An Appropriate Interpretation Approach for Land Use/Land Cover Map in Chomthong, Phitsanulok, Thailand

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ABSTRACT

The study of land use/land cover (LU / LC) has belonged to an important aspect of resource management, planning and mapping, etc. The acquisition of these results is due to the interpretation process, consists of two methods which are visual interpretation and digital interpretation. The tools used in the interpretation are classifiers in image processing software. Currently, there are many classifiers, but there is one method that provides better results than the other, maximum likelihood classifier (MLC). MLC is one of supervised classifiers, this method classifies the calculation of the probability for each given pixel in LU/LC class. The comparative study of the interpretation results with MLC through three image processing software (ERDAS, ENVI, QGIS) is the purpose of this study. Interpretation results show that ERDAS (OA = 83%, Kappa = 76%) provides better overall accuracy (OA) and kappa coefficient (Kappa) than ENVI (OA = 81%, Kappa = 74%) and QGIS (OA = 79%, Kappa = 71%).

Keywords: Chomthong, Interpretation, LU/LC, MLC

INTRODUCTION

Land use /Land cover (LU/LC) map is a significant spatial information for decision maker who are planning, managing and designing any matter related to particular area(Giri, 2016, Natya & Rehna, 2016). For example, LU/LC map of Nakhonnayok province of Thailand (Diem et al., 2015) showed the change of LU/LC between 2004 and 2015. The governor could design an economic plan or a city plan for coming year. The results of the LU/LC change in Nakhonnayok presented as Figure 1. Another example is a LU/LC map of Hawalbagh block, district Almora, Uttarakhand in India (Rawat & Kumar, 2015). This map displayed the change of this district during 1990-2010 which assisted in planning for urban development. next example is assessment of LU/LC changes Island in Italy (Mei et al., 2016) showed the changes in LU / LC between 1984 and 2014 to get spatial and temporal data of changes that occurred on the island. Next example is LU/LC mapping in Bhopal city of Madhya Pradesh State of India (Paliwal & Katiyar, 2015) illustrates classification and accuracy assessment of LU/LC mapping using satellite imagery. next example is a classification of LU/LC map in Zonguldak city, Turkey (Sekertekin et al., 2017) conduct accuracy analyses of LU/LC mapping in 2016 for sustainable land

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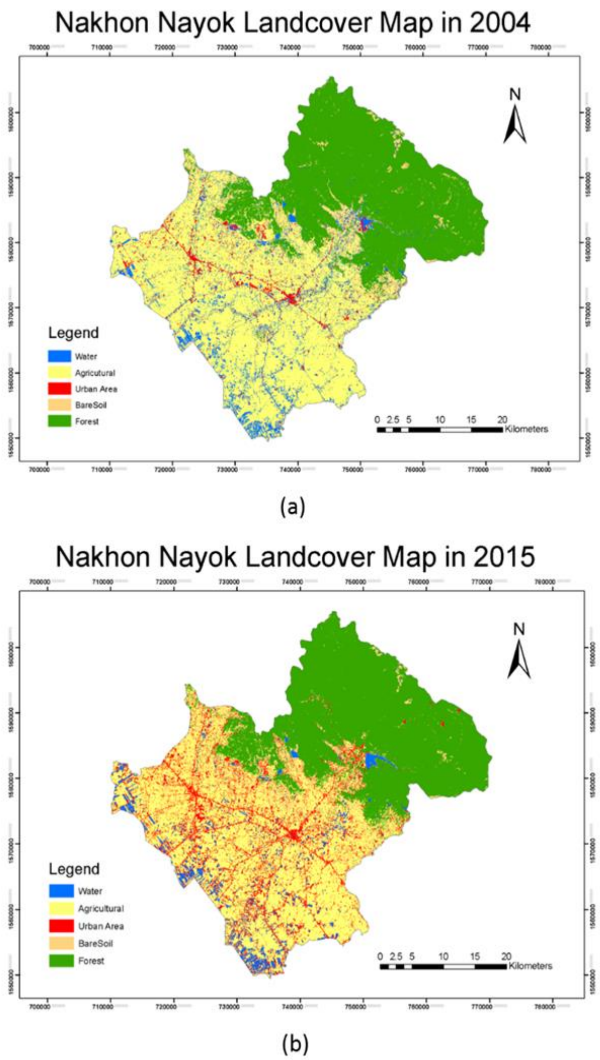


Figure 1 Sample of LU/LC maps in Nakhonnayok in 2004(a) and 2015(b)

management, landscape ecology and climate related researches. The last example is on environmental management in Tirupati, India (Mallupattu et al., 2013). LU/LC map was generated in order to determine the changes in Tirupati from 1976 to 2003. To obtain LU/LC map, the satellite images of interested area have to be interpreted. There are two types of image interpretation: visual interpretation and digital interpretation (Dalsted & Queen, 1999). The first type is analyst the image based on human being sense. Another type always involves in interpreting by image processing software. Three popular software are ERDAS Imagine (ERDAS), Environment for Visualizing Images (ENVI) and Quantum Geographic Information System (QGIS). Using data and remote sensing techniques urgently makes geographic processes fast and efficient, even though the increased complexity makes more opportunities for errors. This paper aims to interpret LU/LC of the study area by using remote sensing and images processing software and conducting an accurate assessment to assess how well the classification is doing. Most of LU/LC maps are generated from digital interpretation. The consistency of digital interpretation depends on satellite image, classifier and accuracy assessment. There are two main types of digital interpretation: unsupervised and supervised approaches. Both of them will return the result on the form of information group (e.g. agriculture, wetland, forest). However, supervised approach will generate the class signature from the training set before identifying the pixel into each group. In this paper, we focus on the supervised approach. It outlines the image interpretation, a case study on interpreting the satellite image of Chomthong, Phitsanulok, result and discussion and conclusion.

IMAGE INTERPRETATION

Image interpretation process consists of detecting, identifying, describing and estimating the importance of objects and pattern imaged. Interpretation methods can be either visual or digital. Both interpretation techniques have pros and cons, even if analyzed with digital, the final result must be analyzed visually (Lillesand et al., 2015). The ability of humans to identify objects through the content of images by combining many interpretive elements. There are two types of data extraction from images: Interpretation with visual analysis and digital interpretation (digital image processing) followed by visual analysis such as vector layer models from raster images via on-screen digitization and Digital Terrain Model (DTM) / Digital Elevation Model (DEM) creation (Zhou, 2016). Similarly, aerial imagery is interpreted through 3D visualization through visual study. In general, analog form in remote sensing data is being used to visual interpretation. This involves systematic data validation, studying existing maps, collecting field data and working at various complex levels. The analysis depends on the perception of the individual and the experience of the interpreter, the nature of the material, the quality of the data, size, combination of special bands, etc. The whole process of visual interpretation can be divided into the following phases: object detection, interpretation, perception and identification, analysis, classification, deduction and optimization, and depends on the inference of the object.

Therefore, the interpretation is the sum of identifying properties through the composition, photo recognition, field examination and final thematic mapping. Interpreting images that are helped by satellite imagery. The general flow of the interpretation process is shown in the Figure 2.

In the case of digital interpretation refers to managing digital images with the help of computers that is programmed to perform calculations using mathematical equations on the value of pixels and groups of pixels taken from the raw image as input. The output of the digital image processing is a new digital image whose pixel values are the result of those calculations. There are some disadvantages in visual interpretation techniques. However, they may want extensive training and intensive labor. In addition, the spectrum characteristics are not evaluated when attempting in visual interpretation images. In part because of the limited ability of the eye to see the tonal values in the image and the difficulty of interpreters in the analysis of multiple spectral images simultaneously. In applications that have high spectral data, Therefore it is popular to analyze digital data instead of visual data (Ratanopad & Kainz, 2006).

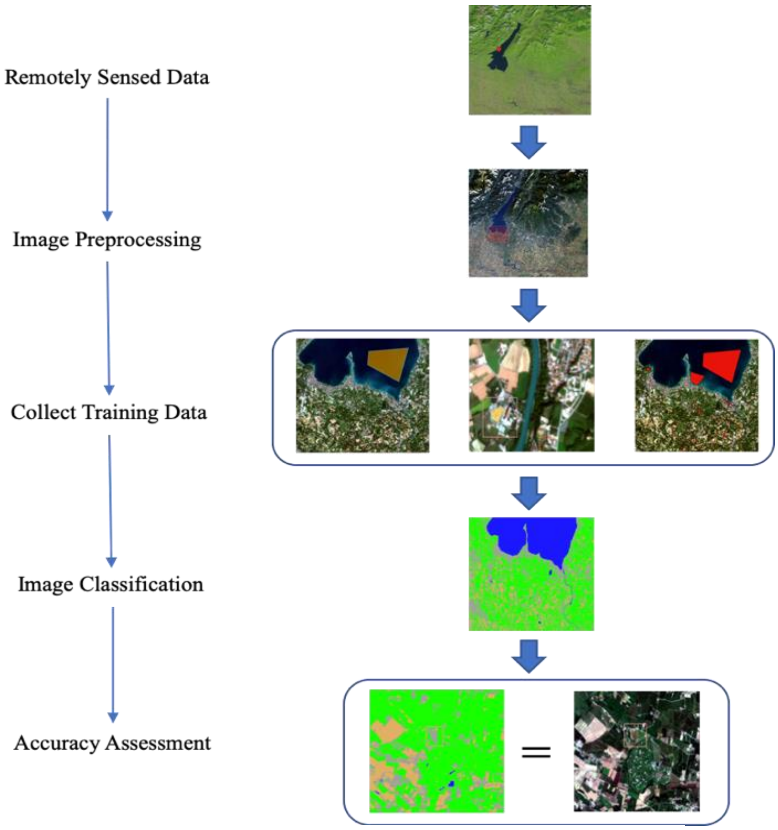


Figure 2 Flow for the image interpretation process

Image interpretation applications are used extensively such as monitoring, resource management, planning activities and mapping (Bayoudh et al., 2015, Du et al., 2014, Jagadeeswaran et al., 2018, Rawat & Kumar, 2015, Rujoiu-Mare & Mihai, 2016). For the application of the LU/LC classification interpretation. In practice, the remote sensing method can be used to classify LU/LC types, saving and duplicate pattern, in a large area. As the case study in the next section.

CASE STUDY

This study focused on a process of image interpretation for LU/LC classification. This process consists of an image pre-processing step, specifying of LU/LC as training areas, Image classification with maximum likelihood classifier (MLC), and accuracy assessment.

Image Pre-processing

The study area is an area of 35.8 km^2 including and surrounding Chomthong subdistrict Muang district, Phitsanulok province (Figure 3). The Nan river flows north-south through the study site. The whole area is flat river plain. The agricultural usage areas are completely under irrigation.

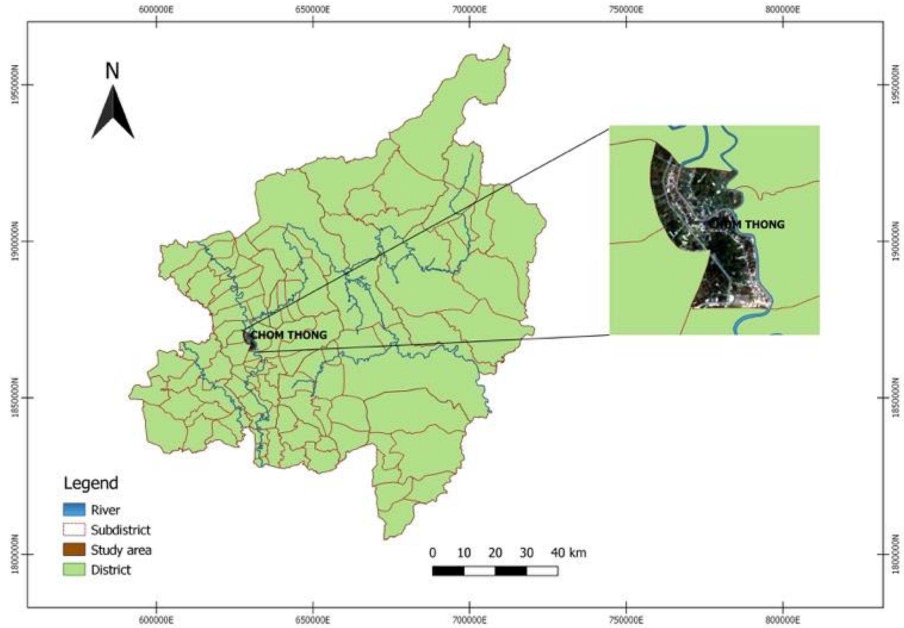


Figure 3 The location of Chomthong

A multi-temporal satellite data observed by LANDSAT 8 Operational Land Imager (OLI) from USGS (https://earthexplorer.usgs.gov/) on March 8, 2018 (Path 130/Row 48) was used for the analysis. The LANDSAT 8 satellite payload consists of two scientific instruments; the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). Both of these sensors provide a seasonal coverage of the earth with a spatial resolution of 30 meters visible (Near infrared (NIR), Shortwave infrared (SWIR)), 100 meters thermal, and 15 meters panchromatic (Lillesand et al., 2015). The initial processing is done using a 6-spectral-band layer stack comprised of Band-2 (blue, 0.450 - 0.51 µm), Band-3 (green, 0.53 - 0.59 µm), Band-4 (red,0.64 - 0.67 µm), Band-5 (NIR, 0.85 - 0.88 µm), Band-6 (SWIR 1, 1.57 - 1.65 µm) and Band-7 (SWIR 2, 2.11 - 2.29 µm), with false color composites, RGB: 5-6-4 for OLI. This combination of NIR (Band 5), SWIR 1 (Band 6) and red (Band 4) offers additional definitions of land-water scope highlights subtle details not readily apparent in the visible bands alone. Lakes and freshwater streams can be located increasingly precision when using more infrared bands. By this band combination, vegetation type and condition show as different of hues (oranges, browns, and greens), as well as in tone. The 5-6-4 combination shows different moisture content and is useful for soil and vegetation condition analysis. In general, the wet soil will be darker due to the infrared absorption of water. The relationship between the remotely sensed data and data used to reference geographic coordinates in systems is subject to geometrical correction and cutting out sub images of the study area from the remote sensing imagery (Subset image) (Figure 4).

Figure 4 False colour composites: 5 6 4

Training Area

Supervised classification is a technique commonly used for analysis of remote sensing image. Supervised classification depends on the user to select sample pixels in the image that is used to represent a particular class and then use the image processing software on the training area as a reference for the classification all other pixels in the image.

The training area is chosen from the raw images. The data in the training area must be good quality and be representative of the data from the area on the remote sensing image to be classified as a reference. The training area data pixel characteristics must have the same relative characteristics as the reference area, making the comparison between the training data and the reference data more accurate. As well, the training area must overlay the reference area accurately in regard to geographical coordinates. These factors will enhance the accuracy of the statistical analysis of the reference area and reduce the bias potentially in the statistical analysis of the reference area (Figure 5).

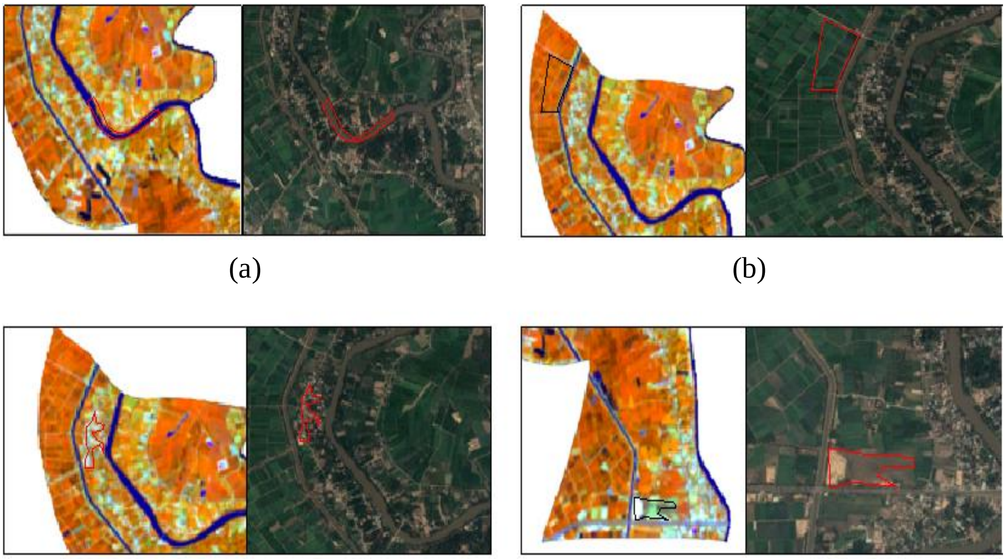


Figure 5 The training area for classifier; water area (a), vegetation area (b), built-up (c) and bare soil (d)

The LU/LC was generated based on field visits and interpretation of remote sensing imagery. The total number of pixels is chosen randomly from each type of land cover as training areas. Every pixel in the training area is additionally examined using high-resolution images of Google Earth and Landsat images to assure the land cover labels were correctly assigned (Zhu et al., 2016).

The training area were extracted from four categories (Table 1) of land use/land cover.

Table 1 Landcover desciption

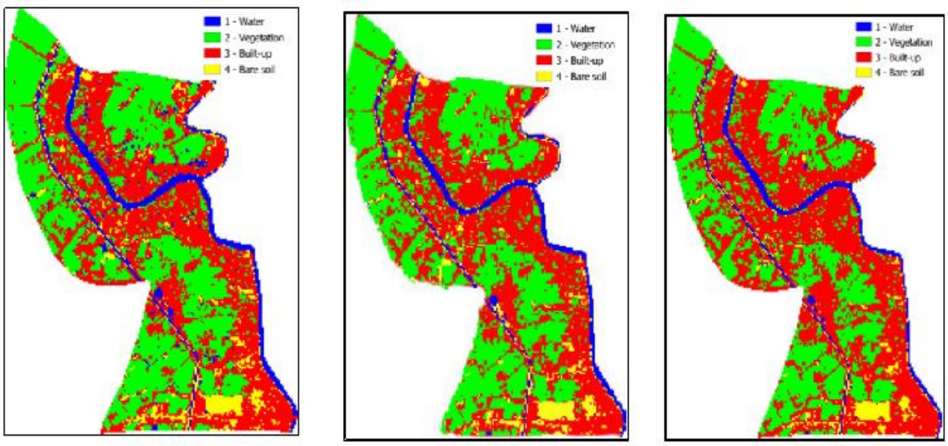
Classes	Description
Water	Reservoirs, stream, river, swamps
Vegetation	All plants and trees collectively, forest, agriculture, shrubs
Built-up	Land covered by buildings or houses structures, residential, urban area
Bare soil	The land has sandy, rocky, soil, never has more than 10% plant cover all year round

Image Classification with MLC

According to the idea that various types of properties on the surface of the earth has different spectral reflections and transmittance properties, their awareness is applied through the classification process into the widest sense. Image classification is described as the process of classifying all pixels in an image or remote sensing data to take a set of labels or land cover themes (Al-Doski et al., 2013). This paper classifies the data based on the type of LU/LC, divided into four types; bare soil, built-up water and vegetation.

Image classification of remotely sensed data is one step in the information extraction process. This is done using different techniques in image classification whether training samples are used or not. Other relevant factors to be considered in the information extraction process include the use of parametric or non-parametric statistical analysis, the kind of pixel information used, whether or not the output will provide a definitive decision about land cover class, and whether or not spatial information is used (Rong, 2016). These techniques are used to classify each pixel as representing a water area, or a vegetation area, or a built-up area and area of bare soil, based on its spectral response.

In our analysis the classification method known as Maximum Likelihood Classifier (MLC), was used to map out the four classes. This method is a supervised classification method that calculates the probability of a pixel being representative of each class thereby allowing them to be allocated to a particular class with the maximum probability. MLC calculates from the mean and covariance matrix for the training area and assumes that the pixel values are normally distributed. A class can stated as a feature by using the mean and covariance matrix value (Domadia & Zaveri, 2011; Nair & Bindhu, 2016). MLC is one of the most potent methods for processing training data when available and is one of the most widely used algorithms (Chutia et al., 2016; Perumal & Bhaskaran, 2010). In our research, MLC was used with three image processing software tools; Erdas Imagine, ENVI and QGIS to assess the accuracy of pixel classification in each method, and thus indicating the ability of each method to accurately classify LULC. The classification results of LULC areas by each of the three software tools is shown in Figure 6.



(a) (b) (c)

Figure 6 Classification results using MLC of Erdas Imagine (a), ENVI (b) and QGIS (c)

Accuracy Assessment

Accuracy assessment is the verification process which evaluates how accuracy of classification result or LU/LC map. Comparing this LU/LC map with reference maps is performed by comparing pixel per pixel, point per point and polygon per polygon based on the reference objects stated. The result determined correct and error of each of them and display in the format of an error matrix. Error matrix is an array of numbers given in rows and columns. Particularly, the number of sample units selected to a specific category is related to the actual category obtained from the ground truth. The column shows the reference data while the row defines the classification that is created from the remote sensing data (Congalton, 1991, 2001; Story & Congalton, 1986). The diagonals represent sites that are categorized correctly as references. Diagonal outside being wrongly made type. The error matrix of MLC classification on these three software (ERDAS, ENVI and QGIS) are shown below (Table 2 to Table 5).

Table 2 Error matrix of LU/LC classification of ERDAS

		Reference data				
		Water	Vegetation	Built-up	Bare soil	Total
Classified data	Water	37	1	6	6	**50**
	Vegetation	1	45	1	3	**50**
	Built-up	1	3	33	13	**50**
	Bare soil	0	0	0	50	**50**
	Total	**39**	**49**	**40**	**72**	**200**

Table 3 Error matrix of LU/LC classification of ENVI

		Reference data				
		Water	Vegetation	Built-up	Bare soil	Total
Classified data	Water	37	1	6	6	**50**
	Vegetation	1	44	2	3	**50**
	Built-up	1	3	33	13	**50**
	Bare soil	0	0	2	48	**50**
	Total	**39**	**48**	**43**	**70**	**200**

Table 4 Error matrix of LU/LC classification of QGIS

Classified data	Reference data	Water	Vegetation	Built-up	Bare soil	Total
	Water	37	1	6	6	**50**
	Vegetation	1	40	6	3	**50**
	Built-up	1	6	30	13	**50**
	Bare soil	0	0	0	50	**50**
	Total	**39**	**47**	**42**	**72**	**200**

Information of each error matrix table are used to calculate overall accuracy (OA), producer accuracy (PA) and user accuracy (UA). These values are useful for decision maker to design which software are appropriate for their works. OA can calculate from equation (1) below:

$$OA = \frac{Number\ of\ correct\ pixels}{Total\ number\ of\ pixels} \quad (1)$$

OA is the average. It does not reveal whether the errors are equally distributed between classes or if some classes are certainly not good and some are good. Hence, the other two values, UA and PA, may be considered. User accuracy shows the map accuracy from the user's perspective in the classified map. A pixel which is grouped into one of the classified class on the image, can be two or more types of matter on the reference map. The 'correct' class, which refers to the same land cover class on the map and on the ground, and the 'incorrect' class, which shows the different land cover for the ground than those classified on the map. The following classes are called a commission error. More commission errors, the lower the user accuracy (Banko, 1998; Congalton & Green, 2002; Nagamani et al., 2015). The calculations of UA and commission error (CE) are shown as in equation (2) and (3).

$$UA = \frac{Number\ of\ correctly\ identified\ in\ a\ given\ map\ class}{Number\ claimed\ to\ be\ in\ that\ map\ class} \quad (2)$$

$$CE = 1 - UA \quad (3)$$

Producer accuracy comes from dividing the correct number of pixels in one class divided by the total number of pixels obtained from the reference data. PA is a measure of how well the category is classified. It includes omission errors which refer to the proportion of features seen on the ground that are not classified in the map. More omission error, the lower the producer accuracy (Banko, 1998; Congalton & Green, 2002; NAGAMANI et al., 2015). The calculations of PA and omission error (OE) are shown as in equation (4) and (5).

$$PA = \frac{Number\ of\ correctly\ identified\ in\ ref.pixels\ of\ a\ given\ class}{Number\ actually\ in\ that\ reference\ class} \tag{4}$$

$$OE = 1 - PA \tag{5}$$

Kappa is a statistical value which measures the different of agreement or accuracy between the classification map obtained from remote sensing and the reference data specified. Can calculate the Kappa coefficient (Kappa) as follows,

$$K = \frac{P_o - P_c}{1 - P_c} \tag{6}$$

Where,
P_o = proportion of units agreed, OA
P_c = proportion of units for expected chance agreement

The Kappa coefficient is not sensitive to the difference in sample size between classes, so it is considered a more reliable measurement. The general range for Kappa values is divided into three groups: a value greater than 0.80 indicates a high agreement, values between 0.40 and 0.80 indicates medium agreements, and a value lower than 0.40 indicates poor agreement (Banko, 1998; Congalton, 2001). In Table 5 show all accuracy measurement for classification.

Table 5 Classification accuracies for various image processing software tools

	Name of image processing software											
	ERDAS				ENVI				QGIS			
	Accuracy measurement (%)											
	PA	UA	CE	OE	PA	UA	CE	OE	PA	UA	CE	OE
Water	94.87	74	26	5.13	94.87	74	26	5.13	94.87	74	26	5.13
Vegetation	91.84	90	10	8.16	91.67	88	12	8.33	85.10	80	20	14.90
Built-up	82.50	66	34	17.50	76.74	66	34	23.26	71.43	60	40	28.57
Bare soil	69.44	100	0	30.56	68.57	96	4	31.43	69.44	100	0	30.56
OA	**83**				**81**				**79**			
Kappa	**76**				**74**				**71**			

Note: PA= producer accuracy, UA = user accuracy, CE = commission error, OE = omission error, OA = overall accuracy, and Kappa = kappa coefficient

The comparison of classification results in LU/LC map was based on the value of accuracy assessment. An error matrix table was generated for each result map, and calculate the overall accuracy (OA), producer accuracy (PA), user accuracy (UA), and kappa coefficient (Kappa). Moreover, the main focus for pixel selection, accuracy assessment, is in areas that can be identified, both in high resolution and Landsat images. The pixel selection uses reference data to classify from Google Earth and Google maps. Create a total of 200 points from classified images in the study area using stratified random sampling. Stratified sampling is suggested according to the minimum number of samples to choose from in each category (Congalton, 1991). Accuracy assessment results have shown in Table: 2, 3, 4 and 5 respectively.

RESULTS AND DISCUSSION

Comparison of interpretation on satellite image of Chomthong with three image processing software is shown in Table 5. The results of the accuracy assessment in Table V show the OA received from the process of sampling for the images of 83%, 81% and 79% (ERDAS, ENVI and QGIS). UA is between 60% to 100% while PA is between 68.57% to 94.87%. Multiple accuracies in predicting specific categories. The UA shows the reliability of classification to users. UA is a more pertinent measurement of true classification in the field. Found that bare soil is more reliable with 100% of UA except for ENVI (96%). To indicate the strong complexity of built-up with other land cover classes. In addition, PA measurements show CE, reflecting the pixels included in the category while not in that category. For example, CE is the highest level in the case of the built-up area, which means that many pixels not in this category will be categorized as the built-up area. Nearly, OE shows the number of pixels that are not included in the same category in that category. The OE in the case of bare soil is more (30.56% in ERDAS and QGIS, 31.43% in ENVI) with 22 pixels which be members of this category, are not classified in this class. In this study, Kappa of 76%, 74% and 71% (ERDAS, ENVI and QGIS) were received which is rated as considerable. As stated earlier, Kappa is over 70% higher. It may be interpreted that the classification is more accurate than expected by a random class assignment. Kappa value of 76% for ERDAS indicates better classification of LU/LC map. But that does not mean that the other software is not effective in identifying LU/LC, which can be seen from the Kappa values (74% and 71%) that are similar. It is possible that each software will hide the adjustment of various parameters in the background, resulting in different classification performance. Because the study area, identifier and training are the same.

CONCLUSIONS

In this study, MLC is done through image processing software, to interpret LULC in Chomthong, in which leads to the conclusion. MLC classifies existing classes in the study area with good agreement with the reference area. MLC classified the study area through ERDAS, ENVI, and QGIS into four classes (e.g. water, bare soil, vegetation and built-up). The accuracy assessment is useful in evaluating the effectiveness of the model for a specific interest class for the study. The error matrix has been carried out, with OA of more than 79% of the three-image processing software and Kappa is better by 70%. Kappa is ranked as important and makes the classified images suitable. The result shows that OA and Kappa are better for ERDAS compared to ENVI and QGIS. Therefore, it can be concluded that ERDAS is a better tool for effective LULC classification in Chomthong. Selection of a suitable software requires consideration of main factor, such as classifier performance, classification accuracy and software type (e.g. commercial software or open source software). Which it depends on the user's decision to use the software. If you want to use open source software, QGIS is as effective in interpreting LULC as well as commercial software.

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REFERENCES

Al-Doski, J., Mansorl, S. B., & Shafri, H. Z. M. (2013). Image classification in remote sensing. *Department of Civil Engineering, Faculty of Engineering, University Putra, Malaysia*.

Banko, G. (1998). *A review of assessing the accuracy of classifications of remotely sensed data and of methods including remote sensing data in forest inventory*.

Bayoudh, M., Roux, E., Richard, G., & Nock, R. (2015). Structural knowledge learning from maps for supervised land cover/use classification: Application to the monitoring of land cover/use maps in French Guiana. *Computers & Geosciences*, *76*, 31–40.

Chutia, D., Bhattacharyya, D. K., Sarma, K. K., Kalita, R., & Sudhakar, S. (2016). Hyperspectral remote sensing classifications: A perspective survey. *Transactions in GIS*, *20*(4), 463–490.

Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, *37*(1), 35–46.

Congalton, R. G. (2001). Accuracy assessment and validation of remotely sensed and other spatial information. *International Journal of Wildland Fire*, *10*(4), 321–328.

Congalton, R. G., & Green, K. (2002). *Assessing the accuracy of remotely sensed data: Principles and practices*. CRC press.

Dalsted, K., & Queen, L. (1999). Interpreting remote sensing data. *The Site-Specific Management Guideline SSMG-26*.

Diem, P. K., Sitthi, A., Pimple, U., & Pungkul, S. (2015). Mapping Land Cover Dynamics in Nakhon Nayok Province of Thailand. *Suan Sunandha Science and Technology Journal*, 1.

Domadia, S. G., & Zaveri, T. (2011). Comparative analysis of unsupervised and supervised image classification techniques. *Proceeding of National Conference on Recent Trends in Engineering & Technology*, 1–5.

Du, P., Liu, P., Xia, J., Feng, L., Liu, S., Tan, K., & Cheng, L. (2014). Remote sensing image interpretation for urban environment analysis: Methods, system and examples. *Remote Sensing*, *6*(10), 9458–9474.

Giri, C. P. (2016). *Remote sensing of land use and land cover: Principles and applications*. CRC press.

Jagadeeswaran, R., Poornima, A., & Kumaraperumal, R. (2018). Mapping and classification of crops using high resolution satellite image. *Journal of Applied and Natural Science*, *10*(3), 818–825.

Lillesand, T., Kiefer, R. W., & Chipman, J. (2015). *Remote sensing and image interpretation*. John Wiley & Sons.

Mallupattu, P. K., Reddy, S., & Reddy, J. (2013). Analysis of land use/land cover changes using remote sensing data and GIS at an Urban Area, Tirupati, India. *The Scientific World Journal*, *2013*.

Mei, A., Manzo, C., Fontinovo, G., Bassani, C., Allegrini, A., & Petracchini, F. (2016). Assessment of land cover changes in Lampedusa Island (Italy) using Landsat TM and OLI data. *Journal of African Earth Sciences*, *122*, 15–24.

Nagamani, D. K., Jayakumar, K., Suresh, Y., & Ganesh, J. S. (2015). Study on Error Matrix Analysis of Classified Remote Sensed Data for Pondicherry Coast. *Journal of Advanced Research in Geo Sciences & Remote Sensing*, *2*(3).

Nair, M., & Bindhu, J. S. (2016). Supervised techniques and approaches for satellite image classification. *International Journal of Computer Applications*, *134*(16).

Natya, S., & Rehna, V. J. (2016). Land cover classification schemes using remote sensing images: A recent survey. *Current Journal of Applied Science and Technology*, 1–11.

Paliwal, M. C., & Katiyar, S. K. (2015). Accuracy Assessment of Land Cover /Land Use Mapping Using Medium Resolution Satellite Imagery. *International Journal of Scientific & Engineering Research*, *6*(7), 1428–1432.

Perumal, K., & Bhaskaran, R. (2010). Supervised classification performance of multispectral images. *ArXiv Preprint ArXiv:1002.4046*.

Ratanopad, S., & Kainz, W. (2006). Land cover classification and monitoring in northeast thailand using landsat5 TM data. *ISPRS Technical Commission II Symposium, Vienna*, *7*.

Rawat, J. S., & Kumar, M. (2015). Monitoring land use/cover change using remote sensing and GIS techniques: A case study of Hawalbagh block, district Almora, Uttarakhand, India. *The Egyptian Journal of Remote Sensing and Space Science*, *18*(1), 77–84.

Rong, R. (2016). Research and analysis of hyperspectral remote sensing image classification algorithms. *2016 Chinese Control and Decision Conference (CCDC)*, 3960–3964.

Rujoiu-Mare, M.-R., & Mihai, B.-A. (2016). Mapping land cover using remote sensing data and GIS techniques: A case study of Prahova Subcarpathians. *Procedia Environmental Sciences*, *32*, 244–255.

Sekertekin, A., Marangoz, A. M., & Akcin, H. (2017). Pixel-based classification analysis of land use land cover using Sentinel-2 and Landsat-8 data. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *42*(6), 91–93.

Story, M., & Congalton, R. G. (1986). Accuracy assessment: A user's perspective. *Photogrammetric Engineering and Remote Sensing*, *52*(3), 397–399.

Zhou, Q. (2016). Digital elevation model and digital surface model. *International Encyclopedia of Geography: People, the Earth, Environment and Technology: People, the Earth, Environment and Technology*, 1–17.

Zhu, Z., Fu, Y., Woodcock, C. E., Olofsson, P., Vogelmann, J. E., Holden, C., Wang, M., Dai, S., & Yu, Y. (2016). Including land cover change in analysis of greenness trends using all available Landsat 5, 7, and 8 images: A case study from Guangzhou, China (2000–2014). *Remote Sensing of Environment*, *185*, 243–257.