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Analysing the local geography of the relationship between residential property prices and its determinants

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Abstract. This paper analyses the local geography of the relationship between residential property prices and its determinants. A semiparametric geographically weighted regression (S-GWR) technique is employed to explore this relationship. Selling prices, structural and locational attributes data were collected from the database of the Department of Valuation and Services of Malaysia, selected maps and reports. The outcome of this paper shows a strong geographically varying relationship between residential property prices and its determinants in which the residential property price determinants have a positive impact on prices in some areas but negative or no impact on the others. The magnitude of the effect is also found to be geographically varied; the capitalisation in residential property prices is found greater in some areas but less or with no effect in some other parts of the areas. The use of S-GWR technique makes it possible to reveal such geographically varying relationships, thus leading to a better understanding of the relationship between residential property prices and its determinants.

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1. Introduction

Property price, in particular residential property price, is a great concern of the government, real estate developers and general population. This is due to the fact that housing market and changes in residential property prices can affect the entire economy: economic growth, inflation, interest rates and the banking sector. In the social perspective, changes in residential property prices, especially a rise in prices can affect social equity and affordability. In most parts of the world today, particularly in big cities, affordability is the biggest housing concern among residents. For instance, a survey carried out by The Guardian in the United Kingdom (UK) in 2014 indicates that affordability is found to be the biggest housing concern among general population in the UK. Similarly in Malaysia, issues pertaining to home ownership have been the biggest concern among people over the years, especially for those who reside in more developed regions such as in the Klang Valley, Johor Bahru and Penang (1). In addition, changes in residential property prices can also indicate better/worse accessibility to the central business district (CBD) and amenities, good/ /poor schools and high/low crime rates in a neighbourhood etc.

An important question to ask is upon what factors residential property prices depend. If we asked economists, they would tell us that the price of residential properties depends on the supply and demand of housing on the market. But if real estate practitioners were asked this question, the most likely answer would be "location, location and location" and consequently it becomes the main interest of this paper. This implies that the surrounding area where a unit of residential property is located is found to be the key factor in determining its price. For instance, a unit of residential property located in a peaceful neighbourhood is more desirable than the very same property in an area with high crime rates. Based on this reasoning, we expect that a residential property will fetch a better premium when located in the former rather than the latter area. However, it is important to note here that the physical characteristics (structural attributes) of the property itself also play an important role in determining its desirability and price. Therefore, it has been established that a combination of both structural (physical) and locational attributes contributes significantly to the formation of residential property prices (see, for example, Powe et al., 1995; 1997; So et al., 1997; Orford, 1999; Irwin, 2002; Tse, 2002; Cohen, Coughlin, 2008; Anderson et al., 2009; Dziauddin et al., 2013; Dziauddin, 2013). This is due to the fact that the selling price of a residential property reflects both structural and locational attributes, such as the size of floor area, tenancy, the age of the residential property, proximity to central business district (CBD), schools, rail transit stations etc. By regressing the transaction prices against structural and locational attributes, one can estimate the contribution of these attributes to residential property prices. The next important question to ask is whether structural and locational attributes have similar effects and magnitudes on residential property prices across geographical area. If not, how varied are they across geographical area? And do we have a better approach and tool to reveal this geographically varying effects and magnitudes?

The purpose of this paper therefore is to analyse the local geography of the relationship between residential property prices and the attributes that they possess. As these attributes are not directly traded, a number of techniques are available to estimate their effects. The literature has shown that there are two broad categories of non-market techniques: stated preference techniques on the one hand and revealed preference techniques on the other. In the context of this paper, one of the revealed preference techniques, namely hedonic pricing, is used to analyse this relationship.

The hedonic price method (HPM) is a well-established method used to analyse a market for a single commodity with many attributes, in particular that of residential property. In other words, the HPM is based on the idea that properties are not homogeneous and can differ in respect to a variety of attributes. It is worth mentioning that since it was first introduced over 40 years ago, the HPM has been used extensively in urban economic study and examples include construction of house indices (Mills, Simenauer, 1996; Can, Megbolugbe, 1997), school quality (Mitchell, 2000), public transport (Du, Mulley, 2006; Hess, Almeida, 2007; Dziauddin et al., 2013), woodland/urban forest (Powe et al., 1997; Tyrvainen, 1997; Dziauddin, 2013), golf courses (Do, Grunditski, 1995), environmental quality (Lansford, Jones, 1995; Jim, Chen, 2009) and sports arenas (Tu, 2005; Ahlfeldt, Maennig, 2010).

Yet, producing a hedonic price model is best suited to non-spatial commodities. It is unlikely to sufficiently capture the geographical context and variation (2) within which properties are located (Fotheringham et al., 1998). Thus a relatively new spatial econometric technique known as semiparametric geographically weighted regression (S-GWR) which addresses the issue of spatial heterogeneity is also used to analyse the relationship between residential property prices and its determinants in this paper. Using S-GWR makes it possible to estimate local rather than global parameters and thus provides a way of accommodating the local geography of the above stated relationship. Moreover, it is used to verify the heterogeneity of the relations, which in turn can indicate the degree of misspecification in the global model.

The paper is organised as follows. The next section discusses the estimation methods, that is, the use of the HPM and S-GWR techniques. The study area and data acquisition are then described in the subsequent section. This is then followed by empirical analysis and findings. The paper concludes with a review of the implications of the findings.

2. The estimation methods

The discussion in this section focuses on the methods used in this paper, that is, the use of the S-GWR. The GWR in general, however, is based on a global regression model (a hedonic price model) which is then modified by GWR to calibrate local regression parameters by weighting the distance between one data point and another through the coordinates of data (Fotheringham et al., 1998) and S-GWR is a new version of the GWR technique to analyse geographically varying relationship between dependent variable and its explanatory variables which is available in a new version of the GWR software (GWR 4.0) developed by Nakaya et al. (2009). In this framework, one can implement model selection in order to judge which explanatory effects on the dependent variable are globally fixed or geographically varying in generalised linear modelling (GLM) (Nakaya et al., 2009: 1).

2.1. The hedonic price model

The general form of a hedonic pricing model can be presented as:

$$Pi = f\ (S, L,) + \varepsilon \qquad (a)$$

where,

P_i = the market price of property *i*,
S and L = the vectors of structural and locational variables,
ε = a vector of random error terms.

2.2. Semiparametric geographically weighted regression (S-GWR) model

As widely recognised, in estimating residential property prices by means of the HPM one of the main problems is that the parameter estimates are normally applied constantly over the whole geographical area. In other words, the relationships analysed are assumed to be 'stationary' across geographical area, although in reality relationships are arguably not stationary and said to exhibit spatial heterogeneity. In response to that, a relatively new spatial econometric technique known as GWR which addresses the issue of spatial heterogeneity is used in this paper. Fotheringham et al. (1998) pointed out that this spatial heterogeneity if not carefully handled, may cause problems for the interpretation of parameter estimates from a global regression model.

It was argued in the literature that any relationship that is not stationary across geographical area will not be represented well by a global regression model. Fotheringham et al. (2002) have argued further that, failing to address issues related to spatial heterogeneity may cause the estimated parameter produced by a global regression model to be misleading locally. The GWR on the other hand has the capability of dealing with spatial heterogeneity, that is, by taking into account the coordinates in estimated parameter. The standard GWR model can be mathematically expressed at location i in space as follows (Crespo, Grêt-Regamey, 2013: 667):

$$P_i = \beta_0 (u_i, v_i) + \sum_{k=1}^{p} \beta_k (u_i, v_i)\, x_{ik} + \varepsilon_i, \qquad i = 1, \ldots, n, \tag{b}$$

where,
P_i = the response variable at point i,
u_i, v_i = the spatial coordinates of point i,
$\beta_0 (u_i, v_i)$ = the location-specific intercept term parameter,
$\beta_k (u_i, v_i)$ = the kth location-specific parameter,
p = the number of unknown local parameters to be estimated (excluding the intercept term),
x_{ik} = the kth explanatory variable associated with $\beta_{k,}$
ε_i = a random component assumed to be independently and identically distributed,
n = the number of observations

Based on equation 2 above, location-specific parameters $\beta_k (u_i, v_i)$ are estimated using weighted least squares and can be expressed as follows (Crespo, Grêt-Regamey, 2013: 667-668):

$$\beta (u_i, v_i) = [X^T W_i X]^{-1} X^T W_{iy}, \qquad i = 1, \ldots, n, \tag{c}$$

where,
$\beta (u_i, v_i)$ = a (p x 1) vector parameter estimates at location i,
X = an (n x p) matrix of observed explanatory variables,
W_i = a distance decay (n x n) matrix
y = an (n x 1) vector of observed response variables,

Note that p and i are as defined in the equation 2 above. Location i is also denoted as the regression point; the point at which parameters are being estimated. As expressed in the equation above, the weighting of an observation is done through a distance decay matrix (W_i) so that observations located near to the point in space are weighted more than observations located further away. As mentioned above, a new version of GWR called S-GWR developed by Nakaya et al. (2009) is actually the extension from the previous version of GWR; in this new version the user is able to implement model selection through semiparametric approach. As semiparametric includes partially linear terms of explanatory effects on the dependent variable in the canonical parameter and it can be expressed as follows (Nakaya et al., 2009: 3):

$$P_i = \beta_0 (u_i, v_i) + \sum_{k=1}^{p} \beta_k (u_i, v_i)\, x_{ik} + \sum_{l=1} \gamma l Z l_i \qquad i = 1, \ldots, n \qquad \text{(d)}$$

where Zl_i is lth explanatory variable and γl is its coefficient that is globally fixed across geographical area. By these geographically weighted calibration and semiparametric approach, continuous and smooth surfaces of local parameter estimates can be mapped over geographical area and the effects of explanatory variables on dependent variable can be judged whether it globally fixed or geographically varying.

3. The study area and data acquisition

3.1. The study area

The empirical study was conducted in Tanjung Malim, Perak, Malaysia which is located approximately 70 kilometres north of Kuala Lumpur and 130 kilometres south of Ipoh via the North-South Expressway, and in recent years a lot of development can be observed particularly after the operating of heavy industry such as PROTON (national car maker), vendors for PROTON and the completion of phase one Sultan Azlan Shah Campus (Sultan Idris Education University) in Proton City. Tanjong Malim was chosen because there were enough housing transactions during the period of study (2011) and also a sufficient variation within the locational attributes. It encompasses an area of 949.86 square kilometres and had a population of about 41,693 in 2010. There are three biggest employers in Tanjong Malim: national car maker PROTON Company (which has a production plant in Tanjong Malim) and its vendors, Sultan Idris Education University (two campuses) and Sultan Azlan Shah Polytechnic.

Tanjong Malim itself is a medium sized town which lies on the Perak-Selangor state border, with Bernam River serving as the natural divider and also at the foot of Titiwangsa range. The main features in the landscape are natural greens and commodity crops such as palm oil and rubber plantations. The buildings in the town are typically not higher than three stories. In most of the housing areas detached, terraced and traditional Malay houses predominate. Thus, the general profile of the town is almost flat. As a newly developed area, residents of Tanjong Malim are served by basic amenities such as local banks, post office, district hospital, worship places, local shops, commuter service, medium size shopping mall and small size fast food restaurants. Furthermore, the only recreational facility available in Tanjong Malim is located 10 kilometres away from main residential areas and it was developed by a private company as part of an integrated township known as Proton City consisting of residential, commercial, institutional as well as industrial areas. For private transport, Tanjong Malim benefits from good arterial road access.

3.2. Sampled data and selection of independent variables

House price transactions for 2010 and 2011 were chosen to be the sample for this study. In total, 350 units of residential property selling prices were collected. However, after going through several steps to clean the sample dataset by eliminating the unsuitable data and unavailable data (3), the study was left with 217 observations across 14 housing estates. The selling price of an individual house and its structural attributes were collected from the Department of Valuation and Property Services, Malaysia (Teluk Intan, Perak branch).

Variables used in this paper were selected on the basis of their inclusion in previous studies (see, for wexample, Powe et al., 1995; 1997; So et al., 1997; Orford, 1999; Irwin, 2002; Tse, 2002; Cohen, Coughlin, 2008; Anderson et al., 2009; Dziauddin et al., 2013; Dziauddin, 2013) and most importantly, on the basis of their availability and multicollinearity. According to Laakso (1997 cited by Tyrvainen, Miettinen, 2000), the number and quality of explanatory variables vary considerably from one study to another. In Laakso's review of 18 hedonic price studies the number of explanatory variables in the models varied from three (Linneman, 1981) to 30 (Palmquist, 1984).

A list of variables for inclusion in the HPM and S-GWR is given in Table 1. It has been argued by Tyrvainen and Miettinen (2000) that in hedonic models multicollinearity between explanatory variables commonly exists. As a result, 'estimating accurate and stable regression coefficients may be difficult' (Tyrvainen, Miettinen, 2000: 209). To handle this problem Tyrvainen and Miettinen suggest that one can omit a highly collinear variable from the model, provided this does not lead to serious specification bias. For example, Ohlsfeldt (1988) implies that restricting the number of variables may also make the interpretation of results easier.

Table 1. List of explanatory variables and their expected effects on residential property prices

Explanatory variables (Structural attributes)	Expected sign*	Explanatory variables (Locational attributes)	Expected sign*
Size of floor area	+	Proximity to CBD	-
Size of lot area	+	Proximity to primary school	-
Bedroom	+	Proximity to secondary school	-
0 = <3 rooms,		Proximity to university	-
1 = 3 rooms or more		Proximity to mosque	?
Freehold,	+		
0 = no, 1 = yes			

Explanation: + increasing/- reducing effect on the selling price. ? indicates an a priori undetermined sign

Source: Author's own work

In order to measure the distance to locational attributes from a given residential property, the geographical information systems (GIS) was used in this study. GIS was used to organise and manage large spatial datasets (that is, units of residential properties) and of course their structural and locational attributes too. Most importantly GIS was used to position each observation accurately on a local map by using the geographical coordinates. Moreover, the combination between GIS and spatial analysis has been particularly useful in this study in which the distance and proximity were measured accurately by measuring the distance from one point to another using network distance.

4. Empirical results

The results of the HPM and S-GWR models using the above specification are presented below in two stages. The first part shows the results from the hedonic price model and the second part shows the results from the S-GWR model.

4.1. The HPM estimation

The next stage of the estimation process using the HPM is to choose the functional form which best portrays the relationship between a property's market price and each of the variables describing its characteristics. There were four common functional forms used in the HPM: linear, semi-log, double-log and Box-Cox linear (Garrod, Willis, 1992; Cropper et al., 1988; Palmquist, 1984). Unfortunately, economic theory does not generally give clear guidelines on how to choose a particular functional form for property attributes (Tu, 2000; Garrod, Willis, 1992). However, Cropper et al. (1988) suggest that linear, semi-log, double-log and Box-Cox linear perform best, with quadratic forms, including the quadratic Box-Cox, faring relatively badly. Based on the advice given by Cropper et al. (1988), double-log specification was used to measure the effects of the LRT system on residential property values in this study. The model is regressed on a set of eterminants as follows:

$$\ln P_i = \beta_0 + \beta_1 \ln FLRAREA_i + \beta_2 \ln LOTAREA_i + \beta_3 BEDROOM_i + \beta_4 FREEHOLD_i + \beta_5 \ln CBD_i + \\ + \beta_6 \ln PRIMARYSCH_i + \beta_7 \ln SECONDARYSCH_i + \beta_8 \ln MOSQUE_i + \beta_9 \ln UNIVERSITY_i + \varepsilon \quad (e)$$

where i is the subscript denoting each property; P_i is the price of property i in Malaysia Ringgit (RM); ln is natural logarithm; FLRAREA is the floor area of the property in square metres; LOTAREA is the size of lot area of the property in square metres; BEDROOM is 1 if property has 3 or more bedrooms, 0 otherwise); FREEHOLD is 1 if the property is classified as free hold, 0 otherwise (least hold). CBD, PRIMARCHSCH, SECONDARYSCHL, MOSQUE and UNIVERSITY are Tanjong Malim town, primary school, secondary school, mosque and university respectively. These continuous explanatory variables are all measured in metres. Finally, $\beta_0,\ldots,\beta_9$ denotes a set of parameters to be estimated associated with the explanatory variables (including the intercept term), and ε denotes standard error of the estimation, which is assumed to be independently and identically distributed. The descriptive statistics of the model's variables are shown in Table 2.

Table 2. Descriptive statistics of the model's variables

Variable	Type[a]	Description	Units	Minimum	Maximum	Mean
Dependent variable						
SELLING	C	Residential property price transactions	Malaysia Ringgits (RM)	38,000	550,000	137,221.09
Explanatory variables						
Structural variables						
FLRAREA	C	Size of floor area	Square metre	46.50	233.74	106.19
LOTAREA	C	Size of lot area	Square metre	55.60	709.00	176.19
BEDROOM	C	Number of bedroom	Dummy (0 or 1)			
FREEHOLD	D	Free hold type of house	Dummy (0 or 1)			
Location variables						
CBD	C	Proximity to central business district	Metre	50	709	4,249.68
PRIMARYSCH	C	Proximity to primary school	Metre	20	9,900	2,805.67
SECONDARYSCH	C	Proximity to secondary school	Metre	88	7,500	1,602.71
MOSQUE	C	Proximity to mosque	Metre	750	8,600	3,756.45
UNIVERSITY	C	Proximity to university	Metre	850	9,800	3,543.09

Explanation: [a]C = continuous; D = binary

Source: Author's own work

Table 3 presents the summary of the parameter estimates associated with the 'best' model for double-log specification together with geographical variability tests of local coefficients procedure for S-GWR model. In general, the model fits the data reasonably well and explained 81.2 per cent of the variation in the dependent variable. Within the final model most of the explanatory variables that influenced residential property prices are significant at the 1 per cent level and have the anticipated positive and negative signs except for two variables: central business district (CBD) and secondary school (SECONDARYSCH).

Table 3. Global regression statistics and ANOVA table

Hedonic price model (HPM)				
	Coefficient	**t-value**	**Implicit price (RM2011)**	**Geographical variability tests of local coefficients***
Intercept	4.905	11.747	134.96	-1,283.448
Structural Variables				
FLRAREA	0.838	19.155	1,082.88	-25.866
LOTAREA	0.326	8.241	253.89	-1.791
BEDROOM	0.083	1.120	11,389.35	-0.448
FREEHOLD	0.133	2.924	18,250.40	NA
Locational Variables				
CBD	0.088	4.220	2.84	-0.012
PRIMARYSCH	-0.035	-1.166	-1.71	-53.251
SECONDARYSCH	0.069	2.017	5.91	-36.716
MOSQUE	0.049	0.487	1.79	-1,083.553
UNIVERSITY	-0.002	-0.014	-0.07	-715.174
Summary Statistics				
No of observations = 217				
Dependent mean = 137229.09				
R^2 (adjusted) (HPM: 81.2; GWR: 84.6)				
Akaike Information Criterion (HPM: -9.93 ; GWR: -16.32)				
ANOVA	*Sum of squares*	*Degrees of freedom*		*F value*
OLS residuals	12.507	211.000		
GWR improvement	2.296	15.559		
GWR residuals	10.211	195.441		2.824

Explanation: * = negative value indicates that these variables are varies across geographical area
NA = FREEHOLD variable was classified as global therefore were not included in geographical variability test

Source: Author's own work

The implicit prices of the continuous explanatory variables were calculated by holding all other variables at their mean level.The parameter estimates associated with floor area (FLRAREA) are found to be the most dominant factor in determining the residential property price. For every square-metre increase in floor area, the expected selling price of a residential property increases by RM1082.88. The greater magnitude of the effect of floor area was expected since floor area is always associated with the size of the property – this is consistent with most of the hedonic house price literature.

The parameter estimates concerning size of lot area (LOTAREA) indicate that every metre increase in lot area can add RM253.89 to residential property prices. The probable explanation for this is that bigger lot size can provide more land space that can be used in different and exciting ways. For example, the children can have a larger yard to play in. Furthermore, those who are creative can beautify the property with plenty of plants and shrubs through gardening and landscaping. In other words, extra space is a big advantage when it comes to entertaining friends and family members. Based on the advantages listed above it can be expected that the size of lot area of properties has a positive effect on their prices.

The results also tell us that a unit of residential property with three or more bedrooms (BEDROOMS) is sold at RM11,389.35 more than a property with less than three bedrooms. However, the t-value for this explanatory variable is found to be statistically insignificant. Note that the insignificant t-value in the HPM may be found to be significant in the S-GWR model.

Another structural attribute with a positive effect on residential property prices is tenancy attribute (FREEHOLD). The parameter estimates for tenancy indicate that a residential property with freehold title is worth RM18,250.40 more than a residential property without that title (leasehold). The positive effect of freehold tenancy was expected since freehold of a residential property means that one owns the property and the land it is on outright, whilst in the case of leasehold tenancy the length of lease can affect the selling price if one decides to sell the property. In Malaysia for example, majority of leasehold properties are granted only for up to 99 years.

In terms of the locational attributes of explanatory variables, the parameter estimates for a primary school (PRIMARYSCH) suggest that the selling price of a residential property decreases by RM1.71 for every away which is rather small and with insignificant t-value. In the case of secondary schools (SECONDARYSCH) and central business district (CBD) the estimation for these two variables is significantly positive. This is somewhat counterintuitive: we might expect that residential property price would decrease as the distance from a secondary school and CBD increases. The results from the HPM also show that residential property price experiences increase for every metre away from a mosque (MOSQUE). The possible reason for this is that traffic, parking congestion and noise are always associated with a mosque, in particular during Friday prayers or when some community activities are organised. Traffic and parking congestions that occur can potentially cause residential properties located around a mosque to become less favourable among buyers, hence they will bring down the value of the residential properties. Similarly, the use of loudspeakers by a mosque when calling to prayer by 'muezzin' is also perceived as an annoyance to some people and residential properties around a mosque may also become less favourable among buyers. Finally, for proximity to university (UNIVERSITY) the model suggests that for every metre away from a university house price experiences decrease by RM0.07 but with insignificant t-value.

The conclusion that can be drawn from the above findings is that structural attributes of the property played a greater role in determining residential property prices in the study as compared to locational attributes. As discussed above, the size of floor and lot area have been shown to contribute more greatly to the residential property price. The possible explanation that could be given is that majority of housing estates in Tanjong Malim were developed in the late 1990s and early 2000, therefore as they are new properties, it is reasonable to expect that home buyers have to pay more for the structural attributes rather than locational attributes. Furthermore, as mentioned in the above discussion Tanjong Malim itself is a newly developed area and as a newly developed area the number of amenities available in TanjongMalim is rather basic, hence the influence of these amenities on residential property prices could not be observed or they are too small to make a greater impact.

It has been argued by Orford (1999) that the significant and greater effect of locational attributes on residential property prices is frequently observed in a well-established area, whilst in a newly developed area structural attributes of the property normally play a greater role. The above finding is in line with the study carried out by Dziauddin (2009) in the Klang Valley where he found home buyers in Petaling Jaya paid marginally more for locational attributes, whilst in Wangsa Maju-Maluri area they paid more for structural attributes. This is because the former area is a very well established area with a good number of amenities as compared to the latter area which emerged as a new town in the late 1990s. Furthermore, most of the housing estates in WangsaMaju-Maluri were developed in the late 1980s and early 1990s, compared to housing estates in Petaling Jaya which were developed during the 1970s. It is clear that the newest housing built during the 1980s and 1990s has the highest value over residential properties built during the 1970s. In other words, the value of houses tends to decrease with increasing age. In order to fully understand how structural and locational attributes interact with residential property prices further analysis needs to be carried out in the local environment, that is, with the use of S-GWR model. Perhaps by using the local model we would be able to confirm the above findings and maybe some more important findings can be revealed.

4.2. Calibration of the HPM: S-GWR estimation

As highlighted in the literature, the main contribution of the GWR technique is the ability to explore the spatial variation of explanatory variables in the model. Thus, the coefficients of explanatory variables may vary significantly across geographical area. The analysis using S-GWR software in this paper presents two diagnostic types of information: the information for the HPM and S-GWR model – including general information on the model and an ANOVA (it can be used to test the null hypothesis that the S-GWR model has no improvement over the HPM).

In this analysis, the local model benefits from a higher adjusted coefficient of determination (adjusted R^2) from 81.2 per cent in the HPM to 84.6 per cent in the S-GWR model and the Akaike Information Criterion (AIC) of the S-GWR model (-16.318) is lower than for the HPM (-9.933) suggesting that the GWR local model gives a significantly better explanation, after taking the degrees of freedom and complexity into account.

As mentioned above, one of the advantages of S-GWR is the ability to explore the spatial variation of explanatory variables in the model. Based on geographical variability tests of local coefficients procedure, the S-GWR software can examine the significance of the spatial variability of parameters identified in the local parameter estimates and the results of the test are shown in Table 3 above.

4.2.1. Analysing the spatial variation of parameter estimates and T-surfaces

All the local parameter estimates can be mapped but due to space limitations, this paper concentrates merely on two variables: floor area and secondary school. These parameter estimates are mapped using inverse distance weighted (IDW) interpolation that is available in ArcGIS. These two variables are chosen because they represent both structural and locational attributes. Thus, they can be used to confirm and answer the above findings. Besides that, with respect to the variable secondary schools it was estimated that residential property price experiences increase for every metre away from a secondary school, which is counterintuitive. To confirm this results further analysis needs to be carried out in the local model.

According to Mennis (2006) the best interpretation comes from maps of local parameter estimates alongside the maps of local t-value since the local t-value maps exhibit the local significance that accounts for the local varying estimate errors. The parameter estimates for Figure 2 and 3 show the spatial variation over geographical area of a premium on residential property prices provided by two explanatory variables: floor area and secondary schools. In these two figures, the local estimated parameters are shown as different colour bands and the points represent the *t*-value. Note that for variables to be classified as statistically significant, the *t*-value of those variables needs to be at 1.96 or greater (positive and negative signs). It is clear from the maps that the estimated parameters and *t*-values exhibit significant spatial variation across geographical area – this information is completely invisible in the global estimation and is only seen in the local model.

4.2.1.1. Size of floor area (FLRAREA)

In the HPM, the value of floor area is estimated at an average of RM1,082.88 per square metre. However, the S-GWR model illustrates how the implicit price of floor area varies from one place to another (see Fig.1). As can clearly be seen on the map, the implicit price of floor area is estimated to be between RM275 and RM1,370 per square metre, with positive significant *t*-value. Indeed, the implicit prices of floor area that have been estimated to be constant across geographical area by the HPM in fact vary between locations.

As shown on the above map, the implicit price of floor area for some residential properties in Tanjong Malim is estimated at a much cheaper rate compared to the rate estimated by the HPM. For example, there are some residential properties located in the north-east and south-west which experience increase in selling price of between RM275 to RM823 (white and light red bands). Meanwhile, there are also some residential properties located in north-west, east and south-east where their floor area is estimated at a much higher price – the implicit price of floor area is estimated to be between RM1,098 to RM1,380per square metre (red band).

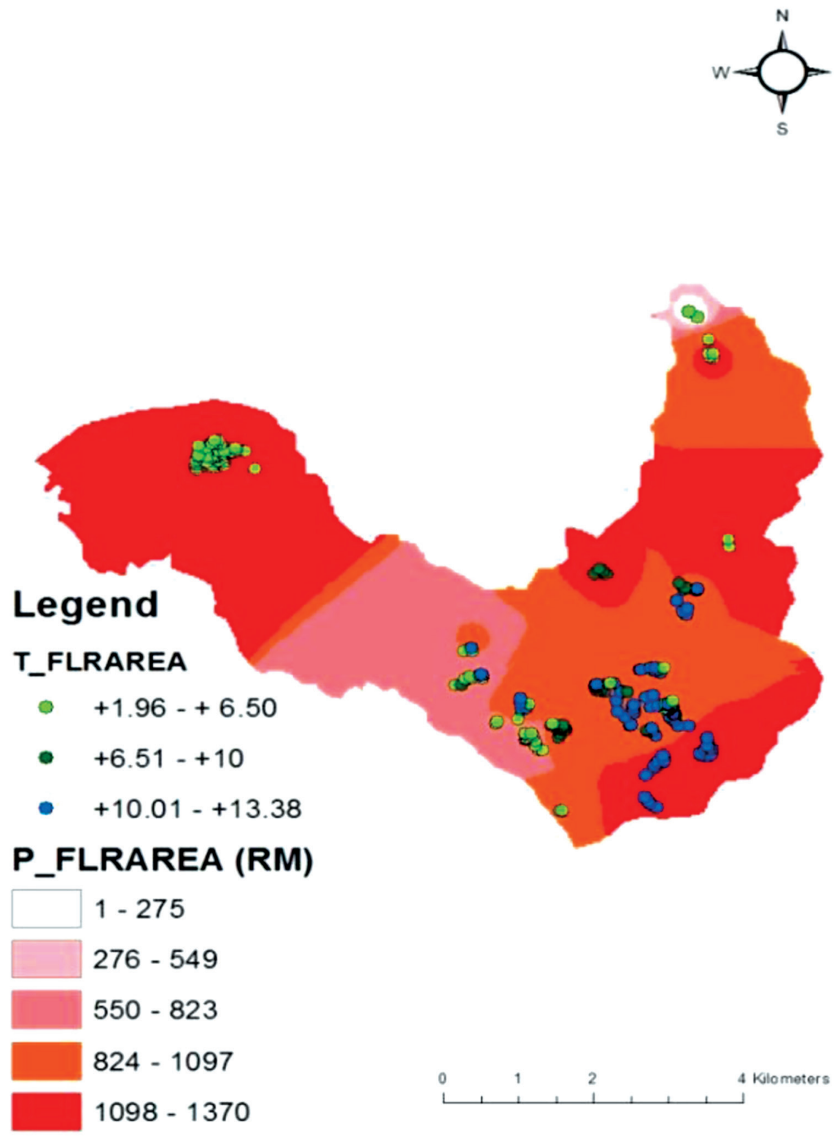

Fig. 1. Map of t-values and parameter estimates associated with floor area

Source: Author's own work

4.2.1.2. Proximity to secondary schools (SECONDARYSCH)

In the case of secondary schools, it has been estimated by the HPM that residential property prices would increase by MYR5.91 for every metre away from a secondary school. An examination of Figure 2 shows that the t-values and estimated parameters illustrate considerable spatial variation on the impact of secondary schools on residential property prices which is hidden in the HPM. Generally, a majority of buyers in this area do not positively value the existence of secondary schools when they buy a property. As can be seen from Figure 2 below, the majority of houses increase in value for every metre away from a secondary school. Yet, there are some buyers who positively value the existence of secondary schools in the neighbourhood by spending marginally more money to be closer to a secondary school. It can be seen from Figure 2 that residential properties located in south experience decrease in selling price of between RM9.67 to RM34.24 (red and light red bands) for every metre away from a secondary school together with significant t-value. Observation that can be made here is that there is degree of importance to be closer to a secondary school for the affected residential property owners in the areas being dissected.

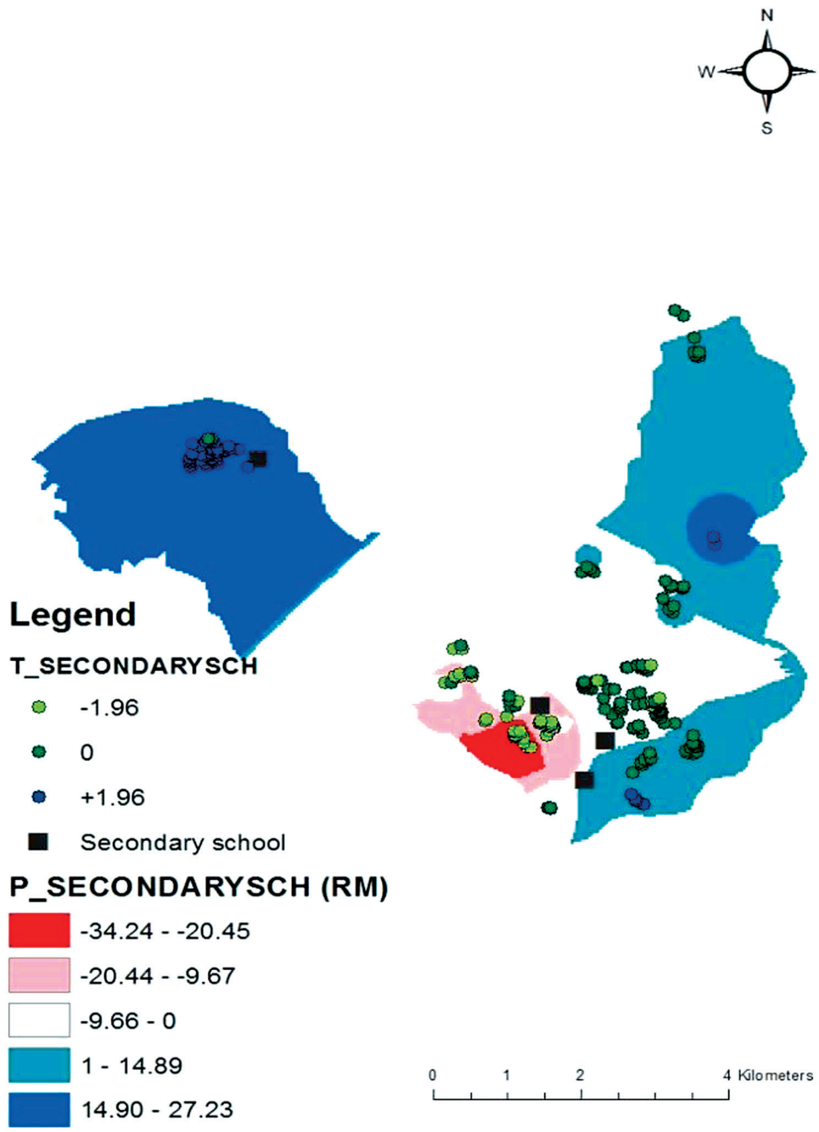

Fig. 2. Map of t-values and parameter estimates associated with secondary schools

Source: Author's own work

5. Conclusions

As stated previously, the purpose of this paper is to analyse the local geography of the relationship between residential property prices and its determinants in Tanjong Malim, Perak. This paper established that the results of the HPM used were insufficient for drawing conclusions about the relationship between residential property prices and its determinants in Tanjong Malim. This insufficiency was due to the nature of the HPM as a global model which does not have the capability to capture the geographical context and variation within which properties are located. To correct for this, further analysis determined that a spatial econometric model would be a better tool for analyzing the relationship. Therefore, the S-GWR model was employed to analyse more directly the relationship locally.

In terms of its overall findings, the results of the HPM demonstrated that structural attributes of the property played a greater role in determining residential property prices in the study. As discussed above, the size of floor area has been shown to contribute more greatly to the residential property price. The results of the HPM analyses also indicated that the effect of some locational attributes such as CBD and secondary schools is positive; that is, the residential property values tend to increase with increasing distance from CBD and a secondary school.

However, further analysis using the S-GRW revealed that such elementary analysis effectively hides a more complex relationship between residential property prices and its determinants under study. The results of the S-GWR model clearly demonstrated that this relationship varies across geographical area; that is, the magnitude and direction of the relationship is geographically dependent, with residential property prices in some areas affected positively and greatly, and in other areas positively but with lesser magnitude. This is evidently true for floor area where the results from the HPM indicated that the size of floor area has been shown to contribute more greatly to the residential property price. However, the analysis using the S-GWR model revealed that the effects and magnitudes of this attribute on residential property prices vary across geographical area. Similar to secondary schools where it was estimated by the HPM that residential property prices tend to increase with increasing distance from a secondary school. But the results from the S-GWR suggest that the relationship between residential property prices and a secondary school also varies geographically, that is, in terms of magnitude and direction, with residential property prices in some areas affected positively and in other areas negatively by distance from a secondary school.

The conclusion that can be drawn from this study is that structural and locational attributes indeed do have an impact on pricing, but this impact varies depending on residential location. Along with its contribution to knowledge in this field, at very least, then, such information may be relevant and beneficial to future urban development in Tanjong Malim and other urban settings where attention should be given to providing more amenities within close proximity to residential area in order to boost residential property prices – increases in residential property prices indirectly can generate more revenues for local council through taxing.

Notes

(1) Following Hashim (2010: 38) affordability issues in Malaysia have never been dealt with in great detail and no specific study on housing affordability has been done. The connotation 'affordable house' which has been widely used by housing developers in Malaysia is mainly their selling point without reference to any established facts or index as base point.

(2) The presence of spatial effect on the validity of traditional statistical methods has long been recognised as a potential problem (see, for instance, Anselin, 1988). For example, spatial effects such as heteroscedasticity can pose severe problems, particularly a violation of underlying independence assumptions, identically distributed errors in the ordinary least squares (OLS) regression model (assumptions four and five) used to estimate the hedonic model.

(3) The following criteria were implemented for the purpose of sales transactions data cleaning; non year 2011 transactions, non-residential property use, incomplete information and suspected error in data entry.

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References

Ahldelft, G.M. and Maening, M., 2010: Impact of sports arenas on land values: evidence from Berlin. In: *The Annals of Regional Science*, Vol. 44 (2), pp. 205-227. DOI: http://dx.doi.org/10.1007/s00168-008-0249-4

Anderson, H., Jonsson, L. and Ogren, M., 2009: Property prices and exposure to multiple noise sources: Hedonic regression with road and railway noise, available at: www.toulouse.inra.fr/ierna/seminaires/Anderson_etal_Noise_Hedonic_Lerun.pdf , DoA: 26 July 2009.

Anselin, L., 1988: Spatial Econometrics: Methods and Models, Dordrecht: Kluwer Academic.

Can, A. and Megbolugbe, I., 1997: Spatial dependence and house price index construction. In: *Journal of Real Estate Finance and Economics*, Vol. 14, pp. 203-222.

Cohen, J.P. and Coughlin, C.C., 2008: Spatial hedonic models of airport noise, proximity, and housing prices. In: *Journal of Regional Science*, Vol. 48, pp. 859–878. DOI: http://dx.doi.org/10.1111/j.1467-9787.2008.00569.x

Crespo, R. and Grêt-Regamey, A., 2013: Local hedonic house-price modelling for urbanplanners: advantages of using local regression techniques. In: *Environment and Planning B: Planning and Design*, Vol. 40, pp. 664–682. DOI: http://dx.doi.org/10.1068/b38093

Cropper, M.L., Deck, L.B. and McConnell, K.E., 1988: On the choice of functional form for hedonic price functions. In: *The Review of Economics and Statistics*, Vol.70 (4), pp. 668-675.

Do, A.Q. and Grunditski, G., 1995: Golf-course and residential house prices: An empirical examination". In: *Journal of Real Estate Finance and Economics*, 10 (3), pp. 261-270.

Du, H. and Mulley, C., 2006: Relationship between transport accessibility and land value: Local model approach with geographically weighted regression. In: *Transportation Research Record,* Vol. 1977 (1), pp. 197-205.

Dziauddin, M.F., Alvanides, S. and Powe, N.A., 2013; Estimating the effects of light rail transit (LRT) system on the property values in the Klang Valley, Malaysia: A hedonic house price approach. In: *Jurnal Teknologi (Sciences and Engineering*), Vol. 61, pp. 37-49.

Dziauddin, M.F., 2009: Measuring the effects of the light rail transit (LRT) system on house prices in the Klang Valley, Malaysia, Ph.D. Thesis, Newcastle University.

Dziauddin, M.F., 2013: Estimating the effects of urban forests on house prices: A geographically weighted regression (GWR) approach. In: *Geografia*, 1 (2), pp. 80-100.

Fotheringham, A.S., Brunsdon, C. and Charlton, M.E., 1998: Geographically weighted regression: A natural evolution of the expansion method for spatial data analysis. In: *Environment and Planning A*, Vol. 30, pp. 1905-1927.

Fotheringham, A.S., Brundson, C. and Charlton, M.E., 2002:Geographically weighted regression: The analysis of spatially varying relationships, West Sussex: John Wiley and Sons Ltd.

Garrod, G. and Willis, K., 1992: Amenity value of forests in Great Britain and its impact on the internal rate of return from forestry. In: *Forestry*, Vol. 65 (3), pp. 331-346.

Hashim, Z.A., 2010: House price and affordability in housing in Malaysia. In: *Akademika*, pp. 37-46.

Hess, D.B. and Almeida, T.M., 2007: Impact of proximity to light rail rapid transit on station-area property values in Buffalo, New York. In: *Urban Studies*, Vol. 44 (5-6), pp. 1041-1068. DOI: http://dx.doi.org/10.1080/00420980701256005

Irwin, E.G., 2002: The effects of open space on house prices. In: *Land Economics*, Vol. 78 (4), pp. 465-480.

Jim, C.Y. and Chen, W.Y., 2009:Value of scenic views: Hedonic assessment of private housing in Hong Kong. In: *Journal of Landscape and Urban Planning*, Vol. 91, Issue 4, pp. 226-234. DOI: http://dx.doi.org/10.1016/j.landurbplan.2009.01.009

Lansford, N.H. and Jones, L.L., 1995: Recreational and aesthetic value of water using hedonic price analysis. In: *Journal of Agricultural and Resource Economics*, Vol. 20 (2), pp. 341-355.

Linneman, P., 1981: The demand for residence site characteristics. In: *Journal of Urban Economics*,Vol.9, pp. 129-149.

Mennis, J., 2006: Mapping the results of geographically weighted regression. In: *The Journal of Cartographic*, Vol. 43 (2), pp. 171-179. DOI: http://dx.doi.org/10.1179/000870406X114658

Mills, E.S. and Simenauer, R., 1996: New hedonic estimates of regional constant quality house prices. In: *Journal of Urban Economics*, Vol. 39, pp. 209-215.

Mitchell, D.M., 2000: School quality and housing values. In: *Journal of Economics*, Vol. 26, pp. 53-68.

Nakaya, T., Fotheringham, A.S, Charlton, M.E. and Brunsdon, C., 2009: Semiparametric geographically weighted generalised linear modelling in GWR 4.0, available at: http://www.geocomputation.org/2009/PDF/Nakaya_et_al.pdf, DoA: 7 March 2014.

Ohsfeldt, R.L., 1988: Implicit markets and the demand for housing characteristics. In: *Regional Science and Urban Economics*, Vol. 18, pp. 321-343.

Orford, S., 1999: Valuing the Built Environment: GIS and House Price Analysis, Aldershot: Ashgate Publishing Ltd.

Palmquist, R.B., 1984: Estimating the demand for the characteristics of housing. In: *Review of Economics and Statistics*, Vol. 66, pp. 394-404.

Powe, N.A., Garrod, D. and Willis, K.G., 1995: Valuation of urban amenities using an hedonic price model. In: *Journal of Property Research*, Vol. 12, pp. 137-147.

Powe, N.A., Garrod, G.D., Brunsdon, C.F. and Willis, K.G., 1997: Using a geographic information system to estimate an hedonic price model of the benefits of woodland access. In: *Forestry*, Vol. 70 (2), pp. 139-149.

So, H.M., Tse, R.Y.C. and Ganesan, S., 1997: Estimating the influence of transport on house prices: Evidence from Hong Kong. In: *Journal of Property Valuation and Investment*, Vol. 15 (1), pp. 40-47.

Tse, R.Y.C., 2002: Estimating neighbourhood effects in house prices: Towards a new hedonic model approach. In: *Urban Studies*, Vol. 39 (7), p. 1165-1180.

Tu, C.C., 2005:How does a new sports stadium affect housing values? The case of FedEx field. In: *Land Economics*, Vol. 81 (3), pp. 379-395.

Tyrväinen, L. and Miettinen, A., 2000: Property prices and urban forest amenities. In: *Journal of Environmental Economics and Management*, Vol. 39, pp. 205–23.

Tyrvainen, L., 1997: The amenity value of the urban forest: An application of the hedonic pricing method. In: *Landscape Urban Planning*, Vol. 37, pp. 211-222.