**Abstract:** That urban rail transit brings large benefit to the adjacent area is well recognized; however, to what extent it has influence over space is still questionable, especially in a city being young in urban railway experience. This paper presents hedonic analysis of residential property value in order to examine the factors that determine the sale price. The case study is an area along a corridor of BTS Sukhumvit line, which is Bangkok’s the first urban rail transit having been in service for over 10 years. The area has undergone rapid development, reflecting on the appreciated land value and increased number of tall building. Three hedonic models are presented: ordinary least square regression, spatial autoregressive model, and geographically weighted regression. It is found that the spatial effects present in the study area both spatial dependence and spatial nonstationarity. The results provide insight to improve railway services such as station access or feeder service.

**Keywords:** Hedonic, Spatial Effect, Autocorrelation, Nonstationarity

1. INTRODUCTION

Since 1960, Bangkok Metropolitan Region of Thailand has undergone rapid urbanization. The total population in 2005 takes 16.8% of the country and produces 44.2% of GDP. Presently the city is extremely busy with almost all kinds of activities. Physically, resident and employment locations are largely concentrated in the inner core. Such urban structure unavoidably generates huge amount of travel demand, which are mostly made by long distance trips by private vehicles. The transportation in Bangkok is presently based on road. Private modal share was 53% while the public modal share 44% in 2005. The reason is that travel on private car is far superior to travel on crowded bus running in heavily congested traffic. The present 404 bus routes are still not enough to accommodate the travel demand,
especially from/to suburban areas. Bangkok is still young to its rail transit history although the intercity railway lines (called SRT lines under the State Railway of Thailand) have provided services for travel from/to sub-urban areas. Recently, the urban rail transit has been introduced. In 1999, 23-kilometer elevated urban railway (named BTS lines belonging to BTS Corporation) has started its service with two initial green lines. Five years later, a 20-kilometer urban subway line (called MRT under the Mass Rapid Transit Authority) has started in 2004. Among those BTS, MRT, and SRT lines, there are five transfer stations in the system namely Asoke, Mo Chit, Siam Square, Hualumphong, and Bangsue stations. Nowadays travel by railway in Bangkok has increasingly obtained interest due to its safe, punctual, and convenient service.

Due to its popularity, the urban railway has large influence on its surrounding area, especially around the stations. After the BTS railway in Bangkok has opened, land price along the corridor has remarkably increased especially at the transfer stations (Vichiensan et al. 2007). It was claimed that the premium of transit accessibility adding to the property value is approximately $10 for every meter closer to the station (Chalermpong 2007). The benefit due to railway service is also reflected by land speculation along the recently announced future railway lines such as in Rattanathibet and Bang Yai areas along the subway blue line extension to the north. Developers have been expecting a tremendous increase in land value after the project is completed. This is similar in Hong Kong, there were positive price expectation effects well before the completion of the tunnel (Yiu and Wong 2005). The expectation effects allow the government to finance infrastructure projects by selling land in the affected districts in advance.

The objective of this study is to examine the impact of urban railway on land development by spatial hedonic analysis. The rest of the paper is organized as follows. The next section examines the impact of urban rail transit by considering the change in land value and the number of tall building in the study area. Hedonic price models are presented in the section that follows. The models are estimated with the sample data. Finally, the paper concludes with implication for transit development, i.e., station access improvement.

2. STUDY AREA

The case study is an area along a corridor of BTS Sukhumvit line, which is the first urban rail transit in Bangkok, having been in service for over 10 years. The elevated track of BTS is constructed on the median of Sukhumvit Road. The area has undergone rapid development as a result of BTS and MRT railway services. This study investigated the change by observing the changes in land value and number of building.

2.1 Land Value

The information on land value is obtained from the four-year-period assessed land value reports, which were published by two agencies at different periods: Department of Land for the data from 1992 to 2003; and Treasury Department for the data from 2004 to 2011. Although the assessed land value is often lower than the market transaction price, it is used in this study because the market transaction price data is not consistent and reliable in Thailand. The change in land value is observed by considering the official land value appraisal at representative locations beside Sukhumvit Road. It is found that land value has appreciated substantially as can be seen in Figure 1. Notice the stations of the two railway lines in the figure. The color dots indicate location of the residential properties: the blue are condominium
for sale while the red are apartment for rent. These data will be used in the hedonic analysis in the later part. The color bars at representative locations compare the appraised land values at different years. It is apparent that land value is appreciated in the later year after the railway has opened in 1999.

![Figure 1 Land Value Appreciation](image)

2.2 Building Construction

The study has investigated the change in building stock in the study area. The existing tall buildings, including office buildings, hotels, condominium, etc., in the areas along Sukhumvit Road were investigated. They are presented in three-dimensional graphics with the aid of Google Earth and Google Sketch Up, as shown in Figure 2. Let notice, in the figure, the railway lines, both BTS and MRT, and their stations locating about 1 kilometer apart each other, among these station, there is a transfer station at Asoke interchange. The buildings may be classified into three groups by their age generations. The first group consists of those existed before BTS started its construction in 1992, as colored in green. The second group includes those constructed during the construction of BTS from 1992 to 1998, as colored in red. The third ones are those constructed after BTS opened in 1998, as colored in blue. Visual inspection informs that there are so many buildings that have been constructed after the rail transit development. This is claimed to be caused by the BTS development, which brings many benefits to the area. In the past, certainly before BTS project, Asoke intersection was one of the most congested intersections in Bangkok; its surrounding area had unavoidably became less accessible and valued due to the traffic congestion. But after BTS exists and provides high level of public transport service, Asoke area has returned to be attractive for the developers. The previously unfinished construction sites were continued and the abandon buildings were renovated. It has become one of the most convenient locations where modern office buildings, high-rise condominiums, luxury hotels are rising up; as obviously shown in
blue buildings in Figure 2. They are, therefore, the main beneficiaries of the railway development. Nowadays Asoke is no longer forgotten but a transfer station area where two railway lines cross; BTS and MRT. If there were no BTS, no one can imagine how Sukhumvit would be congested nowadays because those buildings attract huge amount of travel demands.

Figure 2 Buildings Attracted by the Railway

This is strong evidence that the urban rail transit has played significant role in accelerating urban development in Bangkok. It is furthermore interesting to examine what exactly push up the property value by the hedonic study of the property value in the next section.

3. MODEL SPECIFICATION

The term hedonic is often 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 independent variables in the modeling process. Classical hedonic approach has long been employed. For example, The model for Bogota advised that walk access to BRT has great impact on property value (Raskin 2007). Some studies have taken into account the neighborhood effects. The neighborhood composition have great influence on land value in California (Cervero and Duncan 2004).

In terms of model specification, different forms of hedonic price models are constructed. It ranges from classical regression model to complicated spatial regression models. A simple hedonic model is employed in Seoul and indicated that distance to Line-5 subway station has less impact than other factors such as quality of school district, proximity to high-status sub-center, and accessibility to recreational resource (Bae et al. 2003). Likewise, San Diego study
showed with simple regression that access to highway is significant to office rent while access to LRT is not (Ryan 2005). A similarly simple hedonic regression in Shanghai showed the land value premium of proximity to train station (Pan and Zhang 2008).

Taking into account the spatial effects, models with spatial lag variable were proposed. In Chicago, a spatial autoregressive model examines the impacts of vehicle traffic having on the property values along selected arterial corridors (Kawamura and Mahajan 2005). In Seoul, the impact of transportation accessibility on residential property value in Seoul is examined through a model with similar form (Shin et al. 2007). In Bangkok, a spatial autoregressive regression model was proposed to examine the impact of BTS urban railway on property price (Chalermpong 2007). In Buffalo, NY, the impact of the LRT in New York on station-area property value was determined with an individual regression model for each among 14 LRT stations (Hess and Almeida 2007). Moreover, the effects are not felt evenly throughout the system. The proximity effect is positive in high-income station areas but negative in low-income station areas. In Lisbon, a spatial lag model informs that the proximity to one or two metro lines leads to significant property value changes (Martínez and Viegas 2009).

Recently, literatures in urban studies have shed light to the local variation of the impact by incorporating nonstationarity; a situation when parameter estimates vary with different spatial entity used. For example, geographically weighted regression has been employed to examine the impact of transportation on land use change by looking at local effect (Paez and Suzuki 2001). Similarly, a study in Tyne and Wear Region, UK also employed GWR and found that nonstationarity existing in the relationship between transport accessibility and land value (Du and Mulley 2006). It also showed that transport accessibility may have a positive effect on land value in some areas but in others a negative or no effect. The important conclusion was that a uniform land value capture would be inappropriate. Moreover, based on GWR framework, a nonstationary spatial interpolation method was proposed, in which spatial autocorrelation and nonstationarity were accommodated (Vichiensan et al. 2006).

In this paper, essentially, the spatial effect is considered in order to determine the factors that influence price setting along with the variation of the influence over the study area. Three types of model specification are presented. A classical regression model is a reference model. The other two models are specified to determine the existence of the spatial effects: spatial autoregressive model and geographically weighted regression model, respectively.

### 3.1 Ordinary Least Square 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.

\[ \mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \]

\[ E[\boldsymbol{\varepsilon}] = 0 \]

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

where \( \mathbf{y} \) is a vector \((n\times1)\) of observations corresponding to a dependent variable, \( \mathbf{X} \) is a matrix \((n\times k)\) of observations of \( k \) independent variables, \( \boldsymbol{\beta} \) is a vector \((k\times1)\) of regression parameters, \( \boldsymbol{\varepsilon} \) is a vector \((n\times1)\) 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 $\Omega$ of size $n \times n$. Classical ordinary least squares (OLS) is obtained by defining $\Omega = \sigma^2 I$ and the solution for the coefficients is obtained as Equation (4).

$$\hat{\beta} = (X'X)^{-1} X'y$$

(4)

### 3.2 Spatial Autoregression

A spatial autoregressive model, or abbreviated by SAR, consists of a spatially lagged term of the dependent variable $y$ adding with the explanatory terms and the error as follows.

$$y = \rho Wy + X\beta + \epsilon$$

(5)

This model is similar to a standard linear regression model with the addition of the autoregressive component, which is constructed from a predefined $n$ by $n$ spatial weighting matrix, $W$, applied to the observed variable, $y$, together with a spatial autoregression parameter, $\rho$, which can be estimated from the data. The model communicates that the value of a variable at a given location is related to the values of the same variable measured at nearby locations, representing the spatial autocorrelation, with the influence of other aspatial predictor variables. The solution to the model in Equation (5) can be obtained in the closed form, i.e., the model coefficients in Equation (6) and the variance in Equation (7) can be estimated by maximizing the log likelihood function in Equation (8) in a straightforward manner.

$$\beta = (X'X)^{-1} X'(I - \rho W)y$$

(6)

$$\sigma^2 = \frac{1}{n} y'[1 - X(X'X)^{-1} X']y$$

(7)

$$\ln(L) = -\left(\frac{N}{2}\right) \ln(2\pi) - \left(\frac{N}{2}\right) \ln(2\sigma^2) + \ln|I - \rho W| - \frac{1}{2\sigma^2}(y - \rho Wy - X\beta)'(y - \rho Wy - X\beta)$$

(8)

### 3.3 Geographically Weighted Regression

Geographically Weighted Regression, or abbreviated by GWR, (Fotheringham et al. 2002) is the term used to describe a family of regression models in which the coefficients, $\beta$, are allowed to vary spatially. The regression model in Equation (1) may be rewritten for each local model at observation location $o$ as follows.

$$y_o = X_o \beta_o + \epsilon_o$$

(9)

where the sub-index $o$ indicates an observation point where the model is estimated. The coefficients $\beta_o$ 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 Akaike Information Criterion (AIC). Following the framework of Equation (3), the variance-covariance matrix for the GWR model may be defined as follows.

\[ \Omega_o = \mathbb{E}[\varepsilon, \varepsilon_o] = \sigma_o^2 C_o \]  

(10)

The diagonal elements of matrix \( C_o \) are given by

\[ g_o(\gamma_o, d_{oi}) = \exp(\gamma_o d_{oi}^2) \]  

(11)

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

The variance is defined as a function of two parameters, namely \( \sigma_o^2 \) and \( \gamma_o \), and \( d_{oi} \) is the distance between focal point \( o \) and observation \( i (=1,\ldots, n) \). The advantage of using an exponential function such as (11) is that the \( i \)-th 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 (10) and (11), the local parameter estimates can be obtained:

\[ \hat{\beta}_o = (X'C_o^{-1}X)^{-1}X'C_o^{-1}y \]  

(12)

\[ \hat{\sigma}_o^2 = \frac{1}{n} (y - X\hat{\beta}_o)'C_o^{-1}(y - X\hat{\beta}_o) \]  

(13)

These are conditional upon a structure of matrix \( C_o \). These estimators, when substituted and introduced into the corresponding log-likelihood function, result in a concentrated function that depends on a single parameter, namely \( \gamma_o \):

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

(14)

The above function can be numerically maximized with respect to \( \gamma_o \) to obtain a parameter that can be substituted in (14) to obtain the maximum likelihood estimates for \( \hat{\beta}_o \). This paper considers the nonstationarity in the hedonic price model parameters and presents a hedonic price model with GWR framework. It is estimated in reference with an OLS model. The coefficient parameters can be estimated; following Equation (4), (12), and (13) respectively. The bandwidth kernel is solved by maximizing the function in Equation (14).

4. MODEL ESTIMATION

The model coefficients are estimated with the sample data, which is obtained from different sources.

4.1 Variables

The field data collection was conducted in order to obtain detail information of the residential property. Following the local nomenclature, the property for sale is called condominium and the one for rent is called apartment. In the field data collection, three types of information is
collected from each sample: the characteristics of the building: age and the number of storey; the characteristics of the unit being advertised for sale or for rent: price, floor location, and the other amenity or service; and the walking distance to major facilities, e.g., railway station, hospital, or educational institutions. Among the information from 415 samples, the offering price of sale condominium is used as the dependent variable in the analysis. Five explanatory variables are as summarized in Table 1.

Table 1 Description of the Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description (Unit)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRICE_ADS</td>
<td>Offering price of the condominium for sale (Baht/sq.m.)</td>
</tr>
<tr>
<td>AGE_BLDG</td>
<td>Age of the building (year)</td>
</tr>
<tr>
<td>FLOOR_LOC</td>
<td>Floor location of the selling condominium unit</td>
</tr>
<tr>
<td>STATION_DIST</td>
<td>Distance to the urban railway, i.e., BTS or MRT station (km)</td>
</tr>
<tr>
<td>ACCESS_JOB</td>
<td>Employment accessibility</td>
</tr>
<tr>
<td>ROADCONNECT</td>
<td>Dummy variable: the value is 1 if the condominium is facing to the road that can be accessed from many main roads; and 0 otherwise</td>
</tr>
<tr>
<td>WALK_ENV</td>
<td>Dummy variable: the value is 1 if the surrounding is walker-friendly; and 0 otherwise</td>
</tr>
</tbody>
</table>

The offering price is taken as the dependent variable in the hedonic analysis. The age of the building represents the physical condition of the whole property. It is considered as the time since the last renovation for those refurnished. The floor location is normally the basic price setting factor; the higher the floor location, the more expensive it is. The station proximity is represented as the reasonable walking distance, which might not be the shortest one but with preferable environment such as width and cleanliness of the walkway, security, shopping attraction, etc.

Figure 3 Employment Accessibility
The accessibility to employment is calculated by the exponential expression as 
\[ A_i = \sum \limits_j Emp_j \exp(-0.1t_{ij}) \] 
where \( Emp_j \) is the number employment in zone \( j \) and \( t_{ij} \) is the travel time from zone \( i \) to \( j \) calculated by the travel demand model. Figure 3 shows the concentration of the employment accessibility in the inner area by the color of the dot symbols, which are the location of the investigated condominium. This variable is a proxy to represent the urban structure. In this case the city is relatively monocentric where the BTS railway serves as radial railway line bringing workers in to the city from the southwestern area.

Reminding that BTS is on the main road of Sukhumvit, most of the condominiums are located on small roads branching out of Sukhumvit road. Some of these sub-roads connects to the adjacent main road, i.e., Petchburi road in the north and RamaIV road in the south of the study area, shown in Figure 4. The dummy variable is employed; the value is determined whether the facing sub-road provides access to the adjacent main road. The walk-friendly environment is also represented by a dummy variable. The value is set to 1 if the surrounding attracts people to walk, and set to 0 otherwise. Example of good and poor environment are shown in Figure 5.

\begin{figure}[h]
\centering
\includegraphics[width=0.8\textwidth]{fig4.jpg}
\caption{Access roads connecting to main roads}
\end{figure}

a) Wide and clean walkway  

b) Walkway Obstructed

\begin{figure}[h]
\centering
\includegraphics[width=0.8\textwidth]{fig5.jpg}
\caption{Walk-Friendly Environment}
\end{figure}
4.2 Parameters

The three models, i.e., OLS, SAR, and GWR, were coded in MATLAB for the parameter estimation. The results are summarized in Table 2 where the goodness-of-fit of each model is reported.

Table 2 Estimation Results

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>SAR</th>
<th>GWR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>Coeff.</td>
<td>Coeff.</td>
</tr>
<tr>
<td>Age of building</td>
<td>-2,464.2</td>
<td>-4,107.3</td>
<td>-4,107.3</td>
</tr>
<tr>
<td></td>
<td>-11.2</td>
<td>-1,525.8</td>
<td>-2,682.6</td>
</tr>
<tr>
<td>Floor location</td>
<td>721.1</td>
<td>185.7</td>
<td>1,189.8</td>
</tr>
<tr>
<td></td>
<td>3.8</td>
<td>4.2</td>
<td>671.8</td>
</tr>
<tr>
<td>Distance to railway station</td>
<td>-8,815.8</td>
<td>-28,597.1</td>
<td>21,148.4</td>
</tr>
<tr>
<td></td>
<td>-2.5</td>
<td>-2.6</td>
<td>-4,157.7</td>
</tr>
<tr>
<td>Employment accessibility</td>
<td>2,430.6</td>
<td>-14,262.4</td>
<td>38,486.7</td>
</tr>
<tr>
<td></td>
<td>2.6</td>
<td>2.4</td>
<td>6,226.7</td>
</tr>
<tr>
<td>Road connectivity (dummy)</td>
<td>9,876.1</td>
<td>-4,010.4</td>
<td>25,156.7</td>
</tr>
<tr>
<td></td>
<td>2.8</td>
<td>3.0</td>
<td>7,398.0</td>
</tr>
<tr>
<td>Walk environment (dummy)</td>
<td>20,387.8</td>
<td>7,232.9</td>
<td>36,912.5</td>
</tr>
<tr>
<td></td>
<td>5.4</td>
<td>4.9</td>
<td>18,756.4</td>
</tr>
<tr>
<td>Constant</td>
<td>73,039.5</td>
<td>25,029.5</td>
<td>122,117.9</td>
</tr>
<tr>
<td></td>
<td>14.1</td>
<td>10.4</td>
<td>73,237.2</td>
</tr>
<tr>
<td>Autocorrelation ($\rho$)</td>
<td>0.1</td>
<td>0.1</td>
<td>3.5</td>
</tr>
<tr>
<td>R²</td>
<td>0.576</td>
<td>0.563</td>
<td>0.826</td>
</tr>
<tr>
<td>AIC</td>
<td>4,008.9</td>
<td>4,011.1</td>
<td>3,982.8</td>
</tr>
<tr>
<td>Residual Sum of Square</td>
<td>64.65x10⁸</td>
<td>72.26x10⁸</td>
<td>45.45x10⁸</td>
</tr>
</tbody>
</table>

The OLS model is estimated where the resulting coefficients are global, i.e., the coefficients are constant over the study area. Every coefficient has intuitive sign. For the property characteristic variables, the older building is intuitively cheaper. The floor location where the selling unit is located has positive coefficient, meaning that a unit located on higher floor is more expensive. Such premium is probably due to better scenery and wider opening space. For the transport-related variables, the proximity to railway station, either BTS or MRT stations has negative coefficient; indicating that a property locating closer to the railway station will be more valuable due to convenience to commute and travel. The employment accessibility variable coefficient indicates that the property with greater accessibility is more expensive. Moreover, this proxy variable represents the closeness to the city center, i.e., farther condominium is again cheaper. The other two dummy variables also have positive coefficients indicating positive impacts, i.e., access to the two main roads and walk-friendly environment raise up the sale price. The OLS model has moderate goodness-of-fit based on three indicators: the coefficient of determination ($R^2$); Akaike Information Criterion (AIC), which 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; and the Residual Sum of Square (RSS). Next, based on the hypothesis that the spatial effect is present in the data, firstly, spatial dependence is examined by the spatial autoregressive model (SAR) by adding spatial lag term, $\rho$, to the OLS model. The spatial lag is statistically significant while the other coefficient estimates are similar to the OLS model. This indicates that spatial dependence in the form of spatial autocorrelation is present; implying that price setting of a condominium depends on price of the neighborhood. However, from the goodness-of-fit evaluation, it is difficult to judge if it is improved.
a) Employment accessibility (Closeness to the city center)

b) Station Proximity

c) Walk Environment s

Figure 6 Nonstationarity of the Coefficients

Another form of spatial effect, spatial nonstationarity, is examined by the Geographically Weighted Regression (GWR) model. Since GWR estimates a model at each data point, the number of estimated parameters is equal to the number of data points available, i.e., totally 180 sets of parameters are obtained. For ease of presentation, the results of GWR model are presented by three representative statistics: minimum value, maximum value, and mean of the coefficients, also shown in Table 2. The GWR estimates have the same trend as that of OLS. The goodness-of-fit based on the three indicators show that GWR is superior to the other two reference models, implying that the nonstationarity has played significant role in improving
the model goodness-of-fit. In the other words, the extent of the effect of each explanatory variable to the property value varies spatially in the study area. To illustrate this, the coefficients are interpolated by the inverse distance weighting method. The interpolated contour maps of the three representative variables are shown in Figure 6. Obviously, the coefficients vary substantially within the study area; indicating that there is a varying spatial relationship, i.e., nonstationarity in the model parameters.

Considering the variation of the employment accessibility, a proxy to the city center, Figure 6a shows the negative coefficient in the blue areas, where there are many office and commercial buildings, centered to many workplace and job opportunities. It is more accessible than the red areas, which is the residential areas in the outer part, resulting in opposite sign of the coefficient. Next, the coefficient of the distance to railway station, it is found that the coefficient is negative showing in blue in Figure 6b. The premium is approximately 25,000 Baht per kilometer or 25 Baht per meter closer to the station. In these areas, there are rapid developments as can be seen by the continuous rise of new commercial, residential, and office buildings due to the highly convenient access to the urban railway lines. On the other hand, the coefficient is positive in the red areas, which are the outer area in the map, to the right end of BTS line. Although the distance to station is large, the price is still not decreasing because the access to the station is based on the other mode than walk. So the walk distance will not be the primary factor driving up the price. Therefore, such variation in the relationship between station distance and property value has indicated the level of service of station access. This could be good information to suggest local government or transport operator in improving certain station area to more effectively. Likewise, variation of the size coefficient in Figure 6b is very intuitive that it is a consequence of locational convenience around Asoke transfer station, i.e., in the blue area in the map that make the property more valuable when compared to the other property at similar price. For the walk environment variable, it has positive impact to the property value but the extent of the impact is pronouncedly strong in the inner area where walk is the important mode of access to transportation; on the other hand, it has less impact in the outer area where the other motorized modes dominate.

5. CONCLUDING REMARKS

This study has shown that the influence of the rail transit on residential property value is large; indicated by the increasing land value and the increasing number of tall building in the study area. It is, furthermore, found that the impact is quite complicated and varied over space. The spatial hedonic analyses are presented. The global model, OLS, informs the direction of the predictors. The spatial effects are considered: spatial dependence and nonstationarity. The spatial lag model, SAR, suggests that spatial dependence exists in the data. The local model, GWR, reveals the varying relationship between property values and the influencing factors, e.g., closeness to the city center, station proximity, walk-friendly environment, etc. It is found that ease of station access varies substantially along the railway corridor. This may be a usual case in many cities in the developing countries. Previous studies mostly paid attention to interpreting the coefficients as premium of the location, i.e., what determines price. Alternatively this paper looked at the coefficient variation as a reflection of the present circumstance in the study area; i.e., what the price informs. In conclusion, this paper has shown that the spatial effects, i.e., spatial dependence and nonstationarity, are active in the hedonic analysis, which is learnt from the two separate spatial models, i.e., SAR and GWR; however analysis of the combined spatial effects is left for further study.
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