

## Optimizing land cover change detection using combined pixel-based and object-based image classification in a mountainous area in Mexico

Jesus Aguirre Gutiérrez<sup>1\*</sup>  
Arie Seijmonsbergen<sup>1+</sup>  
Joost Duivenvoorden<sup>1§</sup>

<sup>1</sup>Institute for Biodiversity and Ecosystem Dynamics (IBED), Universiteit van Amsterdam  
Science Park 904, 1098 HX, Amsterdam, The Netherlands.

jeaggu@gmail.com\*  
A.C.Seijmonsbergen@uva.nl<sup>+</sup>  
J.F.Duivenvoorden@uva.nl<sup>§</sup>

### Abstract:

Inventories of past and present land cover changes form the basis for future conservation strategies and landscape management. In this study Landsat images of a mountainous area in Mexico are used in an object-based and pixel-based image classification. The land cover categories with the highest individual classification accuracies determined with these two methods are extracted and merged into combined land cover classifications. Seven land cover categories were extracted and combined into single combined best classification layers. Comparison of the overall classification accuracies for 1999 and 2006 of the pixel-based (0.74 and 0.81), object-based (0.77 and 0.71) and the combined (0.88 and 0.87) classifications shows that the combination method produces better results. These combined classifications then form the input for change detection between the two years, by applying post-classification object-based change analysis using image differencing. It is concluded that post-classification object-based change detection analysis leads to an improved land cover change detection result with an overall accuracy of 0.77. This approach has the potential to be applied in similar mountain areas using medium resolution imagery for land cover change analysis.

**Keywords:** accuracy assessment, Landsat, segmentation, post-classification, remote sensing

### 1. Introduction

Satellite images and aerial photographs form the basis for land cover classifications and change analyses since the early 1970s. During this period numerous unsupervised and supervised classification methods have been developed to derive standard land cover maps (Boyd and Foody *in press*). Pre- and post-classification change detection techniques such as image differencing, change vector analysis, image regression and image ratioing (Lunetta and Elvidge 1999; Berberoglu and Akin 2009) have been applied to quantify land cover changes from multi-temporal and multi-spectral datasets. Recently developed object-based classifiers are tested in combination with pixel-based classification on Landsat data in this study, in order to increase classification accuracies and to improve change analysis results. This is of particular interest for the mountain forests in northern Mexico, where land cover is rapidly changing, due to the natural dynamics of geomorphic processes and the interference of man. Forests clearance is here responsible for increased landscape fragmentation, which is an important reason for the decline in biodiversity and other key ecological functions (Turner et al. 1994; Vitousek 1994). Land use changes are thus potential threats to terrestrial ecosystems (Çakir et al. 2008; Harris 1984; Kilic et al. 2006).

The detection of land cover changes using remote sensing techniques strongly depends on the spatial, spectral and temporal characteristics of the sensors used (Burnett and Blaschke 2003). Pixel-based land cover classification methods, such as the maximum likelihood classifier, use the spectral information contained in individual pixels to generate land cover classes. This approach has recently been challenged because textural and topological relationships are not included in the classification process (Matinfar et al. 2007; Yan et al. 2006). Object-based methods use contextual information such as texture and compactness, plus topological relationships to first generate image objects or segments, which are then

categorized using for example, the standard nearest neighbour classifier (Desclée and Defourny 2006; Geneletti and Gorte 2003; Smith 2008; Yu et al. 2006). The object-based method produces more accurate and robust classifications than the pixel-based method when using high-resolution imagery (Cleve et al. 2008; Corcoran and Winstanley 2008; Hájek 2008). However, it has been shown that pixel-based land cover classification may sometimes outperform the classification accuracy results for certain land cover categories (*see* Flanders et al. 2003). In such cases a combination of the best classification results of both methods yields better results.

The objective of this study is to apply a combination of pixel-based and object-based land cover classification for optimizing post classification change detection applied to multi-temporal Landsat ETM+ satellite images of the Mexican Sierra Madre Occidental mountain region. The focus is on forest land cover changes, since (illegal) deforestation is a major issue in loss of biodiversity and species richness in this area. A comparison is made between the accuracy assessments of the pixel-based and object-based methods and the combined classification method. The resulting land use classification maps are used to improve change detection analysis.

## 2. Study area

The study area is located in the Sierra Madre Occidental, in the northern state of Chihuahua, Mexico (Figure 1). It comprises an area of 8404.57 km<sup>2</sup> located within the 107°56'24''W-107°01'5''W and 28°06'57''N-27°16'58''N coordinates. The main land cover of the area is pine forest and mixed pine-oak forest. The altitude ranges between approximately 650 m and 3300 m above sea level. The geomorphology is characterized by deeply incised steep canyons and contrasting low gradient slopes and broad interfluves, which results in a strong climatic gradient. The mean annual precipitation varies between 200 mm in the valleys to 2500 mm in the upper areas and the mean annual temperature ranges from -3°C to more than 22°C (Arriaga 2000). The region is recognized by the Conservation International Foundation (CIF) as an international biodiversity hotspot (CIF 2009) and is one of the most biologically rich regions in northern America.

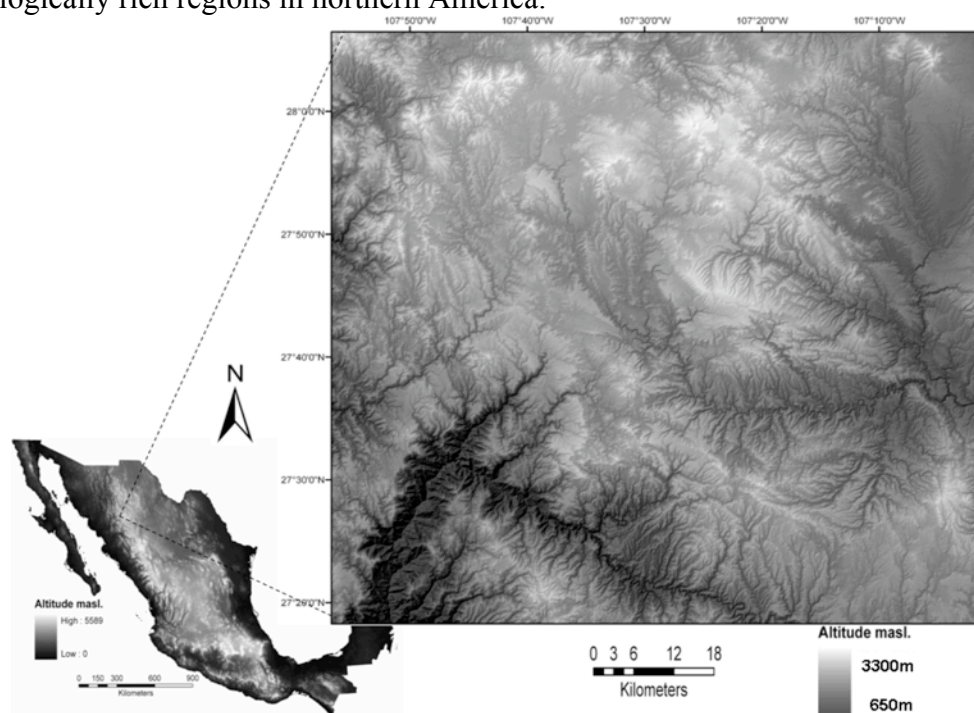


Figure 1. Study area location. Lighter colours reflect higher altitude

### 3. Methods

#### 3.1 Data Collection and Pre-Processing

Two cloud free Landsat ETM+ datasets were downloaded from the Global Land Cover Facility database ([www.landcover.org](http://www.landcover.org)) from October 14, 1999 and October 17, 2006 (WGS 84, UTM zone 13N, path 033, row 041) with a pixel size of 30 x 30 m for the spectral bands used. The images were orthorectified using a 30 m resolution digital elevation model (INEGI 2009) in ArcInfo 9.3 (ESRI 2009). The false colour band combination 4, 3 and 2 was used in the pixel-based approach using Erdas Imagine v.7 (ERDAS Imagine 2010), whereas all spectral bands were used in the object-based segmentation process, except for the thermal band 6. Using Definiens Developer v.7 (Definiens 2010).

Seven land cover classes were distinguished for the classification process of the 1999 and 2006 datasets, a) Coniferous forest, b) Scattered vegetation, c) Non coniferous forest, d) Water, e) Bare soil, f) Agriculture and g) Urban. Fifty field sites were visited in 2009 to inspect the land cover categories for use as training samples. These training samples were used as input information in order to train the Maximum Likelihood (ML, pixel-based) and Standard Nearest Neighbour (SNN, object-based) classifiers during the classification analyses (Campbell 2002). This resulted in six classified layers (3 per year).

#### 3.2 Image Classification process

Traditional pixel-based image classification was applied to the 1999 and 2006 Landsat imagery using training samples of the seven land cover classes which were recognized in the field. ML classification was used because is recognized as an efficient parametric method for image classification (Bayarsaikhan et al. 2009; Bontemps et al. 2008; Kozak and Ostapowicz 2008). The sample pixels for each of the land cover classes were selected in user specified regions with the 8-neighbourhood rule (Barsi 2000). The bands 2, 3 and 4 of the Landsat images were used as input data during the classification process.

In the object-based classification method the Landsat images are first segmented into image objects that resemble landscape features. The following segmentation parameters: scale = 5, shape = 0.1 and compactness = 0.5, and a weight of 2 for the infrared layer resulted in a satisfactory visual match of image objects and landscape features which proved accurate during field visits in the spring of 2010.

For this study the multi-resolution segmentation method was used (Baatz and Schäpe 2000). This region merging technique has been successfully applied in similar mountainous regions (Dragut and Blaschke 2008; Gao et al. 2009). The Standard Nearest Neighbour (SNN) classifier was then used in the classification process. For the seven land cover classes, user-specified image objects samples were selected on screen on the basis of field observations and by inspection of high-resolution imagery available in Google Earth (Google Earth v.5 2010) as additional reference data.

The best classification results per category are then extracted from the object-based and the pixel-based classification results and merged into final combined land cover classification maps. The merging order first started with the forest classes and was then completed with the other categories in order of decreasing accuracy. The newly generated combined land cover maps contain the most accurate information for each of the datasets (1999 and 2006). 'No data' areas that appeared on the combined land cover maps are the result of edge mismatches between the areas covered by the various classes. These occasional small gaps were filled with cell values derived from the original object-based or pixel-based classified layer with the highest overall accuracy. The final result is a combined land cover classification map.

#### 3.3 Change Detection

Post classification change analysis was selected in order to minimize possible effects of

atmospheric variations and sensor differences (Fan et al. 2007; Lu et al. 2004; Yang 2002). The change detection analysis method of Zhou et al. (2008), which is based on comparison of polygons, was applied.

The first step in the object-based change detection analysis is image segmentation to create an analysis layer that holds all the objects which are necessary for the change detection analysis. These objects are derived from both the 1999 and the 2006 combined land cover maps. To prepare such a map, the 2006 ETM+ satellite image is used as an analysis layer for the segmentation, while the 1999 and 2006 combined land cover maps were used as thematic layers in polygon format during the segmentation process. The use of thematic polygon layers restricts the segmentation to the boundaries that separate different land cover classes. By setting the weight of the ETM+ Landsat image to '0' only the information obtained from the thematic layers is used for the segmentation.

In the second step, knowledge rules were developed to detect land cover changes by comparing all the polygons resulting from the segmentation process with the land cover classification layers of 1999 and 2006. Actual land cover changes occurred if a corresponding polygon has different land cover in the 1999 or 2006 thematic layers. This process was automated by using knowledge rules. The knowledge rules for change were structured as follows: 'If "class name" in combined classification layer 1999  $\neq$  "class name" in combined classification layer 2006 then "change" to that cover class'. The knowledge rules for 'no change' corresponded to: 'If "class name" in combined classification layer 1999 = "class name" in combined classification layer 2006 then 'no change' is recorded.

### **3.4 Classification and change detection accuracy assessment**

The classification accuracy assessments of the resulting land cover maps was carried out by comparing samples of the classified layer and reference layer as described by Congalton (1991). Two hundred randomly generated points were used for comparing classified cells and reference cells in each of the pixel-based, the object-based and the combined classification methods. Fifty reference points were verified by field visits and 150 reference points through comparison with recent Google Earth imagery of 2007-2009. A total of 400 randomly selected polygons were used in the change detection accuracy assessment. 264 polygons for the "change" and 136 for the "no change" category.

## **4. Results**

### **4.1 Classification Accuracy**

In Table 1a and 1b the results of the classification accuracy assessment is presented. The resulting maps of the "combined classification method" produced the highest overall accuracy values of 0.88 for 1999 and 0.87 for 2006. These results show that extraction and merging of the best-classified classes from the pixel-based and object-based methods produces a land cover map with improved accuracy in comparison to the individual object-based and pixel-based classification methods.

### **4.2 Change Detection Accuracy**

The classified dataset has a good classification agreement as shown by its Kappa statistics value of 0.56. The Producer's accuracy of 0.95 for the "no change" class and the User's accuracy of 0.96 for the "change" class supported the reliability of the classification. The results showed that the majority of the "change" class objects were appropriately classified, however, 82 objects (31%), were wrongly classified as "no change".

Table 1. Classification results for the pixel-based, object-based and the combination classification methods, 1999 (a) and 2006 (b).

a) 1999	Pixel-Based		Object-Based		Combination method	
	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy
Coniferous	0.88	0.98	0.89	0.70	0.88	0.98
Scattered	0.64	0.92	0.76	0.84	0.86	0.92
Water	1.00	0.83	1.00	0.83	1.00	0.83
Non coniferous	0.87	0.93	0.67	0.71	0.87	0.93
Bare soil	0.84	0.41	0.91	0.74	0.91	0.77
Agriculture	1.00	0.06	0.57	0.71	1.00	0.88
Urban	1.00	0.25	0.60	0.75	0.60	0.75
<b>Overall accuracy</b>		<b>0.74</b>		<b>0.77</b>		<b>0.88</b>
<b>Kappa statistic</b>		0.64		0.69		0.84

b) 2006	Pixel-Based		Object-Based		Combination method	
	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy
Coniferous	0.90	0.92	0.85	0.86	0.94	0.89
Scattered	0.68	0.75	0.44	0.78	0.88	0.83
Water	1.00	0.60	1.00	1.00	1.00	1.00
Non coniferous	1.00	0.60	0.43	0.60	0.80	0.80
Bare soil	0.78	0.85	0.85	0.55	0.81	0.93
Agriculture	0.50	0.10	0.83	0.50	1.00	0.40
Urban	1.00	1.00	0.80	0.67	1.00	0.83
<b>Overall accuracy</b>		<b>0.81</b>		<b>0.71</b>		<b>0.87</b>
<b>Kappa statistic</b>		0.70		0.60		0.82

### 4.3 Land Cover Change

Most land cover changes are the result of urbanization, increased agricultural use and of wood logging. A summary of land cover change results is presented in Table 2. Approximately 5921 km<sup>2</sup> (70.5 %) of the total study area (8404 km<sup>2</sup>) remained unchanged and 2483 km<sup>2</sup> (29.5 %) has changed. Forested areas were subject to most reduction (Table 2).

Table 2. "From-To" confusion matrix for the changes obtained from the LULC change analysis (km<sup>2</sup>).

To \ From	Coniferous	Scattered vegetation	Water	Non coniferous	Bare soil	Agriculture	Urban	Total recover
Coniferous	-----	9.3699	-----	28.1646	0.2079	0.2025	-----	37.9449
Scattered vegetation	11.8665	-----	0.0234	17.8047	326.7162	39.5415	-----	395.9523
Water	0.0720	0.5841	-----	0.0099	0.4356	0.0522	-----	1.1538
Non-coniferous	15.7086	52.7814	-----	-----	0.9468	1.0386	-----	70.4754
Bare soil	454.4478	1229.6160	0.0252	29.0979	-----	5.4792	-----	1718.6661
Agriculture	0.7767	124.8129	-----	1.4346	118.3680	-----	-----	245.3922
Urban	0.2430	3.4893	-----	0.0063	9.6759	0.0450	-----	13.4595
Total change	483.1146	1420.6536	0.0486	76.5180	456.3504	46.3590	0	-----
Actual change	-445.1697	-1024.7013	1.1052	-6.0426	1262.3157	199.0332	13.459	-----

The original extent of the "Coniferous" forest (3271.1 km<sup>2</sup>) was reduced by 13% only by changes to the 'Bare soil' class. Moreover, 7.8% of the "Non coniferous" forest original area was also transformed to the 'Bare soil' class during the period analyzed. The changes from 'Forested areas' to 'Bare soil' are likely the result of (illegal) logging, which is an ongoing problem in the region (Gingrich 2005; Guerrero et al. 2001). Furthermore, over 1000 km<sup>2</sup> of the 'Scattered vegetation' class was lost between 1999 and 2006 and mostly transformed into "Bare soil" and "Agriculture" (Table 2). Urban areas replaced 13.46 km<sup>2</sup> of forested and not forested areas. The 'Scattered vegetation' class accounted for 3.48 km<sup>2</sup> of this change, the

“Coniferous” class for 0.24 km<sup>2</sup> and the “Non coniferous forest” class for only 0.0063 km<sup>2</sup>. These three classes together accounted for a reduction of 1475.91 km<sup>2</sup> of forest in the region (Table 2). The reduction in cover area of the three forest types was also reflected in a decrease in the number of forest patches per class (Table 3).

Table 3. Forest classes attributes and their change between 1999 and 2006.

Forest class	Coniferous		Scattered vegetation		Non-coniferous	
	1999	2006	1999	2006	1999	2006
<i>Class attributes</i>						
<i>Number of fragments</i>	56413	45919	85054	77221	74617	38975
<i>Biggest fragment area (km<sup>2</sup>)</i>	101.65	67.24	93.14	24.84	3.27	1.47
<i>Average fragments' area (km<sup>2</sup>)</i>	0.058	0.055	0.037	0.024	0.005	0.007
<i>Total class area (km<sup>2</sup>)</i>	3271.11	2560.08	3166.92	1855.42	372.41	305.82

## 5. Discussion

The results of the combined land cover classifications using object-based and pixel-based techniques show that the two methods can be used to classify different land cover classes with accurate results in mountainous regions based on medium-resolution satellite imagery.

The pixel-based approach rendered better results when classifying homogeneous areas such as the ‘Coniferous’ and ‘Non-coniferous forest’ classes, which are more contiguous and have lower spectral variability, which was also observed by Flanders et al. (2003). The object-based approach proved more effective for the classification of land cover categories with objects composed of mixed pixels, for example the “Bare soil” (Table 1). The combined classification approach has the advantages that only the classes with the highest classification accuracies of the pixel-based and object-based methods are used to construct a final land cover map. Wang et al. (2004) also obtained higher classification accuracies by applying object-based and pixel-based classification in mangrove areas using IKONOS 1-m. high-resolution imagery. Studies of Flanders et al. (2003), Matinfar et al. (2007) and Yan et al. (2006), also suggest that a combined classification method may lead to optimization of land cover classification and change detection. The overall accuracy obtained for the land cover change map demonstrates the capabilities of the object-based approach for change detection. It is worth mentioning that the decrease in number of fragments for the three forest classes (Table 3) does not indicate a less fragmented landscape but shows the pattern of logging actions, in which the complete forest fragment and not just part is cut, thereby decreasing in this way the forested area and the number of forest patches.

## 6. Conclusions

The proposed method to prepare combined land cover change maps based on extraction and subsequent merging of land cover categories with the highest individual classification accuracies in the pixel- and object-based classification methods, leads to higher classification accuracies. The proposed method is useful and can be applied in terrain with irregular topography and variable spectral characteristic using medium-resolution imagery to improve the land cover classification accuracy. In addition, the accuracy of the land cover change detection analyses are also increased.

The presented approach emphasizes that the extraction of land cover classes with different spectral, textural and topological characteristics by means of object-based and pixel-based classification approaches may lead to improved workflows for land cover classification. Post classification object-based change detection of 1999 and 2006 Landsat ETM+ classified images using the combined pixel- and object-based classification methods leads to high change detection accuracies. This suggests that the combination of methods used in this study improve the land cover classification and change detection accuracy results in mountainous regions, when applied to medium resolution satellite imagery, such as Landsat ETM+.

### **Acknowledgements:**

This research was funded by the Netherlands Universities Foundation for International Cooperation (Nuffic), the 'Amsterdamse Universiteits Vereniging' (AUV) and a 'STUNT' grant, University of Amsterdam.

### **References:**

- Arriaga, L.; Espinoza, J. M.; Aguilar, C.; Martínez, E.; Gómez, L.; Loa E. (coordinadores). **Regiones terrestres prioritarias de México**. México: Comisión Nacional para el Conocimiento y uso de la Biodiversidad, 2000.
- Baatz, M.; Schäpe, A. Multiresolution Segmentation—an optimization approach for high quality multi-scale image segmentation, 2000. In: *Angewandte Geographische Informationsverarbeitung XII. Beiträge zum AGIT-Symposium Salzburg*, 200:12–23.
- Barsi, A. The impact of data compression and neighborhood information on the classification accuracy of artificial neural networks. **International Archives of Photogrammetry and Remote Sensing**, v. 33, n. 7, p. 140–147, 2000.
- Bayarsaikhan, U.; Boldgiv, B.; Kim, K. R.; Park K.; Lee, D. Change detection and classification of land cover at Hustai National Park in Mongolia. **International Journal of Applied Earth Observation and Geoinformation**, v. 11, n. 4, p. 273–280, 2009.
- Berberoglu, S.; Akin, A. Assessing different remote sensing techniques to detect land use/cover changes in the eastern Mediterranean. **International Journal of Applied Earth Observation and Geoinformation**, v. 11, n. 1, p. 46–53, 2009.
- Bontemps, S.; Bogaert, P.; Titeux N.; Defourny, P. An object-based change detection method accounting for temporal dependences in time series with medium to coarse spatial resolution. **Remote Sensing of Environment**, v. 112, n. 6, p. 3181–3191, 2008.
- Boyd, D.S.; Foody, G.M. An overview of remote sensing and GIS based research in ecological informatics. **Ecological Informatics**, in press doi:10.1016/j.ecoinf.2010.07.007.
- Burnett, C.; Blaschke, T. A multi-scale segmentation/object relationship modelling methodology for landscape analysis. **Ecological Modelling**, v. 168, n. 3, p. 233–249, 2003.
- Çakir, G.; Sivrikaya F.; Keleş, S. Forest cover change and fragmentation using Landsat data in Maçka State Forest Enterprise in Turkey. **Environmental Monitoring and Assessment**, v. 137, n. 1, p. 51–66, 2008.
- Campbell, J. B. **Introduction to remote sensing**. London, UK: Taylor & Francis. 621 p.
- CIF, Conservation International Foundation. <http://www.conservation.org>. Accessed 04 January 2009.
- Cleve, C.; Kelly, M.; Kearns F. R.; Moritz, M. Classification of the wildland–urban interface: A comparison of pixel-and object-based classifications using high-resolution aerial photography. **Computers, Environment and Urban Systems**, v. 32, n. 4, p. 317–326, 2008.
- Cohen, J. A Coefficient of Agreement for Nominal Scales. **Educational and Psychological Measurement**, v. 20, n. 4, p. 37–46, 1960.
- CONAFOR, Comision Nacional Forestal. [http://conafor.gob.mx/index.php?option=com\\_content&task=view&id=56&Itemid=122](http://conafor.gob.mx/index.php?option=com_content&task=view&id=56&Itemid=122). Accessed 21.May.2010.
- Conchedda, G.; Durieux L.; Mayaux P. An object-based method for mapping and change analysis in mangrove ecosystems. **ISPRS Journal of Photogrammetry and Remote Sensing**, v. 63, n. 5, p. 578–589, 2008.
- Congalton, R. G. A review of assessing the accuracy of classifications of remotely sensed data. **Remote sensing of environment**, v. 37, n. 1, p. 35–46, 1991.
- Corcoran, P.; Winstanley A. Using texture to tackle the problem of scale in land-cover classification. In: Blaschke, T.; Lang, S.; Hay, G. (Eds.) **Object-Based Image Analysis**. Berlin: Springer, 2008. p. 113–132.
- De Bano, L. F. **Biodiversity and the Management of the Madrean Archipelago: The Sky Islands of Southwestern United States and Northwestern Mexico**. Darby, PA: Diane Publishing, 1994. 669 p.
- Definiens AG. Definiens Developer v7. <http://www.definiens.com>.2010.
- Desclée, B.; Bogaert P.; Defourny, P. Forest change detection by statistical object-based method. **Remote Sensing of Environment**, v. 102, n. 1, p. 1–11, 2006.
- Dragut, L. D.; Blaschke, T. Terrain Segmentation and Classification using SRTM Data. In: Q. Zhou, Lees, B., & Tang, G. (Eds.). **Advances in Digital Terrain Analysis**. Berlin: Springer, 2008. p. 141–158.
- ERDAS Imagine. <http://www.erdas.com>.2010.
- ESRI. ESRI Inc. Redlands, CA, USA. <http://www.esri.com>. 2009
- Fan, F.; Weng Q.; Wang Y. Land use and land cover change in Guangzhou, China, from 1998 to 2003, based on Landsat TM/ETM+ Imagery. **Sensors**, v. 7, n. 7, p. 1323–1342, 2007.
- Flanders, D.; Hall-Beyer, M.; Pereverzoff J. Preliminary evaluation of eCognition object-based software for cut block delineation and feature extraction. **Canadian Journal of Remote Sensing**, v. 29, n. 4, p. 441–452, 2003.

- Gao, Y.; Mas, J. F.; Navarrete, A. The improvement of an object-oriented classification using multi-temporal MODIS - EVI - satellite data. **International Journal of Digital Earth**, v. 2, n. 3, p. 219-236, 2009.
- Geneletti, D.; Gorte B. G. H. A method for object-oriented land cover classification combining Landsat TM data and aerial photographs. **International Journal of Remote Sensing**, v. 24, n. 6, p. 1273-1286, 2003.
- Gingrich, R. Building effective international, multicultural alliances for restoration of ejido forests in the Sierra Madre Occidental. In: G. J. Gottfried et al. **Connecting mountain islands and desert seas: biodiversity and management of the Madrean Archipelago**. II and 5th Conference on Research and Resource Management in the Southwestern Deserts: May 11-15, 2004, Tucson, Arizona.
- Global Land Cover Facility, GLCF. <http://www.landcover.org>. 2010.
- Google Earth v.5. URL: <http://earth.google.com>. 2010.
- Guerrero, M. T.; De Villa, F.; Kelly, M.; Reed C.; Vegter, B. The forestry industry in the state of Chihuahua: economic, ecological and social impacts post-NAFTA. 2001. In: **The Environmental Effects of Free Trade**. North American Symposium on Assessing the Linkages between Trade and the Environment: October 11th, 2000. Washington, D.C.
- Hájek, F. Process-based approach to automated classification of forest structures using medium format digital aerial photos and ancillary GIS information. **European Journal of Forest Research**, v. 127, n. 2, p. 115-124, 2008.
- Hall, O.; Hay, G. J. A multiscale object-specific approach to digital change detection. **International Journal of Applied Earth Observations and Geoinformation**, v. 4, n. 4, p. 311-327, 2003.
- Harris, L. D. **The fragmented forest: island biogeography theory and the preservation of biotic diversity**. Chicago: University of Chicago Press, 1984. 211 p.
- INEGI. "Fuente: Sitio del INEGI en Internet: [www.inegi.org.mx](http://www.inegi.org.mx)". 2009.
- Kilic, S., Evrendilek, F., Berberoglu S., & Demirkesen, A. (2006). Environmental Monitoring of Land-Use and Land-Cover Changes in a Mediterranean Region of Turkey. **Environmental Monitoring and Assessment**, 114(1), 157-168.
- Kozak, J., Estreguil, C., & Ostapowicz, K. (2008). European forest cover mapping with high resolution satellite data: The Carpathians case study. **International Journal of Applied Earth Observation and Geoinformation**, 10(2), 44-55.
- Lu, D., Mausel, P., Brondízio E., & Moran, E. (2004). Change detection techniques. **International Journal of Remote Sensing**, 25(12), 2365-2401.
- Lunetta, R. S.; Elvidge, C. **Remote sensing change detection: environmental monitoring methods and applications**. UK: Taylor & Francis, 1999.
- Matinfar, H. R.; Sarmadian, F.; Panah, A. S. K.; Heck, R. J. Comparisons of Object-Oriented and Pixel-Based Classification of Land Use/Land Cover Types Based on Landsat7, Etm+ Spectral Bands (Case Study: Arid Region of Iran). **American-Eurasian Journal of Agricultural & Environmental Sciences**, v. 2, n. 4, p. 448-456, 2007.
- Smith, G. M. The development of integrated object-based analysis of EO data within UK national land cover products. In: Blaschke, T., Lang, S., & Hay, G. (Eds.). **Object-Based Image Analysis**. Berlin: Springer, 2008. p. 513-528.
- Turner, B. L.; Meyer, W. B.; Skole, D. L. Global Land-Use/Land-Cover Change: Towards an Integrated Study. **Ambio**, v. 23, n. 1, p. 91-95, 1994.
- Vitousek, P. M. Beyond Global Warming: Ecology and Global Change. **Ecology**, v. 75, n. 7, p. 1861-1876, 1994.
- Iter, V. Object-based classification of remote sensing data for change detection. **ISPRS Journal of Photogrammetry and Remote Sensing**, v. 58, n. 3, p. 225-238, 2004.
- Wang, L.; Sousa, W. P.; Gong, P. Integration of object-based and pixel-based classification for mapping mangroves with IKONOS imagery. **International Journal of Remote Sensing**, v. 25, n. 24, p. 5655-5668, 2004.
- Yan, G.; Mas, J. F.; Maathuis, B. H. P.; Xiangmin, Z.; van Dijk P. M. Comparison of pixel-based and object-oriented image classification approaches—a case study in a coal fire area, Wuda, Inner Mongolia, China. **International Journal of Remote Sensing**, v. 27, n. 18, p. 4039-4055, 2006.
- Yang, X. Satellite monitoring of urban spatial growth in the Atlanta metropolitan area. **Photogrammetric Engineering and Remote Sensing**, v. 68, n. 7, p. 725-734, 2002.
- Yu, Q.; Gong, P.; Clinton, N.; Biging, G.; Kelly, M.; Schirokauer, D. Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery. **Photogrammetric Engineering and Remote Sensing**, v. 72, n. 7, p. 799-811, 2006.
- Zhou, W.; Troy, A.; Grove, M. Object-based land cover classification and change analysis in the Baltimore metropolitan area using multitemporal high resolution remote sensing data. **Sensors**, v. 8, n. 3, p. 1613-163, 2008.