UNIVERSITI PUTRA MALAYSIA

COMPARISON BETWEEN SPECIFICATIONS OF LINEAR REGRESSION AND SPATIAL-TEMPORAL AUTOREGRESSIVE MODELS IN MASS APPRAISAL VALUATION FOR SINGLE STOREY RESIDENTIAL PROPERTY

EBRAHIM JAHANSHIRI

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By

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Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirement for the Degree of Doctor of Philosophy

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Chairman: **Assoc. Prof. Abdul Rashid b. Mohamed Shariff, PhD**

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Property valuation is an area of interest for property owners, real estate agents, government bodies and researchers. There are various approaches to estimate a property value. Among them, the statistical and spatio-temporal methods incorporate the location and time in the valuation modelling. These models however, are not widespread as the simple linear models due to scarcity of proper data and incomprehensive research findings on their implementation issues. Effects such as normality treatment, definition of neighbourhoods and weights and choice of autocorrelation parameter and parameter estimation are some of the complexities that are inherent to these models. This study therefore, was designed to investigate different aspects of spatial and spatio-temporal autoregressive modelling. Further, the performance of these models compared to the standard linear model that is widely used in mass appraisal of real properties, was studied. Datasets of transacted terrace houses over the period 1999-2009 from Selangor, Malaysia were obtained and geocoded for analyses using cadastral and topographic maps and online mapping services. A complete data analysis was carried out on the datasets. Furthermore, various spatial, temporal and spatio-temporal neighbourhood and weighting schemes, optimization algorithms and lag and error modelling scenarios were created and tested with the data. A hold-out validation was performed for different sets of experiments. The best set of parameters that could produce more accurate results in the validation process, were selected and their associated neighbourhood and weights were used to compare with the linear models. The experiments were replicated on three different treatments based on removal of outliers and transformation of variables with high value of skewness. The results showed that although there was a strong presence of spatial autocorrelation in the dataset, especially when the outliers are removed, the results of linear and spatio-temporal models are mixed. The best result using criteria of coefficient of determination and the uniformity level of prediction belonged to the spatio-temporal lag and spatial lag models respectively. The error variant of the abovementioned models could only reduce the problem of heteroscedasticity in regression error residuals. Linear regression model could provide better uniformity level at the expense of very low R^2 and higher heteroscedasticity in residuals. It was also found that the graph based neighbours would increase the chance of the spatial model to predict better. Furthermore, the row-standardized or stochastic weight matrices showed to be more effective compared to other weighting schemes. Finally, it was demonstrated that incorporating the space and time interaction (S×T or T×S) autocorrelation in the spatio-temporal model along with higher time interval between dates of transactions in temporal neighbourhood selection would produce more reliable results in prediction for spatio-temporal autoregressive models.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia
sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PERBANDINGAN ANTARA SPESIFIKASI BAGI LINEAR REGRASI DAN MODEL autoregresif SPATIAL-keduniaan MASS PENILAIAN PENILAIAN UNTUK STOREY SINGLE RUMAH BERKELOMPOK

Oleh

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Penilaian hartanah adalah kawasan yang menarik untuk pemilik harta, ejen hartanah, badan-badan kerajaan dan penyelidik. Terdapat pelbagai pendekatan untuk menganggarkan nilai hartanah. Antaranya, kaedah statistik dan spatio-temporal menggabungkan lokasi dan masa dalam pemodelan penilaian. Model-model ini bagaimanapun tidak meluas sebagai model linear mudah kerana kekurangan data yang betul dan hasil penyelidikan mengenai isu-isu Partial pelaksanaannya. Kesan seperti rawatan normal, definisi kawasan kejiranan dan berat dan pilihan parameter autokorelasi dan penganggaran parameter adalah beberapa kerumitan yang wujud untuk model ini. Kajian ini oleh itu, telah direka untuk menyiasat aspek pemodelan autoregresif ruang dan spatio-temporal. Selanjutnya, pelaksanaan model ini berbanding dengan model linear standard yang digunakan secara meluas dalam penilaian besar-besaran hartanah sebenar, telah dikaji. Dataset rumah teres yang diurusniagakan dalam tempoh yang 1999-2009 dari Selangor, Malaysia telah diperolehi dan Geocode untuk

analisis menggunakan kadaster dan peta topografi dan perkhidmatan pemetaan dalam talian. Analisis data lengkap telah dijalankan ke atas dataset. Tambahan pula, pelbagai kejiranan dan pemberat skim spatial, temporal dan spatio-temporal, algoritma pengoptimuman dan lag dan kesilapan senario telah dimodelkan yang dicipta dan diuji dengan data. Satu pengesahan memegang keluar telah dilaksanakan ke atas set eksperimen. Set terbaik parameter yang boleh menghasilkan keputusan yang lebih tepat di dalam proses pengesahan, telah dipilih dan yang berkaitan kejiranan mereka dan berat telah digunakan untuk membandingkan dengan model linear. Kajian ini telah ditiru kepada tiga rawatan yang berbeza berdasarkan penyingkiran unsur luaran dan transformasi pembolehubah dengan nilai yang tinggi kepencongan. Hasil kajian menunjukkan bahawa walaupun terdapat kehadiran yang kukuh autokorelasi spatial dalam dataset, terutamanya apabila unsur luaran dikeluarkan, keputusan model linear dan spatio-temporal dicampurkan. Keputusan terbaik menggunakan kriteria pekali penentuan dan tahap keseragaman ramalan milik lag spatio-temporal dan model lag ruang masing-masing. Varian ralat daripada model tersebut di atas hanya dapat mengurangkan masalah heteroskedastisiti dalam sisa ralat regresi. Model regresi linear boleh menyediakan tahap keseragaman yang lebih baik dengan mengorbankan sangat rendah R^2 dan heteroskedastisiti lebih tinggi dalam sisa. Ia juga mendapati bahawa jiran graf berdasarkan akan meningkatkan peluang model ruang untuk meramalkan yang lebih baik. Tambahan pula, matriks berat badan barisan seragam atau stokastik menunjukkan untuk menjadi lebih berkesan berbanding dengan skim pemberat lain. Akhirnya, ia telah menunjukkan bahawa menggabungkan ruang dan masa interaksi (S × T atau T × S) autokorelasi dalam model spatio-temporal bersama-sama dengan jarak waktu yang lebih tinggi di antara tarikh urusniaga dalam pemilihan kejiranan duniawi akan menghasilkan keputusan yang lebih tepat dalam ramalan untuk spatio model autoregresif-sementara.

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I certify that an Examination Committee met on 9 May 2013 to conduct the final examination of Ebrahim Jahanshiri on his Doctor of Philosophy thesis entitled "Comparison Between Linear Regression, Spatial and Spatial-Temporal Autoregressive Models in Mass Appraisal Prediction for Single Storey Residential Property" in accordance with Universiti Pertanian Malaysia (Higher Degree) Act 1980 and Universiti Pertanian Malaysia (Higher Degree) Regulations 1981. The Committee recommends that the candidate be awarded the relevant degree. Members of the Examination Committee are as follows:

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DECLARATION

I hereby declare that the thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Univerisiti Putra Malaysia or other institutions**.**

EBRAHIM JAHANSHIRI

Date: 9th May 2013

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LIST OF ABBREVIATIONS

BP:	Breusch-Pagan
CBD:	Central Business District
COD:	Coefficient of Dispersion
DGP:	Data Generating Process
ESDA:	Exploratory Spatial Data Analysis
GIS:	Geographic Information Systems
GWR:	Geographically Weighted Regression
KURT:	Kurtosis
ML:	Maximum Likelihood
MRA:	Multiple Regression Analysis
OLS:	Ordinary Least Square
OR:	Outlier-removed
ORTR:	Outlier Remove and Transfomred
PDP:	Percentage Deviation of *i*th prediction (PDPi)
PRD:	Price Related Differentials
SAR:	Spatial Autoregressive
SD:	Standard Deviation
SHM:	Spatial Hedonic Modelling
SKEW:	Skewness
STAR:	Spatio-temporal Autoregressive
TR:	Transformed

CHAPTER 1

INTRODUCTION

1.1 General Introduction

Statistical methods are now important part of the data analyses in disciplines that deal with data and information. These methods provide a level of assurance for the uncertain activities like measurements, pattern recognition, forecasting and prediction.

The methods of data analyses are always evolving due to increase of our understanding of natural and human induced phenomena through science of data analysis. The growth of data collection facilities, computing power and infrastructure in the recent years has definitely leveraged scientific conclusions (Anselin, 1998; Rowley, & Fisher, 1998).

One of the most important advancements in the statistical methods was the introduction of spatial analysis, based on the laws of geography, to the statistical methodologies (De Smith; Longley, Goodchild, Maguire & Rhind, 2006). These methods that are now classified into the spatial statistical methods have become widespread in the regional sciences that deal with the geographical data. This introduction provided an exciting opportunity for econometric researchers to apply these methods to real estate data. These methods were then improved and a branch of research called spatial econometrics was proposed (Anselin, 1988). The foundation of spatial econometrics is spatial regression that deals with the two important criteria, spatial autocorrelation and heterogeneity. Positive or negative spatial autocorrelation reduces the total information derived from the observations, because “nearby observations can be used to predict each other” (Cliff & Ord , 1970; Bivand, Pbesma & Gómez-Rubio, 2008).

Real estate valuation have also benefited from these methods through analyses of economic variables or econometrics, hypothesis testing and prediction using multiple regression analysis (MRA). Numerous spatial statistical methods have been devised to use spatial autocorrelation in prediction. Nonetheless, MRA is still considered the standard method for prediction of house prices and many computer-assisted mass appraisal systems (CAMAs) have been developed using MRA methodology. In these systems the “spatial” characteristics of real estate data is only available in the form of simple maps showing the location of properties. The proximity as locational indicator in the form of closeness to amenities and central business district are closest that these systems can get to utilize the spatial effects in prediction. The spatial methods however, are gaining appreciation in the mass appraisal through extensive research on different aspects of these methods. Many of the functions specific to spatial econometrics are now available to researchers (Bivand, et al., 2012) and lots of research is going to be done on these methods that will facilitate the adoption of these methodologies into the CAMAs (McCluskey & Adair, 1997).

Similar to other data that happen on the space-time continuum, the real estate data has also temporal characteristics. Time series forecasting has been used in econometrics analysis. The interaction of space and time and its impact on the spatial autocorrelation are gaining attention and the use of spatio-temporal methods that only recently have been introduced in the literature is becoming widespread (Cressie, 2011).

One of the important challenges in spatial hedonic modelling (SHM) using the autocorrelation effect is to identify the "relationships or influences" over the spatial, temporal and spatio-temporal domains. Issues such as the degree of effectiveness of spatial neighbours and time frame of temporal neighbours need to be addressed as well.

Such effects are normally added to the hedonic model with the weight matrices that aim to filter the spatial, temporal and spatial temporal effects, thus, increasing the prediction accuracy. The variables used in the model were designated as lagged variables for both dependant (price) and also error terms (residuals). One question to investigate is the definition of these lagged variables and how to improve the model using the contiguity weight matrices. Also as the real estate data can be considered mostly irregularly spaced data both in space and time, there is a challenge on the decomposition of spatial dependence into spatial and temporal weight matrices so that the integrity of prediction results are preserved. These aspects make the research on the spatial methods interesting.

1.2 Problem Statement

Property managers are mandated by the tax laws and rates policies to standardize their valuations of market. Creating standard models in addition to consistency will lead to stable real estate market and macro economy. A value that is announced by the real estate companies need to be justified through declaring all its components and therefore using specifically tailored and standardized models will assist both real estate companies and the government bodies to stabilize the market. In Malaysia, the appraisal is done through professional valuers that are trained both in industry and university. Valuer's judgment is an important part of any appraisal. However, repeatability, measurement of error and speed of assessment are some of the reasons that using manual valuation is not suggested in tasks that need mass appraisal. The assessment techniques can help the appraisers to achieve higher accuracy in relatively shorter amount of time. However the initial modelling effort is needed to fine tune these somewhat complex techniques.

Multiple regression models are long being used in Malaysia and other parts of the world to create values for the rating and other purposes. Rigorous assumptions like independency of observations may render the results of these models invalid. Spatial autoregressive models as the extension of the simple linear models have been introduced before, however, their specifications, modelling aspects and implications especially when the time domain is added to the data, have not been comprehensively studied. The evidence for it is the hesitation of the mass appraisers to use these somewhat theoretically complicated models in the prediction of valuation and CAMA.

Therefore, more detailed studies such as comparison between their different specifications and overall performance compared to the de facto model (MRA) is required. Therefore, it is important to address the behaviour of these models, and to provide insight as to how these models can be easily used in the prediction given the availability of data and computing power.

Some other issues that have not been well addressed:

- The effect of time and space-time contiguity on the prediction of irregularly spaced real estate data that are dispersed both in space and time domain, using spatial and spatio-temporal autoregressive models.
- The effect of increasing the number of autocorrelation parameters in spatial autoregressive models and their interaction on the prediction and accuracy of spatial models.
- The effects of different treatments i.e. removal of outliers and transformation on the results of prediction neither for autoregressive models nor for the MRA model have been studied.
- The implication of different model specifications on real estate prediction scene in Malaysia is not well known.
- The concept of “market delineation” using the known categories of houses in Malaysia has not been considered.

Using the above problem set several hypotheses can be developed. For example a null hypothesis can be formed on the efficiency of the prediction using the submarkets based on the type of houses. Also between the removing of the outliers and transforming the variables, a hypothesis can be developed so that the efficiency of each of these methods can be examined against the other. Also usage of time in the autoregressive models of mass appraisal prediction can be formulated into a hypothesis.

1.3 Objectives of the Study

Appraisal community has used the benefits of multiple regression analysis in mass appraisal prediction. This type of model provides the basic necessities, but fails to make accurate prediction due to assumptions and it's complete negligence of inherent characteristics of transacted data. One of the major advancements in the prediction models is the introduction of spatial and quite recently spatio-temporal effects to the regression modelling. The specification of these models especially the latter have not been studied well in the literature and it is possible that the lack of clear methodology on the performance of these models have hindered the broad usage of these models in the real estate sector. Therefore, this research was devised to comprehensively study the important spatial regression models. Specifically, the objectives of this research are:

1. To compare the performance of different "spatial" and "spatio-temporal" "neighbourhood" and "weight" as well as "lag" and "error" specifications of autoregressive models using Malaysian transacted data.
2. To ascertain the kind of normality treatment that provides the spatial models the means to do better predictions.

3 To determine the best optimization algorithms for the maximum likelihood (ML) estimation of spatio-temporal models.

1.4 Scope of the Study

In this experiment, the main purpose is to show the strength and weakness of spatial and spatio-temporal modelling that utilize spatial autocorrelation using available data from Malaysian real estate market. Therefore, this study was set to examine the modelling results using different normality treatments, maximum likelihood parameter estimation, performance in validation and their reaction to different data treatments both in space and space-time domain. This study considered a relatively homogeneous market data so that determining the best model that utilizes spatial autocorrelation is possible. The scope of research covers a hold-out validation on a randomly selected portion of the original data so that the best models that emerge can be recommended to the industry for implementation.

As different specifications of the neighbourhood (both space and time) and weight matrices lead to different results and predictions, these models need to be compared to the widely used multiple regression model. Moreover, for the multi-autocorrelation parameter models there is an uncertainty on how these parameters would perform in optimization and between themselves and also in comparison to other models. This objective was added to the study so that pinpointing the best characteristics of the models is easier for the mass appraisal practitioners.

1.5 Significance of the Study

Although using statistical methodology is straightforward, the process of reaching to the point of fair value is far too difficult and involves many important considerations (Slack, 2001). That is the reason for the common mass appraisal firms and institutions adherence to only the application of multiple regression analysis which is the regression of the dependant variable over a series of independent variables. These variables are either endogenous to the dependant variable or exogenous variables. Using of the inherent nature of data that is dependency, adjacency and relativeness are neglected by the industry that often need a readymade and tailored methodology and robust results to reach the decisions. Therefore, research on advanced models and standards of mass appraisal is absolutely necessary for each country. Moreover given the complexity of these models, different aspects of data and models are not normally studied extensively in a typical mass appraisal prediction project.

The situation with mass appraisal prediction in Malaysia does not differ significantly from the world. Malaysia as a developing country that aims to become a developed country, is dealing with the same challenges in mass appraisal prediction. For example justifying the re-evaluation by the government bodies is challenging since in most cases the subjectivity can influence the results and also lack of consensus on the usage of unified modelling systems has caused many disputes in the recent years. The current re-evaluation period which is 10 years in Malaysia does not reflect the current pace of developing in the country. This may result in the decrease of government revenue and therefore, down-pacing growth in the future (Daud, Alias & Muthuveerappan, 2008).

Moreover neglecting the inclusion of standards in mass appraisal that utilize the spatial domain that is already implemented in some countries like US and Australia (Parker, Lockwood & Marano, 2011), will result in disputes over the fairness of the process of mass appraisal.

This research therefore, strives to pave the way for the use of the advance models in the mass appraisal prediction by the industry contributing towards (i) automated valuation for real estate properties particularly the determination of the regression coefficients and (ii) elimination of subjectivity in the valuation or properties (iii) providing methodologies to encourage the usage new methods in the mass appraisal prediction. There is a great need for increasing our understanding about the state of the art statistical and regression based models globally, and this research will contribute to that understanding. Moreover, as the ultimate integration of spatial and spatio-temporal mass appraisal models into valuation systems is inevitable, the methods and codes developed for this research will be part of such systems in the future.

1.6 Organization of Thesis

Chapter one introduces the work and provides motive on how the research on the spatial models are necessary so that these models can be used widely in the real estate sector. Chapter two provides the literature review of the models, theoretical basis for the models and parameter estimation. Chapter three describes the methodology of the experiments, the organization of code and preparations of the results. Chapter four presents the results and discussion on different specifications of the spatio-temporal autoregressive models as well as the discussion on the performance of all of the models. Chapter five concludes the thesis and provides key achievements and challenges of the research based on the objectives of the current study as well as recommendations and future work.

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