Image Classification towards Mapping of Vegetation Structure: A practical approach

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Abstract. Assessing and monitoring vegetation as a grazing resource is often an integrated part of environmental, geographical and ecological research. This research paper explores the results and limitations of employing a supervised Maximum Likelihood Classifier (MLC) and an unsupervised classifying approach to identify vegetation structure in a diverse savanna biome. The two classification approaches are described, evaluated, and compared with in-situ field recordings and photographic field evidence. From this study it can be concluded that the use of medium resolution multispectral imagery like the 10m SPOT 5 for pixel based classification of vegetation structure in the study area is limited in its application value. The suitability of MLC and a hierarchical unsupervised classification is subject to the scale and accuracy requirements of the project. While uncertainties are present in all levels of the classification process, the inclusion of values from seasonal vegetation indices like the Normalized Difference Vegetation Index in a supervised classification may improve the accuracy of the result.

Keywords: Vegetation structure, Savanna, Classification, SPOT5

1. Introduction

Background

A common challenge faced within wildlife management and ecological studies is the establishment of cost effective methods for vegetation classification, particularly in regions with high spatial variation in vegetation type and structure. Even when broad scale vegetation information for a study area is available, the spatial and temporal characteristics of the data sources are often restrictive and not appropriate for the particular application needed.

In recent years the use of satellite imagery became a focal point of numerous vegetation related studies. As reported by Tucker (1979), vegetation indices for vegetation classification derived from Landsat imagery was already in use during the early 1970's. Since then, the applicability of remotely sensed data for vegetation studies has been reported widely in the literature (e.g. Nagler, *et al.*, 2002, Zhang, *et al.*, 2003 & Kawamura, *et al.* 2004) and a myriad of sensors and remote sensing methods developed in quick succession. Various factors impact on the cost and expediency of a particular solution and will influence its suitability towards a specific purpose. In southern Africa data with a high temporal frequency, high spatial resolution or high spectral resolution are presently too expensive to be widely used as part of a geographic or environmental analysis.

Study Area and Motivation

Since 2003, the establishment of transfrontier conservation areas in southern Africa (*Figure 1*) facilitates the roaming of wildlife across international borders.

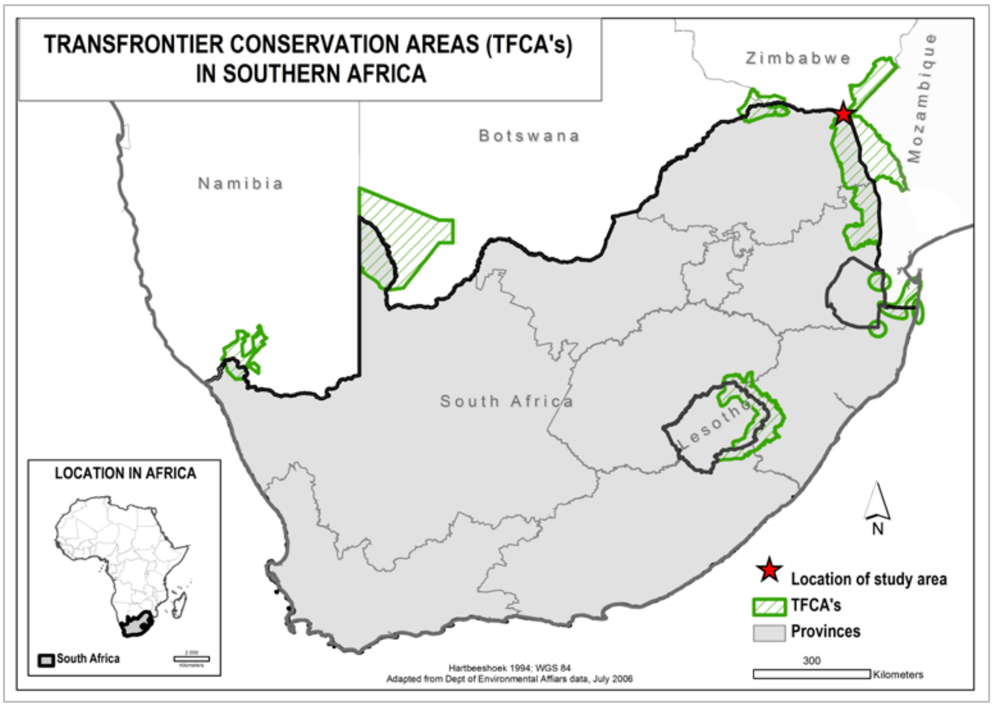

Figure 1. Southern African Transfrontier Parks.

Among South-African wildlife, the African Buffalo is known to be one of the main species responsible for the maintenance and potential spread of diseases such as Bovine tuberculosis (BTB) and Foot and Mouth disease (Garine-Wichatitsky et al. 2010). Concern exists about the spread and control of these wildlife related diseases which may generate substantial economic losses for the livestock sector of beef producing regions (Jori et al. 2009). Recent research suggests an association with the dispersion of pathogens and the movement of buffalo (and cattle) across international borders (Garine-Wichatitsky et al. 2010). Amongst several biotic and abiotic factors which affect the movement dynamics of animals, available forage is frequently noted as one of the main drivers (Baile et al. 2010, Bar-David et al. 2009, Winnie et.al. 2008). To deal with the concerns mentioned above, a project aiming to study the trans-boundary movements of buffalo within the Greater Limpopo Transfrontier Conservation Area (GLTFCA) was launched by CIRAD[1] in 2010.

Due to the lack of detailed vegetation information in the study area an updated description of vegetation structure will be a first step towards a better understanding of current animal movement patterns. The vegetation classification for this research is applied to a total area of 87.243km^2 which coincides with movement data associated with three buffalo and seven cattle herds tracked along the far northern boundary of the Kruger National Park (KNP), often referred to as the Pafuri area and an extended application area along its northern and western borders.

Although the KNP has been the focus of scientific studies for decades, the Pafuri land system is remote with limited road access in some areas. According to the most recent national vegetation map for South Africa (Mucina & Rutherford, 2006) the entire area falls within a savanna biome, but the zone is complex and diverse in natural characteristics and includes the Makuleke Wetlands, a system of inland pans within the Limpopo and Luvhuvhu floodplains which has been proclaimed an official Ramsar site in 2007 (www.ramsar.org) .

The Limpopo river valley and other areas where fence lines have been removed to aid natural movement of game between all sectors of the Great Limpopo Transfrontier Park, facilitates probable contact between buffalo and livestock.

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[1] CIRAD is a French research centre working with developing countries to tackle international agricultural and development issues

Problem statement

The fact that savanna vegetation is essentially a double layered system with a canopy formed by varying densities of trees and shrub and a lower layer of sub-strata consisting of grass and herbaceous vegetation – also in varying densities, results in a very complex problem when classifying vegetation with remotely sensors that essentially measures what is perceived from above (Hill et al. 2011). The applicability of image data for vegetation structure analysis is restricted by the scale of the pixel footprint, the size of the study area, the accuracy requirements of the project and the availability of imagery with appropriate spatial and temporal resolution.

Research Objective

Because researchers in South Africa have reasonable access to SPOT imagery, the principle objective is to evaluate the potential of using SPOT 5 multi-spectral imagery with a 10m spatial resolution to categorize the vegetation structure. An additional aim is to evaluate the usefulness of field survey as a ground truth validation tool within this research context.

2. Materials and Methods

2.1. Imagery

Three SPOT5 images at a 1B processing level with suitable acquisition dates were obtained from the National Space Agency of South Africa (SANSA). Image processing software was used to co-register the images to an earlier 2.5 m panchromatic geo-corrected SPOT image. Due to the natural status of the area and the lack of discernible man-made features, co-registration proved challenging but was achieved with a high level of accuracy and correlation between two images, one coinciding with the end-of-growing-season (30/04/2011) and the other typical of the end-of-dry season (12/08/2011). Subsets representing the study area are used for the classification procedures investigated in this paper. Radiance and reflectance values of the pixels in all the images were derived to facilitate the stacking of bands from more than one image during classification.

2.2. Classification of Vegetation Structure

Within a multi-dimensional continuum of physical data like vegetation cover, any classification is essentially an abstraction (Edwards, 1983). The choice of the number and type of vegetation structural classes is in part dependent on the required product but also dependant on what can reasonably be derived from the imagery. Available vegetation classification results specific to savanna regions in South African conservation areas are essentially once-off studies depending heavily on extensive fieldwork, precise sampling methods and expert botanical knowledge (Gertenbach 1983, Van Rooyen 1978). The requirements of this project dictate a more robust process that is repeatable and adaptable to work already in motion in other parts of the GLTFCA. Four short field visits by a geographically inclined researcher did not warrant a floristically based approach or even very precise field measurements. The study is therefore mostly reliant on the SPOT5 image classification supported by the in-situ field recordings.

2.3. In-situ structural classification

Vegetation structure is described as the combination of the horizontal distribution and vertical characteristics of dominant plants in an area (Hnatiuk et.al 2009). For the field-based observations in the Pafuri study region, a very practical approach developed and described by Edwards (1983) is applied. Edwards acknowledged the need for a stable classification scheme that may be used in non-plant specific research disciplines and refers to his structural classification as “purely complementary to” and “independant of” floristic and other forms of vegetation classification.

With the introduction of a two-way matrix depending on structural groups and formation classes, the method that Edwards offers provides a practical and hierarchical structural procedure using estimations based on growth form, cover and height - aided by information about the substrata. In a simplified description, the observable “growth forms” are represented by trees, shrubs, grasses and herbaceous plant forms whilst “cover” refers to the vertical projection of the plant onto the ground. The cover of the upper growth form stratum is fundamental to the definition of class irrespective of height. Height is then added as an ordinal measure adapted to each growth form. (*Figure 2*)

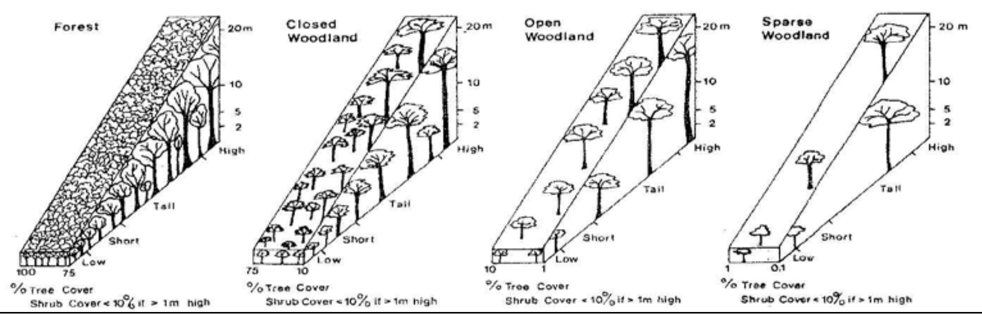

Figure 2. Example of ordinal measures applied to the “tree” growth form (Edwards, 1983).

An adapted "Edwards" classification sheet were used during four seasonally based field surveys. A convenience sampling method was adopted as each site had to be accessible from a road. Several factors restricted the field procedure that could be followed by a single researcher in this remote location. Fieldwork in the KNP is constrained by park regulations; field visits had to be planned in advance and could not be altered if conditions were not suitable. As a result only 24 of the 33 control sites could be included in this study.

To evaluate the researcher's ability to estimate projected ground cover of trees in the field, a supervised classification using recent (2008) aerial photography is used to map only trees, sub-strata, and shade in a rectangle broadly presenting each field site where trees are present (*Figure 3*). Class statistics illustrate the percentage cover. Field based canopy estimates in all cases correlated well with the results obtained from the aerial photo classification.

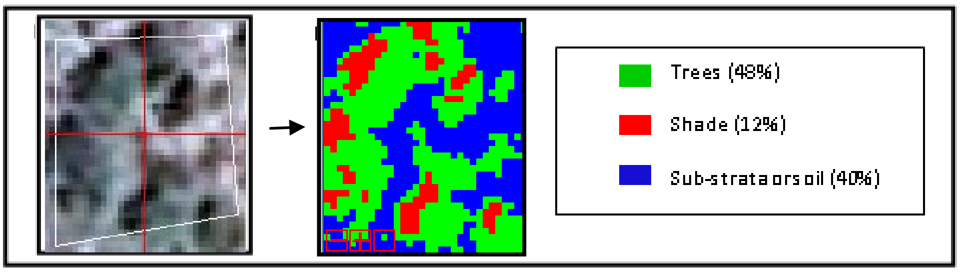

Figure 3. Example of tree canopy and class statistics calculation for one site.

2.4. Class selection for image analysis

As it was anticipated that the 10m spatial resolution of the SPOT 5 data will not be suitable to make clear distinctions between all of the Edwards vegetation classes, several classes were consolidated into seven vegetation classes, as well as a Bare Soil and a Water class (*Table 1*). This was done in collaboration with other researchers from CIRAD working in Zimbabwe and Mozambique.

Consolidated Classes	**Corresponding Edwards classes and characteristics thereof** *(Forbes/Herb cover is treated the same as grassland classes)*
Riverine Forest	Forest: 75-100% tree cover up to 20+ m. Shrub <10% if > 1m high
Woodland	Closed Woodland: 10-75% tree cover up to 20+ m. Shrub <10% if > 1m high
Open woodland	Open Woodland: 1-10% tree cover up to 20+ m. Shrub <10% if > 1m high Sparse Woodland: 0.1-1% tree cover up to 20+ m. Shrub <10% if > 1m high
Bushland	Thicket & Bushland: 1-100% tree cover up to 10 m. Shrub 10-100% and > 1m high Closed Shrubland: 10-100% shrub cover up to 5m high
Open bushland	Open Shrubland: 1-10% shrub cover up to 5m high
Grassland	Closed Grassland: 10-100% grass cover up to 2m+ high Open Grassland: 1-10% grass cover up to 2m+ high
Sparse	Sparse Shrubland: 0.1-1% shrub cover up to 5m high

vegetation cover	Sparse Grassland: 1-10% grass cover up to 2m+ high
Bare soil	Not applicable
Water	Not applicable

Table 1. Summary of class consolidations.

2.5. Image analysis

Two pixel based image classification approaches are investigated in this paper. Firstly the widely used supervised Maximum Likelihood Classifier (MLC) is applied using a set of image specific training areas referred to as Regions of Interest (ROIs). With this classifier each pixel is consistently allocated to the class with which it has the highest calculated probability of class membership (Adams & Gillespie 2006). Thirty ROIs for each class, created by visually inspecting the images using a false colour display, are employed as training areas. To limit statistical distortion in the classification results all vegetation ROIs contain a similar number of pixels. Consistency when selecting similar ROIs is achieved by keeping a record of typical reflectance values and spectral plots for each region.

A first investigative classification of the August image showed severe confusion between classes. A similar classification for the April image demonstrated less confusion but still clear misrepresentation with regards to shade and water in deep river valleys, and also between iron wood forests, shade and other woodland areas. This was addressed by adding two more training regions for the deep river valley and the spectrally distinct iron wood forests respectively.

Due to the differences in temporal changes between various plant species and in a bit to improve the application value of the classification, the Normalized Difference Vegetation Index (NDVI), often referred to as a "greenness" index was calculated for all values in both images. As explained in Beck et al. (2007), vegetation indices are valuable for investigating temporal vegetation dynamics. Work by Van Bommel et al. published in 2006 demonstrates the capability of NDVI-based analysis techniques within a spatially and temporally varied landscape by integrating physiognomy and NDVI in a "nested NDVI-based classification" of forage distribution in the Okavango Delta, Botswana.

To accommodate NDVI values in the classification all available bands from the two images and the derived NDVI bands are stacked and the "separability" of the updated eleven ROIs calculated. Derived pair separability of the chosen ROIs illustrates potential challenges for the supervised classification method. Band segregation probability for the eleven chosen ROIs is shown by displaying the mean spectral profiles for each class in each band in a composite graph (*Figure 4).*

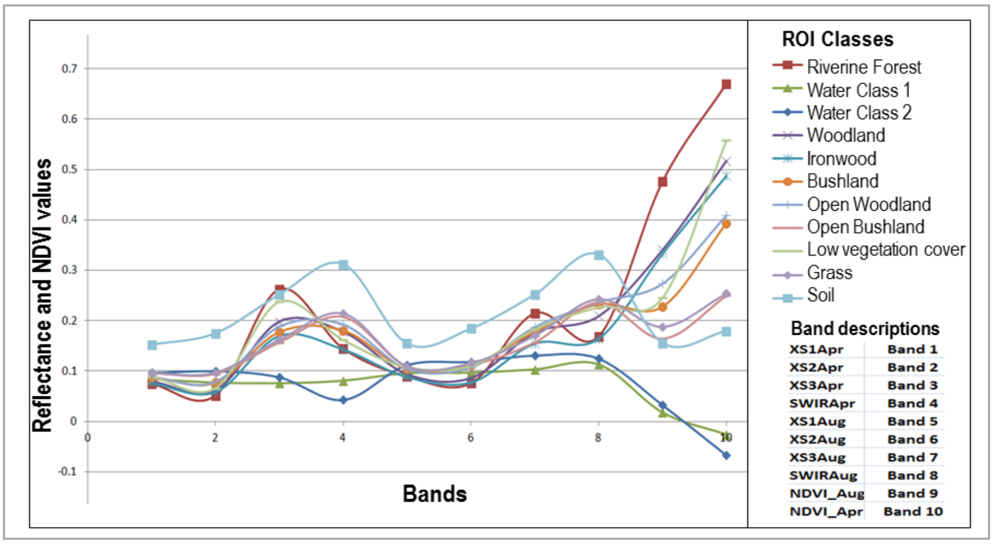

Figure 4: Band segregation probability as derived from spectral profiles using the mean values.

From the graph it is clear that the spectral profiles of several classes are very similar it is also evident that the two NDVI bands may be useful in separating some of the challenging areas. New classifications including different combinations of stacked bands, illustrated visually better results. To reduce fragmentation, post classification procedures are used to interpret the initial product and achieve a more thematically summarized image. The two water classes and the two woodland classes are combined followed by sieving and clumping functions and the application of a median filter.

For the second classification method an unsupervised approach is followed. Unsupervised classifiers (K-means and Isodata) measures and locates clusters in the data space, but an analyst is required to identify these clusters (Adams & Gillespie 2006). The unsupervised classification process used here incorporates a succession of unsupervised classifications on the same data set in the following hierarchical format: A large number of classes are created allowing up to 99 iterations. Clear identifiable classes are determined and a mask created for the rest. Repeat the above process for the remaining pixels each time using the new mask created until all remaining pixels are classified.

Validation

Though it is acknowledged that the in-situ field data from 23 sites is not statistically enough for comprehensive quantitative validation testing a qualitative evaluation is provided comparing results of different classifiers with the estimated field classes as derived from the Edwards (1983) classification (*Table 2*). Results from the MLC classifier consistently out-perform that of the unsupervised classification.

Field Control Site	In-situ classification	Supervised Maximum Likelihood Classifier (MLC)			Unsupervised Classifier
	Structural class	Classification 1 Bands: April image and April & August NDVI values	Classification 2 Bands: April & August images and NDVI values	Classification 3 Results from Classification 2 after post classification	Classification 4 (Unsupervised)
1	Open Woodland	□	□	■	-
2	Woodland	□	□	□	■
3	Bushland	■	□	■	-
4	Open Woodland	-	-	-	-
5	Open Bushland	-	-	-	■
6	Woodland	■	□	■	-
7	Open Woodland	□	□	-	□
8	Open Bushland	-	-	-	-
9	Open Woodland	□	□	□	-
10	Sparse vegetation cover	□	□	■	-
11	Sparse vegetation cover	□	□	■	-
12	Open Bushland	□	-	-	-
13	Grass	□	□	□	-
14	Open Woodland	□	□	□	-
15	Bushland	□	□	■	□
16	Open Woodland	□	□	□	-
17	Riverine Forest	■	■	■	■
18	Open Woodland	-	-	-	-
19	Open Bushland	■	■	■	■
20	Bushland	□	□	■	□
21	Open Bushland	■	□	■	□
22	Sparse vegetation cover	□	□	□	-
23	Open Woodland	■	□	-	□
24	Riverine Forest	□	□	■	■
SUMMARY ■ = Perfect correlation □ = Partial correlation - = No correlation		■ = 6 (25%) □ = 14 (58.3%) - = 4 (16.6%)	■ = 2 (8.3%) □ = 17 (70.8%) - = 5 (20.8%)	■ = 11 (45.8%) □ = 6 (25%) - = 7 (29.2%)	■ = 5 (20.8%) □ = 5 (20.8%) - = 14 (58.3%)

Table 2: Summarized comparison of field classification versus various image classification results from different band combinations.

For a quantitative assessment of Classification 3 in *Table 2* another set of 30 validation points for each class were created from Google Earth and Aerial photography by the skilled botanist Dr Pierre Poilecot, formerly from CIRAD. A confusion matrix derived from the result achieved an overall accuracy of 65% with a Kappa Coefficient of 0.6.

3. Discussion

All classification results illustrate considerable confusion between the more open vegetation classes, e.g. Open Bushland, Open Woodland and the Sparse Vegetation Cover class. Class results from the confusion matrix indicate very high accuracy levels (above 90%) for the Riverine Forest, Water and Bare Soil classes. A qualitative assessment of the points used for validation revealed that using point data for validation may result in misrepresentation as the position of the point may fall just inside or outside of a class. However, using a buffer region around the original validation points did not significantly improve the overall accuracy level. Furthermore it is clear that uncertainty and fuzziness is incorporated in all levels of the classification process, from the choice of vegetation classes, ROI selection (MLC) or class identification (unsupervised classifier) to the selection of ground truth validation data. Sub-pixel classification or the incorporation of ancillary data at suitable scales may assist in improving accuracy levels while integration of “fuzzy” parameters as described by (Welikanna et al, 2012), (Dwivedi et al. 2012) may improve the ability to scientifically assess and report uncertainties within classification results.

4. Conclusion

From this work it can be concluded that the use of medium resolution multispectral imagery like 10m SPOT 5 for pixel based classification of vegetation structure in a diverse savanna biome is limited in its application value. The suitability of MLC and a hierarchical unsupervised classification will heavily depend on the scale requirements of the project. Future work should investigate ways to increase the ability to estimate and describe the level of uncertainty associated with each classification method in order to improve the application value of the result and enable functional thematic mapping of vegetation structure. It is hoped that the issues, limitations and results explained in this work will be of value to other researchers in fields of environmental analysis and management.

References

Adams JB, Gillespie AR (2006) Remote Sensing of Landscapes with Spectral Images. A Physical Modeling Approach. Cambridge University Press, UK

Baley D, Gross JE, Laca EA, Rittenhouse LR, Coughenour MB, Swift DM, Sims PL (2012) Mechanisms that result in large herbivore grazing distribution patterns. Journal of Range Management, Vol 49 No 5 pp 386-400

Bar-David S, Bar-David I, Cross PC, Ryan SJ, Knechtel CU, Getz WM (2009) Methods for assessing movement path recursion with application to African buffalo in South Africa. Ecology, 90(9), 2009, pp. 2467-2479

Beck PSA, Jönsson P, Høgda K-A, Karlsen SR, Eklundh L, Skidmore AK (2007) A ground validated NDVI dataset for monitoring vegetation dynamics and mapping phenology in Fennoscandia and the Kola peninsula, International Journal of Remote Sensing, 28: 19, pp 4311-4330

Caron A, De Garine-Wichatitsky M, Gomo C, Foggin C, Miguel E, Cornelis D**.** 2011. EcoHealth, 7 : S66. International One Health Congress. 1, 2011-02-14/2011-02-16, Victoria, Australia.

Caetano M (2009) Image Classification. An ESA Advanced Training Course on Land Remote Sensing, 28 June-03 July 2009 in Prague, Czech Republic.

http://earth.eo.esa.int/landtraining09/D2L2_Caetano_Classification_Techniques.pdf. Accessed 24 October 2012

De Garine-Wichatitsky M, Caron A, Gomo C, Foggin C, Dutlow K, Pfukenyi D, Lane E, Le Bel S, Hofmeyer M, Hlokwe T, Michel A (2010) Bovine tuberculosis in buffaloes, Southern Africa. Emerging Infectious Diseases, 16: 884-885

Dwivedi R, Kumar A, Ghosh SK, Roy PS (2012) International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XXXIX-B3, 2012 XXII ISPRS Congress, 25 August-01 September 2012, Melbourne, Australia

Edwards D (1983) A broad scale structural classification of vegetation for practical purposes. Bothalia 14.3 & 4: pp 705-712

Gertenbach WPD (1983) Landscapes of the Kruger National Park. Koedoe 26: 9-121 (1983) Department of Research and Information, Skukuza

Hnatiuk RJ, Thackway R, Walker J (2009) Explanatory notes for the Vegetation field handbook, version 2. Bureau of Rural Sciences, Australian Government. http://adl.brs.gov.au/data/warehouse/pe_brs90000004198/FieldVegHandbookV2ExplanNotes_ap14.pdf Accessed 14 August 2012

Hill MJ, Román MO, Schaaf CB, Hutley L, Brannstrom C, Etter A, Hanan NP (2011) Characterizing vegetation cover in global savannas with an annual foliage clumping index derived from the MODIS BRDF product. Remote sensing of the Environment 115 (2011) 2008-2024

Jori F, Vosloo W, du Plessis B, Bengis R, Brahmbatt D, Gummow B, Thomson GR (2009) A qualitative risk assessment of factors contributing to foot and mouth disease outbreaks on the Western Boundary of Kruger National Park. Revue Scientifique et Technique-OIE. 28(3):917-933

Kawamura K, Akiyama T, Yokota H, Tsutsumi M, Yasuda T, Watanabe O, Wang S. (2004). Comparing MODIS vegetation indices with AVHRR NDVI for monitoring the forage quantity and quality in Inner Mongolia grassland, China. *Grassland Science*, 51, 33-40

Nagler PL, Glenn, EP, Huete, AR (2001) Assessment of spectral vegetation indices for riparian vegetation in the Colorado River delta, Mexico. Journal of Arid Environments, 49: 91-110. Doi:10.1006/jare.2001.0844

Mucina L, Rutherford MC (eds) (2006) The vegetation of South Africa, Lesotho and Swaziland. Strelitzia 19, South African National Biodiversity Institute, Pretoria

Tucker CJ (1979) Red and Photographic Infrared Linear Combinations Monitoring Vegetation. Remote Sensing of Environment, 8:127-150

Van Bommel FPJ, Heitkönig IMA, Epema GF, Ringrose, S, Bonyongo C, Veenendaal, EM (2006) Remotely sensed habitat indicators for predicting distribution of impala (*Aepyceros melampus*) in the Okavango Delta, Botswana. Journal of Tropical Ecology (2006) 22:101–110

Van Rooyen N (1978) ‘n Ekologiese studie van die plantgemeenskappe van die Punda Milia-Pafuri-Wambiyagebied in die Nasionale Krugerwildtuin. MSc dissertation (in a local language-Afrikaans), University of Pretoria, Pretoria

Welikanna DR, Tamura M, Tolpekin VA, Susaki J, Maki M (2012) improving Markov Random Field based Super Resolution Mapping through fuzzy parameter integration. ISPRS Annals of the Photogrammetry, remote Sensing and Spatial Information Sciences, Volume 1-7, 2012 XXII ISPRS Congress, 25 August-01 September 2012, Melbourne, Australia

Winnie JA, Cross P, Getz W (2008) Habitat quality and heterogeneity influence distribution and behaviour in African Baffalo (Syncerus caffer) Ecology. 89(5), 2008, pp. 1475-1468

Zhang X, Friedl, MA, Schaaf CB, Strahler AH, Hodges JCF, Gao F, Reed, BC, Huete A (2003) Monitoring vegetation phenology using MODIS. Remote Sensing of Environment (84) 471–475 www.elsevier.com