ACADEMIC
World Academic Union

Proceedings of the 8th International Symposium on
Spatial Accuracy Assessment in Natural Resources and Environmental Sciences
Shanghai, P. R. China, June 25-27, 2008, pp. 203-210

Consistency Analysis of Multi-Source Remotely Sensed Images for Land Cover Classification

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Abstract. The importance of accurately describing the nature of land cover resources is increasing. With the aim to analyze the consistency of remotely sensed images from different sensors for land cover classification, three medium spatial resolution optical image sources in Xuzhou city were classified in the study, including CBERS, ETM, and ASTER. Land cover classification was conducted by Maximum Likelihood Classification (MLC), Support Vector Machines (SVM) and Decision Tree (DT). By comparing the classification results, SVM performed best and the results of SVM classifier were used for consistency analysis. The results we obtained suggested that different images obtained around the same time can lead to dissimilar classification results. Consistency analysis was carried through according to the experimental results of two groups of data. Apart from the individual data source, the two types of image data in each group were combined to form a mixed dataset of multi-source data and then used as the input of SVM classifier. It proved that the mixed dataset consisting of multi-source data could improve the classification performance of singe image so the collaborative use of multi-source data would be feasible for land cover classification.

Keywords: consistency analysis, ASTER, CBERS, Landsat ETM+, classification, support vector machine

1. Introduction

Land cover classification is becoming more and more important to people's life as nowadays we are facing the problem of land resources shortage. With China's economic development, population growth, urban expansion and the increase of infrastructure, the need of land resource is increased correspondingly. The depth and the breadth, as well as the speed of land use and land cover are being increased sharply. It's necessary for the government and public to know the information of land cover information quickly. With such information, the local government agencies can make right judgments and decision on urban planning and regional development. However, conventional methods can't meet the needs of macro decision-making. Modern advanced remote sensing technology, with its accurate description and timely acquisition to the Earth's surface, is one of the most effective tools to rapidly obtain and deliver the land cover information [11]. The series of scientific study programs, issued and promoted by IGBP and IHDP in 1995, make the study of land-use and land-cover change (LUCC)[15] become one of the hot topics in the global environmental change study. But the generalization capacity and performance of classifiers, the selection of suitable data sources and the collaboration of multi-source information are still challengeable, so it is necessary to improve the accuracy of land cover classification by remote sensing and combine the benefits of multi-source remotely sensed data.

Multi-source remote sensing images are used widely in land cover classification, but the classification results generated by different image are often dissimilar, sometimes significantly, even when images are captured around the same time. In order to apply multi-source remote sensing data towards a single research purpose, it is, therefore, necessary to understand the consistency of the results produced by different sensors,

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ISBN: 1-84626-171-6, **ISBN13:** 978-1-84626-171-8

find major differences and develop effective ways to alleviate these differences. The study is designed to evaluate the consistency of multi-source remotely sensed images for land cover classification.

2. Study area and data used

2.1. Study area

Xuzhou City, Located in Jiangsu Province and the central/eastern part of China, is selected as the case study area. Its spatial scope is: 33°43′ to 34°58′N and 116°22′ to 118°40′ E. The longest distance is 210km from the east to west, while 140km from the south to north with a total area of 11258 square kilometers, of which the urban area accounts for 963 square kilometers. In the area, the altitude of southeast is higher than that of northwest, which is between 19m and 45m. There are many hills in the middle and the southeast of the area. In the northwest are Feng county and Pei county, which are alluvial campagna of the yellow river. The prior path of the ancient yellow river and Beijing-Hangzhou Grand Canal run through the city [20]. .

2.2. Data used

The user's need determines the nature of classification and the scale of the study area, thus affecting the selection of suitable spatial resolution of remotely sensed data [8]. As Xuzhou city belongs to a regional scale, medium spatial resolution data is suitable for the study. In the experiment, three kinds of medium spatial resolution optical images are adopted, including Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) with 15 m spatial resolution, China-Brazil Earth Resources Satellites (CBERS) with 20 m spatial resolution and Landsat Enhanced Thamtic Mapper Plus (ETM+) with 30 m spatial resolution at VNIR spectral scope.

Two groups of data are used in order to make the results comparable. The first group consists of the Landsat ETM+ and CBERS images captured in April 2001, and the other group consists of CBERS and ASTER image captured in November 2005, so it can be assumed that land cover is near-identical for each group, therefore the classification consistency between Landsat ETM and CBERS, and between CBERS and ASTER can be analyzed.

The ETM+ bands are useful for water penetration, discriminating vegetation types and vigour, plant and soil moisture measurements, differentiation of clouds, snow and ice and identifying rock types. Similar to Landsat TM, Landsat ETM+ can be used for urban applications but its high spectral resolution makes it more suitable for making the natural characteristics of the landscape [5].

CBERS-02 CCD has been applied to many fields since its launch, such as concentration grading of suspended solids in the Yellow River Mouth and the beach survey, flood disaster monitoring, forestry resources monitoring, as well as the monitoring of geological, flow along the coast and agriculture, and so on[19].

Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) is a high resolution imaging instrument that is flying on the earth observing system (EOS) Terra satellite [12]. Among the 14 ASTER bands, the first three bands at 15m spatial resolution are used for classification in the study. One of the main purposes of ASTER is to improve performance the resource exploration; it is a strong supplement and enhancement to ETM+.

3. Method

3.1. Data processing flow

The consistency analysis of multi-source remotely sensed images for land cover classification consists of four steps.

- Remotely sensed images preprocessing, including radiometrical correction and geographical registration.
- Land cover classification of two groups of images respectively using three kinds of classifiers.
- Land cover classification using the mixed data which are respectively produced by combining the two data sets in each group.
- Consistency analysis by comparing the classification results.

3.2. Image preprocessing

Image preprocessing tasks include the detection and restoration of bad lines, geometric rectification or image registration, radiometric calibration and atmospheric correction, and topographic correction [8].

Accurate geometric rectification or image registration of remotely sensed data is a prerequisite for a combination of multi-source data in a classification process [8].In order to analyze imagery from different sensors, the data layers must be spatially co-registered so that ground measurements and satellite data are in the same spatial reference framework [13].

In the experiment, image registration was carried out in the environment of ENVI. By using image-to-image mode, images from every group to be used are respectively transformed to one cartographic coordinate system. Control points are selected respectively from different images, and then bilinear method is used for resampling. The error of the registration in the experiment is restricted within 0.5 pixels.

3.3. Land cover classification method

Image classification is the most important operation in Remote Sensing applications. Some traditional methods belonging to supervised classification methods and unsupervised classification methods are used widely, but sometimes they are not very efficient for specific applications. So many new image classifiers and classification methods have been proposed and experimented, for example, Decision Tree Classifier (DTC), Support Vector Machine (SVM) classifier, Object-Oriented classification method (OOC), fuzzy classifier and multiple classifier system. In this paper, three popular classification methods, which are MLC, SVM and DTC, are applied to RS images in the study area.

The maximum likelihood algorithm belongs to the category of parametric classification methods. This means that the data is assumed to be distributed according to a previously defined probability model, for which the parameters are determined from a given training set [6].It is widely used in practice, because of its robustness and its easy availability in almost any image-processing software [8].

Decision tree is a fast and effective method of classifying data set owing to its good decision support capabilities. For many problems of classification where large datasets are used and the information contained is complex, even may contain errors, decision trees provide a useful solution [9]. One advantage of DT is that the extracted knowledge is organized in a structure that can be easily interpretable by humans [14].

Support vector machines are discriminative binary classifiers motivated by results from statistical learning theory [6]. It belongs to the category of non-parametric classification methods. SVM is the best statistical learning algorithm, and its criterion is Structural Risk Minimization (SRM). When the sampling errors minimize, the last boundary of model generalization error is reduced too. Generally SVM model is advanced and effective to remote sensing image classification [1, 16].

3.4. Classification implementation

3.4.1. Classification process

The region of interest of every image is selected under ENVI 4.3 software, according to the prior knowledge of Xuzhou city. J-M distance is calculated to test the separability of the training samples. Also, the training samples selected should be pure, not including other land cover classes [18]. In the study, the state of ROI selection was suitable for further land cover classification. Considering regional natural condition and ground characteristics, land cover was classified into six types: water, forest, built-up land, agricultural land, public green space land and barren land.

After training samples being selected, the decision threshold is identified based on RuleGen to build up decision tree, and then DTC is constructed under ENVI 4.3. SVM and MLC are also implemented based on ENVI 4.3. Every image in each group is respectively classified using three kinds of classifiers.

3.4.2 The combination of image data

Apart from the individual data source, the two types of image data in each group are combined to for a mixed dataset of multi-source data and then used as the input of SVM classifier. Images from different sensors contain distinctive features. Data combination of multi-sensor or multi-resolution data takes advantage of the merits of various image data for improvement of visual interpretation and quantitative analysis [8].The combination of multi-source remote sensing data is believed to offer improved accuracies in land cover classification [4].

In the first group, CBERS image and ETM image from April2001 are combined to be one mixed image, and then classified by SVM. In the other group, CBERS image and ASTER image are also combined to be a whole mixed dataset to be classified by SVM.

3.5. Classification accuracy assessment

After image classification, the evaluation of the classification performance is necessary to check if the classification results are effective and creditable. The error matrix approach is the most widely used way in accuracy assessment [3]. Testing samples are selected in order to generate an error matrix, in which we can obtain overall accuracy and kappa coefficient. The diagonal values in the matrix (the number of pixels that are correctly identified) may be summed and divided by the total number of points as a measure of the overall accuracy [7]. The Kappa statistic incorporates the offdiagonal elements of the error matrices (i.e., classification errors) and represents agreement obtained after removing the proportion of agreement that could be expected to occur by chance[2].

4. Results and analysis

4.1. Classification result

As shown in Table 1, by accuracy comparison to the three classifiers to the two groups of images, it is found that SVM outperforms MLC and DTC, so the results of SVM classifier are used for further consistency analysis. Figure 1 is the classification results of two groups of data via SVM classifier. Figure 1(c) and 1(f) are the classification results produced by combing the two types of image data in each group.

Table1.The classification accuracy of MLC, SVM and DTC

method	April 2001				November 2005			
	CBERS		ETM+		CBERS		ASTER	
	Kappa	Overall Acc.	Kappa	Overall Acc.	Kappa	Overall Acc.	Kappa	Overall Acc.
MLC	0.7958	83.4129%	0.8681	89.3795%	0.7201	76.9831%	0.8373	86.7360%
DTC	0.7837	82.4791%	0.8667	89.2601%	0.7497	79.3238%	0.8662	89.2068%
SVM	0.8374	86.7700%	0.8731	89.8082%	0.7051	75.8127%	0.8791	90.2471%

The combined image of two images from group 1 has the overall classification accuracy of 90.8224% using SVM, which is higher than that of any single data source. Also, by combing the two types of data in group 2, overall classification accuracy of SVM reaches to 92.8479%, making the poor classification accuracy of CBERS improved a lot. It is apparent that the classification results of the combined images outperform any single data in terms of overall accuracy.

4.2. Consistency analysis

(1) Total classification accuracy comparison

Overall accuracies of classification results from different images are shown in Table1. In the first group, the overall classification accuracies of CBERS and ETM+ are 86.7700% and 89.8082% respectively. In the second group, the overall classification accuracies of CBERS and ASTER are 75.8127% and 90.2471% respectively. It can be found that applying data from different sensors to land cover classification is suitable, but the quality of classification is not the same. In the first group, the overall classification accuracy of ETM+ image is a little higher than that of CBERS, while in the other group the overall accuracy of ASTER image is fairly higher than that of CBERS.

There are many factors influencing classification accuracy, such as spatial resolution, image registration, the selection of training samples and the selection of parameters et al.

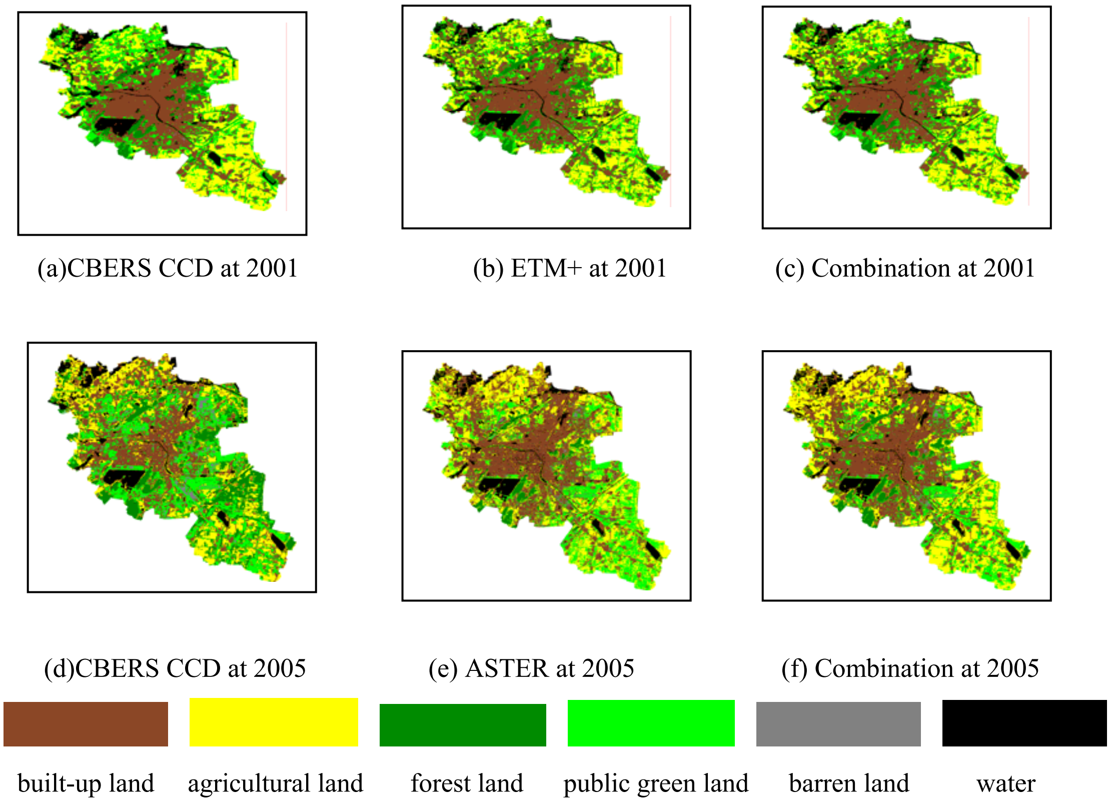

Fig. 1: Classification results of multi-source remotely sensed images in 2001 and 2005 by SVM

(2) Thematic comparison of the consistency of every land cover

Consistency matrix is used to analyze the classification consistency, which is calculated based on the classification results of each group using the similar idea with classification confusion matrix.

In the first group, consistency matrix is created using the result of Landsat ETM+ image as reference and that of CBERS as testing set. That is assuming that the result of Landsat ETM+ is the ground truth image, and then the consistency matrix of CBERS classification image can be calculated, so the data of the consistency matrix reveals the consistency of multi-source remotely sensed images for land cover classification. The total number of the pixels in each image of the group is 947702, among which 738751 pixels are absolutely classified to the same land cover classes, so the overall accuracy of the classification consistency is 77.9518, and correspondingly Kappa Coefficient is 0.6981. Parts of the statistics to consistency matrix are shown in Table 2. From Table 2, it is clear that agricultural land and built-up land derived from the two data sources have the highest consistency among the six land classes, which respectively reach to 83.10% and 87.16%. Public green land, forest land and water have the consistency accuracies of 64.27%, 70.57%, and 73.31%, better than that of barren land. In general, it is effective to use multi-source remotely sensed images in the group for land cover classification.

In the second group, error matrix is calculated using the result CBERS image as reference. The total number of the pixels in each image of the group is 1459212, among which there are 761949 pixels are absolutely classified to the same land cover class, so the overall consistency is 52.2165%, and correspondingly the Kappa Coefficient is 0.3827. Parts of the error matrix are shown as Table 3. From Table 3, it can be seen that built-up land and water have the highest consistency among the six land classes, which respectively reach to 75.65% and 76.51%. Agricultural land has the consistency of 54.70%, better than that of the other three land cover classes. In general, the classification results generated by different images from this group are significantly dissimilar.

Table2.The error matrix of CBERS image in 2001 based on ETM image in 2001

Class	public green land	built-up land	forest land	barren land	agricultural land	water	Total (CBERS)
public green land(percent)	142777 （64.27)	52565 (13.93)	6828 (13.32)	13 (0.50)	26071 (12.26)	6052 (7.41)	234306 (24.72)
built-up land (percent)	30449 (13.71)	313648 (83.10)	371 (0.72)	1611 (62.22)	161 (0.08)	5768 (7.06)	352008 (37.14)
forest land (percent)	7105 (3.20)	1005 (0.27)	36173 (70.57)	0 (0)	1045 (0.49)	9866 (12.08)	55194 (5.82)
barren land (percent)	22 (0.01)	683 (0.18)	0 (0)	958 (37.00)	5 (0)	0 (0)	1668 (0.18)
agricultural land(percent)	37169 (16.73)	2100 (0.56)	585 (0.56)	7 (0.27)	185338 (87.16)	104 (0.13)	225303 (23.77)
Water (percent)	4619 (2.08)	7432 (1.97)	7302 (14.25)	0 (0)	13 (0.01)	59857 (73.31)	79223 (8.36)
Total(ETM+) (percent)	222141 (100)	377433 (100)	51259 (100)	2589 (100)	212633 (100)	81647 (100)	947702 (100)

(3) Specific analysis to those pixels with inconsistent class allocation

In the first group, barren land has the lowest consistency of 37.00%. The classification consistency of the public green land is also not very good. Taking barren land for example, there are 1668 pixels in the classification results of CBERS data, while there are 2589 pixels in the classification results of ETM+ data. By comparing the properties of the barren land of the two classification results pixel by pixel as shown in Table 2, it can be seen that only 958 pixels are exactly the same class. Some of pixels belonging to the barren land from CBERS classification image are classified to other land cover classes in ETM+ classification image, and some pixels of the barren land from ETM +classification image are classified to other land cover classes in CBERS classification result. It can be found that the confusion between built-up land and barren land is remarkable, the reason of which may be the distinct band information from different data sources. Besides, the area of barren land is so small that many pixels of barren land belong to boundary information. They may be classified to different classes due to the different spatial resolution of the image pairs.

In group 2, forest land has the lowest consistency of 19.34%. Public green land, barren land respectively has the lower consistency of 38.93% and 38.33%. Taking public green land as an example, there are 329143 pixels in the classification results of CBERS data, while there are 302647 pixels in the classification results of ASTER data. By comparing the properties of the public green land of the two classification results pixel by pixel as shown in Table 3, it is obvious that only 128149 pixels belong to the same class exactly. Some of pixels of the public green land from CBERS classification image are classified to other land cover classes in ASTER image, and some of pixels of the public green land from ASTER classification image are classified to others in CBERS image. It can be found that public green land is easily confused with forest land, built-up land and agricultural land, as the distribution of public green land in Xuzhou city is so dispersed that there is much boundary information, which is not correctly classified. Besides, the quality of CBERS image obtained in November 2005 is not very good.

The inconsistency may be caused by the differences among multi-source data and the environmental factors during image capture. They may be classified to different classes due to the different spatial resolution of the image pairs, and some other factors occurred during the time interval of image acquisition. The spatial resolution of the optical images used in the paper is not high enough, so inconsistency is inevitable, as many mixed pixels existing. Besides, there are some pixels of different land cover classes may display similar spectral information, leading to incorrect classification.

Table3.The error matrix of ASTER image based on CBERS image

Class	built-up land	agricultural land	forest land	public green land	barren land	water	Total (ASTER)
built-up land (percent)	306877 (75.65)	62957 (19.87)	8028 (3.21)	147638 (44.86)	18220 (45.98)	16562 (14.07)	560282 (38.40)
agricultural land(percent)	57523 (14.18)	173304 (54.70)	109201 (43.63)	44514 (13.52)	139 (0.35)	8169 (6.94)	392850 (26.92)
forest land (percent)	1083 (0.27)	5587 (1.76)	48397 (19.34)	610 (0.19)	0 (0)	2590 (2.20)	58267 (3.99)
public green land(percent)	27891 (6.88)	59786 (18.87)	80445 (32.14)	128149 (38.93)	6052 (15.27)	324 (0.28)	302647 (20.74)
barren land (percent)	1626 (0.40)	20 (0.01)	2 (0)	7494 (2.28)	15189 (38.33)	3 (0)	24334 (1.67)
Water (percent)	10628 (2.62)	15185 (4.79)	4220 (1.69)	738 (0.22)	28 (0.07)	90033 (76.51)	120832 (8.28)
Total(CBERS) (percent)	405628 (100)	316839 (100)	250293 (100)	329143 (100)	39628 (100)	117681 (100)	1459212 (100)

5. Conclusions

Nowadays, many different types of image data are used for land cover classification. It is necessary to know whether classification results are influenced by different data sources. In the paper two groups of image data are used to analyze the classification consistency of multi-source remotely sensed images for land cover classification. By comparing three classifiers used in the experiment, SVM classifier has best results in terms of classification accuracy. Then the classification results of SVM classifier are applied to following consistency analysis. Based on the comparison to the classification results of multi-source remote sensing data from different aspects, it can be concluded that although multi-source remote sensing imagery can obtain similar classification results sometimes to regional land cover, but the classification accuracy are often different and dependent on the land cover classes. While in some circumstance, classification results are significantly different. The reasons for the inconsistency are complicated. By analyzing the consistency matrix generated by the classification results of the two images in each group, it can be deduced that there are several possible reasons. On one hand, the spatial resolution of the image pairs differs from each other, leading to different classification results. On the other hand, image registration also has some influence on the classification results. Besides, the selection of training samples, adjustability of classification parameter, mixed pixels and other factors all affect the classification consistency. Furthermore, it proves that the hybrid dataset consisting of multi-source data can obtain higher classification accuracy than any single data source so the collaborative use of multi-source data is feasible for land cover classification. It is necessary to improve the classification performance of multi-source remotely sensed data by adopting some effective means in future, for example, multiple classifier combination.

6. Acknowledgements

The research is jointly supported by the National High-Tech Program (863 Program) of China (Grant No. 2007AA12Z162), the Program for New Century Excellent Talents in University (Grant No. NCET-06-0476), the Opening Fund of Key Laboratory of Advanced Engineering Surveying of SBSM (Grant No. ES-SBSM-(07)-01) and the China-UK Science Networks by China Scholarship Council and the Royal Society of the UK. The authors thank China Resources Satellite Applications Center for providing the CBERS imagery.

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