

Distinguishing mangrove species with laboratory measurements of hyperspectral leaf reflectance

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As a first step in developing classification procedures for remotely acquired hyperspectral mapping of mangrove canopies, we conducted a laboratory study of mangrove leaf spectral reflectance at a study site on the Caribbean coast of Panama, where the mangrove forest canopy is dominated by *Avicennia germinans*, *Laguncularia racemosa*, and *Rhizophora mangle*. Using a high-resolution spectrometer, we measured the reflectance of leaves collected from replicate trees of three mangrove species growing in productive and physiologically stressful habitats. The reflectance data were analysed in the following ways. First, a one-way ANOVA was performed to identify bands that exhibited significant differences (P value < 0.01) in the mean reflectance across tree species. The selected bands then formed the basis for a linear discriminant analysis (LDA) that classified the three types of mangrove leaves. The contribution of each narrow band to the classification was assessed by the absolute value of standardised coefficients associated with each discriminant function. Finally, to investigate the capability of hyperspectral data to diagnose the stress condition across the three mangrove species, four narrow band ratios (R_{695}/R_{420} , R_{605}/R_{760} , R_{695}/R_{760} , and R_{710}/R_{760} where R_{695} represents reflectance at wavelength of 695nm, and so on) were calculated and compared between stressed and non-stressed tree leaves using ANOVA.

Results indicate a good discrimination was achieved with an average kappa value of 0.9. Wavebands at 780, 790, 800, 1480, 1530, and 1550 nm were identified as the most useful bands for mangrove species classification. At least one of the four reflectance ratio indices proved useful in detecting stress associated with any of the three mangrove species. Overall, hyperspectral data appear to have great potential for discriminating mangrove canopies of differing species composition and for detecting stress in mangrove vegetation.

1. Introduction

Natural habitats and their biodiversity are increasingly endangered by a plethora of human-caused environmental perturbations (Vitousek 1994). Coastal environments are particularly vulnerable as they are often preferred sites for human habitation, centres of commerce, and exploited for a variety of natural resources (Cracknell 1999). Mangrove forests are among the most threatened of coastal habitats, succumbing to various forms of non-renewable exploitation (e.g. aquaculture,

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mining) and extensive coastal development that results in the clear-cutting and filling of thousands of hectares of swampland annually (Ellison and Farnsworth 1996). It is estimated that as much as a third of the world's mangrove forest has been lost in the past 50 years (Alongi 2002). In the Caribbean, the region of our research on mangrove forest dynamics, the rate of mainland mangrove deforestation is estimated to be 1.4–1.7% annually (Ellison and Farnsworth 1996, FAO 2003). Thus, we are rapidly losing a unique, productive and economically important ecosystem (Lugo and Snedaker 1974, Tomlinson 1986, Kathiresan and Bingham 2001, Alongi 2002), that at one time comprised the dominant vegetative cover along most of the world's sheltered tropical coastlines. Furthermore, human-induced changes in global climate are also expected to have important direct and indirect effects on mangrove ecosystems. Robust model predictions and growing empirical evidence indicate that rapid sea-level rise, accelerated by global warming, will submerge and erode away seaward mangrove stands (Ellison and Stoddart 1991, Ellison 1993, Parkinson *et al.* 1994, Ellison and Farnsworth 1997).

Given present and growing threats to the persistence of mangrove ecosystems, there is an urgent need to develop rigorous plans and procedures for their protection and management. To be effective and timely, these conservation efforts must be able to access up-to-date information on forest species composition, species distributions, and canopy condition. Given that these flooded forests are often inaccessible by road and difficult to traverse on foot, it is essential to develop techniques for remotely quantifying their structure, distribution, and health. Previous efforts remotely to map mangrove forests have relied largely on imagery acquired from conventional remote sensing platforms, such as Landsat Multispectral Scanner (MSS), Landsat Thematic Mapper (TM), and SPOT (Venkataratnam and Thammappa 1993, Gao 1998, 1999). As discussed by Wang *et al.* (2004a), the coarse spatial and poor spectral resolution of these sensors compromises their usefulness for discriminating mangrove canopies, particularly at the species level. However, the recent availability of higher spatial and spectral resolution data from both aircraft and satellite sensors has stimulated researchers to develop new methods to exploit this added information to produce more accurate landscape maps.

The objectives of our study were: (a) to investigate the capability of hyperspectral data to distinguish mangrove species at the leaf level; (b) to develop an optimal band selection method to achieve the first objective; and (c) to investigate the capability of hyperspectral data to distinguish the leaves of healthy versus physiologically stressed trees.

2. Background

We have recently examined whether analysis of very high-resolution IKONOS (Space Imaging) and QuickBird (DigitalGlobe) images can yield more accurate maps of mangrove canopy species composition than analyses of conventional imagery. Applying an integrated pixel- and object-based method, Wang *et al.* (2004a) achieved good results when classifying three mangrove canopies of differing species composition and four other land cover types in an IKONOS image (average classification accuracy of 91.4%). Further, Wang *et al.* (2004b, 2008) validated the effectiveness of IKONOS and QuickBird images for discriminating mangrove species based on four different comparisons of the spectral and textural content of the two types of images. While mangrove canopy classification was clearly improved by adding the within-class textural information afforded by the enhanced spatial

resolution of these images, we found it difficult spectrally to discriminate certain canopy types (e.g. *Rhizophora* versus *Avicennia*) owing to the limited range of wavelengths (e.g. no short-wave infrared signal, hereafter SWIR) and relatively broad bandwidths characteristic of this type of image. This spectral confusion remains a challenge to accurate species-level classification of mangrove canopies from multispectral imagery. It is important to determine if this problem can be surmounted with hyperspectral reflectance data, which are typically characterised by tens or hundreds of narrow, contiguous wavebands.

Hyperspectral data have been successfully used to quantify the canopy characteristics of numerous forest types. However, few such studies have been conducted on mangrove forest. Green *et al.* (1998) compared three types of data (SPOT XS, Landsat TM, and Compact Airborne Spectrographic Imager (CASI)) for mapping mangrove species of the Caicos Bank, Turk and Caicos Islands, British West Indies. They found that only CASI data provided an accurate discrimination among mangrove species. Demuro and Chisholm (2003) successfully distinguished the canopies of two different mangrove species in their analysis of a high spectral resolution, EO-1 Hyperion image of the Minnamurra River estuary, New South Wales, Australia. These studies clearly demonstrate that hyperspectral reflectance data can enhance our ability to remotely classify mangrove canopies; however, the generality of this result remains to be determined. Two significant questions that we would like to address in this study include: (a) Will hyperspectral reflectance data be useful in distinguishing the canopies of mangrove species at our study site on the Caribbean coast of Panama?; (b) To what degree would inclusion of such information improve our earlier classifications of mangrove species canopies based on high resolution, multispectral imagery?

As a first step in answering these questions, we quantified, under laboratory conditions, the green leaf spectra of the three mangrove species that dominate the canopy of our study forests: *Avicennia germinans*, *Laguncularia racemosa*, and *Rhizophora mangle* (the black, white, and red mangrove, respectively). These same species are the dominant members of Atlantic coast mangrove forests from Florida to Brazil, and are important components of forests in other geographic regions (Tomlinson 1986). Our aim was to determine whether the three species can be discriminated on the basis of reflectance measured over a wider spectral range (350–2500 nm) and at narrower bandwidths than are available in commercial multispectral imagery (e.g. IKONOS or QuickBird). Our approach was similar to that used in previous laboratory studies of foliar spectral reflectance in various upland tree species (Daughtry *et al.* 1989; Miller *et al.* 1991) and in 16 species of Thai mangroves (Vaiphasa and Ongsomwang 2004). If the species' spectral properties cannot be distinguished under such controlled conditions, there would be little reason to pursue classification based on remotely acquired hyperspectral reflectance data, which can be costly to collect.

For classifications of remotely acquired, hyperspectral reflectance data to generate accurate maps of forest canopy species composition, they must account for more than just the spectral variation attributable to species-specific differences in foliar reflectance. Variation in the spectral properties of background substrates such as water or soil can alter hyperspectral signatures, as can changes in the physiological condition of the trees themselves. A number of studies have demonstrated sensitivity of leaf spectral reflectance, transmittance, or absorbance

to plant stress caused by various agents (Carter 1993, 1994, Carter and Knapp 2001, Gamon, *et al.*, 1997, Gausman, 1984, Horler and Barber 1983). Such intraspecific variation in spectral properties has the potential to both complicate and inform efforts to map plant species using hyperspectral reflectance data. Therefore, in addition to measuring the spectral properties of leaves collected from trees living in areas with good growing conditions, we also measured leaves from slow-growing trees living under stressful conditions of low nutrients and drought. The ability to detect physiological stress from spectral reflectance would be a particularly valuable tool for mangrove forest monitoring and management. As noted earlier, mangrove forests are being subjected to a wide variety of anthropogenic disturbances. Many of these disturbances, including those associated with climate change, alter edaphic conditions in ways that are physiologically stressful to mangrove trees. Examples include changes in local hydrology, sedimentation and erosion rates, patterns of tidal inundation, and levels of precipitation and soil salinity. While such physiological stress may ultimately result in the deaths of many trees, a variety of more subtle symptoms may provide early evidence of stress. Such symptoms may include changes in mangrove physiology (e.g. lower photosynthetic rates), foliar chemistry (e.g. lower C:N ratio), or reductions in growth and reproduction, as demonstrated in Ellison and Farnsworth's (1997) greenhouse study of the effects of simulated sea-level rise on the red mangrove, *Rhizophora mangle*.

To our knowledge, no previous study has evaluated whether physiological stress in mangroves produces a distinct spectral signature in their leaves. As the magnitude of change in spectral reflectance in response to stress will vary at different wavelengths, and such patterns of response are also likely to vary among different tree species, it is still in question whether and how hyperspectral data can be used to unambiguously detect physiological stress in mangroves.

3. Methods

3.1 Study site

The study was conducted using leaves collected from mainland mangrove forests near the Smithsonian Tropical Research Institute's Galeta Marine Laboratory (9°24'18' N, 79°51'48.5' W) at Punta Galeta on the Caribbean coast of Panama, approximately 8 km northeast of the city of Colón.

Leaves of each species were sampled, as described in detail below, from trees growing in two different environmental settings: (a) areas supporting closed-canopy stands of large trees, some growing to more than 25 m, and (b) areas with a sparser cover of mostly short-stature (up to 3 m) trees that exhibited a wizened, shrub-like growth form. The former stands grow on organically rich soils of moderate salinity and relatively high nutrient availability, while the latter grow on sandy, coral reef-derived, soil that has lower nutrient concentrations, dries more rapidly between flood tides and rain storms, and is often higher in salinity (W. Sousa, unpublished data). A nutrient manipulation experiment conducted with *Rhizophora mangle* seedlings in this sandy site demonstrated that their growth was nutrient-limited (L. Robinson, unpublished data). Leaves collected from the two sites differed in appearance and thickness: those from productive sites that support good growth tended to be larger, thinner, and more pliant than those collected from trees in the sandy site.

3.2 Leaf collection, spectral measurements, and preprocessing

To determine whether the reflectance patterns of leaves from healthy individuals of the three mangrove species could be successfully discriminated, we selected 30 trees of each species for sampling from an array of productive stands across the study area. These ranged from fringe red mangrove stands growing at the water's edge to more inland stands dominated by white or black mangroves. Where possible, several trees of each species were sampled in each stand, so as to minimise the confounding influence of location on spectral measurements. Since leaves at different positions in the canopy might exhibit distinct spectral characteristics (owing to differences in photosynthetic properties or water content), we stratified the leaf samples collected from each tree by height. From each tree, we collected one sample of 10 leaves from upper parts of the canopy surface and a second sample of 10 leaves from lower parts of the canopy surface. We were not able to sample leaves from the tops of taller trees at these productive sites, but the trees we sampled were growing in open areas, either at the water's edge or along a roadside, and therefore probably experienced similar levels of incident sunlight as the upper canopy of taller trees. Subsequent statistical analyses found that the reflectance patterns of leaves collected from upper versus lower heights in the canopy did not differ significantly for any of the three species (ANOVA, $P > 0.05$). Therefore, we used the pooled sample of 20 leaves to calculate each tree's mean reflectance curve.

To examine the effect of physiological stress and/or nutrient limitation on foliar spectral properties, we collected leaves from stunted individuals of each species that were growing in an area of sandy soils located approximately 100 m behind fringe red mangrove stands that border the back reef adjacent to the Galeta Marine Laboratory. We sampled leaves from 20 trees of each species, randomly selected from across an approximately 1 ha area of this vegetation type; a sample of 10 leaves was collected from each tree. As the crowns of these small trees were easily reached and contained relatively few leaves, we collected from the entire canopy of each tree; no effort was made to stratify these samples by height.

All leaves were collected on 16 July 2004. They were immediately sealed in plastic bags, kept in a dark cooler, and transported back to the nearby laboratory for analysis. Leaf reflectance was measured with a Field Spec Pro FR (Analytical Spectral Devices, Boulder, CO, USA). The measurement procedure followed that employed by Pu *et al.* (2003). The light source consisted of two 500 W halogen tungsten filament lamps. All spectra were measured in reflectance mode at the nadir direction of the radiometer with a 25° FOV. A white Spectralon panel was employed as the white reference and measured every five minutes to convert leaf radiance to percent reflectance. The spectrometer was configured to yield a spectra with 25 spectral averaging. Each sample of ten leaves was stacked in an overlapping pile on top of a calibrated black cloth and care was taken to make sure the field of view was fully occupied by leaf stacks. The adaxial surfaces of a sample were measured five times, from which an average spectral reflectance curve was generated. Spectral reflectance was originally measured over the ranges of 350–1000 nm at 1.4 nm intervals and 1000–2500 nm at 2.2 nm intervals. The entire spectral range (350–2500 nm) was automatically resampled to 1 nm when exported to the computer. To reduce system noise and redundancy between adjacent bands, we computed an average reflectance for each 10 nm interval, providing a total of 215 wavebands for analysis.

For band selection and classification of leaves from healthy trees, we had a sample size of 30 spectra for each tree species. We randomly split these 30 samples into a

training group comprised of 20 samples and a test group of 10 samples; the latter were used to assess our classification accuracy. This procedure was repeated 10 times on randomly drawn sets of training and test samples.

3.3 Band selection and tree species classification

Owing to the high correlation inherent to adjacent wavebands, it was neither efficient nor reliable to include all 215 measured bands in the classification at one time. Instead, one must first choose a subset of bands that will maximise the likelihood of discrimination before proceeding with a conventional classification. A number of band or feature selection methods have been developed and documented in the remote sensing literature, including Principal Component Analysis (PCA), Fisher's Linear Discriminant Analysis (LDA), Penalised Discriminant Analysis (PDA), and wavelet-based feature selection (Yu *et al.* 1999, Pu and Gong 2004). Among them, LDA is the procedure that has been most widely adopted. However, a critical problem associated with LDA is that it will not provide a reliable solution when reflectance values for many highly correlated wavebands are included in the analysis and the number of available training samples is small. In this circumstance, estimates of within-class covariance matrices from the training samples are poor and unstable. Recall that we had 215 bands of reflectance values while only 20 samples for each species as training samples. The results of an LDA on such data would be highly questionable; the projection axis is likely to be misoriented, giving rise to over-fitting: i.e. a perfect performance on the training data, but a poor performance on the test data. Yu *et al.* (1999) provide a good graphical illustration of the problem.

To circumvent this problem, we applied a series of one-way ANOVAs to filter out wavebands that did not differ significantly in mean reflectance among leaves of the three tree species. A one-way ANOVA, with species as the independent factor, was carried out for each of the 215 wavebands. The resultant probability provided an index of the importance of the tested band to the discrimination of the tree species. We considered $P \leq 0.01$ as an indication that the mean reflectances of at least two of the three species differed in the tested band; all bands meeting this criterion were included in the LDA. One potential criticism of this band selection procedure is that the results of tests on adjacent bands are not statistically independent. However, our objective in applying ANOVA was not to test hypotheses about differences within specific bands; rather, we were seeking to eliminate bands from the analysis that provided no useful information for discriminating species' reflectance patterns, and thereby reduce the number of analysed bands to a level that would be operational for LDA. This band selection procedure was performed on all the training samples.

An LDA was then performed using the wavebands that ANOVA identified as exhibiting evidence of interspecific variation. The rationale of LDA is to project the original redundant data to a new orthogonal space oriented along the axis that can maximise the ratio of between-class to within-class variance matrices of the training samples. The axis of the new space is aligned in the order of discrimination power among groups such that the first axis provides the greatest overall discrimination, the second provides second greatest, and so on. If we denote the total number of groups to be classified as N_G and the total number of original bands as N_B , then the number of dimensions for the new space is equal to either $N_G - 1$ or N_B , whichever is smaller. Because, in practice, N_B is usually larger than N_G , LDA will typically yield a new data set with $N_G - 1$ dimensions. In this way, the data dimensions are significantly reduced.

The significance of a specific wavelength to a discrimination function can be determined by examining the standardised coefficients for that band. The interpretation of the standardised coefficients resembles the logic of multiple regression. The larger the absolute value of standardised coefficient, the larger is the respective variable's unique contribution to the discrimination as specified by the respective discriminant function. As such, by ordering the standardised coefficients the optimal wavebands were determined.

Given the fact that we have three species to classify, LDA generated two discriminant functions, with which the test samples were transformed. Then a Mahalanobis distance classifier was performed. A kappa value was calculated to assess the classification accuracy (Cohen 1960).

3.4 Discrimination between leaves from healthy versus stressed trees

Previous studies have found that leaf spectral reflectance increases in portions of the visible and very-near infrared range (but not in the infrared) as a plant experiences physiological stress (Carter 1993, 1994, Carter and Knapp 2001). This response has been documented for numerous plant species when subjected to various agents of stress. We therefore focused on the 400–800 nm wavelength in our comparison of healthy and stressed leaves. The sensitivity of reflectance to stress (i.e. relative change in reflectance) varies considerably within this spectral range. Sensitivity is greatest for wavelengths (e.g. 605, 695, and 710 nm) at which absorption by chlorophylls *a* and *b* is relatively weak. At these wavelengths, even a slight drop in leaf chlorophyll-*a* and chlorophyll-*b* content caused by stress results in a large increase in leaf reflectance (Carter 1993).

As demonstrated by Carter (1994), reflectance sensitivity can be best expressed as a ratio of reflectance in a stress-sensitive band to reflectance in a stress insensitive band. For our study, we calculated four narrow band leaf reflectance ratios as indices of stress: R_{695}/R_{420} , R_{605}/R_{760} , R_{695}/R_{760} , and R_{710}/R_{760} . Carter (1994) found these ratios to be particularly sensitive indicators of stresses that affect chlorophyll-*a* and chlorophyll-*b* content. We used ANOVA to compare the means of these ratios between leaf samples from trees growing in productive and stressful sites.

4. Results

4.1 Band selection and classification

Figure 1 presents the mean reflectance spectra of leaves from the three mangrove species; values for healthy and stressed trees are plotted separately (figures 1(a) and 1(b)). Figure 1(c) plots the difference between the average spectra of leaves from healthy and stressed trees of each species. We will first examine patterns of reflectance for leaves from healthy trees growing in productive sites. As expected, the general shapes of the species' curves are very similar, with considerable overlap; however, one-way ANOVA tests revealed significant heterogeneity among the species in particular wavebands (figure 2).

Of the 215 10 nm-wide wavebands tested, 116 bands exhibited significant ($P \leq 0.01$) interspecific variation in mean reflectance (figure 2). These bands were clustered in five areas of the spectrum, i.e. 350–510 nm, 610–690 nm, 760–810 nm, 1370–1550 nm, and 1850–2500 nm. Bands within each of these areas are highly correlated and cannot be treated as independent estimates of species-level response. To reduce this correlation, we first regrouped the 116 significant bands into three

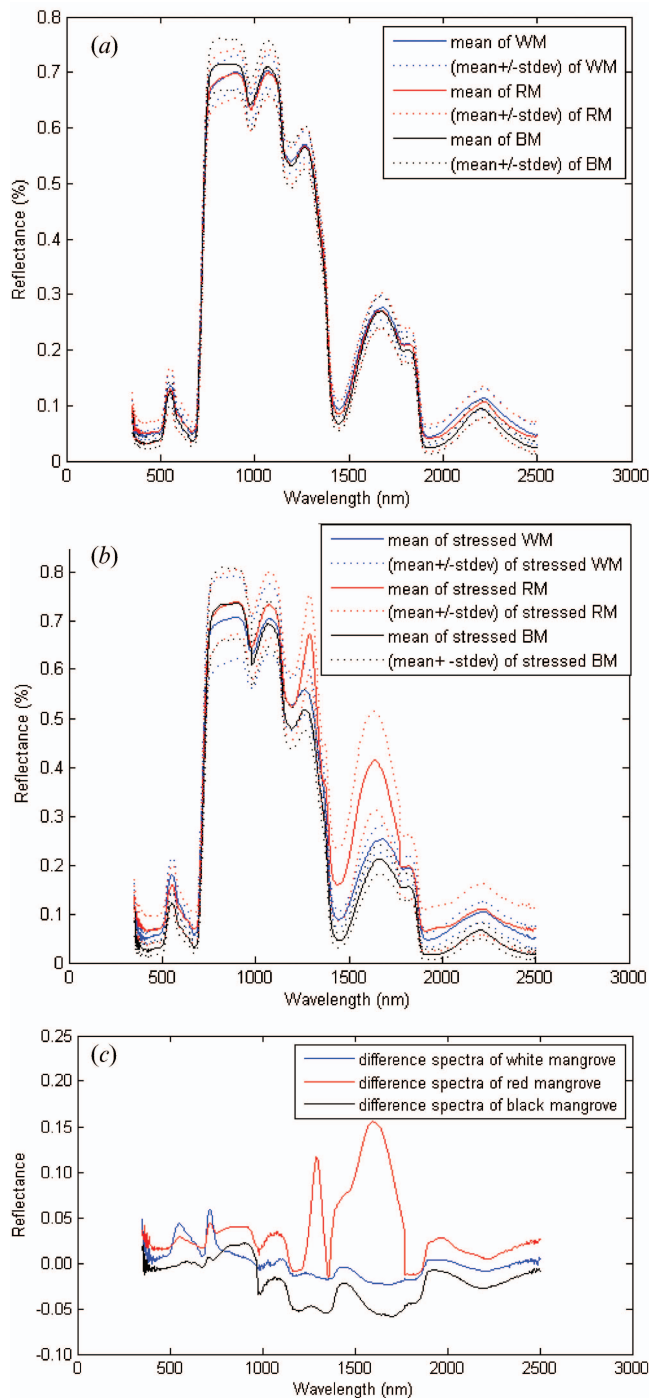


Figure 1. (a) mean and (mean \pm 1 stdev) reflectance spectra for leaves from healthy leaves of the three mangrove species (WM: White Mangrove; RM: Red Mangrove; BM: Black Mangrove); (b) mean and (mean \pm 1 stdev) reflectance spectra for leaves from physiologically stressed leaves of the three mangrove species; c) mean difference spectra by subtracting non-stressed from stressed reflectance for each species.

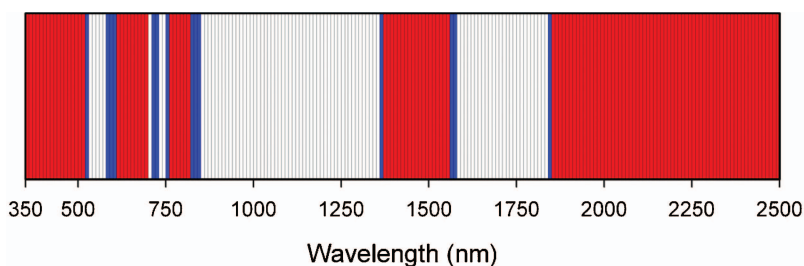


Figure 2. Distribution of wavebands whose p-values are less than 0.01 (in red) derived from one-way ANOVA.

regions as follows: region 1: VNIR (350–510 nm, 610–690 nm, and 760–810 nm); region 2: SWIR I (1370–1550 nm); and region 3: SWIR II (1850–2500 nm). An LDA was executed separately within each region and the standardised coefficients for two discrimination functions were respectively calculated and ranked. We concluded that a band was influential for its particular region if the absolute value of its LDA standardised coefficients were ranked among the top ten for both discrimination functions. Table 1 lists such influential bands for each region of wavelengths considered in the analysis.

The final classification of mangrove species was generated by LDA after pooling the influential bands from each region. Figures 3(a) and (b) present the distribution of training and test samples in the discriminant space, respectively. In both the training and test samples, leaves of the three mangrove species were well separated in discriminant space. The average kappa value for the ten sets of test samples was 0.9, with a range of 0.85 to 1.00. This indicates that our method for extracting influential wavebands from the hyperspectral data, in combination with an LDA-based classification procedure, was very successful in discriminating the leaves of different mangrove species. Our results concur with several other researches that achieved good discrimination through use of the LDA method (Gong *et al.* 1997, Van Aardt and Wynne 2001, Clark *et al.* 2005).

Figure 3(a) shows that the first discriminant function alone is sufficient to distinguish red from either black or white mangrove leaves. Examination of the standardised coefficients associated with the first discriminant function (figure 4(a)), reveals that reflectance at the 780, 790, 800, 1480, 1530 and 1550 nm wavebands contribute most strongly to the first discriminant function. In other words, these bands are critical to the discrimination of red from the other two types of mangrove. The second discriminant function best distinguishes white from black mangrove leaves; this function was most strongly influenced by wavebands at 770, 780, 790, 800, 1430, and 1480 nm (figure 4(b)).

Table 1. Results of one-way ANOVA showing the potentially important wavelengths for discriminating leaf samples from healthy trees of the three mangrove species (all wavelengths in nm).

Spectral region	Region 1: VNIR [350–510, 610–690, 760–810]	Region 2: SWIR I [1370–1550]	Region 3: SWIR II [1850–2500]
Influential wavelengths in each region	490, 500, 630, 770, 780, 790, 800	1400, 1430, 1480, 1530, 1550	1940, 1970, 1990

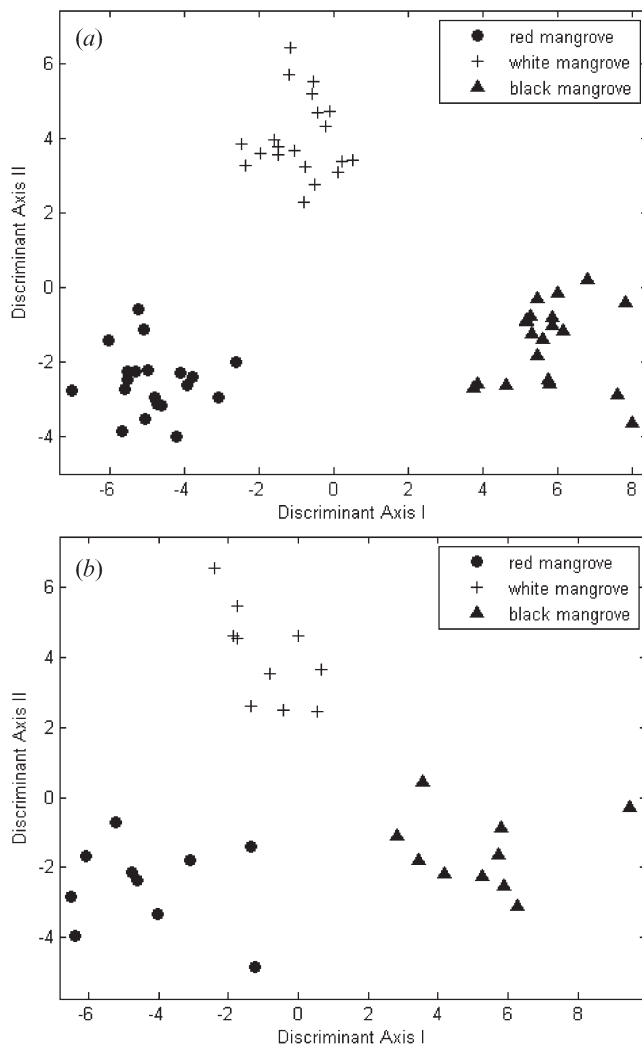


Figure 3. Distribution of leaf samples from healthy trees of the three mangrove species in discriminant space: (a) training samples; (b) test samples.

4.2 Discrimination between leaves from healthy versus stressed trees

One or more of the four reflectance ratio indices proved useful in detecting stress in each of the mangrove species (Table 2). R_{605}/R_{760} , R_{695}/R_{760} and R_{710}/R_{760} were effective in distinguishing stressed from non-stressed red mangrove leaves. In the case of white mangrove, R_{695}/R_{420} was the only ratio that successfully detected the presence of stress. All four ratios were capable of detecting stress in black mangroves.

5. Discussion

The high classification accuracy we obtained in this analysis confirms the great potential of using hyperspectral data to distinguish mangrove species. We are confident that the use of narrow band hyperspectral data can effectively overcome

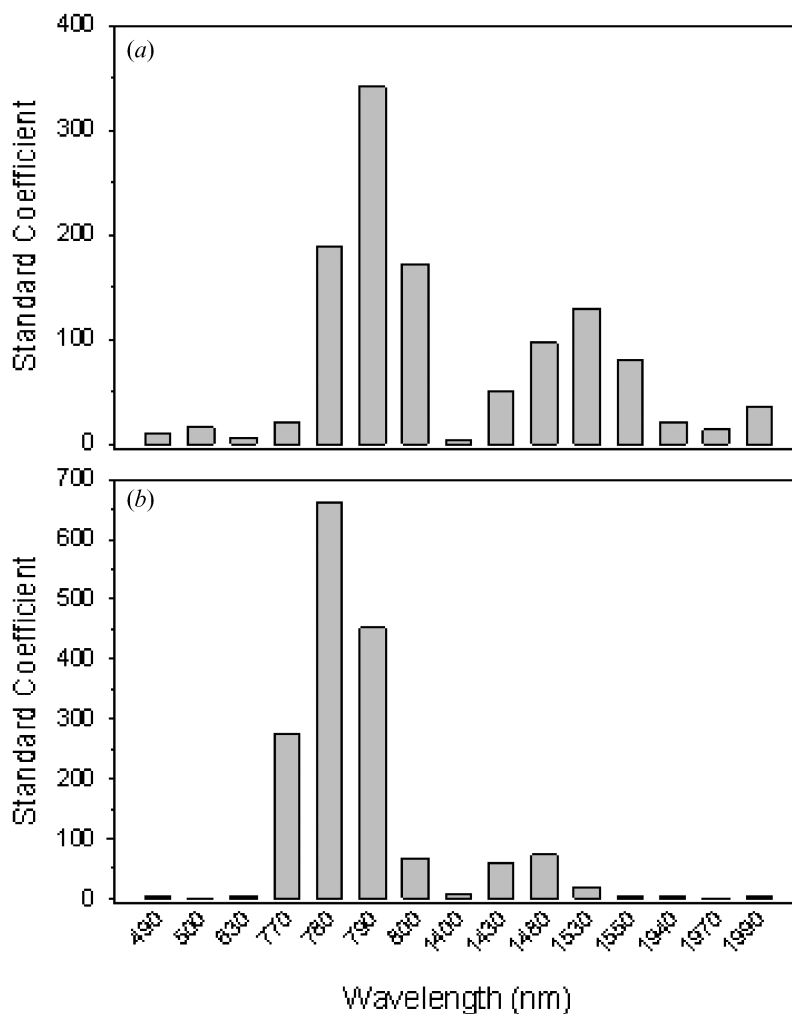


Figure 4. (a) Standard coefficients associated with the first discriminant function; (b) standard coefficients associated with the second discriminant function.

the problem of overlap in spectral characteristics among species observed in our previous analyses of wide band multispectral imagery (Wang *et al.* 2004 a, b).

The large number of highly correlated bands and relatively small numbers of training and test samples are typical challenges to analysing hyperspectral data. The ANOVA procedure we employed is an efficient method of limiting the number of bands included in the classification to those that are most likely to distinguish leaves of the different species. Focusing on this smaller set of bands, LDA proved an effective procedure for building the best discrimination function, and provided a means to assess the contribution of each wavelength to the discrimination via the analysis of standardised coefficients. However, it is worth mentioning that the classification accuracy of LDA, as reported by Clark (2005), can be very high at the leaf level, but may decay markedly at coarser spatial scales.

The LDA of the selected 'optimal' bands confirmed our impressions from an initial visual inspection of the spectral curves. The near infrared plateau from 780–810 nm is

Table 2. Results of ANOVA. Entries are *P* values by comparing the comparing the mean values of the four narrow band ratios between stressed and healthy leaves; bolded values are considered statistically significant (*P* value<0.01).

Two Tail			
Narrow Band Ratios	Mangrove species		
	Red	White	Black
R_{695}/R_{420}	0.371	< 0.001	< 0.001
R_{605}/R_{760}	0.009	0.799	< 0.001
R_{695}/R_{760}	0.008	0.888	< 0.001
R_{710}/R_{760}	0.013	0.613	< 0.001

One Tail			
Narrow Band Ratios	Mangrove species		
	Red	White	Black
R_{695}/R_{420}	0.81	< 0.001	< 0.001
R_{605}/R_{760}	0.005	0.399	< 0.001
R_{695}/R_{760}	0.004	0.444	< 0.001
R_{710}/R_{760}	0.007	0.306	< 0.001

the most important waveband for discriminating the three mangrove species. This same region was found to be critical for distinguishing different types of saltmarsh vegetation (Schmidt and Skidmore 2003). We also found that differential reflectance at 1490, 1560, and 1580 nm, three SWIR bands, enhanced spectral discrimination of the three mangrove species. When the lab measured hyperspectral data are replaced by the remotely sensed data, care has to be taken to avoid including any water vapour absorption bands, among which the two most prominent one occurs in 1450 nm and 1940 nm. In addition, it is interesting to observe that our analysis did not pick up any influential bands in the range 2000–2500 nm, which exhibits some visual difference in figure 1. The reason needs to be further investigated.

Four narrow band ratios that have been demonstrated to discriminate stressed from unstressed foliage in a variety of vegetation types also proved useful for discriminating leaves of the same species of mangrove growing in productive versus unproductive and apparently stressful habitats. We believe this to be the first demonstration of stress sensitive, spectral ratios in mangroves. This promising observation needs additional investigation; the stressed state of the trees must be confirmed with direct measurements of their physiological status and the effectiveness of the narrow band ratios for detecting stress should be tested for different agents of stress. As the narrow band ratios as proposed in Carter (1993, 1994) only employed VNIR bands, the effectiveness of SWIR band, particularly around 1500 nm in this study, has to be investigated by adopting or developing other stress detection methods. Besides the four narrow band ratios employed in this study, stress detection methods such as the photochemical reflectance index (Gamon 1997), the red edge method (Horler 1983), that were established from tree species other than mangrove, will be explored in the future study.

Although the spectral discrimination of mangroves was successfully achieved at the level of individual leaves in this study, this result was obtained in the laboratory under controlled illumination. It is only the first step towards our ultimate goal of

discriminating and mapping mangrove canopies of differing species composition at the landscape scale. Remotely acquired hyperspectral data collected by airborne or satellite-based sensors will be required for this purpose. Whether and how leaf-level methods of spectral discrimination can be scaled up to the canopy level remain important, unanswered questions. The influences of atmospheric conditions and forest structural complexity on remotely acquired reflectance spectra may require reassessment of the wavebands that are most effective for distinguishing canopies of differing species composition. For example, longer NIR wavelengths might be used in ratio denominators to avoid the strong O₂ absorption that occurs at 760 nm. Clearly, this issue begs further investigation; it is central to future efforts to remotely map and monitor the health of endangered mangrove ecosystems.

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