Available online at www.sciencedirect.com
SCIENCE DIRECT®
Estuarine, Coastal and Shelf Science 65 (2005) 371–379
ESTUARINE COASTAL AND SHELF SCIENCE
www.elsevier.com/locate/ECSS

Tropical mangrove species discrimination using hyperspectral data: A laboratory study

Chaichoke Vaiphasa [a,b,*], Suwit Ongsomwang [c], Tanasak Vaiphasa [d], Andrew K. Skidmore [a]

[a] *Natural Resources Department, International Institute for Geo-Information Science and Earth Observation (ITC), P.O. Box 6, 7500 AA Enschede, The Netherlands*
[b] *Department of Survey Engineering, Chulalongkorn University, Bangkok, Thailand*
[c] *Ministry of Natural Resources and Environment (MONRE), Bangkok, Thailand*
[d] *BK School, Bangkok, Thailand*

Received 9 January 2005; accepted 16 June 2005
Available online 1 August 2005

Abstract

The aim of this study is to test whether spectra of crown canopy leaves of various tropical mangrove species measured under laboratory conditions contain sufficient spectral information for discriminating mangroves at the species level. This laboratory-level study is one of the most important prerequisites to the future use of airborne and satellite hyperspectral sensors for mangrove studies. First, spectral responses of 16 Thai tropical mangrove species (2151 spectral bands between 350 nm and 2500 nm) were recorded from the leaves, using a spectrometer under laboratory conditions. Next, the mangrove spectra were statistically tested using one-way ANOVA to see whether they significantly differ at every spectral location. Finally, the spectral separability between each pair of mangrove species was quantified using the Jeffries–Matusita (J–M) distance measure. It turned out that the 16 mangrove species under study were statistically different at most spectral locations, with a 95% confidence level ($p < 0.05$). The total number of spectral bands that had p-values less than 0.05 was 1941, of which 477 bands had a 99% confidence level ($p < 0.01$). Moreover, the J–M distance indices calculated for all pairs of the mangrove species illustrated that the mangroves were spectrally separable except the pairs that comprised the members of Rhizophoraceae. Although the difficulties of discriminating the members of Rhizophoraceae are expected, the overall result encourages further investigations into the use of on-board hyperspectral sensors to see whether mangrove species can be separated when the difficulties of the field conditions are taken into account.

Keywords: data reduction; mangroves; signal processing; spectroscopic techniques; spectral discriminant analysis; Thailand; Chumporn; Sawi Bay

1. Introduction

Remote sensing has become a standard tool for large-scale tropical mangrove management (Blasco et al., 1998), mainly because remote sensing technology allows information to be gathered from areas that would otherwise be, logistically and practically, very difficult to survey. Since the early use of aerial photography for exploring the mangrove-covered Biscayne Bay, Florida in the 1920s (Florida State Photo Archive), there has been mounting evidence – as the record of UNESCO shows (Green et al., 2000) – that remote sensing can be successfully applied to three aspects of mangrove management: (1) resource inventory, (2) change detection, and (3) selection and inventory of aquaculture

* Corresponding author. Natural Resources Department, International Institute for Geo-Information Science and Earth Observation (ITC), P.O. Box 6, 7500 AA Enschede, The Netherlands.
E-mail address: vaiphasa@itc.nl (C. Vaiphasa).

0272-7714/$ - see front matter © 2005 Elsevier Ltd. All rights reserved.
doi:10.1016/j.ecss.2005.06.014

sites. These applications are based on a number of instruments on both airplane and satellite platforms, including visible and infrared photographic cameras (Sulong et al., 2002; Verheyden et al., 2002), video recorders (Everitt et al., 1996), synthetic aperture radar (Aschbacher et al., 1995; Held et al., 2003), and multispectral and hyperspectral sensors (Ramsey and Jensen, 1996; Gao, 1999; Green et al., 2000; Demuro and Chisholm, 2003; Held et al., 2003).

Multispectral sensors on satellite platforms, including synthetic aperture radar (SAR), Landsat TM, and SPOT XS, are most popularly used for mangrove applications because of their cost-effective advantages (Aschbacher et al., 1995; Ramsey and Jensen, 1996; Gao, 1999; Green et al., 2000; Sulong et al., 2002; Held et al., 2003), but they are mainly limited to the regional scale, owing to their relatively coarse spatial and spectral resolutions. Improvements are needed in both these major problem areas in order to enable mangroves to be studied at a finer level (Gao, 1999; Green et al., 2000; Sulong et al., 2002).

With respect to the lack of spectral details of multispectral sensors, the limited number of spectral bands of Landsat TM (seven bands in total), in which each band covers only a broad wavelength region of several tens of nanometers, offers a clear example of how opportunities to exploit spectral responses linked to the physio-chemical properties of plants are lost. The broad spectral information of Landsat TM cannot be used to resolve several key absorption pits as well as reflectance characteristics including the red edge (the unique feature of plant spectral responses between the wavelength of 690 nm and 720 nm that can be used for extracting important physio-chemical characteristics of plants including chlorophyll contents) (Elvidge, 1987; Himmelsbach et al., 1988; Curran, 1989; Elvidge, 1990; Kumar et al., 2001; Williams and Norris, 2001). In contrast, the report of Demuro and Chisholm (2003) demonstrates an example of how more delicate tools such as the satellite-mounted HYPERION sensor (USGS EROS Data Center (EDC), USA) that possesses 220 bands between 400 nm and 2500 nm handles the task of discriminating eight-class mangrove communities (i.e. broad mangrove classes) in Australia – a task considered difficult for any multispectral sensor (Green et al., 2000). Similarly, the 224-band Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor with an approximately 9.6-nm band width ranging between 400 nm and 2450 nm performs just as well in mapping the mangrove communities of the Everglades, Florida (Hirano et al., 2003). Since both HYPERION and AVIRIS sensors collect a contiguous range of narrow-band spectral data, they are technically termed hyperspectral sensors.

The potential of hyperspectral technology has already been successfully established in the field of vegetation research (Green et al., 1998, 2000; Asner et al., 2000; Cochrane, 2000; Kruse et al., 2000; Curran et al., 2001; Soukupová et al., 2002; Goel et al., 2003; Hirano et al., 2003; Mutanga et al., 2003; Schmidt and Skidmore, 2003; Schuerger et al., 2003; Zarco-Tejada et al., 2004). This is because hyperspectral data contain information that relates to important biochemical properties of plants (Gates et al., 1965; Hoffer, 1978; Peterson and Hubbard, 1992; Kokaly, 2001; McDonald, 2003). To highlight just a few, the recent applications of hyperspectral technology include the study of the quality of tropical pastures for animal grazing (Mutanga et al., 2003); the use of hyperspectral sensors to detect zinc stress in plants (Schuerger et al., 2003); a revised method for lignin detection (Soukupová et al., 2002); and the extraction of crop biophysical parameters (Goel et al., 2003). More importantly, recent reports confirm that hyperspectral data have potential for discriminating terrestrial plants at the species level (Cochrane, 2000; Schmidt and Skidmore, 2003).

Although hyperspectral data look promising in the arena of vegetation applications including species level discrimination, the already-published hyperspectral research on mangroves (Green et al., 2000; Demuro and Chisholm, 2003; Held et al., 2003; Hirano et al., 2003) is inconclusive as to the use for tropical mangrove species discrimination. The most unfortunate case of all is the multi-sensor study done by Held et al. (2003). The author should have been the first to conclude whether the on-board hyperspectral sensor could be used for mangrove species classification if the quality of the hyperspectral images in use were not distorted by the high percentage of cloud cover. On the other hand, the other researchers (Green et al., 2000; Demuro and Chisholm, 2003; Hirano et al., 2003) could not explore thoroughly the capability of hyperspectral data for discriminating mangroves at the species level because their study sites were dominated by only a few mangrove species.

Consequently, this study is intended to move one step closer to the conclusion whether hyperspectral technology could be used for tropical mangrove species discrimination. Specifically, laboratory spectra of top canopy leaves of 16 tropical mangrove species are used for the spectral separability analysis to see whether they adequately contain useful spectral information for discriminating mangroves at the species level. Using laboratory data that leave out the difficulties of field conditions (e.g. the fluctuation of light source energy, the change of daily atmospheric states, the effect of canopy formations, the cost of accessibility, the coarser spatial and spectral resolutions of on-board hyperspectral sensors, the effect of seasonal changes, the effect of background soils and water, the difference between the energy of artificial lamps used in the laboratory and the sun, etc.) means that the result of this study cannot be used to make any conclusion whether real-life hyperspectral sensors (e.g. HYPERION, AVIRIS, etc.)

could be used for discriminating tropical mangrove species. Instead, this laboratory study is intended to be a cost-effective test to focus only on one of the most important prerequisites to the future application of on-board hyperspectral sensors: if the laboratory spectra of the mangrove species contain insufficient spectral information for discriminating mangroves at the species level, it is then not worthwhile to invest a lot of time and money to investigate further into the potential of the on-board hyperspectral sensors.

2. Methods

2.1. Acquisition of hyperspectral data

2.1.1. Mangrove leaf preparation

In the morning of February 6, 2001, top tree canopies of 16 tropical mangrove species (Table 1) were collected using a line-transect method in the natural mangrove forest of Ao Sawi (Sawi Bay), Chumporn province, the south of Thailand (10° 15′N, 99° 7′E) (Fig. 1). There were 10 transects randomly placed throughout the area so as to collect tree samples from every mangrove zone (e.g. pioneer, intermediate, and upper zones). Only the trees that are higher than 2.5 m were considered for the sampling campaign. The canopies of the sampled trees were cut off and transported to the laboratory where leaves were picked off for the spectral measurement. The whole process was done within 4 h so as to preserve the quality of the leaves.

2.1.2. Leaf spectral measurements

Freshly-picked leaves were randomly divided into 30 piles of the same size (20–30 leaves) per mangrove species. First, each pile of leaves was spread on top of a black metal plate painted with ultra-flat black paint until the background metal plate could not be seen. Second, the spectral response of each leaf plate was recorded 20 times. Each plate was rotated 45° horizontally after every fifth record in order to correct for the bi-directional reflectance distribution function (BRDF). Third, the 20 records were averaged to construct a radiance curve. Fourth, the radiance was converted to a reflectance curve, using a Spectralon reference panel as well as the correction of the spectrometer internal current (dark current). The steps above were repeated for all the leaf plates. As a result, 30 reflectance curves were constructed for each mangrove species (Table 1). Please note that the whole operation was conducted under laboratory conditions (i.e. dark room, 25 °C) in order to avoid ambient light sources unrelated to the true spectral signal of the leaves.

Table 1
Sixteen tropical mangrove species of different zonations collected from Sawi Bay, Chumporn province, Thailand used for the laboratory reflectance measurement

Mangrove species	Species code
Avicennia alba	AVA
Acrostichum aureum	ACA
Bruguiera cylindrica	BC
Bruguiera gymnorrhiza	BG
Bruguiera parviflora	BP
Ceriops tagal	CT
Excoecaria agallocha	EA
Heritiera littoralis	HL
Lumnitzera littorea	LL
Lumnitzera racemosa	LR
Nypa fruticans	NF
Pluchea indica	PI
Rhizophora apiculata	RA
Rhizophora mucronata	RM
Sonneratia ovata	SO
Xylocarpus granatum	XG

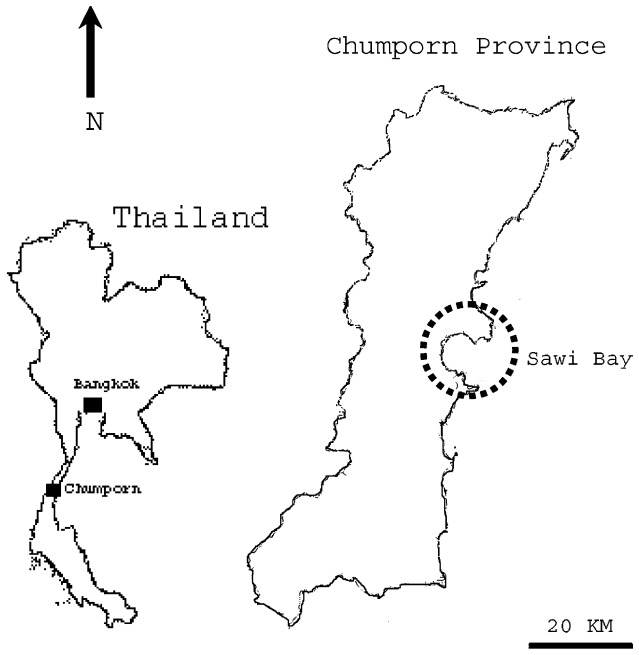

Fig. 1. Sawi Bay, Chumporn province, Thailand (10° 15′N, 99° 7′E).

The whole process was conducted using a spectroradiometer (FieldSpec Pro FR, Analytical Spectral Device, Inc.). This spectroradiometer was equipped with three spectrometers (i.e. VNIR, SWIR1, and SWIR2), covering 350 nm–2500 nm, with sampling intervals of 1.4 nm between 350 nm and 1000 nm, and 2 nm between 1000 nm and 2500 nm. The spectral resolution of the spectrometers was 3 nm for the wavelength interval 350 nm–1000 nm, and 10 nm for the wavelength interval 1000 nm–2500 nm. The sensor, equipped with a field of view of 25°, was mounted on a tripod and positioned 0.5 m above the leaf plate at the nadir position.

Since this laboratory study was intended to be a prerequisite to the future use of real hyperspectral

sensors, the energy source in use should at least provide the same energy range that real hyperspectral sensors capture. In this study, a halogen lamp was selected to provide stable electro-magnetic energy between 400 nm and 1800 nm. This energy range was reconciled with most of the hyperspectral sensors (Lillesand and Kiefer, 2000). As a result, a halogen lamp fixed on the tripod at the same position as the sensor of the spectrometer was used to illuminate the sample plate.

2.2. Data treatments

2.2.1. Statistical test

A statistical test was used to compare between the spectral responses of the 16 individual tropical mangrove species (Table 1) whether at least one pair of them was statistically different at every spectral band, that is to say, the null hypothesis H_0: $\mu_1 = \mu_2,\ldots,\mu_{16}$ versus the alternative hypothesis H_a: $\mu_1 \neq \mu_2,\ldots,\mu_{16}$, where μ_i was the mean reflectance value of the ith species ($i = 1, 2,\ldots, 16$). Before conducting the test, the distribution of the spectral responses at every spectral band was assumed to be normal under the central limit theorem (N spectra ≥ 30) as well as the equality of statistical variances (homoscedasticity) was verified for every spectral location. Then, the hypothesis test was carried out using one-way ANOVA at every spectral location between 350 nm and 2500 nm (a total of 2151 spectral bands) with 95% and 99% confidence limits ($\alpha = 0.05$ and 0.01).

The aim of the ANOVA test was mainly to visualize the spectral differences between the 16 mangrove species. The test was chosen as a replacement for the direct graphical presentation of the mangrove spectral responses because the direct visualization was not an effective visualization tool for comparing as many as 16 mangrove species. In other words, the spectral variations within an individual species (i.e. intra-species spectral variations) caused spectral overlaps that made it very difficult to spot the spectral differences between the 16 mangrove species (i.e. inter-species variations) with the naked eye. The reader is recommended to find more details on the direct visualization versus spectral variations in Landgrebe (1997, p. 8). Unlike the direct display, applying the ANOVA test helped to highlight poor spectral locations at which p-values were greater than α (e.g. $\alpha = 0.05$ or $\alpha = 0.01$). p-Values higher than α at some spectral locations indicated that the spectra of different mangrove species were very similar as none of them was statistically separable from the group. On the other hand, the p-value less than the α threshold indicated that there was at least one pair of mangrove spectra that was statistically different. The ANOVA test was therefore a rapid way to visualize spectral differences. It helped to demonstrate that separating spectral responses of 16 different mangrove species was likely at certain spectral positions.

2.2.2. Spectral separability

Even though the ANOVA test was a practical data exploration tool, the result of the test may not be independently interpreted without additional treatments. One of the major reasons was the increasing chance of the TYPE I error that usually happened when conducting multiple hypothesis testing (Rothman, 1990; Hsu, 1996; Perneger, 1998; Feise, 2002). In this case, the TYPE I error could lead the reader to feel too positive about the capability of hyperspectral technology for separating mangroves at the species level. As a result, the spectral separability index of every mangrove pair needed to be calculated to guarantee the actual differences between the mangrove spectra. The quantification of spectral separability indices for every mangrove pair did not only minimize the chance of the TYPE I error found in the ANOVA test, but it also was the main contribution of this study (i.e. proving whether the laboratory spectra adequately contain useful spectral information for discriminating mangroves at the species level).

The separability index used in this study was the square of Jeffries–Matusita (J–M) distance analysis. The J–M distance method delivers a value between 0 and $\sqrt{2}$ (≈ 1.414), so the squared distance gives a number between 0 and 2. We follow the common practice in remote sensing (Thomas et al., 2003; ENVI software's user guide, RSI Inc.) of using a squared J–M distance threshold of ≥ 1.90 to indicate whether any two mangrove species were spectrally separable. The calculation of the J–M distance in this study was based on Eq. (1). The reader was recommended to consult Richards, (1993) for further details in separability analyses:

$$\text{J–M}_{ij} = \sqrt{2(1 - e^{-a})}$$

$$\text{where } a = \frac{1}{8}(\mu_i - \mu_j)^T \left(\frac{C_i + C_j}{2}\right)^{-1} (\mu_i - \mu_j) + \frac{1}{2}\ln\left(\frac{(1/2)|C_i + C_j|}{\sqrt{|C_i| \times |C_j|}}\right) \quad (1)$$

Note i and j are the spectral responses of two mangrove species being compared; C is the covariance matrix of the spectral response; μ is the mean vector of the spectral response; ln is the natural logarithm function; T is the transposition function; and $|C|$ is the determinant of C.

Because the J–M distance measure in use was a parametric method, it was necessary to reduce the number of spectral features (bands) prior to the calculation. In other words, it was not possible to calculate the J–M distance using all 2151 bands because of the singularity problem of matrix inversion (i.e. the number of spectral samples per mangrove species was

too small). A wrapper feature selection approach (Siedlecki and Sklansky, 1989; John et al., 1994; Kohavi and John, 1997; Kavzoglu and Mather, 2002; Yu et al., 2002; Vaiphasa, 2003) was therefore applied in this study to reduce the number of spectral features. The wrapper approach is generally a kind of feature selection algorithms that combines the strength of a traditional search algorithm (e.g. sequential forward selection, branch and bound technique, genetic search, etc.) with the capability of a classifier (e.g. nearest neighbor classifier, maximum likelihood classifier, etc.). In this case study, the search mechanism of the wrapper tool was based on a genetic algorithm, and its classifier was a nearest neighbor classifier. The algorithm was applied to select the best band combination out of the total of 2151 bands. The algorithm was initialized with the following genetic search parameters: crossover rate = 50%; mutation rate = 1%; and the maximum number of iterations = 1000. The estimated classification accuracy was chosen at an 80% level as an optimizing criterion. Following the USGS guideline (Anderson et al., 1976), the optimizing criterion chosen at the 80% level was adequate for the difficulties of discriminating mangroves at the species level (i.e. Level III or IV of the USGS classification standard).

3. Results

3.1. ANOVA test

The results of 2151 ANOVA tests (p-values) for all spectral bands were plotted in Fig. 2. A reflectance of *Rhizophora apiculata* measured in the laboratory was also drawn in the figure to give an impression of the actual mangrove spectral continuum collected by the spectrometer. The 16 mangrove species under study were statistically different at most spectral locations, with a 95% confidence level ($p < 0.05$). The total number of spectral bands that had p-values less than 0.05 was 1941, of which 477 bands had a 99% confidence level ($p < 0.01$). The exceptions were at the ultraviolet region (350–400 nm) and shortwave infrared region (1800–2500 nm), where the halogen lamp did not radiate strong energy.

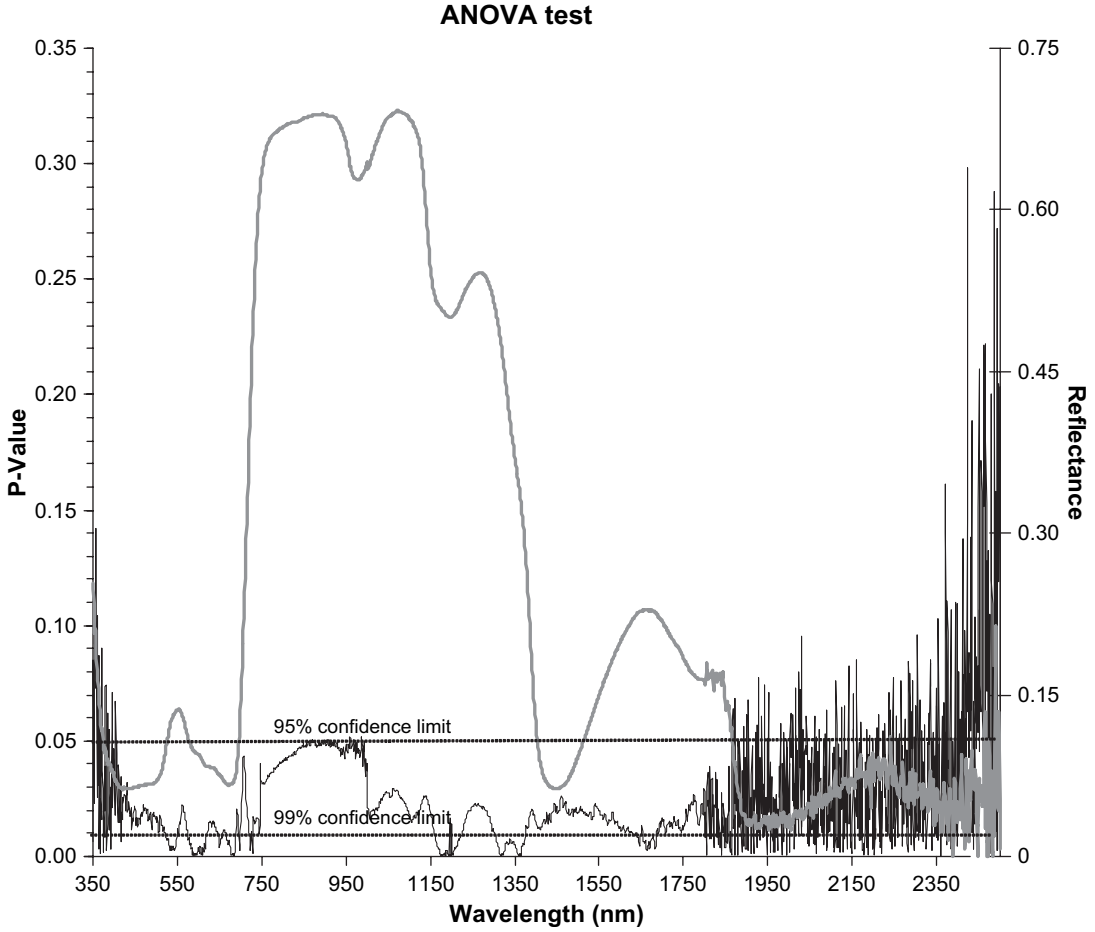

Fig. 2. The plot of p-values of the ANOVA test (black line) showing against a laboratory reflectance of *Rhizophora apiculata* (gray line).

3.2. Wrapper feature selection

The feature selection algorithm was applied to search for the sub-optimal spectral band combination out of the total of 2151 bands. The best combination found by the wrapper tool comprised four spectral members at 720 nm, 1277 nm, 1415 nm, and 1644 nm. These four spectral bands guaranteed an 80% level of estimated classification accuracy. In Fig. 3, the selected bands were shown against a reflectance of *Rhizophora apiculata*. These four selected bands were then used for the calculation of J–M distances in the next section.

3.3. J–M distance

The J–M distance measure was applied to reveal the spectral separability between each pair of mangrove species (Table 2), using the four spectral bands selected in Section 3.2. Please note that the mangrove species of Table 2 were grouped by their family names. The overall spectral separability between the pairs of mangrove species was high, since most of them acquired levels of separability higher than the selected threshold (e.g. 1.90). Only 10 instances where the J–M distances were lower than 1.90 were found. These instances are highlighted in Table 2. One should, however, note that the members of the Rhizophoraceae family (*Bruguiera cylindrica*, *Bruguiera gymnorrhiza*, *Bruguiera parviflora*, *Ceriops tagal*, *Rhizophora apiculata*, and *Rhizophora mucronata*) were spectrally similar as 5 out of 10 highlighted instances were found among them. Moreover, the Rhizophoraceae family was also similar to other mangrove families as each of the other five highlighted pairs contained at least one mangrove species of Rhizophoraceae.

4. Discussion

A laboratory-scale test of spectral separability between various tropical mangrove species, which is one of the most important prerequisites to the future use of airborne and satellite hyperspectral sensors, has been completed in this study. Overall, the results confirmed that discriminating spectral responses of different tropical mangroves at the species level was possible in the laboratory. First, the result of the ANOVA test in Fig. 2 helped visualize the possibility of separating the mangrove species at many spectral locations. Then, the report on pair-wise spectral separability between the 16 mangrove species in Table 2 guaranteed the result of the ANOVA test as most mangrove pairs possessed high separability indices ($\approx$2.00). The results therefore encourage further investigation into the capability of

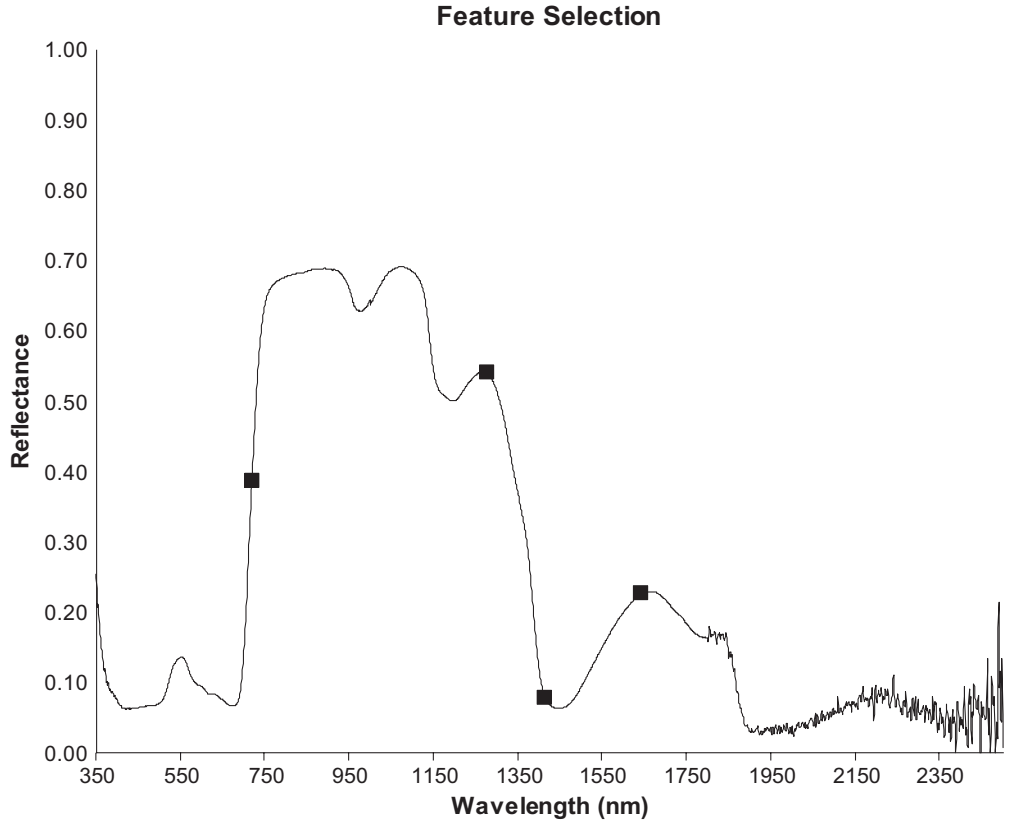

Fig. 3. Four locations of spectral bands selected by the feature selection tool at 720 nm, 1277 nm, 1415 nm, and 1644 nm, respectively.

Table 2
The J−M distances between all pairs of 16 mangrove species (120 pairs in total). The species names are coded in Table 1. The pairs that possess lower than 1.90 separability levels are highlighted in gray color. Mangrove species were grouped by their family names

		Avicennia-ceae	Pterida-ceae	Rhizophoraceae						Euphorbia-ceae	Sterculia-ceae	Combreta-ceae		Wurmb	Astera-ceae	Sonneratia-ceae	Melia-ceae
		AVA	ACA	BC	BG	BP	CT	RA	RM	EA	HL	LL	LR	NF	PI	SO	XG
Avicennia-ceae	AVA																
Pterida-ceae	ACA	1.99															
Rhizophora-ceae	BC	1.99	2.00														
	BG	2.00	1.56	1.99													
	BP	1.99	1.99	1.99	1.82												
	CT	2.00	1.99	1.97	1.99	1.90											
	RA	1.99	1.99	1.93	1.99	1.99	1.99										
	RM	2.00	1.99	1.72	1.99	1.73	1.85	1.86									
Euphorbia-ceae	EA	1.94	1.99	2.00	1.99	1.99	2.00	1.99	2.00								
Sterculia-ceae	HL	1.99	1.99	2.00	1.94	1.99	1.99	1.99	1.99	1.98							
Combreta-ceae	LL	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00						
	LR	2.00	2.00	2.00	2.00	2.00	2.00	1.99	2.00	2.00	2.00	1.99					
Wurmb	NF	1.99	1.99	2.00	1.99	1.99	2.00	1.99	1.99	1.99	1.99	2.00	2.00				
Astera-ceae	PI	2.00	2.00	1.98	1.99	1.99	1.87	1.99	1.89	2.00	2.00	1.99	2.00	2.00			
Sonneratia-ceae	SO	1.99	1.99	1.99	1.95	1.84	1.99	1.98	1.99	1.99	1.99	1.99	2.00	1.99	1.99		
Melia-ceae	XG	1.97	1.99	1.99	1.82	1.96	2.00	1.99	1.99	1.98	1.99	2.00	2.00	1.99	2.00	1.99	

using airborne and satellite hyperspectral sensors for mapping mangrove species when taking field conditions into account (e.g. the fluctuation of solar energy, the change of daily atmospheric states, the effect of canopy formations, the cost of accessibility, the coarser spatial and spectral resolutions of on-board hyperspectral sensors, the effect of seasonal changes, the effect of background soils and water, the difference between the energy of artificial lamps used in the laboratory and the sun, etc.).

Despite the optimism of the overall outcome, one should not ignore the minority (10 instances) of Table 2 where the separability indices were lower than 1.90. The locations of these instances in the table implied that the members of the Rhizophoraceae family were probably the most problematic: the members of this mangrove family were spectrally similar to the other mangroves as well as among themselves. This result reflected the similarity between their spectral responses; hence the closeness between the leaf physio-chemical properties of these mangroves. Since the mangroves of Rhizophoraceae dominated the study area, the difficulties of discriminating these mangroves are expected when implementing the on-board hyperspectral sensors. This statement could also be true for other areas that shared similar floristic conditions (i.e. dominated by the Rhizophoraceae family).

Lastly, the result of the wrapper tool may not be overlooked. Even if the four bands selected by the wrapper tool guaranteed an 80% level of estimate classification accuracy (i.e. complied with the USGS standard; Anderson et al., 1976), only one out of four was reconciled with the locations of the spectral responses of mangrove leaf pigments (e.g. chlorophylls, carotenoids, etc.) between 380 nm and 750 nm (Menon and Neelakantan, 1992; Basak et al., 1996; Das et al., 2002). This could lead us to hypothesize that the spectral responses of mangrove pigments may contain less important spectral information for mangrove species discrimination than the information from the spectral responses of the other leaf components that interacted with electro-magnetic energy at longer wavelengths. This may be because mangroves generally possessed similar amounts of pigment substances across the species but the differences in other leaf components (salt, sugar, water, protein, oil, lignin, starch, cellulose, and leaf structure) that normally interacted with energy at longer wavelengths were more marked. Even if a number of studies on the physio-chemical properties of leaves of different mangrove species were available (Menon and Neelakantan, 1992; Tomlinson, 1994; Basak et al., 1996; Das et al., 2002), it was unfortunate that they could not be readily compared so as to draw any conclusion. This was mainly because these studies were not standardized (i.e. the mangrove leaves used in different reports were collected from different field conditions). A non-bias comparative study was therefore recommended so as to confirm this part of the findings. Then, the four spectral locations selected by the wrapper tool could be seen as a guideline for selecting appropriate spectral locations for the future use of the on-board hyperspectral sensor.

In summary, one of the most important prerequisites to the future investment of the airborne and satellite hyperspectral sensors for mangrove studies was investigated in this study. Specifically, laboratory spectra of top canopy leaves of 16 tropical mangrove species were analyzed to see whether they adequately contain useful spectral information for discriminating mangroves at the species level. The results from the statistical test and the spectral distance analysis provided optimistic evidence that encouraged a full-scale investigation into the capability of on-board hyperspectral sensors for mangrove species discrimination, but the doubt of discriminating some members of the Rhizophoraceae family still remains.

References

Anderson, J.R., Hardy, E.E., Roach, J.T., Witmer, R.E., 1976. A land use and land cover classification system for use with remote sensor data. U.S. Geological Survey Professional Paper 964, 41.

Aschbacher, J., Tiangco, P., Giri, C.P., Ofren, R.S., Paudyal, D.R., Ang, Y.K., 1995. Comparison of different sensors and analysis techniques for tropical mangrove forest mapping. In: Proceedings of the International Conference IGARSS, pp. 2109–2111.

Asner, G.P., Wessman, C.A., Bateson, C.A., Privette, J.L., 2000. Impact of tissue, canopy, and landscape factors on the hyperspectral reflectance variability of arid ecosystems. Remote Sensing of Environment 74, 69–84.

Basak, U.C., Das, A.B., Das, P., 1996. Chlorophyll, carotenoids, proteins and secondary metabolites in leaves of 14 species of mangroves. Bulletin of Marine Science 58, 645–659.

Blasco, F., Gauquelin, T., Rasolofoharinoro, M., Denis, J., Aizpuru, M., Caldairou, V., 1998. Recent advances in mangrove studies using remote sensing data. Marine and Freshwater Research 49, 287–296.

Cochrane, M.A., 2000. Using vegetation reflectance variability for species level classification of hyperspectral data. International Journal of Remote Sensing 21, 2075–2087.

Curran, P.J., 1989. Remote sensing of foliar chemistry. Remote Sensing of Environment 30, 271–278.

Curran, P.J., Dungan, J.L., Peterson, D.L., 2001. Estimating the foliar biochemical concentration of leaves with reflectance spectrometry: testing the Kokaly and Clark methodologies. Remote Sensing of Environment 76, 349–359.

Das, A.B., Parida, A., Basak, U.C., Das, P., 2002. Studies on pigments, proteins and photosynthetic rates in some mangroves and mangrove associates from Bhitarkanika, Orissa. Marine Biology 141, 415–422.

Demuro, M., Chisholm, L., 2003. Assessment of Hyperion for characterizing mangrove communities. In: Proceedings of the International Conference the AVIRIS 2003 Workshop, pp. 18–23.

Elvidge, C.D., 1987. Reflectance characteristics of dry plant materials. In: Proceeding of the International Conference Remote Sensing of Environment, pp. 721–733.

Elvidge, C.D., 1990. Visible and near infrared reflectance characteristics of dry plant materials. International Journal of Remote Sensing 11, 1775–1795.

Everitt, J.H., Judd, F.W., Escobar, D.E., Davis, M.R., 1996. Integration of remote sensing and spatial information technologies for mapping black mangrove on the Texas gulf coast. Journal of Coastal Research 12, 64–69.

Feise, R.J., 2002. Do multiple outcome measures require *p*-value adjustment? BMC Medical Research Methodology 2, 8.

Gao, J., 1999. A comparative study on spatial and spectral resolutions of satellite data in mapping mangrove forests. International Journal of Remote Sensing 20, 2823–2833.

Gates, D.M., Keegan, H.J., Schleter, J.C., Weidner, V.R., 1965. Spectral properties of plants. Applied Optics 9, 545–552.

Goel, P.K., Prasher, S.O., Landry, J.A., Patel, R.M., Viau, A.A., Miller, J.R., 2003. Estimation of crop biophysical parameters through airborne and field hyperspectral remote Sensing. Transactions of the American Society of Agricultural Engineers 46, 1235–1246.

Green, R.O., Eastwood, M.L., Sarture, C.M., Chrien, T.G., Aronsson, M., Chippendale, B.J., Faust, J.A., Pavri, B.E., Chovit, C.J., Solis, M., Olah, M.R., Williams, O., 1998. Imaging spectroscopy and the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS). Remote Sensing of Environment 65, 227–248.

Green, E.P., Clark, C.D., Edwards, A.J., 2000. Image classification and habitat mapping. In: Edwards, A.J. (Ed.), Remote Sensing Handbook for Tropical Coastal Management. UNESCO, Paris, pp. 141–154.

Held, A., Ticehurst, C., Lymburner, L., Williams, N., 2003. High resolution mapping of tropical mangrove ecosystems using hyperspectral and radar remote sensing. International Journal of Remote Sensing 24, 2739–2759.

Himmelsbach, D.S., Boer, J.D., Akin, D.E., Barton, E.E., 1988. Solid-state carbon-13 NMR, FTIR, and NIR spectroscopic studies of ruminant silage digestion. In: Creaser, C.S., Davies, A.M.C. (Eds.), Analytical Applications of Spectroscopy. Royal Society of Chemistry, London, pp. 410–413.

Hirano, A., Madden, M., Welch, R., 2003. Hyperspectral image data for mapping wetland vegetation. Wetlands 23, 436–448.

Hoffer, R.M., 1978. Biological and physical considerations in applying computer aided analysis techniques to the remote sensor data. In: Swain, P.H., Davis, S.M. (Eds.), Remote Sensing: The Quantitative Approach. McGraw-Hill, New York, pp. 227–289.

Hsu, J.C., 1996. Multiple Comparisons: Theory and Methods. Chapman and Hall, London, 277 pp.

John, G.H., Kohavi, R., Pfleger, K., 1994. Irrelevant features and the subset selection problem. In: Cohen, W.W., Hirsh, H. (Eds.), Machine Learning. Morgan Kaufmann, San Francisco, pp. 121–129.

Kavzoglu, T., Mather, P.M., 2002. The role of feature selection in artificial neural network applications. International Journal of Remote Sensing 23, 2919–2937.

Kohavi, R., John, G.H., 1997. Wrappers for feature subset selection. Artificial Intelligence 97, 273–324.

Kokaly, R.F., 2001. Investigating a physical basis for spectroscopic estimates of leaf nitrogen concentration. Remote Sensing of Environment 75, 267–287.

Kruse, F.A., Boardman, J.W., Lefkoff, A.B., Young, J.M., Kiereinn-Young, K.S., Cocks, T.D., Jenssen, R., Cocks, P.A., 2000. HyMap: an Australian hyperspectral sensor solving global problems – results from USA HyMap data acquisitions. In: Proceeding of the International Conference Australasian Remote Sensing and Photogrammetry, pp. 18–23.

Kumar, L., Schmidt, K., Dury, S., Skidmore, A.K., 2001. Imaging spectrometry and vegetation science. In: van de Meer, F., de Jong, S.M. (Eds.), Imaging Spectrometry. Kluwer Academic Press, Dordrecht, pp. 111–155.

Landgrebe, D., 1997. On information extraction principles for hyperspectral data. http://dynamo.ecn.purdue.edu/~landgreb/whitepaper.pdf.

Lillesand, T.M., Kiefer, R.W., 2000. Remote Sensing and Image Interpretation. Wiley, Chichester, 724 pp.

McDonald, M.S., 2003. Photobiology of Higher Plants. Wiley, Chichester, 354 pp.

Menon, G.G., Neelakantan, B., 1992. Chlorophyll and light attenuation from the leaves of mangrove species of Kali estuary. Indian Journal of Marine Sciences 21, 13–16.

Mutanga, O., Skidmore, A.K., Van Wieren, S., 2003. Discriminating tropical grass (*Cenchrus ciliaris*) canopies grown under different nitrogen treatments using spectroradiometry. ISPRS Journal of Photogrammetry and Remote Sensing 57, 263–272.

Perneger, T.V., 1998. What's wrong with Bonferroni adjustments? British Medical Journal 316, 1236–1238.

Peterson, D.L., Hubbard, G.S., 1992. Scientific issues and potential remote sensing requirements for plant biochemical content. Journal of Image Science and Technology 36, 446–456.

Ramsey, E.W., Jensen, J.R., 1996. Remote sensing of mangrove wetlands: relating canopy spectra to site-specific data. Photogrammetric Engineering and Remote Sensing 62, 939–948.

Richards, J.A., 1993. Remote Sensing Digital Image Analysis: An Introduction. Springer-Verlag, Berlin, 340 pp.

Rothman, K.J., 1990. No adjustments are needed for multiple comparisons. Epidemiology 1, 43–46.

Schmidt, K.S., Skidmore, A.K., 2003. Spectral discrimination of vegetation types in a coastal wetland. Remote Sensing of Environment 85, 92–108.

Schuerger, A.C., Capelle, G.A., Di Benedetto, J.A., Mao, C., Thai, C.N., Evans, M.D., Richards, J.T., Blank, T.A., Stryjewski, E.C., 2003. Comparison of two hyperspectral imaging and two laser-induced fluorescence instruments for the detection of zinc stress and chlorophyll concentration in bahia grass (*Paspalum notatum* Flugge.). Remote Sensing of Environment 84, 572–588.

Siedlecki, W., Sklansky, J., 1989. A note on genetic algorithms for large-scale feature selection. Pattern Recognition Letters 10, 335–347.

Soukupová, J., Rock, B.N., Albrechtová, J., 2002. Spectral characteristics of lignin and soluble phenolics in the near infrared – a comparative study. International Journal of Remote Sensing 23, 3039–3055.

Sulong, I., Mohd-Lokman, H., Mohd-Tarmizi, K., Ismail, A., 2002. Mangrove mapping using Landsat imagery and aerial photographs: Kemaman District, Terengganu. Malaysia Environment, Development and Sustainability 4, 135–152.

Thomas, V., Treitz, P., Jelinski, D., Miller, J., Lafleur, P., McCaughey, J.H., 2003. Image classification of a northern peatland complex using spectral and plant community data. Remote Sensing of Environment 84, 83–99.

Tomlinson, P.B., 1994. The Botany of Mangroves. Cambridge University Press, Cambridge, 419 pp.

Vaiphasa, C., 2003. Innovative genetic algorithm for hyperspectral image classification. In: Proceedings of the International Conference MAP ASIA. http://www.gisdevelopment.net/technology/ip/ma03071abs.htm.

Verheyden, A., Dahdouh-Guebas, F., Thomaes, K., De Genst, W., Hettiarachchi, S., Koedam, N., 2002. High-resolution vegetation data for mangrove research as obtained from aerial photography. Environment, Development and Sustainability 4, 113–133.

Williams, P., Norris, K., 2001. Near-infrared Technology in the Agricultural and Food Industries. American Association of Cereal Chemists Press, Minnesota, 296 pp.

Yu, S., De Backer, S., Scheunders, P., 2002. Genetic feature selection combined with composite fuzzy nearest neighbor classifiers for hyperspectral satellite imagery. Pattern Recognition Letters 23, 183–190.

Zarco-Tejada, P.J., Miller, J.R., Morales, A., Berjón, A., Agüera, J., 2004. Hyperspectral indices and model simulation for chlorophyll estimation in open-canopy tree crops. Remote Sensing of Environment 90, 463–476.