

## MIDDLE RESOLUTION REMOTE SENSING IMAGE CHANGE DETECTION BASED ON VECTOR ANALYSIS OF MIDLINE CHANGE

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### ABSTRACT:

The extraction and timely updating of land use /cover information is a key issue in remote sensing change detection. The change vector analysis (CVA) is a better method of change detection. However, the CVA method is the blindness of artificial choice of threshold. Moreover, the direction cosine of CVA cannot represent the unique point in change vector space and it can't distinguish the change category effectively. In order to avoid this defect, the midline vector is added to CVA method. In this paper, we use the midline change vector analysis (MCVA) method to detect the land use /cover change in multi temporal remote sensing images. We proposed the two-step threshold method to get the optimal threshold and determine the change and the unchanged region of the difference remote sensing image. We chose Hefei city of Anhui Province as the study area, and adopted two Landsat5 TM images in 2000 and 2008 year as experiment data. We use the MCVA and two-step threshold method to achieve remote sensing change detection. In order to compare the detection accuracy between MCVA method and the traditional post classification comparison method, the paper choose the same area (178 pixels × 180 pixels) in the two images to analyse the accuracy, and compare the accuracy of MCVA method with that of the traditional post classification comparison method based on SVM. The experiment results show that the MCVA method has higher overall accuracy, lower allocation disagreement and quantity disagreement. What's more, the overall accuracy of MCVA method can reach nearly 60%, much higher than the traditional post classification comparison method (less than 40%). And the MCVA method can effectively avoid the problem of change vector direction cosine values are not unique, and the result is much better than the traditional post classification (SVM) comparison method. It indicates that MCVA is a more effective method in land use / cover change detection for middle resolution multispectral images.

### 1. INTRODUCTION

Using remote sensing images to extract and update the Land Use / Cover Change (LUCC) information timely is one of a key problem of remote sensing change detection. Landsat TM image is a typical and important middle resolution multispectral image source, and has been widely used in LUCC field, for its rich spectral band and sequence image lasting long time. Scholars have developed many remote sensing change detection methods, according to the level of information processing, change detection method can be divided into three levels: pixel level, feature level and target level; according to whether it has been classified, it can be divided into two classes: post classification comparison method and direct comparison method. The quality of the post classification comparison method directly depends on the selection of classification method and the accuracy of classifier. The direct comparison method, including the traditional direct comparison method based on pixel spectrum, is easily affected by atmospheric radiation, sensor difference and image registration accuracy, and the determination of change threshold mainly depends on artificial experience, which has strong subjectivity (Li Dandan et al., 2011; Liu Huanjun et al., 2008; mark J carloto, 2005).

In order to avoid the errors accumulated by the inaccurate classification of the post classification comparison and the shortcomings of the traditional direct comparison method based on pixel spectrum, Malila proposed the change vector analysis (CVA) (Malila, 1980). Comparing with other direct comparison

methods, CVA use more or even all bands to detect the changed pixels and provide the type information of the changed pixels (Li Hengchao et al., 2014). This method is also combined with other methods. Huang Wei (2016) proposed the method of combining principal component analysis (PCA) with CVA, which can reserve more change information and suppress noise compare with the traditional CVA. In the literature (Sartajvir Singh et al., 2013), CVA method was combined with tasseled cap (TC) transformation to detect LUCC in desert areas, and obtain good results.

However, it is difficult to determine the change threshold in CVA. Therefore, researchers proposed various algorithms to get proper threshold. A new method named Double Windows Flexible Pace Searching is proposed to determine the change threshold reasonably and efficiently in land cover change information detection (Chen Jin et al., 2001). Wan Youchuan et al. put forward an automatic change detection method of remote sensing image based on t-test, and further, put forward a series of improved CVA methods (WAN Youchuan et al., 2008), such as change vector analysis method (Cvaps) in posterior probability space. Wei Lifei studied the change detection based on random field model, mainly including the determination of change threshold and the utilization of multi band information (Wei Lifei, 2011).

In traditional CVA, direction cosine cannot be represented as the unique change category's type in change vector space, and cannot effectively distinguish the change category. In order to overcome

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this defect, the midline change vector analysis (MCVA) method was formed by adding the midline vector to CVA, which avoid the problem that direction cosine is not unique (Avnish Varshney et al., 2012). In this paper we use MCVA combined with PCA and the two-step threshold method to extract the change information, to avoid the blindness of threshold determination. The direction cosine of the change vector and midline vector are obtained, so as to facilitate the judgment of the change category in MCVA method.

In the experiment, we chose TM images of Hefei city in 2000 and 2008 year to test the effectiveness of MCVA combined with the two-step threshold method on middle resolution remote sensing image.

## 2. THEORY AND METHOD

### 2.1 The Principle of change vector analysis

CVA method is an extension of the single band difference method. The difference method only use a single spectral band for change detection, and cannot judge the change category. However, CVA can detect the change in multiple or even all bands, and judge the change category. The change vector is a spectral change vector describing the direction and magnitude of change from time 1 to 2. Suppose that the spectral vectors of two  $n$ -dimensional ( $n$  is spectral band number) images in time 1 and time 2 are  $i_1 = (x_{11}, x_{21}, \dots, x_{2n})$  and  $i_2 = (x_{21}, x_{22}, \dots, x_{2n})$  respectively. The change vector is  $\vec{m}$ .  $\vec{m}$  is determined by formula (1).

$$\vec{m} = (d_1, d_2, \dots, d_n) \quad (1)$$

$$|\vec{m}| = \sqrt{\sum_{j=1}^n d_j^2} \quad (2)$$

Where  $d_j = x_{1j} - x_{2j}$  is the spectral difference of pixels in band  $j$  in two different images. The vector  $\vec{\beta} = (\cos \theta_1, \cos \theta_2, \dots, \cos \theta_n)$  also be used to represent the change in direction, where  $\theta_j$  is the angle between  $\vec{m}$  and  $j$  band coordinate axes, which is determined by Formula (3).

$$\cos \theta_j = \frac{d_j}{m} \quad (3)$$

### 2.2 The principle of the vector analysis of midline change

For CVA method, if two change vectors have the same direction cosine in three bands, the two change vectors will be parallel to each other (as shown in Figure 1). They are the same point in the change vector space and cannot correctly distinguish the change category. In order to solve this problem, a MCVA method (Avnish Varshney et al., 2012) is proposed, the midline vector and their direction cosine of each band are introduced in change detection. With them and the change vector of each pixel, a new direction cosine space is formed (as shown in Figure 2). In the new direction cosine space, even if two change vectors have the same direction cosine value, they can represent the unique point. It avoids the change category misjudgement in traditional CVA method.

The midline vector and the direction cosine value are determined as follows:

(1) Calculate the average spectral reflectance of band  $j$ :

$$\alpha_j = \frac{x_{1j} + x_{2j}}{2} \quad (4)$$

Where  $x_{1j}$  and  $x_{2j}$  are spectral reflectance of  $j$  ( $j=1, 2, \dots, n$ ) band at time 1 and time 2. Then we get midline vector  $\vec{k} = (\alpha_1, \alpha_2, \dots, \alpha_n)$ .

(2) Determine magnitude of the midline vector:

$$|\vec{k}| = \sqrt{\sum_{j=1}^n \alpha_j^2} \quad (5)$$

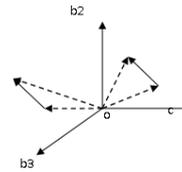


Figure 1 Three band change vector

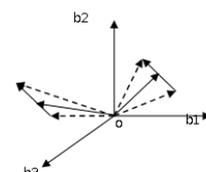


Figure 2 Variation vectors and midline vectors of

(3) Calculate the cosine of the angle  $\alpha_{n+j}$  between  $\vec{k}$  and  $j$  band coordinate axis to obtain the direction cosine of the midline vector as Formula (6):

$$\cos \alpha_{n+j} = \frac{\alpha_j}{|\vec{k}|} \quad (6)$$

The change vector direction cosine  $\cos \theta_j$  and the midline vector direction cosine  $\cos \alpha_{n+j}$  of each pixel are combined to form a new  $2n$  dimensional change vector space, which is recorded as determined by formula (7).

$$\eta = (\cos \theta_1, \cos \theta_2, \dots, \cos \theta_n, \cos \alpha_{n+1}, \dots, \cos \alpha_{2n}) \quad (7)$$

When using the MCVA method to detect changes, two images of different time are differentiated to form a difference image. The changed and unchanged pixels in the difference image need to be distinguished by an appropriate threshold.

### 2.3 The principle of the Two-step threshold method to extract change information

In the traditional difference method, the change information obtained is greatly affected by interference factors and noise, and the change detection accuracy and stability are poor. MCVA is used to construct difference image, which can use multiple bands or even all bands to calculate the difference, and get the difference image with enough information. And PCA transformation is performed to this difference image, construct the differential images with less noise.

The steps are as follows: firstly, the original image is processed with difference operation to get multi band difference image; secondly, PCA transformation is performed to the difference image to get the first few principal components whose cumulative variance contribution rate is greater than 90%; finally, the principal component differential image is obtained, which gray histogram is normal distribution.

We implement two-step method to determine the threshold  $L_1$  and  $L_2$  ( $L_1 < L_2$ ), if the pixel value which obtained after PCA for difference image is greater than  $L_2$  or less than  $L_1$ , it is a changed pixel; if the pixel value between  $L_1$  and  $L_2$ , it is an unchanged one. This method based on the fact that the principal component differential image generally meet the Gauss distribution and the value of the changed pixel can be regarded as the abnormal value in this image. Therefore, the mean value and standard deviation of the principal component differential image are calculated first; then the best threshold value is determined and searched in the range of  $3\sigma$  ( $\sigma$ : standard deviation); finally, the information of change and unchanged is obtained according to the threshold. This method is not completely dependent on the human experience, and can be applied to the difference image with normal distribution.

#### 2.4 The principle of the shortest distance decision method to detect multi changes category

In order to determine the change categories, we classified and recognized all possible classes of a reference image in certain time. Then we use the classic shortest distance method to detect multi class changes category through the following steps:

(1) Use formula (8) to calculate the Euclidean distance between the direction cosine of changed pixel and the direction cosine of each possible change category of reference for each pixel.

$$t = \sqrt{\sum_{j=1}^n (\cos \theta_j - \overline{\cos \theta_j})^2 + \sum_{j=1}^n (\cos \alpha_{n+j} - \overline{\cos \alpha_{n+j}})^2} \quad (8)$$

Where  $t$  is the Euclidean distance between the pixel direction cosine,  $\overline{\cos \theta_j}$  and  $\overline{\cos \alpha_{n+j}}$  are the average direction cosine of the possible change categories:

- (2) Find out the shortest distance and the corresponding change category;
- (3) Group the pixel into this change category;
- (4) Repeat for all changed pixels.

#### 2.5 The process of MCVA method with two-step threshold

There are four steps to detect the change of remote sensing image with MCVA, and the flow chart is shown in Figure 3:

(1) Firstly, the difference operation is carried out on the remote sensing images of different periods to form the difference image, and the change vector and the midline vector are calculated; secondly, PCA transformation is performed to the difference image, and the principal component differential image is obtained; then distinguish the changed and unchanged areas based on the principal component differential image by the two-step threshold method, the change image is formed.

(2) The change vector direction cosine and the midline vector direction cosine value of each change pixel in the change image are calculated by formula (3), (6) and (7), form a new  $2n$  dimensional change vector space.

(3) Supervised classification on reference images, get the land cover class, then calculate the average spectral reflectance of each land cover class, and calculate the change vector direction cosine and the midline vector direction cosine of each possible change category by using formula (3) (6). The two direction cosine are taken as the discrimination criterion of the change category.

(4) Use formula (8) to calculate the Euclidean distance between the direction cosine value of each change pixel and the reference direction cosine value of each possible change category, obtain the change category of the change pixel, and generate the final change detect result.

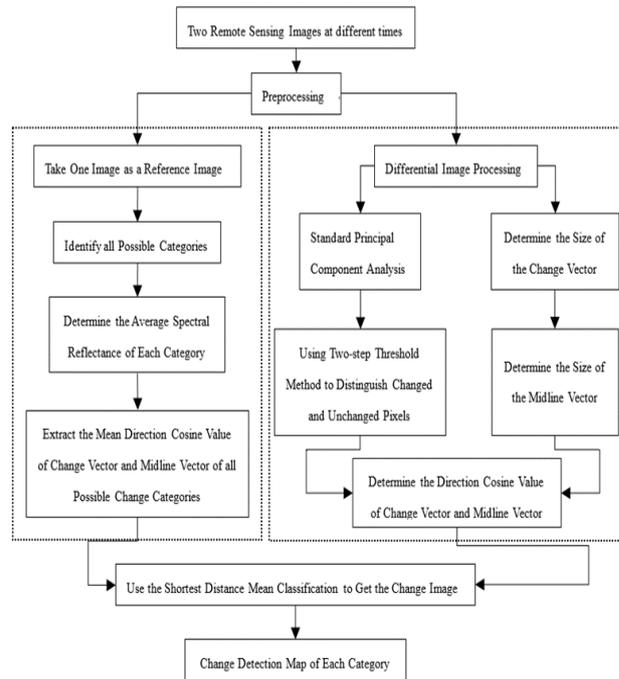


Figure 3 Research route

### 3. EXPERIMENT

#### 3.1 Overview of the study area

We chose Hefei City (area of 11496 Km<sup>2</sup>) as study area, which locates in the middle of Anhui Province, including four districts and three counties of Feixi County, Feidong County and Changfeng County (as shown in Figure 4). There are three geomorphic type in the territory, i.e. hilly land, low mountain residual hill, and low-lying plain. Hefei City is situated in the subtropical monsoon zone. This district is rich in land use types, and the rapid economic development in the past 20 years has led to the aggravation of land use change. So it is a highly representative research area for land use change detection.

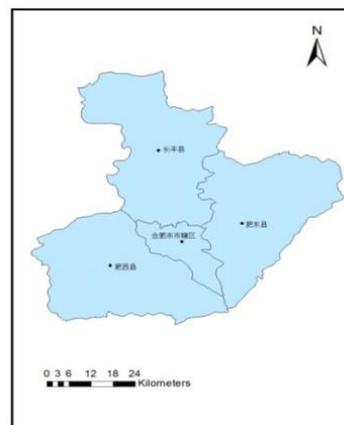


Figure 4 Research area map

### 3.2 Data and pre-processing

#### 3.2.1 Introduction to remote sensing data

We choose two Landsat5 TM images (resolution of 30m) of Hefei City in 2000 and 2008 year as experimental images, and the image information is shown in Table 1.

Table 1 Basic experimental data

Remote sensing image	Image category	Imaging date	Imaging time
Time 1	Landsat5	2000.09.15	02:21:46
Time 2	Landsat5	2008.05.16	02:32:03

#### 3.2.2 Pre-processing

Before the change detection, the original image needs be pre-processed. The pre-processing include radiance calibration, atmospheric correction, projection transform, geometric rectification, image splicing and clipping. Figure 5 is a result after pre-processing.

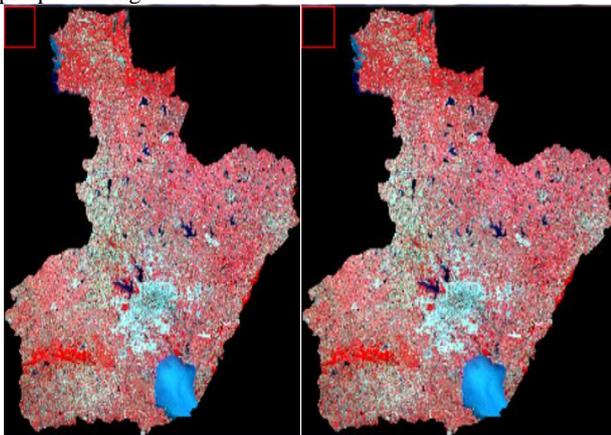


Figure 5 Image map of Hefei city of Anhui Province: the year 2000(left) and 2008(right) ( Band 4,3,2 false color composite map)

### 3.3 Change detection based on MCVA method

#### 3.3.1 Separation of changing and unchanging regions by differential principal component and Two-step threshold method

We calculated the each band difference image of the two images at 2000 and 2008. Then, the PCA is carried out on the series band difference images, and a series of differential principal components were obtained. The first three differential principal components whose cumulative contribution rate of eigenvalues is more than 95% are selected as the main differential principal components for late change detection. Table 2 shows the eigenvalues and cumulative variance contribution rate of differential principal component analysis from 2000 to 2008.

From Table 2, the cumulative variance contribution rate of the first three principal components has reached 96.96%, including

the main ground information, so the first three components are taken to extract the change information.

Table 2 Differential principal component characteristic values and cumulative variance contribution rate of the year 2000 and 2008

Differential principal component	Characteristic value	Cumulative contribution rate of eigenvalue (%)
1	3.1343	52.24
2	1.8735	83.46
3	0.8100	96.96
4	0.1284	99.10
5	0.0290	99.59
6	0.0248	100

The two-step method in section 2.3 is used to determine the optimal threshold for the each differential principal components. In the range of average  $\pm 3\sigma$ , we set step  $0.25\sigma$  to search the optimal threshold which have high change detection accuracy. The experiment shows that the threshold between  $\pm 2.1\sigma \sim 2.4\sigma$  get better result. Three change images are generated respectively, we find that differential principal component 1 is more sensitive to change detection of urban construction area and bare land, differential principal components 2 and 3 are more sensitive to change of vegetation and water body. Then three change images are combined into one change image, as shown in Figure 6, which is used for subsequent multi category change detection.

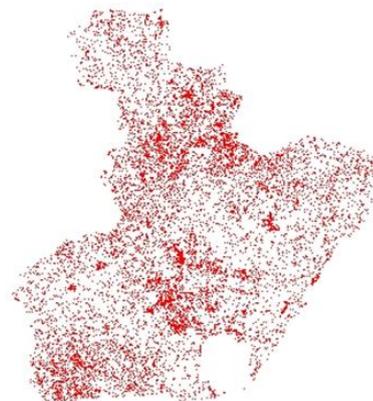


Figure 6 Map of changed and unchanging regions by Two-step threshold

#### 3.3.2 Determine the mean direction cosine of change vector and midline vector in reference image

Taking year 2000 image as the reference image, the region of interest is selected and the land cover is divided into four class by SVM method using Radial Basic function with gamma parameter of 0.167 (Zhou shaolei et al., 2014): vegetation, urban construction area, water body and bare land. Then, we calculate the average direction cosine value of all possible change categories and their change vectors and midline vectors, as shown in Table 3; where numbers 1-12 represent 12 possible change categories, as shown in Table 4.

Table 3 The average direction cosine of change vectors and midline vectors in all possible change categories

No.	$\cos\theta_1$	$\cos\theta_2$	$\cos\theta_3$	$\cos\theta_4$	$\cos\theta_5$	$\cos\theta_6$	$\cos\alpha_7$	$\cos\alpha_8$	$\cos\alpha_9$	$\cos\alpha_{10}$	$\cos\alpha_{11}$	$\cos\alpha_{12}$
1	0.4933	0.1169	-0.2239	0.4901	0.4121	0.5319	0.1915	0.3416	0.4836	0.5273	0.4951	0.2992
2	0.3890	0.2100	0.2324	0.5405	0.2855	0.6140	0.1919	0.3407	0.4877	0.5272	0.4882	0.3048
3	0.6110	-0.4123	0.0923	0.3901	0.0589	0.5409	0.1929	0.3344	0.4927	0.5271	0.4907	0.2993
4	-0.4933	-0.1169	0.2239	-0.4901	-0.4121	-0.5319	0.1915	0.3416	0.4836	0.5273	0.4951	0.2992
5	0.1852	0.2500	0.6313	0.4535	0.0856	0.5401	0.1992	0.3386	0.4771	0.5301	0.4901	0.3114
6	0.0156	-0.6689	0.4391	-0.2464	-0.5321	-0.1254	0.2004	0.3324	0.4817	0.5301	0.4926	0.3061

7	-0.3890	-0.2100	-0.2324	-0.5405	-0.2855	-0.6140	0.1919	0.3407	0.4877	0.5272	0.4882	0.3048
8	-0.1852	-0.2500	-0.6313	-0.4535	-0.0856	-0.5401	0.1992	0.3386	0.4771	0.5301	0.4901	0.3114
9	-0.1369	-0.5561	-0.2590	-0.4884	-0.3535	-0.4913	0.2006	0.3316	0.4858	0.5299	0.4858	0.3115
10	-0.6110	0.4123	-0.0923	-0.3901	-0.0589	-0.5409	0.1929	0.3344	0.4927	0.5271	0.4907	0.2993
11	-0.0156	0.6689	-0.4391	0.2464	0.5321	0.1254	0.2004	0.3324	0.4817	0.5301	0.4926	0.3061
12	0.1369	0.5561	0.2590	0.4884	0.3535	0.4913	0.2006	0.3316	0.4858	0.5299	0.4858	0.3115

Table 4 All possible ground feature class change categories and number

Category No.	Change category (pre change category - post change category)
1	Water body - urban construction area
2	Water body – bare land
3	Water body - vegetation
4	Urban construction – water body
5	Urban construction – bare land
6	Urban construction – vegetation
7	Bare land – water body
8	Bare land – urban construction
9	Bare land – vegetation
10	Vegetation – water body
11	Vegetation – urban construction
12	Vegetation – bare land

### 3.3.3 Using the shortest distance decision method to detect multi category changes

We calculate the change vector, the midline vector and the direction cosine of each pixel, compare them with the change vector of each reference category, calculate the Euclidean distance to each reference change category and find out the category with the shortest Euclidean distance. This pixel belongs to the reference change category with the shortest distance. Generate multi category change map, as shown in Figure 7 in which Table 5 shows the statistical results of each change category.

From Figure 7 and Table 5, 89.55% of the study area has not changed, and the urban construction area has increased the most, accounting for 3.89% of the change area. Due to the rapid economic development, Hefei city has experienced obvious urban expansion between 2000 and 2008, and the land cover/use type has gradually changed from bare land and vegetation to urban construction area.

Table 5 Statistics of change detection results of MCVA method from the year 2000 to 2008

Category No.	Area (Km <sup>2</sup> )	Percentag (%)
0	12453.76	89.55
1	121.56	0.87
2	54.57	0.39
3	152.50	1.09
4	80.14	0.58
5	163.04	1.17
6	211.33	1.52
7	48.24	0.35
8	171.08	1.23
9	41.36	0.30
10	90.75	0.65
11	249.69	1.79
12	68.94	0.50

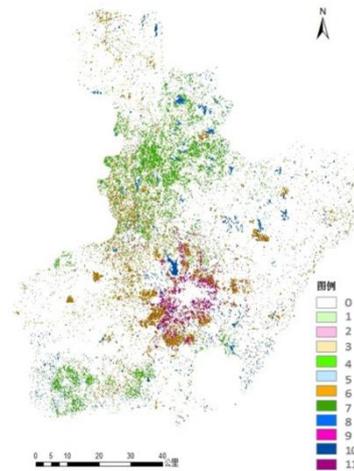


Figure 7 Multi-class change map of MCVA method from the year 2000 to 2008

### 3.4 Post classification comparison

We select the SVM post classification comparison method which has good effect and accuracy in the traditional change detection method as the comparison.

For the two time images (2000 and 2008), SVM classification is used to classify the images into four land cover class: water body, vegetation, urban construction area and bare land, then change detection is conducted by using the classification results. The results are shown in Figure 8, the overall accuracy and kappa coefficient are shown in Table 6, and the statistical results of change categories and situations after classification are shown in Table 7.

Table 6 Overall accuracy and Kappa coefficients of classified images in the year 2000 and 2008

Remote sensing classification image	Overall accuracy (%)	Kappa coefficient
Image of year 2000	98.4380	0.9678
Image of year 2008	99.0500	0.9796

Table 7 Statistics of change detection results of post classification comparison method from the year 2000 to 2008

Category No.	Area (Km <sup>2</sup> )	Percentag (%)
0	11748.60	84.48
1	5.56	0.04
2	5.56	0.04
3	48.67	0.35
4	6.95	0.05
5	38.94	0.28
6	9.73	0.07
7	34.77	0.25
8	8.34	0.06
9	820.51	5.90
10	268.40	1.93
11	197.48	1.42
12	712.04	5.12

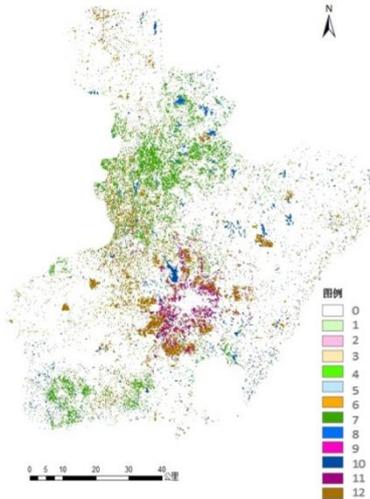


Figure 8 Multi-class change map of post classification comparison method from the year 2000 to 2008

#### 4. ANALYSIS OF CHANGE DETECTION

##### 4.1 Visual comparative the accuracy of the MCVA and SVM result

Take the same area (178×180 pixels) on the two images for accuracy comparison, as shown in Figure 9. The corresponding change detection results of post classification comparison method and MCVA method are shown in Figure 10.



Figure 9 Zone 1: the Landsat 5 image of the year 2000(left) and 2008(right)

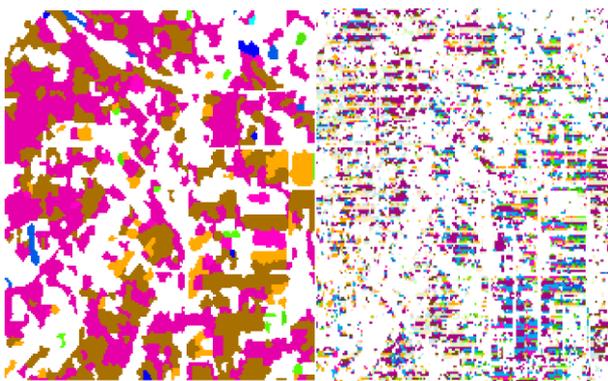


Figure 10 Zone 1: post classification comparison method(left)and MCVA method(right)

From Figure 9 and Figure 10, this small area's land cover / utilization class has gradually changed from bare land and

vegetation to urban construction area between year 2000 to 2008. In the red frame area of Figure 9, new emerging construction area can be seen, but the post classification change detection method erroneously detects it as vegetation change to bare land (the lower part of Figure 10). MCVA detected it accurate. However, the change detection result of MCVA method is little bit striped, which may be caused by the radiation effect of adjacent other ground feature.

##### 4.2 Accuracy evaluation of MCVA method

Due to lack of ground truth statistical data in 2000 and 2008, it is impossible to analyse the accuracy of the experimental results in the whole study area. Therefore, we select a small area and use visual interpretation to obtain the change category as the ground truth. Based on this, we evaluate the accuracy of the two methods. A study area 2 of 21 × 26 pixels is selected, through visual interpretation, 312 changed pixels and 234 unchanged pixels are detected in the total 546 pixels. We use Overall Accuracy (OA), Allocation Disagreement (AD) and Quantity Disagreement (QD) to check the change detection accuracy. Formula (8) (9) (10) are the calculation formulas of these quantities respectively. Table 8 is the change detection results from the MCVA and post classification comparison method and visual interpretation ground true. The OA, AD and QD are shown in Table 9.

$$OA = \frac{\sum_{i=1}^r n_{ii}}{N} \quad (8)$$

$$AD = \frac{\sum_{i=1}^r (2 * \min(\frac{n_{+i}}{N} - \frac{n_{ii}}{N}, \frac{n_{i+}}{N} - \frac{n_{ii}}{N}))}{2} * 100\% \quad (9)$$

$$QD = \frac{\sum_{i=1}^r |\frac{n_{+i}}{N} - \frac{n_{i+}}{N}|}{2} * 100\% \quad (10)$$

Where,  $N$  is the total number of pixels;  $n_{ii}$  is the number of correctly classified pixels;  $n_{i+}$  is the number of pixels of a certain type in the data to be evaluated;  $n_{+i}$  is the number of pixels of a certain type in the reference data;  $r$  is the number of classified pixels.

According to Table 8 and 9, the MCVA has higher OA, lower AD and QD. Although the two methods can effectively distinguish the changed pixel and the unchanged one, and the change category of land cover/use can be judged correctly, there are also some mistake. For the MCVA, the key factor for change category determination is the precision and accuracy of the supervised classification used in reference image, since the average spectral reflectance of four ground classes calculated from the classified result, and the precision and accuracy of land class will infect the calculate result directly. For post-classification comparison method, the effect depends on the classification accuracy of the two images. The post-classification comparison needs to classify two images, which is workload than the MCVA method, for MCVA only classifies one images. In this experiment, MCVA method is more sensitive in urban areas change detection, it is very effective in detecting changes in urban areas, the OA is better than post-classification comparison method.

Table 8 The change detection results of MCVA method and post classification comparison method and true results from visual interpretation

Category No.	Real Change Area (m <sup>2</sup> )	Change Area of MCVA Method (m <sup>2</sup> )	Change Area of Post Classification Comparison Method (m <sup>2</sup> )
0	210600	280800	151200
1	8100	31500	0
2	2700	0	0
3	13500	16200	0
4	0	4500	0
5	2700	900	0
6	5400	1800	0
7	1800	3600	0
9	26100	2700	0
10	6300	5400	0
11	180900	116100	134100
12	8100	900	206100

Table 9 Change detection accuracy of MCVA method and post classification comparison method

Algorithm	Overall Accuracy (%)	Allocation Inconsistency (%)	Quantity Deviation (%)
MCVA	54.03	21.25	24.72
Post Classification Comparison	38.28	21.43	40.29

### 4.3 Result analysis

Combining the above experiments results, we draw the conclusions from the change detection of land cover/use types:

(1) During the study period, the urban construction areas in the study area (Hefei) expanded significantly over 150Km<sup>2</sup>, as shown in Table 10. Rapid urbanization and economic development have caused tremendous changes in land cover/use types in Hefei. Most of the land used for urban construction comes from vegetation, followed by bare land. At the same time, the reduction of urban construction areas is mainly converting into bare land.

(2) The vegetation coverage area decreased by about 300Km<sup>2</sup> as shown in Table 11, and the ecological environment pressure increased. Although in the past eight years, some bare land has gradually convert to vegetation, but more vegetation is constantly changing into urban construction areas or new bare land. The trend of vegetation decrease is gradually serious.

(3) The water area increased (Table 12), however, the overall increase trend is not as obvious as urban construction area in this

eight years. From 2000 to 2008, it can be seen from Figure 7, 8 that a new area of water appeared in the middle of the study area, mainly due to the vegetation change to water body.

(4) From 2000 to 2008, the bare land area decreased. As shown in Table 13, a small amount of bare land becomes water, and a large number of bare land becomes vegetation. We analysis the reasons: The acquisition time of image data in 2000 and 2008 is September and May respectively; since a large number of crops have been harvested in September, a large number of cultivated land on the remote sensing image in 2000 was mistakenly identified as bare land, while crops in May is booming, and a large number of cultivated land on the image in 2008 was correctly identified as vegetation. This results in the decrease of bare land in the change detection due to the increase of vegetation. In order to avoid the agricultural crop harvesting factors which causing farmland to be misjudged as bare land, we should try to use the remote sensing image when the crop is growing vigorously, or introduce other non-spectral information.

### 5. CONCLUSION

In this paper, we focus on the principle of the MCVA with PCA and the two-step threshold method and its application in middle resolution remote sensing image change detection. We compare the research results with the post classified comparative detection method and get the following conclusions:

(1) MCVA with the two-step threshold method can get better results and accuracy for TM images. It achieves a total accuracy of nearly 60%, which is far higher than the traditional post classification comparison method (less than 40%) in the study area. Moreover, MCVA is more sensitive to the change of urban construction area, which is more suitable for the detection of urban land use change.

(2) MCVA method can effectively avoid the problem that the cosine value of change vector direction is not unique in change vector space. The result shows MCVA is a more effective method for land use / cover change detection.

(3) When using the differential principal components of the two-step threshold method to separate the changed and unchanged regions in land use/cover change detection, for TM image, setting the threshold between  $\pm 2.1 \sim 2.4\sigma$  of the mean value of differential principal component image can get better change detection results.

In general, MCVA combined with PCA and the two-step threshold method has great potential in remote sensing image change detection. Comparing with the post classification comparison method, it has the advantage of not requiring a large number of repeated manual classifications. When eliminated atmospheric effect, it can be very suitable for the change detection of middle resolution multispectral images of homogeneous remote sensors (such as TM or CBERS images).

Table10 Urban construction area change from the year 2000 to 2008

Time Interval	Increased area of urban construction area (Km <sup>2</sup> )			Reduced area of urban construction area (Km <sup>2</sup> )			Total change of urban construction area (Km <sup>2</sup> )
	Vegetation	Water Body	Bare Land	Vegetation	Water Body	Bare Land	
2000 - 2008	374.4	60.6	125.86	77.21	54.8	73.12	355.73

Table 11 Vegetation area change from the year 2000 to 2008

Time Interval	Increased area of urban construction area (Km <sup>2</sup> )			Reduced area of urban construction (Km <sup>2</sup> )			Total change area of vegetation (Km <sup>2</sup> )
	Urban Construction Area	Water Body	Bare Land	Urban Construction Area	Water Body	Bare Land	
2000 - 2008	77.21	61.21	210.56	374.4	150.69	46.72	-222.83

Table 12 Water area change from the year 2000 to 2008

Time Interval	Increased area of water body (Km <sup>2</sup> )			Reduced area of water body (Km <sup>2</sup> )			Total change area of water body (Km <sup>2</sup> )
	Urban Construction Area	Vegetation	Bare Land	Urban Construction Area	Vegetation	Bare Land	
2000 - 2008	54.8	150.69	89.84	60.6	61.21	61.45	112.07

Table 13 Bare land area change from the year 2000 to 2008

Time Interval	Increased area of bare land (Km <sup>2</sup> )			Reduced area of bare land (Km <sup>2</sup> )			Total change area of bare land (Km <sup>2</sup> )
	Urban Construction Area	Water Body	Vegetation	Urban Construction Area	Water Body	Vegetation	
2000 - 2008	73.12	61.45	46.72	125.86	89.84	210.56	-244.97

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