MAPPING BIG TREE PRESENCE IN OPEN SAVANNA, USING TREE SHADOW AND HIGH RESOLUTION MULTISPECTRAL IMAGERY

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ABSTRACT

Large scattered trees play an important role in the functioning of savanna landscapes. They act as focal points for various organism activities, which influence the distribution of nutrients and water within the landscape, which in turn influences savanna patch dynamics. They generally are considered as prominent keystone structures associated with a stable ecological stage. A variety of anthropogenic land use and management activities are however putting increasing pressure on the big tree abundance, habitat structure, and ultimately the ecological function of the African savanna biome. Mapping these trees at individual level over large areas could yield valuable information for landscape ecology studies. Recent concerns related to the decrease of large trees in Kruger National Park prompted the development of field protocols for monitoring changes in large trees (Druce et al 2008). Airborne multispectral and LiDAR surveys are technically best suited for this application, but are expensive for large scale studies. Multispectral imagery affords the possibility of regional scale studies, but often lacks the spatial resolution for discriminating tree canopies. High spatial resolution multispectral sensors (i.e. 2-5 m pixel size) do however provide the opportunity to extract large scattered trees (>5 m height and 25m2 canopy surface) using their projected shadow. Available SPOT5 imagery was pan-sharpened (to 2.5m) and then subjected to various image transformation techniques, which all aimed to enhance the shadow. The products of the various image transformations were then used in an object based classifier to produce shadow maps. The shadow maps were validated against tree maps derived from a 3D discrete Carnegie Airborne Observatory LiDAR dataset. Tempered by a challenging accuracy assessment scenario, the methods achieved promising user's accuracy results, which ranged between 64 and 79% depending on tree densities. More research is needed into the factors affecting shadow detection, but we are encouraged about this method becoming an affordable method for mapping trees in savanna landscapes.

INTRODUCTION

Savanna ecosystems are defined by a continuous herbaceous layer interspersed with trees, and are ecologically and economically important systems that cover more than one fifth of the earth's surface (Sankaran et al., 2005, Scholes and Archer, 1997). Savanna ecosystems support high diversities and abundances of herbivores, both wild and domestic, and also provide important goods and services to large human populations (Sankaran et al., 2005; Scholes and Archer, 1997, Treydte et al, 2010).

Within a savanna ecosystem, the scattered trees, particularly big trees (e.g. ≥ 5 m in height and crown diameter), play an important ecosystem function and are considered as keystone structures.

Scattered big trees play important roles in the provision of shade, shelter, resting places, and prime conditions for understory herbaceous layer growth. These functions combine to attract a variety of taxa to these large trees, which further influences their size, spatial arrangement, and influence on the diversity and habitat structures of the ecosystem.

Given the relative influence and importance of big trees within the landscape, it should follow that resource managers be made aware of their distribution, density, and dynamics within the landscape using the tools available to them. Satellite remote sensing can be such a tool, as it is able to provide timely datasets on a substantially larger scale than would be possible using traditional field based methods. For instance, recent concerns related to the decrease of large trees in Kruger National Park prompted the development of field protocols for monitoring changes in large trees (Druce et al 2008). The challenge for most resource managers is being able to do this as cost effectively as possible. Airborne multispectral and LiDAR surveys are technically best suited for this application, but are expensive for large scale studies. High resolution multispectral satellite imagery affords the possibility of regional scale studies.

In order for tree canopies to be successfully mapped, tree crowns need to be larger than the spatial resolution of the imagery (Wulder et al, 2004). Added to this, there needs to be limited spectral confusion between the tree canopy and the background pixels (e.g. soil or grass background). In savanna environments, limiting the spectral confusion between tree canopy signal and background grass/shrub signal can be challenging, but not impossible as Boggs (2010) showed by using object orientated image analysis methods. We are therefore proposing an alternative method that attempts to map the presence of large trees by focusing on the shadow they cast, which we anticipate will mitigate the issue of spectral confusion between tree canopies and background grass.

Our aim was therefore to use affordable multispectral imagery (e.g. SPOT 5) to explore the methodological possibilities of using tree shadow properties as a proxy for mapping the presence of big trees within a savanna environment. The accuracy of our shadow mapping techniques will then be validated using tree positions gained from light detection and ranging (LiDAR) data.

STUDY AREA

The study area is situated in the Lowveld region of the savanna biome at the north-eastern edge of South Africa (See Fig. 1). The Lowveld is a low-lying and gently undulating landscape, with a general decrease in elevation from the west to the east. Mean annual precipitation (MAP) decreases between the western escarpment and the eastern coastal plains by between 800mm and 580mm. Rainfall primarily occurs in the summer months between October and May. The dominant geologies include granites, with local intrusions of gabbro, as well as the basalts in the east (Venter et al., 2003). There are three dominant land uses in the greater region. These consist of (i) state owned conservation, in the form of the Kruger National Park, (ii) privately owned conservation in the form of Sabie Sands Game Reserve, and (ii) state owned communal rangelands (See Fig. 1). This particular study was conducted on a subset that transcends the communal rangelands and private conservation land.

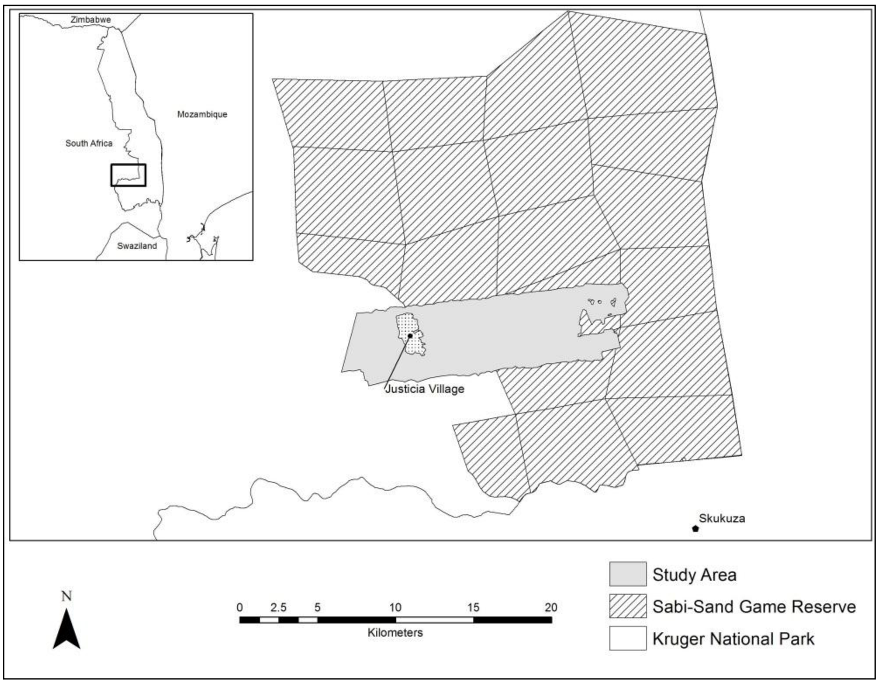

Figure 1. The study area

METHODS

Imagery from the SPOT 5 (April 2010) sensor was geometrically corrected in order that positions in the image accurately reflected those on the ground. This particular date was chosen as it was deemed to represent maximum canopy greenness, and therefore maximum canopy shadow conditions. A 'pan-sharpening' process was then undertaken, which involves merging the high resolution panchromatic band (2.5m) with the lower resolution multispectral bands (10m), in order to create a high resolution colour image of 2.5m (Mather, 2004). There are a variety of 'pan-sharpening' algorithms that were developed to retain and enhance different aspects of the images that are merged. The Gram Shmidt algorithm (Laben and Bower, 2000) was selected as it resulted in the most visually appealing results. The resulting high resolution 2.5m colour imagery was then subjected to a variety of spectral transformations (e.g. principle component analysis, vegetation indices) and filters (e.g. texture, edge detection) in order to investigate image transformation techniques that enhanced the visibility of tree shadows throughout the image. The original pan-sharpened bands, together with the most visually appealing image transformations, in terms of their ability to enhance tree shadows, were then used in an object based classifier to classify the shadow of trees and extract their positions.

The object based classification was done using Definiens eCognition developer software, and consists of segmenting the image in appropriately sized objects based on various homogeneity criteria that are scene dependant. In this study there were two main scales at which segmentation took place. The first segmentation aimed to deliver large enough objects to accurately reflect homogeneous areas of tree density, which were then classified based on LiDAR tree crown cover per image object. This was done purely for data analysis purposes, and is not required for the shadow detection methods to work. The tree cover classes were: High (> 10 % tree cover), Medium (between 5 and 10 % tree cover), and Low (< 5 % tree cover). The second segmentation scale was aimed at deriving small enough objects that accurately reflected tree shadow areas (See Fig. 2).

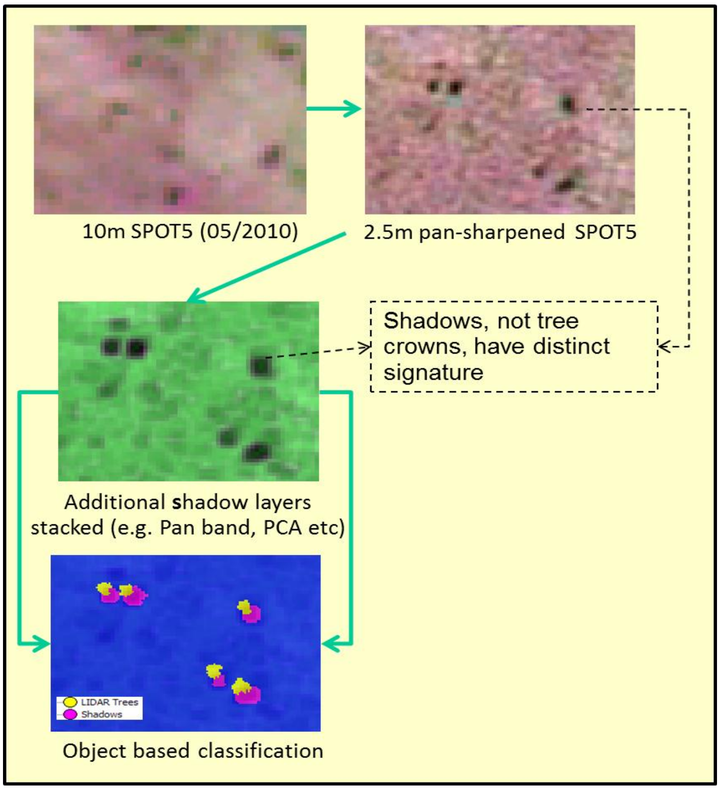

Figure 2. A summarised version of the methods

The mapping technique, described above, produced tree shadow maps that were validated using 2008 LiDAR derived tree crown locations. The exploratory nature of this research project extended to the accuracy assessments, which presented us with unique challenges. The uniqueness exists in the fact that we are classifying objects (i.e. shadows) that were only proxies of the true targets (i.e. LiDAR trees), so the two objects/classes never overlap each other in order to implement more common accuracy assessments methods. A buffer-based method was employed to address this issue. Both the tree shadows and LiDAR crown objects were exported from eCognition as polygon shapefiles, each containing relevant object-based attribute information. Based on *a priori* field knowledge, image observations and the pixel size of the imagery (i.e. 2.5m x 2.5m), it was decided that LiDAR tree crowns that had an area of less than $25m^2$ would be excluded from the analysis. The polygons that were exported were then converted to centroid points. Using the centroid points we manually measured the distance between 90 LiDAR tree points and their shadow point equivalent. Using these 90 measurements we calculated the basic statistics for the dataset, and decided to use the mode, 95^{th} percentile, and maximum values (i.e. 10m, 12.4m, and 14m respectively) in order to create circular buffer distances around the tree shadow centroid points. Using geographical information system (GIS) software, we then derived counts of LiDAR points (corresponding to crowns) that fell within shadow buffers. Counts were done for each of the buffer distances. This paper only reports on the 12.4m buffer results. The buffer-based method has the challenge of dealing with double counting trees that are close together and therefore fall within multiple buffers (See Fig. 4). However, we cannot simply eliminate the multiple counts since we have no way of knowing whether they're legitimate or not. Bearing in mind that our initial aim was to use shadows as proxies for the *presence* of a tree, and not to actually quantify the number of trees present, we felt that our buffer based accuracy assessment method was able to provide an accurate enough measure of the *presence* of a tree, as well as provide a measure of the uncertainty involved when using this accuracy method.

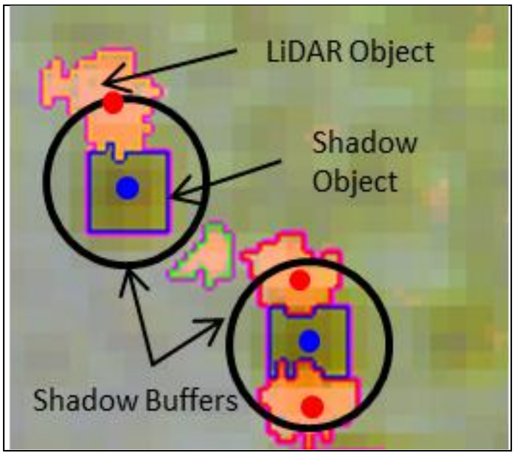

Figure 4. An example of legitimate multiple counts using the buffer method

RESULTS AND DISCUSSION

Table 1 shows the results when a 12.4m buffer was used from a classified shadow object to verify whether there was a LiDAR tree within its boundary. The results are presented considering all data, and the data corresponding to the three classes of tree cover discussed in the methods. The user's accuracies presented in Table 1 range between 64 and 79 percent, while the producer's accuracies range between 34 and 45 percent. The user's accuracy figure over the whole study area (Table 1 A) is 74%, which can be equated to a high likelihood of finding an actual tree should a resource manager go to the real world position of a classified shadow object. More specifically, the user's accuracy figures point to the classification methods working well to produce reasonably low commission errors. Commission errors equate to classifying an object as a tree shadow when it's not. The producer's accuracy points to opportunities to improve the classification methodology with more research into why it is missing almost 60% of the LiDAR trees present. One reason for this may be due to the fact that we used 2010 imagery but 2008 LiDAR data, so a portion of those LiDAR trees may no longer be present, which would influence the number of trees without shadow objects (i.e. the producer's accuracy). Also in Table 1, and contrary to what we expected, the results for mapping trees in low density areas were the lowest, at 64% users accuracy and 46% producers accuracy. The reason for this requires more research. The low density areas also showed the lowest percentage of multiple counts, with almost 12%, which would be more expected since the trees are generally further apart from each other.

Given the experimental approach to using multispectral imagery to map the *presence* of trees, the results show a certain level of success for the methodology, since there is a user's accuracy of above 60% for each scenario. However these results do need to be tempered by the percentage of multiple counts. As alluded to earlier, the low producer's accuracy (i.e. high omission errors), does not necessarily speak to a failure of the classification methods, but more likely to the actual characteristics of the trees, which shadows are not being detected. And this points to the possibility of further improving the classification methods if we can more properly account for these influences. For instance, a number of factors are at play in determining whether or not a tree exhibits a shadow in a satellite image. The factors influencing tree shadow mapping that interest us going forward are

a) the species of tree, which relates to the growth form, the leaf form, crown size and general crown characteristics; and b) the season of image acquisition, which relates to both the phenology of the tree at the time, as well as the angle of the sun and resulting shadows.

Table 1. The buffer based accuracy assessment results

A) 12.4m Buffer All data

		LIDAR TREES			
		Tree	**No Tree**	**Totals**	**Users**
SPOT Shadow	**Present**	20051	7025	27076	**74.05%**
	Absent	30416			
	Totals	50467	10252	* Multiple LiDAR counts	
	Producers	**39.73%**	20.31%	**percent multiple counts	

B) 12.4m Buffer in Low density

		LIDAR TREES			
		Tree	**No Tree**	**Totals**	**Users**
SPOT Shadow	**Present**	5337	2946	8283	**64.43%**
	Absent	6360			
	Totals	11697	1374	* Multiple LiDAR counts	
	Producers	**45.63%**	11.75%	**percent multiple counts	

C) 12.4m Buffer in Medium density

		LIDAR TREES			
		Tree	**No Tree**	**Totals**	**Users**
SPOT Shadow	**Present**	6740	1916	8656	**77.87%**
	Absent	9076			
	Totals	15816	3432	* Multiple LiDAR counts	
	Producers	**42.62%**	21.70%	**percent multiple counts	

D) 12.4m Buffer in High density

		LIDAR TREES			
		Tree	**No Tree**	**Totals**	**Users**
SPOT Shadow	**Present**	7887	2036	9923	**79.48%**
	Absent	14753			
	Totals	22640	5428	* Multiple LiDAR counts	
	Producers	**34.84%**	23.98%	**percent multiple counts	

* The sum of all the instances that a LiDAR tree was counted more than once in a shadow buffer,

** The percentage of trees this represents

As an example, using tree species maps produced from hyperspectral imagery (Cho *et al.*, 2012), we found that the majority of the trees (39%) that did not have their shadows detected were *Acacia nigrescens* trees (See Table 2). This species of tree has a small leaf form and a resultant compact canopy, which could also have been past its primary growth phase and even experiencing leaf drop off at the time the image was taken (i.e. mid April). Whereas, the species with the second highest percentage of missed trees, *S. birrea*, sometimes has a very wide, but very open and sparse canopy, depending on the time of the season (See Table 2). Work is ongoing in attempting to account for reasons why certain trees are not being classified, as well as into improving the efficiency with which we successfully detect trees.

Table 2. The species of trees that did not have shadow objects

Species of trees missed	Percentage
Unclassif	1.85%
Acacia gerrardii / Dicrostachys cinerea	11.86%
Acacia nigrescens	39.21%
Combretum spp.	17.24%
Spirostachys africana	9.37%
Sclerocarya birrea	20.25%
Terminalia sericea	0.21%

CONCLUSION

Big trees play crucial roles in the functioning of savanna landscapes. It therefore follows that all those who benefit from their services would be well served to conserve, and ensure, their continued presence within those landscapes. Resource managers in charge of these, sometimes vast, landscapes could profit from making use of technologies such as remote sensing in order to aid the monitoring of big tree presence. Given the sometimes prohibitive expenses involved with very high resolution imagery, we have embarked on research that aims to map the presence of big trees using affordable medium-to-high resolution satellite imagery. The methods seek to use the (often) unique spectral signature of tree shadows as a proxy for the presence of trees.

The results point to the methodology having a good potential, but are tempered by some uncertainty in the accuracy assessment method used. More research is needed into how best to account for factors that affect a tree shadow in a satellite image, i.e. sun angle, sensor angle, season, and tree phenology and species. As the research into both the classification and accuracy assessment methods continues, we hope to increase the certainty pertaining to the user's accuracy, and show more success in producing shadow objects (i.e. producer's accuracy). Should we be able to achieve these two objectives, we may well be able to start quantifying large tree numbers using multispectral imagery. As it stands now, this method could, depending on the intended application and scale, be used by resource managers to provide an affordable, broad scale, method of retrieving greater than 60% probability of tree presence in a savanna landscape. A manager of a small reserve could in theory identify key indicator species/tress, and then apply the mapping methods in order to monitor the presence or absence of these trees over time.

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