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Assessment of Urban Growth in the Pearl River Delta, China, Using Time Series Landsat Imagery

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3.1 INTRODUCTION

Urban growth has a significant influence on urban environments, including climate change (Liao et al. 2015; Pathirana et al. 2014), biochemical cycles (Hutyra et al. 2014), and environment quality (Panagopoulos et al. 2015; Zhao et al. 2015). Assessment of urban growth is needed for sustainable development and studies on ecological consequences. Since remote sensing technology provides spatially consistent data with high spatial resolution and high temporal frequency, remote sensing imagery makes it possible to analyze and model urban growth over long periods at various scales in a timely and cost-effective manner. Multitemporal coarse or medium spatial resolution imagery has been commonly applied for analysis of urban growth, such as DMSP/OLS (Defense Meteorological Satellite Program/Operational Linescan System) nighttime light data (Liu et al. 2012; Ma et al. 2012; Zhang and Seto 2011), Landsat...
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archive (Bagan and Yamagata 2012; Michishita et al. 2012; Sun et al. 2013; Xian and Crane 2005), China–Brazil Earth Resources Satellites images, and HJ-1 images (Du et al. 2015). The main drawback to using coarse or moderate spatial resolution imagery is the mixed pixel problem, which leads to a salt-and-pepper effect caused by spectral heterogeneity. Multitemporal high spatial resolution imagery has also been used to extract urban areas, such as Spot 5 imagery (Durieux et al. 2008; Jacquin et al. 2008) and RapidEye and IRS data (Dupuy et al. 2012). Although these methods have been applied to analyze urban growth successfully, the successive imagery with high temporal resolution was difficult to obtain. Additionally, the intraclass spectral variability problem is inevitable in high spatial resolution imagery.

Multitemporal analysis for urban growth usually requires single classification or segmentation of all the stacked images and is limited to provide detailed change information because of low temporal resolution. Therefore, time series imagery applied in differentiating land cover has attracted increased attention from researchers in recent years, because temporal domain has showed its advantages in resolving class confusion between classes with similar spectral characteristics (Bhandari et al. 2012; Schneider 2012). Specifically, Landsat time series have been successfully applied to map dynamics of urban areas because of their long record of continuous measurement at effective spatial resolution and temporal frequency (Gao et al. 2012; Li et al. 2015; Sexton et al. 2013a,b). However, these methods focused on spectral differences or temporal consistency after classification. Little attention was paid to temporal data mining method to differentiate urban areas from other land cover using dense time series Landsat images.

Since time series clustering has been shown to be effective in time series data mining (Fu 2011; Liao 2005), in this study, we aimed at extracting urban areas using a semi-supervised fuzzy time series clustering method through the Biophysical Composition Index (BCI) (Deng and Wu 2012) and Land Surface Temperature (LST) time series and applied the method to the Pearl River Delta, China, from 1987 to 2014. Kernel fuzzy C-means (KFCM), proposed by Zhang and Chen (2003), was introduced in this study, because it could provide a more robust signal-to-noise ratio and is less sensitive to cluster shapes in comparison to other clustering algorithms (Du et al. 2005). BCI and LST time series images were derived because of their strong correlation with urban areas. BCI aimed to identify different urban biophysical compositions and has been demonstrated to be effective in identifying the characteristics of impervious surfaces and vegetation and in distinguishing bare soil from impervious surfaces. LST, as a significant parameter in urban environmental analysis, tends to be positively correlated with urban expansion (Weng and Hu 2008; Yuan and Bauer 2007).

3.2 CASE STUDY

3.2.1 STUDY AREA

The Pearl River Delta, as the third most important economic district of China, is located in the developmental core region of Guangdong Province, between 21°N–23°N and 111°E–115°E. It has experienced rapid urbanization since the reform process started in the late 1970s in China. The Pearl River Delta has a subtropical climate
with an average annual temperature of 21°C–23°C, including a dry season from October to April and a wet season from May to September.

Quantifying and analyzing the urban growth in the Pearl River Delta are important to characterize the effects of anthropogenic activities on urban environments during the past years. In our study, 239 Landsat images, covering the period from 1987 to 2014, were used to monitor urban area dynamics. Landsat imagery, including TM, ETM+ (including SLC-off data), and OLI data with cloud cover less than 50%, was ordered and downloaded from the USGS Earth Explorer (Reference system: WRS-2, Path: 122, Row: 44). A clipped region from Landsat imagery with an area of 16,824 km², covering five cities, Guangzhou, Foshan, Zhongshan, Dongguan, and Shenzhen, was used to monitor urban growth. These five cities were the most developed cities in the Pearl River Delta. The geographic location of the study area is shown in Figure 3.1.

FIGURE 3.1 Geographical location of the case study area, Pearl River Delta.
3.2.2 Methodology

This study intended to quantify the spatiotemporal patterns of urban areas in the Pearl River Delta using dense time series Landsat images from 1987 to 2014. In this study, the proposed method included five steps (Figure 3.2): First, time series Landsat subsets were registered in the same projection and converted to surface reflectance using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Masek et al. 2006). Then, cloud, cloud shadow, and snow were masked and their values were set to null. Next, the BCI and LST time series were computed from preprocessed data. Gap filling (Garcia 2010; Wang et al. 2012) and smoothing were adopted to fill missing values in the time series. After that, stable time series were selected based on time series decomposition (Verbesselt et al. 2010). Finally, the semi-supervised KFCM algorithm was performed to clustering time series to map annual urban areas during the study period.

3.2.2.1 Data Preprocessing

All the Landsat data were registered to the 1984 World Geodetic System Universal Transverse Mercator (WGS-84 UTM) Zone 49 North projection system and resampled at 30-m spatial resolution. Each Landsat subset was standardized to surface reflectance using the LEDAPS method (Masek et al. 2006), which applied MODIS (moderate-resolution imaging spectroradiometer) atmospheric correction routines to Landsat L1 data products. Cloud, cloud shadow, and snow mask were calculated using the Fmask algorithm for all scenes (Zhu and Woodcock 2012). The locations of SLC-off data were identified using band-specific gap mask files in each SLC-off data product.

FIGURE 3.2 Procedures for mapping annual urban areas in the Pearl River Delta using time series Landsat images.
3.2.2.2 Calculation of BCI and LST

BCI (Deng and Wu 2012), involving Tasseled Cap (TC) transformation and the V–I–S triangle model, was given as

\[
BCI = \frac{TC_1 + TC_3 - TC_2}{2},
\]

(3.1)

where \(TC_i\) \((i = 1, 2, \text{ and } 3)\) were three normalized TC components: \(TC_1\) was \text{high albedo}, \(TC_3\) was \text{low albedo}, and \(TC_2\) was \text{vegetation}. Each derived TC component was then linearly normalized to the range from 0 to 1.

The LST was calculated using the radiative transfer equation method (Sobrino et al. 2004):

\[
B_T = \frac{[L_\downarrow - L_\uparrow - \tau(1-\epsilon)L_\downarrow]}{\tau \epsilon},
\]

(3.2)

where \(B_T\) was the atmospherically corrected pixel value as brightness temperature. \(L_\downarrow, L_\uparrow,\) and \(\tau,\) derived from an atmospheric correction tool (Barsi et al. 2005), were upwelling radiance, downwelling radiance, and transmittance, respectively. \(\epsilon\) was emissivity, derived from NDVI. \(L_\lambda\) was the pixel values as radiance derived from digital numbers DN:

\[
L_\lambda = \text{gain} \times \text{DN} + \text{bias},
\]

(3.3)

where gain and bias were gain value and bias value for the specific band, respectively.

Then, the radiance was converted to surface temperature (Chander and Markham 2003):

\[
T = \frac{K_2}{\ln\left(\frac{K_1}{B_T + 1}\right)},
\]

(3.4)

where \(T\) was the temperature in Kelvin (K) and \(K_1\) and \(K_2\) were prelaunch calibration constants. For Landsat 5 TM, \(K_1 = 607.76 \text{ W/(m}^2 \text{ sr} \mu\text{m})\) and \(K_2 = 1260.56 \text{ K};\) for Landsat 7 ETM+, \(K_1 = 666.09 \text{ W/(m}^2 \text{ sr} \mu\text{m})\) and \(K_2 = 1282.71 \text{ K};\) for Landsat TIRS 10, \(K_1 = 774.89 \text{ W/(m}^2 \text{ sr} \mu\text{m})\) and \(K_2 = 1321.08 \text{ K}.

3.2.2.3 Gap Filling and Smoothing

Discontinuities existed in the time series Landsat data due to missing values caused by cloud cover and SLC-off data, which made uncertainties under incomplete time series in a subsequent analysis. Gap filling and smoothing were needed to improve the continuity and consistency in the time series. The gap filling method (Garcia 2010;
Wang et al. 2012), as a penalized least square regression based on three-dimensional discrete cosine transform (DCT-PLS), was adopted to predict missing values. It used information from both spatial and temporal variability to provide robust gap filling and it required no ancillary data sets such as alternative geospatial data sets or digital elevation models to model missing values. A smoothing gap filled time series was essential to improve the accuracy of the phenology derived from the reconstructed time series (Atkinson et al. 2012). Fourier fitting, as a most common and useful method, was adopted for smoothing gap filled time series BCI and LST data. Fourier analysis has showed promise in monitoring interannual vegetation changes (Geerken 2009). For the BCI and LST time series, Fourier fitting reduced the amount of noise, which mitigated the effects of outliers, anomalies, and spurious values in the time series.

3.2.2.4 Selection of Stable Time Series

Stable time series were derived from BCI time series. Stable time series means time series of labeled land covers, which have not experienced land cover transition during the study period. Since there was no exponential growth in the time series, an additive decomposition model was applied to separate BCI time series into three distinct components:

\[ T = T_t + S_t + I_t, \]  

(3.5)

where \( T \) was the observed data at time \( t \), \( T_t \) was a nonseasonal secular trend component, \( S_t \) was a seasonal component, and \( I_t \) was an irregular component. \( T_t \) was estimated using the regression model as

\[ T_t = \beta_0 + \beta_1 t + \beta_2 t^2. \]  

(3.6)

\( \beta_0, \beta_1, \) and \( \beta_2 \) were regression coefficients. The seasonal component \( S_t \) was derived from the detrend time series using a parametric regression model. Detrend time series were computed by subtracting the trend component \( T_t \) from the original time series. Given the trend component \( T_t \) and the seasonal component \( S_t \), the irregular component was estimated as

\[ I_t = T - T_t - S_t. \]  

(3.7)

The time series with the trend component as constant and without obvious phenology circle in seasonal variables were selected as stable time series.

3.2.2.5 Semi-Supervised KFCM Algorithm

Time series BCI and LST images were processed using a semi-supervised KFCM to obtain clustering results. Given time series data \( X = \{x_1, x_2, \ldots, x_n\}, x_k \in \mathbb{R}^d (k = 1, 2, \ldots, n) \), where \( d \) was temporal dimension and \( n \) was the number of samples.
KFCM partitions $X$ into $c$ fuzzy subsets by minimizing the following objective function:

$$J_m(U,V) = 2 \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^m (1 - K(x_k, v_i)),$$

(3.8)

where $c$ was the number of clusters, $v_i$ was the $i$th cluster centroid, $u_{ik}$ was the membership of $x_k$ in class $i$, and $\sum_{i} u_{ik} = 1$; $m \in [1, +\infty]$ was the weighting exponent determining the fuzziness of the clusters. $K(x_k, v_i)$ was the kernel function, aiming to map $x_k$ from the input space $X$ to a new space with higher dimensions. In this study, radial basis function kernel was adopted:

$$K(x_k, v_i) = \exp\left(-\frac{\|x_k - v_i\|^2}{\sigma^2}\right),$$

(3.9)

where the parameter $\sigma$ was computed by

$$\sigma = \frac{1}{c} \sqrt{\frac{\sum_{i=1}^{n} \|x_i - m\|^2}{n}}.$$

(3.10)

In order to search for new clusters, the objective function was minimized:

$$\text{Min } J_m(U,V) = 2 \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^m (1 - K(x_k, v_i))$$

(3.11)

$$\text{s.t. } \sum_{i=1}^{c} u_{ik} = 1, k = 1, 2, \ldots, n.$$  

(3.12)

The Lagrange function converted the constrained objective as an unconstrained optimization model. By optimizing the objective function, the membership $u_{ik}$ and centroid $v_i$ could be updated:

$$u_{ik} = \frac{\left(\frac{1}{(1 - K(x_k, v_i))}\right)^{\frac{1}{m-1}}}{\sum_{j=1}^{c} \left(\frac{1}{(1 - K(x_k, v_j))}\right)^{\frac{1}{m-1}}}$$

(3.13)
\[ v_i = \frac{\sum_{k=1}^{n} u_{ik}^m K(x_k, v_i) x_k}{\sum_{k=1}^{n} u_{ik}^m K(x_k, v_i)} . \] (3.14)

Labeled time series samples were derived from stable time series, and unlabeled samples were derived from the remaining time series. Given time series data \( X \) consisted of \( X_l \) and \( X_u \), \( X_l \) was labeled samples and \( X_u \) was unlabeled samples. “l” and “u” indicate labeled or unlabeled data, respectively.

The whole process of semi-supervised KFCM algorithm was shown as follows:

1. Initialize the values of \( \sigma \) and \( u_{ik} \) using \( X_l \) and \( X_u \). For \( X_l \), the value of component \( u_{ik} \) was set to 1 if the data \( x_k \) were labeled with class \( i \), and 0 otherwise. For \( X_u \), positive random values within \([0,1] \) were set to unlabeled data. The initial set of centroid \( v_i \) was calculated as \( v_i^0 = \frac{\sum_{k=1}^{n'} (u_{ik}^l)^m x_k^l}{\sum_{k=1}^{n'} (u_{ik}^l)^m} \), where \( n' \) was the number of labeled data.

2. Update the membership \( u_{ik} \) in \( X_u \) and centroid \( v_i \) until the objective function was minimized.

Finally, inconsistent labeled pixels were mapped comparing the LST \( L \) and BCI \( B \) clustering results. For those pixels, if the maximum membership \( \max(u_{ik})^L \) of the pixel \( k \) in \( L \) was higher than \( \max(u_{ik})^B \) in \( B \), the pixel was labeled as the class with \( \max(u_{ik})^L \) in \( L \), and vice versa. However, if the values were equal, the pixel was labeled as the class with \( \max(u_{ik})^L \).

### 3.3 RESULTS

#### 3.3.1 Quantitative Characteristics of Urban Growth

The urban area distributions for the Pearl River Delta from 1987 to 2014 are shown in Figure 3.3. The dark gray represents urban area, the medium gray shows water bodies, and the light gray shows nonurban area. Because image numbers in 1989, 1992, 1997, and 1998 were fewer than 3 and cloud cover was more than 50% for all images, urban areas in these 4 years were not analyzed.

The annual urban area maps in the Pearl River Delta in Figure 3.3 show a dramatic urban expansion from 1987 to 2014. Urban areas increased from 598 km\(^2\) in 1987 to 5768 km\(^2\) in 2014. To evaluate urban growth in the study area, urban areas by year were calculated from annual clustering maps in Figure 3.4. The spatial distributions of annual urban areas could be divided into four periods.

1. For the period 1987–1991, the Pearl River Delta experienced no significant change in urban areas. The Pearl River Delta was in the early phases of development during this period. Urban areas increased from 3.56% of the study area in 1987 to 5.97% in 1993, with an annual average rate of 13.57%. The average increased urban area per year was 101.53 km\(^2\)/year.
2. For the period 1993–2000, large urban areas formed within and around existing urban areas. The Pearl River Delta experienced its first rapid growth period as a result of the deep development of China’s reform and opening up. Urban areas increased from 6.81% in 1993 to 19.07% in 2000 with an annual average rate of 22.52%. The average increased urban area per year was 412.62 km²/year.
FIGURE 3.4  Annual urban areas in the Pearl River Delta, from 1987 to 2014.
3. For the period 2001–2006, the Pearl River Delta was still experiencing a rapid growth, but the urban expansion was slower than that in the previous period. In this period, the Southeast Asian economic crisis affected urban development to some degree. The driving forces of continuous urban expansion were mainly because China had a fast-growing economy since it joined the World Trade Organization in 2001. Urban areas increased from 20.19% in 2000 to 28.34% in 2006, yielding an annual average rate of 6.73%. The average increased urban area per year was 228.65 km²/year.

4. For the period 2007–2014, Pearl River Delta entered a period of stable development and urban development was slowed down. Urban areas increased from 28.48% in 2007 to 34.28% in 2014 with an annual average rate of 2.55%. The average increased urban area per year was 122.02 km²/year.

3.3.2 Assessment of Urban Growth

Since the 1980s, rapid urbanization in the Pearl River Delta was strongly linked to economic growth and population attributed to reform policies. From 1980 to 2000, the average annual gross domestic product (GDP) growth of the Pearl River Delta grew up to 16.9%. In this period, the driving force of urban growth in the study area was the establishment of Special Economic Zones of Shenzhen, followed by foreign investment from overseas investors. Since the new century, the Pearl River Delta has been continuing to experience strong economic growth with an average annual GDP growth of up to 15% between 2000 and 2007. However, the GDP growth has slowed down since 2008 because of the global financial crisis and industrial structure adjustment. The GDP growth particularly slowed down to below 10% since 2011. According to the Hong Kong Trade Development Council, the Pearl River Delta enjoyed a per-capita GDP of RMB 93,114 in 2013 (approximately $15,000), with real GDP growing by an average of 9.4%.

The urban growth types differed during four periods: 1987–1991, 1993–2000, 2001–2006, and 2007–2014. In the 1987–1991 period, urban growth was dominated by scattered development. In the 1993–2000 period, scattered development was decreased and strip development was increased. Urban areas mainly expanded along transportation networks. According to the fifth national population census, the population of the Pearl River Delta was 4 million in 2000, rising by 1.94 million when compared to the population in 1990. From 2001 to 2014, strip development and compact development became dominant. City clusters and metropolitan stretches came into being in the Pearl River Delta. Accompanying the urbanization process was population growing to 47.72 million in 2008. Since 2011, the population growth affected by economic growth and industrial structure adjustment began to stabilize (Pearl River Delta Region Planning and Guangdong Statistical Yearbook 2014).

3.3.3 Clustering Accuracy Assessment

In this study, historical imagery acquired from Google Earth was used as reference data for each year. Since available historical imagery cannot cover the whole study
FIGURE 3.5 Annual clustering accuracy of the proposed method.
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area and historical imagery from Google Earth for some period was few, reference samples were also selected from time series BCI images using visual judgments. Stable time series derived from stacked cloud free BCI images were used as reference data. Then, the stratified random sampling method was employed for selecting reference data for each year. Five hundred samples were randomly selected to each class and divided into two subsets. One subset was used for classifier training and the second was used for accuracy assessment. It would help eliminate the bias resulting from using the same samples for both training and testing. The annual clustering accuracy is shown in Figure 3.5.

The annual clustering accuracy yielded 78.23% to 91.32%, which shows the effectiveness and feasibility of the time series clustering method. However, the average clustering accuracy in the 1987–1999 period was 81.05%, and the average clustering accuracy in the 2000–2014 period was 89.75%. The reason was that different temporal dimensions in each year led to different clustering accuracy. The available annual average image number before 2000 was smaller than 3, but the available annual average image number after 2000 was larger than 14. The main reason for this phenomenon was that the low temporal resolution in each year could obscure land cover changes and reduce the separability of temporal characteristics for urban areas and nonurban areas. The vegetation phenology characteristic would particularly be weakened. Time series clustering also showed values of imagery with cloud contamination or SLC-off data in identifying urban areas. Although cloud contamination and SLC-off data caused significant temporal noise and resulted in incomplete time series, gap filling and smoothing were helpful for solving missing data problems through enhancing temporal resolution of time series Landsat imagery.

3.4 CONCLUSIONS

This chapter explores urban growth in the Pearl River Delta using time series Landsat imagery from 1987 to 2014 based on the time series clustering method. The annual spatiotemporal patterns of urban areas in the Delta were quantified. The results indicated that urban areas in study areas increased rapidly from 3.56% to 34.28% during the 1987–2014 period. The method proposed in this chapter verifies the feasibility and effectiveness of the time series clustering method in assessing urban growth patterns using time series Landsat imagery. Results from this study can be used by policymakers for urban planning and management and for hydrological modeling to determine the effect of increasing urban areas on urban environments of the study area. This study can also be valuable for exploring the mechanisms of urban areas and environmental relationship for sustainable urban planning and management. However, how to evaluate the differences between two time series and how time series components affect time series clustering remain unanswered in this study. Future studies may include similarity metrics before using the clustering method to solve the above issues.
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