MODELLING LOCATIONAL FACTORS USING GEOGRAPHIC INFORMATION SYSTEM GENERATED VALUE RESPONSE SURFACE TECHNIQUES TO EXPLAIN AND PREDICT RESIDENTIAL PROPERTY VALUES*

By

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Abstract

Locational value residual surface (LVRS) techniques can be suggested as an alternative to resolving the difficulty in the traditional modelling of locational influence on property values in a particular area. The VRS can be generated using spatial interpolation techniques such as Inverse Distance Weighting (IDW) and kriging within a Geographical Information System (GIS). It is then incorporated into a regression model as a locational value adjustment factor. The objective of this paper is to compare the relative performance of models that apply LVRS and the traditional multiple regression models in the prediction of residential property values. A controlled sample of single- and double-storey residential properties was used to construct regression models. Regressions were run in two stages. The first-stage regression excluded locational component. The differences between the actual and predicted values were then used to construct value residual surface using IDW and kriging techniques. This surface was then used to create locational component that was included in the second-stage regressions. It was found that models applying LVRS were marginally better than the traditional models in predicting property values. Besides, the LVRS has allowed for more a visualised locational influence to be evaluated and captured at any geographic points before being statistically modelled in a more effective way.

Keywords: *Locational value residual surface, geographical information system, multiple regression analysis, residential property values)*

Notes:

* Although the term "value" is used in this study, it sometimes refers to "price". For example, the terms property value can mean property price. The use of the term "value" is this study is, therefore, meant to be of general use.

1.0 INTRODUCTION

Residential property values are influenced by a myriad of locational factors such as accessibility to shopping centres, employment, public facilities; environmental factors (e.g. traffic noise and hazard); neighbourhood amenity; and perceived level of neighbourhood security (Gallimore et al., 1996). Few of these factors can be numerically measured, but the measures may not always be valid representation of the locational influence, especially because of the complex interaction of these factors. Consequently, analysing location for the purpose of explaining value differences and for prediction can be very difficult and subjective even through statistical application.

This study tests the usefulness of using locational value response surface techniques through the application of geographic information system and multiple regression analysis (hereinafter called GIS-MRA generated LVRS techniques) for adjusting residential property values arising from the influence of locational factors as mentioned above. It is argued that explicit inclusion of these factors in a multiple regression analysis (MRA) model is not likely to be realistic due to their diverse nature and complex interaction. Notwithstanding this, with the advent of GIS technology, GIS-MRA generated LVRS can be created and used as a composite locational variable, to represent the complex nature and interaction of locational influence on property values.

This paper begins with a theoretical framework on the issue at hand. The locational factors of residential properties are briefly discussed. The fundamental issue in modelling locational influence on residential property values is specifically addressed. Data and analysis procedure follows in the next section. The following section is the empirical analysis. The final section highlights the key findings and some comments on the benefit of the techniques.

2.0 THEORETICAL FRAMEWORK

Residential properties are multi-dimensional commodities, characterised by durability and structural inflexibility as well as spatial immobility. Each residential unit has a unique bundle of attributes such as accessibility to work, public transport, amenities, structural characteristics, neighbourhood, and environmental quality (Ridker and Henning, 1967; Muth, 1960; Stegman, 1969; Kain and Quigley, 1970; Evans, 1973; Lerman, 1979 and So et al., 1997). From the list of factors, locational is arguably the most important component affecting property values. It is also commonly accepted that properties are spatially unique and this means that location is an intrinsic attribute of a dwelling that directly determines housing quality and market value. However, modelling locational factors in property valuation has proved difficult because of the wide range of spatially defined attributes, which may or may not affect value at a particular time and location. Furthermore, the literature has little consensus on the best proxy for locational factors, their measurements, and the way they influence property values.

The multiple regression analysis (MRA) has been considered as a classical technique in the mass valuation of properties, dating back to 1920s when it was first applied in valuing farm properties in the United States (Haas, 1922; Ezeikiel, 1926). However, the MRA models began to be used to estimate residential property values in the United States only in the 1950s and in the U.K since the 1980s (Pendleton, 1965; Greaves, 1984; Adair and McGreal, 1988). It was also applied in other countries such as Australia, New Zealand, and Singapore, but has yet to be adopted in Malaysia.

In applying MRA in property valuation, researchers attempt to identify the relevant types and measurements of data, oftenly in quantitative forms. This task becomes more complicated when locational influence on residential property values has to be identified. Studies that have sought to assess property value determinants have either ignored detailed locational analysis (Wyatt, 1997; So et al., 1997), or dealt with it only in a very general sense. To take easy way out, some researchers simply omit the locational variables (Ferri, 1977).

Scott (1988) suggests that valuers infer a substantial amount of information about a property from its location which, in turn, is based on local knowledge and experience. For example, a common approach to evaluating accessibility is to measure the distance from the Central Business District (CBD), which simply assumes that the location is homocentric. This is based on the traditional location theory that examines the role of accessibility to a central location on house prices.

However, it is argued that house prices are determined not only by accessibility but also by the environmental attributes of the location (Stegman, 1969; Richardson, 1971; Henderson, 1977 and Pollakowski, 1982). Moreover, there are also theories of multiple-nuclei models incorporating the concentric patterns that are more appropriate for analyzing locational influence on property values. In this context, some researchers have employed more sophisticated measurements of location such as using the type of transport, time taken per trip, and transportation cost. Still, such variables could not satisfactorily explain locational characteristics of properties under study.

Apart from the above, attempts to account for locational influence on property values have been made by partitioning a particular area into neighbourhoods and each neighbourhood is categorized using a dummy variable (Hamid, 2003). From the mass appraisal modeling perspective, it is essential to subdivide the study area into "realistic" sub-market or neighbourhoods to reflect the influence of location more accurately. Although some level of improvement in the predictive performance of the regression model can be achieved, delineation of neighbourhoods is still quite subjective.

A problem commonly faced in modeling location is the requirement for subjective judgments about the boundaries of each neighbourhood and the numeric indicator for neighbourhood quality. To solve this problem, some researchers have simply asked local valuers or local experts to rank the neighbourhood quality (Hickman et al., 1984). There is little consensus, however, on which variables are the best proxy for neighbourhood quality (Can, 1990). Therefore, neighbourhood quality is arguably an unobserveable variable (Dubin and Sung, 1987). When an overarching model is adopted, such decisions may lead to disparities or inconsistencies especially for properties adjoining or close to neighbourhood boundaries. A hard edge may be implied at such boundaries, whereas in reality the varying influence of location may operate far more smoothly (Gallimore et al., 1996).

The complexity of locational factors and the problems to identify them, which confront their assessment, can seriously threaten the validity of a MRA model. In fact, location is only one of many variables in the equation, and it is both intuitively and empirically agreed as an important variable influencing residential property values. Therefore, an approach, which accurately accommodates the transitions of locational effects on property values across a particular area from which the data are derived, is required.

GIS-MRA generated LVRS can be used to model differential locational influence on residential property prices in the local context, based on the framework discussed by Gallimore et al. (1996). The modeling is performed in two stages. In the first-stage regression, selected residential value factors, excluding locational components, are specified in an MRA model, utilizing a sample of geo-referenced transacted residential properties. Prediction residuals (predicted values minus actual prices) generated from this stage are then mapped on the respective original observations. In the next step, GIS is used to build LVRS, based on the nearest-neighbour technique available in the GIS software. This LVRS is used to adjust for under- or over-valuation of properties in the study area. The second-stage regression is finally performed to obtain the coefficient of the LVRS together with the coefficients of other variables.

The main focus of GIS-MRA generated LVRS is to improve the statistical quality and predictive performance of the MRA models in relation to predicting unsold properties with unknown sales prices in a particular area. The traditional MRA model, whereby the locational effect is measured using distance from the central business district (CBD), is used to compare model's predictive capability.

3.0 DATA AND ANALYSIS PROCEDURE

The study area, Taman Pelangi, is a medium-sized residential neighbourhood in the northeastern part of the City of Johor Bahru (Figure 1). It has a balanced proportion of Chinese and Malays (44 versus 34 persons per acre) and a small proportion of Indian (3-4 persons per acre). It is a well-planned mixed development consisting residential, commercial, and office properties, apart from complete public facilities and amenities. Like any other housing estates in Johor Bahru, single- and double-storey terrace houses form the major proportion of residential units in this area. Based on a previous study, this residential area has a moderate level of property crimes (920 – 1,500 cases per year) and violent crimes (80-200 cases per year) (Hamid, 2003). It has excellent accessibility and other locational advantages from various internal and external parts of the City of Johor Bahru. However, variation in the micro-locational components can be expected and, thus, LVRS is expected to be able to represent these components in the regression model.

In developing LVRS, the pertinent factors influencing property prices, except for locational components, were included in the first-stage regression. The estimating model was then used to predict the prices of properties in the original sample, without locational components, creating, in the process, "local errors of prediction". Next, a Geographic Information System software was used to generate a geo-referenced surface of these errors, creating what is called "local errors of prediction surface" (GIS-MRA generated LVRS). This surface was used to adjust for locational components in the second-stage regression.

The valuation data were obtained from the Property Valuation and Services Department (JPPH). The GIS data were obtained from the Department of Survey and Mapping Malaysia (JUPEM). This source provided spatial information that was used to locate the transaction at each geo-referenced point with respect to each individual property in the original sample to generate LVRS.

The first step in building an MRA model was selecting the variables to be included in the model. Due to data constraint, the inclusion of value factors in this study was primarily based on the availability of information from the JPPH. The variables included were size of land area, size of gross of floor area, size of ancillary area, property type (1 if single-storey terrace), age of building, building condition (1 if good), type of floor finishes, and distance from the Central Business District (CBD).

The second modeling step was specification of the appropriate functional form of the regression model. Box-Cox transformation was used for this purpose (see Box and Cox, 1964). The resulting model was then evaluated for its statistical qualities, including the ajd R^2, F-value, SSE, SEE and, coefficient sign and size.

Once the regression model has been obtained, LVRS was generated using nearest neighbour method available in the ArcView 3.2 software. This step was carried out to estimate the configuration of the location value response surface from the points generated by the MRA residuals (without locational variables). This response surface was then used to adjust for under-or-over valuation of properties in the study area. This has enabled locational influence to be measured and accurately accommodated into the transition of effect across the study area by using GIS. The locational influence can be measured for any point of property site within the area in relation to a predicted property price. The basic theories and rationale of the interpolation techniques used in this study are briefly discussed in Gallimore et al. (1996).

The ability of the GIS-generated LVRS to improve the predictive model was evaluated on the basis of quality and predictive performance of the model against the conventional MRA, which used CBD as a locational variable. In particular, the predictive performance of the competing models was evaluated based on the range of prediction errors, mean absolute percentage error (MAPE), and proportion of accurate predictions from the holdout sample.

4.0 RESULTS AND DISCUSSION

4.1 GIS-generated LVRS

Figure 2 shows a 2½-D LVRS output generated from the first-stage regression. The purpose of this output is to give a visual profile of prediction residuals (errors of prediction, e) across the study area. “Bumps” represent areas where there was under-valuation of the sampled properties while “”potholes” represent areas where there was over-valuation of the sampled properties. [Note: $e = \hat{Y} - Y$, where $\hat{Y}$ is estimated price from the regression, excluding location components; Y is the actual price of the property; and e is error of prediction.]

Figure 3 shows the same output as Figure 1 but is represented in the form of contours. It is basically useful for locating the geo-referenced point of a particular property so that a specific quantum of locational adjustment can be directly identified at a particular point.

Using Figure 1 and Figure 2, the locational adjustment for each sampled property is determined and is represented in the second-stage regression by using a locational variable. Then, this variable together with other variables were regressed against the selling prices of sampled properties to obtain a final estimating model.

4.2 Basic Statistical Results

The descriptive statistics of the sample are presented in Table 1. The terraced residential market in the study area has a price range between RM 160,000 and RM 433,000 per unit, with the standard deviation of RM 61,576. The range of plot and floor size in the sample has been controlled to a considerably narrow range (143 – 217 sq. m.) in order to avoid too much variation in the sample that can lead to less accurate price predictions. About 56% of the sampled properties were single-storey terrace houses with the mean age of 23 years. However, many of these houses have, in fact, been renovated or remodeled and, for this reason, almost 99% of the properties were in good condition. Almost 96% of the sampled residential properties have a combination of parquet, marbles, and tiles floor finishes. All properties were located in a very close proximity to the CBD, whereby the mean distance was only 2.6 km, with a standard deviation of 0.74 km.

Table 1: Descriptive statistics of the sample variables.

	Min	Max	Mean	Std. Dev.
Price (RM)	160,000	433,000	257,971.30	61,576.24
Land area (sq. m.)	143.06	216.82	163.8916	15.07317
Gross floor area (sq. m.)	69.21	218.32	117.8946	36.07985
Ancillary area (sq. m.)	7.43	70.86	31.4627	11.26152
Property type (1 if single-storey)	.00	1.00	.5604	.49908
Age of building (years)	15.00	28.00	22.6264	3.16104
Building condition (1 if good)	.00	1.00	.9890	.10483
Floor finishes	.00	1.00	.9560	.20613
Distance from CBD (m)	1,842.11	3,421.05	2,560.4395	739.2558

A number of models have been estimated using all the eight independent variables. The Box-Cox transformation was performed on all continuous independent variables to determine the most appropriate function to use, on the basis of highest adj R^2.and test of model's equivalence. Besides, model's significance, coefficient sign and magnitude were also assessed to evaluate overall statistical quality.

Both linear and log-log functions were found to be of equivalent quality on the basis of adjusted R^2, F-value, standard error of estimate, and sum squared error. However, the test of model equivalence found that the linear model fit the sample data better. The linear function has also provided the added advantage of ease of interpretation with regard to attribute estimates. For these reasons, only the linear function is reported in this section.

Table 2 shows the basic results from the first-stage regression, i.e. without LOCATION components, while Table 3 shows similar models but with LOCATION components included. Model I was used as a basis for generating errors of prediction surface as shown in Figure 1 and Figure 2. Model III was estimated after incorporating locational adjustments using these surfaces and representing these adjustments in the variable LOCATION in the second-stage regression.

Table 2: Linear Regression Results Without Location Components (Model I)

Adj. R^2 / F-value	0.830 / 63.78	
SEE	25,404.37	
SSE	645,382,011.9	
	Coefficient	t-value
Intercept	71,341.839	(1.452)
Land area	794.903	(4.247)**
Gross floor area	841.656	(4.863)**
Ancillary building area	685.552	(2.417)**
Property type (single-storey terrace)	-25,715.342	(-2.206)*
Age of building	-4,605.529	(-4.966)
Building condition (good)	59,067.419	(2.242)**
Type of floor finishes	-4,439.743	(-0.328)
LOCATION	-	-

Table 3: Linear Regression Results With Location Components

	Type of Model	
	Model II	Model III
Adj. R^2 / F-value	0.843 / 61.412	0.985 / 731.174
SEE	24,397.44	7,585.01
SSE	595,235,238.1	57,532,385.01
	Coefficient (t-value)	Coefficient (t-value)
Intercept	157,149.255	96,963.217
	(2.800)**	(6.596)**
Land area	553.220	811.425
	(2.780)**	(14.520)**
Gross floor area	714.496	730.482
	(4.149)**	(14.097)**
Ancillary building area	640.337	909.524
	(2.347)*	(10.696)**
Property type (single-storey terrace)	-36,258.665	-29,606.891
	(-3.073)**	(-8.500)**
Age of building	-3,669.648	-5,086.020
	(-3.862)**	(-18.335)**
Building condition (good)	46,785.952	57,247.150
	(1.822)*	(7.276)**
Type of floor finishes	-5,891.814	-9,371.596
	(-0.453)	(-2.316)*
LOCATIONφ	-12.309	2,479.815
	(-2.827)**	(29.139)**

φ Model I used CBD while model II used LVRS as a locational variable. * Significant at $\alpha = 0.05$; ** Significant at $\alpha = 0.01$. Dep. = total selling price (RM per unit property).

Further analysis on the correlation matrix (not reported here, though), show that there was no serious problem of multicollinearity among the independent variables, thus, no variable modification was deemed necessary. The models have explained about 83-98.5 percent variation in the selling prices of residential properties in the study area. The constant could have represented the influence of all attributes not included in the regression models and was the base to which other variables are added.

Table 3 shows that, overall, the magnitudes of regression coefficients were reasonable and there were no conflicting coefficient signs. Except for type of finishes in Model I, all other variables were statistically significant.

Land area, gross floor area, ancillary building area, and good building condition were the most important building physical characteristics affecting residential prices. Each additional physical area, would have added as much as RM 550 – RM 910 to the total selling price. The results also revealed that it pays to maintain one's property under good condition since it would have commanded RM 47,000 – 57,000 higher than say, poorly maintained property.

Not quite surprising, single-storey terrace units were found to be selling at RM 30,000 – RM 36,000 lower than double-storey terrace units in the study area. Apart from that, category I floor finishes would have detracted per unit selling price at much as RM 6,000 – RM 9,000, compared to other categories of floor finishes. Nevertheless, these figures could not be relied upon, since the variable concerned was not statistically significant, except in Model III.

A further look at the regression coefficients in Model II and Model III reveals a large discrepancy in the influence of locational components on the residential selling price differentials across the study area. According to Model II, there would have been a small reduction of approximately RM 12.31 of per unit selling price for properties located each km away from the CBD. For example, a house located at the mean distance (2.56 km) from the CBD would have been sold only RM at 31.51 lower than the mean selling price of RM 257,971.30. This may not auger well with that of Model III, which seems to be more reasonable.

For example, at the location where there was a 12% under- or over-valuation, a property should have been adjusted upward or downward by as much as RM 29,758 from the mean price.

The LVRS can be used to aid in the explanation of factors that influence price differential across a particular geographic location. For example, “potholes” areas represent sites with negative influence such as the proximity of houses to negative elements such as oxidation ponds, industrial area, noisy main roads, poor neighbourhood condition and houses which were located rather far away from clusters of shop houses and other commercial activities. On the other hand, “peaks” and “ridges” may indicate properties located on sites with positive influence such as proximity to public service areas, facilities, parks, and sites with good micro-accessibility.

Checking through “ground truth” can be carried out in some selected areas to ascertain the existence of any negative or positive elements such as mentioned above. This will give an opportunity for a valuer or appraiser to bridge between the theoretical aspects of the techniques proposed and the actual practice of valuation process.

4.3 Statistical Quality and Predictive Capability of the Models

Table 3. provides a comparative analysis of the statistical quality of the competing models. Model with GIS-generated LVRS (Model III) has managed to explain variation in the selling prices of residential properties better, 98.5%, as compared to the one without this component (Model II) which explained 84.3% variation in the selling prices.

In the same way, Model III has a much higher level of significance on the basis of F-value. It also has lower standard error of estimate (SEE) and much lower sum squared errors (SSE). Larger t-values for all regressors in Model III compared to those in Model II were also an argument for the benefit of incorporating GIS-generated LVRS in a value-estimating model.

Apart from the above points, one essential question is whether incorporating GIS-generated LVRS as a locational component is be able to improve the predictive capability of the regression model – the very essence of any statistical-based value modelling.

Comparison of predictive parameters in Table 4 shows that incorporating GIS-generated LVRS as a locational component has led to some improvement in the predictive capability of the regression model. On the basis of range (minimum-maximum) of prediction errors as well as the MAPE, both Model II and Model III have similar predictive quality. Nevertheless, incorporating this locational component in Model III has resulted in more proportion (40%) of residential properties being predicted below ± 10% margin of error. On the other hand, representing locational influence in the normal way (as reflected in the inclusion of CBD) in Model II has resulted in more proportion (70%) of residential properties being predicted between ± 10 % – 20% margin of error.

Table 4: Predictive Capability of the Value Models

Prediction errors	Type of model	
	Model II	Model III
Maximum	18.34	19.97
Minimum	4.76	3.45
Mean absolute percentage error (MAPE)	12.32	12.13
Below ± 10%	30	40
± 10% - 20%	70	60

4.4 Model application

The GIS-MRA-generated LVRS as shown in Figures 2 and 3 can be employed together with location maps such as those shown in Figures 1, 4, and 5 to create a local adjustment table (LAT) that can be used to assess the market value of unsold residential properties in a particular area. LAT gives a general idea about the amount of adjustment that should be given to any particular unsold residential property located within the sample area.

Table 5: Local Adjustment Table for Unsold Residential Properties in the Study Area

Selected location	Recommended Local Value Adjustment Based on Regressed Price (%)			
	IDW technique		Kriging technique	
	Min	Max	Min	Max
Jalan Pasir Pelangi	+2.0	+4.0	+4.0	+6.0
Jalan Serampang: to the west of Jalan Kuning	-3.7	-9.0	-0.8	-2.2
: to the east of Jalan Kuning	-9.0	-14.5	-7.8	-13.0
: to the right of Jalan Serampang	-9.0	-14.5	-3.9	-5.9
: both side to the north of Jalan Sri Pelangi	+1.8	+3.7	+0.1	+2.0
: to the north of Jalan Hijau Muda 3	+7.2	+12.7	+2.0	+4.0
: to the east of Jalan Jerau	+7.2	+12.7	+2.0	+4.0
: Jalan Abiad	-9.1	-14.6	-2.0	-3.9
Jalan Stulang Darat : to the northwest area	+1.8	+3.7	+0.1	+2.0
: to the southwest area	+7.2	+12.7	+6.0	+8.0

Notes: + sign indicates that properties in a particular location need an upward price adjustment, while – sign indicates that the properties need downward price adjustment.

Table 5 shows an example of LAT for residential properties in the selected location in the study area, based on IDW-based and kriging-based LVRS. Instead of a single figure, a range of possible adjustment figures are given so that valuers can decide on, within the range, the figure that is deemed most appropriate before final predictions are made. Table 10 shows an out-sample prediction of residential property prices in the study area. For illustrative purposes, only IDW-based LVRS technique is shown here. The predictions in the middle column used

Model I in Table 7 and the IDW-based LVRS shown in Figure 2. The amount of local value adjustment that was 'deemed' most appropriate for each property was judgmentally derived by looking at the geographic position of a particular property.

On average, the prediction error using IDW-based LVRS technique in Table 6 was 7.41%, which conforms to the generally acceptable standard of ±10% of predictions since a number of properties have indicated serious over-prediction or under-prediction such as those at No. 14, Jalan Jingga 2, Taman Pelangi (-132% prediction error); No. 194, Jalan Sutera, Taman Sentosa (-37% error); and No. 50, Jalan Songkit 8, Taman Sentosa (35% prediction error).

Table 6: Out-Sample Prediction of Residential Properties in the Study Area

		Market Value		
Lot No.	**Address**	**Actual Price (RM)**	**Predicted (IDW-based)**	**Prediction error (%)**
19864	77, Jalan Sri Pelangi, Taman Pelangi	315, 000	267,964.9	14.93
19833	84, Jalan Sri Pelangi, Taman Pelangi	300, 000	224,052.4	25.326
19525	95, Jalan Kelabu, Taman Pelangi	170, 000	143,323.3	15.69
18165	16, Jalan Maju 4, Taman Pelangi	268, 000	261,256.1	2.516
19778	32, Jalan Hijau Muda 5, Taman Pelangi	230, 000	250,248.6	-8.80
17955	6, Jalan Abiad 2, Taman Pelangi	238, 000	217,994.3	8.41
18890	14, Jalan Jingga 2, Taman Pelangi	140, 000	324,323.8	-131.66
18213	16, Jalan Maju 3, Taman Pelangi	260, 000	302,880.9	-16.49
18550	18, Jalan Kuning Muda 5, Taman Pelangi	370, 000	327,902.2	11.38
20209	169, Jalan Biru Muda, Taman Pelangi	288, 000	283,192.6	1.70
11944	14, Jalan Nila 5, Taman Pelangi	275, 000	192,425.5	30.03
9788	23, Jalan Songkit 3, Taman Sentosa	270, 000	220,279.4	18.42
18563	3, Jalan Kuning Muda 5, Taman Pelangi	362, 000	331,530.8	8.42
19692	37, Jalan Hijau Muda 9, Taman Pelangi	240, 000	176,172.8	26.60
9475	27, Jalan Songkit 2, Taman Sentosa	160, 000	178,400.6	-11.5
9912	51, Jalan Songkit 8, Taman Sentosa	266, 000	237,887.0	10.60
15757	28, Jalan Jerau 4, Taman Pelangi	205, 000	249,847.7	-21.88
9515	50, Jalan Songkit 2, Taman Sentosa	250, 000	162,547.4	34.98
8117	137, Jalan Keris, Taman Sri Tebrau	168, 000	183,931.0	-9.48
11156	194, Jalan Sutera, Taman Sentosa	175, 000	239,142.6	-36.65
18490	18. Jalan Kuning Muda 1. Taman Pelangi	360. 000	267.155.0	25.79

4.5 Implications of LVRS techniques on property valuation

If valuer's main purpose of modeling is value prediction, then the LVRS serves as a source of generic variables that represent various locational factors influencing property values and it avoids the difficulty of trying to specifically identify these factors at a particular site. The LVRS, superimposed on a location map, conveniently aids valuers in pinpointing under- or over-prediction of property values on the ground and, thus, in making appropriate adjustments at known addresses or geo-referenced positions thereof. In particular, the local adjustment table (LAT) is a useful value adjustment tool that is justified based on the LVRS, whereby it can be updated from time to time according to the dynamics of local property market.

However, if specification and estimation of influence of locational factors are to be particularly envisaged, one still have to identify these factors within a particular geographic area. Further, an auxiliary model that regresses the levels of spatial residuals of property values against the influencing locational factors may need to be estimated. Certainly, this option goes back to the traditional discrete location modeling. It may have both predictive and explanatory advantages but, at the same time, it is more cumbersome while maintaining the "old problems" of discrete location modeling.

The results from this study should be able to encourage further research in various aspects of spatial modelling in property valuation. Future research may focus on the refinement of GIS-MRA LVRS techniques using a more complete model specification. The effect of sample structure on the resulting LVRS can also be examined further. Sample structure includes elements like the number, distribution, and type (single- or double-storey property value, per square foot or per unit property value) of observation points.

Further investigation on the likely spatial elements that give rise to bumps or ridges and potholes or trenches on the LVRS can be further explored in future studies. By doing so, some factors can be statistically explained with certain locational detail in the local market. As a matter of fact, the practice in the property valuation is that people naturally want to discover the specific locational factors that have actually influenced property values in the local market. This allows back-to-back approaches between GIS-MRA LVRS techniques, the traditional MRA techniques, and the traditional comparison method to be adopted in assessing property prices in a particular area.

And, who knows if this technique will become part of routine valuation process in Malaysia 100 years from now in the same way as what Haas could have thought about the use of regression analysis in property in the United States about 90 years ago?

5.0 CLOSING REMARKS

The main objective of this study was to examine the usefulness of GIS-generated LVRS for creating locational adjustments in the prediction of residential property prices in a particular area. Initially proposed by Gallimore et al. (1996), this technique emphasizes on aggregating various components of location-associated influence (such as accessibility, quality of surrounding, neighbourhood differential, etc.), which are difficult to and cannot effectively be modelled, into a single composite locational variable to obtain more accurate prediction of property prices.

There was evidence that incorporating GIS-generated LVRS in a regression model can lead to improvement in value predictions. Specifically, higher proportion of more accurate predictions (MAPE = ± 10%) could have been obtained using GIS-generated LVRS as a locational variable.

GIS-generated LVRS is another means to enhance the use of comparison method, especially mass appraisal, to adjust property prices for differential locational influence. The LVRS tells something about locational differences in residential property values across a particular geographic area. This can be used as a starting point to examine the cause-and-effect of locational differences in property values in a defined property sub market. This may enhance understanding about the actual market forces that occur spatially. For example, in the low residual-value areas, further investigation can be carried out to ascertain the actual factors giving rise to under-valuation. In the same way, in the high residual-value areas,

further investigation can be carried out to ascertain the factors that may cause over-valuation. It may be discovered that some in-situ factors that have not been taken into account in the MRA have actually determined the prices paid for the properties involved.

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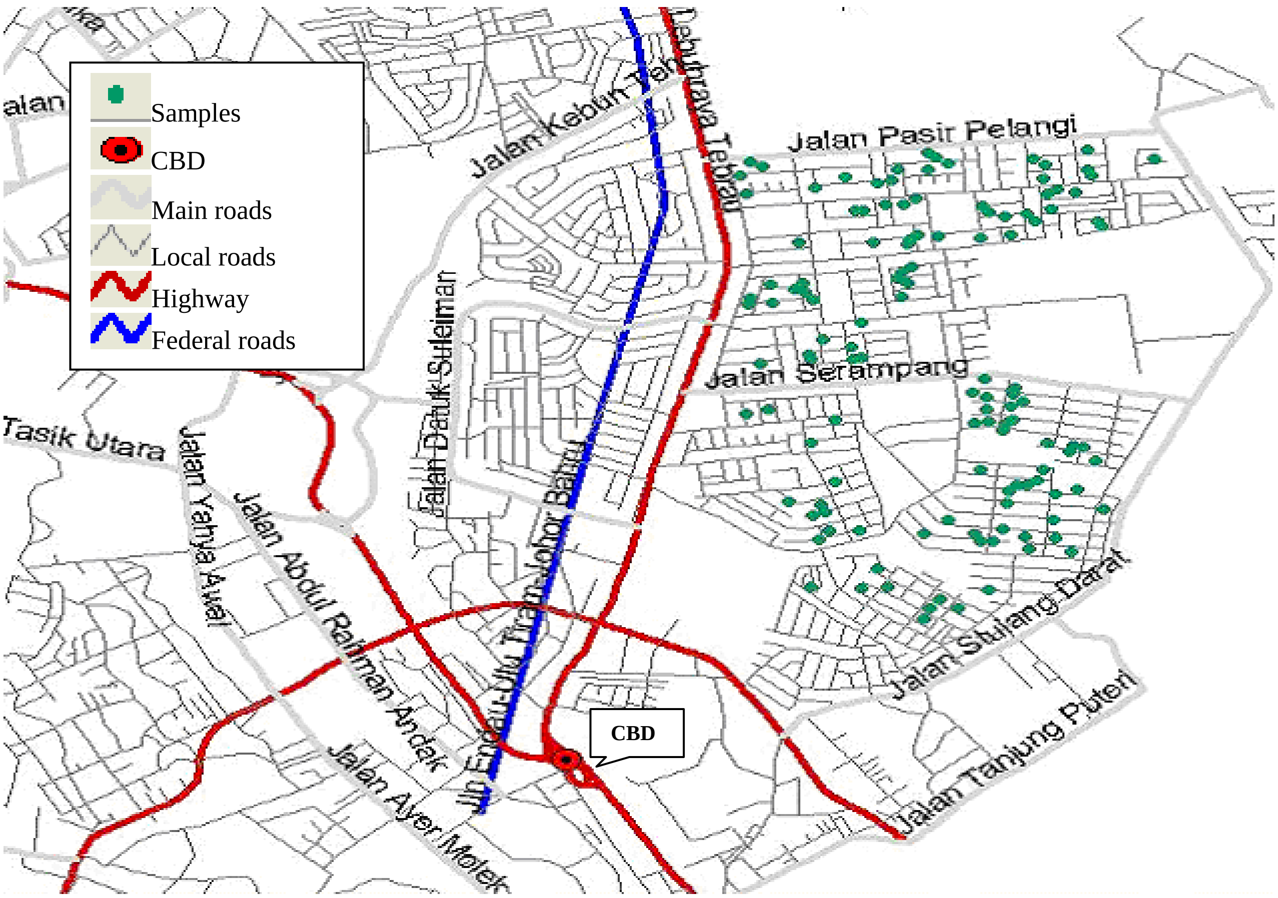

Figure 1: Location map and samples of house lot (house price 2001/03)

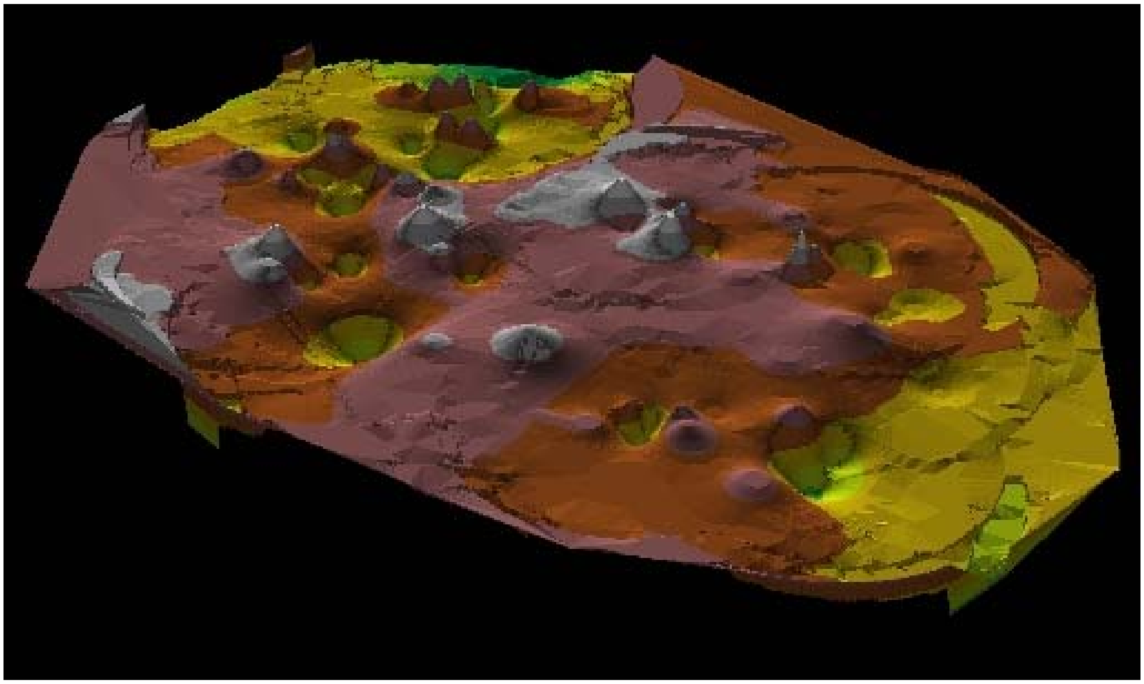

Figure 2: GIS-MRA generated 2½-D local errors of prediction surface (LVRS)

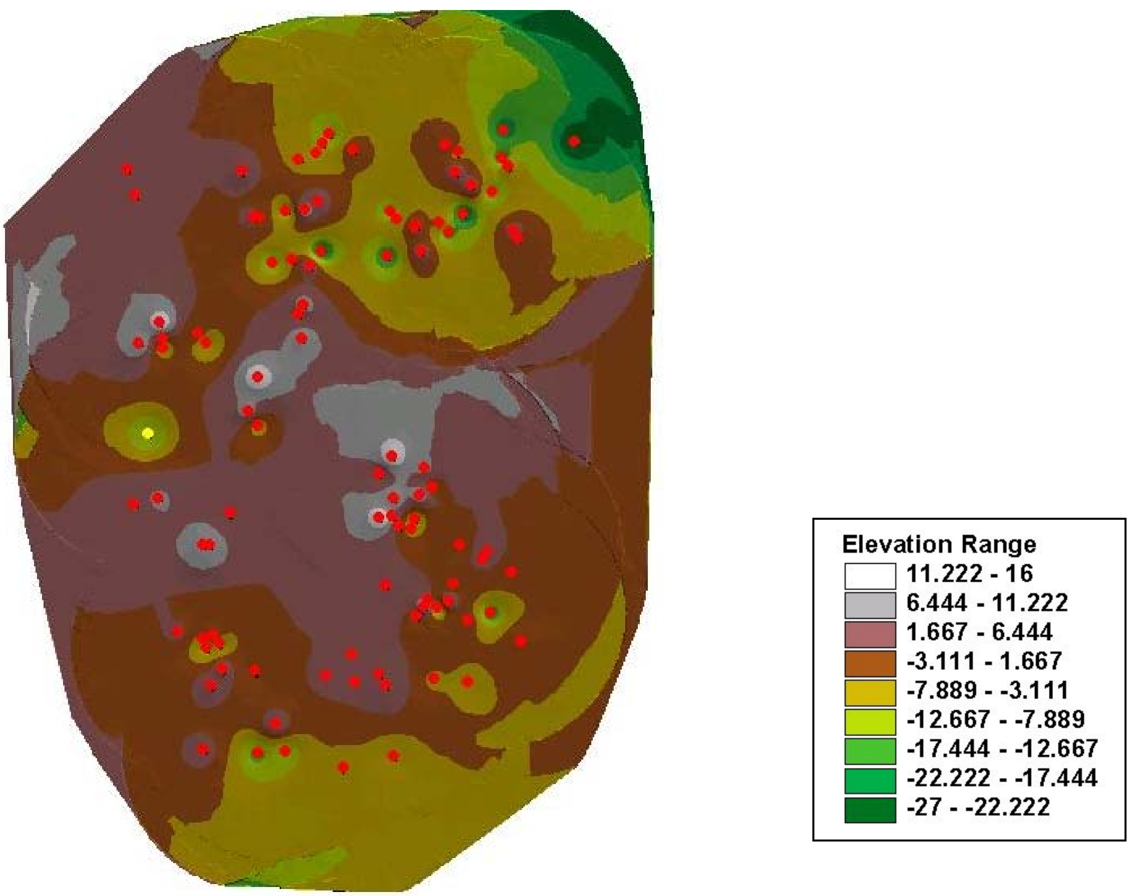

Figure 3: GIS-MRA generated 2-D local errors of prediction surface

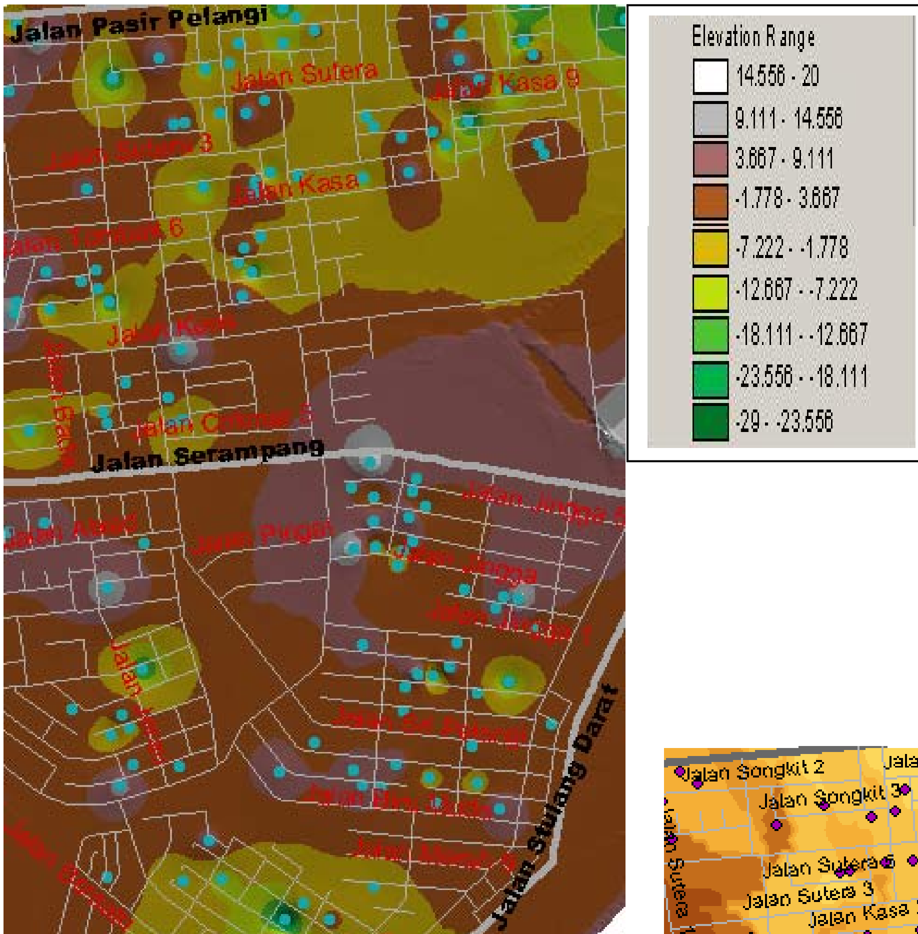

Figure 4: IDW-based 2-D view of VRS

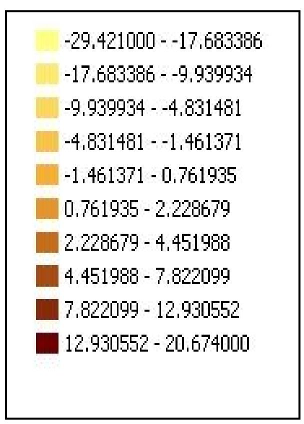

Figure 5: Kriging-based 2-D view of VRS

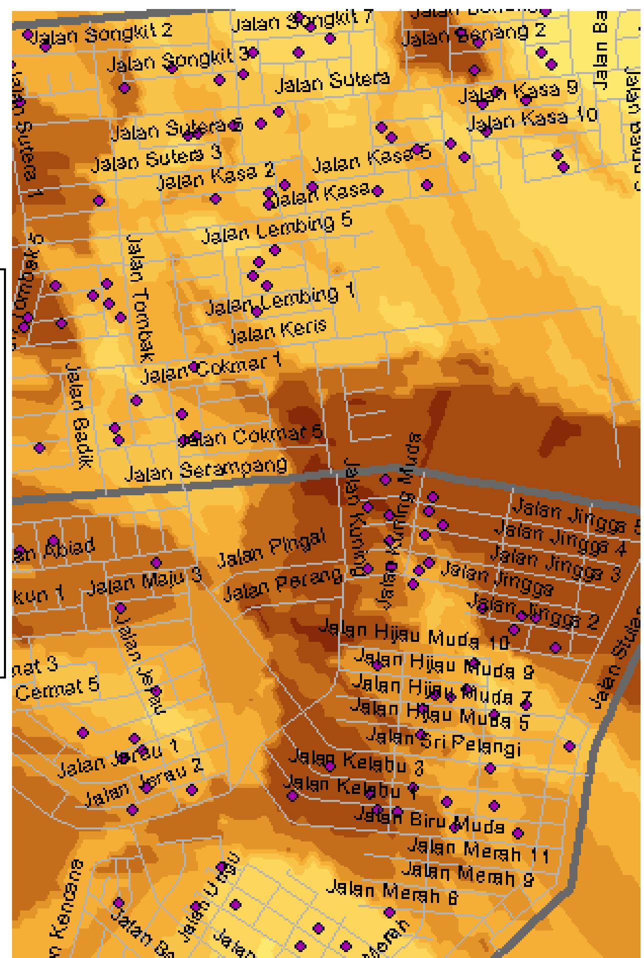

Figure 3: Kriging-based 2-D view of VRS