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Spectral discrimination of papyrus vegetation (*Cyperus papyrus L.*) in swamp wetlands using field spectrometry

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ABSTRACT

Techniques for mapping and monitoring wetland species are critical for their sustainable management. Papyrus (*Cyperus papyrus L.*) is one of the most important species-rich habitats that characterize the Greater St. Lucia Wetlands Park (GSWP) in South Africa. This paper investigates whether papyrus could be discriminated from its co-existing species using ASD field spectrometer data ranging from 300 nm to 2500 nm, yielding a total of 2151 bands. Canopy spectral measurements from papyrus and three other species were collected in situ in the Greater St. Lucia Wetlands Park, South Africa. A new hierarchical method based on three integrated analysis levels was proposed and implemented to spectrally discriminate papyrus from other species as well as to reduce and subsequently select optimal bands for the potential discrimination of papyrus. In the first level of the analysis using ANOVA, we found that there were statistically significant differences in spectral reflectance between papyrus and other species on 412 wavelengths located in different portions of the electromagnetic spectrum. Using the selected 412 bands, we further investigated the use of classification and regression trees (CART) in the second level of analysis to identify the most sensitive bands for spectral discrimination. This analysis yielded eight bands which are considered to be practical for upscaling to airborne or space borne sensors for mapping papyrus vegetation. The final sensitivity analysis level involved the application of Jeffries-Matusita (JM) distance to assess the relative importance of the selected eight bands in discriminating papyrus from other species. The results indicate that the best discrimination of papyrus from its co-existing species is possible with six bands located in the red-edge and near-infrared regions of the electromagnetic spectrum. Overall, the study concluded that spectral reflectance of papyrus and its co-existing species is statistically different, a promising result for the use of airborne and satellite sensors for mapping papyrus. The three-step hierarchical approach employed in this study could systematically reduce the dimensionality of bands to manageable levels, a move towards operational implementation with band specific sensors.

1. Introduction

Papyrus swamps (*Cyperus papyrus L.*) characterize most wetland areas of eastern and central tropical Africa (Bemigisha, 2004). Specifically, the swamp covers great areas in Uganda and Sudan around the Lake Victoria and Nile basins (Beadle, 1974). Other extensive areas are in the Upemba basin, Zaire, and the Okavango Delta, Botswana (Thompson et al., 1979). Papyrus swamps usually create a buffer zone between terrestrial and aquatic ecosystems and play hydrological, ecological, and economic roles in the aquatic systems (Gaudet, 1980; Mafabi, 2000).

Previous studies found that tropical papyrus swamps are characterized by a tremendous amount of combined nitrogen (Mwaura and Widdowson, 1992; Muthuri and Kinyamario, 1989) and a high rate of biomass production (Muthuri and Kinyamario, 1989). In this regard, papyrus plays a vital role in hosting habitats for wildlife species such as the sitatunga antelope (*Tragelaphus spekei*) and African python (*Python sebae*) (Owino and Ryan, 2007). Papyrus also has some grazing potential and could be used as fodder with high nutritive value especially in the dry season when other forage is limited (Muthuri and Kinyamario, 1989). Further, studies found that the highest species richness of birds in marshland was associated with the areas where papyrus and natural vegetation were plentiful (Harper, 1992; Owino and Ryan, 2007). In addition to providing habitat for wildlife, the high biomass production characterising papyrus swamps has seen it being widely used for paper making. The Egyptians for example, were the first people who used papyrus to make paper more than five thousand years ago (Bucci, 2001). Recently, promising results have been obtained in using papyrus as an alternative source of fuel

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in many countries in central Africa such as Rwanda (Jones, 1983; Muthuri and Kinyamario, 1989).

Despite its relative importance, human encroachment and intensified agricultural activities in many parts of Africa have threatened the existence of papyrus (Mafabi, 2000; Owino and Ryan, 2007; Maclean et al., 2006). The continued degradation in papyrus habitat represents a significant threat to biodiversity conservation particularly for papyrus-specialist birds and other papyrus-reliant species in many African countries (Owino and Ryan, 2007; Maclean et al., 2006).

To establish sustainable management of such important species, up-to-date spatial information about the magnitude and distribution of papyrus at several scales is essentially required (Schmidt and Skidmore, 2003; Nagendra, 2001). This can be achieved through remote sensing techniques that can monitor the change in papyrus areas and assessing the species' percentage cover as compared to the other species.

Traditionally, species discrimination for floristic mapping needs intensive field work, including taxonomical information and the visual estimation of percentage cover for each species which are costly and time consuming and sometimes inapplicable due to the poor accessibility (Kent and Coker, 1992; Lee and Lunetta, 1995). Remote sensing, on the other hand, is a technique that gathers data regularly about the earth's features without actually being in direct contact with those features. The main advantages that make remote sensing preferable to field-based methods in land-cover classification, are that it has repeat coverage which allows continuous monitoring, and its digital data can be easily integrated into a geographic information system (GIS) for more analysis which is less costly and less time-consuming (Shaikh et al., 2001; Ozesmi and Bauer, 2002; Mironga, 2004; Schmidt and Skidmore, 2003).

Both multispectral and hyperspectral remote sensing techniques have been used to discriminate and map wetland species. Multispectral data such as Landsat TM and SPOT imagery have been used to identify general vegetation classes or to attempt to discriminate just broad vegetation communities (May et al., 1997; Harvey and Hill, 2001; Li et al., 2005), while hyperspectral data have been successful in mapping wetland vegetation at the species level (Schmidt and Skidmore, 2003; Belluco et al., 2006; Brown, 2004; Rosso et al., 2005; Pengra et al., 2007; Vaiphasa et al., 2005; Enrica et al., 2006). Hyperspectral data has also been used to study vegetation health, water content in vegetation, biomass, and other physico-chemical properties (e.g. Mutanga and Skidmore, 2004; Mutanga et al., 2003; Green et al., 1998; Zarco-Tejada et al., 2005).

In general, the use of multi-spectral data in discriminating and mapping wetlands species is challenging due to spectral overlap between the wetlands species and due to the lack of spectral and spatial resolution of the multi-spectral data (Rosso et al., 2005). On the other hand, hyperspectral data often consist of over 100 contiguous bands of 10 nm or less bandwidth. These contiguous bands and narrow ranges lead to the possibility of discriminating and mapping vegetation species more accurately and precisely than the standard multispectral bands (Ustin et al., 2004; Schmidt and Skidmore, 2003; Borges et al., 2007).

A few previous attempts at using multispectral remote sensing in studies of papyrus swamps have been concentrated mainly on economic benefit and management scenarios of papyrus swamps and promising results have been obtained (Bemigisha, 2004; Owino and Ryan, 2007). However, the spectral discrimination of papyrus (*Cyperus papyrus L.*) has been overlooked in scientific research. No attempt, to our knowledge, has been made to discriminate papyrus swamps using field spectrometry, let alone in South Africa where only a handful of studies have used hyperspectral data to characterize vegetation in general due to high cost and poor accessibility (Ismail et al., 2007; Mutanga et al., 2004).

Although hyperspectral data are critical in discriminating species, its high spectral resolution contains redundant information at band level (Bajwa et al., 2004; Kokaly et al., 2003). This high-dimensional complexity of hyperspectral data can be problematic in terms of image processing algorithms, an excessive demand for sufficient field samples, high cost, and overfitting when using multivariate statistical techniques (Borges et al., 2007; Vaiphasa et al., 2007; Bajcsy and Groves, 2004; Goetz, 1991) Mutanga and Kumar (2007). It is therefore imperative to identify the optimal bands required for discriminating and mapping wetland species without losing any important information. Different univariate and multivariate techniques for dimensionality reduction and band selection with different performance levels have been developed, such as canonical analysis, classification and regression tree (CART), discriminant analysis, principal component analysis, artificial neural network and Jeffries-Matusita (JM) (Vaiphasa et al., 2005; Milton et al., in press; Cochrane, 2000; Schmidt and Skidmore, 2003; Satterwhite and Ponder Henley, 1987). However, inconsistent results have been obtained for different species and environments and the use of a single technique in reducing data dimensionality to acceptable operational levels has not been very successful.

This study aimed to investigate whether field spectrometry data could be used effectively to discriminate papyrus swamps from other species occurring in the swampy wetlands of South Africa. In other words, spectral separability analysis was used to examine whether papyrus swamps could spectrally be discriminated from the other species using field spectrometer measurements at canopy level as well as reducing spectral data dimensionality. More specifically, the objectives of this study were: (1) to determine whether there is a significant difference between the mean reflectance at each measured wavelength (from 350 to 2500 nm) for *Cyperus papyrus L.* and the other co-existing three species (*Phragmites australis*, *Echinochloa pyramidalis*, and *Thelypteris interrupta*). (2) To identify key wavelengths that are most sensitive in discriminating *Cyperus papyrus* from the other three species. In order to achieve this, we used a field spectrometer to measure the spectral reflectance from papyrus swamps and the associated species in Greater St. Lucia Wetland Park in South Africa. To achieve an efficient optimal selection of bands, we propose a new hierarchical method that integrates analysis of variance (first level), classification regression trees (second level) and finally Jeffries-Matusita distance analysis (third level) to assess the relative importance of the selected bands.

2. Material and methods

2.1. Study area

The study area was the Greater St Lucia Wetlands Park (GSWP) which covers about 3,000,000 ha along the eastern coast of South Africa in the Province of KwaZulu-Natal, between longitudes 32° 21′ E and 32° 34′ E and latitudes 27° 34′ S and 28° 24′ S. The GSWP which includes the Futululu natural forest is considered to be the largest estuarine system in Africa (Taylor, 1995). The climate is sub-tropical. The mean annual rainfall varies from 1500 mm in the eastern shore to 700 mm in the western shore of the lake. It is characterized by a high diversity of ecosystems including, marine, inland lake, estuarine, forested dunes, mangrove, and coastal and swamp forest ecosystems. Therefore, it is recognized as both a UNESCO World Heritage Site and a Ramsar wetland of global significance. The papyrus (*Cyperus papyrus*) occurs with *P. australis*, *E. pyramidalis*, and *T. interrupta* in the large area between forested dunes and plantation forest. The area is either wet or flooded permanently with freshwater throughout the year.

Table 1
The papyrus swamp and its associated species, the number of sample plots and the total number of measurements collected.

Species name	Type code	No of plots	No of measurements
Cyperus papyrus	CP	15	134
Phragmites australis	PA	9	111
Echinochloa pyramidalis	EP	7	101
Thelypteris interrupta	TI	10	113

2.2. Field data collection

2.2.1. The identification of papyrus and its associated species

The most common plant species associated with papyrus swamps in the area were identified in the field in the summer of 2007 under the supervision of an experienced ecologist using field observation techniques. These species were then recorded based on their density and estimation of percentage cover (covering at least 40% of the area). In total three species were identified as being the most co-existent species with papyrus. These were *P. australis*, *E. pyramidalis*, and *T. interrupta* (Table 1).

2.2.2. Spectral data acquisition

The Analytical Spectral Devices (ASD) FieldSpec®3 spectrometer was used to measure the spectral reflectance from papyrus and the other species. This spectrometer has a wavelength ranging from 350 to 2500 nm with a sampling interval of 1.4 nm for the spectral region 350–1000 nm and, 2.0 nm for the spectral region 1000–2500 nm, and a spectral resolution of 3–10 nm (ASD, Analytical Spectral Devices, Inc., 2005).

A combination of random sampling and purposive sampling was used to select field sites. Hawth's Analysis Tool extension for ArcMap designed to perform spatial analysis, was used to generate random points in a land cover map developed using an ASTER image. These points were then input in GPS to navigate to the field sites. Purposive sampling was done when the random point was not accessible, or to increase the variation of reflectance measurements of the species. Once the sampling location was identified, a vegetation plot was defined to cover 3 by 3 m in area of each species; then a total of 10–15 field spectrometer measurements were taken randomly from the nadir at about 1.5 m and with a 5° field of view above the vegetation species on each plot. This resulted in a ground field of view of about 13 cm in diameter, which was large enough to cover a cluster of species and to reduce the effects of background such as soil and water in the in situ spectral measurement (Table 1). All the measurements were collected in December 2007 between 10:00 am and 02:00 pm under sunny and cloudless conditions. A white reference Spectralon calibration panel was used every 10–15 measurements to offset any change in the atmospheric condition and irradiance of the sun. Metadata such as the site description (coordinates and altitude, land cover class), and general weather conditions were also recorded accompanying field spectral measurements on each measured point (Milton et al., in press). Due to the atmospheric water absorption noise in the reflectance spectra, a number of bands around 1420 nm, 1940 nm, and 2400 nm were excluded from the analysis.

2.3. Data processing

It was difficult to use one technique to identify a reasonable number of wavelengths that are most sensitive from 350 to 2500 nm ($n = 2151$). This was because the dimensionality still remained high when one technique was used (412 wavelengths from analysis of variance). Moreover, there is no single technique that has universally proven to be superior for the optimal feature selection (Yang et al., 2005), and it is quite possible that more than one subset of wavelengths can discriminate the data equally well (Yeung et al., 2005). We therefore innovated a new hierarchical method for spectral analysis based on three integrated levels. In the first level, we used one-way ANOVA to test if the differences in the mean reflectance between papyrus swamps and the other three species were statistically significant. We tested the research hypothesis that the means of the reflectance between the pairs of papyrus swamp and each one of the co-existing species (PA, EP, and TI) were significantly different at each measured wavelength, from 350 to 2500 nm, viz. the null hypothesis Ho: $\mu 1 = \mu 2$, $\mu 1 = \mu 3$, $\mu 1 = \mu 4$ versus the alternate hypothesis Ha: $\mu 1 \neq \mu 2$, $\mu 1 \neq \mu 3$, $\mu 1 \neq \mu 4$ where: $\mu 1$, is the mean reflectance values from papyrus and $\mu 2$, $\mu 3$, $\mu 4$ the mean reflectance values from *P. australis*, *E. pyramidalis*, and *T. interrupta* respectively.

One-way ANOVA was used with a post-hoc Scheffé test at each measured wavelength for the individual class pair (CP vs. PA, CP vs. EP, and CP vs. TI). We tested ANOVA with two confidence levels: a 99% confidence level ($p < 0.01$), and a 95% confidence level ($p < 0.05$).

2.3.1. Classification and regression trees (CART)

We used CART in this second level of the hierarchical method to further reduce the number of significant wavelengths obtained from ANOVA analysis, with the purpose of reducing data dimensionality. CART, which was developed by Breiman et al. (1984), is a nonparametric statistical model that can select from a large dataset of explanatory variables ($\mathbf{x}$) those that are best for the response variables ($\mathbf{y}$) (Yang et al., 2003; Questier et al., 2005). CART was preferred in our study because the values of the predictor variables (spectral reflectance) are a continuous, as opposed to categorical target (plant species).

The CART model is built in accordance with the splitting rule. This rule performs the function of splitting the data into smaller parts according to the reduction of the deviance from the mean of the target variable (Y_{bar}) (or corrected total sum of the squares). (Y_i) is the target variable of each dataset. The decision tree begins a search from a root node (parent node) derived from all the predictors, and possible split points such that the reduction in deviance, D (total), is maximized (terminal node) as follows (Breiman et al., 1984).

$$D(\text{total}) = \sum (Y_i - Y_{bar})^2. \tag{1}$$

The cut point, or value, always splits the data into two child nodes, the left node and the right node with maximum homogeneity. The reduction in deviance is as shown in the following equation:

$$\Delta_{j,\text{total}} = D(\text{total}) - (D(L) + D(R)) \tag{2}$$

where $D(L)$ and $D(R)$ are the deviances of the left and right nodes.

Hence, the algorithm begins searching for the maximized $\Delta_{j,\text{total}}$ over all the predictor variables and the cut points subject to the constraint that the number of the members in the left and right nodes are larger than some criterion set by the user. The algorithm repeats the procedure of binary splitting for each node (left and right nodes) by treating each child node as a parent node splitting until the tree has a maximum size (Yang et al., 2003).

In this study, we used CART as the second level of the hierarchical method to select the most sensitive wavelengths from the number of significant wavelengths selected in the first level (ANOVA). Therefore, CART generated the optimal bands by selecting only the spectral bands that result in small misclassification rates to discriminate each class pair (CP vs. PA, CP vs. EP, and CP vs. TI) individually. The bands which were common in each class pair were then selected to get the optimal bands for all class pairs.

2.3.2. Distance analysis

After we had the optimal bands selected from the CART analysis, additional analysis was needed to identify the best band or band combinations that could be used for the best spectral separability between papyrus and each one of the three species. Hence, we tested the hypothesis that some bands are relatively more important than others in discriminating papyrus. The separability index used in this level of hierarchical method was JM distance analysis (Schmidt and Skidmore, 2003; Ismail et al., 2007; Vaiphasa et al., 2007). It was impossible to run JM distance analysis on all the significant bands ($n = 412$) from ANOVA analysis because of the singularity problem of matrix inversion (Vaiphasa et al., 2005; Ismail et al., 2007). Moreover, this high-dimensional complexity is very costly, time-consuming, and beyond the capacity of the common image processing algorithms (Schmidt and Skidmore, 2003; Vaiphasa et al., 2007; Borges et al., 2007). We therefore, used the bands derived from CART. The JM distance between a pair of probability functions is seen as a quantification of the mean distance between the two class density functions (Richards, 1993). When classes are normally distributed, this distance turns out to be the Bhattacharyya (BH) distance (Richards, 1993; Schmidt and Skidmore, 2003). The JM distance has upper and lower bounds that vary between 0 and $\sqrt{2}$ ($\approx$1.414), with the higher values indicating the total separability of the class pairs in the bands being used (Richards, 1993; ERDAS Field Guide, 2005). In this study we decided to use higher separability values $\geq$97% as a JM distance threshold to identify the most important band or band combinations for best discrimination of papyrus swamp. The formula for computing JM distance is as follows (ERDAS Field Guide, 2005):

$$\alpha = \frac{1}{8}\left(\mu_i - \mu_j\right)^{\mathrm{T}} \left(\frac{C_i + C_j}{2}\right)^{-1} \left(\mu_i - \mu_j\right) + \frac{1}{2}\ln\left(\frac{\left(\left|C_i + C_j/2\right|\right)}{\sqrt{\left|C_i\right| * \left|C_j\right|}}\right) \tag{3}$$

$$JM_{ij} = \sqrt{2\left(1 - \mathrm{e}^{\alpha}\right)} \tag{4}$$

where: i and j = the two classes being compared, C_i = the covariance matrix of signature i, μ_i = the mean vector of signature i, ln = the natural logarithm function, $|C_i|$ = the determinant of C_i (matrix algebra).

3. Results

3.1. First level: ANOVA test

ANOVA results indicate that there is no significant difference between the two class pairs (CP vs. EP, and CP vs. TI) when a 99% confidence level ($p < 0.01$) is used. However, the 95% confidence level ($p < 0.05$) indicates that there is a statistically significant difference in the spectral reflectance between all the class pairs (CP vs. PA, CP vs EP, and CP vs. TI) at $n = 412$ wavelengths. These significant wavelengths were highlighted using a histogram for every individual class pair. The results of the ANOVA test for each class pair (CP vs. PA, CP vs EP, and CP vs. TI) are shown in Fig. 1(a, b, and c). The shaded areas show the wavelengths where the spectral reflectance from the papyrus swamp is statistically different from the other three species, with a 95% confidence level (p-value < 0.05).

The conclusions from the ANOVA test are that the mean reflectance between papyrus and the other three species is significantly different in many measured wavelengths. These significant wavelengths are located in three different regions of the electromagnetic spectrum (red-edge, near-infrared, and mid-infrared).

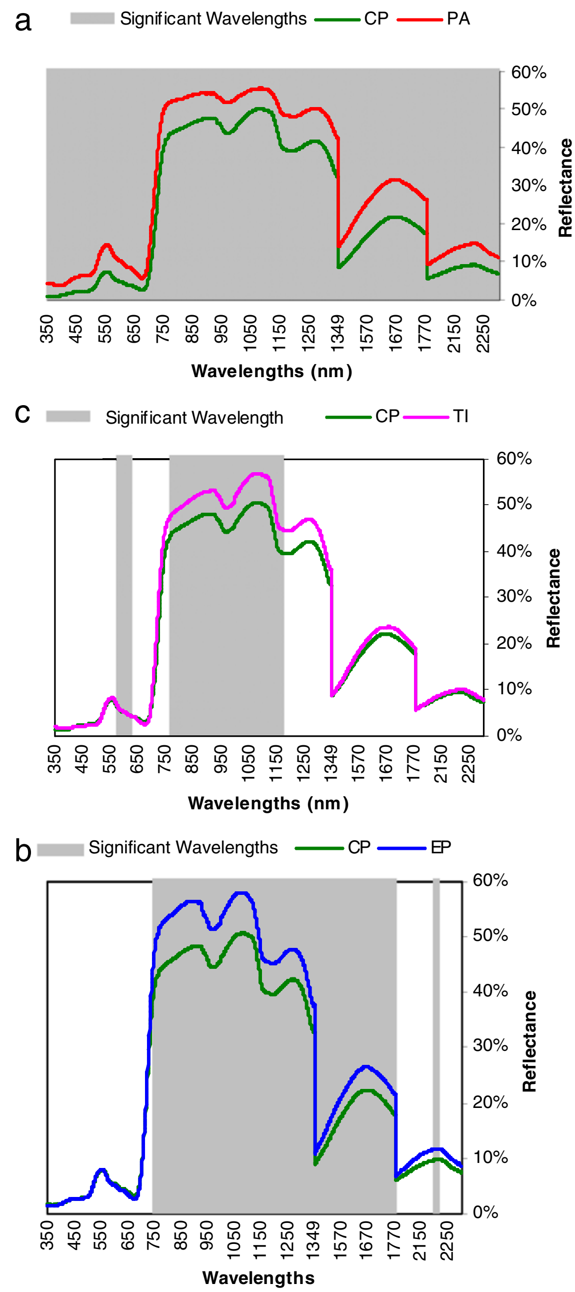

Fig. 1. ANOVA results for each class pair (a) CP vs. PA, (b) CP vs. EP, and (c) CP vs. TI The grey areas show the wavebands where there are significant differences between the class pairs within the electromagnetic spectrum.

Table 2 shows the frequency of the significant bands adapted into the four spectral domains which is widely used in the hyperspectral remote sensing of vegetation (Kumar et al., 2001). The table shows that there are no statistically significant wavelengths located in the visible region for the class pairs CP vs. EP, and CP vs. TI. However, the class pair CP vs. PA has more significant wavelengths located all over the spectral regions than any other class pair (CP vs. EP, and CP vs. TI). All the wavelengths from 350 to 1300 ($n = 950$) are significant for CP vs. PA as well as 49.95% ($n = 600$) of wavelengths located in the mid-infrared region, whereas the statistically significant wavelengths for the pair CP vs. TI are located only in the red-edge and near-infrared portions of the electromagnetic spectrum ($n = 449$). It can also be seen from Table 2 that the red-edge and near-infrared are the most important regions where each class pair has the most statistically significant wavelengths.

Table 2
Frequency of significant bands for each class pair adapted into the four spectral domains defined by Kumar et al. (2001).

Wavelength region (nm)	Description	Number of bands	Significant bands					
			CP vs. PA	%	CP vs. EP	%	CP vs. TI	%
350–700	Visible	351	351	100.00	0	0.00	0	0.00
680–750	Red-edge	71	71	100.00	10	14.08	45	63.38
700–1300	Near-infrared	601	601	100.00	560	93.18	451	74. 04
1300–2500	Mid-infrared	1201	600	49.95	367	30.55	0	0.00

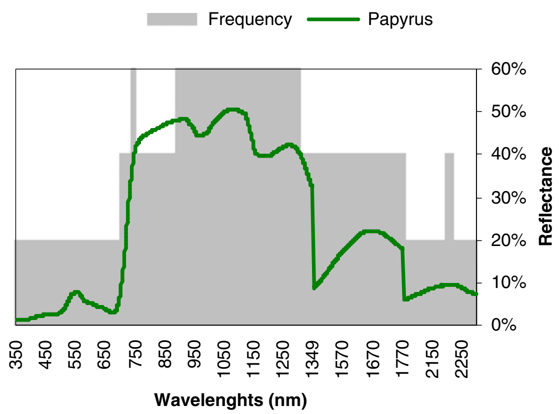

Fig. 2. Frequency of statistical difference using ANOVA with 95% confidence level ($P < 0.05$) between the mean reflectance of papyrus and all other species.The maximum grey shading shows the wavelengths where papyrus could be discriminated from all the other three species.

The results can be clearly seen in the histogram in Fig. 2 which shows by maximum grey shading the wavelengths with the maximum frequency. These significant wavelengths have the potential to discriminate papyrus swamps from all other species (PA, EP, and TI).

Results of frequency analysis (Fig. 2) reveal that there is no wavelength that maximized the discrimination of papyrus from the other species in the visible region. There are however, a few significant wavelengths located in the red-edge (741–746) nm = ($n = 6$) and a majority of wavelengths located in the near-infrared part of the electromagnetic spectrum (982–1297) nm = ($n = 406$). Further analysis was then conducted to reduce the number of these significant wavelengths ($n = 412$).

3.2. Second level: CART results

CART analysis was applied to reduce the numbers of significant bands ($n = 412$) selected by ANOVA analysis to fewer bands that could optimally discriminate the papyrus from the other three species. The selection of the optimal wavelengths was done for each individual class pair; CP vs. PA ($n = 17$), CP vs. EP ($n = 13$), and CP vs. TI ($n = 15$). The misclassification rate was 0.014, 0.014, and 0.029 for each class respectively. The results are shown in Table 3. The common wavelengths among all class pairs: (CP vs. PA, CP vs. EP, and CP vs. TI) were then selected to find the optimal wavelengths for all class pairs. It also interesting to note that in Table 3 there are eight spectral bands that appeared commonly in every class pair. These spectral bands are: 745 nm, 746 nm, 892 nm, 932 nm, 934 nm, 958 nm, 961 nm, and 989 nm. From this analysis, these eight wavelengths could potentially discriminate papyrus swamps from all the three species.

3.3. Third level: Distance analysis results

The Table 4 shows the results of JM distance. The band located at 892 nm appeared to be the best single band because it produces best separability when used individually with a JM value of 1.342 (94.91%). Furthermore, it has the highest frequency (100%) by appearing in every best band combination. The table also reveals that the use of more bands improves the separability of the papyrus. Whereas the single band (892 nm) produces an unacceptable JM value of 1.342, the acceptable average JM values (≥97%) are reached when using three band combinations, which achieved 97.45%. The JM value then is improved considerably until it reaches the best value with the best eight band combinations.

Table 3
Wavelengths selected by CART for each individual class pair and the misclassification rate. Wavelengths that were able to differentiate between all three pairs of classes are highlighted in grey.

Class pair	Wavelengths (nm) selected	No of wavelengths (nm)	Misclassification rate
CP vs. PA	741, 745, 746, 892, 932, 934, 958, 961, 985, 989, 1037, 1107, 1120, 1125, 1130, 1153, 1291.	17	0.014
CP vs. EP	745, 746, 892, 932, 934, 958, 961, 989, 1056, 1119, 1123, 1124, 1153.	13	0.014
CP vs. TI	741, 745, 746, 892, 932, 934, 958, 961, 989, 1010, 1038, 1056, 1119, 1130, 1146.	15	0.029

Table 5 shows the JM distance values for each individual class pair (CP vs. PA, CP vs. EP, and CP vs. TI) within each best band combination. For the class pairs, CP vs. PA and CP vs. TI, a single band located at 892 nm produced an acceptable JM distance value. However, the class pair, CP vs. EP, reached the acceptable value of JM distance (≥97%) only when using six band combinations located at 745 nm, 746 nm, 892 nm, 934 nm, 958 nm, and 961 nm, where the other two class pairs (CP vs. PA and CP vs. TI) reached total separability of 100% (upper JM value). Unlike the other two class pairs (CP vs. PA and CP vs. TI), the CP vs. EP pair does not reach the total separability even when using all eight bands (JM distance value 1.405). However, total separability starts for the other two class pairs (CP vs. PA and CP vs. TI) from using the best four band combinations located at 892 nm, 934 nm, 958 nm, and 961 nm.

4. Discussion

The use of field spectrometry for species discrimination is widespread at both field measurement and laboratory level (Skidmore et al., 1988; Schmidt and Skidmore, 2003; Belluco et al., 2006; Brown, 2004; Rosso et al., 2005; Pengra et al., 2007; Vaiphasa et al., 2005; Enrica et al., 2006). The removal of redundant data and relevant data identification are critical considerations in field spectrometry data processing. One should seek to ensure that this dimensionality reduction would not cause any loss of important information relevant to the object under study. Various researchers have used different techniques to identify important bands of the electromagnetic spectrum for discriminating vegetation species with inconsistent results.

In this paper, it was difficult to use one technique to identify a reasonable number of wavelengths that are most sensitive from

Table 4
The averages of JM distance analysis for all the three class pair (CP vs PA, CP vs. EP, and CP vs. TI). The symbol (X) indicates the selection of optimal bands in each band combination.

Best band combinations	745	746	892	932	934	958	961	989	JM value	%
Single band			X						1.342	94.91
Two bands			X		X				1.362	96.32
Three bands			X		X			X	1.378	97.45
Four bands			X		X	X	X		1.386	98.01
Five bands	X	X	X			X	X		1.393	98.51
Six bands	X	X	X		X	X	X		1.402	99.15
Seven bands	X	X	X	X		X	X	X	1.409	99.65
Eight bands	X	X	X	X	X	X	X	X	1.411	99.79

Table 5
The values of JM distance for each individual class pair within the selected best band combinations.

Best combination	CP vs. PA		CP vs. EP		CP vs. TI	
	J-M value	%	J-M value	%	J-M value	%
892	1.409	99.64	1.210	85.57	1.408	99.58
892, 934.	1.412	99.86	1.263	89.32	1.410	99.72
892, 934, 898.	1.413	99.93	1.308	92.50	1.413	99.93
892, 934, 958, 961,	1.414	100.00	1.329	93.99	1.414	100.00
745, 745, 892, 958, 961.	1.414	100.00	1.351	95.55	1.414	100.00
745, 745, 892, 934, 958, 961.	1.414	100.00	1.379	97.52	1.414	100.00
745, 746, 892, 932, 958, 961, 989.	1.414	100.00	1.399	98.94	1.414	100.00
745, 746, 892, 932, 934, 958, 961, 989.	1.414	100.00	1.405	99.36	1.414	100.00

2150 bands, because the dimensionality remained still high when only one technique was used (412 wavelengths from analysis of variance). This could be explained by firstly the agreement that there is no single technique that has universally proven superior for the optimal feature selection (Yang et al., 2005), and secondly, the possible existence of a different subset of features that discriminates the data equally well (Yeung et al., 2005). Hence, a new hierarchical method was developed based on the integration of three analysis levels (ANOVA, CART, and JM) to reduce the dimensionality in the field spectrometry measurement data conducted to discriminate papyrus from three other species. This is an important prerequisite for mapping papyrus swamps using airborne and satellite hyperspectral sensors. Results of this study show that the discrimination of papyrus from its associated species is possible at the field level using field spectrometry.

4.1. Differences in mean reflectance between papyrus and its associated species

Our results from the ANOVA test presented in Fig. 1 and Table 2 have shown that there is a significant difference in the mean reflectance between papyrus and each of the three species studied (PA, EP, and TI) in the red-edge, near-infrared, and mid-infrared regions. The wavelength regions with the greatest frequency of significant differences between papyrus and other species can be seen in a histogram in Fig. 2. These significant wavelengths are located in the red-edge region from 741 to 746 nm ($n = 6$) and in the near-infrared region from 892 to 1297 nm ($n = 406$). This confirms the results of previous studies that state that green leaves have greatest variation in the near-infrared and red-edge regions (Asner, 1998; Cochrane, 2000; Thenkabail et al., 2004; Daughtry and Walthall, 1998; Vaiphasa et al., 2005; Schmidt and Skidmore, 2003). Although no leaf biochemical properties were directly measured in this study, it is likely that the occurrence of significant wavelengths in the red-edge region (680–750 nm) is due to the variation between papyrus and other species on chlorophyll concentration, nitrogen concentration, and water content, (Mutanga and Skidmore, 2007; Curran et al., 1990, 1991; Fillella and Penuelas, 1994). This is because of the physiological evidence that papyrus is characterized by a tremendous amount of combined nitrogen, higher chlorophyll concentration, and higher rates in biomass production than most other wetland species (Muthuri and Kinyamario, 1989; Mwaura and Widdowson, 1992). Unlike the other species, papyrus is basically restricted to the area that is permanently either wet or flooded throughout the year. This results in a higher water content in a papyrus leaf compared to the other species. It is therefore assumed that the chlorophyll and nitrogen concentrations and water content vary significantly between papyrus and other species. The significant wavelengths in the near-infrared region, on the other hand, may be due to variation between papyrus and other species in the canopy structure (Kumar et al., 2001; Schmidt and Skidmore, 2003). The differences in canopy and leaf structure of the different species are shown in Fig. 3.

4.2. Band selection using classification and regression trees (CART)

CART has helped to reduce dimensionality in the significant wavelengths ($n = 412$) obtained from ANOVA as well as to identify the most sensitive wavelengths to discriminate papyrus (Questier et al., 2005; De'ath and Fabricius, 2000; Breiman et al., 1984; Van Aardt and Norris-Rogers, 2008). As we aimed to discriminate only papyrus swamp, CART was applied for each class pair individually (CP vs. PA, CP vs. EP, and CP vs. TI). Table 3 shows the bands selected and the misclassification error rate. Relative to other studies; the misclassification error rate of this study is very low (Questier et al., 2005; De'ath and Fabricius, 2000; Van Aardt and Norris-Rogers, 2008). Therefore we conclude that the selected bands in this analysis level are optimal bands for discriminating papyrus. The selected wavelengths were compared to wavelengths selected in the other previous studies as shown in Table 6. From Table 6 one can note that the bands selected not only in this study but also in the previous studies do not totally coincide with one other. This is explained mainly by the variation in concentration of pigments and the other optical properties and biochemical contents of the leaves between species, which leads to the different interactions within wavelengths of the electromagnetic regions (Asner, 1998; Schmidt and Skidmore, 2003; Kumar et al., 2001).

However, the general trend, especially within the red-edge and near-infrared regions, does exist between the studies which

Table 6
Frequency of wavelengths selected for species discrimination adapted into the four spectral domains defined by Kumar et al. (2001).

Wavelength regions (nm)	Reference	Selected bands (nm)
Visible (400–700)	Daughtry and Walthall (1998)	550, 670
	Schmidt and Skidmore (2003)	404, 628
	Vaiphasa et al. (2005)	0
	Thenkabail et al. (2002)	490, 520, 550, 575, 660, 675
	Thenkabail et al. (2004)	495, 555, 655, 675
	This study	0
Red-edge (680–750)	Daughtry and Walthall (1998)	720
	Schmidt and Skidmore (2003)	0
	Vaiphasa et al. (2005)	720
	Thenkabail et al. (2002)	700, 720
	Thenkabail et al. (2004)	705, 735
	This study	745, 746
Near-infrared (700–1300)	Daughtry and Walthall (1998)	800
	Schmidt and Skidmore (2003)	771
	Vaiphasa et al. (2005)	1277
	Thenkabail et al. (2002)	845, 905, 920, 975
	Thenkabail et al. (2004)	885, 915, 985, 1085, 1135, 1215, 1245, 1285
	This study	892, 932, 934, 958, 961, 989
Mid-infrared (1300–2500)	Daughtry and Walthall (1998)	0
	Schmidt and Skidmore (2003)	1398, 1803, 2183
	Vaiphasa et al. (2005)	1415, 1644
	Thenkabail et al. (2002)	0
	Thenkabail et al. (2004)	1445, 1675, 1725, 2005, 2035, 2235, 2295, 2345
	This study	0

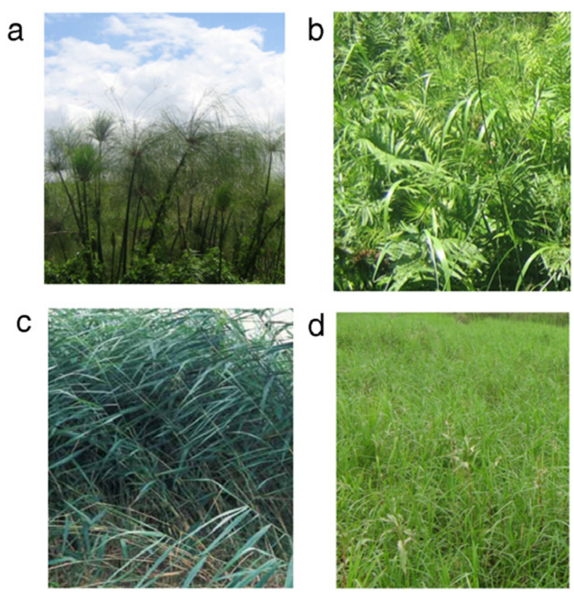

Fig. 3. Variations on canopy and leaf structure between the four species: (a) *Cyperus papyrus*, (b) *Thelypteris interrupta*, (c) *Phragmites australis*, and (d) *Echinochloa pyramidalis*. Surface leaf structure in *Cyperus papyrus* is relatively different from the other species.

reveal the relative importance of using different wavelengths of electromagnetic spectrum for species discrimination.

The study also confirms the advantages of CART as mentioned by De'ath and Fabricius (2000) which can be summarized as being: (1) a simple, easy, and fast nonparametric method regarding the input data and output, (2) in variance to monotonic transformation of the explanatory variables, (3) flexible in handling different dependent variables and highly discriminatory data. This data can be easily separated into individual classes or ignored without influencing the predication.

4.3. JM distance analysis

The JM distance analysis was used to assess the relative importance of band combinations in discriminating between papyrus and other species (CP vs. PA, CP vs. EP, and CP vs. TI) using selected bands by CART. We opted to use higher acceptable separability values (≥97%) rather than ≥95% which was used by Vaiphasa et al. (2005). This was done in order to achieve a precise selection of the most sensitive bands to discriminate papyrus. We found that some bands have more power for discriminating between papyrus and the other three species by having higher values of JM distance. This is clearly shown in Table 4, which shows that three bands located at 892 nm, 934 nm, and 989 nm can produce acceptable average separability (97.45%). The two class pairs CP vs. PA, and CP vs. TI are spectrally more distant than the other class pair (CP vs. EP) as is shown in Table 5. Papyrus, therefore, has greater potential of being separable from these two species (PA and TI) even with a single band located at 892 nm. This is explained by the differences in the distance separability between the vegetation species (Skidmore et al., 1988). As shown in Table 5, increasing the number of bands leads to an increase in the distance between the class pairs. For example, the four bands located at 892 nm, 934 nm, 958 nm, and 961 nm show maximum JM values for the two class pairs (CP vs. PA, and CP vs. TI). These maximum values (as measured using the JM distance) indicate best discrimination between papyrus and the two species at these selected bands. CP and EP are similar in spectra. Therefore, only six band combinations located at 961 nm, 745 nm, 934 nm, 746 nm, 892 nm, and 958 nm have the acceptable separability for the class pair, CP vs. EP. These six bands have the potential to discriminate papyrus from its entire co-existing species. These numbers of bands are consistent with previous studies that state that the best six band combinations have the greatest potential for better species discrimination (Schmidt and Skidmore, 2003). The results from this distance analysis predict the potential of correct discrimination of papyrus from its co-existing species using hyperspectral remote sensing (Schmidt and Skidmore, 2003; Vaiphasa et al., 2005).

5. Conclusions

From this study we can conclude that:

1. Field spectrometer measurements at canopy level can be used to discriminate *Cyperus papyrus* from *P. australis*, *E. pyramidalis*, and *T. interrupta*. This implies that the mean spectral reflectance of *Cyperus papyrus* is different from the other species associated with it in the same ecosystem (swamp wetlands).

2. Classification and regression trees (CART) can be used to reduce considerably the dimensionality and to select the most important bands for discriminating papyrus from the other species with a low rate of misclassification.

3. The use of CART has revealed that the greatest discrimination power for papyrus is located in the red-edge and near-infrared regions, specifically at 745 nm, 746 nm, 892 nm, 932 nm, 934 nm, 958 nm, 961 nm, and 989 nm. This shows the importance of the red-edge and near-infrared regions in species discrimination, thereby confirming previous studies that found strong spectral variation among the vegetation species in these regions of the electromagnetic spectrum.

4. Although a single band located at 892 nm can discriminate *Cyperus papyrus* from *P. australis* and *T. interrupta*, only six bands located at 745 nm, 746 nm, 892 nm, 934 nm, 958 nm, and 961 nm, show the potential to discriminate *Cyperus papyrus* from *E. pyramidalis*.

Overall, results of this study offer the possibility of extending field measurements at canopy level to airborne and satellite hyperspectral sensor data for discriminating *Cyperus papyrus* in swamp wetlands in South Africa.

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