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RESEARCH ARTICLE

Detection of short-term urban land use changes by combining SAR time series images and spectral angle mapping

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Abstract Rapid urban sprawl and re-construction of old towns have been leading to great changes of land use in cities of China. To witness short-term urban land use changes, rapid or real time remote sensing images and effective detection methods are required. With the availability of short repeat cycle, relatively high spatial resolution, and weather-independent Synthetic Aperture Radar (SAR) remotely sensed data, detection of short-term urban land use changes becomes possible. This paper adopts newly released Sentinel-1 SAR data for urban change detection in Tianhe District of Guangzhou City in Southern China, where dramatic urban redevelopment practices have been taking place in past years. An integrative method that combines the SAR time series data and a spectral angle mapping (SAM) was developed and applied to detect the short-term land use changes. Linear trend transformations of the SAR time series data were first conducted to reveal patterns of substantial changes. Spectral mixture analysis was then conducted to extract temporal endmembers to reflect the land development patterns based on the SAR backscattering intensities over time. Moreover, SAM was applied to extract the information of significant increase and decrease patterns. The results of validation and method comparison showed a significant capability of both the proposed method and the SAR time series images for detecting the short-term urban land use changes. The method received an overall accuracy of 78%, being more accurate than that using a bi-temporal image change detection method. The results revealed land use conversions due to the removal of old buildings and their replacement by new construction. This implies that SAR time series data reflects the spatiotemporal evolution of urban constructed areas within a short time period and this study provided the potential for detecting changes that requires continuously short-term capability, and could be potential in other landscapes.

Keywords Sentinel-1 SAR, time series images, urban land use change detection, temporal endmember, spectral angle mapping

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1 Introduction

During the past several decades, increasing population and social-economic developments have been leading to dramatic urban sprawl and land use changes in cities of the world (Wang and Weng, 2013). The urban changes have also been taking place in downtowns of cities due to replacement of old buildings by new construction. Monitoring those processes has become a new application for urban remote sensing. Timely and accurate detection of short term (from weekly to monthly) urban land use changes is critical for effective decision-making of city planning and management (Gamba and Dell'Acqua, 2016). Remote sensing data such as Landsat Thematic Mapper (TM) time series images provide rich information for detecting urban sprawl based on continuous and repetitive observations (Wang and Weng, 2013; Gamba and Dell'Acqua, 2016). Substantial research has been conducted in this field (Fugate et al., 2010; Patino and Duque, 2013; Hecheltjen et al., 2014). However, in tropical/subtropical regions such as the Pearl River Delta in South China, frequently cloudy and rainy weather often impedes the acquisition of good quality optical satellite images (Qi et al., 2015). Thus, it becomes almost impossible to use satellite optical images to detect short-term urban land use changes in the Pearl River Delta of South China.

An alternative of remotely sensed data is the use of Synthetic Aperture Radar (SAR) images that capture information of the earth surface using microwave wavelengths. One important advantage of using SAR images over optical data is that SAR can penetrate clouds and light rain, making it possible to collect data during bad weather (Qi et al., 2015; Ban and Yousif, 2016). Moreover, SAR has the ability to discriminate between different objects by features of texture and roughness based on the backscattering intensity of radar signal (Quartulli and Datch, 2004; Esch et al., 2010). Another important consideration for using SAR rather than optical data is that the detection of changed targets in an urban setting should ignore seasonal variations such as vegetation phenology (Kleynhans et al., 2015; Aiazzi et al., 2018). Recently, satellite radar imagery has received an increasing interest for urban remote sensing mapping such as monitoring impervious areas and detecting urban land use changes (Hecheltjen et al., 2014; Ban and Yousif, 2016; Gamba and Dell'Acqua, 2016; Zhang et al., 2016, 2018a).

Different applications call for different approaches, and different types of remotely sensed data require sensor-specific considerations (Ban and Yousif, 2016). SAR data have been widely used for environmental monitoring due to their independence from solar illumination and ability to penetrate clouds. However, SAR data have not been equally utilized for change detection of urban land use types because of limited data, high cost, and limited processing capability due to speckle noise and complex imaging principles (Hecheltjen et al., 2014; Aiazzi et al., 2018). Typical applications of SAR include detecting ground deformation due to earthquakes, glacial movement and subsidence using differential interferometry (DInSAR) (Yun et al., 2015; Watanabe et al., 2016). A land use change detection map derived from a pair of polarimeric SAR images separated by a long time interval (months to years) can be used to retrieve the extent of urban areas (Frate et al., 2008; Esch et al., 2010; Ban and Yousif, 2012). However, most urban land use change detection usually spans a long-time period and focuses on the use of bi-temporal images rather than multi-temporal analysis.

The phase stability of anthropogenic structures among SAR images has led scholars to propose time-scale phase correlation, or coherence, as an appropriate method for mapping urban land use changes. Various change detection methods and algorithms have been developed and tested over the past decades (Hecheltjen et al., 2014; Ban and Yousif, 2016; Aiazzi et al., 2018). Atto et al. (2013) used a multi-date divergence for change analysis of TerraSAR-X to characterize the expansion of urban areas. Frate et al. (2008) adopted a pixel-by-pixel short-term change detection scheme based on a pair of interferometric images. Qi et al. (2015) used monthly short-term Radarsat SAR data for monitoring land developments based on backscatter variation in a time domain. Kleynhans et al. (2015) developed a temporal autocorrelation change detection method for hyper-temporal SAR data just as used in MODIS time series data. Conradsen et al. (2016) proposed a time series of Sentinel-1 SAR to pinpoint land use conversions in a short time period. Most of the change detection methods are conducted for extracting the information of a specific change such as urban sprawl during a long time period. To date, however, only a few studies are found to be related to the detection of short-term land use changes and the discrimination of temporal patterns in urban areas based on SAR time series data.

In recent years, more and more orbital radar systems are available for preprogramed collection of high resolution earth observations (Milillo et al., 2016). The orbital systems include Radarsat (Canada), ALOS-PALSAR (Japan), COSMO-SkyMed (Italy), Terra-X (Germany) and Gaofen-3 (China). Although there is a lack of spectral details, SAR images perform well in capturing back-scattered amplitude and textural information (Ban et al., 2015). Moreover, SAR data are particularly suitable for rapid and real-time detection of land use changes in urban settings if the data can be regularly acquired on a predefined satellite orbit (Grey et al., 2003; Muro et al., 2016). With the launch of a global-coverage SAR satellite, Sentinel-1, timely data delivery has become routinely available (Ban et al., 2015). Sentinel-1 SAR data provide excellent opportunities for operational urban monitoring. Moreover, thanks to the new policies for the data availability, the archive of SAR data can expand application research from simple individual image mapping to time series data analysis.

The objectives of this study were the detection of short-term urban land use changes based on Sentinel-1 SAR data by improving the pre-processing of time series images and combining spectral angle mapping, which led to a novel and integrative SAR time series-based classification scheme for the detection of short-term urban land use changes.

2 Study area and data

2.1 Study area

The study area is located in Tianhe District of Guangzhou City in Southern China (Fig. 1(a)). Tianhe District is the geographical center of Guangzhou City in which commercial, industrial, cultural, and educational activities take place. The economic development is characterized by highly developed tertiary industry and rapidly developed high technologies (Zhou, 2014). In the southwestern Tianhe District, Zhujiang New Town has become a central business district and financial center of Guangzhou City,

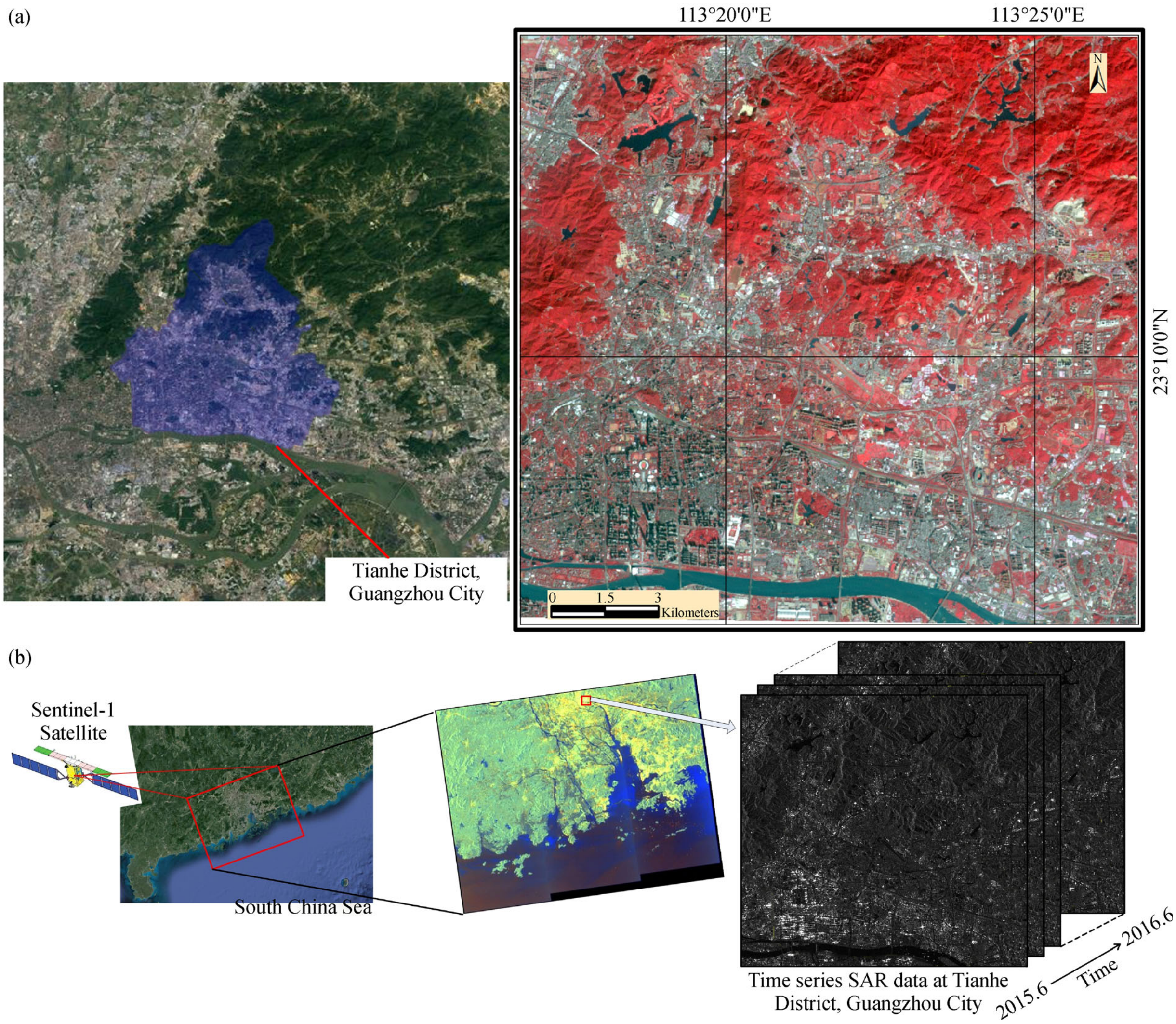

Fig. 1 (a) The study area—Tianhe District shown with an ASTER image and its location in Guangzhou City; and (b) time series of Sentinel-1 SAR data for the study area.

and a modern commercial trade center of Southern China (Fig. 1(a)).

Tianhe District has witnessed an astonishing rate of land use conversion during its urbanization within the past two decades. With an increasing population and shortage of land resources, urban land use management and re-planning is urgently needed (Fig. 2). Therefore, urban re-planning and redevelopment has become a major policy agenda in this region. Rapid urban land use changes owing to the booming land development activities has made the Tianhe District become an ideal study area to perform a short-term land use change detection.

2.2 Sentinel-1 SAR data

Sentinel-1 as an imaging radar mission is undertaken by European Space Agency (ESA) and the development of a European Radar Observatory, a polar orbiting two-satellite constellation for the continuation and improvement of SAR operational services and applications (https://sentinel.esa.int/web/sentinel). Sentinel-1A and 1B satellites were launched in 2014 and 2016, respectively, enhancing the earth observation capability by doubling the revisiting cycle (Torres et al., 2012). The data open-access is provided by ESA (https://scihub.copernicus.eu/dhus/#/home). Sentinel-1A and 1B satellites were built in the same orbital plane to provide continuous, six-day-repeat, day-and-night, all-weather and medium resolution observation capability. The Sentinel-1 constellation provides high reliability and improves the re-visit cycle, geographical coverage and rapid data dissemination to support operational applications in the priority areas of marine monitoring, land monitoring, and emergency service (Europe-Space-Agency, 2013).

Sentinel-1 C-band SAR instrument operates in four acquisition modes: Strip map (SM), Interferometric Wide

Fig. 2 The examples of old villages, buildings and factories within the study area (courtesy of Guangzhou Urban Renewal Bureau).

swath (IW), Extra-Wide swath (EW), and Wave (WV) (Europe-Space-Agency, 2013). The Level-1 Ground Range Detected (GRD) data of IW as the main operational mode with vertical-vertical + vertical-horizontal (VV + VH) polarization imaging were employed in this study. This mode meets most currently known service requirements, avoids conflicts, and preserves re-visit performance. Additionally, the Level-1 GRD products have been projected on the WGS-84 datum with local geographical coordinates, have a 10 m spatial resolution and high quality SAR images (Fig. 1(b)). Due to its high-repeat cycle and high quality imaging, several scholars have investigated the potential of Sentinel-1A polarimetric SAR data (Nagler et al., 2015; Conradsen et al., 2016; Muro et al., 2016, Perrou et al., 2018). Irrespective of sun illumination and cloud cover, Sentinel-1 SAR data are very suitable for rapid and real-time monitoring of land use changes in urban settings and have the potential for capturing the impacts of human activities on land use changes. In this study, a total of 22 Sentinel-1A SAR images were acquired during the period of Jun 2015 to May 2016 (Table 1). The VH polarization imaging mode of these products was employed to form a time series dataset (Fig. 1(b)).

3 Data preprocessing

Typically, the image preprocessing procedure for multi-temporal SAR data includes radiometric calibration, geometric co-registration, image enhancement, forming a time series image dataset, and time domain smoothing (Fig. 3). The image preprocessing procedure was conducted using ESA-SNAP (Sentinels Application Platform) software (https://sentinel.esa.int/web/sentinel/toolboxes/sentinel-1).

The radiometric calibration of the SAR images was carried out so that the pixel values truly represented the radar backscattering strength of the reflectance surface. We used a conversion toolkit in ESA-SNAP to convert the original digital number (*DN*) values into physical units. The backscatter coefficient (Sigma Nought, σ) is the conventional measure of the strength of radar signals reflected by a distributed scatter, usually expressed in *dB*. The backscatter values represent the radar signal amplitude of ground features. The ESA-SNAP software converted the *DN* values to the backscatter coefficient values by reading the incident angle Look Up Table (LUT) using the following equation:

$$\sigma^0 = \frac{DN^2}{A_\sigma^2}, \tag{1}$$

where A_σ is the transformation coefficient for the radar image pixels that are the areas falling between points in the LUT, and σ^0 is the backscatter coefficient, usually Sigma Nought.

The geometric co-registration of the time-series images is an essential step for accurate detection of changes. This

Table 1 Image product checklist in the time series dataset

No.	Image product	Acquisition date
1	S1A_IW_GRDH_1SDV_20150615T103312_20150615T103341_006383_0086AA_07EC.SAFE	20150615
2	S1A_IW_GRDH_1SDV_20150627T103313_20150627T103342_006558_008B9C_100F.SAFE	20150627
3	S1A_IW_GRDH_1SDV_20150709T103312_20150709T103341_006733_009049_CF8D.SAFE	20150709
4	S1A_IW_GRDH_1SDV_20150721T103313_20150721T103342_006908_009560_6200.SAFE	20150721
5	S1A_IW_GRDH_1SDV_20150802T103314_20150802T103343_007083_009A41_715F.SAFE	20150802
6	S1A_IW_GRDH_1SDV_20150814T103315_20150814T103344_007258_009F0C_B933.SAFE	20150814
7	S1A_IW_GRDH_1SDV_20150907T103316_20150907T103351_007608_00A898_4C6E.SAFE	20150907
8	S1A_IW_GRDH_1SDV_20150919T103316_20150919T103345_007783_00AD3B_5EEA.SAFE	20150919
9	S1A_IW_GRDH_1SDV_20151001T103316_20151001T103351_007958_00B1F9_7B09.SAFE	20151001
10	S1A_IW_GRDH_1SDV_20151013T103316_20151013T103345_008133_00B69F_093F.SAFE	20151013
11	S1A_IW_GRDH_1SDV_20151212T103310_20151212T103339_009008_00CEA9_F2C9.SAFE	20151212
12	S1A_IW_GRDH_1SDV_20151224T103309_20151224T103338_009183_00D39A_BF49.SAFE	20151224
13	S1A_IW_GRDH_1SDV_20160105T103309_20160105T103344_009358_00D892_2822.SAFE	20160105
14	S1A_IW_GRDH_1SDV_20160117T103308_20160117T103337_009533_00DD94_83AB.SAFE	20160117
15	S1A_IW_GRDH_1SDV_20160129T103308_20160129T103343_009708_00E2BE_6878.SAFE	20160129
16	S1A_IW_GRDH_1SDV_20160210T103308_20160210T103337_009883_00E7C2_99AA.SAFE	20160210
17	S1A_IW_GRDH_1SDV_20160305T103308_20160305T103337_010233_00F1DB_C69B.SAFE	20160305
18	S1A_IW_GRDH_1SDV_20160329T103308_20160329T103338_010583_00FBDA_D2EC.SAFE	20160329
19	S1A_IW_GRDH_1SDV_20160422T103309_20160422T103338_010933_010659_9465.SAFE	20160422
20	S1A_IW_GRDH_1SDV_20160504T103310_20160504T103339_011108_010BD3_47E3.SAFE	20160504
21	S1A_IW_GRDH_1SDV_20160516T103313_20160516T103342_011283_011177_7199.SAFE	20160516
22	S1A_IW_GRDH_1SDV_20160528T103314_20160528T103343_011458_011737_2431.SAFE	20160528

step was conducted using the spatial co-registration function of ESA-SNAP software and then the same pixels throughout the image stack were collocated with each other. Moreover, speckle noise inherently exists in SAR images. The speckle noise stochastically fluctuates associated with the radar reflectivity (brightness) of the image pixels, affects the texture of the intensity images, and has to be minimized. In this study, a filtering technique called Enhanced Lee filter was applied to smooth the images and to preserve major texture edges. The Enhanced Lee filter is an evolution of the Lee filter and similarly uses local statistics (coefficient of variation) within individual filter windows. A moving window filter represents a combination of a "selective" mean value with the values of the surrounding pixels (Lopes et al., 1990).

High frequency noise may also exist in time domain of the SAR time series data. Noise reduction related to time series curve filtering should be done to retrieve the essential shapes of the curves. In this study, Savitzky-Golay (S-G) smoothing filter, also known as leastsquares or digital smoothing polynomial, was used to smooth noisy signals (Savitzky and Golay, 1964). Smoothing process and effect are assessed by the goodness of trajectory fitting. Basically, a wide smoothing window and low power fitting function should be used. As a result, the time domain SAR image series were averaged.

4 Change detection

Change detection can be achieved by generating a map that increases the contrast of changed and unchanged areas (Ban and Yousif, 2016; Aiazzi et al., 2018). In urban setting, there are two basic patterns of change detection: increase and decrease. They reveal the processes of urban redevelopments as new constructions and removing of old buildings that are represented by backscatter turbulation in the SAR images.

Substantial research has been conducted for detecting land use and land cover changes (LULCC) using SAR images. However, most of the existing studies account for the dramatic changes of land use and land cover (LULC) during a long-term period with bi-temporal images. There have been only a few reports that deal with situations of changes within a short-term period based on the backscatter turbulation of SAR images (Gong et al., 2016; Markus et al., 2017; Aiazzi et al., 2018). Also, it is not easy to select proper training sites for extracting the signatures of LULCC types. It is especially true in complex urban environmental setting (Gamba and Dell'Acqua, 2016). Moreover, when the change detection is conducted based on rules such as threshold values, it is challenging to determine the rules and parameter values for discriminating the change types. Overall, bi-temporal SAR image

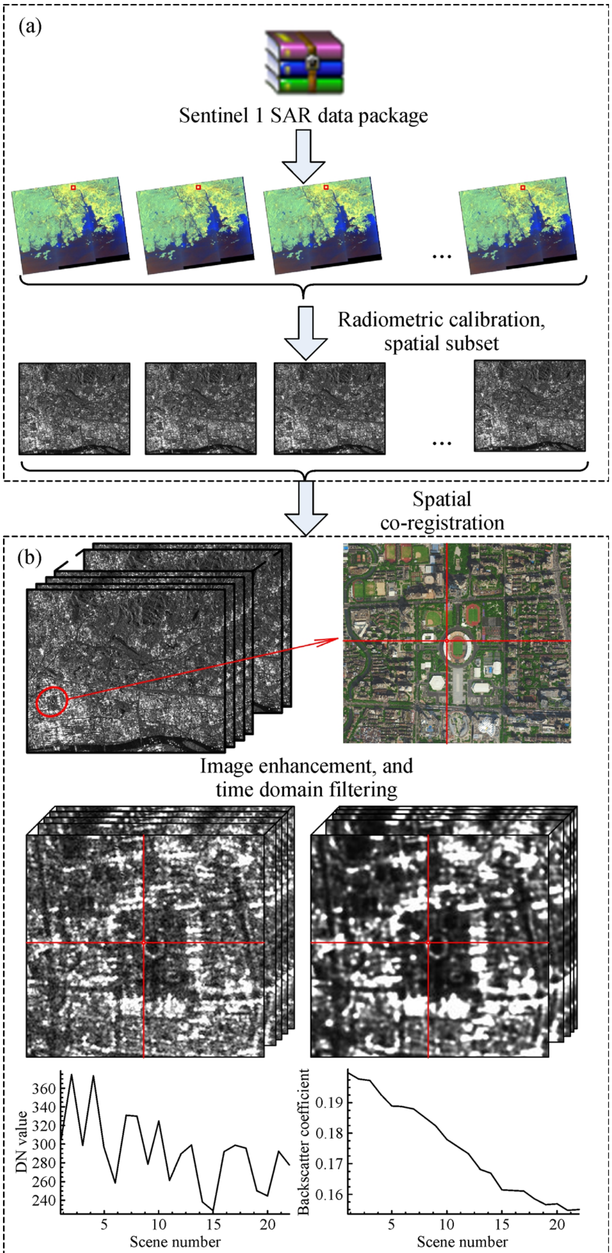

Fig. 3 The flowchart of image preprocessing. (a) Radiometric calibration; and (b) spatial co-registration, image enhancement and time domain filting.

analysis is inherently affected by backscatter turbulation. Correspondingly, time series based analysis of change detection can provide the potential to overcome the limitations of using bi-temporal images (Hecheltjen et al., 2014).

Time series based change detection is to use images acquired from more than two times and offers the capacity to detect various LULCC such as seasonal variation and abrupt changes (Small, 2012; Hecheltjen et al., 2014). In this study, an integrative methodology that combines SAR time series data and a spectral angle mapping (SAM) was proposed and applied to detect the short-term urban land use changes of Tianhe District of Guangzhou City. The idea behind this method is that the SAR backscattering intensity could depict the roughness and spatial variability of the ground surface and the SAR time series images could thus reveal the changes of urban land uses within a short time period due to removal of old buildings and emergence of new buildings. Moreover, a linear transformation of the SAR time series images revealed the trends of the changes in every pixel series. Therefore, a vector angle could be utilized to spatially identify the differences of the change trends. Given the reason, the SAR time series data have characteristics similar to those of hyperspectral; thus spectral image analysis methods could be borrowed for analyzing the SAR time series images (Small, 2012; Hecheltjen et al., 2014; Gamba and Dell'Acqua, 2016). The proposed methodology consisted of following steps: linear trend tranformation of SAR time series data, extraction of temporal endmembers (changing samples), and spectral angle mapping (Fig. 4).

4.1 Linear trend transformation

SAR data capture the backscattering strength of ground features. In urban areas, backscatter turbulation in time series of SAR data may cause difficulties in identifying change patterns of LULC since the same urban LULC types can produce different backscattering intensities depending upon the azimuth angles of radar antenna and/or real-time weather condition (Esch et al., 2010; Atto et al., 2013). To solve this problem, we suggest that a linear trend transformation of the backscattering intensities may provide an intuitive inspection on time domain changes of SAR data by fitting irregular time series into a linear pattern. This method uses a continuous linear trend to represent the backscatter variation instead of using a complex mathematical equation.

Suppose that pixel-based time series profiles can be characterized by linear trends. That is, if each individual pixel-based time series profile is fitted using a linear trend function, the time series profile that fluctuates would be transformed into a linear trend that reveals the change pattern. The classification of LULCC can be then conducted based on the linear trends. When the changes are linear, a simple linear function can be selected, for example, $y = ax + b$, where x is the date in time domain; y is the backscatter intensity that represents the transformed results; a and b are the coefficients. Figure 4(a) demonstrates the examples of linear trend transformations using Sentinel-1A SAR data for four LULCC types including a water body, an under-construction area, a complete construction area, and excavation area. Thus, the LULCC types are easily identified.

4.2 Temporal endmember extraction

To define training samples for change detection, the

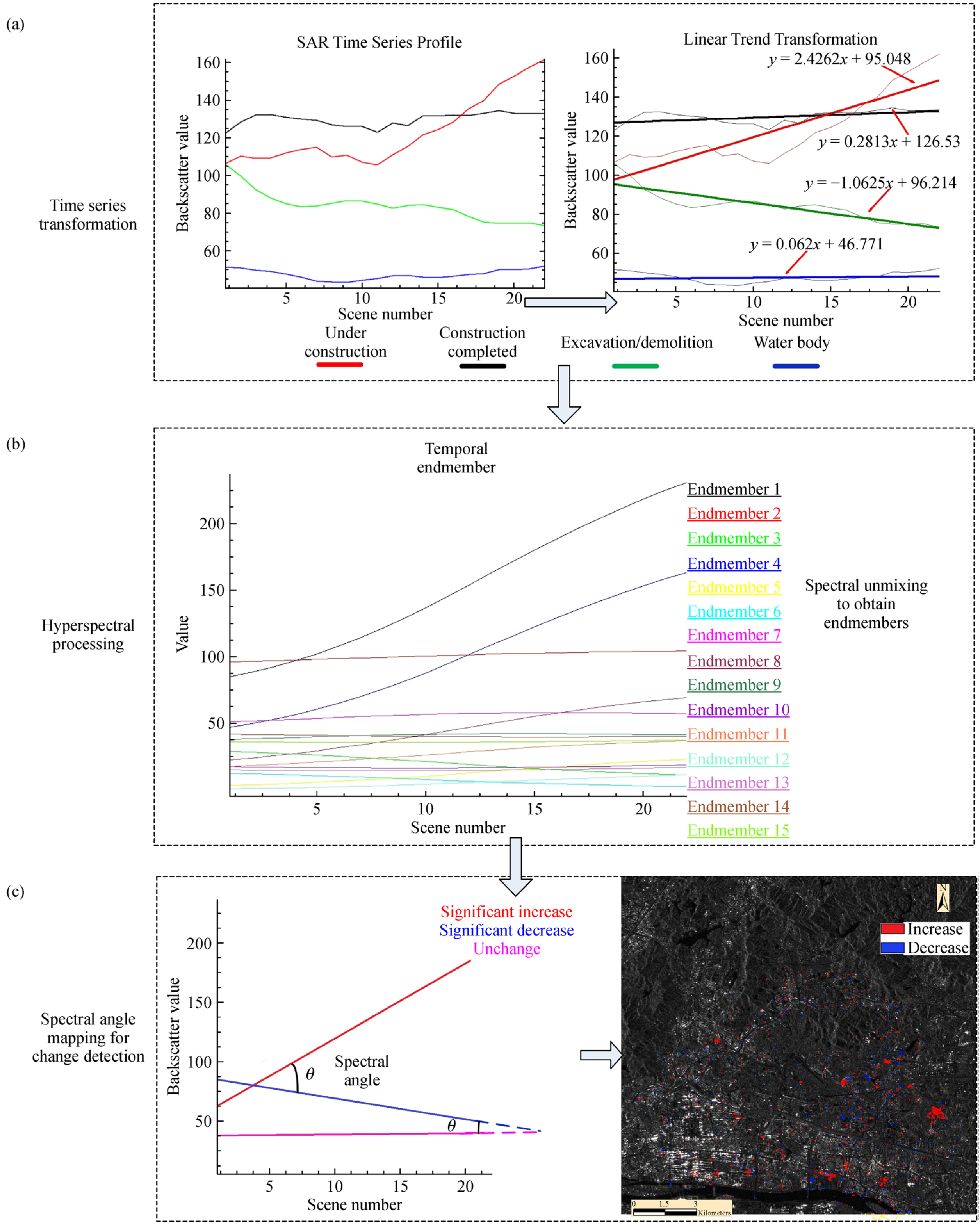

Fig. 4 Methodological framework of time series-based change detection. (a) Linear transformation of SAR time series data; (b) spectral unmixing analysis to obtain temporal endmember; and (c) spectral angle mapping for change detection.

representative pixels that reveal change patterns should be selected. Remote sensing time series data have the characteristics of a spectral-like data set that can be processed with spectral-based methods such as spectral mixture analysis. Endmember extraction is a process of selecting a collection of signature spectra of pure materials present in an image (Plaza et al., 2011; Pan et al., 2013). In this sense, endmembers were considered to be the typical image pixels that contain one unique material or a pure LULCC type. We performed a Sequential Maximum Angle Convex Cone (SMACC) analysis which has been widely used in hyperspectral image analysis for spectral unmixing and endmember extraction (Gruninger et al., 2004). The SMACC is a spectral analysis tool of ENVI software for endmember extraction and can be applied to extract the temporal endmembers of the hypertemporal SAR time series data set. The temporal endmembers of LULCC types were automatically generated and their corresponding time series profiles were considered as ideal training samples for change detection mapping. Figure 4(b) presents the examples of 15 endmembers of LULCC types. The temporal endmembers were characterized by both temporal and intensity features of SAR backscatter.

4.3 Spectral angle mapping with SAR time series data

The time series data represent the spatiotemporal variability of the ground features in terms of continuum temporal patterns (Small, 2012). In this study, SAR time series data were used to classify change patterns based on temporal backscatter. As presented in Fig. 4(c), the selected temporal endmembers were the representatives of temporal backscatter intensities for three change patterns: unchanged, significant increase, and significant decrease. In a hyperspectral point of view, the differences among these can be quantified with spectral angles. SAM is a spectra-based classification method to match unknown pixels with reference pixels (Kruse et al., 1993). The algorithm determines the similarity of the SAR time-series change trend of an unknown pixel with each of the temporal endmembers by calculating a vector angle between two series vectors with a number of dimensionality equal to the number of bands. Thus, each pixel vector in the SAR time series data was compared with that of each temporal endmember. The vector angle was calculated using Eq. (2),

$$\theta = \arccos\left(\frac{\sum_{i=1}^{n}\mathrm{Endmember}_i \times \mathrm{SAR}_i}{\sqrt{\sum_{i=1}^{n}\mathrm{Endmember}_i^2} \times \sqrt{\sum_{i=1}^{n}\mathrm{SAR}_i^2}}\right), \quad (2)$$

where θ is the vector angle between a unknown pixel and the temporal endmember in terms of SAR time series data and measured in radians; n is the corresponding time series images. The smaller the vector angle value, the closer the unknown pixel vector to the temporal endmember. In order to classify the change patterns of LULC types, a set of threshold values of the vector angle was determined based on the vector angles among the temporal endmembers, which provided quantitative measures of the differences among the temporal endmembers.

4.4 Comparison with an ENVI change detection method

To demonstrate the superiority of the time series based methodology proposed in this study, a comparative study using an ENVI change detection method was performed. The ENVI change detection tool provides a simple tool to capture the changes by comparing two images acquired at different dates and highlighting the changed features. Theoretically, this is an image differencing-based method with a user-defined threshold value for increase and decrease change. In this study, the bi-temporal images that were acquired on June 15 of 2015 and May 16 of 2016 were employed for the ENVI change detection of LULC types.

5 Results

5.1 Time series-based spectral angle mapping

According to the trend patterns in Fig. 4(c) and the time series profiles of the SAR backscattering intensities, the LULCC samples were categorized as unchanged, significant increase, and significant decrease, and an urban LULCC detection map was then generated (Fig. 5). Those areas highlighted in red and blue respectively indicated significant increase and decrease over the time. The unchanged ground surfaces such as water bodies and built-up areas showed constant backscattering intensities throughout the period and dominated the study area. Because the study area was located in a southern subtropical region, most of the vegetated areas were evergreen and in which phenological effects did not appear obvious.

In Fig. 5, the red spots indicated an increasing trend of radar backscattering intensity because the surfaces became rougher due to new construction or building development. The blue spots indicated a decreasing trend of radar backscattering intensity. This was because the ground surfaces were smoothed due to old buildings disappearing, ground leveling, and removal of vegetated areas. As mentioned in the background of this study area, Tianhe District of Guangzhou City has been going through redevelopment of some urban areas in recent years, leading to the rapid changes of LULC types.

In this study, six specific sites were selected to interpret the results of the LULCC detection based on Google Earth

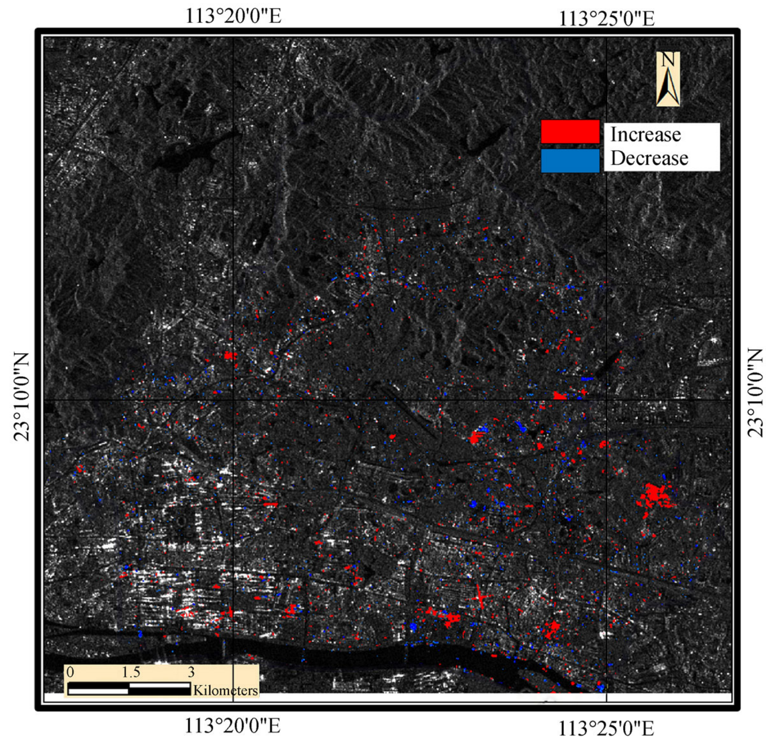

Fig. 5 Change detection results by combining the time series of SAR data (2015–2016) and spectral angle mapping.

historical images (left of Fig. 6). Figs. 6(a)–6(f) showed the detailed LULC changes validated by the Google Earth historical images during the detection period. For each site, there were 3 to 4 scenes of the Google Earth images available to validate the results of the LULCC detection. Site 1 showed that some new buildings were developed from April 2015 to September 2016 and validated in the Google Earth images (Fig. 6(a)). Site 2 indicated that several old buildings were removed and new buildings appeared (Fig. 6(b)). Site 3 showed that some new construction took place and some old buildings disappeared during the time period (Fig. 6(c)). In site 4, there was a large construction area happening and vegetation removed (Fig. 6(d)). In site 5, some newly built constructions were detected (Fig. 6(e)). In site 6, several new buildings were constructed from April to December of 2015 and validated in the Google Earth images (Fig. 6(f)).

The successful detection of LULCC could be attributed to the significant changes of the SAR time series images. The validation results showed that the land development typically consisted of two phases: 1) Old residential areas and factories were leveled down to barren lands. These activities would also be accompanied with vegetation removal. This resulted in significantly weaker radar backscattering intensities, that is, a decreasing trend over time; and 2) the reconstruction took place and new buildings began to be piled up, the ground surface became rougher over time, leading to stronger radar backscattering intensities and thus a significant increasing trend.

5.2 Method comparison

The results in Fig. 7 indicate that the time series-based SAM change detection provided similar spatial distributions with those from ENVI change detection method, but the latter led to the errors of change detection in many places (Figs. 7(a) and 7(b)), including the areas detected as change, but in fact had no changes taking place, that is "Incorrect detection"; and the areas detected as unchanged, but actually had changes occurring, that is "Change undetected". Moreover, there were a total of 6 sites selected to compare the results from these two methods based on the Google Earth historical images (Right of Fig. 7). The Google Earth image showed that a large amount of changes took place in the Site 1 from December of 2015 to September of 2016 and the time series-based SAM change detection picked up most of the changes, while the ENVI change detection method missed most of them. The similar results could be found in other five sites.

5.3 Overall accuracy assessment

On the 10 m resolution Sentinel-1 SAR time series images, it was not easy to visually identify the individual LULC changes throughout the whole study area. In this study, a total of 100 sites were randomly selected for conducting an overall accuracy assessment (Fig. 8). The red and blue patches indicate that significant increases and decreases took place. The 100 sites were carefully inspected on the

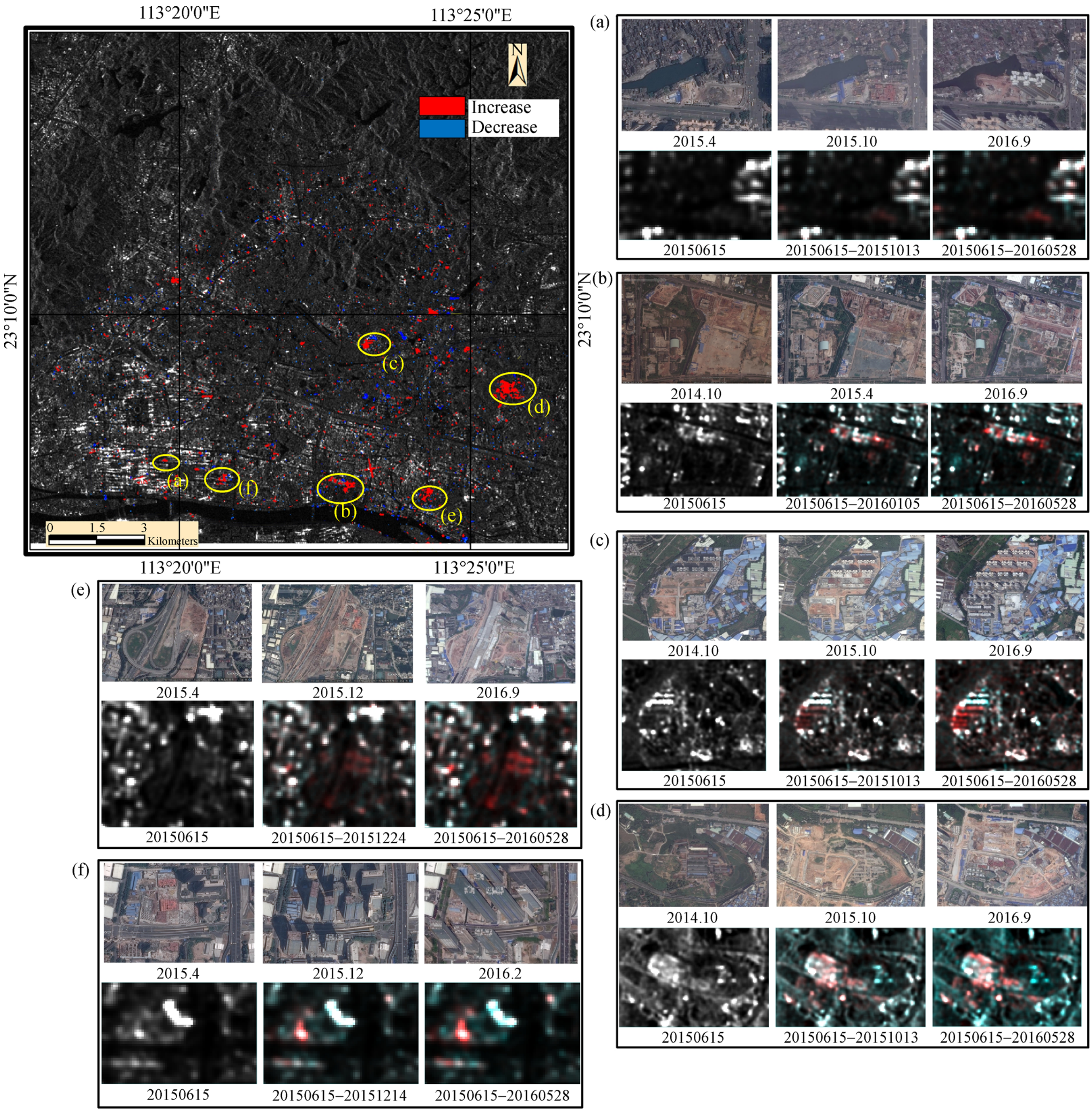

Fig. 6 The locations of the selected six sites on the land use and land cover change (LULC) detection image (upper left) with the details of the changes for the selected (a) site 1; (b) site 2; (c) site 3 and (d) site 4 (right); and (e) site 5 and (f) site 6 (lower left) validated by the Google Earth images.

Google Earth historical images. In Fig. 8, 65 sites were marked with "√" representing correct detection and "×" representing incorrect detection. The other 35 sites were marked as "⊙" meaning unchanged. For the 65 changed sites, there were 49 sites correctly detected and 16 incorrectly classified. For the 35 unchanged sites, a total of 29 sites were correct. A confusion matrix was developed (Table 2) and an overall accuracy of 78% was achieved with a Kappa coefficient of 0.67.

6 Discussion

Thanks to the recently launched Sentinel-1 SAR satellite and open data access policy, the applications of high spatiotemporal resolution SAR images become more promising. With a sufficient amount of data available, it is possible and necessary to develop methods that can be used to perform a short-term urban LULCC detection using Sentinel-1 SAR time series data. This study

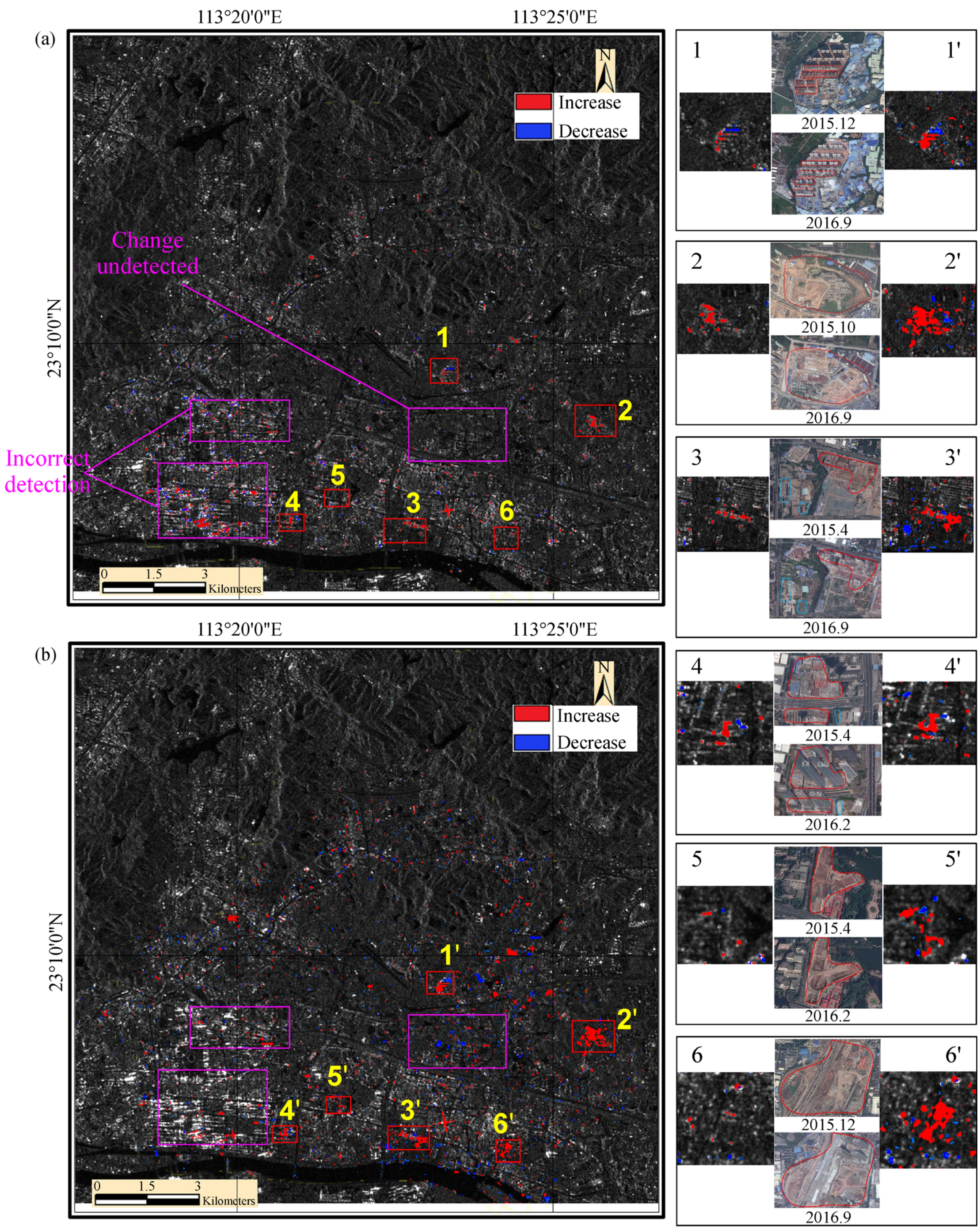

Fig. 7 Comparison of the results from two change detection methods. (a) ENVI change detection method; (b) time series-based SAM change detection method; and right: ENVI change detection method versus time series-based method.

Table 2 Confusion matrix of change detection results

Result		Actual changed			
		Increase	Decrease	Unchanged	Total
Detected changed	Increase	24	10	2	36
	Decrease	6	25	4	35
	Unchanged	0	0	29	29
	Total	30	35	35	100

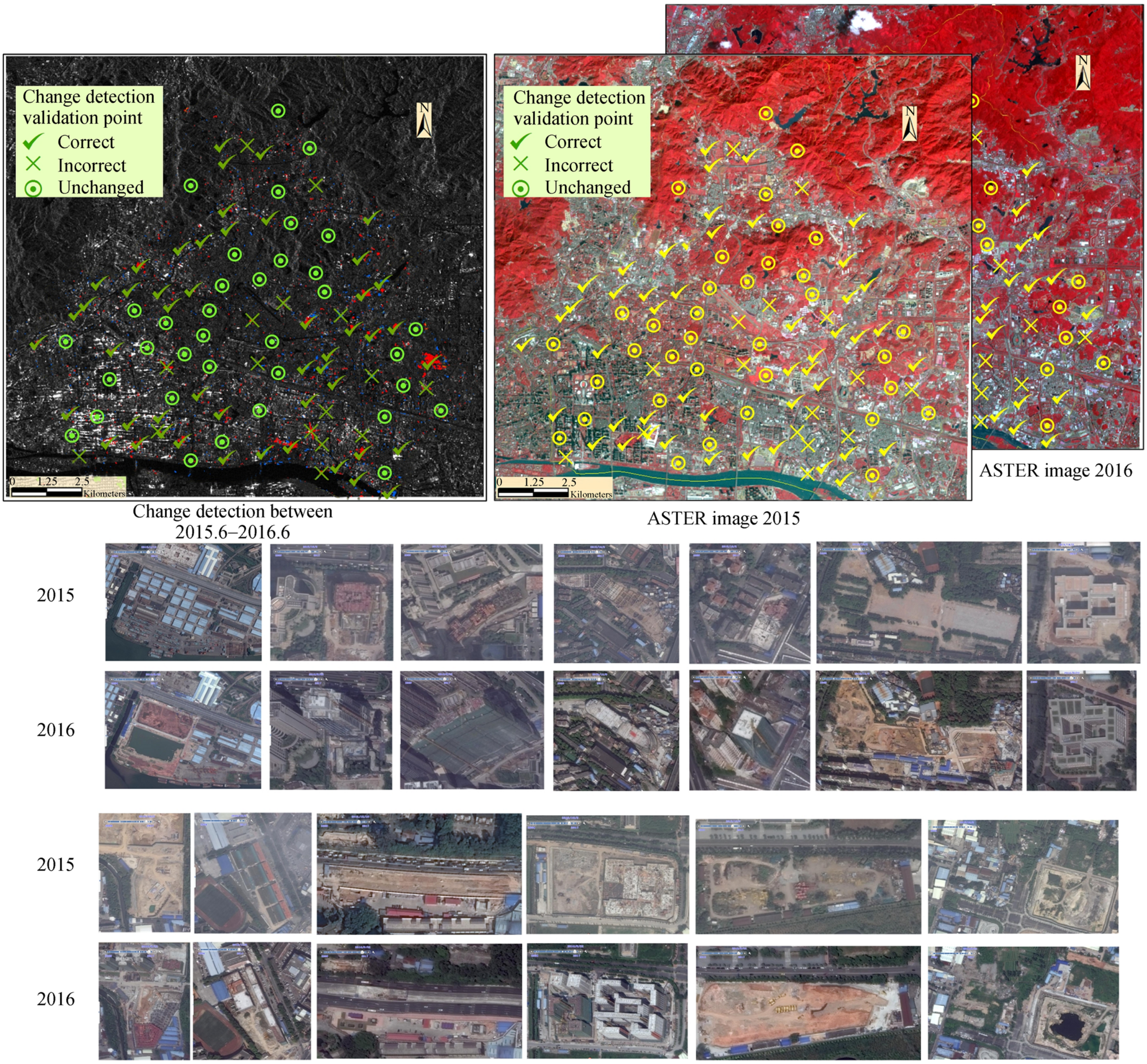

Fig. 8 The spatial distributions (upper) of 100 sites randomly selected for overall accuracy of change detection results with 13 specific validation areas (lower).

integrated Sentinel-1 SAR time series images with spectral angle mapping, which led to a method that successfully captured the changed areas due to urban reconstruction in Tianhe District of Guangzhou City.

As economy develops, the land demand in Tianhe District has become greater. However, the land supply is limited. Thus, urban redevelopment becomes a good alternative. The old buildings have been removed and new construction has been carried out within a few months, even a few days. The short-term urban land use conversion needed to be detected. Due to frequently cloudy and rainy weather, optical images lack the capability of detecting the short-term urban land cover conversion. The combination of Sentinel-1 SAR time series data with hyperspectral analysis offers a solution for this purpose. The proposed method was validated in Figs. 6 and 7, and Table 2, which demonstrated a significant capability of Sentinel-1 time series data for detecting urban land use changes. Within a short time period, the urban land cover conversions occurred. The old buildings changed to bare lands, and the bare lands converted to new buildings. The proposed method provides the potential to capture the short-term LULC changes. In addition, this study also shows that Sentinel-1 SAR satellite might be an ideal data source to construct time series images for the applications related to seasonal changes such as crop phenology and wetland dynamics that require a high frequency of repeated images (Muro et al., 2016).

Although numerous studies have been carried out to develop change detection methods, most of them analyze LULCC based on bi-temporal images that are unable to capture the temporal trends of land use development. Time series image-based methods have been proposed for many years (Hecheltjen et al., 2014). In this study, however, we considered the SAR images acquired at different dates as bands of spectral images. Thus, the times series of SAR backscattering intensity can function as a hyperspectral image. Furthermore, we performed linear trend transformations of the SAR time series images, which resulted in the trend vectors of LULCC on the basis of pixel-by-pixel. Then, the spectral analysis methods such as spectral unmixing analysis and SAM could be used to analyze the SAR time series images for LULCC detection.

The results of this study validated that the time series-based change detection method more accurately captures the short-term land cover changes than the ENVI change detection method. The reasons included: 1) The ENVI change detection uses a pair of bi-temporal images and is a labeling-based method that lacks the ability to eliminate the inherently time-induced noise in the SAR images, leading to misdetection of changes; 2) The SAR time series-based SAM change detection is characterized by multi-temporal SAR data and has the ability to reveal the temporal trends of land cover dynamics; 3) The proposed change detection method quantifies the similarity between each unknown pixel and each of the temporal endmembers in terms of change vector angles; and 4) The ENVI change detection method requires users to define threshold values for increase and decrease, which is very subjective. Therefore, the proposed method provides the potential to overcome the limitations of conventional change detection methods by capturing the patterns of LULC change trends in urban environments.

In addition, there is still concern on the accuracy assessment of LULC change detection mainly due to various sources of errors and the limited availability of validation data (Foody, 2010; Hecheltjen et al., 2014, Aiazzi et al., 2018). Especially for SAR image-based change detection, it is not easy to use pixel-base or object-base accuracy assessment (Hussain et al., 2013; Gamba and Dell'Acqua, 2016). In this study, Google Earth historical images were used for validating the results of LULC change detection by selecting specific sites where LULC changes took place and by randomly sampling 100 sites within the whole study area. The achieved accuracy result was convincing.

In the future, SAR time series data will become more widely used for land use classification with considerable high accuracy. However, the current Sentinel-1 SAR GRD product has only one C-band with VH and VV polarization. Using the SAR images for classification of LULC types is also limited by signal saturation in complicated urban areas. Although many efforts have been dedicated to improving the classification for the use of SAR images, the lack of spectral features and relying on the backscattering intensity images lead to difficulties in classification. The classification accuracy of using the SAR data in urban environments can be further improved by data fusion with optical images (Zhang et al., 2014; Ban and Yousif, 2016; Zhang et al., 2018b; Zhang and Xu, 2018).

7 Conclusions

Conducting the detection of short-term urban LULC changes in a subtropical region such as Tianhe District of Guangzhou is challenging due to the difficulty of acquiring cloudless optical images. In this study, we proposed a method that integrated Sentinel-1 SAR time series image with spectral angle mapping. The method consisted of linear trend transformations of the SAR time series images, extraction of temporal endmembers, and spectral angle mapping to detect changes. The results demonstrated a significant capability of both the Sentinel-1 SAR time series data and the proposed method for detecting the short-term urban LULC changes in Tianhe District where the city has been undergoing urban redevelopment practices. The method more accurately identified the LULC changes with increase/decrease patterns than the conventional bi-temporal change detection method. The result also showed that the land use conversions were mainly attributed to the removing of old buildings and their replacements by new construction. This method provided the potential of using SAR time series images for the short-term LULC change detection in urban environments, enhanced the understanding of SAR time series data and advanced their applications.

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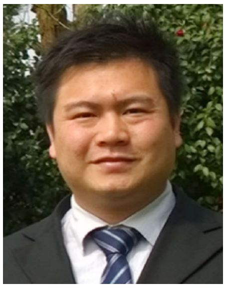

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