Estimation and Mapping the Rubber Trees Growth Distribution using Multi Sensor Imagery With Remote Sensing and GIS Analysis

Hayder Dibs[a], Thulfekar Habeeb Hussain[b]

[a]*Hydraulic Structures Department, Faculty of Water Resources Engineering, Al-Qasim Green University, Hilla, Iraq*

[b]*Faculty of Water Resources Engineering, Sustainable Management Department, Al-Qasim Green University, Hilla, Iraq*

haiderdibs@gmail.com haiderdibs@yahoo.com

Abstract

The plantation of rubber tree in different countries throughout the world are expanded rapidly in areas that are not known before in planting such as these vegetation species. Estimating and mapping the distribution of rubber trees stand ages in these regions is very necessary to get better understanding of the effects of the changes of land cover on the Carbon and Water Cycle and also the productivity of the latex in different ages. Many remote sensing techniques that have been used to estimate the land cover / land use for mapping and monitoring the distribution of rubber trees growth based on different remote sensing classification algorithms (Maximum likelihood, SAM classification, Decision Tree and Mahalanobis Distance) with different types of data (Multispectral, Hyperspectral or statistical) by using many sensors

Keywords: Remote sensing, Rubber trees stand age, Maximum likelihood, SAM classification, Decision Tree, Mahalanobis Distance

1. Introduction

The continuing capacity of ecosystems to maintain biological processes in order to provide their many of advantages is the one of the important priorities of life. Until yet, from a long time and in different countries throughout the world in both rich and poor countries, priorities have been focused on how can the humanity use and take from ecosystems, and in other side there is too little attention have been paid to the our negative actions on ecosystem [1] [2] [3] [4]. Nowadays understanding of identifying, delineating, monitoring, surveying and reporting of globally and nationally very important, and ecosystems have been appeared at the highest level global environmental keynote meetings such as the Convention on Biological Diversity (CBD), the Convention on Migratory Species (CMS), the Convention on International Trade in Endangered Species (CITES), The World Heritage Convention (WHC) and others [5]. However, the rate of land cover and the changing over the large areas and the developing and providing new procedures is very important and necessary; all the ground surveys cannot keep pace with all that [6] . The needs of data and information nowadays become more complexity [5] . In the couple of last two decades the quality, accessibility and collection ways of spatial data have been improved significantly by using the applications of both Remote Sensing (RS) and geographic information system (GIS), especially the spatial data that related to natural resources management and conservation that deal with replanting of old rubber trees that have low productivity of latex with new generations. The remote sensing has been got a good acceptance to use for protection, management and of Natural resources and that coincide with wide spread modification reporting of natural system and wildlife habitats in the three decades ago. Experts and users of remote sensing quickly catch up with the evolving technology because there are some Concerns that guide to increase in adverse environmental conditions prompted. The developing in the ability and the reliability of Geographic Information System (GIS) has made the processing of the large data can be generated through remote sensing [7].

Remotely sensed imagery classification for discovering land use/land cover information is a good way and plays significant role in both global and national change studies in management of natural resources and environmental applications. Throughout the world, national and global markets are driving the conversion of traditional agriculture and occupied non-agricultural lands to more permanent cash crops. In many countries of Southeast Asia rubber plantations are expanding dramatically in areas where this kind of crop was not historically found [4][8][9]. Over the last decades many countries like Thailand, Chain, Myanmar, Vietnam and loas witness conversion of hundreds hectares of land have been changed with rubber plantation just in non-traditional rubber planting areas [10] [11]. There are numbers of researches about monitor rubber trees growth distribution have been conducted in Southeast Asia, like in Yunnan, China [12][13][14][15] Indonesia [16] and Laos [17]. The rubber trees spatial analysis has been limited to suitability analyses in Thailand [18].

Limited training samples to mapping land cover over large areas is one of the challenging problems that limit the capability of the classifier to make generalization to the patterns that located in sampled areas. There are two significant challenges always faced analysts when conduct to map rubber trees growth. Firstly, the confusing that occurs between mature rubber trees and tropical evergreen vegetation and that because the similarity in the spectral reflectance characteristics. Mature rubber trees areas are often overestimated by misclassifying with forests as rubber trees. Secondly, mixed scrub and bare ground, or intercropped that occurred with economic crops like cassava and pineapple are revealed in young rubber trees areas. Rubber tree growth canopies even after (3- 4) years has a small fraction of overall planted area in the land cover scale. Thirdly, the small area that covers with rubber trees very small if compared with the features in surrounding area. Fourthly, the high different of intra class – variability between the rubber trees at different age levels. All these conditions make it mapping rubber trees very difficult [19]. Nowadays machine learning techniques [20] like neural networks and decision tress [21] have been widely used in remote sensing imageries classification because they demonstrate many benefits over other conventional classifiers [22][23][24].

On the other hand, the essential computation time and heuristic training process of these classifiers make mapping of rubber tree growth over a large area inefficient. Zhe [25] have been conducted research and they suggested that using decision trees and neural networks with vegetation indices and spectral information overestimated the number of rubber tree pixels. Moreover, these kinds of classifiers require a large numbers of training sites to contain sufficient both “presence” and “absence” details, that means, the analyst must collect information from the training sites. In reality, it is very difficult to acquire sufficient training samples in the study area to cover all the stages patterns of rubber tree that appear up in an analysis. Given this fact, a presence-data only model looks increasingly promising in dealing with species distribution mapping, especially when knowledge about available land-cover types is limited. [26] [27] conducted experiments of using a presence- data-only model and Mahalanobis distance classifier to model distribution of species, they found that Mahalanobis classifier provided information about how instances being analyzed are compared to those used as a reference [26] Selection of remote sensed imageries is another difficult step for mapping and monitoring of land-cover mapping. currently the selection of remote sensing imageries and data for land-cover mapping at a global or a national scale is considered the balance between given temporal and spatial resolutions to use either low spatial resolution but with high temporal resolution images, such as Moderate Resolution Imaging Spectro-radiometer (MODIS)[28], or use low temporal resolution but with high spatial resolution images such as a group of Landsat satellites, Enhanced Thematic Mapper (ETM+)/Thematic Mapper (TM) etc. [29] [30] [31] [32] [33] Recently using ASTER data to improve the mapping of rubber trees by integrating both of Mahalanobis distance classifier with a neural network model. [25] conducted a successful application by using Mahalanobis distance classifier for monitoring and mapping of rubber trees in the Southeast Asia using the MODIS time-series of NDVI with Mahalanobis typically and some of statistical data.

Recently Image classification has been became a very widely used to mapping vegetation distribution. There are many kinds of remote sensed imageries and data that can be used under investigation of land cover depending on the type of the sensors that fit with method that applied for land cover investigation. Data from different sensors can use based on their resolution. There are four categories of resolution consist of; spatial, temporal, spectral, and radiometric [34]. Jingxiong [35] conducted mapping land cover of geographical area by using aerial photographs and employed Fuzzy approaches for boundary delineations and derive fuzzy maps of land cover obtained by photogrammetry data from aerial photographs. For each approach, many methods for accuracies assessing of maps has been employed, including the overall classification accuracy, entropy, and cross-entropy. The most useful approach to deriving fuzzy maps of land cover is from aerial photographs data, especially when fuzziness is properly advised in the assumed reference data. Geir [36] conducted a study to examine the field experience to the maps accuracy of land cover based on aerial photographs. A photogrammetrist using true color aerial photographs to determine the land cover polygons in two regions, is not to identify land cover features. Ten experts with aerial photographs have been asked to label polygons of land cover. The experts fell into two broad categories: ‘field trotters’ and ‘photogrammetrists’ according to their professional background. After finishing labeling of the polygons in the first study area, the experts took one day in the field to compare their results with the ground truth. After that the experts do the polygons labeling to the second area. But unfortunately the results did not appear significant differences between the both of study areas.

Satellite images are another source of data that used for monitoring land use/land cover, but between these images some differences in some scales related to the spectral, spatial, temporal and radiometric resolution of the satellites (sensors) that use to perform mapping of land use/ land cover or any other applications [37] [38].

2. Classification Algorithms

2.1. Maximum likelihood

This kind of algorithm has been widely used to find out the land cover / land use and it consider the spectral reflectance of the features to perform the classification. The Maximum likelihood is one of the algorithms that classified under per pixel classification. Nageswara et al [39] in their study integrated the remote sensing and GIS techniques to estimate the distribution of rubber trees and soil map to develop database related to rubber cultivation. The study area was in India in Kottayam district of Kerala State. The data that has been used was kerala surveyed map with scale 1:50000 and LISS – III data of IRS-1D that acquired in 28-02-2002. They used the software PCI Geomatics version 9.0 to do the processing and analyzing the data. They collect Ground Control Points (GCPs) to geocoded from topographic sheet has scale 1:50,000 then they image digitized the map of kerala to extract the boundaries of district and soil map by using this digitized layer for clipping the satellite image.

The resampling of satellite imagery done by using the nearest neighborhood algorithm. The supervised classification algorithm that conducted to classify the image, it was Maximum likelihood classifier. The study area was grouped into nine classes under this classification and null class to group the unclassified pixels these classes were: rubber trees that have more than 5 years old, rice cultivation, forest, and coconut plantation, shallow and deep water. The thematic map of classification converted to vector format by used the software R2V (raster to vector). Classification results of this approach revealed high classification accuracy and it was 94.5 % and the overall accuracy was 97%, the supervised classification approach indicted a better reliability with the value of kappa coefficient of 0.97 .The sig- nature separability was 1.96 that reflects better separability. The rubber trees less than 5 years not considered in this study that will lead to loss of getting statistical database and thematic maps about these areas that covered with rubber trees have ages less than 5 years old, that related to mixed forest and the similarity of spectral characteristics of vegetation, and that a problem need to solve.

Another research done for monitoring and mapping the distribution of rubber trees to generate database that match the government and smallholders' needs. Rubber Research Institute of India (RRII). Nordin et al., [40] performed the study of distribution different rubber ages and the study area was in south of India, into two areas in the Kerala and Tamil Nadu state, in the 2005, and the digital data was obtained by LISS III sensor of IRS P6 on the 13.02.2005, the ancillary data was involved in this study be downloaded the DEM that got from shuttle radar topography Mission (SRTM) with spatial resolution 91.7m clipped to satisfy with the study area. The imagery was geo-referenced to Survey of India topographic sheet with scale 1:50,000 and then by using district boundary map in scale 1:250,000 the imagery clipped. The classification algorithm method that has been used for this study was maximum likelihood classifier to generate thematic map for rubber distribution. The classification has been done with limited number of ground truth samples that have been collected from field work by using handheld GPS (Garmin). DEM was used to generate the Slope of the map that has eight classes of Rubber trees distribution that suggested [41].

The software that has been used Geomatica (version10.1)for doing the processing, classification slope extraction and vectrisation the overlaying of raster layers was perform by using ILWIS (version 3.4).The result revealed that the young rubber trees below 4 years old difficult to classify related to partial closure of canopy. The overall accuracy of maximum likelihood was (97%) and the Kappa coefficient was about (0.95). The area that covered with rubber trees that have more than 4 years old was 66,106 hectares, and the distribution of rubber was 30% in midland of distric, Meenachil taulk has 44.7%, while in Kanjirapally taluk around 23.6, area around 17.4% was covered Kottayam taluk and for Chengassery taluk and Vaikom taluk were 10.4%, 3.9% respectively. The results of this study revealed high level of accuracy for rubber tree more than 4 years with these districts .However, the distribution of rubber tree in Kottayam district not found that because the age of rubber there is below 4 years there were not considered and did not count, that related to the sim- ilarity of spectral characteristics of vegetation features that located in surrounding area of rubber area and also to the mixed pixel. By increasing the number of ground truth samples that should collect from field work the study will be able to estimate the distribution of rubber trees that have age below 4 years.

Hongmei et al, [42] in their study collected date for 27 years from satellite and statistical inventory data to estimate the changing that occurred in biomass carbon stocks. Study area was in china over area about (1.9 million hectares) in Xishuangbanna that located longitude and latitude between (21^o 80’ 80”–22^o 83’ 60” N, 99^o 85’ 60”–101^o 85’ 00”E), in Yunnan Province, southwest China, covers 19150 km^2, this area consists of three counties and they are: Jinghong, Menghai and Mengla in the southwestern china in the upper of Mekong River. The study area was covered with tropical forest, rain forest and evergreen forest. Their study was about the helping the expansion of rubber trees cultivation to decrease the deforestation rates and carbon emissions to the atmosphere in the study area and the researchers employed the imageries were classified by employing the Maximum likelihood classifier to perform the classification of land use and then estimated the changes over the period of study from (1976 - 2003). The data that used for this study were imageries captured from Landsat (MSS) images captured in 25.04.1975, the second image captured in the 24.02.1976 from Landsat (TM) then the third and fourth imagery was captured in the 02.02.1988 and in the 07.03.2003 from Landsat (ETM) respectively, then by using topographic map with scale 1:50,000 and digital topographic information to generate the digital elevation model (DEM) with counter interval to 100 m. The RMS of registration imageries were 0.5 and less than one. All bands of MSS were used and the non-thermal bands of TM and ETM were used. The identification of training sites for each class was done for 2003 by field observations collected in 2004 but for Landsat TM and MSS the training sites generated by using topographic map related to 1988, 1991 and 1993 respectively after that the classification results compared with ground truth site to get the overall accuracy in assessment stage and the accuracy of each classification were: 77.3%, 86.4%, and 87.9% over the years 1976, 1988 and 2003 image respectively. The study shows that using the ancillary data of forest inventory will increase the ability to get the precision result to estimate the deforestation and the emissions of carbon in tropical area. Result of study will reach higher accuracy if the satellite images capture in the dry season that because the Rubber tree has the similar spectral characteristics of tropical evergreen forest that leads to make confusing to differentiate the different species of forest trees with rubber trees, and the rubber trees are known as deciduous tree and their leaves fall in dry season between February and April that make the differentiation more easier to conduct, and the spectral reflectance will be different, another reason the poor of deforestation data reduce the ability to obtain the highest level of accuracy.

2.2. SAM classification

Another classification technique has been conducted to explore the plantation's volume of Rubber wood from using hyperspectral remote sensing data that has the high spatial and high spectral data that obtained by using the UPM_APSB' AISA airborne is known as commercial hyperspectral sensor. Airborne hayperspecral sensor was flying with altitude about 1000m above the study area when images captured with (1 m) the spatial resolution and the speed of flying was 120 knots or 60 ms. The study area was in Lebuh Silikon, University Putra Malaysia (UPM), that located in Serdang, Selangor state, Malaysia, the area of study area was 1,214 hectares .The Radiometric and Geometric correction of imageries was conducted with using ENVI software to increase the quality of the images and to reduce the unwanted effects. The Sobel edge detection filter has been used in the next step to reveal the best effects in the imagery to find out the edges of rubber trees. From the field work and the analysis of image the knowledge about spectral reflectance that related to individual of standing the rubber wood was obtained, and then find the spectral reflectance for some randomly sites in imagery to examine the spectral reflectance curve and it was the same.

The researchers found that the correlations for different crown of rubber tree and diameter were height with using the help of ancillary data, then they employed a supervised classifier method, which called Spectral Angler Mapper (SAM) to separate the end- members of crown rubber trees and by applying the spectral matching knowledge that has been derived from using the spectral library to help in image classification to estimate the rubber wood volume in area of study and .The ground truth spectral samples were collected in field work with using the handheld spectroraidometer instrument. The sieving technique was used in the post classification stage to remove the isolated classified pixels after run the SAM classifier. The accuracy was determined by using the formula:

% of Accuracy = 100% - error % ——- (2.1)

The study revealed that the individual rubber wood volume of matured rubber trees can predicted precisely with a good accuracy by using this classifier approach and the overall accuracy of mapping rubber wood was 89.84% over the study area. The study revealed the capability of using airborne hyperspectral sensor like UPM_APSB's ASIA for mapping and estimation of individual rubber trees and the rubber wood volume with acceptable accuracy. Norhidayah et al., [43]. The researches using spectral library range between (800 - 100) to perform estimation about plantation, By using values spectral library spectral of different features between range of (400-2500) will help to increase the accuracy of this classification that because even with knowing the spectral reflectance of rubber from both of spectral library and field work still there is subtle difference not measure between vegetation species over the large area of study .The image covered with different color (Red, Green, Yellow or false color) due to different reflectance and all these reflectance are not constant ,the plantation reflect different spectral reflectance related to its status if it's healthy ,diseases effected or because the stress of its leafs due to lack of water or arising in the temperature or another factors.

Jan [44] presented study for land use-land cover to determine the features that distributed in study area especially rubber trees in different ages. The main objective of this research to classify, quantify and make identification of land use - land cover. The study area was in Setiu, Terengganu in Malaysia and the total area was 130,436.3 hectares.by using another technology of remote sensing by airborne hyperspectral data that obtained from UPM APSB'ASIA and the hyperspectral image was captured on 20.04.2006, ancillary data was involved in this study by using land use – land cover maps. There were 30 points collected from field work as ground truth samples and some parameters recorded also from the field work to accuracy assessment of classification. The software that used to do the analysis and processing was by ENVI version 4.0. There were 20 bands involved in data analysis but band 20, 22 and 17 (RGB) respectively to generate the false color combination image (FCC) that revealed the better visualizing for identification of features over other bands. Enhancement the image was performed before classified the image, the area of study classified to eight classes: (mature rubber trees 15 -17 years old, young, rubber trees 3-4 years, old oil palm 2 - 3 years old, oil palm 4-5 years old, vegetation crops, road, river and open area).

Supervised classification algorithm has been used to classify the study area, Spectral Angular Mapper classifier was employed for classification. The classification accuracy was (89.51) and the value of kappa coefficient is (0.86).The study revealed the ability of hyperspectral remote sensing data for identification, quantification, classification and mapping land use – land cover. However, with increase the number of ground-truth samples for rubber trees and oil palm will increase the classification accuracy, because both of them have some of similarity in spectral signature, and by increasing the number of references samples will support the visualization interpretation then give better identification to features that cover the study area.

2.3. Decision Tree

Shafri et al, [45] that have been conducted DT classifier and NDVI vegetation index with using Spot image and the study area was located in Langkawi Islands, Malaysia to classify the land cover then to extract the distribution of rubber trees. In this classification the rules that have been used to classify the study area were the NDVI and using the Band 4 (SWIR), were used as input variables in Decision Tree classifier and in this classification the classes were (Mangrove, Rubber, Water, non-Vegetation area, Forest L and Forest D), the result of this classification was 69%. After that there was another classifier was used to generate the thematic map it was Support Vector Machine (SVM) and there were many kernels that have been used to performed this classification (Sigmoid, radial basis function and polynomial), the result of SVM classifier was better than the DT result and the accuracy assessment for this classification was 73%. However, using the elevations as parameters into the DT rules and increase the number of training side will overcome the misclassification or overestimate that occurred between the rubber trees and Mangrove areas.

Yafei et al., [46] studied over the period of time (2000 - 2007) the vegetation change detection after planting rubber trees there and made to grow another tropical vegetation species that lead to do fragmentation for these species and the study area was located central of Xishuangbanna in China, the study area was 19,125 km^2. The research done by using remotely sensed imageries that obtained from two types of sensors Landsat ETM and Spot HRG and PAN. The Landsat ETM image was acquired on 14-03-2000; the SPOT image was captured on March of 2007, both imageries obtained in the same month to make sure they have the same conditions of vegetation growth to do the comparison to extract the changes in vegetation, then both of the geo-referencing correction and the radiometric correction performed. 0.51 pixels were the registration accuracy of SPOT HRG and for Landsat ETM image were 0.62 pixel, both of them less than 1 pixel and matches the requirements for performing the monitoring vegetation changes. The field reference samples collected based on prior knowledge and also spectral reflectance information, there were 63 reference samples have been collected covering six classes of study area types these classes: (rubber trees, primary vegetation, artificial vegetation, bare area and water bodies). NDVI for ETM and SPOT bands were calculated. They uses the short-wave infrared (band 4 and 5) as one of their parameters in conducting the Decision tree approach because the vegetation features in the study area have the similarity in spectral reflectance characteristics.

The researchers conducted two aspects for this study, the first is vegetation type conversion and the second is vegetation change. then by using both of NDVI values of each kind of vegetation and spectral information, the analyzing was performed and then the classification was conducted for imageries that got from ETM and SPOT PAN. The images classification performed to generate maps for different period of time. The classification accuracy of classified image should be high in order to do the vegetation change detection, therefore, there were 100 samples randomly generated on both of classified imageries for testing the accuracy to find the overall accuracies, the results demonstrated the overall accuracy for ETM and SPOT imageries were 92.3% and 93% respectively, this results satisfied for doing detection of vegetation species. Then the Fusion between the ETM image (1-5 and band 7) and SPOT PAN Imagery was done to extract more information about the vegetation changes such as the gain or loss of vegetation. The result demonstrate that large area of Xishuangbanna are transformed to rubber plantation and the conversions in vegetation is frequent between the vegetation types that located in study area and there were increased in the area of rubber trees and bare soil. Supporting the Decision tree classification with another vegetation index such as Modified Normalizes Differences Vegetation Index (MNDVI) or using ancillary data about forest inventory, land use / land cover map or digital elevation model will help to extract more vegetation information and improve the classification accuracy.

2.4. Mahalanobis Distance

Another research done to estimate and to map the distribution of the rubber trees to provide understanding about the land use and land cover changes on carbon in 2010 .In this study the researchers applied the Mahlanobis typicalities method (MD) to perform hard classifier to improve located with the longitude and latitude the ability of generalization by integrate this approach with another technique is called (MLP) neural network to find out the distribution of rubber .The study area include two areas the first is Thai Lao and the second is Sino Lao. The data that has been used captured by Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and it is a combination between nine bands included both of Visible, Near Infrared that have spatial resolution 15 m and also Short

Wave Infrared that has spatial resolution 30 m (VNIR and SWIR). The researchers chose the (ASTER) imageries for both of study areas in dry season examine the spectral reflectance of vegetation phenology in dry season. The imagery was captured in 24-04-2005 for Thai Lao and for Sino Lao the imagery acquired in 08-02-2005. The training sites were generated by using NASA's Landsat GeoCover products and by using the global positioning system (GPS) for reference samples (ground truth samples) in the fieldwork and the high resolution IKONOS imagery from Google Earth to identification the rubber trees.

The researchers collected training sites in two of study areas and the percentage of the rubber trees samples it was about 0.21% out of the total number of image's pixels, then the testing sites also generated to perform the assessment of classification accuracy .There is a fusion done between the VNIR and SWIR to make both of them in same spatial resolution. Researchers divided the study area in six classes were (Rubber, Eucalyptus, Water, Paddy, Bare, and Forest) but the overall classes were 10 classes that generated from the combination between VNIR and SWIR bands .With using one vegetation index ,the Normalized Difference Vegetation Index (NDVI) as a variable for input in the classification algorithm. By conducting the Mahalanobis typicalities classifier there were six imageries the output of this classifier each one represent each class of the classes above, then the researchers employed these output and the result of NDVI as input variables in another stage with MLP. Results of Mahalanobis typicalities classifier demonstrated a good result and that observe clearly from the result of validation that conducted for all classes. The validation done by using the fusion matrix and it was as follow in Sino Lao study area : Total accuracy, Overall Kappa coefficient, User's accuracy for rubber, Producer's accuracy for rubber and Kappa coefficient for rubber equal to : 0.98, 0.96, 0.98, 0.99 and 0.98 respectively and for Thai Lao the validation was: Total accuracy, Overall Kappa coefficient, User's accuracy for rubber, Producer's accuracy for rubber and Kappa coefficient for rubber equal to: 0.68, 0.03, 0.01, 0.65, 0.62, 0.16 and 0.40. By using the Mahalanobis typicalities classifier as one of the input variables in MLP will increase the accuracy of mapping the rubber tress specially the user's accuracy [23]. However the result with this a novel technique by using the NDVI, MD and MLP is high for Sino Lao but on the other hand the result that related to other study area of Thai Lao is not satisfied, that simply because the lack of using inventory data for example (topographic map, land use and land cover ancillary data, forest inventory and statistical provinces) these will help to better performing the classification for rubber distribution and will improve the user 'accuracy in each class.

Zhe Li et al., [25] performed study about the estimation and mapping rubber trees growth in different ages, the study area was located in mainland Southeast Asia. Because the rubber growth is expanding rapidly in areas where the crop was not historically found. They generated a map of distribution of rubber tree growth by using remotely sensed imagery took from Landsat 5 TM data without using the thermal bands this imagery with 30m spatial resolution for nineteen provinces in the region involved for this study located in Northeast Thailand and the satellite imageries were collected in different period of time and that because the cloud cover over the study area from (2004 - 2009). The ground truth samples were collected from the field work by using Global Position System (GPS) to identify the rubber trees area that was on January and March of 2009 and by using the QuickBird / IKONOS satellite images from Google Earth. Generating the training sites by using NASA's Landsat GeoCover products (web site) to identify land use /land-cover types. Atmospheric and geo-metric correction was done to Landsat TM and the nearest neighborhood used to perform the resampling, then the registration of all images done to the UTM system zone 48N, after that performed the masking to remove the cloud and shadow from images. Vegetation indices such as Normalized difference vegetation index (NDVI) was used to determine the activity of photosynthetic that reflected the sensitivity of canopy structural, chemical, and tasseled cap as model for input metrics. It also to give them a good differentiated about which bands is most useful over others in differentiation the rubber trees in different ages.

The NDVI employed the band 4 and band 5 to make the differentiation and to find the patterns of rubber and other features in study area. With using the Mahalanobis distance method for generating map for Rubber trees growth in different ages, the classification of the area was done in six categories (rubber, forest, bare soil, water bodies, paddy and other).They classified the rubber age in four classes. They did the validation for sixteen provinces and it was conducted by using some of ancillary statistical data of rubber trees at the provincial scale. The result with mature and middle age is satisfy and the estimated result and the statistical data are correlated equal to (0.7766, 0.7911) respectively and that means the estimation of rubber trees from satellite image is satisfied for the mature and middle age of rubber trees but with the young rubber tree not so match good and reveals not good correlation between the estimated data and the statistical data over the study area correlated equal (0.034).

These result with the regional scale is seem to be satisfied with mature and middle ages over a small area like this study area but over a large area reaching a good result especially with the young rubber trees is difficult, that simply because the difficult to differentiation of spectral reflectance of area that covered by young rubber, and the mixed pixels that reflected from the young rubber and bare soil. Collecting training sites will increase the difficulties especially with regions that difficult to reach, that leads to lack of training sites that can be applied in performing the classifier. Another thing the spatial resolution (30 m) and the spectral resolution (7 bands) of landsat 5 TM, make the satellite imagery that have been used to perform the research goal was not satisfied to give more accurate and precise results over a large area. Over large area need to perform the classification with other types of satellites that have higher spatial and spectral resolution to be able to identify between different features and vegetation species that located in the area of study . These reasons will limit the classification to create the correct patterns that represented each feature in study area and in the end the result will show misclassification regions and overestimation with others.

Liu [47] studied the monitoring of distribution of rubber trees growth because the rubber has influenced in local energy, water and carbon fluxes. Getting precision and accurate and up to day data is one of critical issues facing the researchers with the rubber distribution. The study was conducted in Mainland Southeast Asia, over a large area (2,000,000) hectare that located in six countries. The researchers conduct this study to examine the capability of a Mahalanobis typicality classifier to classify the mixed pixels and find out the result of combine the data from Moderate Resolution Imaging Spectroradiometer (MODIS) images. The area of interest was covered with MODIS tiles (h27v06, h27v07, h28v06 and h28v07), with statistical data that related to the distribution of the rubber trees, this data was collected between the period of (2007 - 2009). The data that have been used was time series

MODIS Terra 16-day /250m composite with the vegetation index Normalized Difference Vegetation Index (NDVI) products (MOD13Q1). The date of acquiring the data between March of 2009 until May 2010 over the period of time about 15 months, then generate 29 NDVI images over the dry season (January to July) and wet (August to December) seasons respectively.

NDVI values revealed the consistent trend for both Mature and young rubber trees, but Mature rubber indicated higher NDVI values than young rubber that simply because the distribution density of mature rubber is very high. The area of study divided to 12 classes and the training were generated by using the recent data of land cover / land use based on the Glob Cover land use / land cover data. The Testing sites (ground truth samples) identification for rubber by using the Global Position System (GPS) that collected in the field work part from January until March of 2009 and also by interpretation of using the high resolution IKONOS/Quick Bird images from Google Earth. The classification of study area has been done by using soft classification and the Mahalanobis typicality method was employed to perform this classification that because its ability to classify the area that has mixed pixels. The 29 images that got from MODIS NDVI have been used as variables input in Mahalanobis typicality and the output of this method was thematic map for each class not like any type of hard classification thus there are 12 map generated from this technique, the researchers studied just the distribution of rubber trees they merged the 12 classes into two classes for rubber trees, the first one for mature rubber equal and more than 4 years and the second class for the young rubber that younger than 4 years and the merged all the another classes in one class that mean they had three classes.

The results of this research were found that the area that covered with mature rubber trees about 1,569,481 hectares and that equal to 73.89% of the whole rubber tree area and the young rubber covered area about 554,606 hectares and occupied around 26.11% of the total of rubber area. The validation for the classification accuracy and the viability of Mahalanobis classifier in this study was perform by using the Relative Operating Characteristic (ROC) statistic it was good for soft images and also by using error matrix. ROC that has high values over 0.8 can be achieved with this type of classifier for both of mature and young rubber tree. Using Mahalanobis classifier in this study the commission errors for the growth of two classes were 1.87% and the other 2.8% respectively and the use's accuracies were 98.1% and 97.2% respectively and overall kappa coefficient of (0.76). The limitation of collecting ground samples by using the GPS guide to limit the ability to discriminate the different ages of rubber trees from MODIS imageries, that related to the spatial resolution of MODIS imageries equal 250m and the accuracy of GPS is around (5 – 10)m for testing sites collection in other words the collected samples will not represent accurately the same sites onto the images and that will give inaccurate result about the rubber trees that have age less than 4 years related to the similarity in the multispectral reflectance between the rubber and surrounding features, make the classes of rubber into just two classes.

3.0 Summary

Recently, there is obvious concerning about monitoring and mapping the distribution of Rubber trees growth, that concern come from the importance and the role that the rubber trees play in the economical scale, many countries became very interesting to plant this kind of tropical plantation. The latex and the rubber wood are good raw material that has been used in industrial level. China, Indonesia, Thailand and other countries looking for new knowledge for managing the rubber trees and that related to the needs of statistical data and temporal information about the distribution of rubber tree to estimate the rubber trees growth. Several techniques have been used to overcome this issue and the traditional method is just field work. But, using the new technology like Remote Sensing and Geographic information System show the good ability to overcome this issue. There are many classification algorithms that demonstrate in this review to monitoring the growth of Rubber trees such as (Maximum likelihood, SAM classification, Decision Tree and Mahalanobis Distance) and some of this classification classify under object oriented classification or per – pixels classification, with using Maximum likelihood many types of data use for monitoring the rubber trees ages such as; LISS-III data of IRS, Landsat (MSS), (TM), (+ETM) and with using ancillary data like DEM, statistical data and Topographic map, this algorithm reveals accuracy better than 90% for mature and Middle ages , however, difficult to detect the Young rubber tree. The SAM classifier applied with using Hyperspectral data

Shows accuracy more than 85%, the Decision tree algorithm with using satellite images such as; Spot HRG and Landsat ETM shows accuracy more than 90%, however, it needs many input parameters to reach a good accuracy an d result. Using Mahalanobis classifier with ASTER images and statistical data shows accuracy more than 90% for monitoring the rubber trees ages. That because it is assuming all the features are normal distributed.

References

[1] S. M. R., M. Rohweder, Grassland ecosystems, World Resources Institute, Washington, D.C, 2000.

[2] A. Hayder, Feature extraction and based pixel classification for estimation the land cover thematic map using hyperspectral data, International Journal of Engineering Research and Applications, coordinates magazine 3 (3).

[3] A. Hayder, H. Alnajjar, Maximum likelihood for land-use/land-cover mapping and change detection using landsat satellite images: A case study south of johor, International Journal of Computational Engineering Research 3 (2013) 26.

[4] H. Dibs, S. Mansor, N. Ahmad1, B. Pradhan, Registration model for near-equatorial earth observation satellite images using automatic extraction of control points, ISG conference, 2014.

[5] A. D. Sherbinin, Remote sensing in support of ecosystem management treaties and transboundary conservation (2005).

[6] P. Osborne, J. Alonso, R. Bryant, Modelling landscape-scale habitat use using gis and remote sensing: a case study with great bustards, Journal of Applied Ecology 38 (2001) 458–471.

[7] R. Lunetta, Applications, project formulation and analytical approach, in: R. C. Lunetta (Ed.), Remote sensing Change Detection : Environmental Monitoring and Applications. Taylor &, Francis, London, 1999.

[8] J.Fox, Land-use and land cover change in montane mainland southeast asia,", Environmental Manage- ment 3 (2005) 394–403.

[9] H. Dibsa, S. Mansora, N. Ahmadab, B. Pradhan, Band-to-band registration model for near-equatorial earth observation satellite images with the use of automatic control point extraction, International Journal of Remote Sensing.

[10] A. D. Ziegler, J.M.Fox, J. Xu, The rubber juggernaut, Science 324 (5930) (2009) 1024–1025.
[11] C. C. Mann, Addicted to rubber, Science 325 (5940) (2009) 565–566.
[12] H. Li, Y. Ma, T.M.Aide, W. Liu, Past, present and future land-use in xishuangbanna, china and the implications for carbon dynamics, Forest Ecology and Management, 255 (1) (2008) 16–24.
[13] H. Hu, W.Liu, M. Cao, Impact of land use and land cover changes on ecosystem services in menglun, xishuangbanna, southwest china,, Environmental Monitoring and Assessment 46 (1-3) (2008) 147–156.
[14] D. H., M. O. Idree, V. Saeidi, S. Mansor, Automatic keypoints extraction from uav image with refine and improved scale invariant features transform (ri-sift), International Journal of Geoinformatics 12 (3).
[15] H. Dibs, M. O. Idrees, G. B. A. Alsalhin, Hierarchical classification approach for mapping rubber tree growth using per-pixel and object-oriented classifiers with spot-5 imagery, The Egyptian Journal of Remote Sensing and Space Sciences, Production and hosting by Elsevier B.V.
URL http://dx.doi.org/10.1016/j.ejrs.2017.01.004.
[16] A. Ekandinata, A. Widayati, Rubber agroforest identification using object-based classification in bungo district, in: The 25th Asian Conference on Remote Sensing, Chiang Mai, Jambi, Indonesia, 2004.
[17] K. Hurni, Rubber in laos: Detection of actual and as- sessment of potential plantations in lao pdr using gis and remote sensing technologies, master thesis," (2008).
[18] E. V. Ranst, H. Tang, R. Groenemans, S. Sinthurahat, Application of fuzzy logic to land suitability for rubber production in peninsular, Thailand, Geodema 70 (1) (1996) 1–19.
[19] L. Zhe, M. F. Jefferson, Integrating mahalanobis typicalities with a neural network for rubber distri- bution mapping, Remote Sensing Letters 2 (2) (2011) 157–166.
[20] C. Bishop, Characterization of branching in two hevea brasiliensis clones, Journal of Experimental Botany, "Pattern Recognition and Machine Learning," 55 (399) (2006) 1045–1051, springer, New York.
[21] J. R. Quinlan, Induction of decision trees. machine learning 1 (1) (1986) 81–106.
[22] D. L. Civco, Artificial neural networks for land cover classification and mapping, International Journal of Geographical Information Science 7 (2) (1993) 173–186.
[23] Z.Li, J. R. Eastman, Commitment and typicality measures for the self-organizing map,", International Journal of Remote Sensing 31 (16) (2010) 4265–4280.
[24] C. D. Lippitt, J. Rogan, Z. Li, J.R.Eastman, Mapping selective logging in mixed deciduousforest: A comparison of machine learning algorithms,"photogrammetric, Engineering and Remote Sensing 74 (10) (2008) 1201–1211.
[25] Z. Li, undefined Jefferson, Mapping rubber tree growth in mainland southeast asia using time-series modis 250 m ndvi and statistical data, jefferson 960 carling avenue, Vol. 1, Ottawa, Ontario, 2011.
[26] F. Sangermano, R. Eastman, Linking gis and ecology:the use of mahalanobistypicalities to model species distribution, in: G. D. BuzaiMemorias (Ed.), XI Conferencia Iberoamericana de Sistemas de Informa- ción Geográfica, Buenos Aires, 2007.
[27] P. A. Hernandez, I. Franke, S. K. Herzog, V. Pacheco, L. Paniagua, H. L. Quintana, A. Soto, J. J. Swenson, C. Tovar, T. H. Valqui, J. Vargas, B. E. Young, Predicting species distributions in poorly- studied landscapes, Biodiversity and Conservation 17 (6) (2008) 1353–1366.
[28] J. Chang, M. C. Hansen, K. Pittman, M.Carroll, C. Di-Miceli, Corn and soybean mapping in the united states using modis time-series, Data Sets, Agronomy Journal 99 (6) (2007) 654–1664.
[29] R. Katawatin, P. H. Crown, D. L. Klita, Mapping dry season crops in thailand using landsat-5 tm data,", Canadian Journal of Remote Sensing 22 (4) (1996) 349–472v.

[30] A. J. W. D. Wit, J. G. P. W. Clevers, Efficiency and accuracy of per-field classification for operational crop mapping,", International Journal of Remote Sensing 25 (20) (2004) 4091–4112.
[31] M. A. Wulder, S. M. Ortlepp, J.C.White, S. Maxwell, Evaluation of landsat-7 slc-off image products for forest change detection,", Canadian Journal of Remote Sensing 34 (2) (2008) 93–99.
[32] F. Rembold, F. Maselli, Estimating inter-annual crop area variation using multi-resolution satellite sensor images, International Journal of Remote Sensing 2525 (2004) 2641–2647.
[33] F. Rembold, F. Maselli, Estimation of inter-annual crop area variation by the application of spectral angle mapping to low resolution multitemporal ndvi images,"photogrammetric, Engineering and Remote Sensing 72 (1) (2006) 55–62.
[34] H. R. Matinfar, F. Sarmadian, S. K. A. Panah, R. J. Heck, Comparisons of object-oriented and pixel- based classification of land use/land cover types based on lansadsat7, etm+ spectral bands (case study arid region of iran), American-Eurasian J. Agric. & Environ. Sci 2 (4) (2008) 448–456, iSSN 1818-6769.
[35] Z. Jingxiong, R. P. K, An evaluation of fuzzy approaches to mapping land cover from aerial photographs, EHS 9Xc UK, Street, Edinburgh, 1997.
[36] G. H. S, D. Wenche, E. Gunnar, Norwegian institute of land inventory, Vol. 115, P.O. Box, 2002, p. 1430.
[37] S. Khorram, J. A. Brockaus, H. M. Cheshire, Comparison of landsat mss and tm data for urban land use classification, IEEE Trans. on Geoscience and Remote sensing 25 (1987) 238–243.
[38] J. R. Baker, S. A. Briggs, V. Gordon, A. R. Jones, J. J. Settle, J. R. G. Townshend, B. K. Wyatt, Advances in classification for land cover mapping using spot hrv, International Journal of Remote Sensing 12 (1991) 1075–1085.
[39] D. V. K. N. Rao*, S. Meti, A. S. Nair, K. I. Punnoose, Rubber research institute of india, in: Agron- omy/Soils Division, Rubber Research Institute of India, Kottayam", 2002, pp. 686–9009.
[40] L. Nordin, A. Shahruddin, H. Mariamni, Application of airsar data to oil palm tree characterization, in: MACRES Bulletin, Kuala Lumpur, 2002.
[41] C. Kontoes, An experimental system for the integration of gis data in knowledge-based image analysis for remote sensing of agriculture, Int J Geogr Inf Syst 7 (1993) 247.
[42] H. Li, Y. Ma, T. M. Aide, W. Liu, Xishuangbanna tropical botanical garden, Chinese Academy of Sciences, 88 Xuefu Road, Kunming 650223.
[43] N. Ali, K. Jusoff, S. Ali, N. Mokhtar, A. S. A. Salamat, The factors influencing students' performance at universiti teknologi mara, Management Science and Engineering 3 (4).
[44] J. S., B. E, Methodology for mapping non-forest wood elements using historic cadastralmaps and aerial photographs as a basis for management, czech university of life (2009).
[45] H. M. Z. shafri, F. S. H. Ramle, A comparison of supper vector machine and decision tree classification using satellite data of langkawi island, in: Department of Civil Engineering, Faculty of Engineering, University Putra Malaysia ,43400 serdang, Selangor ,Malaysia, 2009.
[46] J. R. Anderson, E. E. Hardy, J. T. Roach, R. E. Witmer, land use and land cover classification system for use with remote sensor data, u.s, Geol. Survey Prof. Paper 964.
[47] C. C. Liu, Image processing of formosat-2 data for monitoring the south asia tsunami, International Journal of Remote Sensing 28 (13–14) (2007) 3093–3111.
8 (13–14) (2007) 3093–3111.

الخلاصة

زراعة اشجار المطاط في مختلف البلدان حول العالم توسعت بشكل سريع باراضي لم تكن معروفة في زراعة مثل هكذا انواع من النبات. تقدير ورسم خرائط توزيع نمو أشجار المطاط في هذه المناطق هو ضروري جدا للحصول على فهم أفضل للآثار التغيرات في الغطاء الأرضي على الكربون ودورة المياه، وكذلك إنتاجية اللاتكس (المطاط) في مختلف الأعمار. العديد من تقنيات الاستشعار عن بعد التي استخدمت لتقدير الغطاء الأرضي / استخدام الأراضي لرسم الخرائط ومراقبة توزيع نمو أشجار المطاط استنادا إلى مختلف خوارزميات تصنيف الاستشعار عن بعد (احتمال الحد الأقصى، تصنيف SAM، شجرة القرار وخوارزمية مسافة المهنالبس) مع أنواع مختلفة من البيانات (المتعددة الأطياف، الطيفي أو إحصائية) باستخدام العديد من أجهزة الاستشعار.