THE EVALUATION OF IMAGE CLASSIFICATION METHODS FOR RICE PADDY INTERPRETATION

Kuo-Hsin HSIAO*

Chi-Chung LAU**

Wei-Chen HSU***

*Researchers, Remote Sensing Lab., Energy and Resource Labs, ITRI
Bldg. 24, 195-6, Sec. 4, Chung-Hsing Road, Chutung, Hsinchu 310
Tel: +886-3-5918587; Fax: +886-3-5820038,
E-mail : hks@itri.org.tw
China Taipei

**Researchers, Remote Sensing Lab., Energy and Resource Labs, ITRI
Bldg. 24, 195-6, Sec. 4, Chung-Hsing Road, Chutung, Hsinchu 310
Tel: +886-3-5918587; Fax: +886-3-5820038,
E-mail : hks@itri.org.tw
China Taipei

***Researchers, Remote Sensing Lab., Energy and Resource Labs, ITRI
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Tel: +886-3-5918587; Fax: +886-3-5820038,
E-mail : hks@itri.org.tw
China Taipei

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ABSTRACT: Multi-temporal imageries and cadastral GIS datasets were combined to interpret the rice paddy distributions, by applying the following means: (1) NDVI intervals approach on basis of multi-temporal SPOT images, (2) the statistic probability classifier, (3) the object oriented fuzzy classifier, (4) the Bayesian classifier based on spectral reflectance curve measured from different growth stages. Results of last three classification approaches were coupled with a prediction of probability. A selected threshold was applied to the results to obtain a dichotomy category. These results were compared with visual interpreting data from aerial photos for assessing accuracy. It shows that the overall accuracies and $\hat{k}$ for the four means are 92.22% & 0.83, 91.89% & 0.82, 90.97% & 0.81 and 96.27% & 0.92, respectively. Similar approach is applied to a contrast test site for the rice paddy in the first season. The results of the above-mentioned classifiers show overall accuracies and $\hat{k}$ of 94.27% & 0.83, 92.75% &

0.79) and 95.43% & 0.87 that deducted from the object oriented fuzzy classifier. For the rice paddy in the second season, results of the above-mentioned three classifiers show overall accuracies and $\hat{k}$ of 93.99% & 0.79, 93.47% & 0.77 and 95.33% & 0.84. It is concluded that the Bayesian classifier not only can generate probability of each class, but also give better classified results after thresholding process.

1.INTRODUCTION

It is highly important for the government to gain an overall estimation of rice planting area and rice yield both because rice is the principal food provision in Taiwan and water for irrigation is competitive with other purposes in TAIWAN. Developing methodology for interpreting the paddy with combined multi-temporal imageries and cadastre GIS datasets is deemed a proper action. Chen & Tseng (1999) applied Difference-Image Classification combining rice growth knowledge, Temporal Profile Matching and Peak Detection classified methods that draw into account of rice optical spectrum reflectance. It is showed that the Difference-Image Classification can obtain the optimum overall accuracy. This study also confirms the parcel-based classified accuracy is better than pixel-by-pixel classification that combined the multi-temporal imageries, cadastre and rice spectrum reflectance data for a study are in Chang-Hwa County of central TAIWAN. Lau (2000) also used the same classified method to identify the paddy at Tai-Nan County of southern TAIWAN. The area difference of paddy fields obtained both from interpretation of large-scaled air-photos and that from classification of multi-temporal imageries is less than 2.10%.

The merit of relatively high accuracy given by parcel-based classification is attributed to the access of a cadastre database. In this study, we integrate the statistical probability for soft category that each cadastre category is showed with 0~1. The higher the possibility of rice category, the probability is nearer to 1. Among the soft classification, we computed the statistical probability in two mapsheets of a scale of 1/5,000 and evaluated the classification accuracy and $\hat{k}$ index that transfer the probability to dichotomy category through selecting appropriate threshold. Furthermore, similar approach is applied to Miao-Li County of northern TAIWAN. In the classification results, the probability of rice category of each cadastral parcel and the dichotomy category are also generated and compared with the results of aerial photos interpretation.

2. THE RELATIONSHIP OF NDVI INDEX AND CADASTRE ATTRIBUTE

The spectrum reflectance of NIR and IR can obviously response the variation of green vegetation. Therefore, the NDVI index could reveal the vegetation growth conditions and leaf area density. Wu (2001) reported that the NDVI index changes with the crop stage of rice growth, which can be obtained from the rice planting records published by Taiwan Agriculture Research Institute (TARI) (figure 1).

For proving the feature that NDVI is a proper index of rice growth stage, multi-temporal SPOT imageries were used to generate NDVI image. Chi^2 test was used to check the relationship. About the relative statistical analysis, firstly, it was divided NDVI index into 10 grades (NDVI intervals is 0.05) according to the histogram distribution of rice and no-rice. Then, each cadastral land parcels were matched with NDVI image and a statistics of rice or no-rice parcels are computed. After calculating the parcel numbers of rice and no-rice in theory and accumulative the total Chi^2 of each NDVI index grade (table 1). Lastly, Ho hypothesis test is done to compare the Chi^2 value with accumulate Chi^2.

Table 1 NDVI index grade corresponding to Chi^2 value

Cadastre attribute	NDVI index grades										
	1	2	3	4	5	6	7	8	9	10	Total
Rice	14.42	44.31	17.13	21.78	67.68	0.83	11.47	41.25	35.74	2.27	256.87
No-rice	12.01	36.90	14.26	18.14	56.36	0.69	9.55	34.35	29.76	1.89	213.92
Total	26.43	81.20	31.39	39.91	124.04	1.52	21.02	75.60	65.50	4.16	470.79

Chi^2 observation value = 470.79, $Chi^2 = (Oi\text{-}Ei)^2/Ei$; Chi^2 theory value [alpha=0.05, d.o.f. = (2-1)*(10-1) =9] = 16.919; Chi^2 observation >Chi^2 theory, accept Ho hypothesis.

The Chi^2 observation and theory values of multi-temporal SPOT NDVI index using 4 imageries at the first crop season in 2000 were computed. Chi^2 observation is larger than Chi^2 theory (table 2). Therefore, we confirm that the cadastre attribute and NDVI index are in a good agreement. So, accept the Ho hypothesis (Lau, 2001).

Table 2 The Chi^2 observation values using 4 scenes imagery in 2000 (Lau,2001)

Date	Chi^2 observation	Accept Ho	Date	Chi^2 observation	Accept Ho
04/18	470.79	Yes	07/25	732.91	Yes
05/09	847.40	Yes	07/25-09	1961.49	Yes

3. IMAGE CLASSIFICATION METHODS

Four kinds of classification methods were employed in this study including parcel-based classification, namely, (1) the interpretation of SPOT images NDVI intervals for hard dichotomy category. And the soft classification including (2) the statistic probability classifier, (3) the object oriented fuzzy classifier, (4) the Bayesian classifier based on spectral reflectance curve measured from different growth stages. The last three classified results were displayed with the probability. However, it was also processed to the dichotomy category adopted the appropriate threshold of probability.

3.1 The statistic probability classifier

The statistic probability classifier is designed to decide the probability of a certain range of NDVI index being rice paddy. Two steps are required in the processes, i.e. the determination of a membership function and probability consolidation of multi-temporal images. Among the membership function, we adopted a trapezoid shape to decide the optimum probability including the consideration of the image acquisition dates and referred to the distribution curve of figure 1. Furthermore, considering the situations that the rice in large area does not growth uniformly, due to mixed pixels or other irrigation factors. Therefore, it has the descending and outward slopes membership function at the rice NDVI index margin region (Figure 2).

While integrated multi-temporal imageries or statistic probability classifier, it can be re-combined the membership function to decide the probability that using the geometric mean computed manner. The formula is:

$$P(Ai/V1\text{-}n)=\sqrt[n]{P(Ai/V1)*P(Ai/V2)*P(Ai/V3)*...*P(Ai/Vn)} \quad (3\text{-}1)$$

P(Ai/V1-n):The probability of interpreted rice paddy,

P(Ai/Vn):The probability of rice paddy in images of different acquisition dates.

3.2 The object oriented fuzzy classifier

For object oriented fuzzy classifier, objects are the minimum classification unit. In the first stage of classification process, pixels with the same or similar statistic characters are merged into small parcels. Secondly, a multi-layers process is executed (figure 3) for parcel segmentation or merging on basis of features in a cadastral parcel such as areas, perimeter and texture or gray level value and so on. Lastly, decide the membership function of each object according to the fuzzy theorem. In this study, we used commercial E-cognition software to process the object oriented fuzzy classification test (Definiens, 2000).

3.3 The Bayesian classifier

The Bayesian classifier was to ascertain the relationship of SPOT image to cadastre attribute in some certain condition. Bayeas Theorem is applied for deriving the statistics of the rice or no-rice probability using multi-temporal SPOT NDVI index corresponding to cadastre boundary. Results are tested and evaluated by classification accuracy and $\hat{k}$ index.

Using single SPOT NDVI index to interpret the rice or no-rice probability, the condition probability is showed as P(Ai|VI). If we quote from the Bayeas principle and spread up using fully-probability theorem. It shows

$$P(Ai|VI) = P(VI|Ai) * P(Ai) / S [P(VI | Aj) * P(Aj)]$$
$$=P(VI|Ai)*P(Ai)/\{P(VI|A1)*P(A1)\}+P(VI|A2)*P(A2)\}\} \quad (3\text{-}2)$$

P(Ai|VI): if NDVI = VI, the cadastre attribute probability of Ai; A1: attribute 1 = rice, A2: attribute 2 = no-rice; P(VI|Ai) : The # of NDVI=VI and attribute is Ai/ The # of attribute is I;

P(Ai): The probability of cadastre attribute is Ai (The cadastre # of Ai /total cadastre #)

Furthermore, if two imageries or multi-temporal NDVI index are combined, it can be expanded as formula (3-3) and (3-4). Figure 4 is the rice or no-rice condition probability distribution corresponding to cadastre attribute using two imageries (Lau, 2001).

P(VI1|Ai) * P(VI2|Ai) * P(Ai)/sum [P(VI1|Aj)*P(VI2|Aj)*P(Aj)] (3-3)

P(Ai| VI1, VI2, … VIn) = P(VI1|Ai)*P(VI2|Ai)*…* P(Vin|Ai) * P(Ai) /

[P(VI1|A1)* P(VI2|A1)* ? ? ? * P(Vin|A1) * P(A1)] +……

[P(VI1|Aj)* P(VI2|Aj)* ? ? ? * P(Vin|Aj) * P(Aj)] (3-4)

4. THE RESULTS OF IMAGE CLASSIFICATION

The pre-processing for the image classification in this study includes normalizing the multi-temporal SPOT images, filtering the cloud and shadow area, reviewing the histogram of rice and no-rice (Hsiao, 2000). The best classifier is selected on basis of the overall accuracy and $\hat{k}$ index. Verification of the applicability of the classifier is then applied to the image data in a new test area covering two mapsheets in Miao-Li County.

4.1 The classified results of test area

The parcel-based classification of test area includes hard and soft classification. They are showed dichotomy category for the interpretation of SPOT images NDVI intervals and probability for soft classification. The latter also transferred the probability to absolute classified category that selected appropriate threshold. Furthermore, for assessing accuracy, a comparison between the classification results and manual interpretation of aerial photos are made (figure 5).

Results showed that the Bayesian classifier give an optimum overall accuracy and $\hat{k}$ index (table 3). They are 96.27% & 0.92 (figure 6). The classified results of interpretation of SPOT images NDVI intervals and statistic probability classifier are 92.22% & 0.82, 91.89% & 0.82.

Table 3 Evaluate dichotomy category classified accuracy in two mapsheets

Classified methods	Accuracy	$\hat{k}$ index	Classified methods	Accuracy	$\hat{k}$ index
NDVI intervals	92.22%	0.83	Object oriented fuzzy classifier	90.97%	0.81
Statistic probability	91.89%	0.82	Bayesian probability	96.27%	0.92

4.2 The classified results of Miao-Li county

We used the parcels number for computing the prior probability at section 3.3. It has a little difference in real cases because each parcel area is different. In this section, we selected the paddy pixels number corresponded to parcel area to replace the parcels number and the NDVI intervals are reduced to 0.01.

The results of the first crop season in 2000 give an overall accuracy and $\hat{k}$ index of 94.27% & 0.83, 92.75% & 0.79 and 95.43% & 0.87. This is better than the results by applying object oriented fuzzy classifier (table 4). In proportion to the second crop season, overall accuracy and $\hat{k}$ index are 93.99% &

0.79, 93.47% & 0.77 and 95.33% & 0.84. It is showed that the Bayesian classifier not only give a result with corresponding probability, but also give optimum results when the probability are transformed to the dichotomy category.

Table 4 Evaluate dichotomy category classified accuracy of Miao-Li county

Classified methods	The classified results of 1'st period		The classified results of 2'nd period	
	Accuracy (%)	$\hat{k}$ index	Accuracy (%)	$\hat{k}$ index
NDVI intervals	94.27	0.83	93.99	0.79
Statistic probability	92.75	0.79	93.47	0.77
Bayesian probability	95.43	0.87	95.33	0.84

5. CONCLUSION

The statistic probability classifier, object oriented fuzzy classifier and Bayesian classifier were used to interpret the rice paddy probability for soft classification, Moreover, transferred the probability according to the appropriate threshold to dichotomy category for assessing accuracy and $\hat{k}$ index that compared the classified results generated by aerial photo interpretation. The evaluation of the classification accuracy was done in two mapsheets area in Miao-Li County in two crop periods. The rice paddy classification accuracies for Bayesian classifier are 96.27% & 0.92, 95.43% & 0.87 (1'st period) and 95.33% & 0.84 (2'nd period). It is showed that the Bayesian classifier can give a result not only with the probability, but also give an optimum result when the probability was transformed into dichotomy category.

REFERENCES

Chen, I. H., and Tseng, Y. H., 1999, Automatic Recognition of Rice Fields from Multi-Temporal Satellite Images. Journal of Photogrammetry and Remote Sensing, Volume 4, No. 3, pp.1~15.

Hsiao, K. S., Lau, C. C., and Shih, T. Y., 2000, Combined Remote Sensing and GIS Data for Rice Paddy Landuse Interpretation, Journal of Photogrammetry and Remote Sensing, Volume 5, No. 4, pp.1~22.

Lau, C. C., Hsiao, K. S., and Lee Y. Y., 2000, A Paddy Interpreting System Using Remote Sensing and GIS (2/4), ERL report 063-89-W025, pp. 60~94.

Lau, C. C., Tseng, Y. H., and Hsiao, K. S., 2001, A Paddy Interpreting System Using Remote Sensing and GIS (3/4), ERL report 063-90-W010, pp. 72~76.

Wu, C. N., and Hsiao, K. S., 2001, The Monitoring Application Using SPOT and NIR CCD Imagery. ERL report 063-90-W011, pp. 23.

DEFINIENS, 2000, *ECOGNITION Object Oriented Image Analysis User Guide,* Version 1.0.

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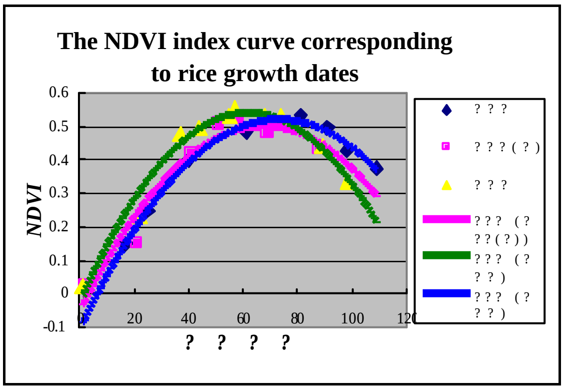


Figure 1 The distribution of multi-temporal NDVI index corresponded to growth dates

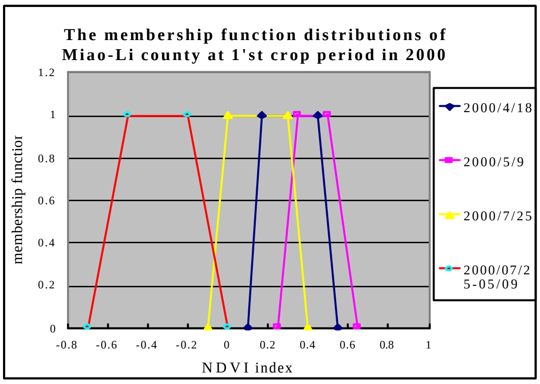


Figure 2 The membership function of four scenes NDVI index of Miao-Li county

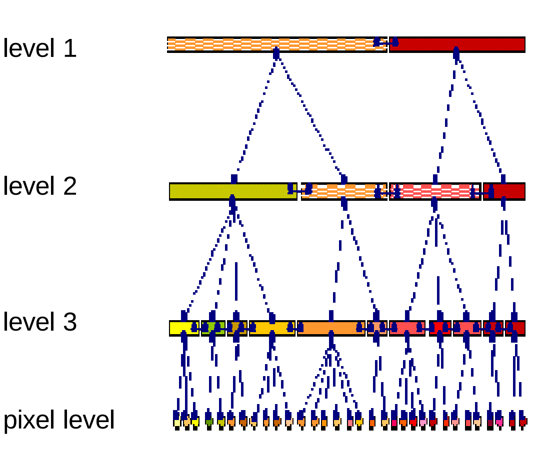
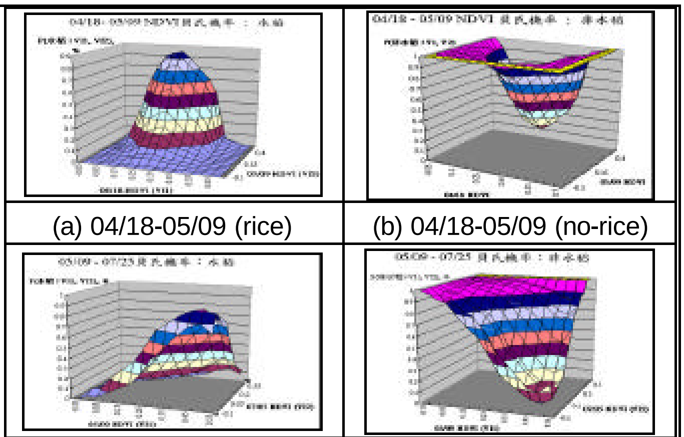


Figure 3 The structure of multi-layer objects (Definiens, 2000)



(a) 04/18-05/09 (rice)

(b) 04/18-05/09 (no-rice)

(c) 05/09-07/25 (rice)

(d) 05/09-07/25 (no-rice)

Figure 4 The Bayesian probability distribution of rice and no-rice for two scenes NDVI and difference index (Lau, 2001)

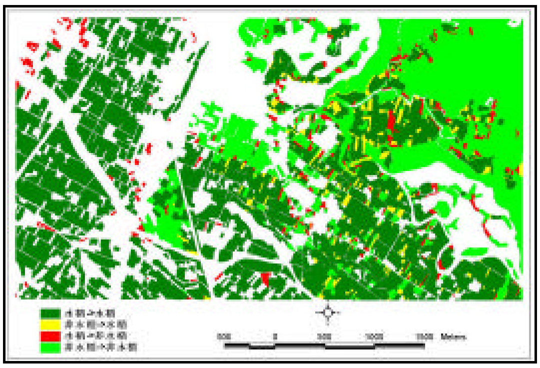


Figure 5 Classified map of test area applying Bayesian probability classifier.

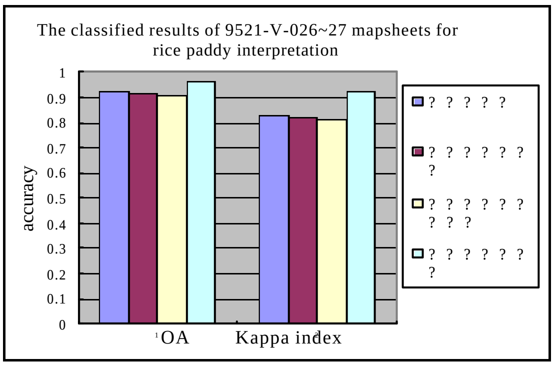


Figure 6 The classified accuracy of four kinds of classification methods of test area