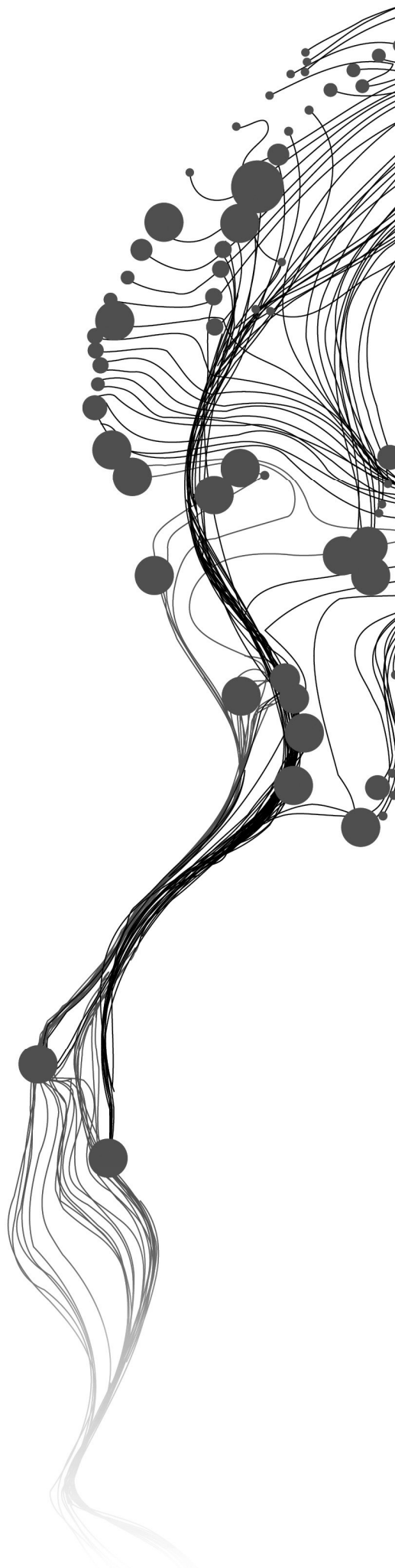


MAPPING CHLOROPHYLL CONCENTRATION IN A MANGROVE FOREST BY MODEL INVERSION APPROACH APPLIED TO HYPERSPECTRAL IMAGERY

LOISE NANCY NANGIRA WANDERA
February, 2011

SUPERVISORS:
Prof.Dr.Ing, W, Verhoef
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LOISE NANCY NANGIRA WANDERA

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SUPERVISORS:

Prof.Dr.Ing, W, Verhoef

Dr, M, Schlerf

THESIS ASSESSMENT BOARD:

Dr, Y, Hussin (Chair)

Prof. Dr. T. Udelhoven, (External Examiner, Trier University)

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ABSTRACT

The mangrove forests of the Mahakam Delta in East Kalimantan, Indonesia are being subjected to high nutrient levels due to the environmental impacts of the prevailing human activities, particularly shrimp farming. The need to create space for construction of shrimp ponds facilitates deforestation process that accelerates downstream sedimentation and eutrophication. The effluent from existing shrimp ponds have high ammonia and organic matter content that contribute to nutrient enrichment in the system. In this study we apply advanced remote sensing techniques to retrieve mangrove leaf chlorophyll and link the spatial variation to nutrient regime within the mangrove system.

A physical method of leaf chlorophyll retrieval was used. The method involved simulating canopy reflectance followed by model inversion to obtain leaf chlorophyll estimates. The Soil Leaf Canopy (SLC) model was parameterized to suite canopy characteristics of the mangrove for reflectance simulation. Model inversion using a look-up table (LUT) approach was applied to a HyMap hyperspectral image. Sensitivity of the top of canopy reflectance to variation in canopy parameters was ascertained prior to the inversion. Two inversion strategies were used based on spectral band to obtain chlorophyll estimates. Initially only bands within the VIS domain were used followed by bands ranging from VIS domain up to NIR region. Statistical relationship between the estimated and measured chlorophyll was done using RMSE and R^2 values. All available data was used for the validation regardless of species. In a second approach data was portioned based on leaf structural differences during validation. A map with leaf chlorophyll values was finally generated.

The match between simulated and measured reflectance of pixels with field sample points used in validation was good. Sensitivity analysis indicated variations in leaf chlorophyll, brown pigment, water, dry matter content and leaf mesophyll structure, LAI and fraction of brown leaves influenced reflectance at the top of canopy. Inversion using bands in the VIS regions gave better estimation of chlorophyll. Data partition based on species improved the strength of the relationship between estimated and measured chlorophyll. The chlorophyll map displayed distinct variation in leaf chlorophyll within the delta. This could be taken as an indication of nutrient enrichment in mangrove system among other factors.

Key words: SLC model, Hyperspectral image, LUT, Inversion, Chlorophyll map.

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**To my family
I am lucky to be one of you!**

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1. INTRODUCTION

1.1. Mangroves

Mangroves are forest communities found in tropical and subtropical coastal and/or estuarine tidal or intertidal zones (Macnae, 1969). The mangrove trees adapt well to freshly silted up sandy beaches and salt marshes within the sheltered intertidal flat deltaic plains, broad estuarine mouths and shallow coastlines (Thom, 1982). Effective growth and natural regeneration of mangrove trees is favoured by atmospheric temperatures ranging between 20°C and 35°C, humidity conditions between 60%-90% and annual rainfall of between 1000mm and 3000mm (Naskar & Mandel, 1999). Mangroves are intolerable to frosty conditions (Tomlinson, 1994). Hence their zones are restricted within 30° N-30° S (Macnae, 1969). The current global coverage of mangrove forest is reported to be at 15.2 million hectare, distributed over the continents Africa 20.7%, Asia 38.4%, North and Central America 14.8%, Oceania 13.0% and South America 12.9%. East Asia harbours 35% of the world total of which 59.8% is taken up by Indonesia (FAO, 2007).

Mangrove forest have been classified using different schemes that include coastal settings where they occur, physical processes taking place in their ecosystem and species. Based on coastal settings mangrove forests have been categorized into ; large deltaic systems mangroves; tidal plains mangroves; composite plains mangroves; fringing barriers with lagoons mangroves; drowned bedrock valleys mangroves and coral coasts mangroves (Thom, 1982). In terms of species, mangroves have been classified into two broad categories; true mangroves and associate mangrove. True mangroves occur exclusively within typical mangrove habitat (Tomlinson, 1994). The latest report on global mangrove taxonomy distinguishes 90 mangrove species with majority of the species falling under the class of true mangroves (Spalding et al., 2010).

Mangroves plants exhibit distinct characteristics in terms of their anatomy, morphology, physiology and succession mechanism governed by their habitat conditions (Naskar & Mandel, 1999). Their canopy usually displays a zonation pattern based on species as a result of succession along salinity gradient (Macnae, 1969). The zonation pattern implies variation in sets of environmental conditions experienced by different sections of the forest stands because of natural differences in topography. However these variations could also be as a result of proximity to anthropogenic activities taking place within. In terms of ecosystem productivity mangrove forests have been ranked highly by forming the base of food chain in sea and coastal waters (Macnae, 1969). Mangrove forests are source of fuel wood, building material, and also act as fishing grounds to the local communities. In terms of ecology, mangrove forests provide habitat, food, and breeding ground to animals while at the same time protecting the coastal ecological communities from sedimentation, strong winds, waves, and water currents.

The Mangrove forest of the Mahakam Deltas along the East coast of Kalimantan is the focus of this research. They are river dominated in terms of physical processes taking place in their ecosystem (Woodroffe, 1992). The dominant species include *Nypa fruticans* and *Rhizophora mucronata*. The mangrove area in the Mahakam Delta has been reported to have declined in coverage from 96,288 ha to 78,799 ha between the years 1982 and 1996 (Mahfud et al., 2001). The decline is as a result of creating room

development for other land uses particularly shrimp pond construction (Dahuri, 2001). Presently the situation in this mangrove forest is that the environmental impacts of the surrounding land uses are overwhelming and in turn posing a serious threat to the mangrove survival. Having a better understanding of mangrove forest current state is essential if effective management and conservation strategy have to be put into place. But in order to achieve this, appropriate bio-indicators have to be identified that can be directly linked to the mangrove condition.

1.1.1. Nutrients in mangrove systems

Nutrients availability in mangrove environment is an important factor that defines their anatomy, morphology and physiology (Reef et al., 2010). Phosphorous and Nitrogen are the key nutrients limiting mangrove growth (Lovelock & Feller, 2003; Naidoo, 2009). The Natural sources of nutrient in mangrove are sediments and water during tidal inundation and in more special circumstances during cyclone and hurricanes (Lugo & Snedaker, 1974; Naskar & Mandel, 1999). Decomposition of litter from mangrove has been found to contribute towards nutrient supply in their ecosystem (Reef et al., 2010). However, supply of nutrients from these natural sources is limited and dependent on other factors like topography and frequency of tidal inundation. The naturally low nutrient availability in mangrove ecosystems has facilitated development of nutrient conservation strategies in mangrove plants that guarantees their survival in their habitat while at the same time maintaining high productivity e.g. evergreenness, high ratio of root to shoot, nutrient resorption from leaves before being shed, propping roots (Reef et al., 2010).

The ultimate implication of increased nutrient supply to the mangrove ecosystem is that it compromises their resilience to environmental variability for instance elevated salinity levels or lower rainfall amounts (Lovelock et al., 2009; Naidoo, 2009; Reef et al., 2010). Under optimal nutrient conditions in mangrove systems, their leaves life span is higher hence less nutrients is used in regular leaf tissue formation especially for the broad leaves species and also the leaves retain more water, a key adaptation to high salinity (Komiya et al., 2008). In addition mangrove biomass partition ratio between roots and shoots is higher for roots. Roots are important for mechanical support in areas with poorly consolidated and frequently inundated soils (Komiya et al., 2000; Reef et al., 2010). the roots also aid in respiration and in nutrient absorption from frequently tidal inundated saline sea water (Naskar & Mandel, 1999; Tomlinson, 1994). Processes that alter the shoot-root biomass partition ratio are considered threatening to mangrove survival under undesirable environmental changes like drought and low atmospheric humidity (Komiya et al., 2000; Komiya et al., 2008; Lovelock et al., 2009).

Studies have been conducted to demonstrate effect of nutrient enrichment in mangrove ecosystem. In an experimental study by Naidoo (2009) the results revealed changes in resource allocation between roots and shoots of mangrove seedling upon enrichment with Nitrogen. In the works of Lovelock et al.(2009), it was established that mortality rate of mangrove trees under hypersaline conditions increased upon fertilization with Nitrogen. The same study showed that no mangrove tree mortality was experienced in areas of moderate salinities upon being subjected to fertilization with Nitrogen. A consistent finding to the two studies , Naidoo (2009) and Lovelock et al. (2009) was that introduction of Phosphorous as nutrient to the mangrove resulted in canopy loss of mangrove trees.

This is to say that, mangrove trees are sensitive to increase in nutrients in their system. In order to understand how well the mangrove trees can withstand unforeseen changes in environmental conditions, information on nutrient regime within their system is needed, most importantly Nitrogen. In a study by Lovelock & Feller, (2003), they established that mangrove fertilization using Nitrogen increased their foliar Nitrogen and photosynthetic capacity concurrently. In a different study based on remote sensing

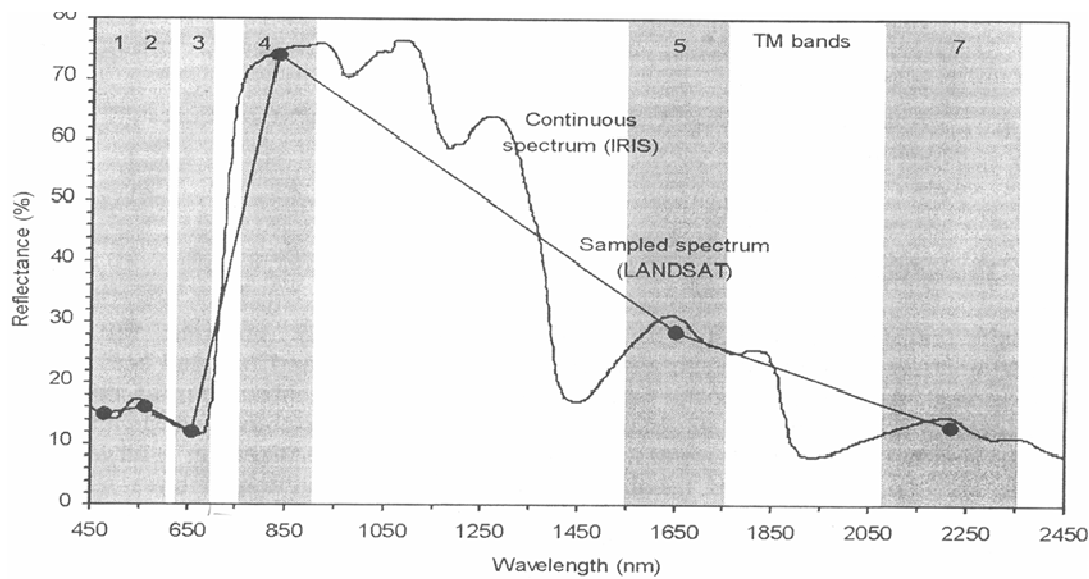
application by Mutanga et al. (2003) they demonstrated that increased fertilization by nitrogen in a grass enhanced chlorophyll absorption feature, this is a desirable in when using remote sensing application for vegetation study. In general leaf chlorophyll concentration could be used to infer on nutrient variation in mangrove systems.

1.1.2. Remote sensing of foliar biochemical

The foliar biochemical are made up of pigment and non pigment elements whose characteristics are well represented in optical image reflectance (Kokaly et al., 2009). The foliar biochemical include chlorophyll, water, leaf structure, nitrogen, cellulose and lignin (Curran, 1989). Estimates of foliar biochemical using remote sensing techniques have often been used to understand ecosystem functions (Peterson et al., 1988). This is because most biochemical processes taking place within the terrestrial ecosystems are related to foliar biochemical for instance photosynthesis, nutrient cycling and decomposition (Curran, 2001; Vitousek, 1982). Various studies have been able to link leaf reflectance to leaf biochemical content (Daughtry et al., 2000; Delegido et al., 2010; Yoder & Pettigrew-Crosby, 1995). However, the ability to link reflectance to plant biochemical within ecosystem depends on sensitivity of reflectance to variation in leaf biochemical within and across systems (Kokaly et al., 2009).

Retrieval of plant biochemical has mostly been carried as an application related to monitoring state of vegetation speculated to be experiencing stress arising from environmental conditions like pollution, drought, and diseases since the effect of environmental changes on vegetation can easily be detected from the pattern of leaf reflectance (Carter & Knapp, 2001; Lorenzen & Jensen, 1989). Among the leaf biochemical retrievable by remote sensing, Nitrogen, leaf water and chlorophyll have commonly been used to monitor vegetation conditions. Chlorophyll has already been used in precision agriculture to keep an eye on crops net primary production (Haboudane et al., 2002). Chlorophyll has also been used to establish the optimum fertilizer application rates in crop fields so as to minimize on nutrients loss through run off and sippage (Blackmer & Schaepers, 1995; Hawkins et al., 2007). This implies that chlorophyll can be indirectly used to study soil nutrient dynamics (Carter & Knapp, 2001; Curran, 2001; Zarco-Tejada et al., 2004). In the case of forest canopies and grassland, chlorophyll has often been quantified in an attempt to comprehend ecosystem properties (Ustin et al., 2004). In the climate change scenario, leaf chlorophyll has been indirectly linked to amount of carbon dioxide emitted into the atmosphere as chlorophyll forms the base where carbon dioxide is absorbed by plants and converted into useful forms (Piao et al., 2006).

Using remote sensing application in ecological study introduces the issue of appropriate image choice. For identification and quantifying size of various land cover land use types, conventional multi-spectral images could be used effectively (Curran, 2001). However, for studies that require detailed information of canopy biochemical properties for instance detecting water stress in vegetation, using finer spectral resolution images is essential. Presently Hyperspectral images have been recommended in retrieval of leaf biochemical like chlorophyll in ecosystem studies (Curran, 2001; Kokaly et al., 2009; Schut & Ketelaars, 2003). Hyperspectral images are associated with better quality data in vegetation studies because they allow characterisation of vegetation in different wavelength regions since different vegetation characteristics influence specific parts of the electromagnetic spectrum (Blackburn, 1998; Curran, 1989; Curran et al., 1992; Kokaly et al., 2009). When multispectral sensors are used instead of hyperspectral sensors to acquire data on vegetation, there is often loss of information because multispectral sensors have limited number of channels and as a result data on plant reflectance is lost due to the averaging (Kumar et al., 2001). A demonstration of differences in information intensity between hyperspectral and multispectral images in remote sensing of plant biochemical is shown in the figure 1 adopted from Kumar et al. (2001). The multispectral image is represented by LANDSAT TM bands.



Advancement in technology usually demands better methods to go with it. This has also been the case with hyperspectral remote sensing techniques which requires algorithms capable of synthesising information from the numerous numbers of bands efficiently. There has been development in empirical methods to accommodate hyperspectral data based on different multivariate approach e.g. Partial Least Square regression (PLSR) and Stepwise Multiple Linear Regression (SMLR) (Mutanga et al., 2004; Schlerf et al., 2010). Physical methods have also been used to generate information from hyperspectral images (Schlerf & Atzberger, 2006; Zarco-Tejada et al., 2004). Moreover, some studies opt to combine both empirical and physical method to retrieve vegetation characteristics from hyperspectral images (Daughtry et al., 2000; Houborg et al., 2007). However on standalone basis among the two methods, physical approach is a more robust method.

In statistical approach, a relationship is established between image reflectance and canopy properties mainly through regression equations. The regression equations are either univariate e.g. for the case of spectral indices like Normalised Difference Vegetation Index (NDVI) or the equation may be a multivariate. Multivariate equations are more advanced and they involve use of spectral information over a wider wavelength range e.g. Partial Least Square Regression (PLSR). Nevertheless, statistical models have a downside especially the spectral indices. In most cases you will find that relating the spectral indices to a specific plant parameter like chlorophyll might be biased because the information they provide is often related to multiple canopy properties. Currently narrow band indices are used aimed at limiting information obtained from image data to specific canopy properties. Examples of narrow band indices include Chlorophyll Absorption Ration Index (CARI) and Soil Adjusted Vegetation Index (SAVI). For the multivariate methods there usually exists an overfitting problem since many independent variables are used to predict a single dependent variable (Kokaly et al., 2009). But generally, when it come to statistical method a major drawback still lies in the inability to transfer the findings to other similar ecosystems (Colombo et al., 2003; Houborg et al., 2009). This is because most statistical methods are developed under ideal conditions which rarely exist in multiple places. Physical methods on the other hands are not area specific since they apply universal laws of solar energy transfer within a canopy (Liang, 2004). This implies

that findings from one research could be easily applied to a different area with similar ecosystem properties. Studies have been successful in applying physical methods to estimate plant chlorophyll e.g. Houborg et al., (2009) for a corn field, Darvishzadeh et al.,(2008) on a grassland and Daughtry et al. (2000)also on corn field. In forest canopies, there has been successful studies done using physical method e.g. Verrelst et al. (2010) Schlerf & Atzberger,(2006) and Zarco-Tejada et al.(2004). In this study we apply a physical method of forest parameter retrieval to map chlorophyll of the mangrove forest based on a hyperspectral image.

1.1.3. Canopy Modelling and Inversion

Inference of canopy characteristics using remote sensing requires information on surface reflectance. Models using bidirectional data have been developed to simulate surface reflectance (Liang, 2004).The importance of bidirectional reflectance data is that it enhances accurate retrieval of land surface information especially when coupled with robust radiative transfer models (Jones & Vaughan, 2010). The radiative transfer models factor in anisotropy of radiation field in canopies by treating radiation in canopies as sum of different components making extraction of specific land surface characteristic convenient (Liang, 2004). The radiative transfer models used range from basic ones which either do not include or they simplify higher order scattering in canopies to complex models applying sophisticated techniques (Jones & Vaughan, 2010).

Radiative transfer models are categorized into four classes based on the concept under which they operate, turbid medium models, geometrical-optical models, Monte-Carlo ray tracing and radiosity models and kernel-driven and empirical models (Jones & Vaughan, 2010). But currently there exists unclassified variety of hybrid models that integrates components of the four conceptual model classes. Applications of these models have been done on both virtual and real canopies. In virtual canopies, ray tracers are commonly used since they are theoretical and cannot be inverted to retrieve canopy parameter (Kumar et al., 2001). For the case of real canopies, radiosity models have been employed because they hold the ability of being inverted to extract real canopy characteristics (Kumar et al., 2001).

A review on canopy reflectance models compiled by Goel & Thompson (2000) give an account of canopy reflectance models being used. From the review, we find that, the canopy reflectance models vary from simple linear 1D models e.g. Scattering by Arbitrarily Inclined Leaves (SAIL) model (Verhoef 1984) to complex 3D hybrid models e.g. Discrete Anisotropic Radiative Transfer (DART) model (Gastellu-Etchegorry et al., 1996). 1D models are best suited for horizontally homogenous closed canopies and are relatively less complex to invert as compared to 3D models (Gastellu-Etchegorry, Zagolski et al. (1996). the 3D models are designed to model reflectance for complex heterogeneous discontinuous canopies (Gastellu-Etchegorry et al., 1996). Successful use of physical models in chlorophyll retrieval has been the case recently (Darvishzadeh et al., 2008; Houborg et al., 2009; Zarco-Tejada et al., 2004). In studies where physical models have been used, the model performance have been enhanced by coupling more than one model in order to maximise on the information of the canopy structure that is necessary for accurate inference of specific canopy property. An example of the so called hybrid models is the Soil Leaf Canopy (SLC) model (Verhoef & Bach, 2007). This model integrates soil background, canopy structure and leaf properties in order to retrieve specific vegetation parameter.

Retrieving canopy characteristics using reflectance models requires an inversion process since the simulated reflectance properties are a function of canopy structure (Jones & Vaughan, 2010; Kimes et al.,

2000). The aim of inversion process is to find best set of model parameters that closely describes the observed bidirectional reflectance. However according to Jacquemoud et al.(2000) the performance of model inversion process depends on; choice of model used to simulate canopy reflectance, the inversion approach applied and the calibration of reflectance upon which the inversion is applied. But still these conditions do not guarantee eliminating the problem of having multiple solution referred to as ill-posedness which is a key problem in model inversion (Combal et al., 2003). Techniques known to minimising on ill-posedness have often been in-cooperated in studies where model inversion was used. Houborg et al.(2009)combined a merit and penalty function which ensured that not only residuals were minimized between the observed and simulated reflectance values but also eliminated non-physical values. Prior knowledge of canopy structure also helps limit the solutions of the inversion process and making the inversion process more robust (Atzberger et al., 2003). In addition the prior information could be used as a better cost function in that not only is the difference between residuals is minimized but also difference in estimated and prior known input values are minimized (Combal et al., 2003).

There are various methods of model inversion. Conventionally, a numerical function was applied to the model output in order to minimise residuals between measured and simulated reflectance in a process called optimization (Bicheron & Leroy, 1999; Jacquemoud et al., 1995).A downside of this method is that it is computationally demanding and it presents a challenge to find optimum minima for the solution (Kimes et al., 2000). Look-up Table (LUT) approach (Combal et al., 2003; Houborg et al., 2009) has become a common method of model inversion due to its simplicity. A LUT is a database of simulated reflectance generated by running the model numerous times in a forward mode with predefined set of parameter covering the potential range of canopy characteristics which is later searched to find best fit for the bidirectional data stored in the image in an inversion process. An alternative to LUT approach in model inversion are machine intelligence methods which include the Artificial Neural Networks (ANN), genetic algorithms (GA) and Support Vector Machine (SVM). So far studies have been successful in applying ANN for model inversion (Atzberger et al., 2003; Schlerf & Atzberger, 2006). ANN approach requires training using numerous forward mode model runs in order to establish relationship between canopy reflectance and the canopy parameters.

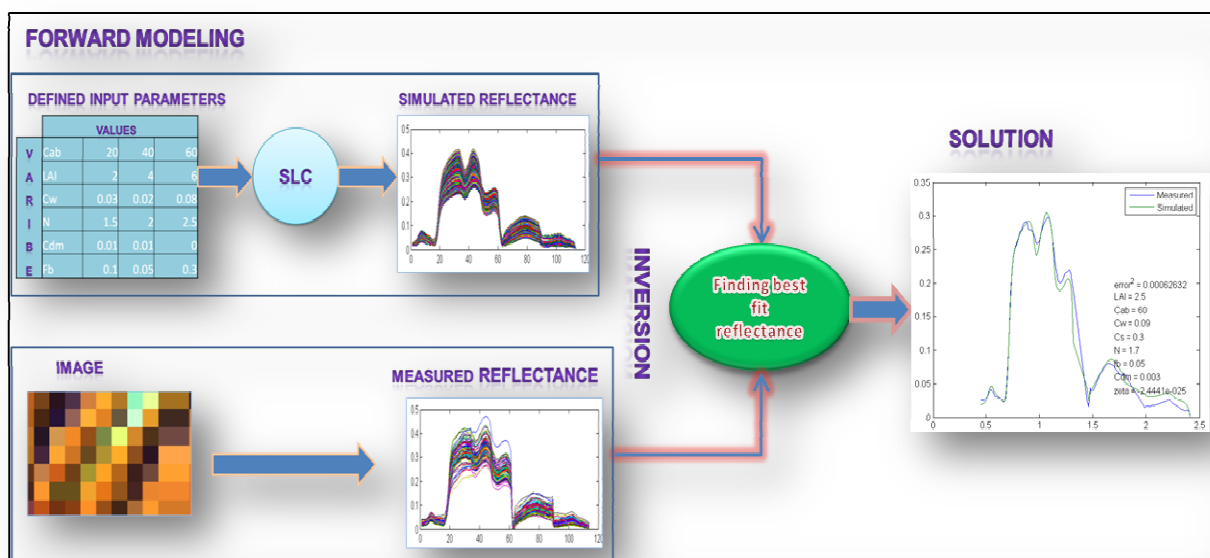


Figure 2 Process of canopy reflectance modelling and inversion

1.2. Problem Statement

Increase of human activities within mangrove ecosystem is a current global trend (FAO, 2007). In the case of the Mahakam Delta, there is increased deforestation rate as a result of creating room for development of shrimp ponds and also to supply raw material in pulp industry (Dutrieux et al., 1990). The process of deforestation in turn accelerates sedimentation and eutrophication in the mangrove surrounding by washing nutrients and soils downstream. Consequently, discharge from existing shrimp ponds load the mangrove environment with ammonia and organic matter which are a direct result of management practices associated with shrimp farming.

The motivation behind this study is that, human activity forms a big subsystem of the Mahakam Delta whose integral output tends to involve increase in nutrient as one of the bi products. Therefore it is justifiable to claim that the impact of elevated nutrient amounts in the system might have an effect on the growth and survival of the mangroves forest. This speculation of negative effect of nutrients on the mangrove trees is derived from the pre-established fact that ideal mangrove environment generally has low nutrient (Lovelock et al., 2009; Reef et al., 2010). Over the years, there have been debates about nutrient enrichment not presenting a problem to the growth of mangroves in proposals related to using mangrove ecosystem for treatment of sewage and aquaculture effluent. However in mangrove study by Lovelock et al (2009) they show that nutrient enrichment actually threatens mangrove survival . In the study the authors hypothesise that increase in nutrients leads to poor investment in their root system which is key factor in their survival and in turn they become susceptible to environmental changes for instance development of hypersaline conditions, low rainfall amounts and humidity. Vaiphasa et al. (2007) also shows that shrimp pond effluent affected growth of mangroves and increased their mortality rate in a study based in Thailand. Although from the work of Trott & Alongi (2000) their finding imply that mangrove have some capacity, at least over short spatial and temporal scales, to process intermittent inputs of pond-derived nutrients, this is arguable in the case of mangrove forest of the Mahakam Delta since they have been exposed to shrimp pond discharge for long periods of time.

In order to be able to make solid conclusions regarding the effect of nutrient enrichment on the mangrove forest of the Mahakam Delta, a reliable indicator of nutrient enrichment in an ecosystem is required. Foliar biochemical in general have often been linked to processes taking place within ecosystems using remote sensing techniques (Peterson et al., 1988). Among the leaf biochemical, leaf nitrogen and chlorophyll have been widely used leaf biochemical in ecosystem studies (Ollinger et al., 2002; Ustin et al., 2004). In this work chlorophyll is chosen to be used as an indicator of nutrient enrichment based on the fact that other similar studies were successful in using chlorophyll to understand nutrient dynamics although in different types of ecosystem (Blackmer & Schaepers, 1995; Hawkins et al., 2007; Mutanga et al., 2004). We are optimistic to establish a spatial variation trend in the mangrove leaf chlorophyll concentration that can be linked to nutrient dynamics in the mangrove system.

Mapping chlorophyll concentrations of the mangroves forest will enable provide first hand information on nutrient variation. The information is essential for developing and enforcing effective management and conservation measures aimed at safeguarding the resilience of the mangrove to unforeseen changes in environmental conditions since elevated nutrients quantities in mangrove systems only becomes a problem when the mangrove are exposed to extreme environmental conditions as a result of compromised survival mechanism. Also the findings from this study are expected to contribute towards bridging the information gap that exist based on available literature on methods of monitoring state of mangrove ecosystem. In addition, the method used in mapping chlorophyll in this study is transferable to other similar mangrove ecosystems making monitoring of mangrove a cost effective process.

1.3. Objectives

The main objective of this study is to apply advanced remote sensing techniques, in terms of image attributes (hyperspectral) and method (physical) to map chlorophyll concentration in the mangrove forest to provide an inference on nutrient regime within the system.

1.3.1. Specific objectives

- To simulate mangrove canopy reflectance and perform model inversion by LUT approach in order to retrieve chlorophyll concentration estimates at leaf level.
- To assess the accuracy of the inversion process by correlating estimated chlorophyll against field measurements.
- To generate a map of chlorophyll concentration for the mangrove forest and use the information to understand spatial variation of nutrients

1.3.2. Research questions

- Are the simulated and measured reflectances comparable enough to give realistic chlorophyll values?
- Which mangrove canopy parameters influence the reflectance at the top of canopy that need to be varied during LUT generation process?
- What is the statistical relationship between the measured and estimated chlorophyll values?
- Can we link the chlorophyll distribution trend displayed on the map to nutrient regime within the system

1.3.3. Hypothesis

- The input parameters specification in the SLC model will help minimize mismatch between simulated and measured reflectance hence estimated values will be reliable
- Cab, Cdm, Cs, N, LAI, and fB have significant influence on the visible part of TOC reflectance and need to be varied during LUT process
- The predicted chlorophyll will have a significant correlation with the field measurements
- Chlorophyll will vary with proximity to shrimp ponds and areas prone to frequent tidal inundation.

2. MATERIALS AND METHODS

2.1. Study area

The mangrove forests under study occur in a river delta called the Mahakam located on (latitude 117°28''E and longitude 0°29'S). The Mahakam Delta is an active delta system whose general morphology can be divided into three systems: the delta plain, the delta front, and the prodelta. The environmental conditions within the Mahakam Delta are mostly tropical humid, tidal action are high with low wave-energy with large fluvial input. The delta covers an area of about 1800 km². The mangrove forest occurs within the delta plain. The delta plain is located in an intertidal zone with water level variation of about 2.5m. The topography of the delta plain is flat with about 0.1% slope. The delta plain has a network of two channel types; distributaries channels linked to River Mahakam and tidal channels for water evacuation during high tide. *Nypa fruticans* and *Rhizophora mucronata* are the dominant mangrove species whose distribution is distinct. *Rhizophora mucronata* is found near the shore of the delta plain while *Nypa fruticans* is found in the central areas of the delta plain. Other than mangrove forest, there is also lowland forest within the delta. Recent fishery development in this area has converted a vast area of mangrove forest into shrimp ponds (tambak).

The delta also supports a number of human activities e.g. salt production, coal mining, fishing and aquaculture. However, the natural structure of the Mahakam Delta has greatly been altered to accommodate human activities. A great portion of the mangrove habitat has been converted into human settlements areas and agricultural developments. There has been interference with the hydrological regime to suite human activities and also pollution has been the case from oil spills and industrial waste.

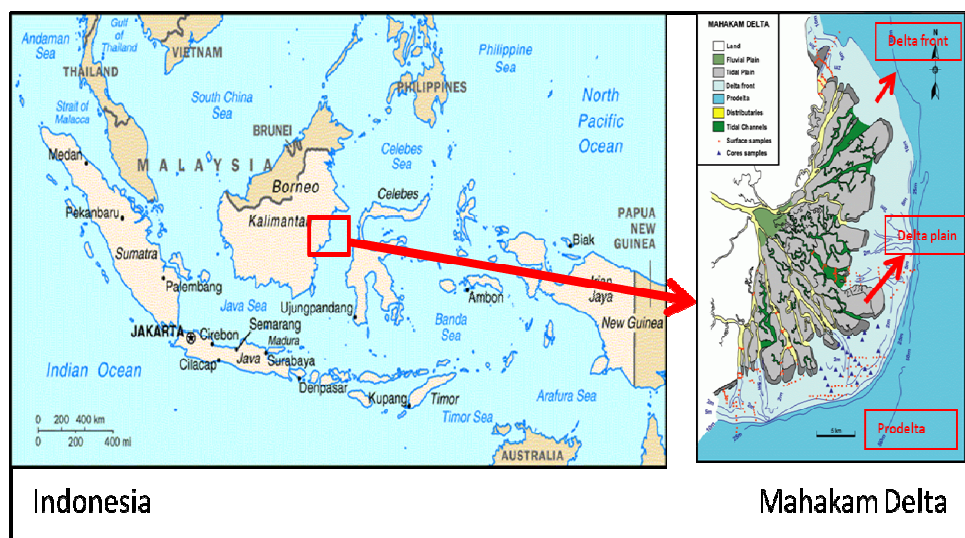


Figure 3 Study area

2.2. Image data

An airborne Hymap image was used in this study provided by HyVista Cooperation, Sydney, Australia. The image was acquired on the 16th of August 2009 between 0623 and 0705hours (UTC) from a Hymap campaign as a prerequisite of an ongoing project. The sensor was mounted on a plane flown at an altitude of 1.45km at nadir over the study area in eight flight lines in the W-E direction. The full scene was covering an area of about 11km by 11km. However, there were cloudy conditions and hence parts of the scene were covered with clouds. The data had a ground resolution of 3.1m and was captured using 126 channels of the Hymap sensor with an average spectral resolution of 10 nm between the 450nm and 2500nm wavelength.

2.2.1. Image processing and pre-processing

Image processing was carried out by the provider, HyVista Cooperation, which included image geocoding, atmospheric correction and radiometric calibration. The geocoding was done using 48 ground control points obtained from the study area along roads, bridges and ponds followed by the radiometric and atmospheric correction using Hycorr programme. First the radiances in the image were converted to apparent surface reflectance then atmospheric correction was based on ATREM3 processing whose specifications are listed in Table 5.

Image pre-processing included testing accuracy of the geocoding and radiometric correction carried out as shown on Appendix 1. The results were acceptable. This was followed by image mosaic since the full scene had been acquired in eight flight lines. During mosaicking, image data from 12 Hymap channels were eliminated because they considered being noisy leaving with bad bands leaving 114 bands of the image dataset to be used in the analysis. As mentioned earlier, the image was acquired when there were moments of cloudy conditions and a few areas in the image suffered cloud patches. The areas with clouds and cloud shadows in the image were removed by manually digitizing over the regions and masking them out. ENVI 4.5 image software was mainly used in the image pre-processing.

MODULE	SPECTRAL RANGE (um)	BANDWIDTH ACROSS CHANNELS (nm)	CHANNELS	AVERAGE SPECTRAL INTERVAL (nm)
VIS	0.42-0.88	15-16	32	16
NIR	0.881-1.335	12-14	42	13
SWIR	1.40-1.81	11-13	13	12
SWIR	1.95-2.49	15-18	18	16

Courtesy of the Hyvista Cooperation products

Table 1 Hymap hyperspectral instrument specifications

2.3. Ground data

The idea for field data collection was to obtain measurement of mangrove leaf chlorophyll concentration that was required for validation of the model estimates of chlorophyll concentration. But also prior knowledge of the general mangrove canopy structure was necessary in the SLC model parametrization process

2.3.1. Chlorophyll measurements

The ground data was collected between August 2009 and August 2010. Sampling strategy was random representative sampling limited to accessible areas which were identified from the image because mangrove forests are highly inaccessible (Green et al., 1998). In the field, predefined sampling points were located with the assistance of a Global Positioning System (GPS) which was linked to a mini computer (IPAQ) that allowed reading the image interactively and recording data on the same IPAQ. Sampling was conducted from river banks towards inland. A 350m transect was used constituting 7 sample points in between. For each sample point, a tree of the dominant species was randomly identified. Relative total Chlorophyll of the leaves was measured without destruction using a SPAD -502 Leaf Chlorophyll Meter (Minolta, Inc). SPAD gives relative unitless values which are highly correlated with chlorophyll concentration (Haboudane et al., 2002). Branches were cut off the upper part of the tree crown. From the branches, leaves were collected upon which 10 individual SPAD readings were taken and the average calculated was used. The SPAD values ranged between 30 and 75.

Appropriate calibration equations were applied on the SPAD values to obtain values of chlorophyll concentration. An equation by Markwell et al. (1995) was used in the case of *Nypa fruticans* given by, $\text{Chl}(\mu\text{mol m}^{-2}) = (M^{0.264})$ where Chl is chlorophyll concentration and M is the SPAD value. The equation was seen appropriate for the species because the relationship between M and chlorophyll concentration was developed using *Zea mays* (corn) as one of the species. This is relevant because leaf structure has been found to play a major role when establishing relationship between SPAD values and chlorophyll concentration therefore *Nypa fruticans* and *Zea mays* both being monocots was the theoretical rationale for using the equation due to some similarity in leaf structure. The *Nypa fruticans* chlorophyll concentration values obtained from the equation were converted from molarity per square meter to grams per square centimetre. In the case of *Rhizophora mucronata*, an equation by Richardson et al. (2002) was used. The relationship between leaf chlorophyll concentration and SPAD values found in the equation was established based on the species *Betula papyrifera* (paper birch) given by; $\text{Chl}(\text{mg cm}^{-2}) = 5.52 \cdot 10^{-4} + 4.04 \cdot 10^{-4} M + 1.25 \cdot 10^{-5} M^2$. The rationale for using the equation was based on close similarity of leaf structure for the two species, *Rhizophora mucronata* and *Betula papyrifera* in addition to both species being forest trees. However the rationale for using the two equations was not substantiated in depth.

Species	Measured variable	Min	Mean	Max	Stdev	Var_coeff
Nypa n=35	SPAD(unitless)	44.4	52.3	59.4	4.1	0.08
	Cab($\mu\text{g}/\text{cm}^2$)	48.6	64.5	80.4	8.7	0.13
Rhizophora & others n=46	SPAD(unitless)	34.9	54.7	69.2	7.6	0.14
	Cab($\mu\text{g}/\text{cm}^2$)	29.9	60.8	88.3	13.2	0.22

Table 2 Statistics on measured chlorophyll concentration based on mangrove leaves SPAD values

2.3.2. LAI measurements

Leaf Area Index (LAI), defined here as total one sided leaf area per unit ground area, was measured using LAI-2000 Plant Canopy analyser (LI-COR, 1992). Two methods of LAI measurements were applied; initially a one sensor mode was used. However, the method was challenging since LAI computation requires above canopy and below canopy measurements. Obtaining pseudo above canopy measurement with the LAI 2000 needed open spaces within the canopy which proved to be quite hard to find. A two sensor mode method was an alternative where one of the LAI-2000 devices was left in an open space outside the canopy to continuously take above canopy measurements in a remote mode. An assumption that both devices were observing the same sky conditions had to be adapted which was practical since they were only 350m maximum distance away from each other. Latter the output from both devices were synchronised to compute an LAI measurement for each sample point. However taking LAI measurements was subject to prevailing sky conditions. The LAI ranged between 1 and 5.

2.3.3. Ancillary ground data

Observations relevant for the model parametization were also made in the field. Percentage canopy cover was estimated at all sample points in addition to tree crown height and crown diameter. Tree height of dominant species identified was measured. Images of the trees were taken to establish their leaf angle distribution function. Canopy background observations related to soil and brown materials were also made.



Figure 4 Leaves of dominant mangrove species found in the study area

2.4. The model

This study uses the Soil Leaf Canopy (SLC) model, Verhoef & Bach (2007). The SLC is an integration of three reflectance sub models, for soil, for leaves and the canopy with parameter shown on Table 3.

4SOIL(SOIL)	PROSPECT (Green leaf)	PROSPECT (Brown leaf)	4SAIL2(CANOPY)	External (Geometry)
BRDF(B0,c,h)	Chlorophyll (Cab_g)	Chlorophyll (Cab_b)	Leaf Area Index (LAI)	Solar Zenith angle(sza)
All Reflectance (b,SM)	Water (Cw_g)	Water (Cw_b)	Leaf inclination distribution function (LIDF)	Viewing Zenith angle(vza)
	Dry matter (Cdm_g)	Dry matter (Cdm_b)	Hot spot(hot)	Azimuth angle(azi)
	Senescence(Cs_g)	Senescence(Cs_b)	Fraction brown leaves(fB)	
	Structure(N_g)	Structure(N_b)	Canopy dissociation factor(Diss)	
			Crown clumping(Cv)	
			Crown diameter to height(zeta)	

Table 3 The SLC input parameters

The model functions in the spectral region between 400 -2500nm at 1nm resolution. The Soil sub model called 4SOIL is a bi-directional reflectance (BRDF) model modified from the earliest version of Hapke (1981). It includes the soil moisture effect. However in this study we assume a lambertian soil background upon which only soil moisture effect has been applied due to the soil characteristics of mangrove forest. A reference mangrove soil spectrum background is shown in figure 5. The reflectance patterns were consistent with differences in soil moisture content.

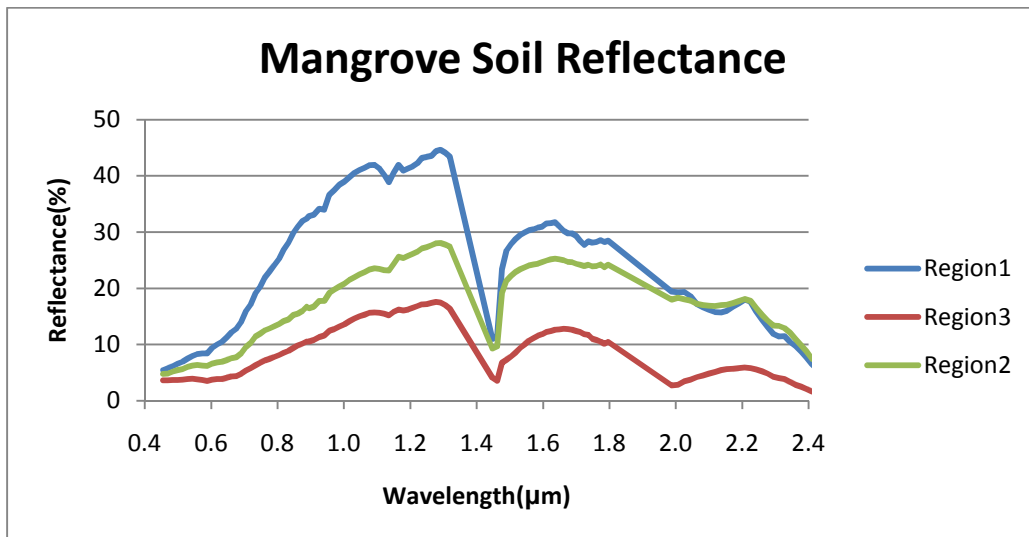


Figure 5 Mangrove soil background reflectance extracted from different regions in the image

For the Leaf model, a modified version of PROSPECT by Jacquemoud & Baret (1990) is applied. It factors the brown pigment in leaves as one of the parameters in-cooperated. 4SAIL2 model Verhoef & Bach (2007) is used to simulate the canopy reflectance. This is a hybrid canopy reflectance model with two layers for different leaf colour, green and brown. The different layers allows combining of green and brown material within a canopy through defining fraction of brown element (fB) and specifying the dissociation factor (Diss) which indicates the manner in which green leaves and brown material have been vertically distributed within the canopy. In a situation where Diss tends towards 1, it implies majority of green material within the canopy is at the top layer. The 4SAIL2 model in-corporate crown clumping effect which is very important for modelling the reflectance of a discontinuous canopy (Gastellu-Etchegorry et al., 1996). Moreover, Leaf Inclination Distribution Function (LIDF) and hot spot parameter are also included in the canopy model.

In order to predetermine how well the SLC model could simulate mangrove canopy to match the measured reflectance, a test was carried out based on three mangrove species *Rhizophora mucronata*, *Bruguiera gymnorhiza* and *Nypa fruticanas*. This was achieved by:

1. Identifying homogenous areas in the image with species of interest, *Rhizophora mucronata*, *Bruguiera gymnorhiza* and *Nypa fruticanas*.
2. Delineating region of interest within the respective homogenous areas made up of 5 pixels upon which average reflectance were extracted.
3. The three extracted reflectance were independently input into the SLC model to act as the reference spectrum.
4. Manual adjustment of SLC parameters were done independently to simulate the three extracted reflectance.
5. The values of the simulated reflectance obtained for the three different species were plotted against the respective measured reflectance for comparison.

The process of predetermining capability of the SLC model to simulate mangrove canopy also played an important role in establishing the potential range for some of the mangrove canopy parameter which are required as input in the SLC model but had not been measured in the field. The parameters included leaf mesophyll structure, leaf water content, brown pigment in leaves and the leaf dry matter content.

2.4.1. Sensitivity analysis

The response of the Top of Canopy (TOC) reflectance to variation in mangrove canopy parameter was carried out prior to canopy modelling and inversion. The input reflectance for the sensitivity analysis were the three extracted reflectance (r) that had been used to test performance of the SLC model in simulating the mangrove canopy with reference to three species *Rhizophora mucronata*, *Bruguiera gymnorhiza* and *Nypa fruticanas*. The input parameters used in the sensitivity analysis included, Cab, Cdm, Cs, N, LAI, Cv and fB. The sensitivity analysis was expressed in the Jacobian Matrix (**J**). This is a matrix of partial derivatives of the model's relative reflectance (r_{rel}) upon change of input parameter by 1% of their maximum potential range and is a function of change in reflectance for wavelength $1 < \lambda < n$ for the input parameter $1 < p < m$.

$$where = \begin{pmatrix} \frac{\Delta r_{\lambda_1}}{\Delta p_1} & \frac{\Delta r_{\lambda_1}}{\Delta p_2} & \frac{\Delta r_{\lambda_1}}{\Delta p_m} & \dots \\ \frac{\Delta r_{\lambda_2}}{\Delta p_1} & \frac{\Delta r_{\lambda_2}}{\Delta p_2} & \dots & \\ \vdots & \vdots & \dots & \end{pmatrix}$$

$$J = [j_{ik}]_{1 \leq i \leq n, 1 \leq k \leq m}, \text{ with } j_{ik} = \Delta r(\lambda_i) / \Delta p_k$$

Input parameters(p)	Min value	Max value	Range	1% of range
Cab	20	80	60	0.6
Cw	0.01	0.2	0.19	0.002
Cdm	0.001	0.03	0.029	0.0003
Cs	0.1	0.5	0.4	0.004
N	1.5	2.5	1	0.01
LAI	1.5	5	3.5	0.035
Cv	70	90	20	0.2
fB	0.01	0.4	0.39	0.004

Table 4 1% parameter change used in the sensitivity analysis

2.4.2. Forward modelling of mangrove canopy

A combination of inputs variables shown in Table 5 were used to generate mangrove canopy simulated reflectance. In the PROSPECT model the green leaf parameters range were derived from the solution of the reference spectrum that were used to test the performance of the SLC model to simulate mangrove canopy apart from Cab_g which was derived from fields measurements range. Since there was a possibility of having more than one solution that would have matched the same reference spectra; the parameters were varied within the neighbourhood of the chosen solutions. For the brown leaf, values of 10, 0.5, 15 and 10 were used for Cab_b, Cw_b, Cdm_b, Cs_b and N_b respectively. In the 4SAIL2 model, LAI was varied between values of 1 and 5 based on field measurements. From field observations, the Cv was generally high, hence a fixed value of 80% was used. Fb value were assigned low values due to high Cv as

suggested in the work Verrelst et al. (2010). The hot spot parameter was fixed at a value of 0.05. For the soil model, a background soil spectrum was obtained from the image upon which only soil moisture effect was applied at an average value of 25%.

Parameters	Units	Symbol	Min	Max	Steps	Fixed
Canopy parameters						
Leaf area index	m ² m ⁻²	LAI	1.5	5	5	
Leaf distribution function	Degree	LIDF				Spherical
Hot spot	m m ⁻¹	hot				0.05
Fraction of brown leaves		Fb	0.03	0.05	2	
Vertical distribution of brown and green leaves	%	Diss				80
Clumping parameter	%	Cv				80
crown diameter to height		zeta	0.3	0.8	3	
Leaf Parameters						
Chlorophyll a+b content	µg/cm ²	Cab	20	80	7	
Leaf water thickness	g/cm ⁻²	Cdm	0.05	0.09	3	
Leaf dry matter	g/cm ⁻²	Cw	0.005	0.009	3	
Leaf brown pigment		Cs	0.3	0.5	2	
Leaf mesophyll structure		N	1.4	2.2	3	
Soil						
Soil moisture	%	H_SM				25
External/atmospheric parameters						
Aerosol model						Continental
Atmospheric model						Tropical
Total ozone	cm-atm					0.34
Visibility	km					50
Sun Zenith angle	Degree	tts				42
Relative azimuth angle	Degree	psi				157
View zenith angle	Degree	tto				0

Table 5 Set of input parameter used in LUT generation

The SLC model generated a total of 11,341 elements based on varying 8 parameters each with the values 5*2*3*7*3*3*2*2 respectively as shown in Table 5. The elements generated were stored in a LUT which was later used for the inversion process. The variation in the input parameters used in the forward modelling factored in structural differences of the mangrove tree species found within the study area; hence the LUT generated was seen fit for the inversion regardless of the species.

The best match between the measured reflectance (R_{meas}) and simulated reflectance ($rLUT$) used to provide the solution for the chlorophyll concentration estimates was picked based on cost function Weighted Root Mean Square relative Error ($WRMSE_{rel}$) with the least distance between $rLUT$ and R_{meas} . Relative error was used to give more weight to visible part which has low reflectance as compared to the NIR. Error was calculated by

$$WRMSE_{rel} = \sqrt{\sum \left(\frac{rLUT - R_{meas}}{rLUT} \right)^2 * \omega}$$

Two approaches were used to search for the best fit between simulated and measured reflectance based on weight function (ω) assigned to spectral bands. In the first approach, chlorophyll concentration estimation was based on assigning weight value of 1 to the visible part of the spectra, band 1-33, with the rest of spectra having 0 weights. In the second approach, the weight value of 1 was assigned up to the NIR part of the spectra, bands 1-61.

2.4.3. Validation

The PROSPECT model which is used to retrieve chlorophyll concentration estimates in this study has been validated a number of times although the studies were not based on canopy structure similar to mangrove forest. Validation of the chlorophyll concentration estimates retrieved in this study was done against field measurements based on SPAD readings. Accuracy of predications was based on coefficient of determination (r^2), root mean square error (rmse) and distribution around the 1:1 line.

2.4.4. Chlorophyll map generation

To come up with the chlorophyll map, forested regions within the study area were initially delineated. The LUT generated was then applied to the pixels within the forested areas. Best fit between LUT reflectance and image reflectance used to develop the map was based on minimum $WRMSE_{rel}$. Upon completion mapped regions were overlay over the image of entire study area.

3. RESULTS

3.1. Image reflectance simulation

The selected measured reflectance obtained from the Hymap image within homogenous pixels of the respective species displayed on fig 6, showed differences in their spectral characteristics. In the visible domain, *Bruguiera gymnorrhiza* and *Rhizophora mucronata* had almost similar values as opposed to *Nypa fruticandas* which has distinct different values. This region is associated with chlorophyll content with higher values representing low chlorophyll concentration. Another significant difference was in the 0.65-0.8 μm interval. This spectrum region shows variations in brown pigment in the leaves. *Bruguiera gymnorrhiza* reflectance indicated lower brown leaf pigment. The near infrared (NIR) generally indicated differences in the leaf structure of the three species. There was variation in leaf water content observed in the 1.45 and 1.9 μm wavelength. *Nypa fruticandas* and *Bruguiera gymnorrhiza* had almost similar water content. Upon manual adjustment of the variables in the SLC model to match the spectra, a good fit was obtained for all the three representative reflectance as shown in figure 7, 8 and 9. Mismatch was observed in the SWIR region for all the three species.

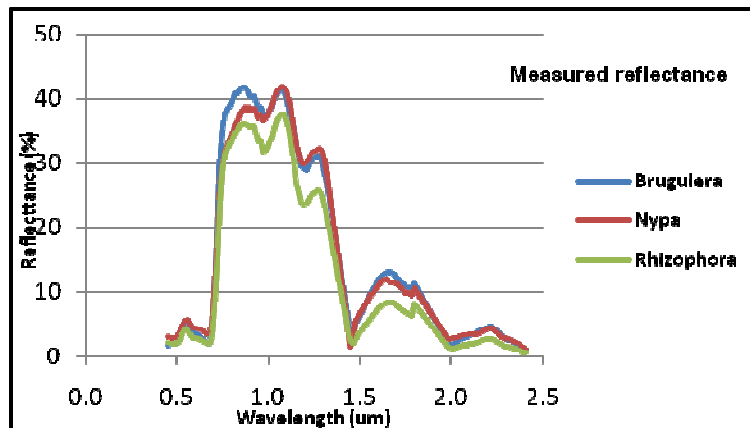


Figure 6 A display of measured reflectance for the 3 different mangrove species

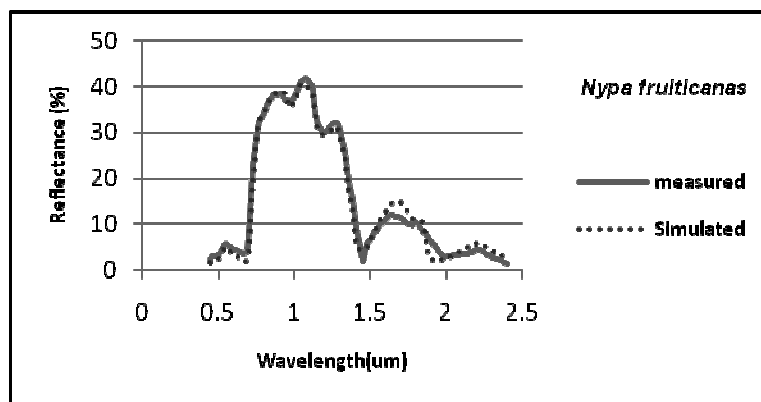


Figure 7 Comparison between measured and simulated reflectance for the species *Nypa fruticandas*

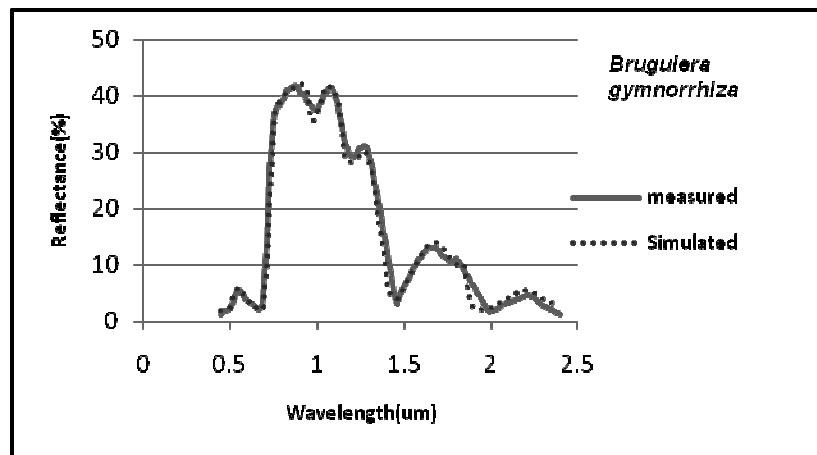


Figure 8 Comparison between measured and simulated reflectance for the species *Bruguiera gymnorhiza*

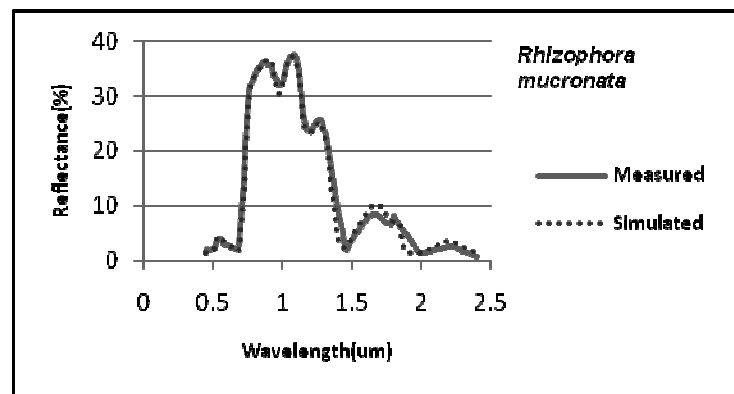


Figure 9 Comparison between measured and simulated reflectance for the species *Rhizophora mucronata*

3.2. Sensitivity analysis

The results from the sensitivity analysis were consistent with published literature on influence of different vegetation parameter on specific region of the TOC reflectance (Botha et al., 2007; Houborg et al., 2007; Jacquemoud et al., 1996; Verrelst et al., 2010). The analysis helped in identifying parameters which had greater influence at the TOC that was essential to include in the LUT. All parameters tested showed that their influence to the TOC reflectance was significant that required consideration during model parametrization.

The sensitivity results also showed that some mangrove leaf optical properties could be used to differentiate species for instance sensitivity to dry matter (C_{dm}), leaf water thickness (C_w), fraction of brown leaves (f_B) and mesophyll structure (N). The results on the mentioned parameters were distinctively different among the three species as shown in figure 11, 13, 14 and 16.

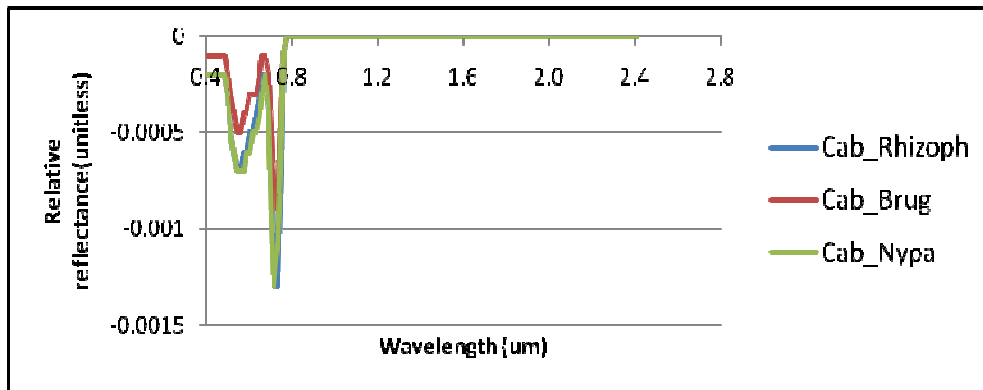


Figure 10 Sensitivity of mangrove canopy to variation in chlorophyll in 3 different species

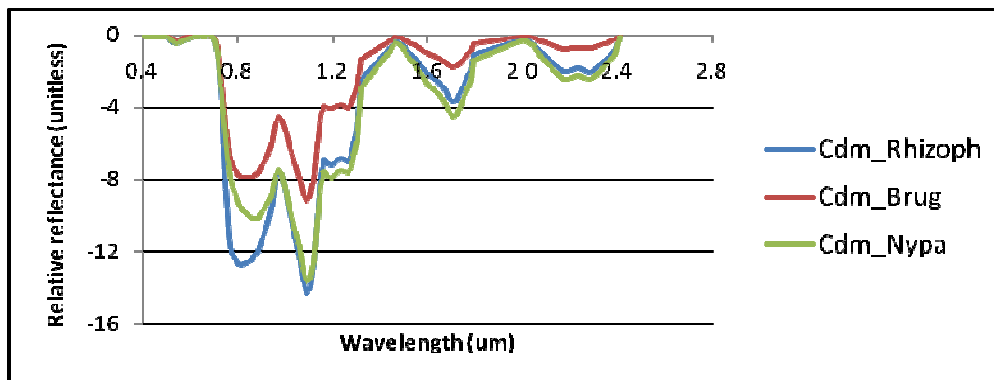


Figure 11 Sensitivity of mangrove canopy to variation in dry matter content in 3 different species

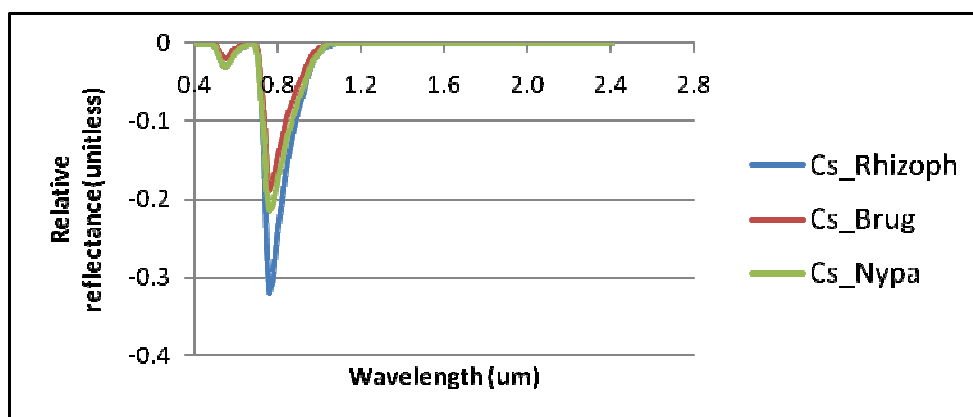


Figure 12 Sensitivity of mangrove canopy to variation in leaf brown pigment in 3 different species

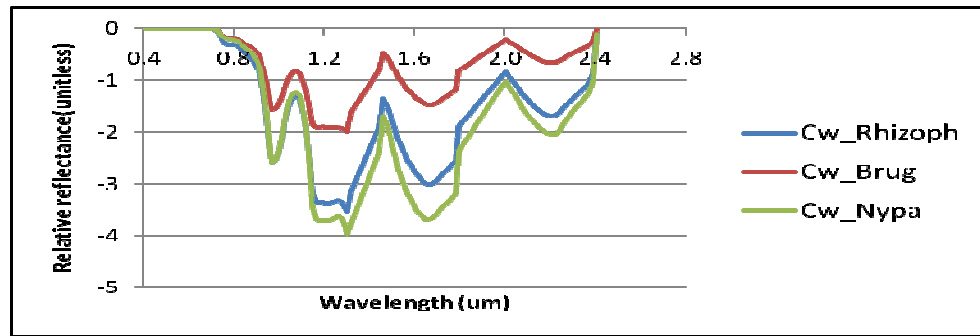


Figure 13 Sensitivity of mangrove canopy to variation in leaf water in 3 different species

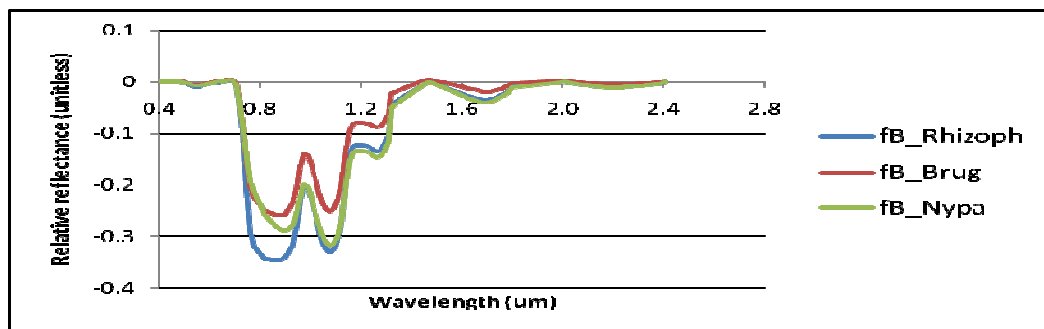


Figure 14 Sensitivity of mangrove canopy to variation in fraction of brown leaves in 3 different species

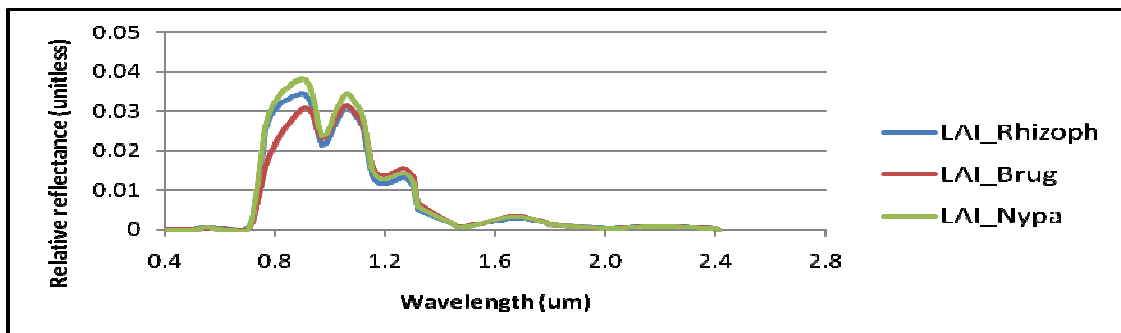


Figure 15 Sensitivity of mangrove canopy to variation in LAI in 3 different species

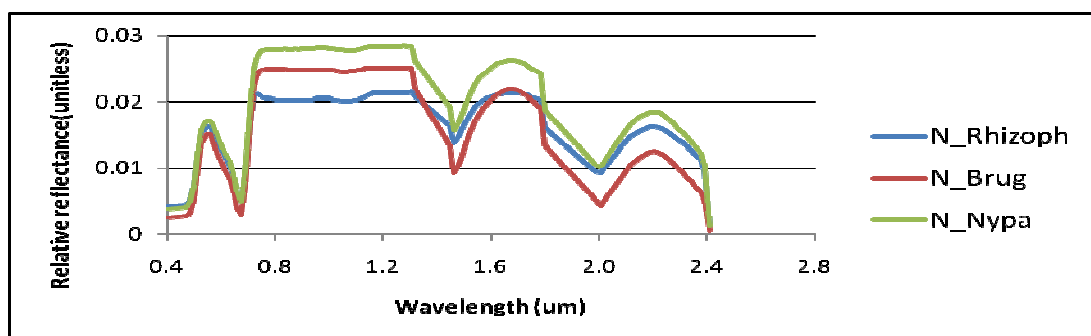


Figure 16 Sensitivity of mangrove canopy to variation in leaf mesophyll structure in 3 different species

3.3. Validation of model estimates for leaf chlorophyll concentration

Various ways of determining model performance were tried out based on species leaf structural difference. In the first method both VIS and from VIS up to the NIR region were independently used in the inversion process with data set comprised of all the species regardless of leaf structural differences. The results obtained when estimated and measured chlorophyll were compared had an rmse was $14.3\mu\text{g}/\text{cm}^2$ and $14.8\mu\text{g}/\text{cm}^2$ as shown in figure 7 and 8. In the second method where also the two spectrum regions were independently used but this time the data partitioned into two sets based on leaf structural difference with one data set containing the species *Nypa fruticanas* while the second data set was made up of *Rhizophora mucronata* and other minor species with similar leaf structure, the rmse was 14.4 and $15\mu\text{g}/\text{cm}^2$ shown in figure 9 and 10.

Determining the relationship between the estimated and measured chlorophyll based on coefficient of determination (r^2) showed differences in the result especially when the data was stratified based on species leaf structural differences displayed in figures 7, 8, 9 and 10. All the data set showed a good distribution around the 1:1 line.

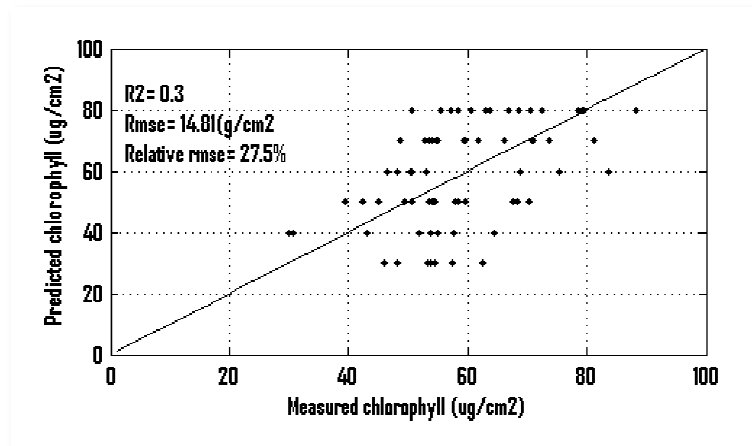


Figure 17 Correlation between estimated and measured chlorophyll when VIS up to NIR part of the spectrum was used for all the species.

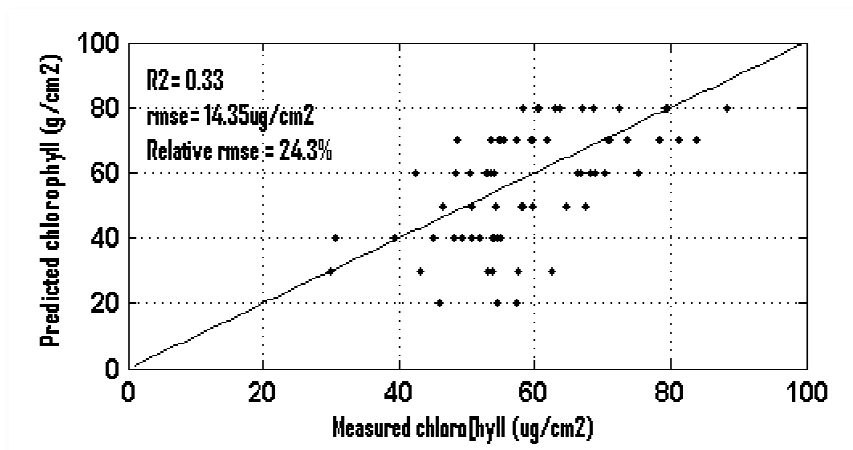


Figure 18 Correlation between estimated and measured chlorophyll when only VIS part of the spectrum was used for all the species

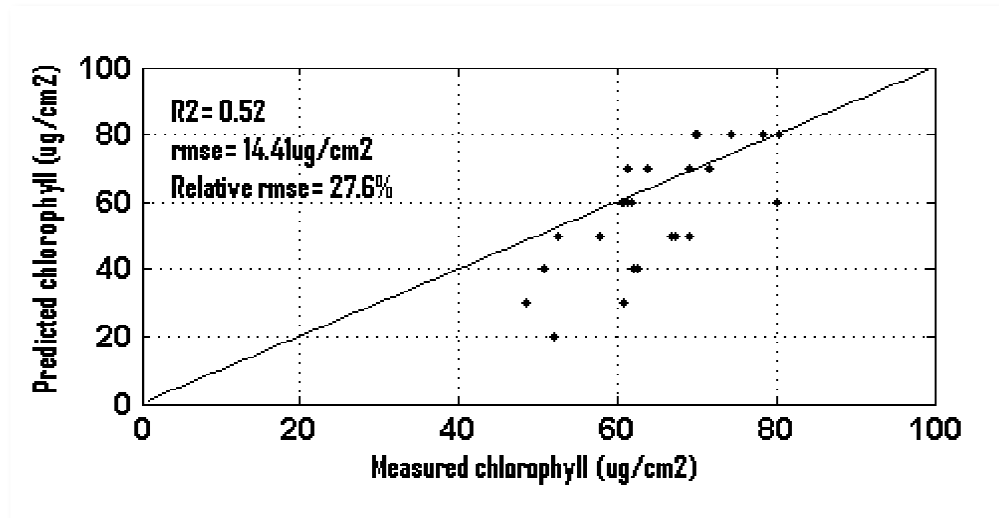


Figure 19 Correlation between estimated and measured chlorophyll when only VIS part of the spectrum was used for the species *Nypa fruticans*

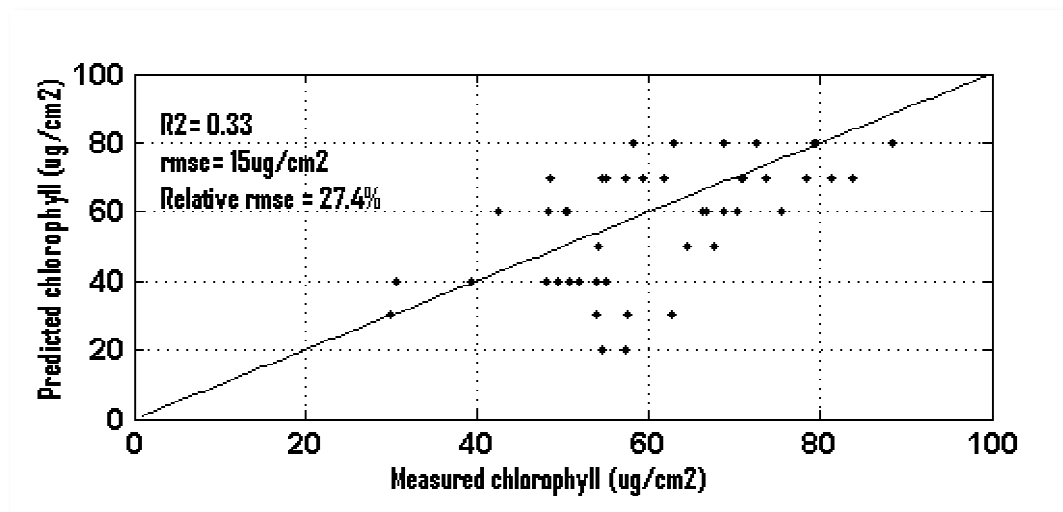


Figure 20 Correlation between estimated and measured chlorophyll when only VIS part of the spectrum was used for the species *Rhizophora mucronata*

3.4. Spatial variation in leaf chlorophyll concentration

The result from mapping leaf chlorophyll concentration within the forested regions of the study area displayed variations. The south-west and central-west region had relatively lower values ranging between 20 and 50 $\mu\text{g}/\text{cm}^2$. The north-east part region had generally high values ranging between 60 and 80 $\mu\text{g}/\text{cm}^2$. The differences could imply a variation in sets of environmental processes they are exposed to and that included differences in nutrient levels.

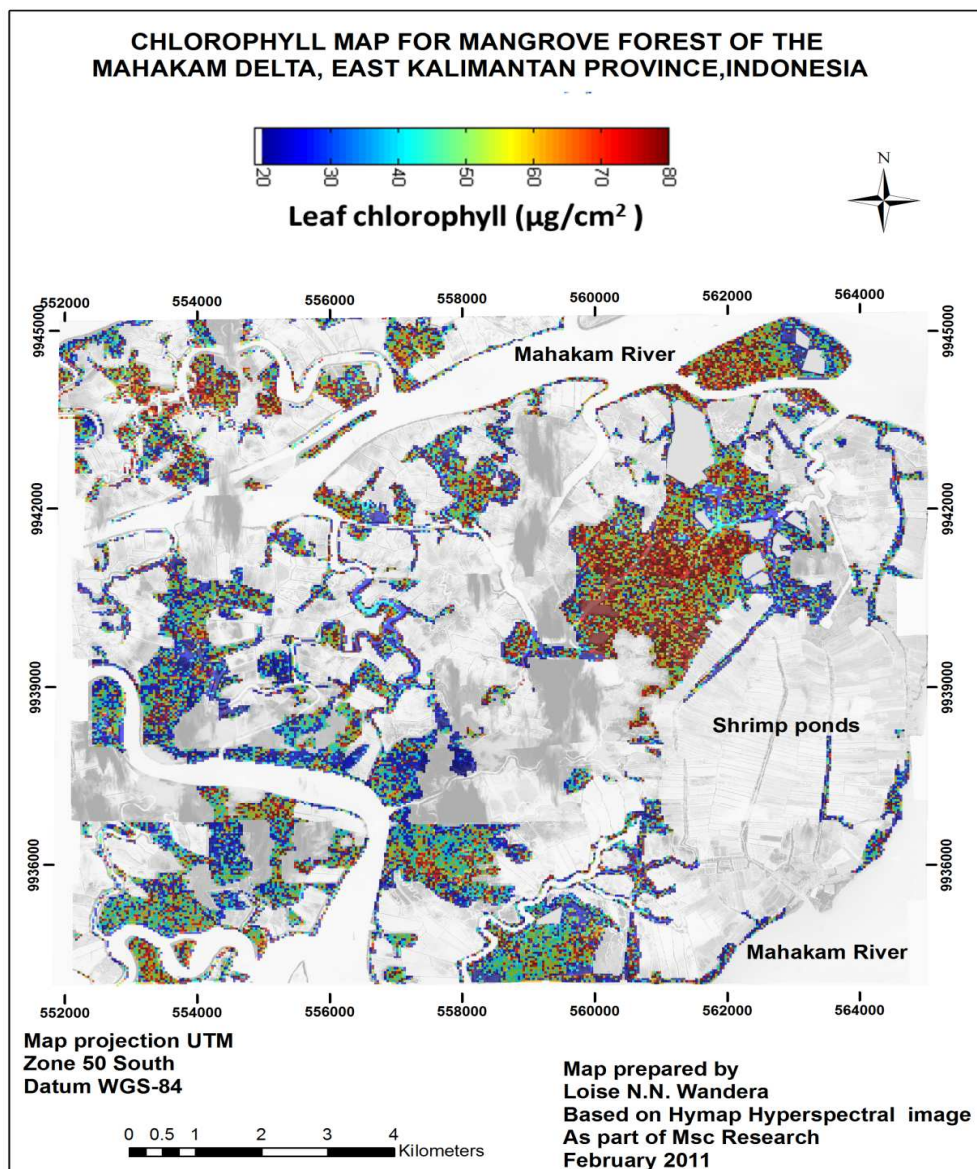


Figure 21 Chlorophyll map of forested areas overlay on background of entire study area

4. DISCUSSION

The method applied to retrieve leaf chlorophyll concentration in this study required an understanding of the radiative properties of mangrove canopy as whole as well as its components like leaf structure, brown material and soil background. From observation, the mangrove trees displayed a wide variation in their structural characteristics and the variation was expected to extend to the chemical characteristics as a result of intrinsic properties of natural forest e.g. tree age differences, succession along environmental gradient and also species physiology. Apart from the wavelength, the variations in canopy structural and chemical characteristics have been known to be significant in determining the interaction of radiation in a canopy and hence the magnitude of spectral reflectance (Asner & Martin, 2008). The choice of model to simulate the spectral reflectance of the mangrove canopy was a crucial aspect for successful retrieval of leaf chlorophyll concentration (Jacquemoud et al., 2000). A robust model that factored in possible variations within the canopy was needed. Using the SLC model in this study gave the confidence in proper simulation of mangrove canopy spectral reflectance because the components of the SLC model account for radiative properties of individual elements of a vegetation system, as well as detailed canopy architecture related to angular distribution of incident radiation (Verhoef & Bach, 2007).

From observing a number of measured vegetation reflectance curve of the mangrove which were obtained from the image, there was an indication of variation in spectral characteristics of the reflectance which implied differences in leaf biochemical content. The VIS domain of the spectrum was an area of interest in this study since the intensity of reflectance in this region is primarily influenced by quantity of chlorophyll (Fourty et al., 1996). But since the main leaf biochemical being studied was chlorophyll, the SLC model played a role in ensuring that the simulated mangrove canopy reflectance incorporated important factors that contributed to the overall reflectance in the VIS domain apart from chlorophyll as would be the case in measured reflectance at the top of canopy for instance soil background (Verrelst et al., 2010). For the soil background, the soils was wet and had an implication on the overall reflectance because the soil moisture in the soil does not only decrease reflectance within bands with water absorption features but also in the other bands as a result of internal reflections of water film covering the soil (Bach & Mauser, 1994; Baret & Jacquemoud, 1994). Misrepresentation of reflectance in the VIS part was an aspect that had to be avoided for instance simulations that would result in low reflectance in the VIS domain would imply high chlorophyll content but if in reality the low reflectance was an effect of high soil moisture, then the results would be invalid. Hence using the SLC model helped minimise such uncertainties. Atzberger et al. (2003) also demonstrates how important it is to include soil background when using an inversion approach to retrieve vegetation properties.

Including the effect of woody elements within a canopy has been found to improve simulations in retrieval of chlorophyll (Verrelst et al., 2010). The SLC model gives an allowance to include woody elements through the canopy sub-model 4SAIL2 and to specify how the distribution of green and woody elements occurs within the canopy. Generally the model caters for heterogeneity in the canopy as a result of having multiple leaf layers with different optical characteristics and the turbid layer assumption is not violated, therefore chlorophyll estimates given are close to what we would observe in reality (Liang, 2004). Furthermore, the leaf reflectance sub-model PROSPECT has been modified to include brown leaf pigment which eliminated the influence of other leaf pigments other than chlorophyll on the reflectance in the VIS domain. In addition the PROSPECT model has widely been validated by many other studies using it gave us confidence in the chlorophyll estimates.

Chlorophyll estimates in this study was done at leaf level. According to some previous studies, relating measured chlorophyll and estimated chlorophyll from reflectance at leaf level introduces uncertainties as compared when estimating at canopy level especially when using model inversion because of obvious variations within pixel (Baret & Jacquemoud, 1994; Curran et al., 1992). However there are practical suggestions from other studies that helped minimise uncertainties related to chlorophyll retrieval at leaf level (Atzberger et al., 2003; Combal et al., 2002; Jacquemoud et al., 1995). Having a prior knowledge of canopy properties upon which vegetation parameter is being retrieved, has proved to help improve vegetation parameter retrieval at leaf level. The mangrove trees observed during the field survey revealed differences in leaf structural characteristics. The species *Nypa fruticans* was a monocotyledon among the species present with the rest of the species being dicotyledon. This difference was expected to have an influence on the measured spectral characteristics in image areas where the two species occurred since according to Allen et al. (1969) in optical remote sensing, great variations arise from difference in arrangement of the layers inside the leaf. Monocotyledon leaves have compact mesophyll tissue with few airspace as compared to dicotyledon hence less scattering of light (Jones & Vaughan, 2010). The aspect was considered during model parameterization. In addition information on the mangrove general canopy structure for instance LIDF, LAI fB which influence a canopy reflectance were based on field observation were also used in the parameterization. The other factor that enhanced estimating chlorophyll at leaf level in this study was mangrove physiology. Majority of the species found in the study area are evergreen and this implies that senescence which has been established to lower model performance was not a very influential issue (Bacour et al., 2002; Verhoef & Bach, 2003). Also the bands selected for use during the inversion were related to leaf chlorophyll. The concept of band selection with specific information on variable of interest has been successfully applied in other studies although with the aid of statistical methods (Darvishzadeh et al., 2008; Knox et al., 2010).

The chlorophyll map generated as an end product of the model inversion process displayed variations in leaf chlorophyll concentration within the mangrove forest. Based on previous ecosystem studies, variation in chlorophyll within a vegetation system is a clear indication of differences in their ecosystem structure and rates of processes taking place within the ecosystem (Turner et al., 2004; Ustin et al., 2004). Mangrove forest are usually affected by a number of ecological factors which include wave action, rainfall amount, freshwater runoff, erosion and sedimentation rates, nutrient inputs and soil quality (Lugo & Snedaker, 1974). The effect of these ecological processes on the mangroves trees are in turn facilitated by geomorphology of the surrounding for instance topography, and species succession along salinity gradient (Kathiresan & Bingham, 2001). However in this study area the effect of topography is not pronounced because in the delta plain where the mangrove forest occur, the topography is mostly flat (Dutrieux, 1991). The lack of topography effect within the delta leaves effect of salinity gradient on species distribution as the probable explanation to the spatial differences in leaf chlorophyll concentration displayed in the map and also reflects on the process that might be taking place within the mangrove environment, particularly nutrient enrichment which is the key issue in this study.

The species *Nypa fruticans* is distributed in the South West and central west forested region of the study area which according to the map has generally low leaf chlorophyll concentration. According to Siddiqi (1995) *Nypa fruticans* colonizes zones with low tidal inundation. This could mean that excess nutrients regularly brought in by the tides would not be available. Another implication of low tidal inundation would be that soils are prone to develop hypersaline conditions due to lack of regular tidal inundation which usually helps to maintain salinity balance (Lovelock et al., 2009). When the mangrove ecosystem conditions are hypersaline, mangroves trees have been found to spend more energy in maintaining water

balance and ion concentration rather than primary production (Clough, 1984). This concept might explain the low chlorophyll levels within the *Nypa fruticans* zones. In a study of mangroves carried by Diop et al. (1997) the results showed that hypersaline conditions favoured growth of salt marshes which compete for resources with the mangroves. If that was the case in the south west and central west regions of the study area, the impact of nutrient enrichment would not be pronouncedly indicated by high leaf chlorophyll concentration.

The north east part of the map that displayed high levels of leaf chlorophyll concentration is composed of mainly *Rhizophora mucronata*. The proximity of this region to the sea as compared to the *Nypa fruticans* zones is higher. This means that their level of salinity is expected to be relatively lower because the regular tidal inundation buffers the zone from developing hypersaline conditions. Low salinity conditions favour primary production in mangroves (Kathiresan et al., 1996). This concept would partly explain the high chlorophyll values in the north east zone. But also the frequency of tidal inundation indicates high regular nutrient supply by the tidal action. The high chlorophyll region is surrounded by shrimp ponds whose effluent may also be causing elevation of nutrients levels within the zone when released to the tidal and distributary channels. These channel cover the mangrove zone extensively compared to the *Nypa* zone.

Studies done on mangrove to establish the effect of nutrient enrichment in their ecosystem have had consistent conclusion (Komiya et al., 2000; Lovelock et al., 2009; Naidoo, 2009; Reef et al., 2010). However, one lacking factor to accompany these studies are methods of monitoring nutrient changes within the mangrove ecosystems for effective management, especially where the cause of nutrient increase is associated with human activities which could easily be controlled. This study demonstrates the potential of putting effective monitoring systems in place. From the derived chlorophyll map in this study, we see obvious differences in leaf chlorophyll concentration within the forested area. Although we cannot limit the cause of the chlorophyll variations to only nutrient enrichment, it is one of the most probable causes. A comparison between chlorophyll distribution maps against other intrinsic mangrove canopy properties for instance species distribution, topography, prevailing climate condition during image acquisition and tidal regime would reduce uncertainty of relating variation in chlorophyll to increased nutrient in mangrove ecosystem. Also having pre existing information on optimum chlorophyll concentration values for mangroves would be an asset in interpretation of the chlorophyll distribution map.

5. CONCLUSION

Mapping chlorophyll as a potential indicator of nutrient enrichment in mangrove forest is possible using advanced remote sensing application. However to be able to link the variation to specifically nutrient enrichment, we require additional information on other intrinsic mangrove canopy characteristic. The variation in leaf chlorophyll concentration in the mangrove forest of the Mahakam Delta is very elaborate and certainly indicates difference in ecosystem characteristics which would include nutrient among other unknown factors. The variation are clearly displayed along species distribution zones with low levels in areas prone to low tidal inundation and surrounded by less shrimp farms. Mapping chlorophyll as a potential indicator of nutrient enrichment in mangrove forest is possible using advanced remote sensing application. However to be able to link the variation to specifically nutrient enrichment, we require additional information on other intrinsic mangrove canopy characteristic. The SLC model demonstrated the capability of using hybrid radiative transfer models to simulate canopy reflectance of a vegetation system with variation in species structural characteristics. The inversion process by LUT approach was a simple and efficient method of chlorophyll retrieval.

For future study it is recommended that retrieval of more than one parameter could be done concurrently to have more information on the vegetation characteristics that would enhance inference of the ecosystem properties since the SLC model provides that allowance. Also the efficiency of the retrieval could be enhanced by coupling the SLC model with atmospheric model that applying similar concept of energy transfer for instance MODTRAN. Finally applying statistical techniques in band selection would improve quality of retrieved information since other bands that are rendered irrelevant and introduce noise to the data are eliminated. In addition when using hyperspectral bands, identifying specific bands holding information on parameter to be retrieved reduces computation time.

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APPENDICES

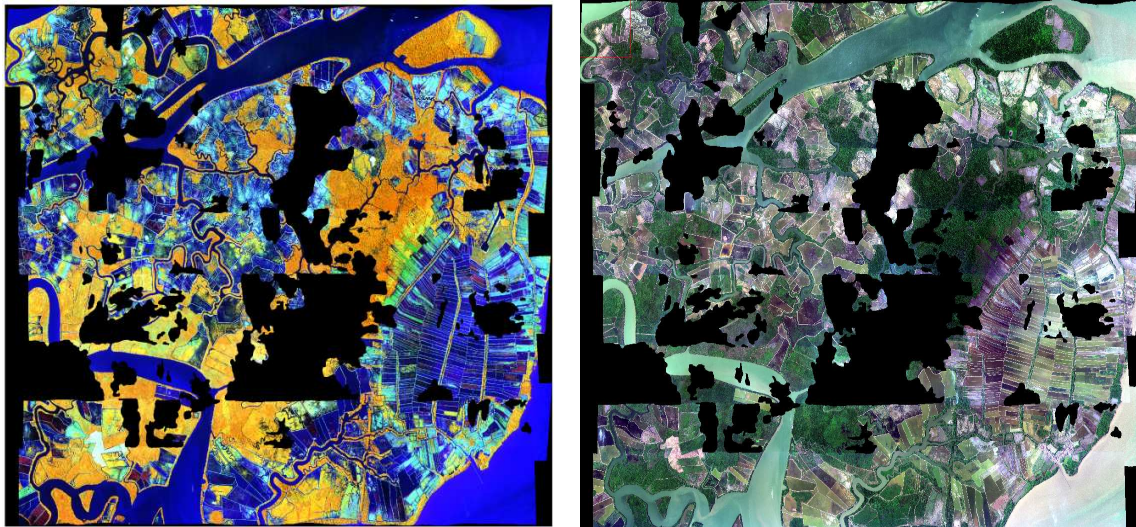


Plate 1 Hyperspectral image of false (TM4, TM5, TM3) and true colour, TM3, TM2, TM3)

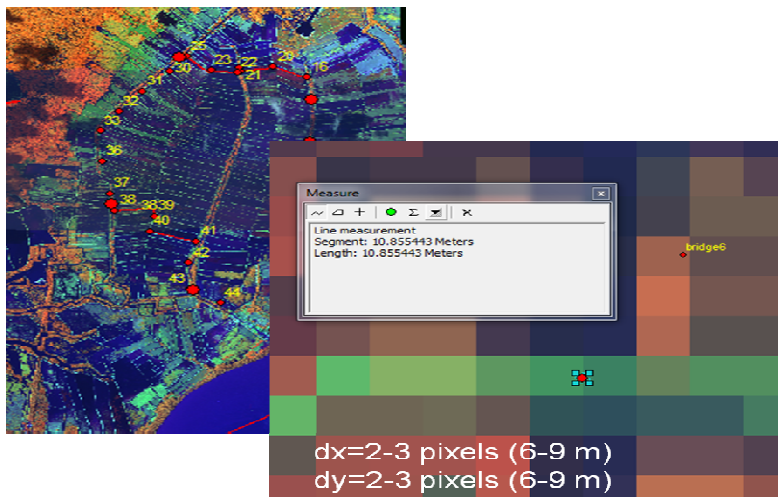


Plate 2 Geocoding accuracy



Plate 3 Taking LAI measurements using two devices for below and above canopy readings



Plate 4 Different mangrove soil background in terms of moisture content