

# BRIDGING REMOTE SENSING ANALYSTS AND DECISION-MAKERS; THE SUPPORT OF AGGREGATE-MOSAIC THEORY TO MONITOR TROPICAL DEFORESTATION

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## ABSTRACT:

The land cover mosaic (LCM) classification concept, which is based on the aggregate-mosaic theory, improves geo-information on tropical deforestation for decision-makers. Land cover mosaics are spatial units constituting mixtures of different land cover types. They are defined by two parameters, that is the mix of different land cover types and the spatial size of these land cover types. In this paper, a sensitivity analysis was performed to test the impact of the parameter spatial size on LCM classification results using two Landsat TM images of a peatswamp forest in Kalimantan, Indonesia. Five methods were selected to evaluate the LCM-classification results, the standard remote sensing accuracy method KHAT, and four Landscape Pattern Metrics as applied in landscape ecology. Results showed that for spatial sizes up to 150 ha, the total area of forest cover remained constant for both the 1990 image and the more fragmented 1996 image. This finding is very useful for assessing the area of forest cover, which often differ widely between various sources. From a decision-making point of view it is important that maps are produced with identical parameter settings, when comparing temporally different images, because spatial size has effect on the spatial arrangement of forest cover. Combining results of KHAT and Landscape Pattern Metrics thematic classes causing significant differences could be indicated. Finally, based on variations in LCM classifications, it can be concluded that between 1990 and 1996 forest was depleted not due to logging practices, but due to agricultural practices. Such a finding could be very useful to support planning and development strategies, and to improve governmental policies to manage tropical rainforests in a sustainable way.

## 1. INTRODUCTION

Global studies of tropical deforestation are based on information sources compiled at regional levels. Parts of these regional information sources are based on digital maps derived from remote sensing data, where forest cover information is classified and stored at pixel level. These maps are static and, without further interpretation, they do not have much explanatory or predictive power about the driving forces and mechanisms behind forest cover changes (the actors). Decision-makers, however, need such explanatory information on actors to decide when and where to take action concerning undesirable developments in tropical rainforest areas. Consequently, remote sensing image analysts should expand their monitoring task of land cover at pixel level towards identification of actors, design models on actors behavior, and prepare scenario's on the impact of the actors. This calls for an underlying remote sensing theory that describes how to retrieve such explanatory information from remote sensing data. An important issue of such a theory is handling the problem that vegetation in tropical rainforest areas is extremely heterogeneous (Whitmore, 1998). It often consists of different mixtures of trees, shrubs and grasses at different spatial aggregation levels resulting in different vegetation structures. Consequently, vegetation heterogeneity should be expressed as variations in vegetation composition and vegetation structure at different spatial aggregation levels. As such, variations in land cover mosaics can be related to different actors.

A range of innovative processing techniques have been developed to improve per-pixel based classifications. However, the majority of the techniques either address vegetation mixture

(to reduce autocorrelation or spectral overlap) or vegetation structure (to handle image texture). Examples of reducing autocorrelation are segmentation algorithms (Hill, 1999), filtering (Palubinskas et al., 1995), and Markov random fields (Cortijo & Perez de la Blanca, 1998). Examples of reducing spectral overlap are co-occurrences (Kushwada et al., 1994), semi-variograms (Woodcock & Strahler, 1987), and cover-frequencies (Bandibas et al. 1995). Examples of handling image texture are wavelet transforms (Carvalho et al., 2001), multi-resolution segmentation (Burnett & Blaschke, 2003), and post-classification aggregation (Beurden van & Douven, 1999). Aggregate-mosaic theory describes the concept of land cover mosaic (LCM) classification to address both vegetation mixture and vegetation structure at higher aggregation levels than the pixel when classifying remote sensing data (Obbink, et al., 2002). Land cover mosaics are spatial units constituting mixtures of different land cover types. They are defined by two parameters, that is the mix of different land cover types and the spatial size (expressed as minimum -area) of these land cover types. Based on expert knowledge, variations in land cover mosaics can be related to different actors. The objective of this paper is to demonstrate the LCM classification concept for two temporal images of a peatswamp forest in Kalimantan, Indonesia. Specifically, a sensitivity analysis was performed to test the impact of the parameter spatial size on LCM classification results, and on variability and arrangement of forest cover and forest cover pattern using KHAT and four Landscape Pattern Indices.

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## 2. METHOD

### 2.1 Study area, remote sensing data and software

The Pelangkaraya study area is situated in an extensive peat swamp forest, roughly between the cities Palangkaraya and Banjarmasin, South Kalimantan, Indonesia (Figure 1). It covers roughly 115.000 ha (45 by 25 Km). Three main rivers (i.e., *Barito*, *Kahayan* and *Kapuas*) cut across the flat area. For centuries, shifting cultivation has been the main practice in this area. Since the eighties, however, numerous logging firms and large transmigration projects have been active in the area. As a result of both logging and transmigration, the forest changed into a mosaic of logged forest, heavily logged forest, patches of original forest, agricultural fields (trees and crops), fields covered mainly with grasses (as a result of fire in the past), abandoned fields covered mainly with shrubs, and water areas.



Figure 1: Location of study area

In this research, two Landsat TM remote sensing images of 30/08/1990 and 10/05/1996 covering the Pelangkaraya study area were used. Colour composites (Landsat TM bands 453) of both images are given in Figure 2. The images were geometrically corrected using cubic convolution for resampling to a spatial resolution of 30 meters. Software packages ILWIS academic 3.0 and eCognition 3.0 were used for LCM classification. SPSS was used to calculate KHAT and Z statistics, and Fragstats 3.3 was used to calculate four Landscape Pattern Indices.

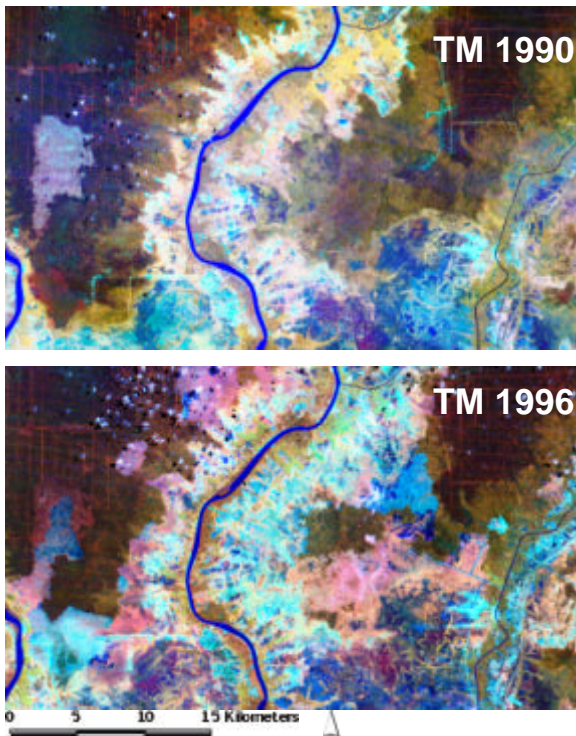


Figure 2: Colour composites of two Landsat TM images of 1990 and 1996 (bands 453, histogram equalization)

### 2.2 LCM classification method

The LCM classification concept is a multi-scale classification approach based on two levels (Figure 3). The first level contains elementary objects consisting of conventional land cover classes. The second level contains composite objects consisting of land cover mosaic classes, which are based on two LCM parameters that is the size and mix of elementary objects (Obbink, et al., 2002; Schaijk-Obbink et al., 2000).

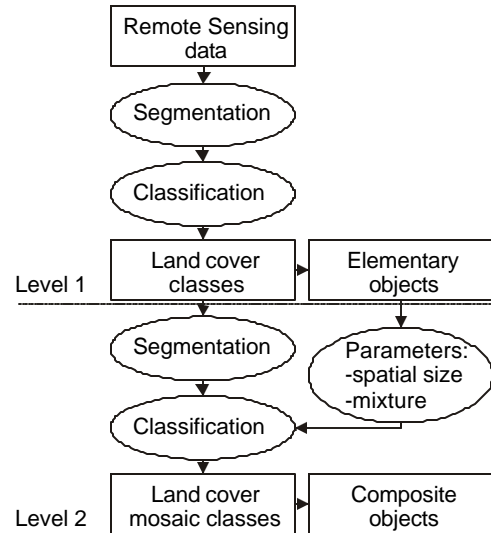


Figure 3: The Land Cover Mosaic (LCM) classification concept

In this study, elementary objects were created by segmenting the remote sensing image into (radiometrically) homogeneous segments. The eCognition segmentation algorithm was used to segment the Landsat TM images (band 3,4,5,7) using the following parameters: scale 10, color 0.9, shape 0.9. Nearest neighbor was used for a supervised classification of the elementary object into eight land cover classes (i.e., logged forest, heavily logged forest, shrub, agriculture, grass, water, river, and clouds). Composite objects were created by merging all adjacent elementary objects that represent similar land cover classes. Based on the spatial size (expressed as minimum-area, *MA*) and mix (expressed as relative-border-to-neighbor, *BN*) of the elementary objects, composite objects were classified into seven land cover mosaic classes (i.e., mainly logged forest, mainly heavily logged forest, mainly shrub, mainly agriculture, mainly grass, mainly water, and mainly clouds), and one land cover class (i.e., river). Mainly refers to predominance of a land cover class. This means that if the size of an elementary object with a certain land cover type is smaller than a certain threshold (*MA in ha*), and it is surrounded by another elementary object with a different land cover type as set by a threshold (*BN in %*), then both elementary objects are part of a higher level thematic class that is a land cover mosaic class.

### 2.3 Sensitivity Analysis and evaluation methods

A sensitivity analysis was performed to test the impact of the LCM parameter size (*MA*) on classification outcome. Fourteen different *MA* values were selected ranging from 5 ha to 18800 ha (i.e., 5, 5.5, 15, 25, 50, 100, 150, 200, 250, 300, 350, 400, 15000, 18800 ha). These values were chosen according to the size of the image objects present in the classified images: from

| p 1990 image       |            |                   |                 |         | p 1996 image       |            |                   |                 |         |
|--------------------|------------|-------------------|-----------------|---------|--------------------|------------|-------------------|-----------------|---------|
| Elementary objects |            | Composite objects |                 |         | Elementary objects |            | Composite objects |                 |         |
| LC class           | PLAND in % | LCM class         | mean PLAND in % | SD in % | LC class           | PLAND in % | LCM class         | mean PLAND in % | SD in % |
| LF                 | 25.13      | mLF               | 25.51           | 1.89    | LF                 | 21.25      | mLF               | 21.26           | 2.43    |
| HLF                | 27.65      | mHLF              | 26.99           | 2.08    | HLF                | 16.30      | mHLF              | 12.25           | 2.38    |
| SH                 | 24.60      | mSH               | 24.95           | 0.52    | SH                 | 33.99      | mSH               | 38.20           | 3.60    |
| AG                 | 14.77      | mAG               | 15.44           | 0.96    | AG                 | 14.53      | mAG               | 14.40           | 0.74    |
| GR                 | 6.13       | mGR               | 5.62            | 0.79    | GR                 | 11.40      | mGR               | 11.60           | 2.57    |
| WA                 | 0.37       | mWA               | 0.18            | 0.14    | WA                 | 1.17       | mWA               | 1.00            | 0.13    |
| RI                 | 1.35       | mRI               | 1.32            | 0.02    | RI                 | 1.29       | mRI               | 1.29            | 0.03    |
| CL                 | 0.00       | -                 | -               | -       | CL                 | 0.00       | -                 | -               | -       |

Table 1: Elementary objects versus composite objects expressed in cover percentages (PLAND) for respectively the land cover classes (LC) and land cover mosaic classes (LCM); the latter are based on the mean PLAND values resulting for the 14 different MA values (p1990 image and p1996 image).

the smallest elementary object up to the largest composite object. In addition, the values should also include the minimum -area of tree covered land that should be considered as 'forest', which ranged from 0.01 ha in the Czech Republic to 100 ha in Papua New Guinea (Lund, 1999). During the sensitivity analysis, the LCM parameter mix was kept constant (BN=0.55). A total of 28 LCM classifications were carried out on two Landsat TM images of the Pelangkaraya study area of 1990 and 1996 further referred to as p1990 and p1996.

Five methods were selected to evaluate the LCM-classification results, the standard remote sensing accuracy method KHAT (Congalton and Mead, 1983) and four Landscape Pattern Metrics as applied in landscape ecology (Forman, 1995; McGarigal et al., 2002). The discrete multivariate analysis technique KHAT and the Z-statistic for significance testing are used to evaluate the overall classification results (Hudson and Ramm, 1987). The elementary objects are used as reference to calculate the similarity matrices. The Landscape Pattern Metrics were used to evaluate the LCM classification results on variability and arrangement of forest cover and forest cover pattern. The metrics *Percentage of Landscape* (PLAND) and *Number of patches* (NP) evaluate forest cover, whereas the metrics *Simpson's Diversity Index* (SIDI) and *Landscape Shape Index* (LSI) evaluate forest cover pattern. PLAND and SIDI are spatially independent metrics, which refer to composition or variability of the landscape, or 'how different things are'. NP and LSI are spatially dependent metrics, which refer to the configuration or arrangement of the landscape, or 'how things are distributed' (Forman, 1995; Gustafson, 1998).

### 3. RESULTS

#### 3.1 LCM classification results

Figure 4 shows the LCM classification results for two different values for minimum area, i.e., MA is 25 ha and 300 ha, for the p1990 image (with BN=0.55). For comparison, figure 5 shows a standard per-pixel classification result using the maximum likelihood classifier. Figure 4 clearly shows that LCM classification results provide crisp maps. In addition, the LCM-classification with the larger minimum-area results in fewer small objects; it is more aggregated.

Table 1 shows the classification results of elementary objects versus composite objects expressed in cover percentages (i.e., PLAND). Overall, both aggregation levels show similar ranking of major and minor classes. For the p1990 image, there

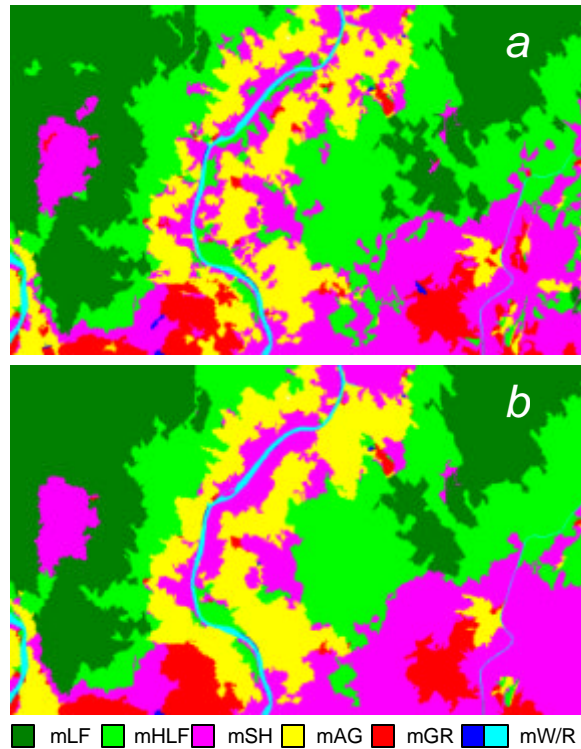
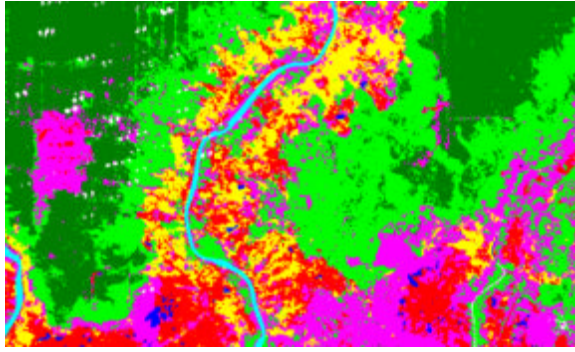


Figure 4: LCM-classification results for the p1990 image; MA is 25 ha (a), and MA is 300 ha (b), both with BN at 0.55.

is almost no difference (<1% cover) in PLAND values between the two aggregation levels for all thematic classes. However, for the 1996 image two striking differences ( $\approx 4\%$  cover) exist for the thematic classes related to heavily logged forest and shrub. From 1990 to 1996, shrub vegetation and grass vegetation have enormously increased, reducing the vegetation of heavily logged forest. The increase of grass vegetation is depicted by both aggregation strategies meaning that grass tends to occur in (homogeneous) clusters. However, the increase of shrub is differently depicted by both aggregation strategies meaning that shrub tends to be (heterogeneously) distributed over the landscape. This finding supports the fact that shrub is an intermediate vegetation between the transition of forest to agriculture and vice versa.



■ LF ■ HLF ■ SH ■ AG ■ GR ■ W ■ R  Cl

Figure 5: Standard per-pixel classification result using the maximum likelihood classifier.

### 3.2 Classification performance (KHAT & Z-statistic)

Figure 6 shows the LCM classification results expressed in KHAT values for the fourteen different MA values. The figure clearly shows that varying MA values have more effect on the more fragmented p1996 image than on the p1990 image. However, the sensitivity of both images towards different MA values is similar. Overall, KHAT values decrease for increasing MA. Specifically, the largest decrease is for MA values between 5.5 ha and 100 ha, whereas MA shows a small decrease between MA<sub>100</sub> and MA<sub>250</sub>, and a minor decrease between MA<sub>250</sub> and MA<sub>400</sub>.

The Z statistics showed that the majority of MA settings are significantly different at the 0.05 probability level. This means that almost all LCM-classification results are different. Specifically, the more the MA values are dissimilar, the higher the Z values. However, no significant difference occurs between MA<sub>100</sub> and MA<sub>150</sub>, MA<sub>200</sub> and MA<sub>250</sub>, and MA<sub>300</sub> and MA<sub>350</sub> for the p1990 image. For the p1996 image a similar 'pattern' occurs, but with a small shift of plus 50 ha, that is, no significant difference occurs between MA<sub>150</sub> and MA<sub>200</sub>, MA<sub>250</sub> until MA<sub>350</sub>, MA<sub>350</sub> and MA<sub>400</sub>. It seems that both images react similarly on different values for MA, although the p1996 image is more fragmented than the p1990 image.

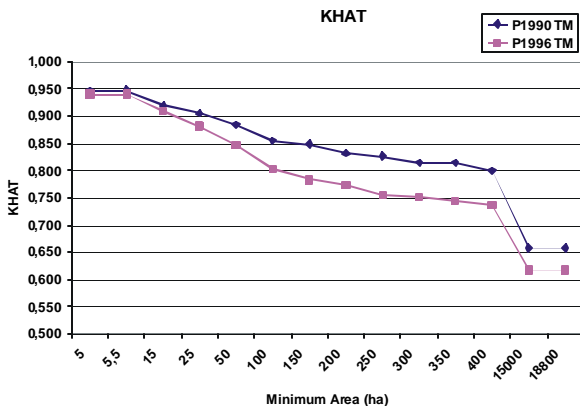


Figure 6: KHAT values for different values of minimum-area (MA) in LCM classification.

### 3.3 Variability and arrangement of forest cover (PLAND & NP)

Figure 7 shows the LCM classification results as measured by the two class-related metrics PLAND (percentage of landscape) and NP (number of patches) for the two LCM forest classes mainly logged forest (mLF) and mainly heavily logged forest (mHLF), and the intermediate LCM class mainly shrub (mSH). For all MA values up to 400 ha, PLAND is almost constant (less than 2% cover difference) for all three LCM classes in both images, except for the LCM class mainly shrub of the p1996 image. This LCM class increases between MA<sub>25</sub> and MA<sub>150</sub> from 34% to 39%. For MA values higher than 400 ha, PLAND changes for all three classes about 5% (cover). The figure shows also clearly that NP for p1996 is higher than NP for p1990 for the entire MA range. For the class mainly heavily logged forest NP of p1990 is higher, because of the enormous reduction of this class in 1996.

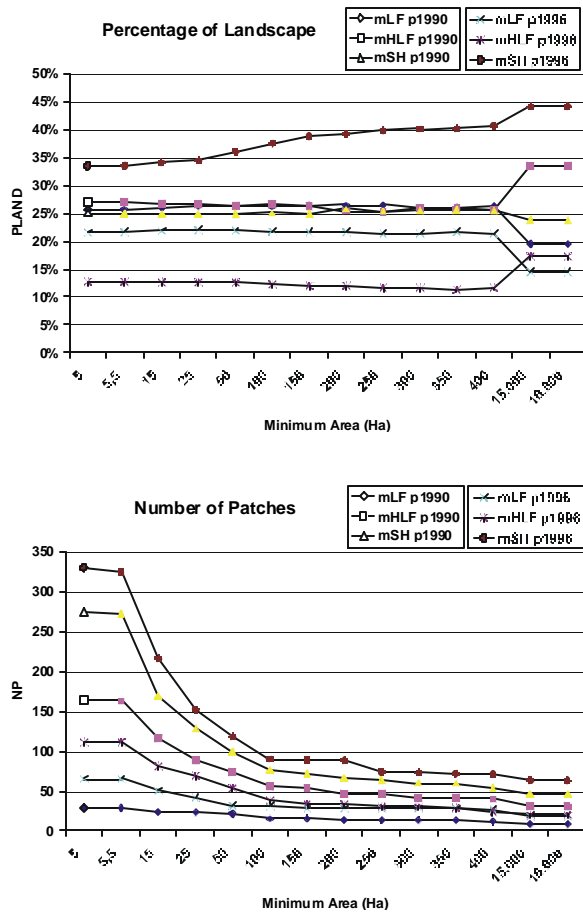


Figure 7: LCM classification results as measured by the two landscape pattern metrics PLAND (percentage of landscape) and NP (number of patches) for forest cover.

Being a fragmentation measure of the patch type, higher NP values for the p1996 image means that indeed this image is more fragmented than the p1990 image for all three vegetation classes. Generally, NP tends to decrease when increasing MA for all LCM classes and for both images. Specifically, the influence of MA on NP is largest for MA values smaller than 100 ha; above MA<sub>100</sub> NP stays constant for all classes. This

means that the spatial arrangement of the classes varies up to MA<sub>100</sub> and remains constant for larger MA values. However, the intensity at which classes vary differs between the three LCM classes. The class mainly logged forest (mLF) is less sensitive for MA than the class mainly heavily logged forest (mHLF), which on his turn is less sensitive than the class mainly shrub (mSH).

### 3.4 Variability and arrangement of forest cover pattern (SIDI & LSI)

Figure 8 shows the LCM classification results as measured by the two landscape-related metrics SIDI (Simpson's diversity index) and LSI (landscape shape index). Simpson's index literally means the probability that any two pixels selected at random would be different LCM classes. For the p1990 image, SIDI remains constant up to MA<sub>400</sub>, meaning that the relative proportions of the LCM classes do not change. For the more fragmented p1996 image, however, SIDI shows a distinct decrease between MA<sub>25</sub> and MA<sub>150</sub>. This means that the dominance of one or a few LCM classes increases. Both images show a distinct decrease in SIDI between MA<sub>400</sub> and MA<sub>15000</sub>.

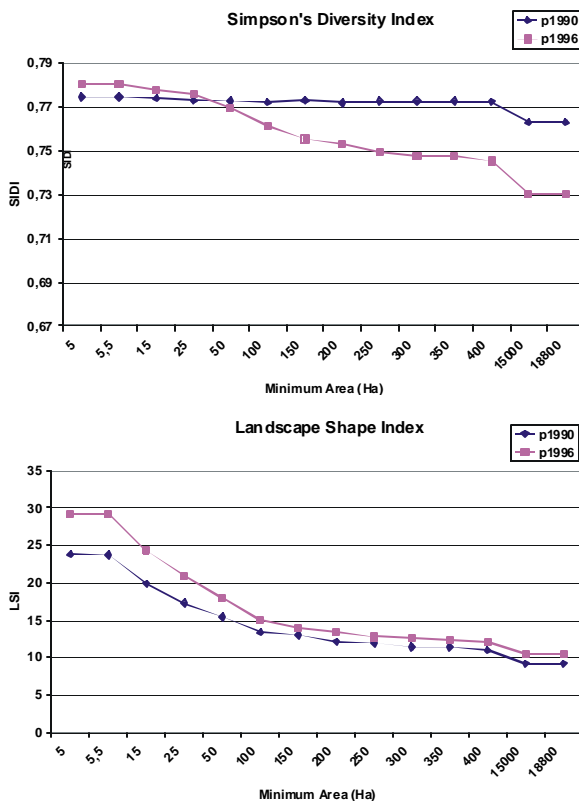


Figure 8: LCM classification results as measured by the two landscape pattern metrics SIDI (Simpson's diversity index) and LSI (landscape shape index) for forest cover pattern.

The metric LSI measures the perimeter-to-area ratio for the entire landscape. An increase in LSI means that patches become increasingly disaggregated, thus the spatial heterogeneity of the landscape increases. Overall, LSI is higher for the p1996 image than for the p1990 image. Thus, p1996 has a more heterogeneous landscape than p1990. For both images, LSI decreases when MA increases. Specifically, LSI shows a

significant decrease between MA<sub>5.5</sub> and MA<sub>100</sub> for both images; in this range LSI shows a 50% decrease. In addition, spatial heterogeneity of the p1990 image and the more fragmented p1996 image shows a similar trend for the entire MA range.

## 4. DISCUSSION

The setting for the minimum-area (MA) in LCM classification has an impact on classification outcome, especially from MA<sub>5.5</sub> to MA<sub>150</sub>. However, for MA values up to 150 ha the total area of forest cover (mLF + mHLF) remained constant for both the p1990 image and the more fragmented p1996 image. This finding is very useful for assessing the area of forest cover in a certain area. Forest area is an easily understood baseline figure that provides the first indication of the relative importance of forests in a country or region (FAO, 2001). In addition, the results show that according to Van Beurden and Douven (1999), decision-makers (at different decision-levels) can make sensible consistent decisions on forest area, because several levels of aggregation provide the same forest area. However, in the more fragmented p1996 image, PLAND (percentage of landscape) of the LCM class mainly shrub (mSH) did not remain constant for MA values up to 150 ha. Realizing that HLF and SH share very similar spectral signatures, it depends very much on the accuracy of the input level (elementary objects) whether the total area of forest cover is independent of MA. MA has an effect on NP (number of patches), meaning that it has an effect on the spatial arrangement of forest cover. Consequently, from a decision-making point of view it is important that maps are produced with identical MA values, when comparing temporally different images. In addition, the indices NP and KHAT seem to be a useful combination to indicate which classes are causing significant differences between classification results.

Simpson's diversity index (SIDI) remained constant for the p1990 image. However, for the p1996 image it showed a distinct decrease between MA<sub>25</sub> and MA<sub>150</sub>. This difference in SIDI between the two images can be explained by combining the results of PLAND and SIDI. PLAND of all seven LCM classes did not change along the entire MA range (i.e., MA up to 400 ha) for the p1990 image. However, for the p1996 image, PLAND did change for the LCM class mainly shrub, especially at the range between MA<sub>25</sub> and MA<sub>150</sub> for which SIDI changed. A constant PLAND and a constant SIDI mean that the LCM classes in the image have their own specific composition in the landscape. Nevertheless, for certain classes like mainly shrub for which PLAND changed, SIDI quantifies this compositional change. In this respect, SIDI is a useful index to quantify changes in LCM classifications in addition to standard PLAND values. The indices KHAT and LSI, showing a similar trend, are complementary to each other. From a decision-point of view, such a combination seems to be useful to indicate which classification results differ significantly.

## 5. CONCLUSIONS

From the classification results it can be concluded that the LCM classification concept provided explanatory information on vegetation changes in tropical rainforest areas. Based on the findings of the LCM parameter spatial size, three conclusions can be made towards decision-making:

1. Decision-makers at different decision-levels can make sensible consistent decisions on forest area, because several levels of aggregation provided the same total forest area.

2. Decision-makers at different decision-levels can make sensible consistent decisions on forest area change, because overall the two images responded quite similar to the LCM parameter spatial size (with restriction of conclusion 3).
3. Decision-makers at different decision-levels need temporal maps that are produced with identical parameter settings to avoid comparing apples and oranges, because the LCM parameter spatial size proved not to be consistent in the arrangement of forest cover.

In addition, regarding the sensitivity estimators it can be concluded that the composition and configuration measures as used at both the class and landscape level are very useful for remote sensing based classifications in addition to conventional KHAT statistics and cover values (as measure by PLAND). In this respect, the indices LSI and KHAT seem to be a useful combination to indicate the levels of disaggregation at which classification results differ significantly. The indices NP and KHAT seem to be a useful combination to indicate which classes are causing significant differences between classification results. The indices LSI and PLAND, or NP and PLAND (a configuration and a composition measure) seem to be a useful combination to indicate suitable combinations of parameter settings for the LCM parameter size to compare temporally different images. Moreover, the indices SIDI and PLAND (both composition measures) seem to be a useful combination to indicate underlying change processes in forest areas. SIDI provided the area range (35-100 ha) at which a striking diversity change occurred, whereas PLAND indicated the vegetation class most likely involved (shrub vegetation). Combining both measures, it can be concluded that shrub, which is an intermedial vegetation in the transition from forest to agriculture and vice versa, contributed significantly to the change in SIDI and thus plays an important role in the underlying change process. This means that between 1990 and 1996 forest is depleted not due to logging practices, but due to agricultural practices. This type of information can be very useful for decision-makers at local, provincial and national level, who are urged to preserve rainforest for future generations.

## REFERENCES

- Bandibas, J.C., Bruce, R.C. & Daels, L., 1995. Using frequency based classifier for remote sensing of spatially heterogeneous land-use/land-cover systems in the tropics. *Asian-Pacific Remote Sensing Journal*, 7(2), pp. 65-70.
- Beurden, A.U.C.J. van & Douven, W.J.A.M., 1999. Aggregation issues of spatial information in environmental research. *International Journal of Geographical Information Science*, 13(5), pp. 513-527.
- Burnett, C. & Blaschke, T., 2003. A multi-scale segmentation/object relationship modelling methodology for landscape analysis. *Ecological Modelling*, 168(3), pp. 233-249.
- Carvalho, L.M.T. de, Fonseca, L.M.G., Murtagh, F. & Clevers, J.G.P.W., 2001. Digital change detection with the aid of multiresolution wavelet analysis. *International Journal of Remote Sensing*, 22(18), pp. 3871-3876.
- Congalton, R.G., Oderwald, R.G. & Mead, R.A., 1983. Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques. *Photogrammetric Eng. & Remote Sensing*, 49(12), pp. 1671-1678.
- Cortijo, F.J. & Perez de la Blanca, N., 1998. Improving classical contextual classifications. *International Journal of Remote Sensing*, 19 (8), 1591-1613.
- FAO, 2001. *The Global Forest Resources Assessment 2000 (FRA 2000)*. FAO Forestry Paper 140, <http://www.fao.org/forestry/fo/fra/main/index.jsp> (accessed 5 Nov. 2003).
- Forman, R.T.T., 1995. *Land mosaics: the ecology of landscapes and regions*. Cambridge University Press, Cambridge, pp. 317-321.
- Gustafson, E.J., 1998. Quantifying landscape spatial pattern: What is the state of the art. *Ecosystems*, 1(2), pp. 143-156.
- Hill, R.A., 1999. Image segmentation for humid tropical forest classification in Landsat TM data. *International Journal of Remote Sensing*, 20(5), pp. 1039-1044.
- Hudson, W.D. & Ramm, C.W., 1987. Correct formulation of the Kappa coefficient of agreement. *Photogrammetric Engineering and Remote Sensing*, 53(4), pp. 421-422.
- Kushwada, S.P.S, Kuntz, S. & Oesten, G., 1994. Applications of image texture in forest classification. *International Journal of Remote Sensing*, 15 (11), 2273-2284.
- Lund, H.G., 1999. Forest classification: a definitional quagmire. In: *The World's Natural Forests and their Role in Global Processes*, Khabarovsk, Russia, 17 p. <http://home.att.net/~gklund/quagmire.htm> (accessed 7 Nov. 2003).
- McGarigal, K., S.A. Cushman, M.C. Neel, and E. Ene (2002), FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. University of Massachusetts, Amherst. [www.umass.edu/landeco/research/fragstats/fragstats.html](http://www.umass.edu/landeco/research/fragstats/fragstats.html) (accessed 23 Feb. 2004).
- Molenaar, M., 1998. *An introduction to the theory of spatial object modelling for GIS*. Taylor & Francis, London, pp. 20-31.
- Obbink, M.H., Clevers, J.G.P.W. & Viergever, K.M., 2002. Multi-level segmentation of remote sensing imagery for mapping forest transitions. In: *Operational tools in forestry using remote sensing techniques* Edinburgh, Scotland, 10 p.
- Palubinskas, G., Lucas, R.M., Foody, G.M. & Curran, P.J., 1995. An evaluation of fuzzy and texture-based classification approaches for mapping regenerating tropical forest classes from Landsat-TM data. *International Journal of Remote Sensing*, 16 (4), 747-759.
- Schajk-Obbink, M.H. van, Molenaar, M. & Gier, A. de, 2000. Tropical forest change assessment: the use of aggregates, a semantic approach. In: *International Archives of Photogrammetry and Remote Sensing*, Amsterdam, The Netherlands, Vol. XXXIII, Part B7, p. 1601-1608.
- Whitmore, T.C., 1998. *An introduction to tropical rain forests* – 2<sup>nd</sup> ed. Oxford University Press, Oxford, 282 p.
- Woodcock, C.E. & Strahler, A.H., 1987. The factor of scale in remote sensing. *Remote Sensing of Environment*, 21, pp. 311-332.

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