A Comparison of Neural Network and Maximum Likelihood Method for Landuse/Landcover Mapping in Khon Kaen Province, Thailand.

R. Suwanwerakamtorn and P. Supunee Department of Computer Science Khon Kaen University, Khon Kaen 40002, THAILAND. Tel : 6643342910, Email : <u>rasamee@kku.ac.th</u>

KEY WORD: Landuse/land cover, Neural Network Classification, Maximum Likelihood Classification.

ABSTRACT: With increasing human settlement and land development, it is necessary to have an inventory of land resources. The optimizing of land use for agriculture and for other purpose has been identified as a very important requirement for the achievement of economic and social benefit. The satellite data gives up-to-date information; it can monitor the change of the things on the earth at once. Mapping can apply the information from the satellite images especially land use mapping. Therefore, in order to increase the accuracy of land use/land cover map based on digital image classification, this study was to compare the categorization of land use with the maximum likelihood classification and the neural network classification. Both methods were the supervised classification. LANDSAT-7 ETM+ band 3, 4 and 5 images of a portion of Khon Kaen Province in the Northeast Thailand were used to be areas of identifying signature set. The result obtained from both methods can discriminate land use category such as dry evergreen forest, deciduous forest, field crops, paddy fields, wet land, aquatic plants, water bodies and urban. The land use classification with the maximum likelihood method was totally correct about 45.53 %. In the aspect of land use classification with the neural network classification method was totally correct about 43.96 %. When compared with the landuse map obtained from visual interpretation method using the false color composite of Landsat-7 ETM+ band 4, 5 and 3 in red, green and blue color.

1. INTRODUCTION

Due to human settlement and land development are increasing rapidly, it is necessary to have an inventory of land resources. The optimizing of landuse for agriculture and for other purpose has been identified as a very important requirement for the achievement of economic and social benefit. The satellite data gives up-to-date information; it can monitor the global change in near real time. In the last two decade, traditionally, image classification is performed by a maximum likelihood, or Bayesian classifier, which assigns the most likely class to the observed data, and is known to be optimal if the assumptions about the probability density functions are corrected. Neural networks, on the other hand, with their ability of learning, have no need of assumptions about the probabilistic model. Moreover, recent results on classification of multisource remote sensing data and on multispectral Landsat images have shown that neural networks are often able to perform better than maximum likelihood classifiers. For the above reason neural network technique may be useful for landuse/landcover in Northeast region which agriculture lands are very complicate due to multidisciplinary use.

2. OBJECTIVE

The objective is to compare the accuracy of the landuse/landcover map obtained from maximum likelihood and neural network classification.

3. STUDY AREA

The study area is in the east portion of Khon Kaen and vicinity area, Northeast Thailand. It is located in between the latitudes of $16^{\circ}40^{\circ} - 17^{\circ}15^{\circ}$ N and the longitudes of $101^{\circ}24^{\circ} - 102^{\circ}32^{\circ}$ E (Figure 1). It is almost flat areas that mainly are used for agriculture which are mostly paddy fields and field crops. The mountain areas are the Phu Wiang national park with evergreen forest and Phu Kao - Phu Phan Kham national park which are mostly covered with deciduous forest. Geologically, it is underlain by thick sequence of Mesozoic rock which mainly consists of sandstone which gave sandy soil in this area. In the flat plain it is composed of alluvial deposits of sand, silt and clay.

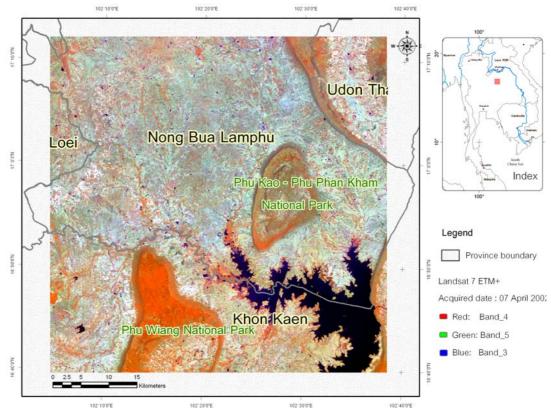


Figure 1. Location of the study area.

4. METHODOLOGY

4.1.1 Data Use

Band 3, 4 and 5 of Landsat-7 ETM+ data acquired on April 07, 2002 were used to classify landuse/land cover in Khon Kaen and vicinity area. Landuse map produced by Computer Center of Khon Kaen University in 2002 based on the same Landsat-7 ETM+ data was used to be reference data to assess the accuracy of each method.

4.1.2 The Procedures of Image Processing

The digital image processing was carried out using Geometicas software. This software provides both of maximum likelihood classification (MLC) and neural network classification (NNC).

The steps of classification are shown in Figure 2 which have detailed as follows:

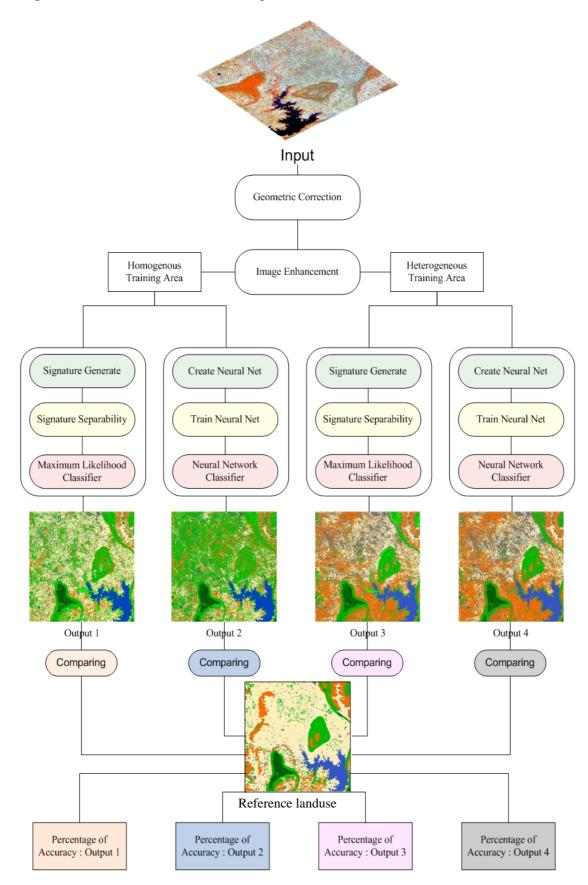
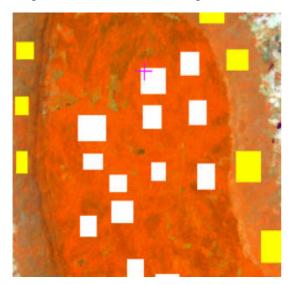


Figure 2 The Procedures of Image Processing

The first step is to define training area to be trained the classifiers. Training pixels represented landuse classes were selected under classes of reference landuse (8 classes). There were 21 training classes for the homogenous set and 8 classes for heterogeneous set. The examples of training data are illustrated in Figure 3.



Heterogeneous training data



Homogenous training data

Figure 3 Example of training data

In case of maximum likelihood classification, the next step is to generate signature set from training data which is consist of mean, standard deviation, variance and covariance of classes. The appropriated signature set were employed to classify landuse/land cover.

In the case of neural network the training data set were used to be trained the classifier. With its ability of learning, it can identify the unknown pixels based on pattern recognition.

4. ACCURACY ASSESSMENT

The output maps obtained from both methods were assessed an accuracy by comparing with reference landuse (Figure 2 and Figure 4). Confuse matrix are shown in Table 1-4.

5. RESULT

The result of this study found that the maximum likelihood and neural network classification can extract landuse/land cover category from Landsat data. The main landuse/land cover were identified to 8 classes such as dry evergreen forest, deciduous forest, field crops, paddy fields, wet land, aquatic plants, water bodies and urban (Figure 4). Based on 2 training set, it was found that the percentage of average accuracy of the results from maximum likelihood is not much different from neural network classification. Table 3-4 are shown that the result from maximum likelihood classification has an overall accuracy of 45.53 %, and neural network gave 43.96 %.

	C1	C2	C3	C4	C5	C6	C7	C8
C1	74.8	0.3	9.8	1.1	2.8	7.8	0.0	3.4
C2	48.7	1.7	13.5	0.0	17.1	4.9	0.1	14
C3	22.8	0.1	56.6	0.0	1.6	11.6	0.0	7.2
C4	27.4	0.0	0.1	70.5	1.7	0.2	0.0	0.1
C5	51.0	0.4	10.3	0.0	26.8	2.3	0.3	8.9
C6	34	0.2	32.9	0.0	1.5	24	0.0	7.3
C7	10.8	0.0	2.1	0.0	4.3	0.4	79.5	2.9
C8	17	0.2	13.5	0.0	1.5	4.6	0.0	63.3

 Table 1 Confuse matrix of output from maximum likelihood and reference map based on homogeneous training data

Average Accuracy = 49.65% Overall Accuracy = 57.03% Kappa Coefficient = 0.37380 Standard Deviation = 0.00036

Remark: C1 = Deciduous forest, C2 = Wetland, C3 = Paddy field, C4 = Dry evergreen forest, C5 = Aquatic plants ,C6 = Field crop, C7 = Water bodies, C8 = Urban

Table 2 Confuse matrix of output from neural network and reference map based on homogeneous training data

	C1	C2	C3	C4	C5	C6	C7	C8
C1	77.7	0.3	7.3	2.6	1.5	9.1	0.1	1.5
C2	53.0	6.0	8.0	0.0	16.0	7.0	1.0	9.1
C3	51.9	0.1	23.8	0.0	0.6	18.7	0.1	4.8
C4	16.0	0.0	0.3	81.4	1.8	0.4	0.0	0.0
C5	54.2	2.5	11.5	0.2	17.3	3.7	3.2	7.4
C6	48.8	0.1	19.4	0.0	0.3	25.9	0.1	5.4
C7	9.2	0.2	0.7	0.0	0.3	0.6	87.9	1.1
C8	32.5	0.2	9.5	0.0	0.3	5.6	0.1	51.9

Average Accuracy = 46.49% Overall Accuracy = 38.08% Kappa Coefficient = 0.21714 Standard Deviation = 0.00043

Remark: C1 = Deciduous forest, C2 = Wetland, C3 = Paddy field, C4 = Dry evergreen forest, C5 = Aquatic plants C6 = Field crop, C7 = Water bodies, C8 = Urban

Table 3 Confuse matrix of output from maximum likelihood and reference map based on heterogeneous training data

							C7		
	C1	C2	C3	C4	C5	C6		C8	
C1	58.3	3.6	1.3	1.6	9.5	11.2	0.0	14.5	
C2	12.0	23.5	1.4	0.0	16.2	16.5	0.1	30.3	
C3	4.3	1.5	35.3	0.0	1.6	35.9	0.0	21.4	
C4	20.0	0.1	0.0	76.9	2.0	0.2	0.0	0.8	
C5	18.9	24.0	0.2	0.1	26.0	14.8	0.4	15.4	
C6	14.9	3.6	8.9	0.0	1.6	52.8	0.0	18.4	
C7	1.7	0.2	0.3	0.0	7.5	1.3	81.4	7.6	
C8	2.3	7.1	1.9	0.0	2.0	16.9	0.0	69.7	

 Average Accuracy
 = 52.99%
 Overall Accuracy
 = 45.53% Kappa Coefficient = 0.31421

 Standard Deviation = 0.00036

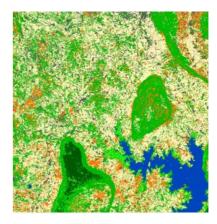
Remark: C1 = Deciduous forest, C2 = Wetland, C3 = Paddy field, C4 = Dry evergreen forest, C5 = Aquatic plants C6 = Field crop, C7 = Water bodies, C8 = Urban

Table 4 Confuse matrix of output from neural network and Reference map based on heterogeneous training data

	C1	C2	C3	C4	C5	C6	C7	C8
C1	59.6	10.9	0.9	1.6	0.1	14.2	0.1	12.6
C2	12.9	33.6	0.9	0.0	3.4	22.9	0.6	25.7
C3	4.2	1.9	30.8	0.0	0.3	40.9	0.1	21.9
C4	16.4	3.3	0.0	79.4	0.0	0.2	0.0	0.6
C5	15.0	45.1	0.3	0.0	6.5	17.9	3.1	12.3
C6	12.3	5.3	7.9	0.0	0.1	58.4	0.1	15.9
C7	5.3	0.7	0.3	0.0	0.1	1.9	87.1	4.6
C8	2.0	8.0	1.6	0.0	0.1	23.0	0.0	65.3

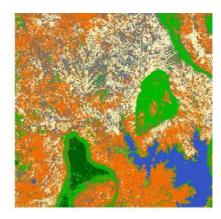
Average Accuracy = 52.58% Overall Accuracy = 43.96% Kappa Coefficient = 0.30586 Standard Deviation = 0.00036

Remark: C1 = Deciduous forest, C2 = Wetland, C3 = Paddy field, C4 = Dry evergreen forest, C5 = Aquatic plants, C6 = Field crop, C7 = Water bodies, C8 = Urban









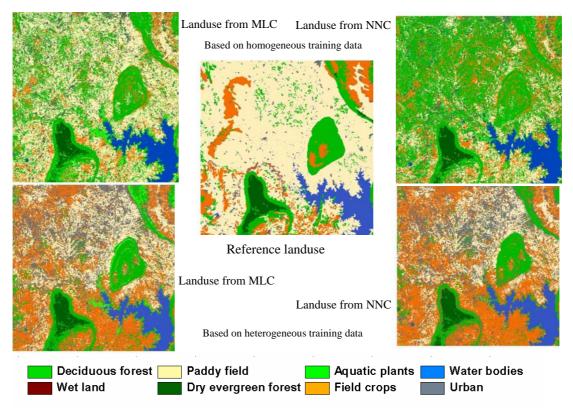


Figure 4 Comparison of Landuse from MLC, NNC and reference landuse

6. CONCLUSION AND RECOMMENDATION

This study concluded that Landuse/Landcover obtained from both classifiers is not much difference. Although maximum likelihood classification gave better results than neural network classification, but it is not significant. The reasons may come from a limitation of Landsat data resolution and the period of data acquisition. The data was record in dry season which almost agricultural lands are harvested. Therefore it makes difficult to select the training areas. Multidisciplinary use in this area also impacts to miss classification. Therefore, in order to increase the lansuse/land cover map in complicated area or mixed use, very high resolution data is need.

7. BIBLIOGRAPHY

Avrithis, Y.S. and Kollias, S.D., 1997. Fuzzy image classification using multiresolution neural networks with applications to remote sensing. Proceedings of the 13th International Conference on Digital Signal Processing. Santorini, Greece,

July 2-4 ,1997, Volume 1, pp. 261-264.

Foody G. M., 2004. Supervised image classification by MLP and RBF neural networks with and without an exhaustively defined set of classes. International Journal of Remote Sensing. Vol 25, No 15. pp. 3091 - 3104.

German G.W.H., and Gahegan M., 1996. Neural network architectures for the classification of temporal image sequences. Computers & Geosciences,

Volume 22, Issue 9, Pergamon Press, Inc. Tarrytown, NY, USA, pp. 969 – 979.

Lerner et al., 1996. Feature Extraction by NN Nonlinear Mapping for Pattern Classification. Proceedings of the 13th International Conference on Pattern Recognition, ICPR13, Vienna, vol. 4, pp. 320-324.