Available online at http://www.journalijdr.com

International Journal of DEVELOPMENT RESEARCH

ISSN: 2230-9926

International Journal of Development Research
Vol. 3, Issue, 12, pp.008-013, December, 2013

Full Length Research Article

COMPARING THE NEW GENERATION WORLD VIEW-2 TO HYPERSPECTRAL IMAGE DATA FOR SPECIES DISCRIMINATION

***Khalid Mansour**

University of Al-Fashir, Geography Department, P/Bag 125, Al-Fashir, North Darfur State, Sudan

ARTICLE INFO

Article History:
Received 18th September, 2013
Received in revised form
20th October, 2013
Accepted 04th November, 2013
Published online 18th December, 2013

Key words:
Hyparrhenia hirta,
Eragrostis curvula,
Sporobolus africanus,
Aristida diffusa and
Effectiveness compared

ABSTRACT

Discriminating indicator species in mountainous rangelands is critical for better understanding the condition of the rangeland and their levels of degradation. The objective of this study was to compare whether canopy reflectance spectra, resampled to WorldView-2 and HyMap resolution could discriminate four increaser species representing different levels of rangeland degradation. Canopy spectral measurements were taken from the four indicator species: *Hyparrhenia hirta*, *Eragrostis curvula*, *Sporobolus africanus*, *and Aristida diffusa*. The random forest algorithm and a forward variable selection method were applied in order to identify optimal variables (HyMap and WorldView-2 wavelengths) for discriminating the species. Results revealed that 8 optimal wavelengths from HyMap and 6 from Worldview-2 yielded the lowest OOB error (15.82%) and (17.36%) for HyMap and WorldView-2, respectively, in discriminating among the four increaser species. The random forest algorithm could discriminate species with an overall accuracy of 84.1% (KHAT =0.79) using HyMap wavelengths and an overall accuracy of 82.9% (KHAT = 0.77) using the WorldView-2 wavelengths. Overall, the study demonstrated the potential of WorldView-2 in terms of cost effectiveness compared to HyMap data for mapping indicator species of rangeland degradation.

INTRODUCTION

The degradation of rangeland grass is currently one of the most serious environmental problems in South Africa. Increaser grass species have been used as indicators to evaluate rangeland condition (Foran *et al*., 1978; Tau, 2005). Increaser species are species that increase their relative abundances through overgrazing and/or underutilisation, and these are therefore indicators of the poor condition of a rangeland (Van Oudtshoorn, 1992). Increaser species have been classified into the following four types: increaser I, increaser IIa, increase IIb, increaser IIc and increaser III (Oluwole and Dube, 2008). The relative abundances and distribution of increaser species have been used to assess the condition of South Africa's rangeland (Oluwole and Dube, 2008; Trollope, 1990). This is because increaser species are well adapted to environmental conditions and their numbers will reduce or increase dramatically if these conditions change (Hurt and Hardy, 1989).

***Corresponding author: Khalid Mansour**
University of Al-Fashir, Geography Department, P/Bag 125, Al-Fashir, North Darfur State, Sudan

In the past few decades, the mapping and monitoring of rangeland degradation in South Africa has primarily focused on commercial rangeland (Palmer and van Rooyen, 1998; Shackleton *et al*., 2005), meaning communal rangeland has not as yet enjoyed the same degree of attention (Mansour *et al*., 2012). The continued degradation of communal rangeland is a major threat to livestock production, biodiversity and human livelihoods (Hoffman and Todd, 2000). Different agronomic and ecological techniques have been developed over the past two decades to evaluate and monitor rangeland based on the relative abundance and distribution of increaser species. These techniques have achieved differing degrees of success for evaluating and monitoring rangelands over small geographic areas. However, these agronomic and ecological techniques require intensive and difficult fieldwork in terms of species identification and this exercise is often too expensive and time-consuming because rangeland often cover large spatial extents and are, moreover, frequently to be found in isolated, inaccessible areas (Trollope, 1990). The best method, which includes generating real-time, consistent, repeatable and spatially explicit data, is required for mapping and evaluating rangeland degradation. In this regard, remote sensing techniques offer a practical and economical means for quantifying rangeland degradation over large areas (Wessels, 2007) because they are capable of providing rapid, relatively inexpensive, and near-real-time data that can be used for the sustainable and effective management of rangelands (Wessels *et al*., 2004). The application of remote sensing in rangeland degradation has been explored by various scientists and has been found to be potentially useful for assessing, mapping and monitoring rangeland degradation when using different indicators such as soil properties and vegetation (Paudel and Andersen, 2010; Wessels *et al*., 2008).

Currently, hyperspectral remote sensing is considered one of the most advanced techniques for species level discrimination due to its detailed features on many, very fine and contiguous spectral wavelengths (Vaiphasa *et al*., 2007). Imageries from sensors, such as Hyperion, HyMAP and AISA Eagle, are critical for the mapping and classification of small vegetation units (less than 2 m) at species levels (Mutanga and Kumar, 2007). However, in spite of the detailed spectral information of hyperspectral data, processing tends to be more difficult due to the statistical properties associated with high dimensional data, the high cost of images, and the need for an excessive number of field samples (Bajcsy and Groves, 2004; Vaiphasa *et al*., 2007). Recent developments in multispectral sensor technology, such as WorldView-2 satellite provides high-resolution 8-wavelength multispectral (Omar, 2010; Sridharan, 2010). Therefore, since there is now the availability of relatively high spectral resolution sensors such as WorldView-2, it might be useful if the specific spectral wavelengths of this sensor for discriminating increaser species were investigated through the visible, red-edge, NIR-1, and NIR-2 of the electromagnetic spectrum and compare them with hyperspectral. The objective of this study was therefore to compare WorldView-2 to HyMap resolution and random forest as a classification algorithm could discriminate between four dominant increaser species associated with rangeland degradation in Okhombe communal rangeland, KwaZulu-Natal, South Africa.

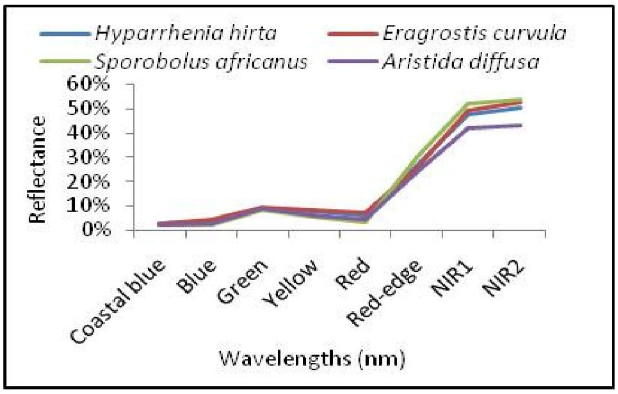
MATERIAL AND METHODS

Study area

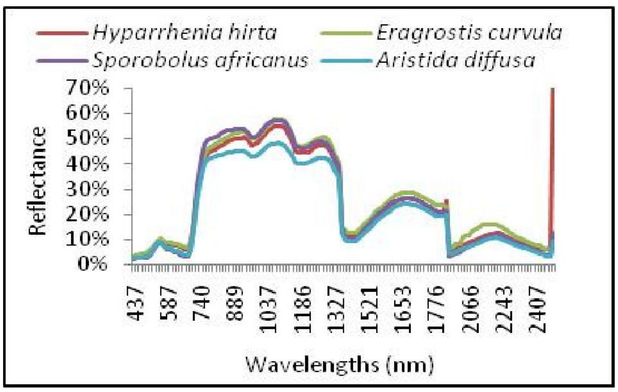
Okhombe is a communal rangeland situated in the mountainous region of the northern Drakensberg, which lies within the province of KwaZulu-Natal, South Africa (latitudes 28° 30' S and 30° 30' S and longitudes 28° 30' E and 29° 30' E). The average altitude for the site varies from about 1200 to 3350 m with an average air temperature of 11.5 to 16 °C in the summer months (October– March). In winter (June and July), the mean monthly temperature reaches 5 °C (Temme, 2008). The mean annual rainfall of the area is about 800–1000 mm, and it receives about 82% of this rainfall in the summer months (Temme, 2008). Visual indicators of rangeland degradation have been found in Okhombe - such as soil erosion, rills, gullies, shrub and bush encroachment, sedimentation in streams, and the dominance of unpalatable grass species throughout the foot, mid and upper slopes (Everson *et al*., 2007; Von Maltitz, 1998). The most common species associated with the rangeland degradation in the study area were identified. Four indicator grass species were then selected based on their high relative abundance. These species are: Hyparrhenia Hirta (HH), Eragrostis Curvula (EC), Sporobolus Africanus (SA), and Aristida Diffusa (AD).

Canopy spectral measurements for increaser species

Spectral measurements were taken with the Analytical Spectral Devices (ASD) FieldSpec® 3 to measure the spectral reflectance at canopy level from four species: *Hyparrhenia hirta*, *Eragrostis curvula*, *Sporobolus africanus*, and *Aristida diffusa*. The ASD has a wavelength range is 350 nm to 2 500 nm with a small sampling intervals of 1.4 nm (350 nm to 1000 nm) and 2.0 nm (1000 nm to 2 500 nm) range (ASD *et al*., 2005). A species plot area of 3 m × 3 m was defined, where the selected species (n = 4) were more homogenous and unmixed. Surveys encountered a total of 75 plots were generated for each grass species (HH, EC, SA, and AD). A total of 10 to 15 spectral measurements were then taken randomly in each plot at nadir from 1.5 m using a 5° field of view. This yielded a ground field of view of about 13 cm above the leaves on clear sunny days on the period of 21st to 25th of November between 11:00 am and 2:30 pm local time. These spectral measurements from each plot (n = 10 to 15) were then averaged to represent the spectral reflectance of the vegetation plot (n = 300). The spectral measurements were then resampled to the World View (n = 8) and HyMap (n = 126) spectra using ENVI 4.3 image processing software (Figure 1). The resampled World View and HyMap spectra were then used for subsequent analysis. The split of 70/30 is used to divide the data set into training (n = 53) and testing (n = 22) sets respectively (Ismail and Mutanga, 2011).



A



B

Figure 1. Mean reflectance spectrum data for *Hyparrhenia hirta*, *Eragrostis curvula, Sporobolus africanus*, and *Aristida diffusa* using WorldView-2 bands (A) and HyMap bands (B)

Statistical analysis

The Random Forest Algorithm (RF)

A machine learning algorithm known as "random forest" for classification developed by Breiman (Breiman, 2001) was examined to discriminate four increaser species using WorldView-2 and HyMap data. Random Forest (RF) grows multiple classification trees (*ntree*) and uses the entire forest as a complex composite classifier. Each tree is independently grown to its maximum size without any pruning and has a randomised subset of predictors (*mtry*) to determine the best split at each node of the tree (Breiman, 2001). The classification trees in the ensemble then vote by plurality on the correct classification. In RF algorithm, the permutation accuracy importance measure is considered to be the best measure because of its ability to assess the variable importance, which relies on mean decreases in accuracy as measured using the Out-Of-Bag (OOB) samples (Breiman, 2001). The OOB error produces a measure of the importance of the variables by comparing how much the OOB error of estimate increases when a variable is permutated whilst all other variables are left unchanged (Archer and Kimes, 2008). In this paper, the importance of each WorldView-2 and HyMap wavelength in discriminating the increaser species is determined using OOB estimates of classification error. Each tree is built based on a bootstrap sample of reflectance of WorldView-2 and HyMap wavelengths and about one - third of the original data are left out of the sample in the tree construction (OOB) (Breiman, 2001).

These modified OOB data are then passed down each tree to obtain new estimation of the classification error for that bootstrap sample. The difference between the misclassification rate for the modified and original OOB data over all the trees that are grown in the forest was then averaged to measure the importance of the variables (WorldView-2 and HyMap wavelengths). The variable importance measurement was then used as a ranking index (mean decrease in accuracy) to identify the wavelengths are able to better classify the increaser species (Archer and Kimes, 2008). The RF library (Liaw and Wiener, 2002) developed in the R software package for statistical analysis (R Development Core Team, 2008) was applied to carry out the RF algorithm. The two RF indicators –*mtry* and *ntree*– were optimised based on the OOB estimate of error rate in order to obtain the highest classification accuracy (Breiman, 2001). The *ntree* values were tested from a default setting of 500 to 10,000 trees with intervals of 500 (Prasad *et al*., 2006), while the *mtry* values were optimised by creating random forest ensembles using all possible *mtry* values (3) and (11) for WorldView-2 and HyMap wavelengths respectively.

Selection of variables using forward selection technique

The Forward Selection Function (FSF) technique was carried out for variable selection. The importance of the variables (World View-2 and HyMap wavelengths) in discriminating four increaser species as measured by the random forest algorithm were ranked, and a forward selection function (Guyon and Elisseeff, 2003) was implemented to determine the least number of WorldView-2 and HyMap wavelengths that could discriminate increaser species with greater accuracy. Forward selection function builds randomly numerous random forests with repetitions on all the ranked WorldView-2 wavelengths (n = 8) and HyMap wavelengths (n = 126). At each iteration, one variable (WorldView-2 wavelengths) and two variables (HyMap wavelengths) were added to the model respectively, and the error was calculated using the OOB estimate method.

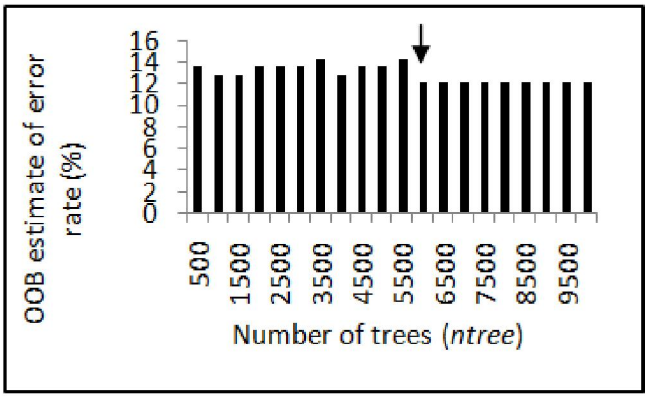
Classification accuracy assessment

In this study, the OOB estimate of error rate was used to estimate the classification accuracy. Nevertheless, the reliability of the OOB error was tested (Lawrence *et al*., 2006), an independent test data set (n = 22) was used for variables selection and classification. A confusion matrix was constructed so as to compare the true class with the class assigned by the classifier and to calculate the overall accuracy as well as the producer's and user's accuracies. Furthermore, we calculated the Kappa (KHAT) statistic in order to determine if the values are one or close to one, then there is perfect agreement between the test and training datasets (Cohen, 1960).

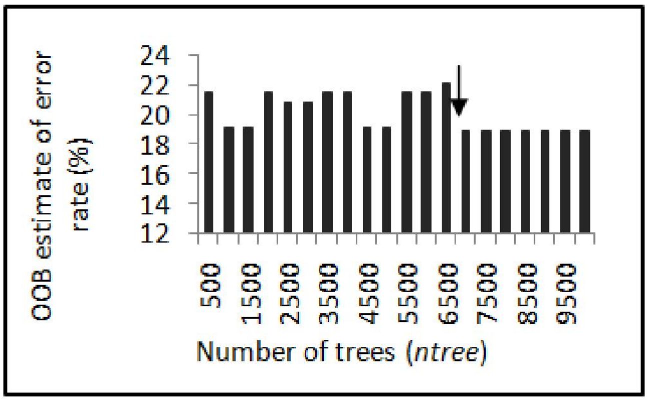
RESULTS

Optimization of *ntree* and *mtry*

Following the experiment, the optimization of the number of trees (*ntree*) and the number of variables at each split yielded an *mtry* value of 2 and 11 (which is the default setting) and an *ntree* of 6000 and 7000 resulting in the lowest and stable value of the OOB error rate of 12.23% and 18.35% for WorldView-2 and HyMap respectively (Figure 2(A and B)). Therefore, the subsequent analyses were done for optimization results.



A

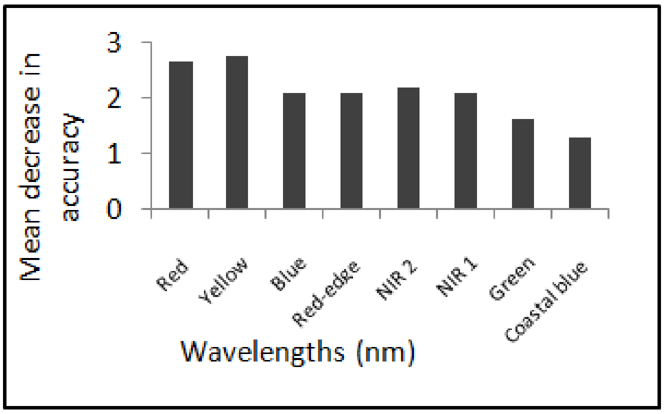


B

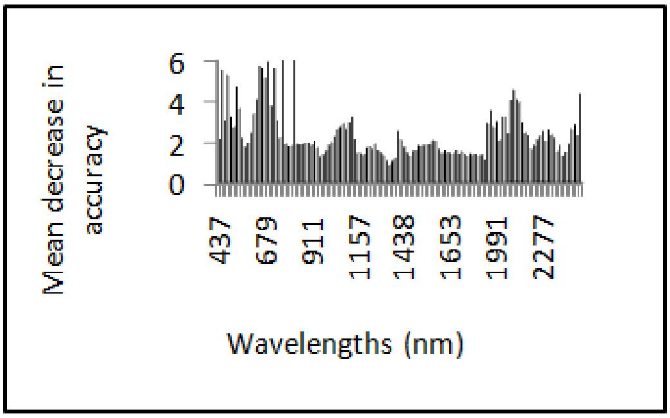
Figure 2. Optimizing the number of trees (*ntree*) based on the default setting of *mtry* (2 and 11) using the OOB estimate of error rate for WorldView-2 (A) and HyMap (B). The black arrows show *ntree* where OOB error has become lowest and stable

Variables selection using the OOB method

The most important wavelengths with the highest mean decrease in accuracy are located at Yellow, Red, NIR 2, Red-edge, Blue, and NIR 1 for WorldView-2 (Figure 3(A)), and 452 nm to 694 nm, 724 nm to 830 nm and 1990 nm to 2137 nm for HyMap (Figure 4(B)). The OOB estimate of error rate produces a ranking for all wavelengths, so that the only top WorldView-2 wavelengths (n = 6) and HyMap (n = 8) of the highest ranked wavelengths are considered for classification the four increaser species (Figure 4 (A and B)).

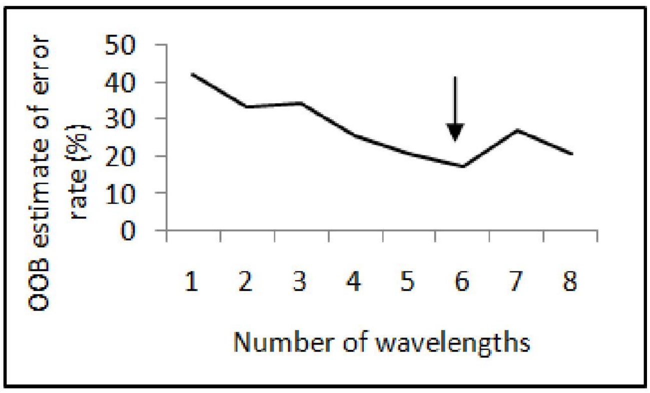


A

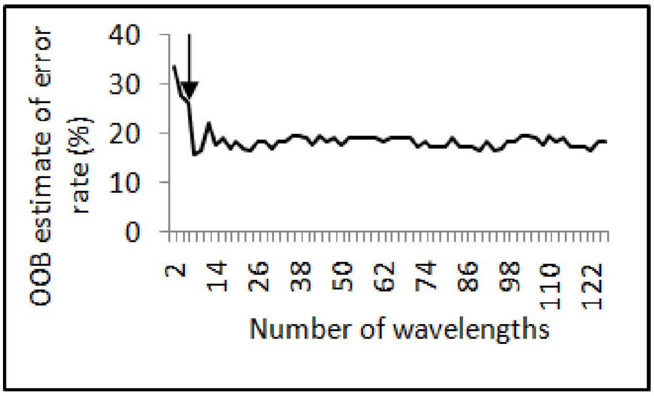


B

Figure 3. The importance of variables (WorldView-2 (A) and HyMap (B) wavelengths) in discriminating the increaser species as determined by the way of random forest algorithm. Wavelengths with the highest mean decrease in accuracy represent the most important wavelengths



A



B

Figure 4. Selection of the optimal number of variables (WorldView-2 (A) and HyMap wavelengths (B)) using the forward variable selection method. The optimal number of wavelengths that yielded the lowest OOB error is shown by arrows

Classification accuracy

To The important 6 WorldView-2 wavelengths (Yellow, Red, NIR2, Red-edge, Blue, and NIR1) and The 8 HyMap wavelengths (770 nm, 831 nm, 694 nm, 725 nm, 649 nm, 480 nm, 526 nm, and 452 nm) were used to discriminate the four increaser species using RF. Tables 1 and 2 Show that RF using an independent test data set successfully discriminated the species (HH, EC, SA and AD) with an overall accuracy of 82.9% (KHAT 0.77) and 84.1% (KHAT 0.79) for WorldView-2 and HyMap respectively.

Table 1. Confusion matrix for WorldView-2 wavelengths (n = 6) from the test data set showing the classification error obtained for the species (HH, EC, SA and AD). The confusion matrix includes overall accuracy (ACC), KHAT, Commission Error (CE), user's accuracy (UA), Omission Error (OE) and Producer's Accuracy (PA)

Species	HH	EC	SA	AD	Row total	CE %	UA%
HH	20	1	1	0	22	9.1	90.9
EC	0	16	4	2	22	27.3	72.7
SA	1	3	17	1	22	22.7	77.3
AD	0	1	1	20	22	9.1	90.9
Column total	21	21	23	23	88		
OE	4.76	23.81	26.09	13.04		ACC (%)	82.9
PA (%)	95.24	76.19	73.91	86.96		KHAT	0.77

Table 2. Confusion matrix for HyMap wavelengths (n = 8) from the test data set showing the classification error obtained for the species (HH, EC, SA and AD). The confusion matrix includes overall accuracy (ACC), KHAT, Commission Error (CE), User's Accuracy (UA), Omission Error (OE) and Producer's Accuracy (PA)

Species	HH	EC	SA	AD	Row total	CE %	UA%
HH	20	1	1	0	22	9.09	90.91
EC	1	17	3	2	23	26.09	73.91
SA	1	2	17	1	21	19.05	80.95
AD	0	1	1	20	22	9.09	90.91
Column total	22	21	22	23	88		
OE	9.09	19.05	22.73	13.04		ACC (%)	84.1
PA (%)	90.91	80.95	77.27	86.96		KHAT	0.79

DISCUSSION

The study aimed to compare the effectiveness of advanced multispectral to hyperspectral remote sensing in discriminating between four increaser species (HH, EC, SA and AD). Specifically, to compare WorldView-2 (n = 8) to HyMap (n = 126) data using RF as a classification algorithm could discriminate among increaser species as indicators of rangeland degradation. Results showed that HyMap data has the potential to accurately discriminate species with an overall accuracy of 84.1% when using the eight wavelengths compared to 6-WorldView-2 wavelengths (82.9%). The study demonstrated the potential of WorldView-2 wavelengths in discriminating increaser grass at species level with an overall accuracy of 82.9% which is only 1.2% less than an overall accuracy achieved by HyMap hyperspectral data. The selected HyMap wavelengths (n = 8) are located in the VIS region (0.45 – 0.89 nm). These results are identical to the previous studies made by Mansour *et al*. (2012), who were discriminated the same species using field spectrometer data resampled to AISA Eagle resolution. The optimal WorldView-2 wavelengths (n = 6) are located Yellow, Red, NIR 2, Red-edge, Blue, and NIR 1. These results are comparable to those of (Dlamini, 2010; Kumar and Roy, 2010; Omar, 2010), who mention that the WorldView-2 Yellow, Red, NIR2, Red-edge, Blue, and NIR1 wavelengths have great potential for species discrimination. Although the results have shown the possibility of airborne hyperspectral data (HyMap) to discriminate the increaser species by identifying specific wavelengths located in the visible region of the electromagnetic spectrum. However, hyperspectral data comes with difficulties in terms of cost and high dimensionality (Bajcsy and Groves, 2004; Vaiphasa *et al*., 2007). Therefore, the potential use of advanced multispectral remote sensing such as WorldView-2 data and tested the RF as a classification algorithm, as an alternative, particularly for low income countries.

Conclusions

In this study, an advanced multispectral WorldView-2 to hyperspectral data was used to discriminate the four increaser species in the communal rangelands of Okhombe, South Africa. The study indicates the feasibility of using 6-WorldView-2 to 8-HyMap wavelengths yielded an accuracy of 82.9% and 84.1% respectively. As determined by the RF algorithm, the wavelengths located at (770 nm, 831 nm, 694 nm, 725 nm, 649 nm, 480 nm, 526 nm, and 452 nm) and (Yellow, Red, NIR2, Red-edge, Blue, and NIR1) for HYMAP and WorlView-2 respectively, have the greatest potential for discriminating among the four increaser species. WorlView-2 data are relatively inexpensive, accessible, and do not require complex pre-processing and processing techniques. In this regard, the use of advanced multispectral sensors such as WorlView-2 is particularly useful for mapping increaser species areas as an indicator of rangeland condition.

Acknowledgements

We gratefully acknowledge the financial support that was given to us by the University of KwaZulu-Natal. We would like to the staff and technicians at the Geography Department and the Centre for Environment, Agriculture and Development (CEAD) for their encouragement and support.

REFERENCES

Archer, K., Kimes, R., 2008. Empirical characterization of random forest variable importance measures. *Computational Statistics & Data Analysis* 52(4), 2249-2260.

ASD, Analytical, Spectral, Devices, Inc, 2005. Handheld Spectroradiometer: User's Guide, Version 4.05, Boulder, USA.

Bajcsy, P., Groves, P., 2004. Methodology for hyperspectral band selection. Photogrammetric *Engineering and Remote Sensing* 70(7), 793-802.

Breiman, L., 2001. Random forests. Machine learning 45(1), 5-32.

Cohen, J., 1960. A coefficient of agreement for nominal scales. *Educational and psychological measurement* 20(1), 37-46.

Dlamini, W.M., 2010. Multispectral detection of invasive alien plants from very high resolution 8-band satellite imagery using probabilistic graphical models, *Digital Globe® 8Bands Research Challenge*, pp. 1-17.

Everson, T.M., Everson, C.S., Zuma, K.D., 2007. Community based research on the influence of rehabilitation techniques on the management of degraded catchments. *WRC Report* No. 1316/1/07 97pp., pp. 1-97.

Foran, B., Tainton, N., Booysen, P., 1978. The development of a method for assessing veld condition in three grassveld types in Natal. Proceedings of the Annual Congresses of the Grassland Society of Southern Africa 13(1), 27-33.

Guyon, I., Elisseeff, A., 2003. An introduction to variable and feature selection. *The Journal of Machine Learning Research* 3(7-8), 1157-1182.

Hoffman, M., Todd, S., 2000. A national review of land degradation in South Africa: the influence of biophysical and socio-economic factors. *Journal of Southern African Studies* 26(4), 743-758.

Hurt, C.R., Hardy, M.B., 1989. A weighted key species method for monitoring changes in species composition of Highland Sourveld. *African Journal of Range and Forage Science* 6(3), 109-113.

Ismail, R., Mutanga, O., 2011. Discriminating the early stages of Sirex noctilio infestation using classification tree ensembles and shortwave infrared bands. *International Journal of Remote Sensing* 32(15), 4249-4266.

Kumar, A., Roy, P.S., 2010. Effect on specific crop mapping using WorldView-2 multispectral add-on bands- A soft classification approach, *Digital Globe® 8Bands Research Challenge*.

Lawrence, R.L., Wood, S.D., Sheley, R.L., 2006. Mapping invasive plants using hyperspectral imagery and Breiman Cutler classifications (RandomForest). *Remote Sensing of Environment* 100(3), 356-362.

Liaw, A., Wiener, M., 2002. Classification and Regression by randomForest. *R news* 2(3), 18–22.

Mansour, K., Mutanga, O., Everson, T., Adam, E., 2012. Discriminating indicator grass species for rangeland degradation assessment using hyperspectral data resampled to AISA Eagle resolution. *ISPRS journal of photogrammetry and remote sensing* 70, 56-65.

Mutanga, O., Kumar, L., 2007. Estimating and mapping grass phosphorus concentration in an African savanna using hyperspectral image data. *International Journal of Remote Sensing* 28(21), 4897-4911.

Oluwole, F.A., Dube, S., 2008. Land degradation evaluation in a game reserve in Eastern Cape of South Africa: soil properties and vegetation cover. *Scientific Research and Essays* 3(3), 111-119.

Omar, H., 2010. Commercial Timber Tree Species Identification Using Multispectral Worldview2 Data, *Digital Globe® 8Bands Research Challenge*, 2-13.

Palmer, A., van Rooyen, A., 1998. Detecting vegetation change in the southern Kalahari using Landsat TM data* 1. *Journal of Arid Environments* 39(2), 143-153.

Paudel, K.P., Andersen, P., 2010. Assessing rangeland degradation using multi temporal satellite images and grazing pressure surface model in Upper Mustang, Trans Himalaya, Nepal. *Remote Sensing of Environment* 114(8), 1845-1855.

Prasad, A.M., Iverson, L.R., Liaw, A., 2006. Newer classification and regression tree techniques: bagging and random forests for ecological prediction. *Ecosystems* 9(2), 181-199.

R Development Core Team, 2008. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, available online at: http://www.R-project.org. (Accessed 21 January, 2011).

Shackleton, C., Guthrie, G., Main, R., 2005. Estimating the potential role of commercial over harvesting in resource viability: a case study of five useful tree species in South Africa. *Land Degradation & Development* 16(3), 273-286.

Sridharan, H., 2010. Multi-level urban forest classification using the WorldView-2 8-band hyperspatial imagery, *Digital Globe® 8Bands Research Challenge*, pp. 1-39.

Tau, M.S., 2005. Grazing management in the communal rangelands of the upper Thukela, KwaZulu-Natal. In, School of Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa.

Temme, A., 2008. Understanding landscape dynamics over thousand years: combining field and model work: with case study in the Drakensberg foothill, KwaZulu-Natal, South Africa.

Trollope, W., 1990. Development of a technique for assessing veld condition in the Kruger National Park using key grass species. Journal of the Grassland Society of Southern Africa 7(1), 46-51.

Vaiphasa, C., Skidmore, A., de Boer, W., Vaiphasa, T., 2007. A hyperspectral band selector for plant species discrimination. ISPRS Journal of Photogrammetry and Remote Sensing 62(3), 225-235.

Van Oudtshoorn, F.P., 1992. Guide to grasses of South Africa. Briza, Pretoria.

Von Maltitz, G.P., 1998. Communal rangeland management options for the Okhombe community in: de Bruyn, T.D., Scogings, P.F. (Eds.), Communal rangelands in southern Africa: a synthesis of knowledge, Proceedings of a symposium on policy-making for the sustainable use of southern Africa communal rangelands, University of Fort Hare, South Africa, p. 68.

Wessels, K., Pretorius, D., Prince, S., 2008. Reality of rangeland degradation mapping with remote sensing: the South African experience. *Ecological Applications* 17(3), 815–827.

Wessels, K., Prince, S., Frost, P., Van Zyl, D., 2004. Assessing the effects of human-induced land degradation in the former homelands of northern South Africa with a 1 km AVHRR NDVI time-series. *Remote Sensing of Environment* 91(1), 47-67.

Wessels, K.J., Prince, S. D., Carro, M., and Malherbe, J., 2007. Relevance of rangeland degradation in semi-arid northeastern South Africa to the nonequilibrium theory. *Ecological Applications* 17 (3), 815–827.

****