Seventh Annual Pacific-Rim Real Estate Society Conference
Adelaide South Australia, 21st to 24th January 2001

USING RESPONSE SURFACE ANALYSIS IN MASS APPRAISAL TO EXAMINE THE INFLUENCE OF LOCATION ON PROPERTY VALUES IN HONG KONG

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Key words: Mass Appraisal, Location Value Response Surface Modeling, Regression

Abstract

In mass appraisal, Location Value Response Surface (LVRS) modeling has proven to be a powerful and sophisticated tool in the analysis of the influence of location on the values of single-family houses in the United States. The technique uses a "smoothed" response surface as a function of location adjustment, representing the relative variation of location value within the whole area geographically. Unlike traditional approaches such as geographical stratification, the LVRS removes the location value inconsistency problem at neighbourhood boundaries. This paper proposes to illustrate in a case study, how the technique can be used to value high-rise office units for rating purposes in Hong Kong by adopting a standardisation method to derive the location factor. The prediction of property values is improved using the model.

Introduction

In Hong Kong, rates are collected by the Hong Kong Special Administrative Region (HKSAR) Government as a form of tax levied on properties. Rates are calculated as a percentage (currently fixed at 5%) of the rateable value, which is, in short, the net annual rental value of the property expected to be fetched in an open market at a designated historical (reference) date. At present, the Government carries out reassessment of rateable values once every year. This Annual General Revaluation exercise involves appraising about two million assessments as at a new reference date and has to be completed within two to three months. The assessments consist of different types of properties, such as flats, houses, offices, shops, factories, open land, and special properties, etc.

For efficiency and cost effectiveness, computer assisted mass appraisal (CAMA) based on statistical models – in particular, multiple regression analysis (MRA) – is used to value residential, commercial and industrial properties. In general, these appraisal models attempt to disaggregate rental values into various “contributing” components or property characteristics for analysis of the supply and demand forces operating in the rental market.

Past research on CAMA has been focused on improving and refining the various processes of the techniques. The procedure is still basically a hedonic one. For the CAMA models to be accurate and effective, it is imperative that all the attributes are properly accounted for. Among these attributes, location has been considered one of the most important in the real estate market, especially in international cosmopolitan cities, where some sharp variations of property values are noted. The value of a residential property could drop drastically in the next block because it is located at the beginning of a slum area (Eichenbaum, 1995). Similarly, some shops have substantial value differential round a street corner; and offices are worth more if located in the central business area than in decentralized districts.

In examining the effect of location on property values in CAMA models, the tax appraisers in Hong Kong adopt the traditional method of geographical stratification. It basically delineates the whole of Hong Kong into neighbourhoods. For a property type, a separate valuation model is specified for each neighbourhood. In this way, it is assumed that properties within a neighbourhood have the same location value, which is that of the average typical property. Although some subjective location qualifiers are specified for properties within the neighbourhood, this stratification method cannot properly account for the sudden and sharp value changes for similar properties right on different sides of a neighbourhood boundary, simply because the neighbourhoods are valued by different models or assigned different location factors.

To improve the value measurement of location, a technique called “Location Value Response Surface (LVRS) Analysis” has been introduced in the U.S. (O’Connor, 1982). The LVRS technique endeavours to better analyze the effect of location on property values, through the integration of Geographical Information Systems (GIS).

While the LVRS analysis has successfully been put into use for the mass appraisal of primarily private single-family houses in selected cities and counties in the U.S. (Eichenbaum, 1989 & 1995; Ward et al., 1999), in England (Gallimore et al., 1996), and Northern Ireland (McCluskey et at., 2000), the present applications of the technique are still limited, as it has not yet been fully tested for other property sub-classes, such as apartments, commercial or industrial properties. It has neither been applied outside North America, Britain or Northern Ireland.

This paper examines the possible applications of the LVRS analysis in Hong Kong. The focus here is on Asian cities where they differ from cities or counties in the U.S. in the economic, social, cultural, legal or political context. For instance, Hong Kong is a small city with a population of 6.7 million. The mountainous landscape further intensifies the land constraint, and thus high-rise living is predominant. This poses a problem in determining the location values or location adjustments of the building blocks from the rental evidence of individual units. Besides, land use in Hong Kong is often mixed and that location values may vary on a building-by-building basis, rather than a "grid" or street/city block basis as in the U.S. There is therefore arguably a greater need for a more refined location analytical tool, such as the LVRS. The case study in Hong Kong tries to illustrate how such an analysis may be incorporated in the mass appraisal process.

Literature Review

Almost all past studies of the LVRS model have been carried out in the U.S and Canada. The LVRS technique was first introduced by O'Connor (1982) for the appraisal of single-family houses in Lucas County, Ohio. Subsequent applications included a small suburban residential community in Sylvania, Ohio (O'Connor, 1985). The technique was first comprehensively documented by Cook (1988) and O'Connor and Eichenbaum (1988). In their paper, O'Connor and Eichenbaum developed the location value response surfaces by using Value Influence Centres, and concluded that the LVRS technique is more superior and sophisticated than traditional ones such as the fixed neighbourhood approach, localized models or cluster analysis.

These traditional approaches basically delineate the jurisdiction on a geographical basis or stratify the properties into clusters. Each neighbourhood / cluster or stratum either (i) has its own valuation model to analyse the location influence (as in Hong Kong) or (ii) has a separate location adjustment factor in a single model for the whole jurisdiction. In view of the value inconsistency problem at neighbourhood or cluster boundaries, manual amendments are often necessary to adjust for variations of location values within the neighbourhoods or clusters. These amendments may include manual overrides or creating additional qualitative variables such as closeness to a neighbourhood center, contour, view or traffic, etc.

Notwithstanding that these traditional approaches may produce overall effective results when used appropriately (International Association of Assessing Officers (IAAO), 1990) – for instance, fixed neighbourhood approaches and localized models perform well when boundaries are clear-cut and properties tend to differ more across neighbourhoods than within, O'Connor and Eichenbaum further criticized these approaches for their inherent vulnerability to environment changes, the difficulty in explaining to taxpayers, and the considerable resource required in building and maintaining the models.

On the contrary, the LVRS analysis is able to overcome these problems by interpolating or "smoothing out" a response surface as a function of location adjustment and thus eliminating value inconsistencies. The applications of LVRS analysis in the CAMA of residential properties in New York City (Eichenbaum, 1989 & 1995) have demonstrated that the technique may also be suitable for large cosmopolitan cities. The models used not only show extreme variances of location values from one part to another of the city, but also detect subtle adjustments in relatively homogeneous areas.

At the same time, several counties in the U.S. started to utilize the technique to appraise single-family domestic units. Some forms of the GIS were first used to interpolate property values in Quebec, Canada (Des Rosiers and Theriault, 1992), while Ward, and others (1999) of the Lucas County further incorporated tools of commercially available

GIS to analyse the location adjustment and effectively merged these with the CAMA process.

Research Framework

This section of the paper provides the description of data used in the study and outlines the methodology of the regression and LVRS model that is adopted.

Data

The case study makes use of private office properties in the district of Causeway Bay on Hong Kong Island. The district is the regional shopping and commercial centre of all of Hong Kong. It has also emerged as a prominent decentralized business district over the past 20 years. The area consists mainly of mixed-use buildings, typically with shopping complexes on lower floors, and offices, hotels and/or residential properties on upper floors of the buildings.

Altogether 1,212 rental transactions of office units with commencement dates in 1998 and 1999 are obtained from the Rating & Valuation Department (RVD) of the HKSAR Government, which is the authority to appraise properties for rating and taxation purposes. The rents are screened for their validity and completeness of data. After discarding missing data cases, transactions between related parties and other outliers, a total of 1,022 rents from 49 office developments are used for analysis in this study.

These data are representative of the spectrum of office properties in Hong Kong; there are small (about 15 – 30 sq. metre) units, as well as whole floor and multiple floor properties, of superior quality of construction (grade A) to poorer ones (grade D), on low to medium to high floor levels, and scattered within the entire district.

The information available includes the rental details and property attributes of each of the office units. Rental data consist of the rent in HK$, lease commencement date, term of the lease, rent-free periods, fresh letting or renewals, rates and Government rent liabilities by landlords or tenants, etc.

Property attributes are the previous year rateable value (reference date as at 1 October 1998), floor area, floor level, lift access, building age, provision of central air-conditioning, grade/quality, view/orientation, management quality, provision of furniture and added facilities, e.g. clubhouses.

Multiple Regression Model

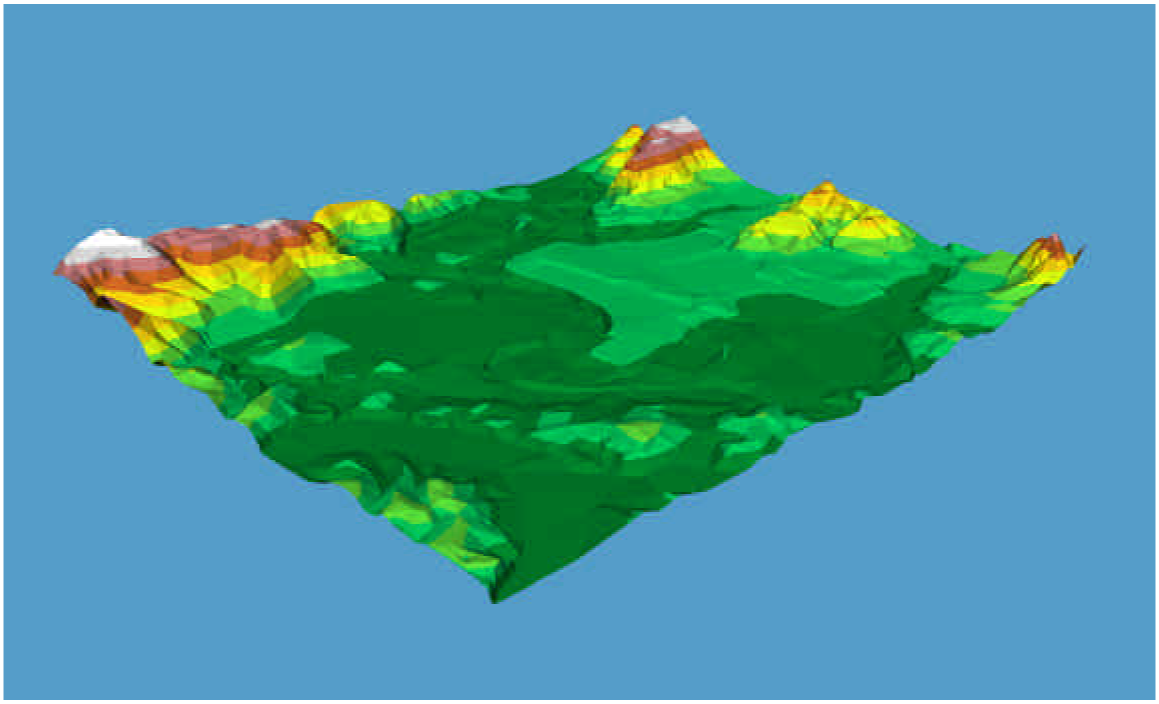
The MRA model is used in the CAMA process to predict the rateable values of the offices, with a reference valuation date of 1 October 1999. The rental data and property attributes described in the above section all become independent variables in the regression model, after data transformation of some variables is taken. More specifically, a hedonic additive hybrid log-linear regression is employed in our study. Details of the models and variables are given in the later sections.

Location Value Response Surface Model

The key objective of the LVRS model is to establish the relationship between location and its corresponding value. It analyses the location adjustment, in value or relative terms, of each rental observation, and then approximates this location value for the rest of the properties, as a function of a response over a geographical region comprising the properties' x- and y-coordinates. This is achieved by using a three-dimensional space or two-dimensional contour plot. An example of a location value response surface is given in Fig. 1.

The interpolated response surface provides a location value adjustment for each property, which in turn is treated as one of the variables, among other attributes, such as size, age, condition or quality of construction, in any valuation model. It is assumed that one universal valuation model is used for appraising all properties in the jurisdiction, and thus no district boundaries are set up within.

Figure 1 Example of Location Value Response Surface



Geometrical Concepts

The LVRS model further contains the following key geometrical concepts, namely the Value Influence Centres (VIC), proximity variables, the location value response surface and its interpolation (O'Connor and Eichenbaum, 1988).

The VIC refers to a specific point(s), line(s) or area(s) on an x-, y- plane where it shows the relative maximum (positive) or minimum (negative) location values among all the properties studied. It follows a notion that the VIC may affect the value of adjacent properties. This influence varies according to the distance from the VIC, the VIC's type, and the value barriers or breaklines, which may be the result of topographical, economic, social or political discontinuities.

A VIC's influence is dictated by its proximity variables. Some distance decay functions, such as half-Gaussian and gravity models, are used to transform the physical distance into proximity variables, which are usually expressed as a percentage of the location effect of the VIC.

In most cases, there will be more than one VIC. VICs with relatively high location values are typically the city centre, central business district, major shopping centres or prime high street shops. On the contrary, cemeteries, slum neighbourhoods, highways or railway tracks are examples of negative VICs with minimum location values.

After studying the VICs and possible proximity variables from the responses, it is essential to interpolate all these rents to create a smooth surface. This surface can be visualized as a terrain of the Earth's surface, substituting the elevation or altitude with the location value adjustment at any point.

The response surface is interpolated by utilizing spatial analyst tools available in GIS (Ward et al., 1999). In this study, the GIS software is ArcView, and the interpolation method adopted is the inverse distance weighting (IDW) approach. IDW assumes that the location value of any property has a local influence that diminishes with distance. This location value is computed as a weighted average of those of the sales/rents within a certain distance, or from a specified number of nearest sales/rents.

The mathematical algorithm for the location value of a property p is given as (Burrough, 1986 & Watson, 1992):

$$L(p) = \sum_{i=1}^{r} w_i z(p_i) = \sum_{i=1}^{r} z(p_i) \times \frac{\sum_{j=1}^{r} \left| p - p_j \right|^n}{\sum_{i=1}^{r} \left| p - p_i \right|^n} \tag{1}$$

where r is the number of nearest neighbours

w is the weight for each sales/rent observation

n is the power parameter applied to the distance

z is the location value adjustment for sales/rents

Derivation of the Location Value Adjustment

The crux of the matter is how to ascertain the location adjustment factor for the surface interpolation from the rental observations. O'Connor and Eichenbaum suggested two methods, the residual regression method, and the standardisation method.

(a) Residual regression method

It specifies a cost approach for the regression model to predict the sales price[1], and comprises both the building costs, cost of improvement and land values, without any location qualifiers. Equation (2) is a general cost model (IAAO, 1990):

$$V_{nl} = \pi GQ\left[\left(\pi BQ \times \sum BA\right) + \left(\pi LQ \times \sum LA\right) + \sum OA\right] + r \qquad (2)$$

where V_{nl} is the estimated market value, without location components

GQ is the product of general qualitative components, for example, time adjustment

BQ is the product of building qualitative components (including depreciation), for features such as construction quality, design or condition.

LQ is the product of land qualitative components for features such as shape and contour; caution needs to be exercised to exclude those variables associated with location, e.g. convenience, environment, proximity to city centre or traffic, etc.

BA is the sum of building additive components. These components (expressed in value terms) may include among others, the size of building area for different levels, number of bedrooms, number of bathrooms or kitchen area; each multiplied by its corresponding unit prices

LA is the sum of land additive components, being the product of the size of the land and its unit price.

OA is the sum of other additions' additive components, such as garages, car parking spaces, swimming pools, covered or open yards or storage sheds, etc. expressed in value terms.

r is residuals of the regression model.

[1] CAMA is used in the U.S. to appraise real estate for property tax purposes. The tax chargeable is based on the capital values of the properties. This differs from Hong Kong where rates are calculated with reference to the annual rental value of the properties.

In the above model, the unit prices for the building, land, and additions (in *BA*, *LA*, *BA*) are, in fact, their corresponding coefficients derived from the regression model, whereas the qualitative components (*GQ, BQ, LQ*) are expressed as a factor, with those above 1.00 increasing relative values, and vice versa.

The residuals r of the model at equation (2) represent the location effect and unexplained errors of the model. By comparing V_{nl} with the sales price of the property, its location factor is defined as:

$$LC = \frac{SP}{V_{nl}} \tag{3}$$

where *SP* is the actual sale price of the property

This method is able to produce consistent results for single-family landed properties in the U.S. since the cost model is a good location comparison independent of the sales price. However, in our study, it is not applicable because of the difficulty to apportion the building cost, and more significantly, the land value component of individual office units, especially in mixed-use developments comprising offices and shops.

(b) Standardisation method

A typical property with the most common features is chosen within a jurisdiction. Its sales price[2] acts as a proxy for location. The estimated location factor of any property is then derived by dividing its sales price with this proxy. Another similar approach is to adopt the average sales price of all observations as the proxy (Ward et al., 1999).

As this method disregards differences in the other attributes such as size and quality of construction, it is only suitable in jurisdictions comprising homogenous properties. It is therefore inadequate to apply this method in this study, where the office units vary in size amongst other attributes, and may have different values within the same office block.

[2] See footnote 1.

A "constant quality" approach is therefore considered in our study. In addition to assigning a typical, standard property as the proxy, a multiple regression analysis without any location variables is also undertaken. By substituting the dependent variable with the rental value, a hybrid log-linear regression specification used in our study is as follows:

$$LnV_{nl} = \boldsymbol{b}_0 + \sum_{i=1}^{M} \boldsymbol{b}_i LnX_i + \sum_{j=1}^{N} \boldsymbol{b}_j X_j + \sum_{d=1}^{T} \boldsymbol{b}_d X_d \qquad (4)$$

where LnV_{nl} is the log of the rental value, without location variables, using a market approach.

$_0$ is a constant value.

$_i$ are coefficients of the Mth property/rental attributes X_i, (as both qualitative and quantitative independent variables) and where $i = 1, 2, \ldots .M$.

$_j$ are coefficients of the Nth property/rental attributes X_j, where $j = 1, 2, \ldots .N$.

$_d$ are coefficients of the dummy variables X_d, and where $d = 1, 2, \ldots .T$.

With the coefficients estimated in the above model, the value difference $_p$ of the property attributes between a property p and the typical standard property s can be calculated as:

$$\boldsymbol{d}_p = \sum_{i=1}^{M} \boldsymbol{b}_i \left(LnX_{ip} - LnX_{is} \right) + \sum_{j=1}^{N} \boldsymbol{b}_j \left(X_{jp} - X_{js} \right) + \sum_{d=1}^{T} \boldsymbol{b}_d \left(X_{dp} - X_{ds} \right) \qquad (5)$$

where X_{ip}, X_{jp}, X_{dp} are values of the property p's attributes X_i, X_j, and dummy variables X_d respectively.

X_{is}, X_{js}, X_{ds} are values of the property / rental attributes X_i, X_j, and dummy variables X_d respectively of typical property s.

An adjusted rent for p is:

$$Adj.R_p = R_p - \boldsymbol{d}_p \qquad (6)$$

where R_p is the actual rent of the property

This *Adj.* R_p represents the rent of a typical office unit as if this typical property is situated at the current location of *p*. Adopting the average rent of the typical property(s) from all observations in a sample, or using equation (4) above to estimate the rental value of the typical property V_s, the location factor for property *p* is as follows:

$$LC_p = \frac{Adj.R_p}{V_s} \tag{7}$$

As there are a number of rental transactions in the same office block, an appropriate method is to take the mean of the location factors of all rents in the block:

$$LC_{block} = \frac{\sum_{p=1}^{Q} LC_p}{Q} \tag{8}$$

where Q is the number of rents in the block

The averaged LC_{block} is then plotted in the LVRS model and interpolated to form a response surface as described in the above sub-section. This location factor is then put back into the regression model as one of the variables.

Empirical Results

The empirical results are broken down into three sections. The summary results from the MRA model (without location variables) are depicted in the first section, followed by an analysis of the LVRS model. The results of the MRA model (with location variables) are then given in the final section.

Multiple Regression Model (without Location Variables)

In our study, the net rental is analysed on a per unit area basis and this *Ln_R* is adopted as the dependent variable. After exploratory data analysis, transformation is taken heuristically to some variables. The definitions of the variables subsequently adopted in the analysis are given in Table 1.

Table 1 Definition of Variables

Variable Name	Type	Valid Values	Description	See Note
***Ln_R* (Dependent)**	Numeric	Continuous	Log of Rents on a sq. metre basis	
Ln_Area	Numeric	Continuous	Log of Floor Area	
Datedif	Numeric	-21 to 2 (i.e. Jan 98 to Dec 99)	Difference of Lease Commencement Date and Valuation Date (1 Oct 99), in number of months	(1)
Ln_Flr	Numeric	Continuous	Log of Floor Level	
View	Dummy	0 = Average 1 = Good	View or Orientation	
Lift	Dummy	0 = No; 1 = Yes	Lift Access	
AC	Dummy	0 = No; 1 = Yes	Central Air-conditioning	
GradeA	Dummy	0 = No; 1 = Yes	Grade A office	
GradeB	Dummy	0 = No; 1 = Yes	Grade B office	
GradeC	Dummy	0 = No; 1 = Yes	Grade C office	
GradeD	Dummy	0 = No; 1 = Yes	Grade D office	(2)
Anc	Dummy	0 = No; 1 = Yes	Ancillary Accommodation for the Office. Examples are flat roof, balcony, and other structures not part of the building	
Ln_Age	Numeric	Continuous	Log of the Building's Year of Completion	
HdrmL	Dummy	0 = No; 1 = Yes	Low Headroom (< 2.9 metres)	(2)
HdrmO	Dummy	0 = No; 1 = Yes	Ordinary Headroom (between 2.9 and 3.5 metres)	
HdrmH	Dummy	0 = No; 1 = Yes	High Headroom (> 3.5 metres)	
Term00	Dummy	0 = No; 1 = Yes	Lease Term unknown	
Term06	Dummy	0 = No; 1 = Yes	Lease Term (between 1 and 6 months)	
Term12	Dummy	0 = No; 1 = Yes	Lease Term (between 7 and 18 months)	
Term24	Dummy	0 = No; 1 = Yes	Lease Term (between 19 and 30 months)	(2)
Term30	Dummy	0 = No; 1 = Yes	Lease Term (> 30 months)	
StatusF	Dummy	0 = No; 1 = Yes	Fresh Letting	
StatusR	Dummy	0 = No; 1 = Yes	Lease Renewal	
StatusX	Dummy	0 = No; 1 = Yes	Unknown	(2)
Premat	Dummy	0 = No; 1 = Yes	Lease Terminated or Lease Terms revised before end of the Lease Term	
Rate_I	Dummy	0 = No; 1 = Yes	Rates Liability by Tenant, inclusive in rent	
Rate_E	Dummy	0 = No; 1 = Yes	Rates Liability by Tenant, exclusive of rent	(2)
Rate_X	Dummy	0 = No; 1 = Yes	Rates Liability unknown	
A3Rent_I	Dummy	0 = No; 1 = Yes	Government Rent Liability by Tenant and included in rent	
A3Rent_L	Dummy	0 = No; 1 = Yes	Government Rent Liability by Landlord	
A3Rent_X	Dummy	0 = No; 1 = Yes	Government Rent Liability unknown	(2)
Furn_F	Dummy	0 = No; 1 = Yes	Fully Furnished	
Furn_P	Dummy	0 = No; 1 = Yes	Partly Furnished	(2)
Furn_N	Dummy	0 = No; 1 = Yes	Unfurnished	
Ln_PRV	Numeric	Continuous	Log of Previous Rateable (Assessed) Value as at 1 Oct 98 on a sq. metre basis	

Notes: (1) The office leasing market has been depressed in 1998 and 99 following the Asian financial crisis. According to the office rental indices compiled by the RVD of HKSAR Government, the office rents have been declining from Jan 98 to Dec 99, and the decrease appears to be a linear relationship from 98 to mid-99.

(2) Dummy variables are created for each of the categories for their respective variables, for instance, *GradeA*, *GradeB*, etc. are converted for Building Grades A to D respectively. The indicated dummy variables are excluded from the regression analysis.

These variables are then tested for linearity amongst them by way of a correlation matrix. A stepwise MRA is then carried out to help derive the location factor. Of the variables listed in Table 1, the previous rateable value *Ln_PRV* has already reflected the value of the office attributed to its location, and is therefore excluded from the model specification. The rest of the independent variables in Table 1 (unless otherwise noted) are entered iteratively into the analysis until every significant one has been included in the regression model. Table 2 gives the summary and coefficients of the best-fit model adopted (model 15), together with the corresponding statistics of the model at each step. The variables are displayed according to the sequence of their selection into the model.

The first variable to enter the regression and the most significant is *Datedif*, explaining about 26.8% of the variance in *Ln_R*. The negative coefficient is justified by the bearish office leasing market from Jan 1998. The next variable selected into the model is *GradeA*, because it has the highest correlation with the residual errors of the first model. As a result, an extra 16.5% of the total variance in *Ln_R* is explained by this added variable. At the same time, the standard error of estimate is also reduced to 0.243. The variable selection process is repeated, and other variables showing a level of significance (pre-determined at 0.05) are also included into the regression model.

Table 2 Summary of Stepwise Regression Model (without location variables)

Step	Variable Name	Best Fit MRA Model (Step 15)		Regression Statistics at Each Step		
		Est'd Coefficients	**t-statistic***	Adjusted R^2	F* (variance ratio)	Standard Error of Estimate
	Intercept	**2.934**	**7.01**	-	-	-
1	***Datedif***	**-0.0241**	**-20.79**	0.268	373.95	0.2766
2	***GradeA***	**0.382**	**16.22**	0.433	390.83	0.2434
3	***StatusF***	**-0.417**	**-11.46**	0.503	345.17	0.2279
4	***Ln_Age***	**0.671**	**7.23**	0.523	280.33	0.2233
5	***StatusR***	**-0.245**	**-6.65**	0.551	251.60	0.2166
6	***Premat***	**0.188**	**4.19**	0.561	218.87	0.2140
7	***Rate_I***	**-0.180**	**-5.36**	0.571	195.15	0.2117
8	***Anc***	**-0.161**	**-3.74**	0.579	176.39	0.2098
9	***A3Rent_L***	**-0.0876**	**-5.40**	0.583	159.61	0.2087
10	***Ln_Area***	**-0.0364**	**-4.10**	0.588	146.65	0.2075
11	***GradeB***	**0.0758**	**4.77**	0.594	137.01	0.2059
12	***Term00***	**0.120**	**3.44**	0.598	127.78	0.2048
13	***Term06***	**0.107**	**2.52**	0.602	119.68	0.2040
14	***A3Rent_I***	**-0.0816**	**-3.52**	0.604	112.21	0.2034
15	***HdrmO***	**-0.0766**	**-3.33**	0.608	106.51	0.2024

Step	Variable Name	Best Fit MRA Model (Step 15)		Regression Statistics at Each Step		
		Est'd Coefficients	t-statistic*	Adjusted R^2	F* (variance ratio)	Standard Error of Estimate
No. of Observations		1022				
Predicted Value (mean)		5.734				
Adj. R Square		0.608				
R Square		0.614				
R		0.783				
Standard Error of Estimate		0.2024				
F* (variance ratio)		106.51				
Durbin-Watson		1.126				

* F-values and t-statistics: Significance level at 0.05

The positive coefficients for variables *GradeA*, *GradeB* and *Ln_Age* are self-explanatory, and support the general view that prospective office tenants favour newer and high-quality buildings and are prepared to pay a premium for these property attributes. The coefficients for *Ln_Area* and *Anc* are less than zero, indicating the existence of quantum allowance to the per sq. metre rate, as the size of the office increases. The coefficient for *StatusF* is lower than that of *StatusR*, suggesting in our sample that existing tenants are likely to pay a higher rent on renewal than a fresh tenant, possibly due to the tenant's "lock-in" effect and the highly competitive leasing market. Besides, short-term tenants of lease term less than 6 months are also expected to pay more than yearly or two-yearly lessees, as denoted by the positive coefficients for *Term00* and *Term06.*

Variable *Premat* has a positive coefficient since the contracted rent is apparently on the high side if subsequently the lease is terminated before the end of the term. While the coefficients for *A3Rent_I* and *A3Rent_L* are explained by the assumption that the hypothetical landlord is responsible to pay Government Rent in the calculation of rateable values, it is puzzling to register a negative coefficient for *Rate_I*. This result implies that rates-inclusive rents are likely to be lower than similar ones that are rates-exclusive. However, since the rateable value is estimated on an exclusive of rates basis, assuming the tenant pays the rates; if rates are included in the rent payable, the rent should be higher than one that is rates-exclusive. It is probable that landlords in the sample may not have factored in the effect of their rates liability on an inclusive basis as it is often considered as a "final" concession given during rental negotiations.

Residual analysis is used to test non-linearity, independence and heteroscedasticity for the best-fit model accordingly. This regression model without location variables accounts for 60.8% variance of the dependent variable *Ln_R*.

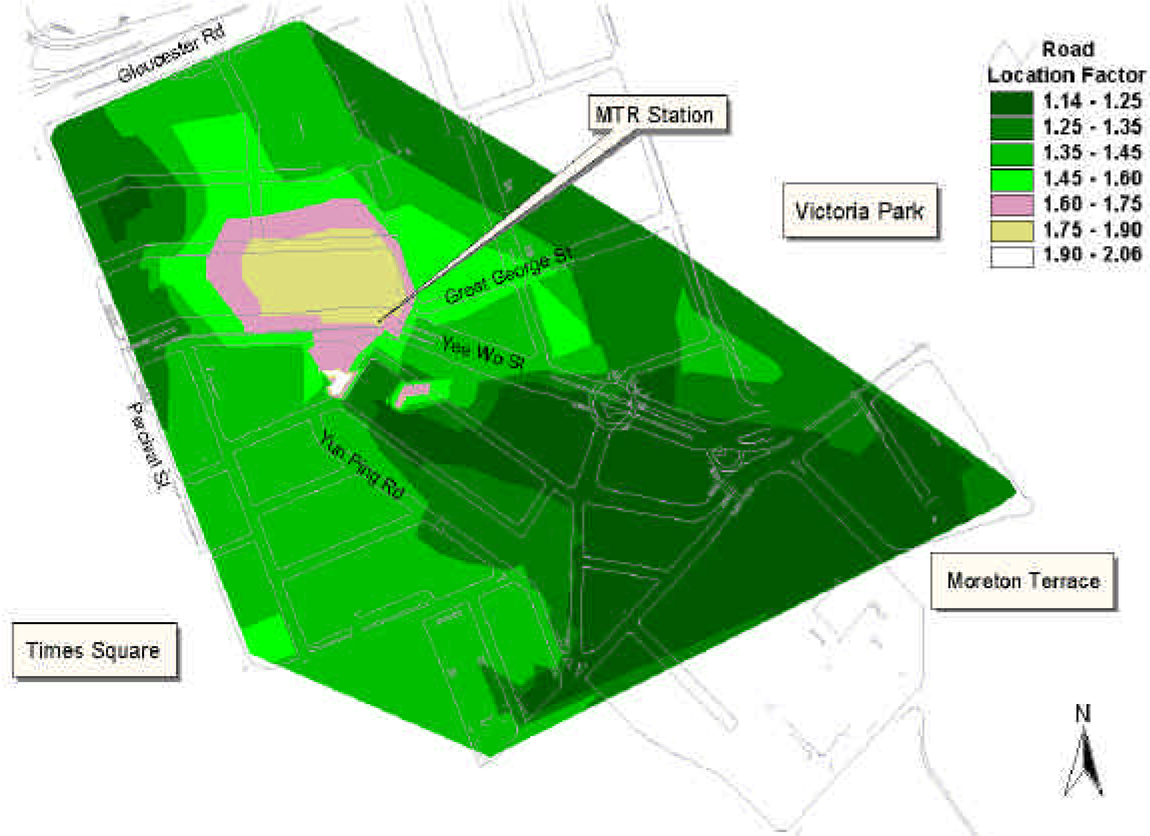
LVRS Model

The location factor *LC* is computed with reference to the value of a typical office unit. By analysing the 1,022 rents, the typical property is designated as a 50 sq. metre unit on mid-floor in a grade B office building built in the early 80's. The lease of this typical office unit is on a renewal basis, and the term is two years, commencing at around the valuation date of 1 Oct 1999. From our sample, the average rent of this typical property is about \$263/m^2. Applying the derived regression model in Table 2 to estimate the rental value without location variables, the *LC* is worked out for each of the observations and also for the blocks.

The *LC* for each block is judged of its reasonableness, in terms of continuity and consistency with that of its neighbouring office blocks. Caution has to be given not to disregard any anomaly because some may be genuinely caused by the unique value attributed to its location. Another possibility is that value breaklines are present, giving rise to the apparent inconsistency in location values. Valuation judgment and expertise, together with a thorough knowledge of the local market are paramount in the analysis of *LC*.

As a result, five blocks are considered to be outliers in the analysis of *LC*. The rest of the *LC*'s are plotted on the map and then interpolated to form the LVRS, representing a logical pattern as expected. The contour plot of the response surface for offices in Causeway Bay is illustrated in Fig. 2.

Figure 2 Contour Plot of Location Value Response Surface for Offices in Causeway Bay



For instance, higher values or peaks (factors around 1.8 to 2.0) of the response surface are observed at around Causeway Bay Mass Transit Railway (MTR) station. This area is also one of the busiest areas in Hong Kong with the highest rental values for shops. As it turns out, the proximity to MTR also boosts the location value for offices. The *LC* then radiates out and diminishes to the surrounding areas of Gloucester Road to the north, Great George Street to the east and Yun Ping Road to the south. Average values (factors around 1.3 to 1.6) are noted in these areas, while even lower values (factors about 1.15 to 1.2) are recorded near the Moreton Terrace area further east, where it is less convenient and is more of a residential neighbourhood. It should also be noted that the *LC* seems to ascend again towards Percival Street in the southwest, as it leads to Times Square, another prestigious office/commercial development which is often used as an office market pointer.

Multiple Regression Model (with Location Factors)

In the above sub-section, each of the office blocks has been assigned a location factor from the LVRS. This factor is transformed to *Ln_LC*, which is the log of *LC*. Variable *Ln_LC* is then put back into the stepwise regression model together with *Ln_PRV* and the rest of the independent variables in Table 1. The summary and statistics of the model finally adopted is tabulated in Table 3.

The regression results show that previous rateable value is most significant of all in the prediction, as it is the first variable selected into the model. The smoothed *Ln_LC* is the fourth variable, elucidating an extra 2.7% of the variance of *Ln_R*. Note the inclusion of *Ln_PRV* and *Ln_LC* has pushed the intercept to below zero, while other regression coefficients generally tally with the previous regression. Overall, this model with location variables explains about 78.3% of total variance and standard error of estimate is about 0.150.

Using the interpolated location factors for the rest of the office buildings, plus their property attributes and details of the hypothetical tenancy on which the rateable value is based, this MRA model is able to predict the values of all offices units within the jurisdiction.

Table 3 Summary of Stepwise Regression Model (with Location Factors)

Step	Variable Name	Best Fit MRA Model (Step 15)		Regression Statistics at Each Step		
		Est'd Coefficients	t-statistic*	Adjusted R^2	F* (variance ratio)	Standard Error of Estimate
	Intercept	**-1.208**	**-3.24**	-	-	-
1	***Ln_PRV***	**0.699**	**16.49**	0.432	776.92	0.2436
2	***Datedif***	**-0.0246**	**-28.59**	0.661	994.88	0.1883
3	***StatusF***	**-0.150**	**-14.98**	0.707	823.20	0.1749
4	***Ln_LC***	**0.530**	**10.77**	0.734	704.77	0.1667
5	***Ln_Age***	**0.601**	**9.27**	0.746	600.80	0.1629
6	***Rate_I***	**-0.170**	**-6.79**	0.753	518.74	0.1608
7	***GradeA***	**0.146**	**6.75**	0.759	459.67	0.1588
8	***Anc***	**-0.130**	**-4.09**	0.763	412.36	0.1573
9	***A3Rent_I***	**-0.0846**	**-5.14**	0.767	374.72	0.1560
10	***Term00***	**0.121**	**4.69**	0.771	345.34	0.1546
11	***A3Rent_L***	**-0.0502**	**-4.26**	0.776	321.90	0.1531
12	***Premat***	**0.111**	**3.28**	0.779	300.53	0.1520
13	***Ln_Area***	**-0.0201**	**-2.97**	0.780	279.90	0.1515
14	***Term06***	**0.0862**	**2.75**	0.782	262.19	0.1510
15	***Rate_X***	**-0.157**	**-2.74**	0.783	246.79	0.1505
No. of Observations		**1022**				

Predicted Value (mean)	5.734	
Adj. R Square	0.783	
R Square	0.786	
R	0.887	
Standard Error of Estimate	0.1505	
F* (variance ratio)	246.79	
Durbin-Watson	1.789	

* F-values and t-statistics: Significance level at 0.05

A similar model with *Ln_PRV*, but without the variable *Ln_LC*, is also specified as a control regression. Table 4 presents the summary of this model. The model explains about 75.9% of the variance in *Ln_R*, while the standard error of estimate is 0.159. It is clear that the regression with location factor is more superior, not only because its R^2 is higher, but also it has reduced the standard error during the prediction process.

Table 4 Summary of Stepwise Regression Model (without *Ln_LC*)

Step	Variable Name	Best Fit MRA Model (Step 13)	
		Est'd Coefficients	t-statistic*
	Intercept	-2.600	-7.22
1	*Ln_PRV*	0.972	28.06
2	*Datedif*	-0.0240	-26.73
3	*StatusF*	-0.153	-14.48
4	*Ln_Age*	0.591	8.64
5	*Premat*	0.154	4.37
6	*A3Rent_I*	-0.109	-6.38
7	*A3Rent_L*	-0.0594	-4.81
8	*Rate_I*	-0.152	-5.79
9	*Term00*	0.130	4.78
10	*Anc*	-0.125	-3.73
11	*Term06*	0.104	3.15
12	*Rate_X*	-0.145	-2.40
13	*GradeA*	0.0364	2.03
No. of Observations		1022	
Predicted Value (mean)		5.734	
Adj. R Square		0.759	
R Square		0.762	
R		0.873	
Standard Error of Estimate		0.1588	
F* (variance ratio)		247.83	
Durbin-Watson		1.637	

* F-values and t-statistics: Significance level at 0.05

Limitations of the LVRS Model

In the above location factor analysis, it is important to satisfactorily establish a spatial relationship representing the variations in location value. The prerequisite is to have reasonably sufficient data in each, though not necessarily all, main area of the jurisdiction. In reality, the property market is reputable for the scarcity of data, and under such circumstances, some second-guessing may produce results as accurate as those from the LVRS model.

This leads to the question of what should be the minimum number of observations, which is still a subject of contention. It largely depends on the size of the jurisdiction and availability of data. One way to assist the ascertainment of the reasonableness is to display all observations on the map of the jurisdiction. This will help to ensure that visually, a good spread of observations has been obtained.

It must be also noted that the explicit location adjustment of the response surface may not denote the "real" value of a certain location, as the LVRS only represents the comparative location values for the specific type(s) of property under consideration.

The above LVRS analysis has improved the mass appraisal process of individual units in multi-storey or strata-titled buildings. However, unlike the LVRS analysis practised in the U.S. which uses a CAMA model based on the cost approach, our analysis derives the location factor from the same dependent variable, and is therefore not suitable to appraise landed properties, such as single-family houses. Yet it is appropriate in our study, as the location adjustment of building blocks has been smoothed by averaging the tentative factors of individual units. This smoothing process has thus solved the problem of independence associated with the regression model.

At present, although it is not difficult to maintain, it is still costly for a jurisdiction to set up a GIS with LVRS capability and integrate it with its existing CAMA system. This requires capturing property data and digitalizing the maps, and can be quite time-consuming to the tax appraiser.

Conclusion

The above analysis using the standardisation method shows how the LVRS model can be adopted in Hong Kong or other cities for the valuation of multi-storey or strata-title units. The interpolated response surface serves as a sophisticated analytical tool to estimate the location adjustment factors for other properties or blocks of properties. In a CAMA model using these adjustment factors, the predicted values can be improved.

The LVRS analysis eliminates the need to specify a combination of different qualifiers or variables to portray the various effects of location, as all its influence on a particular property is depicted in one single adjustment factor obtained from the LVRS. In addition, by visualizing the change and its magnitude of the location adjustments across a jurisdiction, the LVRS no longer involves the identification of neighbourhood boundaries, and thus eradicates the occurrence of value inconsistencies near these boundaries. As one single CAMA model is now used to appraise all properties of the same sub-class, the process is also simplified, easily understood and less resource-hungry in terms of the model's maintenance. Although a hybrid log-linear regression model is illustrated in our study, there is no reason why the LVRS analysis cannot be extended to other CAMA techniques, e.g. artificial networks, or other forms of regression.

This study provides some insight of the LVRS model's possible applications in Hong Kong. Yet, the model's contributions should not be limited as such. The integration with GIS further brings about opportunities to improve and streamline the analysis and appraisal process, assist in management decision-making, and monitor work progress. In fact, the model should be put to full use so as to justify the resources set aside in building the data and developing a GIS-CAMA model.

References

Burrough, P.A. (1986) Principles of Geographical Information Systems for Land Resources Assessment. Oxford, Clarendon Press

Commissioner of Rating & Valuation (1999) Rating & Valuation Department, Hong Kong – Annual Summary 1998-99

Commissioner of Rating & Valuation (2000) Hong Kong Property Review 2000

Commissioner of Rating & Valuation (2000) Property Market Statistics 2nd Quarter 2000

Cruden, Gordon N. (1986) Land Compensation and Valuation Law in Hong Kong. Singapore, Butterworths

Des Rosiers, Francois & Theriault, Marius (1992) Integrating Geographic Information Systems to Hedonic Price Modeling: An Application to the Quebec Region. *Property Tax Journal Vol.11:1 Mar 1992* p.29-58

Detweiler, John H. & Radigan, Ronald E. (1999) Computer-assisted Real Estate Appraisal: A Tool for the Practicing Appraiser. *The Appraisal Journal July 1999* p.280-286

Eichenbaum, Jack (1989) Incorporating Location into Computer-assisted Valuation. *Property Tax Journal Vol.8:2* p.151-169

Eichenbaum, Jack (1995) The Location Variable in World Class Cities: Lessons from CAMA Valuation in New York City. *Journal of Property Tax Assessment & Administration Vol.1:3 May 1995* p.46-60

Fibbens, Michael (1995) Australian Rating and Taxing: Mass Appraisal Practice. *Journal of Property Tax Assessment & Administration Vol.1:3 May 1995* p.61-77

Gallimore, Paul, Fletcher, Michael & Carter, Matthew (1996) Modelling the Influence of Location on Value. *Journal of Property Valuation & Investment Vol.14 No.1 1996* p.6-19

Gloudemans, Robert J. (1999) Mass Appraisal of Real Property. Chicago, International Association of Assessing Officers

Hensley, Tim (1993) Coupling GIS with CAMA data in Johnson County, Kansas. *Property Tax Journal Vol.12:1 Mar 1993* p.19-36

International Association of Assessing Officers (1990) Property Appraisal and Assessment Administration. Chicago, IAAO

Isakson, Hans R. (1986) The Nearest Neighbors Appraisal Technique: An Alternative to the Adjustment Grid Methods. *Journal of American Real Estate & Urban Economics Association Vol.14 No.2* p.274-286

McCluskey, William J., Deddis, William G., Lamont, Ian G. & Borst, Richard A. (2000) The Application of Surface Generated Interpolation Models for the Prediction of Residential Property Values. *Journal of Property Investment & Finance Vol.18 No.2 2000* p.162-176

Morrison, Donald F. (1990) Multivariate Statistical Methods. New York, McGraw-Hill

Newsome, Bobby A. & Zietz, Joachim (1992) Adjusting Comparable Sales using Multiple Regression Analysis – The Need for Segmentation. *The Appraisal Journal Jan 1992* p.129

O'Connor, P.M. & Eichenbaum, Jack (1988) Location Value Response Surfaces: The Geometry of Advanced Mass Appraisal. *Property Tax Journal Vol. 7:3* p.277-296

Ramsland, Maxwell O. Jr. & Markham, Daniel E. (1998) Market-supported Adjustments using Multiple Regression Analysis. *The Appraisal Journal Apr 1998* p.181-191

Stevenson, D. Ross (1996) Regression Based Indexing. *Paper presented at 62nd IAAO Annual Conference at Houston, Texas* p.79-100

Waller, Bennie D. (1999) The Impact of AVMs on the Appraisal Industry. *The Appraisal Journal July 1999* p.287-292

Ward, Richard D., Weaver, James R. & German, Jerome C. (1999) Improving CAMA Models using Geographic Information Systems/Response Surface Analysis Location Factors. *Assessment Journal Vol. 6:1 Jan/Feb 1999* p.30-38

Watson, D.F. (1992) Contouring: A Guide to the Analysis and Display of Spatial Data. Oxford, Pergamon

Youngman Joan M. & Malme Jane H. (1994) An International Survey of Taxes on Land and Buildings. Lincoln Institute of Land Policy, Organisation for Economic Co-operation and Development, International Association of Assessing Officers. Deventer, Boston, Kluwer

Acknowlegdement

The authors wish to express their deepest gratitude to the Commissioner of Rating & Valuation (CRV) of the Hong Kong Special Administrative Region Government (HKSARG) for making the data available for this study. The views expressed and the methodology adopted in this paper are the authors' alone and should not be taken to imply the agreement of CRV or HKSARG.