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Article

Application of Object Based Classification and High Resolution Satellite Imagery for Savanna Ecosystem Analysis

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Abstract: Savanna ecosystems are an important component of dryland regions and yet are exceedingly difficult to study using satellite imagery. Savannas are composed are varying amounts of trees, shrubs and grasses and typically traditional classification schemes or vegetation indices cannot differentiate across class type. This research utilizes object based classification (OBC) for a region in Namibia, using IKONOS imagery, to help differentiate tree canopies and therefore woodland savanna, from shrub or grasslands. The methodology involved the identification and isolation of tree canopies within the imagery and the creation of tree polygon layers had an overall accuracy of 84%. In addition, the results were scaled up to a corresponding Landsat image of the same region, and the OBC results compared to corresponding pixel values of NDVI. The results were not compelling, indicating once more the problems of these traditional image analysis techniques for savanna ecosystems. Overall, the use of the OBC holds great promise for this ecosystem and could be utilized more frequently in studies of vegetation structure.

Keywords: savannas; vegetation structure; tree canopies; object based; IKONOS

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1. Introduction

Savannas are geographically extensive and socioeconomically important, covering approximately 25% of the terrestrial landscape and supporting a growing proportion of the world's human population [1-3]. Savannas contribute greatly to global net primary productivity (NPP) and play a significant role in the carbon cycle [4,5]. Savanna ecosystems are undergoing rapid changes in composition and structure driven by natural and anthropogenic causes [6]. These changes hold the potential to greatly influence socio-ecological functioning within savanna systems [6-8]. African savannas in particular are projected to be under risk of extensive change largely due to changes in climate patterns [9], which may exacerbate the challenges presently facing humans living in this region. The discussion of ecological change in African savannas focuses on shifts in tree and shrub cover, specifically the decline in tree cover and change in spatial arrangement of trees, which impacts the productivity of the system, modifies availability of resources for both wildlife and humans, and could have large impacts on earth-atmosphere interactions [10-12]. It is thus imperative that the quantification and characterization of tree canopies in savannas is improved to inform management policies aimed at ensuring sustainable use of resources in savanna regions and to better understand the impact of changes in savannas at multiple scales [6,13].

Unlike forests, savannas have a discontinuous tree canopy, and are defined by the complex interactions between trees and grasses [14]. Tree cover is fundamental to savanna functioning, moderating the floristic and faunal composition, structure and function of savannas [2]. Trees increase structural complexity and alter resource availability, creating microhabitats by altering soil temperature, fertility, and biomass allocation, increasing diversity within the system [2,15-18]. Declines in tree cover may thus reduce availability of herbaceous resources, which can result in degradation of habitat for wildlife, and loss of resources for local human populations. In light of this, the critical challenge for understanding the functioning in savanna systems lies in understanding the spatiotemporal dynamics of trees.

Spatiotemporal variation in tree cover, and the relationship between trees and savanna composition and function is dependent upon tree size, age and length of presence [2]. Field experiments have been used to explore the relationship between trees (of varying size and age cohorts) and other savanna components (grass, herbivores *etc.*). For example, Cramer *et al.* [19], explore the relationship between leguminous trees and C_4 grasses, determining that the ability to fix N_2 enables trees and C_4 grasses to coexist despite limited availability of N_2. Goheen *et al.* [20] show that large mammalian herbivores suppress the reproduction of Acacia, and can influence population dynamics within savannas. These approaches successfully establish baseline understandings of the influence of trees within specific contexts; however they are limited in spatial and temporal scale and as such the role of trees in savanna functioning is still insufficiently quantified. The lack of time series data which captures tree demographic characteristics (ex. crown size) and is specifically related to tree cover change across the landscape contributes to the limited understanding of the initial states of tree biomass and environmental thresholds present within savanna systems. Furthermore, the dearth of data quantifying tree demographics and spatiotemporal changes restricts our understanding of the regional and global impacts of ecological changes in savannas and the vulnerability of savannas to global change.

Appropriate management of extensive savanna landscapes requires the need for tools which enable monitoring across larger spatial scales than is feasible with field based studies alone.

Savanna landscapes in southern Africa possess ecological limitations such as highly variable climates which constrain agricultural profits; however there exists a wealth of charismatic and endemic wildlife species of high economic value within the region [21,22]. Countries in this region have therefore relied on a wildlife-centric approach to managing their savanna landscapes. This approach has emphasized local management scales, with great variation existing not only in the actual management of vegetation but in the management of the drivers of vegetation structure—herbivory, fire, human activity, and biotic factors such as tree-grass interactions [23]. Concern about the widespread decrease in the number of large trees, changes in the clustering patterns of trees, and corresponding impacts of these habitat changes on wildlife have focused management approaches on the larger landscape matrix [24], again necessitating vegetation monitoring tools which can accommodate larger spatial and temporal scales than field measurements. The increased isolation of tree dominated savanna habitat in a largely shrub dominated landscape matrix, and the recognition of the need for scale appropriate management of megafauna has led to a shift toward landscape scale management practices, which cross administrative boundaries [24-28].

The collaborative management of these larger land areas demands a standardized approach to monitoring and surveying habitat status and changes in tree cover. The trajectory of a savanna and corresponding wildlife habitat is dependent upon initial tree cover, the distribution of trees across size cohorts and the spatial distribution of tree clusters. Large-scale plot studies require extensive manual sampling which is a practical limitation in much of southern Africa, where human populations are low—generally ≤ 5 per/km^2—and poor accessibility limits the applicability of large-scale standardized field based habitat monitoring efforts [29,30]. Currently in southern Africa much of the savanna which is being incorporated into various collaborative or transboundary management schemes is not systematically surveyed or monitored [25].

Remotely sensed data provides an alternative to field based vegetation plots and captures landscape scale vegetation data [29]. Due to its repeat nature remotely sensed data is useful for tracking changes in tree cover over longer periods of time and at more varied temporal scales than what is typically done with field experiments. Remote sensing offers access to longer term, continuous data for larger extents than traditionally used for ecological monitoring [31,32]. Analysis of medium resolution data (such as Landsat TM) has successfully partitioned the phenological patterns of trees versus grasses [33-35]. However, in highly heterogeneous landscapes, such as savannas, it is limiting to solely rely on medium resolution data to capture tree demographic information (ex. tree crown shape, or membership in a given age or size cohort). The incorporation of high resolution satellite imagery potentially offers the ability to bridge the scale gap between plot field studies and larger spatiotemporal studies which rely on medium to course resolution imagery. Incorporating high resolution data (for the purpose of this research we focus on satellite imagery although aerial photography could also be used as a source of high resolution data) addresses the need for repeat quantification of tree cover, clustering patterns and demographics. Furthermore integration of high resolution data into analyses of vegetation patterns holds the potential to establish the relationship between tree cover and patterns on the ground, high spatial resolution pixel signatures and potentially even up to the spectral signatures of a medium resolution pixels (ex. Landsat 30 m × 30 m). Thenkabail [36] demonstrates the use of high resolution data to better characterize the relationship between ecological variables and medium resolution spectral indices. Although medium resolution has proven useful for research questions which address phenology without emphasis on vegetation structure and demographics, insufficient research has focused on the incorporation of high resolution imagery in studies of landscape change within savanna systems [37,38]. Thus further work incorporating multi-resolution remotely sensed data in combination with field data is needed to assess the suitability of the plethora of satellite imagery currently available to researchers [37].

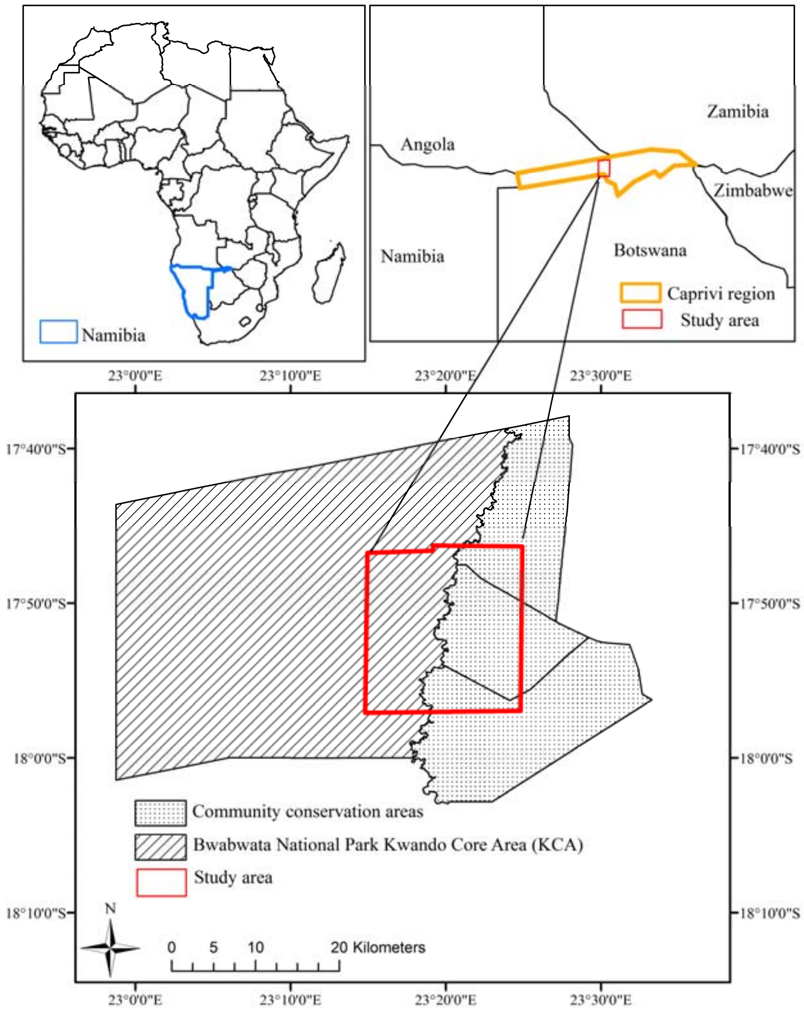
The increased number and availability of air and space borne sensors has improved our access to remotely sensed data and enhances our ability to monitor and characterize components of the landscape [39]. The combined use of high resolution remotely sensed data and socioeconomic data has proven useful for understanding the causes and consequences of ecological change and thus is useful for ecosystem management [40]. This study contributes to the savanna ecology and remote sensing literature by exploring the utility of IKONOS high resolution data and advanced remote sensing methodologies for characterizing tree cover, clustering and demographics in southern African savannas. We investigate the use of object based classification and IKONOS imagery as a possible tool for scaling from field observations to medium resolution data. In response to criticisms of the inadequacies of conventional methods of remote sensing analysis which relies heavily on spectral characteristics of a single pixel, along with increase in commercially available higher resolution images, object based classifications have gained popularity in recent years [39-47]. Though not a new technique [48-51], the overreliance on traditional pixel based maximum likelihood classifications has dominated studies of land cover change. Object based classification relies on both spectral and spatial (size, shape, texture, association with neighboring objects) data to characterize the landscape, and thus proves useful in landscapes where there are similar spectral characteristics of different vegetation types, as is the case in southern African savannas, where trees and shrub have similar spectral signatures, but differing ecological roles [52,53]. As such we expect that object based classification of IKONOS imagery will prove useful for: identifying trees and quantifying spatial patterns of trees in savanna systems; for exploring variation in these characteristics across different land management units; and for scaling between field observations and medium resolution data. We employ a descriptive case study approach, similar to that used by Hartter and Southworth [54], Nagendra *et al.* [55] and Munroe *et al.* [56], to identify spatial patterns of trees and explore possible linkages between land management strategies and variation in the spatial distribution of trees. Due to the lack of repetition of each land management type the generalizability of the study is limited; however the study design offers a useful descriptive analysis of tree distribution across the study region, and a useful example of an application of object based analysis conducted on high resolution satellite imagery. Specifically, we ask (1) Can object based classification of high resolution imagery be used to identify and monitor tree demographics and distribution in a savanna system? (2) How does the distribution of trees vary spatially across two study areas representing different management strategies of government managed protected areas versus community conservation area? (3) What are the current clustering patterns for large trees within the landscape? and (4) Can we then scale OBC data from IKONOS to Landsat to enable a regional scaling of the findings?

2. Methods

The study area covers approximately 278.6 km^2 and is located in the Caprivi, Namibia (Figure 1). A comprehensive treatise of the Caprivi region may be found in Mendelsohn and Roberts [57], and we draw mainly from this reference in the subsequent site description, accompanied by more contemporary sources, and environmental history interviews conducted in 2007 and 2008. Most of the Caprivi region is a part of the larger Kalahari woodlands landscape, which stretches into all of the surrounding countries (Botswana, Angola, Zambia, and Zimbabwe). The study area is divided between the Bwabwata National Park Kwando Core Area (KCA) on the western side of the Kwando River (132.1 km^2), and the communal conservancy areas on the eastern side (146.48 km^2). The KCA has historically had local people within it, with forced removal beginning in the 1940's due to the decimation of cattle by the spread of sleeping sickness. Subsequent to this, local peoples were officially restricted from entering this area when the Caprivi Game Park was declared in 1968 [58]. The South African Defense Force (SADF) occupied the northern part (north of the main tar road) of KCA during the Angolan war for independence (1960's) and continued to occupy this area until Namibian independence in 1990. Since the mid 1990's KCA has been managed using an exclusionary approach which limits land and resource use mainly to photographic tourism. In the conservancy region, improvements in the treatment of cattle diseases allowed these populations to rebound beginning in the 1980's [57]. This in turn created increased grazing pressure in communal regions, as well as an increase in draught power allowing people to clear land for more cultivation. The human population in Caprivi as a whole has increased, leading to an increase in the pressure placed on vegetation resources. The land uses on either side of the river therefore lie in contrast to one another, with the KCA having considerably less anthropogenic conversion and less direct human manipulation (e.g., the use of fire to manage grass growth was until 2009 suppressed, when in the KCA the management of savanna vegetation started utilizing managed or prescribed burns with anthropogenic fires to manipulate vegetation growth), while the communal conservancies are multiple use lands with areas designated for settlement, wildlife corridors, agriculture, and cattle. The communal lands and vegetation are directly manipulated to accommodate the variety of land uses occurring within this area, for example, fire is actively used to clear land for agriculture or to encourage grass growth for cattle. In contrast, interviews with government officials (park managers) indicate that in the KCA fire was not used as a management tool to enhance grass growth, and in certain cases naturally occurring fires were controlled from spreading through the use of fire breaks. In the KCA management practices are determined by local and regional government officials, while in the community conservation areas savanna management practices are decided by committees consisting of local community members. However, recent (2007) implementation of a collaborative management scheme for the study area has resulted in collaborative management practices across the land units and generated the demand for a standardized approach to monitoring wildlife quantities and tree cover.

The study area is typical of much of savanna present in the surrounding countries, consisting of woodlands interspersed with open grassland areas. Common tree species found in the study area include: camel thorn (*Acacia erioloba)*, karamoja (*Acacia tortilis)*, rhodesian teak (*Baikea plurijuga)*, wild seringa (*Burkea Africana)*, silver terminalia (*Terminalia sericea)*, and russet bushwillow (*Combretum hereorense).* Rainfall is seasonal (influenced by the movement of the inter-tropical convergence zone (ITCZ)) and ranges from 400 to 700 mm with sticallan annual average of 600 mm accompanied by an average annual temperature of 21.8 °C [59]. The area provides habitat for diverse wildlife, including 430 species of birds, and various game such as the sitatunga (*Tragelaphus spekii*), red lechwe (*Kobus leche*), buffalo (*Syncerus caffer*), and elephant (*Loxodonta africana*).

Figure 1. Study area showing the larger regional context and the boundaries of the two dominant land management types used in the region.



2.1. Satellite Imagery and Field Data

High resolution IKONOS imagery (4 m × 4 m—visual infrared bands) and medium resolution Landsat TM imagery (30 m × 30 m) was acquired for the study area, from the Geoeye Foundation and the Council for Scientific and Industrial Research (CSIR) respectively. The images selected are from the dry season (IKONOS: May 21st 2006, Landsat: May 1st 2007) to minimize cloud cover and phenological variation between the two data sources. The one year time lag is unavoidable, as is the case with many studies which rely on previously collected satellite imagery, however both years experienced similar precipitation patterns, which is the dominant driver of interannual variation in vegetation in the region. The Landsat image was subset to match the spatial extent of the IKONOS image and geometric registration was conducted using image-to-image registration and a nearest neighbor resampling algorithm, with root mean square error (RMSE) of <0.3 pixels. The geometric accuracy for the IKONOS image was verified using 29 ground control points collected in the field (RMSE < 6). The digital numbers were converted to reflectance values using radiometric calibration and incorporating post-launch calibration gains and biases [60]. Water bodies and clouds were masked out of the two images using a binary mask. An unsupervised classification enabled spectral identification of cloud cover and water bodies. The unsupervised classification was combined with spatial data (shapefiles of water bodies) acquired from the Ministry of Environment and Tourism to determine the extent of the riparian zone and ensure that tributaries to the Kwando river were also included in the mask. Removal of clouds and water bodies was done to reduce the likelihood of misclassifications during the object based classification.

Field data was collected in the form of training samples (n = 77) and vegetation transects (n = 32). The sample design was limited by accessibility to certain areas within the study site and as the design used was stratified random. Both approaches identified spatial location of individual trees (n = 118) and associated tree demographic data (species, canopy size, dbh, height), dominant vegetation type (woodland, grassland, and shrub, and bare), and general land cover measurements (% canopy cover, dominant understory), and land use history. The training sample protocol was adapted from the CIPEC protocol [60], while the Walker [61] vegetation transect methodology was used as this has proved suitable for characterizing vegetation in southern African savannas. The combined use of training samples and vegetation transects enabled the collection of spatial location of trees and of tree demographic data, while simultaneously maintaining the spatial distribution of field data collection across the study area (Figure 2). During the field season we also conducted 27 key informant interviews aimed at understanding who determined management practices for both KCA and the community conservation management areas, and what factors contributed to (specifically trees) development, and how vegetation disturbances (ex. fire, herbivory) are managed and used. The key informant interviews helped develop an understanding about the possible drivers of tree distribution differences in KCA versus community conservation management areas, this is further discussed in the results and discussion section.

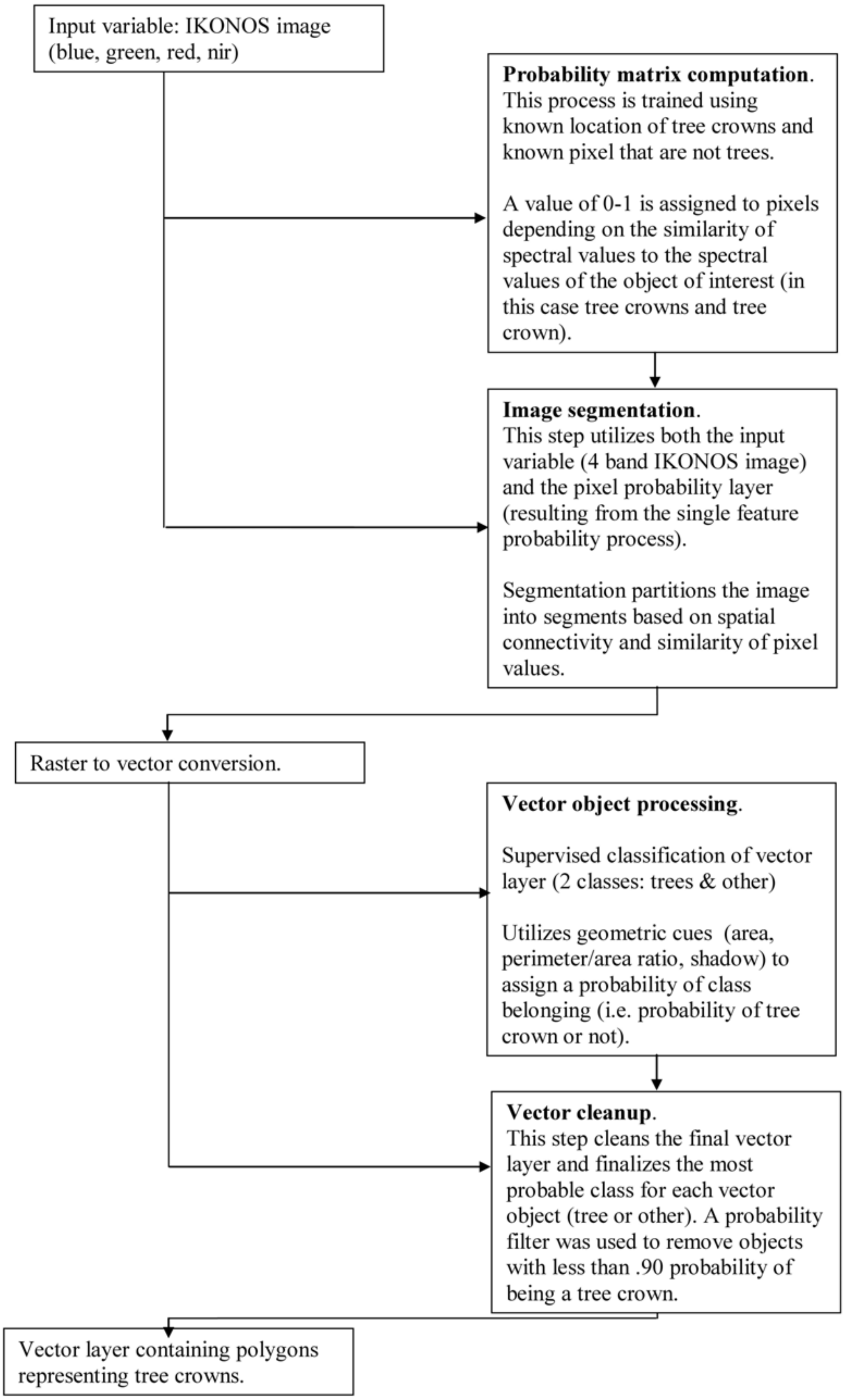
2.2. Tree Crown Identification and Spatial Analysis

Image processing was conducted in ERDAS Imagine 9.3, using the Imagine Objective tool which enables automated feature extraction. An object based classification was used to identify trees in the IKONOS image. Object based classification is defined as assigning classes to image objects [45,62] which are the result of segmentation of an image into discrete non-overlapping units based on specific criteria [45,63-65]. The object based classification consisted of five processes: probability matrix computation, image segmentation, raster to vector conversion, vector processing, vector cleanup (Figure 3). The probability matrix computation is a supervised procedure which was trained using the location of known tree crowns. Although we tested a variety of input variables derived data from the original IKONOS image (e.g. NDVI, texture) the best results were acquired using the original four band visual infrared IKONOS image. The probability matrix computation assigns a probability of being a tree or not to each pixel. The probability of being a tree or not is determined based on the similarity of spectral values of the given pixel to the spectral values of the pixels of known trees identified during the training process.

Figure 2. Distribution of field site locations within the focus region (as depicted in Figure 1) where vegetation transect and/or training sample data was collected, overlaid on the IKNOS image (color composite RGB = near infrared, red, green where red represents vegetation and cyan represents bare earth).

Segmentation of an image is the process of partitioning a digital image into multiple regions to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze [66]. The segmentation based on spectral values and spatial characteristics created objects that are useful in classifying land cover in regions such as southern Africa where trees and shrubs are spectrally similar but different spatially and ecologically. The segmentation process was performed on the original four band visual infrared IKONOS image; however, the pixel probability layer was also used to calculate the probability zonal mean for each generated segment. The segmentation approach used combined splitting and merging of the input image with the use of edge detection to identify segments with similar characteristics. The parameters used for image segmentation included: Euclidean distance (the compute settings function was used to determine the minimum value difference and the variation factor, 36 and 3.5 respectively), edge detection with an automatically generated threshold of 53, and a minimal edge length of three pixels.

Figure 3. Object based classification workflow.



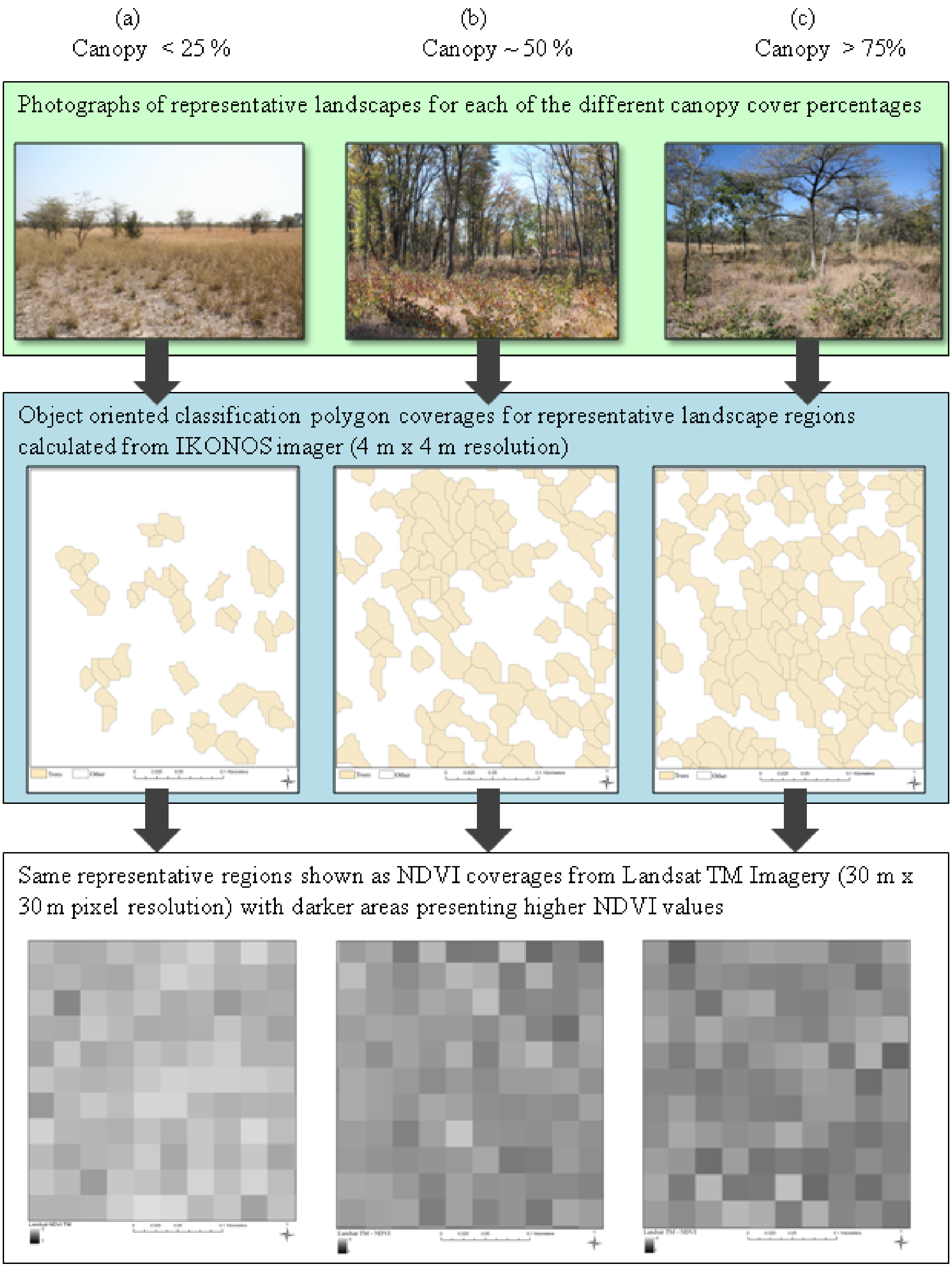
The segmented image was then converted into a vector file, which was used for the vector object processing and cleanup procedures. Vector object processing consists of another supervised classification which utilizes geometry to refine the identification of trees. A variety of geometric cues are available for use in vector object processing, however after experimenting with the cue options we selected the following cues for use: area, a perimeter-area ratio, and shadow. The thresholds used for the cues were determined by training the classification with the area and perimeter-area characteristics of the trees observed in the field. The area characteristic had a minimum value of 48.6 square meters and a maximum of 405.55 square meters, and the perimeter-area ratio had a minimum of 10.7 and maximum of 20.56. The shadow cue measures the association (determined based on adjacency) of the vector objects generated from the first three steps of the object based procedure to a shadow polygon created using a separate unsupervised classification. The vector cleanup process consisted of applying a probability filter to the vector file. The probability filter removed all object with less than 0.9 probability of being a tree crown, thereby ensuring that the final vector layer only included polygons that had a high certainty of being tree crowns. An assessment of the accuracy of the object based classification was conducted comparing the location of tree polygons as identified in the final vector layer from the object based classification with the actual spatial location of individual trees as determined in the field.

The resulting object based classification was then used to assess the current differences in initial tree cover across the two dominant management types. The spatial distribution of the larger trees (canopy diameter ≥ 12 m) was examined using point pattern analysis. Since much of the concern within the study area is regarding the decrease in large trees, this analysis is limited to trees with crown diameters of 12 meters or greater. The ≥12 m threshold was determined based on field observations of tree canopy collected during training sample and vegetation transect collection. This threshold aimed to limit the analysis to the larger trees and target tree species which are thought to be keystone species for African savannas, such as *Acacia erioloba* [66,67], and reduces the size of the dataset for processing purposes. Point pattern analysis was used to identify tree clusters and the possible corresponding vegetation development processes. The Getis-Ord Gi* statistic was used to analyze the spatial clustering of individual trees based on crown size. This statistic measures the local association amongst features and explores the spatial clustering [68], and as such is a useful tool to detect clusters of trees with similar crown sizes, which might result from environmental conditions. The Getis-Ord Gi* statistic calculates a standardized z-score for each tree, which identifies the magnitude of deviation from the expected tree crown size as determined by surrounding tree crowns, thus allowing you to identify significant clustering of large and small tree crowns. Since the Getis-Ord Gi* statistics incorporates more than one statistical test, we utilized Bonferroni's adjustment ($\beta = \alpha/n$) to identify the critical values for determining significance of clustering.

The tree cover extracted from IKONOS data was also linked to medium resolution Landsat imagery (Figure 4) in two ways. First, the spatial distribution of trees within a 30 m × 30 m cells was assessed. The 30 × 30 m cells correspond in both size and alignment to the Landsat TM data. This approach allowed us to calculate the number of trees per cell of the medium resolution Landsat imagery (*i.e.*, the number of trees per 30 m × 30 m grid cell). The possibility that a cell containing multiple small trees had similar spectral values to one containing a single large tree was addressed by looking not only at tree counts per cell but also at the proportion of tree cover per Landsat pixel. Proportion of each

Landsat pixel covered by tree polygons was calculated and compared to the corresponding normalized difference vegetation index (NDVI) value of the Landsat image (Figure 4). NDVI is the most widely used vegetation index, and is an indicator of vegetation growth ideally suited for semi-arid regions

Figure 4. Schematic to show the relationships between the actual landscape in terms of tree coverage or crowns, the idealized object based classification results in polygon form, and then related to the same area but at a Landsat scale, illustrated with an NDVI image. The results shown are for the actual study region, photos though were representative from that region for **(a)** area with <25% canopy closure, **(b)** an area of approximately 50% canopy closure, and **(c)** and area of greater than 75% canopy closure.



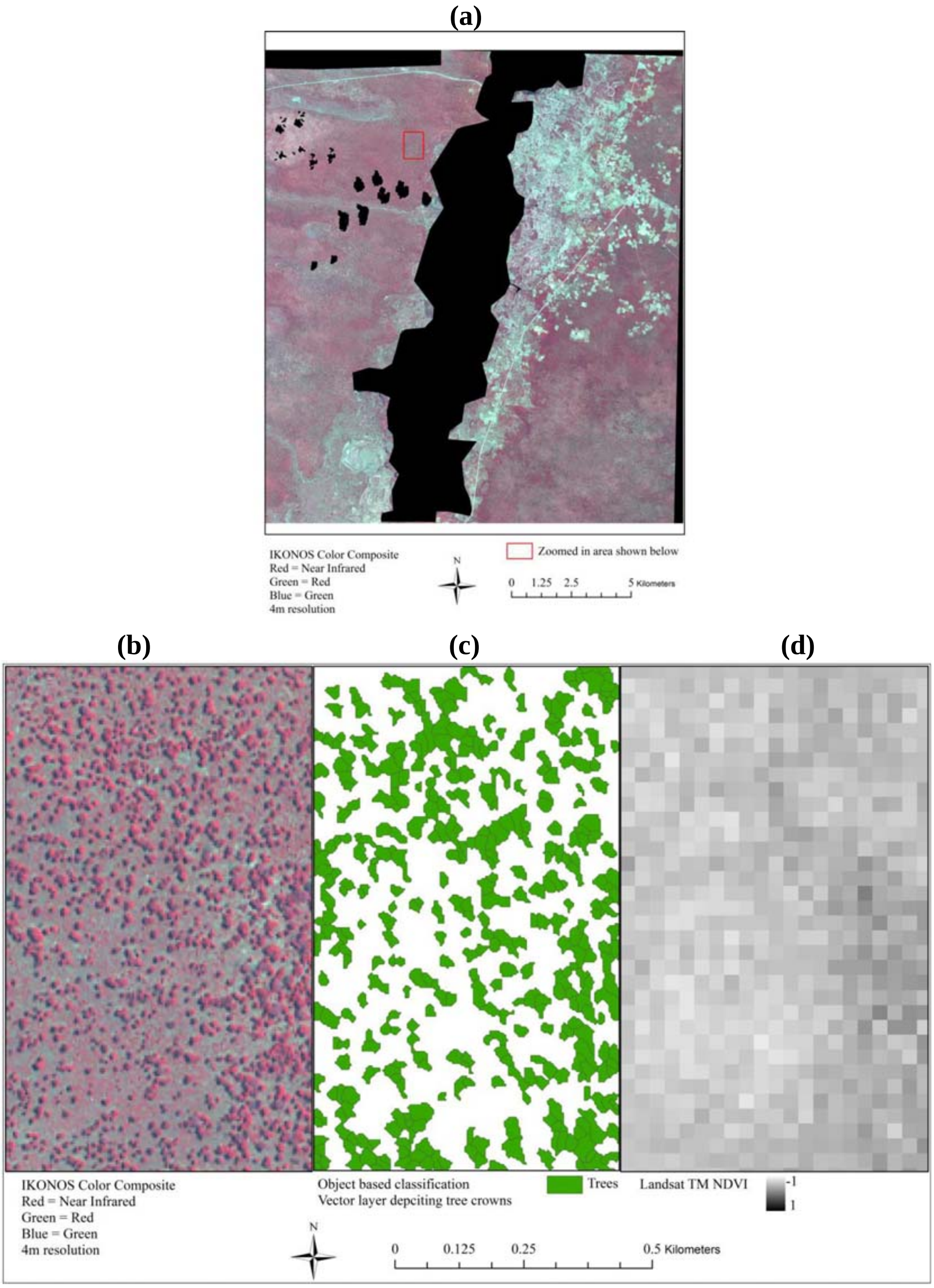
where the index does not saturate at high foliage biomass [70,71]. Additionally, this index is widely used, allowing our research findings to be easily interpreted and compared to other land cover studies. Tree proportion classes are developed by grouping pixels based on amounts of polygon coverage. For example, tree class 1 consists of all pixels with 0–20% tree coverage, class 2 consists of all pixels with 21–40% coverage, and so forth, ultimately resulting in 5 tree cover classes. The variation in NDVI as a function of proportion of trees is quantified by examining the difference amongst NDVI values for each tree cover class and is using graphical outputs and the Kruskal-Wallis test. The Kruskal-Wallis test is a non parametric approach, with the test statistic H, used to determine whether two or more groups differ [72].

3. Results and Discussion

3.1. Object Based Classification

The object based classification results in a vector file containing polygons which are associated with one of two classes: class 1—trees, class 2—non tree. For the purpose of this study we are interested in utilizing object based classification to discriminate trees from the background mosaic landscape. Figure 5 shows the classification for a subset of the study area as well as both the IKONOS and Landsat data for the subset and larger study area. The object based classification improves upon a pixel based classification by incorporating shapes and spatial associations (e.g., association with shadow) of tree crowns; additionally, the resulting vector layer includes shape and size in the characterization of tree crowns. The results from the object based classification were considered in terms of number of correctly identified tree crowns, as determined by comparing the location of trees identified in the object based classification to the actual spatial locations of individual trees identified in the field. The overall accuracy was 84%. The ability to monitor tree presence, growth via measurements of size and spatial pattern, and change in savannas through the examination of realistic objects (trees) as opposed to pixel based classifications of tree cover is particularly useful in an ecosystem where tree presence and demography greatly influences ecological processes and the conditions of microhabitats [2,15-18]. As Figure 5 shows, the object based classification results in a vector layer, which contains spatial characteristics such as size and shape of crown that can potentially be linked to tree species and ages. Classifications such as the one demonstrated here provide standardized baselines for initial tree distribution and demographics across the multiple management units (protected area and community conservations areas) present in this landscape. In the study area the concern that selective removal of large trees is occurring (as a result of herbivory) could be quantified and monitored using an object based classification of the ecosystem.

Figure 5. Results of the object based classification for the region, illustrated with the larger study are and then a blow up of the focus region to enable the reader to "see" actual polygon results from the landscape. Figures shown are for **(a)** the IKONOS imagery for the entire study region, **(b)** the focus region in the IKONOS imagery (color composite RGB = near infrared, red, green where red represents vegetation and cyan represents bare earth), **(c)** the resultant OBC of individual tree polygons calculated from the IKONOS data which though not perfect offers an alternative to pixel based approaches, and **(d)** the Landsat NDVI image of the focus region, clearly illustrating the differences in scale.



3.2. Spatial Distribution of Trees

An examination of differences in tree distribution across the two management areas indicate that there is a greater density of trees present in the protected area than in the community conservation areas (Table 1). Thus there is more land in the community conservation areas which consist of grass, shrub, and bare land covers. This pattern is most pronounced when looking at the trees within the diameters ≥ 12 m crown-size cohort (Figure 6). These findings are consistent with the field observations. Key informant interviews indicated that this difference is likely the result of the different management practices utilized in the protected area and community conservation areas. In the community conservation areas clearing land for agriculture and/or homesteads, and collection of timber resources reduces the presence of trees. Fire has historically been actively used in the community conservation areas and until 2009 was suppressed in the protected area. This difference likely contributes to historical differences in tree development and thus in differences in current observed tree demographics. Within the community conservation areas the large trees are predominantly located in the western portions of the management units, along the river. The community management strategies include designating the riverfront lands as wildlife areas and placed land use restrictions on land closer to the river, likely resulting in a different resource use pattern in the western versus eastern portions of the community managed lands. Agricultural lands are maintained further away from the river in areas where the soil is considered more fertile and agricultural plots are closer to the main road and homesteads. Agriculture in this area, as in much of sub Saharan Africa, is largely rainfed [73] and proximity to the river is less of a concern than soil quality and market accessibility. The land along the riverfront is managed in a manner more similar to that of the protected area than the remainder of the community conservation areas.

The Getis-Ord Gi* statistic was mapped (Figure 7) for the selected size cohort (diameter ≥ 12m), which represents trees with large crowns either due to age or species characteristics or a combination of both. Results indicate significant clustering of trees at the upper end of this size cohort (ie. trees with extremely large crown size relative to the total tree population in the study area) in southern portions of the study area, while trees with smaller crowns within this size cohort tended to have more evenly distributed clusters across the landscape. The tree spatial location of tree clusters is probably the result of both historical stand development processes and the influence of variation in other biotic parameters (such as soil moisture, herbivory) which influence tree growth. Significance was determined using the Bonferroni adjusted critical value of 1.68. As spatial processes gain increasing attention in ecology and ecosystem management [74-76], the identification of tree clusters within the landscape aids with developing an understanding of the interactions between spatial processes and heterogeneity in savanna vegetation [77]. Standardized characterizations and quantifications of tree clustering offer useful ecological information for monitoring and managing the spatially heterogeneous processes (e.g., herbivory, fire, anthropogenic land use) which influence the maintenance of savanna vegetation. The origin and continuation of clustering of larger trees in the southern portion of the protected area is likely attributed to development patterns and spatial heterogeneities in the ecological mechanisms which influence savanna composition. Additionally, key informant interviews confirmed that although the South African Defense Force (SADF) historically occupied parts of the protected area, land and resource use was limited to the southern portion of the protected area, as such this historical variation in land use patterns within the protected area also likely contribute to the current vegetation patterns.

Table 1. Density of large trees within each of the two land management types – KCA, government managed (~132.1 km^2) versus community managed lands (~146.48 km^2).

	KCA (government managed protected area)	Community Conservancy Areas (Community managed)
Total no. of trees/km^2	580.2	352.7
No. of large trees*/km^2	11.5	3.4

*Large trees are defined as those with crown diameter ≥ 12 m

Figure 6. Distribution of trees within the diameter ≥ 12 m crown-size cohort.

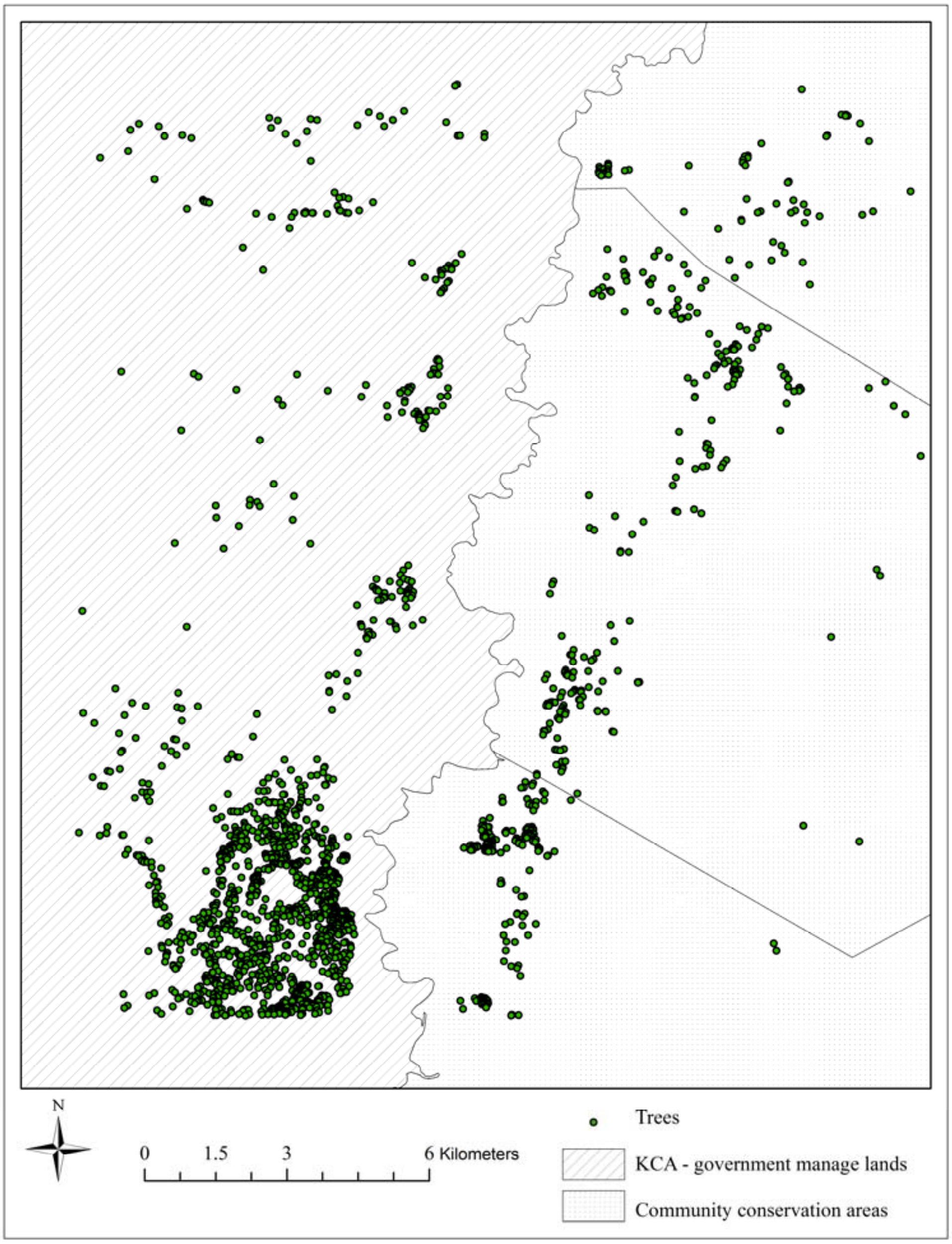
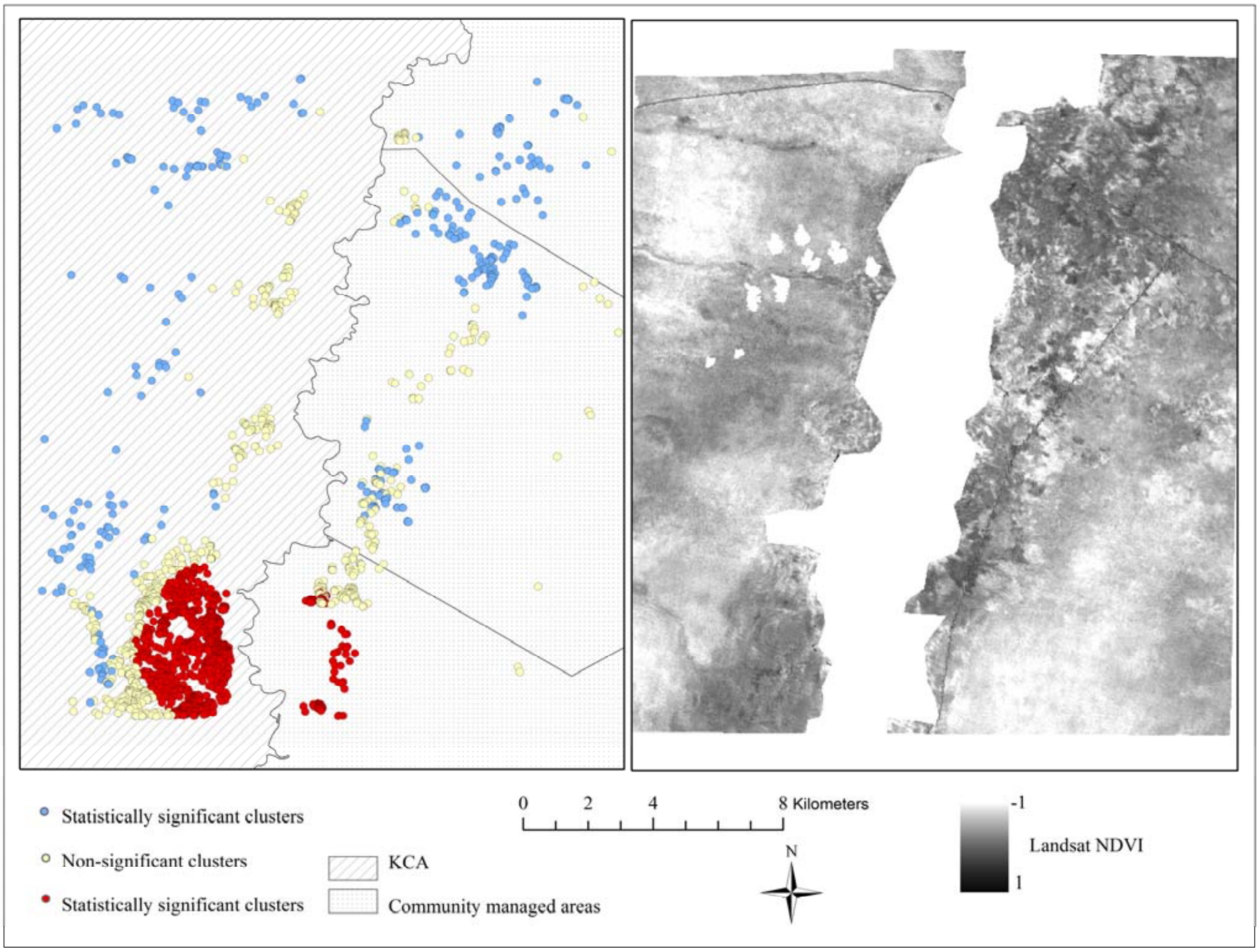


Figure 7. Spatial clustering of trees within the study region for **(left)** Spatial results of the Getis-Ord Gi* statistic with Bonferroni correction applied to determine statistically significant tree clusters **(right)** Landsat TM NDVI shown for the same study region.



3.3. Scaling from Field to Landsat TM

The frequency count of trees per 30 × 30 m grid cell (cells correspond to the actual 30 x 30 m Landsat pixels), facilitates the assessment of the relationship between NDVI and number of trees per cell. The number of trees per cell ranged from 0 to 5, this range was similar to that observed during vegetation transect collection. Cells with 3 or fewer trees are evenly distributed over the landscape, while those with 4 or 5 trees appear more clustered (Figure 8). The mean NDVI values for cells containing 1–5 trees ranged from 0.170 to 0.2 suggesting little variation in the NDVI values based on the number of trees per cell. This would suggest that NDVI is not particularly useful for discriminating tree cover, however, it could also be a factor of the size of the tree crown. A cell containing a single large tree may in fact have similar proportions of canopy cover to a cell containing numerous small trees, thus resulting in similar NDVI values for those two cells. To address this we examine the proportion of tree cover per Landsat NDVI pixel.

Graphical analysis of NDVI values for the five tree coverage classes (determined by grouping proportion coverage %) show similar distribution patterns and mean values for all five tree coverage classes (Figure 9). The results from the Kruskal-Wallis test (H = 4.39, significance level 0.05) support the graphical analysis, indicating that the distribution of NDVI values for each coverage class is not statistically different. The mean NDVI for all pixels with tree coverage is 0.289, while that for cells with no portion of the cell covered by trees is 0.211. The similarity in mean and distribution of NDVI values across the tree coverage classes and the small difference in mean NDVI value for cells with tree coverage versus those without suggests that the land covers in the background matrix (*i.e.*, class 2: shrub, grass, or bare lands) contribute greatly to NDVI values observed for the study region. Similar to Moleele *et al.* [78] and Ringrose [79] we find that although NDVI offers a good approximation for overall vegetation cover, more potentially rigorous quantification of vegetation structure require the incorporation of advanced remote sensing techniques such as object based classification. The high accuracy of the object based classification combined with the ability to quantify tree demographics per Landsat pixel indicates that object based classification of high resolution imagery is a potentially successful scaling tool for linking field and coarse resolution vegetation studies.

Figure 8. Spatial distribution of Landsat pixels with greater than four trees per 30 × 30 m cell.

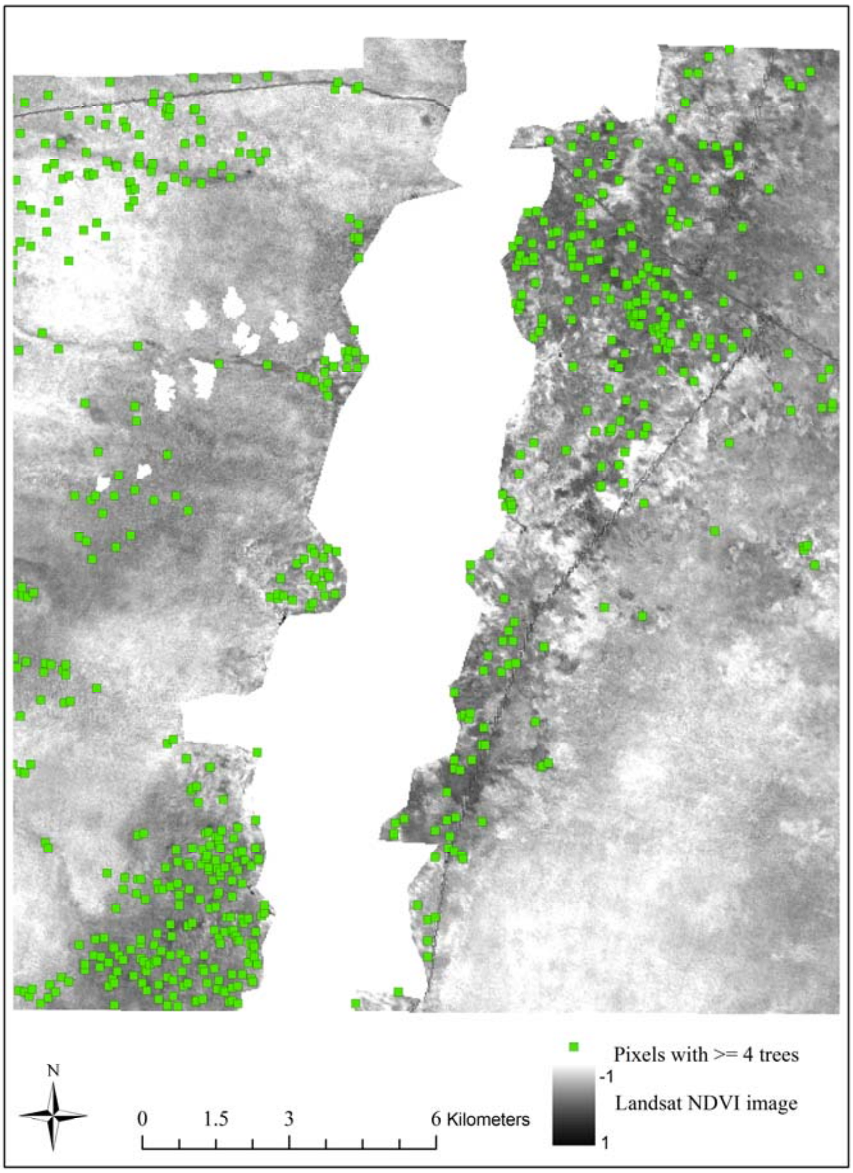
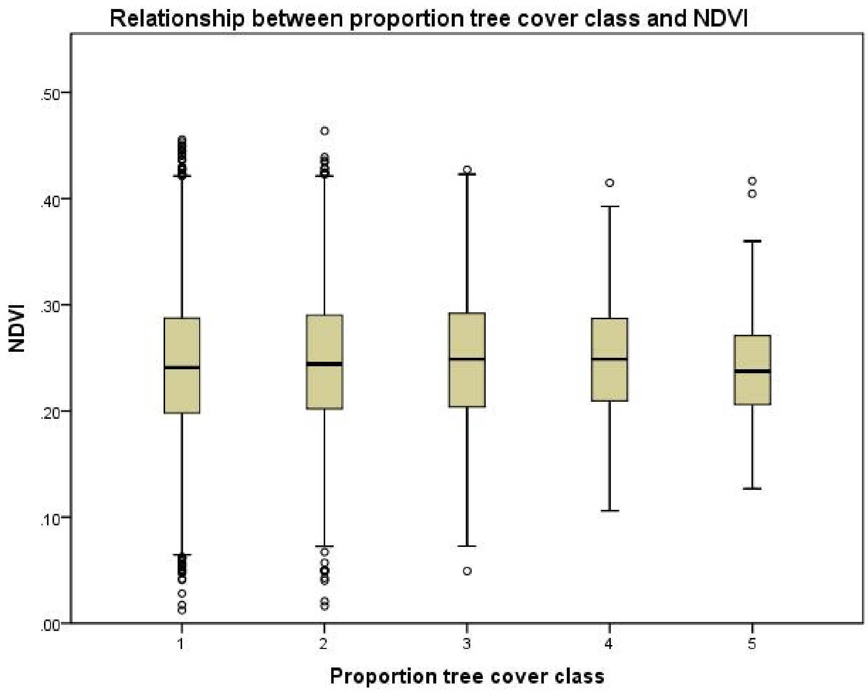


Figure 9. Boxplots of the NDVI values for each tree coverage class (1–5) as determined by proportion tree cover per Landsat TM 30 × 30 m pixel.



4. Conclusions

To address the limitations of traditional pixel based methods of remote sensing analysis and maximize the use of higher resolution imagery within this landscape we employ an object based classification to characterize vegetation structure within a savanna landscape. High resolution satellite imagery has become increasingly available yet the scientific applicability of these datasets remains limited [37]. Here we examine the utility of such a dataset for classifying a savanna landscape through an object based approach and then link it to Landsat data, to scale up to a more regional landscape level. We use field data to verify and test the suitability of the object based classification and find that the classification of the IKONOS imagery successfully identifies tree locations and depicts demographic characteristics (ex. crown size). Tree distribution and clustering corresponds to field data collected for this area and the spatial patterning across the land management units is as observed and expected, with larger quantities of trees and larger sized trees found within the protected area and greater quantities of other land covers found within the community conservation areas where local residents live and farm. In addition to characterizing tree location and demographics, the results from the object based classification prove useful for point pattern analyses offering an assessment of the spatial location and characteristics of the trees relative to surrounding vegetation. Point pattern analyses contribute to the determination of presence or absence of spatial interactions, and thus enhance inferences about processes based on pattern.

Although many studies use vegetation indices for assessments of savanna vegetation, our findings suggest that the addition of spatial data is critical for the accurate characterization of vegetation components within this ecosystem. This is congruent with studies of savanna vegetation [78,80], where commonly used vegetation indices such as NDVI are limited in their ability to characterize the complexity of vegetation composition. The limited differences found here in NDVI values across the tree count and tree cover classes reemphasizes the need to combine spectral and spatial data to characterize savanna landscapes since relying solely on spectral datasets to characterize trees in savanna landscapes could lead to misclassification of vegetation. Similarity in spectral reflectance of shrubs and trees in this region makes discriminating structure solely using spectral information challenging, especially at the courser Landsat scale. We show that in ecosystems such as savannas where vegetation structure is distinguishable by object shape and spatial characteristics the incorporation of this additional information is useful for differentiating structural types.

Due to the difficulty in scaling from field observations to satellite data integrating these data sources and analyses is one of the challenges in studies of plant phenology and ecosystem change [81]. This study utilizes high resolution IKONOS imagery to bridge scale and link field observations and medium resolution Landsat TM imagery in an explicit manner, thereby providing a method to integrate field data (plot data) with continuous measures of biomass derived from satellite data. Furthermore, the results from this study suggest that the scale of environmental change in savanna systems is critical. While quantification of overall changes in biomass is possible with course resolution NDVI, characterizing and partitioning tree biomass and monitoring tree cover trajectories requires finer scale analysis [50]. The use of a hierarchical multi-scale approach for characterizing southern African savanna landscapes offers detailed and ecologically relevant information.

Currently the limitations of using remote sensing for ecological studies include the over-reliance on traditional maximum likelihood classifications [82]. Although pixel based approaches certainly can be useful for characterizing the land cover, and are particularly useful when landscape components of interest have very different spectral signatures, this case study demonstrates the use of an alternative approach to pixel based classifications which incorporates both spectral and spatial information. The addition of spatial information to the classification process is particularly useful when trying to identify landscape objects which may have similar spectral characteristics. The object based approach applied here captures tree demographics, which when assessed spatially and temporally can be used to infer process from pattern. One challenge of the object based approach is the ability to discriminate between polygons of individual trees as opposed to those representing patches of trees. We attempted to address this challenge by calibrating the area cue within the vector object processing using individual tree crown locations as determined in the field. This ensured that rather than generating large polygons of similar spectral values, the output consisted of multiple smaller polygons. Although this does not completely remove the presence of polygons which represent multiple trees as opposed to individual trees, it certainly reduces the occurrence. The obvious logistical limitation of the analysis shown here is the cost of the high resolution imagery. Rocchini [83] shows that the cost of hyperspatial imagery limits access to these datasets, however as multi institutional collaborations form and commercial high resolution imagery becomes available through data grants access to imagery sources such as IKONOS is increasing. Additionally, the trade-off between high spatial and spectral resolution means that imagery with high spatial resolution is not necessarily appropriate for all research questions. While possibly useful for characterizing landscape components that are require higher spatial resolution than commonly relied upon Landsat imagery (30 m × 30 m), the loss of spectral information may limit the ability to differentiate between certain characteristics. Possibly more limiting is challenges associated with data management of the large amounts of data that accompany processes such as image segmentation of high resolution imagery. Laliberte *et al.* [84] determined that combining object based classification and decision tree modeling is a useful approach for managing the large amounts of spatial data inherent in high resolution imagery.

Object based classification of high resolution imagery provides the tools to differentiate vegetative classes—shrub and trees—with little spectral separability in savanna ecosystems. This method is useful for heterogeneous landscapes where spatial characteristics define vegetation groups, spectrally similar vegetation types have differing ecosystem functions and the integration of multi-scale analyses are needed to effectively quantify ecological change. Having tested the applicability of this methodology and data source for characterizing tree cover in southern African savannas, future research will examine direct linkages between proportional tree coverage as derived from the object based classification and proportions derived from a sub pixel classification of Landsat TM imagery.

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