FOREST CANOPY SHADOW EXTRACTION USING AERIAL PHOTOGRAPHS IN THE ECUADORIAN AMAZON

O. Wang [a, *]

[a] School of Earth Sciences and Environmental Sustainability, Northern Arizona University, Flagstaff, AZ 86001, USA
Ophelia.wang@nau.edu

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ABSTRACT:

Forest canopy gaps have been characterized by using remote sensing techniques for quantification of canopy properties, as they have been well known to play a key role in forest structure and ecological processes. Within two indigenous communities in the Ecuadorian Amazon, I classified forest canopy shadows from high resolution aerial photographs using object-based feature extractions in 18 aerial photomosaics at a 15-cm resolution. I then constructed an error matrix and computed a Khat value in KAPPA analysis using both pixel- and object-based samplings under a binary (canopy shadow vs. non-shadow) classification scheme to evaluate the classification accuracies. In addition, I selected classified polygons and categorized the selected polygons into a fuzzy agreement in their proportion coverage of real canopy shadows. Mean overall accuracies of the pixel- and object-based sampling methods were 86%-91%. Mean producer's and user's accuracies for the two classes were 84%-92% using pixel- and object-based samplings. In both communities, the average conditional Kappa for both classes reached over 0.8. The categorization of canopy shadowiness based on a fuzzy logic showed that 78%-89% of sampled features in the two communities had real canopy shadow coverage in > 50% of the areas in extracted features. As the first study that successfully extracted forest canopy shadows from very high resolution aerial photographs using object-based classification techniques, my research offers repeatable and semi-automated methods that can be applied on studies in which features need to be extracted from non-multispectral remote sensing imagery.

1. INTRODUCTION

The vertical perspective of forest structure elements, such as canopy gaps, canopy profiles of height and crown size, or tree stand diameter, constitute tree diversity properties. Most up-to-date canopy studies that mapped and characterized canopy gaps using remote sensing techniques have focused on extracting canopy crowns or canopy gaps (Greenberg *et al.*, 2005), estimating canopy shadows properties and heterogeneity (Barbier *et al.*, 2010), and relating canopy metrics to field-based ecological data (Chubey *et al.*, 2006). A few studies aimed to extract and quantify canopy gaps or shadows by using automated characterization of forest canopy properties (Plowes, 2005; Morales *et al.*, 2008) The majority of canopy gap characterization studies took advantage of the high resolution and vertical profile brought by the light detection and ranging (LiDAR) images to delineate and map gaps (Koukoulas and Blackburn, 2004), to model canopy height and surfaces in order to mask out gaps and canopy shadows (Asner *et al.*, 2008), to document canopy regeneration and disturbance regimes (Vepakomma *et al.*, 2008), and to mask out canopy gaps for a better characterization of canopy properties (Blackburn, 2002).

However, traditional pixel-based canopy shadow classifications are not applicable for areas that are not covered by high-resolution multispectral imagery or by LiDAR data. An alternative is to conduct object-based extraction that delineates segments of real world objects, considers topological relations among neighboring pixels, provides great details of canopies, and differentiates canopy shadows in high-resolution images (Bunting and Lucas, 2006; Hájeck, 2006). Differing from traditional pixel-based classifications, important parameters for object-based classifications include spatial patch, grey level, color, and shape textures (Wang *et al.*, 2004; Ivits *et al.*, 2005). Among the abovementioned canopy gap studies, only Morales et al. (2008) and Vepakomma et al. (2008) took the object-based classification approach to delineate and study spatially extensive short-term dynamics of canopy gaps.

To obtain a better understanding of canopy shadows that may inform about forest dynamics, in this study the extraction of canopy shadows was conducted in aerial photomosaics of two indigenous communities in the Ecuadorian Amazon using an object-based machine-learning classifier. The analysis of aerial photomosaics employed object-based classification after extracting textural and color features from the imagery. This classification method has not been used previously in aerial photographs for studying forest gaps.

2. DATA AND STUDY AREA

The Yutsuntsa and Sawastian indigenous communities in the Amazon of southeastern Ecuador are within an area that has an annual precipitation that ranges between 2558-3715 mm. There is no distinctive dry season in the area, but seasonal variation is stronger within precipitation data than with temperature data (Figure 1).

Between 2005 and 2006 S. Lopez collected aerial photographs with a Nikon D2X still camera within an area of 6 X 6 km for the Yutsuntsa and Sawastian communities with 32 flight lines separated by 180 m intervals. Flyovers occurred at a height of 500 m aboveground. GPS and a video mapping system were used for collecting the positional information. Images were geometrically corrected using differentially corrected GPS data and a third order polynomial transformation (Lopez, 2008). With the aid of differentially corrected ground control points, the mosaics' errors were reduced to approximately 5 m. Nine preliminary photomosaics of forested, residential, agricultural, and pasture areas were created with a spatial resolution of 10 cm in each community (Lopez, 2008) (Figure 2).

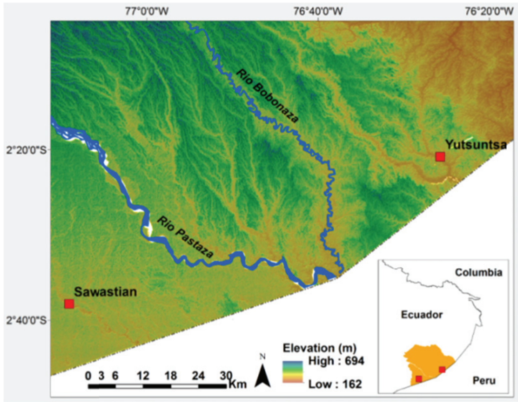

Figure 1. Map of the study area showing the two communities of data acquisition (data provided by R. Sierra and M. Peralvo).

Figure 2. An aerial photomosaic at 10-cm resolution.

3. METHODOLOGY

3.1 Imagery preprocessing

These 18 photomosaics (2 X 2 km each) did not go through color balancing during the image mosaic processes, thereby showing variations in brightness and illumination throughout the images. To avoid bias during canopy shadow extractions due to these variations, trial and error of preprocessing was conducted aiming to minimize the variations and produce images with the most consistent colors and textures representing different features in the images. Convolution filtering, a process of averaging small sets of pixels across an image, showed the best performance (Jensen, 2004). The software Erdas Imagine 9.2 provided more than 30 filters in the convolution kernal library to choose from. After trying all the applicable filters I found that the 7 X 7 kernal with a summary filter offered the best preprocessing results (Figure 3).

3.2 Feature extraction

This study used the software Feature Analyst 4.2 (Overwatch Systems, Ltd.) for feature extraction to identify and locate canopy shadows. Feature Analyst requires a series of data training and processing steps. I first delineated at least 85 haphazardly selected canopy shadows in various sizes, textures, and shapes in each photomosaic as training samples. The canopy shadows here represented dark canopy openings resulting from topography relief, tree fall gaps, or natural forest canopy openings.

Figure 3. A comparison between aerial photomosaics before (left) and after (right) convolution filtering. The uneven brightness and illumination were significantly reduced.

The preprocessed aerial photomosaics were rescaled into 15-cm resolution. I employed the following analytical criteria within the Feature Analyst environment: 1) determine the feature type as “natural features”, 2) use band type of “reflectance”, 3) apply histogram stretch, 4) use a specified input representation pattern, 4) aggregate the result polygons to a minimum object size of a specific number of pixels, and 5) smooth output shapes with a threshold of one pixel. Selecting the type and parameter of the input representation depended on trial and error for the best performance. Input representation allows a particular pattern algorithm to examine image pixels within a spatial pattern adjacent to the pixel of interest as well as other pixels to be considered during the classification. It determines the shape and size of the input pixels through which Feature Analyst gathers spatial and spectral information for each pixel. Feature Analyst creates a learning profile that defines the characteristics of the target feature and then searches for pixels similar to the training pixels (Visual Learning Systems, 2009). The Bull’s Eye 3 pattern appeared to be the most ideal input representation.

Post-classification pixel aggregation combined objects created after classification that comprised less than a particular number of pixels into neighboring objects. The aggregation pixel number varied among images, depending on the best extraction performance. I applied a smoothing threshold of one pixel during classification to lower the computational effort by reducing vertices between feature class boundaries. A few important post-classification processes were conducted to improve the classification algorithm and to refine the output. I haphazardly visualized and selected correctly and incorrectly classified features (at least 200 for each type per image) as training examples and then reclassified the image using Feature Analyst’s Clutter Removal function (Figure 4). The clutter-removed classification produced a more precise but underclassified product, thereby requiring another step of adding missed features during the classification. After manually delineating more canopy shadows that were not extracted during the clutter removal classification, I reran the feature extraction based on added missing features and the previous extraction. I repeated the clutter-removal and adding missed feature processes for several times until the classification presented a satisfactory result to minimize errors of omission (Congalton and Green, 2008) (Figure 5). To connect adjacent small canopy shadow polygons, I applied a dilate morphology filter that buffered pixel regions by the width of one pixel.

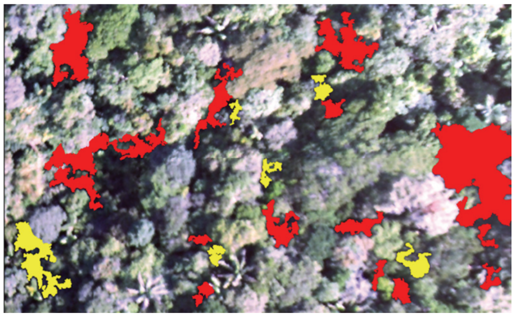

Figure 4. Feature Analyst Clutter Removal process. The polygons represent features that were correctly (red) and incorrectly (yellow) identified.

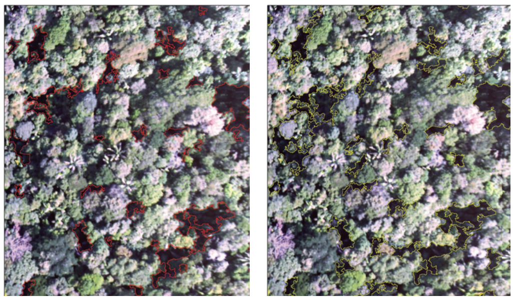

Figure 5. Canopy shadow extraction during repeats of clutter removal and adding missed features. The polygons represent the classifications that slightly underestimated (left in red) and overestimated (right in yellow) canopy shadows.

3.3 Accuracy assessment

Object-based classification differs from traditional pixel-based classifications by extracting spatial objects of relatively homogenous segments. Hence, accuracy assessment of object-based classification must ensure that the thematic accuracy is based on the object. An extracted canopy shadow may encompass mixed pixels of varying colors and textures, thereby yielding different levels of canopy shadowiness. To consider this uncertainty introduced by mixed pixels, a fuzzy logic approach may be appropriate for accuracy assessment (Fritz and See, 2005). The fuzzy expression consists of several conditions that define the feature as typical, less typical, or atypical of a class. These conditions are often described as a degree of probability (Rahman and Saha, 2008).

I evaluated the canopy shadow extraction with a standard error matrix method. I constructed the error matrix using both traditional pixel-based sampling and object-based sampling under a binary (canopy shadow vs. non-shadow) classification scheme. The object-based sampling used the classification output polygon as the validation unit because it corresponded to a single canopy shadow (Mathieu *et al.*, 2007). In addition, I computed a Khat value in KAPPA analysis to evaluate the level of agreement between the classified and reference data. An overall Khat for the entire error matrix and conditional Khat for individual classes (shadow and non-shadow) were calculated (Congalton and Green, 2008). Z statistics was used to determine how much better the classification was compared to a layer where class value was randomly assigned to each pixel (Mathieu *et al.*, 2007; Rahman and Saha, 2008). An additional pairwise Z value was computed to determine whether the pixel-based and the object-based sampling methods showed significant differences (Congalton and Green, 2008).

Congalton and Green (2008) suggested collecting a minimum of 50 samples for each classification class. Nevertheless, considering the massive number of extracted polygons in each image, 50 samples appeared to be insufficient. Congalton and Green (2008) suggested another computation of sampling size based on a multinomial chi square distribution and the proportion of each class in the map area. As the result, the total samples for assessing each classification ranged from 72-149 among the 18 images. To ensure that there would be sufficient samples for both canopy shadow and non-shadows classes, I doubled the above sample size to collect 72-149 samples within each respective class of canopy shadow vs. non-shadow.

For the pixel-based assessment method, I conducted stratified random sampling to generate spatially stratified random points in each image (Gao and Mas, 2008; Zhou *et al.*, 2008). The binary error matrix was derived from visualizing whether or not the random point that fell inside or outside a classification polygon belonged to a real canopy shadow visualized in the image. For the object-based assessment method, the sampling objects that were within the canopy shadow class were created by selecting classified polygons with a probability proportional to their area. Radoux et al. (2008) proposed this selection method in order to account for the fact that misclassifying a large object had greater impact on the overall accuracy than misclassifying a small object. The binary error matrix was derived from visualizing whether or not > 50% area of the selected polygon overlapped with a real canopy shadow visualized in the image, or if the polygon covered < 50% area of a canopy shadow. I also spatially stratified 10 X 10 m vector grids that were in the non-shadow class and visualized whether or not the grid overlapped with a real canopy shadow for at least the minimum area of a classified polygon selected by the above weighed sampling.

In addition, I selected spatially stratified random classified polygons (unweighed) and categorized the selected polygons into a fuzzy agreement in their proportion coverage of real canopy shadows from the image into >75%, 50-75%, 25-50%, and < 25% area of the real canopy shadows. This categorization summarized the level of agreement between canopy shadow extraction and the aerial photomosaic.

4. RESULTS AND DISCUSSION

4.1 Classification accuracies

Overall, in both Yutsuntsa and Sawastian communities, the pixel-based sampling for accuracy assessment showed higher producer's and user's accuracies in classifying both canopy shadow and non-shadow classes than the object-based sampling. Mean producer's and user's accuracies for the two classes in Yutsuntsa were 90%-92% when using pixel-based sampling and were 86%-89% according to object-based sampling. With accuracies slightly lower in Sawastian, the pixel-based sampling showed 86%-92% mean producer's and user's accuracies for the two classes, whereas the object-based sampling showed 84%-89% accuracies (Table 1). Likewise, mean overall accuracies of the pixel- vs. object-based sampling methods were 91% and 88% in Yutsuntsa and 89% and 86% in Sawastian, respectively (Table 1).

Method	Mean ± SE of the measures					
	Producer's accuracy (%)	User's accuracy (%)	Overall accuracy (%)	Conditional Kappa	Overall Kappa	Z statistics
Yutsuntsa						
Pixel-based			91.1±1.1		0.8±0.02	21.6±1.7
Shadow	92.1±1.2	90±1.4		0.8±0.03		
Non-shadow	90.3±1.3	92.2±1.3		0.8±0.02		
Object-based			87.6±1.4		0.8±0.03	17.6±2.1
Shadow	88.9±1.5	86.2±2.2		0.7±0.04		
Non-shadow	86.8±1.9	89.1±1.6		0.8±0.03		
Sawastian						
Pixel-based			89.3±0.6		0.8±0.01	19.1±1.2
Shadow	91.4±0.9	86.9±1		0.8±0.02		
Non-shadow	87.6±0.8	91.8±0.9		0.8±0.02		
Object-based			86.7±1		0.7±0.02	16.5±1.1
Shadow	89.1±1.2	84.5±1.4		0.7±0.02		
Non-shadow	85.3±1.2	89.6±1.3		0.8±0.03		

Table 1. Summary of mean ± SE of producer's accuracy, user's accuracy, overall accuracy, conditional Kappa, overall Kappa, and Z statistics for error matrices constructed in pixel-based and object-based sampling methods in Yutsuntsa and Sawastian.

In Yutsuntsa, the average conditional Kappa for both canopy shadow and non-shadow classes using pixel-based sampling were over 0.8, reaching an "almost perfect" agreement between classified and reference data (Ladis and Koch, 1977). The average conditional Kappa for both canopy shadow and non-shadow classes using object-based sampling were under 0.8, but were still considered to have a "substantial" agreement between classified and reference data (Table 1). A higher average overall Kappa was shown in pixel-based sampling than in object-based sampling. Z statistics for both sampling methods exceeded a threshold value of 1.96 at a 95% confidence interval, indicating that the classifications were much better than random placement of pixels (Table 1). The average conditional and overall Kappa values according to pixel-based sampling were higher than object-based sampling in Sawastian. All Kappa values suggested at least a substantial agreement between classified and reference data (Landis and Koch, 1977), especially for the conditional Kappa of non-shadow class using pixel-based sampling, which reached an "almost perfect" agreement (Table 1). Similar to the observation in Yutsuntsa, the Z statistics in Sawastian indicated that the classifications were much better than random placement of pixels (Table 1).

The pixel-based sampling showed higher producer's, user's, and overall accuracies than the object-based sampling in almost all images in Yutsuntsa and Sawastian. For the canopy shadow class, producer's and user's accuracies in Yutsuntsa were 1.5%-9% and 1%-12%, respectively, higher in pixel-based sampling than in object-based sampling whereas in Sawastian the respective differences were 1.4%-7% and 0%-8%. For the non-shadow class, pixel-based sampling in Yutsuntsa had 1.6%-12% and 0.9%-9%, respectively, greater producer's and user's accuracies than object-based samplings. In Sawastian, 0%-7% and 1.3%-7.5% respective differences in producer's and user's accuracies between pixel-based vs. object-based samplings were found. Similarly, pixel-based sampling showed greater overall accuracy than object-based sampling for both Yutsuntsa and Sawastian. Differences in overall accuracy between the two sampling methods were 2%-10% in Yutsuntsa and 0.8%-7% in Sawastian. Both methods for assessing classification accuracies performed well, but the object-based sampling approach appeared to be more congruent with the classification unit, which was based on individual "objects" of canopy shadows.
The conditional Kappa for canopy shadow and non-shadow classes in both Yutsuntsa and Sawastian had greater values according to pixel-based sampling method than object-based sampling. Pixel-based sampling also showed higher overall Kappa in both Yutsuntsa and Sawastian than object-based sampling. All conditional and overall Kappa values in pixel-based and object-based samplings reached "almost perfect" or "substantial" agreement between classified and reference data. Z statistics indicated that all classifications in Yutsuntsa and Sawastian were much better than random pixel placement. In Yutsuntsa, the pairwise Z statistics in five out of nine images showed significant differences between error matrices using pixel-based vs. object-based samplings. For Sawastian, significant differences between error matrices using pixel-based vs. object-based samplings occurred in two out of nine images.

The categorization of canopy shadowiness based on a fuzzy logic showed that the majority of extracted features contained real canopy shadows. Overall, 78%-88% of sampled features in Yutsuntsa and 79%-89% of samples in Sawastian had real canopy shadow coverage in > 50% of the areas in extracted features (Table 2). Percentages of sampled features that contained real canopy shadows varied among different images in both Yutsuntsa and Sawastian, suggesting that the feature extraction effort and success might be uneven. Such unevenness could result from heterogeneous canopy structures and micro-habitats in the forests that caused different textures, colors, and spatial arrangement of canopy shadows.

Mosaic	Sample size	% area of sampled features > 75	50-75	25-50	<25
Yutsuntsa					
A	118	54.2	25.4	14.4	5.9
B	110	47.3	30.9	13.6	8.2
C	105	61.9	24.8	8.6	4.8
D	124	53.2	31.5	9.7	5.7
E	72	48.6	34.7	9.7	6.9
F	110	57.3	28.2	8.2	6.4
G	91	55.0	30.8	7.7	6.6
H	101	50.5	37.6	6.9	5.0
I	80	53.8	30.0	11.3	5.0
Sawastian					
A	149	42.3	42.3	8.1	7.4
B	123	36.6	45.5	10.6	7.3
C	126	37.3	50.0	5.6	7.1
D	73	32.9	49.3	8.2	9.6
E	107	16.8	62.6	8.4	12.2
F	113	27.4	59.3	7.1	6.2
G	78	17.8	63.0	8.2	11.0
H	96	26.0	62.5	7.3	4.2
I	121	18.2	64.5	10.7	6.6

Table 2. Percentage of sampled features that contained real canopy shadows in > 75%, 50-75%, 25-50%, and < 25% of the total area in each extracted feature.

4.2 Discussion

The classification showed nearly or slightly over 90% producer's, user's, and overall accuracies according to both pixel- and object-based accuracy assessment approaches. Kappa statistics indicated that agreements between the references and classified features reached "substantial" to "almost perfect" levels. The accuracy assessment method that took a fuzzy logic approach also suggested that nearly or over 80% of extracted features covered over 50% area of real canopy shadows. Due to the lack of other high-resolution remote sensing data in the study region, this study took a novel approach of using the same sources for both input and reference images for accuracy assessment. Previous object-based classification studies had overlaid selected polygons for validation on the data used for classification (e.g. Grenier *et al.*, 2008), but this study did not rely on any ancillary data to build an interpretation key. This approach yielded high accuracies that supported both the object-based classification and the accuracy assessment methods.

This study showed that using pixel-based, object-based, or fuzzy logic-based sampling method for accuracy assessment is effective for object-oriented classifications. Furthermore, under the condition of unavailable reference data, any of these methods can still provide high accuracies when source and reference data come from the same imagery. A shortage of cloud-free and high-resolution remote sensing images is a persisting challenge in remote areas, especially in the wet tropics. Frequent rainfalls enhance difficulty in obtaining high-resolution images with the least cloud cover. My research provides a unique solution by using the same images as references and inputs for accuracy assessment. This solution offers researchers great flexibility and confidence in accuracy assessment for analysis in remote locations.

Although this study is not the first that used object-based classification techniques for canopy gap/shadow extraction, it serves as a pioneer for applying object-based classification on canopy gap/shadow extraction by using fine-resolution aerial photographs. Lacking multispectral information which provides spectral signals to facilitate distinguishing different forest features, feature extraction out of aerial photographs solely relies on color, texture, and spatial relationship among targeted objects. Furthermore, the 18 images used in this study are mosaicked aerial photographs that were obtained along multiple flight paths, and were not color balanced during the mosaicking processes. Therefore, I faced a two-phased challenge to first reduce the effects of illumination and unbalanced colors, and then to develop the best feature extraction parameters. Challenges in both phases were overcome during the data pre-processing stage, given that the classification accuracies were exceptional.

The object-based feature extraction in this study reached high accuracies that were comparable to the preceding work that reached very high classification accuracies (Castillejo-Gonzalez *et al.*, 2009; Zhou and Troy, 2009). The majority of these object-based classification studies used multispectral images, unlike this research in which the extractions were derived from aerial photographs. Extracting features from aerial photographs is more challenging than using multispectral imagery because the training samples do not contain spectral signals that can contribute to a reference library. Therefore, this aerial photograph-based canopy shadow extraction performed exceptionally well despite the challenges described above.

5. CONCLUSIONS

Using remote sensing techniques for characterizing tropical forest canopies is a more efficient approach to address the major challenge in lack of tropical forest data in remote areas. As the first study that successfully extracted forest canopy shadows from very high resolution aerial photographs using object-based classification techniques, my research offers a set of repeatable and semi-automated methods that can be applied on other studies in which features with distinctive colors and texture need to be extracted from non-multispectral remote sensing imagery. For instance, the methods of image preprocessing and hierarchical learning can become templates for feature extractions of particular tree crowns with discernible phenological traits, tree trunks with unique architecture, or canopies with distinct structure. Researchers who have access to fine-resolution non-multispectral images will be able to take advantage of object-based feature extraction techniques as an alternative of the pixel-based classification approach.

All three accuracy assessment methods used for evaluating the object-based extraction of canopy shadows from aerial photographs indicated high accuracies and success of feature extraction techniques for non-multispectral remote sensing data. The classification showed over 90% overall accuracies using object- and pixel-based assessment approaches, and over 80% of extracted features are in areas with over 50% cover of real canopy shadows. This study did not rely on any ancillary data to build an interpretation key for accuracy assessment, but still gained satisfactory results. This approach yielded high classification accuracies that not only supported the object-based classification, but also proved the objectivity of the accuracy assessment methods. Therefore, this study also demonstrated a novel approach of efficient accuracy assessment by using the same imagery as classification input and accuracy assessment reference data. This approach proves that despite limits in data availability and spectral information, object-based feature extraction is an effective and a flexible method that retains high classification accuracies.

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