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Mapping Paddy Rice Agriculture using Multi-temporal FORMOSAT-2 Images

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***Abstract*—**Most paddy rice fields in East Asia are small parcels, and the weather conditions during the growing season are usually cloudy. FORMOSAT-2 multi-spectral images have an 8-meter resolution and one-day recurrence, ideal for mapping paddy rice fields in East Asia. To map rice fields, this study first determined the transplanting and the most active tillering stages of paddy rice and then used multi-temporal images to distinguish different growing characteristics between paddy rice and other ground covers. The unsupervised ISODATA (iterative self-organizing data analysis techniques) and supervised maximum likelihood were both used to discriminate paddy rice fields, with training areas automatically derived from ten-year cultivation parcels in Taiwan. Besides original bands in multi-spectral images, we also generated normalized difference vegetation index and experimented with object-based pre-classification and post-classification. This paper discusses results of different image classification methods in an attempt to find a precise and automatic solution to mapping paddy rice in Taiwan.

***Keywords*—**paddy rice fields; multi-temporal; FORMOSAT-2 images, normalized difference vegetation index, object-based classification.

I. Introduction

PADDY rice fields account for over 11% of global cropland area [1-2]. Over half of the world's population live in major rice-producing countries of Asia, where rice represents over 35% of their daily caloric intake. Monitoring and mapping paddy rice agriculture in a timely and efficient manner is therefore important for agricultural and environmental sustainability, food and water security, and greenhouse gas emissions [2]. Paddy rice needs flooded soils during the growing period, so water resource management is also a major concern. Irrigation for agriculture accounts for over 80% of the fresh water withdrawals in South-East Asia and South Asia, with several countries in this region reporting over 95% of fresh water used for irrigation [3].

The Agriculture and Food Agency in Taiwan monitors cultivated paddy fields by manually interpreting aerial photographs. This manual method, however, has some disadvantages. First, because field parcels in Taiwan are usually small, interpreting paddy fields in aerial photographs is both time and energy consuming. Second, the cloudy climate in Taiwan hinders the work of getting aerial photographs for the proper growing time. Third, although aerial photographs have a good resolution, each shot can cover only an area of 10 km^2 areas or less. As satellite technology has improved in recent years, satellite images have become good alternatives to aerial photographs. Unlike aerial photographs, satellite images can cover wide areas and have higher temporal resolutions.

Various methods have been evaluated for assessing the potential of computer-aided classification for mapping traditionally-managed rice fields. Image-derived data such as the normalized difference vegetation index (NDVI) have improved classification of rice fields and other land covers [2, 4-7]. The normalized difference water index (NDWI), when used with NDVI temporal anomalies, has shown to be effective for detecting flooding and rice transplanting [5]. The land surface water index (LSWI), enhanced vegetation index (EVI), and NDVI derived from MODIS images have also been used to identify changes in the mixture of surface water and green vegetation in paddy rice fields over time [2]. This study chose NDVI and differential NDVI (dNDVI) from primary images as possible aids for classifying paddy rice fields in Taiwan.

Additionally, this study experimented with two other techniques. The first relates to the selection of training areas, a manual and often difficult task. Rather than interpreting satellite images with naked eyes or investigating in the field, we used published cultivation data and an overlay method to automatically select training areas. The second relates to the object-based approach. Besides pixels, we also used parcels as objects for both pre-classification and post-classification. For high-resolution imagery, the object-based analysis and segmentation allows homogeneous groups of pixels, such as cultivation parcels, to be classified as real objects of interest [8-10].

II. Study Area

The 30 km^2 study area is located in Yunlin County, Taiwan (120°22'28''—120°25'31''E and 23°37'30''—23°40'30''N) (Fig. 1). Paddy rice fields account for half of this study area; hence, paddy rice plays an important role for the livelihood of local inhabitants. In Yunlin County, there are first and second rice crops. Like most regions of East Asia, paddy rice goes through the stages of flooding, transplanting, tillering, flowering, and harvesting for each cultivation period. Paddy

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fields during these specific stages have special spectral characteristics that can separate them from other land covers.

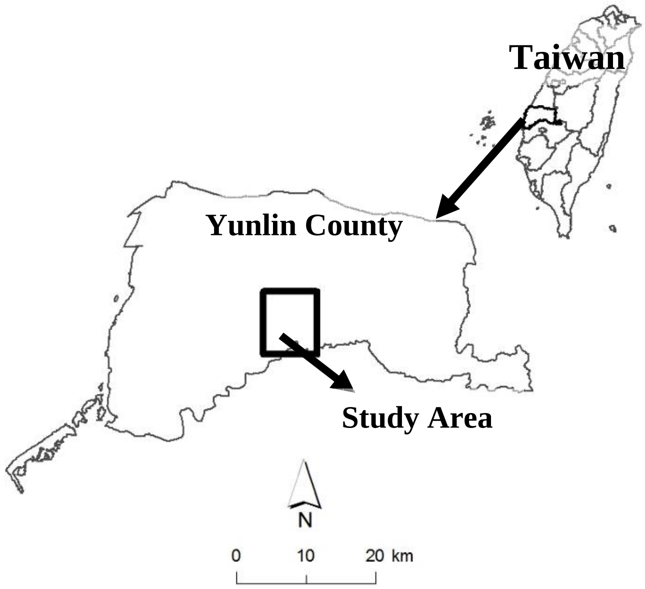

Fig. 1 The study area in Yunlin County, Taiwan

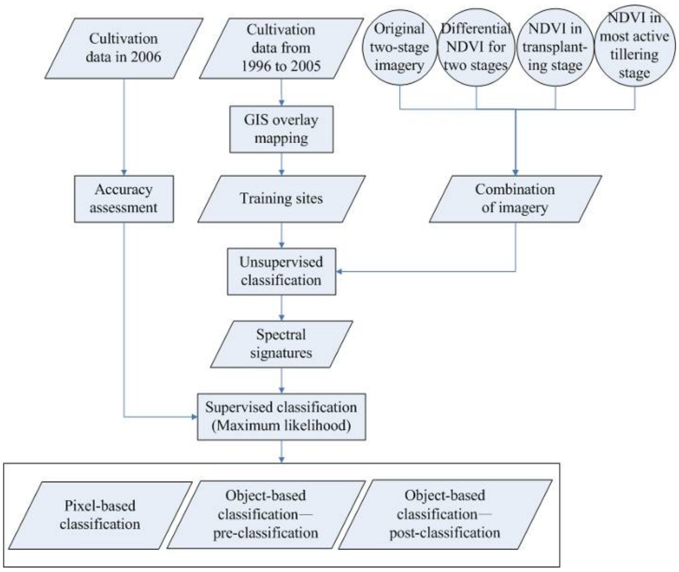

Fig. 2 The schematic flowchart of the methodology

III. Data and Method

Following the flowchart in Fig. 2, this study gathered past ten-year cultivation parcel data, used cultivation parcels as an overlay to extract training sites, and applied ISODATA (iterative self-organizing data analysis techniques) to purify the spectral signature information from four different combinations of imagery data. Then we used the maximum likelihood classification to classify the four different combinations of imagery data. Besides the pixel-based classification method, we also experimented with object-based pre-classification and post-classification.

A. *Cultivation parcels*

The Agriculture and Food Agency in Taiwan has more than ten-year cultivation parcel data produced by the Chinese Society of Photogrammetry and Remote Sensing. Based on the digitized boundaries of cultivation parcels, these data record for every parcel if it is paddy field or not. The accuracy of these data is claimed to be 96% or higher. We acquired cultivation parcel data of Yunlin County from 1996 to 2006 for this study. The data from 1996 to 2005 were used to produce training areas for the supervised classification, and the data of 2006 to validate the classification results.

B. *FORMOSAT-2 satellite images processing*

It is hard to recognize the texture of agricultural crops directly on FORMOSAT-2 multi-spectral satellite images. Fortunately, paddy rice has special growing characteristics that are different from most other crops. Different spectral characteristics occur in the transplanting stage and, especially, the most active tillering stage. Hence this study acquired FORMOSAT-2 satellite images for the following two periods: March 10, 2006, representing the transplanting stage; and April 7, 2006, representing the most active tillering stage. Images from these two periods were stacked into one image with 8-layer spectral information for the supervised classification. In addition to the stacked image, we also included NDVI values during the transplanting and tillering stages to create the following two combinations for classification:

(1) 8-layer stacked images from the transplanting and tillering stages; and
(2) 8-layer stacked images and NDVI data during the transplanting stage;

C. *Training sites extraction with GIS overlay mapping*

According to the experience of the Agriculture and Food Agency, if farmers cultivate rice this year, they will most likely cultivate rice during the same periods in the next year. The longer the farmers have cultivated rice, the more likely the farmers will repeat the rice crop in the next year. This study therefore made the following two assumptions for the selection of training areas: (1) a field, which had been a paddy field for the past ten years (1996 to 2005), will still be a paddy field for this year (2006); (2) a field, which had been a non-paddy field for the past ten years, will not be a paddy field for this year.

Specifically, training areas were selected by executing the following steps:

(1) intersect cultivation data from 1996 to 2005;
(2) dissolve the intersected results to eliminate the shared boundaries between two adjacent paddy fields;
(3) produce inside buffer zones of the dissolved results to select areas, where mixed pixels may exist; and
(4) erase the buffer zones in the dissolved results to get 2006 training areas.

D. Image Classification

This study used the pixel-based classification as well as object-based pre-classification and post-classification. For the pixel-based classification, the stacked images from the transplanting and tillering stages were masked using the extracted rice and non-rice sites before acquiring the spectral information from these sites. Then we used the unsupervised ISODATA to classify the spectral information into 20 each of rice and non-rice categories. By this process, we got the statistics and covariances for all 40 categories. These spectral signatures were then used for the supervised classification. We classified the paddy rice information into 20 categories because, if we regarded all paddy rice spectral information as one category, the information might easily be mixed with the non-rice spectral information. The same would happen if we regarded all non-rice information as one category. In other words, the unsupervised classification separated mixed spectral information into pure categories. The 40-category signature information was then used with the maximum likelihood algorithm to classify the stacked images. The classification resulted in 40 categories of which the first 20 categories represented rice paddy classes and the last 20 categories non-rice classes. Finally, we recoded the results into rice and non-rice classes.

For object-based pre-classification (pre-classification hereafter), cultivation parcel rather than pixel was the classification unit. We first found pixels that were contained in each parcel before calculating their mean values. The mean values represented the average of every original band and the average NDVI value during the transplanting stage. The training areas were the same as for the pixel-based classification method, but the spectral information was calculated from every parcel in the training site.

For object-based post-classification (post-classification hereafter), we also used parcel as the classification unit but determined the class of a parcel by using the pixel-based classification results. If half of the pixels covered in one parcel are rice, then the parcel is assigned the class of rice, and vice versa.

E. Accuracy assessment

The reference data used for accuracy assessment was cultivation data for the first rice crop in 2006. The file format of cultivation data is vector-based ArcInfo coverage. For accuracy assessment of pixel-based results, we converted the reference data into grid file format with a cell size of 8 meters (i.e. the same cell size as the spatial resolution of multi-spectral FORMOSAT-2 images). For accuracy assessment of object-based results, we calculated the areas (m^2) rather than numbers of parcels with correct and incorrect classification results in order to compare with the pixel-based results.

IV. Results

Table I(a) and (b) show the best and the worst of the error matrices of the pixel-based classification results. The overall accuracy ranges from 83.8% to 84.5%, and the kappa values from 0.613 to 0.632. **Error! Reference source not found.**. 3(a) and (b) show the omission errors of paddy rice, which occurred mostly in the northwest quadrant of the study area and also around each parcel.

The overall accuracy of the pre-classification results ranges from 84.4% to 87.7%, and the kappa values from 0.558 to 0.665. Table I(c) and (d) show the best and the worst of the error matrices. Unlike the pixel-based classification results, more commission errors, rather than omission errors, happened in the northwest quadrant of the study area shown in Fig. 3(c) and (d). Although the training areas of the pixel-based classification and pre-classification were the same, the classification performances were different. This might have been caused by different land cover features contained in some training sites and parcels, and these different land cover features might have different spectral characteristics, which could not be represented by the mean values. Although cultivation parcels are supposed to be homogeneous, some may not be so.

The overall accuracy of the post-classification results ranges from 91.2% to 91.3%, and the kappa values from 0.781 to 0.785. Table I(e) and (f) show the best and the worst of the error matrices. Like the pixel-based classification results, the omission errors of paddy rice happened mostly in the northwest quadrant of the study area shown in Fig. 3(e) and (f). But compared with the pixel-based results, the accuracy increases considerably because the post classification decides the class of parcels by the majority class of pixels; thus, the minority of non-rice pixels (most likely mixed pixels) does not influence the classification of parcels.

V. Discussion

A. Post-processing of thin and long parcels

Many thin and long non-rice parcels are often classified erroneously as rice fields because of mixed pixels and imperfect registration between cultivation parcel data and satellite imagery. These errors also happen in the pixel-based and pre-classification results.

According to cultivation parcel data over the years, parcels thinner than 8 meters (spatial resolution of FORMOSAT-2 multi-spectral images) are mostly canals and paths in the fields and not paddy rice parcels; hence, we enforced parcels thinner than 8 meters to non-rice fields in post-processing. Table II shows the error matrices of the new results. Compared Table II(a) and (b) to the pre-classification results in Table I(c) and (d), the overall accuracy is increased by about 2% and the kappa values by about 5 to 7%. Compared Table I(e) and (f) to the post-classification results in Table II(c) and (d), the overall accuracy is increased by about 1% and the kappa values by about 3%. The degree of increase in accuracy is higher for the pre-classification, especially for the kappa values. These results show the feasibility and necessity of such a post-processing step.

B. Addition of NDVI

Table 1 (a) ,(b), (e), and (f) show the addition of NDVI or differential NDVI did slightly improve the accuracy of the pixel-based and post-classification results. But the addition of NDVI actually degraded the accuracy of the pre-classification results in Table 1 (c) and (d). Although NDVI has been successfully used in many previous studies to map paddy rice [2, 5-6], it does not appear to have improved the classification accuracy in our case. This may be because some crops have the same spectral characteristics as paddy rice. This study did not use NDWI or LSWI, because FORMOSAT-2 images do not cover the needed bands of mid-infrared or shortwave infrared. EVI, on the other hand, uses the blue, red, and near-infrared bands, which are all covered by FORMOSAT-2 images. Further work may consider adding EVI for classification.

C. Discrepancy of paddy rice cultivation habits

Some farmers planted rice earlier or later than other farmers. Therefore, in those 'irregular' areas, we cannot observe the transplanting pattern of rice in early March images and the tillering pattern in late April images. This discrepancy of cultivation habits may result in the omission errors of paddy rice. For example, the paddy rice parcel can show up in satellite imagery as a vegetation pattern during the transplanting stage and as a soil pattern during the tillering stage. This unusual growing pattern causes the omission errors of paddy rice.

However, some unusual growing patterns of paddy rice can still be classified correctly. For example, the paddy rice parcel can also shows up as a vegetation pattern during the transplanting stage and as a water pattern during the tillering stage. This is because the GIS overlay method happened to choose this kind of crop growing pattern as paddy rice training sites. One advantage of the overlay method in selecting training sites is that it can cover various kinds of spectral characteristics that would be difficult to do artificially.

D. Similarity of growing pattern for rice and non-rice crops

Some crops have the same growing pattern as rice paddy, i.e. they show up as a water pattern during the transplanting stage but a vegetation pattern during the tillering stage. This kind of non-rice parcel contributes to the commission errors of paddy rice.

E. Homogeneity of land features

Tables I and II show that both the user's accuracy and the producer's accuracy of rice are usually higher than those of non-rice, perhaps due to the total area of paddy rice fields being larger than non-rice fields in this study area. Many and successive rice paddy fields tend to make homogeneous areas and ease the task of classifying satellite images. Fig. 3 shows that land cover features in the northwest quadrant, where many erroneous pixels are located, are smaller and more complex than other quadrants. This suggests that regional homogeneity can play an important role in image classification. .

VI. Conclusions

This study has experimented with NDVI, pre-classification, and post-classification for mapping paddy rice fields in Taiwan. The post-classification performed better than the pixel-based method, but the pre-classification did not. Because the post-classification involves relatively simple data processing, it can be used for future paddy rice mapping if land parcel data are available. The addition of NDVI or differential NDVI to original images did improve the performance of the pixel-based classification and the post-classification slightly but lowered the pre-classification performance. The usefulness of NDVI for paddy rice mapping, at least in Taiwan, is therefore questionable.

Many classification errors in this study came from two conditions: the discrepancy of paddy rice cultivation habits, and the similarity of the growing pattern for rice and some non-rice crops. These errors may be reduced by adding more images from different time periods. By lengthening the temporal observation, it may help differentiate rice and other crops. Classification errors also happened because of mixed pixels and imperfect registration between cultivation parcel data and satellite imagery. These errors often occurred in thin and long parcels. In this study, we used 8 meters, the resolution of FORMOSAT-2 images, as the threshold to identify these parcels. Depending on the data source, this threshold can be changed in future work.

Defining homogenous area for growing paddy rice should be an important topic for future research, especially for large study areas. Given a large area, the degree of heterogeneity for paddy rice growing characteristics is likely to increase. In Taiwan, seedling centres provide seedlings for farmers before the transplanting stage starts. Each centre distributes seedlings at a specific time within a specific service area. Thus, farmers in the same service area start to cultivate paddy rice almost at the same time. The service area of a seedling centre can be a good reference for homogeneous area.

TABLE I
THE BEST AND THE WORST OF THE ERROR MATRICES OF THE CLASSIFICATION RESULTS: (A) ORIGINAL 8-LAYER DATA FOR PIXEL-BASED CLASSIFICATION, (B) COMBINATIONS OF ORIGINAL 8-LAYER DATA AND FIRST-STAGE NDVI DATA FOR PIXEL-BASED CLASSIFICATION, (C) ORIGINAL 8-LAYER DATA FOR PRE-CLASSIFICATION, (D) COMBINATIONS OF ORIGINAL 8-LAYER DATA AND FIRST-STAGE NDVI DATA FOR PRE-CLASSIFICATION, (E) ORIGINAL 8-LAYER DATA FOR POST-CLASSIFICATION, AND (F) COMBINATIONS OF ORIGINAL 8-LAYER DATA AND FIRST-STAGE NDVI DATA FOR POST-CLASSIFICATION.

(a)

		Reference data			
		Rice	Non-rice	total	User's accuracy
Classified result	Rice	238771	24999	263770	90.52%
	Non-rice	37507	83888	121395	69.10%
	total	276278	108887	385165	
	Producer's accuracy	86.42%	77.04%		83.77%
				Kappa	0.613

(b)

		Reference data			
		Rice	Non-rice	total	User's accuracy
Classified result	Rice	239976	23276	263252	91.16%
	Non-rice	36302	85611	121913	70.22%
	total	276278	108887	385165	
	Producer's accuracy	86.86%	78.62%		84.53%
				Kappa	0.632

(c)

		Reference data			
		Rice	Non-rice	total	User's accuracy
Classified result	Rice	17180271	2528469	19708740	87.17%
	Non-rice	481663.4	4337631	4819295	90.01%
	total	17661934	6866100	24528034	
	Producer's accuracy	97.27%	63.17%		87.73%
				Kappa	0.665

(d)

		Reference data			
		Rice	Non-rice	total	User's accuracy
Classified result	Rice	17228346	3389505	20617851	83.56%
	Non-rice	447372	3550546	3997918	88.81%
	total	17675718	6940051	24615769	
	Producer's accuracy	97.47%	51.16%		84.41%
				Kappa	0.558

(e)

		Reference data			
		Rice	Non-rice	total	User's accuracy
Classified result	Rice	16624918	1131790	17756708	93.63%
	Non-rice	1047155	5825407	6872562	84.76%
	total	17672073	6957197	24629270	
	Producer's accuracy	94.07%	83.73%		91.15%
				Kappa	0.781

(f)

		Reference data			
		Rice	Non-rice	total	User's accuracy
Classified result	Rice	16626330	1097926	17724256	93.81%
	Non-rice	1047323	5855808	6903131	84.83%
	total	17673653	6953734	24627387	
	Producer's accuracy	94.07%	84.21%		91.29%
				Kappa	0.785

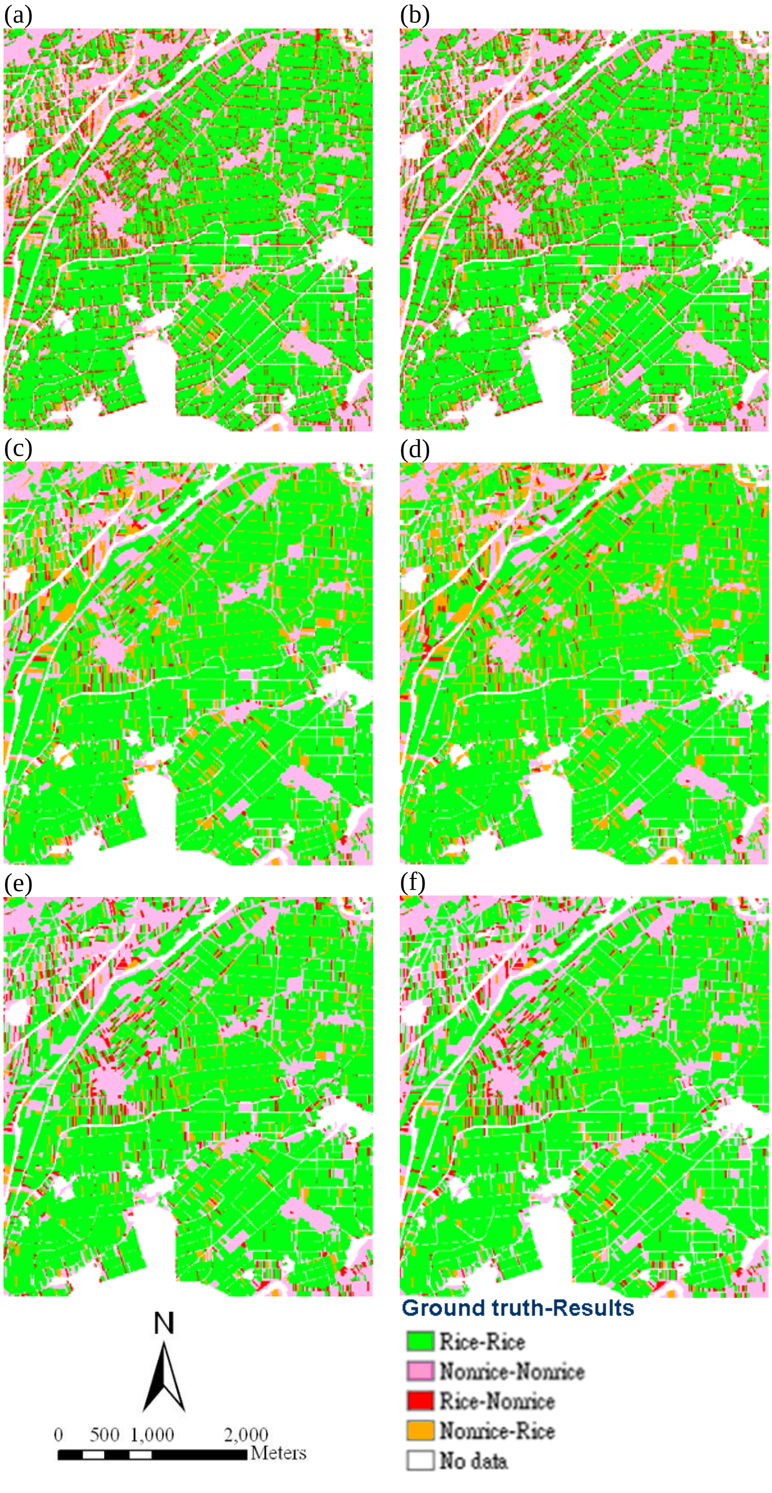

Fig. 3 pixel- and object-based classification results: (a) Original 8-layer data for pre-classification, (b) combinations of original 8-layer data and first-stage NDVI data for pre-classification, (c) Original 8-layer data for pre-classification, (d) combinations of original 8-layer data and first-stage NDVI data for pre-classification, (e) original 8-layer data for post-classification, and (f) combinations of original 8-layer data and first-stage NDVI data for post-classification.

TABLE II

ERROR MATRICES OF OBJECT-BASED CLASSIFICATION AFTER ENFORCING THIN AND LONG PARCELS TO NON-RICE: (A) ORIGINAL 8-LAYER DATA FOR PRE-CLASSIFICATION; (B) COMBINATIONS OF ORIGINAL 8-LAYER DATA AND FIRST-STAGE NDVI DATA FOR POST-CLASSIFICATION, (C) ORIGINAL 8-LAYER DATA FOR PRE-CLASSIFICATION, AND (D) COMBINATIONS OF ORIGINAL 8-LAYER DATA AND FIRST-STAGE NDVI DATA FOR POST-CLASSIFICATION

(a)

		Reference data			
		Rice	Non-rice	total	User's accuracy
Classified result	Rice	17149467	2111797	19261264	89.04%
	Non-rice	522178	4838357	5360535	90.26%
	total	17671645	6950154	24621799	
	Producer's accuracy	97.05%	69.62%		89.30%

Kappa 0.716

(b)

		Reference data			
		Rice	Non-rice	total	User's accuracy
Classified result	Rice	17192671	2842288	20034959	85.81%
	Non-rice	487041	4127249	4614290	89.44%
	total	17679712	6969537	24649249	
	Producer's accuracy	97.25%	59.22%		86.49%

Kappa 0.629

(c)

		Reference data			
		Rice	Non-rice	total	User's accuracy
Classified result	Rice	16601246	852798	17454044	95.11%
	Non-rice	1075506	6116528	7192034	85.05%
	total	17676752	6969326	24646078	
	Producer's accuracy	93.92%	87.76%		92.18%

Kappa 0.809

(d)

		Reference data			
		Rice	Non-rice	total	User's accuracy
Classified result	Rice	16602582	811153	17413735	95.34%
	Non-rice	1075748	6155290	7231038	85.12%
	total	17678330	6966443	24644773	
	Producer's accuracy	93.91%	88.36%		92.34%

Kappa 0.813

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