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EFFICACY OF THE GEOGRAPHICALLY WEIGHTED MODEL ON THE MASS APPRAISAL PROCESS

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ABSTRACT

Single transparent models are increasingly being sought to account for site and capital value as well as location in the geographically smaller outer metropolitan urban suburbs in which there was often assumed little or no spatial variation. This paper compares the use of a Geographically Weighted Regression (GWR) hedonic model with the more traditional hedonic models where there is market evidence of both vacant land and improved residential values. This study found that where there is evidence of spatial variation and a presence of both improved and at least some vacant land sales the GWR model exhibited specification limitations that the more traditional models such as hybrid models did not and that the latter were able to more accurately predict vacant land prices while also accounting for location.

Keywords: CAMA, Mass Appraisal, Geographically Weighted Regression

INTRODUCTION

Many jurisdictions around the world use various mass appraisal techniques to generate a property value base (fiscal cadastre) to support the property taxation system. Increasingly there is pressure from stakeholders for more accountability and transparency as to the derivation of the fiscal cadastre. This is particularly relevant as the revaluation cycle becomes more frequent to align the updated values with the levying of the property tax so as to ensure a higher degree of fairness and equity. For many years automated valuation models (AVM) have played an important role in helping to achieve this through increasing the speed of generating values while at the same time accounting for location, which is now accepted as a necessary part of the mass appraisal process. This, however, places a professional obligation on the valuer to specify and calibrate such models to produce the accuracy required. One of the traditional methods of accounting for location is the use of *a priori* administrative boundaries such as suburbs as denoting smaller, more homogeneous submarkets in which more accurate AVMs can operate. This assumes no spatial variation within that *a priori* submarket (Adair, Berry & McGreal 1996; Watkins 2001). As this may not be valid, perhaps AVMs now need to accommodate this even at such smaller geographic scales.

The objective of this paper is to contribute to the ongoing process of enhancing modelling techniques to achieve an acceptable standard in an acceptable timeframe for all stakeholders. In particular, the question of modelling so as to produce an acceptable site value and capital value from the same set of sales data and from the one calibrated model while at the same time accounting for spatial variation at the suburb level is investigated. In this paper hedonic models in a linear and log-linear form are compared to more complex hedonic models developed using Geographically Weighted Regression (GWR) and a hybrid model to accommodate both the prediction of site and capital values while at the same time accounting for the spatial variation that may be present.

The International Association of Assessing Officers (IAAO) assists in the process of establishing guidance and standards that provide accountability and transparency to stakeholders. These standards are being accepted among Australian jurisdictions as a basis for a draft of Australia's own standards through the Australian Property Institute (API).

Automated Valuation Models

The IAAO standards define an automated valuation model (AVM) as

"… a mathematically based computer software program that produces an estimate of market value based on market analysis of location, market conditions, and real estate characteristics from information that was previously and separately collected. The distinguishing feature of an AVM is that it is a market appraisal produced through mathematical modelling. Credibility of an AVM is dependent on the data used and the skills of the modeller producing the AVM." (IAAO, 2003 p.148).

They further recognise that these may be in an additive, multiplicative or hybrid form where the hybrid form is a

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“model that incorporates both additive and multiplicative components” (IAAO, 2003 p.150)

and that these are normally hedonic models that attempt

“to take observations on the overall good or service and obtain implicit prices for the goods and services. Prices are measured in terms of quantity and quality. When valuing real property, the spatial attributes and property specific attributes are valued in a single model. Calibration of the attribute components is performed statistically by regressing the overall price onto the characteristics.” (IAAO, 2003 p.149)

McCluskey, Deddis and Lamont (1999) discuss various methods of building spatial variation into mass appraisal. They discuss the problems of using submarket analysis where the submarkets often become small and the statistical analysis becomes unsound and biased (they do not discuss this in terms of non-statistical methods but the same problem applies). They then discuss the problems of using dummy variables for discrete locations such as suburbs. They point out that this “presupposes that the effect of location is uniform across all properties within a particular neighbourhood”. This method also causes problems for mass appraisal authorities because of the lumpiness of assessments and border conflicts. They suggest a more continuous approach using methods such as surface response analysis and the kriging method, which may be applied through several of the standard GIS packages.

In a study researching the valuation of land and improvements in the City of Philadelphia, McCain, Jensen and Meyer (2003) use some 40,000 arm’s length transactions to develop a two-stage hybrid model. The first stage involved estimating a neighbourhood index for each property which was then used as input to a hybrid regression model. The neighbourhood index was estimated from the residuals of a simple hedonic model (using building and site characteristics) and then a kriging process was used to smooth out the variation.

This neighbourhood variable was then combined with land area, liveable area and building condition in a non-linear regression. The hybrid model was specified as (sic)

$$p = (b0(LiveableArea)^{b1}(Condition)^{b2}(Neighborhood)^{b3}) + (b4(LandArea)^{b5}(Neighborhood)^{b6})$$

where p is the price of the property.

This model is applied using both improved and unimproved sales and allows for the neighbourhood influence to be attached to both the land and improvements components at a different rate. Values for improved properties use the whole equation while vacant land estimates effectively use only the second component (since liveable area and condition are zero). This model proved to be effective even with a small set of descriptive variables.

A study of three alternative models (additive, multiplicative and non-linear) was reported by O’Connor (2002) based on work in Calgary. This used a large geographical area with some 35,000 records randomly split into about 4/5th for model building and 1/5th for testing. A two-level cleaning process involving the removal of the lowest and highest 2.5% of estimate-to-sale ratios was employed. Location was accounted for in two ways: a location value response surface (LVRS) based on median prices and one based on fixed neighbourhood boundaries. Models are generated for each of the three model types and using both locational methods. The results are compared using the coefficient of dispersion (COD), coefficient of variation (COV) and price-related differential (PRD) as specified by the IAAO Standards on Ratio Studies (1999). They found a multiplicative model with LVRS to be superior for both the within model and the holdout data with a COV of 7 and 7.91 respectively.

In a similar study involving Calgary, Gloudemans (2002, see also Gloudemans, 2002a) followed similar procedures but used more discriminating sales selection based on transaction characteristics as well as high AS ratios. The data were split into testing and model build subgroups of 5000 and 25,303 sales respectively using random selection. Additive (linear), multiplicative (log-linear) and Hybrid (non-linear) models were then created. Location was included in the model via a large number (hundreds) of neighbourhood dummies. The non-linear model is specified in a similar manner to that of McCain, Jensen and Meyer (2003) with the site and building parts being multiplicative and added together. While all three models produced good results, the multiplicative model produced the best results. However, as this latter model might not have produced the best results across the whole city they felt that the non-linear specification most closely fitted the appraisal theory.

More recently Geographically Weighted Regression (GWR) has grown in popularity amongst real estate modellers in accounting for ‘location’ in the mass appraisal process (Kauko & d'Amato 2008). In an American example (City of Milwaukee) Spatial Regression and GWR were used to investigate the spatial dimensions of housing prices and it was found that they both produced more accurate predictive results than the ordinary least squares estimates (Yu, Wei & Wu 2007). Moore and Myers (2010) took the GWR model one step further and incorporated similar attributes of the parcel itself as well as location in selecting comparable sales. Their Geographic-attribute Weighted Regression (GAWR) produced a significant improvement in the results. McCluskey and Borst (2011) used GWR to assist them in the mass appraisal process in detecting submarkets and found an effective improvement in predictive accuracy. However, as Des Rosiers and Theriault (2007) point out, even though such techniques seem intuitively sensible they should not be viewed as a panacea to the long-recognised problem of accounting for location in the valuation process.

Estimating Site and Capital Values

One important advantage of modelling both improved and vacant land sales in the same model is that such models may offer a suitable solution to the valuation of land for site value purposes in situations where the number of sales is low, generally called a “thin market”. In the High Court of Australia case Maurici (2003), summarised by Collins (2003) and applauded by Robbins (2003), the valuer was criticised for failing to consider improved properties when estimating the unimproved value and relying upon a small number of sales from a very thin market. All improved sales fundamentally include land, and in markets devoid of transactions of vacant land it is typical for valuers to consider sales of improved properties that are suitable for redevelopment as setting a benchmark for land values. Jointly modelling vacant and improved sales supplement the thin vacant land market and if the building characteristics can be held constant it should be possible to make good estimates of land values. One particular use of such analysis is in the derivation of site values for rating and taxation purposes. In thin markets the values do not rely on a small selection of vacant land sales that may lack comparability. In effect, site values can be “backed-out” of comparable (in terms of land) improved sales in a systematic manner.

In Australia the basis for valuation for rating and taxation purposes varies from state to state. New South Wales and Queensland use site value; Victorian councils have a choice of assessing capital value, net annual value or site value; Tasmania assesses capital improved value, land value and assessed annual value; Western Australia assess gross rental value, site value (urban), unimproved value (rural) and capital value (government-owned properties) and South Australia assesses both capital value and site value for every property. Generally, site or unimproved value is used for land tax while the other bases may be used for other purposes. Site or unimproved value is assessed in all jurisdictions but is fraught with difficulties in many of the established urban (and rural) areas due to the low number of market transactions. While unimproved value is a hypothetical and non-market testable construct in most cases, its foundation is in the market for vacant rather than improved sales. If the findings of Maurici (2003) are accepted as reasonable then the scarce sales of vacant land may not be sufficient to indicate the true market value of vacant land (and therefore unimproved land) and transactions of improved properties should also be considered. Since the cost of construction rarely equals the added value of improvements (the added value tends to be either above or below the cost of construction depending on the relative supply–demand situation) this is not a suitable method for “splitting” improved sales prices into a land and building component. But this may be possible using market analysis that jointly considers the sales of both improved and vacant properties. A properly calibrated model may meet these demands. In South Australia, where every property must be assessed for both capital and site value on an annual basis, such a hybrid model may serve the purpose of completing all valuations from a single model and lead to acceptable estimates of both site and capital value. The results are also useful for “component” assessment adjustments, such as an increase in assessment for new additions.

Evaluating the Accuracy of the Models

Evaluations of AVMs is generally conducted using the IAAO Standards on Ratio Studies (IAAO, 1999), which is currently being reviewed (IAAO, 2005). The standard is based on the comparison of assessed values to market sale prices or independent valuations. Typically it is used to test assessed values against market sales data during the assessment creation process and then to test the assessment against sales that occur after the assessments have been finalised. In this way it is useful to determine if the assessment is likely to be accurate prior to release and then as a tracking mechanism to test for actual accuracy after the assessment is released. Ratio studies rely upon the use of the A/S ratio – the ratio of assessed value to the sale price (or independent valuation). The A/S ratios are then charted in various ways, and described and inferential statistics are used to determine the accuracy of the assessments. Typically this study uses a variety of parametric and non-parametric tests, including:

1. Measures of assessment level; mean; median; weighted mean and geometric mean ratios.
2. Measures of Variability; Coefficient of Dispersion (COD); Coefficient of Variation (COV) and quartile ranges.
3. Measures of Reliability; confidence intervals and standard errors.
4. Vertical Inequities; Price-Related Differential (PRD)

METHODOLOGY

Study Area

The study area is the Adelaide southern suburb of Morphett Vale, graphically shown in Appendix 1. In 2006 (the last available census data) the total population for Morphett Vale was approximately 23,000 with approximately 40% of these in the 25–54 year-old age bracket. The labour force was predominately comprised of technicians, trade workers, labourers and clerical and administrative workers (approximately 50%), with professionals and managers comprising only 18%. The median average household income was below the national average with 85% of dwellings being separate housing (Australian Bureau of Census and Statistics 2006 census).

Study Period

The study was completed using data between January 2010 and March 2011. This reflects a period when the residential property market in the area was relatively stable and therefore time adjustments are not necessary within the models.

As in previous studies the data was broken into two groups. The first group was used to create models and the second group to test the models. This is a standard holdout sample procedure typical of most forecasting and prediction methodologies and is designed to prevent overestimating the accuracy of the models where over-fitting occurs. For this study, designation of these two data sets was based on a logical rather than random approach similar to that used in commercial AVMs. If the model were to be used to assess capital and site values then the normal procedure would be to use sales from one period to estimate the values for the forthcoming assessment period. In this study we assume that the task is to create capital and site assessments in mid-2011 using the data from the previous year (2010) and that the assessments are then evaluated using data from the first quarter in 2011 based on 'the sales that occurred in the previous 12 months (2010).

Data

For this study only detached houses and vacant land are used and allotment sizes are limited to those between 200 and 2000 sq metres. This would include the vast majority of all land uses in the study area. A large amount of data is available for each property but much of this is in the form of descriptors (such as the title reference) that are not used in AVMs and some other variables that are not collected for every property. Data are then imported into a GIS environment and joined to the fiscal cadastre giving the sales data a spatial framework.

The following data attributes are available for each of the 770 sales used for model calibration and the 169 sales used for testing in the holdout sample.

Table 1 – Variables used in the Models

Variable	**Variable Name/Description**
Sale Price	SalePrice/in dollars
Land Area	Larea/in square metres
Building Size	BArea/in square metres
Building Age	BAge/in years old
Building Style	Converted to Dummy Variables covering three housing styles found in the study area, namely D_SConvent/Housing Trust conventional (1 yes else 0) D_Colonial (1 yes else 0) and D_Contempory (1 yes else 0)
Improved or vacant land sale	D_House/Dummy Variable (1 for improved sale else 0 for Vacant Land)

All relevant transactions were extracted from the sale history file and cleaned for observations with missing data or where the price was demonstrably incorrect. Further sales were deleted that had A/S ratios that were outside the range 0.6 to 2. Unlike previous studies, properties that did not accurately model were not excluded. All data removed was on an *a priori* basis rather the ex-post approach taken by both O'Conner and Gloudemans where properties that are poorly estimated in the models are removed. That approach will tend to overestimate the accuracy of the models as some of these will be properties that are genuine transactions with correct data but that the model is incapable of properly estimating. The likely cause of this is omitted variables. By removing such data the opportunities to investigate these omitted variables is lost and the accuracy of the model appears better in terms of both the model statistics and the test statistics where difficult-to-assess properties have been removed. The approach taken in this study is to remove only those observations that are clearly incorrect or where there are missing data that make it impossible to use the observations. Thus, the estimates of model accuracy become quite conservative and would only be improved by diligent sales analysis and data rechecking. These would normally be carried out by a rating authority in the process of mass appraisal. As a result it is likely that a number of gross outliers will appear in the test assessments that would not occur in a true mass appraisal.

Modelling

The following is a summary of the process used in the multi-stage modelling.

Step 1. Split the data into model and test data.

Step 2 Use the model data to develop a simple global linear model using the building and site characteristics and save the Relative Location Factor (RLF) as being a new variable calculated by dividing the sale price by the estimated value. This leads to an interpretation that an RLF greater than 1 means, that compared with the average, there was money paid for the dwelling over and above the dwelling itself, namely location. Conversely, a RLF of less than 1.0 would indicate that less was paid for the property than indicated by the dwelling alone and relative to the average RLF of 1.0 of a less desirable location. This RLF can then be assigned to each property centroid and plotted spatially, demonstrating the varying residential market structure expressed in terms of the RLF so observed. Part of this step is to demonstrate that there is significant spatial variation of the RLF, indicating that location is important and needs to be accounted for. A global Moran's I is used to demonstrate such significance. A positive index value indicates a bias towards clustering while a negative index value indicates a bias towards randomness and no spatial variation.

Step 3 Use the residuals from step 2 to establish an LVRS by interpolating the RLF so calculated across the entire study area using Ordinary Kriging with a 25 metre cell size. Sales used in the data set to calibrate the models included sales from surrounding contiguous suburbs and thus a RLF at each sale point. This was done so as the interpolated LVRS would not abruptly finish at the Morphett Vale suburb boundary thus eliminating the edge effect created by no supporting evidence beyond the boundary.

Step 4 Use the surface in step 3, to estimate a new spatial variable (LOCATION) for all observations. This should account for special major effects primarily in the land component and is a surrogate for a variety of spatial characteristics.

Step 5 Develop GWR, linear, log-linear and non-linear (hybrid) models using the location, site and building characteristics.

Step 6 Estimate the value (assessments) for all properties using each of the three models developed at step 5.

Step 7 Calculate A/S ratios and associated statistics for model and test data and for both vacant and improved properties for assessments from step 6 based on the IAAO standard for ratio studies (IAAO, 1999).

As the models are developed over a staged process, model specifications and estimates are shown for the various stages.

Step 1 – Data splitting

The data is split into 4 data types. The frequency of these data types is shown in Table 2.

Table 2 – Summary of data by type and year

TYPE	Date of Sale	Frequency
Dwelling – Model	2010	756
Dwelling – Test	Q1 – 2011	158
Vacant – Model	2010	14
Vacant – Test	Q1 – 2011	11

Step 2 – Initial models to find residuals for use in the LVRS

Basic linear regression models are established to find systematic error to model in the LVRS. For this model only 2010 sales (dwelling-model and vacant-model) are used. This model is specified as

$$P = b_0 + b_1 X_1 ... b_n X_n + (\theta + \varepsilon)$$

where

P	=	transaction price
b_0	=	a constant
$b_{1...}b_n$	=	market determined parameters
$X_{1...}X_n$	=	a vector of property characteristics
θ	=	systematic spatial component captured in the residual
ε	=	stochastic errors included in the residual

The systematic spatial component and stochastic error are captured in the residuals from this model. These residuals become the inputs to the model to establish the smoothed LVRS from the raw RLF values expressed as:

$$RLF = P / b_0 + b_1 X_1 ... b_n X_n$$

Step 3 – Estimating the LVRS

The smoothed LVRS surface is estimated using ordinary kriging applied to the RLF. This raster surface is converted into a point file and spatially joined to the out-of-sample sales-point data set with each sale given the location factor equivalent to the mean of the nearest point from the raster surface (modelling step 2). A graphical representation of the value surface is shown in Appendix 2.

Step 4 – Estimating the location variable to allow for spatial effects

The model from step 3 is used to estimate the new location variable for every property in the data base using the properties' relative position on the LVRS. This variable is added to the data set and the models re-estimated with the inclusion of the location variable.

Step 5 – Develop GWR, linear, log-linear and non-linear (hybrid) models

Four different models are developed for comparison and are derived as follows:

GWR

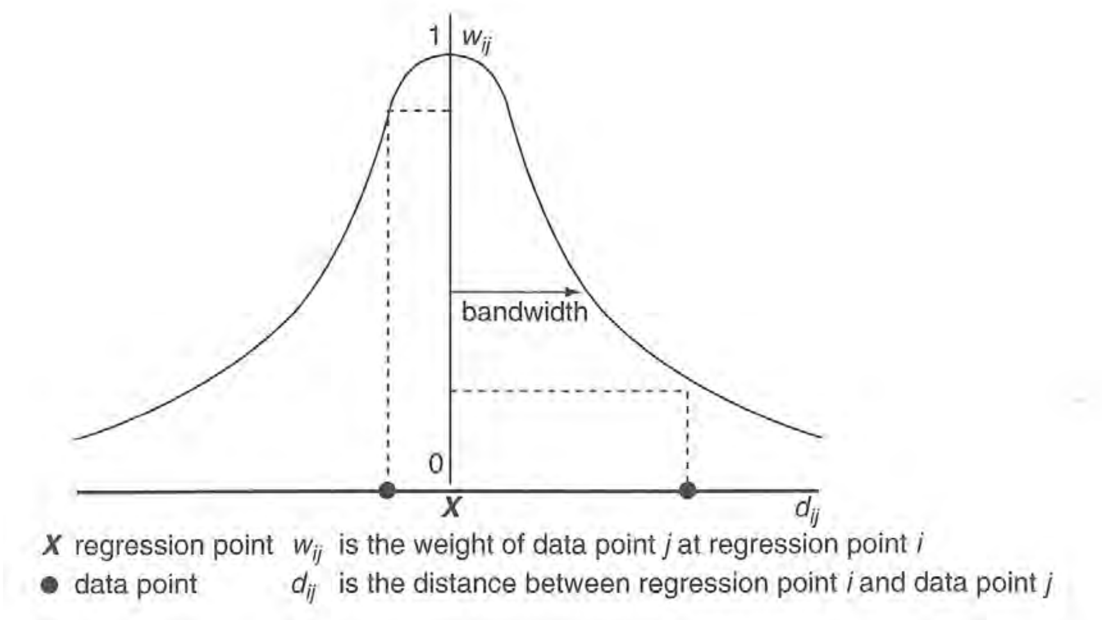
$$P = b_0(u,v) + b_1(BArea)(u,v) + b_2(Larea) + b_3(Bage)(u,v) + b_4(DSConvent)(u,v)$$
$$+ b_5(DColonial)(u,v) + b_6(DContempory)(u,v) + \varepsilon$$

where:

(u,v) are the location coordinates of the Sale Price

b_0 to b_6 are the parameter estimates

Figure 2 Concept of a spatial kernel adopted in GWR Source: Fotheringham, Brunsdon and Charlton, 2002.



This OLS hedonic model accounts for location by allowing the regression coefficients to vary across geographical space. It makes no assumption as to the non-stationarity or otherwise of the coefficients and is not limited by the artificial (*a priori*) administrative boundaries.

Figure 2 shows conceptually how a weighting is applied using the GWR model. For a given regression point X those sales closest to X are given the highest weight. The weight decreases the further away a sale is from the given regression point. At subsequent regression points the same method of weighting is applied, meaning that even though different regression points may share some common sales data they will be weighted differently. It is in this way that GWR uniquely calibrates the local models as it moves across the geographical surface and can thus capture local variations not possible in global models. Figure 2 shows the spatial kernel used in GWR modelling that can either be fixed or adaptive. In a GWR model with fixed kernels the bandwidth does not vary as it crosses geographic space. The disadvantage of this is that in areas of low density the local GWR model may be calibrated on the evidence of very few sales and in some cases may not have sufficient data to calibrate a model. To help overcome this problem GWR kernels have the capability to adapt themselves in size to accommodate available data. In areas where data have low density the bandwidth of the spatial GWR kernel increases to include sufficient data to calibrate the local model. Conversely, GWR can decrease the bandwidth where the data have high density, giving it the capability to calibrate a more local model. In this study the GWR models used an adaptive kernel allowing the bandwidth to vary so as to incorporate enough sales data to calibrate the model (Fotheringham, Brunsdon & Charlton 2002; Borst & McCluskey 2008).

This study uses an adaptive kernel to include the required sales to calibrate the model.

Linear

$$P = b_0 + b_1\theta + b_2 X_1 ... b_n X_n + \varepsilon$$

Log-Linear

$$P = e^{b_0 + b_1\theta + b_2 X_1 .... b_n X_n}\varepsilon$$

Where

P	=	transaction price
b_0	=	a constant
$b_{1...}b_n$	=	market determined parameters
θ	=	a vector of spatial location factors (step 4)
$X_{1...}X_n$	=	a vector of property characteristics including some variables in X^2 form
ε	=	stochastic errors

Non-Linear (Hybrid)

$$P = (b_1 + b_3 Larea) b_2^{\ \theta} + BArea(b_6 + b_7 BArea + b_8 Bage)(b_8^{\ D1} .... b_n^{\ Dn}) + \varepsilon$$

where

P	=	transaction price
$b_{1...}b_n$	=	market determined parameters
θ	=	a vector of spatial location factors (step 4)
$Larea$	=	a vector of land areas
$BArea$	=	a vector of building areas
$Bage$	=	a vector of building ages
$D_{1...}D_n$	=	a vector of building styles as dummy variables
ε	=	stochastic errors

This model is specified exactly and is based on the finding of research in the same study area (Rossini, 2006) and a certain amount of trial and error. The model is specified along traditional valuation lines where land and buildings are considered separately and summed together. In this instance land value is a function of area and location and the building is assessed on a square metre basis where the rate varies with area, age and style. This can be compared in terms of accuracy against the previous models that make no such assumptions about the summation effect of value. Since the non-linear model uses a generalised least squares (GLS) approach (as opposed to ordinary least squares OLS) that is based on an iterative approach, it is necessary to provide starting estimates for all the model parameters (regression coefficients). These starting values were estimated from two preliminary regression models, first using vacant land sales and then the improved sales. This followed the procedure taken by McCain, Jensen and Meyer (2003).

RESULTS AND DISCUSSION

Initial Stages

The initial test for spatial autocorrelation was carried out using Moran's I global test, which indicated that there was a less than 1% likelihood that the clustered pattern of the RLF (calculated in stage 2) could be the result of random chance indicating location was a significant factor in the estimation of both site and capital value. This demonstrates that even at the relatively small geographic scale of the urban metropolitan suburb there can be spatial variation that should be accounted for.

Model Results

Linear Model

The linear model produced a satisfactory result with an R-squared value of .815 and a series of variables that passed the various significance tests (see Appendix 4 for these results). Only the dummy variable for Colonial style did not pass the 90% significance test with all other variables showing logical coefficient values. Neither land area nor building area showed diminishing marginal returns, with the tests supporting some progression in the marginal values. This is not uncommon in narrow samples of housing especially at the low end of the price range where marginal prices at low values increase before reverting to diminishing returns when values become higher. The housing in this sample is restricted to the bottom end of the market, with the few larger properties (particularly land) being removed to ensure greater homogeneity since larger land parcels will have significant development potential, placing them outside the normal housing market. The values for the Variance Inflation Factor (VIF) show the expected high correlations between the various variables and their squared terms but otherwise there is no significant problem of multicollinearity. The residuals (not shown) appear to behave normally.

Log-Linear Model

The log-linear model closely mirrors the linear result. The transformation to the log-linear (exponential) form in small homogenous housing markets rarely produces very different results to that of the linear model. The decision to use the exponential model is more often based on the ability to interpret the results in the form of percentage premiums (as opposed to additive dollar terms) rather than expecting a significantly greater level of fit. This is the case in this instance where, in statistical terms, the model is almost identical to the linear form but may have some variations in the estimation accuracy, especially in the holdout sample. While both models produce similar statistical evaluations the form of the model may lead to significant changes in estimates when applied to a holdout sample.

Hybrid Model

The hybrid model is being estimated using GLS and hence produces a different set of statistical evaluation tools to those typically reported for an OLS regression. These are shown in Appendix 4. An R-squared proxy is shown, suggesting the model produces similar results to the linear and exponential models in terms of fit. The coefficients are tested for significance in a similar manner to the OLS regression but typically estimates of the parameters and standard errors are estimated by bootstrapping in addition to the asymptotic calculations. Both the asymptotic and bootstrapped values suggest that all parameter estimates are significant at greater than a 95% confidence interval except for b10[2] (D_colonial), which is consistent with the linear and log-linear results.

Geographically Weighted Regression

Having calibrated the various models, the GWR model was unable to be calibrated using the same nine variables' specification as the global models. This was due to severe local multicollinearity which resulted in omitting three of the independent variables (the dummy variable, indicating whether the sale property was an improved sale or vacant land, and the square of the land area and the square of the building area). The two area variables that were squared to account for non-linear effects upon price were highly correlated with their non-squared counterparts. The inability to include the dummy variable indicates that the presence of an improved sale was unable to be calibrated, which may be due to the small number of vacant land sales that presented no variation in that variable at certain regression points. This resulted in a differently specified GWR model to the global counterparts, providing an area of further research in deciding the comparative merits of the models in accounting for location in terms of valuation theory. The difficulty in sometimes specifying GWR models when using dummy variables was also highlighted by Des Rosiers and Theriault (2007).

The results of using the specified models above are shown in Table 3. They were run on both data sets and also separately for houses and vacant land in the holdout sample.

Accuracy Statistics

When predicting back all the properties, the model data sales results appear to be acceptable across all of the evaluator criteria, with the uniformity indicator being marginally worse using the GWR model as evidenced by the COV value

[2] Note that because the parameter estimate is a power term similar to the log linear model a value of 1 has no influence on the model and in effect the test is for the coefficient to be significantly different from 1 and in this instance the 95% confidence interval is from .945 to 1.057 for the asymptotic estimate and from .94 to 1.062 for the bootstrap estimate. Both show 1 within the 95% range.

being slightly higher than in the other three. This same relativity between models appears to be maintained when applied to the holdout sample. There was no appreciable denigration in outcome between the model data and the holdout data, with all models being acceptable across both groups.

However, when the same models are applied to houses only in the holdout data, all models predict with better uniformity than occurred across all properties (lower COV scores for all models) and have slightly better 'hit rates'.

Applying the same models to vacant land only in the holdout data the uniformity of prediction decreases significantly, as is expected for vacant land, although it is probably still marginal in terms of acceptability for vacant land. Interestingly, the comparison between the GWR and the global counterparts shows noticeably better uniformity (both the COV and COD statistics are lower) using GWR but a noticeably higher level of assessment. This may suggest that, with quite acceptable uniformity for vacant land, a downward adjustment in the estimated value may be all that is required to produce an acceptable outcome for estimating site value. However, given that the model specification lacks as good a valuation theory as the other three models, the outcome would not be acceptable even with a downward adjustment. Another noticeable feature of the vacant land results is the distribution of the 'hit rate'. There appears to be two separate groups, one of 36% between + or – 10% and another between + or – 50% with 9% above that again. This apparent bi-modal result may be due to the low number of vacant land sales (only 11 in the holdout data).

The advantage of the GWR model is the relative simplicity both in terms of specification of the model and the interpretability of the results. The question in valuation terms, however, may suggest that the GWR model is not as indicative of the market as are the other models through not being able to include as many variables. This may question the valuation sense of this GWR model compared to the others, especially in terms of being able to distinguish between site and capital value prediction as the dummy variable could not be included in the specification.

CONCLUSION

The objective of this paper is to contribute to the ongoing process of enhancing the efficacy of AVMs both in terms of the ability to predict both site and capital values as well as recognised spatial variation over smaller geographic areas. While all four models handled the prediction of the 'All Properties' and 'Houses' holdout samples within acceptable levels of accuracy, the ability to predict vacant land only presented some interesting outcomes for the GWR model. The specification issues and therefore the inability to reflect as a good model in valuation terms needs more research. Intuitively the GWR concept is a natural tool for use in AVMs, and therefore investigating the idiosyncrasies not encountered with the more traditional modelling approaches is highly desirable. The most notable of these may be the use of the GAWR model as a means of more exactly defining comparable sales for use in terms of both similar attributes as well as similar location. In addition, the use of a fixed kernel at differing bandwidths may help to understand the use of the GWR concept in overcoming what appear to be variability issues when specifying certain dummy variables as part of the model. It is still relatively early days in experience with such concepts and a potentially rewarding area of future research.

In this study the hybrid model, with its ability to incorporate more variables in a specified manner that satisfies valuation theory, appears the most likely option. It provides a transparent outcome with understandable predictions based on sound valuation theory.

Table 3 – Accuracy Results

Model Data - All Properties

Evaluator	GWR	Linear	Exponential	Hybrid
MAPE	7.2%	6.5%	6.5%	6.6%
RMSE	$ 26,802	$ 25,152	$ 25,508	$ 25,762
Percentage within + or - 5%	48%	49%	49%	50%
Percentage within + or - 10%	76%	78%	79%	78%
Percentage within + or - 15%	90%	91%	91%	92%
Percentage within + or - 20%	95%	96%	97%	97%
Percentage within + or - 50%	100%	100%	100%	100%
FSD	9.3%	8.4%	8.6%	8.7%
Mean A/S	1.010	1.007	1.004	1.008
Median A/S	0.997	1.000	0.997	1.005
Normality test (JB)	181.7	71.2	219.2	246.0
COV	10.056	8.523	8.605	8.796
COD	7.190	6.550	6.548	6.590
PRD	1.010	1.007	1.007	1.008
R - Squared	0.791	0.815	0.811	0.806
F Test (ANOVA)	2901	3393	3288	3198

Holdout Data - Morphett Vale - Houses

Evaluator	GWR	Linear	Exponential	Hybrid
MAPE	7.7%	7.7%	7.6%	7.4%
RMSE	$ 28,952	$ 29,673	$ 29,342	$ 28,951
Percentage within + or - 5%	46%	48%	46%	54%
Percentage within + or - 10%	76%	76%	76%	76%
Percentage within + or - 15%	85%	84%	85%	85%
Percentage within + or - 20%	94%	91%	93%	93%
Percentage within + or - 50%	100%	100%	100%	100%
FSD	9.4%	9.6%	9.7%	9.5%
Mean A/S	1.022	1.023	1.017	1.022
Median A/S	1.006	0.998	0.993	0.998
Normality test (JB)	2.9	3.5	4.1	5.1
COV	10.258	10.561	10.567	10.453
COD	7.683	7.855	7.732	7.528
PRD	1.007	1.007	1.007	1.007
R - Squared	0.373	0.342	0.335	0.364
F Test (ANOVA)	39	34	33	37

Holdout Data - All Properties

Evaluator	GWR	Linear	Exponential	Hybrid
MAPE	8.9%	8.3%	8.3%	7.9%
RMSE	$ 31,323	$ 32,048	$ 34,973	$ 29,678
Percentage within + or - 5%	42%	47%	44%	50%
Percentage within + or - 10%	71%	70%	71%	73%
Percentage within + or - 15%	82%	84%	86%	86%
Percentage within + or - 20%	91%	92%	91%	92%
Percentage within + or - 50%	99%	100%	100%	100%
FSD	11.0%	10.8%	11.0%	10.4%
Mean A/S	1.024	1.007	1.003	1.008
Median A/S	1.004	0.991	0.988	0.993
Normality test (JB)	8.6	7.7	14.8	8.9
COV	12.261	11.660	11.666	11.143
COD	8.860	8.370	8.361	7.950
PRD	1.017	1.008	1.006	1.008
R - Squared	0.795	0.792	0.773	0.817
F Test (ANOVA)	648	636	567	747

Holdout Data - Morphett Vale - Land

Evaluator	GWR	Linear	Exponential	Hybrid
MAPE	23.7%	15.3%	15.8%	15.2%
RMSE	$ 36,759	$ 28,528	$ 29,879	$ 26,208
Percentage within + or - 5%	9%	36%	9%	18%
Percentage within + or - 10%	36%	36%	36%	36%
Percentage within + or - 15%	36%	36%	55%	55%
Percentage within + or - 20%	36%	82%	64%	64%
Percentage within + or - 50%	91%	100%	100%	100%
FSD	11.1%	19.0%	20.1%	18.5%
Mean A/S	1.235	0.971	0.952	0.987
Median A/S	1.260	0.953	0.929	0.951
Normality test (JB)	0.3	0.5	0.2	0.4
COV	13.526	20.405	19.530	19.441
COD	10.880	17.193	17.183	17.084
PRD	1.022	1.033	1.034	1.029
R - Squared	0.606	0.111	0.111	0.215
F Test (ANOVA)	14	1	1	2

APPENDICIES

Appendix 1 – Accuracy Tests

The accuracy tests used in this study are based on the findings of Rossini and Kershaw (2008) as to acceptable levels of accuracy against which comparison of results can be made and are calculated as follows:

The Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{\Sigma\left|(S - A)/S\right|}{n}$$

The Root-mean-squared Error (RMSE)

$$RMSE = \sqrt{\frac{\Sigma(S - A_i)^2}{n}}$$

Coefficient of Variation (COV)

$$COV = \frac{100}{\overline{AS}}\sqrt{\left(\frac{\sum_{i=1}^{n}\left(A_i/S_i - \overline{AS}\right)^2}{n-1}\right)}$$

Coefficient of Dispersion (COD)

$$COD = \frac{100}{A\tilde{S}}\left(\frac{\sum_{i=1}^{n}\left|A_i/S_i - A\tilde{S}\right|}{n-1}\right)$$

Price Related Differential

$$PRD = \frac{\overline{AS}}{\sum_{i=1}^{n} A_i \Big/ \sum_{i=1}^{n} S_i}$$

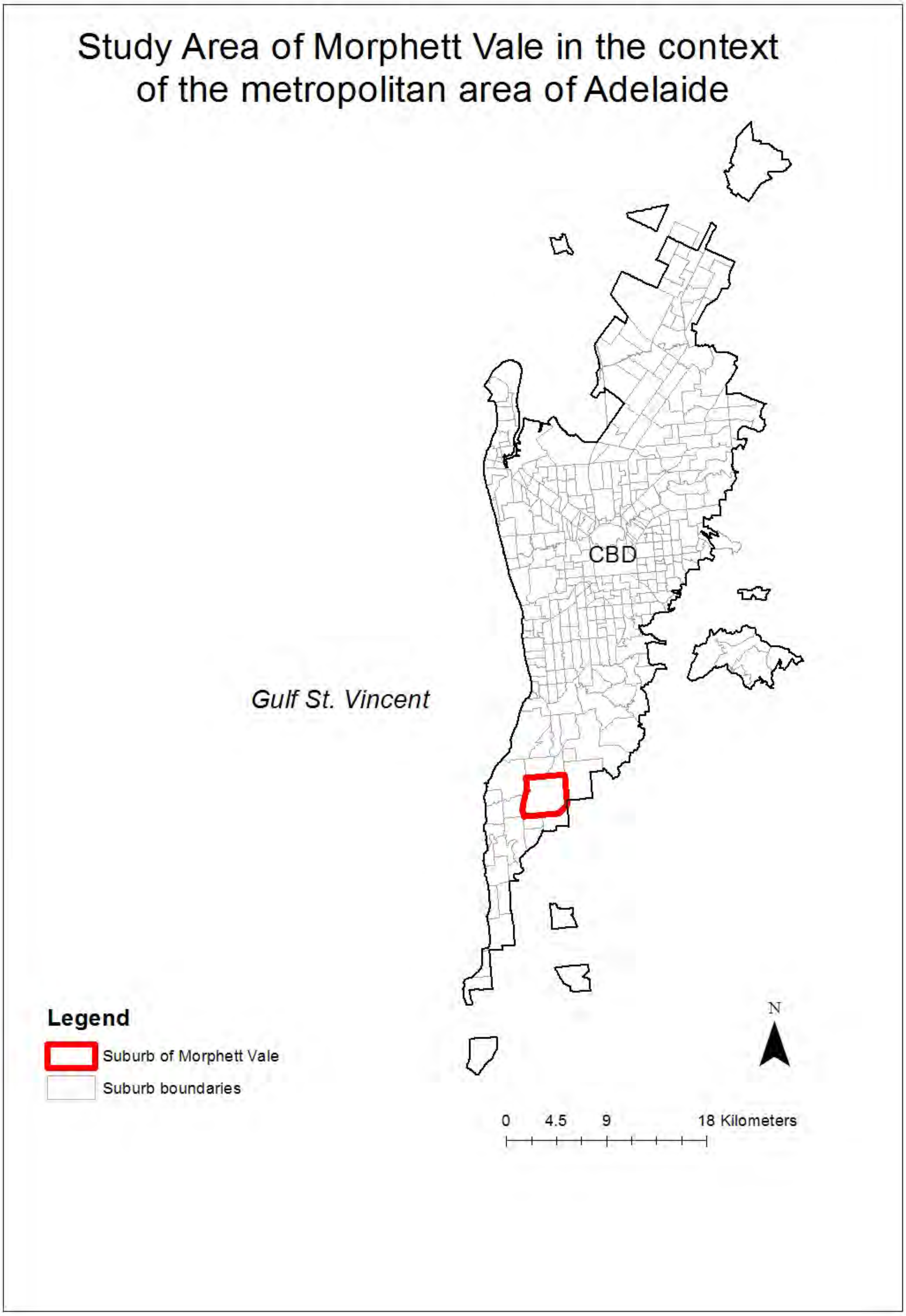
where

$A\tilde{S}$	=	median assessment
$\overline{AS}$	=	mean assessment
n	=	number of ratios
A_i	=	assessment for property i
S_i	=	Sale price for property i

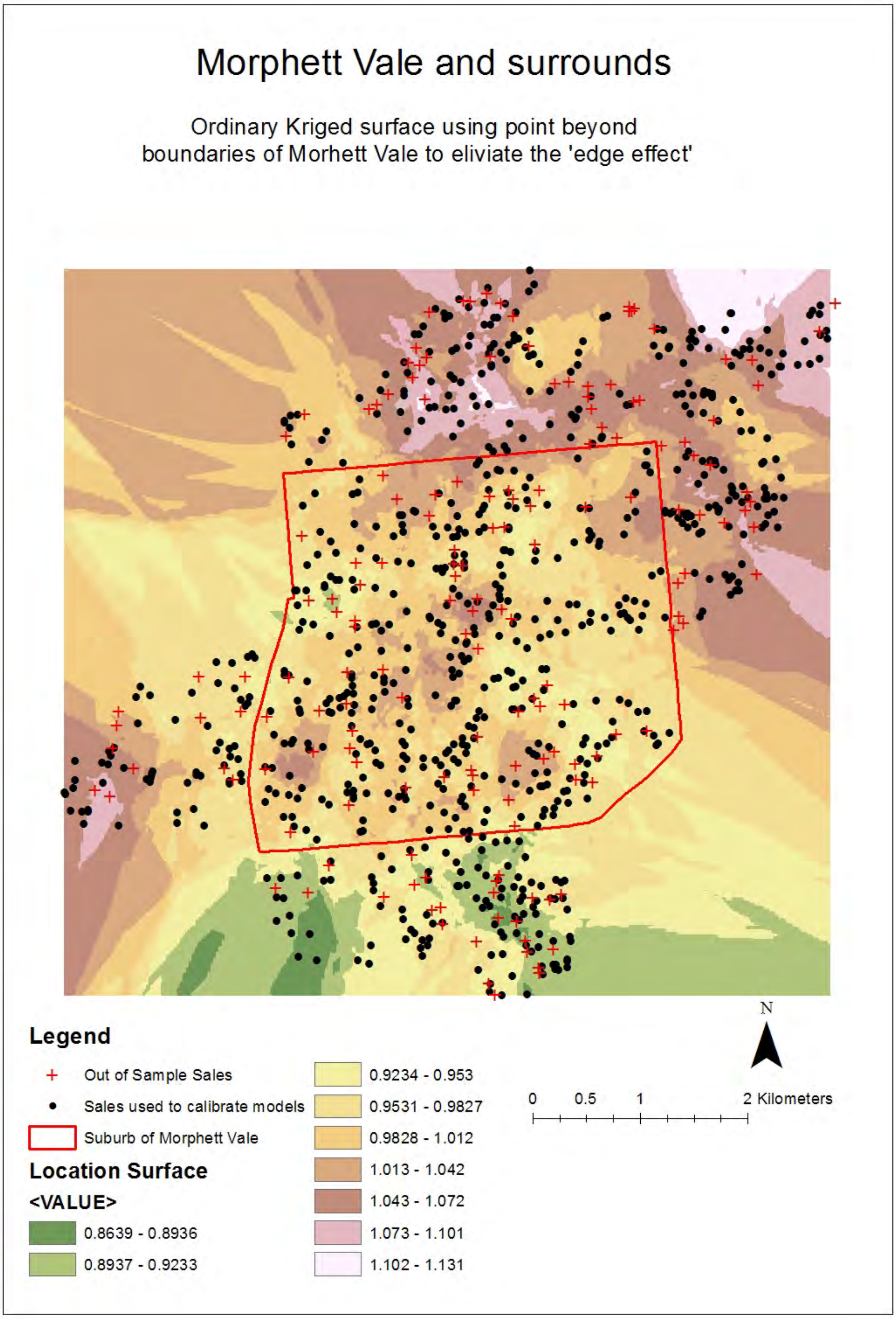
The Forecast Standard Deviation (FSD) is defined as the standard deviation of percentage forecast errors where

$$PercentageError = \frac{S_i - A_i}{A_i}$$

Appendix 2 – The study area



Appendix 3 – Data Points and Land Value Response Surface



Appendix 4 – Model Results

Linear

R	R-Square	Adjusted R-Square	Std. Error of the Estimate
.903	.815	.813	25334.054

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	2.1522E+12	10	2.15E+11	335.326	.000
Residual	4.8714E+11	759	6.42E+08		
Total	2.6393E+12	769			

Variable	Unstandardised Coefficients		t	Sig.	90.0% Confidence Interval for B		
	B	Std. Error			Lower Bound	Upper Bound	VIF
(Constant)	–214646.98	22571.28	–9.51	.000	–251818.8	–177475.2	
LocFactor	356586.81	19916.84	17.90	.000	323786.5	389387.1	1.1
LArea	–50.12	20.35	–2.46	.014	–83.6	–16.6	13.7
LArea^2	.08	.01	7.00	.000	.1	.1	11.3
D_House	108401.39	16762.32	6.47	.000	80796.1	136006.7	5.6
BArea	516.68	193.29	2.67	.008	198.4	835.0	56.1
BArea^2	1.46	.62	2.36	.019	.4	2.5	45.0
BAge	–1209.38	111.54	–10.84	.000	–1393.1	–1025.7	2.4
D_SConven	–21452.33	2896.72	–7.41	.000	–26222.8	–16681.8	1.2
D_Colonial	1374.88	4155.75	.33	.741	–5469.1	8218.8	1.0
D_Contemp	–11482.66	5520.42	–2.08	.038	–20574.0	–2391.3	1.1

Log-Linear

R	R Square	Adjusted R Square	Std. Error of the Estimate
.903	.816	.813	.08604

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	24.880	10	2.488	336.112	.000
Residual	5.618	759	.007		
Total	30.499	769			

Variable	Unstandardised Coefficients		t	Sig.	90.0% Confidence Interval for B		
	B	Std. Error			Lower Bound	Upper Bound	VIF
(Constant)	10.611	.077	138.423	.000	10.484	10.737	
LocFactor	1.229	.068	18.174	.000	1.118	1.341	1.1
LArea	–.0002	.0001	–2.427	.015	.000	.000	13.7
LArea^2	2.58E-07	3.68E-08	7.000	.000	.000	.000	11.3
D_House	.495	.057	8.698	.000	.401	.589	5.6
BArea	.003	.0007	5.166	.000	.002	.004	56.1
BArea^2	–2.09E-06	2.105E-06	–.996	.319	.000	.000	45.0
BAge	–.004	.0004	–10.449	.000	–.005	–.003	2.4
D_SConven	–.077	.010	–7.830	.000	–.093	–.061	1.2
D_Colonial	.005	.014	.367	.714	–.018	.028	1.0
D_Contemp	–.040	.019	–2.123	.034	–.071	–.009	1.1

Hybrid

ANOVA[a]

Source	Sum of Squares	df	Mean Squares
Regression	7.2495E+13	9	8.06E+12
Residual	5.1104E+11	761	6.72E+08
Uncorrected Total	7.3006E+13	770	
Corrected Total	2.6393E+12	769	

Dependent variable: SalePrice

a. R-squared = 1 – (Residual Sum of Squares)/(Corrected Sum of Squares) = **.806.**

Parameter Estimates

	Parameter	Estimate	Std. Error	95% Confidence Interval		95% Trimmed Range	
				Lower Bound	Upper Bound	Lower Bound	Upper Bound
Asymptotic	b1	14192.093	2740.508	8812.240	19571.946		
	b2	7.750	1.158	5.477	10.024		
	b3	11.052	1.856	7.407	14.696		
	b6	1632.721	96.837	1442.621	1822.821		
	b7	–1.423	.346	–2.103	–.743		
	b8	–11.804	.789	–13.352	–10.256		
	b9	.792	.027	.739	.845		
	b10	1.001	.029	.945	1.057		
	b11	.875	.051	.775	.975		
Bootstrap[a,,b]	b1	14192.093	3224.377	7855.348	20528.838	9496.710	22124.774
	b2	7.750	1.481	4.840	10.660	5.669	11.461
	b3	11.052	3.554	4.067	18.036	4.629	17.967
	b6	1632.721	117.336	1402.125	1863.317	1387.235	1822.527
	b7	–1.423	.405	–2.219	–.627	–2.096	–.578
	b8	–11.804	1.265	–14.290	–9.318	–13.860	–9.222
	b9	.792	.038	.717	.866	.711	.859
	b10	1.001	.031	.940	1.062	.943	1.064
	b11	.875	.058	.761	.989	.761	.986

a. Based on 450 samples.

b. Loss function value equals 511042403854.188.

GWR – results

Neighbours	**310**
AIC$_c$	**17968.67**
R^2	**0.790**
Adjusted R^2	**0.776**

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