Influence of Urban Rail Transit on House Value: Spatial Hedonic Analysis in Bangkok

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Abstract: The benefit of railway to the adjacent area has been well accepted; however to what extent it has influence over space is still questionable. The objective of this study is to examine the varying relationship between the property value and its determining factors such as accessibility to urban rail. A hedonic price model of medium-income-class housing in Bangkok taking into account the varying relationship (Geographically Weighted Regression, GWR) is estimated in reference to the standard regression model (Ordinary Least Square, OLS). The GWR model exhibits better performance and has revealed that the influence of urban rail transit having on the residential property (townhouse) value is substantially varying over space. This implies that urban railway has large contribution to land and property value uplift in the station catchment areas.

Keywords: *Spatial Hedonic, Geographically Weighted Regression, Urban Railway*

1. INTRODUCTION

7,758 square-kilometer area of Bangkok Metropolitan Region (BMR), Thailand, covers the large city core of Bangkok and its five surrounding provinces, namely Nonthaburi, Pathumthani, Samut Prakarn, Samut Sakorn, and Nakorn Pathom. BMR has undergone rapid urbanization and industrialization since 1960. Total population of BMR in 2005 accounts for 16.8% of the country population and produces 44.2% of the country's GDP. This shows that BMR is the major economic center where every economic activity can be found. Figure 1a and b show the concentration of residence and employment in the inner core of the city. However, travels in Bangkok are mostly based on road. Private mode share in 2005 is 53%; while the public mode share is only 44%. The reason behind this is that private mode of travel on private car is far superior to public mode of travel on crowded bus running in heavily congested traffic. The existing 404 bus routes are still not enough to accommodate the travel demand, especially from/to suburban areas. For the rail transit, the SRT lines under the State Railway of Thailand have long been a choice of travel from and to sub-urban areas. The rrban rail transit has just been introduced recently. In 1999, a 23-kilometer elevated urban railway (named BTS) has started its two-line service; presently it receives over 400,000 passengers daily. Five years after BTS opened, a 20-kilometer urban subway line (called MRT) has commenced its service in 2004. Integrating the BTS, MRT, and SRT lines, there are 5 transfer stations at Asoke, Mochit, Siam Square, Hualumphong, and Bangsue stations.

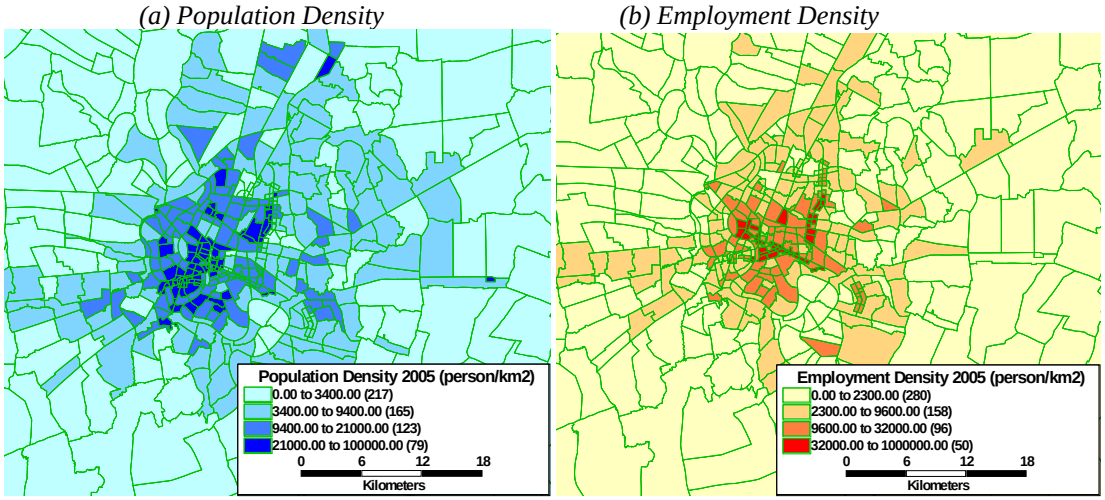

Figure 1 Population and Employment Concentration

It is apparent that railway has great influence on the surrounding area development, especially around the stations. (Vichiensan et al. 2007) showed that after the BTS railway in Bangkok has opened, the land price along the corridor has remarkably increased especially at the transfer stations. Quantitatively, (Chalermpong 2007) has shown that the premium of transit accessibility is approximately $10 for every meter closer to a station. The benefit of railway can also be seen from the land speculation along the future railway corridor such as Rattanatibeth and Bang Yai area. Nowadays developers expect increase in land value when the railway project is completed. In Hong Kong, (Yiu and Wong 2005) showed that there were positive price expectation effects well before the completion of the tunnel. The expectation effects allow the government to finance infrastructure projects by selling land in the affected districts in advance.

Although the effect of railway to the adjacent area is accepted and well understood, but to what extent the effect is strong in each area is yet to explore. The objective of this study is to examine the varying relationship between the property value and its determining factors such as accessibility to urban rail. A hedonic price model of medium-class housing is presented by taking into account the varying relationship. It is estimated with reference to the standard regression model. The finding helps understand such complicated and spatially varying relationship and has implication on land value uplift by urban railway service. The reminder of the paper is organized as follows. Section 2 describes the models in an analytical setting. Section 3 presents the model of the case study. Finally, Section 4 concludes the paper.

2. REGRESSION

Regression analysis is used to model the relationship between one (or more) dependent or response variables and a number of independent or predictor variables. The general regression model can be specified as follows.

$$y = \boldsymbol{X}\boldsymbol{\beta} + \varepsilon \tag{1}$$

$$E[\boldsymbol{\varepsilon}] = \mathbf{0} \tag{2}$$

$$\boldsymbol{\Omega} = E[\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}'] = \sigma^2\mathbf{C} \tag{3}$$

where $\boldsymbol{y}$ is a vector (n×1) of observations corresponding to a dependent variable, $\mathbf{X}$ is a matrix (n×k) of observations of k independent variables, $\boldsymbol{\beta}$ is a vector (k×1) of regression parameters, $\boldsymbol{\varepsilon}$ is a vector (n×1) of errors, and $\mathbf{C}$ is a positive definite covariance matrix. The errors are

often assumed to be normally distributed with an expected value of 0 and a variance-covariance matrix $\mathbf{\Omega}$ of size $n \times n$.

Classical ordinary least squares (OLS) is obtained by defining $\mathbf{\Omega} = \sigma^2\mathbf{I}$ and the solution for the coefficients of is obtained:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\boldsymbol{y} \tag{4}$$

2.1 Geographically Weighted Regression (GWR)

GWR is the term introduced by (Fotheringham et al. 2002) to describe a family of regression models in which the coefficients, $\boldsymbol{\beta}$, are allowed to vary spatially. The regression model in (1) may be rewritten for each local model at observation location *o* as follows.

$$y_o = \boldsymbol{X}_o\boldsymbol{\beta}_o + \varepsilon_o \tag{5}$$

where the sub-index *o* indicates a observation point where the model is estimated. The coefficients $\boldsymbol{\beta}_o$ are determined by examining the set of points within a well-defined neighborhood of each of the sample points. This neighborhood is essentially a circle, radius *r*, around each data point. However, if *r* is treated as a fixed value in which all points are regarded as of equal importance, it could include every point (for r large) or alternatively no other points (for r very small). Instead of using a fixed value for r it is replaced by a distance-decay function, *f(d)*. Various functional forms of *f(d)* are available. A simple function may be defined such as $f(d) = \exp(-d^2/h)$, where *d* is the distance between the focus point *o* and other data points, and *h* is a parameter (is also called bandwidth). A small bandwidth results in very rapid distance decay, whereas a larger value will result in a smoother weighting scheme. This parameter may be defined manually or alternatively by some forms of adaptive method such as cross-validation minimization or minimization of the Akaike Information Criterion (AIC). Following the framework of (3), the variance-covariance matrix for the GWR model may be defined as:

$$\mathbf{\Omega}_o = E[\boldsymbol{\varepsilon}_o\boldsymbol{\varepsilon}_o] = \sigma_o^2\mathbf{C}_o \tag{6}$$

The diagonal elements of matrix $\mathbf{C}_o$ are given by

$$g_{oi}(\gamma_o, d_{oi}) = \exp(\gamma_o d_{oi}^2) \tag{7}$$

whereas the off-diagonal elements are all equal to 0.

The variance is defined as a function of two parameters, namely σ_o^2 and γ_o, and d_{oi} is the distance between focal point *o* and observation *i* (=1,…, n). The advantage of using an exponential function such as (7) is that the ith diagonal element of the covariance matrix $\omega_{oi} > 0$ as long as $\sigma_o^2 > 0$, thus ensuring positive definiteness. Assuming normally distributed errors with a variance-covariance matrix as in (6) and (7), the local parameter estimates can be obtained:

$$\hat{\boldsymbol{\beta}}_o = (\mathbf{X}'\mathbf{C}_o^{-1}\mathbf{X})^{-1}\mathbf{X}'\mathbf{C}_o^{-1}\boldsymbol{y} \tag{8}$$

$$\hat{\sigma}_o^2 = \frac{1}{n}(\boldsymbol{y} - \mathbf{X}\hat{\boldsymbol{\beta}}_o)'\mathbf{C}_o^{-1}(\boldsymbol{y} - \mathbf{X}\hat{\boldsymbol{\beta}}_o) \tag{9}$$

These are conditional upon a structure of matrix $\mathbf{C}_o$. These estimators, when substituted and introduced into the corresponding log-likelihood function, result in a concentrated function that depends on a single parameter, namely γ_o:

$$-\frac{n}{2}\ln\left[\frac{1}{n}(\boldsymbol{y}-\mathbf{X}\hat{\boldsymbol{\beta}}_o)'\mathbf{C}_o^{-1}(\boldsymbol{y}-\mathbf{X}\hat{\boldsymbol{\beta}}_o)\right]-\frac{1}{2}\sum_{i=1}^{n}\gamma_o d_{oi}^2 \tag{10}$$

The above function can be numerically maximized with respect to γ_o to obtain a parameter that can be substituted in (10) to obtain the maximum likelihood estimates for $\hat{\boldsymbol{\beta}}_o$.

3. SPATIAL HEDONIC PRICE MODEL

The term hedonic regression is used in economics, especially in real estate (property) economics, to estimate demand or prices as a combination of separate components, each of which may be treated as if it had its own market or price. In the context of regression these separate components are often treated as the independent variables in the modeling process. Classical hedonic approach has been long employed. (Pan and Zhang 2008) employed a simple hedonic regression to show the land value premium of proximity to train station in Shanghai. (Ryan 2005) also employed a simple hedonic model in San Diego showed that access to highway is significant effect to office rent while access to LRT is not. (Munoz-Raskin 2007) found that walk access to BRT in Bogota has great impact on property value. Alternatively, some studies have taken into account the neighborhood effects. (Cervero and Duncan 2004) showed that composition of neighborhood has great influence on land value. (Bae et al. 2003) proved by a standard hedonic model that distance to the line-5 subway station in Seoul has less impact than other factors such as quality of school district, proximity to high-status sub-center, and accessibility to recreational resource. (Chalermpong 2007) examined the impact of BTS urban railway on property price in Bangkok by employing a spatial autoregressive regression model. (Shin et al. 2007) observed the impact of transportation accessibility on residential property value with a spatial lag model. (Hess and Almeida 2007) examined the impact of the LRT in New York on station-area property value with individual regression models for each of the light rail system's 14 stations. It was found that effects are not felt evenly throughout the system. Proximity effects are positive in high-income station areas and negative in low-income station areas.

Some studies focus on local variation of the impact by incorporating the nonstationarity; a situation when parameter estimates vary with different spatial entity used. A study in Tyne and Wear Region, UK has employed the Geographically Weighted Regression (GWR) approach and revealed that nonstationarity existing in the relationship between transport accessibility and land value (Du and Mulley 2006). It is showed that transport accessibility may have a positive effect on land value in some areas but in others a negative or no effect, suggesting that a uniform land value capture would be inappropriate. (Paez and Suzuki 2001) examined the impact of transportation on land use change by looking at local effect by using GWR. (Vichiensan et al. 2006) has proposed a nonstationary spatial interpolation method based on GWR framework and has taken into account the spatial autocorrelation and nonstationarity.

This paper considers the nonstationarity in the hedonic price model parameters and presents a hedonic price model of medium-income-family housing within the GWR framework. The GWR model is estimated in reference with an OLS model.

3.1 Data and Variables

Among various types of housing in Bangkok, this study focuses on a type of housing that are popular for medium-income households, so-called townhouse, a term originated in United Kingdom being known as a house in town. It is also called terraced house in North America and Australia. Figure 2 shows sketches of modern townhouse in Bangkok, mostly featuring two or three stories.

Figure 2 Example of Modern Townhouse in Bangkok

The variables used in the analysis are summarized in Table 1.

Table 1 List of Variables

Variable	Name	Description
Y	PRICE	Advertised sell price (Baht)
X1	LAND_AREA	Size of land (m^2)
X2	NO_STOREY	Number of storey of house
X3	NO_BATH	Number of bathroom
X4	AGE	Age (year)
X5	FLRSPACE	Floorspace area (m^2)
X6	TIME_SILOM	Average travel time to city center, Silom (minutes)
X7	TIME_MRT	Average travel time to the nearest railway station (minutes)

The townhouse sell price data is obtained by observing the sell advertisements in real estate magazines in 2008. The valid observations include 447 townhouses spreading throughout Bangkok shown in Figure 3. The station catchment area such as the south eastern areas will require traveling for less than 20 minutes to reach MRT station while the far north areas are less accessible to MRT service. The rest attributes are obtained from the information appeared on the advertisement, i.e., land size, number of storey, number of bathroom, age, and floorspace. It is also cross-checked by telephone queries. In addition, two transportation variables are considered. The average travel time from each property to city center, which is assumed to be Silom, is calculated from the official transport model of Bangkok, so-called e-BUM, which is built on CUBE proprietary software, (Office of the Commission for the Management of Road Traffic 1997). It also computed the average travel time on different modes, i.e., private mode, high-comfort public mode (rail), and low-comfort public modes (bus), to the nearest station on the existing railway lines (the red lines in Figure 3). This reflects the fact that traveling on different modes takes time differently. The distance between

observation points that is used when calculating the weights in the GWR model is calculated by the aid of GIS functionality in TRANSCAD.

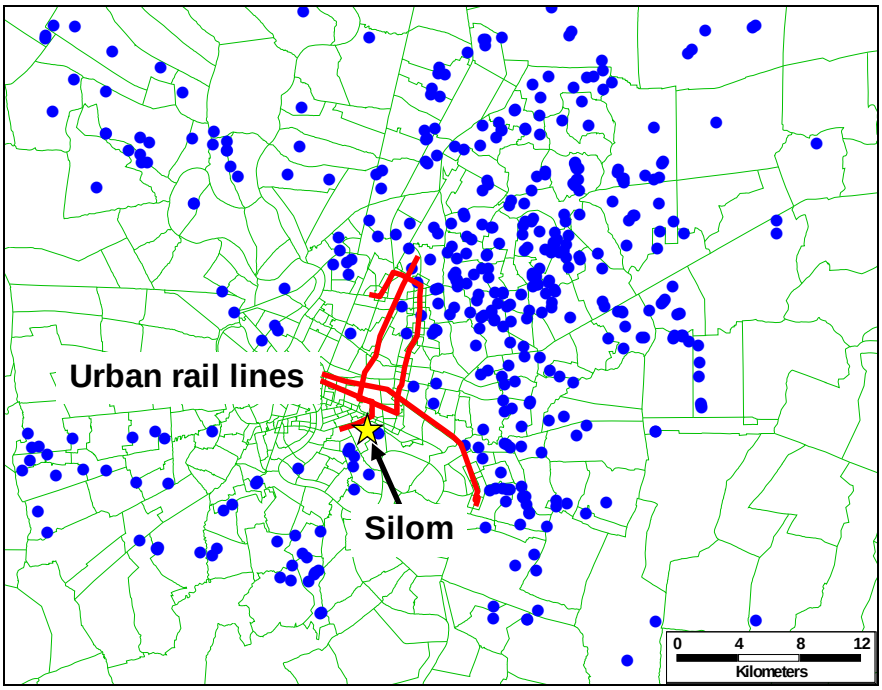

Figure 3 Locations of the Observed Data

3.2 Results

The two models, i.e., OLS and GWR, were coded in MATLAB programming language. The coefficient parameters are estimated; following to the equation (4), (8), and (9). The bandwidth in equation is obtained by maximizing the function in (10) as described earlier. The results are summarized in Table 2.

Table 2 Model Estimation Results

	OLS		*GWR*		
	Coefficients	*t-Stat*	*Coefficients*		
			min	*max*	*mean*
LAND_AREA	10,444	5.459	9,375	13,548	10,485
NO_STOREY	243,921	1.583	26,472	411,443	281,192
BATHROOM	382,999	3.863	252,781	437,570	394,932
AGE	-22,042	-1.991	-26,003	-7,310	-18,045
FLRSPACE	8,190	6.899	6,037	12,521	7,734
TIME_CITY_CENTER	-22,562	-3.301	-22,562	3,405	-17,930
TIME_MRT_STATION	-9,848	-3.886	-11,692	-8,076	-9,466
Number of observation	447		447		
Number of parameter	7		8		
AIC	13,658.8		13,625.0	13,691.4	13,669.8

The OLS model gives a set of parameters that is global over the study area. All coefficients have intuitive sign and are statistically significant. It follows our expectation that the travel time to MRT station is a significant factor to house price. On the other hand, the GWR model gives local parameter estimates for each observation points, i.e., totally 477 sets of estimates are obtained. Table 2 shows the minimum, maximum, and average values. It is observed that averagely the estimates have the same trends as OLS. In terms of the goodness of model fit, Akaike's Information Criterion (AIC) is evaluated. It is based on the value of the likelihood function and weighs in the trade-off of how much information is obtained and the number of variables used. It is found that in some locations, the GWR model is out performed to the OLS, indicating that the nonstationarity plays significant role in improving the model goodness of fit as indicated by some lower AIC values. In the other words, the extent of effect of each explanatory variable to the house price varies locally in the study area.

A plot of the parameter estimates associated to the variable Time to MRT Station in Figure 4 shows the variation in its relationship to the house price. In the areas that are served by MRT (such as the purple), the house price is strongly influenced by the proximity to MRT station compared with the area not being served by MRT (such as the red). In the other words, if MRT station can be reached from house at the same travel time, houses in the purple area will be more expensive than in the red one. This implies that price of houses in the station catchment area is substantially influenced by the station proximity.

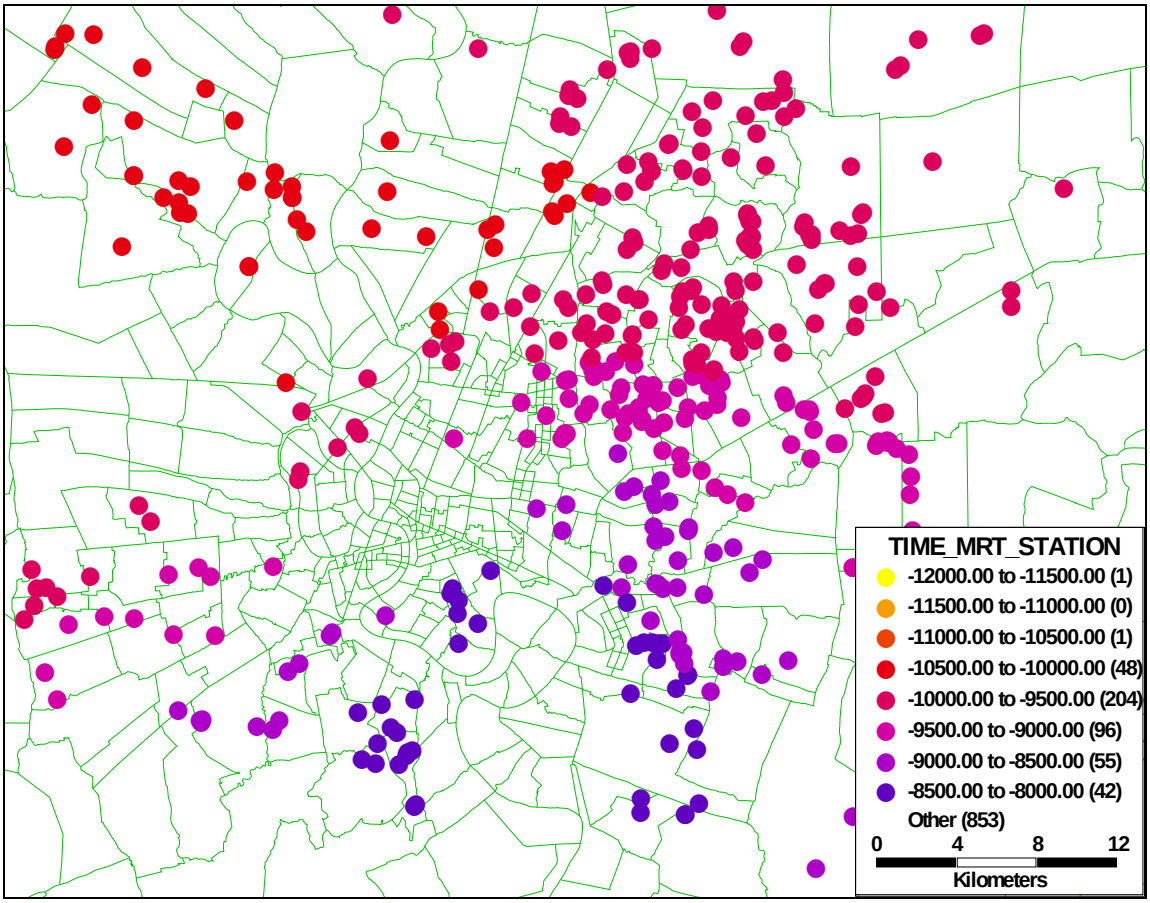

Figure 4 Distribution of the Time-to-MRT-Station Parameter

Due to the benefit of MRT, the age of house will unavoidably deteriorate the price of the house in the station catchment area (red and orange in Figure 5) but at a slower rate than the one not served by MRT (pink and purple in Figure 5).

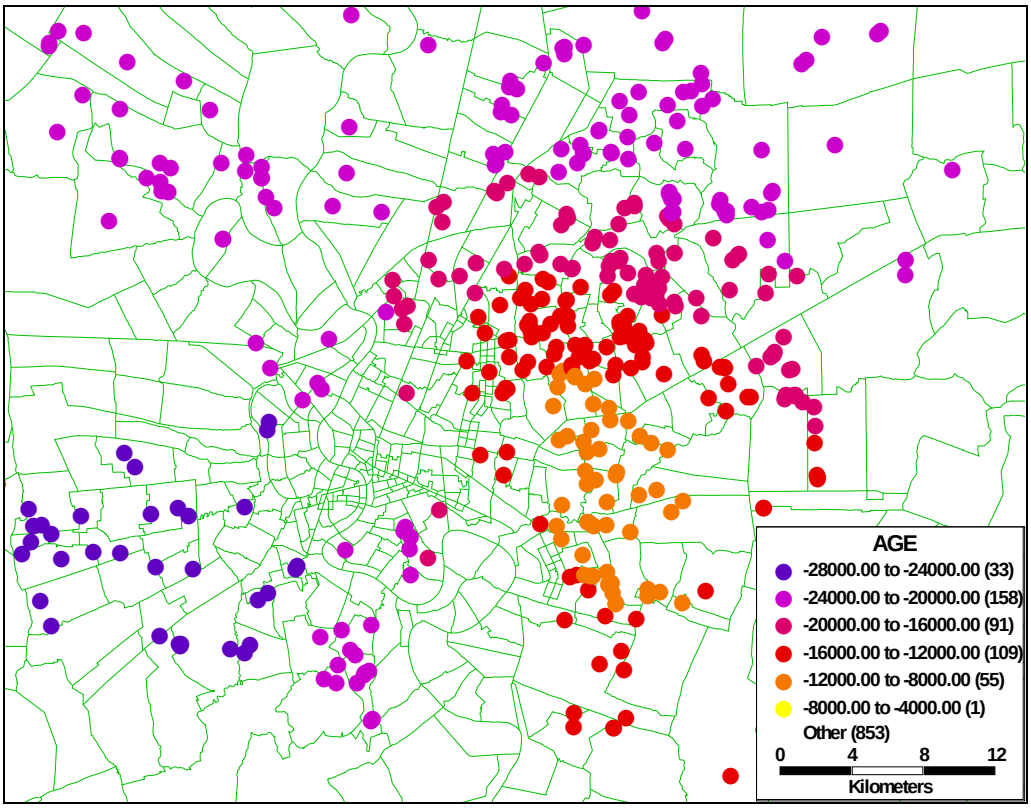

Figure 5 Distribution of the Age Parameter

For those variables with positive coefficients such as the land area variable and the number of storey variable, they may be interpreted to represent density of the residential area. That is, smaller coefficient of land area variable (shown in Figure 6) and larger coefficient of number of storey variable (shown in Figure 7) represent the high density area, i.e., along the corridor of MRT, especially along Sukhumvit BTS line. This implies that old townhouse can be highly valued if it is well accessible to railway station; but will be less valued otherwise. This is considered as huge benefit brought by the urban railway.

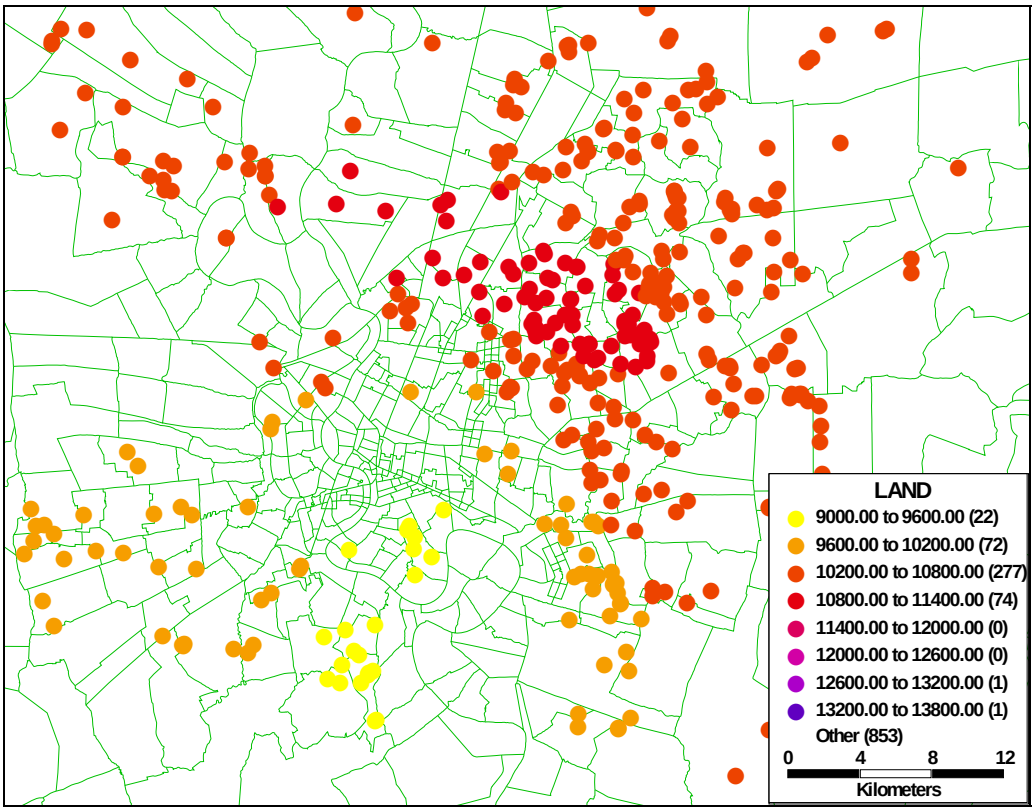

Figure 6 Distribution of the Land Area Parameter

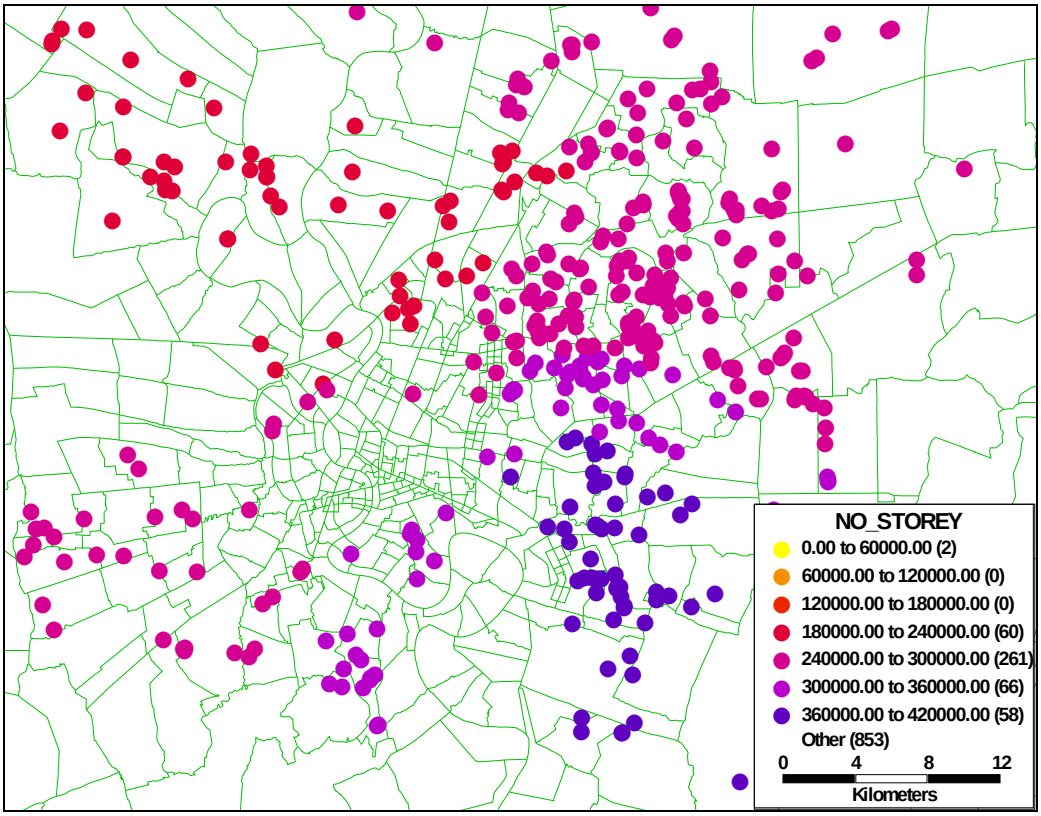

Figure 7 Distribution of the Number of Storey Parameter

4. CONCLUDING REMARKS

The analysis presented in this paper has clearly showed that the influence of rail transit having on the residential property (townhouse) value is complicated and greatly varied over space. The global regression model provides information in selecting the independent variables. The study is significantly distinguished by the spatial hedonic model in which the autocorrelation of housing price is modeled by the geographically weighted regression. The local GWR model has clearly revealed the varying relationship between house price, station accessibility as well as other attributes. It has important implications in many ways such as determining the property tax, which should be higher for the area serviced by urban railway.

There are some remaining issues worthwhile to address here. Firstly, this study is based on the advertised sell price, which is often different than the real transaction price. However, the real transaction price is difficult to obtain and less reliable in such developing country as Thailand. It is left for future study to evaluate to what extent the analysis result is distorted by using the advertised price than the transaction one. Secondly, the weighting scheme in the analysis is based on the physical distance among observations, equation (7). This may not be very appropriate in Bangkok where Chaopraya River is dividing the city into two parts, i.e., the west and the east parts are connected with several bridges. This makes any two locations on the opposite site of a narrow section of the river get similar weights although they may not have similar characteristics because they are not really nearby. In this sense, composite travel time may be more appropriate in calculating the weight and left for further study. Lastly, it is also worthwhile to mention that GWR has not clearly improved the model goodness-of-fit by solely considering AIC, it will be necessary to conduct ANOVA test or considering other goodness-of-fit evaluation such as Cross-Validation (CV) score, which is a summation of the residuals from the leave-one-out estimations.

ACKNOWLEDGEMENTS

This study is supported by Thailand Research Fund (TRF) Grant - MRG4880122.

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