SUB-PIXEL AND MAXIMUM LIKELIHOOD CLASSIFICATION OF LANDSAT ETM+ IMAGES FOR DETECTING ILLEGAL LOGGING AND MAPPING TROPICAL RAIN FOREST COVER TYPES IN BERAU, EAST KALIMANTAN, INDONESIA

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ABSTRACT:

The tropical forest is depleting at a fast rate due to deforestation and degradation. Illegal logging was reported to be the cause of 50% of the deforestation. Illegal logging is a very pressing issue in Indonesia that is threatening the sustainability of forest management. The detection of the single felling tree which can be characterized as a specific type of illegal logging can provide information for the assessment of related Criteria and Indicator (C&I) of Sustainable Forest Management (SFM) and therefore support the certification of Sustainable Forest Management. This study aims to detect single tree felling in the tropical forest using Landsat-7 ETM+ satellite data and two types of classifiers i.e. maximum likelihood classifier and the sub-pixel classifier. Furthermore, it aims to assess the output of the first objective to support SFM through evaluation of specific C&I. Field data of new logged points representing single tree felling was collected during fieldwork in East Kalimantan, Indonesia in September 2003. The Landsat image was classified using maximum likelihood and sub-pixel classification. The results showed that the accuracy of the sub-pixel classification was higher than the maximum likelihood classification of the 30 m resolution image with an overall accuracy and kappa of 89% and 0.75 versus 79 % and 0.57 respectively. Consequently, more accurate detection of single tree felling can be achieved using the sub-pixel classifier and Landsat-7 ETM+ image. The extracted information can be characterized as planned or illegal with the use of GIS and expert knowledge which helped to identify specific indicators of SFM related with illegal single tree felling. The measurement of these indicators will ultimately support the SFM assessment.

1. INTRODUCTION

Forests are one of the world's most important renewable natural resources that serve various economical, social and environmental functions. Tropical forest, which comprises 47% of the worlds total forest area, has the highest economic and environmental value. Although, tropical forests have high importance due to its values, they are decreasing quantitatively as well as qualitatively because of various problems. Deforestation and forest degradation have been emerging as more and more important issues of the world's forestry sector. An area of 16.1 million ha of forests was lost every year during the 1990s, of which 15.2 million ha were in the tropics. The continuous depletion of forest resources is not only creating a serious threat to the regular supply of forest products but also resulting in a lot of negative environmental impact e.g. global warming, biodiversity loss etc. However, the world community has already realized the consequences and started to emphasize the sustainability of forest resources. United Nations Conference on Environment and Development (UNCED) held in June 1992 in Rio de Janeiro was the significant milestone in this regard.

Indonesia is rich in its forest resources. About 60% of country's total land area is covered by forest representing approximately 10% of the world's total tropical forest area. Timber has been an important source of national income since commercial logging started in the early 1960s. Concession holders carry out most of the management and harvesting activities. Selective Cutting and Planting (TPTI) is the commonly used silvicultural system in natural production forests of Indonesia. A series of activities has been established by the national guidelines for the implementation of the system to achieve the goal of sustainable forest management.

But, there are a lot of problems toward achieving the goal of sustainable forest management in Indonesia. Massive deforestation due to transmigration and illegal felling is one of the big problems. It has been estimated that about 50% of Indonesian total timber production comes from illegal means. The situation is worsening these days due to the change arising from the economic crisis, a decline in law and order, legal change arising from a movement calling for democracy, reform and change and new decentralization law. The new laws have empowered the district government to issue the small forest concession and even to collect some revenue on their own decision

The importance of remote sensing (RS) to generate information for forest management has been widely recognized. It is the only way to acquire repetitive biophysical data for large geographic area at reasonable cost, accuracy and effort.

Many studies have been carried out on the use of RS products to detect tropical deforestation. These studies mainly concentrated with land cover change from forest to non-forest etc and have been proved very useful for that purpose. But the possibility of using RS data to detect selective logging is poorly studied. As the selective felling is the adopted silvicultural practice of the Indonesian Forest Management System, only land cover change does not fully support the detection of spatial extent and intensity of such logging. In addition, Illegal loggers, who are only interested with timber quality and easy accessibility, generally carry out the selective logging. Though, it is clear that the selectively logged points become similar to other area in short period of time due to the fast growing nature of tropical forest it should be quite different for some period as felling of single tree creates an average of about 400 m^2 of opening in such forest. Therefore, there is a possibility of detecting such newly logged points using medium resolution image data. In addition, integration of some geographic information system (GIS) operation with remote sensing data can strengthen the analysis. For example, the location of road is quite important for planned as well as unplanned, legal or illegal logging. Whatever be the methods, there is no doubt that if such selectively logged points can be identified with known level of error, it will be quite useful to support SFM certification, to monitor illegal logging and to take rehabilitation measures.

Moreover, most of the work that has been done to detect illegal logging so far used the traditional maximum Likelihood Classifier. So far Maximum Likelihood has not achieved a good accuracy in classifying illegal logging using medium spatial resolution satellite data such as Landsat TM images. Sub-pixel classifier has better chance to classify illegal logging because in most of the cases it is a one or less than one pixel issue when one tree is cut.

The objective of this research was to compare the ability of Sub-pixel Classifier and the traditional Maximum Likelihood Classifier in detecting illegal logging and mapping tropical forest cover types in Labanan Forest, East Kalimantan, Indonesia.

2. STUDY AREA

2.1 Description

The study area is located in East Kalimantan in the Island of Borneo (Indonesia) between latitude 2°10' N and 1°45'N, and longitude 116°55' E and 117°20' E. The Labanan forest is located in a lowland dipterocarp forest and is currently under adaptive collaborative management (ACM) to achieve sustainable management of the forest.

The average rainfall is 2000 mm per year. The topography is undulating to steeply rolling, raising from sea level in the east near the confluence of the Segah and Kelai river to over 500 m in the foothills of the mountains to the west of Labanan (Bhandari, 2003). The study area is surrounded by four transmigration villages with a total population of 3,000. There are nine indigenous villages in the area with a population of 4,000. The center city of Berau is Tanjung Redeb with a population of 13,000. Most of the transmigrated people are active in agriculture.

2.2 Forest Management System

Forest management operations started in the Labanan concession in 1974 under PT Inhutani I. The area was co-managed by the BFMP (Berau Forest Management Project) from 1996 (BFMP, 2002) to 2002. BFMP is a European Union project, which was intended as an operational level demonstration of sustainable forest management of tropical forest. Environmental and economic sustainability of the management were assessed through a variety of criteria and indicator.

This area is now under adaptive collaborative management headed by the ACM company PT. Hutan Sanggam Labanan Lestari. The main actors in this ACM are (a) Pemerintah Kabubaten Berau with 50% share; (b) PT. Inhutani with 30% share; and (c) Perusda Sylva Kaltim Sejahtera with 20% share.

Adaptive collaborative management (ACM) is founded on a learning process of adapting forest management strategies in the course of time. Collaboration among the stakeholders is an essential part of ACM in which the local community is unavoidably involved. The issue in ACM is to learn from knowledge and experience, and to improve the capability of dealing with the complex and dynamic interaction between humans and the natural components in forest management. However, this newly implemented system is under heavy pressure of illegal logging.

The entire concession area covers 83,300 ha; 54,600 ha under permanent production, 27,000 ha under limited production and 1,700 ha used for other purposes. Logging activities are carried out according to the Indonesian Selective Cutting and Planting (TPTI) sylviculture system. Based on this system the Labanan concession area is divided into seven RKL's (Recana Karya Lima tahun or 5 years plan) (Figure 1). Each RKL, representing a 5-year plan, is further divided into five annual coupes (RKT's). An average of 8 trees per ha are logged at 35 years interval; only commercial species with dbh ≥ 50 cm are logged (Sist *et al.*, 2003). Logging has been taking place progressively since 1976. Large parts of the natural forest in Labanan have already been logged over (RKL1 to 5). At present logging is carried out in RKL6 whereas RKL7 is still unlogged.

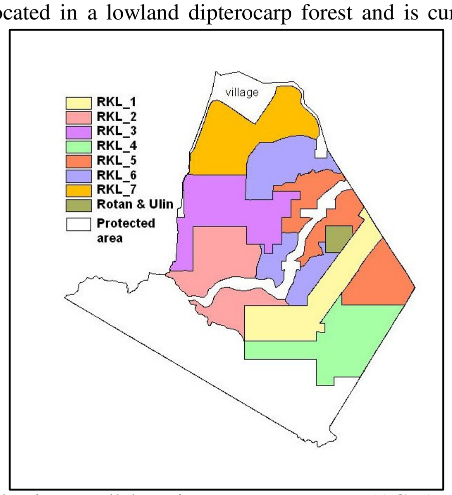


Figure 1. Labanan concession: 5 year working plan

2.3 Illegal Logging of Single Tree

Like in many forested areas in Indonesia, the Labanan concession is also affected by illegal logging. Previous research in this area by Bhandari (2003) showed evidence of a particular type of illegal logging in RKL one i.e. illegal felling of single trees. Detection of single-tree felling can assist the actors in ACM to assess the occurrence, location and extent of this particular type of illegal logging and therefore contribute to the sustainable management of the Labanan concession. The test site for the purpose of classifying and detecting single tree felling in the Labanan concession is reduced to the area of RKL1 for the following reasons:

2.3.1 Evidence of illegal logging

Previous research by Bhandari (2003) showed evidence of single tree felling in RKL1. In addition early investigation with the local people, company officers and my own field observations revealed that RKL1 has suffered a lot from single tree felling.

2.3.2 Accessibility

RKL1 is located at the official entrance to the concession area through the existing road network which provides access to the villages and the market in Tanjung Redeb. Further more, a major part of RKL1 is located alongside this road (Figure 2). Consequently the accessibility of RKL1 is very good which makes it attractive for illegal loggers.

2.3.3 Oldest logged RKL

RKL1 was the first logged RKL in 1976 and will be re-entered in 2011 for the second harvest cycle according to the long-term management plan of the company. The forest has regenerated itself and the chance of finding good quality timber with a diameter larger than 50cm is high compared to the other areas in the concession. This situation also creates opportunities for illegal loggers.

2.3.4 Terrain condition

The terrain condition in RKL1 has no very steep slopes as compared to the protected area and is thus favorable for felling activities

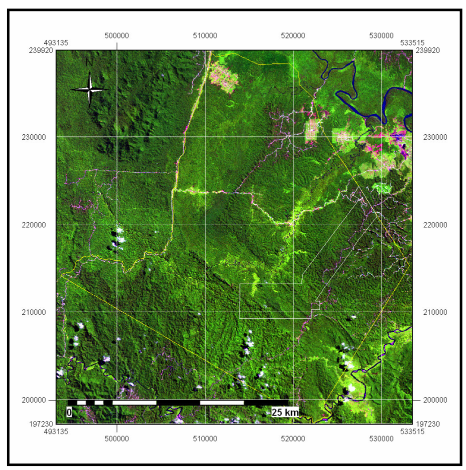


Figure 2. Location of RKL1 within Labanan concession

2.4 Collection of Ground Truth

The purpose of the fieldwork was to collect training data for the image classification and testing data for the accuracy assessment of the classification output. The fieldwork was conducted in September 2003 in the Labanan concession, East Kalimantan, Indonesia. Before going into the field for data collection, a consultation session was arranged with the head of planning & inventory of Pt. Inhutani 1. This was to identify areas in the concession where illegal felling of single trees was taking place. Four areas were identified i.e. RKL1, RKL4, RKL5 and the protection area. However, RKL1 was found to have the highest number of single tree felling which was the reason to reducing the area for analysis to RKL1.

3. REMOTE SENSING DATA ANALYSIS

This method section describes the activities that were carried out to detect single tree felling using remotely sensed data. The first step was pre-processing of the Landsat-7 ETM+ image. The image was shifted using the main road map and georeferenced using the ground control points collected in the field. The second step was the image classification using the Maximum Likelihood ML (Figure 3) and the Sub-pixel SP classifier (Figure 4).

3.1 Image classification

The ML image classification was performed on two data sets i.e. 30 m resolution and 15 m resolution. The signature for each class was selected by displaying the ground truth shape file (training data set) over the image and selecting the pixels with the respective ground truth one by one. The scatter plot space was used to evaluate the selected pixels in each category. New logged points (NLP) that were located close to the road were excluded, since these were likely to be misclassified as road.

3.1.1 Sub-pixel Classification

Although the SP classifier requires raw data, a georeferenced image was used because selecting *aoi* for the training set was not possible using a raw image. Prior to the signature derivation, pre-processing and environmental correction were performed. During the environmental correction cloud pixels were selected and removed.

Signature derivation:

Signature derivation and evaluation is an important part in the subpixel classification. There are two ways to derive a signature, manual and automatic. Manual derivation is used when whole pixel MOI can be used as training set. In this case, the material of interest (MOI) is the opening or disturbance caused by single tree felling was in subpixel fraction. For that reason the automatic signature derivation was used. The training set *aoi* was selected using the same NLP as in the ML classification. There are two other *aoi* files that can be used as input for the signature derivation (i.e. valid and false *aoi*). NLP outside RKL1 were used for valid *aoi.*

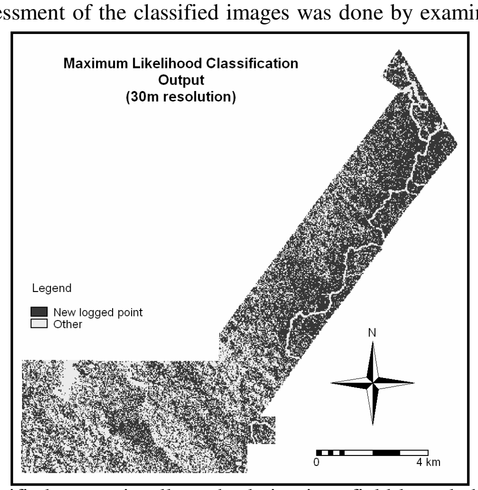
Signature evaluation:
The automatically generated signatures were evaluated upon the material fraction detection and the SEP value. It was also compared with the gap fraction found in the field.

Image Classification:
The classification was run using the selected signature. The default tolerance value was set at one and the number of output classes at eight which will result in eight different MOI fraction classes ranging from 0.20 to 1.0 with increments of 0.1. The eighth class with MOI fraction 0.90-1.0 was considered as the NLP class and the final result was a map with two classes, NLP and other.

Accuracy assessment and comparison

Fifty percent of the collected ground truth data (test data set) was used for the accuracy assessment. The test points were carefully chosen making sure that the test and the training data set were equally spread geographically. Each classified image was then crossed with the test data to generate a confusion matrix. The respective confusion matrices were then used to calculate the different accuracy measures i.e., producer's, user's accuracy, class mapping accuracy for each class and the overall accuracy. Kappa statistics and its variance were also calculated to test the significance of difference in accuracy. The significance of difference test between the confusion matrices was done using the *Z* test with $\alpha = 0.05$.

In addition to the quantitative assessment, a qualitative assessment of the classified images was done by examining the



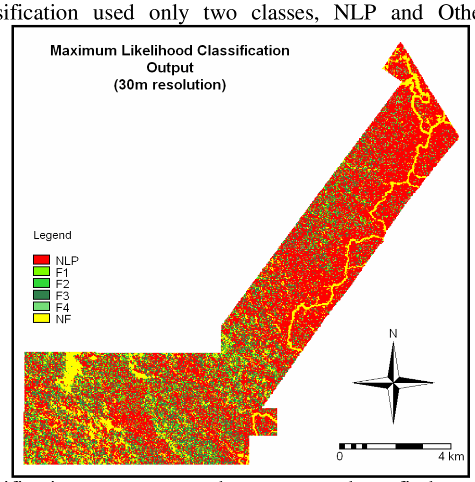
classified maps visually and relating it to field knowledge. This is to find out if the map reflects reality.

4. RESULTS AND DISCUSSIONS

The ML classification was performed using different numbers of input classes and two different image resolutions 30 and 15 meters.

4.1 ML Results Using Landsat 30 m Resolution Data

The ML classification of the original data was performed using different numbers of input classes. The first classification was done using six input classes (i.e. NLP, F1, F2, F3, F4 and NF). In the second classification no distinction was made between the forest classes, thus the input was NLP, F and NF. The third classification used only two classes, NLP and Other. The



classification output was then compared to find out which number of input classes gave the highest class accuracy for NLP. The best classification output in terms of NLP class accuracy was selected for comparison with the SP classification output.

Figure 5 presents the classification result using six input classes. The total detected NLP covers 3,946 ha of RKL1 which accounts for approximately 58.48% of the total area. The map shows a large amount of NLP detections along the main road in the upper right part of the image. The lower left part shows less NLP detections compared to the upper right part. Notice the road and the agriculture area in the upper left corner of the image. Figure 6 shows the same image in which the forest classes and the non forest classes were merged after classification.

Figure 5. Classified map of the original image using ML Classifier (6 classes)

Figure 7 presents the classification output using 3 input classes. This map shows less NLP detections compared to the first classification output. Again most of the NLP detections are found along the main road and smaller amount in the lower left part of the image. The total NLP detections amount to 2,193 ha of RKL1, approximately 32.5% of the area. This is less then the area found in the first classification.

Figure 6. NLP Detection Map derived from the 6 classes ML output map.

The result of the third classification shows much more NLP detections compared to the previous classifications. The total area covered by NLP is 5,362 ha which corresponds to 79.46% of the total RKL1 area. Observe the detection of the road and agriculture area in the left part of the image.

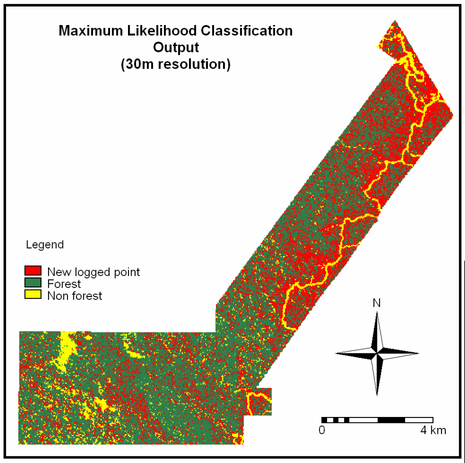


Figure 7. Classified map of the original image using ML Classifier (3 classes

4.2 ML Results Using Landsat 15 m resolution data

Figure 8 shows the output of the classification of the improved image. In general, the same trend in distribution of NLP detections can be observed as for the original image. However, the image shows a more distinct pattern. The area covered by NLP is 1,624 ha, which is about 24.07% of the total RKL1 area.

Figure 8. Classified map of the improved image using ML Classifier (3 classes).

4.3 Accuracy Assessment of the ML Classification

4.3.1 Landsat-7 ETM+ 30 m resolution data

The quantitative accuracy assessment was performed to obtain more exact information on how accurate the image classification method can detect single tree felling. The quantitative accuracy assessment was carried out by calculating the overall accuracy, class mapping accuracy and kappa statistic based on the confusion matrix. The confusion matrix was generated after crossing the classified map with the test data set. Confusion matrices are presented a graphical representation of these accuracy measures for the three ML classifications. Notice the kappa value of the second classification (KA= 71). It is much higher compared to the first (KA= 53) and the third classification (K= 46). The overall accuracy (OA= 81%) is also much higher than the other two classifications (OA= 66% versus OA= 71%). This explains the more distinct classes that were observed in the output map (Figure 9) as compared to the other two outputs. However, the class mapping accuracy of NLP (CA nlp= 58%) which is the major issue in this research is slightly lower than in the first classification output (CA nlp= 61%). For this reason, the first classification was selected for further analysis

Figure 9. Comparison of Accuracies of ML Classified Maps with different number of classes. Note: OA= Overall Accuracy; KA= Kappa; CA nlp= Class Accuracy NLP.

4. 3.2 Landsat-7 ETM+ 15 m Resolution Data

Classification of the improved image increased the different accuracy measures slightly compared to the second classification of the original image. The kappa and the class accuracy of NLP were increased with 2% and the overall accuracy with 1%. The NLP class accuracy is 1% lower than the first classification of the original image. It would have been interesting to perform the classification using six input classes for a better comparison with the first classification of the original image. However, there was not enough time to carry it out.

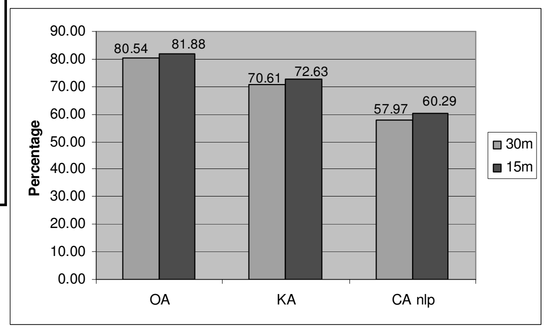
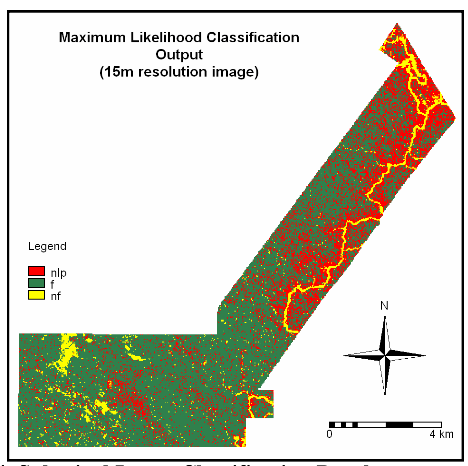


Figure 10. Comparison of Accuracies of ML Classified Maps (15 m versus 30 m). Note: OA= Overall Accuracy; KA= Kappa; CA nlp= Class Accuracy NLP.



4.4 Sub-pixel Image Classification Results

The image classification was performed using band 1–5 and 7 of Landsat-7 ETM+ (30 m resolution). The output of the SP classification shows eight different MOI fraction classes ranging from 0.2 to 1. There are no detections for MOI fractions less than 20%, because this is below the SP classifier threshold.

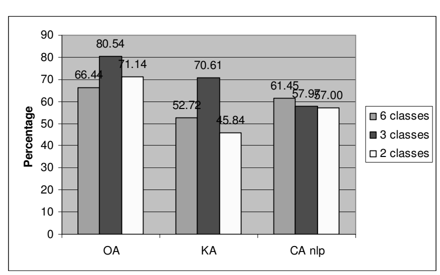


Figure 11 shows the classified image after the merge. This map gives better view of the NLP detections compared to the original map. The map illustrated in Figure 11 shows the NLP detections in RKL1. It shows a large amount of NLP detections. The area covered by these detections is 3019ha which equals to approximately 44.47% of the total area of RKL1. Notice the spatial distribution of the NLP in the map. It shows a large concentration of NLP along the main road seen here as a curved line feature. Moving in North West direction down the road the concentration of NLP decreases slightly at first but increases again up to where the road ends. From then on it decreases again in East West direction with some variation in intensity

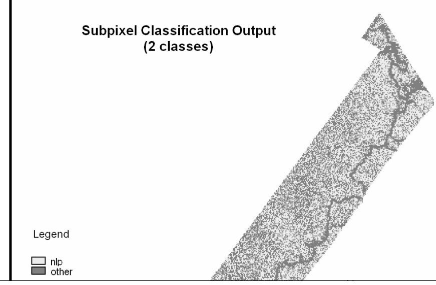


Figure 11. NLP Detection Map derived from SP output map

4.5 Accuracy Assessment of the Classification Result

The class mapping accuracy of NLP is 70.69% which is higher than what the ML classifier produced. Moreover, the kappa is 0.75 which can be considered acceptable.

4.6 Comparison of Classification Method

4.6.1 Classification Accuracies

Figure 12. shows a comparison of accuracies between the ML and the SP classified images. The SP classification scored higher in all three accuracy measures compared to the ML classification. The significance of this difference was tested using the Z-test. The Z-test showed that the kappa of the ML map (0.57 versus 0.75) is significantly lower than the kappa of the SP map (Z-test for kappa, Z= 2.04, P= 0.042). Therefore, it can be concluded that the SP method performed better in detecting single tree felling

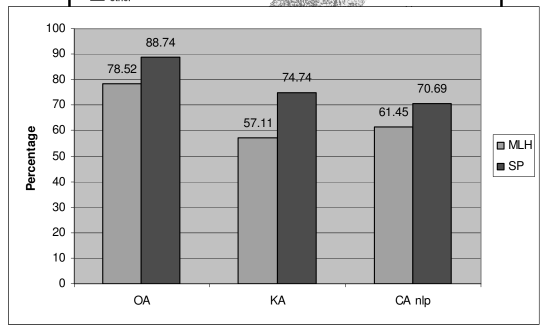


Figure 12. Comparison of accuracies between ML and SP classified maps. Note: OA: Overall Accuracy, KA: Kappa, CA nlp: Class Accuracy of NLP.

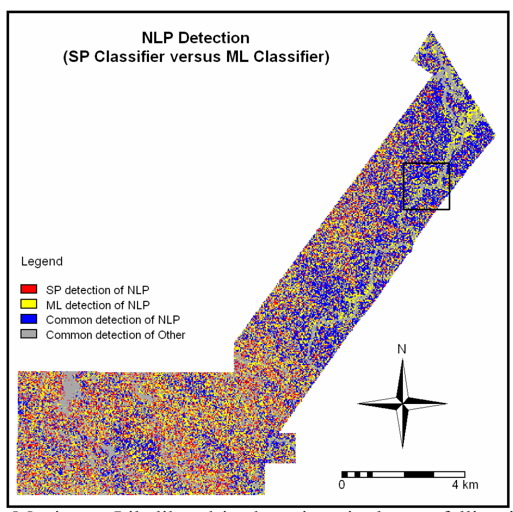
4.7 Single Tree Detection

This section deals with the detection of NLP by the ML classifier compared to the SP classifier since the latter was proven to perform better (see previous section). NLP detections by both classifiers are shown in Figure 14, which is a subset of the map shown in Figure 13. NLP detection by SP classifier is depicted in red, while ML detections are shown in yellow. Common NLP detections are depicted in blue. A quantification of the difference in detection between the classifiers is done. Approximately 14% of the NLP detected by the SP classifier was misclassified as other by the ML classifier. Moreover, the ML classifier misclassified 28% of the pixels that was detected as other by the SP classifier, as NLP. This illustrates the difference in detection between the ML classifier and the SP classifier.

The map in Figure 14 gives an idea where the ML misclassified pixels as NLP and where it missed pixels containing NLP. The red colour depicts SP detections of NLP which were missed by the ML classifier which is about 14% of the total amount of pixels detected. Most of these pixels are found in the lower left part of the image. The pixels that were misclassified as NLP by the ML are coloured yellow. Most of these pixels are also locate in the lower left part of the image, but many are also found along the main road. The pixels that were correctly classified by ML classifier is shown in blue. These are concentrated along the road.

The accuracy of the Maximum Likelihood classification of the 30 m resolution image was found lower than the IMAGINE Subpixel classifier. This finding is in agreement with the finding of Bhandari (2003) who found similar results in detecting selective logging in the Labanan concession using the IMAGINE Subpixel classifier.

The significance of difference was tested positive which means that the IMAGINE Subpixel classifier is a better method than



the Maximum Likelihood in detecting single tree felling in the tropical forest using Landsat-7 ETM+ imagery. Furthermore, the class mapping accuracy of single tree felling by the Maximum Likelihood classifier was also lower than the IMAGINE Subpixel classifier (61% versus 71%). The second additional data set used in the Maximum Likelihood classification improved the class mapping accuracy of single tree felling with 2% compared to the 30 m resolution image. But due to time limitation it was not studied more in depth.

Comparison of both classified maps revealed that 31% of the NLP was commonly detected by both classifiers. The ML classifier detected 28% more NLP than the Subpixel classifier, but missed 14% of NLP that was detected by the SP classifier. The 28% that was detected by ML classifier was classified as "Other" by the SP. The superior performance can be explained by the different signature derivation process between these two classification techniques. The Maximum Likelihood classifier develops signatures by combining the spectra of training set pixels which includes the contributions of all the materials in the training set. Whereas, the signature developed in the IMAGINE Subpixel classifier is the extracted component of the pixel spectra that is most common to the training set. Upon deriving the signature, the Maximum Likelihood classifier identifies pixels in the scene that have the same spectral properties as the signature. The IMAGINE Subpixel classifier, however, estimates and removes the subpixel background and compares the residual spectrum with the signature.

The IMAGINE Subpixel classifier also addresses the spectral distortion of atmosphere and sun angle effects within an image. For this reason, the developed signature of the new logged points (i.e. single tree felling) in this research can be applied to other Landsat-7 ETM+ images captured at different times and other parts of the concession. However, the discrimination of single tree felling from other materials with similar reflectance should be carried out using GIS and additional data such as logging maps and land use maps.

Furthermore, the Maximum Likelihood classifier has been used for many years and is supported by many GIS & RS based software such as ILWIS and ERDAS. It is also straight forward in implementation. The MAGINE Subpixel classifier on the other hand is a relatively new product that is only available with ERDAS. It is one of the few RS image processing software that deals with mixed pixels. The IMAGINE Subpixel classifier is not straight forward in use. A user with prior experience in using traditional supervised multi-spectral classifiers can get acquainted with the software in less than a day by running the tutorial. However, the specific signature derivation and image classification technique is more complex and will thus take more time to learn. But given the superior result of the IMAGINE Subpixel classifier compared to the Maximum Likelihood classifier it is worth to invest in the purchase and use of this new software. More importantly, the increasing number of illegal single tree felling RKL1 makes it necessary to have to an accurate method for detection of this type of logging

Figure 13. Comparison of NLP Detection by SP versus ML Classifier.

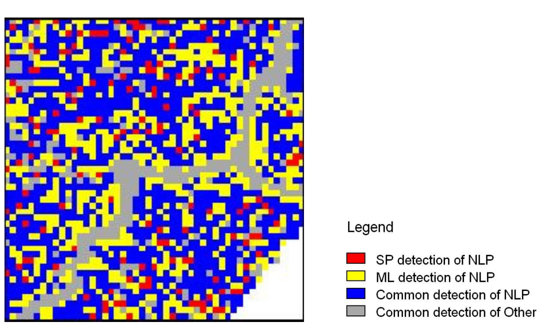


Figure 14. Subset of Map showing NLP detections by ML and SP Classifier.

5. CONCLUSIONS

The results of this study showed that single tree felling can be detected using Landsat-7 ETM+ image and the IMAGINE Subpixel Classifier. Detection was studied using logged points that were less than a year old. In addition, the use of GIS and other ancillary data combined with expert knowledge can help improve the result of image classification as well as characterize the felling as planned or illegal. The findings are listed according to the research questions stated in chapter one.

The IMAGINE Subpixel classifier produced a higher accuracy compared to the Maximum Likelihood Classifier in detecting single tree felling in the tropical forest using Landsat-7 ETM+ image.

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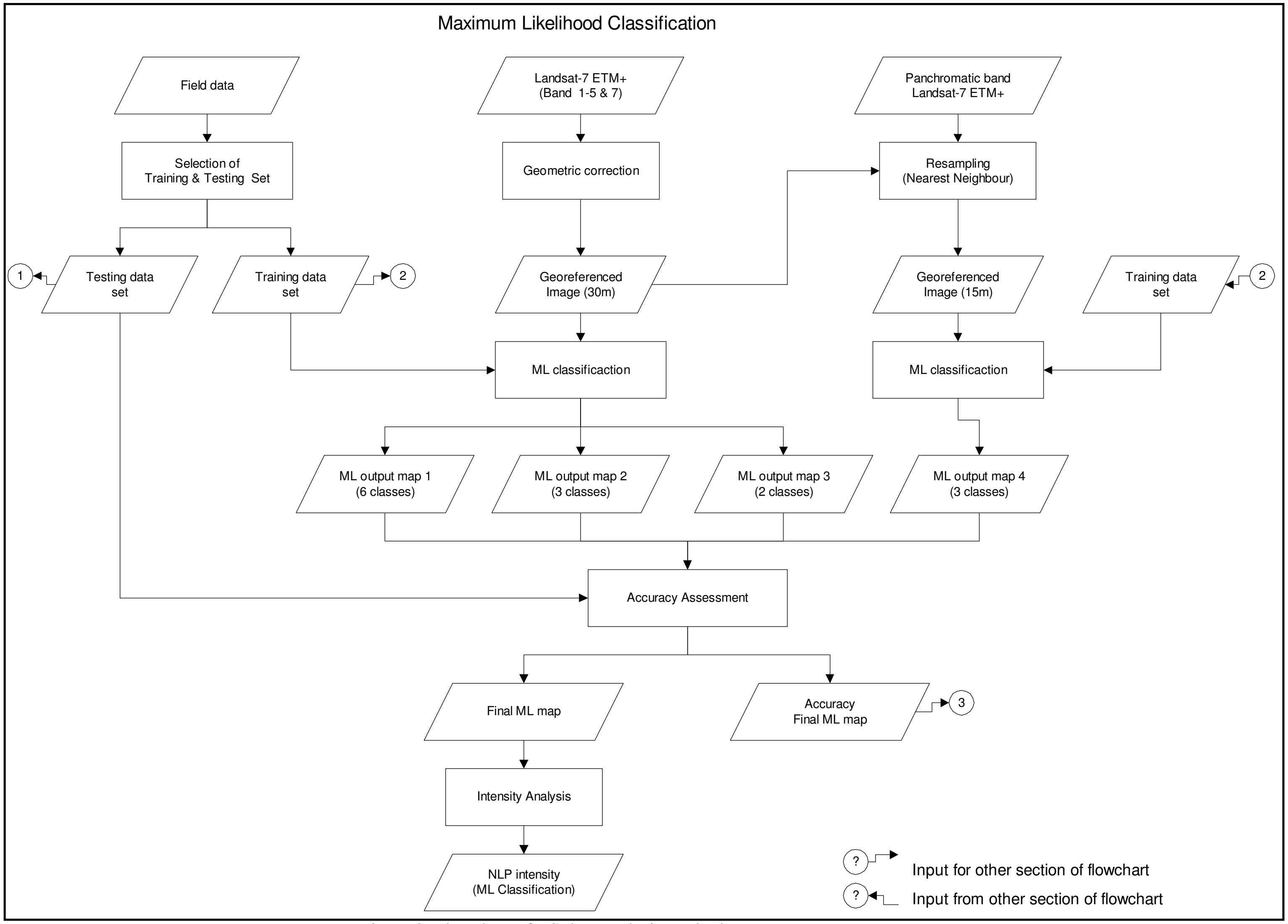

Figure 3. Flowchart of RS data analysis method

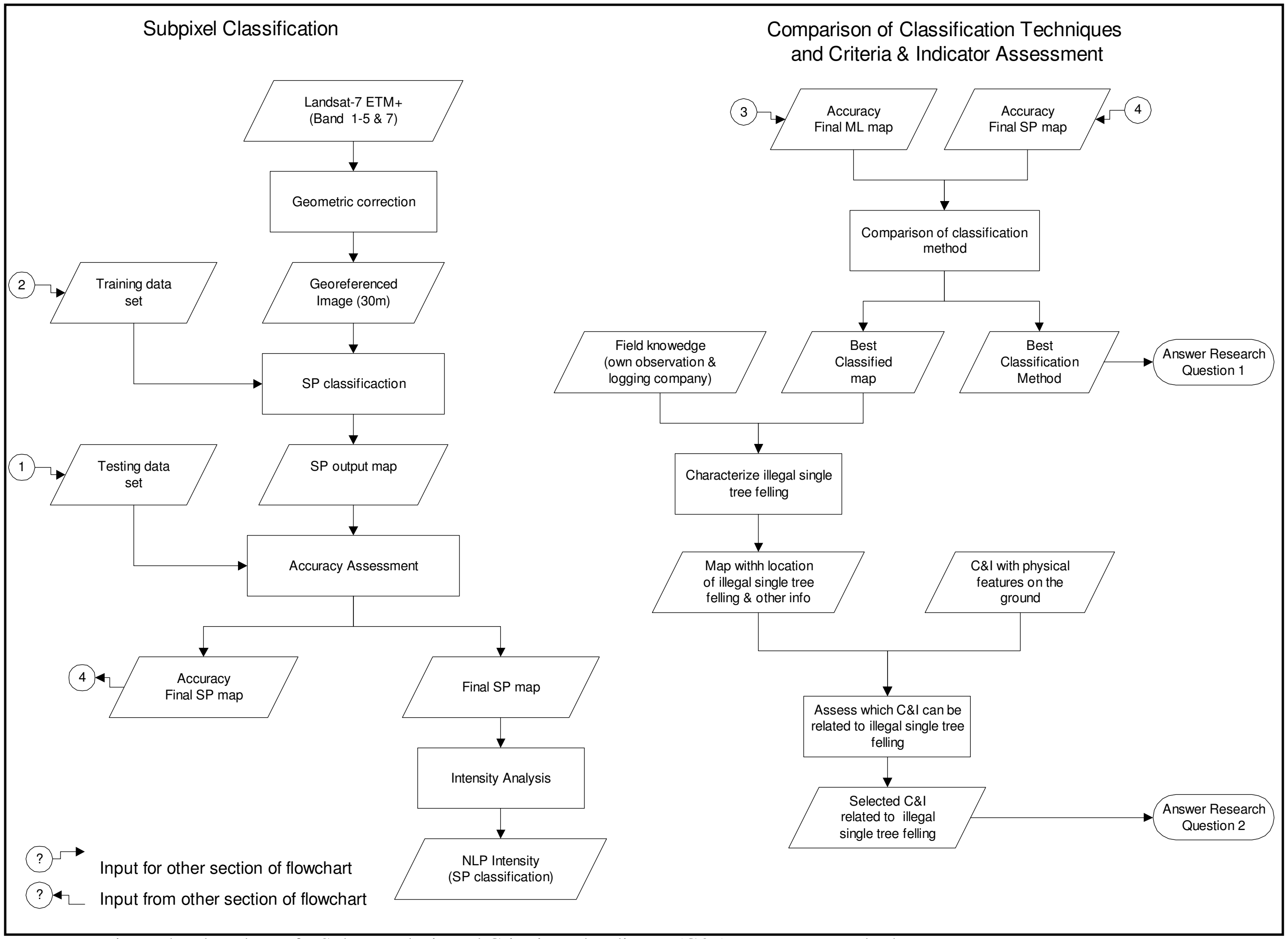

Figure 4. Flowchart of RS data analysis and Criteria and Indicator (C&I) assessment method