A STUDY ON LANDUSE CLASSIFICATION USING ORTHO-RECTIFIED AERIAL PHOTOGRAPHS AND HIGH RESOLUTION SATELLITE IMAGES

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ABSTRACT: For the purpose of the national landuse mapping launched in 2006 with a scale of 1:5000, a scheme combining manual interpretation of orthorectified images and intensive field checks is adopted. The aerial photographs or satellite images required for this study are limited to those originally taken with a ground resolution better than 3m and with a time after 2004. A classification framework with three levels of classes was established in the beginning of the program. Manual interpretation is adopted for orthophotos, whereas automated supervised and unsupervised classifications are adopted for satellite images. Results of the 1:5000 landuse maps show that lands used for agriculture, forestry, hydrology, and transportations can be visually interpreted and classified with an accuracy of 95~98%. However, Building-up areas require ancillary information in GIS format to improve the classification to achieve the level 3 requirements. Satellite images can give an accuracy of about 70~85% for level 1 and level 2 classification for lands used for agriculture, forestry, hydrology, and transportations. In this study, classes of building-up areas in level three are not achieved by automated classification.

1. INTRODUCTION

Ground resolution of aerial photographs generally is as high as submeter. Details of ground features such as landcover types can be recognized on such images, especially for discrimination of crop types. However, for classification of up to level 3, features required to reveal include various landuse of buildings and recreation features which may not be recognized solely on basis of aerial photographs. Supplementary information may be required for further discrimination in a higher level of classification. In addition, high resolution satellite images can explicit more detailed ground features as compared to medium to low resolution images. However, they cannot fulfill the requirements for level 3 classification. In this study, pansharpened images of SPOT-5 are used in both supervised and non-supervised classification for attempting to know the suitability of these images for national landuse inventory.

Multi-temporal images are usually available for obtain the information of ground covers, especially for agricultural lands. If ancillary data such as land parcels and phenological information are available, the classification accuracy will be improved significantly. Therefore, experiment with multi-temporal images complimentary with parcel data and phenological information is also carried out in this study to evaluate the suitability for the purposes of national landuse survey.

2. THE STUDY AREA AND IMAGES USED UN THE STUDY

The study area covers the map with map number designated as 95204096 and map name as Ping-Ding in 1/5000 national base map series. This area cover a variety of land cover types including hills, plains, rivers, farm lands, forestry and villages. Thus, it becomes a suitable area for testing the capability of automated landcover classification. The pansharpened SPOT images have a resolution of 2.5 m by 2.5 m (Fig. 1). For the study of multi-temporal images, the study area is located in Jia-Yi Plain in middle Taiwan with images of Formosat-2 (Fig. 2).

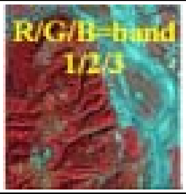


Fig. 1 Pan-sharpened SPOT5 images

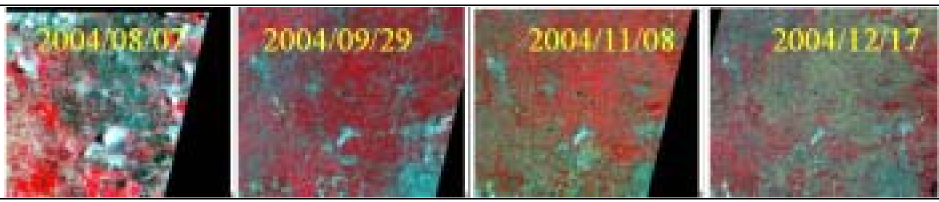
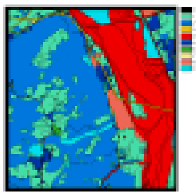


Fig.2 Multi-temporal Formosat-2 images

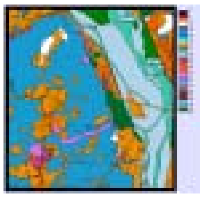
3. CLASSIFICATION METHODS

3.1 Aerial Photograph Interpretation

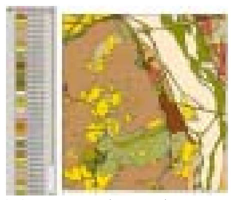
Geo-referenced orthophotos of the study areas are used for visual interpretation. Boundaries of a landcover type are on-screen digitized and saved as GIS layers. In addition, field surveys are conducted to verify the attributes within landtype boundaries. The result of this map is then used as a basis for accuracy validation for automated classification (Fig. 3).



(a) Level 1classes



(b) Level 2 classes



(c) Level 3 classes

Fig. 3 Ground truth obtained by visual interpretation of orthophotos

3.2 Automated image classification

First, spectral discriminant analysis is carried out for various landcover types. Stratified random sampling strategy is used with 70 samples representing level 3 classes (Fig. 4). Fig.5 shows the means, maxima, minima, and standard deviations of each class. The variations of each class in different spectral bands can be readily observed.

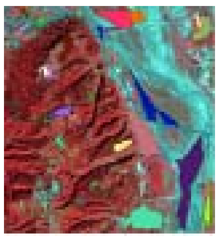


Fig. 4 Sample distribution

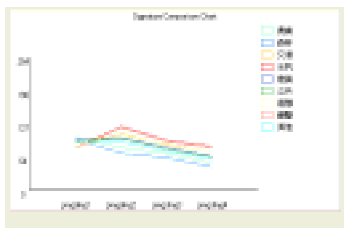


Fig.5 Spectral features for level 1 classes

(a) unsupervised classification

Unsupervised classification is statistically a clustering analysis which is to separate image pixels into groups of similar spectral characteristics. A pixel is classified on basis of the value of itself. The processes include: (i) designation of total class numbers N to be grouped; in this study, 27 classes are given to catering for level 3 classification scheme; (ii) N seeds are generated to initialize the grouping process; (3) the pixel with a value similar to the seed will be grouped into the class of the seed; (4) class mean is computed for all the pixels belonging to the same class; (5) iteration between step 3 and 4 until no significant change taking place. Finally, the 27 classes are compared with the ground truth to obtain the attribute of each class. Some of the classes are merged together on basis of the knowledge of ground truth. Some minor classes are deleted.

(b) supervised classification

Supervised classification is statistically a discriminant analysis. Training samples are taken to obtain statistics of known classes. The most popular classifier is Maximum Likelihood classification. The premise of this approach is the normality of the spectral distribution of pixel values for each landcover type. A priori probably is applied for each class. First, conditional probability (i.e. the discriminant function) of the vector of a pixel is computed by following equation:

$P(\omega_i \mid x) \quad i=1, 2, \ldots, m$ where ω_i represents class i, m is total number of classes

If $P(\omega_i \mid x) > P(\omega_j \mid x) \quad j \neq i, j=1, 2, \ldots, m$

Then the conditional probability of $x \mid \omega$ can be computed by following Bayesian equation:

$$P(w_i \mid x = \frac{P(w_i)P(x \mid w_i)}{P(x)}$$

where $p(\omega_i)$ is the probability of class ω_i. Prior probability can be set by known information or presume all classes are equal. Thus, $p(x \mid \omega_i)$ is the distribution of probability of class ωi. Because a normal distribution is assumed for maximum likelihood classification, therefore, the following equation can be deducted:

$$p(x \mid w_i) = \frac{1}{(2\pi)^{N/2} \mid \sum_i \mid^{1/2}} \exp\left[-\frac{1}{2}(x - M_i)^T \sum_i^{-1} (x - M_i)\right]$$

where N is the number of feature space or spectral bands, Mi is mean vector, Σi is the covariance matrix of class i. The estimator of Mi becomes:

$$M_i = \frac{1}{n_i}\sum_{j=1}^{n_i} X_j \quad \sum_i = \frac{1}{n_i - 1}\sum_{j=1}^{n_i}\left[(X_j - M_i)(x_j - M_i)^T\right]$$

ni is the pixel number of class ω_i, j is the label, T is the transpose matrix, Mi and Σi can be obtained by pixel values.

(c) Multi-temporal Bayesian classification

Multi-temporal Bayesian classification is applied for rice paddy binary classification. On basis of NDVI and their differences, the Bayesian probability is calculated to assign a certain pixel to either a rice paddy pixel or not. And, then they are verified by ground truth obtained by visual interpretation.

For single time of image, the binary classification with NDVI, the conditional probability function can be expressed as P(Ai|VI). With Bayesian theorem, this can be expanded as:

$$P(Ai|VI) = P(VI|Ai) * P(Ai) / \Sigma [P(VI | Aj) * P(Aj)]$$
$$=P(VI|Ai)*P(Ai)/\{P(VI|A1)*P(A1)\}+P(VI|A2)*P(A2)\}\}$$

where, P(Ai|VI): the probability of parcel Ai when NDVI = VI; A1: attribute 1=paddy rice; A2: attribute 2= non-paddy rice; P(VI|Ai): the parcel # when NDVI=VI and attribute is Ai divided by the parcel number when attribute is Ai; P(Ai): the probability that the attribute of a parcel is Ai.

If expanded to a multi-temporal classification, the equation becomes:

$$P(Ai| VI1, VI2, \ldots VIn) = P(VI1|Ai)*P(VI2|Ai)*\ldots* P(Vin|Ai) * P(Ai) \quad / \quad [P(VI1|A1)* P(VI2|A1)*\ldots* P(Vin|A1) * P(A1)] + [P(VI1|A2)* P(VI2|A2)*\ldots* P(Vin|A2) * P(A2)] + \ldots\ldots\ldots [P(VI1|Aj)* P(VI2|Aj)*\ldots* P(Vin|Aj) * P(Aj)]$$

4. CLASSIFICATION RESULTS

4.1 Results of unsupervised classification

The result of unsupervised classification is shown in Fig.6. It shows that the landuse features of telecommunication and hydraulic facilities can not be identified, where as some of the features in agricultural and forestry areas are merged. When the result of Fig. 6 is compared with ground truth, the commission error for hydraulic and forestry classes are 0.252 and 0.275, respectively. However, the commission errors for roads, utilities, creation, minerals, etc are more than 0.8. The omission error for hydraulic and forestry features are 0.221 and 0.353, respectively. Similarly, the omission errors for roads, utilities, creation, minerals, etc are more than 0.8. There are many pixels of agricultural classes are wrongly assigned to forestry, recreation, and hydraulic classes. The mean error for unsupervised classification is 0.4358. Kappa indices are shown in Table 1. The sequence of kappa indices is forestry, hydraulic, building, agricultures, others, minerals, roads, utilities, and recreation facilities. In general, all classes except forestry and hydraulic classes are subject to serious errors.

Table 1 Error matrix of unsupervised classification

Class	Classification KIA	Class	ClassificationKIA
1-agriculture	0.1993	6-utilities	0.0200
2-forestry	0.5487	7-recreation	0.0016
3-roads	0.0589	8-minerals	0.0942
4-hydraulic facilities	0.6611	9-others	0.1087
5-buidings	0.3428	Overall Kappa	**0.4032**

4.2 Results of supervised classification

Fig. 7 and Fig. 8 are classified results using 80 training samples. The errors for level 2 classifications are too enormous and thus error matrix analysis is not conducted. For level 1 classification, both equal probability and prior probability are applied. The prior probability is given by using the proportion of each landcover classes. The results are similar to those obtained from unsupervised classification. Both commission and omission errors are relatively low for forestry and hydraulic features. However, the omission errors for other classes are generally from 0.8 to 0.9, the commission errors from 0.7 to 0.8. The error of equal probability is the same as that of prior probability. Or the mean error with equal probability is 0.4265 which is a little bit better than 0.4530 with prior probability.

Table 2 shows the error matrix of supervised classification. Relatively low errors are for forestry and hydraulic utilities. The worst results are for recreation, utilities, minerals, roads, and others. The complexity of each class dominates the accuracy of classification. Agriculture features include crops, pastures, ancillary agricultural facilities which possess different spectral properties. Thus, the classification accuracy is not so high as expected.

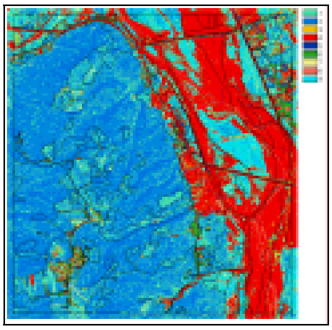


Fig. 6 Level 1 unsupervised classified map

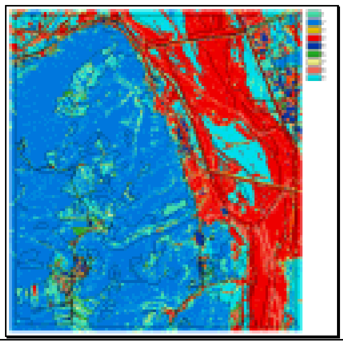


Fig. 7 Level 1supervised classified map

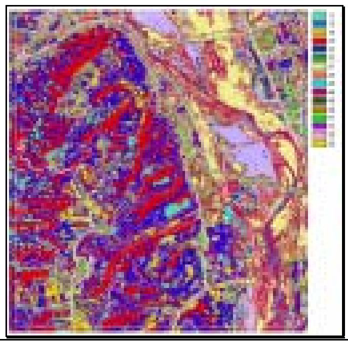


Fig. 8 Level 2 supervised classified map

Table 2 Kappa analysis for supervised classification

Class	Kappa By equal probability	Kappa by prior probability	Class	Kappa By equal probability	Kappa by prior probability
1-agriculture	0.3564	0.1614	6-utilities	0.0290	0.0274
2-forest	0.6049	0.5132	7-recreation facilities	0.0042	0.0049
3-roads	0.0997	0.0998	8-minerals	0.0827	0.1128
4-hydraulic utilities	0.6876	0.7326	9-others	0.1109	0.0984
5-buildings	0.5341	0.2823	Overall Kappa	0.4299	0.3833

4.3 Results of multi-temporal Bayesian classification

For the interpretation of multi-temporal images of rice paddies, factors that should be taken into account include (a) the phenological stages, (2) the reflectance of rice in mature stage, (3) the diagram of reflectance versus seasons change, (4) the registration of GIS parcels with image parcels (Lau et al., 2002; Hsiao et al., 2004). The result of multi-temporal image classification for Jia-Yi area in 2004 with Bayesian classifier is shown in Table 3. The overall accuracy and kappa index are 91.55% and 0.81, respectively. The classification result is shown in Fig. 9, which can be compared to the ground truth in Fig. 10. The producer’s accuracy and user’s accuracy are 87.66% and 86.21%, respectively. The overall accuracy is 91.55% (Hsiao et al., 2005).

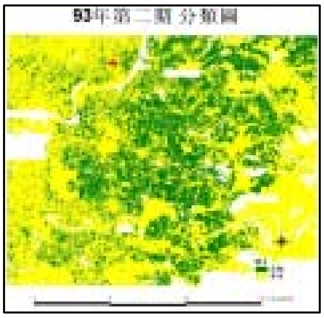


Fig. 9 Classification result of Jia-Yi area

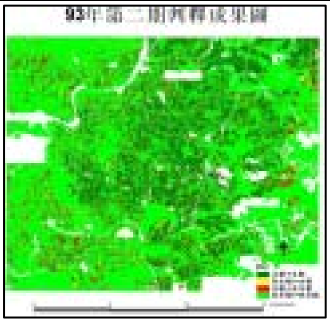


Fig. 10 Ground truth for Jia-Yi area

Table 3 Classification result with Formosat-2 images

	Class	Rice	Non-rice	Total (Hectares)	Producer's Accuracy	
Ground Truth	Rice	7,803.09	1,098.90	8,901.99	87.66 %	Overall accuracy: 91.55 % Average accuracy: 90.52 % $\hat{k}$ index: 0.8069
	Non-rice	1,248.02	17,639.24	18,887.26	93.39 %	
	Total	9,051.11	18,738.14	27,789.25		
	User's accuracy	86.21 %	96.14 %			

5. CONCLUSIONS AND SUGGESTIONS

In this study, pansharpened SPOT5 images are employed for both supervised and unsupervised classification to evaluate the suitability of these images for national landuse inventory. The map number 95204096 in one of the 1/5000 national base map series is selected as a study area. Results of unsupervised classification for agricultural, forestry, hydraulic and communication facilities are rated as a capability of level 1 to level 2. The overall accuracy is 70~85%. However, if all 9 classes are considered, the overall accuracy is only 56.42% and kappa is 0.40. The result of supervised classification with equal probability has an accuracy of 57.35% and kappa of 0.43; whereas, with prior probability, the overall accuracy is 54.705% and kappa is 0.38. These results cannot fulfill the requirements of a national landuse inventory. In addition, for forestry, hydraulic, and agricultural lands, the accuracy is far below the requirement of 90%. The transformation processes of the original spectral bands to the pansharpened bands can cause some loss in spectral information. The problem whether this is the major issue posed by using SPOT5 for the classification purpose remains to be further explored.

With multi-temporal images, the ancillary information from GIS parcels, and the knowledge of phenological information, the classification accuracy can be better than 91.5%. If prior knowledge of crops is accurately known, the accuracy can be further improved. National land inventory for specific crop area can adopt this approach.

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