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Land cover change detection with a cross-correlogram spectral matching algorithm

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Timely extraction of reliable land cover change information is increasingly needed at a wide continuum of scales. Few methods developed from previous studies have proved to be robust when noise, changes in atmospheric and illumination conditions, and other scene- and sensor-dependent variables are present in the multitemporal images. In this study, we developed a new method based on cross-correlogram spectral matching (CCSM) with the aim of identifying interannual land cover changes from time-series Normalized Difference Vegetation Index (NDVI) data. In addition, a new change index is proposed with integration of two parameters that are measured from the cross-correlogram: the root mean square (RMS) and $(1-R_{\max})$, where $R_{\max}$ is the maximum correlation coefficient in a correlogram. Subsequently, a method was proposed to derive the optimal threshold for judging 'change' or 'non-change' with the acquired change index. A pilot study was carried out using SPOT VGT-S images acquired in 1998 and 2000 at Xianghai Park in Jilin Province. The results indicate that CCSM is superior to a traditional Change Vector Analysis (CVA) when noise is present with the data. Because of an error associated with the ground truthing data, a more comprehensive assessment of the developed method is still in process using better ground truthing data and images at a larger time interval. It is worth noting that this method can be applied not only to NDVI datasets but also to other index datasets reflecting surface conditions sampled at different time intervals. In addition, it can be applied to datasets from different satellites without the need to normalize sensor differences.

1. Introduction

Human and natural alterations of land cover have occurred at an increasing rate in space and time during the past century. Such alterations could affect multiple aspects of the environmental system such as energy balance, biogeochemical cycles, hydrological cycles and the climate system, which are regarded as crucial elements in global change studies (e.g. Turner *et al.* 1995). Therefore, timely extraction of reliable land cover

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change information is increasingly needed at a continuum of scales ranging from local and regional to continental and global. At continental and global scales, NOAA/AVHRR, SPOT/VEGETATION, TERRA or AQUA/MODIS are valuable data sources, as they are able to cover a large area with high temporal resolution at low cost and their availability can be traced back to 1981 (Townshend *et al.* 1991). With such data sets, the time trajectories of the Normalized Difference Vegetation Index (NDVI) are effective for the purpose of land cover classification based on the assumption that different land cover types are discriminated by their specific time trajectories of the NDVI (e.g. Tucker *et al.* 1985, DeFries *et al.* 1995, Loveland *et al.* 2000). Following this assumption, interannual variation of land cover, especially vegetation types, could also be detected by addressing the changes in NDVI time trajectory during a certain period, as evidenced in a series of studies such as those by Lambin and Strahler (1994*a*,*b*), Lambin and Ehrlich (1995, 1997), Borak *et al.* (2000) and Lunetta *et al.* (2006).

Although a number of approaches for land cover change detection using satellite imagery have been formulated, applied and evaluated over the past two decades (Singh 1989, Coppin *et al.* 1996, Jensen 1996), most of these approaches have been developed based on multispectral data acquired at limited discrete time periods, and are thus not appropriate for high temporal resolution satellite data. There are only four types of approaches that have been widely used for land cover change detection based on NDVI datasets: time-series derived change metrics (e.g. Borak *et al.* 2000), linear data transformation (such as Standardized Principal Component Analysis (SPCA) (e.g. Eastman and Fulk 1993)), Change Vector Analysis (CVA) (e.g. Lambin and Strahler 1994*a*) or the hybrid approach (Zhan *et al.* 2000). Despite the success with the above algorithms, few methods have proved to be robust when noise, changes in atmospheric and illumination conditions, and other scene- and sensor-dependent variables are present in the images that are acquired in different years. Therefore, it is necessary to develop new change detection techniques to consistently achieve a similar or even better accuracy when such problematic circumstances occur. In this study, we present a new method that is based on cross-correlogram spectral matching (CCSM) with the aim of identifying interannual land cover changes from time-series NDVI data. We tested the new method in the study area of Jilin Province, China, where we have acquired high spatial resolution satellite data. The 10-day Maximum Value Composite (MVC) SPOT VGT-S product in 1998 and 2000 with a spatial resolution of $1\,km \times 1\,km$ was used in the study (VEGETATION Programme 1998).

2. Methods

Land cover change detection using remotely sensed data can be divided into two stages: (1) detection of where changes occur ('change/no-change' detection) and (2) identification of what type of changes they are ('from-to' change identification). The CCSM-based method proposed in this study was developed for the first phase to serve as a warning system rather than a comprehensive land cover change monitoring system. As to the second phase, considering the mixed pixel problem due to low spatial resolution of the adopted datasets, we recommend a strategy that identifies 'from-to' changes by using higher spatial resolution satellite data after the changed areas are revealed from the first phase.

2.1 *Background of CCSM*

CCSM is an approach proposed by van der Meer and Bakker for mapping minerals from imaging spectrometer data (van der Meer and Bakker 1997, van der Meer

2000). It provides a statistically meaningful tool to compare a target spectrum (i.e. a remotely sensed spectrum) with a reference spectrum (i.e. a laboratory mineral spectrum) by constructing a cross-correlogram at different match positions and calculating the goodness-of-match between them. CCSM has demonstrated its merits as being insensitive to difference in gain and noise associated with multitemporal remote sensing data when noise is low enough so as not to perturb the shape of key absorption features. Although efforts have been made to adapt the CCSM approach to various applications, such as the assessment of pollution caused by mining (Ferrier 1999) and the identification of green and dry vegetation components (Datt 2000), to our knowledge CCSM has not yet been adopted to detect land cover change. As NDVI time-series data (hereafter referred to as an NDVI profile curve) can be plotted as a spectrum in the manner of NDVI value *vs.* date, which resembles the spectral reflectance spectrum that is acquired at different wavelengths, we were motivated to develop and test the feasibility of CCSM in the context of NDVI analysis towards the final goal of a robust land cover change detection. The rationale here is that differences that existed in the NDVI profile curve between the test and reference year would affect the shape, significance and correlation of the cross-correlogram values, from which changes of land cover types are expected to be revealed. A detailed implementation scheme of the CCSM-based change detection method is provided in figure 1 and explained in the following section.

2.2 *Development of the CCSM-based technique*

2.2.1 Preprocessing NDVI time-series data. Although atmospheric correction has been applied to the SPOT VGT product, evidence of noise is still apparent. It is primarily attributed to two factors: cloud contamination and sensor noise. In this study, a method based on the Savitzky–Golay filter as reported in Chen *et al.* (2004) was taken to construct high-quality NDVI time-series datasets. In brief, the method was built on two assumptions: (1) an NDVI time-series should follow an annual cycle of growth and decline as a portrait of vegetation phenology change; (2) due to clouds and atmospheric variation, NDVI values were degraded, manifested in the form of sudden falls on the NDVI profile curve, which is in contradiction to the gradual change that should occur when such noise is not present. This method, by using an iteration process, can approach the upper envelope of NDVI data and reveal patterns of change in NDVI. As a result, high-quality NDVI time-series datasets for both test year and reference year are obtained.

2.2.2 Calculating a new change index. Following van der Meer and Bakker (1997), in this study we calculated the correlation coefficient (R_m) between an NDVI profile curve in the test year and its counterpart in the reference year at different match positions (m). The match position refers to the number of units (1 unit is 10 days in this study) along the x axis to be shifted with the test year data in order to calculate correlations. The NDVI profile curve in the reference year will remain unchanged. By convention, we define a negative match position when shifting the test year curve to an earlier date and a positive match position when shifting it to a later date. For example, the match position 0 means a direct calculation of correlation between test and reference data while the match position -1 means the whole NDVI curve in the test year will be shifted by one unit of time towards the lower end direction to derive a correlation, which is based on the overlapped portions of the two curves. The cross-correlation, R_m, at each match position m is equivalent to the ordinary linear

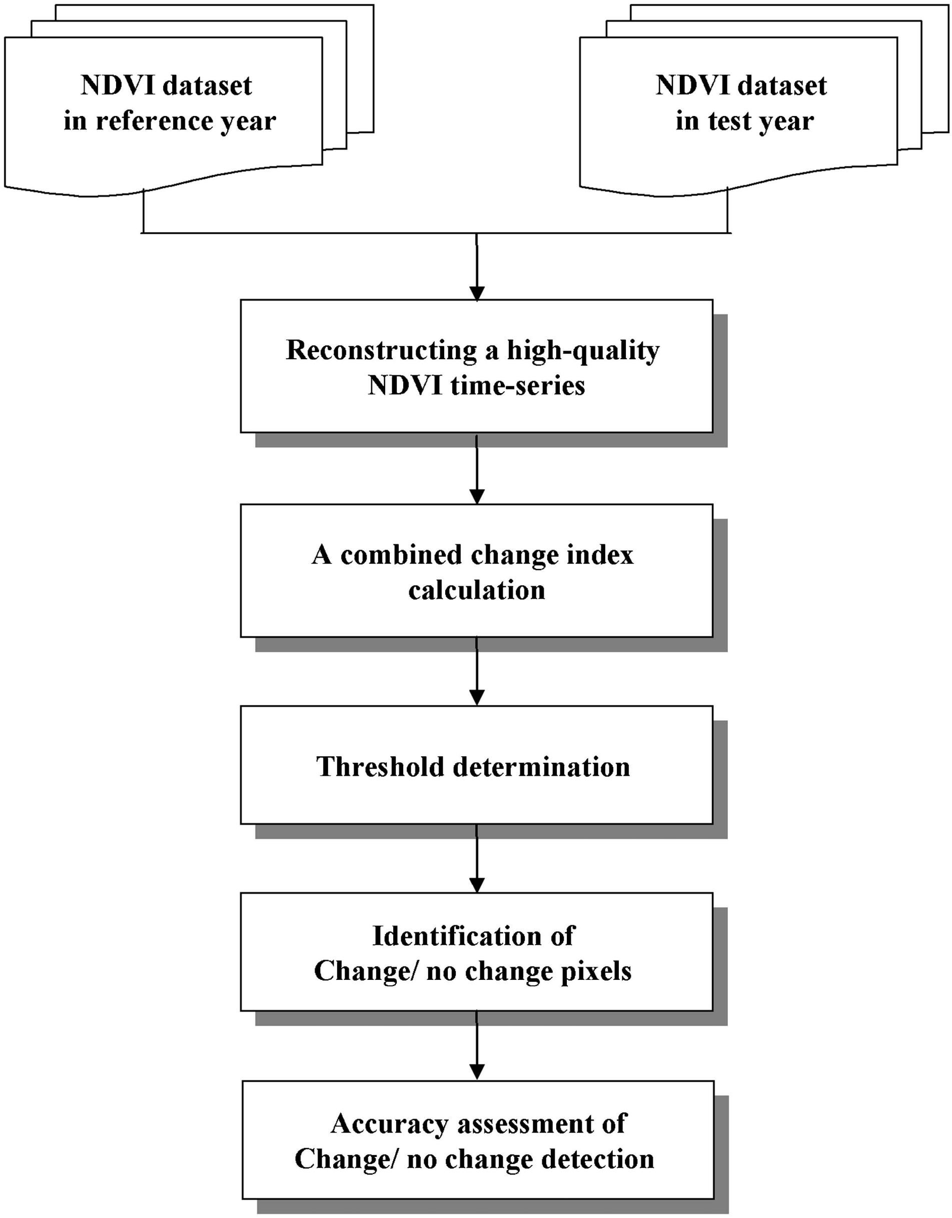

Figure 1. Flowchart of the CCSM-based land cover change detection method.

correlation coefficient and can be computed as follows (van der Meer and Bakker 1997):

$$R_m = \frac{n\sum \lambda_r \lambda_t - \sum \lambda_r \sum \lambda_t}{\sqrt{\left[n\sum \lambda_r^2 - \left(\sum \lambda_r\right)^2\right]\left[n\sum \lambda_t^2 - \left(\sum \lambda_t\right)^2\right]}} \tag{1}$$

where λ_t and λ_r are NDVI profile curve values for the test year and reference year, respectively, and n is the number of overlapping positions. In this study, the matching position m is set in the range from -5 to 5 because vegetation phenology changes are usually limited to 50 days (five date units in the 10-day MVC dataset) even in an extreme case.

A cross-correlogram is then constructed by plotting the correlation coefficient (R_m) *vs*. respective match positions (figure 2). In theory, should there be no changes, the cross-correlogram would exhibit a symmetrical parabolic shape such that the correlation value peaked at the match position 0 and declined at the same pace as the match position goes towards the two ends, that is the skewness is zero. Conversely, if the shape of the cross-correlogram and the position where the maximum correlation occurs deviate from an ideal profile curve, as described above, evidence of changes between the two NDVI profile curves can be concluded. Arising from this idea, two parameters were adopted to assess the degree of difference between the two NDVI profile curves, the root mean square (RMS) and $(1-R_{\max})$.

As defined in equation (2), the RMS is used to measure the discrepancy between the empirical cross-correlogram and the ideal cross-correlogram. Specifically, the empirical cross-correlogram comprises correlation coefficients (R_m) that are derived from the NDVI test profile curve and the NDVI reference profile curve, while the ideal cross-correlogram consists of correlation coefficients (R'_m) that are derived from the NDVI reference profile curve and itself (figure 1).

$$\mathrm{RMS}=\sqrt{\frac{\sum_{-m}^{m}\left(R_m-R'_m\right)^2}{k}} \tag{2}$$

where R_m is the cross-correlation at match position m, R'_m is the reference cross-correlation at match position m, and k is the number of match positions. The magnitude of the RMS is a reflection of the deviation between the NDVI test profile

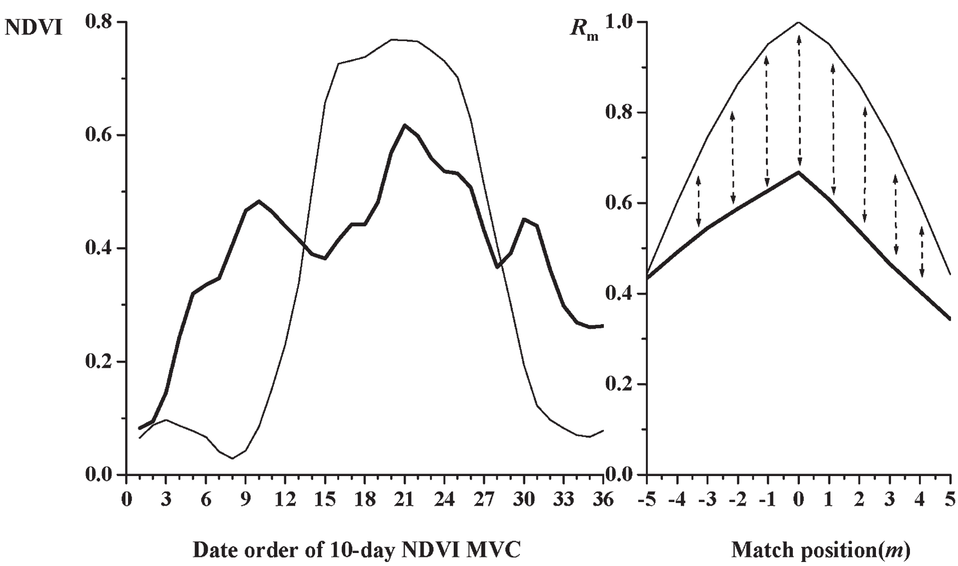

Figure 2. The concept of the CCSM-based land cover change detection method. The thick black is the NDVI profile curve (*left*) in the test year and its cross-correlogram (*right*), respectively; the thin black line is the NDVI profile curve (*left*) in the reference year and the perfectly matching cross-correlogram (*right*), respectively.

curve and the NDVI reference profile curve. The higher the RMS value, the more likely it will be that changes have occurred. As atmospheric variability, sensor differences and sensor noise in most cases do not affect the shape of the NDVI profile curves and thus influence the correlation coefficients equally at different match positions, the shape of the resulted correlogram will be kept authentic. As a result, the RMS is only sensitive to land cover change and vegetation phenology change. Therefore, the RMS is capable of capturing land cover changes regardless of the presence of such noise in the data. In addition, the RMS is calculated from correlation coefficients that depend to a greater extent on the shape of the NDVI profile curve than on the absolute values of NDVI; thus, the RMS is similarly sensitive to all kinds of changes. However, the RMS has one shortcoming in that it is difficult to differentiate long-term land cover change with vegetation phenology changes caused by climatic events. Therefore, another index was designed.

In the index $(1-R_{\max})$, $R_{\max}$ stands for the maximum correlation coefficient in a correlogram. $R_{\max}$ can be obtained by comparing the correlation coefficients (R_m) at different match positions ($-m$ to m) as follows:

$$R_{\max} = \arg\max\{R_{-m}, \ldots R_{-1}, R_0, R_1, \ldots R_m\} \tag{3}$$

Changes occurring between the NDVI test profile curve and the reference profile curve will affect not only the shape of the cross-correlogram but also the match position at which maximum correlation is achieved. Although the index $(1-R_{\max})$ functions similarly to the RMS index to some extent, it is particularly effective in differentiating long-term land cover changes from vegetation phenology changes because most vegetation phenology changes, which are not related to land cover change, only affect the shape of the cross-correlogram and do not alter $R_{\max}$ values. After obtaining $R_{\max}$, its significance is assessed using the following t-test (equation (4)). Here the null hypothesis of the test is that the correlation between the two profile curves at a specific match position is zero:

$$t = R_{\max}\sqrt{\frac{n-2}{1-R_{\max}^2}} \tag{4}$$

where n is the number of overlapping positions. If $R_{\max}$ cannot pass the significance test, it is set as 0; otherwise the value will be kept.

As the RMS and $(1-R_{\max})$ complement each other, they can be combined together to assess land cover changes from NDVI profile curves. To this end, we developed a synthetic change index (ΔD) defined as follows:

$$\Delta D = \mathrm{RMS} \times (1 - R_{\max}) \tag{5}$$

Given the above definition, it is evident that the value of ΔD will increase along the increase in magnitude of land cover changes. For example, a low value of ΔD may indicate a low-intensity land cover modification while a large value of ΔD may suggest a land cover conversion. Meanwhile, the changes caused by atmospheric variability, vegetation phenology changes, sensor differences and sensor noise cannot significantly raise the value of ΔD.

2.2.3 Determining the optimal threshold for the change index. At this point, it is still necessary to set up a threshold value for ΔD in discerning whether a land cover change has occurred with the corresponding pixel. To this end, we used an iterative trial-and-error procedure that was introduced by Fung and LeDrew (1988) to decide the optimal threshold for ΔD. First, we selected a set of training images in which each pixel's status of change has been known. Once ΔD for all the pixels in the training images are derived, a histogram of ΔD is constructed and the mean and standard deviation of ΔD are computed. The two parameters are then used to formulate a potential threshold in the form of (mean + $N \times$ standard deviation) in the iterative trial-and-error procedure. An initial value 0.1 is set for N. In the subsequent iterations, N is increased in steps of 0.1 until it reaches 3.0. At each step, the threshold value calculated is used to generate a binary image representing changed and unchanged pixels, respectively. Given the training dataset, the binary image is compared with the reference to build an error matrix by which a kappa value can be obtained. Ultimately, the optimal threshold for ΔD is assigned to the value at which the maximum kappa value is achieved. Given the optimal threshold for ΔD from the training data, the task to identify land cover change is easily carried out in the study site.

2.2.4 Accuracy assessment. To assess the reliability of the extracted land cover change information with our CCSM methods, an accuracy assessment was performed similar to a traditional classification. Two classes were to be examined: change and non-change. An error matrix was formed and the kappa value derived based on ground reference data that were acquired from a field survey and visual interpretation of finer spatial resolution remotely sensed data. In light of the fact that in most practical cases changed pixels occupy only a small proportion in an image, an equalized random sampling technique was first applied in the process of test sample selection so that changed and unchanged classes were equally represented in the total population of randomly sampled pixels.

3. Results and discussion

3.1 *Sensitivity analysis of the CCSM-based method*

To test the performance of the CCSM-based method as a tool for revealing the land cover changes and excluding 'false' changes caused by atmospheric variability, changes in vegetation phenology, sensor differences and sensor noise, we applied the method to a number of simulated experiments that represent typical cases affected by the above noise.

The first experiment was designed to examine how vegetation phenology change affects the detection results from the CCSM-based method (figure 3(*a*)). An NDVI profile curve representing deciduous forest was taken as the reference and a new NDVI profile curve, generated by shifting the reference curve to the earlier date by 1 unit of 10 days, was treated as the test curve for representing vegetation phenology change. The second experiment was designed to examine how the noise caused by atmospheric variability (e.g. volcano ash) or climatic events such as drought affect the detection results from the CCSM-based method (figure 3(*b*)). As noise of this type often depresses the absolute NDVI values but does not influence the shape characteristics of the NDVI profile curve, an NDVI profile curve from deciduous forest was taken as reference and a new NDVI profile curve, generated by decreasing the reference curve values by 10%, was treated as the test curve to represent this noise. In the third experiment, we aimed to examine how the noise occurring in local NDVI value points affected the detection results from the CCSM-based method (figure 3(*c*)). The selection of a reference curve was the same as in the above

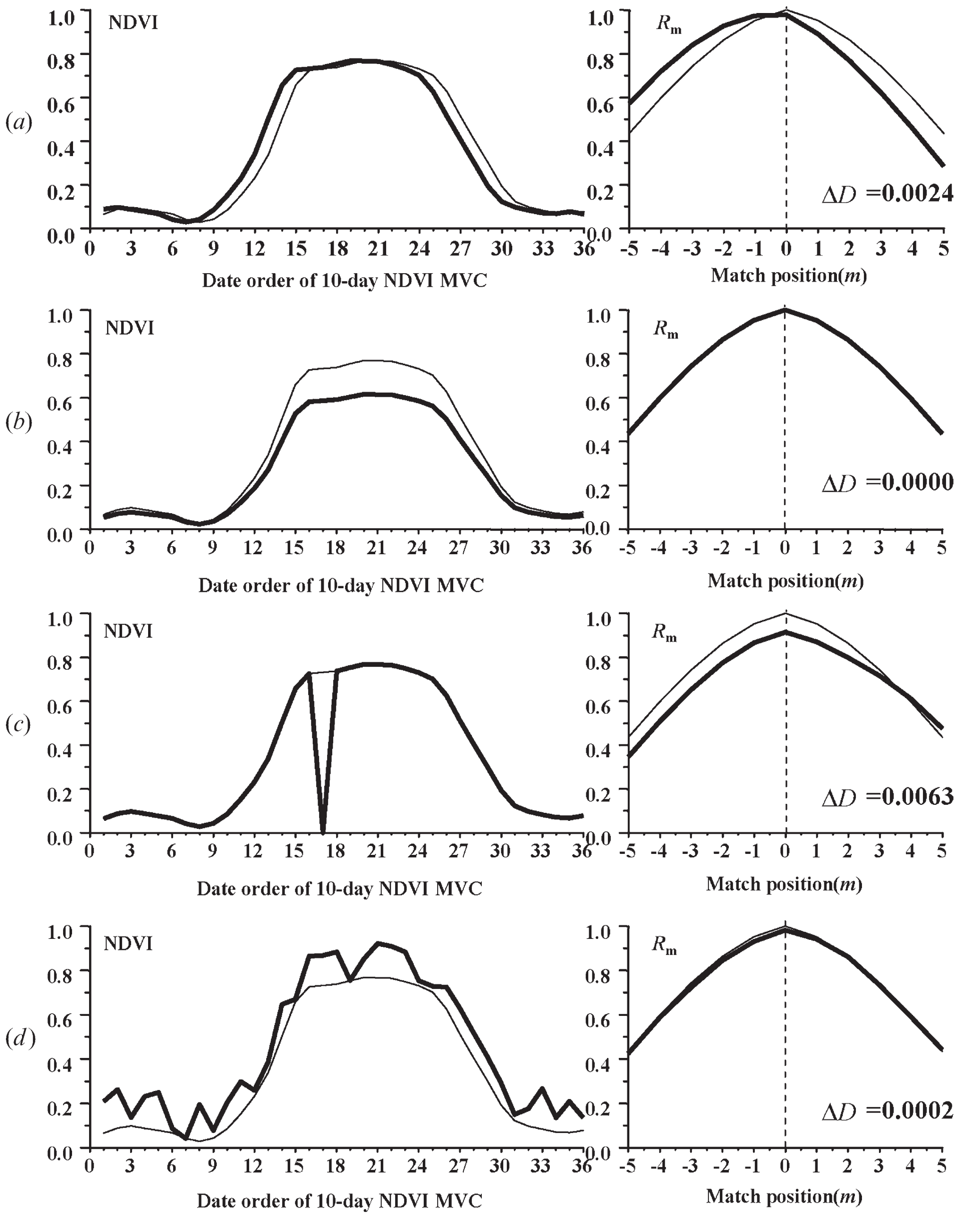

Figure 3. Simulation experiments to test the CCSM-based method in special cases: (*a*) phenology change, (*b*) noise due to atmospheric variability or extreme climatic events, (*c*) noise in local NDVI, (*d*) sensor noise. The thick black line is the NDVI profile curve (*left*) in the test year and its cross-correlogram (*right*), respectively; the thin black line is the NDVI profile curve (*left*) in the reference year and the perfect-matching cross-correlogram (*right*), respectively.

experiments, and the test curve was produced from the reference curve by significantly changing one NDVI value. Clearly, such noisy values can be found to correspond to cloud contamination and poor atmospheric conditions in local NDVI value points. The fourth experiment was designed to examine how the random noise generated by sensors and atmospheric variability affects the detection results from the CCSM-based method (figure 3(*d*)). The reference profile curve was also from a deciduous forest, and the test profile curve was generated by adding a component of 10% random noise to the reference curve. Figure 3 shows the NDVI profile curves in the simulation experiments and the corresponding cross-correlograms with the combined change index ΔD. The results of the experiments show that the ΔD in every experiment was obtained as a much smaller value, indicating that the CCSM-based method is insensitive to these types of noise.

3.2 *A case study: land cover change detection in Xianghai Park, Jilin Province, China*

A pilot study was carried out in Xianghai Park, Jilin Province, China. Xianghai Park is a national nature reserve park located in northeast China (121°24′–124°10′ E, 43°39′–45°46′ N), covering an area of 60 368 km^2. The main land cover types of the area are grassland, wetland, cropland, water and shrub land. To evaluate the performance of our proposed CCSM method, a 10-day 1 km × 1 km SPOT VGT-S product (MVC Product) from the years 1998 and 2000 were used in this study (figures 4(*a*)) and 4(*b*)). The 1998 dataset includes 36 bands acquired during the period from April 1998 to March 1999 and the dataset in 2000 during the period

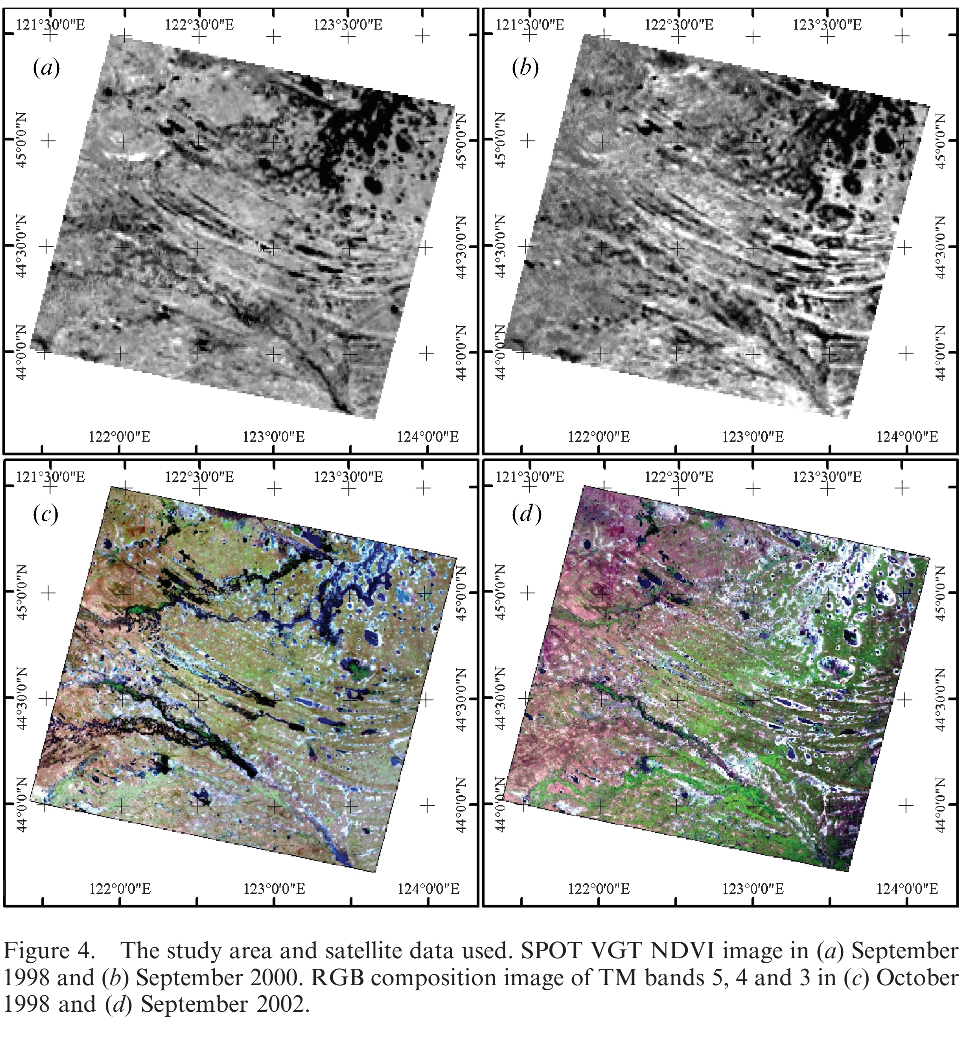

Figure 4. The study area and satellite data used. SPOT VGT NDVI image in (*a*) September 1998 and (*b*) September 2000. RGB composition image of TM bands 5, 4 and 3 in (*c*) October 1998 and (*d*) September 2002.

from April 2000 to March 2001. For the purpose of ground truthing, two scenes of Landsat Thematic Mapper (TM) image data (path/row: 120/29, 5 October 1998 and 24 September 1999) with good image quality were used (figures 4(*c*) and 4(*d*)). The boundaries of the TM images were used to clip the study area from the SPOT VGT dataset so that all the satellite data covered the same area.

As validation data, land cover change information at high spatial resolution was obtained by using the post-classification comparison method, in which land cover information in 1998 and 2000 was extracted with a maximum likelihood classifier respectively based on Landsat TM images in 1998 and 2000. Figure 5(*a*) shows the resultant changed pixels in red after the post-classification comparison and aggregation to 1 km $\times$ 1 km spatial resolution. By using SPOT VGT-S datasets, we then detected land cover changes in the study area based on the CCSM-based method and on the CVA method proposed by Lambin and Strahler (1994*a*,*b*) (figures 5(*b*) and 5(*c*)). To avoid possible sampling bias, the whole 'change/no-change' image obtained from TM data (figure 5(*a*)) was used for accuracy assessment instead of random sampling. Tables 1 and 2 present the error matrix of 'changed/unchanged' detection from the CCSM-based method and CVA, respectively. It is

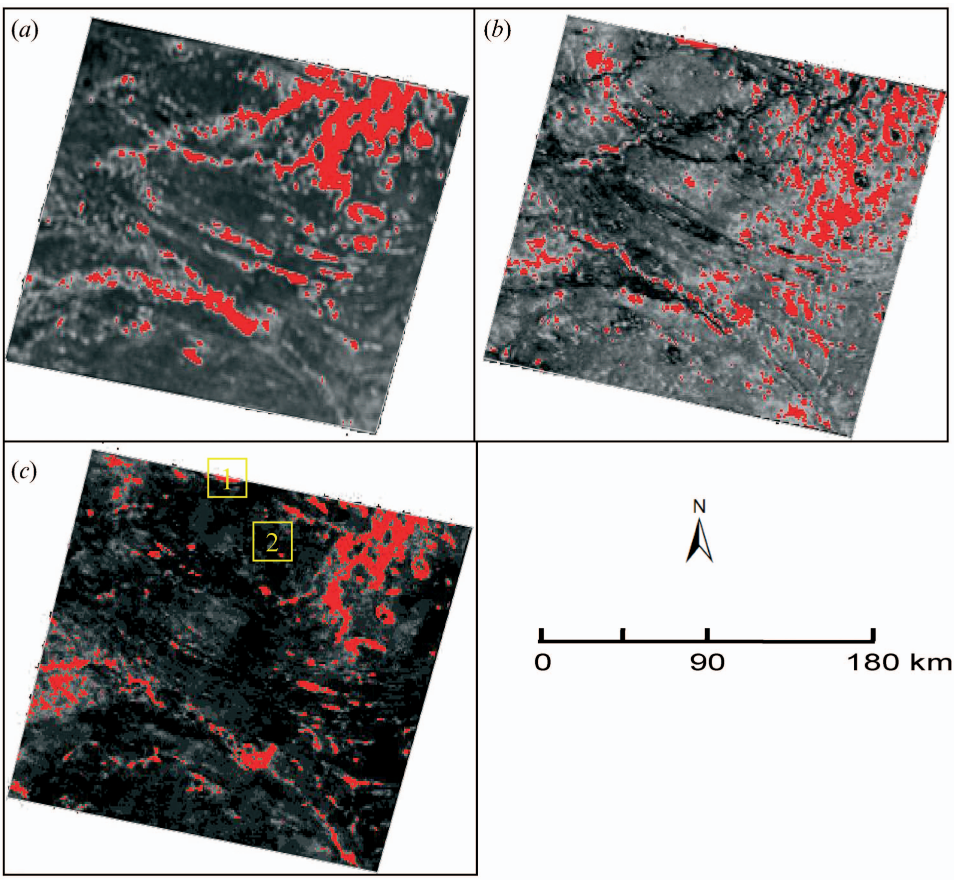

Figure 5. The results of land cover change detection by the CCSM-based method and the CVA method. (*a*) The detected changed pixels (in red) from TM images. (*b*) The detected changed pixels by the CVA method. (*c*) The detected changed pixels by the CCSM-based method. The locations of the sub-images in figures 6 and 7 are given as yellow rectangles 1 and 2, respectively.

Table 1. Error matrix for 'change/non-change' detection using the CCSM-based method.

	Reference change			
Detected change	No-change pixels	Change pixels	Sum	Commission error
No-change pixels	24 750	1567	26 317	5.95
Change pixels	1101	1088	2189	50.30
Sum	25 851	2655	28 506	
Omission error	4.26	59.02		
	Overall accuracy=90.64%; kappa coefficient=0.3986			

clear that two methods achieved high overall accuracy but a relatively low kappa index: for the CCSM-based method the kappa coefficient is 0.39 and the overall accuracy is 90.64%; for CVA the kappa coefficient is 0.09 and the overall accuracy is 80.14%. The high overall accuracy is attributed to the fact that all pixels in the study area were included in the assessment and unchanged pixels covered a much larger proportion of the study area. Moreover, a better result was obtained when our proposed CCSM-based method was compared with the CVA. However, results from the CCSM-based method were not as promising as we had expected.

To explain why the CCSM-based method cannot achieve a good result with a higher kappa index, detailed visual interpretation was carried out on TM images and NDVI profile curves from the SPOT VGT dataset, focusing on incorrectly labelled change areas (commission errors) and undetected change areas (omission errors). Several reasons for commission and omission errors were found.

(1) The TM images did not detect several change areas from grassland to cropland (an example is shown in figure 6). It is clear that land cover changes have occurred from grassland to crop land from the TM data; however, because the spectrum of the grassland is similar to that of the crop land, these changed areas were classified as the same land cover by the maximum likelihood classifier. However, because of the major differences in the NDVI profiles of the two land cover types, the CCSM-based method successfully detected these areas. It should be noted that some incorrectly labelled change areas (commission errors) were produced by the errors existing in ground truth data acquired from the TM images.
(2) There was also a problem with undetected change areas (omission errors). Figure 7 shows an example of such areas. From the TM images, it can be seen that a change from water to grassland took place in the area, while the corresponding NDVI profiles in 1998 and 2000 did not show evidence of this change. An investigation of the precipitation record in 1998 and 2000 showed that the precipitation in September and August in 1998 was more than twice

Table 2. Error matrix for 'change/non-change' detection using the CVA method.

	Reference change			
Detected change	No-change pixels	Change pixels	Sum	Commission error
No-change pixels	23 496	2166	25 662	8.44
Change pixels	2354	490	2844	82.77
Sum	25 850	2656	28 506	
Omission error	9.11	81.55		
	Overall accuracy=84.14%; kappa coefficient=0.0905			

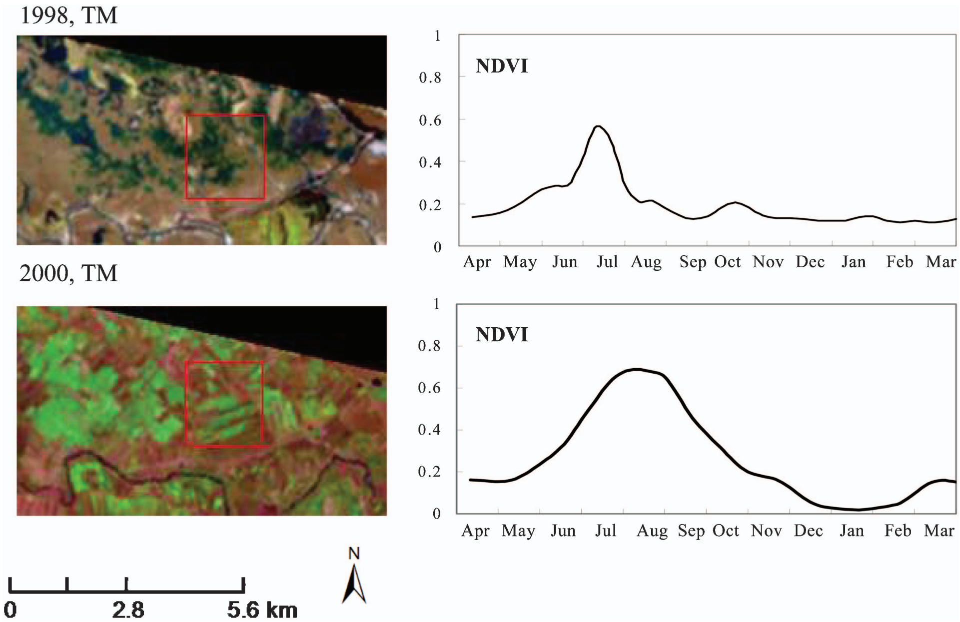

Figure 6. TM images of an example area in 1998 and 2000 and their corresponding NDVI profile curves.

that of 2000. It can be inferred that the change shown in figure 7 was a temporary phenomenon caused by a climatic event. Although the TM images provided correct land cover classification results, considering that the TM

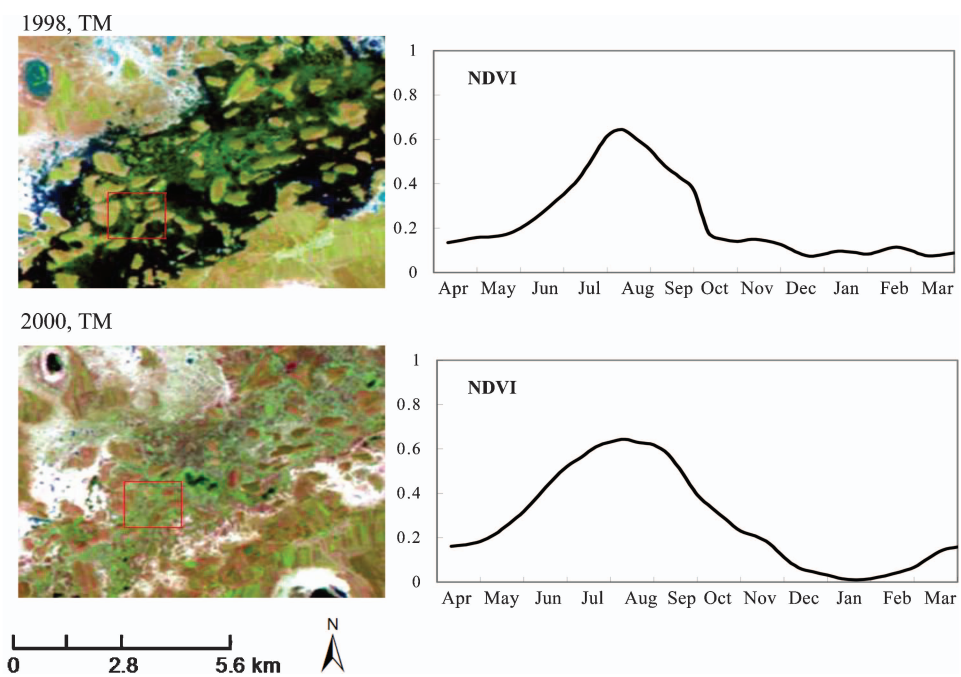

Figure 7. TM images of an example area in 1998 and 2000 and their corresponding NDVI profile curves.

image acquired on a particular date only reflects the land surface condition at that time, the ground truth data from TM images clearly included 'false' changes caused by temporary events and thus affected the change accuracy assessment.

(3) Besides the above problems existing in the validation data, we also found that the CCSM-based method tends to ignore the type of land cover change in which two land cover types have almost the same NDVI profile pattern but show an apparent difference in absolute NDVI values. Although it is rare to find such land cover changes in our case study area, it is necessary to take into account this kind of land cover change if the CCSM-based method is used on a global or continental scale. Our proposed solution is the following. After applying the CCSM-based method, pixels that have significantly smaller RMS but larger differences in absolute NDVI values should be extracted again and further analysed to identify this kind of land cover change. The extreme case reveals the imperfections of the new method, and hence caution should be taken when the new method is applied.

(4) Another imperfection of the CCSM-based method is that it may sometimes overestimate land cover changes that occurred in areas with very low NDVI values such as water. As is well known, water is considered as a Pseudo Invariant Feature (PIF) and is widely used for radiometric correction with the assumption that spectral values do not change appreciably over time. Although small changes in spectral reflectance from water can occur throughout a year due to sparse vegetation or low chlorophyll content, such changes cannot be captured by the NDVI as it is insensitive to very high/very low chlorophyll content, as claimed by Dash and Curran (2004) while developing the Meris Terrestrial Chlorophyll Index (MTCI) for MERIS data. However, in extreme cases, the NDVI profile of water is not maintained constantly throughout the year because of the relatively higher coverage of sparse vegetation or higher content of chlorophyll. Moreover, these interannual fluctuations are always different between any 2 years. In such a case, the CCSM-based method may overestimate this phenomenon and misidentify it as changes in land cover because it is designed to identify the curve shape difference rather than compare absolute NDVI values. To solve this problem, we suggest using a preprocessing procedure to smooth out these interannual fluctuations, before applying the CCSM-based method, such as the Savitzky-Golay filter as reported in Chen *et al*. (2004).

As described above, the low accuracy of land cover change detection by the new method may be attributed to the unreliable validation data as well as the imperfections of the new method. Further validation of the proposed CCSM-based method is still in process using another pair of images acquired at an interval of more than 10 years, with which it is thought that small changes in landscape can be revealed despite the coarse spatial resolution of SPOT VGT-S (1×1 km^2). Correspondingly, we will collect high-quality ground truth data from higher spatial resolution satellite data (such as TM) and detailed field surveys. Until then, an objective evaluation of the CCSM-based change detection method cannot be established.

4. Conclusion

The time-series dataset of the NDVI derived from high temporal resolution satellites is a valuable data source for extracting information on land cover and its changes on global, continental and largely regional scales. However, existing approaches, such as SPCA and CVA, are not sufficiently flexible or effective in discriminating between long-term land cover change and other changes caused by atmospheric variability, vegetation phenology changes, climate events, sensor differences and sensor noise. Based on the assumptions that different land cover types have different NDVI temporal profiles and the NDVI profile curve can be regarded as a spectrum in which an NDVI value for a certain date corresponds to one band value of the spectrum, we developed a new land cover change detection method based on CCSM. Our method was developed to detect land cover changes, particularly for land cover conversion, by reducing the effects of 'false' changes. The CCSM-based method was also designed to be similarly sensitive to all kinds of land cover changes no matter where the changes occurred and thus to be able to avoid the painstaking process of normalization of the change index for each biome. With current ground truth data, the CCSM-based change detection method presents a better performance than CVA. However, a reliable value of the absolute accuracy of the CCSM-based method will not be known until further work is completed that uses images acquired at longer time intervals and ground truthing data with higher accuracy. In general, from the pilot study, we can conclude that the new method is effective and has the potential for land cover change detection compared with the CVA method. Furthermore, it is worth noting that the method can be applied not only to NDVI datasets but also to other index datasets such as surface temperature reflecting surface conditions sampled at different time intervals. It can also be applied to datasets from different satellites without the need to normalize sensor differences.

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