International Journal of Remote Sensing and Earth Sciences Vol. 7: 36-52 (2010) © IReSES

MODIFICATION OF INPUT IMAGES FOR IMPROVING THE ACCURACY OF RICE FIELD CLASSIFICATION USING MODIS DATA

I Wayan Nuarsa[1,2], Fumihiko Nishio[1], And Chiharu Hongo[1]

Abstract. The standard image classification method typically uses multispectral imagery on one acquisition date as an input for classification. Rice fields exhibit high variability in land cover states, which influences their reflectance. Using the existing standard method for rice field classification may increase errors of commission and omission, thereby reducing classification accuracy. This study utilised temporal variance in a vegetation index as a modified input image for rice field classification. The results showed that classification of rice fields using modified input images provided a better result. Using the modified classification input improved the correspondence between rice field area obtained from the classification result and reference data (R2 increased from 0.2557 to 0.9656 for regency-level comparisons and from 0.5045 to 0.8698 for district-level comparisons). The classification accuracy and the estimated Kappa value also increased when using the modified classification input compared to the standard method, from 66.33 to 83.73 and from 0.49 to 0.77, respectively. The commission error, omission error, and Kappa variance decreased from 68.11 to 42.36, 28.48 to 27.97, and 0.00159 to 0.00039, respectively, when using modified input images compared to the standard method. The Kappa analysis concluded that there are significant differences between the procedure developed in this study and the standard method for rice field classification. Consequently, the modified classification method developed here is significant improvement over the standard procedure.

Keywords: rice field mapping, modified classification, temporal analysis, Modis

1. Introduction

Rice is the primary food source for more than three billion people and is one of the world's major staple foods. Paddy rice fields account for approximately 15% of the world's arable land (Khush, 2005; IRRI, 1993). A unique physical feature of paddy fields is that the rice is grown on flooded soils. This feature is significant in terms of both trace gas emissions and water resource management. Seasonally flooded rice paddies are a significant source of methane emissions (Denier, 2000), contributing over 10% of the total methane flux to the atmosphere (Prather *et al.*, 2001), which may have substantial impacts on atmospheric chemistry and climate. Agricultural water use (in the form of irrigation withdrawals) accounted for ~70% of global freshwater withdrawals (Samad *et al*, 1992). Mapping the distribution of rice fields is important not only for food security but also for the management of water resources and the estimation of trace gas emissions (Xiao *et al.*, 2005; Matthews *et al.*, 2000). Therefore, more accurate data related to the total rice field area, its distribution, and its changes over time are essential.

Satellite remote sensing has been widely applied and is recognised as a powerful and effective tool for mapping land use and land cover (Harris and Ventura, 1995; Yeh and Li, 1999). The

[1] Center for Environmental Remote Sensing, Chiba University, Chiba 263-8522, Japan
[2] Agroecotechnology Department, Faculty of Agriculture, Udayana University, Bali

Moderate Resolution Imaging Spectroradiometer (MODIS) instrument offers considerable potential for rapid and repetitive large-area crop classification given its near-daily global coverage of science-quality observations and products (Justice and Townshend, 2002), which are available at moderate spatial resolutions (250, 500 and 1000 m). Several studies have used multi-temporal MODIS data to classify specific crop types (Lobell and Asner, 2004; Doraiswamy *et al*., 2005; Chang *et al*., 2007; Potgieter *et al*., 2007; Wardlow and Egbert, 2008), cropping rotations (Morton *et al*., 2006; Sakamoto *et al*., 2006; Brown *et al*., 2007; Wardlow *et al*., 2006), and crop-related land use practices (e.g., irrigation and fallow) (Wardlow and Egbert, 2008) as well as to monitor crop phenology (Sakamoto *et al*., 2005; Niel and McVicar, 2001).

Image classification is one of the most popular remote sensing applications. This process primarily uses the spectral information provided in remotely sensed data to discriminate between perceived groupings of vegetative cover on the ground (Niel and McVicar, 2001). The spatial and temporal information included in single date and time series data usually plays a secondary role but can aid in the classification procedure. The discrimination of crops is usually performed with ‘supervised’ or ‘unsupervised’ classifiers. The basic difference between these types of classification is the process by which the spectral characteristics of the different groupings are defined (Atkinson and Lewis, 2000). Common classification algorithms include maximum likelihood, minimum distance to mean, and parallelepiped (Jensen, 1986). Research on classification algorithms to identify rice fields is widespread (Bachelet, 1995; Okamoto and Kawashima, 1999; Fang, 1998; Fang *et al*., 1998; Niel *et al*., 2003).

Agricultural rice fields have a large variety of land cover states that can range from water bodies just before rice transplanting to mixed water, vegetation, or bare soil just after harvesting. The use of a single procedure for rice field classification is difficult because of the high variability of rice field land cover states. The large variety of land cover states could cause increases in commission and omission errors, thereby decreasing overall accuracy. This is caused by non-rice field pixels being classified as rice field pixels while, at the same time, not all rice field pixels are correctly classified as rice fields (Lillesand and Kiefer, 2000). A standard image classification procedure is to only use a multispectral image from one acquisition date. In supervised classification, a training area is selected from this image and one of several image classification methods is then applied. In this study, we modified the input to the image classification process. We used the variance of three vegetation indices over time as an input to the rice classification procedure. The objective of this study was to compare the accuracy of rice field image classification between the standard method and the modified input method using reference data.

2. Data, and Method

2.1. Background and study area

The study area is located in the Bali Province of Indonesia and is centred at latitude 8°40’00” S and longitude 115°19’00” E (Figure 1). In addition to being a popular international tourism destination, Bali Island, although relatively small, is also historically one of the prime rice-producing areas in Indonesia. Approximately 0.5 million tons (1.6% of Indonesia’s rice production) is contributed by the Bali Province. Agricultural rice fields in Bali consist of irrigated fields and non-irrigated fields. The water source for the irrigated rice fields is rivers, whereas the water for non-irrigated rice fields comes from rainfall. At different times of the year, both irrigated and non-irrigated rice field lands are not only used for rice paddies but also for seasonal crops such as corn, soybeans, and nuts. However, the type of seasonal plant grown from year to year is usually similar from one place to another. In humid tropic regions, such as the study area, rice plants can be planted at any time. However, planting is influenced by water availability. Therefore, on irrigated land, rice planting alternates between regions, whereas on non-irrigated land, rice planting occurs in the rainy season. Farmers usually plant rice two or three times per year and use the remaining time for other seasonal crops (Food Crops Agriculture Department, 2006). Rice plants are typically harvested after three months, with a production of around five tons per hectare per crop rotation. The total agricultural rice area in Bali is 107,437.50 ha.

Figure 1. Map of the study area. Bali province consists of nine regencies

2.2. MODIS images

Among the suite of standard MODIS data products available, we used the 16-day composite MODIS Vegetation Indices Product (MOD13Q1). Each 16-day composite image includes blue, red, and near-infrared reflectances, centred at 469-nanometers, 645-nanometers, and 858-nanometers, respectively, Normalised Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) at a spatial resolution of 250 m as a gridded level-3 product in the Sinusoidal projection. In the production of MOD 13Q1, atmospheric corrections for gases, thin cirrus clouds and aerosols are implemented (Vermote and Vermeulen, 1999). In addition, The MODIS NDVI and EVI products are computed from atmospherically corrected bi-directional surface reflectances that have been masked for water, clouds, heavy aerosols, and cloud shadows. The products are Validated Stage 2, meaning that accuracy has been assessed over a widely distributed set of locations and time periods via several ground-truth and validation efforts. Although there may be later, improved versions, these data are ready for use in scientific publications (https://lpdaac.usgs.gov/lpdaac/products /modis_products _table/). In this study, we downloaded MOD13Q1 data for 2008 (twenty-three 16-day composites) from the USGS EROS Data Center (http://edc.usgs.gov/).

2.3. Calculation of vegetation index (VI)

The vegetation indices used in this study were NDVI, EVI, Normalised Difference Water Index (NDWI), Ratio Vegetation Index (RVI), and Soil Adjusted Vegetation Index (SAVI). NDVI and EVI were directly obtained from the USGS EROS Data Center, whereas NDWI, RVI, and SAVI were calculated from the red, near-infrared, and middle-infrared bands of the MODIS product. The equations for these vegetation indices are as follows:

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}} \tag{1}$$

$$EVI = 2.5\ x\ \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + (6\ x\ \rho_{red}) - (7.5\ x\ \rho_{blue}) + 1} \tag{2}$$

$$NDWI = \frac{\rho_{nir} - \rho_{swir}}{\rho_{nir} + \rho_{swir}} \tag{3}$$

$$RVI = \frac{\rho_{nir}}{\rho_{red}} \tag{4}$$

$$SAVI = \frac{(1 + L)(\rho_{nir} - \rho_{red})}{\rho_{nir} + \rho_{red} + L} \tag{5}$$

where *swir*, *nir, r, and b* are the middle-infrared, near-infrared, red, and blue band of the MODIS images, respectively, and *L* is a constant (related to the slope of the soil-line in a feature-space plot) that is usually set to 0.5.

While NDVI correlates with the leaf area index (LAI) of rice fields (Xiao *et al.*, 2002), it has several limitations, including saturation under closed canopies and soil background (Huete *et al.*, 2002; Xiao *et al.*, 2003). The blue band is sensitive to atmospheric conditions and is used for atmospheric correction. EVI directly adjusts the reflectance in the red band as a function of the reflectance in the blue band, and it accounts for residual atmospheric contamination (e.g., aerosols) and variable soil and canopy background reflectance (Huete *et al.*, 2002). The SAVI index can minimise soil brightness influences from spectral vegetation indices involving red and near-infrared (NIR) wavelengths (Huete, 1988), while RVI is a good indicator of crop growth for the entire growth cycle (Gupta, 1993).

The advantage of using a vegetation index compared to single bands is the ability to reduce the spectral data to a single number that is related to physical characteristics of the vegetation (e.g., leaf area, biomass, productivity, photosynthetic activity, or percent cover) (Baret and Guyot, 1991; Huete, 1988). At the same time, it is possible to minimise the effects of internal (e.g., canopy geometry, and leaf and soil properties) and external factors (e.g., sun-target-sensor angles and atmospheric conditions at the time of image acquisition) on the spectral data (Baret and Guyot, 1991; Huete and Warrick, 1990; Huete and Escadafal, 1991).

2.4. Image classification

Image classification was performed using two different procedures. The first used a standard image for input and the second used a modified image for input. For the standard classification procedure, a multispectral image from one acquisition date was used. We used a multispectral image from 6 to 21 April 2008 (16-day composite) due to the fact that this image was free from clouds. From the four bands available in this MODIS product, we used bands 1, 2 and 3 in the blue, red, and near-infrared regions, respectively, as inputs for multispectral image classification.

For the second classification procedure, we used variance maps of three selected vegetation indices as inputs for image classification. The variance maps of the VIs were derived from a layer-stacking process that produced a multi-band image consisting of 23 images (all composite images in 2008). From the multiband image, we calculated the variance of each pixel across time periods, producing a variance map. To select the three best VIs from the five VIs evaluated in this study, we used the difference in the variance value between rice fields and other land uses. Higher variance differences between rice fields and other land uses indicated an improved ability to discriminate these classes. Hence, the three VIs that had the highest variance difference values between rice fields and other land uses were selected as inputs in the multispectral image classification.

The algorithm developed in this study was only designed to discriminate rice fields from other land uses because the standard procedure had limitations due to the high variation in land cover states of rice fields. Therefore, the selection of training areas for the classification was only performed in rice fields. However, for improved results, we divided rice fields into two sub-classes: irrigated and non-irrigated. For consistency, we used the same training area for image classification in the modified procedure developed in this study and the standard procedure. Image classification was performed using the Maximum Likelihood algorithm for both procedures.

2.5 Quantitative evaluation of classification results

The quantitative evaluation was performed by comparing the classification result with the existing land use maps released by the National Land Agency. The results of the modified classification procedure developed in this study were compared to the results of the standard classification procedure. To determine which classification procedure more accurately classified rice fields, we used two evaluation methods. First, we used a regression method under the general assumption that the method with the higher coefficient of determination (R^2) and lower root mean square error (RMSE) with respect to the reference data was more accurate. These comparison methods were performed at the regency and district levels using 9 and 52 samples based on the number of regencies and districts in the study area. R^2 and RMSE were calculated as follows:

$$R^2 = \frac{\Sigma(y-\hat{y})^2}{\Sigma(y-\bar{\hat{y}})^2} \tag{8}$$

where R^2, y, $\hat{y}$, $\bar{\hat{y}}$, and $\hat{y}$ are the coefficient of determination, a measured value, an estimated value, and the mean of the estimated values, respectively, and

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{9}$$

where $RMSE$, $\hat{y}_i$, y_i, and n are the root mean square error, an estimated value of the ith sample, a measured value of the ith sample, and the number of samples, respectively.

The second evaluation method was the Kappa analysis (Congalton and Green, 1999). The Kappa analysis was used to determine whether the modified procedure developed in the study was significantly different from the standard methods. The first step of the Kappa analysis was to create an error matrix for both classification procedures. In this study, only two classes were used, rice field and non-rice field. From the error matrix, we can calculate the commission error, omission error, and overall accuracy as follows:

$$\text{Commission error} = \frac{\text{Total pixel of non rice field is classified as rice field}}{\text{Total pixel of rice field classification result}} \times 100 \tag{10}$$

$$\text{Omission error} = \frac{\text{Total pixel of rice field is not classified as rice field}}{\text{Total pixel of actually rice field}} \times 100 \tag{11}$$

$$\text{Overall accuracy} = \frac{\text{Total pixel of correctly classified}}{\text{Total sample}} \times 100 \tag{12}$$

The next step of the Kappa analysis is to calculate the estimated Kappa statistic, Kappa variance, and z-score as follows:

$$\hat{K} = \frac{n\sum_{i=1}^{k} n_{ii} - \sum_{i=1}^{k} n_{i.}n_{.i}}{n^2 - \sum_{i=1}^{k} n_{i.}n_{.i}} \tag{13}$$

where $\hat{K}$ is the estimated Kappa, n is number of sample tests, n_i is the sample row i, n_j is the sample column j, and k is 'row x column.' The formula for Kappa variance is

$$\hat{\mathrm{var}}(\hat{K}) = \frac{1}{n}\left(\frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2-\theta_3)}{(1-\theta_1)^3} + \frac{(1-\theta_1)^2(\theta_4-4\theta_2^2)}{(1-\theta_2)^4}\right) \tag{14}$$

where $\hat{\mathrm{var}}(\hat{K})$ = Kappa variance,

$$\theta_1 = \frac{1}{n}\sum_{i=1}^{k} n_{ii},$$

$$\theta_2 = \frac{1}{n^2}\sum_{i=1}^{k} n_{i.}n_{.i},$$

$$\theta_3 = \frac{1}{n^2}\sum_{i=1}^{k} n_{ii}(n_{i.}+n_{.i}),$$

$$\theta_4 = \frac{1}{n^3}\sum_{i=1}^{k}\sum_{j=1}^{k} n_{ij}(n_{i.}+n_{.j})$$

$$Z = \frac{|\hat{K}_1 - \hat{K}_2|}{\sqrt{\hat{\mathrm{var}}(\hat{K}_1) + \hat{\mathrm{var}}(\hat{K}_2)}} \tag{15}$$

where Z is the z-score for two methods, $\hat{K}_1$ and $\hat{K}_2$ are the estimated Kappa values for

Method 1 and Method 2, and $\hat{var}(\hat{K}_1)$ and $\hat{var}(\hat{K}_2)$ are the Kappa variances for Method 1 and Method 2.

The z-score resulting from the above calculation was then compared with the standard normal critical value. For a confidence level of 0.95, or $\alpha = 0.05$ in the two-tailed Z-test, the standard deviation from the mean of the Z-distribution is 1.96. This means that if the z-score is greater than 1.96, we reject a null hypothesis (H0), and Method 1 and 2 are significantly different. Otherwise, we accept the H0, and there is no difference between Methods 1 and 2. The research procedure is shown schematically in Figure 2.

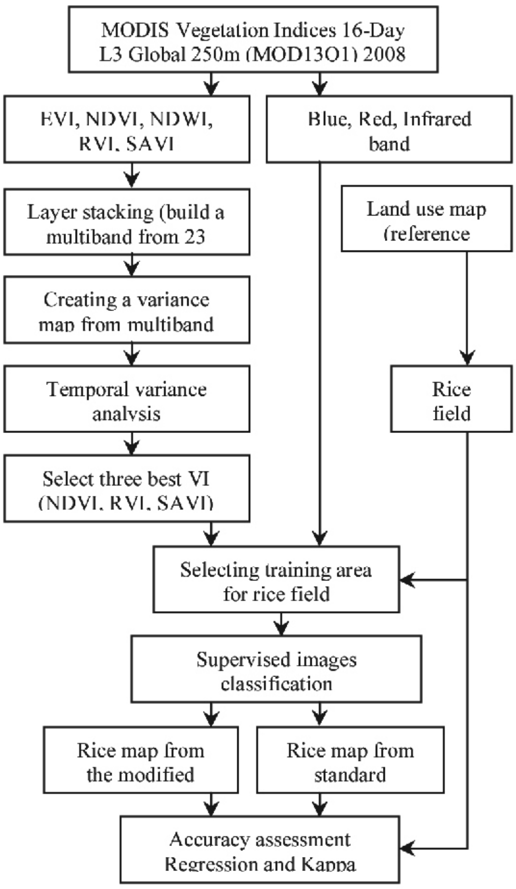


Figure 2. Data analysis procedure used in this study

3. Results and Discussion

3.1. Temporal variability of the vegetation index of land uses.

The entire vegetation index of land uses varied in the study area during 2008. The highest variability occurred in the irrigated rice fields, followed by the non-irrigated rice fields. The other land uses, such as settlement, mixed forest, mixed garden, shrub, and dry land, had low variability in the vegetation index for the year. The NDVI of irrigated rice fields was high at certain times and overlapped with mixed forest, mixed garden, and dry land. However, the value was low at other times and was similar to the values for settlement (Figure 3 and Figure 4). Non-irrigated rice fields also had a similar tendency, although NDVI values were not as high as irrigated rice fields. The large fluctuations in the vegetation index of irrigated and non-irrigated rice fields were due to the high degree of variation in their land covers. When the areas were being planted with rice plants or other seasonal crops, the vegetation index was similar to that of mixed forest or mixed garden. However, if no crops were planted, the land cover resembled settlement.

To select the three best vegetation indices for rice field classification, we had to determine the average variance of land uses and the difference in the variance of irrigated and non-irrigated rice fields versus other land uses. Table 1 shows the average temporal variance of the VIs for the main land uses in the study area. The average variance of EVI for irrigated and non-irrigated rice fields compared with shrubs was similar. This means that it will be difficult to separate rice field and shrub classes. A similar situation occurred with NDWI, where irrigated rice fields had a similar average variance as shrub and mixed garden classes.

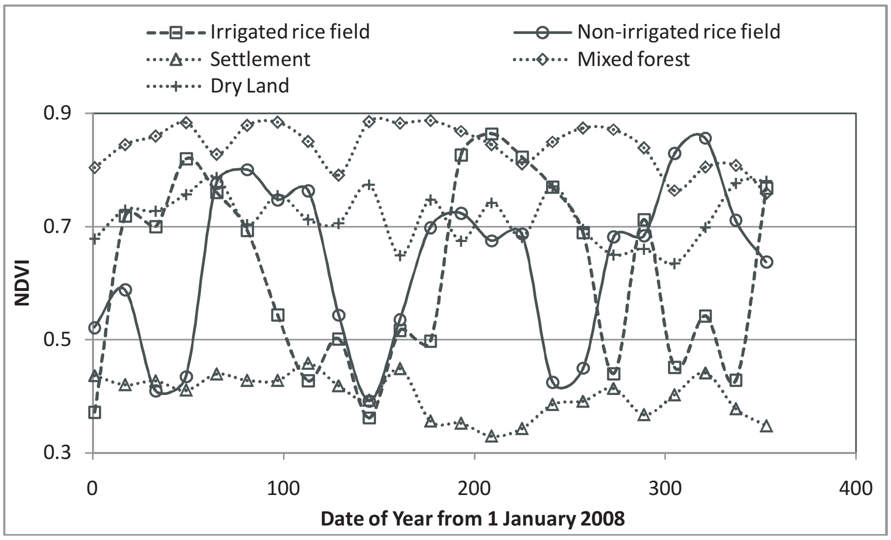


Figure 3. Temporal variability of NDVI for irrigated rice fields, non-irrigated rice fields, settlement, mixed forest, and dry land.

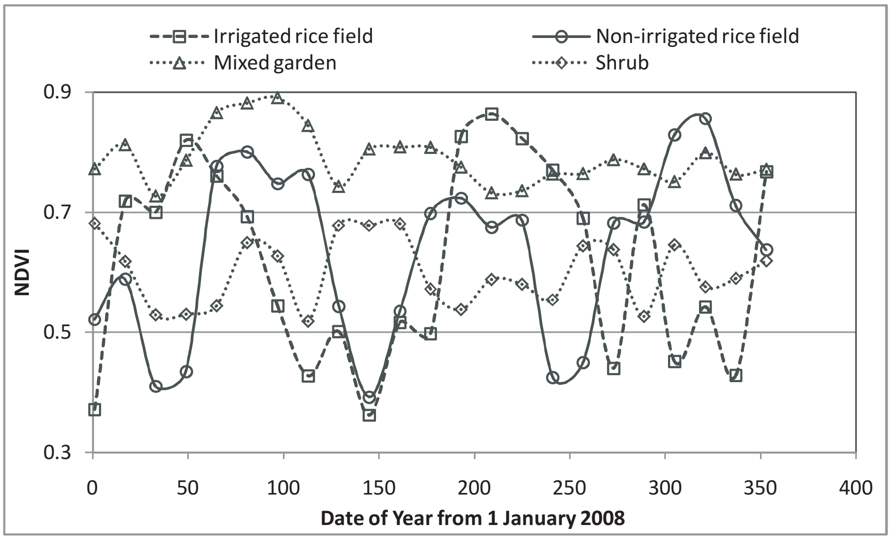


Figure 4. Temporal variability of NDVI for irrigated rice fields, non-irrigated rice fields, mixed garden, and shrub

On the other hand, the average variance of SAVI, RVI, and NDVI for irrigated and non-irrigated rice fields was significantly different from the average variance for the other land uses (Table 1). The difference in average variance between irrigated rice fields compared to other land uses for SAVI was between 2.1465 to 53.9397 (not including non-irrigated rice fields because irrigated and non-irrigated are classified as a single class). For RVI and NDVI, these differences were between 2.9309 to 672.5265 and between 2.1973 to 12.2630, respectively. However, for EVI and NDWI, the differences usually approached one (Table 2). Therefore, SAVI, RVI and NDVI were selected as the best vegetation indices for distinguishing irrigated and non-irrigated rice fields from the other land uses. These VIs were then used for multispectral rice field classification.

Table 1. Average temporal variance of several VIs for the main land uses.

Main Land Uses	EVI	NDWI	SAVI	RVI	NDVI
Irrigated rice field	0.0311	0.0218	0.0250	117.4982	0.0362
Non-irrigated rice field	0.0313	0.0111	0.0205	61.1684	0.0330
Settlement	0.0019	0.0031	0.0005	0.1747	0.0030
Mixed forest	0.0209	0.0155	0.0053	40.0893	0.0084
Mixed garden	0.0129	0.0232	0.0080	35.3451	0.0058
Shrub	0.0311	0.0204	0.0084	23.5978	0.0156
Dry Land	0.0195	0.0324	0.0117	12.6876	0.0165

Table 2. Difference in variance values between rice fields and other land uses.

Main Land Uses	EVI	NDWI	SAVI	RVI	NDVI
Non-irrigated rice field	0.9920	1.9700	1.2203	1.9209	1.0956
Settlement	16.0864	6.9503	53.9397	672.5265	12.2630
Forest	1.4837	1.4051	4.7582	2.9309	4.2933
Mixed garden	2.4092	0.9402	3.1470	3.3243	6.2029
Shrub	0.9998	1.0715	2.9927	4.9792	2.3223
Dry Land	1.5938	0.6737	2.1465	9.2609	2.1973

3.2. Comparison of image classification results

Before the supervised classification was performed, a training area from the same location was selected for both input images. The training area included both irrigated and non-irrigated rice fields. For the standard classification procedure, irrigated and non-irrigated rice fields were classified into different classes and then merged into one class (rice field) after the classification process. In contrast, the modified classification procedure combined the irrigated and non-irrigated fields in the training area before the classification was performed because the variance values of these objects were similar. The results of the classification are shown in Figure 5.

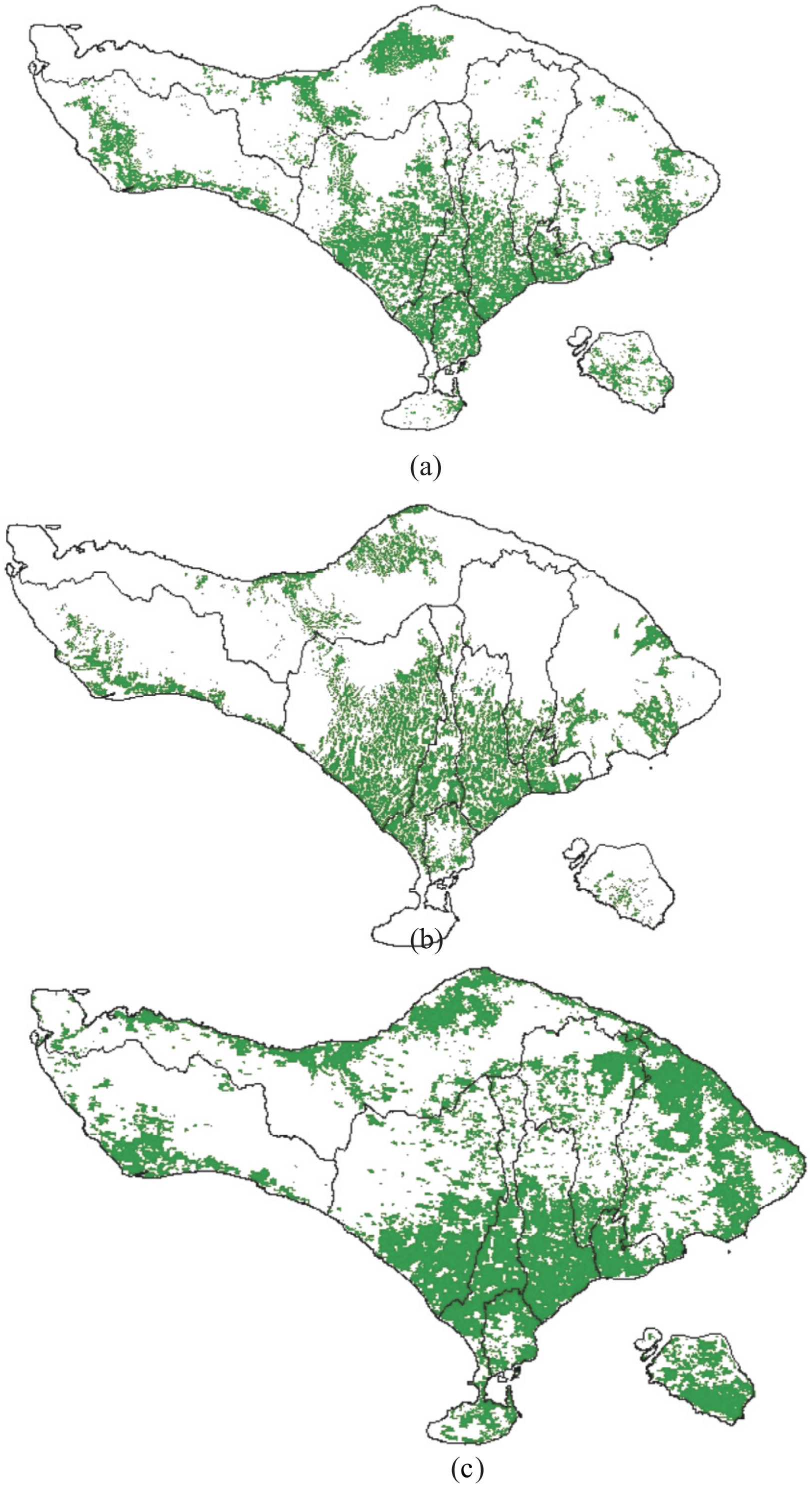


Figure 5. The result of the rice field classification using: (a) the standard procedure; (b) the modified procedure; and (c)

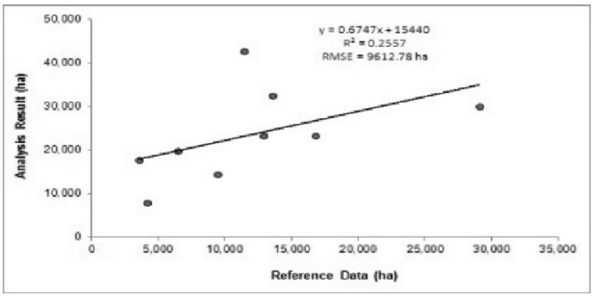
Visually, the standard classification procedure yielded a higher density of predicted rice field areas when compared with the reference data (Figure 5a and 5c). However, the modified procedure resulted in a distribution and density of rice fields that was more similar to the reference data (Figure 5b and 5c). Based on Table 3, both procedures predicted a larger coverage of rice fields in all regencies compared with the reference data. However, the modified procedure had a smaller difference from the reference data than the standard procedure (16.73% versus 96.81%, respectively). The high variability of the rice field coverage caused high variance of the training area. This produced non-rice field pixels that were classified as rice fields in the standard classification procedure. Using the temporal variance of VIs as an input for the rice classification could reduce classification errors by approximately 80.08%.

Table 3. Comparison of predicted rice field area obtained from the modified procedure and the standard procedure compared with reference data.

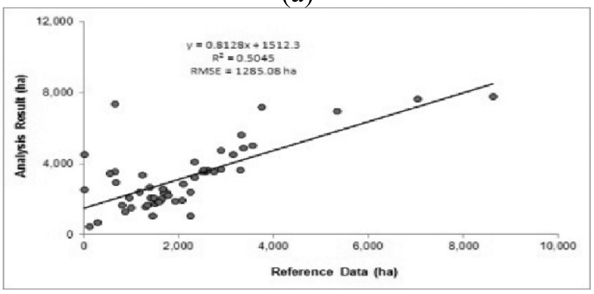
Regency	Reference data		Modified procedure		Existing Procedure	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Badung	12,887.50	12.00	13,687.50	10.91	23,212.50	10.98
Bangli	3,537.50	3.29	4,156.25	3.31	17,700.00	8.37
Buleleng	13,606.25	12.66	15,868.75	12.65	32,531.25	15.39
Denpasar	4,181.25	3.89	7,831.25	6.24	7,843.75	3.71
Gianyar	16,800.00	15.64	16,812.50	13.41	23,181.25	10.96
Jembrana	9,462.50	8.81	13,275.00	10.59	14,456.25	6.84
Karangasem	11,418.75	10.63	14,325.00	11.42	42,712.50	20.20
Klungkung	6,462.50	6.02	10,118.75	8.07	19,718.75	9.33
Tabanan	29,081.25	27.07	29,337.50	23.39	30,087.50	14.23
Total	107,437.50	100.00	125,412.50	100.00	211,443.75	100.00

3.3. Accuracy assessment of classification results

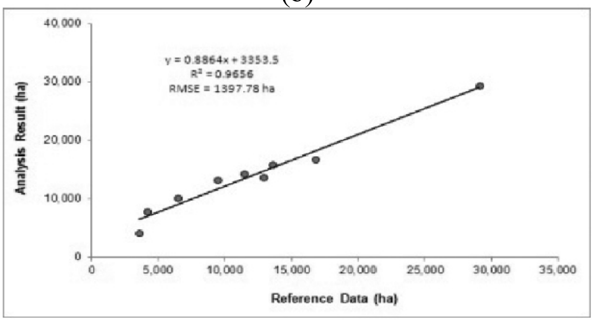
Accuracy assessments of the classification results were performed with two methods: regression analysis and the Kappa statistic. Based on the regression analysis, the coefficient of determination (R^2) of the relationship between rice field area resulting from the standard procedure and the reference data was low (0.2557 and 0.5045 for regency- and district-level comparisons, respectively). However, the modified procedure that was developed in this study produced high R^2 values of 0.9656 and 0.8698 for regency- and district-level comparisons, respectively. The Root Mean Square Error (RMSE) for estimations from the standard classification procedure was higher than for the modified procedure. The RMSE of the standard procedure was 9612.78 ha and 1285.08 ha for regency- and district-level comparisons, respectively, whereas for the modified procedure, it was 1397.78 ha and 551.27 ha, respectively (Figure6)



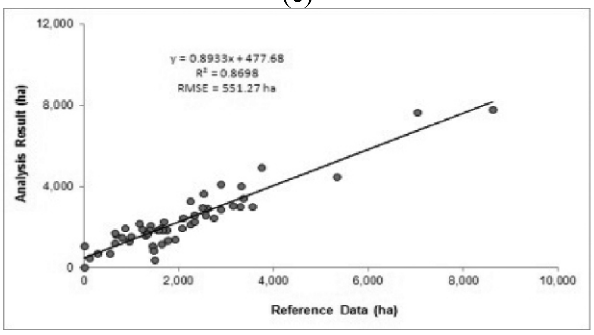
(a)



(b)



(c)



(d)

Figure 6. Relationship between rice field areas resulting from the image classification versus the reference data. (a) and (b) were produced using the current procedure, whereas (c) and (d) were derived from the modified procedure. (a) and (c) are for regency-level comparisons, while (b) and (d) are for district-level comparisons.

The first step for the Kappa analysis was to create an error matrix for both classification procedures evaluated in this study (Table 4). As much as 896 points (one percent of the total pixels in the study area) were used as ground truth samples from the reference data by means of stratified random sampling of rice field and non-rice field classes.

Based on Table 4, the commission error, omission error, and overall accuracy of the standard classification procedure were 68.11%, 28.48%, and 66.63%, respectively, while for the modified procedure, these values were 42.36%, 27.07%, and 83.71%, respectively. The modified procedure showed lower errors and higher accuracy compared with the standard procedure. Commission error represents cases where non-rice field pixels were classified as rice fields, while omission error represents cases where rice field pixels were classified as non-rice fields (Lillesand and Kiefer, 2000).

Both commission errors were higher than omission errors. This indicated that the spectral reflectance of rice fields had a wide range due to high variation of land cover states. High variability of rice fields caused a high standard deviation of training areas; thus, the possibility of classifying a non-rice field pixel as a rice field pixel was higher. Using temporal variance of VIs as input images in rice field classification can reduce commission and omission errors and improve overall accuracy (Table 5).

Table 4. The error matrix of the rice field classification results.

(a) Standard Procedure

		Reference data		
		Rice Field	Non-rice field	Total
Classification Result	Rice field	118	252	370
	Non-rice field	47	479	526
	Total	165	731	896

(b) Modified procedure

		Reference data		
		Rice Field	Non-rice field	Total
Classificatio n Result	Rice field	131	97	228
	Non-rice field	49	618	667
	Total	180	715	895

Table 5. Errors and accuracy of rice field classification results for both the standard and modified procedures.

Errors & Accuracy	Existing procedure	Modified procedure
Commission error (%)	68.11	42.36
Omission error (%)	28.48	27.07
Overall accuracy (%)	66.63	83.71

Additional parameters used to assess the accuracy of the rice field classification were the Kappa statistic and Kappa variance. A higher estimated Kappa value and lower Kappa variance value showed better agreement between the analysis result and reference data (Congalton et al., 1983). The modified procedure improved the kappa estimate from 0.49 to 0.77 and reduced kappa variance from 0.00159 to 0.00039 compared with the standard method (Table 6).

Although the regression analysis, error matrices, and estimated kappa statistics illustrated that the modified classification procedure developed in this study provided better results for rice field classification than the standard procedure, further analysis was needed to know whether the improvement was significant. Comparison between z-scores using a Z-table was used to examine whether the two methods were significantly different (Congalton and Green, 1999). The z-score was derived from equation 15, and a Z-table was consulted for a confidence level of 0.95, or $\alpha = 0.05$ in the two-tailed was 1.96. Based on the Kappa analysis, a z-score was 6.43 (Table 7). This means that the z-score value was greater than the Z-table value, and the H0 was rejected. The modified procedure provided a significantly higher level of accuracy than the standard procedure for rice field classification.

Table 6. The estimated kappa statistic and kappa analysis of both standard and modified procedures for rice field classification

Classification Method	Estimated Kappa	Kappa Variance
Standard procedure	0.49	0.00159
Modified procedure	0.77	0.00039

Table 7. z-score and Z-table values for the comparison between the standard procedure and the modified procedure for rice classification.

z-score	Z Table (α = 5%)	Decision
6.43	1.96	Reject H0

4. Conclusions

Rice field reflectance had higher temporal variability than other land uses. The greatest differences were observed in NDVI, RVI, and SAVI. Both visual comparisons and statistical analyses demonstrated that the modified procedure for rice field classification produced better results than the standard procedure. Regression analysis demonstrated that using temporal variance in VIs as an input for rice field classification improved the R^2 from 0.2557 to 0.9656 for regency-level comparisons and from 0.5045 to 0.8698 for district-level comparisons. The RMSE of the modified procedure produced lower values of 1397.78 ha and 551.27 ha when compared with the RMSE of the standard procedure of 9612.78 ha and 1285.08 ha for regency- and district-level comparisons, respectively. Classification accuracy and estimated Kappa statistics from the modified classification procedure also showed more accurate results than the standard method. Commission error, omission error, and kappa variance were smaller for the modified procedure than the standard procedure. The Kappa analysis concluded that there are significant differences between the modified procedure developed in this study and the standard procedure for rice field classification. Thus, using modified input for rice field classification with MODIS images provides a significantly more accurate result compared with the standard classification procedure.

Acknowledgments
I would like to express my profound gratitude to my advisor for his invaluable support, encouragement, supervision, and useful suggestions throughout this research. I am also very thankful to JSPS Ronpaku for their funding support for this PhD research program.

References

Atkinson, P.M. and Lewis, P., 2000, Geostatistical classification for remote sensing: an introduction. *Computers and Geosciences* 26:361–371.

Bachelet, D., 1995, Rice paddy inventory in a few provinces of China using AVHRR data. *Geocarto International* 10:23–38.

Baret, F. and Guyot, G., 1991, Potentials and limits of vegetation indices for LAI and APAR assessment. *Remote Sensing of Environment*, 35:161–173.

Brown, J.C., Jepson, W.E., Kastens, J.H., Wardlow, B.D., Lomas, J. and Price, K.P., 2007, Multi-temporal, moderate spatial resolution remote sensing of modern agricultural production and land modification in the Brazilian Amazon. *GIScience and Remote Sensing* 44:117–148.

Chang, J., Hansen, M.C., Pittman, K., Carroll, M. and Dimiceli, C., 2007, Corn and soybean mapping in the United States using MODIS time-series data sets. *Agronomy Journal* 99:1654–1664.

Congalton, R.G. and Green, K., 1999, *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*, Lewis Publishers, Florida.

Congalton, R.G., Oderwald, R.G. and Mead, R.A., 1983., Assessing Landsat Classification Accuracy Using Discrete Multivariate Analysis Statistical Techniques, *PERS* 49:1671–1678.

Denier Van Der Gon, H., 2000., Changes in CH4 emission from rice fields from 1960s to 1990s: 1. Impacts of modern rice technology. *Global Biogeochemical Cycles,* :1:61– 72.

Doraiswamy, P.C., Sinclair, T.R., Hollinger, S., Akhmedov, B., Stern, A. and Prueger, J., 2005, Application of MODIS-derived parameters for regional crop yield assessment. *Remote Sensing of Environment* 87:192–202.

Fang, H., 1998., Rice crop area estimation of an administrative division in China using remote sensing data. *International Journal of Remote Sensing* 17:3411–3419.

Fang, H., Wu, B., Liu, H. and Xuan, H., 1998, Using NOAA AVHRR and Landsat TM to estimate rice area year-by-year. *International Journal of Remote Sensing* 3:521–525.

Food Crops Agriculture Department, 2006, *Annual report of food crops,* Agriculture Department of Local Governent, Bali.

Gupta, R.K., 1993, Comparative study of AVHRR ratio vegetation index and normalized difference vegetation index in district level agriculture monitoring. *International Journal of Remote Sensing* 14:53–73.

Harris, P. M. and Ventura, S. J., 1995, The integration of geographic data with remotely sensed imagery to improve classification in an urban area. *Photogrammetric Engineering and Remote Sensing*, Vol. 61, pp. 993–998.

Huete, A.R., 1988, A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment* 25:295–309

Huete, A. R. and Escadafal, R. 1991 Assessment of biophysical soil properties through spectral decomposition techniques. *Remote Sensing of Environment* 35:149–159.

Huete, A. R. and Warrick, A. W., 1990, Assessment of vegetation and soil water regimes in partial canopies with optical remotely sensed data. *Remote Sensing of Environment* 32:115–167.

Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X. and Ferreira, L. G., 2002, Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment* 83:195–213.

IRRI, 1993, *1993–1995 IRRI Rice Almanac*, International Rice Research Institute, Manila.

Jensen, J. R., 1986, *Introductory digital image processing: A remote sensing perspective*. Prentice-Hall, New Jersey.

Justice, C.O. and Townshend, J.R.G., 2002, Special issue on the moderate resolution imaging spectroradiometer (MODIS): a new generation of land surface monitoring. *Remote Sensing of Environment* 83:1–2.

Khush, G.S., 2005, What it will take to feed 5 billion rice consumers in 2030. *Plant* Molecular *Biology* 59:1-6.

Lillesand, T. M. and Kiefer, R. W, 2000. *Remote sensing and image interpretation*. Wiley & Son, New York.

Lobell, D.B. and Asner, G.P., 2004, Cropland distributions from temporal unmixing of MODIS data. *Remote Sensing of Environment* 93:412–422.

Matthews, R. B., Wassmann, R., Knox, J. W. and Buendia, L. V., 2000, Using a crop/soil simulation model and GIS techniques to assess methane emissions from rice fields in Asia: Upscaling to national levels. *Nutrient Cycling in Agroecosystems* 58:201– 217.

Morton, D.C., Defries, R.S., Shimabukuro, Y.E., Anderson, L.O., Arai, E., Del Bon Espirito-Santo, F., Freitas, R. And Morisette, J., 2006, Cropland expansion changes deforestation dynamics in the southern Brazilian Amazon. *Proceedings of the National Academy of Sciences USA* 103:14637–14641.

Niel, T.G.V. and McVicar, T.R. Remote Sensing of Rice-Based Irrigated Agriculture: *A Review. Rice CRC Technical Report*, 2001, Available from www.ricecrc.org (Accessed 5 October 2009).

Niel, T.G.V., McVicar, T.R., Fan g, H. and Liang, S., 2003, Calculating environmental moisture for per-field discrimination of rice crops. *International Journal of Remote Sensing* 24:885–890.

Okamoto, K. and Kawashima, H., 1999, Estimating of rice-planted area in the tropical zone using a combination of optical and microwave satellite sensor data. *International Journal of Remote Sensing* 5:1045–1048.

Potgieter, A.B., Apan, A., Dunn, P. and Hammer, G., 2007, Estimating crop area using seasonal time series of enhanced vegetation index from MODIS satellite imagery. A*ustralian Journal of Agricultural Research* 58:316–325.

Prather, M., D. Ehhalt, F. Dentener, R. G. Derwent, E. Dlugokencky, E. Holland, I. S. A. Isaksen, J. Katima, V. Kirchhoff, P. Matson, P. M. Midgley, and M. Wang., 2001, Chapter 4. Atmospheric Chemistry and

Greenhouse Gases. In *Climate Change 2001*. Edited by J.T. Houghton, Cambridge U. Press 239-287.

Sakamoto, T., Nguyen, N.V., Ohno, H., Ishitsuka, N. and Yokozawa, M., 2006, Spatiotemporal distribution of rice phenology and cropping systems in the Mekong Delta with special reference to the seasonal water flow of the Mekong and Bassac rivers. *Remote Sensing of Environment* 100:1–16.

Sakamoto, T., Yokozaawa, M., Toritani, H., Shibayama, M., Ishitsuka, N. and Ohno, H., 2005, A crop phenology detection method using time-series MODIS data. *Remote Sensing of Environment* 96:366–374.

Samad, M., Merrey, D., Vermillion, D., Fuchscarsch, M., Mohtadullah, K., & Lenton, R., 1992, Irrigation management strategies for improving the performance of irrigated agriculture. *Outlook on Agriculture* 21:279– 286.

Vermote, E. F. and Vermeulen, A., 1999, Atmospheric correction algorithm: Spectral reflectance (MOD09), *MODIS algorithm technical background document*, version 4.0. Department of Geography, University of Maryland.

Wardlow, B.D. and Egbert, S.L., 2008, Large-area crop mapping using time-series MODIS 250 m NDVI data: an assessment for the U.S. Central Great Plains. *Remote Sensing of Environment* 112:1096–1116.

Wardlow, B.D., Kastens, J.H. and Egbert, S.L., 2006, Using USDA crop progress data for the evaluation of greenup onset date calculated from MODIS 250-meter data. *Photogrammetric Engineering and Remote Sensing* 72:1225–1234.

Xiao, X., He, L., Salas, W., Li, C., Moore, B. and Zhao, R., 2002, Quantitative relationships between field-measured leaf area index and vegetation index derived from VEGETATION images for paddy rice fields. *International Journal of Remote Sensing* 23:3595–3604.

Xiao, X., Braswell, B., Zhang, Q., Boles, S., Frolking, S. and Moore, B., 2003, Sensitivity of vegetation indices to atmospheric aerosols: Continental-scale observations in Northern Asia. *Remote Sensing of Environment* 84:385–392.

Xiao, X., Boles, S., Liu, J., Zhuang, D., Frolking, S., Li, C., Salas, W. and Moore, B., 2005, Mapping paddy rice agriculture in southern China using multi-temporal MODIS images. *Remote Sensing of Environment* 95:480–492.

Yeh, A.G.O. and Li, X., 1999, Economic development and agricultural land loss in the Pearl River Delta, China. *Habitat International* 23:373–390.