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SPATIAL AUTOCORRELATION ANALYSIS OF HOUSING DISTRIBUTION IN JOHOR BAHRU

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Abstract

Geographic location naturally generates spatial patterns that are either clustered, dispersed, or random. Moreover, Tobler's First Law of Geography is essentially a testable assumption in the concept where geographic location matters and one method for quantifying Tobler's law of geography is through measures of spatial autocorrelation. Therefore, the purpose of this study is to identify the spatial patterns of housing distribution in Johor Bahru through the spatial autocorrelation method. The result of the global spatial autocorrelation analysis demonstrates a high degree of clustering within the housing distribution, as well as the identification of a clustered pattern with a highly positive Moran's I value of 0.995207. Following that, the LISA cluster map successfully identified individual clusters of each housing unit with their neighbours through the red and blue colours displayed on the map, as well as revealing home buyers' preferences for a property in each location.

***Keyword**:* Tobler's First Law of Geography, housing distribution, spatial patterns, spatial autocorrelation

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INTRODUCTION

Housing is seen as a unique commodity with a variety of characteristics such as design, neighbourhood condition, location, accessibility and other attributes that influence customer decision-making in order to achieve maximum use (Tam *et al*., 2019). Numerous factors influence home ownership, including housing characteristics, employment and income trends, and socio-cultural and demographic descriptors (Lim & Chang, 2018). In addition, housing continues to be one of the primary growth engines for developing economies, as it contributes to urbanization and infrastructure development (Nor *et al.,* 2019). Apart from that, real estate is one of the most important economic activities in the world, influencing settlement patterns and shaping built environments (Cecchini *et al*., 2019). Moreover, three qualities of a house that are frequently emphasized by home buyers are the building quality, location of the property, and neighbourhood conditions, all of which can affect housing prices (Mohamad *et al.*, 2016).

According to Scott (2015), data associated with locations can be mapped, and mapping geographic data is an important first step in analyzing spatial patterns. The following steps entail identifying, describing, and measuring data's spatial characteristics (Scott, 2015). Bivand (1998) agreed, emphasizing that in cases where data are located at geographical coordinates, mapping the data alone is insufficient because it appears imprudent not to investigate the possibility of dependence. Thus, in the context of this study, the housing distribution data containing location information can be visually mapped, allowing for further spatial analysis research.

Naturally, everything that has a geographic location will create or contribute a spatial pattern that is either clustered, dispersed, or random (Klippel *et al.,* 2011). Furthermore, spatial distributions or patterns are of interest in many fields of geographic research because they can identify and quantify patterns of features in space, allowing the underlying cause of the distribution to be determined (Er *et al*., 2010). Besides, Laohasiriwong *et al*. (2018) affirmed that spatial pattern detection could be an effective tool for understanding geographical distribution. These statements demonstrate that identifying the spatial patterns of housing distribution can lead to a better understanding of the housing distribution.

As a matter of fact, a testable assumption in the concept where geographic location matters are Tobler's First Law of Geography (TFL). In addition, TFL stated that: "everything is related to everything else, but near things are more related than distant things", which has become central to the core of spatial analytical techniques as well as geographic conceptions of space (Miller, 2004). The concept of TFL is implied in spatial analysis practice because near and related are useful concepts at the heart of spatial analysis and modelling (Miller, 2004). TFL also claims that spatial data are defined by their spatial dependence or spatial autocorrelation (Waters, 2018). Similarly, Miller (2004) emphasized that TFL is at the heart of spatial autocorrelation statistics, which are quantitative techniques for analyzing correlation in relation to distance or connectivity. Spatial autocorrelation refers to the pattern in which observations from nearby locations are more likely to have a similar magnitude compared to those from distant locations (Nunung & Pasaribu, 2006).

Therefore, according to TFL, it is possible to conclude that spatial association existed in geographic data, with proximity playing a significant role. Because the housing distribution in Johor Bahru has a geographical location, the existence of spatial association and spatial pattern can be measured by taking TFL into account. Miller (2004) emphasised that one method of quantifying TFL is through measures of spatial autocorrelation. Hence, the purpose of this research is to identify the spatial patterns of housing distribution in the Johor Bahru area through a spatial autocorrelation analysis.

This paper is divided into four sections. The first section is dedicated to the introduction. The methodology section, which is the second part of the paper, goes into great detail about the two types of spatial autocorrelation analyses used in this research. Following that, the results and discussions section includes an in-depth discussion of the findings from both spatial autocorrelation analyses. The conclusions section, which comes last, wraps up all the findings and makes recommendations for further research.

METHODOLOGY

Spatial Autocorrelation Analysis

The spatial autocorrelation method was used in this study to identify the patterns of housing distribution in the entire Johor Bahru area, including the Kulai district. The Department of Town and Country Planning Johor provided the 2018 housing data used in this analysis. The global spatial autocorrelation was computed first to demonstrate the presence of clustering within the data set. The individual clusters of the housing distribution were then visualized using local spatial autocorrelation.

Spatial autocorrelation primarily exists because geography is important (Griffith & Chun, 2018). Tsai *et al.* (2009) defined spatial autocorrelation as the relationship between the values of a single variable caused by the geographic arrangement of areal units on a map. In fact, spatial autocorrelation is a pattern component limited to object clustering or dispersion rather than measuring geometric aspects of the pattern (Boots, 2003). Furthermore, the spatial autocorrelation concept aids in pattern analysis by measuring the relationship between values of a variable based on their spatial arrangements and determining whether the data is clustered, random, or dispersed based on the similarity of the values and their spatial proximity (Bandyopadhyay *et al*., 2012).

Clusters form in a geographic distribution when features are found close to one another or when groups of features with similarly high or low values are discovered together (Aghajani *et al*., 2017). According to Griffith and Chun

(2018), the spatial autocorrelation perspective focuses on clustering similar or dissimilar phenomena in geographic space to form map patterns typified by TFL rather than random mixtures of phenomena. Furthermore, the indicators used to calculate spatial autocorrelation can be divided into two types which are global spatial autocorrelation indicators and local spatial autocorrelation indicators (Wang *et al.*, 2019).

Global Spatial Autocorrelation Analysis

Moran's I, developed by P. A. P. Moran in 1948, is a significant indication of spatial autocorrelation (Wang *et al*., 2019). It is a measure of global spatial autocorrelation, which indicates whether similar values of a particular variable are closer together in space, detecting the presence of similar value clustering (Bandyopadhyay *et al*., 2012). Moran's I measures spatial autocorrelation based on both feature location and feature values simultaneously (Er *et al.*, 2010). The value of Moran's I ranges from -1 to +1. The Moran's I is positive when the observed values of locations within a certain distance or their contiguous locations are similar (Ma *et al*., 2008). It is negative when they are dissimilar (checkered pattern), and it is close to zero when the observed values are distributed randomly and independently across space (Musakwa & Niekerk, 2014).

However, global autocorrelation tests are unable to distinguish between high and low clustering within the data set (Wang *et al.*, 2019). As Boots (2003) emphasizes, global approaches produce a single value for the entire data set, whereas local approaches produce a local value for each data site in the data set. Aside from that, Zhang *et al.* (2010) suggested that it is important to remember that the spatial autocorrelation level of different census areas is not exactly the same, which prompted the need for a local indicator. Therefore, local Moran's I statistics must be performed in order to identify the individual locations of the clustering within the entire data set.

Local Spatial Autocorrelation Analysis

Local Moran's I, in contrast to global Moran's I, which assumes homogeneity of the entire dataset, is a local indicator of spatial association and shows the level of spatial autocorrelation at various individual locations within the data set (Musakwa & Niekerk, 2014). Local Moran statistics, also known as Local Indicator of Spatial Association (LISA), are more commonly used to quantify local spatial concentration or clustering (Ayadi & Amara, 2009). According to Zhang *et al.* (2008), local Moran's I does not range between -1 and +1. However, a positive value still implies positive spatial autocorrelation (clusters), and a negative value indicates negative spatial autocorrelation (outliers). The LISA cluster map basically categorises those locations based on the type of association either high values with high values (HH), low values with low values (LL), high values with low values (HL), or low values with high values (LH) (Anselin *et al*., 2006).

Moran's I, both global and local, sought to quantify spatial autocorrelation. The most notable difference between the two measures, as most scholars pointed out, was the method by which the spatial autocorrelation was computed. Since global Moran's I refers to the dataset as a whole while implying homogeneity, it fails to identify individual clustering, necessitating the use of local measures, which can identify spatial autocorrelation at the local level as well as identifying high and low clustering and spatial outliers. Moreover, Anselin *et al.* (2006) distinguished between the two measures by stating that global Moran's I is used to test for clustering in the data set, whereas local Moran's I is used to identify the location of the cluster. Therefore, to overcome the limitation of global Moran's I, additional analysis of local Moran's I must be performed in order to obtain deeper and more thorough results.

RESULTS AND DISCUSSIONS

The housing distribution in Johor Bahru was used to measure the degree of spatial autocorrelation in this study. The data entry contains a total of 403 606 housing locations for the year 2018. In fact, TFL can be used to further investigate housing distribution, which is the arrangement of housing in space. It can be deduced from TFL that things that are closer together are more related than things that are farther apart. Moreover, spatial autocorrelation is a technical term that refers to the measure of similarity or correlation between nearby observations. Since both TFL and spatial autocorrelation place a premium on the nearest distance, this study employs the spatial autocorrelation method to identify the spatial patterns in the studied area.

Global Moran's I Scatter Plot

First, a global autocorrelation measure based on global Moran's I was used to test for homogeneity and the presence of clustering across the entire housing data set. Figure 1 depicts the results of the analysis using a Moran's I scatter plot.

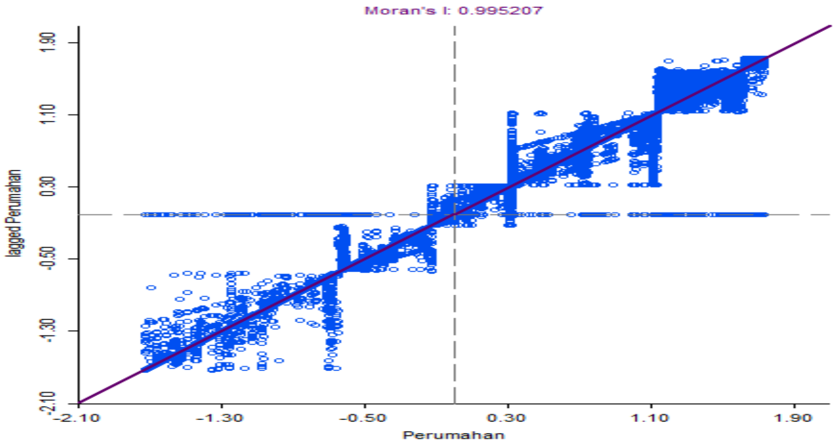

Figure 1: Global Moran's I Scatter Plot for Housing Distribution in Johor Bahru
Source: own study

Moran's I scatter plot yielded a clustering result, as shown in Figure 1. The highly positive Moran's I value of 0.995207, which is also close to the value 1, demonstrated the presence of clustering among housing units in the Johor Bahru area, indicating a strong clustered pattern of housing units in Johor Bahru. Furthermore, the above scatter plot clearly shows that the points from the housing data form a square-shaped pattern. This result implies that the same housing types are distributed within the same residential area as according to Anselin (2017), the upper right and lower left, indicate a positive spatial autocorrelation, which depicts similar values at neighbouring locations; nonetheless, similar values in this study are from structural and locational characteristics of housing.

Although global Moran's I has successfully demonstrated clustering among Johor Bahru housing data, it fails to specify whether the structural characteristics and locational characteristics were clustered with similar or dissimilar values with its neighbours. As a global Moran's I can suggest clustering without designating any specific location as clustered; the next step is to identify the individual location of the clusters using Local Indicator of Spatial Association (LISA) while detecting the types of association between the structural and locational characteristics of housing in Johor Bahru.

LISA Cluster Map

Based on the LISA cluster map depicted in Figure 2, the results revealed specific locations with different colours of either red or blue, revealing the type of associations between housing units and their neighbours. Both the Johor Bahru city centre and the Kulai area displayed red colour within their region, in contrast to the Iskandar Puteri and Pasir Gudang areas, which both displayed blue colour. As a result, it was determined that housing units in Johor Bahru city centre and

Kulai share similar structural and locational characteristics with their neighbours (HH). In contrast, Iskandar Puteri and Pasir Gudang housing units are clustered together with dissimilar structural and locational characteristics with their neighbours (LL), indicating clustering patterns in both cases.

A house's structural characteristics may include building quality, space arrangement, and physical characteristics such as land size, building scale, and housing age, as well as attributes such as having a garage and the number of bedrooms and bathrooms (Chung *et al*., 2018). The locational characteristics of a residential community, on the other hand, are linked with the accessibility to the targeted location, which is related to the evaluation of transportation accessibility (Tam *et al.,* 2019). As per the traditional definition of location, accessibility is measured in terms of proximity to the Central Business District (CBD) (Kemunto & Nyangena, 2017). Furthermore, location and accessibility are important factors in a household's choice of a home (Aluko, 2011).

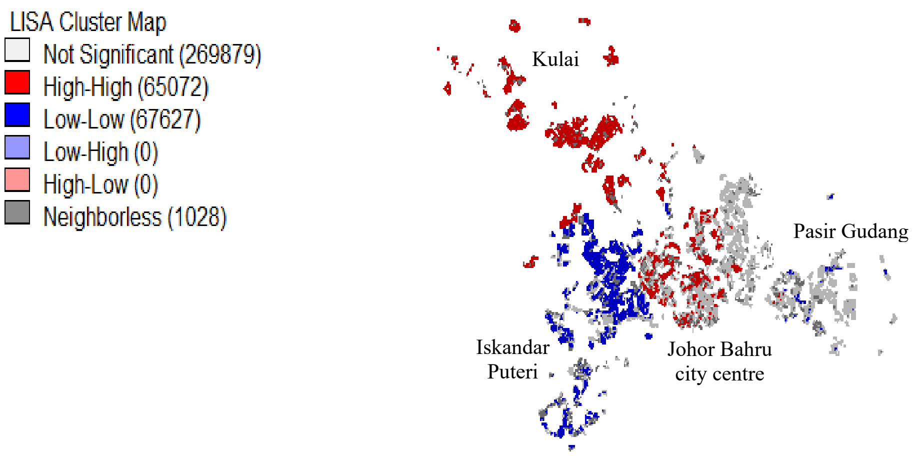

Figure 2: LISA Cluster Map for Housing Distribution in Johor Bahru
Source: own study

Aside from revealing the type of associations within each location, the clustering patterns visible on the map via the red and blue colours aid in identifying housing submarkets and buyer preferences based on their perception of the structural and locational characteristics of the housing units. As previously discussed, spatial autocorrelation measures feature similarity based on both feature locations and feature values, and in this case, it was based on both locational and structural characteristics of the house. It was also mentioned in the preceding paragraph that locational characteristics influence buyer preferences and housing choices. Thus, the results also hinted at detecting buyers' housing preferences for each area via the red and blue clusters. Housing preferences are verbal expressions for the quantitative and qualitative housing characteristics that residents would prefer to have in their homes (Thanaraju *et al*., 2019).

Johor Bahru city centre serves as the CBD in the Johor Bahru area. The decision to buy property near the CBD is typically motivated by the fact that the CBD provides more job opportunities, enticing buyers to relocate closer to their workplace (Taubenbock *et al.,* 2013). The red colour that appeared in the Johor Bahru city centre area indicated that the housing units in the city centre shared similar locational characteristics with their neighbours, explaining the role of CBD as a factor influencing buyers to purchase properties in that area. However, due to the high residential prices in the CBD, not all buyers are able to purchase properties there. This fact also aids in determining the economic background of property buyers in the Johor Bahru city centre area, as only households with higher incomes can afford to purchase expensive housing in the city centre. In fact, among 140 other administrative districts, Johor Bahru had the six highest income groups (Department of Statistics Malaysia, 2017). This statistic manages to back up the findings of the LISA cluster map.

The existence of Kulai Highway, which is part of Federal Route 1, in the Kulai district may have contributed to the similarity of locational characteristics within that area. The Kulai Highway connects to other highways such as the Skudai-Pontian Highway 5, Senai Airport Highway 16, Jalan Kulai-Kota Tinggi 94, and Diamond Interchange, which connect to Bandar Putra and Indahpura. As previously discussed, although properties closer to Johor Bahru are more expensive, buyers benefit from lower transportation costs and less time on the road. Residents living in Kulai but working in the CBD, on the other hand, can enjoy affordable properties but must pay more for transportation. Senai airport and Kulai railway station are also located in Kulai. Therefore, it can be concluded that the Kulai district provides a reasonable level of accessibility to the area's residents while attracting a group of buyers with similar locational preferences. According to Kaur (2019), an efficient transportation system would not only help to reduce congestion, but it would also help to increase demand for residential units in the area.

Iskandar Puteri, a rapidly developing area that is currently serving as the new administrative centre for Johor state, demonstrated a clustering of dissimilar values. This reveals that before purchasing a property in Iskandar Puteri, each home-owner has different locational preferences. It is reasonable to suggest that Iskandar Puteri has it all. Apart from Kota Iskandar, which serves as the administrative centre for the state government of Johor, Iskandar Puteri is home to a number of prestigious educational institutions, including Marlborough College Malaysia and the well-known University of Technology Malaysia. Iskandar Puteri also draws visitors with its well-known Legoland Malaysia and Puteri Harbour. Since Iskandar Puteri is home to a diverse range of key economic activities such as education and medical tourism, entertainment and recreation, and state administration, each buyer is expected to have distinct purchasing objectives. Fewer households may purchase the property because it is closer to their place of employment. Because Iskandar Puteri is home to a plethora of important economic activities, their working place may vary. Furthermore, the presence of higher education institutes attracts buyers to purchase residential properties for the purpose of renting to students. Nasongkhla and Sintusingha (2013) found that the economic transformation of Iskandar Malaysia benefits upper-middle-income groups while encouraging cultural diversity and community participation in development.

Pasir Gudang is well-known for various industrial activities, including transportation and logistics, shipbuilding, petrochemicals, and other heavy industries. Despite being Johor's most well-known industrial city, the results revealed a clustering of dissimilar values. According to Gasper (2013), Pasir Gudang has grown well over the years due to the development of an education hub, shopping complexes, and several private hospitals. Furthermore, the presence of high education institutes such as Politeknik Ibrahim Sultan, Kolej Komuniti Pasir Gudang, and UiTM Pasir Gudang influenced a wide range of buyer preferences. Apart from that, infrastructural improvements such as the construction of the second bridge in Permas Jaya that connects directly to the Eastern Dispersal Link, which leads to the city centre, serve to make the area more accessible (Gasper, 2013). As a result, the residents of Pasir Gudang have different reasons and preferences for purchasing properties there, resulting in the clustering of dissimilar locational characteristics.

Aside from that, both spatial and structural factors were revealed to aid in determining the dimensions of housing submarkets (Watkins, 2001). Thus, the clustering patterns and spatial factors identified by the LISA cluster map also revealed the submarkets for each area. For example, higher property prices in Johor Bahru city centre due to its role as the CBD indicate that the households in that area are from a higher income group. On the other hand, householders in Kulai form a submarket with similar locational preferences as Kulai provides easy access to other regions in addition to being home to the Kulai railway station and Senai airport.

CONCLUSIONS

In a nutshell, the results of both spatial autocorrelation analyses confirm the existence of clustering in the housing distribution in Johor Bahru while also identifying a clustered pattern of the housing distribution. The significantly positive Moran's I value of 0.995207 from global measures of spatial autocorrelation revealed the presence of clustering within the housing distribution in Johor Bahru. Then, the local measures of spatial autocorrelation through the LISA cluster map were able to identify the type of clustering within the study area specifically. The red color seen in Johor Bahru's city centre and Kulai area represents the clustering of similar structural and locational characteristics with their neighbour (HH). In contrast, the blue color seen in Pasir Gudang and Iskandar Puteri area represents the clustering of dissimilar structural and locational characteristics with their neighbour (LL).

The LISA cluster map results provide valuable information not only on the clustering of structural and locational characteristics but also on buyer preferences, household incomes, and the actual housing scenario in Johor Bahru. As previously stated, each of the areas included in this study, namely Johor Bahru city centre, Kulai, Iskandar Puteri, and Pasir Gudang, has its own set of locational factors that entice home buyers and even investors to purchase property there. Among the locational factors influencing buyers' housing choices in the study areas are the presence of higher education institutes, job opportunities, the city center, and accessibility. However, it is important to note, that the spatial autocorrelation analysis was carried out using a simple housing location data without knowledge of the specific housing characteristics that cause the clustering. As a result of the LISA cluster map findings, additional research into the structural and locational characteristics of housing units that cause red and blue clustering in the Johor Bahru area is recommended.

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