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GEOGRAPHICALLY WEIGHTED REGRESSION MODEL: A POTENTIAL APPROACH FOR BETTER MANAGEMENT OF URBAN GROWTH

Noresah Mohd Shariff (a)*, Sanjay Gairola (b)
*Corresponding author

(a) School of Distance Education, Universiti Sains Malaysia, Penang, Malaysia, noreshah@usm.my
(b) Sharjah Research Academy, P.O. Box 60999, Sharjah, United Arab Emirates, sgairola@sra.ae

Abstract

Many urban areas are experiencing high impact of urbanization pressures and loss of potential biodiversity due to rapid pace of urban development and economic restructuring. The urban areas are expanding at an alarming rate and their frequency, intensity and distribution of growth vary spatially. Given the dynamic nature of urban development and environmental conditions, it is imperative to understand urban growth in order to strategize and regulate urban land use more efficiently. In this context, spatially explicit models are helpful to land use planners and managers because these models consider the arrangement of urban development and its relationship with urban variables over space and time. It provides more insight on patterns and processes thus provide information on future developments to support decision making. This paper discusses the potentials of Geographically Weighted Regression (GWR) model as a spatial modelling for better understanding and as management strategies of urban growth. GWR has gaining increasing interest in many urban studies to address diverse urban issues. Parameter values in GWR are distributed according to proximity to the observation and those parameter values are assigned higher weights to nearby observations. GWR provides a framework for evaluating how the strengths of relationships change with the spatial resolution of the analysis. In Malaysia, GWR may have potential in better managing urban growth and predicting urban growth patterns.

Keywords: Geographically Weighted Regression, spatial modelling, non-stationarity, urban growth management, Malaysiat.

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1. Introduction

Malaysia is experiencing rapid urbanization resulting from population increase and in-migration to urban areas (Abdullah, 2003). Recent projections indicated that the urbanization process in Malaysia would result in urban population exceeding 65 percent by the year 2020 (Government of Malaysia, 2010). This trend results in urban areas expanded to fulfil the increasing demands of the population. The dynamic growth of the urban population will call for adequate housing and infrastructures (Osman, Nawawi, & Abdullah, 2008). To model current and future urban development, the driving factors of urban growth need to be recognized. Over the years, some areas of small isolated human settlements in Malaysia have been transformed into interconnected metropolitan regions. Sprawl is the relocation of development to urban peripheral areas due to the change in lifestyles and preferences (Osman et al., 2008). This influx into the city's periphery areas has increased the housing, transportation and other infrastructure needs, thus acknowledged as a phenomenon of global importance and serious threat to urban ecosystems (Mundia & Aniya, 2006; Jat, Garg, & Khare, 2008).

Rapid urban growth is the characteristics of developing countries (Dewan & Yamaguchi, 2009; Thapa & Murayama, 2010; Patra, Sahoo, Mishra, & Mahapatra, 2018). To relate the spatial pattern of rapid urbanization and its driving forces, explicit spatial models and analysis methods are needed. Modelling and simulation of diverse urban growth scenarios has become paramount progress in land use and sustainable urban development researches. The processes of land use change in quantitative terms and for testing our understanding of the processes can be described by spatial models (Serneels & Lambin, 2001). The growing issues of spatial non-stationarity in many traditional urban models have prompted urban researchers to develop various local regression techniques. Among them is the geographically weighted regression (GWR) technique which is used to identify the potential non-stationarity in the relationship between the dependent and independent variables (Fotheringham, Brunsdon, & Charlton, 2002). A group of local parameter coefficients are estimated for each observation points and GWR lets the model parameters to vary in space (Fotheringham et al., 2002, Fotheringham, Charlton, & Brunsdon, 2001). The technique assigns higher weight to the observations spatially closer to the location being predicted than those farther away. While traditional regression models estimate only one global parameter estimate for all observations, GWR generates spatial data that expresses the spatial distribution in the relationships between variables and uses maps to generate and interprete spatial non-stationarity (Mennis, 2006). Like other nations, Malaysia is also striving to achieve a sustainable urban growth and natural resources management. In this article, we discuss the potentials of GWR as a spatial regression modelling tool in urban growth management in Malaysia.

2. Problem Statement

Numerous applications have proven the usefulness of GWR as a local model for spatial relationship (Brunsdon, McClatchey, & Unwin, 2001; Fotheringham et al., 2001; Huang & Leung, 2002; Malczewski, Poetz, & Iannuzzi, 2004; Lloyd & Shuttleworth, 2005; Yu, 2006; Lochl & Axhausen, 2010; Chen, Han, & de Vries, 2020). GWR has become a more commonly used technique in urban studies by addressing diverse urban problems. GWR applications have widespread in the fields of ecology (Zhang & Shi, 2004; Kimsey,

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Moore, & McDaniel, 2008), climatology (Brunsdon et al., 2001), education (Fotheringham et al., 2001), marketing research (Mittal, Kamakura, & Govind, 2004), regional science (Huang & Leung, 2002), political science (Calvo & Escolar, 2003), and transport research (Nakaya, 2001; Lloyd & Shuttleworth, 2005; Zhao, Chow, Li, & Liu, 2005; Chow, Zhao, Liu, Li, & Ubaka, 2006; Du & Mulley, 2006; Clark, 2007). Moreover, GWR has been applied to examine regional variations in the link between environmental variables and socio-economic indicators and to investigate geographic heterogeneity in urban and regional growths (Yu, 2006; Partridge, Rickman, Ali, & Olfert, 2008). Páez, Uchida, and Miyamoto (1999) used GWR to determine the spatial variation of spillovers in land markets, whereas McMillen (2001) identified urban sub-centers using the local regression model. Laffan (1999) used it to assess spatial model errors, while other substantive applications include a study on regional industrialization in China by Huang and Leung (2002). Li, Corcoran, Pullar, Robson, and Stimson (2009) developed GWR models to compute forecasts of regional employment for South East Queensland in Australia. Helbich and Leitner (2009) examined the driving factors of urban-to-rural migration in the Austrian metropolitan area of Vienna and used GWR approach to determine whether the suburban or post-suburban determinants are essential to predict urban-to-rural migration. Those studies indicated that the GWR models have better predictive power and provides an improved understanding of the spatial variations.

In Malaysia, studies on the issues of urban growth and land use, sustainable urban development, urban planning and conservation had long used traditional regression approach (e.g. Abdullah, 2003; Jaafar, 2004; Rainis & Noresah, 2004; Tahir & Roe, 2006; Samat, 2007; Lee, Lim, & Nor'Aini, 2008; Osman et al., 2008; Tan, Lim, MatJafri, & Abdullah 2009). On the other hand, studies which used GWR include modelling urban spatial structure Noresah and Rainis, (2009), analyzing land use change (Noresah, Gairola, & Talib, 2010), assessing the rental value of shop houses (Eboy, Ibrahim, & Buang, 2006) and examining the locational attributes effect on residential property values (Dziauddin & Idris, 2017). This indicates that studies on understanding the spatially varying relationship between urban growth patterns and determinants using the GWR approach in the Malaysian context are yet to be explored.

3. Research Questions

1. What is the application of Geographically Weighted Regression in urban studies?
2. What is the potential use of Geographically Weighted Regression model as a spatial regression modelling in urban growth management?

4. Purpose of the Study

Generally, there are two properties of spatial data which are spatial autocorrelation and non-stationarity. Geographically weighted regression (GWR) has become popular when non-stationarity issue is suspected. GWR was proposed by Brunsdon, Fotheringham, and Charlton (1996) as a method to examine spatially varying relationships (Fotheringham et al., 2002). In an ordinary regression (for e.g. OLS) it is assumed that the regression parameters are "whole-map" statistics. However, in many cases, the residuals (the difference between the observed and predicted data) may reveal the variation and can be visualized by mapping. Many different solutions have been proposed for dealing with spatial variation in the relationship,

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but GWR provides an elegant and easily grasped means of modelling such relationships. GWR model captures spatial variations in the regression parameters that change over the geographical space. Thus, the purpose of this study is to analyze the use of GWR in urban growth management to understand the spatially varying relationship between urban growth patterns and the determinant factors.

5. Research Methods

Geographically Weighted Regression model analyzes spatially varying relationship between dependent variable and the explanatory variables. GWR weighted data samples based on their spatial proximity and every observations across the study area have different regression parameters (Li et al., 2009). The weighting of all neighbouring observations utilized the distance decay function to obtain the local estimation of model parameters as observations nearer to the location of the sample point have more influence on the regression point than the observations farther away. GWR generates parameter estimates for every regression point in a given neighbourhood thus allows for the measurement and mapping of local as opposed to global models of relationships. The parameters can be mapped (using GIS) to represent non-stationarity over the study space. Similarly, local measures of standard errors and goodness-of-fit statistics can be obtained (Fotheringham, Brunsdon, & Charlton 2000). Therefore, the additional feature of GWR is that it offers the potential of increased understanding on the nature of varying relationships between variables across space (Cheng, Masser, & Ottens, 2001). Mennis (2006) and Gao and Li (2011) also provided a brief, comprehensive overview and theoretical background of GWR model.

The traditional global regression model can be expressed as:

$$\hat{y}_i = \beta_0 + \sum_k \beta_k \, \mathrm{x_{ik}} + \varepsilon_\mathrm{i}$$

where $\hat{y}_i$ is the estimated value of the dependent variable at location i, β_0 represents the intercept, β_k expresses the slope coefficient for independent variable x_k, $\mathrm{x_{ik}}$is the value of the variable x_k at location i, and ε_i denotes the random error term for location i. In this equation, the estimates of the model parameters are assumed to be spatially stationary. But in reality, there will be intrinsic differences in relationships over space which may imply non-stationary character. This non-stationarity problem can be measured using GWR (Fotheringham et al., 2002; Platt, 2004). Conceptually, the GWR extends conventional global regression by generating a local regression equation for each observation. Each equation is calibrated using a different weighting of the observations contained in the data set.
The GWR equation can be written as:

$$\hat{y}_i = \beta_0 \, (\mu_i , v_i) + \sum_k \beta_k \, (\mu_i , v_i)\mathrm{x_{ik}} + \varepsilon_\mathrm{i}$$

where (μ_i , v_i) denotes the coordinate location of the ith point (Fotheringham *et al.*, 2002), $\beta_0 \, (\mu_i , v_i)$ is the intercept for location i, $\beta_k(\mu_i , v_i)$ represents the local parameter estimate for independent variable x_k at location i. Parameter estimates in GWR are obtained by weighting all observations around a specific point i based on their spatial proximity to it. The observations closer to point i have higher impacts on the

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local parameter estimates for the location and are weighted more than observations farther away. The parameters are estimated from:

$$\hat{\beta}\ (\mu, v) = (X^T\ W\ (\mu, v)X)^{-1}\ X^T W\ (\mu, v)Y,$$

where $\hat{\beta}\ (\mu, v)$ represents the unbiased estimate of β, $W\ (\mu, v)$ is the weighting matrix which functions to ensure that observations near to the specific point have bigger weight value. The weighting function (i.e. kernel function) can be stated using the exponential distance decay form:

$$W_{ij} = \exp\left(\frac{d_{ij}^2}{b^2}\right)$$

where W_{ij} represents the weight of observation j for location i, d_{ij}expresses the Euclidean distance between points i and j, and b is the kernel bandwidth. If observation j coincides with i, the weight value is one. If the distance is greater than the kernel bandwidth, the weight will be set as zero (Fotheringham *et al.*, 2002).

The spatial kernel can take either a fixed (distance) or adaptive (number of samples) to establishing the radius of the local GWR model (Fotheringham et al., 2002). Figure 1 show fixed spatial kernel and adaptive spatial kernel. Windle, Rose, Devillers, and Fortin (2009) cautioned on the selection of the size of the kernel bandwidth as it has a significant impact on the outcome of the GWR analysis.

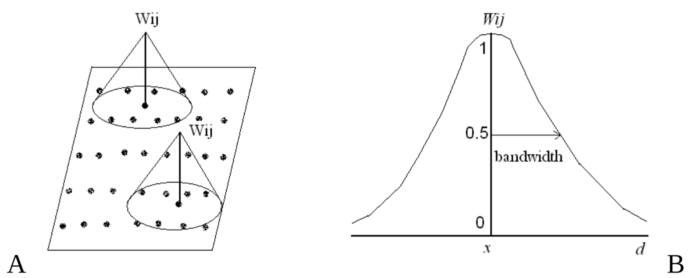

Figure 01. Fixed spatial kernels (A) and adaptive spatial kernel (B). (Propastin, Martin, & Stefan, 2008)

Cross-validation score using algorithm as stated below can be optimized to set the bandwidth.

$$CV = \sum_{i=1}^{n} (y_i - \hat{y}_i \neq_i)^2$$

where n is the number of observations, and observation i is omitted from the calculation so that in areas of sparse observations the model is not calibrated solely on i. Alternatively, the bandwidth may be chosen using the Akaike Information Criteria (AIC) score (Mennis, 2006). More details on the theory and practical application of GWR technique can be found in the literature (Brunsdon, Fotheringham, & Charlton, 1998; Fotheringham et al., 2002).

In addition, spatial relationships depend greatly on scale, which exist in natural and man-made patterns and processes (Lü and Fu, 2001). Gao and Li, (2011) suggested changing the bandwidth of GWR to estimate local parameters and to detect spatial non-stationarity at multi scales analysis. The book ‘Geographically Weighted Regression: the analysis of spatially varying relationships’ authored by

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Fotheringham et al. (2002) is recommended for anyone who are interested in applying GWR in their research.

6. Findings

Studies on urban growth using GWR had shown an increased in the strength of association between urban builtup area and factors associated with urban growth change mainly in terms of the goodness-of-fit statistics (R^2) (Noresah & Rainis, 2009; Noresah et al., 2010), the slopes of the parameter to be general over the observed area. When the global (OLS) model and the local (GWR) model were compared the studies found that R^2 for OLS global model was lower than for GWR model, with individual regression coefficient for GWR model ranging from 0.0 to 0.99. The regression parameters for GWR varied accross the study area. While Noresah et al. (2010) reported the spatial variation of the regression parameter over the space when mapped using Geographic Information System. GWR method has the advantage of revealing interesting pattern of spatial variation or nonstationarity of parameters which is useful for urban growth management strategy.

7. Conclusion

With the new paradigms on sustainable development, the study of urban structure changes is becoming one of the important global challenges. Urban researchers have recognized GWR as a spatial regression modelling approach capable to develop more comprehensive understanding about complex urban systems and thus improve strategies for urban growth management. Nevertheless, there are some limitations to the method and that the findings from GWR should be interpreted with caution (Cheng et al., 2001; Shearmur, Apparicio, Lizion, & Polèse, 2007). Hence, GWR is valued more in providing the urban modeller with an alternative approach to data management, spatial analysis and visualization. In the context of Malaysia, some researchers used GWR approach to comprehend the relationships between urbanization and its influencing factors, in modelling urban spatial structure and transportation and in market research etc. However, substantial effort is still needed for better understanding of urbanization patterns, spatial structure of rapidly growing cities, sustainable transportation as well as urban environmental modelling. This clearly indicates that GWR can also be used in ecological and environmental studies to better understand the patterns and in planning the strategies for conservation of the unique urban biodiversity and landscape of Malaysia.

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