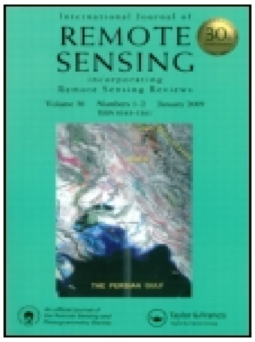

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Detecting changes in high-resolution satellite coastal imagery using an image object detection approach

Jianyu Chen[a], Zhihua Mao[a]*, Bill Philpot[b], Jonathan Li[c], and Delu Pan[a]

[a]*State Key Laboratory of Satellite Ocean Environment Dynamics, Second Institute of Oceanography, State Oceanic Administration, Hangzhou 310012, PR China;* [b]*School of Civil and Environmental Engineering, Cornell University, Ithaca, NY 14853, USA;* [c]*Department of Geography and Environmental Management, University of Waterloo, Waterloo, ON, Canada N2L 3G1*

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This article presents a spatial contrast-enhanced image object-based change detection approach (SICA) to identify changed areas using shape differences between bi-temporal high-resolution satellite images. Each image was segmented and intrinsic image objects were extracted from their hierarchic candidates by the proposed image object detection approach (IODA). Then, the dominant image object (DIO) presentation was labelled from the results of optimal segmentation. Comparing the form and the distribution of bi-temporal DIOs by using the raster overlay function, ground objects were recognized as being spatially changed where the corresponding image objects were detected as merged or split into geometric shapes. The result of typical spectrum-based change detection between two images was enhanced by using changed spatial information of image objects. The result showed that the change detection accuracies of the pixels with both attribute and shape changes were improved from 84% to 94% for the strong attribute pixel, and from 36% to 81% for the weak attribute pixel in study area. The proposed approach worked well on high-resolution satellite coastal images.

1. Introduction

Remote-sensing change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh 1989). It is one of the most important applications for analysing multitemporal remotely sensed images. Change detection is also a meaningful tool for monitoring and managing natural resources and urban development in a coastal zone because it can quantitatively measure the spatial variation of relevant ground objects during a given period (Malthus 2003; Bontemps et al. 2008). Furthermore, a shape-based approach has been introduced to change detection (Li and Narayanan 2003). However, the most common approach has been to classify each image pixel as an independent observation regardless of its spatial context (Marcal et al. 2005). Unfortunately, this is fraught with the limitations imposed by pixel-based image analysis. With the increasing spatial resolution of remotely sensed imagery, new applications in coastal zones require the generation of change detection maps characterized by both a high geometric resolution and the capability of properly modelling the complex areas present in the scene (Bovolo 2009).

*Corresponding author. Email: mao@sio.org.cn

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Remote sensing has made enormous progress over the last few years from what has been predominantly a per-pixel, multispectral (MS)-based approach to the development and application of multiscale object-based methods (Hay et al. 2005). Blaschke (2010) gave an overview of the development of object-based methods. Recently, the development of geographic object-based image analysis (GEOBIA or OBIA) has nevertheless provided a new, critical bridge between the spatial concepts applied in multiscale landscape analysis. In the segmentation process, natural complexity can be effectively explored using spatial analysis tools based on the concept that landscapes are process continuums which can be partially decomposed into objects or patches (Burnett and Blaschke 2003). Walter (2004) adopted object-based classification and a geographical information system (GIS) to improve the capability of change detection. Desclée, Bogaert, and Defourny (2006) detected forest land-cover change using a statistic object-based method. Yu et al. (2006) found that using objects as minimum classification units helped overcome the problem of salt-and-pepper effects resulting from pixel-based classification methods. Tian and Chen (2007) proposed a framework to find optimal segmentations for a given feature type using an image object-based method. Object-based applications have been performed for mapping and change analysis in mangrove ecosystems (Conchedda, Durieux, and Mayaux 2008) and in urban sprawl areas (Durieux, Lagabrielle, and Nelson 2008). Im, Jensen, and Tullist (2008) introduced a change detection method based on object/neighbourhood correlation by image analysis and image segmentation techniques. Some unsupervised approaches have been presented based on the comparison between features computed on homogeneous regions that are obtained according to segmentation procedures (Hall and Hay 2003; Bruzzone and Carlin 2006). Even if these object-based change detection methods are implicitly suitable to analyse high-resolution images, they get the final change detection by pixel-to-pixel comparison, which is not an effective region descriptor like object-to-object comparison. Partly, this is because most of these techniques do not generate explicit object topology, nor even incorporate the concept of an object within their analysis (Hay et al. 2003).

The relatively homogeneous and semantically significant groups of pixels produced after multiscale segmentation have been designated ‘object candidates’, which are to be recognized by further processing steps and to be transferred into meaningful objects (Burnett and Blaschke 2003). Considering the oversegmentation or the undersegmentation problem, there exists a large matching gap between the theoretically hierarchical network of image object candidates and real-world objects of a landscape. In many cases, the delineation of relatively homogeneous areas is the basic method, and the common denominator of various realizations of image object-based change detection is the objective to derive meaningful objects. Moreover, the dominant landscape objects have their intrinsic scales and are composed of structurally connected parts. In this article, the image object detection approach (IODA) (Chen, Pan, and Mao 2006, 2009) is adopted to choose appropriate scales and produce meaningful image objects from any possible image candidates, and to distinguish intrinsic scale from any segmentation scale. The newly developed method is also an update to the work presented in Chen, Pan, and Mao (2009) by the same authors.

2. Materials and methods

2.1. Related work

Multiscale segmentation is a procedure by which an image is precisely separated into mutually exclusive region sets by computing the defined heterogeneity. The criteria for stopping the segmentation procedure are the degree of difference between two regions. These differences are optimized in a heuristic process by comparing the attributes of the regions

(Baatz and Schäpe 2000). Only one segmentation scale was set as the criterion in the segmentation procedure. As may be known, there are various optimal segmentation scales with respect to diverse intrinsic scales of ground objects in remotely sensed images. So, the IODA method chooses the meaningful object candidates as image objects from whole multiscale representations (Chen, Pan, and Mao 2009).

In the IODA, for MS remotely sensed images, the spectral mean distance (SMD) was defined commonly to describe the distance of two adjacent candidates using their spectral mean values, μ_d and μ'_d, for spectral band d:

$$\mathrm{SMD} = \sqrt{\sum_d (\mu_d - \mu'_d)^2}. \tag{1}$$

The combined standard deviation (CSD) which characterizes the homogeneity for each candidate can be defined as follows:

$$\mathrm{CSD} = \sum_d w_d \sigma_d, \tag{2}$$

where w_d is the user-defined weight for spectral band d, and σ_d is its standard deviation of candidate a. Here, the difference distinctive feature (DDF) was defined as follows:

$$\mathrm{DDF} = \mathrm{SMD} - \mathrm{CSD}, \tag{3}$$

where the DDF of candidate a is determined by the SMD and the standard deviation. The minimum DDF (MD) is used in the measurement of the distinguishability of an object candidate against its surrounded candidates at one segmentation scale:

$$\mathrm{MD} = \mathrm{Min}\{\mathrm{DDF}\}. \tag{4}$$

In the segmentation procedure, the pixel p belongs to a series of object candidates, along with the increasing of scale s. Each candidate has its minimum distinctive, which makes up the MD curve. The maximum distinctive feature (MDF) is defined as the maximum MD from the initial scale to a given scale in the MD curve. The scale order is constructed by a series of the original scale of ordinal MDF. For a simple object, the original scale at which its meaningful image object formed must be in scale order, and this can be adopted as the segmentation scale at the intrinsic scale (Chen, Pan, and Mao 2009).

2.2. Image object-based spatial change detection

The proposed approach was dependent on the homogeneous image objects yielded from the IODA method (see Figure 1), which was based on the multiscale segmentation result; scale order sequences for each pixel were then established. Subsequently, the nonsignificant candidates were removed and the potential image objects in the MDF object candidate set were retrieved from multiscale representations. As described above, the image object identification here was making heterogeneity of inter-neighbourhood image objects maximized as well as the homogeneity of intra-image object individually.

According to the provocative question that Blaschke and Strobl (2001) raised, 'What's wrong with pixels?', an increasing dissatisfaction was identified with pixel-by-pixel image

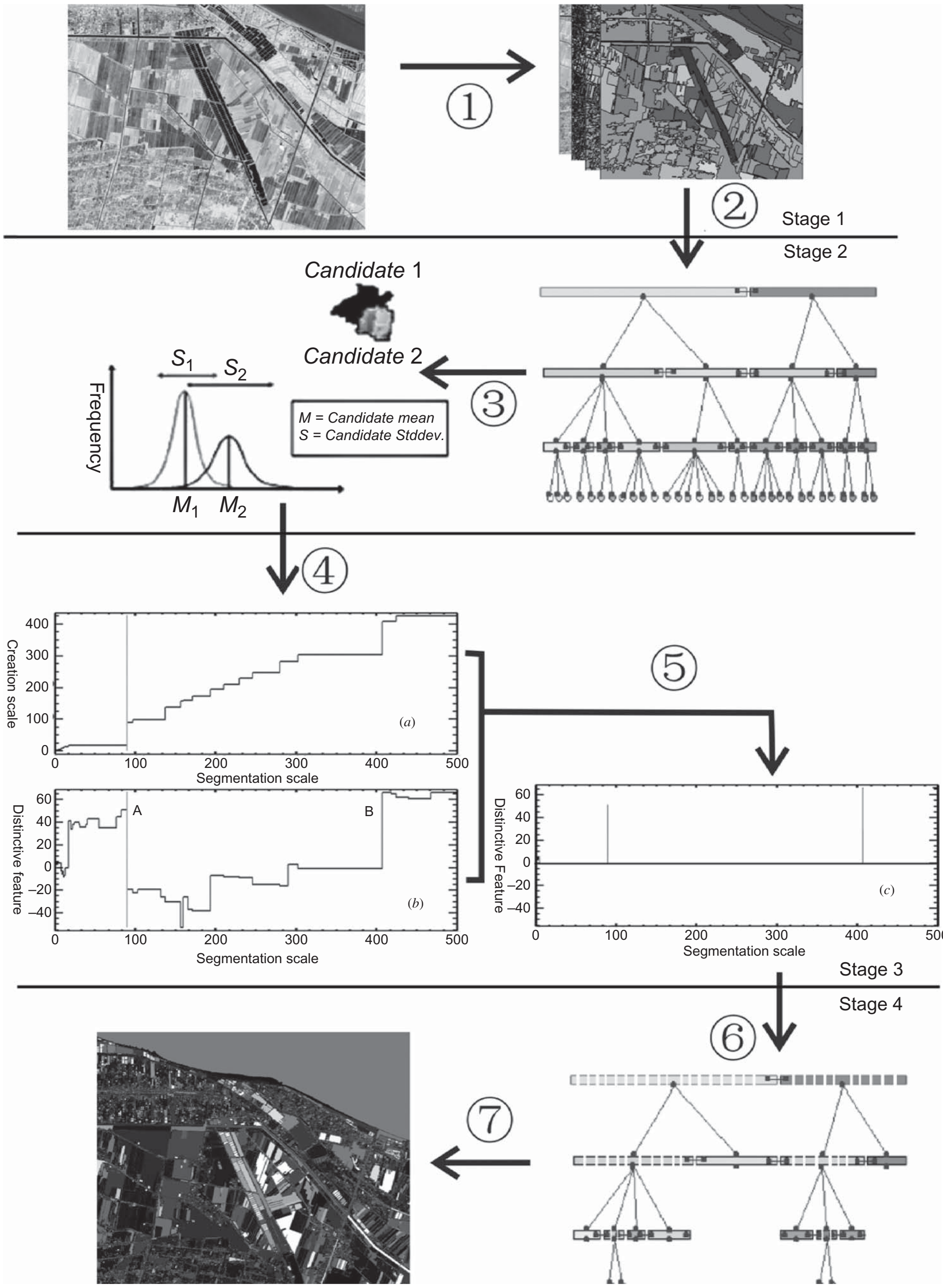

Figure 1. Four stages and seven steps in the IODA. Stage 1: ① multiresolution segmentation and ② its multiscale representation. Stage 2: ③ DDF calculation for each object candidate. Stage 3: ④ distinctive feature curve of object candidate evolution in the multiresolution segmentation and ⑤ the scale order sequences are set up based on each pixel. On one pixel, for example, there is a scalar curve (a), a DF curve (b), and a scale order sequence (c), which are built up from curves (a) and (b). Stage 4: ⑥ potential image objects identification and ⑦ the Case 1 objects, Case 2 objects.

analysis. Under the assumption that the landscape of interest is a finite population of objects (Bian 2007), the spatial information about these objects is integrated in the ultimate change detection method. Considering the Shannon sampling theorem, we expected that an object should be of the order of one-tenth of the dimension of the sampling scheme – the pixel – in order to ensure that it would be completely independent of its random position and its orientation relative to the sampling scheme (Blaschke 2010). Accordingly, image objects larger than twice or three times the minimum needed by Shannon's sampling theorem and the pixels satisfying 3 × 3 pixels distribution were focused mainly in the application. These image objects are called dominant image objects (DIOs). Spatial information of these DIOs are included in the following image object-based change detection procedure.

The workflow of the image object-based change detection algorithm is shown in Figure 2. Two temporal remotely sensed images were geo-corrected using in image registration mutually in image preprocessing. At the second stage, two parallel processes were performed for traditional change detection based on spectral information and image object-based spatial contrast-enhanced change detection, respectively. In the latter approach, both images were segmented using the IODA. Then, the DIO presentation was identified from the product of optimal segmentation and labelled with a unique reference number. Next, two DIO sets from bi-temporal images were compared by the raster overlay function by using their unique reference numbers. The corresponding image objects were recorded as shape changed when they were detected as merged or split in the overlay function. Concurrently,

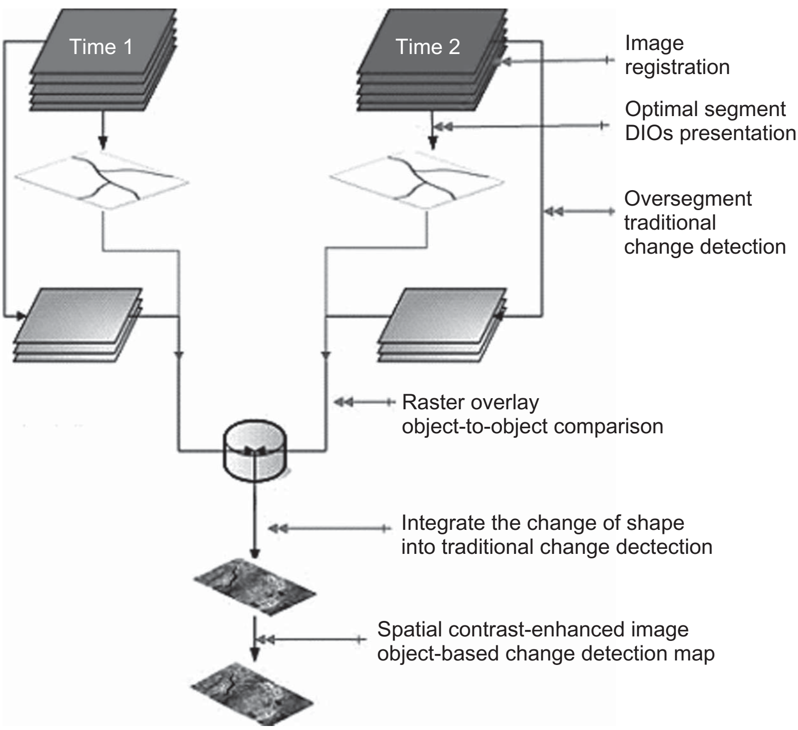

Figure 2. Workflow of the change analysis procedure. Two temporal images are registered first. Then, both images are segmented using the IODA method. Next, the DIO presentation is filtered from the product of optimal segmentation, i.e. the DIO sets from the two temporal images are compared by the raster overlay function. The corresponding image objects are labelled when they are detected as merged or split into geometric shapes.

the typical change detection approach was performed through calculating the image object-based average spectral data. At the third stage, the difference map that was created based on object-to-object comparison with the change of shape as a result was integrated into the result of traditional detected change using the spectral approach. Finally, the change map was produced by enhancement of the spatial information of the image object.

The overlay function was executed by taking each DIO as a raster zone by using a unique reference number. The image objects from two temporal images which merged or split were divided into small parts in the overlay function. If the DIO from the former image contained or intersected with more than one latter DIO and the intersected parts also met the condition of DIO, we considered the situation as the split procedure of the former image object. When the image object from the latter image contained or intersected with the former DIOs, their intersected parts were taken as the DIO, and the merged state occurred. Admittedly, there were both merging and splitting procedures when we compared with the image objects from two temporal images. The merged or split state means that the change of shape has occurred.

2.3. Integration of spectral and spatial information

Shape change means some or all parts of ground objects are changed. Other information is also required for identification of the changed parts or for other regions where the shape is not changed. Change detection algorithms in the remote-sensing literature can be roughly divided into two categories (Yuan and Elvidge 1998; Mas 1999): preclassification and postclassification change detection. Image object-based change detection adopting a strategy of postclassification takes three steps: segmentation, classification, and comparison. Such high-resolution imagery presents a new class of change detection problems to which existing remote-sensing techniques are not well suited. Classification techniques for thematic labelling, based on spectral and textural attributes, cannot describe within-class changes like new construction in cities, since the area is classified as urban before and after such changes (Pollard et al. 2010). This meant that most were detected as changed areas because of misclassification. In our approach, the segmented results were classified using the supervised maximum likelihood classifier (MLC) method. The MLC is the most common supervised classification method used with remote-sensing image data and is based on the Bayesian probability theory (Richards 1995). Then, the overall accuracy, the kappa coefficient, producer's accuracy, and user's accuracy were calculated for each class. For illustrating the performance of spatial change detection, the classes were divided into two groups: high accuracy classes (above the overall accuracy) and low accuracy classes (below the overall accuracy) in the case study. Therefore, the former classes were called obvious classes and the latter classes were called unobvious classes. When the change happened, the change among obvious classes or between obvious classes and unobvious classes was assumed as a strong attribute pixel change. Only the change among the unobvious classes was assumed as a weak attribute pixel change. Then, the strong or weak attribute pixel change was enhanced by a shape changed result derived from DIOs. Therefore, the detected results were divided into strong attribute pixel and shape change, strong attribute pixel change only, weak attribute pixel and shape change, and weak attribute pixel change only.

2.4. Study site and data

Two high-resolution satellite images covering the same area were used in this study, which were both 1024×1024 pixel subimages of an IKONOS scene (see Figure 3). The area represents a portion of the highly fragmented agro-waterfront landscape. IKONOS provides

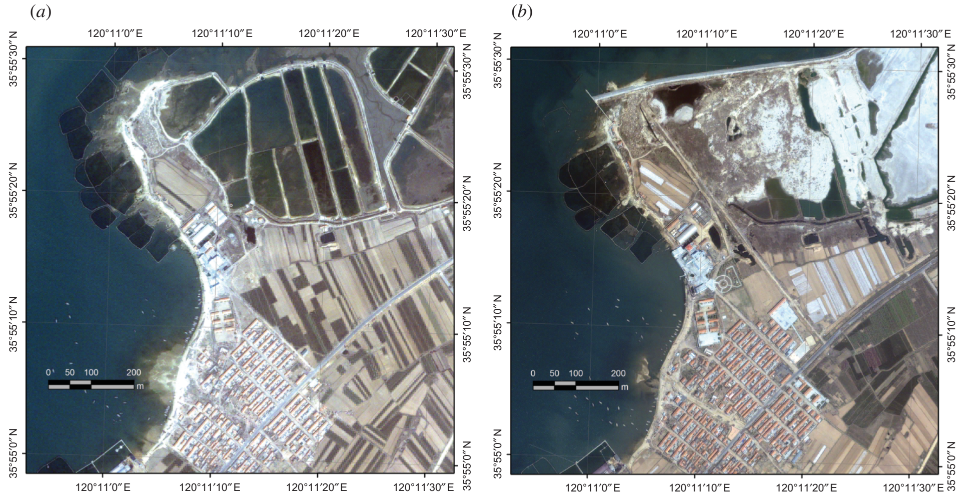

Figure 3. The image size is 1024 × 1024 pixels. The resolution is 1.0 m, generated by fusing the MS bands of 4.0 m resolution and a PAN band of 1.0 m resolution. The left image (*a*) was obtained on 17 April 2001 and the right image (*b*) was obtained on 25 April 2007.

16-bit MS data in blue, green, red, and near-infrared (NIR) channels at 4 m spatial resolution and a 16-bit panchromatic (PAN) channel at 1 m resolution. The used image resolution is generated by fusing MS bands with the PAN band. Herein, the Gram–Schmidt spectral sharpen function was utilized supported by sensor type. The auxiliary data include field survey data and a topographic map. The study area is located in the Xiejiadao Peninsula, Huangdao District, Qingdao City, between latitudes 35° 54″10′ N and 35° 55′40′ N, longitudes 120° 10′30′ E and 120° 12′00′ E. There are mudflats, aquacultures, boats, seawater below the coastline, residential areas (including building and yard), ponds, and agrarian fields above the coastline, and the agrarian fields are in different stages of planting. Two images were acquired at different years and during the same season. The acquisition of former images was at 02:43 GMT, 17 April 2001 and the latter was acquired at 03:00 GMT, 25 April 2007.

3. Results

3.1. Result of change detection

The image registration procedure was carried out in the preprocessing, and the root mean square error (RMSE) was 0.54 pixels. As a reference for change detection, the land-cover change of the study area was identified in the vector layer (see Figure 4) through image interpretation under the support of commercial GIS software (ArcGIS; Esri, Redlands, CA, USA). The land-cover classification scheme referred to the standard used in Chinese offshore investigation and assessment, which was slightly different compared to recent research (Teodoro et al. 2011). About half of the coastline had been modified in a short period. Two of the three aquaculture areas also disappeared during this period. The proportion of residential areas was increasing and almost simultaneously, the small ponds were changed either in part or as a whole. The agrarian fields were changed not only into the other types but also changed with respect to the planting and farming state. The result indicated that land-cover changed rapidly. The change pattern was similar to the closer coastal area in East China (Liu, Liu, and

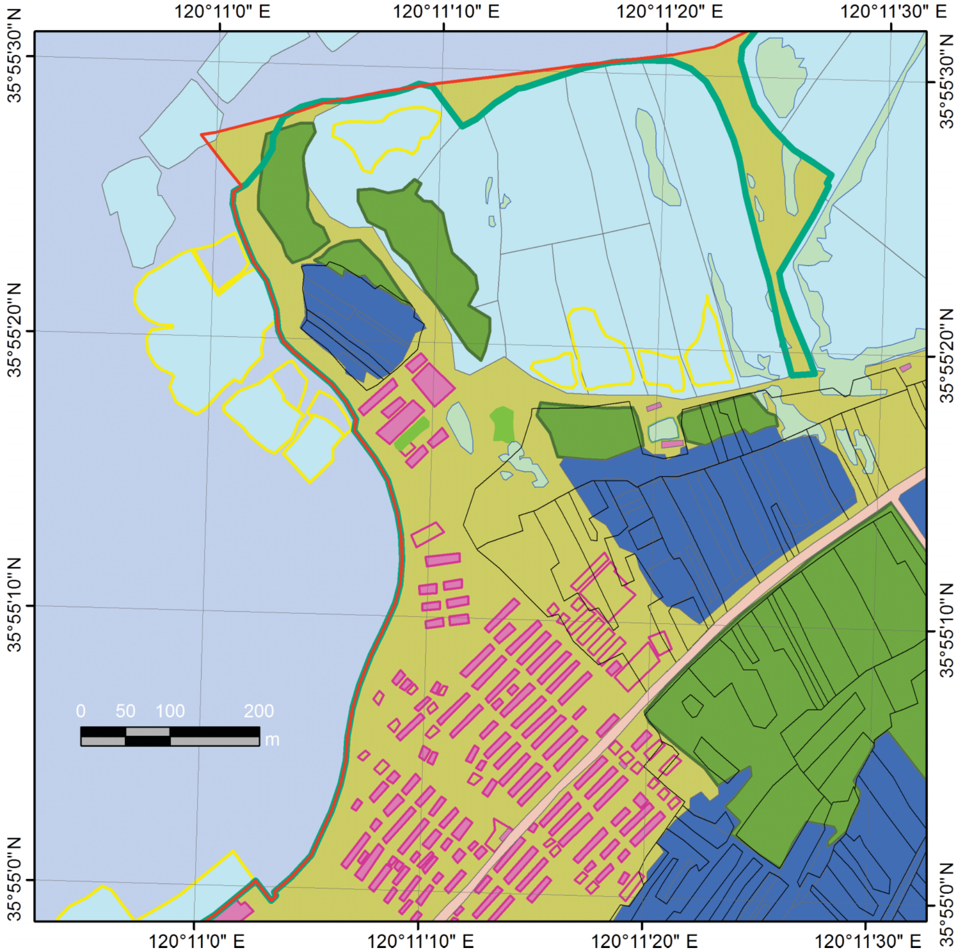

Figure 4. Map of GIS-based change detection of the study area. The exploitation and development lead to rapid changes in land cover in the coastal zone. The settlement extended and the aquaculture area decreased meanwhile.

Tian 2005). The total area of the Xiejiadao Peninsula is 28.26 km^2 and it increased 10.7% between 2001 and 2007, mainly from the tidal zone. Meanwhile, 11.0% of arable land area decreased and the main cause of occupation was built-up and settlement land.

In the postclassification change detection procedure, the segmentation scale was 30 for both MS images. The result of segmentation was oversegmentation for most objects. The overall accuracy of the 2001 image was 88.65%, and the kappa coefficient was 0.84. The overall accuracy of the 2007 image was 84.59%, and the kappa coefficient was 0.79. Actually, the producer and user accuracies (see Table 1) of waterbody, cropland, soil (reaped crop), woodland, and uncovered area were all larger than average. But the accuracies of building, yard (area between buildings), road, and silt were less than the average accuracy. The total accuracy of postclassification change detection without spatial information supported was 73% (see Table 2). The strong attribute pixel change accuracy increased to 84% and the weak attribute pixel change accuracy decreased to 36%

Table 1. Classification results of both images (%).

	Water body	Crop	Soil	Building	Yard and lane	Road	Wood land	Silt	Uncovered area
2007 Producer's accuracy.	97.99	96.87	74.53	61.8	45.86	69.39	93.75	39.18	
2007 User's accuracy	98.78	99.96	99.45	40.06	38.86	51.96	72.58	100	
2001 Producer's accuracy	96.37	94.37	92.14	75.01	40.52	83.9	81.9	64.64	85.94
2001 User's accuracy	99.94	97.45	98.9	76.23	37	49.35	96.95	36.29	93

Table 2. Change detection accuracy.

Type	Overall accuracy	Number of pixels
Strong change and shape	0.94	256, 037
Strong change only	0.68	161, 563
Weak change and shape	0.81	22, 452
Weak change only	0.26	101, 702
Strong change	0.84	417, 600
Weak change	0.36	124, 154
Total	0.73	541, 754

when the changed area was partitioned according to the classes. After integration with spatial change information (see Figure 5), the pixels that were of weak attribute pixel and shape changed occupied 22,452 pixels and its accuracy was 0.81. And the pixels that were only weak attribute pixel changed occupied 101,702 pixels and its accuracy was down to 0.26. In contrast, the pixels that are of strong attribute pixel and shape changed occupied 256,037 pixels and its accuracy was up to 0.94, and the pixels that were only strong attribute pixel changed occupied 161,563 pixels and its accuracy was 0.68. Furthermore, the result of change detection of the proposed approach has potential improvement in case more meticulous works are performed like relative radiometric normalization.

3.2. *Traditional change detection enhanced by spatial change information*

The IODA had been applied on the hierarchical network of image object candidates with the ultimate scale 800. Here, the DIOs had different segmentation scales with different DDFs (see Figure 6). In the vector layer shown in Figure 4, most of the filtered DIOs were anthrop-impacted ground objects. The proposed method has produced improved results (see Table 2), but not all land covers benefitted equally. The image object detection results varied in the ability to reveal different ground objects (see Table 3). The exhibitions of image object candidates were perfect, especially in residential areas and agrarian fields. The changed inland aquacultures were detected well by the signal that the merge and/or split of the corresponding image objects occurred (see Figure 6, below). The land covers consisting of those image objects had a larger improvement in accuracy. In contrast, the changed aquacultures under the coastline were not detected ideally because in the fused image their small or narrow border could not be protected from

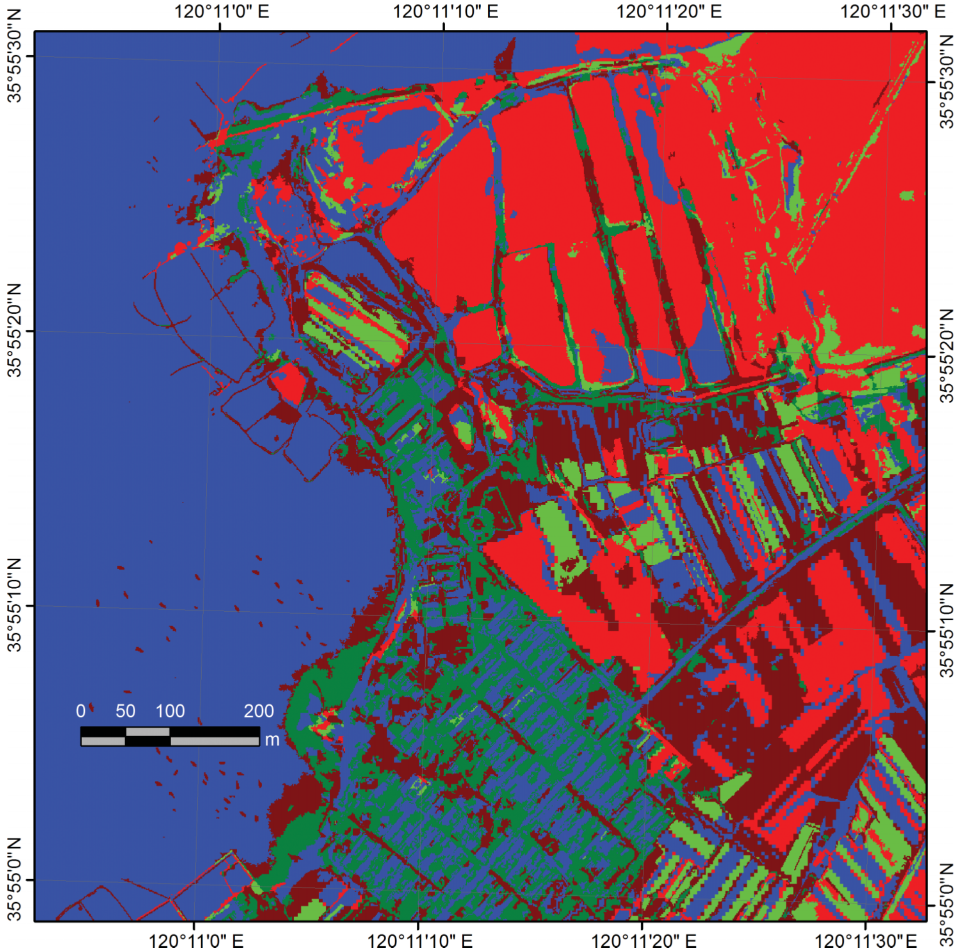

Figure 5. Difference map of supervised MLC; segmentation was performed before classification with segmentation scale 30. The result of change detection was enhanced by spatial information.

merging with their surroundings because of the same materials. The image objects in the areas where land cover was changed from agrarian fields to settlements were acceptable although their ground object size was relatively small. However, the built-up areas of the settlement could not be identified well because of their size, and they were not considered as DIOs. The accuracy for land covers with those image objects improved less. Many agrarian fields were detected as changed areas according to their changed shape. Such a case meant that the planting and farming state would change the result of IODA. The segmentation is relative to the accuracy of the classification (see Table 1). The higher accuracy of classification indicated that the ground object could be identified from other classes, that also meant they were segmented from the surroundings easily.

As a traditional preclassification method, the spectral change vector approach (CVA) helped to determine whether there were any DIOs changed on the whole or whether there were parts changed in the merge or split procedure (Johnson and Kasischke 1998). The result of the image object-based change vector is clearer than the pixel-based result of the

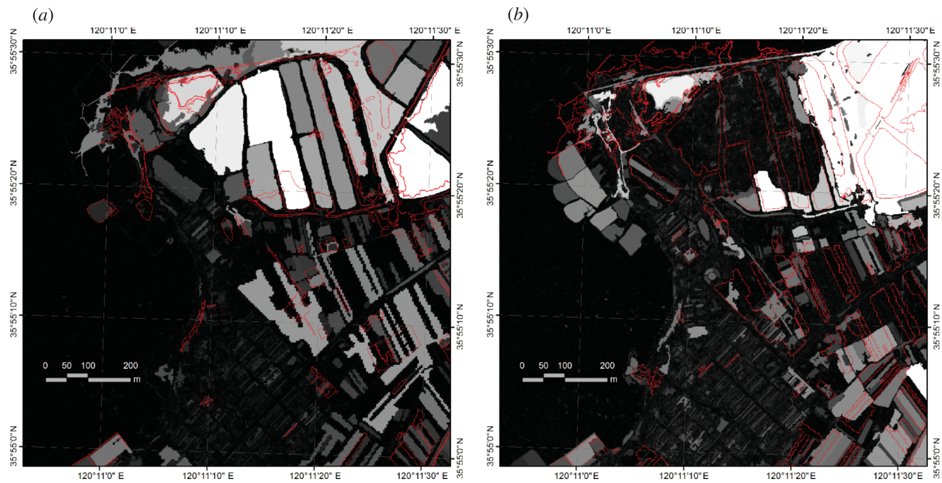

Figure 6. The left image (*a*) is the DIO presentation of the earlier image covered with the red plots of the DIO presentation of the latter image. The right image (*b*) is the DIO presentation of the latter image covered with the red plots of the DIO presentation of the earlier image.

Table 3. Comparison between the interpreted ground objects and the DIOs segmented from bi-temporal images.

	Aquaculture	Coastal aquaculture	Pond	Crop	Soil	Building	Road	Wood land	Silt
2007 Interpreted	5	16	17	17	51	143	3	27	2
2007 Segmented	5	14	17	14	33	92	1	15	1
2001 Interpreted	15	10	3	41	48	98	2	3	2
2001 Segmented	14	3	3	39	4	73	1	1	1

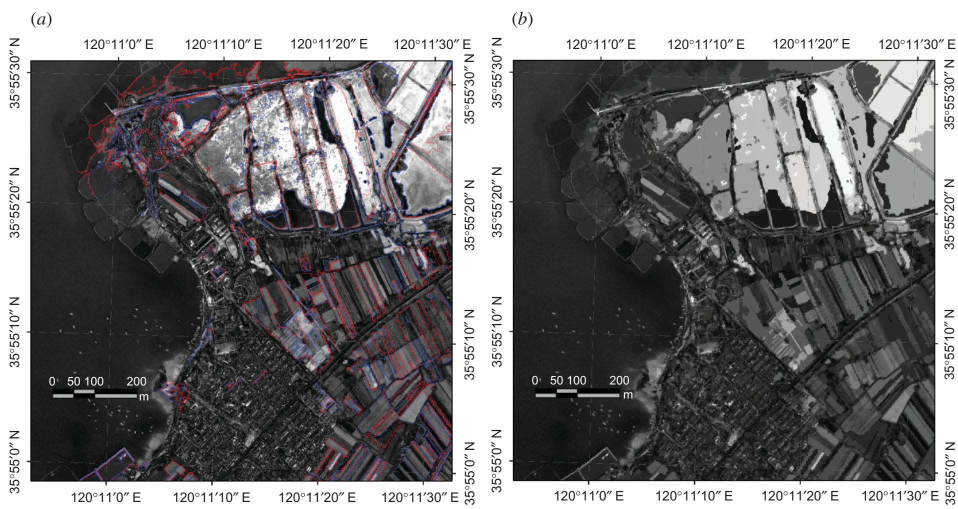

Figure 7. The left image (*a*) is the result of pixel-based CVA covered with red plots of shape changed DIOs of early image and blue plots of shape changed DIOs of latter image. The right image (*b*) is the result of object-based CVA of the result of overlay of DIOs.

CVA method (see Figure 7). On comparison with the pixel-based CVA method, the image object-based method avoids the 'salt-and-pepper' phenomenon. The false small polygon, which usually emerged in the result without accurate geometric registration, did not emerge when we used the concept of DIO. Generally, the larger value of the spectral change vector indicates the changed region and the lesser value indicates unchanged parts. The result of the proposed approach would be more significative in high-resolution remote-sensed images, where the DIOs can be obtained. In the study area, the traditional change detection method is still important in image object-based change detection. But the image object-based change detection method adds more extra information on spatial information such as merge or split.

4. Discussion

4.1. Changed shape means changed spectrum

Changed shape means either a merge or a split or both have occurred. It also indicates the spectral difference in the parts of them. For multiscale segmentation, the spectral features of two image objects f_1 and f_2 are considered to be similar when they are near to each other. For an l-dimensional spectral space, the heterogeneity h is described as follows:

$$h = \sqrt{\sum_d \left(\frac{f_{1d} - f_{2d}}{\sigma_{fd}}\right)^2}, \tag{5}$$

where d represents bands. These distances of f_1 and f_2 can be further normalized by the standard deviation σ_{fd} of the spectrum. There are several possibilities for describing the heterogeneity change before and after a virtual merge (a detailed discussion is described by Baatz and Schäpe (2000)). Given an appropriate definition of heterogeneity, the growth in heterogeneity of a merge should be minimized. Obviously, the adjacent pixels set belonging to the same class would be segmented together before.

The derived criteria from multiscale segmentation can convey useful information concerning the discriminatory capability associated with an adopted spectral space. If one candidate can be separable from surrounding candidates, on the classification view it can be reflected by the derived criteria of classification such as the maximum inter-class distance and the minimum intra-class diversity. For each image candidate, there are three phases passed from being a one-pixel object to being an undersegmented object at a relatively large segment scale, along with the multiscale segmentation procedure. In the oversegmentation phase, for each object candidate in the range of one image object, there must be one or more neighbourhood candidates in the same image object. The spectral mean of the candidate can be considered as the sample's mean $\bar{x}$ and the variance of the candidate is the variance of the sample's standard deviation S. For innate merge, the sample's means were $\bar{x}_1$, $\bar{x}_2$ and standard deviations were S_1, S_2 before and the same statistics were $\bar{x}_{\mathrm{m}}$ and S_{m} after merge. The DDF of two candidates which came from the same image object, the candidates were oversegmented, was relatively small in this phase. The optimal segmentation phase followed the ending of the oversegmentation phase; there was a case where both the candidate a and the candidate a' belonged to the same image object. Apparently, the only two bordering candidates would merge together at the optimal scale. This is related to the spatial resolution of the image being used. The heterogeneity in the oversegmentation phase was less than in the optimal phase. Subsequently, it was in the undersegmentation phase. When two candidates included more than one image object, and n and m were the sample numbers of these two candidates, the merged candidate had the difference in feature as follows:

$$S^2 = S_1^2 + S_2^2 + \frac{nm(\bar{x}_1 - \bar{x}_2)^2}{n+m}. \tag{6}$$

However, as is known, the variance of the candidate increased monotonously, so the DDF tended to decrease. Two adjacent regions belonging to different classes were obliged to merge together in the segmentation procedure. But they were not satisfying the condition of optimal segmentation in IODA.

If DIOs existed and were neighbours together, they were considered to be belonging to different classes. When the shape changed, the merge procedure indicated that two DIOs separated in early time but did not separate in latter time. That also meant that two DIOs did belong to two classes in former time but they belonged to the same class later. The split procedure indicated that DIOs need to be classified into one class before but should be classified into different classes later. That meant the shape of the image object could be used in detection of the spectral change.

4.2. The meaningful image object is critical in using spatial information

In image object-based analysis, the pixel entities that are expected in remote-sensing images can be related to real entities in the landscape. These regions are later related to geographic objects through some object-based classification. To extract meaningful image objects, users are required to focus on different intrinsic scales because all attributes of image structure are almost highly scale dependent. Spatial information that we want to obtain from the overlay function should be derived only from the image objects of intrinsic scales but not of any general scales. Otherwise, it will lead to unreasonable results. This is why the general result from traditional multiscale analysis cannot be adopted directly. And the optimal segmentation and intrinsic scale identification are the predetermination of the image object-based change detection.

Actually, these more important simple meaningful objects are the explicit homogeneous objects, which have similar spectral characteristics yet differ from surrounding objects in high-resolution remote-sensing imagery. In our study area, these objects included water-bodies, residential areas, agrarian fields, and such anthropogenic-impacted ground objects. Furthermore, the Shannon sampling theorem should be considered. In fact, if the border of two ground objects or the size of the ground object is similar to the pixel size, the spectral average of the image candidate will not be a real spectrum of a ground object because of the problem of mixed pixels. Therefore, many man-made or anthropogenically influenced objects are coincident with the defined term meaningful objects. The basic task of segmentation algorithms is to merge image elements based on homogeneity parameters or on the differentiation to neighbouring regions (heterogeneity), respectively. In other words, these criteria can be explained as follows: in the segmentation procedure, the increased heterogeneity can be interpreted as a border between the segments, which has to be overcome for merging. The higher this border is for a certain segmentation parameter combination, the more stable is the result (Benz et al. 2004). As long as the scale is the best, meaningful objects can be obtained. Furthermore, in many cases significant objects appear at different scales of analysis of the same image.

5. Conclusions

Image object-based change detection can be enhanced by spatial information in change identification for both postclassification and preclassification approaches. Obviously, the important information for understanding an image is not represented in a single pixel but is embodied in meaningful image objects as well as their mutual relationships. The spatial information of image objects is also an important cue to identify the change. In this study, an image object-based method is presented to identify the changed areas using shape difference of an image object between bi-temporal images of a coastal zone. We proposed the concept and its definition of DIO. The DIO presentation was identified from the results of optimal segmentation through the IODA. By using raster overlay analysis to bi-temporal DIOs, the shape of image objects can be used to recognize the change evolution by knowing its merge or split procedure. The classes conducted in postclassification change detection were divided into a strong attribute pixel group and a weak attribute pixel group according to its accuracy. After integration with spatial change information, the accuracy of both weak attribute pixel and shape change was 0.81, and the only weak attribute pixel that was changed was decreased from 0.36 down to 0.26. In contrast, the accuracy of both strong attribute pixel and shape change was increased from 0.84 up to 0.94, and the accuracy of only the strong attribute pixel change was 0.68. The improved accuracy depended on the ability that the obtained DIOs revealed the different ground objects. The present method would be more significant in high-resolution remote-sensed images. The spatially unchanged information can reduce overdetected areas and the spatially changed information can certify the judgement of change. By analysis of the three phases of the image segmentation procedure, the IODA was considered as a rational way to derive intrinsic image objects from a hierarchic candidate. Thereby, the typical spectral difference based change detection between bi-temporal images was instead of spatial change detection between ground objects based on the spectral difference which would be compared in an optimal segmentation procedure. The latter can be helpful in avoiding some spectral reflection corrections caused by many image acquisition conditions in typical change detection processes.

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