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Per-pixel and sub-pixel classifications of high-resolution satellite data for mangrove species mapping

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Abstract: High spatial resolution sensors such as IKONOS and QuickBird, are expected to classify mangrove species more accurately than coarse spatial resolution satellite images. Conventional per-pixel classification techniques could not improve the classification accuracy when such high-resolution images are applied. Such failure has encouraged the invention of more sophisticated and deterministic techniques i.e. sub-pixel classifications. In this study, the mangrove forest at Sungai Belungkor, Johor, Malaysia was classified using IKONOS data. Two classification approaches were applied, namely per-pixel and sub-pixel techniques. The conventional per-pixel classifiers used in this study were Maximum Likelihood (ML), Minimum Distance to Mean (MDM) and Contextual Logical Channel (CLC) while the Linear Mixture Model (LMM) was selected as the sub-pixel classification approach. The classification results revealed that the CLC classification with a contrast texture measure at window size 21 x 21 yielded the highest accuracy (82%) in comparison to the ML (68%) or MDM (64%). The spatial distribution of the classified mangrove species and classes coincided with the common mangrove zones in Malaysia. For the results of the LMM, the fraction of pixels measured from the satellite imagery and observed in the field gave a good correlation with an R^2 value of 0.83 for Bakau minyak, a moderate correlation with an R^2 of approximately 0.71 for Bakau kurap and an R^2 of 0.75 for the 'Others' type of mangrove species. An error image was also created to compare the best fitting spectrum produced by the inversion of the LMM with the original observed spectrum, where the maximum RMS error was only 5%.

Keywords: Mangrove, IKONOS, per-pixel classification, sub-pixel classification, contextual logical channel classification, linear mixture model.

1. Introduction

Satellite images have not been extensively used for mapping mangrove species due to the limited spectral and spatial resolution of conventional imageries (Wang et al., 2004). Despite their coarse spatial and spectral resolutions, some satellite data, primarily TM (Thematic Mapper), SPOT (Satellite Pour l'Observation de la Terre), XS (multispectral), HRV (High Resolution Visible), NOAA (National Oceanic and Atmospheric Administration) and AVHRR (Advanced Very High Resolution Radiometer) have been used for mangrove mapping (Green et al. 1998; Gao 1998 and Rasolofoharinoro et al. 1998).

Traditional per-pixel multispectral classification approaches have been used by many researchers in the attempt to achieve accurate mapping of mangrove area (Aschbacher et al. 1995; Green et al. 1998; Gao 1998; Rasolofoharinoro et al. 1998; Mitchell and Lucas 2001 and Wang et al. 2004). Mapping of mangrove species is highly dependent on resolution of the sensor and image processing methods or classification methods adopted in the mapping process. Spectral resolution and spatial resolution of the data play a critical role in order to achieve high mapping accuracy (Green et al. 1998; Gao 1998; Mitchell and Lucas 2001 and Wang et al. 2004) although it also depends on the characteristics of the mangrove area (Mitchell and Lucas 200; Jollineau and Howarth 2002 and Wang et al. 2004).

The Maximum Likelihood (ML) classifier has proven to be the most robust per-pixel classification method in accurate mangrove mapping (Aschbacher et al. 1995; Gao 1998; Rasolofoharinoro et al. 1998; Jollineau and Howarth 2002 and Wang et al. 2004) while the Minimum Distance to Mean (MDM) classifier also showed promising results in several studies (Gao 1998 and Rasolofoharinoro et al. 1998). At the same time, the availability of ground truth is important to assess the accuracy of the final map (Green et al. 1998 and Gao 1998).

Previous studies indicated that accurate discrimination among mangrove species was not possible with conventional (coarse spatial/spectral) resolution data, but was possible using aerial photographs (Sulong et al. 2002; Kairo et al. 2002 and Verheyden et al. 2002) or images from airborne sensors such as CASI (Compact Airborne Spectrographic Imager, see Green et al. 1998 in Wang et al. 2004), MASTER (MODIS/ASTER Airborne Simulator, see Alvin and Mazlan 2003) and AVIRIS (Airborne Visible/Infra-Red Imaging Spectrometer, see Vaiphasa and Ongsomwang 2004). The finer the spatial and spectral resolution of satellite images, the more accurate mangrove species classification results would be. The recent availability of images from high spatial resolution satellite sensors like IKONOS and Quickbird enable the mapping of land covers accurately and they can also substitute the higher cost of airborne images.

There have been several studies using IKONOS imageries for classifying different land cover types. A comparative study was made by Wang et al. (2004) using IKONOS and QuickBird images for mapping mangrove species on the Caribbean coast of Panama in terms of their spectral statistic, textural information and classification accuracy. Results indicated that analysis of first and second order texture information improved the classification accuracy of IKONOS panchromatic band more than that of Quickbird images. Similarly, Franklin et al. (2001) found that second order texture values extracted from a panchromatic IKONOS image effectively increased separability among nine Douglas Fir forest age groups. Another study was conducted by Mumby and Edwards (2002) to compare an IKONOS image with other remote sensing images like Landsat Thematic Mapper, SPOT and CASI, and it found that the fine spatial resolution image of IKONOS could achieve a better thematic accuracy in mapping marine environments.

With the availability of high spatial resolution sensors such as IKONOS and QuickBird, for civilian applications it is expected that more detailed discrimination between mangroves community can be achieved. Nevertheless, the classification accuracy does not increase with the increasing spatial resolution due to the mixed pixel phenomenon (Hsieh et al. 2001). Mixed pixels may cover a region containing different classes of ground cover of varying proportions, and therefore alter the traditional image classification approach which assigns a particular class of ground cover to each pixel.

Problems associated with the mixed pixel phenomenon have promoted a new approach to unmix the spectral characteristics of the mixed pixel. The success of Linear Mixture Model (LMM) in various disciplines seems to meet such a requirement (Abdul Shakoor 2003; Cherchali and Flouzat 1994; Roberts et al. 1998; Shimazaki and Tateishi 2001 and Zhu and Tateishi 2001). The contribution of each pixel is assigned in proportion to the percentage area each ground cover class occupies in that mixed pixel (Boardman 1989). Such an approach is called spectral unmixing which assigns more than one class label to an individual mixed pixel (Keshava and Mustard 2002). Yet to date, very few studies have examined the suitability of IKONOS images for mapping mangrove species (Wang et al. 2004) and none use LMM for mangrove mapping, which is why we here attempt to map mangrove forest species using LMM.

The world's mangrove forests cover at least 14 million hectares, and about 20% of these are found in south-east Asia which has the greatest diversity of mangrove species. In Malaysia mangrove forest covers approximately 641,172 hectares of which 107,720 hectare are located in Peninsular Malaysia (Christensen and Olsen 1999). About 20% of the mangroves (27,000 hectare) on the Peninsular are found in Johor state (Christensen and Olsen 1999). Most of the mangroves in Johor are found in estuaries and on accreting shores with high tidal range and strong bi-directional tidal currents (Christensen and Olsen 1999).

There are 19 mangrove areas in Johor where 7 of them are distributed in the west coast, 9 in the south coast and 3 in the east coast respectively, and Table 1 shows the list of mangrove species usually found in Johor. Although mangrove ecosystems serve many environmental, economic and community functions, the existence of these ecosystems is threatened by coastal development projects. For instance, in Johor about 48% of its total mangrove forests have been destroyed since 1965 (Christensen and Olsen 1999).

Therefore, the demand for accurate mangrove maps that indicate the location and distribution of mangrove species is increasing in order to assist in mangrove resource biodiversity management and protection. Faster and more accurate methods to monitor and assess the forest structure and dynamics are needed for purposes of better conservation and restoration. Remote sensing techniques, especially high spatial resolution imageries, would greatly assist in this effort as they have the ability to accurately map mangrove species.

Family	**Species**	**Local name**
Anicenniaceae	*Avicennia alba*	Api-api putih
	Avicennia lanata	Api-api bulu
	Avicennia marina	Api-api jambu
	Avicennia officinalis	Api-api ludat
Combretaceae	*Lumnitzera littorea*	Terentum merah
Euphorbiaceae	*Excoecaria algallocha*	Buta buta
Meliaceae	*Xylocarpus granatum*	Nyireh bunga
	Xylocarpus moluccensis	Nyireh batu
Palmae	*Nypa fructicans*	nipah
Polypodiaceae	*Acrostichum aureum*	Piai raya
	Acrostichum speciosum	Piai lasa
Rhizophoraceae	*Bruguiera cylindrica*	Berus
	Bruguiera gymnorrhiza	Tumu merah
	Bruguiera parvifloara	Lenggadai
	Bruguiera sexangula	Tumu putih

	Ceriops decandra	Tengar
	Ceriops tagal	Tengar
	Kandelia candel	Berus berus
	Rhizophora apiculata	Bakau minyak
	Rhizophora muscronata	Bakau kurap
	Rhizophora stylosa	
Rubiaceae	*Scyphiphora hydrophyllacea*	Chingam
Sonneratiaceae	*Sonneratia alba*	Perapat
	Sonneratia caseolaris	Berembang
	Sonneratia ovata	Gedabu
aceae	*Heritiera littoralis*	Dungun

Table 1 - Mangrove species usually found in Johor *(Source: Christensen and Olsen, 1999)*

In this study we attempted to use high spatial resolution IKONOS data to classify mangrove species in Sungai Belungkor mangrove forest area. More specifically this study was aimed at

(i) classifying mangrove species using various per-pixel classification techniques

(ii) improving the accuracy of per-pixel classification results by adding texture information from IKONOS panchromatic data

(iii) unmixing the mixed pixels using LMM.

2. Study area

The study area, Sungai Belungkor is located at the south-eastern edge of Johor River in Kota Tinggi District, Johor, Malaysia (Figure 1). It has been a reserved mangrove forest since 1930 has a total area of 1606 hectare. It is categorized as an estuarine and highly disturbed mangrove. It is surrounded by oil palm plantations and two patches of lowland forest on the south of Sungai Belungkor. High species diversities of mangrove plants exist around the river (Christensen and Olsen 1999). However, *Rhizophora apiculata* (Bakau minyak) and *Rhizophora muscronata* (Bakau kurap) are the dominant commercial mangrove species in this area besides other minor species (Field visit and personal communication with forest rangers).

Figure 1 - Study area at Sungai Belungkor mangrove forest, Johor, Malaysia. Polygon on the IKONOS image represents the mangrove boundary that was redrawn from the topographic map of Kota Tinggi district (map title: Pengerang, scale 1:50 000, map sheet number: 4651, year: 1996).

This area was particularly selected for this study because it is one of the mangrove areas in Johor that has never been studied using remote sensing techniques and little data are available on its forest composition due to its inaccessibility (personal communication with forest rangers). In addition, this area exhibits a high rate of mixture among various mangrove species that will certainly impose problems when classifying with per pixel classification techniques.

3. Data

The IKONOS imagery used in this study was acquired on 16^{th} March 2001 at 11:24 am local time (03:24 GMT time). It comes with a standard bundle product consists of one panchromatic image at 1m resolution and one multispectral image at 4m resolution. The image was captured at 96.7° of sun azimuth and 62.8° of sun elevation angles. The cloud cover in this image is approximately 14% of the scene.

Three mangrove forest species, namely *Rhizophora apiculata* (Bakau minyak), *Rhizophora muscronata* (Bakau kurap) and *"Others,"* were selected to be classified in this study. The class *'Others'* includes seven species identified in the field (Nyireh bunga, Berus, Lenggedai, Tumu, Api-api putih, Tengar and Chinggam) (refer Table 1 for the scientific names). This is because, according to Johor Forestry Department, only Bakau minyak and Bakau kurap are the dominant commercial species in Sungai Belungkor, whilst the other species are considered minority and have no significant commercial value. Besides that only these two species and Nyireh bunga could be differentiated spectrally in the IKONOS image (see Figure 2). Therefore we combined all other species as *'Others'*. Most of the mangrove trees here are approximately 15 years old.

3.1 Field data collection

DGPS (Differential Global Positioning System) was used to obtain precise geographical locations in the field. The coordinates were mainly used to create Ground Control Points (GCP) in order to geo-register the satellite image accurately. Two field visits were carried out, one before the image was processed and the other one after the image classification in order to confirm the results derived from the image processing with the field observation.

Thirty sample plots with 4m x 4m spatial resolution that are identical to the size of IKONOS image (4 m) in size were established randomly to estimate the mangrove species fraction on the ground with the aid of the DGPS (Table 2). The fractions were measured based on the mangrove trees canopy or crown size. Fifty percent of the samples (15 points) were used for end member determination and the rest of the points were used as checkpoints to assess the accuracy between the image derived and field measured fractions of the three mangrove species.

To investigate the potential of IKONOS imagery for discriminating mangroves at the species level, field measurement was undertaken to test whether IKONOS image contains adequate information for mapping mangrove species. Species identification was carried out with the assistance of staffs from the Department of Forestry and taxonomy following Tomlinson (1994). The canopies of the sampled trees were cut off and transported to an open area within 2 hours to preserve the quality of the leaves. At the open area measurements of mangrove species spectral reflectance were taken using a portable spectro-radiometer (model FieldSpec® Pro FR) that operates between spectral ranges of 350 - 1000 nm with 10 nm spectral resolutions to build a spectral library of the mangrove species found in the study area.

The spectro-radiometer was first calibrated by shooting the instrument on a fibre (or any white target) for a period until a consistent 100% reflectance was achieved. The sensor, equipped with a field of view of 25° was positioned 0.5 m above each species' leaves surface at 45° with respect to nadir position to take readings of the spectra. Finally the measurements taken were converted into ASCII format and then imported into ENVI software to build a spectral library. The spectral library was then used to unmix the mixed pixels using LMM.

The difference in measured mangrove spectra among different species was tested using the square of Jeffries Matusita (J-M) distance analysis. This test was done to see whether mangrove species are significantly different at every spectral location. The J-M distance values range from 0-$\sqrt{2}$ and indicate how well the classes are statistically separate. Values greater than 1.9 indicate that the classes have good separability (Richards 1994 and Thomas, et al. 2003).

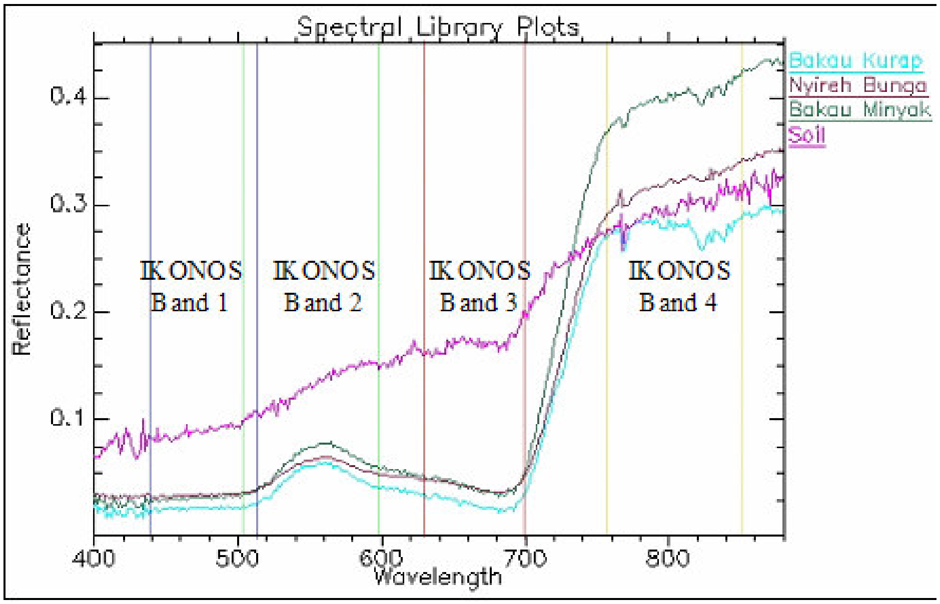
Plot	**Fraction (%)**	**Plot**	**Fraction (%)**
1	Nyireh bunga (50%), Bakau kurap (20%), Bohseng (15%), Lenggedai (10%), Tumu (5%)	16	Bakau kurap (55%), Bakau minyak (45%)
2	Api-api (60%), Tengar (20%), Tumu (20%)	17	Bakau minyak (100%)
3	Bakau minyak (100%)	18	Nyireh Bunga (100%)
4	Bakau minyak (50%), Bakau kurap (30%), Api-api (10%), Nyireh Bunga (10%)	19	Nyireh Bunga (70%), Bakau minyak (30%)
5	Nyireh Bunga (80%), Tengar (10%) Chingam (10%)	20	Bakau minyak (40%), Bakau kurap (30%), Bohseng (30%)
6	Bakau minyak (65%), Nyireh Bunga (25%), Tumu (10%)	21	Api-api (30%), Nyireh Bunga (30%) Bakau minyak (30%), Bohseng (10%)
7	Bakau minyak (85%), Tengar (15%)	22	Bakau minyak (60%), Bakau kurap (40%)
8	Nyireh Bunga (100%)	23	Bakau kurap (100%)
9	Nyireh Bunga (40%), Bakau minyak (35%), Tengar (25%)	24	Bakau minyak (85%), Lenggedai (15%)
10	Bakau kurap (100%)	25	Bakau minyak (100%)
11	Bakau kurap (100%)	26	Bakau minyak (70%), Bakau kurap (30%)
12	Bakau kurap (60%) Bakau minyak (40%)	27	Bakau minyak (100%)
13	Bakau kurap (80%), Nyireh Bunga (20%)	28	Bakau kurap (55%), Bakau minyak (45%)
14	Bakau kurap (100%)	29	Bakau minyak (40%), Bakau kurap (60%)
15	Nyireh Bunga (45%), Bakau kurap (30%), Bakau minyak (25%)	30	Api-api (100%)

Table 2 - Field-measured end-member fractions of various mangrove species at Sungai Belungkor mangrove forest.

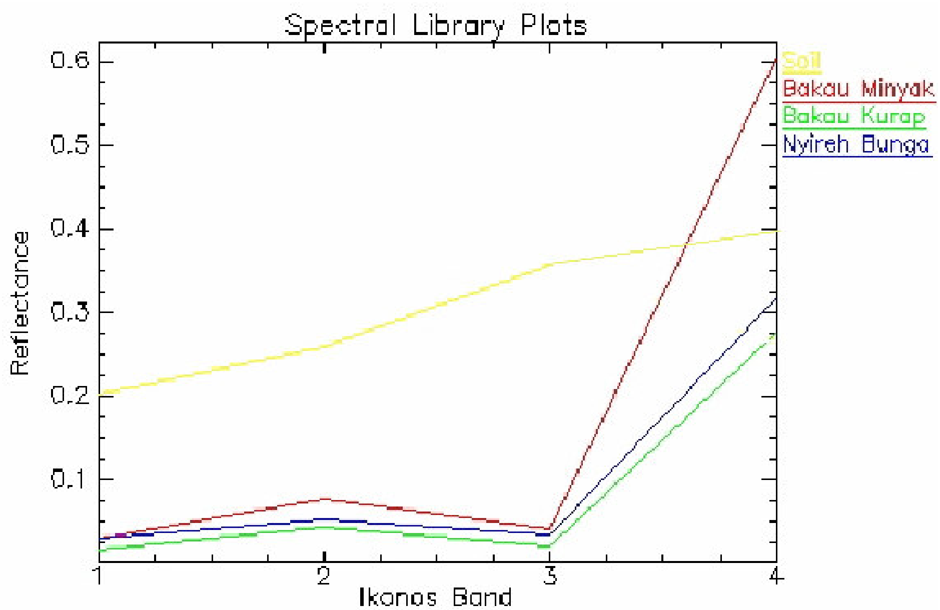
Class	Bakau Minyak	Bakau Kurap	Nyireh Bunga
Bakau minyak		1.9322	1.9222
Bakau kurap	1.9322		1.8441
Nyireh bunga	1.9222	1.8441	

Table 3 - Class separability test using Jefferies Matusita distance analysis.

The separability between Bakau minyak and Bakau kurap as well as between Bakau minyak and Nyireh bunga is high (more than 1.9) (Table 3). The separability between Bakau kurap and Nyireh bunga is relatively low with a value of less than 1.9. This distinctive spectral feature of mangrove permits the classification of the different species of mangrove using IKONOS imagery at Sungai Belungkor mangrove forest.



a.



b.

Figure 2 - Spectral libraries for end-members Bakau minyak, Bakau kurap, 'Others' and Soil from spectro-radiometer readings (a) and image data (b). The four surface features can be separated in bands 4 and 2. Broadly speaking, these mangrove species are spectrally distinct in the wavelength covered by IKONOS images.

The spectral reflectance of all the species measured in the field was further re-sampled to suit the spectral bands of the IKONOS imagery (Figure 2). Image end-members or pure pixels were obtained by locating pixels in the scene with the maximum abundance of the physical end-members they represent. For each class of mangrove species, 20-40 spectra were collected by summing and averaging the spectra that are located in the range of lower band limit to upper band limit of each IKONOS bands (Figure 2b). Comparison between spectral libraries measured during field work (Figure 2a) and aggregated to IKONOS bands (Figure 2b) shows that the spectral response in both graphs exhibit a similar pattern.

Both graphs indicate a clear spectral distinction in band 4 for Bakau kurap, Bakau minyak and Nyireh bunga. The image and the field-measured spectral libraries were input into ENVI 3.6 image processing software to compute fraction values for each end-member.

4. Methodology

The methods adopted in this study are illustrated in Figure 3. The IKONOS imagery was first corrected radiometrically and geometrically. Sub-setting and masking of water bodies and clouds were done to ensure only extent of mangrove forest would be further processed. After that, per-pixel and sub-pixel classification techniques were used to classify the image into different mangrove species and fraction values respectively. Per-pixel classification methods included ML, MDM and CLC, while sub-pixel classification included LMM. The accuracy of the two classification methods were assessed separately. Confusion matrix or error matrix and kappa statistics were used to assess the accuracy of the per-pixel classification accuracy, while for sub-pixel classification results, the accuracy was assessed through regression with ground-measured fraction values. The detailed descriptions of the methods adopted in this study are described in the following sub-sections. The software used to carry out this study was ENVI 3.6 for satellite image processing and Microsoft Excel for statistical analysis.

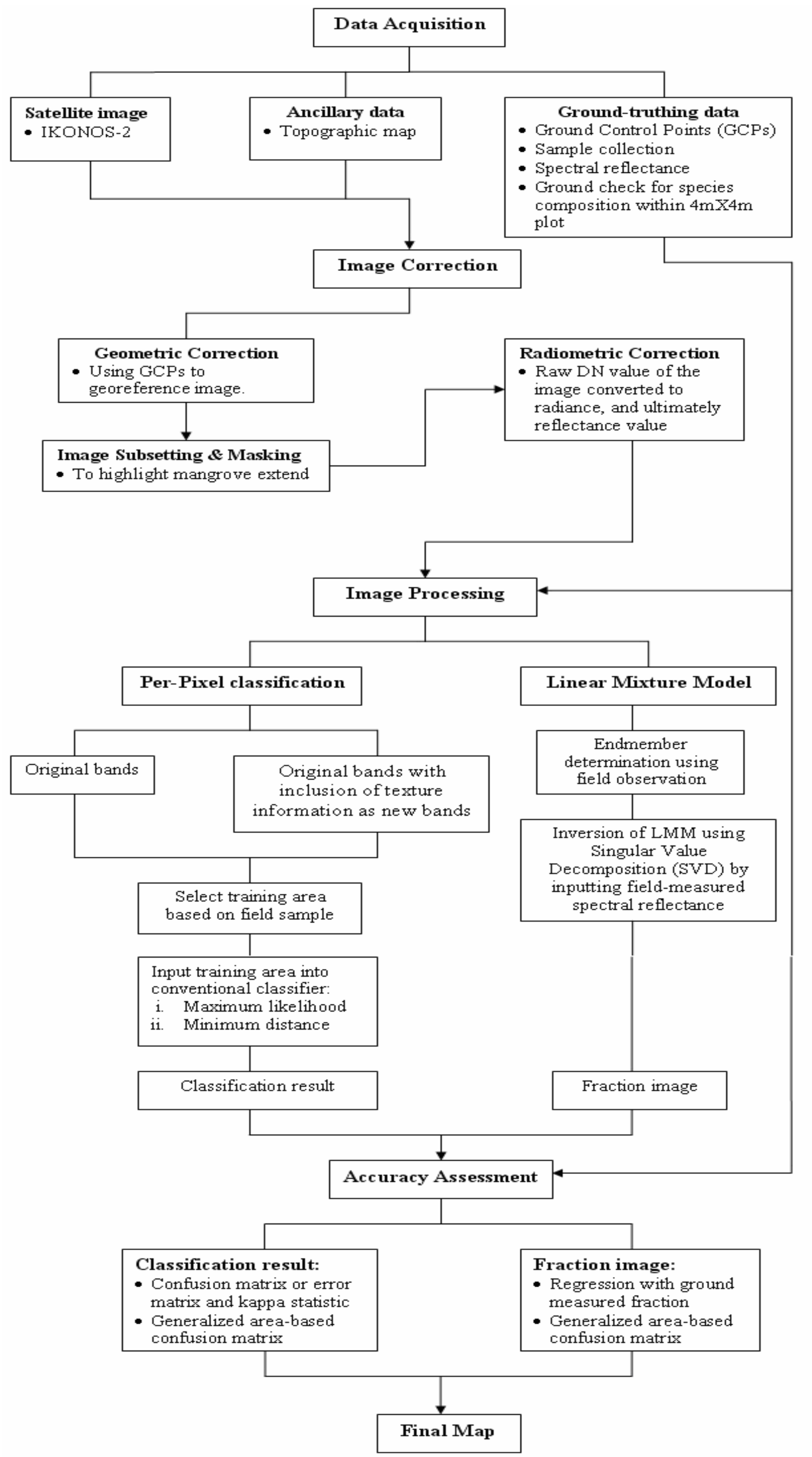


Figure 3 - The methods adopted to produce mangrove species classification.

4.1 Radiometric correction

Reflectance at satellite was calculated using radiometric calibration coefficients (Martin 2005). As for the atmospheric correction, a simple method known as "dark object subtraction" (COST model) was used in this study to atmospherically correct the image (Chavez 1988; Chavez 1996; Mehner et al. 2004 and Vaiphasa 2004).

4.2 Geometric correction

Topography maps are unsuitable for geo-referencing of IKONOS images, because the scale for the topographic map is 1:50 000, which is only able to produce maximum of 50 m accuracy, while IKONOS multispectral images require 4m or less accuracy. Therefore, a DGPS instrument was used to acquire ground control points (GCPs) needed for the geometric correction. The northern part of this area is highly inaccessible and therefore only 6 points (at main road intersections, jetties and buildings) were used for geometric correction and the RMS error of the correction was 0.3725 pixel.

4.3 Sub-setting and cloud masking

The entire scene, which covers approximately 50 hectare, was subset to cover only the mangrove area. This was done to avoid any confusion that would occur in terms of spectral reflectance between mangroves and non- mangrove plants like rubber, forest and other plantations in the study area. Cloud cover in the study area was removed by digitizing the cloud and cloud shadow's boundaries manually using ROI (Regions Of Interest). The ROI was then used as a mask to remove the clouds. Figure 4 shows the satellite image after subsetting, masking and radiometric correction.

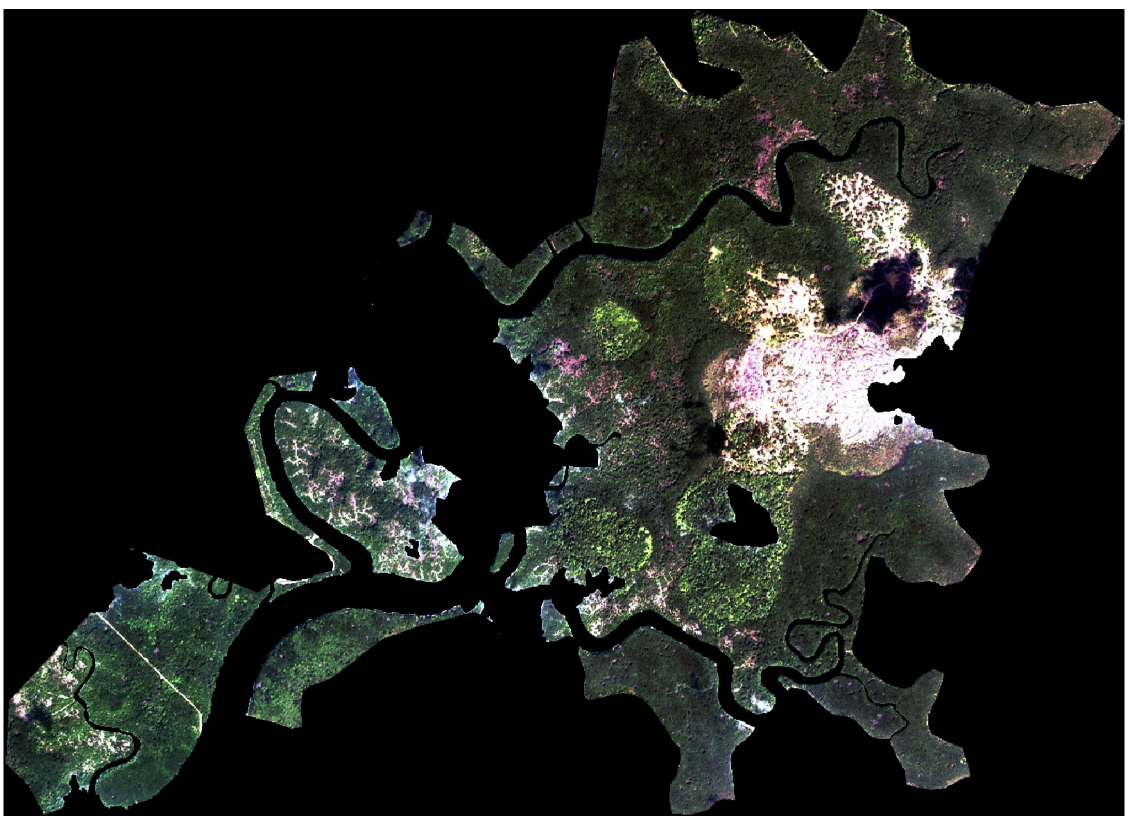


Figure 4 - Satellite image after subsetting, masking and radiometric correction. Note that only the mangrove forest is left after subsetting and masking.

4.4 Processing

4.4.1 Per-pixel classification

The three main per-pixel classification approaches used in this study were ML, MDM and CLC (by using texture information). ML was used in this study because it has proven to be the most robust per-pixel classification method in accurate mangrove mapping, whilst MDM has also shown promising results. For ML and MDM classifications, only the original bands (bands 1, 2, 3 and 4) of the IKONOS image were trained. A scale factor of 1 was applied for ML, whereas no probability threshold value was set for this classifier. For MDM both maximum standard deviation from mean and maximum distance error were not set any values. While in the CLC classification, texture information was added to the original image as an extra channel in the image and then trained together with original bands to improve the classification accuracy. Texture is the visual effect caused by spatial variation in tonal quantity over relatively smaller areas (Wang et al. 2004). Texture information was embedded into the multi-spectral information so that the small scale spatial variability would help discriminate those canopy types that were hard to distinguish from spectral information alone (Wang et. al 2004).

Texture information was extracted from the IKONOS panchromatic band based on second-order grey-level statistics. Many of the second order texture measures are correlated and therefore, Wang et al. (2004) suggested only contrast, correlation and entropy should be used in order to reduce the redundancy. Three parameters affect texture information extraction, namely window size, displacement vector and quantization level. Window size was set on 3x3, 5x5, 11x11 and 21x21 to extensively compare the texture embedded in IKONOS images. The result from Wang et al. (2004) suggested that there is an increase in classification accuracy with higher quantization level and thus, quantization level was set as 64 (highest level in ENVI software). In this study, displacement vectors at four directions (0^o, 45^o, 90^o and 135^o) with a spatial distance of 1 pixel were used to produce an averaged value for each texture statistic. The extracted texture information was then added to the original image (with 4 bands) as an extra channel and then the image (4 original bands + l contrast band + 1 correlation band + 1 entropy band) was trained and the maximum likelihood classifier was run to classify the image. The accuracy of per-pixel classified results was assessed using conventional confusion matrix or error matrix and kappa statistics. The details of the samples that were used in the classification and accuracy assessment of per pixel classification techniques are shown in Table 4.

Sample	**Species**	**Location (RSO)**
1	Bakau Kurap	(673756.96, 160884.38)
2	Nyireh Bunga	(673961.06, 160923.22)
3	Nyireh Bunga	(673945.62, 160969.29)
4	Bakau Minyak	(675630.37, 162086.67)
5	Nyireh Bunga	(676214.74, 162906.48)
6	Nyireh Bunga	(676190.03, 162955.62)
7	Bakau Minyak	(676224.03, 162961.76)
8	Nyireh Bunga	(676551.51, 162473.37)
9	Bakau Minyak	(676529.91, 162611.57)
10	Bakau Kurap	(676536.10, 162654.57)
11	Bakau Kurap	(676669.00, 162666.82)

12	Bakau Minyak	(676749.38, 162734.36)
13	Bakau Minyak	(676743.22, 162783.49)
14	Bakau Kurap	(676406.36, 162884.93)
15	Nyireh Bunga	(676301.28, 162894.17)
16	Bakau Kurap	(676168.29, 162580.96)
17	Bakau Minyak	(676214.63, 162488.82)
18	Nyireh Bunga	(676192.98, 162458.11)
19	Nyireh Bunga	(676304.21, 162326.03)
20	Bakau Kurap	(676233.04, 162022.02)
21	Bakau Minyak	(676155.80, 162092.67)
22	Nyireh Bunga	(676087.77, 161985.20)
23	Bakau Kurap	(675778.66, 161844.02)
24	Nyireh Bunga	(675506.69, 161887.09)
25	Bakau Minyak	(675358.32, 161853.35)
26	Bakau Minyak	(675228.51, 161816.53)
27	Bakau Minyak	(675107.95, 161733.65)
28	Bakau Minyak	(675049.20, 161663.03)
29	Bakau Kurap	(674981.17, 161549.42)
30	Bakau Kurap	(674968.78, 161448.08)

Table 4 - Training samples used in the per-pixel classification (first 15 samples) and samples that were used for accuracy assessments (samples 16-30).

4.4.2 Sub-pixel classification (linear mixture modelling)

Linear mixture modelling is an image classification technique to map the relative abundance of surface materials present within a pixel. When the size of a pixel is larger than the size of the object being sensed, more than one object will be included in the pixel and hence mixed pixels are generated. This problem is obvious in areas with heterogeneous surfaces. In this study, we assume the mixture of more than one feature within a pixel is linear. Linear mixture modelling assumes that the signal received at the satellite sensor depends on the proportion of individual surface components such as soil, water and vegetation present in a particular pixel and on the mixing process (Abdul Shakoor 2003).

Mathematically, LMM can be modelled using Equation (1) (Abdul Shakoor 2003).

$$b_i = \Sigma a_{ei} x_i + \varepsilon_l \qquad (1)$$

where: b_i = reflectance of mixed pixel spectra in band i

a_{ei} = reflectance of the surface component e in band i

x_i = proportion of pixel area covered by the e ground cover type

ε_l = residual error

In general, there are three procedures to unmix the model or to derive proportion images, including dimension reduction, end-member determination and inversion of the LMM (Keshava and Mustard 2002). Dimension reduction is necessary for large volume datasets like hyper-spectral images. In this study, dimension reduction was skipped since IKONOS multispectral image have only four bands.

End-member determination is a technique used to find the number of spectrally distinct surface materials/end members that occupy in the image. There are two categories of end-member determination; *interactive* and *automated* (see Plaza et al. (2002)) for a detailed overview of the existing end member extraction techniques). Interactive end-member determination was chosen in this study. It involves an empirical estimation of end members from a scene through observations and physical intuition. The theoretical limit to the number of end-members is equal to the number of spectral channels plus one. However, the number of end-members is far fewer in practical owing to the spectral information being redundancy for some spectral bands (Keshava and Mustard 2002). So, in this study we used three end-members (Bakau minyak , Bakau kurap, and 'Others'). These three species were found to be abundant in the study area (Field visit and personal communication with forest rangers). One extra class i.e. soil, was also chosen since it is necessary to include classes that are not useful to the user in order to meet the closed-world assumptions (Lewis and Brown 2001). End members may be extracted from the image itself, derived from field spectral measurements or selected from laboratory spectral libraries. In this study, the spectra of the three mangrove species and soil end member were derived from field measurements using the spectro-radiometer as described in the data and methodology section.

Inversion of the LMM was done to estimate the fractional abundances of each mixed pixel from its spectrum and the end-member spectra. It is done by inverting the linear mixing equation (equation 3) through a least square regression technique. In this study, we used the singular value decomposition technique (Boardman 1989) to unmix the mixed pixels into images giving abundance values ranging from 0 to 1. This technique rest on a linear relationship between an observed spectrum and a library composed of spectra associated with the individual mixing components. Then the determination of the unknown abundance values is accomplished by inversion of the library matrix and multiplication by the observed spectrum as shown below (Boardman 1989):

$$A * X = B \tag{2}$$

$$X = A^{-1} * B \tag{3}$$

where: A = total number of bands x number of mixing end members library matrix

X = number of mixing end members x 1 unknown abundance vector

B = total number of bands x 1 observed data vector

During the unmixing process, a unit sum constraint was applied by adding weighting factors in order to decrease the contributions of the smallest singular values. Different weight (0-10) was applied to find out the best solution to the unmixing result. The best result obtained when:

i. the fraction values for each end-members fall between 0.0 to 1.0
ii. the sum of all end-members fraction is equal or less than one for a pixel
iii. the RMS error is between 0.00-0.05.

The result of the unmixing process is a proportion image for each of the end member and a root mean square image. The error images show the error between the original (mixed) spectrum and the best fit spectrum computed from the resulting end member abundances.

The fraction values obtained from the LMM were validated with the field-measured (as described in the field data section) end-member fraction through a simple linear regression analysis. The ground truth data were point information at 15 locations in the study area. The strength of the relationship between the values derived from the both techniques was described using Pearson's product moment correlation coefficient (R^2) values and the residuals were shown by RMS errors.

5. Results and Discussions

5.1 Spatial distribution of mangroves

The spatial distribution of mangrove species at Sungai Belungkor as classified by per pixel classification techniques indicate that Bakau minyak and Bakau kurap dominate the riverside areas. 'Others' type of mangrove species is mostly located in the transitional area between Bakau kurap and Bakau minyak (Figure 5 shows the results of CLC classifier with 21 x 21 window size). The distribution pattern of these species is similar to the field observation. No distinct boundaries were found between these species types. On the contrary, most of these species are mixed even within areas as small as 4 m^2.

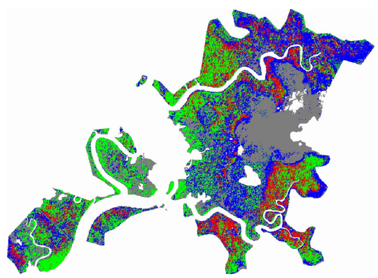


Figure 5 – Result of classification using CLC with 21 x 21 window size

Our study generally coincides with the general description of mangrove zonation in Malaysia given by Sungai Buluh Nature Park (2001), that the seaward edge of the mangrove is dominated by pioneer species of *Avicennia* and *Sonneratia* whereas on the bank of river estuaries *Rhizophora* (such as Bakau minyak and Bakau kurap) replaces the pioneer species. Behind this zone is a zone of mixed mangrove forest species of *Rhizophora, Sonneratia, Brugeria* (such as Tumu and Lenggedai), *Ceriops* (Tengar), *Kandelia* (Berus), *Xylocarpus* (Nyireh bunga), *Lumnitzera* and *Excoecaria*. However, mangroves that are badly disturbed or found on narrow coasts do not show well defined series of zones paralleling the coast (Sungai Buluh Nature Park 2001).

5.2 Classification results

The results of classifications of mangrove species using ML, MDM and CLC with different window sizes are shown in Table 5. The texture information was extracted from entropy, contrast and correlation measures of second order textures. Among these three measures contrast measure with window size 21 x 21 yielded the most promising results whereas entropy was found to be the poorest texture measure (results not shown). The overall accuracy increased from 63.6% using MDM classifier to 68.2% with ML and CLC (with window size 3 x 3 and % x 5) (Table 5). Inclusion of texture information does not increase the accuracy of classification at window size 3 x 3 and 5 x 5. However, increasing the window size to 11 x 11 and 21 x 21 considerably increased the classification accuracy to 77.3% and 81.8% respectively (Table 5). The kappa statistics which is a measure of classification agreement between actual and chance is also higher for texture analysis with window size 21 x 21 compared to others classifiers. When the user and producer accuracies for each mangrove type and for each classification techniques were examined better user and producer accuracies were achieved for

Bakau minyak (Table 5) compared to Bakau kurap and 'Others'. The class separability test (Table 3) proves this result where the spectral separability between Bakau minyak and Bakau kurap as well as Bakau minyak and Nyireh bunga is high. Bakau kurap achieved higher user accuracy than "Others', whereas 'Others' achieved higher producer accuracy than Bakau kurap. It should also be noted that the accuracy of soil was not assessed since it did not provide any meaningful result in mangrove forest classification. It was included in the classification process to complete the closed-world assumption, particularly to avoid misclassification of mangrove communities as a soil class. Soil mainly exists in the gap between mangrove trees.

The comparison of this study with the study of Wang et al. (2004) showed similar results where the addition of texture information significantly increased the kappa statistic and the user and producer accuracies of IKONOS image than that of the Quickbird image. Similar outcomes were also obtained by Mumby and Edwards (2002) by adding textural information to the classification of IKONOS imagery for mapping coral reefs in the Turks and Caios islands. Texture information from IKONOS imagery significantly improved the classification accuracy at both fine and medium levels (more detailed habitat classes) of discrimination. On the other hand, when the texture information was used to classify coral habitats at coarse ecological scale, the classification accuracy did not significantly differ from that of the Landsat imagery.

Classifier	**Inclusion of texture information**	**Window size**	**Overall accuracy (%)**	**Kappa Statistic**	**User accuracy (%)**			**Producer accuracy (%)**		
					Bakau Minyak	Bakau Kurap	"Others'	Bakau Minyak	Bakau Kurap	Others
Minimum distance to mean	No	-	63.64	0.4287	80	66.7	33.3	72.7	50	66.7
Maximum likelihood	No	-	68.18	0.4779	72.7	71.4	50	72.7	62.5	66.7
Maximum likelihood	Yes	3x3	68.18	0.4779	72.7	71.4	50	72.7	62.5	66.7
Maximum likelihood	Yes	5x5	68.18	0.4779	80	75	50	72.7	62.5	66.7
Maximum likelihood	Yes	11x11	77.27	0.6463	88.9	85.7	50	72.7	75	100
Maximum likelihood	Yes	21x21	81.82	0.7047	90	75	75	81.8	75	100

Table 5 - Overall accuracy, kappa statistics, user accuracy and producer accuracy for per-pixel classification techniques.

5.3 Results of Linear Mixture Model

The outputs of unmixing analyses are usually shown in proportion images for each of the surface components and root mean square images. They provide information on the relative abundances of surface components at every pixel and their distribution throughout the image. Dark colours correspond to high fractions and light colours to low fractions. The results of linear spectral unmixing for end members Bakau minyak, Bakau kurap, 'Others' and soil are shown in Figure 6.

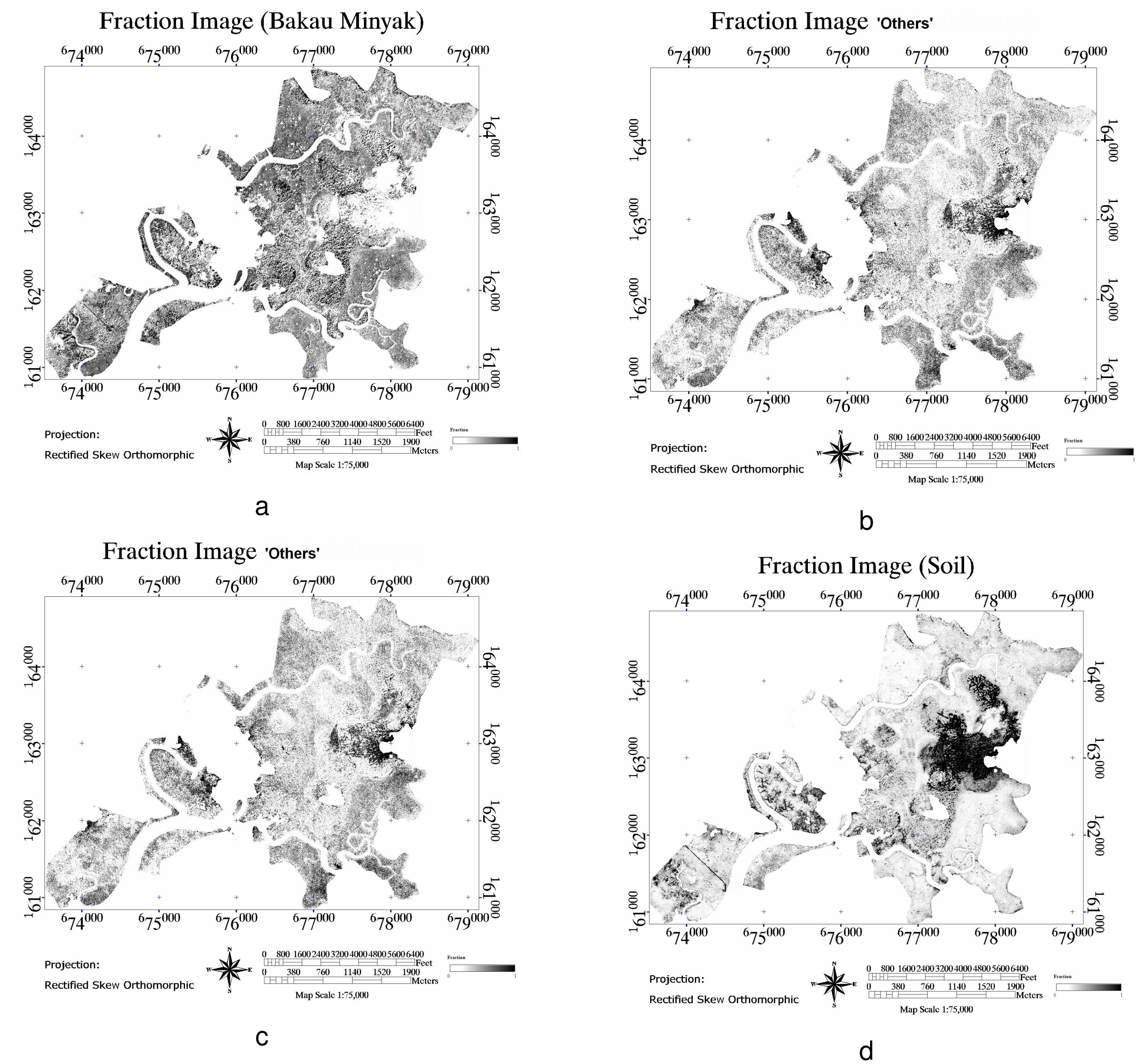


Figure 6 - Results of the unmixing analysis for end members (a) Bakau minyak, (b) Bakau kurap, (c) 'Others' and (d) soil. Fraction images are in grey scale where dark tones represent maximum fractional values and bright tones show lower fractional values.

In the Bakau minyak fraction image (Figure 6a), the species has significantly higher values indicating their widespread concentration over most of the study area. Meanwhile, soil has very small fraction values in this image and this is prominent in the middle east of the image. Fraction image of Bakau kurap (Figure 6b) reveals that high fraction values of this species occur in the centre of the study area in small patches. According to the image, the rest of the study area has close to zero fraction values for Bakau kurap. As for the 'Others' class of mangrove species (Figure 6c), high fraction values of this species occur in the middle east, along the riversides in the west and south of the study area in small patches. Another end member unmixed by the LMM method is the soil In the soil fraction image (Figure 6d), very high fraction values are found in the middle east of the study area.

The results of the unmixed end members in this study show that few pixels were misclassified. Classification error was defined using a qualitative or visual assessment technique by comparing fraction images with the classified image with the ML technique with inclusion of texture information at window size 21 x 21 (Figure 5). This image was chosen for comparison because it produced higher accuracy compared to other classification techniques. For end member Bakau kurap, misclassification occurred in the south east of the image where the fraction values are very low, whilst along the river sides, south west and west of the study area were accurately classified by the LMM. End member 'Others' was misclassified as Bakau minyak in the south and southeast of the study area and as Bakau kurap in the lower western part of the study area. Soil was misclassified as Bakau kurap, and 'Others'. Such misclassifications were also observed by Abdul Shakoor (2003) and Roberts et al (1998) even though the latter used hyper-spectral airborne data and collected more end members to unmix different types of vegetations, non photosynthetic surfaces and soil in southern California.

The accuracy of the LMM produced fraction images were assessed in two ways. First, through an error image (as illustrated in Figure 7) that was produced by comparing the best fitting spectrum generated by the inversion of the LMM to the original observed spectrum. This gives a pixel by pixel estimate for the accuracy of the inversion and the appropriateness of the chosen end members. The lower the Root Mean Square Error (RMSE), the inversion result would fit better the original observed digital numbers or reflectance values. The RMSE range for the LMM results is between 1 to 5 percent, which is very low. Highest accuracy was achieved for river side mangroves because more field data were collected from these areas. On the other hand, areas in the north and east of the study area, where no field data were obtained, showed low accuracy and this is represented by a darker tone. The inaccessibility to locations to the north of Sungai Belungkor inhibited the field survey at these locations.

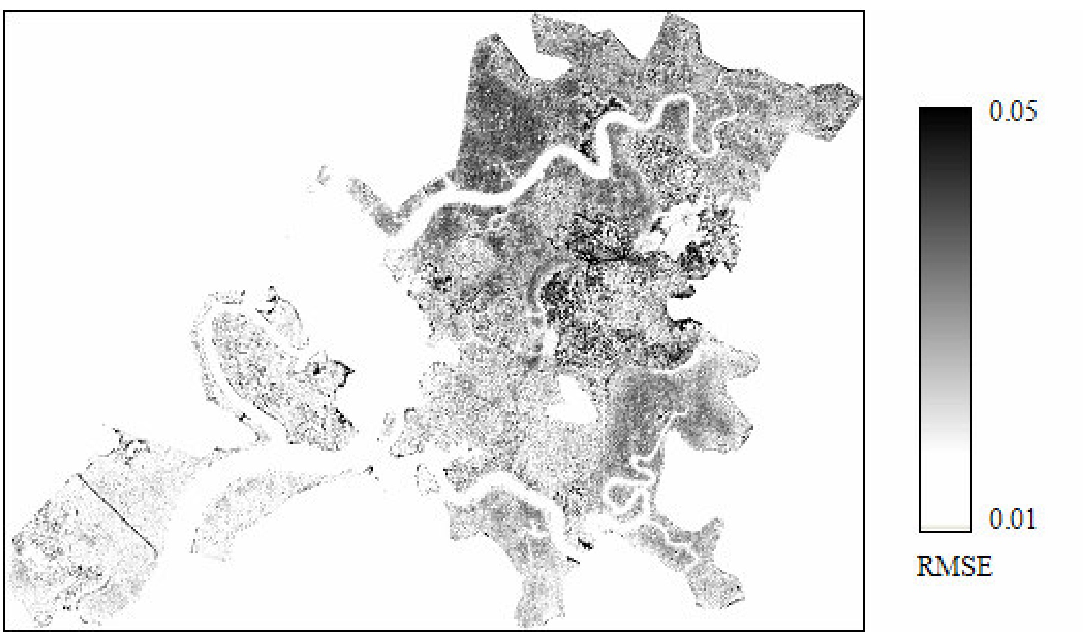


Figure 7 - Root Mean Square Error (RMSE) image for LMM.

Secondly, an accuracy assessment was carried out by matching the fraction of end members derived from the unmixing process and the fraction values for each end member measured in the field (Table 2). Among the three mangrove species, Bakau minyak yielded quite a good accuracy where the R^2 value was 0.83 (Figure 8). Meanwhile, the relationship between the fraction of Bakau kurap and 'Others' derived from the image and measured in the field yielded only a moderate accuracy with R^2 of 0.71 and 0.75 respectively. The R^2 values were further tested for statistical significance using student's t test (one- tailed) (Table 6). The t test results show that the R^2 values for each mangrove species are statistically significant at p value less than 0.001.

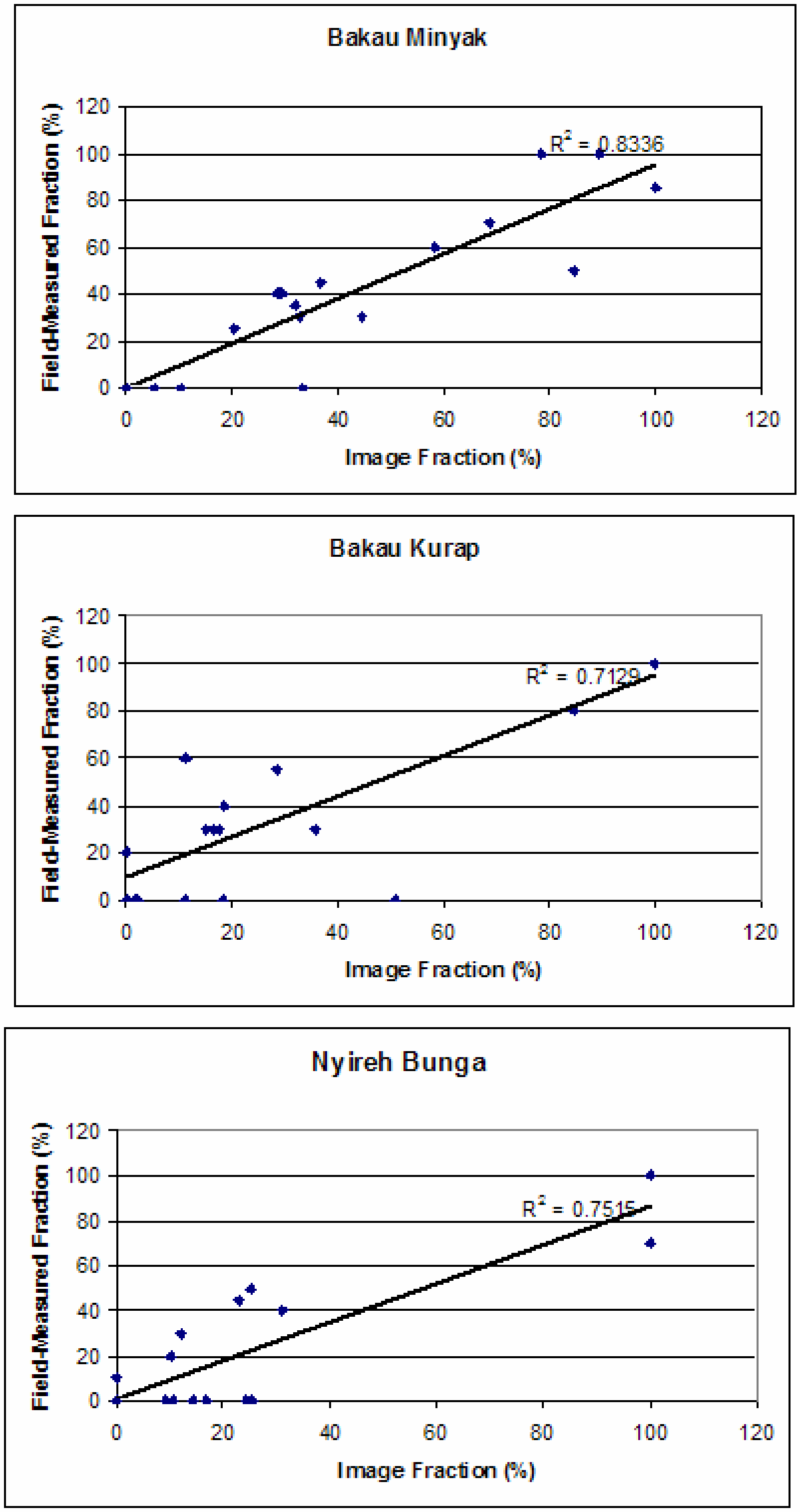


Figure 8 - The relationship between the image derived fraction and field measured fraction values for Bakau minyak, kurap and 'Others'. The strength of the relationships is represented by R^2.

	R^2 value	Correlation Coefficient, R	t value	Degree of freedom	P value
Bakau Minyak	0.834	0.913	8.055	13	0.0000
Bakau Kurap	0.713	0.844	5.680	13	0.0000
‘Others’	0.756	0.867	6.265	13	0.0000

Table 6 - Results of student’s t statistic (statistical significance test for R^2 values)

6. Conclusions

This study used high spatial resolution data to classify various mangrove species. The most robust classification technique of ML performed well in comparison to other classification techniques like MDM. However, in order to improve the accuracy, texture information from panchromatic image was added and as expected the accuracy of the classification was improved significantly. This improvement was mainly due to the second order texture features (contract, correlation and entropy) extracted from the image. Previous studies had shown that texture information from IKONOS data could not improve the classification accuracy if only the first order texture information or local variance was considered.

In addition to per pixel classification techniques, the IKONOS image was also classified using a subpixel technique to improve the classification accuracy. The LMM method produced distribution of fraction images revealing various mangrove species within 4 x 4 meter resolution in the study area. The proportion maps of forest species derived from the LMM of remotely sensed data can be utilized for forest management such as harvesting plan and ecological conservation when such images are combined with age or stand maps of forest species. In the Sungai Belungkor mangrove forest, it was found that the LMM technique can produce reliable results for Bakau minyak but only moderate results for end member Bakau kurap and ‘Others’. The reason for this could be the fewer number of input end members.

Only 3 end members were selected in this study because of the spectral limitation of the IKONOS image that could not differentiate spectrally between different species. The results of unmixing might deteriorate if some end members are missing. Furthermore, the poor accessibility to some parts of the forest also imposed a problem in obtaining more representative samples from the study area. As a conclusion, knowledge of more end-members in the region and also the use of hyper-spectral data with more spectral bands to discriminate various mangrove species and more representative samples would help enhance the results of LMM in this study.

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