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Report

Spatiotemporally Varying Relationships between Urban Growth Patterns and Driving Factors in Xuzhou City, China

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Keywords: remote sensing, urban growth patterns, spatial metrics, geographically weighted regression, spatiotemporal heterogeneity

Summary: Urban spatial patterns are usually affected by different factors in urbanization processes. Scientific interpretations of the effects of underlying determinants of spatial patterns are important for a better understanding of urban developments. However, only few studies have quantitatively examined the spatiotemporal relationships between spatial patterns and driving factors. This study explores the use of remote sensing (RS), spatial metrics and geographically weighted regression (GWR), with a case study in Xuzhou city, China, to analyse the spatial patterns of urban growth as well as their spatiotemporally varying relationships with three driving factors (1) slope, (2) distance to major urban centres, and (3) distance to major roads. The historical urban growth from 1990 to 2010 was derived from multi-temporal remote sensing images. Spatial metrics were used to quantify the urban growth patterns for different periods. The effects of the factors on urban growth patterns were further investigated using GWR. The results indicate that the spatial patterns of Xuzhou have significantly changed along the urbanization process. GWR performs better than ordinary least squares (OLS) in interpreting the relationships indicated by higher adjusted R^2, lower corrected Akaike information criterion (AICc) values and reduced spatial autocorrelations of residuals. The parameters of the driving factors obtained from GWR indicate that their effects on spatial patterns are spatiotemporally varying. The findings help in better understanding the effects of the considered factors on spatial patterns, as well as to provide support for urban planning and management.

Zusammenfassung: *Raumzeitliche Beziehungen zwischen Einflussfaktoren und Stadtwachstum in Xuzhou City, China*. Unterschiedliche Faktoren beeinflussen städtische Flächennutzungsmuster im Urbanisierungsprozess. Gesicherte Erkenntnisse über Einflussfaktoren der Flächeninanspruchnahme sind wichtig für die Stadtentwicklungsplanung. Unser Beitrag beschreibt die Klassifizierung der Flächennutzung der chinesischen Stadt Xuzhou in fünf Flächennutzungsarten anhand der Landsat-Bilder für die drei Zeitpunkte 1990, 2001 und 2010, die anschließende Berechnung von raumstrukturellen Indizes (Class Area, Number of Patches, Mean Shape Index, Largest Patch Index, Area Weighted Mean Euclidean Nearest Neighbour Distance, Edge Density) und die Untersuchung der raumzeitlichen Beziehungen zwischen den drei ersten Kennzahlen und drei treibenden Faktoren der Flächennutzungsänderungen: (1) Steigung, (2) Entfernung zu urbanen Zentren, und (3) Entfernung zu Hauptstraßen. Die Herausarbeitung der raumzeitlichen Beziehungen erfolgt unter Einsatz der geografisch gewichteten Regression (Geographically Weighted Regression, GWR) und der Methode der kleinsten Quadrate (Ordinary Least Squares, OLS), wobei GWR die Zusammenhänge zwischen den genannten Faktoren und Indizes besser erklärt als OLS. Die GWR-Ergebnisse belegen, dass der Einfluss der Faktoren auf das Raummuster räumlich und zeitlich variiert. Dies gilt es bei künftigen Stadtentwicklungen zu beachten.

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1 Introduction

Urbanization has been a universal and important social and economic phenomenon taking place all around the world (Deng et al. 2009). During the past decades, urban growth has been accelerating with the significant increase in urban population, and this process is expected to continue to be one of the crucial issues of global change in the future, especially in less developed regions (Sui & Zeng 2001). Urbanization alters the spatial structure of land use within a region (Jenerette & Wu 2001), which has resulted in a series of environmental problems such as the loss of natural vegetation, loss of open spaces, appearance of heat island effect, and general decline in the spatial extent and connectivity of wetlands and wildlife habitat, which threaten sustainable urban development (Gao & Liu 2010).

Recently, the efforts to understand spatial patterns and mechanisms, and the effects of urbanization have been highlighted. Here the analysis of spatial patterns can help to better understand the urban growth process and to make policy decisions (Dietzel 2005, Schwarz 2010, Thinh et al. 2002). Studies on the qualitative relationships between urbanization and spatial growth patterns have demonstrated that human induced factors play an important role in urban growth patterns (Deng et al. 2009, Kong & Nakagoshi 2006, 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 relationships between urban growth patterns and driving factors while taking into account the spatiotemporal dynamics of driving factors.

Satellite imagery is the most common data source for detection, quantification and mapping of land cover change patterns (Yuan et al. 2005). It provides a cost and time effective tool for obtaining great amounts of multi-temporal information on the geographic distribution of land cover (Dewan & Yamaguchi 2009). Spatial metrics are widely used to quantify the pattern of an urban area by computing them directly from thematic maps (Herold et al. 2005). The temporal variations of spatial metrics have a potential to improve the levels of interpretation and assessment of urbanization processes and thus to contribute to a better understanding of spatial pattern changes, as well as of potential impacts on the environment and ecosystem (Dietzel et al. 2005).

Geographically weighted regression (GWR) has been developed and widely used to explore spatially varying relationships (Brunsdon et al. 1996, Fotheringham et al. 2001). Local rather than global parameters can be estimated for analyzing the spatial dynamics of effects of driving factors on urban patterns.

This study aims at enhancing the understanding of urban growth patterns and the spatiotemporally varying effects of the driving factors on urban growth patterns through the integration of remote sensing, spatial metrics, and GWR, with a case study of Xuzhou city in China. For this purpose multi-temporal land cover data is derived from remote sensing images. A set of selected spatial metrics is computed for the detailed analysis of urban growth patterns and to improve the representation of urban spatial characteristics. GWR methods have been developed to investigate spatiotemporally varying relationships between urban growth patterns and their related factors.

2 Material and Methods

2.1 *Study Area and Data*

Xuzhou city in China is located in eastern part of China (Fig. 1), in the plains of Yellow River and Huaihe River, with an administrative area of 11,258 km². It is regarded as a medium-sized metropolitan area in comparison to other cities in China. Xuzhou city is composed of five districts (Quanshan, Gulou, Yunlong, Jiawang and Tongshan), in which the first three districts are viewed as the city core. Main land cover types are built-up land, farmland, vegetation, and water body. The study area covers the main urban area of Xuzhou city and suburban fringe, with the area of around 2,897 km^2 and the population of over 3 million inhabitants in 2010.

In this research Landsat images for 1990, 2001 and 2010 were obtained from the U.S. Geological Survey (USGS) and used for land cover classification. It is widely acknowledged that spatial pattern analysis is sensitive to the spatial resolution of the image data used for mapping (Weng 2007, Wu 2004). In this study, small urban patches (smaller than 900 m^2) could not be recognized in Landsat data with the spatial resolution of 30 m. This leads to the underestimation of the amount of urban patches and total areas. In addition, the mixed pixel problem, caused by medium resolution, contributes to the low accuracy of the classification results, hereby, affecting the spatial metrics values. However, the settlements in urban fringes of Xuzhou city are typically small-sized but numerous. These settlements are not important to study, but could cause noises in analyzing the urban spatial patterns. By employing the medium resolution Landsat data, this noise can be avoided. Therefore, the spatial resolution of Landsat data seems quite suitable to analyze the urban spatial patterns in this study.

Before the classification process, an atmospheric correction technique called cosine of the sun zenith angle (COST) was applied (Chavez 1988). After the atmospheric correction, all images were georeferenced using well distributed ground control points (GCPs) and topographic maps. A second order polynomial was applied, resulting in root-mean-square errors (RMSE) less than 0.75 pixels. The images were resampled to a pixel size of 30 m × 30 m using the nearest neighbour algorithm to maintain the radiometric properties of the original data. The image processing was performed using ERDAS IMAGINE 2011 software.

A digital elevation model (DEM) at a spatial resolution of 30 m, acquired from the global land cover facility (GLCF), was used to represent topography. Slope gradients were derived from the elevation surface. The major road networks (1990, 2000, and 2010) were collected from Xuzhou Urban Planning Bureau for the further analysis.

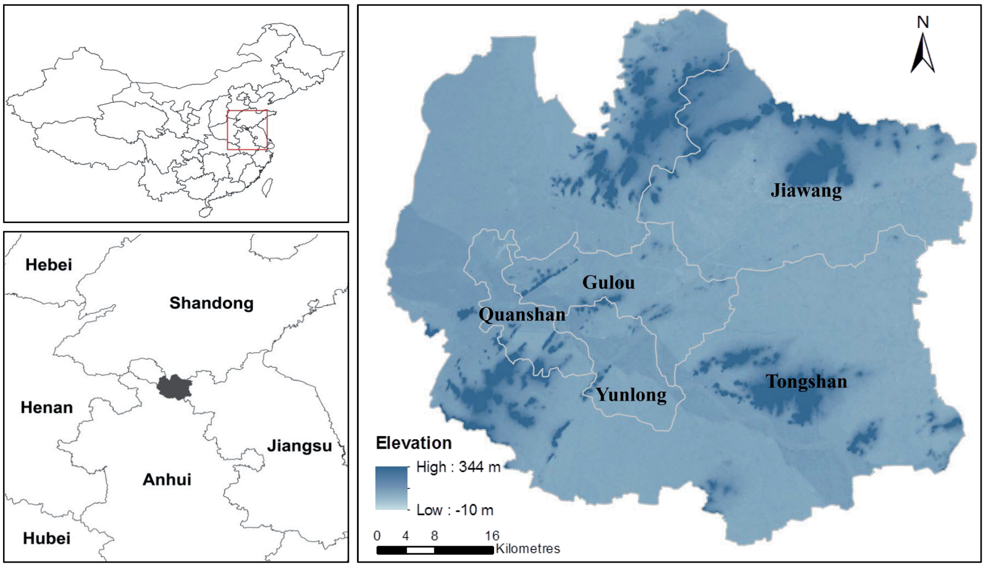

Fig. 1: The study area.

2.2 *Land Cover Classification*

A maximum likelihood classifier (MLC) was selected to classify the Landsat images into four categories: built-up land, farmland, vegetation and water body. Post classification refinement was used to improve the accuracy of the classification. For this study, farmland was not expected to be found in areas with slopes higher than 10 degree. Therefore, the farmland pixels with slopes higher than 10 degree were reclassified as vegetation. The tasseled cap transformation (TCT) is a conversion of the original bands of an image into a new set of bands with defined interpretations that are useful for vegetation mapping (Dymond et al. 2002, Li & Thinh 2013). The built-up and bare soil areas have higher values compared with other classes in the brightness band. In the greenness band the built-up land has lower values, whereas the areas covered by green vegetation have higher values. In the wetness band the water bodies have higher values. Therefore, we defined specific thresholds to distinguish different classes in each band generated by TCT. In addition, a 3×3 majority filter was applied to remove salt and pepper appearances in the images.

In order to check whether the results are suitable for the spatial pattern analysis, an error matrix was calculated to assess the accuracy of the classification. The set of necessary reference data included topographic maps and field survey data. A total of 300 random points generated by stratified random sampling method were adopted to assess classification accuracy. Finally, the classified data and reference data were compared and statistically represented in the error matrix.

2.3 *Spatial Patterns Analysis*

Tab. 1 provides a description of the spatial metrics used in the study. The selection of the metrics was based on the research objective and their values in representing specific spatial characteristics as explored in previous studies on urban areas (Herold et al. 2005, Luck & Wu 2002, Schwarz 2010). SHAPE_AM was

Tab. 1: Description of the spatial metrics used in this study (McGarigal et al. 2012).

Spatial metrics	**Abbreviation**	**Description**
Class area	CA	The sum area (m²) of all urban land use patches, divided by 10,000.
Number of patches	NP	Total number of urban patches.
Largest patch index	LPI	The percentage of the area of the largest urban patch to the total area of the investigation.
Edge density	ED	The ratio of total edge of urban patches to total landscape area.
Shape index (Area weighted mean shape index/Mean shape index)	SHAPE (SHAPE_AM/ SHAPE_MN)	The index describes the complexity of the patch shape. It uses patch area as a weighting factor. It equals 1 if the patch has a square shape and increases as the irregularity of the shape increases. SHAPE_AM averages the shape index of the patches by weighting patch area so that larger patches weigh more than smaller patches. SHAPE_MN equals the sum of shape index of the patches divided by the number of patches of the same type.
Euclidean nearest-neighbour distance (Area weighted mean Euclidean nearest-neighbour distance)	ENN (ENN_AM)	ENN equals the distance (m) to the nearest neighbouring patch of the same type, based on shortest edge-edge distance. ENN_AM averages the ENN index of the patches by weighting with the patch area size.

used for the general description of the urbanization pattern in order to improve the measure of class patch fragmentation as the structure of smaller patches is often determined more by the image pixel size than by characteristics of natural or manmade features found in the landscape (Milne 1991). The higher the value of the ENN (Euclidean nearest neighbour), the greater is the isolation of the patches. In order to consider the different influence of patches according to the areas, ENN_AM is calculated by incorporating patch area size weighting. Since the study focuses on urban growth, the land cover maps were reclassified into two classes: urban and non-urban. Built-up was defined as urban land, while farmland, vegetation and water body were reclassified into non-urban land. The spatial metrics associated with sustainability were calculated using Fragstats 4 (McGarigal et al. 2012).

2.4 *Variables Calculation*

Investigation of the relationships between urban growth patterns and their related factors were performed on a block basis. The square block, the most commonly used shape for spatial pattern analysis (Luck & Wu 2002, Weng 2007), was applied in this study. A preliminary test of the effects of block size on spatial pattern analysis was carried out considering sizes of 1 km, 2 km, 3 km and 5 km. A block size of 2 km was chosen because it retains more details of the spatial pattern than a larger block size does. A block size of 1 km could lead to the situation that no urban patch or only a few urban patches exist in some blocks, which generates noise in the spatial pattern analysis. Therefore, the study area was firstly divided into several square blocks of 2 km × 2 km. The selected metrics (CA, NP, SHAPE_MN in Tab. 1) being suitable at local level, were then calculated for each block to measure the urbanization intensity, fragmentation and irregularity of urban area. After obtaining metrics values for the 1990, 2001 and 2010 data, the changes of metrics were calculated for each block.

Urban growth patterns are the result of the complex interaction of physical, environmental and socioeconomic factors. Slope has been considered as a major factor in several studies on land use change (Aspinall 2004, Dubovyk et al. 2011, He et al. 2006, Hu & Lo 2007, Li et al. 2013, Sui & Zeng 2001). Slope can speed up or slow down the process of urban development as the costs of land development can increase as the slope increases (Aspinall 2004). Socioeconomic development is one of the most important driving factor of urban growth patterns and can best be characterized by the access that a location has to important facilities (He et al. 2006, Li et al. 2013, Verburg et al. 2004). The significant effects of distance to major urban centres on urban growth patterns have been confirmed by several studies (Aspinall 2004, Batisani & Yarnal, 2009, Cheng & Masser 2003, Dubovyk et al. 2011, Hu & Lo 2007, Li et al. 2013, Long et al. 2012, Reilly et al. 2009, Sui & Zeng 2001, Verburg et al. 2004). Transportation plays an indispensable part in urban patterns because a good transportation increases the accessibility of land and decreases the cost of construction (Reilly et al. 2009). Therefore, distance to major roads has been used as a driving factor by many researchers (Cheng & Masser 2003, Dubovyk et al. 2011, He et al. 2006, Hu & Lo 2007, Li et al. 2013, Long et al. 2012, Reilly et al. 2009, Sui & Zeng 2001, Verburg et al. 2004). In this study, distance to major urban centres (abbreviation: Dis2urban) and distance to major roads (abbreviation: Dis2road) were used to represent socioeconomic factors. The gross domestic product (GDP) and population were not considered as their spatial resolutions are much coarser than that of other variables used in this study.

Coefficients could be misleading, if the underlying variables are measured in different units. For comparing the impacts of different variables on the urban spatial patterns, a linear membership function method was adopted to implement the standardization. The variable with the highest value was assigned 1, and the lowest value was assigned 0.

2.5 *Geographically Weighted Regression*

GWR is an extension of global regression method such as OLS (ordinary least squares), and can be used to explore the spatially varying relationships between explanatory variables and spatial patterns by generating a set of local-specific coefficients (Brunsdon et al. 1996, Fotheringham et al. 1996, Fotheringham et al. 2001). In contrast to traditional regression method, GWR is conducted using localized points within geographic space. Thus, instead of producing a single average parameter for each relationship, GWR has a potential to produce a set of local parameters that can be mapped to get insight into hidden possible causes of this pattern.

The GWR model can be expressed as:

$$y_i = a_0(\mu_i, v_i) + \sum_k a_k(\mu_i, v_i) x_{ik} + \varepsilon_i \tag{1}$$

Where (μ_i, v_i) represents the coordinate location of the i^{th} point. $a_0(\mu_i, v_i)$ and $a_k(\mu_i, v_i)$ express the intercept and local parameter estimate for an independent variable x_{ik} at location i, respectively. ε_i is the random error term for location i.

In GWR, the parameters for each observation at location i can be estimated by weighting all observations around a specific point i according to their spatial proximity, which is calculated by the Euclidean distance in this study. The observations which are spatially closer to the location i will have a greater impact on the local parameters for the location than those which originate at more distant points. Gaussian distance decay can be used to express the weighting function:

$$w_{ij} = \exp\left(\frac{d_{ij}^2}{h^2}\right) \tag{2}$$

Where w_{ij} represents the weight of observation j for location i. d_{ij} is the Euclidean distance between points i and j. h is a kernel bandwidth that affects the distance-decay of the weighting function. There are three choices of the bandwidth method: corrected Akaike information criterion (AICc), cross validation (CV) and bandwidth parameter. If the bandwidth is known a priori, bandwidth parameter could be applied. If it is unknown, the first two types allow for using an automatic method to find the optimum bandwidth. In this study, the AICc method was used for the GWR model. The AICc method finds the bandwidth which minimises the AICc value: the model with lowest AICc values suggests a stronger ability of a regression model in reflecting reality.

For the comparison purpose, we also employed OLS models to investigate the relationships between spatial patterns and explanatory factors. Three statistical parameters were used to compare the performance between GWR and OLS: adjusted R^2, AICc, and Moran's I. Adjusted R^2 and AICc measures provide some indications of the goodness of fit of the corresponding model. Higher adjusted R^2 values indicate that more variances can be explained for dependent variables. Moran's I is widely used as an indicator of spatial autocorrelation (range: -1 to 1). Large absolute values of Moran's I indicate that spatial autocorrelation is more significant. Residuals are the differences between observed and predicted values. We employed Moran's I value to examine spatial autocorrelation in the residuals.

3 Results

3.1 *Spatial Patterns Analysis*

The overall accuracies calculated for 1990, 2001, and 2010 were 86.4%, 87.7%, and 88.3%, respectively (Tab. 2). Urban landscape is a complex combination of different land covers. In this study, mixed pixel problems were found between built-up land and vegetation categories. In addition, some farmlands without crop were misclassified as built-up due to their spectral similarities. The producer's and user's accuracy of built-up land cover are consistently high, ranging from 85.0% to 88.7% and meet the minimum USGS total accuracy set out by Anderson et al. (1976). Hence, the classified results are considered suitable as data source for spatial pattern analysis. The multi-temporal land cover classification maps for Xuzhou city are shown in Fig. 2.

Tab. 3 presents spatial metrics values from 1990 to 2010. The CA value of Xuzhou city shows a rapid urbanization process between 1990 and 2010 (see also Fig. 2). The allocation of urban area included both the developing outward from the original city core and the growth of new individual urban patches, which is illustrated by the increases in both

Tab. 2: Summary of Landsat classification accuracies (%) for 1990, 2001, and 2010.

Land cover class	1990		2001		2010	
	Producer's	User's	Producer's	User's	Producer's	User's
Built-up	85.0	87.9	87.1	85.7	88.7	87.5
Farmland	89.0	85.8	90.2	87.5	89.1	89.8
Vegetation	79.2	82.4	81.8	88.2	81.1	86.0
Water body	88.2	90.0	88.2	90.0	93.6	88.0
Overall accuracy	86.4		87.7		88.3	

Tab. 3: Spatial metrics derived from the land cover classification maps.

Date	CA	NP	LPI	ED	SHAPE_AM	ENN_AM
1990	27636	2345	1.8253	12.7665	3.4157	297.0055
2001	38559	2412	3.7846	15.4546	5.2129	275.0119
2010	54938	2509	7.0688	19.5735	8.4627	246.3587

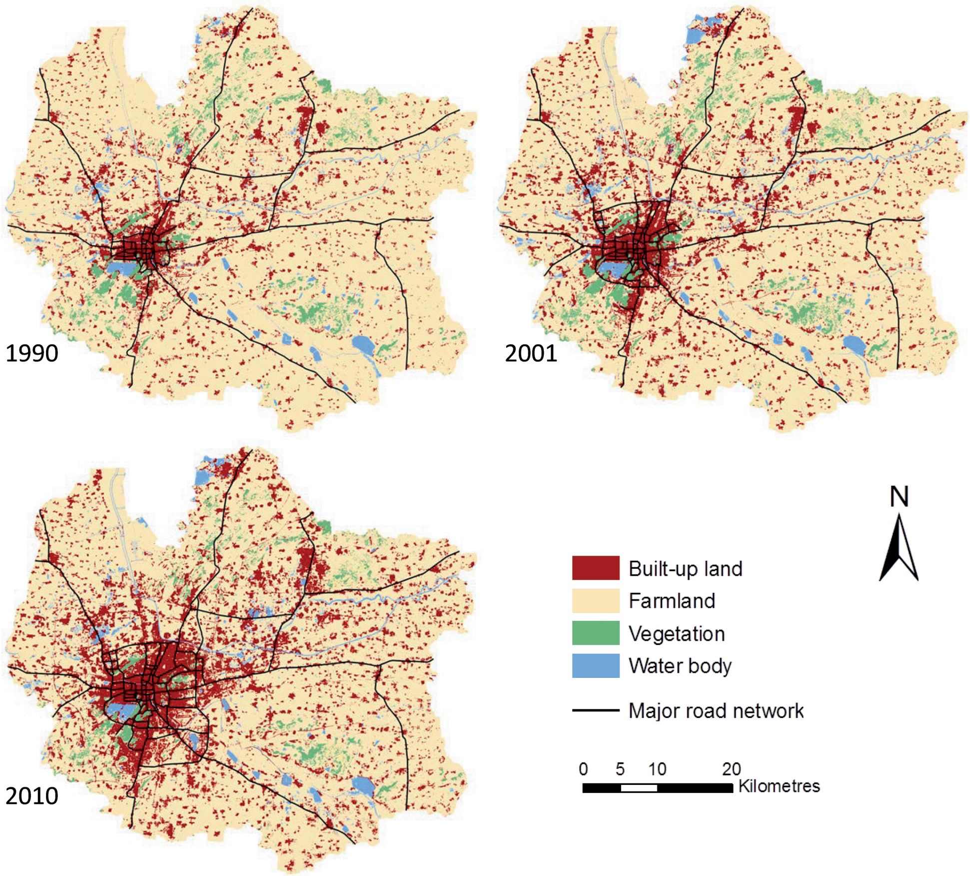

Fig. 2: Multiple temporal land cover classification maps.

metrics: LPI and NP. The development of new individual urban patches created more edges, which leads to the increase in ED value. Some individual urban patches continued to grow together to form larger patches, the connection of individual urban patches increased, according to the decreasing ENN_AM value. It also implies the significant loss of open space between urban patches. As the increasing rapid urbanization process, Xuzhou's irregular and fragmented growth is illustrated by the continuous increasing of SHAPE_AM, NP, and ED.

Changes of spatial metrics across the study area are shown in Fig. 3. The variations of spatial metrics show spatiotemporal heterogenei-

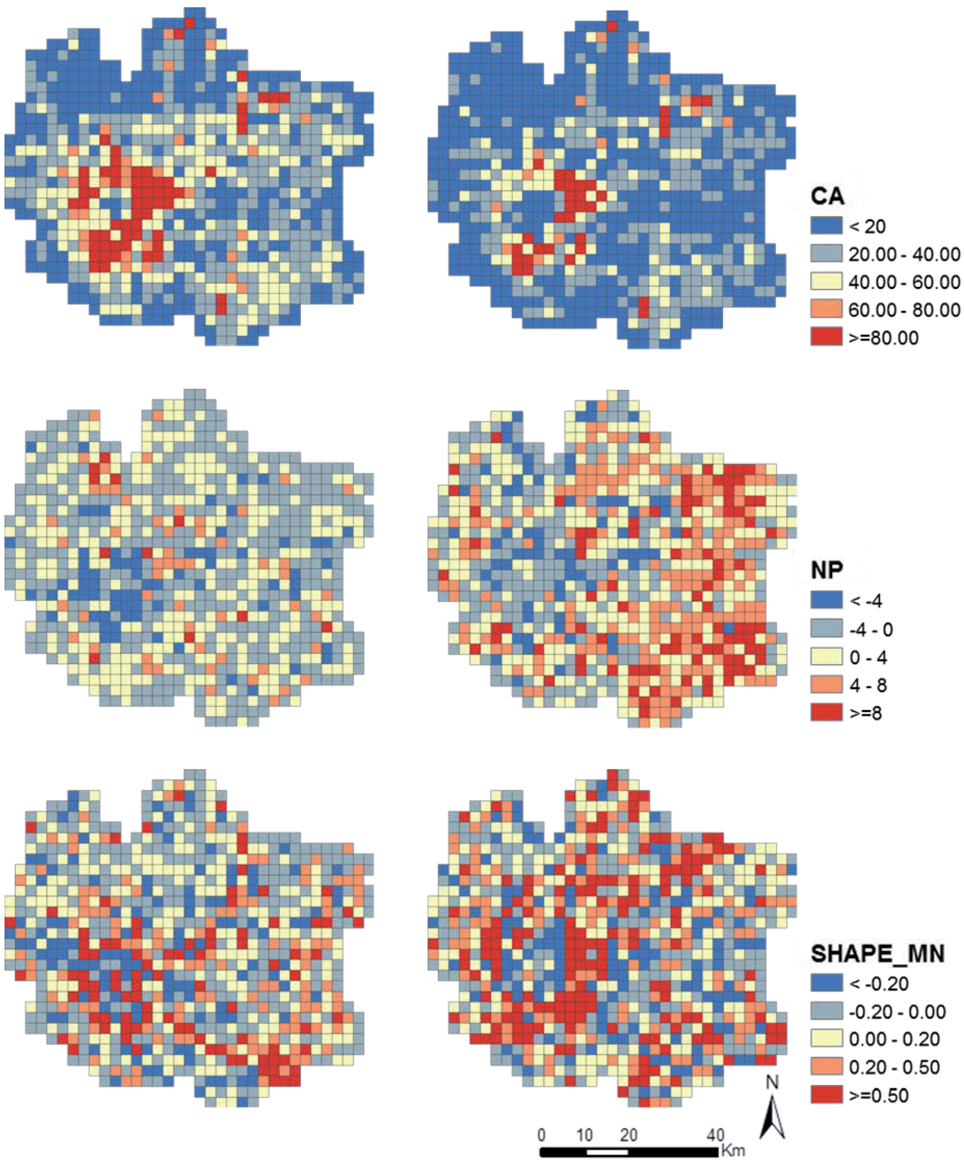

Fig. 3: Changes of spatial metrics selected in this study for 1990 – 2001 (left column) and 2001 – 2010 (right column) (CA = class area, NP = number of patches, SHAPE_MN = mean shape index).

ties. Moreover, the variations of spatial patterns can, in considerable parts, be explained by selected factors. For example, most of the blocks with significant growth of CA values are found around the city core, and the significant decrease of NP values are also observed around the city core.

3.2 *Comparison between OLS and GWR Models*

OLS models only provide one statistical average parameter for the whole study area, whereas the GWR results show variables changes throughout the study area. The adjusted R^2 and AICc values generated by GWR and

Tab. 4: Comparison of adjusted R^2 between GWR and OLS for two periods.

		1990 – 2001			2001 – 2010		
		CA	NP	SHAPE_MN	CA	NP	SHAPE_MN
Dis2urban	Adjusted R^2G	0.523	0.443	0.470	0.474	0.466	0.449
	Adjusted R^2O	0.136	0.175	0.101	0.119	0.079	0.047
Dis2road	Adjusted R^2G	0.560	0.566	0.525	0.463	0.444	0.427
	Adjusted R^2O	0.099	0.057	0.075	0.002	0.007	0.001
slope	Adjusted R^2G	0.509	0.349	0.581	0.461	0.474	0.423
	Adjusted R^2O	0.114	0.017	0.107	0.050	0.012	0.025

R^2G is the R^2 for GWR model; R^2O is the R^2 for OLS model.

Tab. 5: Comparison of AICc between GWR and OLS for two periods.

		1990 – 2001			2001 – 2010		
		CA	NP	SHAPE_MN	CA	NP	SHAPE_MN
Dis2urban	AICcG	6182.2	3957.6	4735.5	7388.5	5128.9	6003.2
	AICcO	6590.6	4064.8	4888.0	7804.5	5541.6	6317.0
Dis2road	AICcG	6170.3	3949.2	4771.1	7403.9	5144.4	6022.2
	AICcO	6622.5	4051.4	4901.5	7804.0	5536.4	6360.5
slope	AICcG	6256.6	3981.7	4812.9	7408.5	5124.5	6030.0
	AICcO	6703.4	4089.5	4901.7	7802.0	5532.3	6340.3

AICcG is the AICc for GWR model; AICcO is the AICc for OLS model.

Tab. 6: Comparison of Moran's I of residuals between GWR and OLS for two periods.

		1990 – 2001			2001 – 2010		
		CA	NP	SHAPE_MN	CA	NP	SHAPE_MN
Dis2urban	Moran's IG	0.175	0.071	0.189	0.054	0.044	0.012
	Moran's IO	0.402	0.258	0.396	0.517	0.550	0.436
Dis2road	Moran's IG	0.095	0.012	0.119	0.069	0.081	0.013
	Moran's IO	0.578	0.390	0.560	0.518	0.544	0.435
slope	Moran's IG	0.120	0.147	0.048	0.073	0.053	0.027
	Moran's IO	0.611	0.421	0.589	0.505	0.547	0.435

Moran's IG is the Moran's I for GWR model; Moran's IO is the Moran's I for OLS model.

OLS models for different periods are shown in Tabs. 4 and 5. For all cases in the different periods, the GWR results are characterized by higher R^2 and lower AICc values compared to the corresponding OLS models. The comparison of these two indicators suggests that GWR models perform better than OLS models in investigating the relationships between urban spatial patterns and related factors. The results obtained from GWR indicate that the variations of selected spatial metrics are significantly associated with the explanatory factors.

Moreover, Tab. 6 summarizes the Moran's I statistics on the models residuals from GWR and OLS. Significant positive spatial autocorrelations are found in all OLS models, which are characterized by higher Moran's I values ranging from 0.258 to 0.611. In contrast, the Moran's I values of GWR models range from 0.012 to 0.189. This indicates that GWR models can improve the expressiveness of relationships by effectively reducing spatial autocorrelations in residuals.

3.3 *Spatiotemporal Heterogeneity of Relationships between Spatial Patterns and Driving Factors*

The GWR model generated a set of parameters for the blocks for each period, which can be used to analyse the spatiotemporally varying effects of the driving factors on urban growth patterns (Figs. 4–6).

Clear relationships between the variations of CA values and three driving factors can be identified (Fig. 4). Dis2urban and Dis2road showed significant negative correlations with the variations of CA near the city core and roads for the period of 1990 – 2001. It suggests that greater urbanization intensity was strongly related to shorter distance to major urban centres and roads within a certain extent, with stronger explanatory power indicated by local R^2. However, the effects of these factors decreased or transformed to positive influence when extending to a certain distance. Slope is also an important factor that can explain more than 30% of the variations of CA outside the city core, whilst it explained less in the city core. Compared to the former period, Dis2urban and Dis2road had positive effects on CA values in a larger area in 2001 – 2010. Furthermore, significant positive influence was found in the area around the city core and roads. This indicates that the rise in distance to centres and roads up to a certain extent can cause

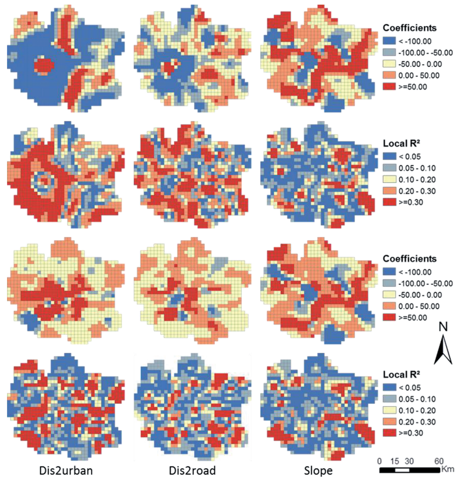

Fig. 4: Spatial distributions of the coefficients and local R^2 for CA. Figures in the two upper rows show the results for 1990 – 2001 and figures in the two lower rows show the results for 2001 – 2010 (CA = class area, NP = number of patches, SHAPE_MN = mean shape index).

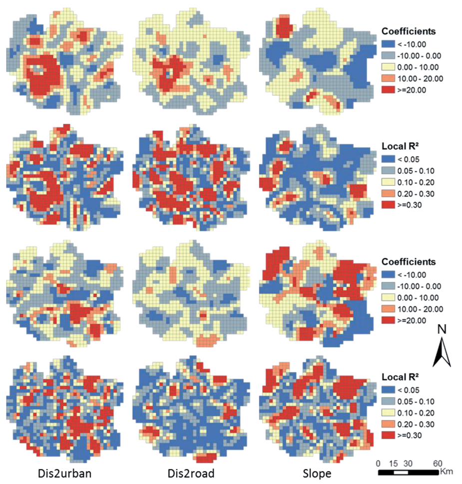

Fig. 5: Spatial distributions of the coefficients and local R^2 for NP. Figures in the two upper rows show the results for 1990 – 2001 and figures in the two lower rows show the results for 2001 – 2010.

a considerable increase in urbanization intensity. The effects of slope on the variations of CA were similar to the former period.

Fig. 5 exhibits both, the positive and negative correlation between the variations of NP and the explanatory factors. In 1990 – 2001, stronger effects of Dis2urban on the variations of NP as well as higher local R^2 were located around the city core, while negative and weaker relationships and lower local R^2 values were found outside the city core. Dis2road had a similar effect on the variations of NP values. The results indicate that the increase in distance to urban centres and roads can lead to more fragmented pattern. Compared to other factors, slope had less significant influence on the fragmentation (lower adjusted R^2 and local R^2, Tab. 2). For the period 2001 – 2010, an increase in distance to the new urban centre had a direct influence on the variations in NP values, whilst weaker correlations with Dis2urban were found around the former city core in 2001 – 2010. Dis2road had a weaker impact on the variations in NP values, according to the coefficients and local R^2. In contrast to the weaker effect of slope in the former period, both significant positive and negative effects were observed in 2001 – 2010. The variations of NP in areas with higher slope received more

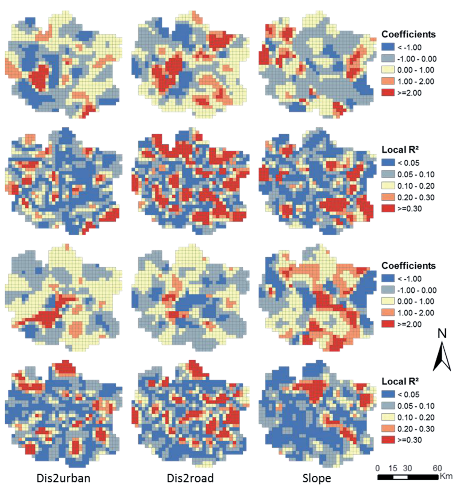

Fig. 6: Spatial distributions of the coefficients and local R^2 for SHAPE_MN. Figures in the two upper rows show the results for 1990 – 2001 and figures in the two lower rows show the results for 2001 – 2010.

significant impact from the factor of slope, where the effects of road and urban centres could almost be neglected.

The spatially varying relationships between the SHAPE_MN values and the three explanatory factors were identified through the GWR model (Fig. 6). A more significant effect of Dis2urban on the variations of SHAPE_MN value concentrated on the city core during 1990 – 2001. The influence varied significantly from positive to negative, if distance to urban centres increases. The roads around the city core also had a significant positive effect on the variations of SHAPE_MN and higher local R^2. This implies that the irregularity pattern received more significant impacts from these two factors in highly urbanized areas than in less-urbanized areas. Relatively weak correlation with slope and higher local R^2 values can be observed in areas far from the city core, which suggests that the irregularity was more strongly influenced by slope outside of the city core. Compared to the previous period, the relationships between explanatory factors and the variations of SHAPE_MN value varied in 2001 – 2010. In particular, Dis2urban had a stronger influence in suburban areas than in the city core. The distance to major roads presented a significant negative effect on the variations of SHAPE_MN value in the eastern part of the city core with higher local R^2. The decrease in distance to major roads in this area could cause more irregular patterns. The effects of slope in 2001 – 2010 also varied from positive to negative across space.

4 Discussion and Conclusion

4.1 *Spatiotemporally Varying Relationships between Urban Growth Patterns and Explanatory Factors*

The study suggests that the historical urban growth patterns in Xuzhou city can, in considerable parts, be affected by distance to urban centres, distance to major roads and slope with relatively high levels of explanation of the spatial variability. This corresponds with the findings in literature related to other cities in the world (Braimoh & Onishi 2007, Clarke et al. 1997, Weng 2007). Our research extends these previous studies by investigating spatiotemporally varying effects of related factors instead of global effects.

Overall, significant correlations were found around the city core and around major roads. This can be linked with the attraction due to locations closer to the urban centres or roads offering more opportunities to access socioeconomic resources. In the city core, the landscape is dominated by a well-connected matrix of built-up land, whereas the expanded built-up areas on the edge of town are always highly fragmented and complex in shape (Solon 2009, Weng 2007). Some unexpected local relationships were also identified by GWR. For example, significant positive influence of slope on urban growth was observed around highly urbanized areas. This can be explained by the shortage of land for development around existing highly urbanized areas.

Furthermore, temporal changes of the effects of driving factors were also assessed in this study. The effects of Dis2urban on the variations of CA varied from negative to positive over the study period, which can be explained by the socioeconomic processes and the consequence of urban development policy. In the first period, urbanization mainly occurred in the city core. Due to the lack of space for further development in the city core, the edges of the town were those places where rapid urbanization occurred in 2001 – 2010. As a result, the influences of related factors on fragmentation and irregularity also varied significantly over time in the city core, because the degree of landscape fragmentation and irregularity gradually decreased when urban use became dominant in city core. In addition, the urban growth was focused more on the development of new urban centres to form a polycentric development pattern in the period of 2001 – 2010.

4.2 *Methodological Implications*

One of the crucial findings in the study is the use of GWR model, which enables to analyse the spatial variability of results. Urban growth patterns and the effects of their causal factors are usually location-dependent and auto-correlated (Gao & Li 2011). Therefore, the way of how causal factors affect the urban growth patterns differently across space should be addressed. However, many studies examined pattern-process relationships using the global relationship estimated over the entire study area (Weng 2007, Batisani & Yarnal 2009). Consequently, spatially varying effects of driving factors on spatial patterns are lost. The use of GWR model includes a spatial component in its specifications. This indicates that the coefficients estimated for this regression vary according to the geographical location. The results show that GWR models can provide detailed information about the different roles of related factors in different parts of the study area, rather than generating an average coefficient for the entire area.

4.3 *Implications for Urban Planning and Management*

The temporal analysis of spatial metrics in Xuzhou city throughout the study period revealed that urbanization not only dramatically increased the size of the built-up areas, but that the urban area became also fragmented and irregular. Fragmented and irregular development patterns are associated with ecological and environmental problems, which threaten the sustainable development (Jenks et al. 1996). Therefore, some related plans and measures should be implemented to facilitate connectivity between built-up fragments instead of random development. Furthermore, the positive effect of slope on urban expansion which has been found in some areas, suggests an increasing pressure for development in the mountainous areas which in turn are regarded as ecologically valuable zones. Therefore, the implementation of policies for protecting such ecologically valuable zones is required.

4.4 *Outlook*

Although some successful results have been obtained, challenges lie ahead. Firstly, different block shape and size can result in different explanatory ability of models. Notwithstanding preliminary tests were conducted, further studies need to be carried out to consider the different block shape and size in order to obtain insight into their effects on spatial pattern analysis. Secondly, three spatial variables were incorporated to analyse the effects of driving factors in this study. The GWR model did not include other possible variables that may affect urban growth patterns, as it lacked input data. Although a good agreement between model results and actual maps was observed, it is recommended to include further potential variables into future studies.

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