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Automatic Classification of Trees outside Forest using an Object-driven Approach: an Application in a Costa Rican Landscape

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Summary: This research presents an automatic algorithm for trees outside forest (TOF) classification on scanned aerial photographs using an objected-oriented approach. TOF is defined as all trees outside the legal forest borders that comprise an area less than 2 ha. For classification purposes, an object must be a minimum distance of one pixel from a forested area (i.e., 3 m) in four directions to be considered a TOF and have a minimum mapping area of 9 m^2. A pixel is considered to be part of a TOF segment when it is no further than 3 m away in four directions. Twenty-three color aerial photographs (acquisition date 02.1997) scale 1:40,000 were digitized at 3 m-pixel size and then orthorectified and mosaicked. Due to variation in the radiometric conditions among the aerial photographs, the final image was subdivided in eighteen subsets; and each one was separately segmented and classified. The TOF information extraction process was carried out using multi-resolution segmentation and fuzzy classification rules available in the commercial software eCognition®. The combination 10, 30, 60 and 150 segmentation levels generated the most appropriate object sizes for forest, TOF and non-forest classification. Mean of channel green and the standard deviation of this channel were the membership functions most utilized to differentiate forest and non-forest classes. Contextual information, specifically the similarity function, proved to be a very suitable method for TOF classification purposes. Forest area corresponded to 43 250 ha, non-forest area was 80 600 ha and TOF-land corresponded to 3 710 ha (3% of the total area).

Zusammenfassung: *Automatische Klassifizierung von Bäumen außerhalb des Waldes durch einen Objekt-basierten Ansatz: Eine Anwendung in einer Landschaft Costa Ricas*. In dieser Untersuchung wird im Rahmen eines Objekt-orientierten Ansatzes ein automatischer Algorithmus für die Klassifizierung von Bäumen außerhalb des Waldes (Trees Outside Forest, TOF) in gescannten Luftbildern vorgestellt. TOF sind definiert durch sämtliche Bäume außerhalb der Waldgrenzen einschließlich Waldflächen kleiner zwei Hektar. Zum Zwecke der Klassifizierung musste die minimale Distanz eines als TOF auszuweisenden Segments zum Wald mindestens ein Pixel (d. h. 3 m) in die vier Himmelsrichtungen betragen. Die kleinste noch zu erfassende Fläche betrug daher 9 m^2 und die geringste Entfernung eines Pixels, um es als Teil eines TOF-Segments zu berücksichtigen, war 3 m. Dreiundzwanzig Farbluftbilder (Aufnahmedatum Februar 1997) mit einem Maßstab von 1:40 000 wurden mit einer Pixelgröße von drei Metern eingescannt, orthorektifiziert und zu einem Mosaik zusammengefügt. Bedingt durch radiometrische Abweichungen bei der Aufnahme der einzelnen Luftbilder ist das Gesamtbild in 18 Untereinheiten eingeteilt worden; jede dieser Einheiten wurde separat segmentiert und klassifiziert. Der Prozess der Extraktion von TOF wurde unter Benutzung von „Multi-Resolution"-Segmentierung und Fuzzy-Classification-Regeln mit der kommerziellen Software eCognition® durchgeführt. Die Kombination der Skalierungsfaktoren 10, 30, 60 und 150 bei der Segmentierung erzeugte die besten Objektgrößen bei der Klassifizierung von Wald, TOF und Nichtwald. Mittelwert und Standardabweichung des grünen Kanals waren die meistgebrauchten Membership-Funktionen zur Unterscheidung von Wald- und Nichtwald-Klassen. Weitergehend resultierte der Gebrauch

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von kontextbezogenen Unterscheidungsparametern, insbesondere die „Similarity-Funktion“, in einer Methode, die sich sehr gut für die Klassifizierung von TOF eignete. Die Waldfläche entsprach 43 250 ha, die Nichtwald-Gebiete hatten eine Größe von 80 600 ha und die TOF-Fläche ergab 3 710 ha (3% der Gesamtfläche).

1 Introduction

According to FAO (1998), trees outside forest (hereafter referred to as TOF) are considered to be "trees on land not defined as forest and other wooded land". These trees can grow in meadows associated with crops and pastures, along rivers, canals or roadsides, or in towns, gardens and parks. TOF definition obviously depends on the "forest" definition used, which can vary according to the objective of the study (e.g., large-area inventory) or to a particular national forest law (Kleinn 2000).

It is recognized that TOF embrace not only many ecological functions such as the conservation of biodiversity, erosion control and carbon sequestration (Schroeder 1994), but also economic functions, such as the provision of firewood, fodder, fence posts and living fence posts (Current et al. 1995). Despite the relevance of these and other important biophysical and socioeconomic roles attributed to TOF, little is known about these resources at scales beyond the farm (FAO 2001). It is therefore clear that methods for providing TOF information at broader scales, including those for its assessment, are required (FAO 2001).

The low density of TOF makes their assessment by conventional methods costly and time consuming. An attractive alternative option for a rapid and precise assessment is remotely sensed data, which has proven to be an efficient source of information in forest inventories on large-scale (Franklin 2001). Although high spatial resolution images have proven to be efficient in extracting TOF information, as is shown by Koukal & Schneider (2001), who developed an automatic classification algorithm for TOF extraction from IRS-1D panchromatic and LANDSAT ETM+ scenes, images with better geometric resolution, such as aerial photographs, could yield a much more reliable estimations of TOF cover. Another sensitive issue that must be taken into account is the cost of aerial photography, which could be prohibitive in Central American countries (Kleinn & Morales 2001). New research initiatives, however, will enable the provision of these type of images in the short term (Personal communication with Andrew Robert, NASA), making possible the development of relatively precise TOF cover estimations at different spatial scales.

The availability of high spatial resolution images has opened a more precise range of land-cover classifications and a new spectrum of applications (Franklin 2001). As these new remotely sensed data have been developed, a number of new technical problems have a risen that were not previously contemplated (Schiewe et al. 2001). While the problem of mixed pixels has been reduced (Schiewe et al. 2001), the internal variability and the noise within the target classes due to the high spatial resolution of the images have increased (Schiewe et al. 2001). This problem can be solved by means of image segmentation techniques, which produce homogeneous image objects and avoid the induced salt-and-pepper effect (Meinel et al. 2001). Image objects contain, aside from spectral information, additional attributes such as shape, texture, relational and contextual information that can be used for TOF classification purposes (Baatz et al. 2000, Blaschke & Strobl 2001).

The aim of this research is to develop an automatic algorithm for TOF information extraction from scanned color aerial photographs of a landscape in northwestern Costa Rica, by means of multi-resolution segmentation and fuzzy classification rules.

2 Materials and methods

2.1 *Study site*

The Costa Rica study site is located in the northwestern zone of the country within the Lambert coordinates 378,314/237,833 and 414,871/272,903 covering an area of 127 500 ha (Fig. 1). Twenty-three color aerial photographs with a scale 1 : 40 000 cover the study area. Altitudinal range within the area is 2–600 m.a.s.l. and slope between 0–50%. Mean annual precipitation range 1400–2500 mm and mean annual temperature is approximately 24°C (Herrera 2003).

Fig. 1: Study site location.

2.2 *TOF definition*

The Costa Rican forest law does not include a definition of TOF (Asamblea Legislativa 1996). However, by analyzing the official forest definition, it is possible to designate what could be considered as TOF by default. Considering the minimum area criterion included in this definition, the Costa Rican forest law designates an area greater than or equal to 2 ha as forest (Asamblea Legislativa 1996). Therefore, by default, TOF can be considered to be all trees outside the legal forest borders comprising an area smaller than 2 ha. The definition here proposed includes agroforestry systems and plantations of fruit trees. TOF-land corresponds to the land covered by the TOF objects. For classification purposes, an object must have a minimum distance of one pixel from a forested area (i.e., 3 m) in four directions to be considered a TOF. A pixel is considered to be part of a TOF segment when it is no further than 3 m away in four directions. The minimum mapping area was 9 m^2.

2.3 *Image pre-processing and classification*

The set of twenty-three-color aerial photographs in the scale of 1 : 40 000 (acquisition date February 1997) were digitized at 3 m-pixel size and then orthorectified[1]. The required reference data was gathered from topographic maps in the scale of 1 : 50 000 and from a digital elevation model with a grid size of 200 m. The selected set of aerial photographs was mosaicked using the tool for such purposes available in ERDAS (ERDAS IMAGINE 2000). Due to variations in the radiometric conditions among the aerial photographs, the final image was subdivided in eighteen subsets; with each one separately segmented and classified. The results were then merged in a GIS. None of the tools available in the software used to prepare the mosaic proved to be efficient in homogenizing the radiometric characteristics of the final image.

The TOF information extraction was carried out using the multi-resolution segmentation technique and fuzzy classification rules available in the commercial software eCognition® Version 2.1 (Baatz et al. 2001). The fundamental algorithm of the multi-resolution segmentation starts by defining a pre-defined threshold, a so-called scale parameter. In this method, the algorithm joins

[1] It was not possible to access the prints of the aerial photographs. A former research project (TROF project EU contract number ERB3514PL973202) scanned the material that was used in this investigation.

the neighboring regions, which are smaller than this scale parameter. This parameter is considered a measure of the maximum change in heterogeneity (variance) that may occur when merging two image objects. The algorithm also allows the segmentation in different resolutions so that the image information can be represented in terms of different scales simultaneously. The segmentations produced allow the construction of hierarchical network of image objects, where each level of the network is produced by a single segmentation run. The classification of the objects primitives is performed using an algorithm based on fuzzy mathematics. The mathematical approach of fuzzy logic is to replace the strict logical statement 0 and 1 (i.e., no or yes) by a continuous range of [0...1], where 0 means "exactly no" and 1 means, "exactly yes" (Baatz et al. 2001). Once the classification is obtained, the results can be refined by means of semantic context information by describing neighborhood relationships or the composition of sub-objects (Baatz et al. 2001).

In order to build up the most appropriate hierarchical network of image objects for defining the relationship between neighboring objects of different sizes (Baatz et al. 2001), the segmentation resolution levels of 150, 100, 80, 60, 30, 20 and 10 were tested. In all cases, the composition of homogeneity criterion was set to 0.8 for color and 0.2 for shape. In the latter criterion, a smoothness value of 0.9 and a compactness value of 0.1 were used. The best segmentation result for TOF classification was the one that provided most favorable information for classification purposes. Since a method for evaluating segmentation results has not yet been developed (Pal & Pal 1993), the evaluation of the segmentation results was performed by visual inspection of the resulting object primitives.

Two land cover classes were defined for the classification process: forest and non-forest, with the latter being the corresponding area where TOF are likely to be observed (i.e., TOF-land). Mangrove areas were included in the forest class; while water bodies, urban areas, clouds and their shadows were included in the non-forest class. Problems with shadowed objects, mainly corresponding to the forest class, were detected in the southeast part of the aerial photographs. Due to the low spectral capacity to separate shadow and forest offered by the three bands of the aerial photographs, a series of texture images were prepared in order to eliminate the shadow influence (see Herrera 2003 for methodological details). This procedure, however, was not effective in automatically separating shadow from the target objects. Nevertheless, its influence on the TOF land estimation was considered to be minimal because most TOF-objects are relatively small.

Once a general classification hierarchy was built, the algorithm was applied to each subset (18) created from the mosaic-image. Different membership functions were used to produce the corresponding class description. These memberships included the mean value of the red, blue and green channels, the standard deviation of the mean and the ratios of these channels, as well as contextual information. Due to the radiometric differences between the subsets, it was necessary to adjust the values of each membership function in the general class hierarchy each time it was applied. Once the forest and non-forest areas were classified, all resulting forest objects with an area smaller than 2 ha were considered to be TOF.

2.4 *Accuracy assessment of classification*

An accuracy assessment of the resulting classification was performed on three representative subsets of the image by means of the specific tools available in eCognition® software (Baatz et al. 2001). Prior knowledge of the study area and the same aerial photographs were used to identify and locate the reference data required for accuracy assessment purposes. For the forest class and non-forest class 150 and 100, sample objects of the lowest segmentation level (i.e., 10) were collected in each class as reference data. The classification was then evaluated using the *Producer accuracy*, *User* *accuracy*, *Overall accuracy*, and *Kappa Index of Agreement* (KIA) measures. It is worth noting that for this analysis TOF were included in the forest class.

3 Results

The combination 10, 30, 60 and 150 segmentation levels generated the most appropriate object sizes for TOF, forest and non-forest classification. The finest segmentation (10) allowed the representation of small objects such as isolated trees and groups of trees (the targets in this study), while the coarser (150) allowed the representation of larger objects such as forest patches and non-forest areas.

Regarding the classification, forest area corresponded to 43 250 ha, non-forest area was 80 600 ha and TOF-land corresponded to 3 710 ha, which represents 3 % of the total study area. Fig. 2 depicts partial results of the classification. In terms of size, approximately 83 % of TOF-objects represented an area of less than 0.05 ha, while only 1.6 % accounted for areas greater than 0.5 ha (Fig. 3).

For the three image subsets selected, all the evaluated accuracy measures presented values very close to 1 (Tab. 1). The agreement between the classification and the reference data, representing by the KIA, was greater than 90 % in the three samples. A detailed inspection of these measures shows that in the three image subsets, *forest* and *non-forest* classes showed a producer's accuracy higher than 90 % and 94 % respectively (Tab. 1). In the case of *forest* class, the producer's accuracy was always higher than 90 %. This implies that more than 90 % and up to 99 % (in the case of image subset 2) of the pixels of the classification and reference data agree (Tab. 1). Meanwhile, in the *non-forest* class, most part of the pixels selected as reference data agree with the resulting classification (94 % up to 100 % in the case of image subset 3, Tab. 1). The user's accuracy was always higher than 89 % and 97 % for *forest* class and *non-forest* class respectively in the subset images selected (Tab. 1). The results suggest that in any case, it is possible to assure that more than 89 % of the pixels classified as *forest* and more than 97 % of those classified as *non-forest* belong in their respective class.

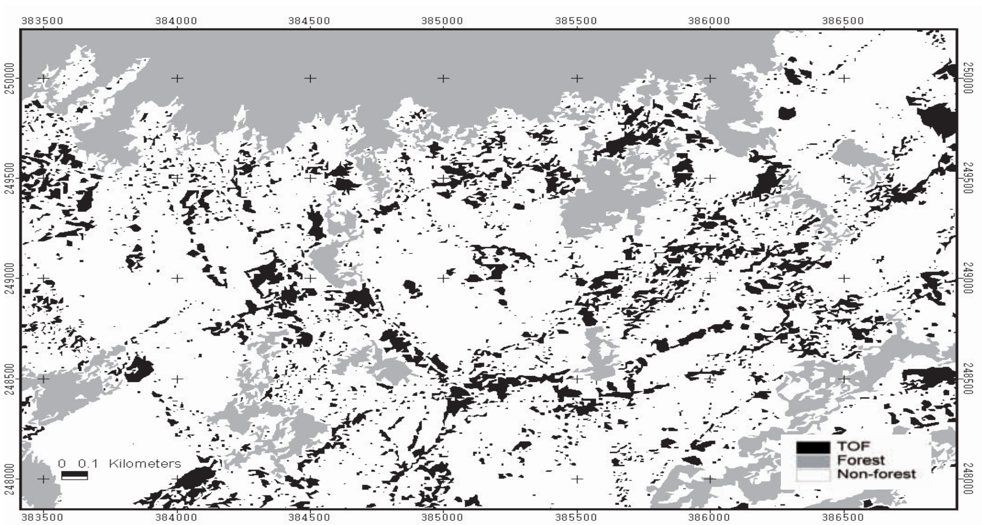

Fig. 2: TOF classification (subject of the final map) resulting from the multi-resolution segmentation and fuzzy classification of 23 aerial photographs. Note that the smallest objects, corresponding to TOF (in black), were extracted using a scale segmentation parameter of 10, while the forest patches (in gray) were classified using combination of segmentation parameters of 30, 60 and 150.

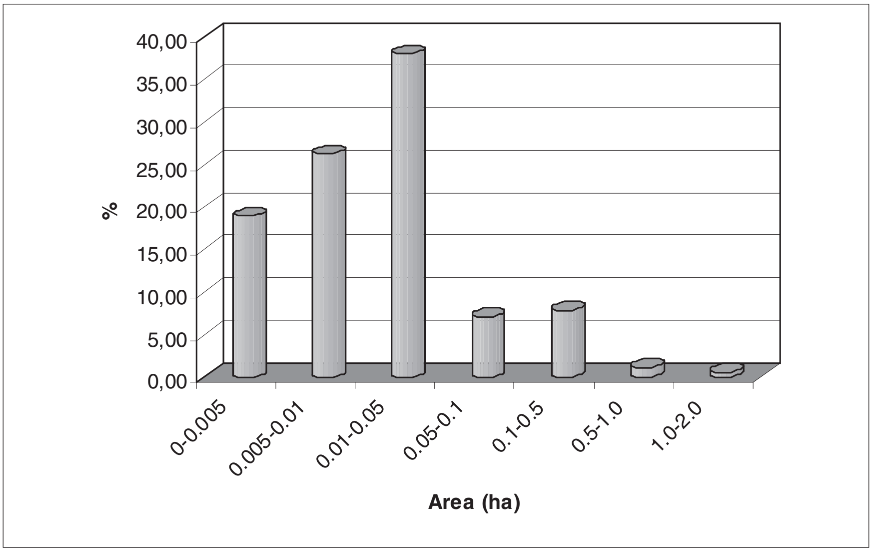

Fig. 3: Distribution of TOF objects extracted from scanned aerial photographs according to area classes.

Tab. 1: Accuracy measures for classification results on 23 color aerial photographs scale 1 : 40 000 and 3 m ground resolution. Note that TOF are included in the forest class.

	Land cover class					
Accuracy measure	Image subset 1		Image subset 2		Image subset 3	
	Forest	Non-forest	Forest	Non-forest	Forest	Non-forest
Producer	0.968	0.991	0.990	0.943	0.906	1.000
User	0.984	0.982	0.896	0.995	1.000	0.978
Overall	0.982		0.958		0.982	
KIA	0.962		0.909		0.939	

4 Discussion

The multi-resolution segmentation method applied has proven to be very efficient in extracting the segments required for the classification of forest, non-forest, and TOF on 3 m ground resolution scanned color aerial photographs. The application of the multi-resolution segmentation method has been demonstrated to be an efficient approach in extracting image objects in other high-resolution images (e.g., HOFFMAN 2001, KOUKAL & SCHNEIDER 2001, MEINEL et al. 2001).

This segmentation approach generated homogeneous objects suitable for classification, avoiding the noise-induced "salt-and-pepper" appearance normally produced when a pixel-driven classification process is performed (LILLESAND & KIEFER 2000, MEINEL et al. 2001). The combination of segmentation resolutions utilized (10, 30, 60 and 150) generated the most appropriate object sizes for classification purposes. Nevertheless, that does not mean that any other combination of segmentation resolutions cannot generate the same or even better results. The segmentation level of 10 proved to be very precise in the geometric delineation of individual trees and groups of trees, which were the target groups in this research. The mean of channel green and its standard deviation were the most utilized memberships functions for differentiating forest and non-forest classes. As was pointed out above, due to the differences in radiometric conditions found in the mosaic-image, it was necessary to adapt the classification algorithm to the particular condition of each of the subset images created. Therefore, in some cases, other membership functions such as the mean of channel red and the ratio of this channel were also useful for classification.

Contextual information, specifically the similarity function, produced a very suitable method for TOF classification purposes. Because non-forest areas surround TOF objects, these objects were segmented using a finer segmentation resolution, while larger objects represented the non-forest areas. Thus, it was possible to define relations between objects of different sizes and use the contextual information in the classification algorithm. This technique allowed the extraction of the smallest objects as depicted in Fig. 2. The classification accuracy measures suggest the algorithm designed produces satisfactory results (Congalton 1991), which is not a surprising result since only two classes were developed.

The use of very high-resolution images for TOF information extraction, produce important differences in comparison to other images of desirable spatial resolutions. In this sense Herrera (2003), using the data from Koukal & Schneider (2001), reported for the same study area of this research 3 477.5 ha classified as TOF-land on IRS (panchromatic, 5.8 m spatial resolution), which is approximately 232 ha less than the TOF-land on aerial photographs. The same author reports that the number of TOF objects extracted from the IRS image was 33 487, while in the present research 77 296 objects were classified as TOF. The area corresponding to forest classified on aerial photographs was 29 % (12 421.7 ha) higher than the forest area classified on a LANDSAT ETM + image (Herrera 2003). These differences could have important implications if the TOF information extracted from remotely sensed data are used in investigations related to automatic TOF inventory, in the assessment of carbon pools, spatial distribution (Herrera 2003) or studies related to the role of TOF in forest connectivity, among others. This latter issue is particularly pertinent in strongly fragmented areas such as Costa Rica (Sánchez-Azofeifa et al. 2001), where forest assessments using coarser image resolutions (e.g., LANDSAT) omit the role of TOF in forest connectivity, which is subsequently not included in information required for decision-making. The consequences for forest connectivity measures resulting from the image spatial resolution used in extracting TOF information has not yet been studied.

Radiometric differences in the images required the splitting of images into more homogeneous subsets. Although it should be recognized that this is not the ideal approach, it is expected that the use of scanned aerial photographs, the use of different photographic films and differences in the illumination conditions during the flight missions, among others, will yield strong variability in terms of radiometric conditions. Other error sources that could reduce the reliability of the classification results include the difficulty of separating shadow from the target objects, the impossibility to differentiate shrubs from trees and the fact that the sensor could not detect some deciduous tree species. It is assumed, however, that these error sources had a minimal influence on our data.

5 Conclusions

The developed algorithm for TOF classification on aerial photographs can be applied to new images of the same or similar geometric and spectral resolutions. Some important changes in the membership functions, however, may be required to compensate for differences in the illumination conditions that can influence the aerial photographs. Although a TOF classification derived from other scenes such as IRS or IKONOS may be prefered due to cost and area covered, new research initiatives in Costa Rica, as mentioned above, will provide aerial photographs of the same or better quality as those used in the present research. The methodological approach proposed in this research, including the membership functions reported, could therefore be used with this new set of data. However, this does not mean that new images with better spectral and spatial resolutions cannot be evaluated as an alternative for TOF assessments. Rather, if studies on TOF temporal dynamic are developed, it could be more appropriate to use remotely sensed data instead of scanned aerial photographs due to the budget and technical limitations of the latter.

The obtained TOF-land reported could be influenced by the TOF definition adopted. In the present research, TOF-land is limited to a maximum area of 2 ha. This area threshold can be considered high in comparison to other definitions used in other research initiatives (e.g., FAO). Therefore, if comparative results are required, a consensus among scientists on the definition of TOF is strongly required.

The availability and application of methods such as the one proposed in this paper will facilitate the integration of TOF into forest inventories, as well as TOF cover information into land cover databases. This will in turn expand the information available for landscape management and lead to the design of new investigations at this scale.

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