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A Study on Spatial Dependence of Housing Prices and Housing Submarkets in Tainan Metropolis, Taiwan

Keywords: Housing prices, Spatial dependence, Housing submarkets, Cluster analysis, Spatial autocorrelation method.

Abstract This study applies different methods including statistical and spatial analysis techniques to delineate spatial submarkets of housing prices and to examine spatial dependence of housing prices. The data comes from housing transaction prices in Tainan Metropolis, 2009. The Tainan Metropolis is a new metropolis amalgamated from former Tainan City and Tainan County. Due to the amalgamation of municipalities, local government boundaries will be adjusted, and in the mean time, it is worthy to identify spatial submarkets of housing prices in the metropolitan area, compared to predefined local government boundary submarkets. It was found that higher housing prices are concentrated in the inner city area while lower prices spread widely around outer ring of the inner city area of Tainan Metropolis. In testing spatial autocorrelation of housing prices, it was found that a significant spatial dependence was occurred among housing prices. In modeling housing prices, the results show that spatial submarkets derived by spatial autocorrelation techniques have stronger and more significant impacts on housing prices, and the model also have better goodness-of-fit compared to two alternative models. The spatial techniques would be appropriate approaches to classify spatial submarkets of housing prices especially in metropolitan areas.

INTRODUCTION

Housing prices are varied by locations and therefore, can be classified into different spatial submarkets. In many cases, spatial submarkets of housing prices are classified on the basis of physical characteristics of residential dwellings, geographical areas, political boundaries, or market areas as perceived by real estate professionals (Goodman and Thibodeau, 1998; Bourassa *et al.*., 2003). However, previous studies have argued that the use of predefined geographical or political boundaries for submarkets in the hedonic price model cannot optimally delineate the impact of spatial attributes on housing prices (Bourassa *et al.*. 2003). As a result, some studies have used alternative methods such as Factor Analysis, Principle Component Analysis and Cluster Analysis to define housing submarkets (Dale-Johnson, 1982; Hoesli and Macgregor, 1995; Maclennan and Tu, 1996; Bourassa *et al.*. 2003). Other studies suggest that the use of spatial techniques in hedonic price estimation can significantly reduce spatial dependence of housing prices and have better estimation accuracy (Basu and Thibodeau, 1997; Dubin *et al.*., 1999; Case *et al.*., 2004; Bourassa *et al.*., 2007).

The purpose of this study is to apply different methods including statistical and spatial analysis

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techniques to delineate spatial submarkets of housing prices and to analyze spatial dependence of housing prices. The data comes from housing transaction prices in Tainan Metropolis, Taiwan 2009. Tainan Metropolis, located in southern Taiwan, is one of the oldest cities in Taiwan and is famous in cultural and historical preservation. Now the city is the second largest city in southern Taiwan. In June 2009, the central government permitted the amalgamation of Tainan City and Tainan County into Great Tainan City or called Tainan Metropolis. Due to the amalgamation of municipalities, local government boundaries will be adjusted, and in the mean time, it is worthy to identify spatial submarkets of housing prices in Tainan Metropolis, compared to predefined political boundary submarkets.

The paper is structured as follows: the next section surveys the literature on residential submarkets and the spatial analysis of the real estate market and housing prices. Subsequent sections examine empirical results, methods and data followed by the paper's conclusions.

LITERATURE REVIEW

A large number of studies have discussed the segmentation of housing market and the identification of submarket since the last three decades. Earlier studies have indicated that the structural characteristics of a dwelling are important in determining housing submarkets (Rapkin *et al.*., 1953; Grigsby, 1963). On the other hand, some studies indicate that the spatial aspect of neighborhood and accessibility attributes of a dwelling are more important than physical structure in determining housing submarkets (Goodman, 1981; Michaels and Smith, 1990). Other studies suggest that housing submarkets are generated by a complicated process which both structural and spatial characteristics of a dwelling should be put into consideration (Adair *et al.*., 1996; Watkins, 2001).

Traditionally, hedonic model has been extensively applied for the interpretation of housing submarkets (Butler, 1980; Goodman, 1981; Allen *et al.*., 1995). Besides, some studies have attempted to use statistical methods for delineating housing submarkets. For example, Dale-Johnson (1982) measures the dimension of housing market segmentation by using Factor Analysis; Abraham *et al.*. (1994) uses cluster analysis to analyze metropolitan housing market in the US, while Hoesli *et al.*. (1997) also employs the same method to investigate local real estate markets in the UK. A few studies like Maclennan and Tu (1996) and Bourassa *et al.*. (1999) use composite methods to define housing submarkets. These studies found that some submarkets classified by these alternative statistical methods have better results than conventional defined spatial submarkets in house prices estimation.

Moreover, a variety of studies have attempted to use spatial statistical techniques for analyzing housing markets and housing prices over the past two decades. Can (1990) applied the Moran Test and the Lagrange Multiplier (LM) to examine the spatial residual autocorrelation of house prices. The results show that spatial dependence exists in the error term of house prices and spatial autoregression models have better explanation powers than OLS regression models. Can and Megbolugbe (1997) further investigated housing transaction prices in Miami, US and found that spatial hedonic price models have better model goodness-of-fit and higher estimation accuracy than traditional hedonic price models. Pace and Gilley (1997) also found similar results that estimated errors in spatial autoregression models reduced by 44%, compared to OLS models. Basu and Thibodeau (1998) and Dubin *et al.*. (1999) use different geostatistical methods to analyze spatial autocorrelation occurred in Dallas's housing transaction prices. They found that the spatial regression model provides better model goodness-of-fit in house price estimation. Hsieh and Tzeng (2010) also use spatial autoregression models to analyze the changes in spatial allocation of new housing development in Tainan City, Taiwan. They found that spatial lag models have better accuracy in housing price estimation than OLS models.

However, Bourassa *et al.*. (2007) indicate that hedonic price models with submarket dummy variables are easier to implement than spatial statistical models. Some studies like Anselin (2002) and

Lipscomb (2006) also indicate that if the house price data contains rich location attributes, then previous non-spatial statistical methods can be applied into house price models to improve estimation accuracy of the model. When there is a lack of detailed location attributes in house price data, spatial statistical methods are adequate to improve spatial dependence existed in house prices. We have seen from above studies that there are still a lot of debates on the identification of housing submarkets of housing prices by using various approaches. With an improvement in GIS techniques, we have seen more opportunities to use spatial statistical approaches in house price models.

METHODOLEDGE

It has been a widely use of local government boundaries to identify housing submarkets. Besides, a cluster analysis and a couple of spatial techniques are employed in this study to delineate housing price submarkets. With respect to spatial techniques, Moran's index is employed to examine whether if it exists a significant autocorrelation among housing prices, and then Local Indicators of Spatial Association (LISA) is used to classify housing price submarkets based on the results of Moran's index. These methods are discussed as follow.

Cluster Analysis

This study uses two-step cluster analysis to classify housing price submarkets. In the first step, this study uses hierarchical clustering approach to determine the number of clusters. The Ward's method is undertaken to form the clusters. In the second step, K means method is used to compute the cluster. The Euclidean distance is selected as the measure of similarity.

The Ward's method classifies clusters by minimizing total within-cluster sums of squares. The within-cluster sums of squares are known as the error sums of squares, presented in equation (1).

$$D_{ij} = n_i \cdot \| \bar{x}_i - \bar{\bar{x}} \| + n_j \cdot \| \bar{x}_j - \bar{\bar{x}} \|^2 \tag{1}$$

Where D_{ij} denotes error sums of squares, n_i, n_j present the number of observation of i cluster and j cluster, respectively $\bar{x}_i$, $\bar{x}_j$ denote the centroid of i and j, respectively, while $\bar{\bar{x}}$ presents the centroid of i, j clusters.

The average error sums of squares derived from the Ward's method are then used to be initial cluster centroids in K means method. The euclidean distance is employed to compute the distance of each observation from the centroid, and until none of observations are reassigned and the change in cluster centroids is zero. The euclidean distance is presented in equation (2).

$$D_{ij} = \left(\sum_{K=1}^{p} (X_{ik} - X_{jk})^2 \right)^{1/2} \tag{2}$$

Where D_{ij} is the distance between observation i and j, X_{ij} is the value of the k^{th} variable for the i^{th} subject, X_{jk} is the value of the k^{th} variable for the j^{th} subject, and p is the number of variables.

Spatial Analysis Methods

The Moran's Index and the Local Indicators of Spatial Association (LISA) are two well-known methods to examine spatial autocorrelation among house prices. If the Moran's Index shows that it exists significant spatial autocorrelation among housing prices, then LISA can be applied to analyze the spatial concentration of higher prices and lower prices based on the results of Moran's Index. In a spatial context, the spatial concentration of higher or lower housing prices can be used to indentify spatial submarkets of housing prices. Their function forms are presented as follows, respectively.

The Moran's Index

The Moran's Index is estimated on the basis of covariance. The function form of the Moran's Index is presented as in equation (3) (Anselin, 1992).

$$I = \frac{N}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \mu)(x_j - \mu)}{\sum_{i=1}^{n}(x_i - \mu)^2}, \text{ for } i \neq j \tag{3}$$

Where the observed variable is the house price; N denotes the sample size; x_i represents the house price in i's spatial unit; x_j represents the other house prices based on i spatial units within a certain boundary; μ represents the average house price; w_{ij} denotes locational proximity matrix, and also represents spatial weight coefficients in spatial units.

The value of Moran's Index is between -1 and 1. House prices are positive correlated while the index value is greater than 0; house prices are negative correlated while the index is smaller than 0. The index values are approached to 1 or -1 meaning higher degree of spatially positive or negative correlation among house prices.

Local Indicators of Spatial Association (LISA)

The LISA method detects whether if it exists a significant spatial dependence of housing prices in a certain boundary calculated from Moran's Index. The method can also analyze spatial concentration of higher or lower housing prices. In particular, the results of LISA can be clustered which are useful to indentify spatial submarkets of housing prices. The LISA statistic can be carried out for a local Moran where the function form is presented in equation (4) (Anselin, 1995).

$$I_i = x_i \sum_j w_{ij} x_j \tag{4}$$

As stated in equation (3), x_i represents the house price in i's spatial unit; x_j represents the other house prices based on i spatial units within a certain boundary. w_{ij} denotes locational proximity matrix, and also represents spatial weight coefficients in spatial units.

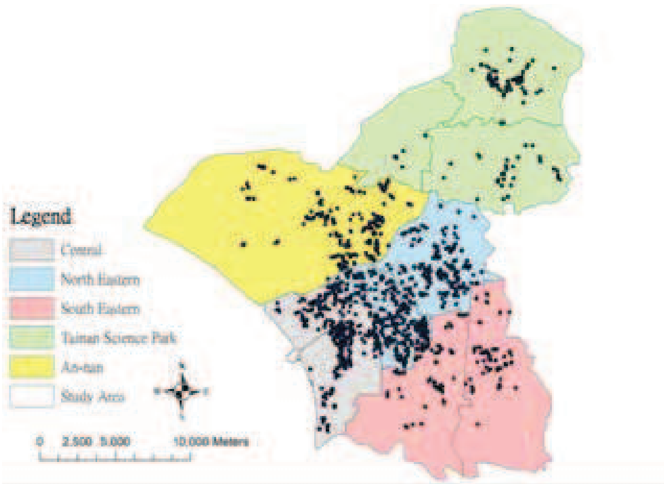
DATA AND VARIABLES

The Data

The data comes from housing transaction prices collected by the Ministry of the Interior. The Ministry of the Interior publishes housing transaction price data quarterly in whole Taiwan area since the 1970s. From 1989, the housing transaction price data is free to download from the internet. In Tainan Metropolis, the housing transaction prices are distributed unevenly in the metropolitan area. In 2009, about three fourth of housing transaction data is concentrated in former Tainan City and adjacent districts where these areas can be seen as core housing development areas of Tainan Metropolis. These 12 districts are selected as the study area (see Figure 1). In 2009, a total of 1,385 valid housing transaction price observations are collected in the study area. The allocation of these observations is presented in Figure 2.

Figure 1 The Study Areas

Figura 2 The Allocation of Housing Transaction Price Observations



The Variables

The dependent variable is the housing transaction price. Fourteen independent variables are selected in the study presenting physical, neighborhood, and location attributes of housing prices. The descriptive statistics of these variables are presented in Table 1. In the study area, the average housing transaction price is 5.22 million NTD (about 130,500 EUR) in 2009. With respect to physical attributes, the average site area is 95.41 square meters, and the average building floor area is 177.05 square meters. The average dwelling age is about 15 years old. In neighborhood attributes, the average width of road adjacent to sites is about 15 meters, and the average distance to city center is about 5.6 kilometers[1]. There are 31 percent of sample dwellings which are adjacent to primary road. About 92 percent of sample dwellings are located in residential zones, respectively.

Regarding location variables, this study combines some homogenous districts into five submarkets as the Central Area (including Anping, Central-West and South districts), the North Eastern Area (including North, East and Yong Kang districts), the South Eastern Area (including Rende and Gueiren districts), the Tainan Science Park Area[2] and An-nan district. The housing transaction price observations are relatively concentrated in Central Area and North Eastern Area while Tainan Science Park Area has the least housing price observations.

Table 1 Descriptive Statistics of Variables

Variable (unit)	Means	S. D.
Housing price (thousand NTD)	5,223.08	3,148.72
Site areas (sqm)	95.41	34.68
Building floor areas (sqm)	177.05	73.09
Dwelling age (years)	14.97	13.37
Width of road to the site (m)	14.83	7.11
Distance to city center (m)	5,642.93	4,133.30
If the site is adjacent to primary road (yes=1)	0.31	0.46
Located in residential zone (yes=1)	0.92	0.27
Located in commercial zone (yes=1)	0.03	0.16
Located in other zones (yes=1)	0.05	0.02
Located in Central Area (yes=1)	0.240	0.43
Located in North Eastern Area (yes=1)	0.407	0.49
Located in South Eastern Area (yes=1)	0.123	0.33
Located in Tainan Science. Park Area (yes=1)	0.077	0.27
Located in An-nan District (yes=1)	0.153	0.36

Total number of observations=1,385. * The exchange rate of NTD to EUR is about 1,000 NTD to 40 EUR.

1 The city center usually can be viewed as the central business district (CBD), this study uses the highest land price area as the city center. In 2009, the highest land price area was located in the Central West district where it is in the inner city area of Tainan City.

2 Tainan Science Park is located in the triangle area of Shanhua, Anding and Xinshi districts and as a result, this study uses Tainan Science Park Area to present these three districts.

EMPIRICAL ANALYSIS

In this section, we first delineate housing spatial submarkets by using three different approaches; then these various spatial submarkets are used to estimate their impacts on housing prices and also compare the estimation accuracy of three different housing price models.

Spatial Housing Submarkets Classification

This study uses three different approaches as local government boundaries, Cluster Analysis and spatial autocorrelation techniques to classify spatial submarket of housing prices in Tainan metropolitan areas. The results are discussed as follow.

Determining Spatial Submarkets by Local Government Boundaries

The allocation of housing prices by five combined local government boundaries are shown in Figure 2, and the means of housing prices divided by five combined local government boundaries are presented in Table 2. It is clear to note that the average housing transaction prices in Central Area and North Eastern Area are higher than other areas. These areas are located in the inner city area with prosperous business activities and therefore, housing transaction prices remain in higher level. On the contrary, An-nan district is located in coastal shore area with many fish farms and biological preservation areas. The average housing transaction price is the lowest in the study area.

Table 2 Descriptive Statistics of Housing Prices by Combined Local Government Boundaries

District	Observations	%	Means of housing prices (thousand NTD)	S. D.
Central Area	333	24.0	5,727.12	3,801.12
North Eastern Area	564	40.7	5,715.21	3,342.22
South Eastern Area	170	12.3	4,624.71	2,354.91
Tainan Science Park	106	7.7	4,490.47	1,941.62
An-nan Dist.	212	15.3	3,968.26	1,727.76
Total	**1,385**	**100**	**5,223.08**	**3,148.72**

Determining Spatial Submarkets by Clustering Analysis

In Cluster Analysis, we use five variables including site areas, building floor areas, dwelling age, the width of road to the site, the distance to city center as selected variables to cluster housing transaction prices into separate homogeneous submarkets. These five variables also have significant impacts on housing prices in hedonic price model. Housing prices are classified into four clusters as shown in Figure 3. The descriptive statistics of housing prices in these four clusters are presented in Table 3.
Cluster one captures around 46% of total housing price observations where it mainly covers Central Area and An-nan District and some part of North Eastern Area. Cluster two mainly covers North Eastern Area and a small part of South Eastern Area. The two clustered areas are located in inner city areas and as a result, the average housing transaction price remains in high level. Cluster three and Cluster four are mainly located in Tainan Science Park Area and South Eastern Area where they are outer ring of the inner city area. The average housing prices in these two clustered areas remain in low level.

Figure 3 the Clusters of Housing Price Submarkets

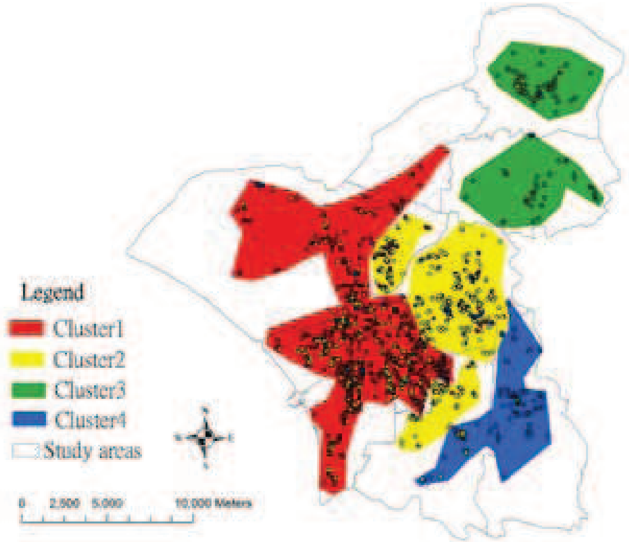


Table 3 Descriptive Statistics of Housing Price Clusters

Cluster	Observations	%	Means of housing prices (Thousand NTD)	S.D.
Cluster 1	635	45.8	5,501.17	3,558.94
Cluster 2	454	32.8	5,218.77	2,705.17
Cluster 3	212	15.3	4,623.11	2,971.95
Cluster 4	84	6.1	4,658.45	2,083.70
Total	**1,385**	**100**	**5,223.08**	**3,148.72**

Determining Spatial Submarket by Spatial Autocorrelation Techniques

This study uses Moran's Index as the global indicator of spatial autocorrelation to examine whether if it exists significant spatial autocorrelation among housing prices. In testing spatial autocorrelation, the first step is to estimate a minimum boundary where it is satisfied that every price observation is correlated to at least one observation within the minimum boundary radius. The minimum boundary radius then can be used to examine the local indicator of spatial autocorrelation. The Moran's Indices of housing prices in Tainan Metropolis are listed in Appendix. In 2009, the minimum boundary radius distance calculated from Moran's Index to examine spatial autocorrelation of housing prices is 2,200 meters. The results also show significant autocorrelation of housing prices occurred in Tainan metropolitan areas. Based on this minimum boundary radius, the Local Indicator of Spatial Association (LISA) is then applied to delineate spatial submarkets of housing prices.

The spatial concentration of housing prices in different price levels is presented in Figure 4. It is clear that higher housing prices (High prices surrounded by High prices, H-H) are mainly concentrated in Central Area and North Eastern Area where they are in central business areas as stated above. As presented in Table 4, in higher price zones, average housing prices are about 8.4 million NTD (about 210,000 EUR). On the contrary, lower housing prices (Low prices surrounded by low prices, L-L) are significantly concentrated in some part of North Eastern Area and An-nan district. Some lower housing price zones are also located in South Eastern Area and Tainan Science Park Area. These areas are outer ring of inner city areas. The average housing prices in lower price zones are about 3.6 million NTD (90,000 EUR). There exists a significant price gap between higher and lower price zones.

Figure 4 Spatial Concentrations of Housing Prices by LISA

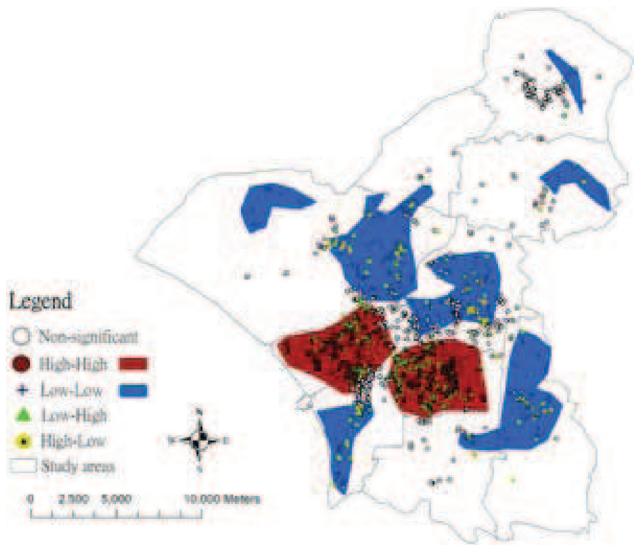


Table 4 Descriptive Statistics of Housing Prices by LISA

Levels	Observations	%	Means of housing price (Thousand NT)	S.D.
High-High	284	20.5	8,399.19	4,268.74
Low-Low	339	24.5	3,625.43	1,477.42
Low-High	218	15.7	4,066.10	1,733.05
High-Low	121	8.7	6,074.63	1,480.05
Insignificant	423	30.5	4,723.74	2,528.07
Total	**1,385**	**100**	**5,223.08**	**3,148.72**

It is clear to note from the results of three different approaches that higher housing prices are mainly concentrated in Central and North Eastern areas where they are in inner city areas while lower prices spread widely around outer ring of the inner city areas of Tainan Metropolis. This indicates that housing prices in some areas of Tainan Metropolis should be categorized into the same submarket due to similar location attributes.

Comparison

These three types of housing price submarkets are used to estimate their impacts on housing prices and also to compare the model's estimation accuracy. The results are shown in Table 5. Model one uses combined local government boundaries as spatial submarkets while model two and model three uses Cluster Analysis and spatial techniques to identify housing price submarkets and to estimate their impacts on housing prices, respectively. Most independent variables have significant influences on housing prices. With respect to spatial submarkets, three of four combined local government boundary submarkets have significant impacts on housing prices in model one. In model two, cluster one and cluster two have significant positive effects on housing prices indicating housing prices in these two clustering areas are higher than other areas. In model three, submarkets classified by spatial autocorrelation techniques have the most important and significant positive effects on housing prices, especially in higher price zones.

Table 5 A Comparison of Housing Price Models with Three Types of Spatial Submarkets

Model	Model 1 - using CLGB		Model 2 - using CA		Model 3 - using LISA	
Variable	Coeff.	t value	Coeff.	t value	Coeff.	t value
Constant	-2035.11	-5.73***	-2981.81	-5.44***	-965.06	-2.95***
Site areas	54.44	10.47***	44.49	8.61***	50.80	10.60***
Building floor areas	82.32	26.40***	90.93	30.34***	76.65	26.46***
Dwelling age	-36.67	-8.08***	-28.99	-6.52***	-32.53	-7.67***
Width of road	32.70	4.57***	35.95	5.02***	30.27	4.58***
Adjoining to primary road	984.64	8.37***	693.89	6.30***	543.43	5.40***
Distance to city center	-0.088	-4.59***	-0.04	0.89	-0.05	-3.97***
Located in residential zone	595.85	2.42**	802.58	3.39***	534.91	2.47**
Located in commercial zone	1688.34	4.53***	1907.68	5.04***	1178.24	3.40***
Located in Central Area	1000.56	4.79***				
Located in N. Eastern Area	1410.09	7.39***				
Located in T.S.P. Area	1105.91	3.93***				
Located in An-nan distr.	230.31	1.03				
Located in Cluster 1			1317.31	3.88***		
Located in Cluster 2			438.75	1.97**		
Located in Cluster 3			-447.47	-1.02		
Located in Higher price zones (H-H)					1701.05	12.40***
Located in Lower price zones (L-L)					-631.28	-5.23***
Located in Lower-high price zones (L-H)					424.63	2.93***
Located in Higher-low price zones (H-L)					-204.22	-1.17
R-square	0.703		0.687		0.735	
Adj-R-square	0.701		0.685		0.732	
F Value	271.096***		274.219***		316.572***	
Observations	1,385		1,385		1,385	

In comparison, model three has the highest estimating accuracy and these spatial submarkets derived by LISA also have most important and significant impacts on housing prices, especially in higher price zones and lower price zones, respectively. This indicates that the use of spatial autocorrelation techniques such as the Moran's Index and LISA not only can explore spatial dependence of housing prices but also can classify spatial submarkets which have better accuracy in estimating housing prices. Model one has the second highest estimating accuracy, and these local government boundary submarkets also have important and significant effects on housing prices. This indicates that the use of a set of dummy political boundary variables to be submarkets also have substantial effects on housing prices. The results also confirm the findings of Bourassa *et al.*. (2007). The submarkets clustered by various housing characteristics have less effect on housing prices, compared to other two methods. This is probably because this study only uses five housing characteristics to classify housing prices. More detailed housing characteristics would be included or alternative methods should be employed to identify housing prices in further research.

CONCLUSIONS

Housing prices are diversified by locations and therefore, can be classified into different spatial submarkets. The common way to define housing price submarkets is to use predefined geographical and political boundaries. However, the use of these types of submarkets would not adequately represent location attributes of housing prices, especially in metropolitan areas. This study employs Cluster Analysis approach and spatial statistical techniques to classify spatial submarkets of housing prices and also makes a comparison to local government boundary submarkets. Our results show that higher housing prices are concentrated in the inner city area while lower prices spread widely around outer ring of the inner city area of Tainan Metropolis. This indicates that housing prices in some areas of the metropolis should be categorized into the same submarket due to similar location attributes. Furthermore, in testing spatial autocorrelation of housing prices, it was found that a significant spatial dependence was occurred among housing prices. In modeling housing prices, the results show that spatial submarkets derived by spatial autocorrelation techniques have stronger and more significant impacts on housing prices, and the model also have better goodness-of-fit compared to two alterative models. As a result, the spatial techniques would be appropriate approaches to classify spatial submarkets of housing prices especially in metropolitan areas.

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APPENDIX The Moran's Index of Housing Price

Bonduary radius distance (m)	Moran's Index	Z(I)	Number of No-Adjoning Sample
100	0.471689	12.541177	511
200	0.378047	14.388436	211
300	0.306034	14.718104	100
400	0.284826	16.338309	55
500	0.254628	16.992329	35
600	0.235960	17.679231	24
700	0.228034	19.029141	20
800	0.217038	20.02823	14
900	0.207337	20.686336	12
1000	0.201242	21.646707	11
1100	0.192719	21.849072	6
1200	0.180368	21.730702	4
1300	0.173101	22.077339	4
1400	0.164608	22.069684	4
1500	0.154092	21.792865	2
1600	0.148592	22.156916	2
1700	0.143266	22.310364	2
1800	0.136614	22.146441	1
1900	0.132105	23.643573	1
2000	0.128711	24.266421	1
2100	0.122219	24.774416	1
2200	0.118471	25.042514	0
2300	0.114794	25.503793	0
2400	0.110346	25.922842	0
2500	0.108803	26.691022	0