WHICH PIXEL IS A FOREST? TREE CROWN DELINEATION USING VHR IMAGES TO ESTIMATE TREE COVER IN LANDSAT BASED CLASSIFICATION

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ABSTRACT

Determining the percentage of tree crown cover is extremely important to establish in advance which forest types can be classified with high resolution sensors such as Landsat. This paper describes the determination of a tree crown coverage threshold to define whether a pixel is classified as a forest or not. The methodology consists in the comparison of forest/non-forest classifications generated from Landsat images with tree crown cover maps obtained from PlanetScope very high resolution images, considering those pixels that exceed a given canopy cover threshold (eg. 5-10-15-...90-95-100%) as forest. The canopy coverage threshold was the one that minimized the difference between the Landsat classification and the maps generated from Planet images.

Index Terms— Vegetation cover, PlanetScope, Image processing, Unsupervised learning

1. INTRODUCTION

To effectively assist decision making, forest mapping should be aligned with conceptual (or legal) definitions of forest [1]. While the latter are straightforward and generally involve specific tree crown cover (or tree density), minimum area and tree height thresholds [2], machine learning satellite-based classification algorithms use training inputs to assess the likelihood that a pixel will belong to a given discrete class based on spectrotemporal features. As a consequence, forest areas estimated from remote sensing may not agree with official statistics, generating inconsistencies in national or global reports [1]. One way to attenuate this problem is to assess a threshold percentage of tree crown cover of the pixels classified as forest. This assessment requires a site (or region) specific approach together with information on tree crown cover at the pixel resolution of the satellite-based classification.

Tree identification can be framed as a particular case of object detection. Available methodologies span from tree detection and delineation by digital image processing to, more recently, artificial intelligence using machine learning and deep learning algorithms.

Tree crown delineation methods can be grouped into three categories: valley following, region growing, and watershed segmentation. In the valley following method, tree boundaries are extracted based on shadow between them [3],[4]. In region growing, tree crowns are generally selected as the starting point and the region grows by inspecting neighboring points. Based on a predefined criterion, the growing stops in this way tree boundaries are segmented [5]. In watershed segmentation, first the negative of the grayscale image is obtained thus local minima are obtained using watershed segmentation, this region corresponds to the tree crown [6].

In recent years an increasing number of studies have successfully applied convolutional neural networks (CNN) for the detection and delineation of tree crowns [7], [8], [9], [10]. However, the volume of data required to train these networks is prohibitive.

We here propose a hybrid pipeline that mixes digital image processing and machine learning to quantify tree crown cover using PlanetScope images. In turn, we use these data to address our main objective: the assessment of the tree crown cover threshold of a Landsat images based random forest classification of native forests in Uruguay.

2. MATERIALS AND METHODS

2.1. Study Area

Seven study areas were selected to include canopy cover gradients of different native forests across Uruguay (Figure 1). The selection of each area was determined according to the availability of cloud-free and close to zenith PlanetScope scenes [11]. Within each of these areas we selected plots with a clear dominance of forest and herbaceous classes, using a land use / land cover classification .

2.2. Forest classification

A native forest mask was obtained from a Random Forest classification for the year 2016 using Landsat images and visual interpretation training samples (REDD-Uruguay Project, 2020). From these training samples we created a spatio-temporal feature space to characterize an 8 class legend following IPCC proposal [12]. We then remapped the classes to a forest and non-forest legend. All processing was done in Google Earth Engine platform [13].

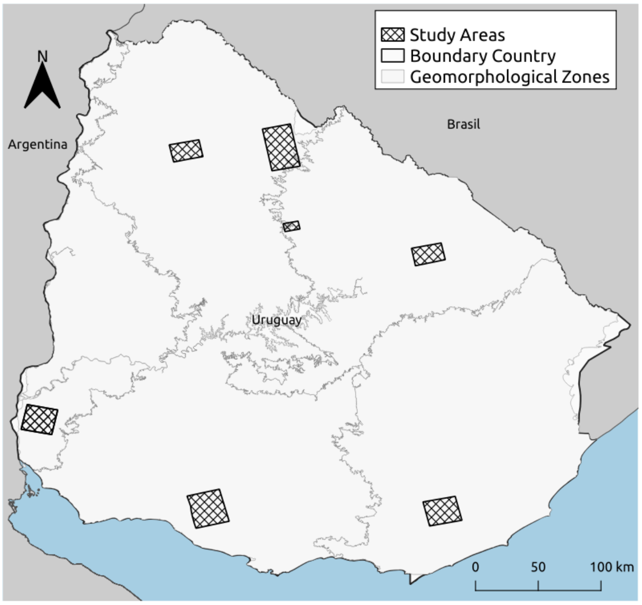

Figure 1: Location of the study areas encompassing the main geomorphological zones (depicted with grey lines) and native forest types.

2.3. Tree Crown Detection Methodology

A hybrid methodology including digital image processing and unsupervised automatic learning was implemented to discriminate tree crowns --or sets of tree crowns when they were spatially continuous--from other surface elements. The processing chain consisted of several stages of pre-processing, histogram-based segmentation using univariate Otsu [14] and the unsupervised K-Means grouping algorithm. Figure 2 shows each of the stages detailed below.

The pre-processing of the Planet images consisted in applying filters and normalizing the band values. This allowed a reduction in the noise of the images - i.e. random variation in the reflectance value of the bands - and rescaling their values to a common scale (Figure 3.a). Specifically, a Gaussian blur low-pass filter was used to reduce the high-frequency components of the image. Blur was applied with a 3x3 Gaussian kernel and a 3x3 convolution. The bands were then normalized using the Z-score (Figure 3.a). This normalization process subtracts from each pixel value the average band value of all pixels in the image and divides it by the standard deviation of the same data set.

An initial binary classification (crown/set of crown - other elements) was done with Otsu on the standard red channel band only (Figure 3.b), since it is a univariate method of segmentation on gray scale. That is, the Otsu algorithm returns the threshold value that separates pixels into two classes by minimizing the intra-class variance or maximizing the inter-class variance. Since this methodology is sensitive to distributions that are not well-defined as bimodal, areas where there are many different forest/tree covers should be avoided.

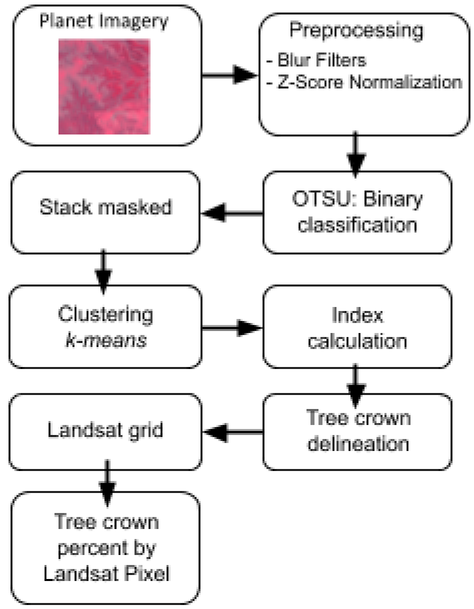

Figure 2: Working scheme for crown tree segmentation and coverage percentage calculation in a Landsat resolution grid (30 meters side) using Google Earth Engine.

From the normalized bands, indices (e.g. NDVI, GCVI, EVI, SAVI and NDWI) were calculated and constituted the inputs to the k-means clustering algorithm. Before running this clustering algorithm, the stack was masked by retaining only the pixels detected by the classification generated with the Otsu algorithm in the previous stage. This mask facilitated the isolation of different canopy covers - with high or low density - and the separation from other covers, such as low quality soils in shallow areas or geometric effects (e.g. shadows) that may have been confused with forest in the Otsu stage (Figure 3.c).

The clusters generated by the k-means algorithm were labeled from visual interpretation of the PlanetScope images. Thus, one of the clusters will correspond to individual treetops or sets of treetops detected in the 3 x 3 m pixel of the Planet scenes (Figure 3.d).

The crown/set values were then resampled to the Landsat spatial resolution using a 30 x 30 m vector grid (Figure 3.e). The value assigned to each cell of the grid corresponded to the percentage of the cell area occupied by crowns/set of crowns estimated in the previous step (Figure 3.f).

2.4. Determination of the tree crown coverage threshold

A quantitative method, Area Under Curve (AUC) was used to determine the tree crown cover value from which the algorithm used for land use/cover classification assigns a pixel to the forest class. This metric (i.e. AUC) is derived from the Receiver Operating Characteristic (ROC) curve that is obtained by plotting the performance of a classification model at all classification thresholds. Classification threshold is defined as the percentage of crown (e.g. 5-10-15%...90-95-100%) above which the pixel is considered to be forest in the forest non-forest classification.

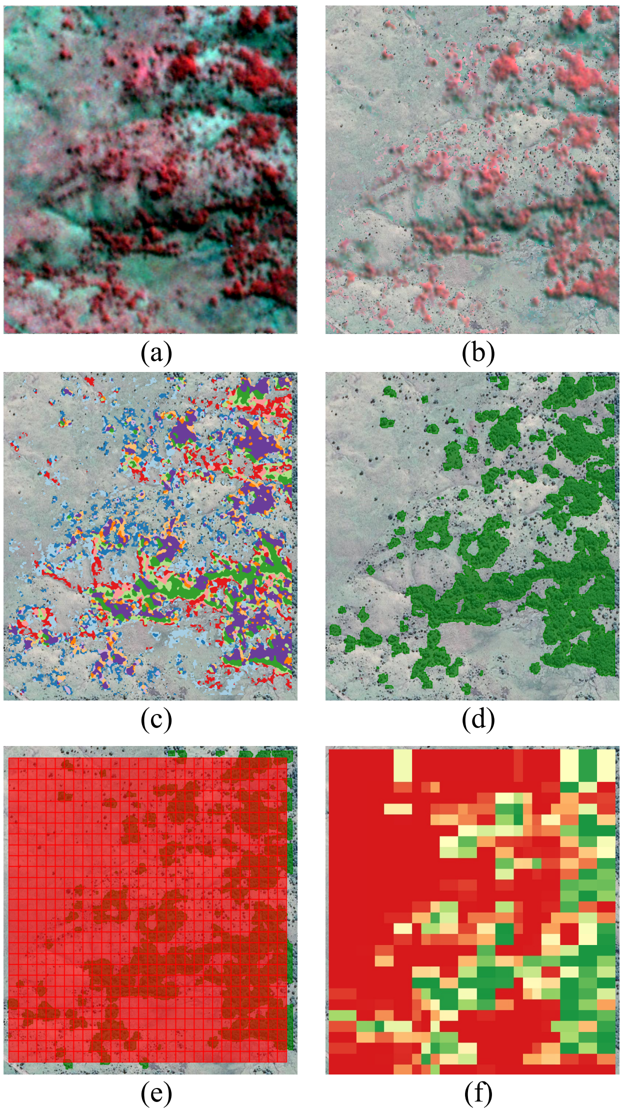

Figure 3: Stages in the canopy coverage calculation methodology for a Landsat pixel: a) pre-processing stage, b) binary classification, c) k-means clustering, d) tree crowns delineation, e) cover calculation by grid Landsat resolution, f) cover percent mapping.

The curve is constructed from two measures: the true positive rate (TPR) and the false positive rate (FPR).

$$TPR = TP/(TP + FN)$$
$$FPR = FP/(FP + TN)$$

where FN and TN indicates the number of false and true negatives and TP and FP the number of true and false positives. A ROC curve represents TPR versus FPR at different classification thresholds. By lowering this threshold more items are classified as positive, so both false positives and true positives will increase. The AUC metric measures the two-dimensional area below the full ROC curve, which is similar to the integral defined between 0 and 1. In this case it was used to evaluate the matches between the canopy mask built with a percentage coverage - similar to the classification threshold mentioned in the previous paragraph - and the Landsat based classification for 2016.

The use of AUC is appropriate for this type of assessment as it is invariant to scale since it measures how well predictions are classified, instead of their absolute values. In addition, the AUC is invariant with respect to the classification threshold. This allows to measure the quality of the predictions of both mappings, regardless of which classification threshold is chosen.

Finally, the tree crown cover threshold of Landsat pixels classified as forest was inferred by comparison between synthetic maps to the Landsat based Random Forest classification. We, thus, built several different synthetic maps by setting 10% incremental thresholds of tree crown cover to assign a pixel to the forest class. For each of these synthetic maps, an AUC was calculated using the Landsat based classifications as reference. Lastly, the Landsat threshold value was equal to the tree crown cover corresponding to the synthetic map that maximized AUC.

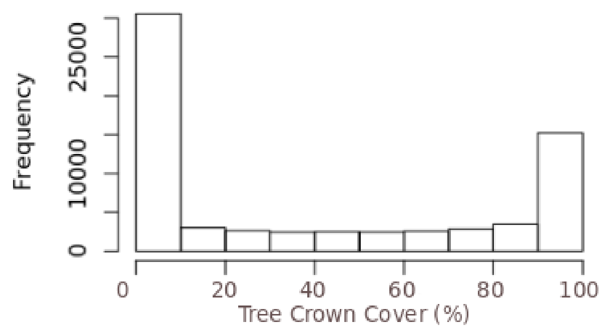

Figure 4: Distribution of tree crown cover that were estimated following the methodology for the 7 study areas altogether.

3. RESULTS

3.1 Tree crown cover

The most frequent canopy cover classes were the extreme bins: 0-10% and 90-100% i.e. areas with no or very few tree crown cover and areas of dense forest (Figure 4). Between these two situations the canopy cover varied evenly, with all intermediate classes having a very similar frequency.

3.2 Tree crown cover threshold calibration

The relationship between AUC and the tree crown cover from the synthetic maps remained relatively constant between 10 to 40% and decreased from 40 to 90%. The maximum AUC occurred at 20-30% of tree crown cover (Figure 5). This is in agreement with the 25% tree cover threshold recently found by [15] in Ukraine using standard global continuous tree cover maps. The reduction in AUC as tree crown cover increases above 40% must be related to the increase in the frequency of false negatives, that is, forest pixels incorrectly classified as non-forest.

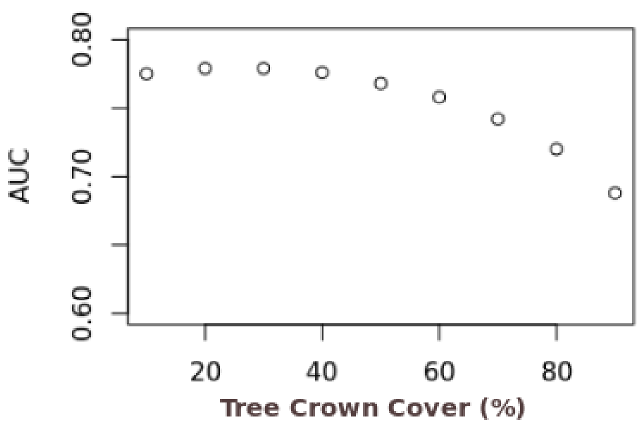

Figure 5: AUC results for the different thresholds of canopy coverage percent. The value that maximizes the area under the curve is 20-30%.

4. CONCLUSION

We here prototyped a simple approach to assess the tree crown cover threshold from Landsat-based forest classifications. The approach combines digital images processing techniques with machine learning algorithms to estimate tree crown cover together with methodology to compare synthetic maps to the reference forest map. In doing so, we addressed a critical need to translate map information into decision making: the sensitivity of the classification method to the tree crown cover. The systematic inclusion of this parameter in remote sensing products will assist the interpretation of potential differences between satellite based forest classification and official forest statistics. Despite our approach needs further testing and refinement -as tree crown cover thresholds are expected to change according to the classification method, training samples and forests phenology and spatial pattern-, our study presented a potentially viable way to generate key information about forest maps.

5. ACKNOWLEDGEMENT

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