

TEXTURE ANALYSIS FOR LAND USE AND LAND COVER SPATIAL PATTERN STUDY USING THEOS IMAGERY

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ABSTRACT: The aim of the study is to classify land use/land cover (LU/LC) in Chok Chai district of Nakhon Ratchasima province in Thailand where there is a variety of LU/LC types. This study evaluates suitable combined datasets of spectral data and texture measure for LU/LC classification using supervised classification with Artificial Neural Networks. In this study, 10 datasets were MS, MS and Mean, MS and Variance, MS and Contrast, MS and Angular second moment, MS and Correlation, MS and Homogeneity, MS and Entropy, MS and Dissimilarity and MS and Semivariogram. All datasets were classified into 10 LU/LC types that consisted of urban and built-up area, paddy field, cassava, sugarcane, eucalyptus, orchard, forest land, water body, scrub and abandoned land. In addition, accuracy assessment of LU/LC classification from each dataset was performed based on overall accuracy and kappa coefficient for evaluating an optimum dataset from THEOS satellite for LU/LC classification. As a result, the most optimum three-first orders (MS, MS and Contrast, and MS and Mean provided kappa hat of coefficient 84.10%, 67.42% and 62.57% respectively. In addition, kappa hat of coefficient for each LU/LC types was showed that applying texture measure with multispectral data of THEOS can increase the accuracy of LU/LC classification with ANNs.

1. Introduction

Remote sensing has become an important tool in wide areas of environmental research and planning. In particular the classification of spectral images has been a successful application that is used for deriving land use and land cover maps (Powell et al 2008 and Joshi et al 2006). Image classification is also commonly applied in other contexts such as optical pattern and object recognition (Muller et al 2001). Therefore, a number of algorithms for supervised classification have been developed over the past to cope with both the increasing demand for these products and the specific characteristics of a variety of scientific problems (Samaniego and Schulz, 2009). Most notable have been classification approaches based on Artificial Neural Networks (ANNs) (Dam et al 2008). ANN approaches have a distinct advantage over statistical classification methods in that they are non-parametric and require little or no a priori knowledge of the distribution model of input data (Benediktsson and Sveinsson, 1997). In addition, this study has used texture analysis that can be helpful when objects in an image are more characterized by their texture than by intensity, and traditional thresholding techniques cannot be used effectively (MathWorks, 2011). Berberoglu and Curran (2006) had identified into 4 group of texture measure as follows:

(1) The first-Order Statistics Texture measures are statistics calculated from the original image values, like variance, and do not consider pixel neighbor relationships

(2) The second-order statistics texture measures is based on brightness value spatial-dependency gray-level co-occurrence matrices (GLCM)

(3) The third-order statistics semivariogram is used to spatial variation analyze. It is a function relating one-half the squared differences between points to the directional distance between two samples.

(4) Fractals are a rough or fragmented geometric shape that can be split into parts, each of which is (at least approximately) a reduced-size copy of the whole, a property called self-similarity.

Then, this study aims to evaluate optimum dataset from multispectral data and texture measure data with 3 group of texture measure (the first order, the second order, and the third order) for land use and land cover classification based on THEOS data. Herein, such prepared datasets are classified into 10 LU/LC types (i.e. urban and built-up area, paddy field, cassava, sugarcane, eucalyptus, orchard, forest land, water body, scrub and abandoned land) using supervised classification with Artificial Neural Networks. Then, accuracy assessment of LU/LC classification from each dataset was performed to consider optimum dataset.

2. Study area

The study area is a part of Chok Chai district where locates in Nakhon Ratchasima province of southeast Thailand. The study area is approximately 150 Sq.km. (Figure 1) where topographic characteristic is the undulating plateau with elevation range varies from 175 m. to 271 m. above Mean Sea Level (MSL). In addition, two main rivers (Moon River and Phra Phloeng River) flow through in the study area.

3. Methodology

In this study the processes of this research is showed in Figure 2. The details of each process were summarized in the following sections.

(1) Satellite data: THEOS data is acquired on 19 February 2010 that multispectral data with band 1, 2, 3 and 4 are used for this study.

(2) Preprocessing consists of three steps as follows:

(2.1) Geometric correction: This process is operated with image to image rectification that is based on ground control points from Orthophoto year 2000-2002 of Land Development Department (LDD).

(2.2) Optimum Index Factor (OIF): Three combined bands are extracted with maximum of OIF value.

(2.3) Principal Component (PC): The output from step 2.2 is used to create the first Principal Component for texture measure.

(3) Data Extraction and preparation consist of two steps as follows:

(3.1) Texture measures calculation: The output of PCA in previous step 2.3 is used to calculate texture measure.

(3.2) Dataset preparation: The output from step 3.1 is used to create 10 datasets: (1) multispectral data (MS), (2) MS and Mean, and (3) MS and Variance (4) MS and Contrast, (5) MS and Angular second moment, (6) MS and Correlation, (7) MS and Homogeneity, (8) MS and Entropy, (9) MS and Dissimilarity and (10) MS and Semivariogram.

(4) Data classification: The output from process 3 are used to classified into land use and land cover using supervised classification with Artificial Neural Network (ANN) algorithm.

(5) Post processing operation: the output of classification from process 4 is used to spatial filtering by Majority filtering algorithm.

(6) Ground verification and accuracy assessment: The output from process 5 is verified in ground reference and then is assessed with calculating overall accuracy and kappa hat of coefficient.

(7) Optimum classification method: The output from process 6 is compared to evaluate optimum dataset for land use and land cover classification

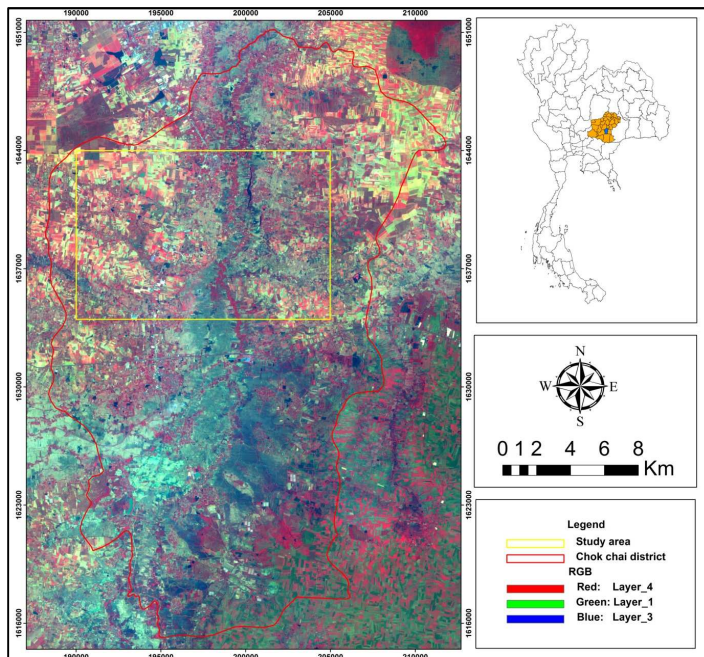


Figure 1 Study area

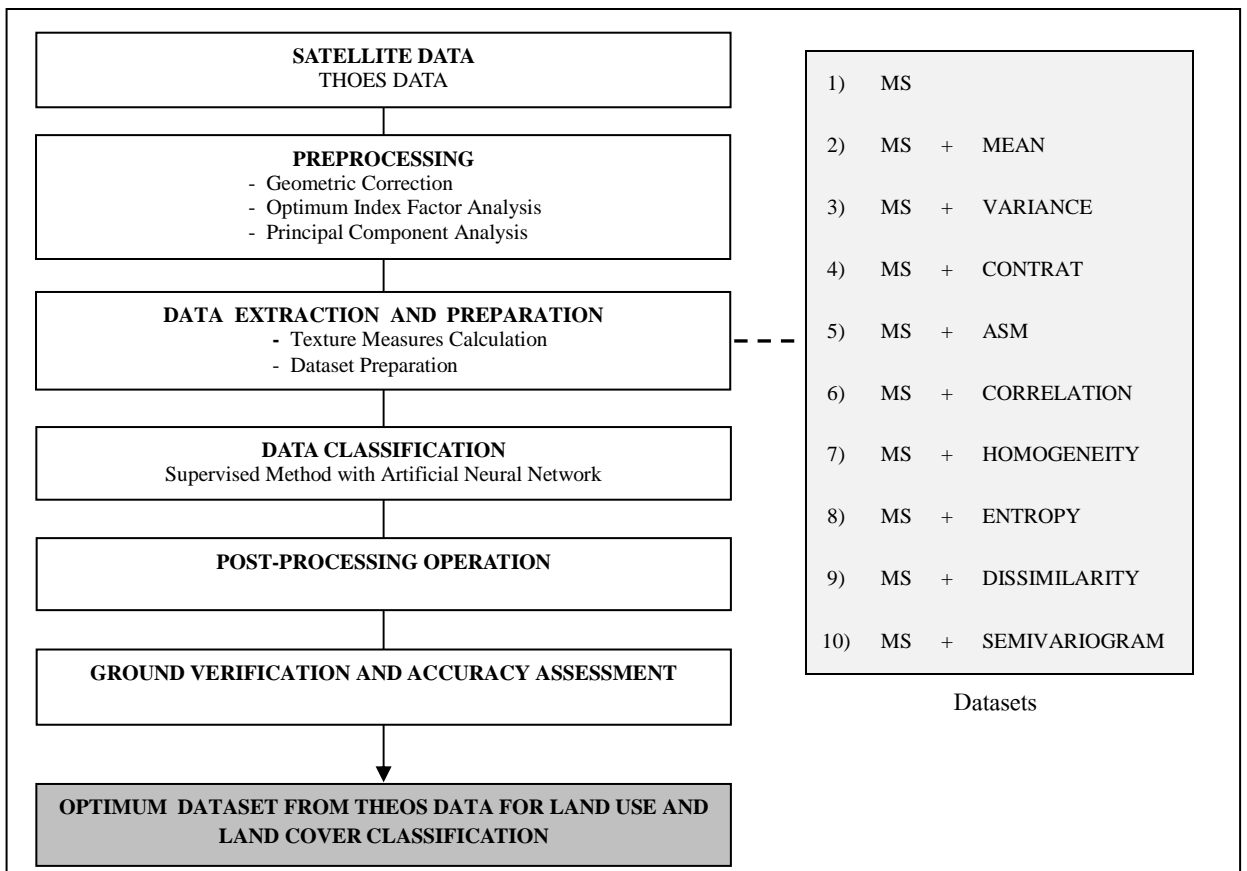


Figure 2 The processes of this research

4. Results

4.1 Land use and land cover classification

The results of land use and land cover classification with 10 datasets were analysed by supervised classification with Artificial Neural Network (ANN) algorithm (as Figure 3). The details of land use and land cover classification with such 10 datasets are showed in Table 1.

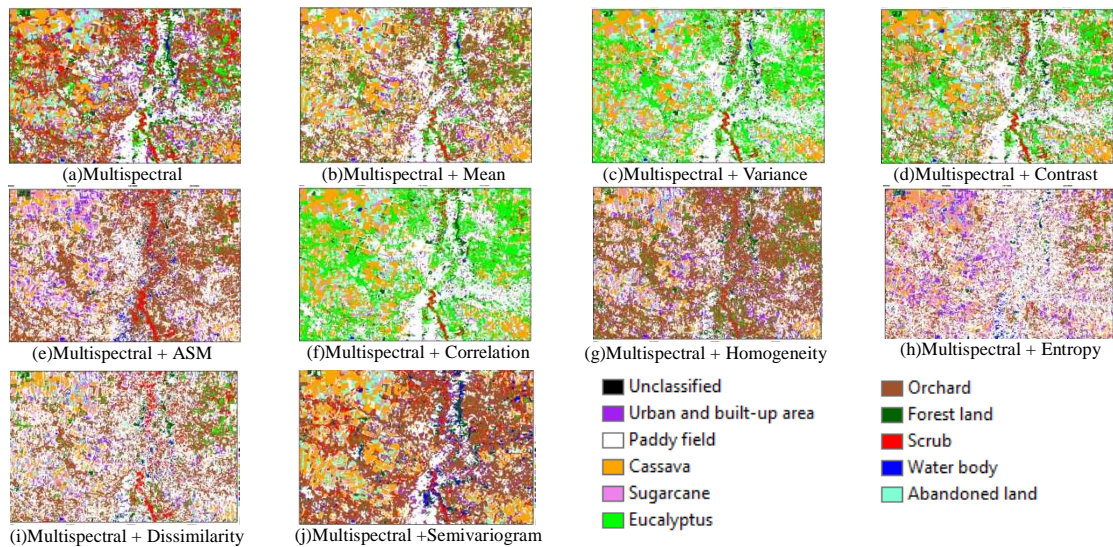


Figure 3 Land use and land cover classification from dataset

Table 1 The details of land use and land cover classification with 10 datasets

Land use and land cover classes (Rai)	Datasets									
	1	2	3	4	5	6	7	8	9	10
Unclassified	153.28	90.14	109.41	114.19	91.55	96.61	107.16	134.72	97.17	84.52
Urban and built-up area	6,565.64	4,026.09	1,852.59	1,677.94	5,132.95	2,197.27	6,758.16	8,661.38	3,595.22	3,223.83
Paddy field	24,456.94	33,391.13	33,235.88	32,980.36	36,869.06	32,505.75	26,470.13	50,386.92	44,648.30	21,255.89
Cassava	9,619.88	13,025.53	13,544.02	12,469.50	5,275.41	16,384.50	5,587.59	6,300.14	4,879.69	13,802.06
Sugarcane	1,822.08	1,368.98	2,633.91	2,504.11	3,137.20	1,626.05	2,395.41	5,038.73	2,545.59	1,552.36
Eucalyptus	6,221.53	6,747.89	26,847.56	16,055.72	1,106.86	27,225.56	3,569.48	1,231.17	2,657.95	1,101.94
Orchard	25,825.92	27,839.53	3,360.66	15,628.36	35,719.59	3,098.11	42,833.11	16,365.94	26,232.33	34,550.30
Forest land	3,806.58	1,113.19	2,246.06	2,616.89	717.75	2,261.67	2,360.39	566.02	1,932.47	3,412.27
Scrub	8,126.44	1,987.17	2,625.05	2,857.64	2,729.39	2,076.33	1,250.44	2,576.53	3,092.20	6,961.22
Water body	568.55	220.08	358.59	277.45	1,630.55	253.83	239.2	1,160.30	683.02	2,477.25
Abandoned land	6,302.11	3,659.20	6,655.22	6,286.78	1,058.63	5,743.27	1,897.88	1,047.09	3,105.00	5,047.31
Total	93,468.94	93,468.94	93,468.94	93,468.94	93,468.94	93,468.94	93,468.94	93,468.94	93,468.94	93,468.94

Note 1 = MS, 2 = MS and Mean, 3 = MS and Variance, 4 = MS and Contrast, 5 = MS and Angular second moment, 6 = MS and Correlation, 7 = MS and Homogeneity, 8 = MS and Entropy, 9 = MS and Dissimilarity and 10 = MS and Semivariogram

4.2 Accuracy assessment

The outputs of land use and land cover classification based on 10 datasets are checked by ground reference. Number of sampling points was calculated based on multinomial distribution theory with desired level of confident 90 percent and a precision of 10 percent was 160 points and sampling method was stratified random sampling. The results of accuracy assessment of three datasets are presented in Table 2.

Table 2 the results of accuracy assessment of 10 datasets

No.	Dataset	Overall accuracy	Kappa hat of coefficient.	Order
1	Multispectral (Multi)	86.25	84.10	1
2	Multi+Mean	68.13	62.57	3
3	Multi+Variance	66.25	60.99	4
4	Multi+Contrast	71.88	67.42	2
5	Multi+ASM	53.13	45.32	8
6	Multi+Correlation	66.25	60.96	5
7	Multi+Homogeneity	49.38	40.95	9
8	Multi+Entropy	47.50	38.44	10
9	Multi+Dissimilarity	56.25	48.53	7
10	Multi+Semivariogram	63.13	57.06	6

From table 2, the results of accuracy assessment with 10 datasets shows overall accuracy between 47.50% - 86.25% and kappa hat coefficient between 38.44% - 84.10%. Herein, it was found that multispectral dataset band 1, 3 and 4 provided the highest accuracy with 86.25% of overall accuracy and 84.10% of kappa hat coefficient. At the same time, multispectral dataset (band 1, 3 and 4) integrating to entropy texture provided the lowest accuracy with 47.50% of overall accuracy and 38.44% of kappa hat coefficient.

Then kappa hat coefficient of agreement for each LU/LC type was found that texture analysis integrating to multispectral data of THEOS band 1, 3 and 4 can increase accuracy for LU/LC classification. The results showed that accuracy of cassava, eucalyptus, orchard, scrub and abandoned land were increased (Table 3).

Table 3 Comparison of kappa hat coefficient of agreement for each LU/LC type of 10 datasets using ANNs

LU/LC type	Datasets									
	1	2	3	4	5	6	7	8	9	10
1. Urban and built-up area	100.00%	50.96%	100.00%	100.00%	35.63%	100.00%	66.90%	32.10%	81.61%	52.71%
2. Paddy field	86.00%	59.06%	65.64%	70.00%	24.41%	67.77%	34.98%	18.11%	27.40%	67.60%
3. Cassava	82.94%	80.10%	80.10%	79.41%	93.37%	76.89%	80.10%	80.10%	71.91%	71.05%
4. Sugarcane	100.00%	100.00%	100.00%	80.07%	67.77%	100.00%	72.60%	48.09%	89.04%	100.00%
5. Eucalyptus	92.91%	65.96%	28.75%	45.09%	81.09%	29.75%	31.91%	62.17%	54.61%	100.00%
6. Orchard	86.63%	39.85%	0.00%	89.97%	26.18%	-20.30%	21.18%	36.99%	34.03%	39.85%
7. Forest land	100.00%	37.25%	65.14%	53.52%	47.71%	47.71%	21.57%	65.14%	47.71%	34.64%
8. Scrub	48.05%	70.32%	65.37%	65.37%	74.03%	65.37%	22.08%	13.42%	65.37%	61.04%
9. Water body	100.00%	100.00%	100.00%	0.00%	17.95%	100.00%	100.00%	26.74%	100.00%	-2.56%
10. Abandoned land	67.40%	86.75%	62.16%	59.25%	73.51%	67.40%	100.00%	100.00%	76.45%	73.51%

Note 1 = MS, 2 = MS and Mean, 3 = MS and Variance, 4 = MS and Contrast, 5 = MS and Angular second moment, 6 = MS and Correlation, 7 = MS and Homogeneity, 8 = MS and Entropy, 9 = MS and Dissimilarity and 10 = MS and Semivariogram

5. Conclusions

Evaluation of optimum dataset for LU/LC classification with ANNs was found that the most optimum three-first orders (MS, MS and Contrast, and MS and Mean provided kappa hat of coefficient 84.10%, 67.42% and 62.57% respectively. In addition, kappa hat of coefficient for each LU/LC types was showed that applying texture measure with multispectral data of THEOS can increase the accuracy of LU/LC classification with ANNs.

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