# Remote Sensing Techniques for mangrove mapping

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THESIS

# Abstract

Mangroves, important components of the world's coastal ecosystems, are threatened by the expansion of human settlements, the boom in commercial aquaculture, the impact of tidal waves and storm surges, etc. Such threats are leading to the increasing demand for detailed mangrove maps for the purpose of measuring the extent of the decline of mangrove ecosystems. Detailed mangrove maps at the community or species level are, however, not easy to produce, mainly because mangrove forests are very difficult to access. Without doubt, remote sensing is a serious alternative to traditional field-based methods for mangrove mapping, as it allows information to be gathered from the forbidding environment of mangrove forests, which otherwise, logistically and practically speaking, would be extremely difficult to survey. Remote sensing applications for mangrove mapping at the fundamental level are already well established but, surprisingly, a number of advanced remote sensing applications have remained unexplored for the purpose of mangrove mapping at a finer level. Consequently, the aim of this thesis is to unveil the potential of some of the unexplored remote sensing techniques for mangrove studies. Specifically, this thesis focuses on improving class separability between mangrove species or community types. It is based on two important ingredients: (i) the use of narrow-band hyperspectral data, and (ii) the integration of ecological knowledge of mangrove-environment relationships into the mapping process.

Overall, the results of this study reveal the potential of both ingredients. They show that delicate spectral details of hyperspectral data and the spatial relationships between mangroves and their surrounding environment help to improve mangrove class separability at the species level. Despite the optimism generated by the overall results, it was found that appropriate data treatments and analysis techniques such as spectral band selection and noise reduction were still required to harness essential information from both hyperspectral and ecological data. Thus, some aspects of these data treatments and analysis techniques are also presented in this thesis. Finally, it is hoped that the methodology presented in this thesis will prove useful and will be followed for producing mangrove maps at a finer level.

***The Synthesis***

## 6.1. Introduction

Mangrove forests are part of the coastal environment and stretch throughout the tropics and sub-tropics of the world (Tomlinson, 1994; Hogarth, 1999). They cover up to 75% of the world's tropical coastlines (Spalding et al., 1997). Their importance is recognisable in such aspects as forestry, fisheries, and environmental conservation (Barbier and Sathiratai, 2004). Similar to many other natural resources, mangroves are declining because of the influence of natural disturbance and human intervention. This has negative effects on economic development and ultimately on the environment as a whole (Barbier and Sathiratai, 2004). These repercussions have subsequently drawn considerable attention to the conservation and management of this unique estuarine ecosystem (Ramsar Convention, 1971; Linneweber and de Lacerda, 2002).

Precise and up-to-date spatial information on the current status of mangroves is a prerequisite for the sustainable conservation of mangrove ecosystems. It is almost impossible to gather this information by using traditional field surveys because mangrove swamps are extremely difficult to access. Fortunately, it has been discovered that remote sensing technology is a promising solution to this problem of accessibility (Green et al., 2000; Held et al., 2003).

To date, the use of remote sensing technology for gathering spatial information from mangrove forests (e.g., mapping and monitoring) at the community levels has been extensive (Aschbacher et al., 1995; Ramsey III and Jensen, 1996; Gao, 1999; Sulong et al., 2002), but the application at the species level, which is necessary for studying mangrove species diversity, is still inconclusive (Demuro and Chisholm, 2003; Held et al., 2003). Therefore, this thesis further explores the capability of remote sensing technology to map mangroves at the species level, using two important ingredients: (i) the use of narrow-band hyperspectral data, and (ii) the integration of ecological knowledge of mangrove-environment relationships into the mapping process.

The key objectives of this study are:

(1) to demonstrate the potential of hyperspectral technology for discriminating mangroves at the species level
(2) to test whether a form of genetic algorithms can be used for selecting a meaningful subset of spectral bands that maintains spectral separability between mangrove species
(3) to investigate one of the most popular methods of reducing noise levels in hyperspectral data (i.e., spectral smoothing), as well as propose a technique for selecting an appropriate smoothing filter for the data at hand
(4) to test whether mangrove-environment relationships can be exploited in order to improve the mapping accuracy.

## 6.2. The main results

### *6.2.1. Hyperspectral data for mangrove discrimination*

Although multispectral sensors are the most cost-effective remote sensing solutions for mangrove mapping (Aschbacher et al., 1995; Ramsey III and Jensen, 1996; Gao, 1999; Green et al., 2000; Sulong et al., 2002; Held et al., 2003), they are still limited to applications for mapping at the regional scale. One of their major constraints is the lack of spectral detail.

Unlike multispectral sensors, hyperspectral sensors that possess 100 or more narrow spectral bands between the visible and shortwave infrared regions have already proved to have the potential for discriminating terrestrial plants at the species level (Cochrane, 2000; Schmidt and Skidmore, 2003). Nevertheless, the hyperspectral research on mangroves published to date (Green et al., 2000; Demuro and Chisholm, 2003; Held et al., 2003; Hirano et al., 2003) remains inconclusive when it comes to using the technology for tropical mangrove species discrimination.

The prerequisite study described in Chapter 2 took the investigation into this issue one step further. It was a laboratory investigation to see whether hyperspectral data contained adequate spectral information for discriminating mangroves at the species level. The study helped us in deciding whether to invest in the expensive acquisition of airborne or satellite hyperspectral data. In brief, the spectral responses of 16 tropical mangrove species were recorded from the leaves, using a 2151-band spectrometer under laboratory conditions. Then, the mangrove spectra at every spectral location were statistically compared using one-way ANOVA to see whether they significantly differed. Finally, the spectral separability between each pair of mangrove species was calculated using the J-M distance in order to confirm the results.

It turned out that the leaf spectra of different mangrove species were statistically different at most spectral locations, with a 95% confidence level (Figure 6.1). Specifically, the total number of spectral bands that had p-values $< 0.05$ was 1941, of which 477 bands had p-values $< 0.01$. Moreover, the J-M distance indices calculated for all pairs of the mangrove species also confirmed that the mangroves were spectrally separable (i.e., J-M distance $\geq 1.90$), except the pairs that comprised members of Rhizophoraceae (Table 6.1).

Overall, the results encourage further investigation into the use of airborne and satellite hyperspectral sensors for discriminating mangrove species. However, one should bear in mind the difficulty in discriminating the members of the Rhizophoraceae family. Since the Rhizophoraceae family usually dominates tropical mangrove forests, difficulty in discriminating these mangroves is expected when implementing the on-board hyperspectral sensors.

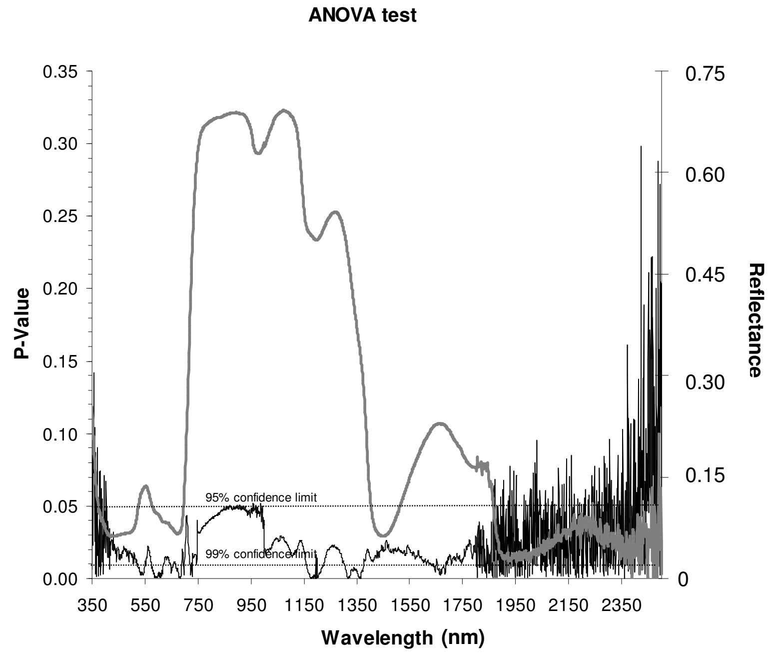



**Figure 6.1**: The plot of p-values of the ANOVA test (black line) showing against a laboratory reflectance of *Rhizophora apiculata* (grey line)

**Table 6.1**

The J-M distances between all pairs of 16 mangrove species (120 pairs in total). The species names are coded in Chapter 2. The pairs that possess separability levels lower than 1.90 are highlighted in grey. Mangrove species are grouped by family name.

| | | 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 | |

### *6.2.2. Hyper-dimensionality problems*

The high-dimensional characteristics of hyperspectral data can trigger the phenomenon known as "the curse of dimensionality" (Bellman, 1961). This phenomenon causes imprecise class estimates in the spectral feature space, which result in low output classification accuracy (Bellman, 1961; Hughes, 1968). Consequently, this situation demands more training samples in order to construct better class estimates, thereby dramatically increasing the cost of the field survey.

Chapter 3 demonstrated an alternative to the existing account of feature selection tools to deal with the curse of dimensionality. This alternative feature selection tool was a form of genetic search algorithms (GA). Pioneering work that gained significant insight into this issue was carried out by Siedlecki and Sklansky (1989). The authors reported that the GA-based band selector performed better than many other popular band selection algorithms (e.g., branch and bound search, exhaustive search, and sequential forward selection). The authors rigorously tested their hypothesis, using a synthetic error model instead of real remotely sensed data in order to eliminate the variables (e.g., sample size, the number of spectral bands, and the number of classes of interest) that could have biased the outcome. Further evidence of the success of GA-based band selection tools can be found in recent hyperspectral remote sensing publications (Yu et al., 2002; Fang et al., 2003; Kooistra et al., 2003, Cogdill et al., 2004).

In contrast to the acid tests completed so far (Lofy and Sklansky, 2001; Kavzoglu and Mather, 2002; Yu et al., 2002; Ulfarsson et al., 2003), the work presented in Chapter 3 was the first time that the GA-based band selector had been tested on spectrometer records of very high dimensionality, comprising 2151 bands of leaf spectra of 16 tropical mangrove species. It turned out that the GA-based band selector was able to cope with spectral similarity at the species level. It selected spectral bands that related to the principal physico-chemical properties of plants (Curran, 1989; Elvidge, 1990; Kumar et al., 2001) and, simultaneously, maintained the separability between species classes at an 80% level of classification accuracy. The selection result is shown in Figure 6.2.

It is worth noting that only one of the six spectral locations illustrated in Figure 6.2 is in the visible region where electro-magnetic energy interacts with mangrove leaf pigments (e.g., chlorophylls, carotenoids) (Menon and Neelakantan, 1992; Basak et al., 1996; Das et al., 2002). This outcome may be interpreted as an indication that the spectral responses of mangrove pigments contain less important spectral information for mangrove species discrimination than the information from the spectral responses of the other leaf components that interact with electro-magnetic energy at longer wavelengths. Unfortunately, the results of studies so far on the physico-chemical properties of leaves of different mangrove species are still inconclusive when it comes to pinpointing which components of mangrove leaves are spectrally separable (Menon and Neelakantan, 1992; Tomlinson, 1994; Basak et al., 1996; Das et al., 2002). A thorough comparative study is therefore recommended in order to confirm this part of the findings.

Lastly, the capability of the GA-based band selector to cope with a very complex band selection problem reported in Chapter 3 encourages the future use of the band selector for detecting spectral bands that show strong vegetation responses to different physico-chemical treatments (e.g., nitrogen, illumination) in both laboratory and field scenarios. It is anticipated that the GA-based band selector will be a viable alternative to the statistical and derivative analyses popularly used at the moment (Tsai and Philpot, 1998; Mutanga et al., 2003).

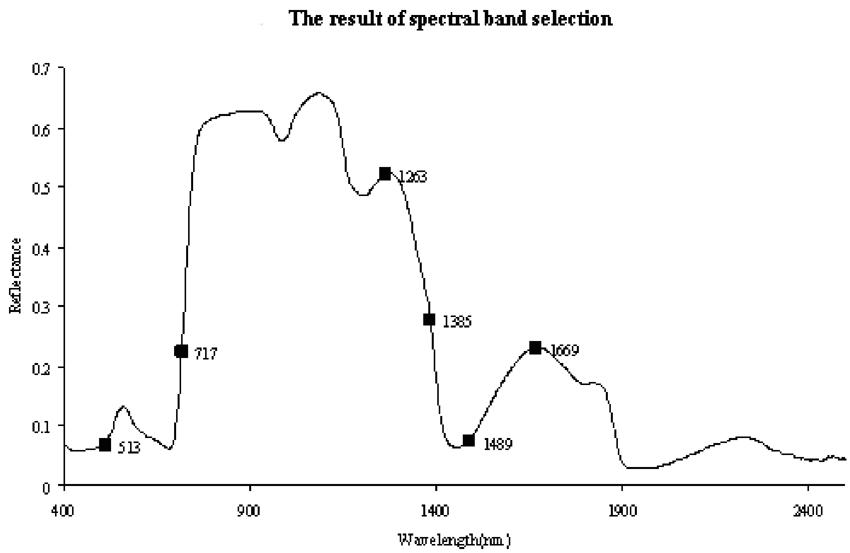



**Figure 6.2**: Six average spectral positions selected by the GA-based feature selection algorithm

*6.2.3. Noise levels*

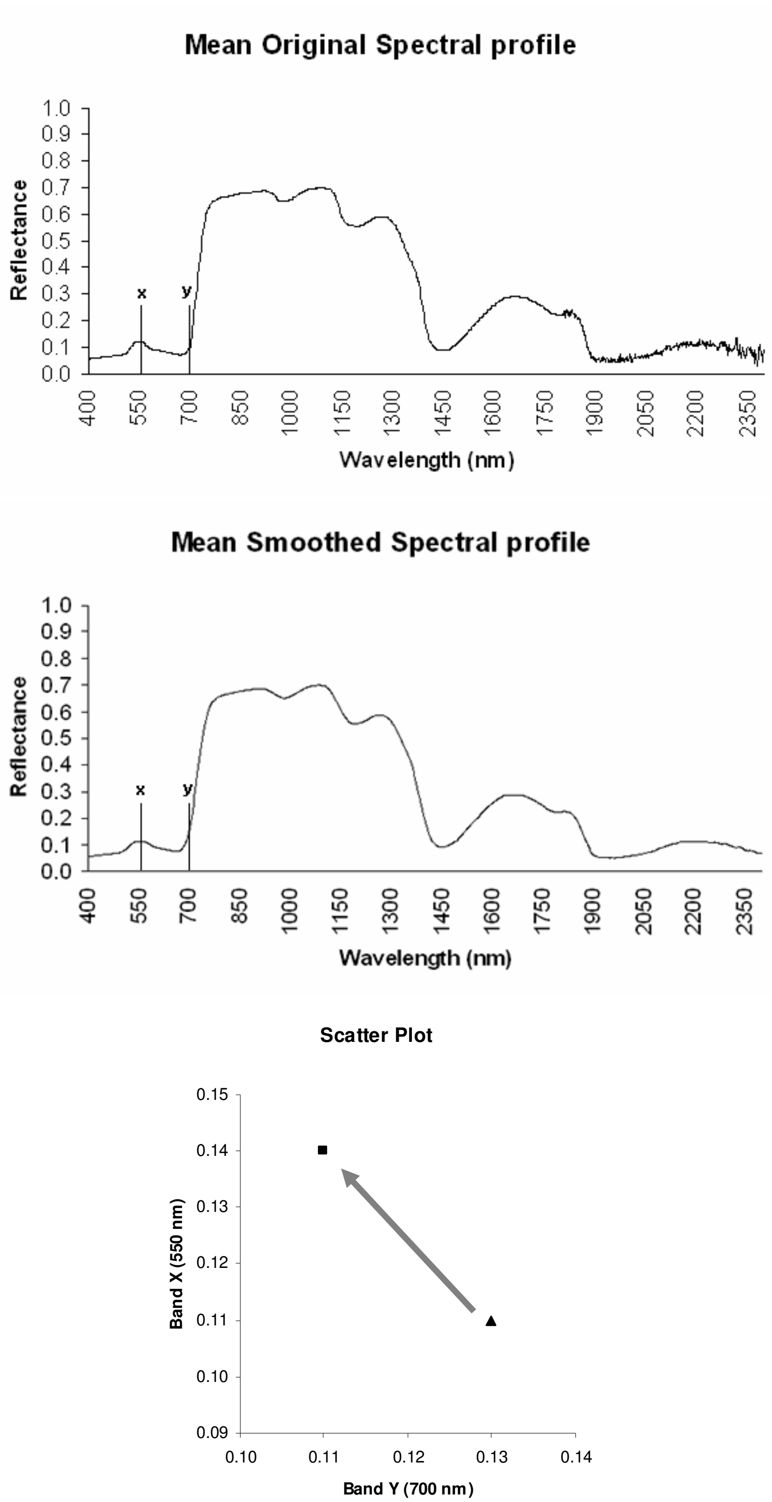
Another important problem when using hyperspectral data is low signal-to-noise ratios. This problem is normally solved by applying spectral smoothing filters to each spectral profile in order to create convolutions of spectral values, thereby reducing the noise level. According to the review in Chapter 4, however, it was found that at least 20 recently published reports used subjective *ad hoc* inspections as their measures for selecting filter types and the parameters. In other words, they did not employ any strict optimizing criterion to select suitable smoothing filters for their studies. It is believed that the *ad hoc* approach is not the most appropriate way. Furthermore, it is hypothesized that smoothing filters can cause significant changes to the statistical properties (e.g., mean) of spectral data (see Figure 6.3). This statistical disturbance could then affect the outcome of subsequent analyses (e.g., maximum likelihood classifier, Jeffries-Matusita distance) that are based on statistical estimates of the data.

In Chapter 4, it was proved that the above hypothesis is true (i.e., the effect of the smoothing disturbances on the class statistics is evident in Table 4.2). Thus, if preserving statistical properties of the original hyperspectral data is desired, smoothing filters that cause the minimum disturbance to the statistical properties of the original data should be objectively applied. One possible solution is to use a simple comparative t-test as a post-smoothing measure for choosing an optimum smoothing filter for the hyperspectral data at hand.

The purpose of the post-smoothing method (the t-test) proposed in Chapter 4 was to control the effect on the statistical estimate of popular smoothing filters such as the moving average and Savitzky-Golay that have no built-in ability to preserve the original statistical properties of the spectral data (i.e., these popular filters are based on underlying non-parametric mathematics that does not preserve statistical estimates of class information) (Kay, 1993). However, the post-smoothing method could have been omitted if the filter used had had the ability to preserve the statistical properties of the data. This ability could be achieved by designing a specialized smoothing filter, using an estimation theory such as maximum likelihood estimation (Oppenheim and Schafer, 1975; Kay, 1993; Deng and Shen, 1997). In this way, class statistics of the original spectral data could be preserved by the filter after smoothing without the need for the post-smoothing statistical verification (i.e., no need to use the t-test method presented in Chapter 4).

Similarly, if preserving other properties of the spectral data, including signal phases or signal-to-noise ratios, is desired, specialized smoothing techniques could be used as a replacement for the generic techniques (e.g., moving average and Savitzky-Golay). With respect to the first case, preserving signal phases is particularly desirable for specific applications such as spectral derivative analyses. In this regard, specialized methods such as the Fourier transformation and wavelet decomposition would be the right choice because it has been proved that they can preserve the signal phase better than the generic smoothing methods (Curran et al., 1992; Schmidt and Skidmore, 2004). As for the second case, signal-to-noise ratios could be preserved by specific filters such as the Kawata-Minami filter, which is equipped with a least mean-square criterion that helps to maximize the signal-to-noise ratio (Kawata and Minami, 1984; Tsai and Philpot, 1998).

Nevertheless, according to the review in Chapter 4, application-specific smoothing methods such as the Fourier and wavelet transformation and the Kawata-Minami filter are less popular in the field of remote sensing than generic methods such as the moving average and Savitzky-Golay filters. Consequently, tailoring specialized smoothing filters to specific requirements as a replacement for generic methods could be an interesting topic for future research.




(a)

(b)

(c)

**Figure 6.3**: An average spectral profile of plant leaves (a) before smoothing and (b) after smoothing; (c) a scatter plot of two principal wavelengths before (triangle) and after (square) smoothing

### *6.2.4. Utilizing mangrove-environment relationships*

Spatial relationships between mangroves and the environment are well known (Macnae, 1968; Clough, 1982; Semeniuk, 1983; Tomlinson, 1994; Hogarth, 1999). These relationships result in the mangrove zonations that are usually found in tropical mangrove forests (Tomlinson, 1994; Hogarth, 1999; Vilarrubia, 2000; Satyanarayana et al., 2002). As a result, it is hypothesized in this thesis that these quantifiable spatial relationships between mangroves and their environment can be exploited for mangrove mapping.

In Chapter 5, the relationships between mangroves and the surrounding environmental gradient were utilized. The relationships were incorporated into the mapping process via a typical Bayesian probability model. The Bayesian model functioned as a post-classifier to improve the quality of a mangrove map already produced. The environmental gradient used was a GIS layer of soil pH data.

The integration of soil pH into the mapping process turned out to be worthwhile as it significantly increased the mapping accuracy: from 76.0% to 88.2%. However, the remaining confusion between *R. mucronata* and *S. caseolaris* points to the fact that soil pH data cannot help to resolve the similarity between the two species, and, as a result, more ancillary data such as leaf texture (i.e., captured by aerial photos) are recommended. Overall, it is anticipated that the methodology presented in this study will be used as a guideline for producing a mangrove map at the community or species level.

Lastly, follow-up research is already underway. First, the performances of other inference engines, such as artificial neural networks and the Dempster-Shafer theory, are now being compared with the outcome of Bayes' rule used in this thesis. Second, despite the problem relating to interoperability (i.e., data incompatibility) (Bishr, 1998), the research question of how to draw a consensus from expert knowledge from different spatial and non-spatial data sources (e.g., mangrove scientific publications, empirical data from other study areas, and opinions from local mangrove experts) is being resolved using recent advances in geo-information theories, including (i) suitability modelling (Bonham-Carter, 1994; Yamada et al., 2003), (ii) the personal construct theory (Kelly, 1955; Zhu, 1999), and (iii) the semantics look-up table method (Comber et al., 2004).

## 6.3. This thesis in a nutshell!

This thesis is all about exploring remote sensing methods that can be used for mapping mangroves at the species level. The significance of this thesis can be synthesised into three major points. First, I point out the reason why there is the need for the continuation of my research on the use of hyperspectral sensors for mapping mangroves at the species level. Second, I tell the reader that there is no real reason to feel panic with the technical complications when working with hyperspectral data. Third, I explain why my attempt to incorporate the mangrove-environment relationships into the mapping process (i.e., an idea that seems to be too expensive to implement) could lead to an operational method in the near future.

### *6.3.1. Why is the follow-on research needed?*

The evolution of remote sensing sensors from multispectral sensors to hyperspectral sensors gives birth to a practical tool for detailed mangrove studies. The hyperspectral sensor does not only share advantageous characteristics of its ancestor, multispectral sensor, particularly on the aspect of cost-effectiveness. It allows us to exploit the relationships between mangroves and their spectral characteristics in finer detail. This successful exploitation is evident in the following examples. Hirano et al. (2003) used the 224-band Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor for producing accurately the map of the mangrove communities of the Everglades, Florida. Furthermore, Demuro and Chisholm (2003) successfully used the HYPERION hyperspectral sensor, accommodated on the satellite platform, for discriminating 8-class mangrove species communities in Australia. The situation looked even more optimistic when we discovered that pure mangrove spectra (laboratory spectra) contained enough information for discriminating most of mangrove species (Chapter 2). Nevertheless, the hyperspectral research on mangroves published to date (Green et al., 2000; Demuro and Chisholm, 2003; Held et al., 2003; Hirano et al., 2003) is still inconclusive. As a result, more research is still needed as to see whether the mangroves can be mapped at the species level when airborne or satellite hyperspectral sensors are used under the field conditions where there are numerous factors that could degrade the spectral signal received by the hyperspectral sensor, thereby making it harder to separate mangrove species.

### *6.3.2. Be at ease with hyperspectral data*

With respect to spatial resolution of hyperspectral sensors, studying mangroves in detail does not require expensive high spatial resolution data as one might think. According to the spatial sensitivity analysis of tropical mangrove distribution reported by Manson et al. (2003) and our own experience in the tropical mangrove forests, it is clear that mangrove forests possess low spatial heterogeneity of mangrove species distribution and, therefore, spatial resolution of commercial hyperspectral sensors installed on the satellite platform such as HYPERION (i.e., 30 m spatial resolution) should be adequate for the study of mangroves at the species level. This means that mapping mangrove species does not require expensive airborne hyperspectral sensors as in case studies of other terrestrial plants at the species level (Schmidt and Skidmore, 2003; Clark et al., 2005).

In addition, using hyperspectral sensors for mapping mangroves at the species level does not necessarily require more complex data treatments than the case of typical multispectral sensors. In other words, one can still use those existing methods (e.g., statistical-based classifiers etc.) that are normally used for the case of multispectral analyses for analysing hyperspectral data except for the requirements of special treatments for (i) high dimensionality, and (ii) high noise levels.

First, high dimensionality of hyperspectral technology is a two-sided sword. On the one hand, the inter-band correlations provide useful information about the shape of the spectral distribution in the feature space. This shape information has been proved that it helps increase the mapping accuracy (Landgrebe, 1997). This author falsified the old notion that the inter-band correlations are not good for classification (Ramsey III and Jensen, 1996). On the other hand, when there is limited number of field samples, using too many spectral bands (e.g., > 20 bands) at the same time could reduce the precision of the mathematical model of class information in the feature space (i.e., the curse of dimensionality (Bellman, 1961; Hughes, 1968)). To our relief, this problem of high-dimensionality can be solved straightforwardly by the use of feature extraction/selection algorithms (Lee and Landgrebe, 1993; Du and Chang, 2001; Kavzoglu and Mather, 2002). In the light of the existing tools, we have proposed an innovative form of genetic search algorithms for reducing the number of bands and, at the same time, maintaining mangrove species separability (see Chapter 3).

Second, it is well-known that narrow-band sensors of hyperspectral instruments can capture a very low amount of energy, thereby resulting in poor signal quality (i.e., noisy signals). This problem could get worse when there are additional external disturbances such as the fluctuation of the atmospheric states (Oppenheim and Schafer, 1975; Landgrebe, 1997; Lyon, 2004). Moreover, the connection points between spectral detectors of the hyperspectral instrument could also play an important role in the quality of the spectral signal recorded (Schmidt and Skidmore, 2004). We have raised awareness of this issue in Chapter 4 and discuss about the spectral convolutions, which are popularly used for solving this signal-noise problem. In addition, we have proposed a method that can be used to visualise the trade-off between the noise levels reduced and the statistical estimate of the original data disturbed by the spectral convolution.

### *6.3.3. Is exploiting non-spectral information promising?*

This thesis supports the idea of incorporating ancillary ecological data into the mapping process. This concept of integrating extra information into the mapping process has been borrowed from successful case studies of mapping other plant species (Skidmore et al., 1997a, 1997b; Lehmann and Lenz, 1998; Berberoglu et al., 2004; Comber et al., 2004; Schmidt et al., 2004). In short, similar to the extra spectral bands (or layers) provided by the hyperspectral sensor, the extra GIS layer produced by exploiting the relationships between mangroves and the environmental gradients can be thought as if it is an extra non-spectral dimension (i.e., ecological dimension). The outcome of this thesis in Chapter 5 points out that the integration of ecological data (soil pH) into the mapping process is worth the extra fieldwork effort. It significantly increases the mapping accuracy of the final mangrove map of Cape Talumpuk from 76% to 88%. More importantly, soil pH is a cost-effective parameter. It is easy to analyse (i.e., using a pH probe), and, in some countries such as Thailand[*], soil-related parameters such as soil pH are often available for the research as they are collected regularly from the mangrove forests to monitor their conditions. In addition to the success of adding soil pH data into the mapping process, I have a plan to test other ecological gradients that can be gathered cost-effectively (e.g., leaf textures captured by aerial photos, LIDAR-derived elevation maps, and inundation frequency maps produced by incorporating elevation maps with automatic tidal records) for improving the mapping accuracy further (e.g., > 90% of accuracy). If this plan is successful, it will strengthen the possibility of exploiting non-spectral information for mangrove species mapping at the operational level.

## 6.4. Conclusion

As the potential of hyperspectral and ecological data for detailed mangrove mapping has already been unveiled, the main goal of this study has been achieved. The achievement of this thesis can be summarized as follows:

(1) The thesis reports that hyperspectral data contain adequate spectral details for discriminating most mangrove species. Further studies using airborne and satellite hyperspectral sensors are therefore encouraged.

(2) A form of genetic search algorithms has been successfully tested on a species-level problem of very high dimensionality. The results point to the capability of the genetic search algorithm to help in solving the problem of high dimensionality.

(3) The mistreatment of hyperspectral smoothing has been investigated, and an alternative method of optimizing the smoothed result is proposed.

(4) Mangrove-environment relationships have been successfully exploited for mangrove mapping, using a Bayesian expert system. It has been found that the relationships help to increase the accuracy of the final mangrove map at the species level

[*] Forest Research Office, Royal Forest Department: www.forest.go.th/Research/English/index.htm

## References

Ahern, C.R., McElnea, A.E., Sullivan L.A., 2004. Acid Sulfate Soils Laboratory Methods Guidelines. Queensland Department of Natural Resources, Mines and Energy, Queensland.

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.

Anderson, T.W., 1984. An Introduction to Multivariate Statistical Analysis. Wiley, New York.

Andréfouët, S., Hochberg, E.J., Payri, C., Atkinson, M.J., Muller-Karger, F.E., Ripley, H., 2003. Multi-scale remote sensing of microbial mats in an atoll environment. International Journal of Remote Sensing 24, 2661-2682.

Ardahanlioglu, O., Oztas, T., Evren, S., Yilmaz, H., Yildirim, Z.N., 2003. Spatial variability of exchangeable sodium, electrical conductivity, soil pH and boron content in salt- and sodium-affected areas of the Igdir plain (Turkey). Journal of Arid Environments 54, 495–503.

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. Proceedings of the International Conference IGARSS: 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.

Bandyopadhyay, S., 2005. Satellite image classification using genetically guided fuzzy clustering with spatial information. International Journal of Remote Sensing 26, 579-593.

Barbier, E.B., Sathiratai, S., 2004. Shrimp farming and mangrove loss in Thailand. Edward Elgar, Cheltenham.

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.

Bellman, R.E., 1961. Adaptive Control Processes, Princeton University Press, Princeton.

Ben-Dor, E., Patkin, K., Banin, A., Karnieli, A., 2002. Mapping of several soil properties using DAIS-7915 hyperspectral scanner data - A case study over soils in Israel. International Journal of Remote Sensing 23, 1043-1062.

Berberoglu, S., Yilmaz, K.T., Özkan, C., 2004. Mapping and monitoring of coastal wetlands of Çukurova Delta in the Eastern Mediterranean region. Biodiversity and Conservation 13, 615-633.

Berlanga-Robles, C.A., Ruiz-Luna, A., 2002. Land use mapping and change detection in the coastal zone of northwest Mexico using remote sensing techniques. Journal of Coastal Research 18, 514-522.

Bishr, Y., 1998. Overcoming the semantics and other barriers to GIS interoperability. International Journal of Geographical Information Science 12, 299-314.

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.

Bonham-Carter, G., 1994. Geographic Information Systems for Geoscientists, Pergamon, New York.

Bruzzone, L., Serpico, S.B., 2000. A technique for feature selection in multiclass cases. International Journal of Remote Sensing 21, 549-563.

Burgess, T.M., Webster, R., 1980. Optimal interpolation and isorithmic mapping of soil properties. I. The semivariogram and punctual kriging. Journal of Soil Science 31, 315–331.

Bruce, L.M., Li, J., 2001. Wavelets for computationally efficient hyperspectral derivative analysis. IEEE Transactions on Geoscience and Remote Sensing 39, 1540-1546.

Castro-Esau, K.L., Sánchez-Azofeifa, G.A., Caelli, T., 2004. Discrimination of lianas and trees with leaf-level hyperspectral data. Remote Sensing of Environment 90, 353-372.

Chalermwat, P., El-Ghazawi, T., LeMoigne, J., 2001. 2-phase GA-based image registration on parallel clusters. Future Generation Computer Systems 17, 467-476.

Chen, L., 2003. A study of applying genetic programming to reservoir trophic state evaluation using remote sensor data. International Journal of Remote Sensing 24, 2265-2275.

Chen, W., Kuze, H., Uchiyama, A., Suzuki, Y., Takeuchi, N., 2001. One-year observation of urban mixed layer characteristics at Tsukuba, Japan using a micro pulse lidar. Atmospheric Environment 35, 4273-4280.

Clark, M.L., Roberts, D.A., David, B.C., 2005. Hyperspectral discrimination of tropical rain forest tree species at leaf to crown scales. Remote Sensing of Environment 96, 375-398.

Clough, B.F., 1982. Mangrove Ecosystems in Australia: Structure, Function and Management. Australia Institute of Marine Science, ANU press, Sydney.

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

Cogdill, R.P., Hurburgh Jr., C.R., Rippke, G.R., 2004. Single-kernel maize analysis by near-infrared hyperspectral imaging. Transactions of the American Society of Agricultural Engineers 47, 311-320.

Comber, A.J., Law, A.N.R., Lishman, J.R., 2004. Application of knowledge for automated land cover change monitoring. International Journal of Remote Sensing 25, 3177-3192.

Congalton, R.G., Green K., 1999. Assessing the accuracy of remotely sensed data: principles and practices. Lewis, Boca Raton.

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

Curran, P.J., Dungan, J.L., Macler, B.A., Plummer, S.E., Peterson, D.L., 1992. Reflectance spectroscopy of fresh whole leaves for the estimation of chemical concentration. Remote Sensing of Environment 39, 153-166.

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. Proceedings of the International Conference the AVIRIS 2003 workshop: 18-23.

Deng, L., Shen, X., 1997. Maximum likelihood in statistical estimation of dynamic systems: Decomposition algorithm and simulation results. Signal Processing 57, 65-79.

Du, Q., Chang, C., 2001. A linear constrained distance-based discriminant analysis for hyperspectral image classification. Pattern Recognition 34, 361-373.

Duda, R., Hart. P., 1973. Pattern Classification and Scene Analysis. Wiley, New York.

Elvidge, C.D., 1987. Reflectance characteristics of dry plant materials. Proceedings of the International Conference Remote Sensing of Environment: 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.

Fang, H., Liang, S., Kuusk, A., 2003. Retrieving leaf area index using a genetic algorithm with a canopy radiative transfer model. Remote Sensing of Environment 85, 257-270.

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

Flink P., Lindell, L.T., Ostlund, C., 2001. Statistical analysis of hyperspectral data from two Swedish lakes. Science of the Total Environment 268, 155-169.

Foody, G.M., Sargent, I.M.J., Atkinson, P.M., Williams, J.W., 2004. Thematic labelling from hyperspectral remotely sensed imagery: Trade-offs in image properties. International Journal of Remote Sensing 25, 2337-2363.

Fukunaga, K., 1990. Introduction to Statistical Pattern Recognition, Academic Press, Orlando.

Gajem, Y.M., Warrick, A.W., Myers, D.E., 1981. Spatial structure of physical properties of a Typic Torrifluvent soil. Soil Science Society America Journal 45, 709–715.

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.

Goldberg, D., 1989. Genetic Algorithms in Search, Optimization and Machine Learning, Addison-Wesley, Reading.

Gong P., Pu, R., Heald, R.C., 2002. Analysis of in situ hyperspectral data for nutrient estimation of giant sequoia. International Journal of Remote Sensing 23, 1827-1850.

Gong, P., Pu, R., Yu, B., 2001. Conifer species recognition: Effects of data transformation. International Journal of Remote Sensing 22, 3471-3481.

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.

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.

Harsanyi, J. C., Chang, C.I., 1994. Hyperspectral image classification and dimensionality reduction: an orthogonal subspace projection approach. IEEE Transactions on Geoscience and Remote Sensing 32, 779-785.

Harvey, N.R., Theiler, J., Brumby, S.P., Perkins, S., Szymanski, J.J., Bloch, J.J., Porter, R.B., Galassi, M., Young, A.C., 2002. Comparison of GENIE and conventional supervised classifiers for multispectral image feature extraction. IEEE Transactions on Geoscience and Remote Sensing 40, 393-404.

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.

Hochberg, E.J., Atkinson, M.J., 2003. Capabilities of remote sensors to classify coral, algae, and sand as pure and mixed spectra. Remote Sensing of Environment 85, 174-189.

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.

Hogarth, P.J., 1999. The Biology of Mangroves. Oxford University Press, Oxford.

Holland, J.H., 1975. Adaptation in Natural and Artificial Systems, University of Michigan, Ann Arbor.

Hsu, J.C., 1996. Multiple comparisons: theory and methods. Chapman and Hall, London.

Hughes, G.F., 1968. On the mean accuracy of statistical pattern recognizers. IEEE Transactions on Information Theory 14, 55-63.

Imanishi, J., Sugimoto, K., Morimoto, Y., 2004. Detecting drought status and LAI of two Quercus species canopies using derivative spectra. Computers and Electronics in Agriculture 43, 109-129.

Isaaks, E.H., Srivastava, R.M., 1989. Applied Geostatistics. Oxford University Press, Oxford.

Jin, Y.Q., Wang, Y.A., 2001. Genetic algorithm to simultaneously retrieve land surface roughness and soil wetness. International Journal of Remote Sensing 22, 3093-3099.

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.

Jones, G.A., Greenhill, D., Orwell, J., Forte, P., 2000. Coastline registration: Efficient optimization in large dimensions using genetic algorithms. Geographical and Environmental Modelling 4, 21-41.

Kailath, T., 1967. The divergence and the Bhattacharyya distance measures in signal selection. IEEE Transactions on Communication Technology 15, 52-60.

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

Kawata, S., Minami, S., 1984. Adaptive smoothing of spectroscopic data by linear mean-square estimation. Applied Spectroscopy 38, 49-58.

Kay, S.M., 1993. Fundamentals of statistical signal processing : estimation theory, Prentice-Hall, New Jersey.

Kelly, G.A., 1955. The Psychology of Personal Constructs, Norton, New York.

Kendall, M.G., 1961. A Course in the Geometry of n Dimensions, Dover Publications, Inc., New York.

Keshava, N., 2004. Distance matrices and band selection in hyperspectral processing with applications to material identification and spectral libraries. IEEE Transaction on Geoscience and Remote Sensing 42, 1552-1565.

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.

Kooistra, L., Wanders, J., Epema, G.F., Leuven, R.S.E.W., Wehrens, R., Buydens, L.M.C., 2003. The potential of field spectroscopy for the assessment of sediment properties in river floodplains. Analytica Chimica Acta 484, 189-200.

Kovacs, J.M., Wang, J., Flores-Verdugo, F., 2005. Mapping mangrove leaf area index at the species level using IKONOS and LAI-2000 sensors for the Agua Brava Lagoon, Mexican Pacific. Estuarine, Coastal and Shelf Science 62, 377-384.

Kruse, F.A., Boardman, J.W., Lefkoff, A.B., Young, J.M., Kierein-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. Proceedings of the International Conference Australasian Remote Sensing and Photogrammetry: 18-23.

Kruse, F.A., Lefkoff, A.B., Boardman, J.W., Heidebrecht, K.B., Shapiro, A.T., Barloon, P.J., Goetz, A.F.H., 1993. The spectral image processing system (SIPS)--interactive visualization and analysis of imaging spectrometer data. Remote Sensing of Environment 44, 145-163.

Kumar, L., Schmidt, K.S., Dury, S., Skidmore, A.K. 2001. Review of hyperspectral remote sensing and vegetation science. In: van der Meer, F.D., de Jong, S.M. (Eds.), Imaging Spectrometry: Basic Principles and Prospective Applications. 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.

le Maire, G., François, C., Dufrêne, E., 2004. Towards universal broad leaf chlorophyll indices using PROSPECT simulated database and hyperspectral reflectance measurements. Remote Sensing of Environment 89, 1-28.

Lee, C., Landgrebe, D.A., 1993. Feature extraction based on decision boundaries. IEEE Transactions on Geoscience and Remote Sensing 15, 388-400.

Lehmann, D., Lenz, R., 1998. Synthetical vegetation mapping within the perimeter of the Berchtesgaden National park, called Vorfeld. A methodical study using Geographical Information Systems and Neural Networks. Verhandlungen der Gesellschaft fur Okologie 29, 89-96.

Lillesand, T.M., Kiefer, R.W., 2000. Remote sensing and image interpretation. Wiley, Chichester.

Linneweber, V., de Lacerda, L.D., 2002. Mangrove Ecosystems: Function and Management. Springer, Berlin.

Liu, Z., Liu, A., Wang, C., Niu, Z., 2004. Evolving neural network using real coded genetic algorithm (GA) for multispectral image classification, Future Generation Computer Systems 20, 1119-1129.

Lofy, B., Sklansky, J., 2001. Segmenting multisensor aerial images in class-scale space. Pattern Recognition 34, 1825-1839.

Lu, F., Eriksson, L.O., 2000. Formation of harvest units with genetic algorithms. Forest Ecology and Management 130, 57-67.

Lugo, A.E., Snedaker, S.C., 1974. The ecology of mangroves. Annual Review of Ecological Systems 5, 39–64.

Luo, J.C., Zheng, J., Leung, Y., Zhou, C.H., 2003. A knowledge-integrated stepwise optimization model for feature mining in remotely sensed images. International Journal of Remote Sensing 24, 4661-4680.

Lyon, R.G., 2004. Understanding Digital Signal Processing, Prentice-Hall, New Jersey.

Macnae, W., 1968. A general account of the fauna and flora of mangrove swamps and forests in the Indo-West-Pacific region. Advances in Marine Biology 6, 73-270.

Madden, H.M., 1978. Comments on the Savitzky-Golay convolution method for least-Squares fit smoothing and differentiation of digital data. Analytical Chemistry 50, 1383.

Manson, F.J., Loneragan, N.R., Phinn, S.R., 2003. Spatial and temporal variation in distribution of mangroves in Moreton Bay, subtropical Australia: a comparison of pattern metrics and change detection analyses based on aerial photographs. Estuarine, Coastal and Shelf Science 57, 653-666.

Mausel, P.W., Kramber, W. J., Lee, J. K., 1990. Optimum band selection for supervised classification of multispectral data. Photogrammetric Engineering and Remote Sensing 56, 55–60.

McDonald, M.S., 2003. Photobiology of higher plants. Wiley, Chichester.

McLean, E.O., 1982. Soil pH and lime requirement. In: editors (eds.), Methods of Soil Analysis. Part II. Chemical and Microbiological Properties. ASA-SSSA, Madison, WI, pp.199–224.

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.

Meroni, M., Colombo, R., Panigada, C., 2004. Inversion of a radiative transfer model with hyperspectral observations for LAI mapping in poplar plantations. Remote Sensing of Environment 92, 195-206.

Mertens, K.C., Verbeke, L.P.C., Ducheyne, E.I., de Wulf, R.R., Using genetic algorithms in sub-pixel mapping. International Journal of Remote Sensing 24, 4241-4247.

Metternicht, G.I., Zinck, J.A., 2003. Remote sensing of soil salinity: potentials and constraints. Remote Sensing of Environment 85, 1-20.

Mutanga, O., Skidmore, A.K., 2004. Integrating imaging spectroscopy and neural networks to map grass quality in the Kruger National Park, South Africa. Remote Sensing of Environment 90, 104-115.

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.

Narendra, P.M., Fukunaga, K., 1977. A branch and bound algorithm for feature subset selection. IEEE Transactions on Computers 26, 917–922.

Oppenheim, A.V., Schafer, R.W., 1975. Digital Signal Processing, Prentice-Hall, New Jersey.

Pal, S.K., Bandyopadhyay, S., Murthy, C.A., 2001. Genetic classifiers for remotely sensed images: Comparison with standard methods. International Journal of Remote Sensing 22, 2545-2569.

Pekkarinen, A., 2002. Image segment-based spectral features in the estimation of timber volume. Remote Sensing of Environment 82, 349-359.

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.

Pudil, P., Novovicova, J., Kittler, J., 1994. Floating search methods in feature selection. Pattern Recognition Letters 15, 1119–1125.

Ramsar Convention, 1971. www.ramsar.org.

Ramsey III, 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.

Ramsey III, E.W., Rangoonwala, A., Nelson, G., Ehrlich, R., Martella, K., 2005. Generation and validation of characteristic spectra from EO1 Hyperion image data for detecting the occurrence of the invasive species, Chinese tallow. International Journal of Remote Sensing 26, 1611-1636.

Rasolofoharinoro, M., Blasco, F., Bellan, M.F., Aizpuru, M., Gauquelin, T., Denis, J., 1998. A remote sensing based methodology of mangrove studies in Madagascar. International Journal of Remote Sensing 19, 1873-1886.

Rees, W.G., Tutubalina, O.V., Golubeva, E.I., 2004. Reflectance spectra of subarctic lichens between 400 and 2400 nm. Remote Sensing of Environment 90, 281-292.

Richards, J.A., 1986. Remote Sensing Digital Image Analysis: An Introduction. Springer-Verlag, Berlin.

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

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

Samra, J.S., Sharma, K.N.S., Tyaki, N.K., 1988. Analysis of spatial variability in sodic soils. I. Structural analysis. Soil Science 145, 180–187.

Satyanarayana B., Raman, A.V., Dehairs, F., Kalavati, C., Chandramohan, P., 2002. Mangrove floristic and zonation patterns of Coringa, Kakinada Bay, East Coast of India. Wetlands Ecology and Management 10, 25-39.

Savitzky, A., Golay, M.J.E., 1964. Smoothing and differentiation of data by simplified least squares procedures. Analytical Chemistry 36, 1627-1639.

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

Schmidt, K.S., Skidmore, A.K., 2004. Smoothing vegetation spectra with wavelets. International Journal of Remote Sensing 25, 1167-1184.

Schmidt, K.S., Skidmore, A.K., Kloosterman, E.H., van Oosten, H., Kumar, L., Janssen, J.A.M., 2004. Mapping coastal vegetation using an expert system and hyperspectral imagery. Photogrammetric Engineering and Remote Sensing 70, 703-715.

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.

Semeniuk, V., 1983. Mangrove distribution in northwestern Australia in relationship to regional and local freshwater seepage. Vegetation 53, 11-31.

Shahshahani, B.M., Landgrebe, D.A., 1994. The effect of unlabeled samples in reducing the small sample size problem and mitigating the Hughes phenomenon. IEEE Transactions on Geoscience and Remote Sensing 32, 1087-1095.

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

Skidmore, A.K., Schmidt, K., Kloosterman, H., Kumar, L., van Oosten, H., 2001. Hyperspectral imagery for coastal wetland vegetation mapping. Beleids Commissie Remote Sensing (BCRS) NRSP-2 report.

Skidmore, A.K., Turner, B.J., Brinkhof, W., Knowles, E., 1997a. Performance of a neural network: mapping forests using GIS and remotely sensed data. Photogrammetric Engineering and Remote Sensing 63, 501-514.

Skidmore, A.K., Varekamp, C., Wilson, L., Knowles, E., Delaney, J., 1997b. Remote sensing of soils in a eucalypt forest environment. International Journal of Remote Sensing 18, 39-56.

Smith, K.L., Steven, M.D., Colls, J.J., 2004. Use of hyperspectral derivative ratios in the red-edge region to identify plant stress responses to gas leaks. Remote Sensing of Environment 92, 207-217.

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.

Spalding, M.D., Blasco, F., Field, C.D., 1997. World Mangrove Atlas. International Society for Mangrove Ecosystems, Okinawa.

Steinier, J., Termonia, Y., Deltour, J., 1972. Comments on smoothing and differentiation of data by simplified least square procedure. Analytical Chemistry 44, 1906.

Strachan, I.B., Pattey, E., Boisvert, J.B., 2002. Impact of nitrogen and environmental conditions on corn as detected by hyperspectral reflectance. Remote Sensing of Environment 80, 213-224.

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.

Swain, P.H., Davis, S.M., 1978. Remote sensing—The quantitative approach. McGraw-Hill, New York.

Swain, P.H., King, R.C., 1973. Two effective feature selection criteria for multispectral remote sensing. Proceedings of the First International Conference on Pattern Recognition: 536–540.

Teeratanatorn, W., 2000. Mangroves of Pak Phanang Bay (in Thai). Royal Forest Department, Bangkok.

Thenkabail, P.S., Enclona, E.A., Ashton, M.S., van Der Meer, B., 2004. Accuracy assessments of hyperspectral waveband performance for vegetation analysis applications. Remote Sensing of Environment 91, 354-376.

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.

Tsai, F., Philpot, W., 1998. Derivative analysis of hyperspectral data. Remote Sensing of Environment 66, 41-51.

Tsai, F., Philpot, W., 2002. A derivative-aided hyperspectral image analysis system for land-cover classification. IEEE transactions on Geoscience and Remote Sensing 40, 416-425.

Tseng, D.C., Lai, C.C., 1999. A genetic algorithm for MRF-based segmentation of multi-spectral textured images. Pattern Recognition Letters 20, 1499-1510.

Ulfarsson, M.O., Benediktsson, J.A., Sveinsson, J.R., 2003. Data fusion and feature extraction in the wavelet domain. International Journal of Remote Sensing 24, 3933-3945.

Vaiphasa, C., 2003. Innovative genetic algorithm for hyperspectral image classification. Proceedings of the International Conference MAP ASIA: 20.

Vaiphasa, C., Ongsomwang, S., 2004. Hyperspectral Data for Tropical Mangrove Species Discrimination. Proceedings of the 25th ACRS Conference: 22-28.

van Niel, T.G., McVicar, T.R., Fang, H., Liang, S., 2003. Calculating environmental moisture for per-field discrimination of rice crops. International Journal of Remote Sensing 24, 885-890.

Vaughan, R.G., Calvin, W.M., Taranik, J.V., 2003. SEBASS hyperspectral thermal infrared data: Surface emissivity measurement and mineral mapping. Remote Sensing of Environment 85, 48-63.

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.

Vilarrubia, T.V., 2000. Zonation pattern of an isolated mangrove community at Playa Medina, Venezuela. Wetlands Ecology and Management 8, 9-17.

Whiting, M.L., Li, L., Ustin, S.L., 2004. Predicting water content using Gaussian model on soil spectra. Remote Sensing of Environment 89, 535-552.

Williams, P., Norris, K., 2001. Near-infrared technology in the agricultural and food industries. American Association of Cereal Chemists Press, Minnesota.

Wu, D., Linders J., 2000. Comparison of three different methods to select feature for discriminating forest cover types using SAR imagery. International Journal of Remote Sensing 21, 2089-2099.

Wu, Y., Chen, J., Wu, X., Tian, Q., Ji, J., Qin, Z., 2005. Possibilities of reflectance spectroscopy for the assessment of contaminant elements in suburban soils. Applied Geochemistry 20, 1051-1059.

Yamada, K., Elith, J., McCarthy, M., Zerger, A., 2003. Eliciting and integrating expert knowledge for wildlife habitat modelling. Ecological Modelling 165, 251-264.

Yamano, H., Chen, J., Tamura, M., 2003. Hyperspectral identification of grassland vegetation in Xilinhot, Inner Mongolia, China. International Journal of Remote Sensing 24, 3171-3178.

Yates, S.R., Warrick, A.W., Matthias, A.D., Musil, S., 1988. Spatial variability of remotely sensed surface temperature at field scale. Soil Science Society America Journal 52, 40–45.

Yost, R.S., Uehara, G., Fox, R.L., 1982. Geostatistical analysis of soil chemical properties of large land areas: I. Semivariograms. Soil Science Society of America Journal 46, 1028–1032.

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.

Zarco-Tejada, P.J., Miller, J.R, Noland, T.L., Mohammed, G.H., Sampson, P.H., 2001. Scaling-up and model inversion methods with narrowband optical indices for chlorophyll content estimation in closed forest canopies with hyperspectral data. IEEE transactions of Geoscience and Remote Sensing 39, 1491-1507.

Zarco-Tejada, P.J., Pushnik, J.C., Dobrowski, S., Ustin, S.L., 2003. Steady-state chlorophyll a fluorescence detection from canopy derivative reflectance and double-peak red-edge effects. Remote Sensing of Environment 84, 283-294.

Zhang, J., Rivard, B., Sanchez-Azofeifa, A., 2004. Derivative spectral unmixing of hyperspectral data applied to mixtures of lichen and rock. IEEE transactions on Geoscience and Remote Sensing 42, 1934-1940.

Zhu, A. 1999. A personal construct-based knowledge acquisition process for natural resource mapping. International Journal of Geographical Information Science 13, 119-141.