LIDAR AND OBECT-BASED IMAGE ANALYSIS AS TOOLS FOR MONITORING THE STRUCTURAL DIVERSITY OF SAVANNA VEGETATION

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KEY WORDS: LiDAR, savanna, heterogeneity, biodiversity, conservation, monitoring, structure, eCognition

ABSTRACT:

Savannas are heterogeneous systems characterized by the coexistence of grasses and woody trees. Riparian zones are dynamic parts of savanna landscapes with structurally diverse woody vegetation. Growing recognition of the importance of the structural component of biodiversity has highlighted the need to understand the spatial distribution and temporal dynamics of woody structural diversity. Most studies of temporal change in savannas have employed the use of satellite imagery or black and white aerial photography. These techniques are useful for examining changes in woody cover over time, but cannot portray the threedimensional structure of vegetation. Advances in LiDAR technology have enabled three-dimensional information of vegetation to be obtained remotely over large areas. Whilst the use of LiDAR has gained considerable momentum in forested areas there has been limited application to savanna systems. We explore the applicability of LiDAR and object-based image analysis to the monitoring of woody structural diversity in a savanna system. LiDAR and colour aerial photography were acquired for the riparian and adjacent upland zones of four main rivers of the Shingwedzi Catchment - Kruger Park, South Africa. The resulting imagery, ground elevation and tree canopy elevation data covered an area of 635km². The tree canopy surface and colour imagery were segmented at two scales with object-based image analysis algorithms (eCognition v4.0) to construct a patch hierarchy. A classification hierarchy was constructed with fuzzy logic membership rules derived from field data. Height, elevation and spectral data were used to distinguish different vegetation types from bare ground. Results suggest that LiDAR can reliably return vegetation height and crown diameter data in savanna systems. The inclusion of object-based image analysis is an important step in fusing height data with colour imagery and generating multi-scale outputs. This approach provides a means for monitoring spatio-temporal changes in savanna woody vegetation structure at multiple scales.

1. INTRODUCTION

1.1 Savanna heterogeneity and management

Savannas are heterogeneous environments driven by a wide range of drivers at multiple scales. A key characteristic of savanna landscapes is the co-dominance of two life forms – grasses and woody trees (Scholes and Walker, 1993). The spatial structure and composition of savannas is controlled at the broad scale by climate and geology, by topography, soil type and rainfall at medium scales, and by fire and herbivory at finer scales (Pickett et al., 2003). In addition to being spatially heterogeneous, savannas are highly dynamic over time. The variability of these systems presents challenges to their management and conservation.

Management of savanna systems has historically taken place under a balance of nature/homogeneity paradigm (Rogers, 2003). Growing recognition of the heterogeneity of savanna systems has, however, led to changes in the management of certain savanna systems. In the Kruger Park (South Africa), for example, management has adopted a heterogeneity paradigm that 'aims to maintain biodiversity in all its facets and fluxes' (Braack, 1997). This statement refers to a holistic view of biodiversity which incorporates the composition, structure and function of ecological systems at multiple scales (Noss, 1990). Given that heterogeneity is considered to be the ultimate source of biodiversity (Pickett et al., 2003), maintaining heterogeneity is of high management priority within the Kruger Park. Fire and elephants are two drivers that have the potential to severely alter the vegetation structure of savanna systems (Trollope et al., 1998). They therefore have the ability to alter the heterogeneity and biodiversity of the savanna landscape. Understanding how these drivers modify savannas over large heterogeneous areas remains a fundamental question in savanna ecology and is essential to successful biodiversity management.

1.2 Vegetation monitoring in savanna landscapes

Monitoring of vegetation has traditionally taken place through aerial photographic analyses and field surveys. Ground based field monitoring can provide detailed information of changes in vegetation but is very time intensive and can only feasibly be conducted over small spatial scales. Within the Kruger Park, a system of fixed point photography has been employed since the 1970's to document changes in woody tree height over time. Although fixed point photography can reveal changes in the three-dimensional structure of vegetation, it suffers the same constraints as field measurements. Extrapolating results obtained at small spatial scales to larger scale is difficult is heterogeneous systems like savannas. Managers need to be able to monitor large spatial areas to in order to encompass system variability. Remote sensing techniques therefore need to be employed. Historically, black and white aerial photographic records have provided a means of exploring vegetation changes over much larger spatial areas. These records provide valuable evidence of changes in woody vegetation cover over time, but they are limited in their ability to document changes in the three-dimensional structure of vegetation. In recent years, however, Light Detection and Ranging (LiDAR) has become commercially available and provides a means of measuring the three-dimensional structure of ground and vegetation surfaces remotely. LiDAR has been utilized extensively in forestry applications and has been shown to reliably return ground elevation and tree height data in forested systems (Lefskey et al., 2002). LiDAR has experienced limited use in savanna systems however and there is little empirical evidence of its reliability in these more structurally complex and sparsely vegetated landscapes.

LiDAR, in conjunction with high resolution aerial photography, may therefore provide a remote sensing solution for monitoring vegetation structural diversity in the Kruger Park, South Africa. Given that savannas are heterogeneous systems at multiple scales, interpretation of remotely sensed data should be multiscalar and should incorporate hierarchical context. The software eCognition, developed by Definiens Imaging, adopts and object-based image analysis (OBIA) approach and provides a platform for incorporating contextual and ancillary data in image classification. OBIA arose through the realisation that image objects hold more real world value than pixels alone (Blaschke and Strobel, 2001).

We explore the potential of coupling LiDAR and OBIA for monitoring the three-dimensional structural diversity of savanna vegetation in the Kruger Park, South Africa.

2. METHODOLOGY AND ANALYSIS

2.1 Study Area

The study area is located in the Shingwedzi Catchment of the Kruger Park, South Africa. The Kruger Park is a conservation area incorporating over two million hectares of semi-arid savanna.



Figure 1. Shingwedzi Catchment, Kruger Park - South Africa

The Shingwedzi Catchment is drained by four main seasonal rivers – the Shingwedzi, Bububu, Phugwane and Mphongolo. Granite substrates dominate the western portion of the catchment whilst the eastern portion is underlain by basalts. The riparian zones of the rivers are often flanked by extensive alluvial deposits.



Figure 2. Riparian zone of Phugwane River

2.2 LiDAR data and high resolution RGB imagery

LiDAR data and high resolution RGB imagery were acquired for a 1.5km wide strip along the length of all four rivers of the Shingwedzi Catchment in November 2003. The resulting area sampled was 635km² and encompassed the riparian zones of the rivers as well as portions of the uplands.



Figure 3. Extent of LiDAR coverage shown in red - overlaid on a Landsat image. Note the granite / basalt divide just to the right hand side of the centre of the image.

The aerial scan was conducted by Airborne Laser Solutions (ALS), South Africa. An ALTM 1225 (Optech, Canada) sensor with an operational frequency of 25 kHz was used. Average height of the fixed-wing aircraft housing the sensor was 500m above ground level. 10cm vertical accuracy was achieved. Digital RGB imagery was simultaneously recorded with a resolution of 30cm. Raw processing was conducted by ALS in Microstation SE/JTM with the TerraModelerTM, TerraScanTM and TerraPhotoTM add-ons from Terrasolid.

2.3 Extracting woody vegetation structural attributes from LiDAR and RGB imagery through OBIA

A summary of the processing workflow is represented in Figure 4. A 500 hectare subset of the data along the Phugwane River was used for this analysis.

2.3.1 Pre-processing of LiDAR and imagery for OBIA. Pre-processing of point and raster data was conducted in ArcGIS 9.1 prior to segmentation in eCognition 4.0. Elevation points derived from LiDAR were interpolated to raster format at 0.5m resolution using the IDW algorithm. Total points were interpolated to create a digital surface model (DSM). Ground points were then interpolated independently to create a digital terrain model (DTM). The DTM was subtracted from the DSM to create a surface of above ground structure.



Figure 4. Processing workflow

Elevation above river channel has been shown to be an important determinant of woody plant distribution in semi-arid savanna systems (van Coller et al., 1997; van Coller et al., 2000). The DTM was therefore remodelled to create a surface of elevation above river channel to be included in the segmentation. The surface of above ground structure, surface of elevation above river channel and RGB imagery were filtered with a 3 X 3 low-pass filter to remove excessive variation. Smoothing of layers prior to segmentation helps produce fewer, and more homogeneous image objects, so that individual trees are represented by fewer polygons (Laliberte et al., 2004).

2.3.2 Segmentation and classification. Image segmentation and classification were conducted within eCognition 4.0. Multi-resolutional segmentation was preformed on the three bands of the RGB image, the surface of above ground structure and the surface of elevation above river channel. Segmentation was initially preformed at two scales. Firstly at a fine scale (Scale parameter = 5, colour = 0.8, compactness = 0.2) to ensure that individual trees were included. The second segmentation (Scale parameter 250, colour = 0.8, compactness = 0.5) was aimed at creating broader scale objects to provide context for the first level in the classification stage.

Image classification. A classification hierarchy was 2.3.3 constructed for the fine scale segmentation level. A division was first made between woody canopy coverage and bare ground/grass coverage. Woody canopy coverage was then further divided into three dominant vegetation classes in the sample area - Riparian thicket, Salvadora australis scrub and Colophospermum mopane scrub. Fuzzy logic membership functions were used for the classification process. Rules were based on object means as well as the mean difference between objects and their broader scale super-object. Spectral and elevation above ground data were used to distinguish woody vegetation from bare ground/grass cover. Elevation above river channel was then included and the spectral rules were refined to separate woody coverage into the three dominant vegetation types.

2.3.4 Crown delineation. In order to automate the measurement of crown attributes it is necessary to first delineate individual tree crown extent. An iterative process of segmentation, classification and classification based object fusion was adopted from (Burnett and Blaschke, 2003). Using the woody classification result as a mask, classification based object fusion was performed on the first object level to create larger objects within each vegetation class. Polygons were created for the resulting image objects and were exported to ArcGIS 9.1. Maximum diameter of each tree polygon (crown) was automatically calculated in the GIS.

2.3.5 Woody vegetation height model. The total woody coverage classification was exported to ArcGIS 9.1 in raster format. The bare ground/grass coverage was reclassified as 'nodata'. The woody coverage was then used as a mask to clip the original input surface of elevation above ground level. The bare ground/grass coverage was reclassified as 0m and was mosaicked with the result of the clipped surface to produce a robust model of tree height above ground.

2.4 Ground truthing.

Ground truthing was conducted in February 2004. Two hundred test points were randomly generated within the sample area. Points were located with a Trimble real time GPS (sub meter accuracy). Broad vegetation type and presence or absence of woody cover was recorded at each point. If woody cover was present – the species, tree height and maximum crown diameter were recorded. Height was measured with a Vertex hypsometer and diameter was measured with a tape measure or with the GPS depending on the size of the crown.

3. RESULTS

3.1 Vegetation classification

Classification of woody canopy cover and bare ground/grass cover achieved 97% accuracy. Riparian thicket was well described (92%) with *Salvadora australis* scrub and *Colophospermum mopane* scrub achieving 88% and 86% accuracy respectively.



Figure 5. Vegetation type classification: Riparian, Salvadora australis scrub and Colophospermum mopane scrub.

3.2 Vegetation height determination from LiDAR

The vegetation height model produced through the OBIA process (Fig. 6) provides a more realistic representation of tree height distribution than a standard DSM-DTM subtraction model (Fig. 7). The height surface is constrained spatially by woody plant coverage and artefacts introduced by interpolation across gaps in the canopy are removed.



Figure 6. Tree height model after OBIA



Figure 7. Standard DSM-DTM subtraction model

A cross-sectional profile comparison between the two models reveals the significant errors produced by a standard DSM-DTM calculation where there are gaps in the canopy (Paired t-test, t = 8.56 > 1.65, p < 0.001). The strength of the correlation between ground measured tree height and that derived from remotely (Fig. 9) indicates that high confidence can be placed in tree height measurements from LiDAR (R²=0.92, p<0.00001).



Figure 8. Cross-sectional profile comparison of model produced with the OBIA process and the standard DSM-DTM model.



Figure 9. Regression of ground truthed height measurements and those obtained from LiDAR (R^2 =0.92, p<0.00001).

3.3 Automated crown diameter measurements. Automated crown diameter measurements produced promising results (Fig. 10) which indicate that reliable crown diameter measurements can be obtained remotely ($R^2 = 0.79$, p < 0.0001) The relationship was weaker, however, than that obtained for tree height. We feel that more detailed classification of species types prior to classification based segmentation will aid in creating image objects that match individual tree crowns more closely.



Figure 10. Regression of ground truthed diameter measurements and those obtained from automated crown polygon measurement (R^2 =0.79, p<0.0001).

4. CONCLUSIONS

4.1 The fusion of LiDAR and RGB imagery with OBIA for classification and analysis in savanna systems

Combining elevation data from LiDAR with high resolution digital colour imagery through OBIA greatly enhances the structural description of a landscape by adding the height component. The heterogeneity of complex systems at different scales can prove problematic for traditional pixel based classification techniques. The object-based approach of eCognition, however, produced an accurate classification of woody cover and showed promise for individual species extraction from RGB imagery and elevation data, despite the heterogeneity of the savanna landscape. By using a multiresolutional segmentation approach, and grouping homogeneous objects together at different scales, contextual and hierarchical information was incorporated in the classification process. The resulting woody tree height model provided a more realistic representation of vegetation height distribution than standard DSM-DTM subtraction approaches. This is primarily due to the fact it accounted for the spatial heterogeneity of savanna woody cover and did not assume continuous vegetation cover.

Comparisons of remotely measured tree height and crown diameters with ground thruthed points indicate that structural attributes of woody vegetation can be reliably obtained from fusing LiDAR and colour imagery through OBIA in a savanna system. This holds significant implications for vegetation management in savannas by providing a tool for monitoring vegetation structure remotely.

4.2 Implications for monitoring the structural diversity of savanna vegetation

Managing the effects of elephants and fire on savanna vegetation is a pressing topic in many conservation areas. These two drivers can greatly influence the vegetation structure of savanna systems (Ben Shahar, 1996; van Langevelde et al., 2003). Issues surrounding the management of elephant populations in particular, and their effects on woody vegetation, have been the centre of much scientific and public debate (Gillson and Lindsay, 2003; Whyte et al., 1999). Differentiating the relative effects of fire and herbivory on the woody layer of savannas has proved difficult due to the co-occurrence of the two processes in these systems (Eckhardt et al., 2000; Trollope et al., 1998). Structural changes in woody vegetation need to be monitored over large spatial areas to firmly establish the role that fire and elephant play in altering system heterogeneity.

Understanding the patterns of spatial and temporal heterogeneity of a system is fundamental to its successful management. If we consider the reciprocal relationship between pattern and process in ecological systems (Turner, 1989), understanding where structural changes occur spatially in the landscape could help elucidate the differential effects of fire and elephant on vegetation structure. The fusion of LiDAR and colour imagery in an OBIA environment provides the means for generating this spatio-temporal understanding. The multi-scale, contextual approach inherent in OBIA provides managers with a powerful tool for monitoring changes in vegetation structural diversity across heterogeneous landscapes at different scales.

5. REFERENCES

Ben Shahar, R., 1996. Do elephants over-utilize mopane woodlands in northern Botswana. Journal of Tropical Ecology, 12: 505-515.

Blaschke, T. and Strobel, J., 2001. What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. GIS - Zeitschrift fur Geoinformationssysteme, 6: 12-17.

Braack, L., 1997. An objectives hierarchy for the management of the KNP, A revision of parts of the management plan for the Kruger National Park.Volume VII.

Burnett, C. and Blaschke, T., 2003. A multi-scale segmentation / object relationship modelling methodology for landscape analysis. Ecological Modelling, 168(3): 233-249.

Eckhardt, H.C., van Wilgen, B.W. and Biggs, H.C., 2000. Trends in woody vegetation cover in the Kruger National Park, South Africa, between 1940 and 1998. African Journal of Ecology, 38: 108-115.

Gillson, L. and Lindsay, K., 2003. Ivory and ecology changing perspectives on elephant management and the international trade in ivory. Environmental Science & Policy, 6: 411-419.

Laliberte, A.S. et al., 2004. Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. Remote Sensing of Environment, 93: 198-210.

Lefskey, M.A., Cohen, B.W., Parker, G.G. and Harding, D.J., 2002. Lidar remote sensing for ecosystem studies. Bioscience, 52(1): 19-30.

Noss, R.F., 1990. Indicators for monitoring biodiversity: A hierarchical approach. Conservation Biology, 4(4): 355-364.

Pickett, S.T.A., Cadenasso, M.L. and Benning, T.L., 2003. Biotic and Abiotic Variability as Key Determinants of Savanna Heterogeneity at Multiple Spatiotemporal Scales. In: J.T. du Toit, K.H. Rogers and H. Biggs (Editors), The Kruger Experience: Ecology and Management of Savanna Heterogeneity. Island Press, Washington, DC, pp. 23-40.

Rogers, K.H., 2003. Adopting a heterogeneity paradigm: Implications for management of protected savannas. In: J.T. du Toit, K.H. Rogers and H. Biggs (Editors), The Kruger Experience: Ecology and Management of Savanna Heterogeneity. Island Press, Washington, DC., pp. 41-58.

Scholes, R.J. and Walker, B.H., 1993. An African savanna: a synthesis of the Nylsvley study. Cambridge University Press.

Trollope, W.S.W., Trollope, L.A., Biggs, H.C., Pienaar, D. and Potgieter, A.L.F., 1998. Long-term changes in the woody vegetation of the Kruger National Park, with special reference to the effects of elephant and fire. Koedoe, 41(2): 103-112.

Turner, M.G., 1989. Landscape Ecology: The effect of pattern on process. Ann. Rev. Ecol. Syst., 20: 171-197.

van Coller, A.L., Rogers, K.H. and Heritage, G.L., 1997. Linking riparian vegetation types and fluvial geomorphology along the Sabie river within the Kruger National park, South Africa. African Journal of Ecology, 35: 194 - 212.

van Coller, A.L., Rogers, K.H. and Heritage, G.L., 2000. Riparian vegetation-environment relationships: complimentarity of gradients versus patch hierarchy approaches. Journal of Vegetation Science, 11: 337-350.

van Langevelde, F. et al., 2003. Effects of fire and herbivory on the stability of savanna ecosystems. Ecology, 84(2): 337-350.

Whyte, I.J., Biggs, H.C., Gaylard, A. and Braack, L.E.O., 1999. A new policy for the management of the Kruger National Park's elephant population. Koedoe, 42(1): 111-132.