provides the technical details for the first four procedures (Figure 2).

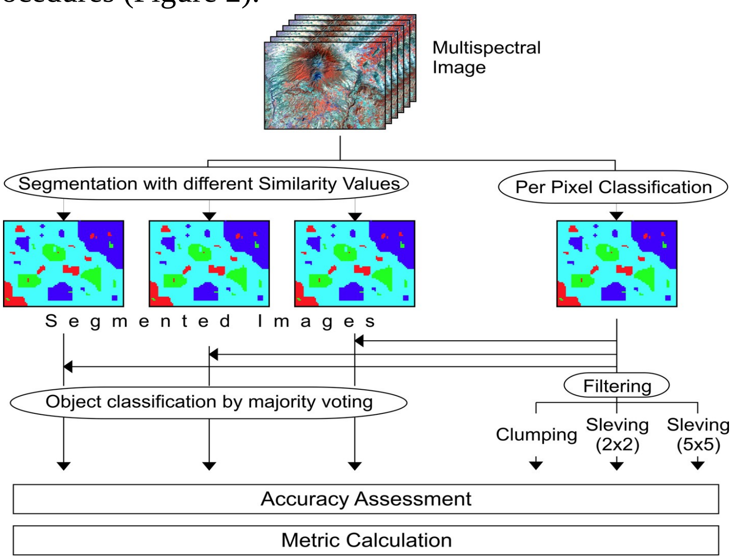

Figure 2. Flow chart of image processing steps.

3.1 Image classifications

Training areas for eight land cover categories (irrigated agriculture, rainfed agriculture, grasslands, orchards, dry tropical forest, temperature forest, human settlement and, bare land) were defined using the Landsat image, the air photographs and field data. Classifications were carried out using the standard pixel-based maximum likelihood method and an object-oriented classification, based upon two steps. First a segmentation based upon a region-growing algorithm was carried out. In order to control the segmentation procedure, two parameters were used, “similarity” and “area”. “Similarity” is a threshold value that determines whether two neighbouring objects are merged, while the “area” threshold is used to filter out the objects smaller than this value (Bins et al., 1996). A set of classified images was produced using the same parameter “area” and a range of values for “similarity”. Then, the entire objects were classified by majority voting whereby pixels of each object are assigned to the most frequent class using the pixel-based.

In order to suppress the salt-and-pepper effect of pixel based classified images, two post-classification processing techniques were applied: 1) applying a clumping (3x3 pixels) analysis to remove the scattered pixels; 2) applying a majority filter (3x3 pixels), and then sieving to remove the remaining small patches, in which two sieving threshold values were applied, based on kernels of 2x2 pixels and 5x5 pixels. These two processes produced three pixel-based classified images. A GIS procedure was applied to eliminate patches with an area below the minimum threshold area used during the segmentation procedure.

3.2. Classification accuracy

The accuracy of classification for all images was evaluated with ground data comprising 305 random points. Point´s category was determined by visual interpretation of the air photographs and by field visits for ambiguous cases. The accuracy values of the classified images were compared to evaluate the significance of the difference in accuracies of each pair of classifications. As the same set of ground truth data were used to assess the accuracy of the classified images to be compared (related samples), the statistical significance of the difference between the two accuracy statements was evaluated using McNemar’s test, which takes into account the lack of independence between samples (Foody, 2004). Only classified images which present a similar accuracy (no significant difference at $p = 0.05$) were considered in the following steps to avoid comparing landscape metrics derived from images which present different values of accuracy due to the choice of inadequate parameters during segmentation.

3.3. Computation of landscape metrics and sensitivity measurement

A total of 85 metrics (Table 1) were considered in the context of the research objective and landscape ecology principles (Turner et al., 1989; Forman, 1995; McGarigal and Cushman, 2002). These metrics are related to landscape composition or landscape configuration and can be grouped into six major categories: 1) area/density/edge, 2) shape, 3) core area, 4) isolation/proximity, 5) contagion/interspersion and 6) diversity (McGarigal et al., 2002). These metrics were computed for each of the classified images. In order to evaluate the sensitivity of each metric to the method of classification, the coefficient of variation of each metric were computed.

4. Results

4.1. Image classification and accuracy assessment

Nine segmentations were generated with similarity thresholds ranging from 19 to 59 in intervals of 5, and a constant area threshold of 22. The selection of the similarity parameter was based on visual checking of the segmentation results. With value 19, it appeared that the image was over-segmented, and with value 59 it was under-segmented (Figure 3). So the tested similarity values were set between these two values. The area threshold set at 22 pixels was in accordance with recommendations by Espindola et al. (2006) who used a Landsat image and found optimal segmentation results with this area threshold. The segmented images were classified along with the unsegmented original image (pixel-based classification).

Classification accuracies ranged from 68.7 % to 75.5 %, which lies in the range of accuracy values of many maps obtained by remote sensing and submitted to rigorous accuracy assessment (Zhu et al., 2000; Laba et al., 2002; Couturier et al., 2010). According to the McNemar's test (with p = 0.05), the values of accuracy of the three pixel-based classified images and object-based classified images obtained with similarity of 24, 29, 34, 39, and 49 are not significantly different. Therefore, the classified images with lower accuracy values were not considered further as the objective was to evaluate the variation of the landscape metrics derived from classified images with no significant difference in accuracy.

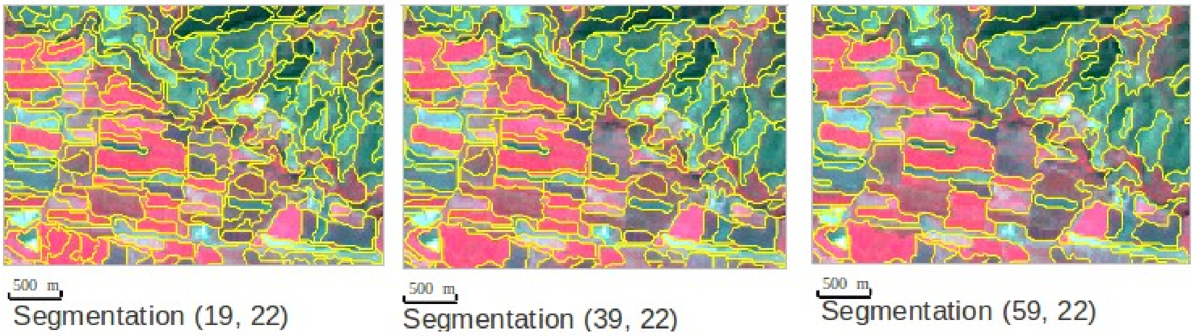

Figure 3. Segmentations with "similarity" threshold of 19, 39 and 59, and a constant "area" threshold of 22.

4.2. Metric calculation and measurement error

Table 1 shows the variation of metrics at the landscape and class level for some categories (for a complete table see Mas et al., 2010). For area/density/edge metrics, and at the landscape level, the more stable metrics (variation coefficient < 4%) were the largest patch index (LPI) and the mean radius of gyration (GYRATE). The largest patch is a temperate forest area that is relatively compact and does not suffer any important change in the different classified images (Figure 4). At the class level, LPI presents a very different behaviour depending on the land cover category. It is stable for more compact categories (forests, grassland) and presents important variations for more fragmented categories (in particular orchards). Gyrate (mean distance between each cell in the patch and the patch centroid) seems to be a quite stable metric, except when weighted by patch size for categories which show important variations of patch areas among classified images.

Among shape metrics, fractal dimension (FRAC) and perimeter-area fractal dimension (PAFRAC) show less variation because they use the logarithm of perimeter and area, which is different from the shape index (SHAPE) and the perimeter-area ratio (PARA). The contiguity index (CONTIG, average contiguity value for the cells in a patch), is also an index with low variations. At the class level, the sensitivity of these indices depends on the compactness of each category.

All core areas metrics exhibit important variations (coefficients of variation between 4% and 40% at the landscape level, reaching 61% at the class level for the orchard category).

In order to estimate isolation/proximity, the Euclidean nearest neighbour distance (ENN) is less sensitive to the classification approach than the proximity index (PROX) because it does not take into account the area of patches. At the class level, this last index has a coefficient of variation higher than 80% for bare lands and irrigated agriculture.

The contagion/interspersion indices based on adjacencies, such as the percentage of like adjacencies (PLADJ), and the aggregation index (AI) are less sensitive than those indices derived from the area of the patches, such as the effective mesh size (MESH) and the splitting index (SPLIT). At class level, these two last indices have a large amount of variation particularly for the category ‘orchards’ (with a coefficient of variation of 75.2 and 33.6% respectively). The connectivity index patch cohesion index (COHESION), based on area and perimeter of the patches, has less variation than the connectance index (CONNECT). CONNECT is derived from the number of functional joints between all the pairs of patches of the corresponding patch type within a distance specified by the user.

The diversity index patch richness (PR) shows no variation because all the classified images have the same number of categories. Simpson’s Diversity Index (SIDI) is more stable because it is less sensitive to change in scarce categories than the Shannon’s Diversity Index (SHDI).

Generally, area-weighted means of metrics are not necessarily more stable than simple means of metrics, because the differences between the classified images obtained by the different approaches of classification and post-processing are not limited to small patches. In fact, the different approaches and parameters lead to the elaboration of images whose structure is different: from one image to another. Small patches can appear or disappear, but also larger patches can be connected or disconnected. Therefore, both large and small patches can vary, depending on the classification and post-classification procedures applied. As expected, the segmentations carried out with larger similarity values produced images with smaller patches, and the landscape shape was less complex. However the effects of sieving and clumping are more difficult to predict.

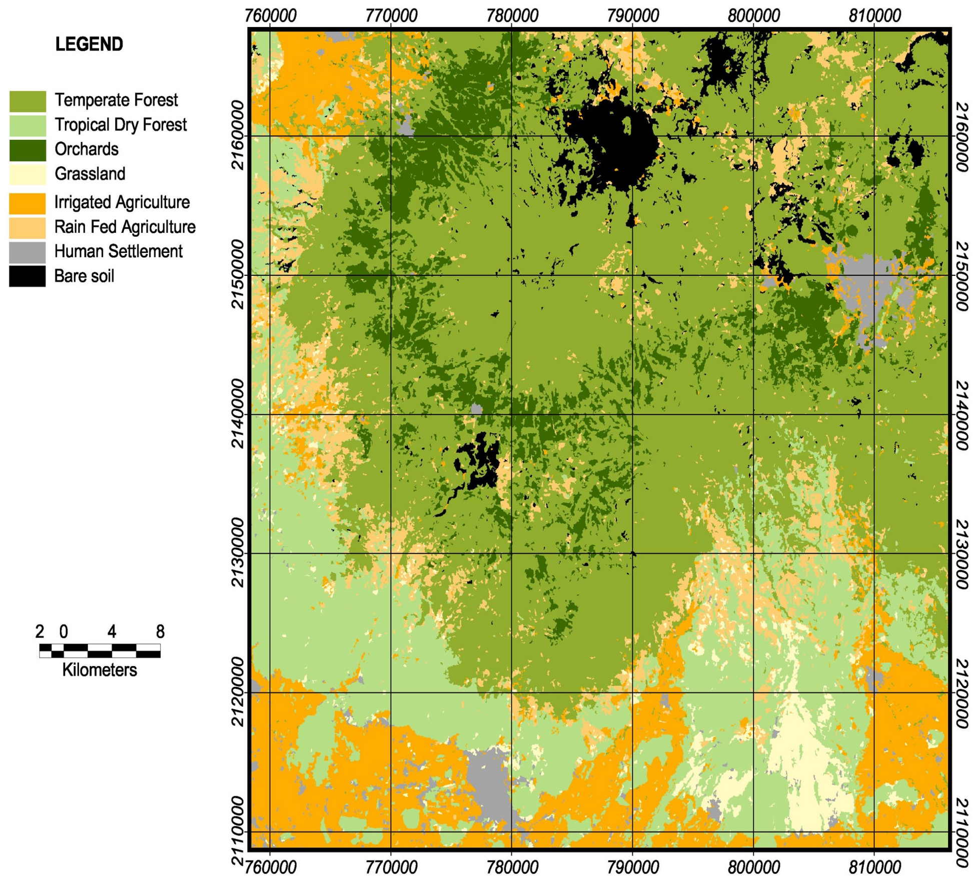

Figure 4. Classified image obtained by pixel based maximum likelihood method followed by majority filtering, sieving and deletion of patches which size is below 22 pixels.

Table 1. Coefficients of variation of landscape metrics at landscape and class level.

Index (Acronym)	Full name	Landscape	Bare lands	Grasslands	Irrigated Agriculture	Orchards	Temperate Forest
NP	Number of parches	8.6	15.3	13.9	20.8	8.2	18.6
PLAND	Percentage of landscape	-	18.4	2.3	8.7	11.1	2.1
PD	Patch density	-	15.3	13.9	20.8	8.2	18.6
LPI	Largest Patch Index	4.0	10.0	5.0	17.8	35.2	4.0
TE	Total edge	8.6	20.7	8.4	15.8	6.0	6.7
ED	edge density		20.7	8.4	15.8	6.0	6.7
LSI	Lanscape shape index	8.5	13.1	7.9	13.3	4.4	7.5
AREA*	Mean patch area	8.69/6.9	7.5 / 13.2	14.5/12.1	18.3/18.9	18.8/56.3	16.5/6.2
GYRATE*	Mean radius of gyration	2.8/2.4	4.2/11.0	5.1/13.8	3.6/17.6	3.4/34.1	5.6/2.0
SHAPE*	Mean shape index	4.8/4.9	5.8/12.3	3.8/13.5	7.6/13.6	3.3/19.0	6.1/6.4
FRAC*	Mean fractal dimension index	0.7/0.4	0.9/0.9	0.5/1.1	1.4/0.9	0.5/1.04	0.9/0.5
PARA*	Mean perimeter-area ratio	3.5/8.4	2.7/8.7	3.9/7.5	8.5/11.8	3.5/6.9	4.5/8.4
CONTIG*	Mean contiguity index	1.2/0.7	1.3/1.3	1.1/1.0	2.9/1.0	1.4/0.7	1.5/0.5
PAFRAC	Perimeter area fractal dimension	1.8	2.1	1.8	2.5	0.5/1.04	2.0
TCA	Total core area	4.3					
CPLAND	Core area percent of landscape	-	17.6	9.0	13.4	20.6	5.6
NDCA	Number of disjunct core areas	6.0	17.8	8.9	6.1	6.2	13.5
CORE*	Mean core area	12.7/9.5	12.9/10.4	21.0/15.6	18.9/20.3	29.7/61.5	19.7/8.8
DCORE*	Mean disjunct core area	10.3/40.5	7.5/6.2	14.0/28.0	16.8/23.7	22.5/70.5	17.0/44.6
CAI*	Mean core area index	7.9/4.4	8.6/7.1	15.6/9.2	27.0/7.2	9.3/8.7	7.9/3.9
PROX*	Mean proximity index	13.3/27.6	12.3/153.9	16.1/32.6	38.4/84.0	33.3/34.6	7.5/28.6
ENN*	Mean Euclidian nearest neighbour distance	6.2/4.0	9.0/13.0	15.4/37.8	8.5/3.8	16.2/3.4	8.7/1.3
CLUMPY	Clumpiness	-	1.2	0.9	1.0	0.6	0.6
CONTAG	Contagion	2.0					
PLADJ	Proportion of like adjacencies	0.6	1.1	0.9	0.8	0.7	0.4
IJI	Interspersion / juxtaposition index	1.7	16.0	2.7	2.8	21.5	1.3
DIVISION	Landscape division index	1.3	0.0	0.0	0.1	0.1	1.4
MESH	Effective mesh size	6.8	32.6	10.7	23.6	75.2	7.9
SPLIT	Spitting index	6.9	19.8	10.9	26.4	33.6	8.0
AI	Aggregation index	0.6	1.1	0.9	0.8	0.6	0.4
CONNECT	Conectance index	3.1	10.3	2.0	7.9	3.7	9.4
COHESIO N	Patch cohesion index	0.0	0.3	0.3	0.1	0.2	0.0
PR	Patch richness	0.0					
SHDI	Shannon´s Diversity Index	1.2					
SIDI	Simpson´s Diversity Index	0.9					
MSIDI	Modified Simpson´s Diversity Index	2.0					
SHEI	Shannon´s eveness index	1.2					
SIEI	Simpson´s eveness index	0.9					
MSIEI	Modified Simpson´s eveness index	2.0					

* Results based on metrics computed using simple mean and area-weighted mean (simple mean/area-weighted).

5. Discussion and conclusion

Many studies have aimed to quantify landscape pattern and/or forest fragmentation over time (Fitzsimmons, 2003; Cayuela et al., 2006; Abdullah and Nakagoshi, 2007). The variations in the values of the indices due to the classification approach that we found in this work are of the same magnitude as the variations due to land cover/use change found by Yung and Liu (2005). Consequently, the interpretation of the variation of landscape metrics of land use/cover maps of different dates obtained through the digital classification of images using 1) different approaches (pixel-based or object-based) or 2) different parameters when carrying out the segmentation of the image or the filtering of a pixel-based classified image must be taken with caution. This is because artifacts can produce significant variations in the value of the metrics.

In studies where metrics are compared between sub-regions extracted from the same image, and therefore classified with the same method/parameters, metrics which are more sensitive can be preferentially used. For multidate comparison, when classification methods are distinct for the different dates, or when other factors such as spatial resolution or vegetation phenology are likely to play a role, more stable metrics should be preferred. However, metrics that are too stable, such as the patch richness, will not detect changes, and therefore a trade-off between robustness (stability) and sensitivity must be found.

As shown in this study, variations in the value of landscape metrics can be the result of the approach used to analyze the images. Therefore, caution must be exercised in making meaningful comparisons and in detecting to what degree variations in metrics are really related to significant changes in the landscape, and not to artefacts derived from methodological problems in their measurement. Comparison of landscape metrics must therefore be made with explicit knowledge of their sensitivity as demonstrated here. In further studies, a similar sensitivity assessment will be applied to landscape evaluation based on different approaches such as landscape connectivity (Saura and Torné, 2009; Saura and Rubio, 2010).

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References

Abdullah, S.A., Nakagoshi, N. Forest fragmentation and its correlation to human land use change in the state of Selangor, peninsular Malaysia. **Forest Ecology and Management**, v. 241, n. 1-3, p. 39-48, 2007.

Bins, L.S., Fonseca, L.M.G., Erthal, G.J., Li, F.M., 1996. Satellite Image Segmentation: a region growing approach. In: VIII Simpósio Brasileiro de Sensoriamento Remoto, Salvador, Bahía, Brazil, p. 677-680.

Câmara, G., Souza, R.C.M., Freitas, U.M., Garrido, J., 1996. SPRING: Integrating remote sensing and GIS by object-oriented data modelling. **Computers & Graphics**, v. 20, p. 395-403, 1996.

Cayuela, L., Benayas, J.M.R., Echeverría, C. Clearance and fragmentation of tropical montane forests in the Highlands of Chiapas, Mexico (1975-2000). **Forest Ecology and Management**, n. 226, p. 208-218, 2006.

Couturier, S., J.F. Mas, E.L.-G., Benítez, J., Tapia, V., Vega, Á. Accuracy Assessment of the Mexican National Forest Inventory map: a study in four eco-geographical areas. **Singapore Journal de Tropical Geography**, n. 31, p. 163-179, 2010.

Espindola, G.M., Camara, G., Reis, I.A., Bins, L.S., Monteiro, A.M. Parameter selection for region-growing image segmentation algorithms using spatial autocorrelation. **International Journal of Remote Sensing**, v. 27, n. 14, p. 3035-3040, 2006.

Fitzsimmons, M. Effects of deforestation and reforestation on landscape spatial structure in boreal Saskatchewan, Canada. **Forest Ecology and Management**, n. 174, p. 577-592, 2003.

Foody, G.M. Thematic Map Comparison: Evaluating the Statistical Significance of differences in Classification Accuracy. **Photogrammetric Engineering & Remote Sensing**, v. 70, n. 5, p. 627-633, 2004.

Forman, R.T.T. **Land Mosaics: The Ecology of Landscapes and Regions**. Cambridge: Cambridge University Press, 1995, 632 p.

Frohn, R.C. **Remote Sensing for Landscape Ecology: New Metric Indicators for Monitoring, Modeling, and Assessment of Ecosystems**. Boca Ratón, Florida, USA:Lewis Publishers, 1998, 99p.

Gustafson, E.J. Quantifying Landscape Spatial Pattern: What Is the State of the Art? **Ecosystems**, n. 1, p. 148-156, 1998.

Kearns, F.R., Kelly, N.M., Carter, J.L., Resh, V.H. A method for the use of landscape metrics in freshwater research and management. **Landscape Ecology**, v. 20, n. 1, p. 113–125, 2005.

Laba, M., Gregory, S.K., Braden, J., D, D.O., E, E.H., Fegraus, E., Fiore, J., DeGloria, S.D., 2002. Conventional and fuzzy accuracy assessment of the New York Gap Analysis Project land cover map. **Remote Sensing of Environment**, v. 81, n. 1-2, p. 443-455, 2002.

Mas, J.F., Gao, Y., J.A. Navarrete Pacheco. Sensitivity of landscape pattern metrics to classification approaches. **Forest Ecology and Management**, v. 259, n.7, p. 1215–1224, 2010.

Mas, J.F., Velázquez, A., Palacio-Prieto, J.L. Bocco, G., Peralta, A., Prado, J. Assessing forest resources in Mexico: Wall-to-wall land use/cover mapping, **Photogrammetric Engineering & Remote Sensing**, v. 68, n. 10, p. 966-968, 2002.

McGarigal, K., Cushman, S.A. Comparative Evaluation of Experimental Approaches to the Study of Habitat Fragmentation Effects. **Ecological Applications**, v. 12, n. 2, p. 335-345, 2002.

McGarigal, K., Cushman, S.A., Neel, M.C., Ene, E., 2002. FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. In. University of Massachusetts, Amherst, computer software program. Disponível em www.umass.edu/landeco/research/fragstats/fragstats.html. Acceso em 10 out 2010.

Saura, S., Rubio, L. A common currency for the different ways in which patches and links can contribute to habitat availability and connectivity in the landscape. **Ecography**, n. 33, p. 523-537, 2010

Saura, S., Torné, J. Conefor Sensinode 2.2: a software package for quantifying the importance of habitat patches for landscape connectivity. **Environmental Modelling & Software**, n. 24, p. 135-139, 2009.

Turner, M.G., O'Neill, R.V., Gardner, R.H., Milne, B.T. Effects of changing spatial scale on the analysis of landscape pattern. **Landscape Ecology**, v. 3, n. 3-4, p. 153–162, 1989.

Vogt, P., Riitters, K.H., Estreguil, C., Kozak, J., Wade, T.G., Wickham, J.D. Mapping Spatial Patterns with Morphological Image Processing. **Landscape Ecology**, v. 22, n. 2, p. 171-177, 2007.

Yang, X., Liu, Z., 2005. Quantifying landscape pattern and its change in an estuarine watershed using satellite imagery and landscape metrics. **International Journal of Remote Sensing**, v. 26, n. 23, p. 5297-5323, 2005.

Zhu, Z., Yang, L., Stehman, S.V., Czaplewski, R.L. Accuracy assessment for the U.S. Geological Survey regional land-cover mapping program: New-York and New Jersey region. **Photogrammetric Engineering & Remote Sensing**, v. 66, n. 12, p. 1425-1435, 2000.