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Urban boundary extraction and sprawl analysis using Landsat images: A case study in Wuhan, China

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ABSTRACT

Periodic monitoring and multi-scale characterization of urban sprawl is essential for improving urban planning and development. However, historical sprawl analysis is not well suited for the neo-urbanization occurring in most cities in China due to the limited data available. This paper proposes a concise and cost-effective method for automating the extraction of urban boundaries (UBs). The method uses integrated land-use information entropy (LUIE) model along with ordinary Kriging based on a gridded land-use map derived from Landsat imagery to extract UBs. Results indicate that overall extraction accuracies greater than 90% were obtained using an 800 m-resolution LUIE combined with Kriging. The method was applied to identify UBs in Wuhan, China during 1987–2010, and the UBs were characterized at multiple scales and analyzed using landscape metrics. Results show varied landscape dynamics at local administrative and city scales. The study demonstrates that the method for UB identification and multi-scale analysis has the potential to contribute to sprawl monitoring and measurement at multiple spatial scales. Moreover, the findings from this study can potentially guide policy makers and urban planners tasked with understanding and controlling development occurring under neo-urbanization strategies in China.

Introduction

Urbanization as a vital human–environment interaction has become a momentous force impacting regional and global sustainability. Numerous cities and metropolitan areas across the world have witnessed rapid urbanization characterized by disorderly urban sprawl, rapid population growth, and persistent economic improvements since the 1960s (Amiri, Weng, Alimohammadi, & Alavipanah, 2009; Arribas-Bel, Nijkamp, & Scholten, 2011; United Nations, 2012). In particular, urban sprawl characterized by unsustainable land-uses and imbalanced land cover dynamics has profoundly impacted urban–rural habitats, local biodiversity, hydrologic networks, and regional climate (Bhatta, Saraswati, & Bandyopadhyay, 2010; Haregeweyn, Fikadu, Tsunekawa, Tsubo, & Meshesha, 2012), among others. Furthermore, intensive sprawl is predicted to continue, particularly in developing countries (Cohen, 2006; Mulligan, 2013). Curbing excess sprawl and working toward sustainable planning strategies have become the focus of both scholars and urban planners (Elmqvist et al., 2013).

Neo-urbanization, which is the transformation of historically rural and impoverished areas into developed cities, has been facilitated by China in the recent years. As the most populous developing country, China has been experiencing unfaltering economic and social strides since the 1980s, and the national urban population has increased from 0.14 billion to 0.71 billion over the period 1970–2012 (National Bureau of Statistics, 2013). Fostered by increasing consumption and investment, the per capita Gross Domestic Product (GDP) rose to 38,325 RMB Yuan in 2012, almost a one hundred-fold increase over the per capita GDP in 1970. Moreover, public services including education, healthcare, and transportation have greatly improved (Knight, 2013). Consequently, to accommodate the demand for urban land to sustain these activities, chronic disorderly sprawl has been occurring nationwide (Hubacek, Guan, Barrett, & Wiedmann, 2009; Oizumi, 2011;

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Taubenböck et al., 2014). As a result of poor planning, many cities have suffered from massive traffic jams, steep rises in home prices, and ecological issues such as water pollution and atmospheric haze (Dhakal, 2009; Hu, Chen, Wang, & Xu, 2013; Siciliano, 2012). Carrying out successful neo-urbanization strategies that focus on curbing accelerated urban expansion, fostering the agglomeration of urban, suburban and rural regions, and promoting a habitable environment is extraordinarily important for achieving sustainability (CDRF, 2013). However, effective strategies for sustainable urban growth have not yet been achieved despite the fact that China's central and local governments are endeavoring to curb excess expansion and shape land-use transitions using policy instruments (Bai, Shi, & Liu, 2014).

One of main reasons that China has not been able to implement effective strategies for sustainable growth is because it has been difficult to identify and explain the intrinsic forces driving sprawl at multiple scales (Hersperger, Franscini, & Kübler, 2014; Kane, Tuccillo, York, Gentile, & Ouyang, 2014). This challenge has inspired researchers to strengthen analyses on the history and drivers of urban sprawl. The first step in this quest is to identify the urban boundaries (UBs), which constitute the bona fide boundaries between urban lands and all other non-urban areas (Han, Lai, Dang, Tian, & Wu, 2009). With rapidly changing urban landscapes, methods for frequent and accurate UB extraction are urgently needed. Additionally, these methods are also extremely useful for regular sprawl monitoring and sustainable land use management, especially in China where most cities do not have historical UB data (Chen, Liu, & Tao, 2013).

In recent years, remote sensing has become a viable method for identifying UBs (Tannier & Thomas, 2013). Since the launch of Landsat 5 in 1984, the Landsat program has provided a continuous set of near-time surface reflectance data at a relatively low cost (Patino & Duque, 2013), and the program is anticipated to continue for many years supported by the recent launch of Landsat 8. The availability of archived historical imagery makes it possible to extract UBs over a prolonged temporal period and monitor areas across large scales.

Theoretically, UBs can be extracted from remotely sensed imagery as soon as the degree of urban development reaches a size that it can be identified at the resolution of the image. Land-use classification is an appropriate and universal method for identifying UBs since urban areas are usually comprised of artificial structures such as residential, commercial, industrial buildings, as well as spectrally different natural areas including green space and water (Weber, 2001). Methods such as artificial neural networks, expert systems, vegetation-impervious surface-soil (VIS) classifications, and support vector machines have been widely applied in urban land-use classifications (Foody, 2000; Pacifici, Chini, & Emery, 2009; Pal & Foody, 2010). Nonetheless, the resolution of the imagery and the heterogeneity characteristic of urban landscapes make it difficult to automatically map detailed urban lands solely using optical remote sensing methods (Cockx, Voorde, & Canters, 2014). The use of ancillary datasets such as census data, road networks, impervious surface coverages, landscape metrics, land parcel attributes, and radar data were recently documented to improve urban classifications (Abed & Kaysi, 2003; Berger et al., 2013; Chaudhry & Mackaness, 2008; Hermosilla, Palomar-Vázquez, Balaguer-Beser, Balsa-Barreiro, & Ruiz, 2014; Hu & Wang, 2013; Schneider, Friedl, & Potere, 2014; Soergel, 2010; Wu, Qiu, Usery, & Wang, 2009). Fractal methods have also been documented as a successful component in aiding in locating UBs (Tannier & Thomas, 2013; Tannier, Thomas, Vuidel, & Frankhauser, 2011). However, ancillary datasets such as the ones described above as well as high-resolution imagery are costly and are seldom available for multiple areas across time and space. In terms of using intelligent algorithms, they are usually time-consuming and computationally expensive (Richards, 2013), and the contemporary frameworks are unrealistic when extrapolating UB identification to regional scales. Indeed, it is becoming more and more difficult to define and identify urban areas with the rapid pace of urban sprawl (Hollis, 2013; Rocchini et al., 2012; Weber & Puissant, 2003). Straightforward methods for automated UB extraction from remote sensing images without the use of ancillary datasets are needed.

This work aims to develop a simple method for UB extraction using Landsat images and use this method to analyze the diverse effects of urban growth at multiple scales for landscapes in China. The paper first introduces the study area and image processing techniques followed by a detailed description of the methodological framework for extracting UBs. Assessment of the UB identification method and the findings from the multi-scale sprawl analyses are reported in the Results section. The effectiveness of the proposed method for UB extraction and the concept of multi-scale sprawl analyses are discussed, and conclusions for potential applications derived from this work are provided in the final section.

Study area and image processing

Wuhan, the capital of Hubei province, is located in central China near the middle reaches of the Yangtze River. It comprises a downtown and six suburbs covering a total area of 8495 km^2 (Fig. 1). The landscape is primarily plains (39.3%), water (26.1%), and mountains (18.2%). The majority of plains except for in the urban extents are used for agriculture. The downtown is divided into three parts (Hankou, Hanyang, and Wuchang) by the Yangtze and Han Rivers. Wuchang is the provincial education and administrative center. Hankou is where the regional commercial, financial and local administrative district is located, and Hanyang is the industrial center. With the Yangtze and Han Rivers as well as the Beijing-Guangzhou Railway (BGR), Wuhan has become the transportation hub of China generating increasing social and economic growth (Cheng, Turkstra, Peng, Du, & Ho, 2006; Wuhan Municipal Statistics Bureau, 2013). As such, Wuhan has experienced accelerated urbanization since 1987 and has benefited from land transaction and economic reform policies. However, unceasing migration, construction, and economic growth have spurred unmitigated sprawl, which is threatening local social and ecological stability (Du, Ottens, & Sliuzas, 2010). Also, due to the dramatic economic and social development in downtown, urban–rural/suburban social gaps are observed. Therefore, the government and planners are now trying to reconfigure the city boundary expansion process and uncover its driving forces in order to moderate the rapid expansion and promote integrated urban–rural planning.

Multi-temporal Landsat (TM/ETM+) images taken from the US Geological Survey were adopted for deriving land-use information in the study (Table 1). Landsat ETM+ images taken during 2010, after the scan line corrector failed, were repaired with a self-adaptive local regression model (Lin & Bao, 2005). Preprocessing including geometric, atmospheric, and radiometric correction as well as mosaicking was performed using ENVI 4.8. Land-use datasets of Hankou, Dongxihu, Hannan, and Huangpi, provided by the Hubei Province Department of Land Resources (DLRH) were used to assess the UB extraction method.

Maximum likelihood classification (MLC) was employed for land-use classification. For generating a relatively high-quality classification, a Principal Component Rotation (PCR) and local statistics were used in the MLC as they have been shown to improve MLC results (Deng, Wang, Deng, & Qi, 2008; Ghinire, Rogan, & Miller, 2010). Specifically, the first three principal components of the original Landsat bands (with an accumulated variance of almost 0.9) were determined using PCR. Next, the Getis-Ord G_i index (Getis