Graph-based block-level urban change detection using Sentinel-2 time series

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ABSTRACT
Remote sensing technology has been frequently used to obtain information on changes in urban land cover because of its vast spatial coverage and timeliness of observation. Block-level change detection with high temporal resolution image data provides fine detail of urban changes, is suitable for urban management, and has gradually received widespread attention. High-dimensional features are required to express the heterogeneous structure of the blocks. High-dimensional high-frequency time series, namely, multivariate time series, are formed by arranging high-dimensional features chronologically. Classic change detection methods treat multivariate time series as univariate time series one by one. Few studies have analyzed the change in a multivariate time series by considering all variables as an entirety. Therefore, a graph-based segmentation for multivariate time series algorithm (MTS-GS) is proposed in this paper. Specifically, 1) we construct a similarity matrix to explore the changing patterns of multivariate time series for seasonal change, trend change, abrupt change, and noise disturbance; 2) a multivariate time series graph is defined based on the changing patterns; and 3) the corresponding graph segmentation algorithm is proposed in the paper to detect the abrupt and trend changes under noise and seasonal disturbances. Sentinel-2 images of the rapidly developing third-tier city of Luoyang, Henan province, China, are adopted to validate the algorithm. The F1-score in the spatial domain is 84.1%; the producer’s and the user’s accuracy in the temporal dimension are 81.8% and 80.1%, respectively. Seven change types are defined and extracted, showing the development pattern and the efficiency of land use in the city. Furthermore, the proposed MTS-GS can be used for pixel-level change detection and performs well under various time intervals and cloud covers.

1. Introduction
Urbanization is a global phenomenon across the world (Nagendra et al., 2018; Gu, 2019). The United Nations reported that over half of the global population lived in urban areas in 2014, and two thirds of the world’s population will reside in urban areas in 2050. Unprecedented urban growth has caused significant changes in the environment, for example, terrestrial and aquatic pollution (Peters and Bratton, 2016; Dvornikov et al., 2021), biodiversity loss and ecosystem degradation (McKinney, 2006; McKinney, 2008; Piano et al., 2020), the greenhouse effect and climate change (Kalnay and Cai, 2003; Li and Lin, 2015; Elhacham and Alpert, 2021).

Urban development is a continual process of expansion and renewal (Li and Zeng, 2020). Urban renewal aims to improve built-up areas where current land functions and resource usage do not fulfill social and economic development requirements (Lee et al., 2016; YE, 2019, Du et al., 2021). Urban expansion transforms non-urban areas into urban areas, driving the loss of habitat, biomass, and carbon storage (Seto et al., 2011; Seto et al., 2012). The spatial-temporal information of changes derived by urban expansion and renewal is the basis for analyzing environmental and social consequences for urban planning (Jin et al., 2019; Shi et al., 2020).

Remote sensing technology has been widely used to obtain land cover changes, due to its vast spatial coverage and timeliness of observation (Ban and Yousif, 2012, Huang et al., 2017b, Leichtle et al., 2017, Moya et al., 2020). Satellite image time series analysis provides an efficient technology to monitor urban land cover changes. Commonly used satellite data are, for example, MODIS, Landsat, and nighttime light

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imagery, from which many urban land cover change models and products with various spatial and temporal scales have been derived (Reba and Seto, 2020).

Urban expansion has received substantial attention, which focuses on the areas transformed from pervious to impervious surface. Nighttime light imagery and Landsat are widely used data to produce 1–5-year interval urban-expansion information to delineate the urban boundaries on global or regional scales (Araya and Cabral, 2010, Xie and Weng, 2016, Li et al., 2018, Melchiorri et al., 2018, Al Rifai and Liu, 2019, Gong et al., 2020). The emphasis on urban renewal has been increasing in recent years. Medium-to-high-resolution data with high frequency (most are shorter than or equal to a 1-year interval) has been employed by scholars to demonstrate changes within urban areas: the distribution of newly constructed buildings (Liu et al., 2019a, Huang et al., 2020), the construction time of impervious surface (Liu et al., 2019b, Deng and Zhu, 2020, Jing et al., 2021), changes in urban green regions (Zhu et al., 2016, Huang et al., 2017a), and so forth (Dai et al., 2010; Michishita et al., 2012; Wan et al., 2019). Thus, high spatial resolution and high temporal resolution dataset can reveal details of urban changes, and this topic is the focus of this research.

Many algorithms for urban change detection using time series have been developed and can be divided into two categories: classification-based methods and time series analysis-based methods (Zhu, 2017; Reba and Seto, 2020). In the classification-based strategy, pre-classification and post-classification techniques are commonly used. Pre-classification approaches treat each change as an independent class and obtain urban changes through trained classifiers (Kennedy et al., 2007; Hansen et al., 2014; Li et al., 2020). However, collecting all change types to train a classifier is challenging, especially over a long monitoring period. As a result, most researchers have adopted post-classification techniques with consistency checking to obtain urban changes, and the accuracy of changes is related to the classification results (Li et al., 2015; Anees et al., 2019; Liu et al., 2019b; Gong et al., 2020). Most of the classification-based approaches are used to examine changes with greater than or equal to 1-year interval data because of the high cost of the classification procedure. Time series analysis-based methods detect continuous changes with high-frequency data, allowing for a fine temporal scale for urban change detection. Classic algorithms include breaks for additive season and trend algorithm (BFAST) (Verbesselt et al., 2010), the continuous change detection and classification (CCDC) (Zhu and Woodcock, 2014), and derived algorithms based on CCDC (Liu et al., 2019a; Bullock et al., 2020; Deng and Zhu, 2020). Observations are decomposed into the trend, seasonal change, and noise components; next, changes are obtained if there is a significant difference between fitted and observed values.

Most time series analysis-based methods require individual pixels. Independently processing each pixel derives the “salt-and-pepper” result in the spatial dimension due to the registration error and high spectral variability in the urban areas (Hussain et al., 2013; Yu et al., 2016). Additionally, street blocks have been considered the basic unit of urban planning and management, at which the urban function can be represented. Scholars have explored the classification algorithms of functional zones based on city blocks (Grippa et al., 2018, Chen et al., 2021, Du et al., 2021), supporting urban land use policy and planning paradigms. Unlike pixel-level change detection, the outcome of block-level change detection helps landscape analysis, potentially revealing the impacts and causes of changes (Kennedy et al., 2015) and providing crucial hints for urban management (Huang et al., 2017b). Researchers have recently attempted to study block-level change detection techniques (Huang et al., 2017b; Al Rifai and Liu, 2019, Jing et al., 2021). Current techniques mainly detect bi-temporal or yearly changes based on post-classification. However, long detection intervals are difficult to adjust to the high pace of urban renewal. Error accumulation in post-classification also affects detection accuracy.

To fulfill the fine requirements of urban planning, this work aims to achieve high-frequency block-level urban change detection using sentinel-2 10 m resolution image data. The following concerns are considered:

1) The complex structure of each block needs to be expressed by high-dimensional spatial features. High-dimensional high-frequency time series, namely, multivariate time series, are formed by arranging the high-dimensional features chronologically. Classic change detection methods treat multivariate time series as univariate time series one by one, which has not considered all variables as an entirety to explore the changing pattern. The new approach to managing multivariate time series (MTS) has seldom been studied.

2) The construction process is prone to be observed in the high-frequency time series because of the continual change in the construction site. This gradual change is defined as “trend change” in this paper, with reference to CCDC. The trend changes in urban land cover show high intensity and short duration, the detection of which has infrequently been studied.

3) Cloud noise and seasonal variation are critical interference factors in high-frequency change detection. The strategy to detect the “abrupt change” and “trend change” from the MTS under the noise and seasonal disturbance should be considered.

This paper proposes the graph-based segmentation for multivariate time series algorithm (MTS-GS) to overcome the aforementioned problems. First, we analyze the changing pattern of MTS for seasonal change, trend change, abrupt change, and noise disturbance. Subsequently, we construct a new connection based on graph theory to represent the changing pattern of MTS, named the graph of MTS (MTS-G). Finally, we propose the corresponding graph segmentation algorithm to detect abrupt and trend changes under noise and seasonal disturbance. The contributions of MTS-GS include:

- Developing a new change detection algorithm for multivariate time series.
- Exploring the changing pattern of multivariate time series.
- Creating a multivariate time series graph.
- Enabling the detection of trend changes with short duration.

2. Data and study area

2.1. Study area

Large cities have been widely concerned and studied by researchers, but small and medium-sized urban areas with rapid growth and renewal have not (Reba and Seto, 2020). Thus, we selected a third-tier city of China with rapid development, Luoyang (population 700,000), Henan province, as the study area. The history of civilization in Luoyang spans more than 5000 years. Luoyang has a total area of 15,200 km², of which the urban core area is approximately 400 km² and located at 112°19’–112°37’ east longitude and 34°32’–34°44’ north latitude. The terrain is high in the west and low in the east. With the construction of rail transportation and an elevated expressway, Luoyang has been undergoing substantial urban changes. The location of the study area is shown in Fig. 1.

2.2. Sentinel-2 data and pre-processing

Sentinel-2 is a wide-swath, high-resolution, multispectral imaging mission supported by Copernicus land monitoring studies. In this study, we selected one scene from each month from the L1C-level (top of atmosphere reflectance) data with maximum cloud cover from June 2017 to December 2020, and 43 images were collected to construct the time series. Notably, 93% of the collection had less than 5% cloud cover, and the maximum cloud cover of the collection was 35.51%. Fig. 2 is the horizontal calendar chart from 2017 to 2020. The horizontal axis represents the month, and the vertical axis represents the week. The yellow
circle indicates when the image is collected in the current month, and the number on the yellow circle is the day of the month.

In this paper, the 10 m resolution bands (“Blue,” “Green,” and “Red”) and the 20 m resolution bands (“RedEdge1,” “RedEdge2,” “RedEdge3,” “NIR,” “RedEdge4,” “SWIR1,” and “SWIR 2”) were selected. L2A data (surface reflectance) were produced by running sen2cor and then resampled to a 10 m spatial resolution with a nearest interpolation to benefit from the highest spatial resolution. Furthermore, cloud removal was not performed on the data in this paper because the amount of cloud was kept to a minimum when choosing the area. A limited quantity of clouds remained in the images to test if the proposed algorithm could manage such noise.

2.3. Road network and blocks extracted

OpenStreetMap (OSM), an open-source platform, has been recently used as auxiliary data for urban remote sensing. In this paper, street blocks were extracted by the processed OSM. The original OSM road network contains levels of roads, and some levels are too fine to be detected as changes, for example, the community interior roads and multiple lanes. Thus, we eliminated the community interior roads by visual inspection and consolidated the multiple lanes of main roads into one lane by using the functions of the Esri ArcMap. Additionally, we added a few roads for the study region according to the online AMAP (https://www.amap.com/), which has the latest digital map content in China. Finally, 963 blocks were extracted, with the areas ranging from 0.03 to 5 km² (Fig. 3). Subsequently, the time-series images were clipped by the boundary of each block for the next procedure.

2.4. Urban land cover classes and change types

The urban construction process can be vividly reflected in the high-frequency time series, displaying a gradual transition from “bare land” to “buildings.” However, the traditional urban land cover classes of “impervious surface, vegetation, water, bare soil” cannot describe this gradual change. As a result, we improve the urban land cover classes by creating three primary classes and five secondary classes based on the functions and characteristics of blocks in the study area. (See Table 1)

(1) Built-up zone: refers to the built-up area: buildings, utilities, and other infrastructure.
(2) Urban green zone comprises vegetation and water for improving the urban environment (e.g., reducing the heat island effect). Water includes inland water and artificial water. Vegetation includes woodlands, shrubs, grasslands, crops, parks, green belts, and other manually built green areas.
(3) Urban transition zone refers to unmanaged areas or areas under construction, including construction sites and wasteland. A construction site is a block under construction or ready for construction. Wasteland refers to bare land with weeds or little vegetation due to mismanagement. A transition zone is often distributed in or near cities and is part of reserve land for urban planning.

Notably, permanent bare land, such as sandy and stony areas, which are contained by urban planning in some regions such as coastal or mining cities, was excluded from wasteland and not considered.

Fig. 1. Study area.
Fig. 2. Dates of the collected images.

Fig. 3. Blocks extracted by the road network.
<table>
<thead>
<tr>
<th>Primary category</th>
<th>Secondary category</th>
<th>Description</th>
<th>Google earth HD image</th>
</tr>
</thead>
<tbody>
<tr>
<td>Built-up zone</td>
<td>Built-up area</td>
<td>Buildings and public facilities, etc.</td>
<td><img src="image1.jpg" alt="Built-up area Image" /></td>
</tr>
<tr>
<td>Urban transition zone</td>
<td>Construction site</td>
<td>Construction site with working on or ready to work</td>
<td><img src="image2.jpg" alt="Construction Site Image" /></td>
</tr>
<tr>
<td>Wasteland</td>
<td></td>
<td>Barren land with weeds or less vegetation</td>
<td><img src="image3.jpg" alt="Wasteland Image" /></td>
</tr>
<tr>
<td>Urban green zone</td>
<td>Vegetation</td>
<td>woodland, shrubs, grassland, crop, park, green belt, etc.</td>
<td><img src="image4.jpg" alt="Vegetation Image" /></td>
</tr>
<tr>
<td>Water</td>
<td></td>
<td>Inland water, artificial water</td>
<td><img src="image5.jpg" alt="Water Image" /></td>
</tr>
</tbody>
</table>
Fig. 4. Change types of urban land cover.

Fig. 5. The flowchart of the proposed MTS-GS.
According to the aforementioned classification labels of urban land cover, we described the change information (Fig. 4). There are seven types of urban land cover changes: “urban expansion,” “urban renewal,” “green recovery,” and “green loss,” were based on changes among the three zones; the “green types’ shift” was based on the inner change of the green zone; and “reconstruction” and “site abandonment” were based on the inner change of the transition zone.

3. Methodology

The graph-based segmentation for multivariate time series algorithm (MTS-GS) is proposed in the paper by using graph theory. A graph is composed of vertices (also called nodes or points) connected by edges (also called links or lines) (Gross and Yellen, 2005). Graph-based segmentation has been applied for image segmentation. The algorithm constructs a graph, where each pixel corresponds to a node of the graph, and undirected edges connect specific pixels. Weights on each edge represent the similarity between pixels (Felzenszwalb and Huttenlocher, 2004). The time series can alternatively be represented as a graph if each time point is treated as a node and specific nodes are connected by edges. However, high-frequency time series are different from images, which contain the trend and abrupt changes, as well as seasonal and noise disturbances. As a result, a new graph structure for connecting time series is discussed.

The flowchart of MTS-GS for block-level change detection is shown in Fig. 5. First, the high-dimensional features are extracted from each temporal image of the block, and the changing pattern of multivariate time series is analyzed based on the features’ similarity between time nodes. Second, the time-series graph is constructed to represent the changing pattern of the multivariate time series. Third, the corresponding graph segmentation algorithm is introduced to extract the abrupt and trend changes under noise and seasonal disturbances. The MTS-GS is an unsupervised change detection approach; consequently, the classification procedure is required to assign the land cover labels for each temporal image. Finally, the accuracy assessment is shown for the proposed MTS-GS.

3.1. Feature extraction and changing pattern analysis

3.1.1. Histogram of oriented gradients (HOG) feature descriptor

HOG (Dalal and Triggs, 2005) is a feature descriptor that focuses on the structure of an object with illumination and shadow invariance and has been widely used to extract features of urban areas (Li et al., 2016, Li et al., 2017, Konstantinidis et al., 2020). In this paper, the HOG feature was extracted to represent the structural information of each temporal image of the block by using the Python package “Skimage.” The red, green, and blue bands were applied to generate the HOG feature.

As shown in Fig. 6, we extracted the HOG feature from each temporal image of the block as high-dimensional features.

The average dimension of the HOG feature in our study area (936 blocks) was 159. Each component of the HOG feature produced a one-dimensional time series; as a result, the time series of the HOG feature is a multivariate time series that accurately describes the structural change of a block.

3.1.2. Changing pattern analysis

This section analyzes the changing pattern of the multivariate time series. Considering that similar ground objects have similar HOG features and vice versa, the change information of each block can be reflected by HOG features’ similarity between time points. Thus, the multivariate time series can be converted into a similarity matrix by calculating HOG features’ similarity values between time points and arranging these values in chronological order (Fig. 7). Pearson’s distance measured HOG features’ similarity between time points (Immink and Weber, 2014), defined as

\[ r = \frac{\operatorname{Corr}(X_t, X_{t+1})}{\sqrt{\operatorname{Var}(X_t) \operatorname{Var}(X_{t+1})}} \]

where \( X_t \) is a vector in which all components of the HOG feature at time \( t \) are assembled, \( X_t \) and \( X_{t+1} \) correspond to the vectors at time \( t \) and \( t+1 \), respectively. \( \operatorname{Corr} \) and \( \operatorname{Var} \) refer to the covariance and variance, respectively. The range of Pearson distance lies in \([0,2] \), as the value decreases, the similarity of time points increases.

A similarity matrix is shown in Fig. 7, where the primary diagonal is zero. The first-order diagonal represents the similarity of two adjacent time points, and the \( n \)-th order diagonal represents the similarity between \( n \)-interval time points.

Three change patterns (i.e., trend, abrupt and seasonal) and noise disturbance information (Zhu and Woodcock, 2014) can be clearly observed through the similarity matrices that were constructed using the multivariate time series based on the HOG feature. In the urban areas, the trend change is mainly induced by site construction, showing the continual-gradual change. The abrupt change corresponds to the shift in urban land cover (e.g., destruction of buildings and vegetation). The seasonal change is caused by the phenology of vegetation and solar angle differences. The noise is mainly caused by clouds and shadows, which may affect change detection accuracy even if processed by a cloud removal method. The aim of change detection is to retrieve abrupt and trend changes under seasonal and noise disturbances.

Similarity matrices for the changing patterns are shown in Figs. 8, 9 and 10. The lower the similarity between time nodes, the redder the similarity matrix, and vice versa.

The vegetation changes periodically with its growth and senescence, which causes the structure of land cover to be alternately changed. Fig. 8 illustrates a 43 x 43 similarity matrix of seasonal change in the greening region from 43 temporal images. The matrix in Fig. 8 can be viewed as the regular combination of the low-similarity area (red) and the high-similarity area (yellow) caused by the changing vegetation state. High-similarity regions are outlined with a solid and dashed line. Blue solid rectangles represent the similarity of images from April to November each year. Every diagonal order inside each solid blue rectangle shows lower values (i.e., the high similarity between any pair of time points) because the vegetation state is similar from April to November with a
high-level vegetation fraction. The blue dashed rectangle represents the similarity of land cover from April to November between adjacent years, with high similarity due to the similar vegetation status in the same seasons each year. Likewise, the solid purple rectangles correspond to a low-level vegetation fraction.

The red areas represent the similarity between the solid blue and purple rectangles, indicating the dissimilarity caused by the polarized seasonal vegetation fractions. The values of the 1st order diagonal periodically increase, showing the alternating changes in vegetation states. Notably, the entire 12th order diagonal (the dashed line) falls into the dashed rectangles, showing the high similarity between the same months in adjacent years. In addition to vegetation, all ground objects exhibit seasonal variation, such as shadows projected by high-rise structures.

Abrupt change is caused by the shift of land cover, which generates a substantial change in the structure of a block. A similarity matrix of abrupt change is depicted in Fig. 9, where the built-up region is suddenly destroyed and changed to a construction site. Before September 2019, the land cover was the built-up area, denoted by a blue rectangle, and after September 2019, the construction site, denoted by a purple rectangle. The similarity within each rectangle is high because the land cover has no change in each period. Because the land cover structure changed before and after the abruption, the similarity between the two areas is low, shown as the red area in the lower-left corner. The values of the 1st order diagonal increase suddenly and then decrease, which reflects the date of the change.

A similarity matrix of a trend change is shown in the purple rectangle of Fig. 10. The three types of land cover are vegetation (blue rectangle), the construction site (purple rectangle), and the built-up area (green rectangle). The similarity is relatively high within the period of vegetation and built-up areas because there are no changes. Different from abrupt and seasonal changes, the structure of the block is gradually changing during the continual construction process, showing that the similarity in the 1st order diagonal is relatively low, and the similarity is gradually decreasing with the increasing order of the diagonal between the time points within the purple rectangle. The large values are continuously distributed on the 1st order diagonal for the trend change. The values of the 1st order diagonal show sudden increases before the trend change and suddenly decrease after the trend change, indicating the two changes in land cover.

Table 2 summarizes the three changing patterns. The 1st order diagonal carries the majority of change information, with dramatic fluctuations indicating change and continuous stable values indicating no change. The continuous low values in the diagonal connecting the same
months in adjacent years imply the seasonal effect.

As listed in Table 2, the periodical fluctuation on the 1st order diagonal depicts alternating land cover structures from seasonal change, and the diagonal connecting the same months in adjacent years would retain low values because of the similar land cover structures in the same season of adjacent years. The dramatic fluctuation of the 1st order diagonal indicates the abrupt change in land cover structures, where the change timing can be found. Trend changes derived from the gradual modification on the surface are shown as continuous high values. Dramatic fluctuations, including a sharp increase or decrease, illustrate the starting and ending points of the trend change.

Clouds often exist in the time series. Fig. 11 illustrates the similarity matrix of the noise disturbance. The structures of noise and noise-free images are significantly different, resulting in a low similarity. Consequently, a similarity matrix displays a red crosshair centered on the noisy point. The 1st order diagonal sharply fluctuates on the noise point, due to the undesirable land cover change. This situation is considered in our algorithms as follows.

3.2. Graph construction of MTS

The graph’s construction is the foundation of the proposed framework. When each time point corresponds to a node in the graph, the weighted edges can be selected from the similarity matrix to connect the nodes. The $n^{th}$-order diagonal of the similarity matrix represents the edges connected to node $i$ and node $i + n$ (Fig. 12).
On the basis of the analysis in Section 3.1, three types of edges are selected to construct the graph:

1. **Series edge**: The 1st order diagonal contains substantial change information, reflecting the earliest change timing, which is essential for graph construction. We call this edge the series edge because the 1st order diagonal connects each time point in a chronological sequence.

2. **Period edge**: Due to the periodic fluctuation caused by the seasonal effect, excessive changes may be retrieved based on the series edge. To alleviate this problem, we selected a diagonal connecting the same months in adjacent years, enabling similar structures in the same seasons to be recognized as one cluster rather than different clusters. This edge is called the period edge.

3. **Noise edge**: Pseudo changes are caused by noise nodes if the analysis is only based on the series edge. The diagonal connecting the $n$-neighbor nodes ($n > 1$) enables the graph to jump over the noise nodes to avoid a false alarm. Therefore, this edge was selected as the noise edge.

The three types of edges were used to construct the multivariate time-series graph (MST-G), which is the basis for block-level change detection. Fig. 13 shows an example of the series edge, period edge, and noise edge, which corresponds to the 1st order, 6th order, and 2nd order diagonals, respectively.

Besides the series edge, the specific order (i.e., the length) of the period and noise edges should be considered according to the quality of the time series images. Based on the changing pattern analysis, the length for the period edge (PL) should be equal to the number of images per year. The length of the noise edge (NL) depends on the number of continuous cloudy images in the time series, which can be set as one more than the maximum number.

### 3.3. Segmentation of MTS graph

#### 3.3.1. Initial segmentation

According to the changing pattern analysis, the time series graph should be cut when a sharp fluctuation is between the nodes. Meanwhile, the nodes connected by the edges with continuous similar values should be gathered to form one cluster. The change information of land cover can be obtained based on the segmentation result of the time series graph.

The graph-based segmentation algorithm (Felzenszwalb and Huttenlocher, 2004) can produce the sub-graphs connected by the edges with similar values based on a minimum spanning tree, which exactly fulfills the requirements of the MST-G segmentation. This algorithm judges if the two sub-graphs should be merged using the rules (2)–(5),

<table>
<thead>
<tr>
<th>Change type</th>
<th>Changing pattern</th>
<th>Diagram of 1st order diagonal</th>
</tr>
</thead>
</table>
| Seasonal change | 1st order diagonal: periodically fluctuate  
Diagonal connecting the same months in neighbor years: retain low values | ![Diagram](image) |
| Abrupt change | 1st order diagonal: sharp increase then a decrease at the change date  
Diagonal connecting the same months in neighbor years: contains high and low values | ![Diagram](image) |
| Trend change | 1st order diagonal: retain high values  
Diagonal connecting the same months in neighbor years: retain high values | ![Diagram](image) |
where $C_1$ and $C_2$ refer to two clusters, $D(C_1, C_2)$ is the inter-class distance between $C_1$ and $C_2$, $\text{Int}(C)$ is the intra-class distance of each cluster, $N(C)$ is the number of nodes in each cluster, and $K$ is the tolerable parameter controlling the fineness of segmentations. The proofs of the algorithm are in the literature (Felzenszwalb and Huttenlocher, 2004).

Fig. 14 illustrates an example for the initial segmentation, in which three types of edges are used to connect the nodes. 12 series edges, 2 noise edges, and 1 period edge are generated by the minimum spanning tree; and the relatively large edges are segmented by the initial segmentation procedure, obtaining four sub-graphs.

### 3.3.2. Merging procedure

Initial segmentation ensures that nodes with similar structures are
gathered. However, the alternate and noise clusters generated by seasonal and noise disturbances should be removed from change detection. Therefore, the merging procedure is required to eliminate these unimportant variations.

First, the temporal filtering in a local window is used for noise removal, where the label of a center point was replaced with a maximum mode within the window (Fig. 15).

Second, in Fig. 15, the period combination is employed to merge the clusters with alternate changes. The symbolic time series is created by combining the nodes of continuous stable labels into a single node (Keogh et al., 2005). The periodic pattern is then identified using the autocorrelation detection method (Guo, 2013). Finally, the nodes with the periodic pattern are merged into a single cluster, and the actual change is acquired.

Finally, the degree of fluctuation of the series edge is essential for MTS-GS. To remove the areas that are not considered actual changes, an absolute inter-cluster measurement $M$, corresponding to the average of the red region of the similarity matrix shown in Fig. 9, is set to merge the clusters by a pre-defined similarity.

Notably, the merging procedure is the ancillary step. Therefore, noise removal and period combination are only performed once. Multiple merging processes may excessively interfere with the graph segmentation results and cause unnecessary omission.

3.4. MTS-GS for block-level change detection

Fig. 16 shows the schematic of the MTS-GS procedure for block-level change detection under different situations, where the time series of the HOG feature had been constructed to the similarity matrix. The first column is the construction of the graph with 2 NL and 6 PL. The second column is the minimum spanning tree of the MTS-G. The third column is the initial segmentation, and the values of $\text{Diff}(C_1, C_2)$ and $\text{Int}(C)$ of the clusters are shown, which fit the segmentation rules in Eq. (2). The last column is the merging procedure, showing the results of change detection.

Fig. 16 (a) shows an abrupt change, where only the series edge is used for the initial segmentation. Two clusters with stable values on the series edge are gathered. Due to the sudden fluctuation of E9–9, the two clusters cannot be merged. Fig. 16 (b) shows a periodic change, where series and period edges were used. The four clusters are gathered only using the series edge. Due to the effect of the period edge, two alternate clusters were obtained, which can be merged by the period combination. Fig. 16 (c) shows a trend change, and the series edges could be segmented into three clusters with stable values. Cluster 2 (Trend change) has larger inner differences than clusters 1 and 3 (no change), which cannot be merged. Fig. 16 (d) is about noise disturbance, where series and noise edges are used for the segmentation. The noise edge helps to jump the noise nodes, and then the noise is isolated due to the sudden change between noise and other nodes on the series edge. Finally, the noise is removed by the merging procedure. Fig. 16 (e) is an abrupt change under noise and seasonal disturbances. Three types of edges are all used to segment the graph, and noise and seasonal interference can be recognized and merged.

The code of MTS-GS was written based on Python; the libraries used were, for example, Skimage and Sklearn. The algorithm has been encapsulated and shared on: https://github.com/liulianni1688/Remote-sensing-time-series-change-detection.

3.5. Determination of MTS-GS parameters

There are four parameters for MTS-GS: the length of noise edge NL, the length of period edge PL, the segmentation scale $K$ in Eq. (4) and the pre-defined inter-cluster measurement $M$. The noise edge is related to the number of continuous noise images, which can be set as one more than the maximum number. In our study site, NL is set to 2. The period edge is related to the number of images per year. The frequency of data in the study area is monthly; thus, PL is set to 12. $K$ is related to the changing patterns contained in the similarity matrix. Generally, when the trend change exists, $K$ should be equal to the larger stable values on the series edge to ensure the merging of the trend nodes. Similarity matrixes have different average values across the blocks; thus, $K$ is best set as a variable. $K$ is set as the 70% percentile of the values in increasing order for each similarity matrix. Furthermore, the inter-cluster measurement $M$ is set to 0.55.
Fig. 16. MTS-GS procedure for types of change. (a) abrupt change (b) seasonal change (c) trend change (d) noise disturbance (e) abrupt change under noise and seasonal disturbances.
3.6. Classification procedure

The classification procedure is performed based on the results of change detection. For each block, the breakpoints divide the entire time series into several groups. We used the CCDC strategy (Zhu and Woodcock, 2014): each group has multitemporal images with the same label, and the multitemporal images generate the time series of any spectral or spatial features. Next, the coefficients of the time series are extracted with the curve fitting method and used as the classifier’s input.

We used the aforementioned strategy to select spectral and texture features to generate the time series waiting to be fitted. Specifically, the average values of the 10 spectral bands and three spectral indexes, the normalized difference vegetation index, the normalized difference water index, and the normalized difference built-up index, are calculated as spectral features. The correlation and dissimilarity properties of the grey-level co-occurrence matrix (Hallbeyer, 2017) using the 10 m resolution bands (BLUE, GREEN, BLUE and NIR) are obtained by the Python package “Skimage” as texture features. The random forest is used for initial classification. Next, post refinement is conducted to show the change types accurately.

3.7. Accuracy assessment

In the experiment, 260 of 936 blocks are visually interpreted as samples, where there are 110 changed blocks and 150 unchanged blocks. The label for each image block is designated with the Label Labeler tool of MATLAB, combined with Google Earth HD images. Some blocks contain multiple classes, the label of which depends on the class with the largest area.

The proposed MTS-GS is an unsupervised algorithm, where all of the samples participate in the assessment of spatial and temporal dimensions. The spatial accuracy refers to the evaluation of CCDC (Zhu and Woodcock, 2014). The time series is labeled as a change in the spatial domain when one or more breakpoints exist. The estimation is correct when the detected label is consistent with the reference label.

The temporal accuracy of change detection is based on the changed blocks that are correctly identified in the spatial domain. Considering multiple changes are in the blocks, temporal accuracy assessment (Bullock et al., 2020) is used to evaluate whether the change timing is detected correctly. Fig. 17 shows the calculation method for the temporal accuracy. The evaluation process is based on the sequence number of the time series. For each time point to be evaluated, true positive (TP) means that the time steps between the estimated and reference changes are less than or equal to the pre-defined size of the response window. If there are two candidate time points for the reference change within the response window, the candidate with the minimum time step between the reference and the estimation is chosen. Each estimation point and reference point are matched only once. (Fig. 17). False positive (FP) means that the current time point is estimated change and no reference change is observed in the response window; false negative (FN) means that the current time point is reference change and no estimated change is observed in the response window. True negative (TN) refers to the time points except for TP, FP, and FN in the time series.

This paper sets the response window to ±2 time steps, meaning ±2 months under the monthly time series dataset. In the example of Fig. 17, there are 12 time points: 2 FN points, 1 FP point, 1 TP point, and 8 TN points.

The producer’s accuracy (PA), user’s accuracy (UA), and F1-score (F1) are used for the spatial and temporal assessments. To discriminate the types of accuracy, SPA_PA, SPA_UA, and SPA_F1 are for spatial assessment, and TEM_PA, TEM_UA, TEM_F1 are for temporal assessment.

As for classification, 50% of samples are used to train the model with 72.2% of overall accuracy in the initial classification before refinement. Because this paper focuses on change detection, only the accuracy of change detection is discussed.

4. Results

4.1. Accuracy of change detection

Table 3 provides the spatial accuracy of change detection, where 224 blocks are detected correctly; the SPA_F1 is 84.1%.

Table 4 provides the temporal accuracy of change detection, with the TEM_UA as 80.1%, TEM_PA as 81.8%, and TEM_F1 as 80.9% for the change timing.

4.2. Change frequency and change types

Fig. 18 illustrates the change frequency of each block in the study area, where approximately 11.9% of the blocks contain changes. 93.7% of the blocks changed once or twice from June 2017 to December 2020. A few blocks changed more than twice. The change blocks exist almost over the entire city, which reflects the significant development of this
city.

Fig. 19 illustrates the change types of Luoyang from two perspectives. Fig. 19 (a) depicts the urban land cover in June 2017, as well as the change types between June 2017 and December 2020. Urban expansion and renewal account for 62.4% of all change types, with urban expansion occurring beyond the core city and renewal occurring within the core city. Wasteland reconstruction (12.8%) usually begins on wasteland inside the core city. Greening loses (20.2%) more but recovers (4.6%) less, indicating a worse quality of the urban ecological environment. Notably, the abandoned site, which marks the transition from a construction site to a wasteland, is invisible in the image because it occurred in the intermediate period of the monitoring, which cannot be retrieved between two temporals.

The timings and types of the latest changes are shown in Fig. 19 (b). Most types of change are urban renewal and expansion. The number of blocks with urban expansion sharply decrease (less than 1%). The number of blocks from construction site to built-up area increase (37.8%), which is caused by the transfer between these two change types, reflecting the high construction efficiency in Luoyang. The spatial distribution of the date of the latest change indicates that most blocks in the inner city have not changed for a long time, and most areas around the city have been changed recently, reflecting the development from the inner to the outer city. Proportionally, there has been a significant increase in the number of changed blocks since 2019, reflecting the city’s rapid development.

4.3. Progress of urban construction

Fig. 20 depicts the construction status in the study area. As shown in Fig. 20 (a), 42.3% of the blocks have been completed, with the majority located in the north part of the city; 44.1% are under construction; and 13.5% are abandoned sites, the majority of which is outside the city center. The construction starts early in the inner city and later beyond the core city, demonstrating the pattern of development from the inner to the outer city.

Fig. 20 (b) illustrates the number of blocks that were under construction or were abandoned during a different time. The number of construction sites has gradually increased since 2019, and the number of abandoned sites has decreased correspondingly, demonstrating the study area’s rapid development and efficient improvement in land use since 2019. The construction and abandonment durations are shown in Fig. 20 (c). The average construction time is 13.6 months, and the average abandonment duration is 24 months. The wasteland that has not changed during the monitoring period was not counted in the abandonment.

5. Discussion

5.1. Connection of the MTS graph

Three types of edges are proposed in this paper. Because the series edge is required, the ablation experiment is only performed to confirm the efficacy of the noise and period edges (listed in Table 5). ONLY PERIOD EDGE means that the length of the period edge (PL) is 12 and...
that the length of noise edge (NL) is 1 (i.e., only series edges); ONLY NOISE EDGE requires PL to be 0 and NL to be 2; NO NOISE AND PERIOD EDGE sets PL as 0 and NL as 1.

With edge removal, spatial accuracy drops because the number of segmentations increases under noise and seasonal disturbances, resulting in an increased commission error and a decreased omission error. Additionally, TEM_UA decreases dramatically, indicating a large commission error of change timing. MTS-GS with both noise and time edges

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**Fig. 19.** Change types in the study area, (a) change types between June 2017 and December 2020. (b) Timings and types of the latest change.
performs the best; thus, the two edges are necessary. Notably, the commission and omission rates are higher under ONLY PERIOD EDGE than under the optimal solution. The number of segmentations increases without the noise edge, increasing the commission error. Meanwhile, if the segmentation with the same class was broken into several pieces, and when one of the pieces connects to the pieces with another class through the period edge, the incorrect period merging is performed. The greater the number of pieces, the more likely false period merging, resulting in the omission rate. Therefore, in addition to cloud disturbance, we generally set the noise edge to $\geq 2$ to avoid excessive segmentation, considering the system imaging noise.

5.2. Performance under various time intervals

Section 4 manually filtered monthly data. However, filtering the data in the manual for large-scale applications is difficult. Data compositing generates available data for different time intervals. We produced time series data for different time intervals with the weighted averaging
cloud-free surface reflectance values over a given period, including 30, 40, 60, and 90 days. Although Sentinel 2 is revisited every five days, our minimum compositing interval is 30 days, which refers to the ESA Sen2-agri system (Defourny et al., 2019) presentation that requires more than 30 days to compose relatively cloud-free data.

We evaluated the performance of the proposed method by referring to the study area and samples in Section 2. We fine-tuned the sample labels to fulfill the actual situations of the various composite intervals. Furthermore, some short-term changes are no longer exist in the long time-interval data, where the proposed technique retains high precision, with SPA_F1 and TEM_F1 remaining at approximately 80%.

The similarity matrixes of a block under various time intervals are depicted in Fig. 22. The primary structure of the similarity matrix is undisturbed by altering the time interval. MTS-GS achieves stable accuracy because the similarity matrixes of different time intervals reflect similar periodical, abrupt, and gradual changes.

5.3. Performance under various cloud coverage

We artificially added noise disturbances to the time series of each sample by adding 5% (2/43), 10% (4/43), 20% (8/43), and 30% (12/43) of the total number of time points, based on the cloudless data in Section 2, to assess the algorithm’s robustness against cloud disturbances. Accuracies of the algorithm under various interference conditions are shown in Fig. 23. The difference plots are displayed to highlight the degree of the declining accuracy.

In Fig. 23, as the cloud coverage grows more extensive, the algorithm’s accuracy gradually decreases. Within 20% of cloud coverage, spatial accuracy reaches more than 70%. From 30% of cloud coverage onward, accuracy starts to fail dramatically: between 20% and 30% of cloud coverage, and the reduction is approximately 7%; before that, the drop is no more than 4%. When cloud coverage is within 10%, the proposed approach achieves more than 70% of TEM F1 in temporal accuracy. The accuracy of the difference plot from 10% to 20% of cloud coverage reaches a considerable decline, up to 10%. When cloud coverage exceeds 20%, the algorithm cannot identify the change timing reliably.

This group of experiments confirms that the proposed method fulfills acceptable accuracy requirements under the condition of 10% or less cloud coverage. The detection accuracy decreases sharply when the cloud coverage is too high.

5.4. Pixel-level change detection of MTS-GS

To increase the applicability of the method, we extended MTS-GS to the pixel level. In this section, based on the sample blocks in Section 2, we select one pixel in each block as the pixel-sample, obtaining 110 changed pixels and 150 unchanged pixels. Because the selected pixel and the whole block may change asynchronously, we interpreted 260 samples again and evaluated the method’s accuracy on this basis. In addition, we compared it with CCDC, a classic method for pixel-level high-frequency change detection.

5.4.1. MTS-GS with different features

Most studies have proved that spatial information helps improve the accuracy of change detection, even if most of them are bi-temporal analyses. Our proposed method used multidimensional features, besides the 10 spectral bands of the pixels, and combined the neighbor spatial features.

Thus far, this paper has proved that the HOG feature has a good advantage in extracting the spatial structure of blocks. Therefore, the HOG descriptor of the pixel neighborhood was adopted as a spatial feature. The window of the center pixel requires an appropriate size, which is sufficiently large to extract the efficient HOG feature but also prevents the center pixel from being too far away. After testing different window sizes (7 × 7, 9 × 9, 11 × 11), the 11 × 11 window was selected for HOG feature extraction, and each center pixel comprised 24 dimensions of the HOG feature. Fig. 24 depicts similarity matrixes under various window sizes. For the similarity matrixes under the 7 × 7 and 9 × 9 windows, it is challenging to discover the changing pattern of the center pixel, whereas the 11 × 11 window is better than the aforementioned two windows to represent neighbor structure changes.

We performed two groups of experiments: those based on the pixel’s spectral bands, and those based on the fusion of the spectral bands and the HOG feature. The fusion feature in MTS-GS refers to stacking the 24 dimensions of the HOG feature and 10 spectral bands to create a new feature vector, which is a 34-dimensional time series. We implemented feature fusion in two ways for CCDC. The first way is the same as MTS-GS, with a 34-dimensional time series as the algorithm input; the second way is to average the 24 dimensions of the HOG feature to 1 dimension, resulting in an 11-dimensional time series. The HOG feature and spectral bands are normalized to ensure scale consistency.

Fig. 25 depicts the accuracies of the two approaches under various conditions. For spectral features, CCDC has a slightly greater F1 score than MTS-GS, with a 2% and 2.2% increase for SPA_F1 and TEM_F1, respectively. MTS-GS improved significantly with the addition of the HOG feature. The F1 score of SPA and TEM is 5.4% and 11.2% higher than without the HOG feature, correspondingly. The accuracy of CCDC is marginally lowered after adding the HOG feature. Although the HOG feature measures an image’s structural information, it is challenging for CCDC to fit the curve because the HOG feature in each temporal image is normalized separately, resulting in the low periodicity of the HOG time series. Fig. 26 illustrates the time series of two HOG components.
Although CCDC improves when only spectral features are available, the TEM_PA is usually relatively low, below 57.7%. The early time of the changes and the short interval between the two changes are the causes for the increased omission. The reason is that CCDC requires sufficient time points to fit the curve (usually those for at least one year), but inadequate fitting data is supplied in both situations. The proposed algorithm identifies the changes by comparing the similarity of adjacent time points without using a time series fitting step, which overcomes the aforementioned two issues with a lower omission rate than that of CCDC.

The advantages and disadvantages of the proposed method and CCDC are further analyzed with an example. A pixel changes from the crop to the construction site and then the built-up area. Fig. 27 (a) is a single-pixel spectral time series used by CCDC. Fig. 27 (b)-(d) are the similarity matrixes of different features used by MTS-GS. Sentinel-2 satellite images and Google HD images are also provided.

Fig. 27 (a), (c), and (d) reflect a remarkable change when the pixel changes from the crop to the construction site (change time is T30). Fig. 27 (a) illustrates the decrease in the amplitude of each spectral band; whereas Fig. 27 (c) and (d) indicate the abrupt increase in the first diagonal. As a result, CCDC and the MTS-GS with the HOG feature and the fusion feature can detect this change. However, there are no visible changes in the spectral similarity matrix, as shown in Fig. 27 (b). This phenomenon is observed because the construction began after the
harvest of the crop. The spectrum of bare soil and the construction site is comparable, resulting in the unchanged similarity matrix. Therefore, the MGS-TS with spectral features cannot identify the change. CCDC discovers this change by fitting historical time series and assessing current and historical data differences. The proposed method cannot deduce the historical condition, leading to the omission phenomena under the situation only with spectral bands. Fortunately, by introducing HOG features, MTS-GS identifies the changes by structural alternating.

When the pixel changes from the construction site to the built-up area (T37), the spectrum is not significantly different, as shown in Fig. 27 (b). The evidence is also shown in Fig. 27 (a), that there is no substantial change for spectral time series after T30. Hence, CCDC cannot infer such a change based on history (additionally, the length of this period is insufficient for fitting). The first diagonal in Fig. 27 (c) and (d) changes somewhat from T30 to T36 and increases dramatically at T37, indicating structural changes. Therefore, the MTS-GS based on the HOG feature and the fusion feature can capture the changing time.

Notably, after T37, the first diagonal of the original HOG feature in Fig. 27 (c) fluctuates dramatically due to the mismatch of window size and ground object complexity. This situation is prone to cause oversegmentation with the MTS-GS based on the original HOG feature at a pixel level. Avoiding commission and omission by only depending on the subsequent merging procedure is challenging. Due to the high similarity of the spectrum after T37, the fused feature in Fig. 27 (d) smoothes the original HOG feature, resulting in improved accuracy.

In conclusion, unlike CCDC, the proposed method has the benefit of not relying on historical data and detecting early and short-term changes. Furthermore, similar to the mechanism of humans judging whether pixels have changed, neighborhood spatial information is incorporated into pixel-level change detection, improving the accuracy by interpreting changes in surrounding neighborhoods.

5.4.2. Performance under different cloud coverage

To compare the cloud robustness of the proposed method and CCDC under the pixel level, we artificially randomly added noise to 43 time series of each pixel, 5%, 10%, 20%, and 30%, respectively, similar to the method in Section 5.3. We adopted the fusion feature for MGS-TS and the spectral features for CCDC. Table 6 lists the accuracies under different cloud covers.

In Table 6, SPA_F1 for the proposed method and CCDC maintains more than 70% under 20% cloud cover, and the proposed method can even maintain a detection rate of 70.6% under 30% cloud cover. CCDC still has a high omission rate but a low commission rate in temporal accuracy. The TEM_PA of CCDC has a minor decrease of 4.7% at 10% cloud cover and a significant decrease of 13.2% for 30% cloud cover. The TEM_PA and TEM_UA of the proposed approach have minor differences. The accuracy of TEM_F1 decreases uniformly, with a maximum decline rate of 4.6% if the cloud cover is less than 20%. A decrease rate of 8.7% if the cloud cover reaches 30%.

Both approaches are equally robust to the cloud cover under the

![Fig. 24. Similarity matrixes under window sizes.](image1)

![Fig. 25. Accuracies for CCDC and MTS-GS under different features.](image2)

![Fig. 26. Time series of two HOG components.](image3)
Fig. 27. An example of the changed pixel during urban expansion, (a) time series of three spectral bands, (b) similarity matrix based on original spectral bands, (c) similarity matrix based on the HOG feature, (d) similarity matrix based on the fused feature.

Table 6
Accuracies of CCDC and MTS-GS under cloud covers.

<table>
<thead>
<tr>
<th>CLOUD COVER</th>
<th>Algorithm</th>
<th>SPA_UA (CHANGE)</th>
<th>SPA_PA (CHANGE)</th>
<th>SPA_F1 (CHANGE)</th>
<th>TEM_UA (CHANGE)</th>
<th>TEM_PA (CHANGE)</th>
<th>TEM_F1 (CHANGE)</th>
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<tr>
<td>5%</td>
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<td>80.3%</td>
<td>85.5%</td>
<td>82.8%</td>
<td>75.3%</td>
<td>72.8%</td>
<td>74.1%</td>
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<td>CCDC</td>
<td>73.2%</td>
<td>84.5%</td>
<td>78.9%</td>
<td>77.4%</td>
<td>56.2%</td>
<td>65.1%</td>
</tr>
<tr>
<td>10%</td>
<td>MTS-GS</td>
<td>76.9%</td>
<td>84.5%</td>
<td>80.5%</td>
<td>71.5%</td>
<td>71.5%</td>
<td>71.5%</td>
</tr>
<tr>
<td></td>
<td>CCDC</td>
<td>73.8%</td>
<td>81.8%</td>
<td>77.6%</td>
<td>72.7%</td>
<td>50.7%</td>
<td>59.8%</td>
</tr>
<tr>
<td>20%</td>
<td>MTS-GS</td>
<td>68.8%</td>
<td>80.0%</td>
<td>73.9%</td>
<td>65.6%</td>
<td>68.1%</td>
<td>66.9%</td>
</tr>
<tr>
<td></td>
<td>CCDC</td>
<td>65.4%</td>
<td>79.1%</td>
<td>71.6%</td>
<td>72.6%</td>
<td>49.6%</td>
<td>59.0%</td>
</tr>
<tr>
<td>30%</td>
<td>MTS-GS</td>
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<td>75.5%</td>
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<td>49.1%</td>
<td>59.4%</td>
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<td>52.2%</td>
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</table>
condition that CCDC ignores the omission rate. In general, the F1 score of the proposed method is higher than that of CCDC under the same conditions, indicating better cloud robustness. The acceptable accuracy of the proposed method is achieved within 10% of cloud cover.

5.5. Implications for multivariate time series analysis

This research has provided two implications of multivariate time series analysis:

First, this paper converts the multivariate time series into a similarity matrix to analyze the changing pattern of three major types of change, which provides a new way to interpret the high-dimensional time series. Besides HOG feature in our study, other attributes, such as texture, spectrum, temperature, can be considered to jointly interpret the time-series images.

Second, a multivariate time series graph is created in this work which provides a new idea for combining time series analysis with graph theory. Based on the graph, the spatial, spectral, and temporal information can be fused for effective analysis.

5.6. Uncertainties and limitations

The following uncertainties and limitations are notable. First, the proposed MTS-GS requires the same number of images per year according to the requirement of the period edge, and retaining the date with similar distribution in each year is helpful to improve the accuracy. Manual filtering or automatic compositing can be adopted to collect the required data. Second, the accuracy of the proposed MTS-GS depends on the effect of feature extraction and the spatial scale of the block. Inappropriate feature extraction and spatial scale may lead to errors in the segmentation procedure and uncertainties. Although noise edges are set to suppress noise, excessive segmentation of the multivariate time series graph would still occur in areas with a large amount of cloud cover, affecting the performance of change detection, which is also the problem encountered by CCDC and other methods.

6. Conclusion

This research aims to achieve high-frequency urban change detection at the block level, providing finer change information for urban planning than is available in the literature. The MTS-GS was proposed and provided a new way to manage the multivariate time series. Most notably, we analyzed the changing patterns of multivariate time series for seasonal change, trend change, abrupt change, and noise disturbance based on similarity matrixed. Next, the graph of multivariate time series was constructed to match the changing patterns. The corresponding graph segmentation algorithm is proposed to detect abrupt and trend changes under noise and seasonal disturbances. We tested the approach in a rapidly developing third-tier city: Luoyang, Henan province, China. The F1-score of spatial accuracy was 84.1%, and the PA and UA of temporal accuracy were 81.8% and 80.1%, respectively. The proposed algorithm extracted the change types and construction status, showing the development pattern and land use efficiency in the city.

Furthermore, MTS-GS performs well under various time intervals and cloud covers. Meanwhile, the proposed algorithm can be used for pixel-level change detection and outperforms the classic CCDC. In further research, more attributes of ground objects, such as texture, spectrum, temperature, should be considered to fuse in the multivariate time series analysis.

Authorship contribution statement

Nan Wang: Conceptualization, Methodology, Software, Writing – original draft, Writing - review & editing. Wei Li: Methodology, Software, Writing - review & editing. Ran Tao: Writing - review & editing. Qian Du: Writing - review & editing.

Declaration of Competing Interest

The authors declared that they have no conflicts of interest to this work. We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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