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Conventional change detection approaches are mainly based on per-pixel processing, which ignore the sub-pixel spectral variation resulted from spectral mixture. Especially for medium-resolution remote sensing images used in urban land-cover change monitoring, land use/cover components within a single pixel are usually complicated and heterogeneous due to the limitation of the spatial resolution. Thus, traditional hard detection methods based on pure pixel assumption may lead to a high level of omission and commission errors inevitably, degrading the overall accuracy of change detection. In order to address this issue and find a possible way to exploit the spectral variation in a sub-pixel level, a novel change detection scheme is designed based on the spectral mixture analysis and decision-level fusion. Nonlinear spectral mixture model is selected for spectral unmixing, and change detection is implemented in a sub-pixel level by investigating the inner-pixel subtle changes and combining multiple composition evidences. The proposed method is tested on multi-temporal Landsat Thematic Mapper and China–Brazil Earth Resources Satellite remote sensing images for the land-cover change detection over urban areas. The effectiveness of the proposed approach is confirmed in terms of several accuracy indices in contrast with two pixel-based change detection methods (i.e. change vector analysis and principal component analysis-based method). In particular, the proposed sub-pixel change detection approach not only provides the binary change information, but also obtains the characterization about change direction and intensity, which greatly extends the semantic meaning of the detected change targets.

Keywords: change detection; sub-pixel level processing; multi-temporal images; spectral mixture model; back propagation neural network; remote sensing

1. Introduction

Owing to its technical advantages of wide coverage, abundant information, multi-resolution, and multi-temporal observation, remote sensing technology has been widely used for monitoring and analyzing land-cover changes, urban growth, and geographic processes. Based on various information and products derived from remote sensing imagery, the spatio-temporal evolution of land use/cover and urban growth can be investigated and modeled. This provides important support for decision making in urban sustainable development and also in other fields. Dynamic change is the essential property of any geographic processes, including urban growth and corresponding ecological environment responses. Generally, for change detection over urban area, the spatio-temporal changes reveal the pattern and structure of urban land-cover transition with the temporal process. There are mainly two kinds of monitoring ways according to the observation period: long-term and short-term change detection. The former aims at detecting the trend of land-cover changes, thus explores their evolution law (e.g. desertification, lake degradation, and urban expansion). The later emphasizes a finer detection of changes for the specific targets in a given observation time slot (e.g. seasonal land-cover change, construction progress monitoring, and traffic monitoring).

In terms of the techniques adopted for urban land-cover change analysis and city expansion monitoring, there are mainly two branches of methods: post-classification comparison (PCC) and direct change detection technique from multi-temporal images. For PCC, the key points are designing effective and robust classifiers to produce high accuracy. It also depends on the availability of reliable ground truth data for training the classifiers. Usually, a pixel is assigned to a specific class label based on its similarity to the statistical parameters of different classes (1–3). On the other hand, direct change detection from multi-temporal remote sensing images has been widely used in land investigation, forest and vegetation change monitoring, urban growth, disaster monitoring, land use/cover change, and other geographic process evolutions (4–7). There are different categories for change detection methods, among which the most popular one is the division of supervised and unsupervised change detection algorithms (1, 3, 8), according to the availability/unavailability of the ground truth.

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Although the applicability and feasibility of different change detection methods have been demonstrated in different cases, most of them belong to the scope of pixel-level detection that is based on the pure pixel assumption. One single pixel is assumed to contain only one land-cover type (or ground object). Thus, the inner-pixel variation is simply ignored in the pixel-level processing, which may lose small but important changes, and finally affects the overall change detection accuracy. In fact, for remote sensing satellite images, especially the medium and low resolution images, the spectral composition within a single pixel is not pure. Thus, the results derived from the pixel-level methods become more ambiguous and uncertain. In order to overcome this problem, some sub-pixel level processing methods are proposed to consider the spectral change inside of a single pixel. The most common way is using the soft classifier instead of using hard classification schemes. By doing soft classification, one pixel on the image may not only belong to a specific class, but have a membership to different several classes, or can be decomposed to derive the abundances of different end members within this pixel (9–11). Unmixing or spectral mixture analysis, which is based on the assumption of mixed pixel structure, is the most popular way for soft classification of remote sensing images. In the study of urban areas, unmixing is often combined with vegetation-impervious surface-soil (V-I-S) model proposed by Ridd in Ref. (12). This is used to analyze and depict the structures and changes of urban land cover and ecological environment responses (12–15). In particular, the change of impervious surface area is an important indicator for urban expansion monitoring and urban biophysical environment analysis.

With increased attention being paid to spectral mixture analysis, for urban expansion monitoring by medium resolution image data, it is important to deal with the change detection problem from the viewpoint of sub-pixel level. This is much closer to the actual situation of the ground surface. Recently, impervious surface area derived from unmixing techniques has been used to change detection for urban growth study, demonstrating the merits of sub-pixel level change detection (16, 17). However, these change detection methods are based on only one indicator and it cannot reveal the land cover transition in detail due to the lack of additional important information. At the same time, the change detection after impervious surface area extraction is still based on the simple comparison (e.g. simply differencing) in order to find the difference, which may produce high level of errors.

Faced with the aforementioned problems and progresses, a sub-pixel level change detection scheme is proposed based on the spectral mixture analysis in this paper, aiming to further investigate the change detection process in the sub-pixel level. The approach is designed mainly for the medium- and low-resolution remote sensing images, which have suffered more from the spectral mixture problem. The nonlinear spectral mixture model is employed to generate the abundances of different endmembers according to V-I-S model, which are then used as the input of sub-pixel change detection. After that, the abundances of all endmembers are analyzed and combined by decision-level fusion to determine detailed change information. Experimental results of land-cover change detection and urban growth monitoring obtained on two real remote sensing satellite data-sets confirmed the effectiveness of the proposed method. Comparing with two benchmark pixel-based change detection algorithms, the proposed approach obtains the detailed information about changed areas, transition state, change direction, and intensity simultaneously, which are usually unavailable in traditional change detection methods. In addition, this scheme has a few requirements on relative radiometric correction of multi-temporal images, thus avoiding the effects of radiometric difference and temporal inconsistency on change detection results.

The remainder of this paper is organized as follows. Section 2 describes the theoretical basis about impervious surface extraction and pixel unmixing techniques for urban study. The proposed sub-pixel change detection technique is presented in Section 3. Experimental results on two remote sensing satellite images and the corresponding analysis are shown in Section 4. Finally, Section 5 concludes the paper with some remarks.

2. Nonlinear spectral mixture model

In the research of urban impervious surface extraction, it was found that unmixing-based method could obtain much richer sub-pixel information than pure pixel-based methods due to the complexity of urban land covers and heterogeneity of impervious surface area materials (18). Although linear spectral mixture model (LSMM) has been widely used in many applications in the past decades, its basic assumption may cause controversy because it is actually unreasonable, even wrong to a great extent (15, 18). Therefore, nonlinear spectral mixture model becomes an important and alternative way for decomposing mixed pixels and extracting impervious surface area (15, 18–20). Artificial neural network, as an effective nonlinear unmixing model for remote sensing, has been recently applied to impervious surface area extraction. According to the idea of extracting impervious surface area by V-I-S model and spectral mixture models proposed in Ref. (13), and developed in Refs. (14, 15), urban land covers can be represented mainly by four types of endmembers: (1) vegetation (e.g. trees, grass, and artificial grass); (2) high-albedo (e.g. building, concrete, and roof); (3) low-albedo (e.g. water and shadow); and (4) soil. Figure 1 shows the 2-D scatterplot of the first three maximum noise fraction (MNF) components representing the mentioned four endmembers in the 2-D feature space. The abundances of endmembers are derived and used for analyzing urban land-cover
changes, where the high-albedo and low-albedo objects are related to the urban impervious surface can be extracted for change detection.

We recall the back propagation neural network (BPNN) model for unmixing that selected in this work in order to derive the abundances of four endmembers within a pixel \( \text{(21)} \). As a well-known nonlinear neural network model, BPNN has been used to solve different problems in remote sensing applications, including landcover classification \( \text{(21)} \), urban impervious surface estimation \( \text{(15)} \), and change detection \( \text{(22)} \). BPNN consists of three or more layers including: one input layer, one output layer, and one or more hidden layers. Usually one hidden layer is sufficient for different applications. Therefore, three-layer structure is adopted in our work. Neurons of each layer are connected to all neurons in the next layer by specific weight values, but in the same layer the neurons are disjointed to each other. For the used three-layer BPNN, where the number of nodes in the input layer corresponds to the number of original remote sensing image bands and nodes in the output layer corresponds to four endmembers. One hidden layer is defined. For a given node \( j \) in the hidden layer or output layer connected to all nodes in its previous layer, the input is:

\[
\text{net}_j = \sum_i w_{ij}I_i
\]

where \( \text{net}_j \) is the input that node \( j \) receives, \( w_{ij} \) represents the weights between node \( i \) and \( j \), and \( I_i \) denotes the output from node \( i \) in the previous layer (input or hidden layer). Then the output of node \( j \) can be obtained according to the following equation:

\[
O_j = f(\text{net}_j)
\]

It should be noted that different functions can be used as \( f(\cdot) \). Here, the nonlinear sigmoidal function is selected. Usually, the number of nodes in the hidden layer can be calculated by Equation (3) \( \text{(15)} \):

\[
N_h = \text{INT} \sqrt{N_i \times N_o}
\]

where \( N_h \) is the number of nodes in the hidden layer, \( N_i \) and \( N_o \) denote the amount of nodes in the input layer and output layer, respectively. \( \text{INT}(\cdot) \) is the Integer function. However, it is just an empirical formula, and usually the number of hidden layer nodes is determined by experiments and comparison. It is worth noting that the parameter setting may affect the performance of the BPNN model. For the land-cover classification, the learning rate usually lies in 0.1 to 0.2, while the momentum factor is between 0.5 and 0.6 \( \text{(21)} \). The structure of BPNN for spectral mixture analysis on remote sensing image is presented in Figure 2.

3. The proposed sub-pixel level change detection method

Conventional change detection methods at pixel level can find abrupt changes occurred on two (or more) images acquired at different dates, but the subtle change variation within a pixel is usually ignored due to the limitation that using of pixel-level change detection methods. In order to deal with the issue of mixed spectral composition within a pixel and take advantage of the spectral unmixing technique, we develop a novel sub-pixel level change detection approach. In the proposed approach, unmixing algorithm (linear or nonlinear) is first used to derive the abundances of endmembers in a pixel (e.g. high-albedo, low-albedo, impervious surface, and soil) according to the theory of V-I-S model. Based

Figure 1. 2-D scatterplot of MNF components representing four endmembers in the feature space: (a) MNF1 vs. MNF2; and (b) MNF1 vs. MNF3 (the used data are described in Section 4).
on the results of endmember extraction, the composition within a single pixel is obtained. Thus how to effectively analyze these fractions and to define suitable rules for identifying the change information becomes a critical issue. Differently from the pixel-based change detection approaches that provide the binary change detection result (i.e. change and no-change), sub-pixel level analysis focuses more on the inner-pixel variance. The final decision for a changed pixel is taken on the combination of all endmembers within it. The abundance difference of each endmember in a pixel over two dates is first calculated. Decision level fusion strategies are then used to combine the differential information to determine the changes. The proposed method also allows us to obtain the additional information including class transition, change direction, and intensity. The proposed change detection method mainly consists of four steps: (1) spectral unmixing; (2) differential information generation from all endmembers; (3) change determination based on the proposed decision rules; and (4) change intensity analysis. Detailed descriptions of the proposed method are given as follows.

(1) BPNN unmixing algorithm is firstly used to generate the abundance of each endmember in a single pixel in images acquired at two dates. Let \( x^1 \) be a pixel in the original multi-spectral image acquired at time 1 and \( x^2 \) be a pixel in the same spatial position corresponding to \( x^1 \) on image time 2. The abundance vector of \( x^1 \) and \( x^2 \) after pixel spectral unmixing is expressed by \( Y^1_k \) and \( Y^2_k \), where \( k \) indicates the \( k \)-th endmember with \( k = 1, 2, \ldots, K \). \( K \) is the number of total kinds of endmembers. In our case \( K = 4 \), representing the considered four endmembers in V-I-S model (i.e. vegetation, high-albedo, low-albedo, and soil), as suggested and adopted by Wu and Murry (13), Lu and Weng (14). The abundance should satisfy the following constraints fully:

\[
\sum_{k=1}^{K} Y^1_k = 1, \quad 0 \leq Y^1_k \leq 1
\]

\[
\sum_{k=1}^{K} Y^2_k = 1, \quad 0 \leq Y^2_k \leq 1
\]

(2) The abundance difference of all endmembers within a pixel on two dates images are calculated, which consist of \( K \) fractions \( D_k \) (\( k = 1, 2, \ldots, K \)), according to the differential operation:

\[
D_k = Y^2_k - Y^1_k, \quad -1 \leq D_k \leq 1
\]

It is easy to know that \( D_k \) may be positive or negative, but a basic rule for analyzing change information by abundance differences is that the sum of positive values and negative values must have the same volume, where the positive value represents the increase of endmember abundance and the negative value represents the decrease of endmember abundance within a pixel from \( Y^1_k \) to \( Y^2_k \). Let us assume that \( D_p \) is the volume with positive \( D_k \) values, and \( D_n \) is the negative one, thus the change magnitude \( \rho \) is expressed as:

\[
\rho = \sum D_p = \sum |D_n|
\]

(3) Determination of change information at sub-pixel level. When the change indicator is obtained, the problem is to find the changed pixels by

\[
\text{Figure 2. The structure of BPNN. Input layer: the original } n \text{ band of the considered remote sensing image; hidden layers: set as one layer, the number of nodes is defined according to Equation (3); and output layer: includes four nodes which are related to four classes of endmembers.}
\]
analyzing the change information. This can be done by thresholding the change magnitude image of all pixels to generate a change map (CM), according to the following decision rule:

$$x \in \begin{cases} \omega_c, & \rho_x \geq T_{\rho} \\ \omega_n, & \rho_x < T_{\rho} \end{cases}$$  \hspace{1cm} (8)

where $x$ is a pixel on the change magnitude map $\rho$, $\rho_x$ is its corresponding magnitude value. $\omega_c$ and $\omega_n$ represent the changed and unchanged class, respectively. $T_{\rho}$ is the threshold value. It can be determined by classical manual trial-and-error procedure algorithm according to the mean value and standard deviation of the change magnitude map:

$$T_{\rho} = \text{Mean}(\rho) + t \times \text{Stdev}(\rho)$$  \hspace{1cm} (9)

where $t$ is a user-defined parameter.

For a changed pixel, the change class transition information can be obtained on the class type of the individual image, which determined by the highest abundance of the endmember. For example, the class of pixel $x^1$ is:

$$\text{class}_{x^1} = \arg \max_{k=1,2,\ldots,K} (Y^1_k)$$  \hspace{1cm} (10)

Similarly, $\text{class}_{x^2}$ is determined and the change state of this pixel can be decided, from class$_{x^1}$ to class$_{x^2}$. $k = 1, 2, \ldots, K$ represents different classes of endmembers. For the adopted V-I-S model, $K = 4$ and the endmembers are vegetation, high-albedo, low-albedo, and soil for representing four main land-cover changes in urban area. It should be noted that other definition of classes can be also used to describe the real land surface classes in the considered scene.

After the class labels are determined, the land-cover transition matrix is derived by relating the changed pixels in Step 3 with their class labels, thus to generate the change class transition information of the bi-temporal images.

(4) Analysis of change intensity. Change intensity or say the change probability is the indicator for revealing possible changes. For changed pixels that obtained in the previous step, the intensity can be also divided into several grades. Higher value of intensity represents the stronger change of a pixel, which is related to the high probability of real change in the urban area. These changes should be identified as key targets in the field investigation. Figure 3 shows the technical flow of the proposed CD method.

4. Experiments and discussions

4.1. Change detection accuracy evaluation

Some basic indices related to the change detection accuracy evaluation are first introduced here. The error matrix (i.e. confusion matrix) is built to derive these indicators as follows (23, 24) (Table 1).

![Figure 3. Flowchart of the proposed sub-pixel level change detection approach.](image-url)
Some common accuracy assessment indicators include:

- **Overall accuracy (OA):**

  \[
  OA = \frac{Cc + Uu}{T} \times 100\% \tag{11}
  \]

  OA describes the percentage of correct changed and unchanged detection pixels to the amount of test samples from the ground truth data.

- **Kappa coefficient:**

  \[
  Kappa = \frac{T(Cc + Uu) - (TC \times Tc + TU \times Tu)}{T^2 - (TC \times Tc + TU \times Tu)} \tag{12}
  \]

  Kappa reveals the internal consistency of change detection results. It describes detection accuracy more objectively than overall accuracy.

- **False alarm rate (Commission error rate):**

  \[
  P_F = \frac{Cu}{TC} \times 100\% \tag{13}
  \]

  It defines the percentage of false change by the ratio of false detected changes to total detected changes.

- **Miss detection rate (Omission error rate):**

  \[
  P_o = \frac{Uc}{Tc} \times 100\% \tag{14}
  \]

  It defines the percentage of omission changes using the ratio of undetected changes to total true changes.

### 4.2. Experiment on multi-temporal Landsat Thematic Mapper images

In the first experiment, Landsat Thematic Mapper (TM) images acquired on 12 August 2005 and 14 May 2007 over Xuzhou city, Jiangsu Province, China were selected to evaluate the proposed sub-pixel level change detection scheme. The size of the image is $900 \times 900$ pixels. The two images were registered using quadratic polynomial with the error less than 0.4 pixels. Since unmixing is performed to each image independently and the digital values are not compared directly, fine relative radiometric correction was not conducted. This is one of the advantages of the proposed method. Figure 4 presents the false color composite two-date images, and some major land-cover change areas are highlighted by blue circles, which are mainly due to the urban constructions during the study period.

For Landsat TM image, in BPNN there are six nodes in the input layer corresponding to six bands of data itself (the thermal infrared band is excluded). The number of nodes in the output layer corresponds to the estimated abundance of four endmembers, thus was set to four. After obtaining the abundance of two-date images, the abundance difference values of each endmember are then calculated and the result was processed based on built the decision rule in Section 3, so the change information can be detected in detail. Especially, for the used BPNN nonlinear unmixing model, there were four neurons in the hidden layer, with 0.2 as the learning ratio and 0.5 as the momentum in the learning process. Figure 5 presents the abundance values of four endmembers at two dates. The threshold $T_o$ is assigned as 0.976, based on Equation (10) and repeated tests. The derived

![Figure 4](image-url)

Figure 4. Study area and its false color composite images (blue circles highlighted are the significant land-cover change during the study period).
binary CM is then overlaid on the Band 7 of 2005 image, as shown in Figure 6(a).

In order to compare the CD results with other popular methods, we tested the multi-band pixel-level change detection methods change vector analysis (CVA) and principle competent analysis (PCA)-based approach to process the same data-set. In particular, for CVA, only the magnitude information was selected in order to compare with the binary change detection result of the proposed method. For PCA method, the first three principal components of the differential image were selected for change detection, which contained more than 97% change information of the original multi-temporal data. Majority voting scheme was used to combine the results from three individual components (25). The binary change detection result was obtained using the $KI$.

| Change detection methods | OA (%) | Kappa   | Omission rate (%) | Commission rate (%) |
|--------------------------|--------|---------|-------------------|---------------------|
| Pixel level              |        |         |                   |                     |
| CVA                      | 86.08  | 0.7191  | 21.16             | 9.41                |
| PCA                      | 84.82  | 0.6937  | 22.61             | 10.82               |
| Sub-pixel level          |        |         |                   |                     |
| The proposed method      | 90.45  | 0.8083  | 11.18             | 9.16                |
thresholding algorithm (26). The results are presented in Figure 6(b) and (c).

With the help of the available ground truth data including the historical land use map, the previous field work and the carefully image interpretation, a group of changed pixels (1064 pixels), and a group of unchanged pixels (1009 pixels) are used as test samples to evaluate accuracies of different methods. The confusion matrix was built and four accuracy indices were derived (see Table 2).

Some basic observations can be found as follows:

1. The proposed change detection approach detected most of the land-cover changes on the considered images, with the highest overall accuracy (90.45%) and kappa coefficient (0.8083) compared with CVA (86.08% and 0.7191), and PCA (84.82% and 0.6937), together with lower commission and omission rates. Especially, the omission error is reduced effectively because the proposed approach considers more change information in a sub-pixel scale, which is usually undetectable in a pixel level.

2. By visual analysis to the detected CMs, we can find that the changed pixels are quite consistent with the real urban development trend. The main changes occurred in the south Tongshan new district, east urban Economic Development Area and the new city area in southeast region, as a result of urban planning and rapid construction.

In addition, the proposed method can also obtain other important change information except detecting the change pixels. Figure 7 shows the change class transitions between two dates, with the transition matrix indicating the quantity of each group of change. Figure 8 shows the change intensity map based on change probability. Different colors indicate different change probability of a pixel. In order to make much clearer the visual analysis, two blocks are selected to demonstrate performances of different methods in a detailed perspective (see Figure 9). We can observe that:

1. The proposed sub-pixel level change detection detects changed pixels and describes the change intensity and direction in detail, providing finer descriptions to land-cover changes;
2. The change intensity obtained in the method is quite important to provide a soft change detection result, by which the pixels with high, medium, and low change probability can be determined and used as the guide of field work according to different requirements to change target areas;
3. From the comparison of two subset image blocks, we can observe that the proposed method describes better change targets than traditional methods, evidenced by the more reliable edges of changed areas and more complete change information; and
4. The transition matrix demonstrates that the land-cover changes from 2005 to 2007 were mainly from vegetation to high-albedo (13,923 pixels), from soil to high-albedo (5591 pixels), vegetation to low-albedo (3107 pixels), and low-albedo to high-albedo (1386 pixels). For the change intensity results, the highest change probability regions in red are related to the real vegetation to high-albedo object change, which is consistent with
actual land-cover change. This is an effective way to describe the rapid urbanization process according to the qualitative and quantitative output results.

4.3. Experiment on multi-temporal China-Brazil Earth Resources Satellite images

In the second experiment, the China-Brazil Earth Resources Satellite (CBERS) images over Shanghai city acquired on 7 March 2005 and 7 May 2009 were used for change detection. The image size is 1000 × 1000 pixels, covering the urban area and Pudong New District of Shanghai. The main land-cover changes during the study period are built-up areas and vegetation changes, together with some minor changes of soil and water. Figure 10 shows the location of the study area and false color composite of two-date images, with blue circles showing some significant change areas determined according to the ground truth data.

Similar to the processing flow in the previous experiment, we obtained the abundance maps of different end-members on two dates (Figure 11). The hidden layer was set as 4 neurons, with 0.2 as the learning ratio and 0.5 as the momentum. The threshold to determine change pixels from abundance different map was set equal to 0.962. The detected changed pixels were then highlighted by red color with the Band 5 image of CBERS as background. CVA and PCA were also used to generate the comparison results. The binary CMs detected by different methods are presented in Figure 12.

The test samples including 1089 changed pixels and 1573 unchanged pixels were used to build the confusion matrix and calculate four accuracy indices. In Figure 12 and Table 3, we can find that the proposed method
obtained higher overall accuracy (i.e. 89.86%) and kappa coefficient (i.e. 0.7791) than CVA and PCA, and the commission rate and omission rate were reduced or remained at the similar level.

The results shown in Figures 13–15 illustrate the land-cover transition result, the change intensity map, and subsets from different change detection results. We can see that:

1. The proposed sub-pixel level change detection approach provides reliable change detection results, which is consistent with the ground truth data and photo interpretation result. It not only provides the changed and unchanged binary change detection results, but also generates the multiple change information including change
transition, direction, and intensity, to the end-user or decision maker. The land-cover transition matrix gives the quantitative evaluation of the changes, thus describing the relevant change areas in a more detailed way. At the same time, the change intensity result provides the additional rich information to represent change probabilities, and especially the high probability regions (e.g., pixels in red on the change intensity map) are much more close to the real changes.

(2) The change matrix, which is directly related to the detected change classes, reflects the land-cover transitions among different classes. From the change matrix, we can find the land-cover changes in the study area during 2005 and 2009 are mainly from low-albedo to high-albedo (5498 pixels), soil to high-albedo (4157 pixels), low-albedo to soil (4008 pixels), and soil to vegetation (2806 pixels). Thus, it is obvious that the urbanization process has high impact on the land-cover changes in urban areas. In particular, the transitions among the low-albedo,
high-albedo, and soil mainly due to the change of built-up areas, and changes from soil to vegetation indicate the improvement of green space.

(3) The extracted results at sub-pixel level detection are more complete and accurate than pixel-level methods, providing multiple change information to facilitate the decision-making and field investigation. For the CVA and PCA-based methods, they produce some errors especially the omission errors, which decrease the overall change detection accuracy.

5. Conclusion and remarks

In this paper, a novel change detection approach based on the spectral mixture model is proposed using the nonlinear BPNN and V-I-S model. It aims to find the sub-pixel level variation in the medium/low spatial resolution multi-temporal remote sensing images, where the change detection task usually faces the spectral mixture problem. By taking advantage of the spectral unmixing techniques, each pixel is decomposed at first to derive the abundance values of four endmembers, and the abundance changes of four endmembers are then compared to detect the change pixels based on the decision rules. The proposed method is validated on two real remote sensing satellite image data-sets (Landsat TM and CBERS) and compared with CVA and PCA-based two pixel-level change detection methods. From the experimental results, we can draw the following conclusions:

(1) The proposed change detection approach is effective to detect land-cover changes over urban area and it can obtain multiple change information (e.g. binary changes and other additional information). The usual sub-pixel change detection is conducted based on PCC or impervious surface analysis, thus mainly relying on the single-time classification accuracy or on the simple impervious surface comparison, which may lose the chance to investigate more detailed changes inside a single pixel. The designed sub-pixel level change detection scheme takes into account of the spectral mixture problem in the practical case of urban land cover using the medium/low resolution remote sensing images, thus avoiding the defect of pure pixel assumption. Moreover, reliable change detection result can be obtained due to the analysis of multiple endmember transition in a sub-pixel processing level.

(2) The proposed method combines the advantages of both supervised and unsupervised approaches. The unmixing process is based on the image spectral properties, especially the mixed spectral composition within a single pixel, thus is free to strict requirement to the relative radiometric correction. Decision rules to find change pixels are unsupervised and easy to be implemented. It can be seen that the proposed method is superior to traditional binary change detection methods, because it explored much more potential change information in the sub-pixel level, which is usually undetectable in the pixel-based approaches. Thus the detection errors especially the omission errors can be reduced due to the limitation of change representation only in the pixel-level of processing;

(3) In addition to provide the binary change information, some other information including change intensity based on change probability and change direction indicating the land-cover transition, can be also obtained. This is helpful to transform the traditional hard change detection to soft change detection, to meet with different requirements in real change detection applications.

However, in the practical change detection applications, the successful implementation of the proposed method depends on the complexity of the data itself and also on the selective use of the effective spectral-unmixing techniques. Nonlinear BPNN is used as the spectral mixture model, because it has been widely used and proved to be superior to LSMM over urban areas in different applications. But it should be noted that other spectral mixture models (both the linear and nonlinear) are also applicable in the proposed process to decompose the endmembers. However, the detection accuracy is affected by some factors (e.g. thresholding), which need to be further investigated in the further future work to improve the automatic level of the processing, and also increase the change detection accuracy.

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