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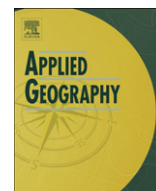
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Optimizing land cover classification accuracy for change detection, a combined pixel-based and object-based approach in a mountainous area in Mexico

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Inventories of past and present land cover changes form the basis of future conservation and landscape management strategies. Modern classification techniques can be applied to more efficiently extract information from traditional remote-sensing sources. Landsat ETM⁺ images of a mountainous area in Mexico form the input for a combined object-based and pixel-based land cover classification. The land cover categories with the highest individual classification accuracies determined based on these two methods are extracted and merged into combined land cover classifications. In total, seven common land cover categories were recognized and merged into single combined best-classification layers. A 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 combined (0.88 and 0.87) classifications shows that the combination method produces the best results. These combined classifications then form the input for a change detection analysis between the two dates by applying post-classification, object-based change analysis using image differencing. It is concluded that the combined classification method together with the object-based change detection analysis leads to an improved classification accuracy and land cover change detection. This approach has the potential to be applied to land cover change analyses in similar mountainous areas using medium-resolution imagery.

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Introduction

For more than 40 years, satellite images and aerial photographs have formed a strong basis for land cover classifications and change analysis. During this period, many unsupervised and supervised classification methods have been developed to derive standardized land cover maps (Boyd & Foody, 2011). Popular techniques include pre- and post-classification change detection methodologies such as image differencing, change vector analysis, image regression, and image ratioing (Berberoglu & Akin, 2009; Lunetta & Elvidge, 1999). These techniques have been applied to quantify land cover changes derived from the analysis of multi-temporal and multi-spectral datasets. The trend toward the use of finer spatial, temporal, and spectral resolutions for more accurate classifications of the Earth's surface is reflected in the more than 100 sensors launched in the 21st century (Boyd, 2009). The idea behind these sensors is that fine-resolution hyperspectral data should gradually

replace traditional medium-resolution sensor data. For large and remote areas, however, medium-resolution images such as Landsat still serve as a valuable information source for the visualization and quantification of past dynamics of land cover change. Recently developed object-based classifiers, intended for use on (hyper) spectral and/or high-resolution datasets, are here tested in combination with pixel-based classification on Landsat ETM⁺ imagery. The objective is to increase classification accuracies, thereby improving change analysis results. This is of particular interest for the mountain forests in northern Mexico, where land cover is rapidly changing in response to the natural dynamics of geomorphic processes and anthropogenic causes. The study area includes an international biodiversity hotspot, in which (illegal) forest clearance is the main cause of increased landscape fragmentation and habitat loss, which are key contributors to the decline in biodiversity and other key ecological functions (Hanski, 2011; Krauss et al., 2010; Turner, Meyer, & Skole, 1994; Vitousek, 1994). As a result of these declines, land use changes are recognized as serious threats to terrestrial mountain ecosystems (Çakir, Sivrikaya, & Keleş, 2008; Harris, 1984; Kilic, Evrendilek, Berberoglu, & Demirkesen, 2006).

The mountain forests of Mexico are known to act as reservoirs for flora and fauna (Rao & Pant, 2001). However, the mountain

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forests have undergone a decline in forest cover between 1990 and 2005, when approximately 48000 km² was converted into other land cover classes (FAO, 2005), although precise numbers and types of land cover change are lacking. Improved deforestation and land cover data derived from remote-sensing images using techniques originally developed for high-resolution imagery may result in more accurate maps of land cover change. This improved mapping should lead to greater insight into (illegal) deforestation activities and may serve as a basis for future conservation strategies and sustainable mountain forest management.

The detection of land cover changes using remote-sensing techniques strongly depends on the spatial, spectral, and temporal characteristics of the sensors used (Burnett & Blaschke, 2003; Vinciková, Hais, Brom, Procházka, & Pecharová, 2010). Two classification methods have been widely applied to remote-sensing imagery: object-based and pixel-based classification. Pixel-based land cover classification methods, such as maximum likelihood classification, use the spectral information contained in individual pixels to generate land cover classes. This method has been shown to perform accurately for the classification of certain land use/cover classes and has proven accurate in change detection analysis (Rozenstein & Karnieli, 2011; Shalaby & Ryutaro, 2007). However, maximum likelihood classification has recently been challenged because textural and topological relationships are not included in pixel-based classifications (Matinfar, Sarmadian, Panah, & Heck, 2007; Myint, Gober, Brazel, Grossman-Clarke, & Weng, 2011; Yan, Mas, Maathuis, Xiangmin, & van Dijk, 2006). Object-based methods use contextual information, such as texture and compactness, in conjunction with topological relationships, such as adjacency. Using object-based methods, image objects or segments are

generated, which are subsequently categorized using, for example, the standard nearest-neighbor classifier (Desclée, Bogaert, & Defourny, 2006; Geneletti & Gorte, 2003; Liu & Xia, 2010; Smith, 2008; Yu et al., 2006). It has been suggested that object-based methods produce more accurate and robust classifications than pixel-based methods when using high-resolution imagery (Cleve, Kelly, Kearns, & Moritz, 2008; Corcoran & Winstanley, 2008; Hájek, 2008). However, it has also been shown that pixel-based land cover classification techniques may sometimes achieve the most accurate classification results for certain land cover categories (Flanders, Hall-Beyer, & Pereverzoff, 2003). In such cases, a combination of the best-classification results from both methods may yield optimal results. In a study carried out by Wang, Sousa, and Gong (2004), combinations of pixel-based and object-based classifications resulted in the improvement of the overall land use classification accuracy for a mangrove ecosystem applied to very high-resolution (VHR) IKONOS imagery.

The objective of the present study is to use optimal combinations of pixel-based and object-based land cover classifications to obtain higher classification and post-classification change detection accuracies. The method is applied to multi-temporal Landsat ETM⁺ satellite images of the Mexican Sierra Madre Occidental mountain region. The focus of our study is on forest cover changes because (illegal) deforestation is a major contributor to the loss of biodiversity and species richness in this area.

Study area

The study area is located in the mountains of the Sierra Madre Occidental in the northern state of Chihuahua, Mexico (Fig. 1). It

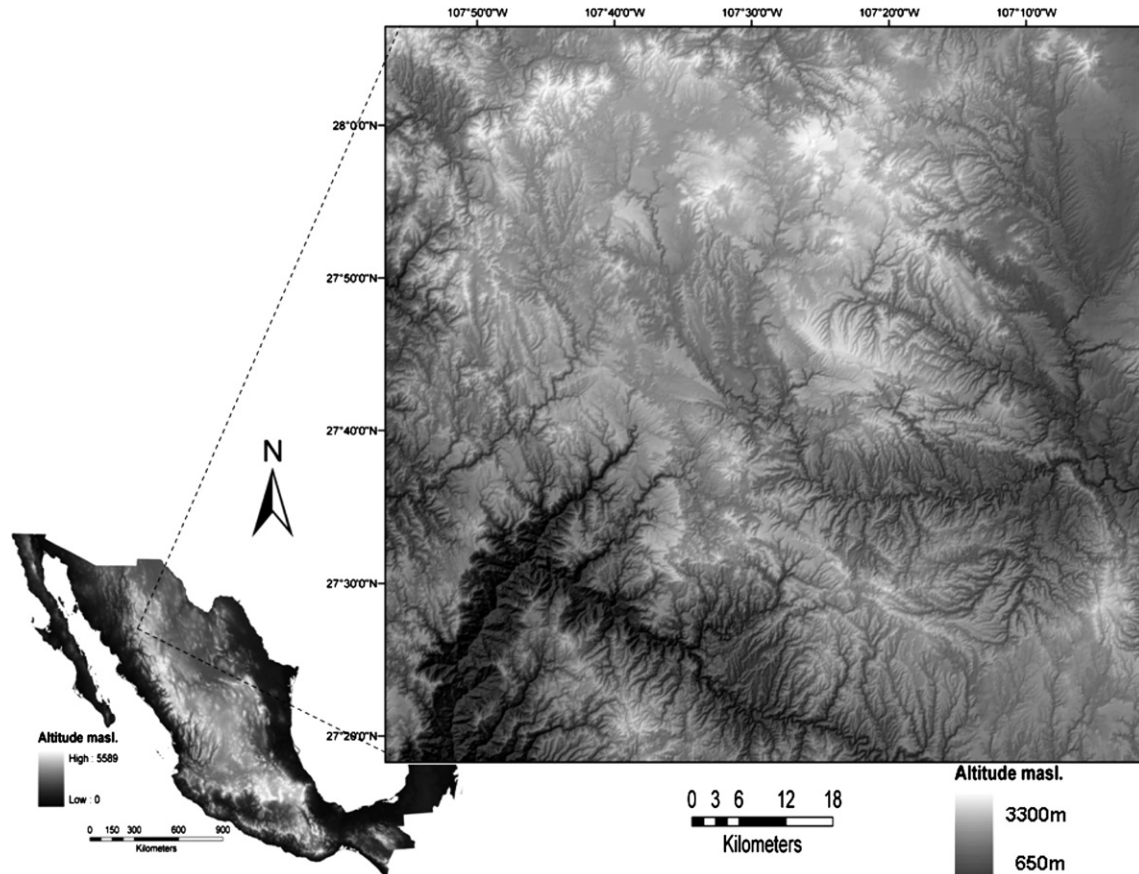


Fig. 1. Study area location. Lighter colors reflect higher altitude.

occupies an area of 8,404.57 km² bounded by the coordinates 107°56'24"W–107°01'5"W and 28°06'57"N–27°16'58"N. The main land cover of the area is pine forest (i.e., *Pinus strobiformis*, *Pinus arizonica*, *Pinus engelmannii*, *Pinus leiophylla* var. *chihuahuana*) and mixed pine-oak forest (i.e., *Pinus* spp., *Quercus depressipes*, *Quercus macvaughii*, *Quercus rugosa*, *Quercus sideroxylla*). The altitude ranges from between approximately 650 m and 3300 m above sea level. The geomorphology is characterized by deeply incised, steep canyons, mainly developed in volcanic rocks, alternating with low-gradient slopes and broad interfluvies, resulting in a strong climatic gradient. The mean annual precipitation varies from 200 mm in the valleys to 2500 mm in the upper areas, and the mean annual temperature ranges from −3 °C to above 22 °C (Arriaga et al., 2000). The region is recognized by the Conservation International Foundation (CIF) as an international biodiversity hotspot (CIF, 2011) and is one of the most biologically rich regions in North America. The region hosts a large number of endemic species and acts as a biological corridor for vascular plants that links the southern United States and northern Mexico (De Bano, 1994).

Methods

Data collection and pre-processing

Two cloud-free Landsat ETM⁺ datasets were downloaded from the Global Land Cover Facility database (GLCF, www.landcover.org), one dataset from October 14, 1999, and one from October 17, 2006 (WGS 84, UTM zone 13N, path 033, row 041), with a pixel size of 30 × 30 m for the spectral bands used. These images were selected on the basis of their availability and the quality of the datasets for the study area. The images were orthorectified using a 30 m resolution digital elevation model (INEGI, 2009) in ArcInfo 9.3 (ESRI, 2009). All spectral bands, with the exception of thermal band 6, were used to aid in the classifications based on the pixel-based and object-based approaches. No atmospheric or radiometric correction was needed because the signature selections of the different land cover classes for each of the two Landsat ETM⁺ images were conducted separately.

ERDAS Imagine v.9.3 software (ERDAS Imagine, 2010) was used to process the Landsat images using the pixel-based supervised image classification, and Definiens Developer software v.7 (Definiens, 2010) was used in the supervised object-based image classification protocol. Seven land cover classes were selected 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 (Table 1). Only 50 field sites could be safely visited in 2010 to inspect their land use/cover classes as a result of accessibility restrictions, mainly as a result of the presence of drug cartels (see Wakild, 2011). The locations of these training-sample sites were captured using an Etrex HC GPS device (GARMIN, 2010). Additional training samples

for each land cover class (150 in total) were derived from high-resolution imagery available in Google Earth (Google Earth v.5, 2010). The training samples were used as inputs for training the maximum likelihood (ML) and Standard Nearest-Neighbor (SNN) classifiers during the classification analysis (Campbell, 2002). The classification process resulted in six classified layers (three per year): two each for the pixel-based and object-based classification methods, and two layers for the combined approach (Fig. 2).

The image classification process

The upper panel of the workflow in Fig. 2 shows the steps for preparing a land cover map that includes the combination of the best-classification results from the pixel-based and object-based land cover classification techniques. Traditional pixel-based image classification was applied to the 1999 and 2006 Landsat imagery using training samples of the seven land cover classes that were identified in the field and using high-resolution imagery. ML classification was used because it is acknowledged as one of the most efficient parametric methods for image classification (Bayarsaikhan, Boldgiv, Kim, Park, & Lee, 2009; Bontemps et al., 2008; Kozak, Estreguil, & Ostapowicz, 2008). The ML classifier takes into account the variance and the covariance of the class signatures to assign a given pixel to a class depending on its feature characteristics.

The sample pixels for each of the land cover classes were selected using the collected and observed training sample locations in accordance with the 8-neighborhood rule (Barsi, 2000). Bands 1–5 and 7 of the Landsat images were used as input data during the classification process.

In the object-based classification method, the Landsat images were first segmented into image objects. The segmentation process creates image objects that reflect groups of spatially homogeneous pixels because neighboring pixels are iteratively clustered until a preset threshold is exceeded. If more weight is assigned to particular spectral layers, these layers have more influence on the resulting segmentation boundaries. The parameters used during the segmentation process are scale, shape and compactness. The scale parameter determines the maximum size of the created object, the shape factor controls for the spectral information and shape, and the compactness factor determines the compactness of the objects' edges/borders (Definiens, 2010).

In the present study, the multi-resolution segmentation method was used (Baatz & Schäpe, 2000). This region-merging technique has been successfully applied in other mountainous regions (Drägut & Blaschke, 2008; Gao, Mas, & Navarrete, 2009). Following a 'trial and error' approach (Im, Jensen, & Tullips, 2008; Robertson & King, 2011), the parameter settings were iteratively changed after the segmentation process if no visual resemblance to potential objects recognized from satellite imagery was observed. This process was repeated until a satisfactory match was achieved. The following values were assigned to the segmentation parameters: scale = 5, shape = 0.1 and compactness = 0.5; a weight of 2 for the infrared layer resulted in a satisfactory visual match between image objects and landscape features, which proved satisfactory during field visits in the spring of 2010.

After segmentation, the SNN classifier was used in the classification process. For the seven land cover classes, user-specified image-object samples were selected on-screen on the basis of field observations and by inspection of high-resolution imagery (years 2007–2010) available in Google Earth (Google Earth v.5, 2010) as additional reference data. The image-object samples served as input information to iteratively train the classifier.

Accuracy assessment reports for individual class categories and overall classification accuracies were generated for both the

Table 1
Description of land cover classes.

Land Cover class	Description
Coniferous forest	Forest dominated by coniferous plant species, mostly <i>Pinus</i> spp.
Scattered vegetation	Mixed vegetation which has a scattered distribution, mostly shrubs
Non-coniferous forest	Forest dominated by non-coniferous plant species, mostly <i>Quercus</i> spp.
Water	Water bodies, as lakes and reservoirs
Bare soil	Surface without vegetation
Agriculture	Crop fields, pastures
Urban	Built-up areas/infrastructure

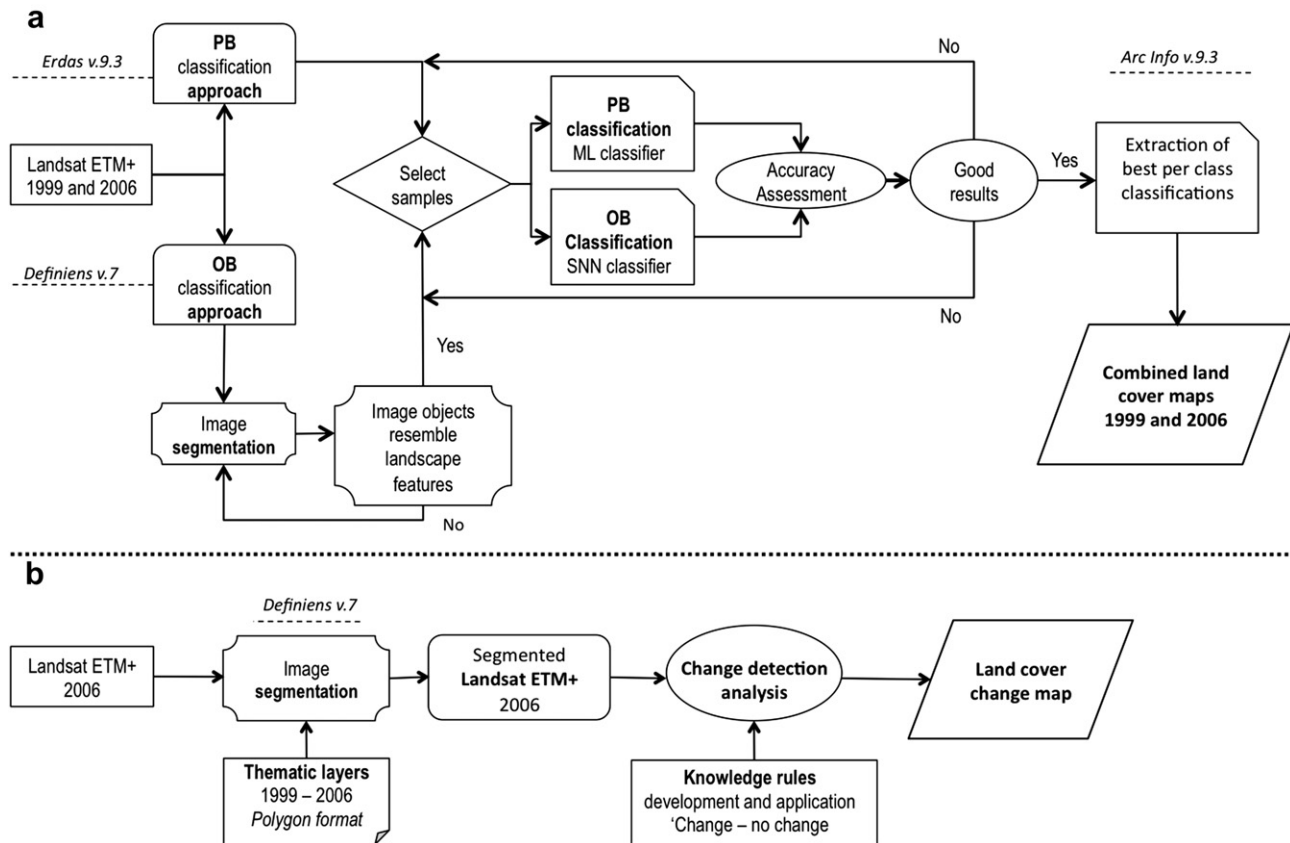


Fig. 2. (a) Workflow showing the procedure of the “Combined classification” layers. OB = Object-Based, PB = Pixel-Based, LC = Land Cover. (b) Stepwise workflow of the Object-Based Change detection.

pixel-based and object-based classifications. The per-class accuracy results of the object-based and pixel-based classifications were compared, and the seven land cover classes with the highest accuracies were then extracted. These extracted classes (Table 1) were then merged into a final combined land cover classification map (Fig. 2, upper panel). The order of merging began with the forest classes followed by the other land cover categories in order of decreasing accuracy. The newly generated combined land cover maps included the most accurate information from each of the datasets (1999 and 2006). Occasional ‘no data’ areas that appeared on the combined land cover maps were the result of edge mismatches between the areas covered by the various classes. These 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 (Fig. 2, upper panel).

Change detection

Post-classification change analysis was used to minimize the possible effects of atmospheric variations and sensor differences (Fan, Weng, & Wang, 2007; Lu et al., 2004; Yang, 2002). The change detection analysis method of Zhou, Troy, and Groove, (2008), which is based on comparison of polygons, was applied. In Fig. 2 (lower panel), the general workflow of the post-classification change detection is presented. The first step in the object-based change detection analysis was to create a layer that contained all the objects that are necessary for a change detection analysis. These objects were derived from both the 1999 and the 2006 combined land cover maps. To prepare this map, the 2006 ETM⁺ satellite

image was used as an analysis layer for the segmentation, and the 1999 and 2006 combined land cover maps were used as thematic polygon layers during the segmentation process. The use of thematic polygon layers restricts the segmentation to the boundaries that separate the various land cover classes. With the weight of the ETM⁺ Landsat image set at 0, only the information obtained from the thematic layers was used for the segmentation.

In the second step, knowledge rules were developed to detect land cover changes by evaluating all the polygons that were prepared during the segmentation process in the first step. Actual land cover changes were determined to have occurred if a corresponding polygon had different land cover in the 1999 or 2006 thematic layers. This process was automated based on the knowledge rules developed. The knowledge rules for change were structured as follows: “If ‘class name’ in combined classification layer 1999 ≠ ‘class name’ in combined classification layer 2006, then ‘change’ to that cover class”. The knowledge rules for ‘no change’ were structured as follows: “If ‘class name’ in the combined classification layer of 1999 = ‘class name’ in the combined classification layer of 2006, then ‘no change’ is recorded”. The minimum size of the changed polygons was set to be equal to or greater than 0.0045 km², which was determined after calculating the mean polygon size in the change image. This threshold value was considered adequate because land cover changes in the region resulting from logging and clear-cutting for agriculture commonly cover larger areas. Changed polygons with an area of 900 m², equal to the Landsat 30 m pixel size, were reclassified as ‘no change’ to minimize changes resulting from spatial registration errors or edge mismatches. A few unrealistic changes, such as of the ‘Urban’ class to other classes, were left out and regarded as ‘no change’.

Classification and change detection accuracy assessment

Assessments of the classification accuracy of the land cover maps were conducted by comparing samples of the classified layer and reference layer following Congalton (1991). Two hundred randomly generated points were used for comparing classified cells and reference cells in each of the pixel-based, object-based, and combined classification methods. Fifty reference points were verified by field visits, and 150 reference points were verified through comparison with recent Google Earth imagery dated between 2007 and 2009. The overall user's and producer's accuracies and Cohen's Kappa statistics (Cohen, 1960), which provide an indication of the classification agreement between two maps (the classified and the ground-truthed maps) that is not attributable to chance, were calculated and are presented as error matrices. For the Kappa statistics values, Monserud and Leemans (1992) suggested that values lower than 0.4 represent poor or very poor agreement, values from 0.4 to 0.55 represent fair agreement, values from 0.55 to 0.7 represent good agreement, values from 0.7 to 0.85 represent very good agreement, and values higher than 0.85 represent excellent agreement between images.

The change detection accuracy was obtained by randomly sampling the study area to calculate an error matrix for the classification (Fuller, Smith, & Devereux, 2003; Yuan, Sawaya, Loeffelholz, & Bauer, 2005). Stratified random sampling of the polygons classified as 'change' and 'no change' in the resulting land cover change layer was conducted. A total of 400 polygons were used in the change detection assessment: 264 polygons for the 'change' and 136 for the 'no change' category. All reference polygons were validated either by field visits or through an inspection of Google Earth imagery.

Results

Classification accuracy

The results of the classification accuracy assessment are presented in Table 2a and 2b. The accuracy assessments show overall

accuracies of 0.74 for the pixel-based and 0.77 for the object-based classifications for 1999. The 2006 accuracies were 0.71 for the object-based and 0.81 for the pixel-based methods (Table 2a and 2b). The resulting maps of the combined classification method (Fig. 3) produced the highest overall accuracy values of 0.88 for 1999 and 0.87 for 2006. Kappa values were 0.64 for the pixel-based method, 0.60 for the object-based method, and 0.82 for the combined method, showing that the classification agreement between images ranged from good to very good (Monserud & Leemans, 1992).

These results show that the 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.

Change detection accuracy

The accuracy assessment of the classified dataset (Table 3) indicated that this dataset reflected good classification agreement (Monserud & Leemans, 1992) 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 support the reliability of the classification. The results showed that the majority of the 'change' class objects were appropriately classified; however, 82 objects (31%) were incorrectly classified as 'no change'. In comparison, most of the 'no change' objects were properly classified, with only seven objects (5%) incorrectly classified.

Land cover change

A total of 32 possible land cover changes were detected (Table 4), of which 18 are larger than 1 km². Most land cover changes are the result of urbanization, increased agricultural use, or logging. A summary of the land cover change results is provided in Table 5. Approximately 5921 km² (70.5%) of the total study area (8404 km²) remained unchanged, and 2483 km² (29.5%) changed. Forested areas were subject to the highest reduction (Table 5). The original

Table 2

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

	Pixel-Based		Object-Based		Combination method	
	User's accuracy	Producer's accuracy	User's accuracy	Producer's accuracy	User's accuracy	Producer's accuracy
1999						
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
Overall accuracy		0.74		0.77		0.88
Kappa statistic		0.64		0.69		0.84
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
Overall accuracy		0.81		0.71		0.87
Kappa statistic		0.70		0.60		0.82

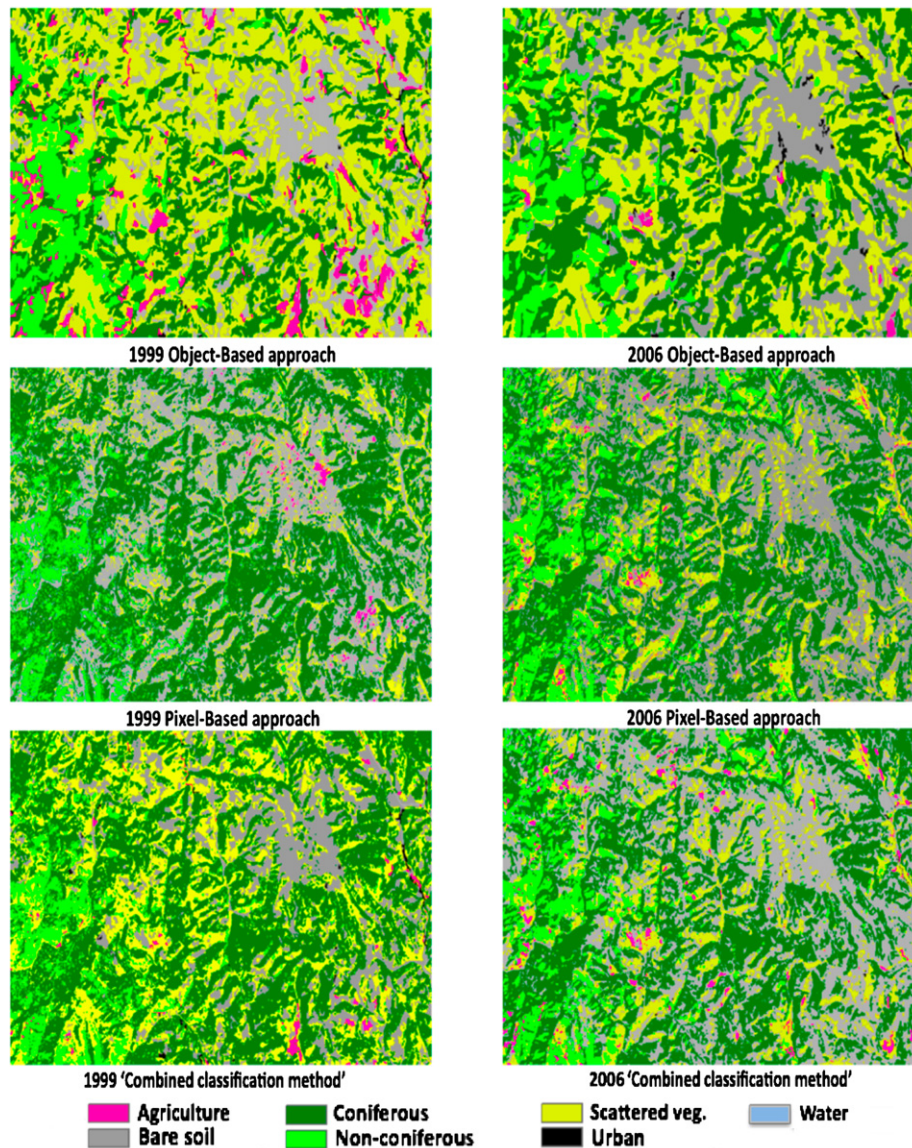


Fig. 3. Classified images using the object-based and pixel-based approaches and the final layers for the 'combined classification method' for the two years analyzed.

extent of the 'Coniferous forest' area (3271.1 km²) was reduced by 13% through conversion to the 'Bare soil' class alone. Moreover, 7.8% of the original 'Non-coniferous forest' area was 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 and fires, which are often accompanied by soil erosion, an ongoing problem in the region (Gingrich, 2005; Guerrero, De Villa, Kelly, Reed, & Vegter, 2001). Furthermore, over 1000 km² of the

'Scattered vegetation' class was lost between 1999 and 2006 and mostly transformed into 'Bare soil' and 'Agriculture' (Table 5).

The construction of a water reservoir close to one of the largest urban areas in the region flooded over 1 km² of land. Reforestation by the indigenous communities and the "Comisión Nacional Forestal" (CONAFOR, 2010, Mexican National Forest Commission) are most likely responsible for the transformation of this area from 'Bare soil' to 'Scattered vegetation'.

Urban areas replaced 13.46 km² of forested and non-forested areas in total. The 'Urban' class replaced 3.48 km² of the 'Scattered vegetation' class, 0.24 km² of the 'Coniferous forest' class, and 0.0063 km² of the 'Non-coniferous forest' class. The changes from forested areas to non-forested classes accounted for a reduction of 1475.91 km² of forest in the region, which is 17.5% of the total study area (Table 5).

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 6) and a slight decrease in the average patch size of 'Coniferous forest' and 'Scattered vegetation'. The most striking findings were that the largest patch of 'Coniferous forest' decreased to approximately half of its original size, the largest patches of

Table 3
Confusion matrix of the land cover change detection results.

Reference\classification	Change	No change	Producer's accuracy
Change	182	82	0.69
No change	7	129	0.95
User's accuracy	0.96	0.61	
Overall accuracy			0.77
Kappa statistic			0.56

Table 4Observed land cover changes and area converted (km²).

#	'From' class	'To' class	Area km ²
1	Agriculture	Bare soil	5.4792
2	Agriculture	Coniferous forest	0.2025
3	Agriculture	Non-coniferous forest	1.0386
4	Agriculture	Scattered vegetation	39.5415
5	Agriculture	Urban	0.0450
6	Agriculture	Water	0.0522
7	Bare soil	Agriculture	118.3680
8	Bare soil	Coniferous forest	0.2079
9	Bare soil	Non-coniferous forest	0.9468
10	Bare soil	Scattered vegetation	326.7162
11	Bare soil	Urban	9.6759
12	Bare soil	Water	0.4356
13	Coniferous forest	Agriculture	0.7767
14	Coniferous forest	Bare soil	454.4478
15	Coniferous forest	Non-coniferous forest	15.7086
16	Coniferous forest	Scattered vegetation	11.8665
17	Coniferous forest	Urban	0.2430
18	Coniferous forest	Water	0.0720
19	Non-coniferous forest	Agriculture	1.4346
20	Non-coniferous forest	Bare soil	29.0979
21	Non-coniferous forest	Coniferous forest	28.1646
22	Non-coniferous forest	Scattered vegetation	17.8047
23	Non-coniferous forest	Urban	0.0063
24	Non-coniferous forest	Water	0.0099
25	Scattered vegetation	Agriculture	124.8129
26	Scattered vegetation	Bare soil	1229.6160
27	Scattered vegetation	Coniferous forest	9.3699
28	Scattered vegetation	Non-coniferous forest	52.7814
29	Scattered vegetation	Urban	3.4893
30	Scattered vegetation	Water	0.5841
31	Water	Bare soil	0.0252
32	Water	Scattered vegetation	0.0234

'Scattered vegetation' and 'Non-coniferous forest' each decreased to less than half of their original sizes in 2006 (Table 6).

Discussion

Both the object-based and pixel-based methods can be used to accurately classify different land cover classes in mountainous regions based on medium-resolution satellite imagery. The variation in the spectral reflection of cells within different land cover classes, however, seems to influence the accuracy of the results. The pixel-based approach gave better results for the 'Coniferous' and 'Non-coniferous forest' classes, which are more contiguous and have lower spectral variability, a finding that was also described by Flanders et al. (2003). However, care should be taken when this approach is applied to other environments because of the possible heterogeneous composition of the forest cover. The object-based approach proved more effective for the classification of land cover categories with objects composed of mixed pixels, such as the

'Bare soil' class (Table 2). For such classes, the pixel-based approach is not recommended because it only uses spectral information during the classification analysis (Walter, 2004). The underlying soil composition in this mountainous area is highly variable as a result of the rapidly changing topographic conditions, and in low altitudes and on flatter terrain, the variation in soil reflection can be less pronounced.

Although the issue of scale is not directly addressed in this research, we are aware that an increased generalization of classes may be observed when working at broader scales (lower-resolution imagery) and that a higher spectral variability might be observed in very high-resolution (VHR) imagery (Addink, de Jong, & Pebesma, 2007). Thus, the appropriate classification rules and method used may depend on the scale at which the classification is carried out. As described by Blaschke, Lang, and Hay (2008), the spectral variability or heterogeneity within a land class at fine scale may make the pixel-based approach less robust, causing it to generate the spurious salt-and-pepper effect and leading to the erroneous classification of pixels. It is expected that the object-based classification method overcomes this spectral variability problematic in very high-resolution imagery by utilizing not only the spectral information but also the topological relationships between image objects (Whiteside, Boggs, & Maier, 2011).

The combined classification approach has the advantage that only classes with the highest classification accuracies contribute to the final land cover map, resulting in a higher overall classification accuracy. Other authors have also obtained higher classification accuracies when applying a mix of classification methods, including Bhaskaran, Paramananda, and Ramnarayan (2010), who used pixel- and object-based methods to detect urban features with VHR imagery, and Wang et al. (2004), who obtained higher classification accuracies by applying these methods in mangrove ecosystems using IKONOS 1 m very high-resolution imagery. However, the use of these combined techniques in mountainous-forested areas with moderate-resolution satellite data such as Landsat and Landsat ETM⁺ imagery is rare. Studies by Flanders et al. (2003), Matinfar et al. (2007) and Yan et al. (2006) also suggest that a combined classification method may lead to the optimization of land cover classification and change detection; these authors' results indicate that the best-classification results cannot be obtained based on pixel- or object-based methods alone. In that respect, a 'From-To' change analysis in the present study produced more accurate results when a combined classification method was applied, providing greater insight into actual land cover change in the study area.

Slight errors resulting from the misregistration of imagery can be overcome by applying correction rules for the size and width of the changed patches. Such rules have proven efficient for eliminating spatial misregistration errors when working with objects in change detection analyses because in the pixel-based approach,

Table 5

'From-To' confusion matrix for the changes obtained from the LULC change analysis (km²). 'Total change' refers to the area that suffered change from one class to another, while 'Actual change' refers to the net loss area of a given class ('Total change' minus 'Total recover').

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	—

Table 6

Forest classes attributes and their change between 1999 and 2006.

Forest class Class attributes	Coniferous		Scattered vegetation		Non-coniferous	
	1999	2006	1999	2006	1999	2006
Number of patches	56,413	45,919	85,054	77,221	74,617	38,975
Biggest patch area (km ²)	101.65	67.24	93.14	24.84	3.27	1.47
Average patch area (km ²)	0.058	0.055	0.037	0.024	0.005	0.007
Total class area (km ²)	3271.11	2560.08	3166.92	1855.42	372.41	305.82

pixels need to be perfectly aligned to allow for an accurate land cover comparison and to discern change (Zhou, et al., 2008). As a result of the process of merging the land use/cover classes, mismatches between the different classes in the final mixed layer were generated, which may reduce the consistency of the information along the boundaries of the images. These mismatches are presented as “no data” areas and are expected when merging classes from images of different classifications. In this study, these areas were filled in with the classifications from the map with the highest overall accuracy (object- or pixel-based), which, in principle, ensures that these regions have the highest possible classification accuracy.

The overall accuracy obtained for the land cover change map demonstrates the capabilities of the object-based approach for change detection. However, the producer's accuracy for the ‘change’ class and the user's accuracy for the ‘no change’ class were relatively low. The Kappa statistic however, showed a good classification agreement, and the overall accuracy was still relatively high. The increase in the accuracy of the land cover change map with the ‘combined classification method’ layers ensured a more accurate ‘change’ to ‘no change’ classification. The observed changes are mainly a decrease in the forest classes and an increase in ‘Urban’, ‘Agriculture’ and ‘Bare soil’ areas, which are commonly associated with biodiversity degradation (Norris et al., 2010; Polasky, Nelson, Pennington, & Johnson, 2011; Schulz, Cayuela, Echeverría, Salas, & Reyes, 2010).

The accuracy of the classification and change detection analysis enabled a reliable comparison between the forest classes in 1999 and 2006 (Table 6). We suggest that the decrease in the number of patches represented by the three forest classes does not indicate a less fragmented landscape but reflects a pattern of logging in which a complete forest patch, and not just a part, is logged, thereby decreasing both the forested area and the number of forest patches.

Conclusions

Higher classification accuracies are obtained when land cover change maps are based on the extraction and subsequent merging of those land cover categories with the highest individual classification accuracies found with the pixel- and object-based classification methods.

The combined method offers advantages over other techniques in mountainous terrain with irregular topography and variable spectral characteristics when applied to medium-resolution imagery.

It is concluded that the determination of land cover classes with different spectral, textural, and topological characteristics using combined object-based and pixel-based classification approaches may lead to improved workflows for classifying past, present and future land cover. We recommend the use of pixel-based classification when classifying spectrally continuous and homogenous areas, as in the case of coniferous and non-coniferous forest. Conversely, we recommend the use of the object-based image

classification method when analyzing areas with high spectral variance in spatially continuous pixels, as in the case of mixed vegetation classes or where different bare soil types intermingle.

We suggest that the combination of methods used in this study can be applied to similar mountainous regions if applied to medium-resolution satellite imagery, such as Landsat ETM⁺, but that the spectral variability resulting from variations in forest composition and soil heterogeneity may affect the final results.

Human activity has resulted in an increase in agricultural land, the expansion of urbanization and infrastructure and an increase in (illegal) logging. The resulting decrease in forested area is accompanied by an increase in bare soil surfaces, which may increase the negative impact of land cover changes on biodiversity.

The improved workflow and resulting land cover change map presented here may serve as starting point for further conservation studies and decision-making processes. This process may be beneficial for researchers and decision makers working in this and other biodiversity-rich mountainous areas where relatively inaccessible regions and high rates of deforestation/habitat loss hinder the production of reliable land cover information.

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