A New Approach for Vegetation Change Detection in Urban Areas

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ABSTRACT  Because of complex change in urban areas, modified CVA application based on mask techniques can minimise the effect of non-vegetation changes and improve upon efficiency to a great extent. Moreover, drawing from methods in polar plots, the technique measures changes with absolute angular and total magnitude of PVI calculated on the basis of linear fit with least-square estimation and GVI calculated using 3D G-S transformation. Finally, this application is performed with Landsat ETM+ imageries of Wuhan in 2002 and 2005, and assessed by error matrix, in the way it could detect change pixels 94.91% correct, and the total consistent coefficient Kappa could reach to 0.85. The evaluation result demonstrates this new application trends as an efficient and effective alternative to urban vegetation change extraction.

KEY WORDS  vegetation; change detection; change vector; mask

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Introduction

Vegetation distribution and change is regarded as an important sign of urban environment. With city expanding and population increasing, here comes a series of problems on environment, and moreover, greening ratio is regarded as a standard of city environment quality, so people pay broad attention to vegetation change and apply a few methods about vegetation change detection, such as image differencing method, post-classification comparison, vegetation index differencing and change vector analysis. Nevertheless, image differencing and vegetation index differencing for vegetation change detection is limited by few using bands; comparison after classification is not only time-consuming, but also running a risk of a few unreasonable change classes because of error cumulating (such as city land changing into paddy filed)\(^1\). Therefore, this paper seeks to apply and develop CVA (change vector analysis) for urban vegetation change detection.

CVA is a proper superior method of change detection which is capable of using several appropriate components to analyze objects’ change providing change classes, and is usually applied to detect land use/cover change\(^2,3,4\), furthermore, widely used to detect vegetation change for forest and rural areas in the recent years\(^5,6\). However, land use/cover change in urban areas is different from forest or rural areas, that is, most of land use/cover change in forest and urban areas is vegetation change while change in urban areas is more complex. Besides vegetation change, there is so much non vegetation change which changes a lot at brightness, such as artificial objects’ tearing down and building, water changing into bare land or sandlot, etc. Non vegetation change of this kind could be also mis-detected as vegetation change if change vector is
constructed simply by spectral bands value or brightness index\(^1\).

Aiming at fitting CVA for urban vegetation change detection, this paper develops an algorithm and a new approach for vegetation change detection in urban areas, which analyzes change vector constructed by PVI (perpendicular vegetation index) and GVI (greenness vegetation index), based on NDVI and mask technique, is proposed. Firstly, vegetation mask is made of plants areas extracted from multi-temporal images with NDVI, which can eliminate non vegetation change information and restrain noise caused by non vegetation change to a great extent; secondly, pixel’s change vector constructed by PVI and GVI one by one in the images of two dates is proposed, which is more pertinent for vegetation change detection than by one pixel’s spectral bands value or brightness index\(^2,4\).

1 Methodology of vegetation change detection

The methodology section is composed of image bands selection and vegetation mask making, PVI and GVI extraction, and change vector analysis. Firstly, extract vegetation areas in the images of two dates with NDVI to produce vegetation mask; secondly, construct each pixel’s change vector by its PVI and GVI extracted from multi bands of two dates, expressed as magnitude and direction angular in the polar coordinates; finally, perform threshold segmentation on magnitude of change vector to determine changed pixels, which are classified on the basis of their own change vector’s direction angular. The whole procedure is introduced in detail below.

1.1 Image bands selection and vegetation mask making

ETM+ imageries are used as the main data in this paper because of its cheaper price and applicability of urban change detection\(^5\). For the sake of using data reasonably and effectively, appropriate bands need to be selected at firstly. Healthy plants’ radiation information between NIR (near infrared) and R (red) wave band is greatly different, so the Band 3 and 4 of ETM+ are selected for calculation of NDVI and PVI, and GVI is calculated with Tasseled Cap using the Band 1, 2, 3, 4, 5 and 7 of ETM+.

Non vegetation change pixels’ magnitude of change vector, which change greatly at brightness, is so big (e.g. change magnitude of water pixels which changed into shoal or sands reaches to 106 in the experiment) that they are easy to be misdetected as vegetation change. Thus, vegetation mask is applied to eliminate these erroneous vegetation change information beforehand.

In respect that NDVI can well indicate plants distribution both on a big scale and on a global scale\(^5,6\), here vegetation area is extracted with NDVI. Firstly, each pixel’s NDVI in images of two dates is calculated:

\[
\text{NDVI} = \frac{(\text{NIR} - \text{R})}{(\text{NIR} + \text{R})} \quad (1)
\]

where NIR refers to the value of the Band 4 of ETM+; \(R\) refers to the value of Band 3.

Secondly, determine threshold of NDVI to image of each date, and pixel is the vegetation pixel if its NDVI is bigger than the threshold; in the opposite, pixel is the non vegetation pixel. NDVI\(_i\), NDVI\(_j\) is defined as NDVI of Pixel \(i\) at two dates, and \(T_1, T_2\) as threshold of NDVI at two dates, respectively. Pixel \(i\) is not the pixel belonging to vegetation mask unless it accords with following expression:

\[
\text{NDVI}_i > T_1 \text{, or NDVI}_j > T_2 \quad (2)
\]

In order to validate NDVI’s ability of distinguishing plants, NDVI’s distribution of water, bare land, artificial objects and vegetation in images of two dates is analyzed in the experiment (Table 1).

According to Table 1, objects’ NDVI in each class distributes in a rule. Vegetation’s NDVI distribute in the range rather different from non vegetation’s, that is, vegetation’s NDVI usually bigger than 0.1 and non vegetation’s smaller than 0.1, so vegetation and non vegetation objects can be distinguished well by NDVI. Nevertheless,
NDVI of objects in same class distributes a litter differently at two dates. For instance, NDVI of vegetables distributes in the range of $[0.020, 0.216]$ in 2002 but between $[0.059, 0.247]$ in 2005, and due to that, it is unauthentic to detect vegetation change simply according to NDVI difference. In this paper, NDVI is just applied to extract vegetation areas of two dates, by which vegetation mask is produced, so that erroneously detected information caused by non vegetation change can be eliminated to a great extent; moreover, the efficiency advances much because pixels just in the mask need to be performed.

### 1.2 PV! and GVI extraction

Vegetation indices include GVI, NDVI, PVI as well as RVI (ratio vegetation index), and mid-infrared ratios. Keeping from soil noise, PVI and GVI are applied to construct change vector for vegetation change detection.

#### 1.2.1 Calculation of PVI

R. L. Weiser found that non vegetation objects usually distribute in a beeline existing in the red-infrared bands plane in 1986[7]. Here non-vegetation beeline can be calculated with linear fit using least-square estimation.

A graphical depiction (Fig. 1) shows the geometry involved in the calculation of PVI. The axes ETM+3 and ETM+4 correspond to Landsat ETM+3 and ETM+4, respectively. $(x_i, y_i)$ is defined as samples’ value of ETM+3 versus ETM+4, and $n$ as the number of samples, thus, $i=1,...,n$, and non vegetation beeline is defined as

$$y = \beta x + a \quad (3)$$

Then regressed beeline $L_r$ takes its expression as

$$Y = X \cdot A \quad (4)$$

where $Y = (y_1, y_2, \ldots, y_n)^T$, $X = \begin{pmatrix} x_1 & x_2 & \cdots & x_n \\ 1 & 1 & \cdots & 1 \end{pmatrix}$, $A = (\beta, a)^T$. Normalize

$$X^T X A = X^T Y \quad (5)$$

And then solution of normal equation Eq. (5) can take its expression as

$$A = (X^T X)^{-1} X^T Y \quad (6)$$

Then, slope defined as $\beta$ and $a$ defined as intercept of regressed beeline are solved, and best-fitted non vegetation beeline $L_r$ is found.

Any pixel in one image is defined as $P_r$, $P_r$’s value of ETM+3 versus ETM+4 as $(x_T, y_T)$, and PVI of Pixel $P_r$ is defined as $D_T$ (Fig. 1), which is just the distance from Pixel $P_r$ to non vegetation beeline $L_r$:

$$PVI(P_r) = D_T = (\beta x_T + a - y_T) / \sqrt{1 + \beta^2} \quad (7)$$

Theoretically speaking, PVI can well restrain noise caused by soil background for it measures energy of vegetation with distance from pixels’ spectral data to non vegetation beeline.

#### 1.2.2 Calculation of GVI

Many change detection projects have opted to work with Landsat data that has been transformed with Tasseled Cap transformation. Nevertheless, this transformation has been always limited to TM and MSS data since it was proposed. In order to expand it for being applied in more cases, Tasseled Cap transformation is modified with the help of 3-dimension Gramm-Schmidt orthogonalization technique to calculate coefficients of Greenness, Brightness and Wetness[8].
Firstly, select a set of transformation vectors of a point in $\mathbb{R}^3$, which acts as the origin in the new coordinate system. The vector selected for this purpose is called the root vector, and about the origin, shifting pixel vectors in this way guarantees that the transformation is capable of identifying the structure of the data. The first axis is created by selecting vector $x_1$ in $\mathbb{R}^3$, which is adjusted by $r$ and divided by its length, and the corresponding transformation coefficient ($s_1$) is gained as

$$s_1 = \frac{(x_1 - r)}{\| x_1 - r \|} \tag{8}$$

Next, create the second vector, which is orthogonal to $s_1$, defining a new dimension of $\mathbb{R}^3$. Any vector $x_2$ which does not lie in the space defined by $s_1$ is suitable for this purpose. The second axis is constructed by projecting $x_2$ onto the subspace defined by $s_1$ given in Eq. (9):

$$P_{x_2 \rightarrow x_1} = (x_2 - r) \cdot s_1 s_1 \tag{9}$$

which is a simplified version of the projection function and is made possible because $s_1$ is a unit vector. The orthogonal vector associated with $x_2$ is denoted by $w_2$. Dividing it by its length may normalize this vector, and the second transformation coefficient $s_2$ is gotten as

$$w_2 = x_2 - P_{x_2 \rightarrow x_1} - P_{x_2 \rightarrow x_1} \cdot s_1 = w_2/ \| w_2 \| \tag{10}$$

If there is additional characteristic space, this dimension can be quantified by use of $x_3$ in the G-S process. Once again, the selected vector is projected onto all existing components, and the result is subtracted from the original vector and normalized as

$$w_3 = x_3 - P_{x_3 \rightarrow x_1} - P_{x_3 \rightarrow x_1} \cdot s_1 = w_3/ \| w_3 \| \tag{11}$$

During the G-S transformation process, mean spectral vectors of samples is used rather than individual pixels as the basic unit of analysis. It can minimize the influence of slight misregistration errors, since such errors affect pixels on the edges of examples but not those well inside them. Sample areas are selected at the pixel level, including at least 1 300 pixels per surface feature, and the areas represent different surface cover and are distributed throughout the image to the extent that the features allowed. To derive any two orthogonal indices, in this case, the mean value of dark soil samples is chosen as the root vector, acting as the origin of the coordinate system. Then, exposed soils, roads and building samples representing soil condition to create first axis $x_1$; next, the vegetation samples are needed to establish an orthogonal vegetation index $x_2$ representing abundance and vigor of living vegetation; at last, the canal and lake samples severed as the third vector $x_3$ orthogonal to the plane of vegetation view.

This transformation reduces the multi-spectral (such as TM data) or even super-spectral data of reflectance bands to three orthogonal indices called brightness, greenness and wetness. Greenness is just GVI, which owns the ability to show green plants’ growing statement and is used to construct change vector with PVI here.

**1.3 Change vector analysis**

Change vector analysis is a change detection application based on pixel comparison. The change vector describes pixel’s spectral change with magnitude and direction from Date 1 to Date 2. Owning the ability to eliminate soil noise, PVI and GVI are selected to construct change vector for detecting vegetation and its growing change information.

The multi-date change values $\Delta C_i$ are analyzed by use of Euclidean geometry given in Eq. (12):

$$\Delta C_i = \left[ \begin{array}{c} \Delta C_{i_1} \\ \Delta C_{i_2} \end{array} \right] = \left[ \begin{array}{c} PVI_i - PVI_i \\ GVI_i - GVI_i \end{array} \right] \tag{12}$$

where PVI_i , PVI_i refer to pixel i’s PVI of two dates; GVI_i , GVI_i refer to Pixel i’s GVI; $(i = 1, 2, \ldots, n)$, $n$ refers to the number of all pixels.

Change vector takes its expression in polar coordinates as $(\rho, \theta)$

$$\rho_i = \sqrt{\Delta C_{i_1}^2 + \Delta C_{i_2}^2}, \quad 0 \leq \rho_i \leq 255 \tag{14}$$

$$\theta_i = \arctan(\Delta C_{i_1}/\Delta C_{i_2}), \quad 0 \leq \theta_i \leq 360 \tag{15}$$

$\rho_i$ is defined as Pixel i’s magnitude of change vector, calculated with Eq. (14), and pixels with bigger magnitude contains much more change possibilities. For enlarging difference between pixels, change vector’s magnitudes of all pixels are stretch to $[0, 255]$ and shown in figure to get a change vector’s magnitude map, which
is dealt with threshold segmentation to get a change threshold for determining changed and unchanged pixels; \( \theta \) is defined as Pixel \( i \)'s direction angular of change vector, calculated with Eq. (15), and then with \( \theta \), changed pixels can be classified.

Threshold segmentation is usually chosen to determine change threshold. In this paper, quadrature invariability segmentation is used to search best threshold (74 in the experiment), derived from a satisfied result, and the pixel with bigger magnitude than threshold is changed one, and in the opposite is unchanged one. Then, According to the angular of change vectors’ direction, changed pixels can be classified into four change classes (Fig. 2): vegetation increased, vegetation decreased, better growing, worse growing. The rest which are not vegetation change pixels are in gray. Table 2 lists the classified results with angular of change vector’s direction in the experiment.

Finally, a definition of change percents is given to analysis vegetation change, \( n \) is defined as the number of all pixels, \( n_i \) as the number of pixels in Class \( i \) (\( i=1,2,3,4 \)), \( \eta_i \) as the change percent of Class \( i \), and \( \eta_i \) can be calculated with Eq. (16):

\[
\eta_i = \frac{n_i}{n} \times 100\%
\]

With statistic of change pixels in each class, vegetation change can be analyzed qualitatively and quantitatively.

### 2 Experiment and analysis

The region at Baishazhou Bridge in Wuhan is selected as test area, where Nanhu Lake economy development area and Donghu Lake economy development area stand. Due to development of economy and need of city expanding in Wuhan, roads, buildings, bare land, lake and vegetation has been changing a lot in recent years.

The registered ETM+ imageries of the areas at Baishazhou Bridge in 2002 and 2005 are used as main experimental data (Fig. 3, Fig. 4).

Firstly, extract each pixel’s NDVI, then give NDVI threshold of each date image to extract vegetation areas, and produce vegetation mask of two dates according to Eq. (2). Fig. 5 shows the 02-05 vegetation mask, where pixels in the mask are white and outside ones are black.

Fig. 5 shows that the mask technique can eliminate non vegetation pixels beforehand, and detection efficiency can be raised to a great extend because the pixels just in mask need to be dealt with.

In view of intuition and visibility, pixels’ PVI

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| Class          | Vegetation increased | Vegetation decreased | Better growing | Worse growing |
|----------------|----------------------|----------------------|----------------|--------------|
| Angular of change vector’s direction (°) | 285-49 | 116-234 | 50-117 | 235-284 |
| Change vector’s magnitude | 74-255 |

\[
\eta_i = \frac{n_i}{n} \times 100\%
\]
and GVI are illustrated in following figures. Fig. 6 and Fig. 7 are PVI maps of 2002 and 2005, respectively, where vegetation pixels present brighter because of their near distance from non-vegetation beeline, and other pixels present darker because of their far distance. It indicates that PVI has the great ability to reflect vegetation and so can be applied to extract vegetation.

Fig. 6 PVI map of 2002

Fig. 7 PVI map of 2005

Calculate change vector’s magnitude with Eq. (12) and Eq. (14), which is stretched to \([0, 255]\), and described in the figures to get a change vector’s magnitude map. Then apply invariable quadrature segmentation to perform change on vector’s magnitude map derived from threshold of 74 and monochrome map (Fig. 10), where changed pixels are in white and unchanged ones in black.

Fig. 8 GVI map in 2002

Fig. 9 GVI map in 2005

Fig. 10 Threshold segmentation (threshold = 74)

For assessing the technique qualitatively, change spots are transformed into vector line to cover raster imageries in 2002 and 2005, where change bounds present white (Fig. 11, Fig. 12 give the added results of rectangle area in Fig. 10). Comparing corresponding areas with each other inside white bound of added result in 2002 and 2005, pixels inside the areas are the ch-

Fig. 11 Added map in 2002

Fig. 12 Added map in 2005
anged ones while outside ones are unchanged from 2002 to 2005. It shows that the technique applied in this paper is an efficient way of detecting vegetation change, which rarely misdetects or misses detecting the change pixels. Besides, invariable quadrature segmentation is a good alternative of threshold segmentation.

Each pixel’s angular of change vector’s direction can be calculated by Eq. (12) and Eq. (15), with which changed pixels are classified. Fig. 13 gives the result of vegetation change classification. The number of pixels in each class is accounted respectively, and then vegetation change percents of each class can be calculated by Eq. (16), results are shown in Table 3.

Table 3 Statistic of vegetation change pixels

| Class              | Spots(color) | Pixels num | Percents(%) |
|--------------------|--------------|------------|-------------|
| Vegetation increased | [ ]         | 3 862      | 2.23        |
| Vegetation decreased | [ ]         | 17 657     | 10.20       |
| Growing better     | [ ]          | 3 046      | 1.76        |
| Growing worse      | [ ]          | 6 597      | 3.81        |

Thanks to the tree planting projects along the beach of Changjiang River, vegetation is increasing here from 2002 to 2005, and owing to the development of economy, the phenomenon of gaining land at the sacrifice of sward and woods appears frequently in the other regions of the city (Fig. 13), resulting in imbalance between vegetation decreasing and increasing, that is, 10.20% pixels in the area changing from plants to other objects but only 2.23% changing to vegetation (Table 3). Meanwhile, in virtue of abundant rainfall in 2005, plants (mostly bulrush) standing at the beach of Changjiang River is growing more exuberance than that in 2002 (left below corner of Fig. 13), but plants (including grass, woods, and cropland) on other regions are growing worse owing to people’s destroying, with 1.76% growing better and 3.81% growing worse. It is in concord with the vegetation change in Wuhan between the two dates.

Error matrix is used to assess detection accuracy quantitatively, and area inside rectangle in Fig. 3 and Fig. 4 is selected as typical samples (including all kinds of vegetation change pixels). Comparing and analyzing land use investigation in 2002 and 2005, class of pixels in typical area can be gotten. There are 1 298 vegetation changed pixels, including vegetation increased and decreased, growing better and growing worse ones, and 4 460 unchanged ones can be obtained from the image which is used to test the accuracy of this application. The results derived from changed/unchanged test are shown in Table 4.

The procedure applied to detect vegetation change is correct totally in 94.91% and consistent coefficient Kappa is 0.85. The results demonstrates the ability of this modified change vector analysis is effective and efficient, may because an alternative to vegetation change detection for urban areas.

Table 4 Error matrix of change/no change

| Test data                      | Remote sensed data |
|--------------------------------|--------------------|
|                                | Changed pixels     | Unchanged pixels  | Sum    | Use correct ratio/% | Error ratio/% |
| Changed pixels                 | 1 103              | 195               | 1 298  | 84.98              | 5.02         |
| Unchanged pixels               | 98                 | 4 362             | 4 460  | 97.80              | 2.20         |
| Sum                            | 1 201              | 4 557             | 5 758  |                    |              |
| Produce correct ratio/%        | 91.84              | 95.72             |        |                    |              |
| Omit error/%                   | 8.16               | 4.28              |        |                    |              |

Total accuracy = 94.91% 
Kappa = 0.85
3 Conclusions

A new application of vegetation change detection is proposed, tested by ETM+ data of Wuhan in 2002 and 2005, and the results show that it is an efficient and effective way to detect vegetation change for urban areas. Firstly, Mask technique eliminates noise of non vegetation change effectively and raise the efficiency of change detection; secondly, it expands the applicability that GVI is calculated based on 3D G-S transformation and PVI based on linear fit with least-square estimation; then, the assess results demonstrate that change vector constructed by PVI and GVI could reflect vegetation change well and the approach proposed in this paper could be a good alternative of vegetation change detection for urban areas.

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