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Examining spatiotemporally varying effects of urban expansion and the underlying driving factors

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ABSTRACT

In the context of rapid urbanization, the comprehensive analysis of urbanization process, urban expansion effects and the underlying driving factors have become increasingly crucial for providing support to the land management and urban planning decision. This study explores spatial metrics, geographically weighted regression (GWR), and cellular automata (CA) model, with a case study in Xuzhou city, China, to analyze the urbanization process. Spatial metrics were applied for quantifying the urban spatial patterns. The spatiotemporally varying effects of urban expansion on spatial patterns were further investigated using GWR. By involving natural and socioeconomic variables, CA model was applied to examine the relationship between driving factors and urban expansion. The results indicate that the spatial patterns of Xuzhou have significantly changed along with the urbanization process. The parameters obtained from GWR imply that the effects of urban expansion on spatial patterns are spatiotemporally varying. CA model helps in better understanding the effects of the considered factors on urban expansion by reproducing historical urban expansion process. The findings provide an effective way to better understand the urbanization process, and to aid the decision making for urban land management.

1. Introduction

In recent decades, urbanization has been accelerating with the massive immigration of population to cities especially in developing countries (Han, Hayashi, Cao, & Imura, 2009). The world urban population was only about 3% of the global population in the 1800s, but increased to nearly 30% in 1950. Currently, over half of the world population live in urban areas, and the figure is projected to reach 67.1% (6.25 billion) by 2050 (United Nations, 2012). Land cover dynamics constitute an important component of the human dimension of global change (Turner et al., 1990). Although urban areas make a very small percentage of the Earth's land surface area, their rapid expansion can mark significant effects on environment. such as loss of natural vegetation and farmland (Tan, Li, Xie, & Lu, 2005), local and regional climate change (Kaufmann et al., 2007), decline in biodiversity (Zimmermann, Tasser, Leitinger, & Tappeiner, 2010), hydrological circle alternation (Barron, Barr, & Donn, 2013), etc.

The comprehensive analysis the effects of the urban expansion has become increasingly important for providing support to the land management and urban planning decision aimed at sustainable development (Dubovyk, Sliuzas, & Flacke, 2011). It is widely acknowledged that urban expansion alters the spatial structure of land use pattern within a region (Jenerette & Wu, 2001). Studies on the qualitative relationships between urban expansion and spatial patterns have demonstrated that urban expansion plays an important role in urban spatial patterns (Deng, Wang, Hong, & Qi, 2009; Weng, 2007). Most of them, however, only focused on describing the characteristics of spatial patterns and their relationships with underlying determinants for the whole study area, and failed to address the spatial heterogeneities in the effects of driving factors on spatial patterns in response to urbanization. In addition, analyzing the change of spatial patterns for one period would overlook the fact that an area experiencing the most intense urbanization is not necessarily static, but could shift its location within the urbanization process, so that the characteristics of urbanization process cannot be fully captured. In order to address these gaps in previous studies and to effectively capture and analyze the urbanization process, it is necessary to explore the quantitative

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relationships between urban spatial patterns and urban expansion while taking into account the spatiotemporal dynamics of driving factors. Geographically weighted regression (GWR) has been developed and widely used to explore spatially varying relationships (Brunsdon, Fotheringham, & Charlton, 1996; Fotheringham, Charlton, & Brunsdon, 2001; Sheehan, Strager, & Welsh, 2012). Local rather than global parameters can be estimated for analyzing the spatial dynamics of effects of urban expansion on spatial patterns.

Urban expansion is a complicated process which involves the spatial and temporal complexity of various natural and socioeconomic factors. Many methods have been proposed and used to identify a set of variables that explain urban expansion and quantify the effects of driving factors, including logistic regression (LR) (Li, Zhou, & Ouyang, 2013), multiple linear regression (MLR) (Seto, Fragkias, Güneralp, & Reilly, 2011), artificial neural networks (ANNs) (Li & Yeh, 2002), analytic hierarchy process (AHP) (Thapa & Murayama, 2010). Of these methods, the most widely used is logistic regression, which is simple and effective method to handle binary dependent variables. However, it has become common knowledge that urban development is a complex dynamic process (Torrens, 2000), which involves various physical, social, and economic factors. The complexity occurs from the unknown amount of factors, the complex neighborhood interactions and their unpredictable dynamics. The logistic regression model suffers from the spatial complexity and temporal analysis (Hu & Lo, 2007). The output map can only suggest where urban expansion will take place, but not when this will occur. In addition, the neighborhood interaction and the stochastic disturbance involved in the complex system are also ignored in logistic regression model. Cellular automata (CA) models are dynamic models for simulating the evolution of a system using local transition rules (Barredo, Kasanko, McCormick, & Lavalle, 2003). They are able to handle large amounts of data and many fields of studies, such as population, economic activity and employment, land use and transport (Batty, 2005). CA models can be used not only to simulate future scenarios but also to reveal the underlying relationship between urban expansion and driving factors (Santé, Marcía, Miranda, & Crecente, 2010). In contrast to LR, the temporal and spatial complexity of urban growth process can be well interpreted and modelled using CA models (White & Engelen, 2000).

This study aims to enhance the understanding of the effects of urban expansion on spatial patterns and the underlying driving factors through the integration of spatial metrics, GWR and CA models, with a case study of Xuzhou city in China. For this purpose, a set of selected spatial metrics are applied to quantify the urban spatial patterns to improve the representation of urban spatial characteristics. GWR model was used to investigate spatiotemporally varying effects of urban expansion on spatial patterns. CA model were applied to explore the relationships between driving factors and urban expansion.

2. Study area and material

2.1. Study area

Xuzhou city (between latitudes 33°43′N and 34°58′N, longitudes 116°22′E and 118°40′E) is situated in the plains of the Yellow River and the Huaihe River. It has a total administrative area of approximately 11,258 km^2, with 1160 km^2 as the city proper area. It is regarded as a medium-sized metropolitan area in comparison to other cities in China. As shown in Fig. 1, the study was conducted within the Xuzhou city, in which Jiawang and Tongshan are composed of fringe and rural areas. Mining and industrial manufacturing have been the source of the strong economic activity of the region. Xuzhou city is well known as one of the most important transportation hubs in China. Jinghu Railway (Beijing to Shanghai), Longhai Railway (Lianyungang to Lanzhou), and some other national main roads provide a good opportunity for development. Benefiting from its industrialization, dramatic changes in local economy have taken place in recent decades. Gross Domestic Product (GDP) of Xuzhou city increased from 2.1 billion RMB in 1979 to 294.2 billion RMB in 2010. Its GDP ranked 37th compared to other cities in China.

2.2. Data

In this study, Landsat images from the years of 1990, 2001, 2005 and 2010, were used to obtain multi-temporal land cover data for Xuzhou city. The land cover classification data was produced through the interpretation from Landsat data (Li & Thinh, 2013). Fig. 2 shows the multiple temporal land cover maps at the extent of the study area with the overall accuracy of more than 85%. The urban land increased from 174.6 km^2 in 1990 to 566.9 km^2 in 2010.

The urban expansion is a complex process which involves the interaction influence of various factors. Some variables need to be incorporated into the model, which include: (1) global suitability factors: distance to district centers (Dis2Cens), distance to major roads (Dis2MajR), distance to minor roads (Dis2MinR), slope (SLOPE), population density (PopDen), layout of potential subsidence areas (Subsidence), and layout of environmental protection areas (Environment); (2) neighborhood variable. However, the estimated coefficients of these variables could be misleading in analysis of urbanization process when the variables are measured in different units. Therefore, all variables should be standardized into the range from 0 to 1 prior to the modeling. For global suitability factors, linear transformation method was applied to conduct the standardization. For spatial policy factors, the area where urban development is limited was assigned 0 and area that is designated for urban development was assigned 1. All the spatial data were registered to the same Universal Transverse Mercator (UTM) coordinate system and sampled to the same cell size of 100 m*100 m, which was sufficient to capture the detailed information about urban dynamics while keeping the volume of computation manageable.

3. Methods

3.1. Spatial pattern analysis

In order to describe and analyze the urban spatial pattern, several landscape metrics were calculated using Fragstats 4 (McGarigal, Cushman, & Ene, 2012). Built-up was defined as urban land, while farmland, vegetation and water body were reclassified into non-urban land. According to the objectives of this study, we chose three class-level metrics which are sensitive to the changes in fragmentation and irregularity of urban area.

Number of Patches (NP) is a simple quantification of the amount of individual urban patches. It provides information on the amount of new developed patches during certain period. Largest Patch Index (LPI) reflects the percentage of the area of the largest urban patch. The LPI value of 100 is obtained when entire urban class consists of a single urban patch. The increase in LPI indicates urban areas become more aggregated and integrated with the urban cores (Pham, Yamaguchi, & Bui, 2011). Mean Shape Index (SHAPE_MN) measures complexity of urban patches by a perimeter-area proportion. SHAPE_MN = 1, when a corresponding patch has a compact square form with a relatively small perimeter relative to the area. If the patches are more complex and fragmented, the perimeter increases and yields a higher fractal dimension.