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Long-term Land Cover Change Detection Using Multisensor and Multiresolution Remote Sensing Images: A Case Study of Chang'an University, China

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Change detection is one of the most important aspects of remote sensing applications. However, owing to the limited conditions of image acquisition, images obtained from the same type of remote sensors are usually used to monitor long-term land use and land cover (LULC) changes. Owing to developments in aerospace technology and new optical remote sensors, LULC change detection can be performed well with multisensor and multiresolution images. The main contribution of this article is to verify that it is feasible and practicable to perform long-term LULC change detection by applying different change detection methods to multisensor and multiresolution remote sensing images. In this study, different change detection methods were used on Landsat, QuickBird, WorldView-4, and GF-2 images to detect LULC changes on Weishui Campus of Chang'an University, China, from 1998 to 2018. Results showed that the direct spectral comparison method using Landsat-5 images could more efficiently detect LULC changes between 1998 and 2008 than the post-classification change detection method using Landsat-7 images. However, for 2008–2018, the object-based change detection method was more applicable than the post-classification method for monitoring LULC changes on campus by using time-series high-resolution images. This study can be used as a reference for the utilization of multisensor and multiresolution remote sensing images and the combination of different change detection methods in the LULC change detection field.

1. Introduction

With the rapid urbanization and increasing population of China over the last few decades, major changes have taken place in the land use and land cover (LULC) patterns of China.[(1)] LULC change detection techniques are an important tool for detecting changes on the earth's surface at different spatiotemporal scales.[(2)] LULC patterns are to a large extent determined by the natural environment and the demand for various economic activities, which also have a

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critical influence on urban development. Thus, toward managing natural resources reasonably, keeping the harmony between human beings and nature, and promoting the sustainable development of society, it is extremely important to utilize various change detection methods to monitor LULC changes precisely and constantly. With the development of aerospace technology, new remote sensing images have become widely available,(3) and LULC change detection using remote sensing methods has become a mainstream technology.(4)

In 1989, Singh(5) defined change detection as "the process of identifying the differences of an object or phenomenon in the state by observing it at different times". With the progress of satellite and sensor technology, remote sensing images have become the main sources of LULC change detection in the last decade.(6) On the basis of the spatial resolution of remote sensing images, change detection methods have been further explored in two directions: low- or medium-resolution image change detection and high-resolution image change detection. Low- or medium-resolution remote sensing images are the main data source for traditional change detection research; because of their simple data structure, concise information, and moderate resolution, they can be applied to most LULC change detection tasks and are the basis of change detection technology. Various image processing algorithms have been proposed to solve the problem of low- or medium-resolution image change detection, such as principal component analysis, image algebraic methods, and image conversion methods, which can detect change information at the pixel level. Many researchers have attempted to use low- or medium-resolution remote sensing images to address LULC change detection problems, such as crop species classification and urban changes. Since 1990, medium-resolution remote sensing images obtained from remote sensors, such as multispectral scanners (MSSs), thematic mappers (TMs), and operational land imagers (OLIs), have been extensively used for LULC change detection analysis worldwide. For example, Fan *et al.*(7) employed TM and ETM+ images to detect and predict LULC changes in the central corridor of the Pearl River Delta, China. Ahmed *et al.*(8) applied TM images to detect LULC changes in northeast Cairo, Egypt. Mariwah *et al.*(9) used multispectral Landsat TM data and performed the post-classification change detection technique to drive the LULC changes in the Tema Metropolis of Ghana from 1990 to 2010. In addition, with the help of recently emerged remote sensing image processing algorithms, many LULC change detection techniques have been developed, such as image differencing,(10) spectral change vector analysis,(11) and post-classification comparison.(12) Change detection methods using low- or medium-resolution remote sensing images are the earliest, most commonly used, and most intensively studied methods. Since 2000, the successful launch and rapid development of high-resolution commercial remote sensing satellites and optical sensors have gradually enhanced the spatial resolution of remote sensing images. Consequently, updated change detection algorithms, such as object-based image analysis, have been applied to the field of change detection. A variety of pixel-based methods were correspondingly introduced in object-based change detection, and good results were obtained in terms of maps and accuracy. For example, Walter introduced a change detection approach based on an object-based classification of remote sensing data.(13) According to Walter's research, the object-based classification method can extract feature information at different scales based on the characteristics of land features. Accordingly, the accuracy of information extraction and classification can be greatly improved.

Moreover, the object-based classification method is fully automatic because all classification information is derived from routinely generated training fields. Furthermore, the outcome is not only a detection of change, but also a classification of the most likely LULC class. Despite the major advantages of this technique, there are also a few disadvantages. For example, when the research area is small, change detection at the pixel level produces many spurious and noisy pixel points, which is mainly because of the variability of the spectrum and the alignment error of the image.

Most change detection applications use multitemporal remote sensing images from the same sensor. However, homogenous remote sensing images may not be able to provide suitable repeat observations due to difficulties, such as a high financial cost and long coverage period. Moreover, despite the fact that homogenous remote sensing images providing suitable repeat observations are comparatively widely available with the help of low- or medium-resolution image satellites, LULC change detection results are still far from satisfactory. To solve the problems mentioned above, several attempts have been made to combine multisensor and multiresolution remote sensing images to obtain the best change detection results for specific LULC change detection applications. For example, Schmitt *et al.*(14) developed a new consistent framework for the production, archiving, and provision of analysis-ready data from multisensor and multitemporal images acquired from satellites and subsequent image fusion. Deng *et al.*(15) combined principal component analysis of multisensor satellite images from SPOT and Landsat-7 data, and used a supervised classification method to detect and analyze the LULC changes in the city center of Hangzhou. These studies of multisensor and multiresolution change detection can greatly expand the application of change detection techniques. Multisensor and multitemporal data can provide multiangle observations due to the different imaging mechanisms and observation characteristics, but it is difficult to establish the relevance of feature characteristics. Gong *et al.*(16) established feature correlation by using two corresponding sparse expression dictionaries. Camps-Valls *et al.*(17) achieved change detection by defining kernel functions for multisource data. An increasing number of general multisensor change detection studies are expected to appear in multitemporal data analysis, such as of high-spectral and high-resolution images. Data with higher resolution often cannot have a revisit period as short as that of low-resolution remote sensing images; therefore, the development of multiresolution change detection can greatly improve the observation density of multitemporal data and obtain change detection results with high resolution. Wang *et al.*(18) used the classification results of high-resolution images and the soft classification results of low-resolution images for subpixel mapping, and then obtained change detection results for subpixel classification maps. Existing research still mainly focuses on change detection methods with single-source remote sensing images, so how to efficiently use multiresolution images to achieve precise LULC change detection results remains to be further explored.

LULC changes are a dynamic and constant process.(19) Thus, extensive research on LULC change patterns is extremely important along with their social and environmental inference at different spatial and temporal scales.(20) At present, remote sensing images obtained from the same types of sensors, especially from low- or medium-resolution sensors, are generally used to apply change detection methods. However, because of the fact that homogenous remote sensing images may lack suitable repeat observations and change detection results acquired from low- or medium-resolution images are far from satisfactory compared with those acquired from high-resolution images, how to make full use of multisensor and multiresolution images to conduct LULC change detection needs to be further studied. This study mainly focuses on the usage of multisensor, multiresolution, and multitemporal remote sensing images, and the application of different combinations of change detection methods to different remote sensing images in the LULC change detection field. During our experiment, change detection methods, such as direct spectral comparison, post-classification comparison, and object-based change detection, were used on Landsat, QuickBird, WorldView-4, and GF-2 images to detect LULC changes on Weishui Campus of Chang'an University, China, in the period of 1998–2018. The experimental results showed that the direct spectral comparison using Landsat-5 images could more efficiently detect LULC changes on Weishui campus between 1998 and 2008 than post-classification change detection using Landsat-7 images. For 2008–2018, object-based change detection was more applicable than the post-classification method using multitemporal high-resolution images. This research provides a new technical approach for LULC change detection on campus, and is expected to play an important role in guiding the future planning and construction of campuses. Moreover, this study can be used as a reference for the utilization of multisensor and multiresolution remote sensing images and the combination of different change detection methods in the LULC change detection field.

2. Methodology

2.1 Research area

The Weishui Campus of Chang'an University is located at the intersection of the Xi'an economic and technological development zones. It is 12 km to the north of the city center and 3 km to the south of the Weihe River, and is located at 34°22′N 108°54′E (Fig. 1). The construction

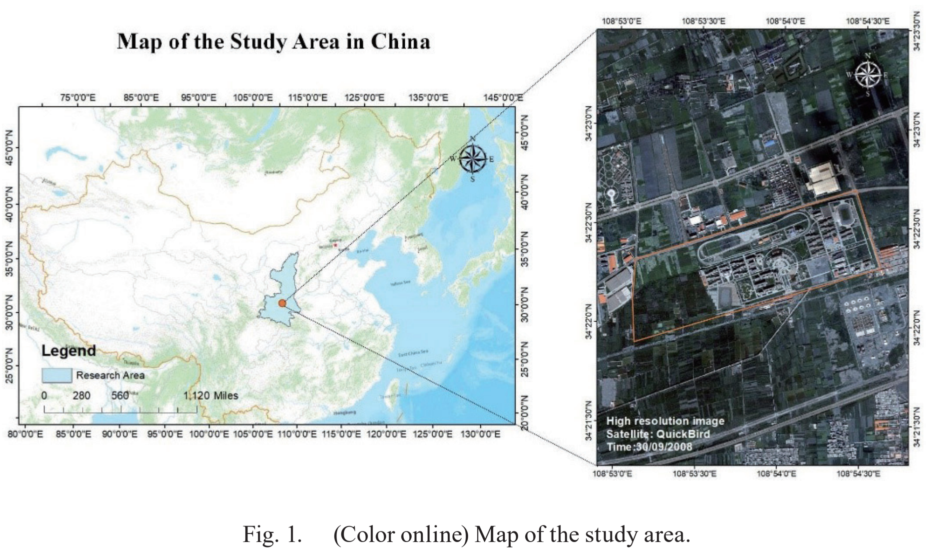


Fig. 1. (Color online) Map of the study area.

of Weishui Campus started in October 2002 and the campus now spans 360000 m^2. Because of the rapid development of modern society and the reform of the education system, the numbers of universities and students enrolled have steadily increased year by year. Weishui Campus, as an example of a domestic university, also faces tough problems such as expansion, reconstruction, and other tasks. After years of hard work, it has become a modern university campus with a reasonable layout, good support facilities, and a beautiful environment, which are essential elements for the personal and academic development of college students. The campus was opened in 2003, and by 2014, more than 20000 undergraduates (including international students) were studying and living there. With the further construction and expansion of the campus, it will become even more beautiful.

2.2 Experimental data

To verify that it is feasible and practicable to perform long-term LULC change detection by applying different change detection methods to multiresolution images, several multisensor and multiresolution images were selected after careful consideration. The low- or medium-resolution remote sensing satellites used in most studies are Landsat series satellites. In this study, Landsat-5 and Landsat-7 images were chosen to conduct low- or medium-resolution change detection. Considering the spatial resolution, image acquisition time, and other factors, high-resolution images such as QuickBird, WorldView-4, and GF-2 images were selected. In addition to these factors, the cloud density should also be taken into consideration when selecting suitable remote sensing images. In China, May to August is the summer season, and June is the most productive month for vegetation. To effectively detect LULC types, for example, artificial structures, vegetation, water, and bare land, images acquired during summer were chosen to conduct change detection. Details of the research data are shown in Table 1.

In this experiment, the resolution of the images plays a key role in the results. Because the study area is small, images with low spatial resolution tend to ignore most of the effective information. Accordingly, even if low- or medium-resolution remote sensing methods are utilized, images with suitable spatial resolution should be selected through cautious decision. Landsat-5 TM and Landsat-7 ETM+ sensors have spatial resolutions of 30 and 15 m, respectively,

Table 1
Detailed information of the remote sensing images used in this study.

Satellite	Path/Row	Acquisition date	Panchromatic image resolution (m)	Multispectral image resolution (m)	Revisit cycle (day)
Landsat-5	127/36	16/06/1998	30	30	16
Landsat-5	127/36	19/06/2005	30	30	16
Landsat-5	127/36	17/06/2010	30	30	16
Landsat-7	127/36	29/06/2000	15	30	16
Landsat-7	127/36	24/06/2004	15	30	16
Landsat-7	127/36	22/06/2009	15	30	16
QuickBird	127/36	30/09/2008	0.61	2.44	1–6
WorldView-4	127/36	29/04/2018	0.31	1.24	1–4.5
GF-2	127/36	26/10/2018	1	4	5

which are sufficient to accomplish low- or medium-resolution change detection in this research. Furthermore, other relevant digital materials such as a corresponding digital elevation model, radiometric calibration coefficients, and a Landsat-7 stripe removal patch were prepared and used throughout the whole process. During the period from 2008 to 2018, various types of high-resolution images have become available, providing high-quality data sources for remote sensing technology applications in various fields. Common high-resolution remote sensing images include IKONOS, WorldView, and QuickBird satellite images. Since high-resolution images are characterized by clear texture features and diverse spectral information, WorldView-4, GF-2, and QuickBird images were chosen to detect the LULC changes on Weishui campus from 2008 to 2018 in this study.

2.3 Technical workflow

The main purpose of this research is to demonstrate that it is feasible and practicable to perform long-term LULC change detection by applying different change detection techniques to multisensor and multiresolution remote sensing images. Because of the unique features of multisensor and multiresolution images, the change detection techniques used for different data in this study were relatively distinct. As shown in Fig. 2, high-resolution images such as WorldView-4, GF-2, and QuickBird images as well as medium-resolution images such as Landsat images were used to detect LULC changes on Weishui campus of Chang'an University over nearly 20 years.

Focusing on the overall steps of change detection, we divided the LULC change detection process on Weishui campus during the past 20 years into two major parts according to the time and resolution. In the first part, low- or medium-resolution change detection methods were utilized to monitor LULC changes on Weishui campus from 1998 to 2008. Among the existing low- or medium-resolution change detection methods, direct image comparison is the most common method, in which the calculation and transformation process are directly performed on the image element values in two time-phase remote sensing images that have been aligned in order to find the areas of change. Because of the very low resolution of Landsat-5 images, it is not easy to clearly distinguish the ground feature classes in a specific small area. Thus, the direct spectral comparison method was used on Landsat-5 images. However, Landsat-7 images have relatively high spatial resolution, and basic ground types such as artificial structures and vegetation can be easily identified. Therefore, to determine the distribution and type characteristics of change information and to generate change images, the post-classification comparison method was utilized on Landsat-7 images. In this method, two time-phase remote sensing images that have been aligned separately are classified, and then the classification results are compared to obtain change information. Although the accuracy of this method depends on the accuracy and consistency of the classification criteria when classifying the images separately, it is still very effective in practical applications. In the second part, high-resolution change detection methods were used to detect LULC changes in the research area from 2008 to 2018. To detect the LULC changes taking place during this period, the post-classification change detection method and the object-based change detection method were

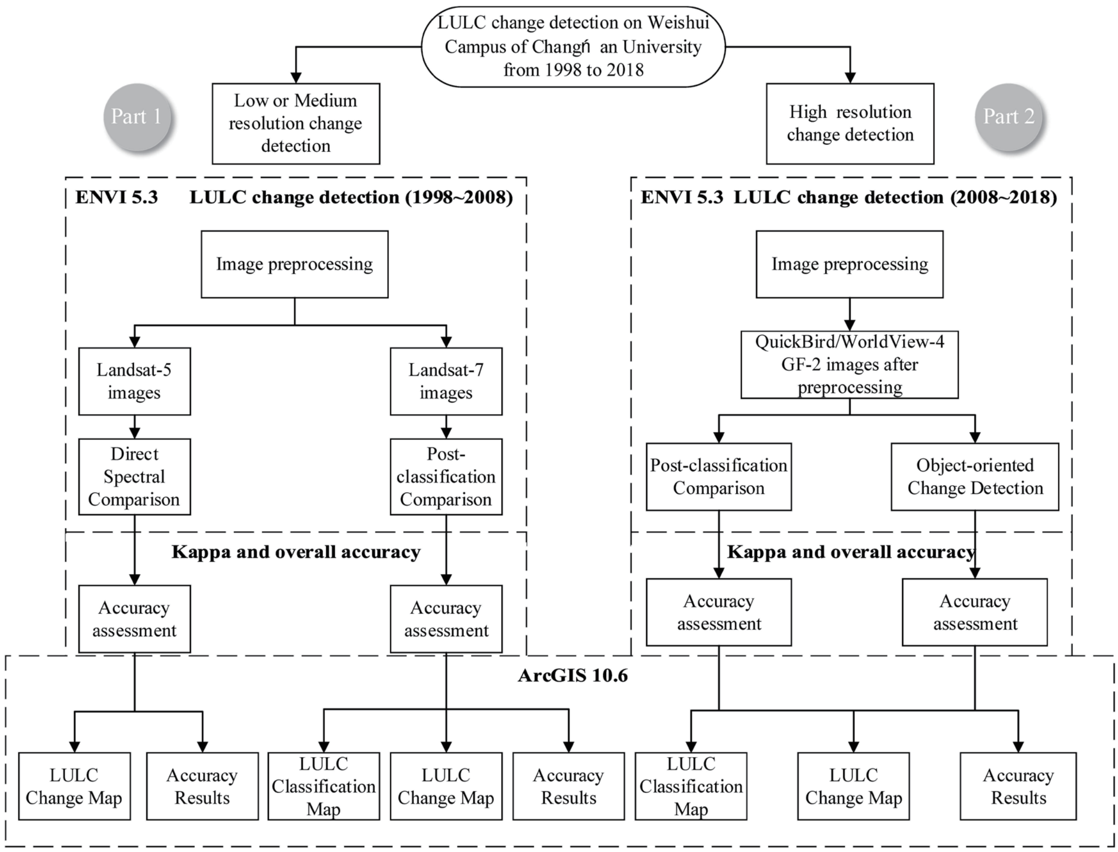


Fig. 2. Technical workflow of the study.

adopted in this experiment. Finally, through comparing and analyzing the experimental results obtained from each part, and taking the accuracy evaluation into account, the change detection method with the better outcome and higher accuracy was chosen from each part, and the final change detection scheme for Weishui campus of Chang'an University was made by combining the superior method for each part.

3. LULC Change Detection

LULC change detection is one of the important aspects of remote sensing applications, and change detection generally uses images acquired by similar sensors. Owing to the limited conditions of image acquisition, change detection can also be performed with sensor images of different resolutions. In this paper, we discuss the methods and processes of using remote sensing images with different resolutions for change detection. The basic process of change detection includes image preprocessing, change detection, threshold segmentation, and accuracy evaluation.

3.1 Image preprocessing

In this experiment, different LULC change detection methods were applied to multisensor and multiresolution images to monitor the LULC changes on Weishui campus of Chang'an University over nearly 20 years. Because the different images have distinctive attributes and characteristics, the preprocessing procedure is different for each type of data. To obtain better change detection results, it is critical to conduct preprocessing on all remote sensing images used in this study. The preprocessing procedures for low- or medium-resolution images and high-resolution images are shown in Fig. 3.

Before applying low- or medium-resolution change detection methods, it was necessary to first carry out five preprocessing steps: radiometric correction, atmospheric correction, image fusion, image mosaicking, and image clipping. Similarly, preprocessing procedures should also first be conducted on high-resolution images. Different from Landsat images, WorldView-4, GF-2, and QuickBird images are composed of panchromatic and multispectral images with red, green, blue, and near-IR bands. Thus, the preprocessing steps of high-resolution images are different from those of low- or medium-resolution images.

The classification and detection accuracy of an image largely depends on the resolution of the image. Therefore, the preprocessing of the original images is particularly important. In the radiometric correction and atmospheric correction steps, the corresponding absolute radiation

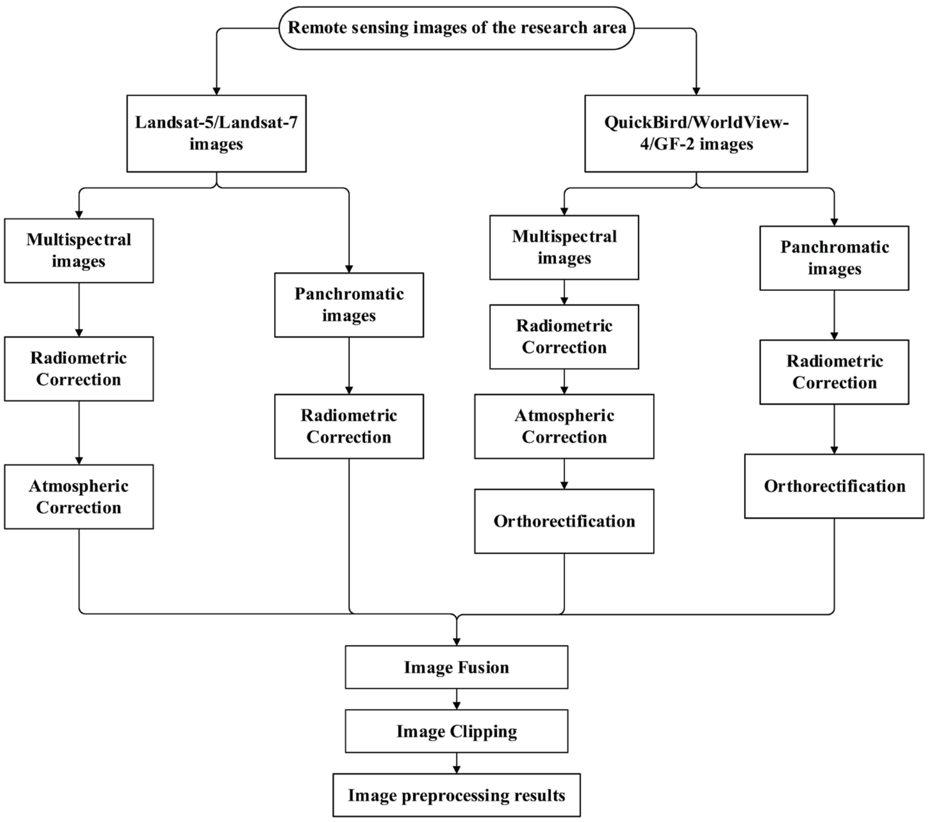


Fig. 3. Preprocessing procedures for images.

correction coefficients and light modulation functions can be downloaded from the Internet. Moreover, the spatial resolution of remote sensing images can be improved through image fusion. Taking high-resolution remote sensing images as an example, after the image fusion process, the resolution of the WorldView-4 images was the highest at 0.31 m, followed by the QuickBird images (0.61 m), with the GF-2 images having the lowest resolution of up to 1 m.

3.2 Low- or medium-resolution change detection

In this part, Landsat-5 TM images of three years, 1998, 2005, and 2010, and Landsat-7 ETM+ images of three years, 2000, 2004, and 2009 were selected as experimental data to detect LULC changes in the study area over nearly ten years.

According to the change detection procedure demonstrated in Fig. 3, the image change detection steps should be carried out after finishing the preprocessing steps. When selecting suitable change detection algorithms, because of the relatively low resolution of Landsat-5 images, making them difficult to classify, the spectral direct comparison method was chosen to process the Landsat-5 images. Regarding the Landsat-7 images, the Landsat satellite carries an enhanced thematic mapper sensor with a ground resolution of up to 15 m, so the post-classification comparison method is often chosen for LULC change detection applications. Direct spectral comparison is the most common change detection method. It directly performs calculations and transformations on the pixel values in registered two-phase remote sensing images to find the changed areas. However, the post-classification comparison method can not only detect the areas with changed features and obtain the specific type of feature change, but also obtain “from-to” change information, which is important for analyzing the distribution of features before and after LULC changes. In this study, a post-classification comparison method based on supervised classification was used on multitemporal Landsat-7 images, which were divided into four categories: artificial structures, vegetation, bare land, and water.

After selecting and applying suitable change detection methods, class thresholds were defined in the Compute Difference Map Input Parameters panel of ENVI software by setting the LULC change level division threshold. Finally, post-processing and accuracy evaluation steps were performed on classified images acquired from each method.

3.3 High-resolution change detection

During the period from 2008 to 2018, various types of high-resolution images have become available, providing high-quality data sources for remote sensing applications in various fields. In this study, WorldView-4, GF-2, and QuickBird images were selected to examine the LULC changes on Weishui campus of Chang’an University from 2008 to 2018. High-resolution images have many merits such as the clear texture of features and diverse spectral information. Thus, the post-classification comparison method and the object-based method were used on the high-resolution images mentioned above to detect LULC changes.

The post-classification comparison method involves classifying two registered remote sensing images separately, then comparing the classification results to obtain change detection information. Although the accuracy of this method depends on the accuracy of the classification and the consistency of the classification standards, it is still very effective in practical applications. When using the post-classification comparison change detection method, it was first necessary to use the supervised classification algorithm to classify the features of the image into four categories: artificial structures, vegetation, water, and bare land. Secondly, two-phase classification result maps were used to perform post-classification change detection through the ENVI change detection workflow tool. When classifying images, it was extremely important to make full use of the spectral and texture features of the images to gradually extract ground feature information. After the classification was completed, the accuracy of the image classification was evaluated using the corresponding confusion matrix.

The object-based change detection method was an inspired idea in the field of high-resolution remote sensing image interpretation. The main features of this method are to segment the ground object as the processing unit, comprehensively consider the spectrum, space, and texture information of the object, and improve the accuracy and completeness of the change detection result. In the experimental part of this study, the object-based change detection process included image band combination, resampling, image clipping, image segmentation, object-based classification, and finally the use of two-phase object-based classification results to perform LULC change detection through the ENVI change detection workflow tool. In this part, ground features of the image were also classified into four types: artificial structures, vegetation, water and bare land.

3.4 Accuracy assessment

At the end of remote sensing change detection, it is necessary to evaluate the accuracy of the detection results and analyze their reliability. There are two commonly used methods for accuracy evaluation: the confusion matrix and the ROC curve.

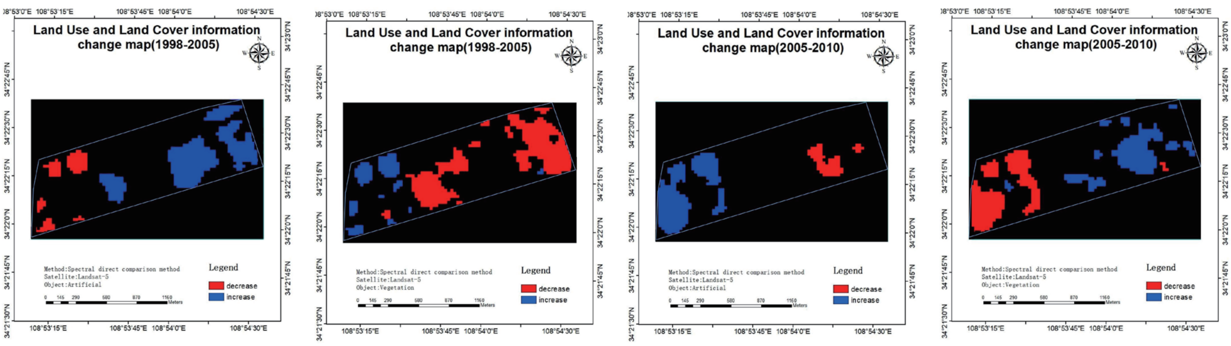
After generating the classified images, the accuracy of the classification results was measured by ENVI software. Classification accuracy assessment is a critical step after image classification. The accuracy assessment tool of the supervised classifier in the software randomly yielded a certain number of reference points by stratified random sampling of the different classified images. Each point had a certain color and pixel value identified by the software automatically. The classes in the classified images were regarded as reference classes. Random yield points were then recognized, and the relevant class was assigned by the user manually. The kappa statistics and error matrix for the two classified images were generated from the self-generated report section of the software. This process was performed for two neighboring classified images.

4. Results and Discussion

4.1 Low- or medium-resolution change detection results

The LULC changes on Weishui campus from 1998 to 2010 were detected using time series multiresolution Landsat images. Since the spatial resolution of Landsat-5 images is up to 30 m, the spectral direct comparison method was selected to detect changes in both vegetation and artificial structures in the study area. However, for Landsat-7 images, the spatial resolution can reach 15 m after image fusion, so the most widely used post-classification comparison method was chosen to detect changes. Different from Landsat-5 images, Landsat-7 images could be classified into four types of ground features: vegetation, artificial structures, water, and bare land. In our first experiment, we used Landsat-5 images for change detection by the spectral direct comparison method, and the results included maps of LULC changes (Fig. 4) and a statistical table of LULC changes (Table 2). In the second experiment, we applied a post-classification comparison method to Landsat-7 images, and the results included maps of classification and LULC change detection (Fig. 5).

In the direct spectral comparison method for Landsat-5 images, the entire procedure was very convenient and simple, but the accuracy was relatively poor. In contrast, for the post-classification comparison method conducted on Landsat-7 images, the process was somewhat tedious and time-consuming, but the results were more intuitive and diverse, and the change detection accuracy was relatively high. Comparison of the two change detection methods shows that the post-classification comparison method had the following advantages: (1) it is theoretically mature, (2) it recognized ground features based on the temporal, spatial, and spectral characteristics of the image features, which greatly reduced misclassification and improved the accuracy of change detection, (3) the information on the distribution of LULC information in a specific year could be obtained from the classification maps, (4) the types of



(a) (b) (c) (d)

Fig. 4. (Color online) (a) Changes in artificial structures in the study area from 1998 to 2005, (b) changes in vegetation in the study area from 1998 to 2005, (c) changes in artificial structures in the study area from 2005 to 2010, and (d) changes in vegetation in the study area from 2005 to 2010.

Table 2
Statistical table of changes in artificial structures and vegetation from 1998 to 2010 in the study area.

Time	Type	Increase (%)	Decrease (%)	Unchanged (%)
1998–2005	Artificial structures	11.56	3.17	85.27
1998–2005	Vegetation	5.70	15.93	78.37
2005–2010	Artificial structures	7.99	2.08	89.93
2005–2010	Vegetation	7.32	8.21	84.47

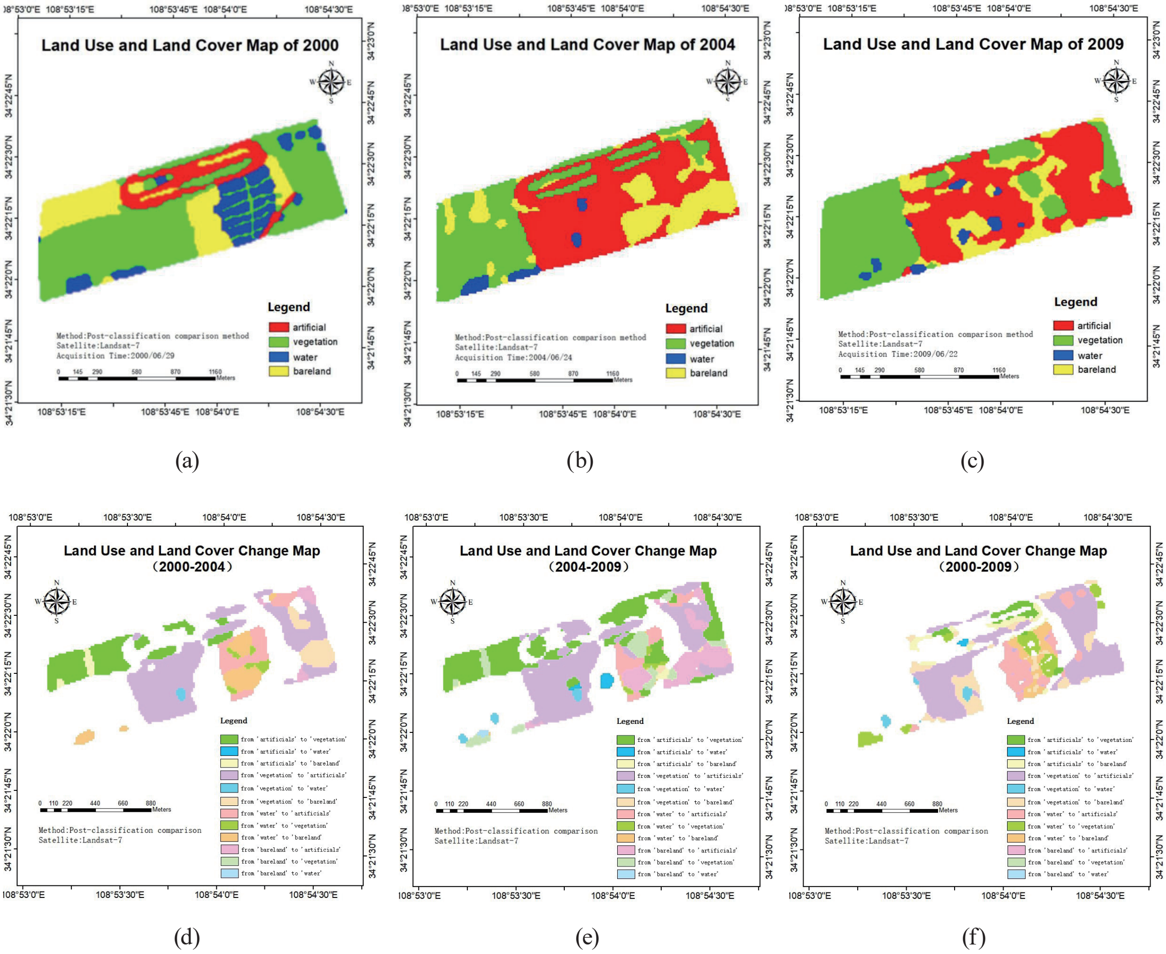


Fig. 5. (Color online) (a) LULC map of 2000, (b) LULC map of 2004, (c) LULC map of 2009, (d) LULC change map (2000–2004), (e) LULC change map (2004–2009), and (f) LULC change map (2000–2009).

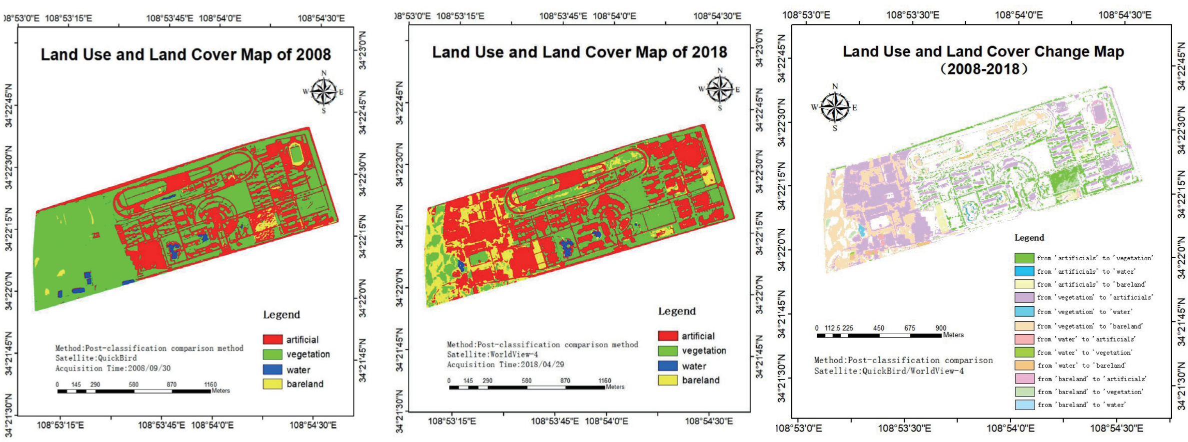
ground features that could be distinguished were more varied than those in the direct spectral comparison method, and (5) detailed information on "from-to" changes could be provided through LULC change maps. However, there were several disadvantages of the post-classification comparison method: (1) because of the satellite malfunction, the Landsat-7 images in 2004 and 2009 had many useless stripes, which would interfere with the LULC classification, so it was necessary to remove the stripes from the images before preprocessing, (2) the change detection by the post-classification comparison method was cumbersome and superfluous because the study area was small and the image resolution was too low to clearly recognize the ground features in the study area, (3) because the pixels located on the image after removing the stripes were corrupted, the classification accuracy of the image was reduced, thus reducing the change detection accuracy, (4) this method places strict requirements on the operator, who must be capable of interpreting and deciphering images, and (5) the entire operation process was complicated and inefficient. For the spectral direct comparison method conducted on Landsat-5 images, its advantages included simple operation steps and high detection efficiency. However, this method was prone to misclassification, false change information, and other problems, which affected the accuracy of change detection, due to the existence of many "same thing, different spectrum" and "same spectrum, different thing" phenomena.

By comprehensively considering the advantages and disadvantages of the two methods, it can be concluded that the direct spectral comparison method using Landsat-5 images is more suitable for detecting LULC changes on Weishui campus between 1998 and 2008 than the post-classification comparison method using Landsat-7 images.

4.2 High-resolution change detection results

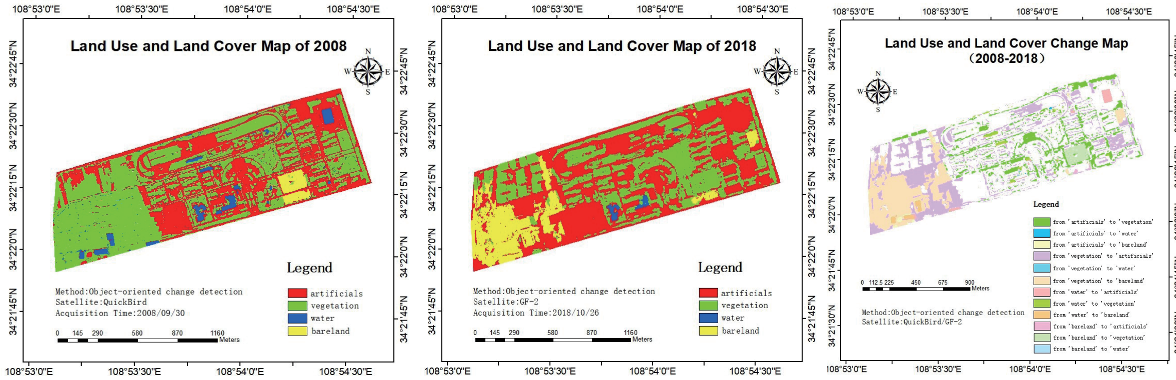
The post-classification change detection method and the object-based change detection method were chosen to classify the multitemporal high-resolution remote sensing images. Multisensor remote sensing images such as QuickBird, WorldView-4, and GF-2 images were used with these methods. The final change detection results were obtained by comparing the classification results of two neighboring images after classification. On the basis of the different acquisition times of images, QuickBird and WorldView-4 images were used to apply the post-classification comparison method, and the QuickBird image was also used for the object-based change detection method together with the GF-2 image. The results obtained by the post-classification change detection and object-based change detection methods can be seen in Figs. 6 and 7, respectively. It can be seen that the change detection results of the two methods are similar.

The post-classification change detection method is one of the most common and mature change detection methods, and many data processing software packages worldwide provide change detection process tools, such as ENVI and ERDAS. However, the object-based change detection method has gradually developed with the development of optical remote sensors. It is important to note that when classifying images, shadows in the images can obscure the original



(a) (b) (c)

Fig. 6. (Color online) Post-classification change detection results: (a) LULC map of 2008, (b) LULC map of 2018, and (c) LULC change map from 2008 to 2018.



(a) (b) (c)

Fig. 7. (Color online) Object-based change detection results: (a) LULC map of 2008, (b) LULC map of 2018, and (c) LULC change map from 2008 to 2018.

feature information and thus affect the classification accuracy. However, this phenomenon can be avoided by using various image processing algorithms.

By analyzing and comparing the experimental results obtained from the two change detection methods, the following common points were found: (1) the change detection results were similar, (2) the accuracy of both classification methods was high (above 95%), (3) both methods required the manual selection of training samples and validation samples, (4) the accuracy of both methods strongly depended on the accuracy of image classification, and the higher the accuracy of image classification, the higher the change detection accuracy. The differences between the two change detection methods were as follows: (1) the classification process was different: the supervised classification method only had to manually select a certain number of training samples for image classification, while the object-based classification method had to perform band combination, resampling, image segmentation, and merging before manually selecting samples for classification, (2) the methods of sample selection were different: the supervised classification method had to manually select all samples, while the object-based classification method could automatically select samples in the image classification process. The object-based classification method automatically generated sample regions using efficient algorithms for sample selection after feature extraction, which ensured that the sample separability index met the required standard and reduced the risk of misclassification, (3) the efficiency was different: from practical experience, the object-based change detection method was more efficient. In contrast with the supervised classification method, the object-based classification method did not need to manually extract a large number of training samples and calculate their separability indexes, thus saving a lot of time, and it was very simple to modify the samples while using the method, (4) the spatial information utilization rate of the two methods was different: the supervised classification method utilized almost no spatial information, while the object-based classification method could make full use of the spectral texture features, geometric information, and structural information.

The classification accuracy of each image data is shown in Table 3. As can be seen from this table, (1) images with higher resolution had higher classification accuracy, (2) the accuracy of the

Table 3
Kappa statistic and overall accuracy of all images.

Image resolution (m)	Image	Year	Classification algorithm	Overall accuracy (%)	Kappa statistic
15	Landsat-7	2000	Supervised classification	81.11	0.78
15	Landsat-7	2004	Supervised classification	84.88	0.82
15	Landsat-7	2009	Supervised classification	82.36	0.79
0.61	QuickBird	2008	Object-based classification	94.45	0.91
1	GF-2	2018	Object-based classification	92.78	0.89
0.61	QuickBird	2008	Supervised classification	95.20	0.92
0.31	WorldView-4	2018	Supervised classification	96.88	0.95

traditional supervised classification-based methods was higher than that of the object-based classification methods. However, considering that the results of the two change detection methods were similar (both above 90%) and that the object-based method was more convenient and efficient to use than the supervised classification method, for this study area, the object-based change detection method using high-resolution remote sensing images was more applicable for detecting LULC changes during the research period than the post-classification change detection method.

5. Conclusions

In this paper, we monitored the LULC changes on Weishui campus of Chang'an University from 1998 to 2018 using multisensor and multiresolution remote sensing images, and provided a new technical approach for long-term LULC change detection of college campuses in China and abroad. The experimental results showed that the direct spectral comparison method using Landsat-5 images was more effective than the post-classification change detection method using Landsat-7 images for detecting LULC changes from 1998 to 2008 on Weishui campus. In contrast, the post-classification change detection method could predict future trends of change, but when using low- or medium-resolution images, this method was inefficient, time-consuming, and had low accuracy. For the LULC change detection of the research area from 2008 to 2018, even though the use of high-resolution data and mature classification algorithms in both methods resulted in high detection accuracy (above 90% for both methods), the object-based change detection method had certain advantages over the post-classification change detection method, such as high image classification accuracy, high data processing efficiency, a high degree of automation, and a simple operation process. Moreover, the object-based classification method could make full use of the spectral, spatial, and textural information of objects. Consequently, the object-based change detection method was more appropriate than the post-classification method for monitoring LULC changes on campus between 2008 and 2018. It can be further concluded from this study that applying different change detection techniques on multisensor and multiresolution remote sensing images to perform long-term LULC change detection can greatly improve the utilization of remote sensing images and expand the application of change detection techniques. Moreover, multisensor and multitemporal data can also provide multiangle observations due to the different imaging mechanisms and observation characteristics. Finally, the technical approach proposed in this research can play an important role in guiding the future planning and construction of other campuses, and can also be used as a valuable reference in the development and utilization of city land.

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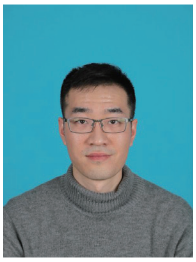

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