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Abstract. Threshold selection is a critical step in using binary change detection methods. The threshold determines the accuracy of change detection results but is highly subjective and scene-dependent, depending on the familiarity with the study area and the analyst's skill. Nearest neighbor classification is a non-parametric classifier, which was applied to remove the threshold. In order to find the most suitable feature to detect construction and farmland changes, a variety of single and multiple variables were explored. They were regional similarity (RSIM), brightness difference images (BDIs), multi-band difference images (MDIs), multi-band ratio difference images (MRDIs), a combination of RSIM and BDIs (RSIMBD), a combination of RSIM and a optimum band difference and a optimum band ratio difference (RSIMDR), MDIs and MRDIs multiple variable groups. All were tested for two study sites of the bi-temporal SPOT 5 imagery, the results indicated that RSIM, RSIMDR, RSIMBD were significantly better than other single and multiple variables.

Keywords: Object-Oriented, Binary Change Detection, Nearest Neighbor Classification, RSIM

1 Introduction

Change detection is the process of indentifying differences in the state of an object or phenomenon by observing it at different times.[1] It is a core problem in resource and environmental monitoring, disaster monitoring, land management, city expansion, geographic information update and dynamic monitoring of the military battlefield. In the past years, researchers have put forward a large number of change detection techniques which can be categorized into two groups: (1) those detecting binary change information (i.e., change vs. no change); and (2) those detecting detailed 'from-to' change information.[2]

'From-to' change detection algorithms (e.g., post-classification comparison) provide detailed information about the location and type of land_use/cover change (e.g., from farmland to building) for every pixel or object under investigation. The key in using these methods is to create accurate thematic classification images. The errors of individual-date thematic images will affect the final change detection accuracy. [3] Even though the ideal goal of change detection is often to extract 'from-to' change information, however, sometimes rapidly obtaining change and no change information is valuable. A variety of methods have been applied to binary change detection, for example, image differencing, image ratioing, vegetation index differencing and PCA.[4-6]

One critical step in using binary change detection approaches is to select the appropriate thresholds to generate binary change mask. Empirical threshold method is usually used for selection of thresholds, which is an interactive procedure or manual trail-and-error procedure. For example, the optimum threshold can be determined by using the mean and standard deviation of the training samples.[7] However, the threshold is highly subjective and scene-dependent, depending on the familiarity with the study area and the analyst's skill. In order to improve the change detection results, many semi-automatic or automatic threshold determination methods are developed. Im et al. used a calibration approach by autonomously testing thousands of thresholds and selected the optimum threshold(s) showing the highest accuracy.[8] The systematic search technique and a Moving Threshold Window (MTW) were proposed to improve the efficiency and accuracy, respectively.[9, 10] Wang et al. put forward adaptive spatial neighborhood analysis and Rayleigh-Gauss distribution fitting for change detection in multi-temporal remote sensing images, while the optimal threshold was calculated automatically and effectively by the improved Kittler-Illingworth (KI) threshold selection algorithm.[11] Although some advanced threshold approaches have been developed, these are still only applied to specific applications for a specific environment due to its complexity. Nearest neighbor classification as a non-parametric classifier, is only determined by the quality of samples and the selection of features, which is independent of threshold.

Change detection is a complicated and integrated process.[12] Successful remote sensing change detection requires careful attention to: (1) remote sensor system considerations, such as radiometric resolution, spatial resolution, look angle, and (2) environmental characteristics of the study areas, including atmosphere condition, complexity of the landscape and topography.[13] After image data and study areas have been determined, selection of an appropriate change detection method assumes considerable significance. Traditional binary change detection methods usually use a single variable (e.g., band 1 difference). However, the use of multiple bands simultaneously might produce better results (e.g., band 1 difference and band 2 ratio difference). Thus, how to customize the optimum multiple variables becomes another problem. In addition, now there is great interest in indentifying change in high spatial resolution multi-temporal data, such as that provided by GeoEye, Inc., DigitalGlobe, Inc., Leica Geosystems, Inc. Unlike medium- to coarse-resolution imagery, there are ample spectral information, textural information, structure information in high spatial resolution imagery. Many traditional change detection methods based on per-pixel analysis may not function successfully in the high-resolution domain. A serious problem found in per-pixel approaches is the 'salt-and-pepper' phenomenon in change detection results, which is meaningless for application. Therefore, objected-oriented change detection methods have been put forward where homogeneous polygons found in two dates of imagery are compared.[14, 15]

Hence, the objectives of this study included: (1) development of an object-oriented binary change detection method using nearest neighbor classification to replace the thresholds, (2) customization of a variety of single and multiple image variables to extract change information, and (3) validation of binary change classifications with the variables, especially focusing on a comparison between the detection results using single versus multiple image variables.

2 Materials and Methods

2.1 Study Area and Data

Two study sites representing new construction in Changping District, Beijing were selected to demonstrate the nearest neighbor classification for object-oriented binary change detection (Fig.1). The first study site (Site A) is located in southeast Changping District, and exhibits new buildings and change between different growth farmlands. The second study site (Site B) is located 1km east of Site A, and exhibits change from farmlands and water to buildings.

SPOT 5 imagery acquired over the two study sites in Changping District on October 01, 2002 and October 16, 2007 was used for validating the binary change detection. The area obtained spectral information in four multispectral bands (i.e., near-infrared (NIR), red, green, and short waved-length infrared (SWIR)) with 10-meter spatial resolution and one panchromatic band with 2.5-meter spatial resolution (wavelength ranges from 0.48-0.71μm).

In the preprocessing, the bi-temporal images were geo-referenced to a Transverse Mercator (UTM) projection in WGS 84. Rectification errors were less than 0.5 pixel (RMSE). Even though they were obtained on near-anniversary dates, it was still necessary to radiometrically normalize the two dates of remote sensor data since the subsequent analysis (e.g., multi-band differencing, multi-band ratio differencing) directly compared the Digital Number (DN) values from the bi-temporal imagery. The radiometric normalization method using histogram matching was applied. Then Principal Component Analysis method was used to do image merge to get high spatial resolution and fine detail.

(a) Site A (October 01,2002) (b) Site A (October 16,2007)

(c) Site B (October 01,2002) (d) Site B (October 16,2007)

Fig. 1. (a)-(d) Bi-temporal SPOT 5 imagery for two study sites (A, B), respectively.

2.2 Methods

This object-oriented change detection research aimed to identify the single or multiple variable(s) that is/are most suitable for extracting buildings and farmlands change regions through a comparison of the customized features using the nearest neighbor classification. In order to generate one–to-one mapping relationship of the object with the bi-temporal imagery, two dates of imagery were used together in multi-resolution segmentation procedure. Then, several training/test data were randomly collected within each study site. The binary change information for each sample location (i.e., change vs no change) was identified through visual interpretation of the bi-temporal SPOT 5 imagery. A variety of variables associated with change information were customized and applied to the nearest neighbor classification. A brief summary of the change detection flow was found in Fig.2.

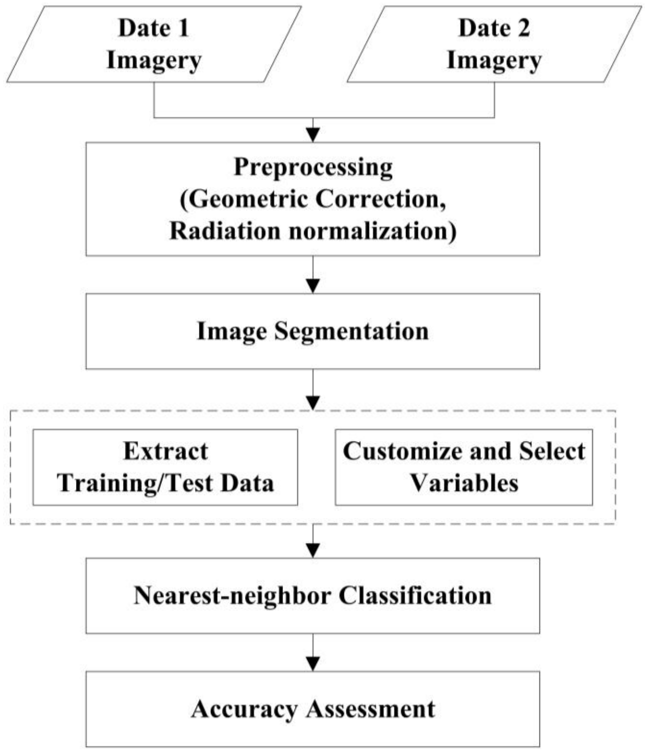


Fig. 2. Flow diagram of the binary change detection method.

Nearest Neighbor Algorithm to Binary Change Detection Method

Nearest neighbor classifier is a popular non-parametric classifier used in many field.[16] When input several samples for each class, the nearest neighbor classifier computes the distance from the object to be classified to the nearest training object and assigns it to the class of the training object. Due to its simplicity and avoiding threshold problem, it is selected as a technique for change classification. However, there are two mainly disadvantages of nearest neighbor classifier. One is that its classification accuracy depends on the training data. Therefore, 24-26 objects as training samples were collected for each study site through visual inspection with at least 12 objects per class. For a reasonable comparison between the change detection results, the same training data for each site were used in the classification. And the other is called the ‘curse of dimensionality’. Dimensionality means the number of features. Usually when the dimensionality is more than 20, the calculation is very slow. What’s worse, the accuracy of the classification tends to deteriorate after the dimensionality up to a specific value. So it is necessary to optimize the feature space.

Single and Multiple Variables

In order to identify binary change detection methods that were most appropriate for new construction, a variety of variables were explored. These variables included regional similarity (RSIM), brightness difference images (BDIs), multi-band difference images (MDIs), multi-band ratio difference images (MRDIs) generated from the bi-temporal imagery were used as input variables. Every variable was introduced as follows:

RSIM[17] is used to detect change by evaluating the degree of regional similarity in the same region in two registered remote sensing images obtained on different dates. If the spectral changes of the object between two image dates are significant, the RSIM will fall off to a lower value. There exists three parts of RSIM, which are correlation, brightness ratio and contrast. See the equations:

$$RSIM=\frac{4\sigma_{12}\overline{BV}_1\overline{BV}_2}{(\sigma_1^2+\sigma_2^2)[(\overline{BV}_1)^2+(\overline{BV}_2)^2]}=\frac{\sigma_{12}}{\sigma_1\sigma_2}\cdot\frac{2\overline{BV}_1\overline{BV}_2}{(\overline{BV}_1)^2+(\overline{BV}_2)^2}\cdot\frac{2\sigma_1\sigma_2}{(\sigma_1^2+\sigma_2^2)} \tag{1}$$

Where

$$\sigma_{12}=\frac{1}{B\text{-}1}\sum_{i=1}^{B}(BV_{i1}\text{-}\overline{BV_1})(BV_{i2}\text{-}\overline{BV_2}) \tag{2}$$

and σ_{12} is the covariance between object mean spectral values found in all bands of the two date imagery, σ_1, σ_2 are the standard deviation of the object mean spectral values found in all bands of each date imagery, respectively. While BV_{i1} is the i th object mean spectral value of image 1, BV_{i2} is the i th object mean spectral value of image 2, B is the total number of the bands for each image, and $\overline{BV}_1$, $\overline{BV}_2$ are the means of object mean spectral values found in all bands of the two date imagery, respectively.

Brightness difference images (BDIs) is used to detect change by computing the brightness difference of the two date imagery. As some classes are quite different in brightness, such as buildings and farmland, this variable is suitable to extract those change regions.

$$Diff\_Brightness=\frac{1}{B}\sum_{i=1}^{B}BV_{i2}\text{-}\frac{1}{B}\sum_{i=1}^{B}BV_{i1} \tag{3}$$

Multi-band difference images (MDIs) are the differences of object mean spectral value in each band for the two date imagery, and multi-band ratio difference images (MRDIs) are the ratio differences of object mean spectral value in each band for the two date imagery.

$$Diff\_Band(\mathrm{i})=BV_{i2}\text{-}BV_{i1} \tag{4}$$

$$Diff\_Ratio(\mathrm{i}) = \frac{BV_{i2}}{\sum_{j=1}^{B} BV_{j2}} - \frac{BV_{i1}}{\sum_{j=1}^{B} BV_{j1}} \quad (5)$$

A total of 20 single variables were tested with the nearest neighbor change classification for the two study sites. Each variable group (i.e., MDIs, MRDIs) was used as the inputs for multiple variables. The another group of multiple variables that consisted of one variable from the BDIs and MDIs, each showing the best performance in the experiments with the single variables, and RSIM were selected and tested, namely RSIMDR. In order to demonstrate BDIs provide change information that can be used as ancillary data to facilitate change detection with RSIM, a combination of RSIM and BDIs (RSIMBD) was also selected and tested. Thus, a total of 8 groups of multiple variables were evaluated with the binary change detection method for two study sites.

Accuracy Assessment

An accuracy assessment was accomplished for the binary change classifications (i.e., change and no change) of Site A and Site B. In each case, the accuracy assessment included overall accuracy (OA), the Kappa coefficient, the user's accuracy (UA) and the producer's accuracy (PA). And test samples for each class were randomly collected within each study site.

3 Results and Discussion

3.1 Object-Oriented Binary Change Detection Using Single Variables

A variety of single variables associated with change information were customized for the binary change detection, including regional similarity (RSIM), brightness difference images (BDIs), multi-band difference images (MDIs), multi-band ratio difference images (MRDIs). The image objects used in generating those variables were created from the multi-resolution segmentation technique in eCognition, one of the widely used object-oriented image processing software. A scale parameter of 70, a spectral factor of 80%, a shape factor of 20%, which was subdivided into smoothness (6%) and compactness (14%), and equal weights for the all eight bands were used in the image segmentation process. While the RSIM and BDIs had only one variable each, the MDIs and MRDIs contained four individual variables each, using the four bands of the SPOT 5 imagery.

The overall accuracy and Kappa coefficients of each single variable for the two study sites were shown in Table 1(a). RSIM achieved the best overall accuracy and Kappa performance for both two study sites, while the band 1(i.e., band NIR) difference resulted in the worst overall accuracy and Kappa performance for both two study sites. In addition, the single variable of the same band from the MRDIs was better than this from the MDIs.

The nearest neighbor change classification using the band 4 difference variable produced the highest overall accuracy and Kappa coefficient among the single variables from the MDIs for Site A. The band 3 ratio difference variable yielded the best performance (OA=85.19%, Kappa=0.707) among the single variables from the MRDIs for Site A. The single variables from the MDIs resulted in larger variation in the OA and Kappa than those from MRDIs (Δ OA=14.83% vs. 7.41%, Δ Kappa=0.295 vs. 0.147) for Site A. Dissimilarly to Site A, the band 3 difference variable from the MDIs, the band 2 and band 3 ratio difference variable from the MRDIs produced the same good performance (OA=76.92%, Kappa=0.538) for the Site B. However, the band 1 difference variable yielded the worst change detection result (Kappa=0.080) among all single variables for the Site B. In addition, the single variables from the MDIs resulted in larger variation in the OA and Kappa than those from MRDIs (Δ OA=23.07% vs. 11.54%, Δ Kappa=0.458 vs. 0.230) for Site B.

3.2 Object-Oriented Binary Change Detection Using Multiple Variables

Based on the change detection results using the multiple variables for the two study sites, as shown in Table 1(b), RSIMBD multiple variable group was slightly better or equal to that based on the RSIMDR group, which produced the highest classification accuracies. However, the change detection results using MDIs, MRDIs multiple variables resulted OA of 74.07% and 77.78% for Site A, which were even lower than the accuracy achieved by the single band 4 differencing and band 3 ratio differencing. Similarly to Site A, the MDIs, MRDIs multiple variables also did not produced higher accuracies than those yielded using single band 3 differencing and band 3 ratio differencing. Therefore, the multiple variables may not always do good performance. On the other hand, as each variable had its own characteristics, representing different capabilities for distinguishing land-use/cover types, a suitable combination may improve the final accuracy of the change classification. For example, the BDIs single variable which only detected the change objects existing large brightness differences, resulted a bad accuracy, however, it facilitated change detection with RSIM. The OA of RSIMBD (RSIM+BDIs) multiple variables increased 11.14% and 3.84% compared with RSIM for Site A and Site B, respectively.

Table 1. OA and Kappa using the single and multiple variables for Site A, Site B.

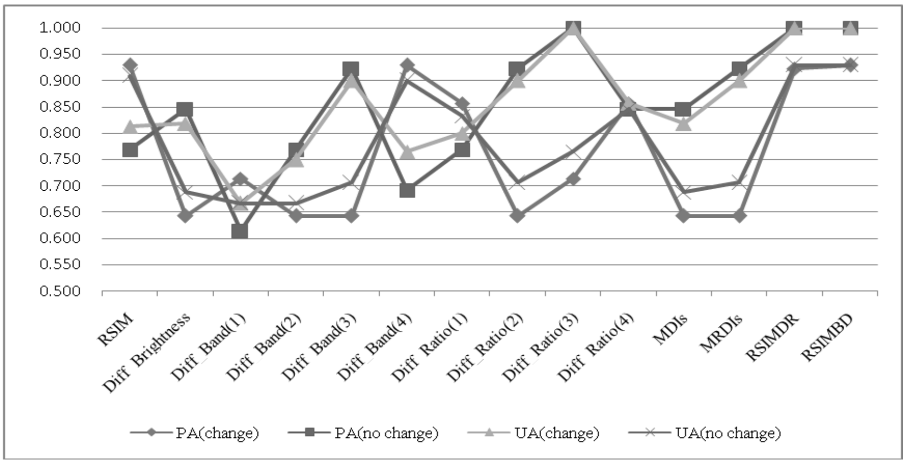
(a) Single variables			
Site	Single varible	OA (%)	Kappa
Site A	RSIM	85.16	0.702
	Diff_Brightness	74.07	0.485
	Diff_Band(1)	66.67	0.331

	Diff_ Band(2)	70.37	0.410
	Diff_ Band(3)	77.78	0.560
	Diff_ Band(4)	81.50	0.626
	Diff_Ratio(1)	81.48	0.628
	Diff_Ratio(2)	77.78	0.560
	Diff_Ratio(3)	85.19	0.707
	Diff_Ratio(4)	85.19	0.703
Site B	RSIM	88.46	0.769
	Diff_Brightness	61.54	0.231
	Diff_Band(1)	53.85	0.080
	Diff_Band(2)	73.08	0.462
	Diff_Band(3)	76.92	0.538
	Diff_Band(4)	69.23	0.385
	Diff_Ratio(1)	73.08	0.462
	Diff_Ratio(2)	76.92	0.538
	Diff_Ratio(3)	76.92	0.538
	Diff_Ratio(4)	65.38	0.308

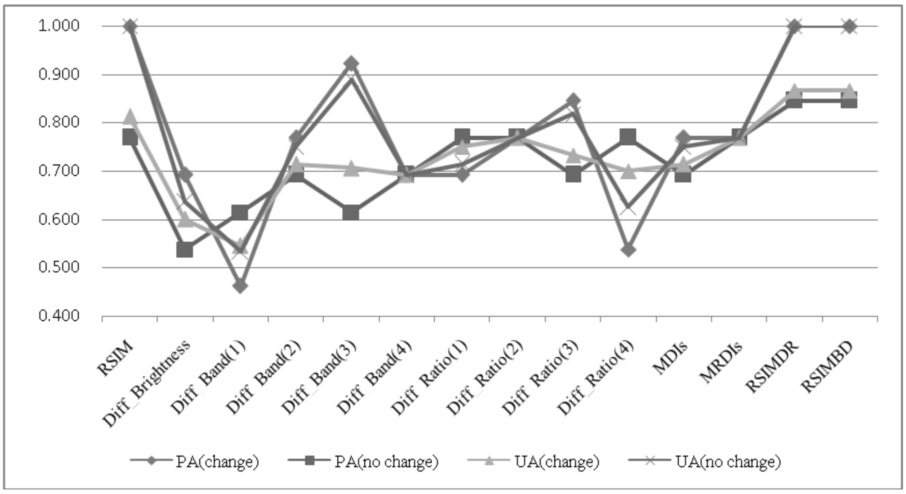
(b) Multiple variables

Site	Multiple variables	OA (%)	Kappa
Site A	MDIs (band 1 through 4 difference)	74.07	0.485
	MRDIs (band 1 through 4 ratio difference)	77.78	0.560
	RSIMDR (Diff_Band(4) + Diff_Ratio(3) + RSIM)	96.15	0.923
	RSIMBD (RSIM+ Diff_Brightness)	96.30	0.926
Site B	MDIs (band 1 through 4 difference)	73.08	0.462
	MRDIs (band 1 through 4 ratio difference)	76.92	0.538
	RSIMDR (Diff_Band(3) + Diff_Ratio(3) + RSIM)	92.30	0.846
	RSIMBD (RSIM+ Diff_Brightness)	92.30	0.846

As the performance of change detection results should not only be based on the indicators of OA and Kappa, but also consider other accuracy statistics such as user's and producer's accuracies. Thus, the PA and UA comparison using the single and multiple variables for the two study sites were shown in Fig.3. Although the OA and Kappa values of single variables were lower than the accuracy using RSIMBD multiple variable group, it was found that some single variables were very suitable to identify certain change class. For example, the band 4 difference was good at identifying the change class and had small errors of omission as the producer's accuracy reached to 0.929 for Site A, while the band 3 difference was suitable to identifying the change class as the producer's accuracy reached to 0.923 for Site B. In addition, the band 3 difference, band 2 ratio difference and band 3 ratio difference all produced a higher producer's accuracy in extracting no change class than RSIM for Site A, and band 3 difference also yielded a higher producer's accuracy in extracting no change class than RSIM for Site B. Thus, the RSIMDR multiple variable group was good at identifying both change and no change class.



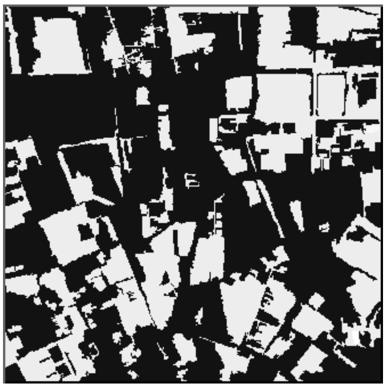
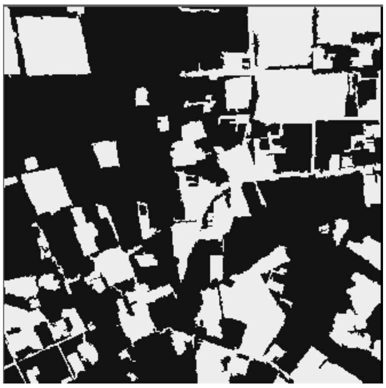
(a) Site A



(b) Site B

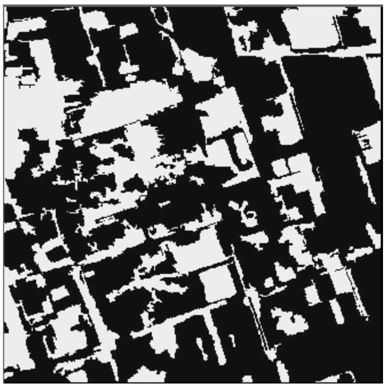
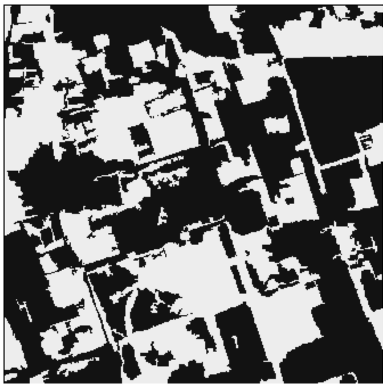
Fig.3. PA and UA comparison using the single and multiple variables for Site A, Site B.

Comparison of binary change detection for the best and the worst performance using the single and multiple variables for each site were shown in Fig.4. The band 1 difference variable misidentified many unchanged buildings as change objects in the upper middle part and down left part of Site A (Fig.4.(a)), and also misidentified some unchanged buildings as change objects in the middle part of Site B (Fig.4.(c)). Besides, the band 1 difference variable did not detect some new construction as change in the middle down part of Site B (Fig.4.(c)). On the other hand, the RSIMBD multiple variables yielding the highest OA and Kappa for each site detected the change areas well, but a few changed objects, such as from water to farmland, were not detected successfully.

(a) Band 1 difference single variables for Site A
Worst

(b) RSIMBD multiple variables for Site A
Best

(c) Band 1 difference single variables for Site B
Worst

(d) RSIMBD multiple variables for Site B
Best

change   no change

Fig.4. (a)-(d) The worst and best change detection results for Site A, Site B.

4 Conclusion

Binary change detection methods have many advantages and disadvantages. Generally, the binary change detection method is a threshold-based calibration process, which the optimum threshold was found through trial and error. However, such an approach is time-consuming and highly subjective. The research successfully employed the binary change detection method with nearest neighbor classification technique, removing the threshold problem existing in the traditional binary change detection method.

Additionally, a variety of single and multiple variables were explored to extract change information for two study site. The results showed that not all multiple variables produced better performance than the single variables. However, a combination of the best performance in the experiments with the single variables, or those achieved good performance in a certain class, usually produces significantly better accuracy than others. The RSIM single variable yielded the best performance in the nearest neighbor change classification when using single variables. What's more, the combinations of RSIM and other single variables from MDIs and MRDIs, or BDIs, produced the highest overall accuracy and Kappa value than any other multiple variables. The fact that the RSIM combined the correlation, brightness ratio and contrast of all eight bands simultaneously explained the superiority.

The drawback of the proposed method concerned only spectral features of high spatial resolution SPOT 5 imagery, so objects of the same class with different spectral value is misidentified changed class easily. Future works could focus on developing other useful texture or structure features to binary change detection method and applying the method with different types of remote sensor data, such as QuickBird, WorldView.

Acknowledgments. The research was funded by the Pre-Development of the High Resolution Application Demonstration System on Land Resource "Research on the Land Use Type Quickly Extraction with High Resolution Data"(E0202/1112/0104)，and "Potential Study on Land Resource Management Applications of Archived Remote Sensing Data" (201109109188). The authors would like to thank the anonymous reviewers for their constructive comments and suggestions.

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