ANALYSIS OF THE DETECTION METHODS FOR RICE PADDY AREA USING MULTI-TEMPORAL TERRA/ASTER DATA

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ABSTRACT: Due to the rapidity of the population growth and the climate change, their impact on food security has been a major concern recently. The distribution of planted area is the basic information for monitoring the growth and predicting the yield of crops. In Asia, where rice is the staple, it is required to detect distribution of planted rice paddy area accurately, and satellite remote sensing has potential to achieve this purpose. Therefore, this study investigated methods to detect accurate distribution of planted rice paddy area using multi-temporal Terra/ASTER data. In this study, pixel-based and object-oriented classifications were selected. Traditional pixel-based image classification method depends only on the spectral characteristics of the image. The object-oriented approach, having been used in the past few years, can also takes into account spatial relationship of them. Study area was chosen in Nakhon Nayok, Thailand and four images in dry season, starting from November 2009 to January 2010, were selected. Normalized Difference Vegetation Index (NDVI) indicates the amount of vegetation in the image, hence its values change corresponding to rice paddy growth stage. To utilize time series change of the NDVI values for detection, both pixel-based and object-oriented classification were applied to the four-layer image created from each NDVI image. In pixel-based approach, unsupervised classification based on K-means algorithm was applied. The object-oriented approach was followed with three steps: i) edge detection, ii) segmentation based on pyramid linking, and iii) K-means clustering. An accuracy assessment was performed by using field survey data. The results indicated that higher accuracy was obtained by object-oriented approach than the pixel-based one, and most of planted rice paddy areas could be detected.

1. INTRODUCTION

The population growth and the climate change have become more serious problems at global scale recently. The global warming and abnormal weather have been observed, and the world population is predicted to grow about 9 billion in 2050. Therefore, their impacts on food security have been also a major concern. For stable food supply, it is necessary to monitor the growth and predict the yield of crops. The distribution of planted area is the basic information for this purpose. And satellite remote sensing has potential to estimate it. It is one of the most important subjects to detect accurate planted area using satellite images and several methods have been examined for this subject.

In Asia, where rice is the staple, the population growth and climate change has been remarkable and it is required to detect accurate distribution of planted rice paddy area for food security. In this regards, this study investigated methods to detect accurate distribution of planted rice paddy area using multi-temporal Terra/ASTER data.

2. STUDY AREA AND MATERIALS

2.1 Study area

The irrigated area in Nakohn Nayok province, located in the northeast of Bangkok, was selected as study area (Figure 1). The area is situated at 14°10' E and 101°10' N.
This area belongs to tropical monsoon climate and consists of the rainy and dry seasons. Farmers can cultivate two or three cropping per year. Planting date depends on each farmer because the area was irrigated and has enough temperature for cultivate through a whole year.

2.2 Materials

For this study, Terra/ASTER data which were achieved on November 20, November 27, December 6 in 2009, and January 14 in 2010 were used to detect the distribution of planted rice paddy areas in the dry season.
As vegetation indicates characteristic behavior in the green, red (RED) and near-infrared (NIR) wavelength range, three bands of ASTER sensor, Band1 (0.52-0.60µm), Band2 (0.63-0.69µm), and Band3N (0.76-0.86µm), were selected for the analysis. Spatial resolution of these bands is 15 meters by 15 meters.

To collect the validation data, field survey was conducted from December 15 to 18 in 2009. The validation data was obtained in 90 sites, including 45 sites in rice paddy and 45 sites in non rice paddy. Non rice paddy includes canal, road, bush, pond, and so on. An accuracy assessment was performed by using error matrix.

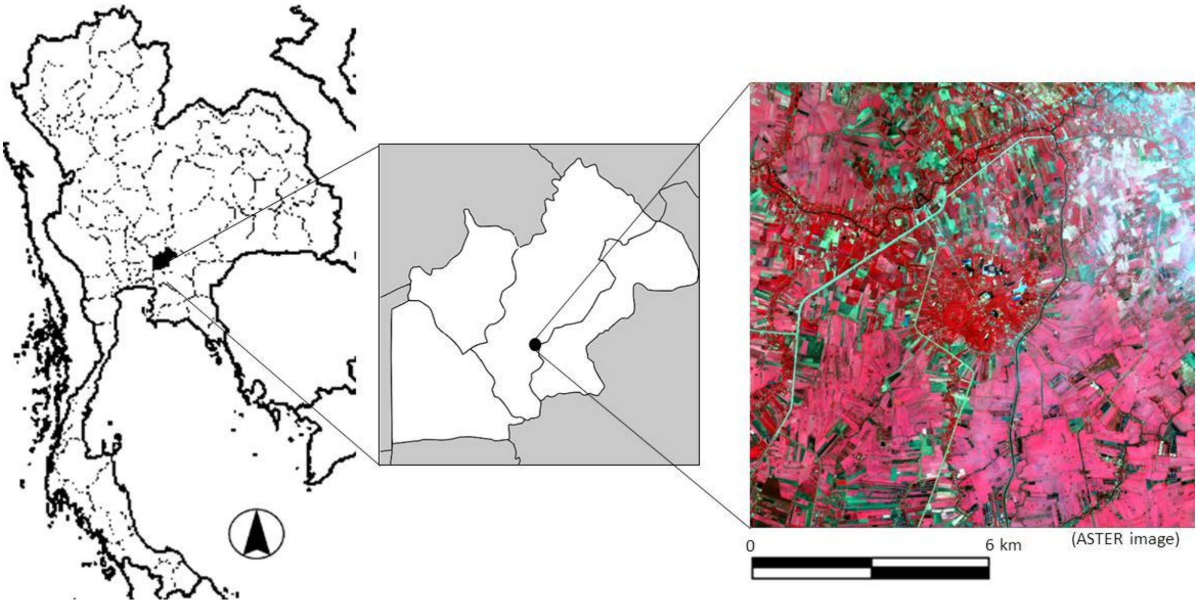


Figure 1. Location of the study area

3. METHODOLOGY

The flow of analysis in this study is shown in Figure 2. Firstly the four–layer Normalized Difference Vegetation Index (NDVI) image was created from each ASTER image (refer to section 3.1). Secondly, both pixel-based and object-oriented classifications were applied to the image (refer to section 3.2). Finally planted rice paddies were detected using classification result (refer to section 3.3).

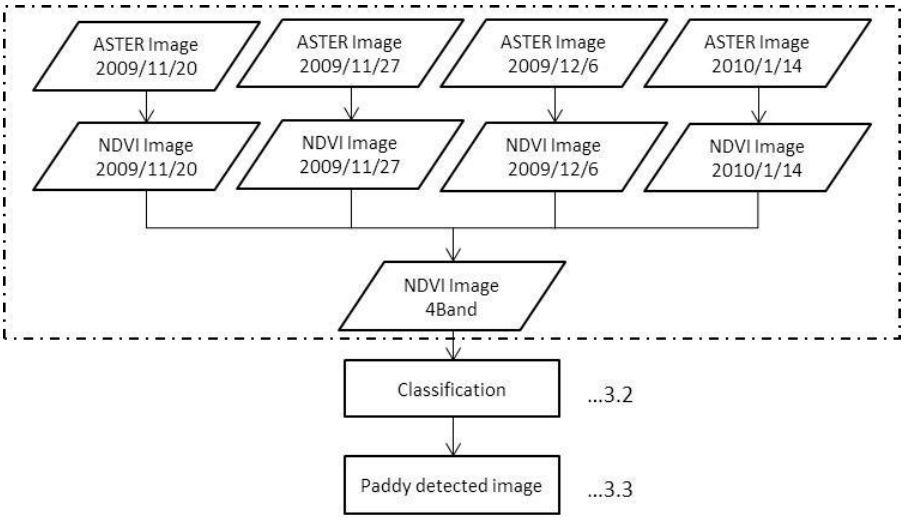


Figure 2. The flow of analysis

3.1 Creating the four-layer NDVI image

Firstly Digital Number (DN) obtained by ASTER sensor was converted into radiance using radiometric calibration coefficients.
Secondly, four NDVI images were created from each ASTER image. NDVI indicates the amount of vegetation in the image and is calculated from following equation.

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

NIR and *RED* are the radiance or reflectance of near-infrared and red wavelength band corresponding to Band3N and Band2 of ASTER sensor, respectively.

Thirdly, to decrease the effect of atmosphere, the values of the NDVI images obtained on November 20, December 6 in 2009, and January 14 in 2010 were approximated to that of the NDVI image obtained on November 27, 2009. Linear regression analysis was performed using the values of twenty points in artificial materials such as road and building in each NDVI image. Then, the four-layer image was created from four NDVI images.

3.2 Classification analysis

The four-layer image was classified utilizing time series change of the NDVI values from November 20, 2009 to January 14, 2010.

There are several kinds of image classification methods, and the suitable one should be selected depending on the situation. In this study, pixel-based and object-oriented classifications were selected. The pixel-based classification is a traditional and a widely used method. Most of image analysis softwares equip this classification algorithm. This method depends only on the spectral characteristics of each pixel in the image. Therefore tiny areas constituted by a few pixels appear due to noise in classified image. On the other hand, the object-oriented classification has been used in the past few years. In this approach the image is divided into sub regions (objects) before classification. This approach takes into account spatial relationship of neighboring pixels and the shape of features. As the shape of rice paddy in this area is rectangle, it is expected to utilize the advantage of object-oriented approach in this study.

The processes of pixel-based and object-oriented classification in this study are as follows. In pixel-based approach, K-means algorithm was applied. K-Means algorithm is a classic unsupervised classification method and a kind of the nonhierarchic clustering which sets the number of classes in advance (Takagi and Shimoda, 1991). The flow of the object-oriented approach in this study is shown in Figure 3. In this approach, firstly the edge of the image was detected by zero crossing method using Laplacian of Gaussian (LoG) filter (Okuda, 1995). After dividing pixels of the image into “Edge” or “Not edge”, segmentation based on pyramid linking (Burt et al, 1981, Hong et al, 1982) was applied only to “Not edge” pixels to create sub regions (objects). Then, the objects were classified by K-Means algorithm. Finally the “Edge” pixels were assigned to a class by comparing with the surrounding eight pixels.

Mixed pixels (mixels) include more than two land covers, and the way of classifying mixels is one of the important problems in the image classification analysis. In the object-oriented classification used in this study, only pure pixels were classified after detecting the mixels which appeared on the boundary of land covers. Hence, it is expected this approach can reduce the effect of mixels.

3.3 Detecting planted rice paddy area

Figure 4 shows the example of time series change of the NDVI values. In planted rice paddy area, the NDVI value changes corresponding to the rice growth stage. On the other hand, in the other land covers in study area such as pond, bush and road, the states of pixels rarely change for three months. Therefore, the NDVI value in these areas does not range so much. Hence planted rice paddies were detected by utilizing the difference of time series change of the NDVI value.

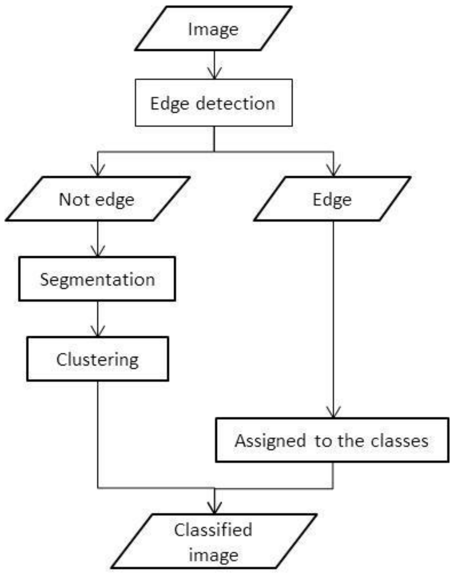


Figure 3. The flow of object-oriented classification

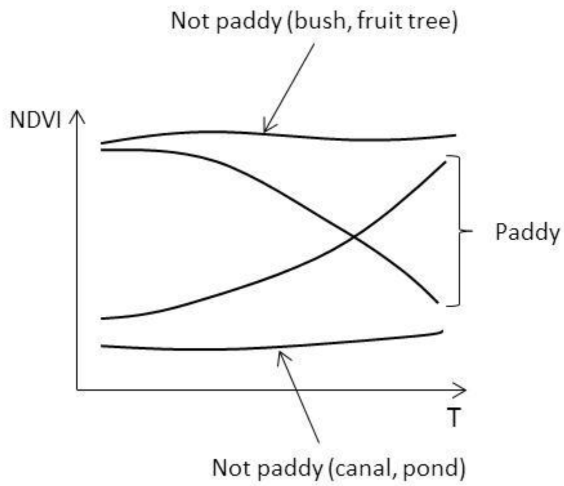


Figure 4. The example of time series change oh the NDVI value

4. RESULTS AND DISCUSSION

The time series changes of the NDVI value obtained by both pixel-based and object-oriented classifications are shown in Figure 5 and Figure 6. The number of classes was empirically set to nine (9) based on field survey data. The planted rice paddy areas were detected using the difference of time series change of the NDVI values between the classes. The paddy detected images obtained by both classifications are shown in Figure 7 and Figure 8.

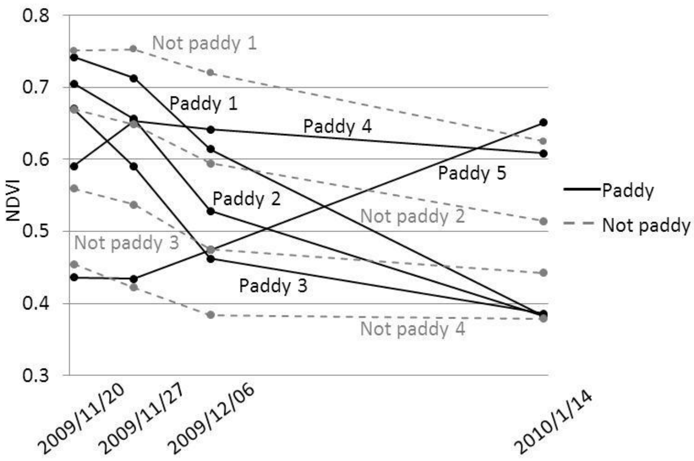


Figure 5. Time series change of the NDVI value by pixel-based classification

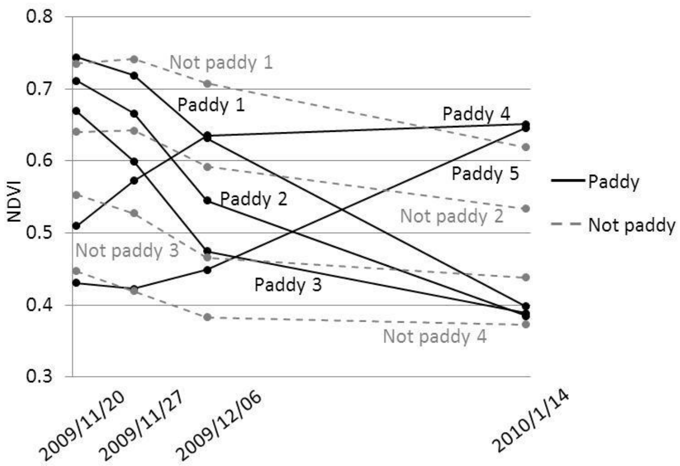


Figure 6. Time series change of the NDVI value by object-oriented classification

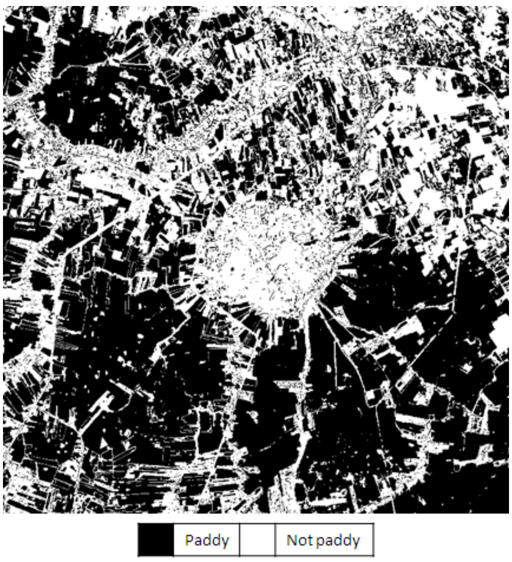


Figure 7. The paddy detected image by pixel-based classification

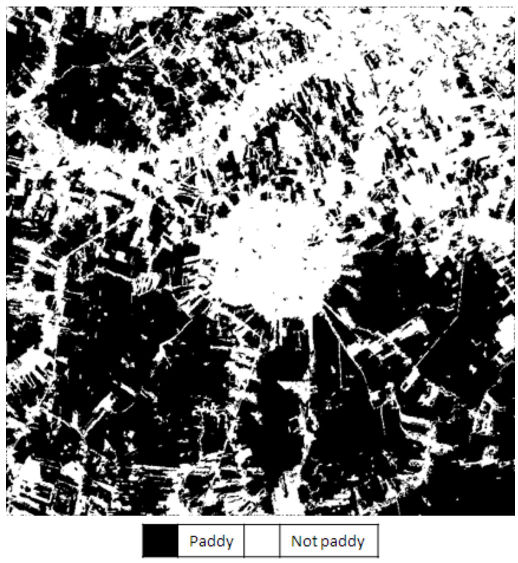


Figure 8. The paddy detected image by object-oriented classification

The results of accuracy assessment are shown in Table 1 and Table 2. To evaluate the effectiveness of both classification approaches, Detected paddy area rate and Kappa coefficient were also calculated as error indices. Detected paddy area rate indicates the ratio of paddy detected area to the total area of 45 paddy fields. Kappa coefficient indicates the reliability of classification result.

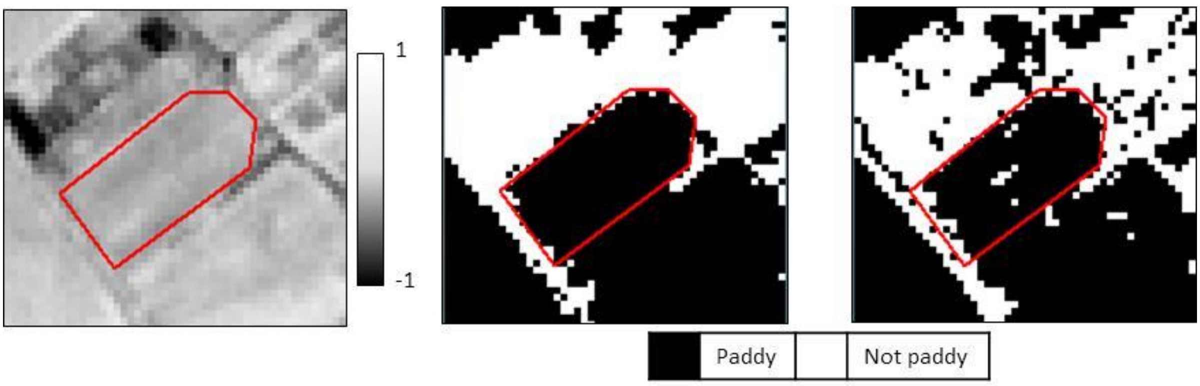
Table 1. Error matrix for pixel-based classification

		Result			*Producer's accuracy (%)*
		Paddy	*Not paddy*	*total*	
Reference	*Paddy*	33	12	45	73.3
	Not paddy	7	38	45	84.4
	total	40	50	90	
User's accuracy (%)		82.5	76.0		**78.9**
Detected paddy area rate (%)	85.6			*Kappa Coefficient*	0.578

Table 2. Error matrix for object-oriented classification

		Result			*Producer's accuracy (%)*
		Paddy	*Not paddy*	*total*	
Reference	*Paddy*	33	12	45	73.3
	Not paddy	2	43	45	95.6
	total	35	55	90	
User's accuracy (%)		94.3	78.2		**84.4**
Detected paddy area rate (%)	87.2			*Kappa Coefficient*	0.689

As shown in Table 1 and Table 2, producer's accuracy of "Paddy" class was equal, but Detected paddy area rate of object-oriented approach was about 2 % higher than that of pixel-based one. This difference was caused by tiny areas appearing in the paddy detected image obtained by pixel-based one. Although there were many tiny areas in the paddy detected image of the pixel-based approach (Figure 7), such areas did not appear in that of the object-oriented one (Figure 8), because the image was classified after segmentation in object-oriented one. Figure 9 shows the example of the area where the paddy detected areas were different between both approaches. While the whole field of paddy was detected by object-oriented approach (center in Figure 9), "Not paddy" area appeared in the paddy field in the result by the pixel-based one (right in Figure 9).



Left: NDVI image
Center: The paddy detected image by object-oriented classification
Right: The paddy detected image by pixel-based classification

Figure 9. The example of area where the paddy detected images were different between both classifications

Producer's accuracy of "Not paddy" class of object-oriented approach was much higher than that of the pixel-based one. This resulted from the difference between "Paddy4" class of both approaches as shown in Figure 5 and Figure 6. While the NDVI values of "Paddy4" class obtained by object-oriented approach gradually increased for three months (Figure 5), that obtained by pixel-based approach showed different behavior (Figure 6). The regions of "Paddy4" class obtained by object-oriented approach were included in rice paddy areas where rice grown gradually. On the other hand, the regions of "Paddy4" class obtained by the pixel-based one appeared in not only rice growing paddy areas but also bush and the boundary of land covers. While in the object-oriented approach mixels that appear on boundary of land cover were detected in advance and only pure pixels was classified, in the pixel-based one mixel was classified as well as pure pixel. Hence, the image was classified more accurately in object-oriented approach than in the pixel-based one.

As a result, the accuracy of the object-oriented approach was higher than that of the pixel-based one with respect to the total accuracy, Detected paddy area rate, and Kappa coefficient.

5. CONCLUSION

For food security, it has been required to estimate the accurate distribution of rice paddy area to monitor rice growth and to predict the yield. Here many methods have been examined in achieving this purpose using Satellite images. In this regards, this study investigated methods to detect accurate distribution of planted rice paddy area using multi-temporal Terra/ASTER data. Comparing pixel-based with object-oriented classifications, the higher accuracy was obtained by object-oriented approach than that by the pixel-based one. The major reasons according to the findings of this study are as follows; i) although there are many fragmented areas in the paddy detected image of the pixel-based approach, such areas do not appear in that of the object-oriented one because the image was classified after segmentation in object-oriented approach, ii) in object-oriented approach mixels that appear on boundary of land use (edges) were detected and only pure pixels were classified.

Most of planted rice paddy areas were detected by object-oriented approach in this study. However, some rice paddies were misclassified as "Not paddy" class. To detect such rice paddy areas, further modifications and improvements is expected with the use of shape based detection and texture analysis.

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