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Mapping annual urban dynamics (1985–2015) using time series of Landsat data

Xuecao Li[a], Yuyu Zhou[a,*], Zhengyuan Zhu[b], Lu Liang[c], Bailang Yu[d], Wenting Cao[a]

[a] Department of Geological and Atmospheric Sciences, Iowa State University, Ames, IA 50011, USA
[b] Department of Statistics & Statistical Laboratory, Iowa State University, Ames, IA 50011, USA
[c] School of Forestry and Natural Resources, University of Arkansas at Monticello, Monticello, AR 71656, USA
[d] School of Geographic Sciences, East China Normal University, Shanghai 200241, China

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ABSTRACT

The information of urban dynamics at fine spatiotemporal resolutions is crucial to urban growth modeling and sustainable urban development. However, there are still challenges in deriving the change information of urbanization in timing and location over a long period. In this study, we developed a framework to map urban expansion at an annual interval from 1985 to 2015 by using the time series of Landsat data. First, the time series of Landsat data (1985–2015) were grouped into three periods, i.e., 1985–2001, 2001–2011, and 2011–2015, according to the available National Land Cover Database (NLCD). Then, a temporal segmentation approach was implemented for each period using three indicators representing changes from vegetation, water, and bare land to urban. Turning years of the start and end of change were identified. Three temporal segments representing phases of prior change, change, and post change, were generated accordingly. Thereafter, urban extents before 2001 and after 2011 were classified using a change vector analysis (CVA) based approach aided by the NLCD and identified temporal segments. Finally, urbanized pixels in each period were determined according to the identified turning years. Our approach of temporal segmentation is reliable for detecting changes caused by urban growth, with an overall accuracy of 90% in identifying turning years (± 1 year). Using an independent validation sample set, the CVA based approach reaches an overall accuracy of 87%. The derived product of urban dynamics shows a relatively stable increment of urban growth in Des Moines and Ames, Iowa, US, and most urbanized areas were converted from vegetated lands within 2–3 years. The proposed framework is capable of mapping long-term dynamics of urban extents at an annual interval and the outcome is useful in effectively updating current products of urban extents and improving urban growth modeling.

1. Introduction

Although the global urban extent only accounts for less than 1% of the Earth's land surface, more than 90% of the global economy, 50% of the world population, 65% of the global energy consumption, and 70% of the global greenhouse gas emission are taking place in the urban domains (Martine, 2007; Schneider et al., 2010). The worldwide rapid urbanization process challenges the sustainable goals of urban development reported by the United Nations (Giles-Corti et al., 2017) in a variety of fields such as public health (Gong et al., 2012; Li et al., 2017c), building energy use (Güneralp et al., 2017; Zhou et al., 2014a), urban heat island (Li et al., 2018a; Li et al., 2017b), anthropogenic emissions (Gurney et al., 2012; Zhou and Gurney, 2010), and ecosystem services (Alberti et al., 2017; Li et al., 2017c). Considering the complexity of urban system, it is of great importance to characterize the long-term spatiotemporal urban dynamics and link them with socio-economic data, which can help to better understand the urbanization process, develop urban growth models, and investigate environmental impacts of urbanization (Li and Gong, 2016b; Li et al., 2018b).

The information of urban dynamics at a fine temporal resolution is highly required in urban growth modeling (Li and Gong, 2016b; Sexton et al., 2013). Although remotely sensed observations have been widely used to map urban dynamics from local to global scales, most of them were carried out with relatively coarse temporal resolutions (e.g., five-year or decade) (Chen et al., 2015a; Friedl et al., 2010; Fry et al., 2009; Zhang et al., 2014; Zhou et al., 2014b), such as the National Land Use/Cover Database (NLCD) in US and China. The information of urban dynamics derived from satellite observations with a coarse temporal resolution can hardly represent the high-order complexity (e.g., accelerated expansion) of urban growth, particularly in rapidly

* Corresponding author at: Department of Geological and Atmospheric Sciences, Iowa State University, Ames, Iowa 50011, USA.
E-mail address: yuyuzhou@iastate.edu (Y. Zhou).

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developing regions (Li et al., 2015; Reynolds et al., 2017; Sexton et al., 2013). In these regions, the pace of urban growth is highly policy/event manipulated, which is temporally uneven and hard to be captured using coarse temporal resolution satellite observations. For example, Sexton et al. (2013) found the changes of impervious surface areas varied across different cities in Washington D.C. – Baltimore MD metropolitan region, US, over the period 1984–2010. Li et al. (2015) observed a notable increment of the urban area after 2000 in Beijing, China, through 1984–2013 using annual urban extent maps derived from time series of Landsat data. Zhang and Weng (2016) detected a rapid growth period during 1995–2003 in the Pearl River Delta through mapping annual impervious surface dynamics. More details of spatiotemporal dynamics can be revealed from annual time series of urban extent (Shi et al., 2017).

Compared with traditional multi-temporal classification approaches (e.g., supervised classification or post-processing (Gao et al., 2012; Mertes et al., 2015; Schneider, 2012; Seto et al., 2002)), the full use of Landsat time series data makes it possible to detect a relatively complete profile of historical urban growth, which is not easily discernible from stacked images with sparse satellite observations (Roy et al., 2014; Woodcock et al., 2008). In addition, it can mitigate the uncertainties caused by classification or post-processing when generating the product of urban dynamics. For example, Kennedy et al. (2010) proposed the Landsat-based detection of trends in disturbance and recovery approach that involved the modeling of temporal signatures of gradual forest infestation from densely stacked images. Zhu et al. (2012) developed the continuous monitoring of forest disturbance algorithm for change detection in forest ecosystems using a harmonic model to delineate the periodical cycle of land surface dynamics, aided by dense Landsat images.

Currently, most studies using indicator-based time series analysis focus on vegetation or water dynamics in the natural ecosystem (Hermosilla et al., 2016; Potapov et al., 2015), with fewer applications in the urban domain because of several potential difficulties. Firstly, the urban landscape is very complicated, with inter-class conversions among different land cover types (Li and Gong, 2016a; Li et al., 2015), i.e., vegetation, water, or bare land are potential to convert to urban. Therefore, different indicators or rules are required to detect these conversions. Secondly, it is hard to distinguish changes induced by urbanization from other pseudo changes that are probably caused by seasonal land surface dynamics or image quality (e.g., covered by cloud) when using stacked images with a relatively coarse temporal resolution for change detection. Thirdly, for some small or medium cities with a low growth pace, detection of the urbanization induced changes requires annual satellite observations at a finer resolution (i.e., 30 m) to identify the changing time more accurately (Song et al., 2016). To address these challenges, we proposed a mapping framework to generate an annual product of urban extent using the Landsat time series data and multiple-temporal land cover data over a long period (i.e., three decades). The remaining of this paper is organized as: Section 2 introduced the study area and datasets; Section 3 showed details about the proposed mapping framework; Section 4 presented the results and assessments; the concluding remarks were given in Section 5.

2. Study areas and datasets

In this study, we chose the cities of Des Moines and Ames in central Iowa, US (Fig. 1a) to test the proposed mapping framework due to their low-pace growth, which can be served as ideal study areas to test our approach in small- and medium-size cities with gradual changes. Suburban areas of these two cities are surrounded by agricultural lands, with rivers and pastures around urban fringe areas. Des Moines is the capital city of Iowa and well-known for its insurance and financial services, whereas Ames is a university predominated city with continuously increasing students/scholars in recent years.

All the available L1T-level Landsat data with a cloud cover less than 80%, including the Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI), were downloaded from the United States Geological Survey (USGS) Landsat archive. The atmospheric correction was already performed using the Landsat ecosystem disturbance adaptive processing system (LEDAPS) (Masek et al., 2006) with the cloud and cloud shadows masked (Zhu and Woodcock, 2012). All the clean-sky pixels were used to build the time series of each pixel in our study areas. A total of approximately 1000 Landsat images were acquired (Fig. 1b).

We also collected other ancillary datasets to aid the mapping. The multi-temporal NLCD was used to identify urbanized areas in different years. The NLCD is a land cover product based on the decision-tree approach using Landsat satellite observations of circa 2001, and it is updated for changed cover types in 2006 and 2011 using a consistent mapping scheme (Homer et al., 2015; Xian et al., 2009). The overall accuracy of years 2001, 2006, and 2011 were reported as 85%, 84%, and 89%, respectively (Wickham et al., 2017; Wickham et al., 2010; Wickham et al., 2013). We also evaluated the performance of NLCD product in the study areas and found it is reliable to support the mapping of urban dynamics in this study (Table S1), with an overall accuracy of 97% and 95% for NLCD 2001 and 2011, respectively and an accuracy of 89% for urban area change during the period 2001–2011. Additionally, the Visible Infrared Imaging Radiometer Suite (VIIRS) nighttime light data show the advanced capacity of detecting city lights at nighttime in a form of radiance (Chen et al., 2015b; Li and Zhou, 2017; Shi et al., 2014). In this study, it was used as a mask of potential urbanized areas occurred after 2011.

3. Methodology

We proposed a framework to map annual urban dynamics (1985–2015) (Fig. 2). The key idea is to identify the change years of urbanized pixels using the time series of Landsat data and fine-quality land cover products (NLCD). First, the time series (1985–2015) was grouped into three periods based on available data of the NLCD product, i.e., B1 (1985–2001), B2 (2001 − 2011), and F1 (2011–2015) (Fig. 2a). Although this scheme may introduce a small amount of uncertainties in detecting the start year of change when the urban growth occurred across two adjacent periods, the reliable NLCD information can be largely used in our three-period strategy for the entire study area. Second, in each period, the turning years were retrieved through a temporal segmentation approach with three indicators representing vegetation, water, and bare land (Fig. 2b). Thereafter, for the periods before 2001 and after 2011, a classification was performed based on the derived results from temporal segmentation approach and NLCD data. Finally, the identified turning years, as well as the conversion sources, were labeled for those urbanized pixels in each period (i.e., B1, B2, and F1). The key procedures in each period include the construction of time series and the temporal segmentation. For period B1 and F1, an additional classification is needed to identify urbanized areas (Fig. 2c).

3.1. Construction of time series

We constructed the annual time series using three indicators that can well represent vegetation, water, and bare land, namely Normalized Difference Vegetation Index (NDVI), Modified Normalized Difference Water Index (MNDWI), and Shortwave Infrared (SWIR) reflectance. The NDVI and MNDWI are ratios calculated using bands that have different responses to vegetation and water, respectively (Eqs. 1–2), and the SWIR is helpful in distinguishing urban and bare land (Ban et al., 2017; Li and Gong, 2016a; Tucker, 1979; Xu, 2006).

$$NDVI = (NIR - Red)/(NIR + Red) \quad (1)$$

$$MNDWI = (Green - MIR)/(Green + MIR) \quad (2)$$