# Integration of Remotely Sensed Data and Experts Knowledge to Detect Illegal Logging in the Production Forest of East Kalimantan, Indonesia (Abstract)

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# APPLICATION OF SOFT CLASSIFICATION TECHNIQUES FOR FOREST COVER MAPPING

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## ABSTRACT

Forest cover mapping is necessary to monitor forest cover changes in order to support sustainable forest management. One of the most important factors that cause deforestation comes from Illegal logging. Illegal loggers were cutting trees selectively, based on tree-diameter and tree-species. Remote sensing is a promising tool, which can be used for detecting this type of logging and deforestation the tropical forest. This study applied two different soft classification techniques, i.e. fuzzy c-means classification and neural network method to classify forest cover as well as to detect illegal logging in a form of single tree felling. The classification results were accurately compared to the result of conventional maximum likelihood classification using confusion matrix. This study found that neural network method resulted in a more accurate detection of single tree felling, followed by maximum likelihood technique. Fuzzy c-means technique gave less satisfactorily result due to a strong overlapping between single tree felling and high density forest training classes.

Keywords : illegal logging, soft classification, fuzzy c-means, neural network, remote sensing

## 1. INTRODUCTION

One important part of the provision of environmental information by remotely sensed data is achieved through image classification [1]. This image classification relies on the assumptions that the study area are structured by a number of unique, internally homogeneous classes and that classification analysis based on reflectance data and ancillary data can be used to identify these unique classes with the aid of ground data.

Several recent studies related to image classification were done in the tropical forest, detecting forests cover changes due to forests harvesting [2-7]. These studies used Landsat images as main input data to perform image classification. One of studies made use of ancillary data, e.g. slope and elevation, in the classification [4]. Another study used combination of optical satellite data and radar data [6].

Different image classification techniques were applied to detect degradation and deforestation on a tropical forest. Fauzi [6] studied on the detection of logged-over forest using neural network method and compared the result with those of maximum likelihood method. Bhandari [7] detected loggedover forest using sub-pixel classifier and forest canopy density mapping and again, compared the classification result with fused image of maximum likelihood classification. Recently, Atmopawiro [3] was able to detect illegal logging by means of sub pixel classification with a reasonable accuracy.

## 2. DETECTION OF SINGLE TREE FELLING WITH SOFT CLASSIFICATION TECHNIQUES

In his study, Elias [8] mentioned that the opening area caused by a single tree felling ranged between 285 to 512 $m^2$, with an average of 396 $m^2$. Using Landsat 7 ETM+ data with 30 meters resolution, one pixel covers 900 $m^2$ of the area. Identification of an object which has size less than a single pixel is not recommended using hard (or conventional) classifier, such as maximum likelihood [9-13]. Detection of single tree felling by means of conventional classifier can not give satisfactorily results, as reported by several recent studies [2, 4-7].

Maximum likelihood method is developed for the classification of classes with the assumption that each pixel is pure and the object of interest is considered to be discrete and mutually exclusive [10, 13]. In the maximum likelihood, pixels are labeled to the class which has the highest posterior probability of membership [1]. This technique is often incapable to perform satisfactorily in the presence of mixed pixels, in which each pixel is occupied by more than one category [11]. Another assumption in maximum likelihood method is that the spectral intensities of the classes follow a normal distribution. Limitations of the algorithm may be one of the reasons, which can reduce the performance of such technique.

Single tree felling, occupying less than one pixel size, may be identified as mixed pixels, so-called fuzzy pixels. Fuzziness often occurs due to the presence of mixed pixels (particularly for coarse spatial resolution remotely sensed imagery) which are not completely occupied by a single, homogenous category [14].

So-called “soft” classifier is a technique that certainly can improve the classification of mixed pixels [10, 15, 16]. There are two “soft” classification methods that are widely used for image classification, namely fuzzy classification [10, 13, 17] and neural network [10, 18]. Fuzzy classifier works based on membership function and membership value [19]. On the other hand, neural network method works based on interconnected network of processing elements in order to find the optimal result [18, 20-22]. This study applied soft classification method of supervised fuzzy classification that is based on fuzzy c-means clustering algorithm [11, 13, 14, 23, 24] and neural network classification method, which can be applied in any type of data distribution as this method does not need normality assumption of data distribution [21].

## 3. METHOD

### 3.1. Datasets

This study considered a forest concession area in Berau District, East Kalimantan, Indonesia. The forest area has a size of about 83,000 hectare and has a type of natural production forest. This study used seven bands of Landsat 7 ETM images with 30×30 meters of pixel size, acquired on 31st of May 2003. The Landsat datasets were geometrically corrected and registered to a WGS 84 datum and UTM projection with an RMS error less than 1.0 pixel. A subset of Labanan concession area with size of 521 x 501 pixels was used for the classification in order to optimize effort and time for forest cover classification.

Fieldwork was carried out in the study area for five weeks from early September until mid October 2004 for collecting ground truth data. Field data recording illegal logging points and other forest classes were divided into two datasets. There were 424 sample data used in order to train the classification. Another 192 independent data were collected separately as test data in order to assess accuracy of the classification results.

### 3.2. Supervised Fuzzy c-means Method

Fuzzy c-means (FCM) method used in the study was proposed by Cannon [15]. In general, this method subdivides a dataset into c-clusters or classes. It begins by assigning pixels randomly to classes and by iterative operations, it moves pixels to other classes to minimize the generalized leastsquared-error [10].

For fuzzy supervised classification as performed in this study, we may change the algorithm that is used to derive an unsupervised classification. For doing this, the class centroids are determined from the training data giving the result of fuzzy membership value for a single pixel in each land cover class.

The supervised fuzzy c-means classification is based on the fuzzy c-means clustering algorithm [19]. Let X = $\{x_1, x_2, \ldots, x_n\}$ be a sample of n observations (pixels) in an s-dimensional Euclidian space (s is a number of spectral bands in the image). A fuzzy clustering is represented by a fuzzy set $\{U_{c \times n} \mid \mu_{ik} \, \varepsilon \, [0.0, 1.0]\}$ with reference to n pixels and c clusters or classes.

The interpretation is that U is a real c × n matrix consisting of elements denoted by $\mu_{ik}$, and $\mu_{ik}$ is the fuzzy membership value of an observation $x_k$ for the ith cluster. The fuzzy membership values range from 0.0 and 1.0 and are positively related to the strength of membership of a pixel to a specified class.

Various algorithms are available that aim to derive an optimal fuzzy c-means clustering. One widely used method operates by minimizing a generalized least squared error function, called $J_m$,

$$J_m = \sum_{k=1}^{n} \sum_{i=1}^{c} (\mu_{ik})^m (d_{ik})^2 \quad (1)$$

where m is the weighting exponent that controls the degree of fuzziness (increasing m tends to increase fuzziness usually, the value of m is set between 1.5 and 3.0), $d^2ik$ is a measure of the distance between each observation ($x_k$) and a fuzzy cluster center ($v_i$) [19].

Often, the Mahalanobis distance algorithm is used for pixels clustering. This distance is calculated with

$$d_{ik}^2 = (x_k - v_i)^T C^{-1} (x_k - v_i) \quad (2)$$

where C is the covariance matrix of the sample x, and superscript T indicates transposition of a matrix.

The Euclidian distance from pixel i to cluster center k is calculated with

$$d_{ik}^2 = \sum_{l=1}^{n} (x_{il} - c_{kl})^2 \quad (3)$$

And the centroids $c_i$ are computed as

$$c_{kl} = \sum_{i=1}^{n} u_{ki}^m x_{il} \Big/ \sum_{i=1}^{n} u_{ki}^m \quad (4)$$

This is simply a weighted average (with the elements u being the weights) of all pixels with respect to center (1 ≤ j ≤ p). The term $x_{il}$ is the measurement of the i-th pixel (1 ≤ i ≤ n) on the l-th spectral band or feature.

Each of the membership grade values $u_{ij}$ is updated according to its Euclidian distance from all cluster centers,

$$u_{ik} = \frac{1}{\sum_{c=1}^{p} \left( \frac{d_{ik}}{d_{ck}} \right)^{\frac{2}{(m-1)}}} \quad (5)$$

where $1 \leq i \leq p$ and $1 \leq k \leq n$ [19]. The procedure converges when the elements of membership grade matrix differ by no more than a small amount between iterations. This study, however, used Euclidian distance as well as Mahalanobis distance algorithm to observe the effect on the classification accuracy.

The minimization of the error function $J_m$ begins from random setting of $\mu_{ik}$. An optimal fuzzy partition is then sought iteratively to derive an unsupervised classification. The algorithm can, however, be modified for the derivation from the training data. This reduces the fuzzy c-means clustering algorithm to a one-step calculation, resulting in the fuzzy membership value for each pixel in each of the defined classes.

The classified pixels resulted from fuzzy classification must be converted to "crisp" in order to properly represent the final map. Some functions may be used for the defuzzification of these classified pixels, such as maximum criterion, mean of maximum and center of the area. This study arbitrarily made use of maximum function in the defuzzification stage.

## 3.3. Neural Network classification

In general, there are three phases in neural network classification. The first phase is a training procedure, using input data. The second is a validation phase that determines the success of training phase and the accuracy of the network when it is applied to unseen data. The last one is a classification phase which produces land cover map of an area [22].

This study implemented three-layered neural network consisting of a single input, hidden, and output layer, so-called multi-layer perceptron (MLP) neural network. The MLP neural network which is trained by back-propagation algorithm is commonly used for the image classification in Remote Sensing [25].

The input to a node in a neural network is the weighted sum of the outputs from the layer below, that is,

$$net_j = \sum_i w_{ji} o_i \tag{6}$$

This weighted sum is then transformed by the node activation function, usually a sigmoid function to produce the output node,

$$o_j = \frac{1}{1 + \exp(-net_j + \theta_j)} \tag{7}$$

where $\theta_j$, m, and k, are constants. The study, however, used sigmoid activation function to produce the output node. This function is often used in the neural network, resulting output from the node, a value between 0.0 and 1.0 [26]

Weights are updated during the training process according to the so-called "generalized delta rule":

$$\Delta w_{ji}(n+1) = \eta(\delta_j o_i) + \alpha \Delta w_{ji}(n) \tag{8}$$

Where $\Delta w_{ji}$ (n + 1) is the change of a weight connecting nodes i and j, in two successive layers, at the (n+1)th iteration, δj is the rate of change of error with respect to the output from node j, η is the learning rate, and α is a momentum term.

Learning rate is an adaptation of simple backpropagation algorithm, which is used to reduce training time and maintain stable convergence. This algorithm is very slow in the training stage, because it requires small learning rates for stable training. Adjusting learning rate to a higher value, the training time may be reduced, however it results in a more unstable training, and the network is more reluctant to be trapped in the local minima rather than the global one.

Momentum, on the other hand, is another adaptation of the simple back-propagation, which allows the neural network to respond not only to the local gradient, but also to recent trends in the error surface. This has effect of acting like a low pas filter, which allows the network to ignore small features in the error surface, so that the network is less prone to becoming trapped in local minima [27]. Further details on the neural network may be found in Atkinson and Tatnall [21].

# RESULT

## 4.1. Fuzzy c-means Classification Result

There were seven Landsat ETM bands, which were used for image classification. Based on training data evaluation, this combination provided the highest separability values among forest classes compared to the use of multi-spectral bands (band 1-5, and band 7) of Landsat ETM data.

The fuzzy exponent, fuzziness or overlap parameter determines the amount of fuzziness or class overlap. If this parameter is close to 1.0, allocation is crisp and no overlap is allowed [23]. For large values, there is a complete overlap and all clusters are identical. The fuzziness of the classification can be modulated by varying the magnitude of the fuzziness parameter. Ideally, it should be chosen to match the actual amount of overlap. However, class overlap is generally unknown. Although the fuzziness parameter is often set between 1.5 and 3.0, no clear arguments for the choice of these values are presented [10, 14]. This study used arbitrarily fuzzy overlap value of 2.0.

Clustering of unclassified pixels was carried out by measuring the distance (dissimilarity) between each observation (pixel) and a fuzzy cluster center by means of certain clustering algorithm. This study applied Euclidian and Mahalanobis clustering algorithms to measure such distance.

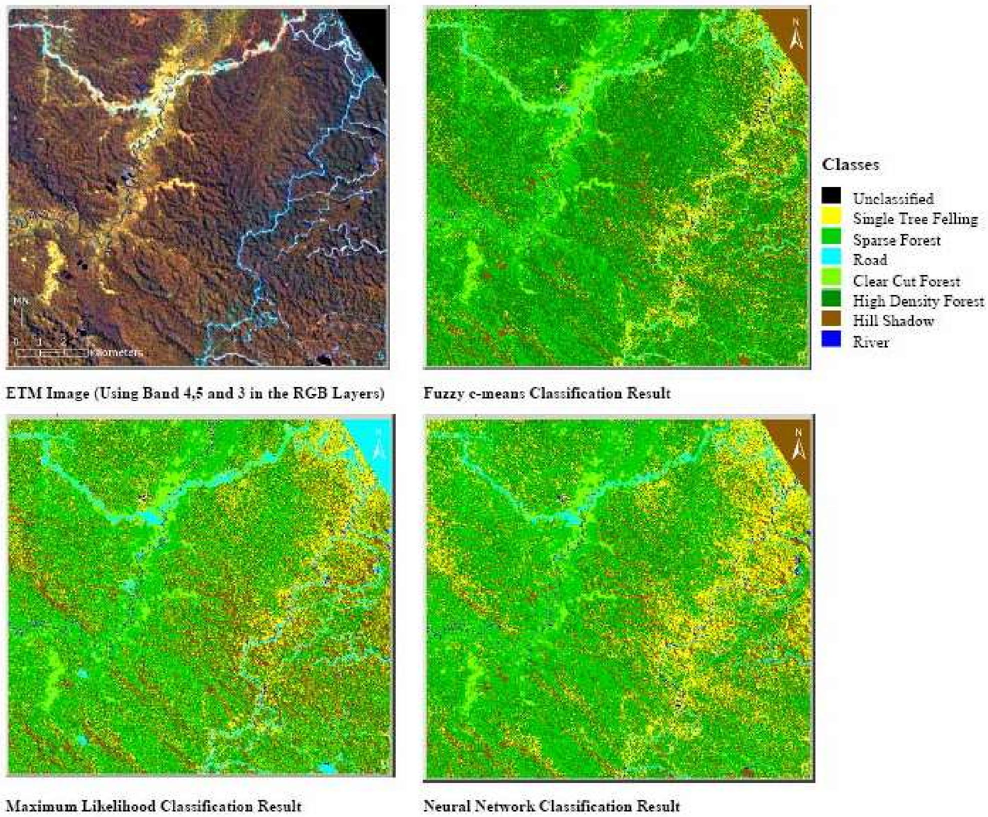


Figure 1. Results of Land Cover Classification in Subset of the Study Area

Using Mahalanobis distance algorithm, the fuzzy c-means was more aggressive to classify single tree felling (STF) class resulting higher classification accuracy of single tree felling class compared to the Euclidian distance algorithm.

In general, classification accuracy of fuzzy c-means using Euclidian distance is slightly higher than the accuracy of Mahalanobis distance.

## 4.2. Neural Network Classification Results

In the following analysis, Landsat ETM data was used as an input for neural network classification and single hidden layer architecture was applied. Kanellopoulos [25] in his study has found that the use of a single hidden layer was sufficient for most classification problems, however, once the number of inputs gets near 20, additional flexibility was required as provided by a two hidden layer network.

Total system Root Mean Squared (RMS) error of 0.0001 was determined as a convergence point. Training was stopped when convergence was reached, or the network reached an asymptote point when training accuracy started decreasing.

By default, neural network application used the equal number of hidden nodes as the number of input variable. Skidmore, et al. [28] found that the use of minimum number of hidden nodes in the neural network significantly reduced the average training accuracy, resulting in a lower accuracy of the classification result.

His study found that mean training accuracy increased as more hidden nodes were added. Another study mentioned that it was sometimes useful to make the number of hidden nodes roughly equal to two or three times the total number of input classes [25]. This study used two variations of hidden nodes number, which are equal and three times of the total input number used in the neural network, while holding other parameters constant.

Analysis on the classification results found that the use of more hidden nodes number in the neural network made the network architecture more complex, causing more complicated computation for training the network, which in turn needed more iterations to reach global minima. As a comparison, neural network with 7 hidden nodes reached convergence point after 5,000 iterations, whereas the use of 21 hidden nodes in the network resulted in longer training of 7,500 iterations in order to generate a similar training accuracy.

Neural network was trained using back-propagation learning algorithm with learning rate and momentum value of 0.2 and 0.4, respectively. Learning rate reflects on the training speed, while momentum describes the sensitivity of the network to error surface. This study tried to use some variations on these parameters, and found that higher learning rate value should be balanced with the higher value of momentum, otherwise training stage became unstable and was trapped into local minima condition.

Table 1 Selected Classification Accuracy Results

| | Original Landsat ETM Data | | |
|---|---|---|---|
| | Single Tree Felling Accuracy | Overall Accuracy | Kappa |
| Maximum Likelihood | 73% | 78% | 0.75 |
| Fuzzy c-means | 53% | 73% | 0.68 |
| Neural Network | 77% | 75% | 0.71 |

According to the accuracy assessment on classification results, the best performance of neural network was achieved with 21 hidden nodes when the network was trained for 7,500 iterations.

## 4.3. Comparison of Classification Results

The performance of those classification approaches was assessed using error matrix, so-called confusion matrix [29]. According to the assessment results, neural network outperformed maximum likelihood in classifying single tree felling class but was less accurate in classifying other land cover classes resulting in a lower overall accuracy (Table 1). In general, fuzzy c-means performed less satisfactorily, compared to other classification approaches i.e. neural network and maximum likelihood, to classify single tree felling class.

Table 2 was computed based on Figure 1 showing percentages of major land cover classes produced by fuzzy c-means, neural network and maximum likelihood. The computation results also showed that all classifiers agreed on the first three major land cover classes (though in different order) in the subset of study area. Fuzzy c-means classifier was more conservative in number (13% of pixels) than other classifiers (22% of pixels) in assigning single tree felling class. This was particularly the case when Euclidian distance was used in the fuzzy c-means classification. This may lead to the less accurate classification result for single tree felling class as compared to the neural network and the maximum likelihood.

Table 2 Percentages of Major Forest Cover Classes

| Land Cover Class | Fuzzy c-means | Neural Network | Maximum Likelihood |
|---|---|---|---|
| High Density Forest | 47% | 24% | 24% |
| Sparse Forest | 26% | 36% | 30% |
| Single Tree Felling | 13% | 22% | 22% |

A qualitative observation on Figure 1 showed that neural network was classifying single tree felling in a large extents area, which was even more aggressive than the maximum likelihood. However, from Table 2 those two classifiers appeared to assign exactly the same number of pixels as single tree felling class (22% of total pixels). In general, both neural network and maximum likelihood produced quite similar spatial distributions of major land cover classes. Fuzzy c-means classifier, on the other hand, produced a different classification result where majority of pixels (47% of total pixels) were assigned as high density forest class. This was quite different compared to the equally-like distribution between those three forest classes (i.e. sparse forest, single tree felling, and high density forest), as shown by neural network and maximum likelihood methods.

## 5. DISCUSSIONS

The fuzzy c-means classification technique plays an important role for this study. Moreover, the performance of this method raises a great important issue, discussed in the following section. Some recent studies reported that the use of fuzzy c-means classifier can accurately improve the classification of mixed pixels [9, 10]. However, given the accuracy assessment results, it was found that the fuzzy c-means classification had lower accuracy compared to neural network and maximum likelihood classifiers.

Less accurate result in classifying single tree felling class can be caused by significant degree of overlapping between training sample of high density forest class and single tree felling class. This overlapping caused high confusion for every classifier; although fuzzy c-means performed worse than the other classifiers for this specific condition.

Analysis of single tree felling pixels was continued by measuring the uncertainty of land cover class represented in a pixel using confusion index [16]. The confusion index (CI) is the ratio of the second highest class membership value to the highest membership value of that pixel which is scaled in the interval of 0.0 to 1.0.The greater the CI value for a pixel, the more the classification uncertainty of that particular pixel is. It is showed that higher CI pixels are located in the area which mostly identified as single tree felling class by fuzzy c-means classification (area indicated inside --- box).

**Table 3 Membership Values and Entropy of Single Tree Felling Pixels Calculated from Test Datasets**

| Single Tree Felling | Sparse Forest | Road | Clear Cut Forest | High Density Forest | Hill Shadow | River | Land Cover | Entropy |
|---|---|---|---|---|---|---|---|---|
| 0.87 | 0.03 | 0.00 | 0.00 | 0.07 | 0.01 | 0.01 | Single Tree Felling | 0.7656 |
| 0.33 | 0.04 | 0.00 | 0.00 | 0.57 | 0.03 | 0.03 | High Density Forest | 1.5062 |
| 0.34 | 0.19 | 0.00 | 0.01 | 0.41 | 0.02 | 0.02 | High Density Forest | 1.8391 |
| 0.46 | 0.05 | 0.00 | 0.01 | 0.32 | 0.07 | 0.08 | Single Tree Felling | 1.9006 |
| 0.44 | 0.07 | 0.00 | 0.01 | 0.19 | 0.12 | 0.17 | Single Tree Felling | 2.1544 |
| 0.19 | 0.20 | 0.07 | 0.19 | 0.15 | 0.09 | 0.11 | Sparse Forest | 2.7225 |

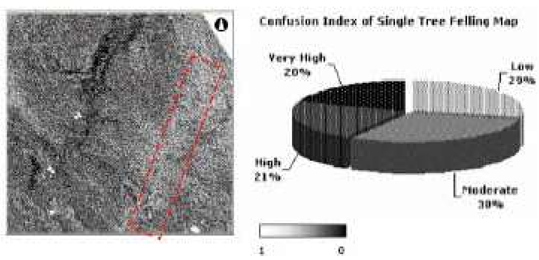


**Figure 2 Confusion Index Map and Chart of Single Tree Felling, indicates that 41% of pixels on the study area have high confusion indexes**

These relatively high confusion indexes values are another indication that the high degree of overlapping of high density forest and single tree felling class caused the fuzzy c-means classifier to perform less accurately.

Inappropriate accuracy assessment procedure used in this study can be another issue that caused less accurate classification results. As mentioned by Foody [10], the measures of classification accuracy derived from the confusion matrix are inappropriate for the evaluation of fuzzy classifications, as it does not take into account the presence of mixed pixels and neither does accommodate fuzzy ground truth data in the assessment.

A number of methods have been proposed to measure classification accuracy of fuzzy classification with emphasis on fuzzy measures. Gopal and Woodcock [30], in their study suggested several classification indicators derived from fuzzy sets techniques which may be used for the situation where there is ambiguity in the ground data but not in classification output.

Other accuracy assessment approaches are based on entropy measures [31]. Entropy is a measure of uncertainty and information formulated in terms of probability theory, which expresses the relative support associated with mutually exclusive alternative classes [10]. Entropy is maximized when the probability of class membership is partitioned evenly between all defined classes in the classification and minimized when it is associated entirely with one class. Therefore, the use of entropy values as an indicator of classification accuracy assessment is implicitly based on the assumption that in an accurate classification each pixel will have a high probability of membership with only one class. Provided the fact that the higher the entropy value of a pixel corresponds to the lower probability of particular pixel belongs to a single class, then the pixel is classified less accurately.

Overlaying the entropy values with the membership values maps, one may conclude that many pixels with high entropy values have almost equal distribution of the membership values. In order to provide more evidence, calculation of entropy values of single tree felling pixels were carried out using Shannon entropy algorithm [31], taking the data from test datasets.

The membership values of single tree felling pixels for the whole subset of the study area were also computed. This resulted in a considerably high mean entropy value of 1.71 within range of 0.04 - 2.80 with a standard deviation of 0.44. Thus, the domination of mixed pixels with close membership values pixels might give difficulties for fuzzy c-means classifier to label these pixels as one land cover class in a map.

As mentioned earlier in this section, the accuracy measure shown by confusion matrix does not take into account the presence of mixed pixels condition. However, the use of confusion matrix makes it possible to compare the result of fuzzy c-means classification with the other techniques, such as conventional maximum likelihood, which cannot be assessed using entropy values or other fuzzy-based measures.

## 6. CONCLUSION

The classification results showed that neural network method resulted in the highest accurate result to detect single tree felling with 77% of accuracy, followed with maximum likelihood and fuzzy c-means with 73% and 53% of accuracy, respectively. There were several factors causing the fuzzy c-means classifier resulted in lower accuracy than maximum likelihood and neural network in classifying single tree felling class. One of the factors was strong overlapping of high density forest training pixels and single tree felling pixels sets, causing higher confusion index for the latter particular class. Another issue is that majority of single tree felling pixels has equal distribution of membership values between classes; as a consequence many of those pixels have more uncertain probability belong to one class, as indicated by entropy values of single tree felling class.

In this study, field data were collected in a pixelbasis. For future study, collection of fuzzy groundtruth data should be taken into account in order to optimize the classification of fuzzy c-means method. Another accuracy assessment technique would also be useful to evaluate fuzzy classified map.

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## REFERENCE

[1] Lillesand, T.M. and R.W. Kiefer, Remote Sensing and Image Interpretation. Third Edition ed. 1994: John Wiley & Sons, Inc.

[2] Dahal, P.P., Determination of forest status using selected criteria and indicators of sustainable forest management : a case study of Labanan concession, east Kalimantan, Indonesia. 2002, ITC The Netherlands: Enschede. p. 76.

[3] Atmopawiro, V.P., Detection of Single Tree Felling in the Tropical Forest Using Optical Satellite Data and Image Classification Techniques (a Case Study in the Labanan Concession, East Kalimantan, Indonesia), in Natural Resource Management. 2004, ITC The Netherlands: Enschede. p. 91.

[4] Zaitunah, A., Analysis of Physical Factors Affecting Single Tree Felling of Illegal Logging Using Remote Sensing and GIS (A Case Study in Labanan Concession, East Kalimantan, Indonesia), in Natural Resource Management. 2004, ITC The Netherlands: Enschede. p. 108.

[5] Cui Yijun, Remote sensing and GIS for supporting sustainable forest management certification in the tropics : a case study in Labanan concession, East Kalimantan, Indonesia. 2003, ITC The Netherlands: Enschede. p. 75.

[6] Fauzi, A., Remote sensing for detecting tropical logged over forest : a case study in Labanan concession, East Kalimantan, Indonesia. 2001, ITC The Netherlands: Enschede. p. 91.

[7] Bhandari, S.P., Remote Sensing for Forest Certification : Detecting and Characterizing Selective logging in Tropical Forest : a Case Study in Labanan Concession, East Kalimantan, Indonesia. 2003, ITC: Enschede. p. 76.

[8] Elias and D.P. Dykstra. A case study on Forest Harvesting Damages, Structure and Composition Dynamic Changes in the Residual Stand for Dipterocarp Forest in East Kalimantan, Indonesia. in Forest Operations for Sustainable forestry in the tropics, Proceedings of a symposium organised by IUFRO subject group S3, 13-27. 1995.

[9] Foody, G.M., Relating the land-cover composition of mixed pixels to artificial neural network classification output. Photogrammetric Engineering & Remote Sensing, 1996. 62(5): p. 491-499.

[10] Foody, G.M., Approaches for the production and evaluation of fuzzy land cover classifications from remotely-sensed data. International Journal of Remote Sensing, 1996. 17(7): p. 1317-1340. 11. Zhang, J. and G.M. Foody, A fuzzy classification of sub-urban land cover from remotely sensed imagery. International Journal of Remote Sensing, 1998. 19(14): p. 2721-2738.

[12] Gopal, S., C.E. Woodcock, and A.H. Strahler, Fuzzy neural network classification of global land cover from a 1[deg]AVHRR data set. Remote Sensing of Environment, 1999. 67(2): p. 230-243.

[13] Zhang, L., et al., Fuzzy Classification of Ecological Habitats from FIA Data. Forest Science, 2004. 50(1): p. 117-127.

[14] Zhang, J. and G.M. Foody, Fully-fuzzy supervised classification of sub-urban land cover from remotely sensed imagery: Statistical and artificial neural network approaches. International Journal of Remote Sensing, 2001. 22(4): p. 615-628.

[15] Cannon, R.L., et al., Segmentation of a Thematic Mapper Image Using the Fuzzy c-Means Clustering Algorithm. IEEE 8 Trannsactions on Geoscience and Remote Sensing, 1986. GE-24 May 1986(3): p. 400- 408.

[16] Hegde, S., Modelling Land Cover Change: A Fuzzy Approach. 2003, ITC The Netherlands.

[17] Atkinson, P.M., M.E.J. Cutler, and H. Lewis, Mapping sub-pixel proportional land cover with AVHRR imagery. International Journal of Remote Sensing, 1997. 18(4): p. 917-935.

[18] Mas, J.F., et al., Modelling deforestation using GIS and artificial neural networks. Environmental Modelling and Software, 2004. 19(5): p. 461-471.

[19] Bezdek, J.C., R. Ehrlich, and W. Full, FCM: The Fuzzy c-Means Clustering Algorithm. Computers & Geosciences, 1984. 10(2-3): p. 191-203.

[20] Moody, A., S. Gopal, and A.H. Strahler, Artificial neural network response to mixed pixel in coarse-resolution satellite data. Remote Sensing of Environment, 1996. 58(3): p. 329- 343.

[21] Atkinson, P.M. and A.R.L. Tatnall, Introduction Neural networks in remote sensing. International Journal of Remote Sensing, 1997. 18(4): p. 699-709.

[22] Gahegan, M., G. German, and G. West, Improving neural network performance on the classification of complex geographic datasets. Journal of Geographical Systems, 1999. 1(1): p. 3-22.

[23] Lucieer, A., Uncertainties in Segmentation and Their Visualisation. 2004, International Institute for Geo-Information Science and Earth Observation: Enschede.

[24] Palubinskas, G., et al., An Evaluation of Fuzzy and Texture-Based Classification Approaches for Mapping Regenerating Tropical Forest Classes from Landsat-TM Data. International Journal of Remote Sensing, 1995. 16(4): p. 747- 759.

[25] Kanellopoulos, I. and G.G. Wilkinson, Strategies and best practice for neural network image classification. International Journal of Remote Sensing, 1997. 18(4): p. 711-725.

[26] Mather, P.M., Computer Processing of Remotely-Sensed Data : An Introduction. Third Edition ed. 2004, Chichester, West Sussex: John Wiley & Sons, Ltd.

[27] Danaher, S., et al., A Comparison of the Characterisation of Agricultural Land Using Singular Value Decomposition and Neural Networks, in Neuro-Computation in Remote Sensing Data Analysis: Proceedings of Concerted Action COMPARES, I. Kanellopoulos, et al., Editors. 1997, Springer.

[28] Skidmore, A.K., et al., Performance of a Neural Network : Mapping Forests Using GIS and Remotely Sensed Data. Photogrammetric Engineering & Remote Sensing, 1997. 63(5): p. 501-514.

[29] Congalton, R.G., A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. Remote Sensing of Environment, 1991. 37: p. 35-46.

[30] Gopal, S. and C.E. Woodcock, Theory and Methods for Accuracy Assessment of Thematic Maps Using Fuzzy Sets. Photogrammetric Engineering & Remote Sensing, 1994. 60: p. 181-188.

[31] Maselli, F., C. Conese, and L. Petkov, Use of Probability Entropy for the Estimation and Graphical Representation of the Accuracy of Maximum Likelihood Classifications. ISPRS Journal of Photogrammetry and Remote Sensing, 1994. 49(2): p. 13-20.