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ORIGINAL PAPER

Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: a review

Elhadi Adam · Onisimo Mutanga · Denis Rugege

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Abstract Wetland vegetation plays a key role in the ecological functions of wetland environments. Remote sensing techniques offer timely, up-to-date, and relatively accurate information for sustainable and effective management of wetland vegetation. This article provides an overview on the status of remote sensing applications in discriminating and mapping wetland vegetation, and estimating some of the biochemical and biophysical parameters of wetland vegetation. Research needs for successful applications of remote sensing in wetland vegetation mapping and the major challenges are also discussed. The review focuses on providing fundamental information relating to the spectral characteristics of wetland vegetation, discriminating wetland vegetation using broad- and narrow-bands, as well as estimating water content, biomass, and leaf area index. It can be concluded that the remote sensing of wetland vegetation has some particular challenges that require careful consideration in order to obtain successful results. These include an in-depth understanding of the factors affecting the interaction between electromagnetic radiation and wetland vegetation in a particular environment, selecting appropriate spatial and spectral resolution as well as suitable processing techniques for extracting spectral information of wetland vegetation.

Keywords Biomass · Leaf area index · Mapping · Remote sensing · Water content · Wetland vegetation

E. Adam (✉) · O. Mutanga
Discipline of Geography, University of KwaZulu-Natal, P. Bag X01, Scottsville 3209, Pietermaritzburg, South Africa
e-mail: 205527619@ukzn.ac.za; emiadam2006@yahoo.com

E. Adam
Geography Department, Elfashir University, P. Bag 125, Elfashir, Sudan

D. Rugege
Centre for Environment, Agriculture & Development (CEAD), University of KwaZulu-Natal, Pietermaritzburg, South Africa

Introduction

Wetland vegetation is an important component of wetland ecosystems that plays a vital role in environmental function (Kokaly et al. 2003; Lin and Liquan 2006). It is also an excellent indicator for early signs of any physical or chemical degradation in wetland environments (Dennison et al. 1993).

Mapping and monitoring vegetation species distribution, quality, and quantity are important technical tasks in sustainable management of wetlands. This task involves a wide range of functions including natural resource inventory and assessment, fire control, wildlife feeding, habitat characterization, and water quality monitoring at a given time or over a continuous period (Carpenter et al. 1999). Moreover, it is essential to have up-to-date spatial information about the magnitude and the quality of vegetation cover in order to initiate vegetation protection and restoration programme (He et al. 2005).

Traditionally, species discrimination for floristic mapping requires intensive field work, including taxonomical information, collateral and ancillary data analysis, and the visual estimation of percentage cover for each species; this is labor intensive and costly and time-consuming and sometimes inapplicable due to the poor accessibility, and is thus, only practical on relatively small areas (Lee and Lunetta 1996). Remote sensing, on the other hand, offers a practical and economical means to discriminate and estimate the biochemical and biophysical parameters of the wetland species and it can make field sampling more focused and efficient. Its repeat coverage offers archive data for detection of change over time, and its digital data can be easily integrated into Geographic Information System (GIS) for more analysis (Shaikh et al. 2001; Ozesmi and Bauer 2002). For this advantage, many researchers have used both multi-spectral data such as Landsat TM and SPOT imagery to identify general vegetation classes or to attempt to discriminate broad vegetation communities (May et al. 1997; Harvey and Hill 2001; Li et al. 2005), and hyperspectral data to discriminate and map wetland vegetation at the species level (Belluco et al. 2006; Schmidt and Skidmore 2003; Rosso et al. 2005; Pengra et al. 2007; Vaiphasa et al. 2005). Moreover, the use of remote sensing techniques has been extended into measuring the biophysical and biochemical properties such as leaf area index (LAI), biomass, and water content of wetland vegetation (Rendong and Jiyuan 2004; Proisy et al. 2007; Penuelas et al. 1993a; Kovacs et al. 2005).

The rapid growth in the number of studies that have investigated the use of remote sensing in studying wetland species makes it necessary to provide an overview of the techniques that have been used and to identify those aspects that still need further investigation. This would be useful practically in wetland management and scientifically through highlighting the priorities and challenges for further research.

Previous reviews on remote sensing of wetlands included those by Silva et al. (2008) who discussed the theoretical background and applications of remote sensing techniques in aquatic plants in wetland and coastal ecosystems. Ozesmi and Bauer (2002) reviewed the classification techniques used to map and delineate different wetland types using different remotely sensed data. Lee and Lunetta (1996) reviewed the use and the cost of airborne and satellite sensors in the inventory of and change detection in wetlands. The review by Klemas (2001) addressed the current use of remote sensing and its opportunities pertinent in monitoring the environmental indicators in coastal ecosystems. Hardisky et al. (1986) reviewed different remotely sensed data for coastal wetlands and estimating biomass.

The limitation of the above-mentioned reviews is that no specific aspect of the application of remote sensing has been addressed individually and most of the reviews have been focused on the use of remote sensing in mapping and identification of wetland types at a broad level. There has been no specific review on the use of both hyperspectral and multi-spectral remote sensing in discriminating wetland vegetation as well as estimating its biophysical and biochemical properties which is essential in wetland management. Hence, this review focuses specifically on the application of remote sensing in discriminating and estimating the biophysical and biochemical properties of wetland vegetation.

The specific objectives of this study were to review the status of application of both multi-spectral and hyperspectral remotely sensed data in wetland vegetation with special focus on: (1) discriminating and mapping wetland vegetation, (2) estimating some of the biophysical and biochemical properties of wetland vegetation, and (3) highlighting the major challenges and further research needed for a successful application of remote sensing in wetland vegetation.

Challenges in mapping wetland vegetation

Wetland plants and their properties are not as easily detectable as terrestrial plants, which occur in large stratification. This is because of two reasons. First, herbaceous wetland vegetation exhibits high spectral and spatial variability because of the steep environmental gradients which produce short ecotones and sharp demarcation between the vegetation units

(Adam and Mutanga 2009; Zomer et al. 2008; Schmidt and Skidmore 2003). Hence, is often difficult to identify the boundaries between vegetation community types (Fig. 1). Second, the reflectance spectra of wetland vegetation canopies are often very similar and are combined with reflectance spectra of the underlying soil, hydrologic regime, and atmospheric vapour (Guyot 1990; Malthus and George 1997; Lin and Liquan 2006) (Fig. 1). This combination usually complicate the optical classification and results in a decrease in the spectral reflectance, especially in the near-to mid-infrared regions where water absorption is stronger (Fyfe 2003; Silva et al. 2008).Therefore, the current efforts which have been successful at mapping terrestrial vegetation using optical remote sensing, may not be able, either spatially or spectrally, to effectively distinguish the flooded wetland vegetations because the performance of near to mid-infrared bands are attenuated by the occurrences of underlying water and wet soil (Hestir et al. 2008; Zomer et al. 2008). However, hyperspectral narrow spectral channels offer the potential to detect and map the spatial heterogeneity of wetland vegetation (Hestir et al. 2008; Vaiphasa et al. 2007; Schmidt and Skidmore 2003).

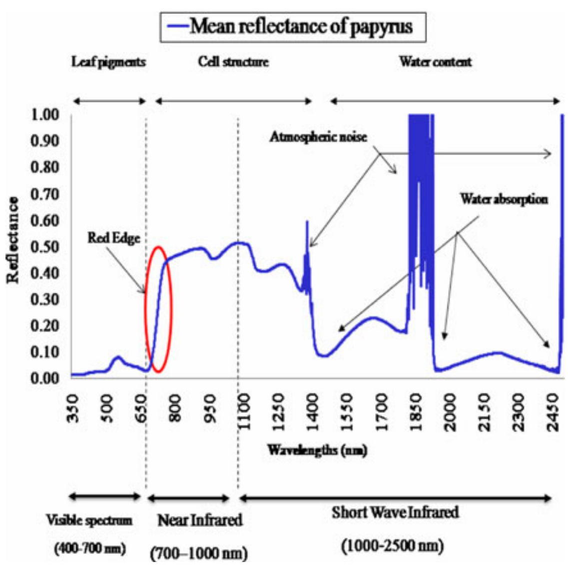

Fig. 1 Mean canopy reflectance spectra of *Cyperus papyrus L.* in swamp wetland with the dominating factor influencing each interval of the curve. Most of short wave infrared wavelengths (water content wavelength) are affected by atmospheric noise

Factors affecting spectral characteristics of wetland vegetation

When light solar radiation interacts with leaves, it may be reflected, absorbed, and/or transmitted. All vegetation species contain the same basic components that contribute to its spectral reflectance, including chlorophyll and other light-absorbing pigments, water, proteins, starches, waxes, and structural biochemical molecules, such as lignin and cellulose (Kokaly et al. 2003; Price 1992). Hence, the spectral separability of vegetation species is challenging due to those limiting factors affecting the spectral response of vegetation species (Price 1992; Rosso et al. 2005). In general, the spectral differences among vegetation species are normally derived from leaf optical properties related to the biochemical and biophysical status of the plants. Leaf optical properties depend on leaf surface and internal structure, leaf thickness, water content, biochemical composition, and pigment concentration (Kumar et al. 2001; Rosso et al. 2005). The spectral reflectance of wetland vegetation is normally subdivided into four domains. Vegetation types generally have a high reflectance and transmittance in the near-infrared region and strong water absorption in the mid-infrared region (Table 1, Fig. 1).

The most important factors affecting the spectral reflectance among wetland vegetation are the biochemical and biophysical parameters of the plants' leaves and canopy such as chlorophyll a and b, carotene, and xanthophylls (Kumar et al. 2001; Guyot 1990). Wetland species appear to vary greatly in chlorophyll and biomass reflectance as a function of plant species and hydrologic regime (Anderson 1995). Spectral behaviour of wetland vegetation is also influenced by leaf water content which determines the absorption of the mid-infrared region (Datt 1999). Red reflectance increases with leaf water stress through an association with a reduction in chlorophyll concentration (Fillella and Penuelas 1994).The relationship between increasing of near-infrared leaf reflectance and decrease of leaf water content has also been reported (Aldakheel and Danson 1997). For example, Lin and Liquan (2006) compared the laboratory and field spectral characteristics of the submerged plant (Vallisneria *spiralis*) in the constructed wetland at Shanghai in China. They found that the spectral reflectance measured by the ground-based spectroradiometer sensor was a

Table 1 The spectral reflectance of green vegetation on the four regions of electromagnetic spectrum defined by defined by Kumar et al. (2001)

Wavelengths region (nm)	Description	Spectral reflectance of vegetation	References
400–700	Visible	Low reflectance and transmittance due to chlorophyll and carotene absorption	Kumar et al. (2001) Rosso et al. (2005)
680–750	Red-edge	The reflectance is strongly correlated with plant biochemical and biophysical parameters	Mutanga and Skidmore (2007) Clevers (1999)
700–1,300	Near-infrared	High reflectance and transmittance, very low absorption. The physical control is internal leaf structures	Kumar et al. (2001) Rosso et al. (2005)
1,300–2,500	Mid-infrared	Lower reflectance than other spectrum regions due to strong water absorption and minor absorption of biochemical content	Kumar et al. (2001)

combination of plant spectra, segmental water, and fundus spectrum.

Leaf area index (LAI) is also a key variable in the canopy reflectance of the wetland vegetation. The canopies with a high LAI reflect more than the canopies with medium or low LAI. However, higher LAI canopies allow only little light radiation to reach to the mature leaves under vegetation canopies and the soil background (Abdel-Rahman and Ahmed 2008; Darvishzadeh et al. 2008). Studies show that the spectral signature of the tropical wetland canopies is also affected by the different seasons, plant architecture, and illumination angle (Cochrane 2000; Artigas and Yang 2005; Darvishzadeh et al. 2008).

Mapping wetland vegetation using multi-spectral data

Historically, aerial photography was the first remote sensing method to be employed for mapping wetland vegetation (e.g. Seher and Tueller 1973; Shima et al. 1976; Lehmann and Lachavanne 1997; Howland 1980). Theses studies concluded that aerial photography is most useful for detailed wetland mapping because of its minimum mapping unit (MMU). However, aerial photography is not feasible for mapping and monitoring wetland vegetation on a regional scale or for monitoring that requires continual validation of information because it is costly and time-consuming to process.

Currently, a variety of remotely sensed images are available for mapping wetland vegetation at different levels by a range of airborne and space-borne sensors from multi-spectral sensors to hyperspectral sensors which operate within the different optical spectrum, with different spatial resolutions ranging from sub-metre to kilometres and with different temporal frequencies ranging from 30 minutes to weeks or months. Among them, aerial photography, Landsat TM, and SPOT images were commonly investigated in mapping vegetation types in wetlands. The common image analysis techniques used in mapping wetland vegetation include digital image classification (i.e. unsupervised and supervised classification) (May et al. 1997; McCarthy et al. 2005; Harvey and Hill 2001) and vegetation index clustering (Nagler et al. 2001; Yang 2007). May et al. (1997) compared Landsat TM and SPOT multi-spectral data in mapping shrub and meadow vegetation in northern California. They concluded that Landsat TM data were more effective than SPOT data in separating shrubs from meadows. But neither Landsat TM nor SPOT data were effective to distinguish meadow subtypes. McCarthy et al. (2005) in Botswana found that the high spatial and temporal variation in vegetation in the Okavango Delta makes ecoregion classification from Landsat TM data unsatisfactory for achieving land cover classification. In Australian wetlands, Landsat TM has proven to be a potential source of defining vegetation density, vigour, and moisture status, but not efficient in defining the species composition (Johnston and Barson 1993).Harvey and Hill (2001) in the Northern Territory, Australia, compared aerial photographs, SPOT XS, and Landsat TM image data to determine the accuracy and applicability of each data source for the spectral discrimination of vegetation types. Their results demonstrated that aerial photography was clearly superior to SPOT XS and Landsat TM imagery for detailed mapping of vegetation communities in the tropical wetland. They also found that the sensitivity of Landsat band 2 (green), band 3 (red), band 4 (near-infrared, NIR), and band 5 (MIR) provided a more accurate classification than SPOT. Ringrose et al. (2003) used NOAA-AVHRR and SPOT to map the ecological conditions at the Okavango delta in Botswana. It was difficult to discriminate grassed floodplain from wooded peripheral drylands. Sawaya et al. (2003) at Minnesota in USA were able to map the vegetation groups at a local scale using IKONOS imagery with a high level of classification accuracy (80%).

Imagery from the Landsat TM and SPOT satellite instruments have proven insufficient for discriminating vegetation species in detailed wetland environments (Harvey and Hill 2001; McCarthy et al. 2005; May et al. 1997).This is due to: (1) the difficulties faced in distinguishing fine, ecological divisions between certain vegetation species, (2) the broad nature of the spectral wavebands with respect to the sharp ecological gradient with narrow vegetation units in wetland ecosystems, and (3) the lack of high spectral and spatial resolution of optical multi-spectral imagery which restricts the detection and mapping of vegetation types beneath a canopy of vegetation, in densely vegetated wetlands.

Although these studies produced reasonable results on mapping wetland vegetation at a regional scale and vegetation communities, more research is needed to explore the benefits of incorporating bathymetric and other auxiliary data to improve the accuracy of mapping wetland vegetation at the species level.

Improving the accuracy of wetland vegetation classification

Spectral discrimination between vegetation types in complex environments is a challenging task, because commonly different vegetation types may possess the same spectral signature in remotely sensed images (Sha et al. 2008; Xie et al. 2008). Traditional digital imagery from multi-spectral scanners is subject to limitations of spatial, spectral, and temporal resolution. Moreover, applications of per-pixel classifiers to images dominated by mixed pixels are often incapable of performing satisfactorily and produce inaccurate classification (Zhang and Foody 1998). Due to the complexities involved, more powerful techniques have been developed to improve the accuracy of discriminating vegetation types in remotely sensed data.

Domacx and Suzen (2006) in the Amanos Mountains region of southern-central Turkey used knowledge-based classifications in which they combined Landsat TM images with environmental variables and forest management maps to produce regional scale vegetation maps. They were able to produce an overall high accuracy when compared with the traditional maximum likelihood classification method. Another example for improving classification accuracy by incorporating vegetation-related environmental variables using GIS with remotely sensed data was the work of that of Yang (2007) at Hunter Region in Australia. He used digital aerial photographs, SPOT-4, and Landsat-7 ETM+ images for riparian vegetation delineation and mapping. The overall vegetation classification accuracy was 81% for digital aerial photography, 63% for SPOT-4, and 53% for Landsat-7 ETM+. The study revealed that the lack of spectral resolution of aerial photograph and the coarse spatial resolution of the current satellite images is the major limiting factor for their application in wetland vegetation mapping,

Artificial neural network (ANN) and fuzzy logic approaches were also investigated to improve the accuracy of mapping vegetation types in complex environments. ANN proved to be valuable in mapping vegetation types in wetland environments. One disadvantage of ANN, however, is that ANN can be computationally demanding to train the network when large datasets are dealt with (Filippi and Jensen 2006; Xie et al. 2008). Berberoglu et al. (2000) at the Cukurova Deltas in Turkey combined ANN and texture analysis on a per-field basis to classify land cover from Landsat TM. They were able to increase the accuracy achieved with maximum likelihood classification by 15%. Carpenter et al. (1999) compared conventional expert methods and the ARTMAP neural network method in mapping vegetation types at the Sierra National Forest in Northern California using Landsat TM data. Their research illustrated that the accuracy was improved from 78% in conventional expert methods to 83% when the ARTMAP neural network method was used. The ARTMAP neural network method was found to be less time-consuming and its production to be easily updated with any new observation.

A fuzzy classification technique, which is a kind of probability-based classification rather than a crisp classification, is also useful in mixed-class areas and was investigated for solving the problem of mapping complex vegetation. Sha et al. (2008) at the Xilinhe River Basin in China employed a hybrid fuzzy classifier (HFC) for mapping vegetation on typical grassland using Landsat ETM+ imagery. It was concluded that HFC was much better than conventional supervised classification (CSC) with an accuracy percentage of 80.2% as compared to 69.0% for the CSC. Promising results have also been achieved in using fuzzy classification for suburban land cover classification from Landsat TM and SPOT HRV data by Zhang and Foody (1998) at Edinburgh in Scotland. They concluded that fuzzy classification not only has advantages over conventional hard methods and partially fuzzy approaches, but also is more feasible in integrating remotely sensed data and ancillary data.

Decision tree (DT) classification has also shown promising results in mapping vegetation in wetlands and complex environments. DT is a simple and flexible non-parametric rule-based classifier and it can handle data that are represented on different measurement scales. This is useful especially when there is a need to integrate the environmental variables (e.g. slope, soil type, and rainfall) in the mapping process (Xu et al. 2005; Xie et al. 2008). Xu et al. (2005) at Syracuse in New York employed a decision tree and regression (DTR) algorithm to determine class proportions within a pixel so as to produce soft land cover classes from Landsat ETM. Their results clearly demonstrate that DTR produces considerably higher soft classification accuracy (74.45%) as compared to the conventional maximum likelihood classifier (MLC) (55.25%) and the supervised FCM (54.40%).

It has been revealed from the present review that no single classification algorithm can be considered as an optimal methodology for improving vegetation discriminating and mapping. Hence, the use of advanced classifier algorithms must be based on their suitability to achieve certain objectives in specific areas.

Spectral discrimination of wetland species using hyperspectral data

In remote sensing, the term 'imaging spectroscopy' is synonymous with some other terms such as 'imaging spectrometery' and 'hyperspectral' or 'ultraspectral imaging' (Clark 1999). In general, hyperspectral remote sensing has hundreds of narrow continuous spectral bands between 400 and 2,500 nm, throughout the visible (0.4–0.7 nm), near-infrared (0.7–1 nm), and short wave infrared (1–2.5 nm) portions of the electromagnetic spectrum (Govender et al. 2006; Vaiphasa et al. 2005). This greater spectral dimensionality of hyperspectral remote sensing allows in-depth examination and discrimination of vegetation types which would be lost with other broad band multi-spectral scanners (Cochrane 2000; Schmidt and Skidmore 2003; Mutanga et al. 2003; Govender et al. 2006). Hyperspectral remote sensing data is mostly acquired using a hand-held spectrometer or airborne sensors. A hand-held spectrometer is an optical instrument used for measuring the spectrum emanating from a target in one or more fixed wavelengths in the laboratory and the field (Kumar et al. 2001). The accurate measurements of the spectral reflectance in the field were established in the 1960s as result of the rapid growth in airborne multispectral scanners (Milton et al. 2007). Historically, the application focused on the structure of matter. Recently, however, the application has been broadened, including other aspects of electromagnetic and non-electromagnetic radiation.

In the last twenty years, field spectrometery has been playing vital roles in characterizing the reflectance of vegetation types in situ, and providing a means of scaling-up measurement at both of field (canopy and leaves) and laboratory levels (Milton et al. 2007). Many attempts have been successfully made to discriminate and classify wetland species based on their fresh leaf reflectance at laboratory levels with the view to scaling it up to airborne remote sensing (e.g. Vaiphasa et al. 2005, 2007) and field reflectance at canopy scale (e.g. Best et al. 1981; Penuelas et al. 1993b; Schmidt and Skidmore 2003; Rosso et al. 2005).

The earliest effort on spectral discrimination of wetland species was that of Anderson (1970) who attempted to evaluate the discrimination of ten marsh-plant species which dominated a wetland in Chesapeake Bay using ISCO Model SR Spectroradiometer. He concluded that the spectral difference between the species is minor in the visible spectrum, but significant in the near-infrared. The variation in the spectral reflectance with the changing seasons was also reported in the study. Best et al. (1981) investigated the use of four bands of Exotech radiometer to discriminate between the vegetation types which dominated the Prairie Pothole in the Dakotas. The spectral measurements were taken from ten common species during the periods of early-emergent, flowering, early-seed, and senescent phenological stages. Their findings showed that the best period to discriminate among the eight species studied was during the flowering and early-seed stages. However, it was difficult to differentiate reed (*Sparganium euryeapum)* from the other species. It was also concluded that a single species, in different phenological stages, showed significant variation in its spectral reflectance. Schmidt and Skidmore (2003) used the spectral reflectance measured at canopy level with A GER 3700 spectrometer from 27 wetland species to evaluate the potential of mapping coastal saltmarsh vegetation associations (mainly consisting of grass and herbaceous species) in the Dutch Waddenzee wetland. It was found that the reflectance in six bands distributed in the visible, near-infrared, and shortwave infrared were the optimal bands for mapping saltmarsh vegetation (Table 2). Fyfe (2003) attempted to discriminate three coastal wetland species (*Zostera capricorni, Posidonia australis*, and *Halophila ovalis*) in Australia. Using a single-factor analysis of variance and multivariate techniques, it was possible to distinguish among the three species by their reflectance in the wavelengths between 530–580, 520–530, and 580–600 nm. However, the differences were more significant between 570 and 590 nm. Rosso et al. (2005) in California, USA, collected spectral reflectance data from five species (*Salicornia, S. foliosa, S. foliosa, S. alterniflora,* and *Scirpus)* using an Analytical Spectral Device (ASD) full-range (0.35–2.5 nm) PS II spectrometer to assess the separability of the marsh species under controlled conditions. Spectral Mixture Analysis (SMA) and Multiple Endmember Spectral Mixture Analysis (MESMA) were used on the AVIRIS data. Using both SMA and MESMA, it was possible to distinguish between the species with higher classification accuracies. However, the MESMA technique appeared to be more appropriate because it could incorporate more than one endmember per class. Similar work was also conducted by Li et al. (2005) who were able to use AVIRIS imagery to discriminate three salt marsh species (*Salicornia, Grindelia,* and *Spartina*) in China and in San Pablo Bay of California, USA. They developed a model that mixed the spectral angle together with physically meaningful fraction and the rms. The results were satisfactory considering the success in discriminating the two marsh vegetation species (*Spartina* and *Salicornia)*, which covered 93.8% of the marsh area. However, it was difficult to discriminate *Grindelia* from *Spartina* and *Salicornia* due to the spectral similarity between the species. Becker et al. (2005) were able to use a modified version of the slope-based derivative analysis method to identify the optimal spectral bands for the differentiation of coastal wetland vegetation. They transformed hyperspectral data measured by the SE-590 spectroradiometer at canopy level into a second-derivative analysis. Six bands were found across the visible and near-infrared region to be powerful for discriminating the coastal wetland species.

In Thailand, Vaiphasa et al. (2005) were able to identify and distinguish 16 vegetation types in a mangrove wetland in Chumporn province. Their research was conducted by collecting hyperspectral reflectance data using a spectroradiometer (FieldSpec Pro FR, Analytical Spectral Device, Inc.), under laboratory conditions. The results of one-way ANOVA with a 95% confidence level ($P < 0.05$), and Jeffries–Matusita (JM) distance indicated that the best discrimination of the 16 species is possible with four bands located in the red-edge and near-infrared and mid-infrared regions of the electromagnetic spectrum (Table 2) Vaiphasa et al. (2007) also used the same spectral data set to compare the performance of genetic algorithms (GA) and random selection using t-tests in selecting key wavelengths that are most sensitive in discriminating between the 16 species. The JM distance was used as an evaluation tool. The results showed that the separability of band combinations

Table 2 Frequency of wavelengths selected in some studies for mapping wetland vegetation adapted into the four spectral domains defined by Kumar et al. (2001)

Wavelengths regions (nm)	References	Selected bands (nm)
Visible (400–700)	Daughtry and Walthall (1998)	550, 670
	Schmidt and Skidmore (2003)	404, 628
	Thenkabail et al. (2002)	490, 520, 550, 575, 660, 675
	Thenkabail et al. (2004)	495, 555, 655, 675
Red-edge (680–750)	Daughtry and Walthall (1998)	720
	Vaiphasa et al. (2005)	720
	Thenkabail et al. (2002)	700, 720
	Thenkabail et al. (2004)	705, 735
	Adam and Mutanga (2009)	745,746
Near-infrared (700–1,300)	Daughtry and Walthall (1998)	800
	Schmidt and Skidmore (2003)	771
	Vaiphasa et al. (2005)	1,277
	Thenkabail et al. (2002)	845, 905, 920, 975
	Thenkabail et al. (2004)	885, 915, 985, 1,085, 1,135, 1,215, 1,245, 1,285
	Adam and Mutanga (2009)	892, 932, 934, 958, 961, 989
Mid-infrared (1,300–2,500)	Schmidt and Skidmore (2003)	1,398, 1,803, 2,183
	Vaiphasa et al. (2005)	1,415, 1,644
	Thenkabail et al. (2004)	1,445,1,675, 1,725, 2,005, 2,035, 2,235, 2,295, 2,345

selected by GA was significantly higher than the class separability of randomly selected band combinations with a 95% level of confidence ($\alpha = 0.05$). Mangrove wetland species were also discriminated and mapped in Malaysia by Kamaruzaman and Kasawani (2007) who were able to use ASD Viewspec Pro-Analysis to collect the spectral reflectance data from five species at Kelantan and Terengganu, namely *Rhizophora apiculata*, *Bruguiera cylindrica, Avicennia alba, Heritiera littoralis,* and *Hibiscus tiliaceus.* The canonical stepwise discriminant analysis revealed that the five species were spectrally separable at five wavelengths (693, 700, 703, 730, and 731 nm) located in the red-edge and near-infrared region.

Wang et al. (2007) attempted to map highly mixed vegetation in salt marshes in the lagoon at Venice in Italy. Six significant bands of Compact Airborne Spectral Imager (CASI) were selected using Spectral Reconstruction (SR).The results showed that accuracy of Vegetation Community based Neural Network Classifier (VCNNC) can be used effectively in the situation of mixed pixels, thus, it yielded an accuracy higher (91%) than the Neural Network Classifier (84%). Another attempt in discriminating marsh species was that by Artigas and Yang (2005) in the Meadowlands District in north-eastern New Jersey, USA. They conducted a study to characterize the plant vigour gradient using hyperspectral remote sensing with field-collected seasonal reflectance spectra of marsh species in a fragmented coastal wetland. Their results indicated that near-infrared and narrow wavelengths (670–690 nm) in the visible region can be used to discriminate between the most marsh species. However, it was difficult to discriminate between the two *Spartina* species because they belong to the same genus. It was concluded that these mixed pixels could be minimized using pixel unmixing techniques to discover the linear combinations of spectra associated with the pixels.

In summary, Most of the previous studies have stated that wetland vegetation 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). Hence, most of the wavelengths selected to map wetland vegetation were mainly allocated in near infrared and red-edge regions of the electromagnet spectrum (Table 2).

More work is needed to build comprehensive spectral libraries for different wetland plants. Hyperspectral imagery proved to be useful in discriminating wetlands species with higher accuracy. However, hyperspectral imagery is expensive to acquire, time-consuming to process, even when small areas are covered. Innovative new methods which take advantage of the relatively large coverage and high spatial resolution of the fine sensors and the high spectral resolution of hyperspectral sensors could result in more accurate discrimination models of wetland species with a reasonable cost.

Estimating biophysical and biochemical parameters of wetland species

The main biochemical constituents found in vegetation are nitrogen, plant pigment, and water. Whereas biophysical properties of the plant include LAI, canopy architecture and density, and biomass (Govender et al. 2006), estimating the biochemical and biophysical properties of wetland vegetation is a critical factor for monitoring the dynamics of the vegetation productivity, vegetation stress, or nutrient cycles within wetland ecosystems (Asner 1998; Mutanga and Skidmore 2004). The most important biochemical and biophysical properties that characterize the wetland species are: chlorophyll and biomass concentration, and leaf water content (Anderson 1995). Few studies, however, have been conducted to study these properties that affect wetland plant canopies using both multi-spectral and hyperspectral remote sensing.

Mapping wetland biomass

Estimating wetland biomass is necessary for studying productivity, carbon cycles, and nutrient allocation (Zheng et al. 2004; Mutanga and Skidmore 2004). Many studies of field biomass have used vegetation indices based on the ratio of broadband red and near-infrared reflectance. Ramsey and Jensen (1996) in the USA used a helicopter platform to measure spectra of the canopies of four species which dominated in south-west Florida to describe the spectral and structural change within and between the species and community types. Reflectance values were generated from the canopy spectral data to correspond with AVHRR (bands 1 and 2), Landsat TM (bands 1–4), and XMS SPOT (bands 1–3) sensors. The relationship between canopy structure and reflectance showed the difficulties of discrimination of mangrove species based on optical properties alone. Moreover, species composition was not correlated to any combination of reflectance bands or vegetation index. However, the study revealed the possibility of estimation of vegetation biomass such as LAI using red and near-infrared bands on various sensors.

Tan et al. (2003) used Landsat ETM bands 4, 3, and 2 false colour, and field biomass data to estimate wetland vegetation biomass in the Poyang natural wetland, China. Linear regression and statistical analyses were performed to determine the relationship among the field biomass data and some transformed data derived from the ETM data. Their results indicated that sampling biomass data has the best positive correlation to Difference Vegetation Index (DVI) data. The authors developed a linear regression model to estimate the total biomass of the whole Poyang Lake natural conservation area. Similarly, Rendong and Jiyuan (2004) at Poyang in China, attempted to estimate the vegetation biomass in a large freshwater wetland using the combination of Landsat ETM data, GIS (for analyses and projecting both the sampling and Landsat ETM data), and GPS for (field biomass data). The results showed that the sampling of biomass data was best relative to the ETM 4 data with the highest coefficient of 0.86, at the significance level of 0.05. The study revealed that the near-infrared band could be used to estimate the wetland vegetation biomass.

The use of coarser spatial resolution sensors e.g. (VHR) IKONOS and AVHRR images has also been investigated in estimating wetland biomass. Proisy et al. (2007) created a new textural analysis method in which they applied Fourier-based Textural Ordination (FOTO) in 1 m panchromatic and 4 m infrared IKONOS images to estimate and map high biomass in forest wetland in French Guiana in the Amazon. Their work yielded accurate predictions of mangrove total aboveground biomass from both 1 m and 4 m IKONOS images. However, the best results were obtained from 1 m panchromatic with the maximum coefficient determination (R^2) above 0.87.

Moreau et al. (2003) investigated the potential and limits of two methods to estimate the biomass production of Andean wetland grasses in the Bolivian

Northern Altiplano from NOAA/AVHRR. The first method was based on monthly field biomass measurement and the second one was based on Bidirectional Reflectance Distribution Function (BRDF) normalized difference vegetation index (NDVI). Their results showed that BRDF normalized NDVI was sensitive to the green leaf or photosynthetically active biomass. The study also revealed that the optimal time for estimating the biomass with remotely sensed data in wetland species is during the growing season.

The limitations of using vegetation indices such as NDVI for estimation of biomass, especially where the soil is completely covered by the vegetation, have been reported in the literature. This is due mainly to the saturation problem (Thenkabail et al. 2000; Mutanga and Skidmore 2004). Nevertheless, Mutanga and Skidmore (2004) developed a new technique to resolve this saturation problem. They compared the use of band depth indices calculated from continuum-removed spectra with two narrow band NDVIs calculated using near-infrared and red bands to estimate *Cenchrus ciliaris* biomass in dense vegetation under laboratory conditions. The results clearly showed that band depth analysis approach proved to be efficient with a high coefficient in estimating biomass in densely vegetated areas where NDVI values are restricted by the saturation problem.

Estimation of leaf and canopy water content in wetland vegetation

Water availability is a critical factor in wetland plants' survival. There has been a rapid growth in remote sensing research to assess the vegetation water content as an indicator for the physiological status of plants, fire potential, and ecosystem dynamics at both laboratory and field level using very high resolution spectrometers such as the ASD spectral device with spectral sampling intervals of less than 2 nm (Toomey and Vierling 2006; Liu et al. 2004; Stimson et al. 2005). However, no significant research has been carried out on estimating water content in wetland plants especially. This is because the studies using remote sensing on wetland plants have been aimed mainly at discriminating and mapping, rather than estimating plant physiology such as water content and water stress.

Quite a number of different indices and techniques have been developed for estimating plant water content using the absorption features throughout the mid-infrared region (1,300–2,500 nm) of the electromagnetic spectrum e.g. in Netherlands (Clevers and Kooistra 2006), Canada (Davidson et al. 2006), and USA (Gao 1996). The authors determined the canopy water content by scaling the foliar water content (FWC, %) with the specific leaf area (SLA, LAI), and the percent canopy cover for a specific forest canopy. However, Ceccato et al. (2001) noted that this technique relies on estimation of SLA, which varies according to species and phenological status.

Work by Penuelas et al. (1993a) found the water band index (WI), which has been developed based on the ratio between the water band 970 nm and reflectance at 900 nm, to be strongly correlated with relative plant water content. Using reflectance at 857 and 1,241 nm, Gao (1996) developed the normalized difference water index (NDWI) in California in USA to estimate the vegetation water. The results showed that the NDWI is less sensitive to atmospheric scattering effects than NDVI and it is useful in predicting water stress in canopies and assessing plant productivity. It was recommended that further investigation is needed in order to understand this index better by testing it with the new generation of satellite instruments such as MODIS and SPOT-VEGETATION. Less sensitive semi-empirical indices for atmospheric scattering have also been developed by Datt (1999) to determine the relationship between spectral reflectance of several *Eucalyptus* species and both the gravimetric water content and equivalent water thickness (EWT). The results showed that EWT was significantly correlated with reflectance in several wavelength regions. However, no significant correlations could be obtained between reflectance and gravimetric water content.

The use of remote sensing in estimating plant water content is challenging because it is difficult to distinguish the contribution made by foliar liquid water and atmospheric vapour on the water-related absorption spectrum. This is because the absorption band related to water content is also affected by atmospheric vapour (Liu et al. 2004) (Fig. 1). Attempts have been made to minimize the atmospheric interference by using red-edge position which is located outside the water absorption bands. In China, Liu et al. (2004) found a significant correlation between plant water content with the red-edge width in six different growth stages of wheat plants. The correlation coefficients were between 0.62 and 0.72 at 0.999 confidence level. The results were more reliable than those obtained using the WI and the NDWI. Similar results were reported in the USA by Stimson et al. (2005) who correlated foliar water content with the red-edge position to evaluate the relationship between foliar water content and spectral signals in two coniferous species: *Pinus edulis* and *Juniperus monosperma*. The results showed significant correlations of $R^2 = 0.45$ and $R^2 = 0.65$ respectively.

As there has been no significant research on estimating water content and water stress of wetland vegetation specifically, additional studies on these aspects are needed to better understand the spectral response of wetland plants. The results of such research could help the researcher to develop accurate models for describing, for example, the separability of wetland plant varieties and for estimating foliar nutrients and developing indicators that can quantify the integrated condition of wetland plants and can identify their primary stressors across a range of scales.

Estimating leaf area index of wetland vegetation

Leaf area index (LAI) is defined as the total one-sided area of all leaves in the canopy per unit ground surface area (m^2/m^2) (Gong et al. 2003). Information on LAI is valuable for quantifying the energy and mass exchange characteristics of terrestrial ecosystems such as photosynthesis, respiration, evapotranspiration, primary productivity, and crop yield (Kumar et al. 2001; Gong et al. 1995). Research efforts on estimating LAI from spectral reflectance measurements have been focused mainly on forests (e.g. Schlerf et al. 2005; Gong et al. 1995, 2003; Pu et al. 2005; Davi et al. 2006) and crops (e.g. Thenkabail et al. 2000; Hansen and Schjoerring, 2003; Pay et al. 2006). However, regardless of the work that has been done at Majella National Park, in Italy by Darvishzadeh et al. (2008), the estimation of LAI for heterogeneous grass canopies has not been done. Moreover, a few studies dealing specifically with estimating LAI of wetland species have been conducted only in forest wetlands and mangrove wetlands (Green et al. 1997; Kovacs et al. 2004, 2005).

In general, the above-mentioned studies have investigated several analytical techniques to estimate LAI from reflectance data. This can be grouped into two main techniques: the stochastic canopy radiation model and the empirical model. The empirical model has been more widely investigated than the stochastic canopy radiation model. The univariate regression analysis with vegetation indices such as NDVI and simple ratio, derived from visible and near-infrared wavelengths, is the most widely used empirical model and has been used in estimating LAI (Thenkabail et al. 2000; Gong et al. 1995, 2003; Green et al. 1997; Kovacs et al. 2004; Schlerf et al. 2005; Kovacs et al. 2005).

Green et al. (1997) in UK developed a model based on gap-fraction analysis and NDVI derived from Landsat TM and SPOT XS to estimate LAI from three species: *Rhizophora mangle, Laguncularia racemosa*, and *Avicennia germinans* in mangrove wetland in West Indies. The model produced a thematic map of LAI with a high accuracy (88%) and low mean difference between predicted and measured LAI (13%).

Vegetation indices derived from high spatial resolution data were shown to be effective in monitoring LAI in mangrove forests. Kovacs et al. (2004) tested the relationship between in situ estimates of LAI and vegetation indices derived from IKONOS imagery in a degraded mangrove forest at Nayarit, Mexico. Regression analysis of the in situ estimates showed strong linear relationships between LAI and NDVI and simple ratio. Moreover, no significant differences were found between the simple ratio and NDVI models in estimating LAI at both plot sizes. In the same area, Kovacs et al. (2005) examined the potential of IKONOS in mapping mangrove LAI at the species level. A hand-held LAI-2000 sensor was also evaluated for the collection of data on the in situ mangrove LAI as a non-destructive alternative for the field data collection procedure. A strong significant relationship was found between NDVI, derived from IKONOS data, and in situ LAI collected with a LAI-2000 sensor. It was concluded that IKONOS satellite data and the LAI-2000 could be an ideal method for mapping mangrove LAI at the species level.

Researchers have shown that vegetation indices (VIs) derived from the narrow-band could be vital for providing additional information for quantifying the biophysical characteristics of vegetation such as LAI (Blackburn and Pitman 1999; Mutanga and Skidmore 2004). In wetland environments specifically, however, only one work, that by Darvishzadeh et al. (2008) at Majella National Park in Italy, has investigated the use of hyperspectral data in estimating and predicting LAI for heterogeneous grass canopies, in Italy. The study investigated the effects of dark and light soil and plant architecture on the retrieval of LAI red and near-infrared reflectance. Using A GER 3700 spectroradiometer, the spectral reflectances were measured from four different plant species (*Asplenium nidus, Halimium umbellatum, Schefflera arboricola Nora,* and *Chrysalidocarpus decipiens*) with different leaf shapes and sizes under laboratory conditions; then many VIs were calculated and tested. A stronger relationship was found between LAI and narrow-band VIs in light soil than in dark soil. However, the narrow-band simple ratio vegetation index (RVI) and second soil-adjusted vegetation index (SAVI2) were found to be the best overall choices in estimating LAI.

Although reasonable results were obtained from narrow-band VIs in estimating LAI (Darvishzadeh et al. 2008; Pay et al. 2006; Thenkabail et al. 2000), some authors noted that the strengths of a large number of hyperspectral bands have not yet been exploited by these methods because only two bands from red and near-infrared regions are used to formulate the indices (Schlerf et al. 2005; Hansen and Schjoerring 2003). A technique such as multiple linear regression (MLR) which uses the advantages of the high dimensionality of the hyperspectral data to select optimal band combinations to formulate VIs, was shown to be effective at estimating the biophysical and biochemical properties of vegetation such as LAI (Schlerf et al. 2005; Thenkabail et al. 2000).

Despite some success in estimating the biochemical and biophysical parameters in some ecosystems, estimation remains challenging in wetland environments where visible and near-infrared canopy reflectance has been revealed to be strongly affected by the background of soil and water, and atmospheric conditions. Further research is needed to develop indices that can reduce the effects of background and atmospheric quality.

Overall challenges and future research

Over the last few decades, considerable progress has been made in applying sensor techniques and data processing in discriminating, mapping, and monitoring wetland species. However, there are still challenges to be addressed in many aspects. First, traditional digital imagery from multi-spectral scanners is subject to limitations of spatial and spectral resolution compared to narrow vegetation units that characterize wetland ecosystems.

Second, despite the agreement on the effective performance of hyperspectral data in discriminating wetland species, the reflectances from different vegetation species are highly correlated because of their similar biochemical and biophysical properties. Furthermore, these properties are directly influenced by environmental factors and therefore the unique spectral signature of the plant species has become questionable (Price 1994). In addition, spectral variations can also occur within a species because of age differences, micro-climate, soil and water background, precipitation, topography, and stresses.

Third, measurement of the biophysical and biochemical properties of vegetation using VIs derived from broadband sensors can be unstable due to the underlying soil types, canopy and leaf properties, and atmospheric conditions. For example, NDVI asymptotically saturate after a certain biomass density and for a certain range of LAI (Mutanga and Skidmore 2004). Hence, the measurement accuracy drops considerably (Thenkabail et al. 2000; Gao et al. 2000).

A fourth research challenge is that in most African countries (e.g. South Africa) there are only a handful of studies that have used hyperspectral data to characterize savanna vegetation due to high cost and poor accessibility (e.g. Mutanga et al. 2004; Mutanga and Kumar 2007; Mutanga and Skidmore 2004) Also, no research has yet been carried out on discriminating wetland vegetation and estimating its biophysical and biochemical parameters using process-based models that use remotely sensed data as input parameters.

Despite these shortcomings, there is no doubt that remote sensing technology could play a vital role in discriminating and monitoring wetland species effectively by selecting appropriate spatial and spectral resolution as well as suitable processing techniques for extracting species spectral information.

From a research perspective, however, there are several major challenges in the application of remote sensing in wetland species that need to be addressed.

First, the most current remote sensing techniques in mapping vegetation have been undertaken in arid and semi-arid regions with low vegetation cover and less complexity within the vegetation unit. These techniques are therefore of little use for narrow vegetation units that characterize wetland ecosystems. Additional research effort is needed to adopt more classiffication techniques to improve the accuracy of the spatial resolution of the current sensors which varies from 20 to 30 m. Hyperspectral radiometers are considered to be the sensors of choice in the future for mapping and monitoring wetland species. This has increased the need to build comprehensive spectral libraries for different wetland plant species under different plant conditions and environmental factors. Additionally, the fundamental understanding of the relationship between the reflectance measurements, wetland species' canopy density, and bottom reflectance parameters should be studied further. The spectral libraries of wetland species will help in discriminating not only between wetland species, but also between wetland species and upland species as there has been no specific research dealing with the difference in spectral response of canopies of wetland species and upland species.

Second, in the southern African region, more research is needed to enhance ability in discriminating wetland vegetation and estimating its biophysical and biochemical properties which have been overlooked in the scientific research. For example, papyrus swamp (*Cyperus papyrus L.*) (which characterizes most of the tropical Africa wetlands, with a high rate of biomass production, a tremendous amount of combined nitrogen, that play vital roles in hosting habitats for wildlife and birds) is omitted in the application of remote sensing in discriminating wetland vegetation.

Third, although some studies have been undertaken on estimating the vegetation biophysical and biochemical parameters (e.g. LAI, water content, biomass, pigment concentration, and nitrogen) in different ecosystems, these is paucity of research on wetland species. After the progress in the field of spectrometry, researchers began to measure vegetation properties in complex ecosystems using new narrow-band indices (Mutanga and Skidmore 2004) and red-edge position (Mutanga and Skidmore 2007). These efforts should be further extended and developed so as to cope with wetland species environments where the saturation and the atmospheric vapour affect the near-infrared region. A fourth research prospect is the availability of hyperspectral sensors which could allow mapping of both species and quality in wetland ecosystems. This will enhance a fundamental understanding of the spatial distribution of wetland species-quality which could lead to the development of early warning systems to detect any subtle changes in wetland systems such as signs of stress, and to develop techniques to classify wetland area conditions (e.g. healthy or disturbed) based on their species quality and quantity.

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