

**SURFACE REFLECTANCE AND
DISCRIMINANT ANALYSIS FOR MAPPING OF
MANGROVE SPECIES IN KUALA SEPETANG
MANGROVE FOREST RESERVE, PERAK**

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UNIVERSITI SAINS MALAYSIA

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by

BEH BOON CHUN

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LIST OF SYMBOLS

ρ	planetary reflectance
d	Earth-Sun distance
ESUN	mean solar exoatmospheric spectral irradiance
kg	kilogram
L	spectral radiance
lb	pound/pound-mass
m	meter
pix	pixel
rpm	revolution per minute
sr	steradian
V	volt
W	watt

LIST OF ABBREVIATIONS

ADC	Analog Digital Converter
AFRI _{MIR}	Aerosol Free Vegetation Index Mid-Infrared
AFRI _{SWIR}	Aerosol Free Vegetation Index Shortwave-Infrared
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
AOI	Area of Interest
ARVI	Atmospherically Resistant Vegetation Index
CASI	Compact Airborne Spectrographic Imager
EM	Electromagnetic
EO-1	Earth Observing-1
ETM	Enhanced Thematic Mapper
FAO	Food and Agriculture Organization
FOV	Field of View
FWHM	Full Width Half Maximum
GCPs	Ground Control Points
GEMI	Global Environmental Monitoring Index
GIS	Geographic Information System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
HyMap	Hyperspectral Mapper
JM	Jeffries-Matusita
JPEG	Joint Photographic Experts Group
LAI	Leaf Area Index
LDA	Linear Discriminant Analysis

LMM	Linear Mixture Model
LSU	Linear Spectral Unmixing
LULC	Land Use/Land Cover
MASS	Malaysian Active GPS Station
MLC	Maximum Likelihood Classifier
MLCNN	Maximum Likelihood Classification Nearest Neighbor
MMFR	Matang Mangrove Forest Reserve
MNF	Minimum Noise Fraction
MSAVI	Modified Soil-Adjusted Vegetation Index
NDVI	Normalized Differential Vegetation Index
NIR	Near Infrared
NN	Nearest Neighbor
NOAA	National Oceanic and Atmospheric Administration
OA	Overall Accuracy
OSAVI	Optimized Soil-Adjusted Vegetation Index
PAN	Panchromatic
PCA	Principal Component Analysis
PPI	Pixel Purity Index
PVI	Perpendicular Vegetation Index
RGB	Red Green Blue
RMS	Root Mean Square
RMSE	Root Mean Square Error
SAM	Spectral Angle Mapper
SAVI	Soil-Adjusted Vegetation Index
SFF	Spectral Feature Fitting

SFS	Sequential Forward Selection
SID	Spectral Information Diversion
SPOT XS	Satellite Pour l'Observation de la Terre Multispectral
SVM	Support Vector Machines
SWIR	Shortwave-Infrared
TM	Thematic Mapper
TOA	Top of Atmosphere
TSAVI	Transformed Soil-Adjusted Vegetation Index
UAV	Unmanned Aerial Vehicles
USM	Universiti Sains Malaysia
UV	Ultraviolet
VHR	Very High Resolution
VNIR	Visible/Near-Infrared

**KETERPANTULAN PERMUKAAN DAN ANALISIS DISKRIMINAN
UNTUK PEMETAAN SPESIES BAKAU DI HUTAN SIMPAN BAKAU
KUALA SEPETANG, PERAK**

ABSTRAK

Pengenalpastian spesies bakau menggunakan pendekatan tradisional telah biasa dibangunkan dan dikaji. Disebabkan kos yang tinggi dalam kerja lapangan dan kesulitan dalam menilai kawasan dataran lumpur di ekosistem bakau menggunakan cara konvensional, maka teknik penderiaan jauh digunakan secara meluas untuk mengkaji spesies bakau sama ada di peringkat skala atau daun. Dalam kajian ini, dua kaedah penderiaan jauh telah dijalankan untuk mengenal pasti dan membezakan spesies bakau di Hutan Simpan Kuala Sepetang, Perak, Malaysia. Kaedah pertama membangunkan satu algoritma berdasarkan permukaan pantulan spesies untuk memetakan spesies bakau menggunakan data resolusi tinggi pesawat udara tanpa pemandu (UAV). Imej-imej pesawat udara diperolehi menerusi saluran tiga jalur (biru, hijau dan inframerah dekat) dari indeks perbezaan normal tumbuhan (NDVI) kamera yang dipasang pada UAV. Pantulan atas atmosfera dijana dari imej mozek pesawat udara yang merangkumi keseluruhan tapak kajian dengan keluasan tanah sebanyak 50.12 ha. Taburan bagi lima spesies bakau telah berjaya dipetakan menggunakan nilai pantulan yang dijana. Plot berselerak antara ramalan dan permukaan piksel memberikan korelasi yang tinggi ($R^2 = 0.873$) dengan sisihan piawai 0.476 (kurang daripada satu spesies per piksel). Hasil kajian ini juga menunjukkan bahawa teknik yang diterbit boleh dipercayai dan menghasilkan keputusan yang baik dengan kejituan yang tinggi (85%). Kaedah kedua menggunakan analisis statistik untuk menganalisis data pantulan bagi spesies bakau.

Analisis varians (ANOVA) dan analisis diskriminan linear (LDA) telah digunakan pada data pantulan spektrum. LDA telah mendapati panjang gelombang berpengaruh yang boleh digunakan untuk membezakan sampel daun di antara enam spesies bakau. Dua puluh enam panjang gelombang penting ($p < 0.05$) diperoleh di kawasan spektrum inframerah dekat (VNIR), inframerah gelombang pendek I (SWIR I) dan inframerah gelombang pendek II (SWIR II). Enam belas fungsi diskriminan telah dijana menggunakan dua puluh enam gelombang berpengaruh. Julat skor bagi setiap spesies bakau dalam fungsi diskriminan telah ditentukan dengan menggunakan spektrum pantulan. Sementara itu, perbezaan antara kombinasi fungsi diskriminan dibandingkan bagi memilih fungsi yang paling sesuai untuk mengelaskan spesies bakau. Perbandingan tersebut memberikan kejitian terbaik apabila sebelas fungsi dipilih untuk pengelasan spesies bakau. Oleh itu, julat skor awal yang dicadang telah digunakan untuk meramalkan daun bakau yang tidak diketahui dengan menggunakan sebelas fungsi diskriminan. Keputusan akhir menunjukkan bahawa walaupun kejitian pengelasan yang dicapai adalah lebih rendah dalam meramal spesies bakau tertentu tetapi algoritma ini masih boleh menentukan spesies bakau dengan betul bagi sampel daun bakau yang tidak diketahui di kawasan kajian pada peringkat daun. Pada amnya, keputusan yang didapati jelas menunjukkan bahawa kedua-dua kaedah penderiaan jauh yang digunakan berjaya membezakan spesies bakau di Hutan Simpan Kuala Sepetang, Perak, Malaysia dan objektif kajian ini telah dicapai.

**SURFACE REFLECTANCE AND DISCRIMINANT ANALYSIS FOR
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MANGROVE FOREST RESERVE, PERAK**

ABSTRACT

The identification of mangrove species by using traditional approach has been commonly developed and studied. Due to the high cost of field work and the difficulty in assessing the mudflat areas of mangrove ecosystem with conventional methods, remote sensing techniques have been widely used to examine mangrove species at either the scale level or leaf level. In this study, two remote sensing methods have been utilized to identify and discriminate the mangrove species in the Kuala Sepetang Mangrove Forest Reserve, Perak, Malaysia. The first method is to develop an algorithm that was based on species' surface reflectance to map the mangrove species by using high-resolution CropCam Unmanned Aerial Vehicle (UAV) data. The airborne images were acquired through the three band channels (blue, green and near-infrared) of the Normalized Difference Vegetation Index (NDVI) camera that was mounted on the CropCam UAV. The Top of Atmosphere (TOA) reflectance was retrieved from the mosaicked airborne image, which covered the entire study site with an area of 50.12 ha. The distributions of five mangrove species were successfully mapped by using the retrieved reflectance values. The scatter plot between the predictions and ground pixels revealed a high correlation ($R^2=0.873$) with Root Mean Square Error (RMSE) of 0.476 (less than one species per pixel). The results also indicated that the developed technique was reliable and produced good results with high accuracy of 85%. The second method used statistical analysis to analyze the hyperspectral reflectance data of the mangrove species. Analysis of Variance (ANOVA) and Linear Discriminant Analysis (LDA)

tests were applied on the reflectance spectra data. The LDA determined the influential wavelength, which could be used to distinguish the leaf samples among the six mangrove species. Twenty-six significant wavelengths ($p < 0.05$) were obtained in the Very Near Infrared (VNIR), Short Wavelength Infrared I (SWIR I) and Short Wavelength Infrared II (SWIR II) spectral regions. Sixteen discriminant functions were generated by using the 26 influential wavelengths. The score range of each mangrove species in discriminant functions was determined by using the reflectance spectra. Meanwhile, different combinations of discriminant functions were compared to determine the most suitable function to classify the mangrove species. The comparison produced the best accuracy when 11 functions were chosen for the mangrove species classification. Therefore, the score range that was established earlier was used to predict the unknown mangrove leaves by using the 11 discriminant functions. The final results showed that even the attained classification accuracy was lower when identifying certain mangrove species, but the 11 discriminant functions could still determine the correct mangrove species of an unknown mangrove leaf sample from the study area at the leaf scale. Overall, these results clearly indicate that the two remote sensing methods that were applied could successfully discriminate five mangrove species in the Kuala Sepetang Mangrove Forest Reserve, Perak, Malaysia and accomplished the objective of this research.

CHAPTER 1

INTRODUCTION

1.1 Overview

Mangrove forests are unique ecosystems that provide a variety of ecological functions along sheltered coastal areas, river estuaries and seashore areas (Jensen et al., 2007). They usually grow in intertidal coastal habitats with brackish water in highly saline and oxygen-depleted soil environments, with special prop root systems known as pneumatophores. Mangroves are an assemblage of tropical and subtropical halophytes (salt tolerant plants), coastal vegetation that lives in tropical and subtropical climates (Aheto et al., 2011; Heumann, 2011). A total of 75% of the world's tropical coastlines are covered by mangrove ecosystems (Vaiphasa et al., 2006). The global distribution of mangrove cover is roughly approximately 170,000 km², covering up to 112 countries in tropical regions (Aizpuru et al., 2000). Appendix A provides the current and past extents of mangrove cover estimation from 1980 to 2005. According to the FAO (2006), Asia is the continent with the largest extent of mangroves (roughly 6 million ha) and has five of the top ten countries with the largest mangrove distribution.

The biological, environmental, ecological and economic values of mangroves are firmly established. Mangroves are known to be the most productive coastal ecosystems, both providing food chains for marine life and its associated community and acting as a breeding ground or habitat for various types of life, such as birds, reptiles, sponges, insects, shrimps and mammals (Holguin et al., 2001; Nagelkerken et al., 2008). Additionally, mangrove forests play an important role in serving as a natural barrier that protects inland and coastal regions from tidal waves, storms,

flooding, erosion and tsunamis (Liu et al., 2007; Alongi, 2008; Spalding et al., 2010). In addition, mangroves act as filters that purify polluted coastal areas, treat sewage trapping and absorb heavy metals and nutrients in soil (FAO, 2007).

Furthermore, mangroves play a growing role globally in the carbon cycle and the reduction of greenhouse gases, such as carbon dioxide (CO₂), by acting as the very efficient coastal carbon sink (Nellemann et al., 2009; Trumper et al., 2009). Moreover, various forestry products that are made from mangroves, such as timber, charcoal and firewood, contribute to the economic development of a country. Some mangrove species such as *Ceriops Tagal*, *Bruguiera Gymnorhiza* and *Aegiceras Corniculatum* can even be used as medicine to cure certain diseases or disorders (Ray, 2014). Undoubtedly, the valuable of this type of ecosystem is vital for human life, flora and fauna. Hence, mangroves should be preserved for future generations to enjoy the beauty and benefits of these unique forests.

Based on statistics from the World Bank (2010), the total land area of Peninsular Malaysia is approximately 328,550 km². The forest area in Peninsular Malaysia covers approximately 204,560 km² (62.3%). This forest area includes land that comprises natural or planted trees that are greater than 5 m but excludes trees in agricultural fields, urban areas and gardens. Mangrove forests in P. Malaysia are mainly concentrated along the western coastal region. The mangrove swamps in these western coastal areas are usually located at lower elevations compared to the mangrove cover in the eastern and southern coastal areas. Most of the states in P. Malaysia contain mangrove cover, with the largest mangrove swamps located in the Matang Mangrove Forest Reserve, Perak.

Due to the selfishness of developers and human anthropogenic activity, these mangrove forests are threatened and have experienced a serious decline from year to

year. In Southeast Asia, almost 12% of the total mangrove forest cover was cleared from 1975 to 2005. Mangroves are usually cleared for aquaculture (shrimp farming), agriculture, urban development and excessive logging (FAO, 2007; Giri et al., 2008). In addition, the prolonged exposure of nitrogen and phosphorous in mangrove ecosystems can weaken roots, which will ultimately result in mortality and leaf loss (Holguin et al., 2006; Reef et al., 2010; Vovides et al., 2011). Globally, mangrove coverage has been declining by approximately 2% per year from 1980 to 1990 and by 1% per year from 1990 to 2000 (Wilkie and Fortuna, 2003).

Information regarding mangrove distribution and growth should be updated regularly to preserve and conserve mangrove forests. The observation and monitoring of the distribution and dynamics of mangroves is central to a wide range of scientific investigations that are conducted in both terrestrial and marine ecosystems. Conventional methods such as ground surveys and field visits to mangrove swamps are more reliable and accurate but are also time consuming and costly. In addition, this traditional approach to monitoring forests usually requires a great deal of time and cannot keep up to date with the latest extent or changes in conditions of mangrove forests within a short time period. In such circumstances, remote sensing techniques, which are cheaper and more time-efficient, can be utilized in forestry applications to monitor mangrove ecosystems. Recent advancements in remote sensing data availability, image-processing methodologies, computing and information technology, and human resource development have provided an opportunity to observe and monitor mangroves from local to global scales on a regular basis. The spectral and spatial resolution and availability of remote sensing data have improved, making it possible to observe and monitor mangroves with unprecedented spatial and thematic detail. Furthermore, remote

sensing techniques, along with Geographic Information Systems (GIS), can provide new tools for rapid and advanced forest monitoring and management. Satellite imagery is one resource that is available in remote sensing that enables humans to view land, water and forest scenes on the Earth's surface without accessing the field site.

1.2 Remote Sensing

Remote sensing is a method that uses scientific technology to acquire and gather useful information about an object or matter on the Earth's surface without having any direct physical contact with the object (James et al., 2010). Remote sensing can measure the reflected, emitted and transmitted energy from an object. Aircraft and satellites are the common vehicles through which remote sensing methods are conducted. The sensors from satellites collect reflected or emitted electromagnetic radiation from the target for analysis (Lewis and Clack, 2005). Remote sensing techniques are particularly important tools for providing input to numerous applications. Hyperspectral remote sensing is performed for forestry and vegetation (monitoring of ecosystems, vegetation mapping), coastal preservation (oil pollution detection, water quality assessment), agriculture (crop mapping or yields), atmospheric studies (greenhouse gases, air pollution) and geological applications (mineral identification and mapping) (HyperTeach, 2005).

Electromagnetic (EM) energy refers to a form of energy that is released into the atmosphere and propagates in a wave-like pattern at the speed of light (3×10^8 m/s). The electromagnetic spectrum is the continuum of all types of EM radiation, whose wavelengths range from kilometers to nanometers. Each portion of the EM spectrum ranges from short wavelengths (gamma ray) to long wavelengths (radio

waves), as illustrated in Appendix B. Different types of EM radiation interact with matter in different ways and produce different outputs in various applications.

In remote sensing, the ultraviolet (UV) portion is widely used for geological studies in the detection of matter on the Earth's surface, primarily rocks and minerals. Rocks and minerals will glow and fluoresce when illuminated with ultraviolet radiation. As these shorter wavelengths are easily scattered by the atmosphere, few remote sensing applications are conducted with ultraviolet light (Geog474, 1999).

Visible light is light that our eyes can sense and detect. These visible wavelengths range from 400 nm (violet colour) to 700 nm (red colour). Blue, green and red are the primary colours in the visible spectrum. Although the sunlight that we see is a homogenous colour, this light is actually composed of different wavelengths of EM radiation, primarily including UV, visible and infrared light along the EM spectrum. Visible light consist of seven colours (red, orange, yellow, green, blue, indigo and purple), which can be observed clearly when sunlight is passed through a prism (Natural Resource Canada, 2015).

Another portion of the spectrum is the infrared (IR) region, which covers wavelengths from 0.7 μm to 100 μm . The infrared region is divided into 2 parts: reflected IR (0.7 μm to 3.0 μm) and thermal IR (3.0 μm to 100 μm). The reflected IR region is widely used for remote sensing purposes, similar to visible radiation. The thermal IR region has different properties from visible and reflected IR light: it is actually a form of heat energy that is emitted from the Earth's surface and is used to detect forest fires and heat loss from buildings (Prakash, 2000).

The last portion of the spectrum is the microwave region, which ranges from 1 mm to 1 m. This portion of the spectrum has been receiving attention in remote

sensing as it has the ability to penetrate clouds or haze and is very suitable for weather forecasting. The shorter wavelengths in the microwave region have the same properties as thermal IR. The longer wavelengths in the microwave region are generally utilized in radio broadcasting (Natural Resource Canada, 2015).

Two types of sensors are available in remote sensing studies: active and passive sensors. Active sensors supply their own light source toward the target that is being examined, and the reflected energy from the target is measured by the sensor. Examples of active sensors include laser scanners and radar. Passive sensors measure the reflected energy from a target using naturally available light sources, such as the Sun. Passive sensor systems cannot obtain measurements during the night, when the Sun does not illuminate the Earth, unless the amount of energy that is emitted (thermal infrared) by the target is large enough to be recorded. The advantage of active sensors is their ability to measure and record reflected energy at anytime, independent of the light source. Examples of passive sensors include film photography and radiometers.

1.3 Vegetation Spectroscopy

Vegetation is a constituent of Earth's surface, and their biophysical and biochemical properties are important in a large variety of agricultural and ecological applications (Houborg et al., 2007). Spectroscopy refers to the study of the interactions between radiation and matter and involves the study of reflected, absorbed and transmitted light from matter (solid, liquid or gas) as a function of wavelength. Optical remote sensing has been developed from multispectral sensing to hyperspectral sensing, which consists of hundreds of narrow spectral bands. These spectral bands have the potential to measure specific vegetation variables and parameters that cannot be

studied with conventional multispectral sensors. With the invention of vegetation spectroscopy (hyperspectral sensors), the quantity and quality of vegetation studies improved significantly compared to studies that used multispectral sensors. The high resolution of hyperspectral data is crucial for providing high-quality information regarding the health, biomass, biochemical and biophysical properties of vegetation (Green et al., 1998; Asner et al., 2000; Mutanga et al., 2004; Zarco-Tejada et al., 2005).

1.4 Problem Statement

Tsunamis are defined as unusually high tidal waves that are triggered by earthquakes. Tsunamis are a natural disaster that can cause wide spread destruction and seriously impact coastal areas. In 2004, Penang State in Malaysia was stricken by a tsunami wave. The Penang Inshore Fishermen Welfare Association reported that fewer lives were lost and less damage was caused by the tsunami in coastal regions that were protected by mangrove forests. These mangrove trees in coastal regions act as a buffer zone to dissipate and impede tsunami waves, thus reducing their impact. Undoubtedly, the importance of mangrove ecosystems as a protective belt during tsunamis cannot be ignored. Malaysia's mangroves forests have rapidly diminished over the past decade and continue to decline at an alarming rate. The average declining rate of these mangrove forests is approximately 1% per year as reported by the Food and Agriculture Organization (FAO, 2007). To protect this valuable ecosystem, conservation efforts must be conducted by all parties to monitor the past and current extent of mangrove cover in a country and maintain up-to-date mangrove distribution information.

Historically, research has focused on mangrove ecosystems in terms of the biophysical, biochemical or biological properties of mangrove plants. Common studies of mangrove ecosystems usually include the mapping, monitoring, identification and discrimination of mangrove trees. Traditional mangrove studies have involved fieldwork or field surveys to the site to detect and monitor these mangrove ecosystems, but this approach is time consuming and costly. Field surveys for mangrove studies become complicated when the mangrove swamp area is difficult to penetrate and access. In such circumstances, remote sensing techniques can be an effective tool to study mangrove ecosystems.

Various satellite data can be used for mangrove studies and mapping, but the mapping of mangrove species may be unsatisfactory if low-resolution satellite imagery is used. In addition, some satellite imagery may contain abundant cloud cover, fog and haze, especially when the scene is obtained from the equatorial line region. To overcome this problem, low-cost and high-resolution Unmanned Aerial Vehicle (UAV) data were used in this study to map mangrove species on a local scale.

Previous studies have shown that measurements of hyperspectral leaf reflectance can be used to distinguish mangrove species (Kamaruzaman and Kasawani, 2007; Wang and Sousa, 2009; Zhang et al., 2014). The ideal wavebands for mangrove species classification are identified and highlighted in their studies. In this study, significant wavebands were identified for determine the mangrove species fraction based on scores that were obtained from discriminant functions.

1.5 Research Objectives

This research has several aims and objectives:

1. To develop an algorithm that uses the surface reflectance to map mangrove species.
2. To verify the reliability and accuracy of the individual mangrove species map.
3. To determine the significant wavelengths that can be used to distinguish the examined mangrove species using statistical analysis.
4. To discriminate mangrove species based on the obtained scores from discriminant functions using reflectance spectral data.

1.6 Scope of Study

This research focused on techniques that were used to discriminate the dominant six mangrove species in Kuala Sepetang Mangrove Forest Reserve which is confined in the Educational Forest of Matang Mangrove Forest Reserve (MMFR). The first method used high-resolution CropCam UAV airborne data that were acquired from field visits to map mangrove species. The retrieved surface reflectance was used to map the distribution of the examined mangrove species. The second method used the reflectance spectral data of healthy mangrove leaves, which were measured with a spectroradiometer, to determine the significant wavelengths that can separate mangrove species. The results of a statistical approach were applied to test the mangrove species that were investigated in this study. Finally, the produced map and results were verified using ground data.

1.7 Novelty of Study

This study mainly involved the utilization of low-cost, relatively cheap and newly emerged high-resolution CropCam Unmanned Aerial Vehicle (UAV) technology (compared to satellite data) over mangrove forests to map mangrove species. UAV technique has been used by Hassan et al. (2011) over Penang Island, Malaysia for land cover mapping with RGB camera sensor consist of blue, green, and red band. However in this study, a three-band (blue, green, and NIR) camera sensor was used to acquire airborne images to map the individual mangrove species at the Kuala Sepetang Mangrove Forest Reserve. Moreover, this study focused on the statistical data analysis of hyperspectral leaf reflectance from six mangrove species in the study area and to discriminate these species based on generated discriminant functions.

1.8 Structure of the Thesis

This thesis comprises seven chapters, with summaries of each chapter briefly discussed below. Chapter 1 provides an overview of this study, including the background of mangrove forests, remote sensing and vegetation spectroscopy. Chapter 2 discusses the literature regarding mangrove mapping at the generic or species level using different remote sensing methods. This chapter also discusses the mangrove mapping and classification techniques that have been utilized in Malaysia. Chapter 3 introduces the CropCam UAV system (background, platform, sensor, camera, setup and configuration, applications) and spectroradiometer system that are used in this study. Chapter 4 describes the study area, materials, image processing

procedure and software that were used. This study's methodology is also highlighted in this chapter. Chapter 5 focuses on the obtained results and includes the data analysis, interpretation and discussion of the airborne UAV data. Moreover, this chapter describes the procedure that was used to validate the mapping accuracy. Chapter 6 concentrates on the analysis, interpretation, discussion and validation results of the statistical analysis, which used hyperspectral data. Finally, the conclusions of this study and discussion regarding future works are presented in Chapter 7.

CHAPTER 2

LITERATURE REVIEW

2.1 Literature Review

Mangrove is an ecological term that refers to shrubs or trees that exist in highly saline soil and brackish water conditions along sheltered coastal region (Lee and Yeh, 2009). Their special prop and tough root systems (pneumatophores) help them to survive in harsh saltwater or mudflat environments. Mangroves can be found in tropical and subtropical climates around the world (Jensen et al., 2007). Almost 75% of the world's tropical coastlines are covered by mangroves (Spalding et al., 1997). Mangrove trees provide food to marine life and its corresponding community and serve as natural barriers that protect shoreline areas from erosion, tidal waves, floods, typhoons and tsunamis (Liu et al., 2007; Howari et al., 2009). Additionally, profits from mangrove forestry products, such as timber, firewood and charcoal, contribute to national economics. Therefore, the importance of mangroves is recognizable worldwide because of their vital environmental, economic, ecological and biological value (Mitsch et al., 2002).

Conventional field surveying methods for monitoring mangrove areas are costly, time-consuming and labor-intensive (Lee and Yeh, 2009). An accurate, fast and cost-reasonable technique is required to effectively monitor temporal changes in mangrove ecosystems (Green et al., 1998; Liu et al., 2007). Thanks to the development of remote sensing technology, remote sensing data have been widely

used as superior tools in many areas, such as land cover and land use, geology, vegetation and water quality mapping, land surface temperature retrieval and long-term environmental change management (Green et al., 1996; Coulibaly and Goita, 2006; Tan et al., 2010).

Recently, the uncontrolled deforestation of mangrove forests for the irrational development of urban areas or aquaculture by humans has led to dramatic declines in mangrove trees. By 1990, 30% of the mangrove forests in Malaysia have been lost, and this decrease is predicted to continue at a rate of 1% per year (Gong and Ong, 1990). To efficiently manage and monitor mangrove ecosystems, researchers have attempted, utilized and invented various remote sensing methods to extract information on mangroves from high-spatial-resolution multispectral and hyperspectral satellite data and airborne data (Jusoff, 2006; Jensen et al., 2007). Initially, artificial interpretations based on aerial photos were used to survey mangrove forests. Prior to 1990, Landsat and SPOT satellite imageries (which consist of panchromatic and multispectral bands) were employed by researchers in mangrove studies (Zhang et al., 2005). With the invention of new generation sensors (hyperspectral sensor) that possess higher spatial and spectral resolutions, finer mangrove studies (mangrove species differentiation) are more reliable and precise (Wang and Sousa, 2004; Vaiphasa et al., 2005; Neukermans, 2008).

2.1.1 Mangrove Mapping at the Generic Level

Green et al. (1998) proposed five different methodologies to separate mangrove and non-mangrove vegetation in the Turks and Caicos Islands. Landsat TM, SPOT XS and CASI data were classified with these five techniques, namely, Visual Interpretation, Vegetation Index, Unsupervised Classification, Supervised

Classification, PCA and Band Ratios. However, all the classifications from SPOT XS data could not satisfactorily distinguish between mangrove and non-mangrove areas for these eastern Caribbean islands because of the very low overall accuracy (35-57%) and no obvious differences between τ coefficients. The classification accuracy for the CASI data was higher than that of the Landsat TM data for these five methods, which meant the former could discriminate more mangrove classes. In conclusion, PCA with band ratio combination classification of Landsat and CASI data was more reliable for discriminating between mangrove and non-mangrove areas and among different mangrove types.

Gao (1999) used the Maximum Likelihood Classifier to map the mangrove forest in Western Waitemata Harbour, Auckland, New Zealand. He used SPOT XS and Landsat TM imagery to map the mangrove forest into lush and stunted classes. The mapping accuracy that was obtained from 30 m Landsat TM data was 95% for lush mangroves and 87.5% for stunted mangroves. The accuracy level was lower when using 20-m SPOT XS data, specifically, 77.5% for lush mangroves and 67.5% for stunted mangroves. Both accuracy levels improved to 80% when the 10-m PAN band was fused with the SPOT XS data for the mapping. These studies concluded that spatial resolutions that were finer than 30 m tended to be suitable for mangrove mapping in the study area.

Nayak and Bahuguna (2001) focused on the use of remote sensing to monitor the extent of mangroves along India's coastline. High-resolution Indian Remote Sensing (IRS) data (23-m multispectral data fused with 5.8-m panchromatic data) have been used to monitor mangroves and other coastal vegetation. In the same year, Held et al. (2001) investigated the usage of handheld spectrometer, airborne and hyperspectral satellite data for mangrove forest mapping in Australia. Compact

Airborne Spectrographic Imager (CASI) and Hyperspectral Mapper (HyMap) data were simultaneously collected from the Earth Observing-1 (EO-1) Hyperion (30 meter resolution, 220 bands) satellite, which bypassed the rainforest near Cape Tribulation in the far north of Queensland, Australia.

Wang et al. (2004) applied a combination of object-based and pixel-based classification to Very High Resolution (VHR) IKONOS imagery to map mangrove canopies at Punta Galeta on the Caribbean coast of Panama. Three distinct image processing approaches were examined: Maximum Likelihood Classification (pixel-based), Nearest Neighbor (NN) classification (object-based) and a hybrid classification that incorporated pixel and object-based approaches known as Maximum Likelihood Classification Nearest Neighbor (MLCNN). A new approach was established to maximize the Bhattacharya Distance (BH) by choosing an optimal scale parameter in the segmentation stage during the object-based classification to increase the mapping accuracies. Among the three methods, the MLCNN results had the best overall classification accuracy (91.4%) in differentiating between red, black, and white mangrove canopies and other non-mangrove cover.

An algorithm was developed by Nuarsa et al. (2005) for mangrove classification at Benoa Bay, Province of Bali. The two formulae, which were produced from the regression analysis of the digital numbers of Landsat ETM+ data were $CE1 = (0.663 * \text{Band 3}) + (0.155 * \text{Band 4}) - (1.4 * \text{Band 5}) + 0.995$ and $CE2 = (36 * \text{Band 4}) + (6 * \text{Band 5}) + \text{Band 3}$. If the CE1 value lies between -31.439 and 0.888 and CE2 is equal to or higher than 2000, then the object will be recognized as a mangrove.

Emch and Peterson (2006) quantified the temporal changes in mangrove forests in Sundarbans in southwestern Bangladesh (1989-2000) using Landsat TM

imagery. Maximum Likelihood Classification (MLC), Normalized Differential Vegetation Index (NDVI) and subpixel classification were performed on Landsat TM data to monitor the mangrove cover. The traditional classifier, MLC, cannot effectively detect fine differences in mixed-water forest environments, whereas both NDVI and the subpixel classification algorithm reveal the spatial distribution changes in mangrove forest cover.

Conchedda et al. (2008) examined an object-based method that was used to map and monitor the extent of mangroves at Low Casamance, Senegal. This object-based approach was performed on SPOT XS data to map the land cover in the mangrove ecosystem. The temporal changes in the mangrove ecosystem over two decades (1986-2006) were evaluated and analyzed. The high user's accuracy for the mangroves (97.1%) implies that the classification between other land cover classes and mangroves was distinguishable with an estimation area of 76,550 ha in 2006. This paper concluded that the 20-m spatial resolution of SPOT imagery was appropriate in mangrove mapping and the object-based approach was able to provide a precise update for the mangrove extent in the study site.

Lee and Yeh (2009) applied distinct remote sensing methods to study the shifting of mangrove vegetation from 1995-2004 in the Danshui River estuary in Taipei, Taiwan. This paper assessed and compared the different spatial resolution of satellite data (Landsat, SPOT, and QuickBird) with a series of aerial imagery as a reference to evaluate the shifting of mangrove communities. Mangrove areas were extracted via a two-stage analytical process. First, the NDVI approach was adopted to acquire the distribution of the vegetation cover. Second, MLC was performed on the NDVI's image to classify the mangrove and non-mangrove areas. The analytical results demonstrated that this two-stage analysis, which compared the changes in mangroves with time

without high-resolution imagery, was a feasible technique for discriminating between mangrove areas and vegetation cover.

An unsupervised classification technique (ISODATA clustering) was conducted on 61 Landsat images from the year 2000 that were acquired from the Global Land Survey to map the spatial distribution and aerial extent of the mangroves in the Philippines (Long and Giri, 2011). According to this statistical analysis, the mangrove distribution in the Philippines in the year 2000 occupied a total area of 256,185 ha with a kappa coefficient of 0.926 and overall classification accuracy of 96.6%.

Kongwongjan et al. (2012) used five different vegetation indices, including Normalized Different Vegetation Index (NDVI), Simple Ration (SR), Soil Adjusted Vegetation Index (SAVI), Perpendicular Vegetation Index (PVI) and Triangular Vegetation Index (TVI), to distinguish mangrove areas in the Pa Khlok sub-district, Phuket, Thailand. The Maximum Likelihood Classifier was performed on 15-m resolution THEOS imagery from 2010 to classify mangrove and non-mangrove areas. The results indicated that a higher overall classification accuracy was obtained using the four original THEOS spectral bands combined with SR vegetation indices (92.38%) instead of using only individual vegetation indices.

The latest paper by Elmahdy and Mohamed (2013) mapped and monitored changes in the mangrove areas at Abu Dhabi, UAE using Landsat ETM+. The fuzzy logic algorithm was applied on multi-temporal Landsat data because this method can classify mixed pixels. Mangroves were discriminated and mapped with Landsat images at different density levels (low, medium and high). In the monitoring period from 1990 to 2006, the results from the fuzzy logic classifier indicated only slight changes in the mangrove ecosystem. Despite the low spatial resolution of the Landsat data in the

mapping and monitoring of mangroves, the fuzzy logic method still provided reliable mapping accuracy for mangrove studies.

2.1.2 Mangrove Mapping at the Species Level

Mangrove studies have been widely reported by researchers all around the world because of the vital role of mangrove trees. To better understanding of extent, species composition and biophysical properties of mangrove ecosystems, additional details regarding mangrove ecosystems must be examined. In addition to general mangrove mapping, one challenging task is to accurately distinguish and map mangrove species using multispectral or hyperspectral satellite data. Abundant research projects have mapped mangroves at the species level, but the outcomes of some of these studies are neither satisfactory nor conclusive.

Vaiphasa et al. (2005) attempted to use laboratory measurements (spectral information) on distinct mangrove canopy leaves to distinguish the mangrove species at Sawi Bay, Thailand. The spectral responses of 16 tropical mangrove species that were collected from the study area were measured with a spectrometer under laboratory conditions. One-way ANOVA analysis was performed on the various mangrove spectra, and the results indicated that all 16 mangrove species were significantly different at most spectral location ($p < 0.05$). In addition, the spectral separability between all pairs of mangrove species was computed using the Jeffries-Matusita (J-M) distance. These J-M distances illustrated that each pair of mangroves, except for pairs of Rhizophoraceae members, are spectrally distinct. In conclusion, this paper offered an approach for mangrove species discrimination (except for the Rhizophoraceae family) that used statistical and J-M distance analysis.

Neukermans et al. (2008) presented an automated fuzzy per-pixel classification to map mangrove species. High-spatial-resolution multispectral QuickBird satellite imagery that was acquired in 2002 was used to map four dominant mangrove species, specifically, *Avicennia marina* (*A. marina*), *Ceriops tagal* (*C. tagal*), *Rhizophora mucronata* (*R. mucronata*) and *Sonneratia alba* (*S. alba*), in Gazi Bay, Kenya. The overall accuracy (OA) for mapping the four mangrove species was 73% for this classification, and the mangrove stand maps were compared with visual delineations, which were performed by a specialist interpreter. The correspondence OA reached 86%. This research's results showed that QuickBird imagery could be used to separate dominant mangroves at the species scale.

Further studies have used the hyperspectral leaf reflectance of mangroves to show that mangrove species can be discriminated at the 780, 790, 800, 1480, 1530 and 1550 nm wavebands (Wang and Sousa, 2009). The reflectance values of *Avicennia germinans* (*A. germinans*), *Laguncularia racemosa* (*L. racemosa*) and *Rhizophora mangle* (*R. mangle*) mangrove leaves along the Caribbean coast of Panama were collected and measured with a high-resolution spectrometer. One-way ANOVA analysis was performed on the mean reflectance data across mangrove species to determine the bands that exhibited obvious differences (p value < 0.01). The selected bands were used in Linear Discriminant Analysis (LDA) to classify the three types of mangrove species. Although the spectral discrimination of mangroves was possible using leaf reflectance measurements, distinguishing mangrove canopies of different species requires hyperspectral data from satellites or airborne sensors.

Kovacs et al. (2010) assessed the mangroves on the estuarine islands of Mabala and Yélitono in Guinea, West Africa and mapped the mangrove species to four classes using a remote sensing approach and field survey data. The four

mangrove classes that were distinguished from IKONONS satellite imagery using an ISODATA unsupervised classification are tall red mangroves *Rhizophora racemosa* (*R. racemosa*), medium red mangroves (*R. racemosa*), dwarf red mangroves (*R. mangle* and *R. harisonii*), and black mangroves *Avicennia germinans* (*A. germinans*). In addition, an LAI map of the mangrove islands at Mabala and Yélitono was estimated.

In the year 2011, a comparative study between pixel-based and object-based approaches for mapping mangrove species using hyperspectral data were reported (Kamal and Phinn, 2011). CASI-2 data at the mouth of the Brisbane River in southeastern Queensland, Australia were used to separate mangroves at the species scale. Three image processing methods, namely, the Spectral Angel Mapper (SAM) and Linear Spectral Unmixing (LSU) from pixel-based classification and multi-scale segmentation from object-based classification, were applied on CASI-2 imagery for the mapping process and analysis. For each method, three mangrove species, namely, *A. marina*, *Rhizophora stylosa* (*R. stylosa*) and *Ceriops australis* (*C. australis*), were discriminated from salt marshes and water bodies. Among the three methods, object-based mapping, which merges a rule-based and nearest neighbor classification approach, achieved the best results with an overall accuracy of 76% and Kappa coefficient of 0.67 for mangrove mapping at the species level.

An article by Koedsin and Vaiphasa (2013) studies the capability of EO-1 Hyperion hyperspectral data, which have 30-m spatial resolution, to discriminate the mangrove species at the Pak Phanang mangrove forest, Thailand. Five different mangrove species were classified, including *A. alba*, *A. marina*, *Bruguiera parviflora* (*B. parviflora*), *Rhizophora apiculata* (*R. apiculata*) and *R. mucronata*, which have very similar spectral characteristics. The Spectral Angle Mapper (SAM) technique

was integrated with Genetic Band Selection and the Sequential Forward Selection (SFS) algorithm, and the overall classification accuracy improved from 86% to 87% and 92%, respectively. The article results anticipated that the methodology that was used in this research can serve as an alternative method for detailed mangrove species mapping.

Muhammad and Waqar (2013) investigated the capability of hyperspectral data to discriminate mangrove species on the coast of the Arabian Sea along Karachi. Hyperion imagery that was acquired in 2012 was used to identify and map the two mangrove types: *A. marina* (White Mangroves) and *A. germinans* (Black Mangroves). The end members were extracted from the output of Minimum Noise Fraction (MNF) and Pixel Purity Index (PPI), which were visualized in n-dimensions. Well-distributed clusters in the n-dimension scatter plot were selected as inputs for classification purposes. The techniques that were used to classify the mangrove species included the Spectral Angle Mapper (SAM), Spectral Feature Fitting (SFF) and Spectral Information Diversion (SID). Among these three techniques, SID provided the best results, even though some areas still contained incorrect classifications between water and mangrove types.

In the year 2014, a study compares the accuracy of mangrove species maps derived from two different layer combinations of WorldView-2 images with those generated using high resolution aerial photographs captures by an UltraCamD camera over Rapid Creek coastal mangrove forest, Darwin, Australia were reported (Heenkenda et al., 2014). Mangrove areas were then further classified into species using a support vector machine algorithm with best-fit parameters. Overall classification accuracy for the WorldView-2 data within the visible range was 89%.

2.1.3 Mangrove Species Studies in Malaysia

Research on mangrove studies has become common for the purposes of mangrove management and conservation. Abundant research, as mentioned in sections 2.2.1 and 2.2.2, has used various methods to study, map and monitor mangrove ecosystems. Many approaches and new algorithms have also been developed to create more advanced, rapid and accurate methods to study the details of mangrove species.

Kanniah et al. (2005) introduced a Linear Mixture Model (LMM) that was applied on IKONOS satellite imagery to study the mangrove forest at Sungai Belungkor, Johor, Malaysia. Three mangrove species, namely, *R. apiculata*, *R. mucronata* and *Xylocarpus granatum* (*X. granatum*), were mapped. The classification steps that used the LMM included preprocessing, endmember selection, the inversion of the LMM and accuracy assessment. Accuracy assessment was performed according to the fraction between pixels that were estimated from the LMM and those that were collected from the study site. The obtained correlation coefficient was ~0.8 for the endmember *R. apiculata* and ~0.6 for *R. mucronata* and *X. granatum*. The accuracy assessment showed that the LMM performed very well compared to the pixel-based Maximum Likelihood and Minimum Distance to Mean techniques.

Research that was conducted in Tok Bali, Kelantan and Setiu, Terengganu by Kamaruzaman and Kasawani (2007) distinguished five mangrove species using imaging spectrometry. The significant wavelengths to separate the mangrove species

were determined by canonical stepwise discriminant analysis, and Student's t-test was used to test the significant differences between mangrove species at the two locations. The five mangrove species under investigation were *R. apiculata*, *Bruguiera cylindrica* (*B. cylindrica*), *A. alba*, *Heritiera littoralis* (*H. littoralis*) and *Hibiscus tiliaceus* (*H. tiliaceus*). At both locations, 15 significant wavelengths were found that could separate the five mangrove species. The t-test indicated that no obvious differences were observed between the mangroves' spectra reflectance at both study areas. This research demonstrated that each mangrove species at Tok Bali and Setiu could be distinguished using their unique spectral reflectance.

Liu et al. (2007) classified the mangroves at the Matang Mangrove Forest Reserve (MMFR) in Malaysia using different classifiers (object-based and pixel-based classification) and different textural features. Six mangrove forests that were detected in the MMFR included *Avicennia* forest, transitional new forest, *B. cylindrica* forest, *B. parviflora* forest, *Rhizophora* forest and dryland. Different window kernel sizes were selected in the pixel-based classification, namely 3x3, 5x5, and 7x7 for SPOT XS and 5x5, 9x9, and 13x13 for SPOT PAN, to compute the images' textural features. Two different segmentation levels corresponding to scale factors of 11.8 and 17.0 were selected to extract the textural features of SPOT fused images in object-based classification. Then, second-order textural features (comprising homogeneity, energy and entropy) were mixed into the extracted spectral feature image. Nearest Neighbor (NN), Maximum Likelihood, and Support Vector Machine (SVM) classifiers were used in this classification. The object-based classification provided better accuracy compared to the pixel-based classification. The accuracy of the NN classifier, which has been ordinarily used in object-based classification, was lower than that of the Maximum Likelihood and SVM classifiers.

These studies indicated that the integration of second-order textural features with different classifier could not enhance the accuracy of the object-based or pixel-based classification.

UPM-APSB's AISA airborne hyperspectral imaging sensor, was assessed by Jusoff (2008) to establish a geospatial database for mangrove species and find the effective wavelength regions that could distinguish the mangrove species at the Port Klang mangrove forest along the Klang River, Selangor. A total of nine mangrove species were identified: *R. apiculata*, *R. mucronata*, *R. stylosa*, *B. parviflora*, *Bruguiera gymnorhiza* (*B. gymnorhiza*), *B. cylindrica*, *S. alba*, *Sonneratia caseolaris* (*S. caseolaris*) and *Avicennia officinalis* (*A. officinalis*). The results from this study showed that the mangrove species could be easily determined and distinguished in the near-infrared (NIR) wavelength region (700 to 900 nm) compared to the visible wavelength region.

Kasawani et al. (2010) used soil-based vegetation indices to distinguish and map the mangrove species in the Kelantan Delta, Peninsular Malaysia. These soil-based vegetation indices, including the Perpendicular Vegetation Index (PVI), Soil-Adjusted Vegetation Index (SAVI), Optimized Soil-Adjusted Vegetation Index (OSAVI), Transformed Soil-Adjusted Vegetation Index (TSAVI) and Modified Soil-Adjusted Vegetation Index (MSAVI), were applied to Landsat TM images to eliminate the soil background. A total of five mangrove classes, specifically, *Avicennia-Sonneratia*, *Avicennia*, *Acanthus-Sonneratia*, *Mixed Acrostichum* and *Mixed Sonneratia*, were mapped via unsupervised classification. The accuracy ranged from 70% to 79% among the five mapping indices, and the SAVI method produced the best results, with a 79% classification accuracy when identifying the four mangrove classes.