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Improving change vector analysis by cross-correlogram spectral matching for accurate detection of land-cover conversion

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Time series of vegetation index (VI) information derived from remote sensing is important for land-cover change detection. Although traditional change vector analysis (TCVA) is an effective method for extracting land-cover change information from a time series of VI data, it has the disadvantage of being too sensitive to temporal fluctuations in VI values. The method tends to overestimate the changes and confuse the actual land-cover conversion with the land covers that have not been converted but experience significant VI changes. Cross-correlogram spectral matching (CCSM) can tell the degree of shape similarity between VI profiles and be used to detect land-cover conversion. However, this method may omit some land conversion in which the before and after land-cover types are rather similar in VI profile shape but differ significantly in absolute VI values. This article proposes a new approach that improves TCVA with an adapted use of CCSM. First, TCVA is employed for preliminary detection of land-cover changes. Second, the changes caused by temporal fluctuations of VI values are identified through the CCSM analysis and excluded to only keep the most likely land-cover conversions. Finally, classification is performed to map the different types of land-cover conversions. The improved change vector analysis (ICVA) was applied to detect land-cover conversions from 2000 to 2008, using a time series of Moderate Resolution Imaging Spectroradiometer (MODIS) enhanced VI images for the Beijing–Tianjin–Tangshan urban agglomeration district, China. The results show that ICVA is able to detect land-cover conversion with a significantly higher accuracy (78.00%, $\kappa = 0.56$) than TCVA (64.00%, $\kappa = 0.35$) or CCSM (66.60%, $\kappa = 0.27$). The proposed approach is of particular value in distinguishing actual land-cover conversion from land-cover modifications resulting from phenological changes.

1. Introduction

Land cover plays an important role in energy balance as well as biogeochemical and hydrological cycles in the Earth system (Wang et al. 2009). Research on land-cover change has been of great value in understanding the impacts of natural and human activities on regional and global ecological balance (Avissar and Pielke 1989; Henderson-Sellers and Pitman 1992; Lunetta et al. 2006). Timely and accurate detection of land-cover changes can (1) provide essential information to enhance our understanding of the mechanisms that drive the spatial-temporal processes of land-cover change and (2) support the simulation and
evaluation of the associated environmental impacts (Bruzzone and Prieto 2000; Coppin et al. 2004; Schmid, Koch, and Gumuzzio 2005; Gillanders et al. 2008; Liu and Deng 2010).

Remotely sensed data have been widely used to extract information about land cover and detect its changes (Dimyati et al. 1996; Zhan et al. 2002; Celik and Ma 2010). Time series vegetation index (VI) data derived from observations made by environmental sensors, such as the Advanced Very High Resolution Radiometer (AVHRR) (Loveland et al. 2000), SPOT VEGETATION (Lupo, Reginster, and Lambin 2001), and the Moderate Resolution Imaging Spectroradiometer (MODIS) (Friedl et al. 2002; Redd and Millington 2011), have made it possible to detect land-cover change on a large scale. A variety of approaches have been developed and used for detecting land-cover changes from such VI data. These approaches include change vector analysis (Lambin and Strahler 1994a, 1994b), time series change metrics analysis (Borak, Lambin, and Strahler 2000), normalized difference vegetation index (NDVI) difference analysis (Lunetta et al. 2006), cross-correlogram spectral matching (CCSM) analysis (Wang et al. 2009), and so on. It may be noted that although each of these methods has its own merits, no single approach is optimal or generally applicable in all cases. Therefore, selecting an appropriate change detection approach is often critical to obtain accurate land-cover change information.

Traditional change vector analysis (TCVA) was first proposed by Malila (1980) for detecting forest changes from multi-spectral Landsat data (Malila 1980). The method was further developed by Lambin and Strahler (1994a) to monitor land-cover changes from multi-temporal remote-sensing observations in West Africa. The different land-cover types were differentiated by their informative trajectories of NDVI over a given time period. Built upon this principle, TCVA has then been widely adopted in land-cover change detection using VI data. For example, Chen, Li, and Xie (2001) applied TCVA to detect vegetation changes in China using a time series of 1-month composites of NDVI data from 1989 to 1999 (Chen, Li, and Xie 2001). Bayarjargal et al. (2006) used TCVA to study the effects of droughts on vegetation using time series data, including NDVI, a land surface temperature index, and the vegetation condition index (Bayarjargal et al. 2006). However, TCVA is sensitive to temporal fluctuations in VI values, which greatly limits the method’s accuracy in two ways. First, the analysis may overestimate the actual changes. Interfering noise induced by different atmospheric conditions or sensors can be misinterpreted as land-cover change in addition to the real changes. Second, the method is not able to determine whether the results represent land-cover conversion (e.g. deforestation, urban expansion) or simply VI variation of the same type of land cover, e.g. due to phenological or growth vigour changes (Lambin, Geist, and Rindfuss 2006). The reason for the confusion is that TCVA often results in comparable change magnitude values for these rather distinct cases. The first problem has been addressed by radiometrically calibrating each data set (Jakubauskas, Legates, and Kasten 2001; Jakubauskas, David, and Kastens 2002; Chen et al. 2004). Nevertheless, the second problem has not been solved and continues to limit the accuracy of land-cover change information.

The CCSM approach was initially proposed for mapping minerals from hyper-spectral remotely sensed data (Van der Meer and Bakker 1997; Van der Meer 2000). It has also been adopted to assess mining pollution (Ferrier 1999), to identify green or dry vegetation (Datt 2000), and to discriminate between mineral species (Ferrier et al. 2002). Time series data, such as the monthly VI data, can be analysed in a way similar to analysing hyper-spectral data, with each month’s data in the time series treated like one band in a hyper-spectral data set. Wang et al. (2009) first pointed out the value of applying the CCSM approach to the detection of land-cover conversion using a time series of NDVI data sets. In this
study, CCSM was used to compare the shape of VI profiles for different periods and to determine land-cover change. A cross-correlogram can be constructed for each pair of VI profiles and a goodness-of-match value can be calculated accordingly. More associated cross-correlograms can be constructed by moving the profile for one period horizontally along the time axis relative to that of the other. This approach has the advantage of its ability to capture the shape similarity of two VI profiles even when there is a time lag between the two. However, CCSM does have limitations in that it tends to ignore the type of land-cover change in which the before and after land covers are almost the same in the VI profile pattern though there is apparent significant difference between the absolute VI values (Wang et al. 2009).

This article proposes a new approach that improves TCVA with an adapted use of CCSM analysis. The proposed approach was applied and validated through a case study of land-cover conversion detection from the MODIS enhanced VI data (EVI) for the Beijing–Tianjin–Tangshan urban agglomeration district (BTT-UAD), China.

2. Methods

2.1. Traditional change vector analysis

Land-cover characteristics can be effectively reflected by a time series of VI values (Tucker, Townshend, and Goff 1985; Zhang et al. 2008). The series of VI data for a given time period $r$ can be defined by a vector in a multi-dimensional domain (Lambin and Strahler 1994a) as follows:

$$
p(i, r) = \begin{bmatrix}
    \text{VI}(t_1) \\
    \text{VI}(t_2) \\
    \vdots \\
    \text{VI}(t_n)
\end{bmatrix},
$$  

where $p(i, r)$ is a multi-temporal VI vector for pixel $i$ over the period $r$ (e.g. 1 year), $\text{VI}(t_n)$ is the VI value for pixel $i$ for an observation bin $t_n$ during $r$ (e.g. a 10 day composite of VI in 1 year), and $n$ is the number of observation bins (e.g. 36 observation bins in 1 year). The changes between the periods $r$ and $s$ can be measured by the change vector $c(i)$:

$$
c(i) = p(i, r) - p(i, s).
$$  

Furthermore, the magnitude of the change vector, or $M$, can be measured by the Euclidean distance between the two vectors:

$$
M = |c(i)| = \sqrt{[\text{VI}(t_1, r) - \text{VI}(t_1, s)]^2 + \cdots + [\text{VI}(t_n, r) - \text{VI}(t_n, s)]^2}.
$$  

A greater value of $M$ normally indicates a higher likelihood of land-cover change. In TCVA, a specific threshold must be chosen to distinguish change pixels from no-change pixels. A pixel is detected as having changed its land cover when the magnitude of the corresponding change vector exceeds the threshold.

As comparable magnitude values of change vectors may also result from the phenological variation of a vegetative type of land cover or change in its growth vigour, a threshold is not always effective in extracting land-cover conversions. Figure 1 shows seven representative pairs of VI profiles for sample sites in the study area and their
Figure 1. Examples of land-cover changes and their corresponding change magnitudes calculated using TCVA. 
(a) From water to built-up area ($M = 0.73$); (b) from cropland to built-up area ($M = 0.78$); (c) phenological earliness ($M = 0.78$); (d) vegetation growth vigour change ($M = 0.77$); (e) from ‘winter wheat-summer maize’ to ‘spring maize’ ($M = 0.82$); (f) water with small changes in chlorophyll content ($M = 0.13$); and (g) no-change ($M = 0.13$).
corresponding change magnitudes. The types of land-cover conversion at the sites were
conversion from water to built-up area (Figure 1(a)), cropland to built-up area (Figure 1(b)),
phenological change of the same land cover (Figure 1(c)), change in vegetation growth
vigour (Figure 1(d)), cropping pattern change from ‘winter wheat–summer maize’ to
‘spring maize’ (Figure 1(e)), water with small changes in chlorophyll content (Figure 1(f)),
and no significant change (Figure 1(g)). Among these seven cases, the first two were
regarded as real land conversion while the other five were pseudo-conversions for which
the land cover actually remained the same as before. The change magnitude values for
the first five cases (0.73, 0.78, 0.78, 0.77, and 0.82, respectively) are rather close to each
other in comparison to the far lower value of 0.13 for the unchanged water and no-change
areas. Thus, it is clear that the strategy of performing TCV A with a pre-determined change
magnitude threshold cannot accurately distinguish among types of land conversions.

2.2. Cross-correlogram spectral matching

Because the difference that existed in the VI profiles of the two time periods would affect
the shape and correlation of the cross-correlogram values, the CCSM analysis is expected
to reveal whether it is a land-cover modification or conversion. The cross-correlation, $R_m$, at
each match position $m$ between two VI profiles of the same pixel can be calculated as follows (Van der Meer and Bakker 1997):

$$R_m = \frac{n \sum \lambda_r \lambda_s - \sum \lambda_r \sum \lambda_s}{\sqrt{\left[n \sum \lambda_r^2 - (\sum \lambda_r)^2\right] \left[n \sum \lambda_s^2 - (\sum \lambda_s)^2\right]},}$$  \hspace{1cm} (4)

where $\lambda_s$ and $\lambda_r$ are the VI values for each observation bin in the time periods $r$ and $s$, respectively; $n$ is the number of common observation bins covered by the two profiles; and $m$ is the relative movement of one profile in the unit of observation bins. For example, an $m$ value of 1 indicates that the profile for the later period is moved one observation bin to the right so that its $i$th observation will correspond and be compared to the $(i + 1)$th observation of the earlier period. Similarly, an $m$ value of $-1$ indicates that the profile for the later period is moved one observation bin to the left and its $i$th observation will correspond and be compared to the $(i - 1)$th observation of the earlier period.

The maximum ($R_{\text{max}}$) among all the correlation coefficients calculated is subsequently
chosen as the shape similarity index of the two profiles:

$$R_{\text{max}} = \max \{R_{-m}, \ldots, R_{-1}, R_0, R_1, \ldots, R_m\},$$  \hspace{1cm} (5)

where $R_{\text{max}}$ ranges from 0 to 1. $R_{\text{max}}$ is equal to 1 when the shapes of the two VI profiles are
identical. Greater and smaller values of $R_{\text{max}}$ indicate higher and lower levels of similarity,
respectively. In CCSM analysis, it is still necessary to set up a threshold value for $R_{\text{max}}$ to
discern whether a land-cover change has occurred on the corresponding pixel.

However, applying a threshold to the results of the CCSM analysis cannot provide an
accurate map of land-cover conversion. Figure 2 shows the same seven representative pairs
of VI profiles as shown in Figure 1. The corresponding shape similarity index $R_{\text{max}}$ to
each pair is also noted. The $R_{\text{max}}$ for the pseudo-conversion, such as case (c) (0.996), case
(d) (0.991), and case (g) (0.996), were much closer to 1 in comparison to the far lower
value of 0.486 for conversion from water to built-up area. However, the $R_{\text{max}}$ for the other
pseudo-conversion (0.421), that is water with small changes in chlorophyll, is even lower.
Figure 2. Examples of land-cover changes and their corresponding shape similarity index calculated using CCSM. (a) From water to built-up area ($R_{\text{max}} = 0.486$); (b) from cropland to built-up area ($R_{\text{max}} = 0.902$); (c) phenological earliness ($R_{\text{max}} = 0.996$); (d) vegetation growth vigour change ($R_{\text{max}} = 0.991$); (e) from ‘winter wheat-summer maize’ to ‘spring maize’ ($R_{\text{max}} = 0.569$); (f) water with small changes in chlorophyll content ($R_{\text{max}} = 0.421$); and (g) no-change ($R_{\text{max}} = 0.996$).
than that for the conversion in case (a). The \( R_{\text{max}} \) for the conversion from cropland to built-up area (0.902) is rather close to that for the pseudo-conversion. Thus, it is clear that simply applying a threshold to the results of a CCSM analysis would only serve to ignore or overestimate some kinds of land-cover conversion.

### 2.3. Improved change vector analysis

Our strategy is to follow a three-step procedure to improve TCVA in the hope of achieving a higher degree of accuracy of land conversion detection. First, TCVA is employed to preliminarily detect any land-cover changes. Second, the CCSM approach is used to identify and eliminate areas in which the land-cover type did not really change but only experienced some degree of VI variation. Third, the type of land-cover conversion (e.g. from cropland to built-up area) is determined by further analysing the change vectors for the remaining pixels of interest. The entire procedure is anticipated to achieve a more accurate detection of land conversion. The three steps are described in detail below.

#### 2.3.1. Preliminary land-cover change detection using TCVA

The preliminary detection of a significant land-cover change is made based on the use of TCVA and a process of threshold determination. At present, the methods used to determine the threshold following TCVA mainly include the use of empirical values (Allen and Kupfer 2000), interactive trial-and-error procedures (Fung and LeDrew 1988), and semi-automated approaches (Chen et al. 2003). In this study, we employed an interactive trial-and-error procedure that was introduced by Fung and LeDrew (1988) and recommended by Wang et al. (2009), to determine the optimal threshold for change magnitude (\( M \)).

First, we selected a set of training images in which each pixel's status of change was known from fine-resolution remotely sensed images and other ancillary data (e.g. ground truthing data). Subsequently, we tested the reliability of the training images by examining the corresponding EVI profile curves. The training sites were selected only if the interpretation of the fine-resolution images and the analysis of the EVI profile curve agreed on the change status. This could help us to avoid the situation in which no-change was found from the fine-resolution images but change occurred after the images were obtained. The training images included, for each land-cover type, as many changed and unchanged cases as possible. Once \( M \) for all of the pixels in the training images are derived, a histogram of \( M \) is constructed and the mean (mean) and standard deviation (sd) of \( M \) are computed. The two parameters are then used to formulate a potential threshold \( T \):

\[
T = \text{mean} + N \times \text{sd},
\]

where \( N \) is the step size. An initial value 0.1 is set for \( N \). And \( N \) is increased in steps of 0.01 until it reaches the maximum of the \( M \). At each step, the threshold value is used to generate a binary image representing change and no-change. Given the training data set, the binary image is compared with the reference to build an error matrix from which a \( \kappa \)-value and an omission error of the change pixel can be obtained. Ultimately, the optimal threshold for \( M \) is assigned to the value at which the maximum \( \kappa \) and lower omission error of the change pixel could be achieved. Given the optimal threshold for \( M \) from the training data, the task to identify land-cover change is carried out in the whole study area.
2.3.2. Identifying and eliminating pseudo-conversion by CCSM analysis

The CCSM analysis is conducted based on the detection results obtained in the previous step. For each pixel that has been detected as changed, the shape similarity index ($R_{\text{max}}$) is calculated between the VI profiles for the two time periods ($r$ and $s$) by moving one profile over the time axis relative to the other using Equations (4) and (5).

An effective threshold for $R_{\text{max}}$ must then be determined. In fact, the common methods used to determine the threshold for $R_{\text{max}}$ are very similar to those introduced in Section 2.3.1. The manual trial-and-error procedure was also used in this procedure. The trial-and-error procedures used on an $R_{\text{max}}$ image and a change magnitude image differ in how the training samples were selected. The training samples were selected on the basis of two principles: (1) they should be randomly distributed in the changed areas obtained from the previous step and (2) they mainly include the changes that are easily omitted by CCSM, especially the changes in the land covers that retained their VI profile pattern but changed significantly in their absolute VI values. Different threshold values were then tested on the sample areas, and the most effective value was selected. The pixels with $R_{\text{max}}$ values smaller than the selected threshold were considered to have experienced significant land-cover conversion over the study period.

2.3.3. Determining the type of land-cover conversion

A variety of TCVA-based methods for classifying land-cover conversion into different ‘from–to’ types have been developed, including principal component analysis (Lambin and Strahler 1994a), supervised classification based on the direction of the change vectors (Chen et al. 2003), the sector coding method (Bayarjargal et al. 2006), and unsupervised classification methods (Bruzzone and Prieto 2000, 2002; Ghosh, Mishra, and Ghosh 2011). Unsupervised classification methods are widely used in change detection because they do not require training data, but are still rather effective in classifying remotely sensed multi-spectral or multi-temporal data. An analyst can attempt an *a posteriori* assignment or transformation of the partitioned classes into a thematic map of interest (John 2005). Therefore, an unsupervised classification method was adopted in this study to determine the actual types of land-cover conversion with the support of ancillary data.

3. Case study: detecting land-cover conversion in BTT-UAD

3.1. Study area

BTT-UAD was chosen as the study area (Figure 3) because it includes a number of important and rapidly growing cities (e.g. Beijing, Tianjin, Tangshan, Qinhuangdao, and Langfang) in terms of both size and economy. It has a total area of about 55,774.5 km$^2$, with latitude ranging from 38°28′ N to 41°05′ N and longitude from 115°25′ E to 119°53′ E. The study area is geographically located on the North China Plain and consists of mountains and hilly areas (37%) and plains and marshy ground (63%) (Yao, Chen, and Zhu 2006). The area has a sub-humid, temperate monsoon climate with a mean annual precipitation of 550–750 mm and a mean annual temperature of 11.4–12.7°C. Cropland, forest, and built-up land are the three main types of land cover found in this area (Tan et al. 2005). Over the past several decades, significant land-cover changes have taken place in the BTT-UAD, mainly driven by rapid economic development and unprecedented urbanization (Tan et al. 2005).
3.2. Data

Three data sets were collected and used in this study.

- MODIS_EVI data (specifically MOD 13Q data version 004) were acquired for 2000 and 2008 from the Earth Resources Observation Science Center of the United States Geological Survey (USGS EROS). The data were provided as 16 day composites with a spatial resolution of 250 m. The image tiles covering the study area are h26v04, h26v05, h27v04, and h27v05 in the MODIS image reference system. The root mean square error of the geometric registration is less than 0.5 pixel (Wolfe et al. 2002). EVI was chosen because it was shown previously to be more effective for land-cover change detection than NDVI (Huete et al. 1997, 2002).

- Landsat Enhanced Thematic Mapper Plus (ETM+) images were also obtained from the USGS EROS Data Center. A time series of four Landsat ETM+ images taken on 20 August 2000, 10 June 2000, 11 September 2008, and 3 August 2008 was selected. In addition, some high-resolution satellite images covering the study area,
such as ALOS and IKONOS images, were used to select training samples and to assess accuracy.

- A land-cover map for 2000 (scale 1:100,000) was obtained from the Resources and Environment Data Centre, Chinese Academy of Sciences. The map was produced by visually interpreting the Landsat Thematic Mapper (TM) remotely sensed data in 2000 and can represent actual situations in the BTT-UAD (Liu et al. 2003, 2005; Tan et al. 2005). According to the classification scheme recommended by the Chinese Academy of Sciences (Liu et al. 2005), six classes of land cover were mapped, i.e. cropland, forest, grassland, water, built-up areas, and barren land.
- Ancillary data included field survey data and images obtained from Google Earth. The field survey was conducted in 2008 in collaboration with the local government of the study area and provided valuable reference data, including land-use planning maps; census data (e.g. gross domestic product and population); and digital photos of typical changed areas such as the Beijing Capital Airport, which used to be cropland, and the Binhai New area of Tianjin, which used to be a wetland.

### 3.3. MODIS_EVI data pre-processing

First, each set of four image tiles of the same time were mosaicked into one single EVI image to cover the entire study area. Second, the mosaicked images were re-projected onto the Albers Conical Equal Area projection, which is commonly used in mapping north China (Zhang et al. 2008). Third, the harmonic analysis of time series (HANTS) algorithm was used on the image series to reduce cloud and other noise (Jakubauskas, Legates, and Kasten 2001; Jakubauskas, David, and Kastens 2002). The basic idea of this algorithm is to calculate a Fourier series for modelling a time series of pixel-wise observations and to identify outliers relative to the model. The algorithm eliminates such outliers and replaces them with the value suggested by the Fourier series. HANTS can screen and remove cloud-contaminated observations and temporally interpolate the remaining observations to reconstruct gapless images at a prescribed time. This operation was only performed to correct the eighteen 16-day composites of EVI images taken during the growing season (49th to 321st Julian day) of the study area and the cloud-free observations were interpolated to 10-day composites in order to facilitate the following research. The selected time range was chosen to be rather inclusive based on our knowledge of the local phenology, and the entire growing season of each year should fall within the range. There were a total of 28 corrected MODIS EVI composites for the growing season of each year. Finally, the boundary of the study area was used to clip the pre-processed EVI images so that later analysis could focus on the area within that spatial extent.

### 3.4. Detecting land-cover conversion using improved change vector analysis

Each pixel in the pre-processed EVI images was represented by a 28-dimensional vector for each year (2000 and 2008). The change magnitude between the vectors for each pixel was calculated using Equation (3) and was mapped. One hundred typical training samples covering about 240 km² of area were selected with the aid of the ancillary data. The training samples included the pixels with the dominating land conversion in the study area, such as conversion from cropland to built-up area, and the unchanged pixels on each land-cover type. Applying the trial-and-error method produced a threshold value of 0.42. The preliminary pixels of land-cover change were then extracted by applying the threshold.

Subsequently, the shape similarity index $R_{\text{max}}$ was calculated for each change pixel for the EVI profiles between the two years, 2000 and 2008. We selected 55 training samples...
Figure 4. Land-cover conversions in the Beijing–Tianjin–Tangshan urban agglomeration district (2000–2008) detected by ICVA.
Note: (a) and (b) are the zoomed-in views of the subsets.

According to the principles described in Section 2.3.2, a threshold value of 0.91 was picked for $R_{\text{max}}$ from a series of trials that were carried out based on the interpretation of the Landsat ETM+ images. Pixels with $R_{\text{max}}$ values greater than 0.91 were regarded as having undergone land-cover modification and were removed from the pixels of interest (Figure 4).

Finally, a land-cover conversion map was obtained by classifying the change vector image of land cover (Figure 5) using an unsupervised classification technique (John 2005). The main types of land-cover conversion were recognized with the aid of field survey and the Landsat ETM+ data (Figure 5). Figure 5 shows the land-cover conversions that took place in the study area from 2000 to 2008. The land-cover conversions were mainly from cropland to built-up area, from water to built-up, and from water to cropland. Other changes include the more complex types, such as the changes in the pattern of cultivation of cropland, which the improved change vector analysis (ICVA) tends to erroneously detect as land-cover conversion.

4. Effectiveness analysis of ICVA

The typical cases of land-cover change shown in Figures 1 and 2 were examined to check the effectiveness of the proposed approach. On the one hand, land-cover changes due to phenological or growth vigour changes were easily detected by TCV A and excluded from the detection of land-cover conversion. On the other hand, land conversions that are likely to be omitted by CCSM due to the shape similarity of the VI profiles for different times were also detected successfully. As shown in Figure 1, the magnitudes of change in the first five cases appeared to be very similar to each other. Applying a threshold to the TCV A result failed to differentiate between these different types of land-cover changes. As can be seen in Figure 2, the $R_{\text{max}}$ for the conversion from crop land to built-up area (0.902) was closer to 1, but the $R_{\text{max}}$ for the unchanged water was even smaller. Using CCSM tends to
Figure 5. The main land-cover change types in the Beijing–Tianjin–Tangshan urban agglomeration district (2000–2008) obtained by unsupervised image classification.

Note: (a) From water to cropland; (b) from cropland to built-up area; (c) from water to built-up area. (a1), (b1), and (c1) show the subsets of Landsat ETM+ images from 2000, while (a2), (b2), and (c2) show the corresponding images from 2008.

Exaggerate some changes, such as the one shown in (f), and to omit some real land conversion, such as the one shown in case (b). Our proposed approach was able to detect the change more accurately by utilizing the strength of TCVA and CCSM to compensate for the limitations of each other. ICVA can fairly accurately differentiate the pixels of land-cover change (Figures 1(a)–(e)) from the unchanged pixels (Figures 1(f) and (g)) when a threshold of 0.42 is applied. Subsequently, the CCSM analysis with a threshold of 0.91 effectively removed pseudo-conversions (Figures 2(c) and (d)) from the land-cover change without missing the actual land conversion (Figure 2(b)). ICVA is, theoretically, more effective for detecting land-cover conversion.
5. Accuracy assessment

The results from ICVA (Figure 4), TCVA (Figure 6), and CCSM (Figure 7) were visually examined and quantitatively assessed for accuracy comparison. The same training samples and the same threshold determination methods were used in the application of the three methods. For the case shown in Figure 8(a), the land cover remained to be cropland from 2000 to 2008, although the peak value of EVI increased significantly from 0.5 in 2000 to 0.73 in 2008. TCVA misidentified the area as having undergone land-cover conversion, while ICVA and CCSM accurately identified it as not converted. For the case shown in Figure 8(b), the land cover also remained to be cropland from 2000 to 2008, but the peak EVI value occurred 20 days earlier in 2008 than in 2000. Again, TCVA misidentified the area as having been converted, while ICVA and CCSM provided the correct result. For the case shown in Figure 8(c), the land cover remained to be water from 2000 to 2008, while the EVI profile of water varies significantly throughout the year because of the different levels of chlorophyll content. As shown in Figure 8(c), CCSM misidentified the area as having been converted, while ICVA and TCVA provided the correct result. It can be found in Figure 8(d) that CCSM omitted some actual land-cover conversions, while ICVA and TCVA had detected them correctly. The reason is that, although the land cover had been converted from water to cropland during the period of 2000–2008 and the absolute EVI value changed significantly, the shape of the EVI profile remained similar for those two years.

Furthermore, the accuracy of each of the detection results from ICVA (Figure 4), TCVA (Figure 6), and CCSM (Figure 7) was assessed and compared. As the areas converted of land cover accounted for a small percentage of the whole study area, 500 sample pixels were chosen by using a randomly stratified sampling technique with 250 sampling pixels

Figure 6. The land-cover change (2000–2008) in the Beijing–Tianjin–Tangshan urban agglomeration district, detected by TCVA.

Note: (a) and (b) are the zoomed-in views of the subsets.
distributed within the changed area (Morisette and Khorram 2000). Supported by a visual interpretation of the remotely sensed data with fine spatial resolution, images from Google Earth, and the field survey data, an error matrix was produced for the results obtained from ICVA, TCV A, and CCSM. As shown in Table 1, TCV A achieved a $\kappa$-coefficient of 0.35 and an overall accuracy of 64.00%, CCSM achieved a $\kappa$-coefficient of 0.27 and an overall accuracy of 66.60%, while ICVA showed a significantly better performance with a $\kappa$-coefficient of 0.56 and an overall accuracy of 78.00%. ICVA had a significantly lower commission error (38.40%) than TCV A (51.82%) and CCSM (49.73%); it also had a significantly lower omission error (8.33%) than CCSM (44.05%).

6. Discussion and conclusions

Although TCV A is one of the most widely used methods for detecting land-cover changes from a time series of VI data, it is over-sensitive to temporal fluctuations in VI values. This method, therefore, tends to exaggerate the extent of land-cover conversion. CCSM can capture the shape similarity between two VI profiles, but it may omit some actual land conversion in which a similar VI profile pattern remained after the conversion. In this article, we have proposed a new approach, termed ICVA, which improves TCV A with an adapted use of CCSM analysis. The basic idea of ICVA is to identify and exclude areas with land-cover modification (not type change) from the total changes detected by TCV A. The strategy is to analyse the multi-temporal VI information with the consideration of not only change magnitude but also VI profile similarity.

In order to test the effectiveness of the approach, ICVA was applied to detect land-cover conversion in BTT-UAD, China, from two time series of MODIS EVI data for 2000 and 2008. The results showed that ICVA is able to map land-cover conversion with a significantly higher accuracy (78.00%, $\kappa = 0.56$) than TCV A (64.00%, $\kappa = 0.35$) or CCSM (66.60%, $\kappa = 0.27$). This improvement is mainly attributed to the effective identification
Figure 8. Comparison of the results among ICV A, TCV A, and CCSM.

Note: (a) Differences in the case of vegetation vigour change; (b) differences in the case of phenological change; (c) differences in the case of chlorophyll content change in water; (d) differences in the case of conversion from water to cropland.
Table 1. Error matrices for assessing the detection of land-cover conversion using ICVA, TCVA, and CCSM.

<table>
<thead>
<tr>
<th></th>
<th>Reference data (pixels)</th>
<th></th>
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<tbody>
<tr>
<td></td>
<td>Change</td>
<td>No-change</td>
<td>Row total</td>
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<tr>
<td>ICVA</td>
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<td></td>
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<tr>
<td>Results (pixels)</td>
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</tr>
<tr>
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<td>No-change</td>
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<tr>
<td></td>
<td>Column total</td>
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<td>332</td>
</tr>
<tr>
<td></td>
<td>Omission error (%)</td>
<td>8.33</td>
<td>28.92</td>
</tr>
<tr>
<td></td>
<td>Overall accuracy = 78.00%, $\kappa = 0.56$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TCVA</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Results (pixels)</td>
<td>Change</td>
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<td>171</td>
</tr>
<tr>
<td></td>
<td>No-change</td>
<td>9</td>
<td>161</td>
</tr>
<tr>
<td></td>
<td>Column total</td>
<td>168</td>
<td>332</td>
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<tr>
<td></td>
<td>Omission error (%)</td>
<td>5.36</td>
<td>51.51</td>
</tr>
<tr>
<td></td>
<td>Overall accuracy = 64.00%, $\kappa = 0.35$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCSM</td>
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<td></td>
<td></td>
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<td>Results (pixels)</td>
<td>Change</td>
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<td>93</td>
</tr>
<tr>
<td></td>
<td>No-change</td>
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<td>Omission error (%)</td>
<td>44.05</td>
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</tr>
<tr>
<td></td>
<td>Overall accuracy = 66.60%, $\kappa = 0.27$</td>
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</tr>
</tbody>
</table>

of those areas for which VI value changes are primarily due to phenological and/or growth vigour changes, and those areas with a significant change of absolute VI value but rather similar VI profiles for the years of interest. TCV A is used because it can effectively measure the change magnitude of VI for each land-cover type. CCSM is here effective because it can be used to compare VI profiles of different years and determine whether they are rather similar in shape, although a significant change may have been indicated by the relatively rigid measure of change magnitude. The proposed approach is therefore promising for the production of more accurate land-cover conversion maps, which often serve as the basis for more advanced studies of landscape ecology, urban planning, human–environmental interaction, etc.

It is worth noting that the application of ICVA has some limitations. The approach is best used in distinguishing land-cover conversions from land-cover modifications resulted from phenological and/or growth vigour changes. But the commission error (38.40%) is still high. There are two reasons for this. First, the reference data for accuracy assessment have a much higher spatial resolution than the detection results being evaluated. The EVI images (250 m resolution) contain lots of ‘mixed’ pixels that can hardly reflect the real situation precisely. Second, the method itself has limitations and cannot handle well more complex types of land-cover changes, such as the cultivation pattern change of double-cropping land to single-cropping land, because both the values and the profile shape of a yearly series of VI tend to change significantly in such cases, although the land-cover type remains the same. Future efforts should be directed to developing methods for more precise detection of land-cover conversion for these challenging cases.

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References


