Spatio-temporal Autocorrelation Analysis for Regional Land-cover Change Detection from Remote Sensing Data

Monidipa Das*  
Department of Computer Science and Engineering  
Indian Institute of Technology, Kharagpur, India  
mondipadas@hotmail.com

Soumya K. Ghosh  
Department of Computer Science and Engineering  
Indian Institute of Technology, Kharagpur, India  
skg@iitkgp.ac.in

ABSTRACT

Of the various applications of remote sensing data, characterizing the land-cover dynamics is of utmost significance, providing insights into science, management policy, and several regulatory actions. Recent research works indicate that there is a need to understand and monitor land-cover dynamics at regional scale rather than local scale. However, the regional change is a more generalized concept and therefore, the use of pixel based analysis alone may not be sufficient to get proper insights regarding the land-cover change in remotely sensed imagery. Moreover, higher spectral variation and mixed pixels are two key challenges imposed by satellite imagery, resulting in poor performance of existing pixel-based methods for regional land-cover change detection. In this work, we have proposed a novel approach for detecting regional land-cover changes in satellite imagery using spatio-temporal autocorrelation analysis. Autocorrelation among the neighborhood pixels at various spatio-temporal lags has been utilized here to address the problem of mixed pixel and spectral variation. An index ($\gamma$), based on the estimated autocorrelations, has been proposed to classify the regions as 'change' and 'no-change' regions. Moreover, a parameter ($\sigma$) has been introduced to provide the measure of regional change significance. The method has been evaluated with Landsat ETM+ imagery (30m resolution) of four zones in and around Kolkata (India), comprising a total of 430 sq. km area ($\approx 4.8 \times 10^5$ pixels). The experimental results are encouraging, with an overall accuracy of 90.66%.

CCS CONCEPTS

• Information systems $\rightarrow$ Spatio-temporal systems; Geographic information systems;

KEYWORDS

Land-cover, Remote sensing imagery, Regional change detection, Spatio-temporal autocorrelation, Change significance

*Corresponding Author, Tel: +91 3212-278222

ACM Reference format:

DOI: http://dx.doi.org/10.1145/3041823.3041835

1 INTRODUCTION

Detection and monitoring of regional land-cover changes, whether produced naturally or by means of anthropogenic effects, are challenging tasks. These play critical roles in environmental studies, facility management, resource monitoring, and other regulatory actions [4], especially for any developing country, like India. In general, there are two major categories of land cover change detection [11]. One category focuses on the detailed change trajectories, while the other focuses on the detection of binary change. In the present work, we have proposed a novel approach for regional land-cover change detection of the second category, by using spatio-temporal autocorrelation analysis (ST-AC).

The use of spatial autocorrelation is not very new to the change detection community. The works proposed in [8] and [13] are a few examples in this regard. However, the novelty in our present study lies in providing a systematic approach of exploiting spatial and temporal autocorrelation in a combined way, to detect regional change along with the notion of significance to each changed region. The case study has been performed over 1198 regions selected from four large spatial zones, each covering $\approx 110$ sq. km area, in and around Kolkata, India. These particular areas in the Indian state of West Bengal are fast-developing areas, experiencing rapid urbanization in recent years. Previously, these areas were mainly comprised of cultivable/barren lands and water bodies, but recently, these have been acquired, and the area is being developed into planned city, full of residential and commercial buildings, health care centers, entertainment facilities, and so on.

Conventionally, various pixel based methods [11][17] are used for change detection purpose. However, the two key challenges faced by the pixel-based techniques are the higher spectral variation and mixed pixels, especially present in the medium-resolution satellite remote sensing data [13]. The presence of pixels with mixture of information on the various ground objects, has significant effect on these methods and diminishes the performance of change detection [4]. The spectral variation, which occurs due to differences in soil moisture...
and vegetation phenology between scenes at different time instants, makes the problem more challenging. Moreover, the regional land-cover change is a broader concept. It is dependent on the relative spatial distribution of various land-cover features within the whole region. This kind of change can be mathematically defined from the perspective of Euclidean plane isometry [15], as follows:

**Definition 1.1.** Let, \( f_i(t) \) be the land-cover feature of any pixel \( i \) in a region \( X \) at time \( t \). Then, the region \( X \) is said to encounter no change during \([t, t + t']\), if there exists an angle \( \theta \) such that for all \( i \) in \( X \),

\[
f_i(t) = f_{R_\theta(i)}(t + t')
\]

where, \( R_\theta(i) \) denotes a pixel (in the region \( X \)), the position of which can be determined by \( \theta \) degree rotation of the pixel \( i \) with respect to the central co-ordinate of region \( X \).

Definition 1.1 ensures that if there is no change in a region, then the neighborhood of each land-cover feature remains relatively same from the perspective of the whole region.

Therefore, in order to properly detect such change, each land-cover feature should consider the spatial contexts, that is, correlation with the nearby features on a regional basis, rather than just performing the local analysis with pixel-based approaches. Following is a toy example to illustrate the challenge in regional change detection.

**Motivating Example:** Consider the various cases of land cover change in the Figure 1 where, two different types of land cover categories have been denoted by the white and the gray colored pixels respectively.

![Figure 1](image-url)

**Figure 1:** Different scenarios of pixel-wise land-cover changes (from \( t \) to \( (t + t') \)) with no regional significance

Now, the traditional pixel-based methods work without considering spatial contexts of the pixels. Therefore, for the various cases of change in land-cover (refer Figure 1), these techniques will detect a rigorous change throughout the area, though there is no such regional change in practice. Therefore, the pixel-based methods alone may not always be sufficient for regional change detection, and further processing is required to get proper insights into the land-cover change.

In this work, we attempt to address these problems by proposing an approach, based on spatio-temporal autocorrelation analysis in the neighborhood of each pixel. The appearance of spatio-temporal autocorrelation pattern between the neighborhood pixels varies significantly, if there is a change in land-cover. It has been found that the regional land-cover change can reliably be detected using the proposed technique based on spatio-temporal autocorrelation (ST-AC) analysis, where we have devised a binary index for the change detection purpose. In this study, the use of various spatial lags in the neighborhood of each pixel handles the problem of mixed pixels, whereas, the consideration of each pair of spatio-temporal lags cancels out the effect of spectral variances over time. Further, unlike the conventional pixel based methods, the proposed change detection approach can automatically determine the quantitative estimate of land cover change on regional basis.

The experimentation has been carried out in and around Kolkata, a place in the tropical zone of India. Since, among the various pixel based binary change detection techniques, the image differencing (ID) methods provide a powerful interpretation of land-cover change in tropical zone [11], the comparative study has been performed with different ID techniques.

### 1.1 Contributions

The major contributions in this work are as follows:

- proposing a new approach for detecting regional land-cover change from multi-temporal satellite imagery by exploring spatio-temporal autocorrelation analysis;
- devising a change index (\( \gamma \)) for classifying the regions as ‘change’ and ‘no-change’ regions, and providing quantitative measure (\( \sigma \)) for indicating land-cover change significance;
- validating the efficacy of the proposed change detection approach with Landsat ETM+ imagery of 1198 regions in and around Kolkata, India, having land-cover changes at different levels of significance.
- analyzing the change detection performance in comparison with various conventional techniques.

We assume that the input satellite images are cloud-cover-free. Moreover, in our case study, the images are considered from the same time period of each representative year so as to eliminate the seasonal effects (e.g., field harvesting, monsoon flood etc.) in land-cover change detection process. However, depending on the objective behind land-cover change detection, the approach is applicable to detect the regional changes between any two time instants.

The rest of the paper is organized as follows: Section 2 discusses on the various related works, especially on pixel-based binary change detection techniques. In section 3, the proposed approach for regional land-cover change detection has been thoroughly discussed together with the required theoretical foundations in behind. The entire experiment on regional land-cover change detection has been extensively...
explained in section [4]. A detailed description of the used data set and study area has been provided in section [4.1]. The experimental specifications, and the various measures used for performance analysis have been described in section [4.2] and [4.3] respectively. The comparative results of regional change detection have been reported in section [4.4]. Finally, we conclude in section [5].

2 BACKGROUND

Analyzing multi-temporal remotely sensed data are often the prerequisite to study the land-cover change processes in any spatial zone. This section provides a brief discussion on the various pixel-based change detection (CD) techniques, popularly used for this purpose.

Over the past few decades, various techniques have been developed that use image pixel as the atomic analytical unit for detecting land cover changes in remote sensing imagery. In a generic sense, these techniques can be categorized as the pre-classification or binary CD and post-classification CD technique. The post-classification techniques [6] are often used to detect detailed ‘from-to’ change trajectory [11], providing the actual nature of change. On the other hand, a binary CD technique only provides the information regarding change and no-change pixel. Let \( \{ I_1, \cdots, I_t \} \) be a sequence of remote sensing images in which each image maps a pixel coordinate \( p \in R^d \) to an intensity or color. Then, a basic binary CD algorithm takes the image sequence as input and generates a binary image \( B_t : R^d \to \{0, 1\} \) that identifies changes in the last image as per the following rule:

\[
B(p) = \begin{cases} 
0, & \text{if there is a significant change at pixel } p \text{ of } I_t \\
1, & \text{otherwise} 
\end{cases}
\]

In general, most of the works assumes \( t = 2 \). Since, our proposed approach can be considered as a binary CD technique, the discussion in the present section will mainly concentrate on the pre-classification or binary CD techniques. The vegetation index differencing [2], image ratioing [9], vegetation index differencing [17], and principal component analysis [5] are commonly used to detect binary change and non-change information. Image differencing (ID) [2] is a simple technique, involving pixel by pixel subtraction of two spatially registered imageries. Though the resultant image in ID is easy to interpret, defining the appropriate threshold to differentiate the change and non-change areas becomes a critical task in such approach. According to Lu et al. [11], ID provides a powerful interpretation of change in tropical region. Image ratioing (IR) [9] also provides a simple and rapid way of detecting change and no-change area. It involves a band-by-band ratio of two registered images from different dates. Vegetation index differencing (VID) [17] is an effective method for detecting land cover change by suppressing topographic and shade effects. The normalized difference vegetation index (NDVI) is a commonly used method of this kind [5]. Principal component analysis (PCA) [5] is a linear transformation technique where the transformed data is re-arranged into two images corresponding to the first and second principal components. The first component images contain no-change information whereas the second component images contain change information between the different dates.

However, a major limitation of the pixel based change detection techniques is that the detection and/or measurement of changes by these methods are mostly performed without considering the spatial context [10]. The spatial relationships among the pixels, their spatial arrangements etc. are not modeled in the pixel-based analysis. Therefore, in a regional change analysis scenario, a significant amount of information is excluded, that could otherwise provide vital insights into the study area. On the contrary, the proposed change detection approach considers both the spatial and temporal context of each pixel by using spatio-temporal autocorrelation analysis, and thereby overcomes the limitation of the conventional methods in regional change detection.

3 METHODOLOGY

This section provides a detailed description of our proposed regional land-cover change detection technique using spatio-temporal autocorrelation analysis.

Figure 2 shows the basic flow diagram of the proposed approach using spatio-temporal autocorrelation analysis for detection of land-cover change in a very large zone by dividing it into smaller regions of interest or grid cells of equal dimensions. The system takes as input two satellite imagery at temporal lag \( t' \), performs per-grid-cell autocorrelation analysis, and finally classifies the ‘change’ and ‘no-change’ regions. As depicted in the figure, the entire process comprises of six
major steps, namely—1) Image pre-processing, 2). Subdivision
of the study area, 3) Spatial weight matrix formation, 4) Estimating spatio-temporal autocorrelation, 5) Defining change index, and 6) Regional change detection. Following are the brief descriptions for each of these steps.

3.1 Image pre-processing
The main objective in this step is to process the band information in the input satellite imagery and obtain the per-pixel normalized difference vegetation index (NDVI) values. According to [7], NDVI is one of the best performing indices for detecting land-cover changes in the ‘biologically complex vegetation communities’ like that can be noticed in India. Therefore, the NDVI, as estimated for each of the remotely sensed images under study, will be used for the autocorrelation analysis in latter stages. Now, NDVI is calculated as follows [1]

\[
NDVI = \frac{(NIR - VIS)}{(NIR + VIS)}
\]

where, VIS and NIR are the TOA (top-of-the-atmosphere) reflectance measurements, captured in the visible red (Band-3) and near-infrared (Band-4) spectral regions respectively. However, before estimating the NDVI, the images are preprocessed for atmospheric correction based on histogram equalization method. Since the images are assumed to be captured for the same time of respective years, the radiometric correction for sensor sensitivity, sun angle and topography may be avoided.

The procedure for NDVI calculation is depicted in Figure 3. The calculation is based on the NDVI conversion modeler tool in ERDAS IMAGINE [ver. 9.2.1][2].

3.2 Subdivision of the study area
As discussed earlier, very often the satellite images suffer from higher spectral variation and also contain mixed pixels, making the regional change detection process more challenging and difficult. In this work, attempt has been made to overcome this problem by considering the spatio-temporal change pattern of each pixel with respect to its neighbors, and for that purpose, the whole area should be split into regions/grid cells containing at least 2 × 2 pixels.

Once the pre-processing is done, the whole study zone/area \( A \), in each image, is divided into smaller regions of interest \( r_1, r_2, r_3, \cdots, r_m \) with equal dimensions, each of which can be treated as a grid cell. For example, if \( A \) is an area of dimension \( D \times D \) pixels, then, if it is divided into regions of size \( n \times n \) pixels, a total of \( m = (\lfloor \frac{D}{n} \rfloor \times (\lfloor \frac{D}{n} \rfloor) \) regions will be produced. The concept is illustrated in Figure 4. However, in case the entire study area \( A \) is the region of interest, this step can be skipped and the whole area can be treated as a single region with \( n = D \).

\[\text{Figure 3: Layer stack image to NDVI image conversion process}\]

\[\text{Figure 4: Division of the study area into regions (grid cell) of desired size}\]

3.3 Spatial weight matrix formation
In this step we define the weight matrix for each of the regions of interest \( r_i (i = 1, 2, \cdots, m) \). A spatial weight matrix \( W \) is a \( N \times N \) symmetric matrix, in which each element \( w_{ij} \) is defined as follows:

\[
w_{ij} = \begin{cases} 1, & \text{if } j \text{ is within spatial proximity of } i \\ 0, & \text{otherwise} \end{cases}
\]

where, \( i \) and \( j \) are any two pixels in the region; \( N(n \times n) \) is the total number of pixels in the region.

Depending on the pattern of spatial proximity (like rook, bishop, queen, square etc.), different types of weight matrix can be formed. In our case, we have considered square as the spatial proximity pattern within each region. Figure 5 shows the square patterns of spatial proximity considering different orders of spatial lag from a particular pixel ‘X’.

\[\text{Figure 5: Square spatial proximity patterns}\]
3.4 Estimating spatio-temporal autocorrelation

Once the spatial weight matrix is generated, spatio-temporal autocorrelation between the two images at temporal lag \( t' \) is estimated with respect to each region \( r_i \) considering all possible pairs of spatial lags. Spatio-temporal autocorrelation basically measures the cross-covariances between all possible pairs of locations lagged in both time and space [14]. In our approach we have utilized it to capture the spatio-temporal change pattern of each region \( r_i \).

With the estimation of spatio-temporal autocorrelation of any region, we determine how the NDVI value of each pixel region, we determine how the NDVI value of each pixel changes pattern of each region \( r_i \). In our approach the problem of mixed pixels, whereas, the consideration of partial lags in the neighborhood of each pixel assists in handling the problem of mixed pixels, whereas, the consideration of each pair of spatio-temporal lags cancels out the effect of spectral variances over time.

In order to calculate the spatio-temporal autocorrelation between the two images \( I(t) \) and \( I(t+t') \) at time \( t \) and \( t+t' \) respectively, we have used the spatio-temporal extension of Moran I coefficient [12]. The *spatio-temporal autocorrelation* \( \xi_{lk}^{t'} \) between the pixels at \( l\)-th spatial lag in \( r_i \) of \( I(t) \) and those at \( k\)-th spatial lag in \( r_i \) of \( I(t+t') \), is estimated as follows:

\[
\xi_{lk}^{t'} = \frac{\chi_{lk}(t')}{\chi_{kk}(0) \chi_{ll}(0)^{1/2}}
\]

where, \( \chi_{lk}(t') \) is the *space-time cross-covariance* between the \( l\)-th order spatial neighbors of any pixel in \( r_i \) and the weighted \( k\)-th order spatial neighbors of the same pixel in the same region at time lag \( t' \) in the future. \( \chi_{lk}(t') \) is defined as follows:

\[
\chi_{lk}(t') = E \left\{ \frac{[W^{(l)}z(t)][W^{(k)}z(t+t')]}{N} \right\}
\]

Here, \( N \) is the number of pixels in \( r_i \); \( W^{(l)} \) and \( W^{(k)} \) are the \( N \times N \) spatial weight matrices at spatial lag orders \( l \) and \( k \) respectively. \( z(t) \) is the \( N \times 1 \) vector of observations of NDVI value at time \( t \), \( z(t+t') \) represents NDVI at time \( t+t' \). \( z' \) denotes the matrix transposition operation.

Though in case of very large region (containing several millions of pixels) the formation of weight matrices may become time-intensive, this can be handled by adopting a similar cost efficient approach, as proposed in [3].

### 3.5 Change index

This is the most significant/novel step in our proposed approach. If a particular region is almost unaltered in two different time instants, then spatio-temporal autocorrelation \( \xi_{lk}^{t'} \) and \( \xi_{lk}^{t''} \) will be almost same, where, \( \xi_{lk}^{t'} \) is the autocorrelation between pixels at \( i\)-th spatial lag at time \( t \) and those at \( j\)-th spatial lag at time \( t+t' \). In other words, the spatio-temporal autocorrelation matrix will be almost symmetric. Moreover, for the same reason, the spatio-temporal autocorrelation at same spatial lag, \( \xi_{lk}^{t} \), will be greater than equal to those at different spatial lag i.e. \( \xi_{lk}^{t} (l \neq k) \).

Considering these two facts, we have defined a binary change index (\( \gamma \)), based on the estimated autocorrelation, to differentiate between regions with significant changes and those with almost no change. Let \( M_r \) be the spatio-temporal autocorrelation matrix (refer to Definition 3.7) of order \( S \times S \), corresponding to the considered region, then \( \gamma \) is defined as:

\[
\gamma = \begin{cases} 
0, & \text{if } \sum_{i,j=1}^{S} \left[ M_r(i,j) - M_r(j,i) \right]^{2} = 0 \text{ or} \forall_{k \in [2,S]} \left[ \min \left( M_r(k,k) - M_r(S,1) \right) \right] \\
1, & \text{otherwise}
\end{cases}
\]  

The value of \( \gamma \) becomes zero only when the autocorrelation matrix becomes symmetric or the spatio-temporal autocorrelation at the same spatial lag is never less than that between the two farthest spatial lag in the whole region.

Further, the spatio-temporal autocorrelation matrix \( M_r \) is utilized to define a measure \( \sigma \) to express the significance of the land cover change as follows:

\[
\sigma = \sqrt{\frac{\sum_{i,j=1}^{S} \left[ M_r(i,j) - M_r(j,i) \right]^{2}}{S}}
\]

The range of \( \sigma \) may differ from scene to scene. However, for a particular scene, the higher is the value of \( \sigma \) the more significant is the regional change in land cover.

**Definition 3.1.** The spatial autocorrelation matrix \( (M_r) \) is a square matrix where the element at the \( l\)-th row and \( k\)-th column represents the autocorrelation between the pixels at spatial lag \( l \) in a region with those at spatial lag \( k \) in the same region at some temporal lag \( t' \), i.e. \( M_r(l,k) = \xi_{lk}^{t'} \) and \( 1 \leq l, k \leq S \). If the region is of size \( n \times n \) pixels, then the maximum value of \( S \) can be \((n-1)\).

The maximum size of spatio-temporal autocorrelation matrix \( (M_r) \) for a \( n \times n \) pixel region is \((n-1) \times (n-1)\). The maximum possible spatial lag order between any two pixels in a \( n \times n \) pixel region can be \((n-1)\) and similarly, the minimum possible spatial lag order can be 1. Hence, considering all the spatial lag orders from 1 to \((n-1)\), there can be maximum \((n-1) \) number of row and \((n-1) \) number of column in the spatio-temporal autocorrelation matrix \( M_r \). Therefore, the
maximum size of matrix $M_t$ can be $(n - 1) \times (n - 1)$, where $n \geq 2$.

The summary of all the notations, used in this section, is given in the Table 1.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I$</td>
<td>Before study area/ zone of size $D \times D$ pixels</td>
</tr>
<tr>
<td>$r_i$</td>
<td>$i$-th region of interest (grid cell) of size $n \times n$ pixels</td>
</tr>
<tr>
<td>$m$</td>
<td>Total number of regions of interest (grid cells) $r$</td>
</tr>
<tr>
<td>$N$</td>
<td>Total number of pixels in a region of interest $r$</td>
</tr>
<tr>
<td>$W^{(t)}$</td>
<td>Spatial weight matrix at a spatial lag order $t$ for a region $r \in {r_1, r_2, \ldots, r_m}$</td>
</tr>
<tr>
<td>$\gamma(t)$</td>
<td>Observed parameter value (in this case, NDVI) at time $t$</td>
</tr>
<tr>
<td>$I(t)$</td>
<td>Remote sensing image at time $t$</td>
</tr>
<tr>
<td>$\beta$</td>
<td>Temporal lag</td>
</tr>
<tr>
<td>$\xi_{ik}(t')$</td>
<td>The spatio-temporal autocorrelation between the pixels at $k$-th spatial lag in region $r$ of $I(t)$ and those at $k$-th spatial lag in region $r$ of $I(t+t')$</td>
</tr>
<tr>
<td>$\chi_{ik}(t')$</td>
<td>Space-time cross-covariance between the $k$-th order spatial neighbors of any pixel in region $r$ and the $k$-th order spatial neighbors of the same pixel in the same region at time lag $t'$ in the future.</td>
</tr>
<tr>
<td>$M_{ij}$</td>
<td>Spatio-temporal autocorrelation matrix of order $S \times S$ (for a temporal lag $t'$)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Proposed binary index for land-cover change detection</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Proposed measure of regional change significance</td>
</tr>
</tbody>
</table>

### 3.6 Regional change detection

This is the final step in the proposed approach where we characterize the land-cover dynamics for each region $r_i$ in the whole study area by using the change index ($\gamma$) as defined in the previous step. For each region $r_i$, the change index is tested, and the change characterization is done as follows:

$$\text{Change in region } r_i = \begin{cases} \text{true}, & \text{if } \gamma = 1 \\ \text{false}, & \text{if } \gamma = 0 \end{cases}$$ \hspace{1cm} (7)

**Example** In order to illustrate the proposed approach, let’s consider the example as stated in Section 1 (refer Figure 1). In this case, each of the regions shown in Figure 1(a)-(c) contains 8 x 8 pixels, where the light and dark pixels denote two different land-cover categories in the region. Therefore, the spatial weight matrix $W$ becomes a 64 x 64 matrix. Now, considering eq. 3 and the square pattern of spatial contiguity, the spatio-temporal autocorrelation matrices for the regions become:

For $M_{ij}^{(a)}$:

$$M_{ij}^{(a)} = \begin{bmatrix} 0.98 & 0.97 & 0.95 & 0.98 & 0.98 & 0.73 & 0.42 \\ 0.97 & 0.99 & 0.97 & 0.97 & 0.85 & 0.61 & 0.42 \\ 0.95 & 0.97 & 0.99 & 0.97 & 0.78 & 0.64 & 0.46 \\ 0.98 & 0.97 & 0.97 & 0.99 & 0.91 & 0.76 & 0.55 \\ 0.89 & 0.85 & 0.78 & 0.91 & 0.99 & 0.86 & 0.64 \\ 0.73 & 0.61 & 0.64 & 0.76 & 0.86 & 1.00 & 0.76 \\ 0.42 & 0.42 & 0.46 & 0.55 & 0.64 & 0.76 & 1.00 \end{bmatrix}$$

And for $M_{ij}^{(b)}$:

$$M_{ij}^{(b)} = \begin{bmatrix} 0.96 & 0.97 & 0.94 & 0.96 & 0.87 & 0.73 & 0.43 \\ 0.97 & 0.94 & 0.96 & 0.96 & 0.84 & 0.59 & 0.41 \\ 0.94 & 0.96 & 0.98 & 0.97 & 0.78 & 0.64 & 0.45 \\ 0.96 & 0.96 & 0.97 & 0.97 & 0.8 & 0.76 & 0.55 \\ 0.87 & 0.84 & 0.76 & 0.9 & 0.97 & 0.85 & 0.64 \\ 0.73 & 0.59 & 0.64 & 0.76 & 0.85 & 0.97 & 0.75 \\ 0.43 & 0.41 & 0.45 & 0.55 & 0.64 & 0.75 & 1.00 \end{bmatrix}$$

And for $M_{ij}^{(c)}$:

$$M_{ij}^{(c)} = \begin{bmatrix} 0.31 & 0.62 & 0.85 & 0.92 & 0.81 & 0.62 & 0.35 \\ 0.62 & 0.83 & 0.92 & 0.97 & 0.85 & 0.61 & 0.4 \\ 0.85 & 0.92 & 0.86 & 0.86 & 0.73 & 0.62 & 0.45 \\ 0.92 & 0.97 & 0.86 & 0.89 & 0.77 & 0.69 & 0.52 \\ 0.81 & 0.85 & 0.73 & 0.77 & 0.91 & 0.82 & 0.62 \\ 0.62 & 0.61 & 0.62 & 0.69 & 0.82 & 0.97 & 0.75 \\ 0.35 & 0.4 & 0.45 & 0.52 & 0.62 & 0.75 & 1.00 \end{bmatrix}$$

It is evident that each of these spatio-temporal autocorrelation matrices (i.e. $M_{ij}^{(a)}$, $M_{ij}^{(b)}$, and $M_{ij}^{(c)}$) are symmetric in nature. Moreover, for all the three cases the eq. 3 yields a change index ($\gamma$) value of 0. Therefore, as per the proposed regional change detection equation (refer eq. 7), there is no regional land-cover change in any of the regions in Figure 1(a)-(c).

## 4 EMPIRICAL EVALUATION

In this work, we have proposed a novel technique for land-cover change detection from regional perspective. The approach is based on the autocorrelation analysis with satellite remote sensing data at various spatio-temporal lags. The theoretical foundations of the work have been thoroughly described in the previous section. This section provides the details of the data set, study area, experimental specifications, and the various outcomes of our experimentation over four recently developing zones in and around Kolkata, India.

### 4.1 Data and study area

The experimentation has been carried out with normalized difference vegetation index (NDVI) data obtained from medium-resolution satellite imagery of two time instants in the year 2005 and 2012. In order to ensure that the land-cover change is not due to seasonal effect, the images are collected from same time period of the year, in the month of April. The primary source of these data is the Landsat 7 Enhanced Thematic Mapper (ETM+) satellite imagery from Land Process Distributed Active Archive Center (LP DACC) of the United States Geological Survey (USGS). Later, in the image preprocessing step, the images have been improved through radiometric correction, and the per-pixel NDVI values have been extracted from the images.

**Figure 6: NDVI imagery of the study zones**

The case-studies have been performed in four spatial zones near Kolkata, India (refer Figure 7). The study zone-1 (central coordinate: 22°34’N, 88°29’E), zone-2 (central coordinate: 22°32’N, 88°17’E), and zone-3 (central coordinate: 22°38’N, 88°22’E) covers approximately 110 sq. km area (1.224 x 10^6 pixels) each; whereas the study zone-4 (central coordinate: 22°36’N, 88°13’E) consists of approximately 100 sq. km area (1.12 x 10^6 pixels). Because of a high level of urbanization, the study zone-1, which is near the Kolkata International airport, have seen significant changes in land-cover during the period from 2005 to 2012. Similar kind of land-cover change is found in the zone-2 and zone-4, which...
Spatio-temporal Autocorrelation Analysis for Regional Change Detection

CoDS’17, March 09-11, 2017, Chennai, India

Figure 7: Location of study zones in and around Kolkata, India

Figure 8: Typical patterns of spatio-temporal autocorrelations in ‘change’ region

are spatially distributed around three important railway stations, near Kolkata, India. On the contrary, the study zone-3 has encountered comparatively less significant changes during this time period, because it is already enough developed area in the northern part of greater Kolkata. Figure 6 depicts the scenarios, in terms of the corresponding NDVI raster.

4.2 Experimental setup

The entire experiment has been carried out using MATLAB 7.12.0 (R2011a) in Windows 2007 (64-bit Operating System, 3.10 GHz CPU, 4.00 GB RAM), and ERDAS IMAGINE tool (version 9.2.1). The image pre-processing step of our approach has been performed using ERDAS IMAGINE to make the radiometric corrections of the imagery and to generate NDVI raster from the input satellite data. ERDAS IMAGINE has also been used to detect pixel based change using image differencing (ID) techniques ($ID_{b1}, ID_{b2}, ID_{b3}, ID_{b4}, ID_{b5}, ID_{b6}, ID_{b7}$) and vegetation index differencing (VID) technique [11]. The rest of the processing has been performed in MATLAB. Each of the study zone-1, 2 and 3 has been subdivided into 306 regions of interest having 600 sq. m area containing 400 pixels each, whereas the study zone-4 has been subdivided into 280 regions of same area.

In order to detect regional change using ID and VID techniques, a region having more than 50% changed pixel is considered as the ‘change region’. On the other side, to detect regional change using our proposed approach, spatial lags of 1 to 19 have been used to estimate the spatio-temporal autocorrelation between each region at temporal lag of $(2012 - 2005) = 7$ years. The typical patterns of spatio-temporal autocorrelation, as obtained for the ‘change’ and ‘no-change’ regions in the study zones, have been depicted in Figure 8 and Figure 9 respectively.

As shown in the figures (refer Figure 8 and Figure 9), the patterns corresponding to the no-change regions are almost symmetric always. These also maintain a regular shape showing higher autocorrelation at same spatial lag and reducing gradually with distance. In contrast, the autocorrelation patterns in the change regions are not always regular and also of opposite characteristics. This pattern information has been used to define the change index ($\gamma$) for detecting regional change in land-cover. For each case of regional change detection, the validation has been made through visual interpretation supported by field data and higher resolution satellite data from Google Earth.

4.3 Performance Analysis

Four popular performance measures (overall accuracy ($O_A$), false alarm ratio (FAR), critical success index (CSI), and Kappa coefficient ($\kappa$)), have been considered for qualitative evaluation of our proposed approach. These performance
Table 3: Performance evaluation of the proposed approach based on ST-AC analysis to detect binary regional land-cover change during 2005-2012: Study Zone-1, Zone-2, Zone-3, Zone-4

<table>
<thead>
<tr>
<th>Study Area</th>
<th>No. of Sub-Region with significant change</th>
<th>No. of Sub-Region with No-change</th>
<th>Change Detection Technique</th>
<th>OA</th>
<th>FAR</th>
<th>CSI</th>
<th>k</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zone - 1</td>
<td>216 (86400 Pixels)</td>
<td>90 (36000 Pixels)</td>
<td>ID_1</td>
<td>67.32%</td>
<td>30.14%</td>
<td>91.12%</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_2</td>
<td>69.05%</td>
<td>27.17%</td>
<td>69.38%</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_3</td>
<td>66.28%</td>
<td>29.58%</td>
<td>66.97%</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_4</td>
<td>68.95%</td>
<td>39.21%</td>
<td>68.44%</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_5</td>
<td>65.69%</td>
<td>26.18%</td>
<td>62.09%</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_6</td>
<td>69.93%</td>
<td>40.52%</td>
<td>67.83%</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_7</td>
<td>66.36%</td>
<td>37.94%</td>
<td>67.12%</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>VIDS_{NDVI}</td>
<td>63.96%</td>
<td>29.03%</td>
<td>64.19%</td>
<td>0.01</td>
</tr>
<tr>
<td>Zone - 2</td>
<td>179 (71600 Pixels)</td>
<td>127 (50800 Pixels)</td>
<td>ID_1</td>
<td>67.65%</td>
<td>35.28%</td>
<td>64.60%</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_2</td>
<td>63.40%</td>
<td>38.16%</td>
<td>60.38%</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_3</td>
<td>67.32%</td>
<td>34.63%</td>
<td>62.59%</td>
<td>0.26</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_4</td>
<td>74.18%</td>
<td>29.17%</td>
<td>68.27%</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_5</td>
<td>65.36%</td>
<td>33.63%</td>
<td>68.27%</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_6</td>
<td>67.41%</td>
<td>32.58%</td>
<td>65.10%</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_7</td>
<td>64.74%</td>
<td>31.72%</td>
<td>65.36%</td>
<td>0.25</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>VIDS_{NDVI}</td>
<td>73.40%</td>
<td>29.36%</td>
<td>66.94%</td>
<td>0.41</td>
</tr>
<tr>
<td>Zone - 3</td>
<td>123 (49200 Pixels)</td>
<td>183 (73200 Pixels)</td>
<td>ID_1</td>
<td>56.14%</td>
<td>52.00%</td>
<td>47.43%</td>
<td>0.24</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_2</td>
<td>47.06%</td>
<td>57.30%</td>
<td>44.73%</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_3</td>
<td>45.59%</td>
<td>64.38%</td>
<td>44.96%</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_4</td>
<td>56.80%</td>
<td>52.02%</td>
<td>44.77%</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_5</td>
<td>51.31%</td>
<td>55.86%</td>
<td>39.68%</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_6</td>
<td>49.01%</td>
<td>54.74%</td>
<td>37.60%</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_7</td>
<td>53.62%</td>
<td>54.55%</td>
<td>38.96%</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>VIDS_{NDVI}</td>
<td>61.76%</td>
<td>48.33%</td>
<td>44.29%</td>
<td>0.26</td>
</tr>
<tr>
<td>Zone - 4</td>
<td>145 (58800 Pixels)</td>
<td>135 (54000 Pixels)</td>
<td>ID_1</td>
<td>75.00%</td>
<td>21.64%</td>
<td>74.55%</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_2</td>
<td>78.14%</td>
<td>20.25%</td>
<td>70.79%</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_3</td>
<td>69.64%</td>
<td>20.01%</td>
<td>62.09%</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_4</td>
<td>75.30%</td>
<td>20.47%</td>
<td>74.54%</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_5</td>
<td>65.36%</td>
<td>20.10%</td>
<td>62.09%</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_6</td>
<td>67.41%</td>
<td>20.14%</td>
<td>65.15%</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ID_7</td>
<td>63.21%</td>
<td>20.71%</td>
<td>60.38%</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>VIDS_{NDVI}</td>
<td>61.07%</td>
<td>19.44%</td>
<td>57.09%</td>
<td>0.07</td>
</tr>
</tbody>
</table>

Table 2: Standard metrics to measure the performance of the change detection techniques

<table>
<thead>
<tr>
<th>Metric</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Accuracy (OA)</td>
<td>( \frac{TP + FN}{TP + TN + FN} )</td>
</tr>
<tr>
<td>False Alarm Ratio (FAR)</td>
<td>( \frac{TP}{TP + FN} )</td>
</tr>
<tr>
<td>Critical Success Index (CSI)</td>
<td>( \frac{TP + TN}{TP + TN + FP + FN} )</td>
</tr>
<tr>
<td>Kappa Coefficient (k)</td>
<td>( \frac{P(a) - P(e)}{1 - P(e)} )</td>
</tr>
</tbody>
</table>

Where, \( N = (TP + TN + FP + FN) \) and \( P(a) = Probability of agreement; P(e) = Probability of random agreement; \)

Additionally, the spatial distribution of change regions throughout each study zone have been graphically plotted in the Figure 12 to get insights on the evolution-pattern of regional change.

4.4 Discussion

Analyzing the various outcomes, as shown in Table 3, the following inferences can be drawn:

- From the tables it is evident that the average overall accuracy (OA) of the proposed approach in detecting the regional change is 90.66%, whereas that for ID
and VID techniques are below 75%, which proves the efficacy of the proposed approach compared to the others.

- For all the study zones, the FAR of the proposed regional change detection approach is 0, indicating an accurate change detection performance, with zero probability of falsely accepting a region with no significant change in land-cover. On the contrary, the FAR of the other CD techniques are significantly high.

- CSI value (threat score) of more than 80%, in all the cases also establishes the accuracy of our proposed approach in regional land-cover change detection. In contrast, the CSI for the other considered ID and VID methods are at most 75%.

- The Kappa coefficient ($\kappa$) is one of the most robust measures in statistics, taking into account the agreement occurring by chance. The sufficiently high values of $\kappa \approx 0.8$, shown in Table 3, implies a very high agreement of our detected regional land-cover
changes with that observed in reality. Conversely, the values of $\kappa$ for the other techniques are low. Overall, though the image differencing (ID) techniques are found to provide good performance in detecting binary land cover changes in tropical zones, in the present case study on regional change detection, these are found not so effective at all. This is evident from their high value of FAR and very low Kappa coefficient (refer Table 3).

Few more interesting inferences can also be drawn from the Figure 11(a)-(d) and Figure 12(a)-(c).

- Figures 11(a)-(d) and Figure 12(b) show that during the period of 2005 – 2012, the land-cover changes in study zone-1, 2, and 4 is more than that in the zone-3. This is because the zone-3, which is in northern Kolkata, is already developed enough before 2005. Moreover, from field data, it is observed that the significantly changed regions in each zone are mostly near the railway stations, and around airport area.

- The graphical plot in Figure 12(a) represents the distribution of regions, coming across various amount of deviation in spatio-temporal autocorrelation with respect to an ideal region with no regional land-cover change at all. These are the plot of number of regions vs. change significance value ($\sigma$). From the plot, it is evident that the land cover change in zone-3 is comparatively less prominent than the other zones.

- Moreover, from the Figure 12(c), it can be noted that during the period of 2005-2012, the number of most significantly changed regions in study zones 1, 2, and 4 is at least four. However, that in zone-3 is only one.

5 CONCLUSIONS

Detection of land cover change by analyzing multi-temporal remote sensing data has gained lot of interest in recent days. An insight into regional land cover change can play vital role in making crucial decision regarding facility management and many other regulatory actions. In the present work we have proposed a novel approach for detecting binary land cover change on regional basis. The novelty in this work is twofold: 1) addressing the problem of land-cover change from regional perspective rather than from local view point; 2) proposing a regional change detection approach, considering both spatial and temporal context of each pixel in the study region, by using spatio-temporal autocorrelation (ST-AC) analysis. Experimentation has been carried out with Landsat ETM+ imagery for detecting land cover change during 2005-2012 in four spatial zones (covering total 4,792 x 105 pixels) in Kolkata, India. An overall accuracy ($\text{OA}$) of more than 90%, critical success index (CSI) of $\approx 85\%$, and the high Kappa coefficient value ($\approx 0.8$) prove and validate the efficacy of the proposed regional change detection technique. At the same time, the 0% false alarm ratio (FAR) indicates an accurate change detection performance, having no false detection of a region where there is no change in land-cover at all. Two major findings, obtained from the experimentation, are: 1) the land cover change in Kolkata, India, which is mainly due to urbanization, is more prominent around the railway stations and near the airport area; 2) conventional pixel-based analyses, like ID, VID techniques, are not sufficient enough to draw insights into regional land cover change.

REFERENCES