Journal of Zhejiang University SCIENCE A
ISSN 1673-565X (Print); ISSN 1862-1775 (Online)
www.zju.edu.cn/jzus; www.springerlink.com
E-mail: jzus@zju.edu.cn

An integrated classification method for thematic mapper imagery of plain and highland terrains

Shan-long LU[1], Xiao-hua SHEN[1], Le-jun ZOU[†‡1], Chang-jiang LI[2], Yan-jun MAO[3], Gui-fang ZHANG[1], Wen-yuan WU[1], Ying LIU[1], Zhong ZHANG[1]

([1]*Department of Earth Sciences, Zhejiang University, Hangzhou 310027, China*)

([2]*Zhejiang Land and Resources Information Center, Hangzhou 310007, China*)

([3]*Zhejiang Climate Center, Hangzhou 310017, China*)

[†]E-mail: zoulejun2006@zju.edu.cn

Received Sept. 3, 2007; revision accepted Jan. 7, 2008; published online Mar. 26, 2008

Abstract: The classification of thematic mapper imagery in areas with strong topographic variations has proven problematic in the past using a single classifier, due to the changing sun illumination geometry. This often results in the phenomena of identical object with dissimilar spectrum and different objects with similar spectrum. In this paper, an integrated classification method that combines a decision tree with slope data, tasseled cap transformation indices and maximum likelihood classifier is introduced, to find an optimal classification method for thematic mapper imagery of plain and highland terrains. A Landsat 7 ETM+ image acquired over Hangzhou Bay, in eastern China was used to test the method. The results indicate that the performance of the integrated classifier is acceptably good in comparison with that of the existing most widely used maximum likelihood classifier. The integrated classifier depends on hypsography (variation in topography) and the characteristics of ground truth objects (plant and soil). It can greatly reduce the influence of the homogeneous spectrum caused by topographic variation. This integrated classifier might potentially be one of the most accurate classifiers and valuable tool for land cover and land use mapping of plain and highland terrains.

Key words: Image classification, Land cover and land use, Thematic mapper imagery, Plain and highland terrains, Integrated classification method

doi:10.1631/jzus.A071469 **Document code:** A **CLC number:** K826.14; TP7

INTRODUCTION

In areas with strong topographic variations, elevation differences between plains and highlands often cause climatic variations, which influence the land cover and land use types (Shrestha and Zinck, 2001). The phenomena of identical object with dissimilar spectrum, and different objects with similar spectrum often occur on the image of these areas. For example, different vegetations living on the plain and highland may have similar spectral reflectance signatures, and vegetations living on sun-facing slopes and sun-shading slopes often have different spectral features. The classification results obtained by running a classifier are often not satisfactory for mapping land cover and land use. In studying such areas, more reliable classification procedure is required to solve the problem.

To improve the accuracy of the classification, a great number of object attributes derived from ancillary data sources are often combined with Landsat data in various ways. Hutchinson (1982) used slope data that derived from digital terrain data to separate the steep sunny sand dunes from the flat playa surface, and to distinguish steep north or northwest facing slopes (shadows) from other dark surfaces. In (Franklin *et al.*, 1989), additional terrain attributes such as landform characteristics, soils and drainage

[‡] Corresponding author

conditions were incorporated into the classification procedure. Wang and Civco (1994) investigated a two stage post-classification approach of using evidential reasoning to handle multi-source spatial data, including multi-spectral, multi-temporal Landsat Thematic Mapper (TM) images, Digital Elevation Model (DEM) derived slope data, and Digital Line Graphs (DLG) transportation and hydrography data, to improve the classification accuracy. Giannetti *et al.*(2001) presented a method for defining eco-pedological cartographic units in mountainous areas with ancillary data of SPOT 4 images, Landsat TM images, DEM, geolithological, geomorphological and soil-landscape maps. Shrestha and Zinck (2001) refined the classification results by using ancillary data of DEM and expert knowledge of the area in a Geographic Information System (GIS) environment. In these studies, digital elevation data and other derivative data such as slope, aspect, convexity and relief were used to help identify different land cover types. And the decision tree and maximum likelihood classifier were used as basic classifier to use the ancillary data. All the results indicated that an integrated classification procedure performed better than either classifier alone.

This study designs a classification method that integrates the decision tree with DEM derived slope data, tasseled cap transformation indices and the maximum likelihood classifier for thematic mapper imagery of plain and highland terrains. In this integrated classifier, the slope data and the tasseled cap transformation indices are ancillary data that are used to help remove topographic variation influence and to identify land cover and land use types. The decision tree is used as basic classification procedure to partition dataset and obtain final results, by using the ancillary data. The maximum likelihood classifier is used to discriminate the classes that are difficult to be identified by ancillary data.

As we know, decision tree is a classification procedure, which allows a dataset to be partitioned in a fashion such that different classification algorithms or datasets may be applied to different parts of the data. It was usually employed as a method of combining different classification algorithms or datasets (McIver and Friedl, 2002; Zhang *et al*., 2006), and had been used successfully for a wide range of classification problems (Friedl and Brodley, 1997; Rogan *et al*., 2002; Pal and Mather, 2003). Maximum likelihood is the most widely used parametric classifier, which creates decision surfaces based on the mean and covariance of each class. The utilization of variance in the classification decision rule provides additional data on which to base the classification, thereby improving overall classification accuracy. It has always been regarded as the most popular and successful classification method (Bolstad and Lillesand, 1991; Wilkinson, 2003; Ramadan *et al*., 2004). Slope data is a widely used ancillary dataset for improving land cover classification. It is one of the DEM-derived data, and has often been used to classify different terrain types (Hutchinson, 1982), to acquire different landscape classes (Franklin *et al.*, 1989), and to help identify different forest types (Wang and Civco, 1994), etc. Tasseled cap transformation is a linear transformation based on spectral analysis. An at-satellite reflectance based transformation can remove most of the influence caused by sun illumination geometry changing (Huang *et al.*, 2002). It rotates the multi-dimensional spectral space and makes the coordinate axes point to some new dimensional space associated with physical scene characteristics. These dimensions are closely related with plant growth and soil characteristics (Crist and Cicone, 1984; Peng, 1991). For Landsat Multi-Spectral Scanner (MSS) data, the tasseled cap transform performs an orthogonal transformation of the original data into a new 4D space consisting of the soil brightness index (SBI), the green vegetation index (GVI), the yellow stuff index (YVI), and a non-such index (NSI) associated with atmospheric effects (Kauth and Thomas, 1976). For Landsat TM data, the tasseled cap vegetation index consists of three factors: brightness, greenness, and a third. The brightness and greenness are equivalent to the MSS tasseled cap SBI and GVI indices and the third component is primarily related to soil characteristics, including soil moisture (Crist and Cicone, 1984). For Landsat 7 ETM+ data, the tasseled cap transformation produces 6 output bands: brightness, greenness, wetness, fourth (Haze), fifth, sixth (Huang *et al.*, 2002). Generally, the first three bands of the derived transformation collectively explained most of the spectral variance of the individual scenes, and they can be used to analyze soil, vegetation, and moisture in more detail and more correctly (Cohen *et al.*, 1995;

Dymond *et al.*, 2002).

By making great use of the merits of the decision tree classifier and the maximum likelihood classifier, and the features of the slope data and the results of the tasseled cap transformation, the integrated classifier obtained high classification accuracy in the study area of Ningbo and its surrounding area in China, with the Landsat 7 ETM+ image. The results indicated that the performance of this proposed classifier is acceptably good in comparison with that of the existing widely used maximum likelihood classifier.

STUDY AREA

The study area, 1762.7 km^2, belongs to Zhejiang Province, China, lies in the southern shore of Hangzhou Bay (121°17′E~121°43′E, 29°36′N~29°59′N) (Fig.1), with a semi-tropical monsoon climate, hot summers and cool winters, precipitation with marked seasonal variations, annual mean temperature of 16.3 °C based on available meteorological data, and an estimated annual precipitation of 1418 mm (Lu *et al.*, 2006). The main landforms are plain and highland, including 59% of plain area, 40% of highland area and 1% of lower elevation mountainous area. Elevation varies from −8.4 m under mean sea level in northeastern of the study area to 712.7 m above mean sea level at the highest mountain ridge. The rivers of Yuyao, Fenghua and Yong are centered in the plain center, and flow northeast to Hangzhou Bay. These abundant water sources make it possible to develop agriculture and aquaculture. Agricultural production is the main land use type in this region, and the main crops are barley, paddy rice, rape, and cotton. Highlands and mountains are surrounding the central plain area like a letter "V". Vegetation patterns change with elevation. At high elevation area, land cover is mainly forest with conifers, broadleaf trees and bamboos, while at low elevation area, land cover is mainly crops and gardens.

DATA AND PREPROCESSING

A cloud free 30-m resolution Landsat 7 ETM+ scene (Path 118/Row 039), acquired on November 11, 2002, over Hangzhou Bay, in eastern China, was used in this study. The six bands (B1, B2, B3, B4, B5 and B7) with 30 m pixel size were used in the classification process. The entire scene was geometrically rectified to 1:50000 scale topographic maps and transformed to a Universal Transverse Mercator (UTM) map projection provided by the Institute of Remote Sensing Application in Beijing. A nearest-neighbor algorithm was used to perform the resampling procedure and the Image-to-Map registration. The root mean square error (RMSE) of the registration process is less than a pixel. Subsequent preprocessing included conversion of digital numbers to radiance and conversion of radiance to at-satellite reflectance.

The slope data used in the study was derived from the digital elevation data, which were offered by Zhejiang Land and Resources Information Center in China. The pixel size of the slope data is 30 m and the slope interval is 0.2°. And the tasseled cap indices (including brightness, greenness, wetness and other indices) were generated from the at-satellite reflectance image using the Tasseled Cap Transform Module of ENVI Version 4.3.

An optimal classification process and a definitive accuracy assessment require the use of ground truth data. In this study, a fusion image with 2.5-m resolution, which was fused by the 10-m resolution multi-spectral bands and the 2.5-m resolution panchromatic band of SPOT-5 scene (It was taken on October 24, 2003, and covered approximately 75% of the study area), was used as ground truth data to choose sample data and assessment data. In fact, on such a high spatial resolution image, boundaries of different land cover/use categories can be clearly identified. After rectifying this image to the same geographic coordinate system with the ETM+ image, the geographic link procedure was performed between the two images of ETM+ and the fusion SPOT to choose sample data and assessment data. A total of 5043 points were manually chosen on the ETM+ image, 3040 points as sample data, 2003 points as assessment data. The sample data were used as training sites in the classification routines and the assessment data were used as ground truth data for classification accuracy assessment.

METHODS

The integrated classifier and the single maximum likelihood classifier were used to classify the selected thematic mapper imagery of the study area, respectively. The resulting classified maps were visually compared with image plate, and statistically compared with the assessment data, to assess their accuracy.

Classification scheme

Landsat TM/ETM+ images are widely used in classification system. They were often used to identify more than 10 land cover/use categories (Franklin *et al*., 1989; Wang and Civco, 1994; Sohn and Rebello, 2002; Seto and Kaufmann, 2005), but it was always difficult to meet the requirements of the land cover/use classification system: the minimum level of interpretation accuracy in the identification of land cover and land use categories from remote sensor data that should be at least 85%; the accuracy of interpretation for the several categories should be about equal; repeatable or repetitive results should be obtainable from one interpreter to another and from one time of sensing to another (Anderson *et al.*, 1976).

In this paper, to meet the above-mentioned requirements of the land cover/use classification system, and to effectively employ the ETM+ image and other ancillary data or derived data, the study area was classified into 5 categories: residential land, build-up land, agricultural land, forest, and water (Fig.2). Residential land includes cities, towns, villages and linear residential developments along transportation routes extending outward from urban areas. Build-up land includes industrial and commercial complexes, highway and railways which often distribute on the periphery of the residential land with low density. Agricultural land includes paddy field, dry land, and garden plots which are often covered by vegetations. Forest is mainly vegetation covering on highlands and mountains. Water includes area of streams and canals, lakes, reservoirs, bays and estuaries. Although agricultural land and forest can be divided into sub-categories such as deciduous, evergreen, paddy field and dry land, to differentiate these categories effectively, it often need sequential data or at least data acquired during the special season for each category.

Classification procedure

The proposed method is composed of two procedures: stratification procedure and post-classification

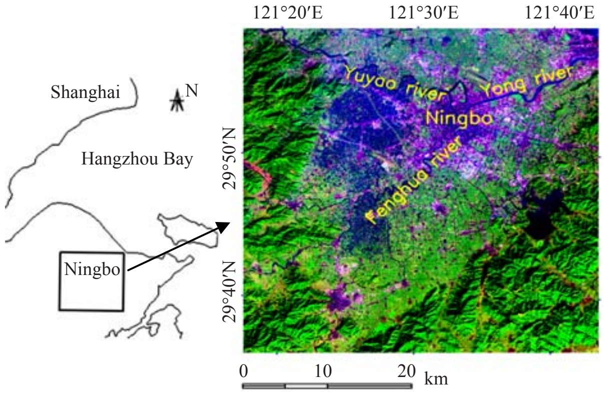

Fig.1 Location and Landsat 7 ETM+ false color (Bands 7, 4, 1) image of the study area

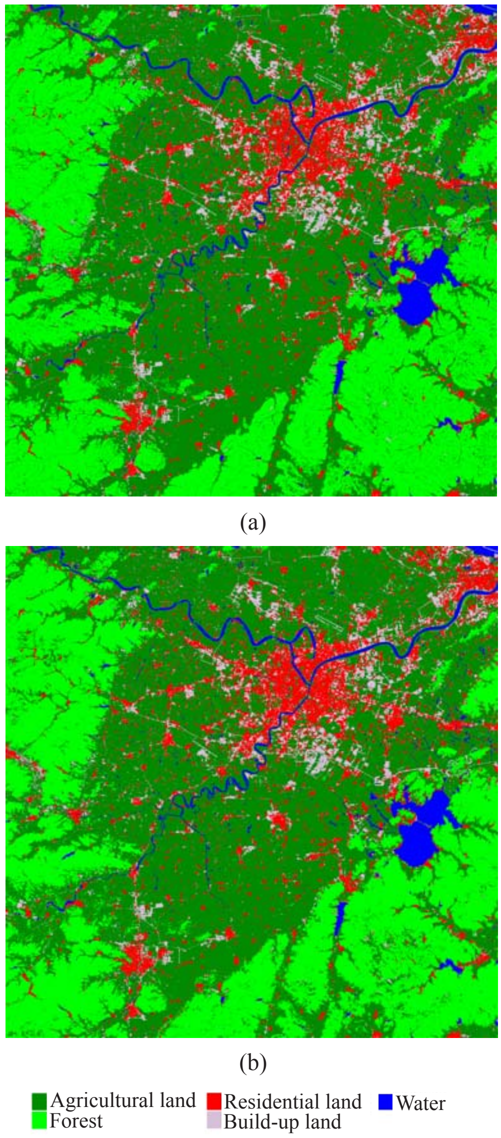

Fig.2 Classification results of the integrated classification classifier (a) and the maximum likelihood classifier (b)

procedure. The stratification procedure means using of ancillary data which involves a division of the study scene into smaller areas or strata based on some criterion or rule. Post-classification procedure means classifying stratum which results from stratification procedure by using a single classifier. In the first procedure, the decision tree is employed for classification improvement to divide the study area into smaller homogeneous units by using the slope data, and to separate different objects that are dissimilar in spectrum using the tasseled cap transformation indices. In the second procedure, the maximum likelihood classifier is used to decompose other land cover/use types that are difficult to be identified by ancillary data, within unique terrain features (Fig.3).

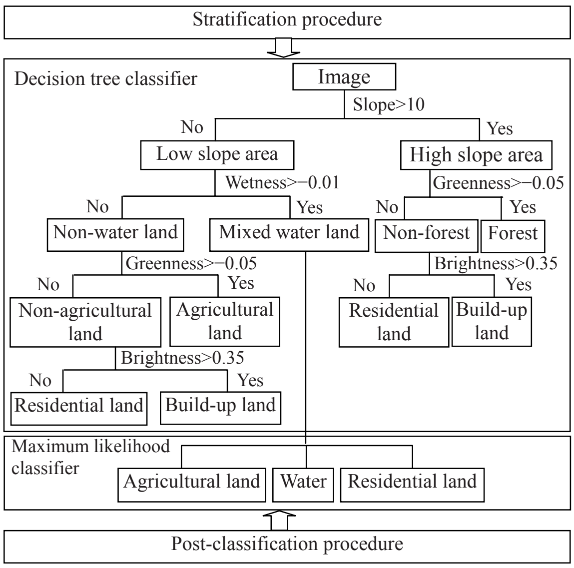

Fig.3 Hierarchical tree structure of the integrated classification method

For the stratification procedure, selecting the stratification criteria is a key step which decides the final classification accuracy. In the study area, the criteria were selected according to the regional features of different land cover/use types. Terrains of the study area mainly consisted of plain and highland. And land cover/use types are dissimilar on different terrains. The main land cover/use types of the plain are residential land, agricultural land, build-up land and water, and those of the highland are mainly forest, with part of residential and build-up land. Water and mountain shadow area in forest, agricultural land and forest are two groups of land cover/use types that could be easily misclassified, due to their similar spectral reflectance signatures. According to our observation, the agricultural lands are often distributing on the areas with slope gradient lower than 10, and the slope gradient for surface of water body is much lower than that of the agricultural land. So, it was a good strategy of dividing the whole study area into two sub-classes as low slope area and high slope area by using the slope gradient threshold of 10, to decompose the agricultural land and water with forest and mountain shadow area. In the high slope area, the forest and non-forest area were easy to be differentiated, because the boundaries between them are clear on the tasseled cap greenness component. The threshold value between them is −0.05. In the low slope area, the water containing area (mixed water land) of water, partial agricultural land (mainly are paddy fields), and partial residential land (mainly are big cities, such as Ningbo, due to some rivers and river branches distributing in the city) were difficult to be decomposed by single threshold, due to their similar spectral features. But it is possible to separate them all with other non-water containing land cover/use types (non-water land), by using a certain threshold of the tasseled cap wetness component. On this component, the threshold between mixed water land and non-water land is −0.01. In the non-water land, the agricultural land was also easy to be differentiated from non-agricultural land with the same tasseled cap greenness component threshold of −0.05 as that of forest. For non-forest land and non-agricultural land, they can be compartmentalized into two parts of residential land and build-up land, by using the tasseled cap brightness component threshold of 0.35. This threshold was selected according to different intensities of residential land and build-up land in the image.

For the post-classification procedure of the study, the maximum likelihood classifier was used to decompose the water, the water containing agricultural land and the water containing residential land of the mixed water land, by using the sample data of the three categories that are acquired in Section 3.

After partitioned water, agricultural land and residential land from the results of the post-classification procedure using the decision tree, the final classified map was obtained by merging similar land cover types from different parts. Then the integrated classification procedure of the study area was completed. Fig.3 showed the hierarchical tree structure of the proposed method. All the thresholds used in the classification procedure were acquired by visual estimation with geographic link procedure between the 2.5-m resolution SPOT fusion image and each of the index images. As mentioned in Section 3, with the assistance of such a high spatial resolution SPOT image, the thresholds between different land cover/use categories on each index images are quite clear and can be obtained easily. Table 1 summarizes the ancillary data used in the method, and describes their threshold, features and use description in this study.

Table 1 Ancillary data used in the method, and their threshold, features and use description of this study

Ancillary data	Threshold	Features and use description
Slope	10	Boundary value of agricultural land and water with forest and mountain shadow area. It was used to partition these land cover/use types into two sub-areas
Tasseled cap wetness	−0.01	Boundary value of water containing area and non-water containing area. It was used to differentiate the non-water land and mixed water land
Tasseled cap greenness	−0.05	Boundary value of vegetation area and non-vegetation area. It was used to extract forest from high slope land, and agricultural land from non-water land
Tasseled cap brightness	0.35	Boundary value of residential land and build-up land. It was used to separate them from each other in the non-forest land and non-agricultural land

For the single maximum likelihood classifier, the classification result was obtained with the total 3040 sample data of the 5 categories, by using the Supervised Maximum Likelihood Classification Module of ENVI 4.3.

Classification comparison

To compare the classification results of the two classification methods (the integrated classifier and the single maximum likelihood classifier), an image plate (Fig.2) was generated for visual comparison. Furthermore, the total 2003 points assessment data were used as ground truth data to generate error matrices with the mapping results from each classifier for statistic accuracy assessment (Tables 2 and 3).

RESULTS

As shown in Fig.2, the differences of each land cover/use types obtained by the integrated classifier (Fig.2a) and the maximum likelihood classifier (Fig.2b) are identifiable by visual interpretation. The main differences of the classification results occur between the agricultural land and forest. Because the vegetation living on plain area and mountain valley are similar in spectral features with the vegetation living on sun facing highland area, the single maximum likelihood classifier cannot decompose them correctly without the assistance of other data. In Fig.2b, a lot of agricultural lands in plain area and valley were misclassified into forest, and partial forest was misclassified into agricultural land. The two images on Fig.2 illustrated the ability of the integrated classifier to account for the phenomenon of different objects with similar spectrum.

Tables 2 and 3 show the statistic accuracy assessment results for the integrated classifier and the maximum likelihood classifier, respectively. The overall measured accuracies of the integrated classifier and the maximum likelihood classifier were 96.16% and 92.51%, respectively, and the kappa values were 0.95 and 0.91, respectively.

Classification accuracy results of the integrated classifier were presented in Table 2 with the overall accuracy of 96.16%. Notice from Table 2 that all the classes show high classification accuracy. Even the lowest accuracy class of water was reaching to 93.22%. The classification accuracy for each category was approximately equal.

The maximum likelihood classifier showed correspondingly lower overall accuracy of 92.51% as presented in Table 3. The error matrix showed that the residential land and build-up land have very high accuracies of 98.86% and 96.25%, respectively. But the agricultural land, forest and water showed relatively low accuracies. The accuracy of the agricultural land is even lower than 85%, due to 78 pixels were misclassified into forest.

Table 2 Error matrix for the classification result of the integrated classifier

Class	Ground truth (pixels)					
	RL	BL	AL	FT	WR	Row total
RL	**346**	0	0	4	7	357
BL	2	**280**	0	1	0	283
AL	5	13	**505**	13	20	556
FT	0	0	11	**410**	1	422
WR	0	0	0	0	**385**	385
Column total	353	293	516	428	413	2003
Accuracy (%)	98.02	95.56	97.87	99.27	93.22	

The correctly classified pixels for each class are on the diagonal in bold. Overall accuracy: 1926/2003×100%=96.16%; Kappa coefficient=0.95. RL: Residential land; BL: Build-up land; AL: Agricultural land; FT: Forest; WR: Water

Table 3 Error matrix for the classification result of the maximum likelihood classifier

Class	Ground truth (pixels)					
	RL	BL	AL	FT	WR	Row total
RL	**349**	0	1	0	4	354
BL	2	**282**	1	0	0	285
AL	2	11	**436**	28	12	489
FT	0	0	78	**400**	11	489
WR	0	0	0	0	**386**	386
Column total	353	293	516	428	413	2003
Accuracy (%)	98.86	96.25	84.50	93.46	93.46	

The correctly classified pixels for each class are on the diagonal in bold. Overall accuracy: 1853/2003×100%=92.51%; Kappa coefficient=0.91. RL: Residential land; BL: Build-up land; AL: Agricultural land; FT: Forest; WR: Water

Comparing Table 2 with Table 3, we can see that the accuracies of residential land, build-up land and water of the two classifiers are about equivalent, while those of the maximum likelihood classifier are a little higher than those of the integrated classifier, and that the agricultural land and forest accuracies of the integrated classifier are much higher than those of the maximum likelihood classifier. These two tables also indicate the ability of the integrated classifier to decompose different objects with similar spectral features.

DISCUSSION

In this paper we proposed an integrated classification method that uses decision tree classifier, maximum likelihood classifier, slope data and tasseled cap transformation results for thematic mapper imagery classification of the plain and highland terrains, which include two procedures of stratification and post-classification. The decision tree and all the ancillary data were used in the first procedure, and the maximum likelihood classifier was used in the second procedure. The results of the study area indicated that the overall accuracy of the integrated classifier is better than that of the maximum likelihood classifier, that the residential land, build-up land and water accuracies of the two classifiers are about equal, and that the agricultural land and forest accuracies of the integrated classifier are better than those of the maximum likelihood classifier.

The major difference between the integrated classifier and the maximum likelihood classifier is that the former depends on the hypsography and characteristics of ground truth objects, while the latter only relies on the statistical distribution pattern or the spectral shape pattern. When hypsography features (DEM, slope, aspect, etc.) are used, pixels that belong to the same physiognomy unit could be classified into the same cluster or information class. When the features (Normalized Difference Vegetation Index, Normalized Difference Water Index, results of tasseled cap transformation, etc.) of ground truth objects are used, pixels that represent the same object will show similar spectral pattern and could be easily extracted with certain thresholds. Furthermore, the integrated classifier is an open classification system composed of useful classifiers and useful data. It can make the best of each part of the classifiers and data. With the assistance of the ancillary data and classifiers, the overall classification accuracy can keep in a stable status because the accuracy of the correctly decomposed categories are impervious when more categories were required. However, for each of the single classifiers like the maximum likelihood, if more categories were required, more sample data will be needed, and the overall accuracy will be decreased rapidly.

The merits of using this integrated classification method over other single classifiers for classification of plain and highland terrains include the following:

(1) The decision tree can partition the image or dataset into parts. This property makes it possible to use other classification algorithms to classify subsets of classes or datasets accurately and to reduce interaction among different classes.

(2) The slope data can be used to differentiate objects according to their special distribution characteristics, and help to reduce misclassification caused by topographic variations.

(3) The at-satellite reflectance based tasseled cap transformation can be used to remove influence of sun illumination geometry changing, and the results can be used to accurately extract objects that have special spectral features, such as vegetation, water and soil.

(4) The maximum likelihood classifier can perform good results without topographic influence and interactive interfere by other classes.

ACKNOWLEDGEMENT

We would like to thank Zhejiang Land and Resources Information Center for supporting this work. Thanks to David Tait, the former Editor-in-Chief of the ISPRS Journal, for revising the paper.

References

Anderson, J.R., Hardy, E.E., Roach, J.T., Witmer, R.E., 1976. A Land Use and Land Cover Classification System for Use with Remote Sensor Data. Geological Survey Professional Paper. A Revision of the Land Use Classification System as Presented in U.S. Geological Survey Circular 671. United States Government Printing Office, Washington, D.C., p.964.

Bolstad, P.V., Lillesand, T.M., 1991. Rapid maximum likelihood classification. *Photogrammetric Engineering and Remote Sensing*, **57**:67-74.

Cohen, W.B., Spies, T.A., Fiorella, M., 1995. Estimating the age and structure of forests in a multi-ownership landscape of western Oregon, U.S.A. *International Journal of Remote Sensing*, **16**(4):721-746. [doi:10.1080/01431169508954436]

Crist, E.P., Cicone, R.C., 1984. Application of the tasseled cap concept to simulated thematic mapper data. *Photogrammetric Engineering and Remote Sensing*, **50**(2):343-352.

Dymond, C.C., Mladenoff, D.J., Radeloff, V.C., 2002. Phenological differences in Tasseled Cap indices improve deciduous forest classification. *Remote Sensing of Environment*, **80**(3):460-472. [doi:10.1016/S0034-4257(01)00324-8]

Franklin, S.E., Peddle, D.R., Moulton, J.E., 1989. Spectral/geomorphometric discrimination and mapping of terrain: a study in Gros Morne National Park. *Canadian Journal of Remote Sensing*, **15**(1):28-42.

Friedl, M.A., Brodley, C.E., 1997. Decision tree classification of land cover from remotely sensed data. *Remote Sensing of Environment*, **61**(3):399-409.

Giannetti, F., Montanarella, L., Salandin, R., 2001. Integrated use of satellite images, DEMs, soil and substrate data in studying mountainous lands. *International Journal of Applied Earth Observation and Geoinformation*, **3**(1):25-29. [doi:10.1016/S0303-2434(01)85018-2]

Huang, C.Q., Wylie, B., Yang, L.M., Homer, C., Zylstra, G., 2002. Derivation of a tasseled cap transformation based on Landsat 7 at satellite reference. *International Journal of Remote Sensing*, **23**(8):1741-1748. [doi:10.1080/01431160110106113]

Hutchinson, C.F., 1982. Techniques for combining Landsat and ancillary data for digital classification improvement. *Photogrammetric Engineering and Remote Sensing*, **48**(1):123-130.

Kauth, R.J., Thomas, G.S., 1976. The Tasseled Cap—A Graphic Description of the Spectral Temporal Development of Agricultural Crops as Seen by Landsat. Proc. Symp. on Machine Processing of Remotely Sensed Data, West Lafayette, Indiana. Laboratory for Applications of Remote Sensing, Purdue University, p.41-51.

Lu, S.L., Shen, X.H., Zou, L.J., 2006. Land cover change in Ningbo and its surrounding area of Zhejiang Province, 1987~2000. *Journal of Zhejiang University SCIENCE A*, **7**(4):633-640. [doi:10.1631/jzus.2006.A0633]

McIver, D.K., Friedl, M.A., 2002. Using prior probabilities in decision-tree classification of remotely sensed data. *Remote Sensing of Environment*, **81**(2-3):253-261. [doi:10.1016/S0034-4257(02)00003-2]

Pal, M., Mather, P.M., 2003. An assessment of the effectiveness of decision tree methods for land cover classification. *Remote Sensing of Environment*, **86**(4):554-565. [doi:10.1016/S0034-4257(03)00132-9]

Peng, W.L., 1991. Computer Processing of Remote Sensed Data and Geographic Information System. Beijing Normal University Press, Beijing, p.132-139 (in Chinese).

Ramadan, E., Feng, X.Z., Cheng, Z., 2004. Satellite remote sensing for urban growth assessment in Shaoxing City, Zhejiang Province. *Journal of Zhejiang University SCIENCE*, **5**(9):1095-1101. [doi:10.1631/jzus.2004.1095]

Rogan, J., Franklin, J., Roberts, D.A., 2002. A comparison of methods for monitoring multitemporal vegetaion change using Thematic Mapper imagery. *Remote Sensing of Environment*, **80**(1):143-156. [doi:10.1016/S0034-4257(01)00296-6]

Seto, K.C., Kaufmann, R.K., 2005. Using logit models to classify land cover and land-cover change form Landsat Thematic Mapper. *International Journal of Remote Sensing*, **26**(3):563-577. [doi:10.1080/01431160512331299270]

Shrestha, D.P., Zinck, J.A., 2001. Land use classification in mountainous areas: Integration of image processing, digital elevation data and field knowledge (application to Nepal). *International Journal of Applied Earth Observation and Geoinformation*, **3**(1):78-85.

Sohn, Y., Rebello, N.S., 2002. Supervised and unsupervised spectral angle classifiers. *Photogrammetric Engineering and Remote Sensing*, **68**(12):1271-1280. [doi:10.1016/S0303-2434(01)85024-8]

Wang, Y.Q., Civco, D.L., 1994. Evidential reasoning-based classification of multi-source spatial data for improved land cover mapping. *Canadian Journal of Remote Sensing*, **20**(4):381-393.

Wilkinson, G.G., 2003. Are Remotely Sensed Image Classification Techniques Improving? Results of a Long Term Trend Analysis. Advances in Techniques for Analysis of Remotely Sensed Data, IEEE Workshop, p.30-34. [doi:10.1109/WARSD.2003.1295169]

Zhang, B., Valentine, I., Kemp, P., Lambert, G., 2006. Predictive modeling of hill-pasture productivity: integration of a decision tree and a geographical information system. *Agricultural Systems*, **87**(1):1-17. [doi:10.1016/j.agsy.2004.10.003]