مجلة العلوم العربية والإنسانية
Journal of Arabic Sciences & Humanities
مجلة دورية علمية محكمة ربع سنوية

مركز النشر العلمي والترجمة
جامعة القصيم
Center of Scientific Publishing and Translation
Qassim Uinversity

E-ISSN: 1658-9602
www.jahs.qu.edu.sa

17، **(4)**، شوّال، 1445
April, 2024

Spatial Variance Modelling for Price Values of Residential Lands in Riyadh

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Abstract

The increasing population and urban growth in Riyadh city during the last decades have been accompanied by an increasing demand for residential and a rise in their prices to meet the growing demographic and economic needs (Royal Commission for the City of Riyadh, 2023). This study aims to estimate the price of land and its distribution in Riyadh by comparing three different spatial regression models: ordinary least squares (OLS), Geographically Weighted Regression (GWR), and Multi-scale Geographically Weighted Regression (MGWR). These models were employed in this study to identify the pattern of the relationship between the price of land and the number and density of the population. Sixty-one land parcels offered for sale were randomly selected as case study. This study illustrates that the MGWR spatial regression model is distinctly better than the OLS and GWR models. Furthermore, this study also reveals that the highest land prices are concentrated along the highway networks closest to downtown.

Keywords: land prices, spatial regression models, OLS, GWR, MGWR, Riyadh, Saudi Arabia

الملخص

رافق النمو السكاني والعمراني المتزايد في مدينة الرياض خلال السنوات الماضية زيادة في الطلب على الأراضي السكنية وزيادة أسعارها لمواكبة النمو السكاني والاقتصادي المتزايد (الهيئة الملكية لمدينة الرياض، 2023). تهدف هذه الدراسة إلى تقدير أسعار الأراضي وتوزيعها في مدينة الرياض من خلال المقارنة بين ثلاث طرق مختلفة وهي الانحدار المكاني التراتبي (OLS) والانحدار المكاني العالمي (GWR) والانحدار المكاني العالمي متعدد المقاييس (MGWR)، والتي تم استخدامها في هذه الدراسة للتعرف على نمط العلاقة بين أسعار الأراضي وأعداد السكان وكثافتهم، حيث تم اختيار (61) قطعة أرض معروضة للبيع بشكل عشوائي كدراسة حالة لاستخدامها في هذه الدراسة، وبينت الدراسة أن نموذج الانحدار المكاني MGWR أفضل بشكل واضح من نماذج OLS وGWRK، كما أظهرت الدراسة أن أعلى أسعار الأراضي تتركز على طول شبكات الطرق السريعة الأقرب إلى وسط المدينة.

الكلمات الافتتاحية: أسعار الأراضي، نماذج الانحدار المكاني، الرياض، المملكة العربية السعودية.

APA Citation:

Ain, J. (2024). Spatial Variance Modelling for Price Values of Residential Lands in Riyadh. *Journal of Arabic Sciences & Humanities*, *17*, (4), 200-214.

استلم في: 10-06-1445/ قُبل في: 08-08-1445/نُشر في: 15-10- 1445
Received on: 23-12-2023/**Accepted on:** 18-02-2024/**Published on:** 24-04-2024

1. Introduction

At the national level, the value of real estate varies greatly according to location, regardless of the spatial scale utilized in analyses (Holly et al., 2009). Numerous theoretical and empirical studies have been conducted and published on the value of real estate and how it decreases with distance from the central business area (Goffette-Nagot et al., 2010). Riyadh experiences one of the highest levels of trade in Saudi Arabia in terms of the buying and selling of real estate. Although service costs are relatively low compared to the price of land, land prices are relatively high due to the circulation of land as a commodity (Royal Commission for the City of Riyadh, 2009). The cost of land constitutes more than a third of the cost of real estate. The average price of residential land on all streets was approximately 1,170 Saudi riyals/m in 2007 (streets of 20 or less) and 3,000 Saudi riyals/m in 2023 (Royal Commission for the City of Riyadh, 2023). It has also been noted that the price of land varies significantly with increases in housing prices, regardless of the spatial scale chosen for analysis.

The value of a property is influenced by a wide range of factors, including the quality of the construction and materials, structural work factors, location factors (e.g., its distance from poles of attraction and influence), neighborhood effects, accessibility, public policies, direct credit for specific income ranges, infrastructure investments, and tax levies. According to Braga and Alves (2014), a property’s physical attributes, such as its area, building quality, and number of parking spaces, must be considered when valuing the property, as well as economic factors (e.g., the property’s payment terms) and the nature of the event (e.g., whether a property is being offered or sold). According to Wang et al. (2017), the variables that affect property prices are complex, and determining the market price of a certain property is a challenging process when such factors are considered (Braga & Alves, 2014).

Given the complexity that results when a property’s features are taken into account, numerous modeling and analytical techniques have been developed in recent years to support the valuation of real estate and calculate market values. There is also an increasing number of studies on these issues, and the demand-and-supply framework approach has been frequently applied (Fortura & Kushner, 1986; Huang & Lu, 2016). Among the most significant factors affecting housing demand are demographic variables (Buckley & Ermisch, 1983; Hui et al., 2016). Low population mobility has been found to lead to a decrease in housing demand, and population expansion and reduction increase and decrease housing demand, respectively, and thereby alter housing prices (Maennig & Dust, 2008).

2. Article structure

There are four sections in this article, each numbered. It includes a description of the study problem, materials and methods, results, discussion, and conclusions**.**

2.1. Study problem.

The increases in Riyadh’s population and urban growth over the past years have been accompanied by high economic growth in Saudi Arabia and ambitious development plans. Together, these factors have resulted in an increase in the demand for residential land and a rise in its price. Hence, during the planning process carried out by governmental authorities, it is crucial to study a city’s capacity to respond to population increases.

2.2 Study objectives.

The aim of this study was to estimate land prices and their distribution in Riyadh by:

- Identifying the pattern of the relationship between land prices and population density.
- Determining the effect of population density on land prices in Riyadh.

- Using and comparing three spatial regression analysis methods: ordinary least squares (OLS), geographically weighted regression (GWR), and multi-scale geographically weighted regression (MGWR).

2.3. Study hypothesis.

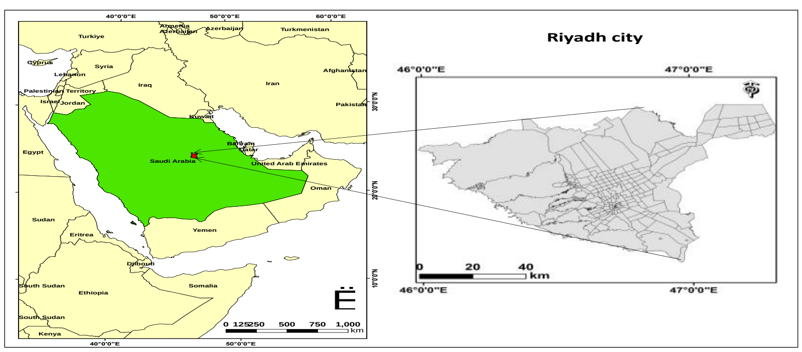
The null hypothesis (H_0) states that there are no statistically significant differences, (Œ±< 0.05), between the geographical distribution pattern of land prices and the population density and distribution in Riyadh.

3. Materials and methods

3.1. Study area.

Riyadh is Saudi Arabia's largest city and capital and the third largest Arab capital in terms of population. It is located on the Najd Plateau, approximately 600 m above sea level, at latitude 24°20' to 25°12' N and longitude 46°14' to 47°20' E (Figure 1). Riyadh, like other cities in Saudi Arabia, has experienced rapid urbanization and the country's most rapid growth in population. In 2022, the population of the whole Riyadh region was 8.591 million (General Authority for Statistics, 2022). In 2021, half a century after its inception, the city area had expanded to 3,115 km^2. All the figures quoted in this study were obtained from the Royal Commission for the City of Riyadh (2023).

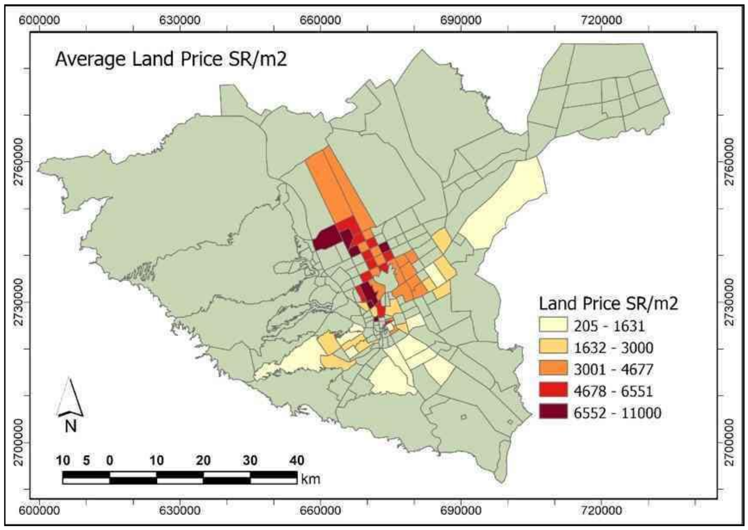
Figure 1. *Location of the study area*



3.2. Data

The data used in this study consisted of vector data containing parcel areas, and Riyadh boundary vector data were obtained from the real estate application Reliance (https://sa.aqar.fm/), which displays many parcels of vacant land for sale. Subsequently, 61 parcels of land for sale were randomly selected for this study. The cadastral layer of the study area was prepared, joined with the land price layer, and converted into point form. The database was created through the spatial joining of the neighborhood layer and the land-plot layer, which represents the sample of the study population for land prices, with the aim of obtaining an average price/m^2 for each neighborhood (Figure 2). The data contained information on the land prices, population in 2019, and population density of Riyadh (Figure 3). A normal distribution statistical analysis was performed to determine the data distribution. The mortgage shapefile data were based on the data of the Royal Commission for the City of Riyadh (2023). In addition, ArcGIS PRO version 10.3 software was used.

Figure 2. *Average land price in Riyadh, 2021 (Saudi riyals/m²)*



The methodology utilized in this study was divided into stages to replicate the approach applied in the creation of the model. The first stage involved performing calculations using a spatial autocorrelation (Moran's *I*) method. The second stage involved detecting hot spots. In the third stage, linear regression was performed using the ordinary least squares (OLS) algorithm. The fourth stage involved the application of a GWR model. In the fifth stage, an MGWR model was applied, which increased the prediction level. In addition, a geographic information system (GIS) was used. Such systems consist of computer hardware and software programs designed for building maps and linking maps to multiple data points retrieved from component programs or other available databases; they have the capacity to encode, store, and retrieve maps and to perform non-geo-specific applications on it (Aziz, 2004, p. 23).

3.3. Spatial autocorrelation (Moran's I)

Moran's index (*I*) is used to evaluate the spatial distribution of a certain factor and to understand whether it is dispersed, concentrated, or random. In this study, Moran's index was used to measure the autocorrelation between land prices and population size and population density. The significance value ranges between −1 and +1. If the value of the index is close to +1, this indicates a concentrated pattern. In contrast, if its value is close to −1, this indicates a dispersed pattern. The normal distribution pattern (random) differs from the concentrated and dispersed distribution patterns.

In ArcGIS, all measurements are based on testing hypotheses. First, it was necessary to determine the initial hypothesis (i.e., the null hypothesis). The null hypothesis states that there is no specific pattern of distribution and that a random pattern is expected, resulting from chance or luck. Moran's coefficient was used to calculate both the *I* and z-score values as follows:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \quad (1)$$

where z_i = deviation of an attribute for feature i from mean $(x_i\text{-}X)$, $w_{i,j}$ = spatial weight between features i and j, n = total number of features, and S_0 = aggregate of all spatial weights:

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \quad (2)$$

The z_I-score is the standard deviation and computed as follows:

$$z_I = \frac{I\text{-}E[I]}{\sqrt{V[I]}} \quad (3)$$

$$uE[I] = \text{-}1/(n\text{-}1) \quad (4)$$

$$V[I] = E[I^2]\text{-}E[I]^2 \quad (5)$$

where $E[I]$ = the expected index, and $V[I]$ = variance, the expected value of Moran's *I* squared minus the square root of Moran's *I*.

The P-value was calculated as the value of the error in rejecting the null hypothesis, which was the probability that the z-score was based on the P-value, through which it was determined whether to accept or reject the hypothesis and whether it was statistically significant. If the significance level was higher than 0.05, then the null hypothesis was to be accepted. If the value was less than 0.05, then the null hypothesis was to be rejected and the alternative hypothesis accepted, which states that the phenomenon is distributed according to a specific pattern, in either a clustered or dispersed manner.

3.4. Hot-spot detection

Hot-spot methods are spatial analysis and mapping techniques used to identify spatial clustering. In this study, regression analysis was used to determine whether hot spots existed and the variance in land prices (values) in selected parcels in Riyadh.

3.5. Ordinary least squares (OLS) regression

The OLS regression model is essentially cross-sectional, which means that no lagged variables are included (Case et al., 2004). OLS linear regression was used in the initial stage. This regression model was used to generate predictions for the dependent variable (parcel prices) based on its associations with a collection of explanatory variables. The utilized OLS model is shown below:

$$y = a_0 + a_1 x_1 + a_2 x_2 + \cdots a_n x_n + \varepsilon \quad (6)$$

where y = dependent variable, a_n = coefficients, x_n = explanatory variable, and Œµ = residual of error, the difference between the model and observations.

The regression tool was used to calculate the coefficients, which are values that describe the strength and nature of the relationships between each explanatory variable and the dependent variable (there is one for each explanatory variable). OLS regression was used to assess the connections between two or more attributes. According to Estupinan and Rodriguez (2008), such relationships must be identified and measured to better understand the factors that affect the calculation of land prices.

3.6. Geographically weighted regression (GWR)

GWR was used to construct the parcel price model. Traditional regression techniques that simulate the relationship between the response and explanatory variables are the ancestors of GWR (Cellmer et al., 2020). The OLS approach is typically used to estimate parameters in traditional linear regression models, while F statistics and t statistics are used to perform significance tests (Rencher & Schaalje, 2008). Traditional regression models assume that the process of price production in geographic space is constant and do not directly account for spatial interactions. However, GWR estimates the global model for every point in a dataset based on location and neighborhood characteristics (Charleton & Fotheringham, 2009); therefore, the spatial structure of the phenomenon under study is not impacted by the parameters, which could result in incorrect interpretation of the findings (Fotheringham et al., 2003). The GWR model is a conventional linear regression model that accounts for spatial interactions by weighting individual data points according to their location. It is derived from non-parametric regression, and at each location where measurement data are present, local linear regressions are built. The GWR model used in this study can be expressed as follows (Fotheringham et al., 2003):

$$y_i = \text{Œ} =_0 (u_i, v_i) + {}^{,}{}_{k=1}^{p} \text{Œ} =_k (u_i, v_i)\, x_k + \text{Œ}\mu_i \qquad (7)$$

where (u_i, v_i) denotes the area represented by the u_i and v_i coordinates. Like the classic models, the GWR model's parameters were estimated while considering the location-dependent weights of the observations, as follows:

$$\widehat{\text{Œ} =} (u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) y \qquad (8)$$

where $W(u_i, v_i)$ is a diagonal matrix of weights that depends on the distance between each point where an observation was made from the place indicated by the coordinates (u_i, v_i).

3.7. Multi-scale geographically weighted regression (MGWR)

The study area may have had varying levels of local GWR coefficient variability. Some coefficients can be viewed as global, stationary, or permanent, whereas others can be viewed as local or non-stationary. To assess the coefficient variability, an MGWR model was used, as proposed by Fotheringham et al. (2003) and represented as follows (Ispriyanti et al., 2017):

$$y = X_a a + X_b b + \text{Œ}\mu \qquad (9)$$

where y = vector representing the response (dependent) variable, X_a = matrix of global variables, a = a vector representing the global coefficients, X_b = matrix of local variables, and b = a matrix representing the local coefficients.

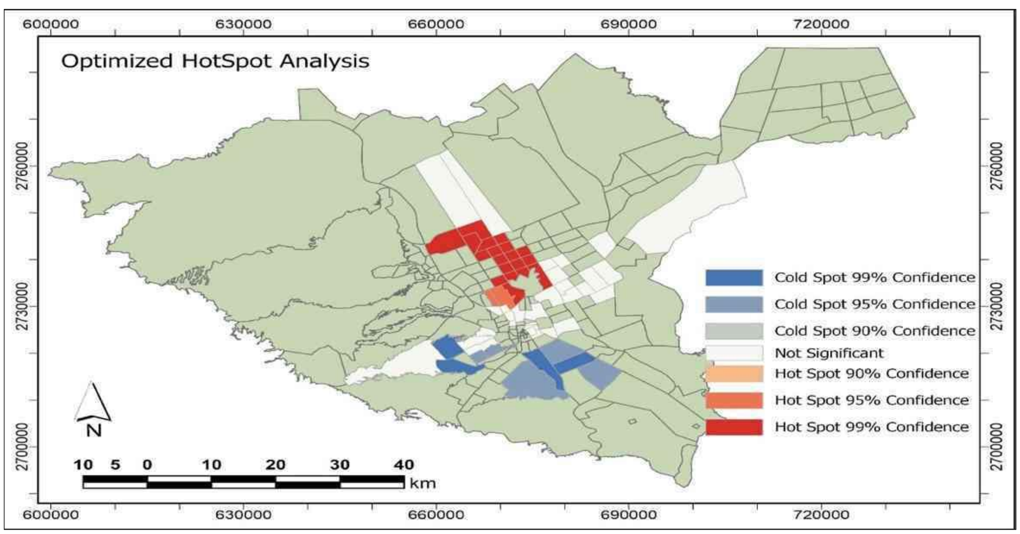
Traditional methods were used to estimate the parameters of multi-scale models. The results of OLS, GWR, and MGWR are important in determining the diagnostics used to establish trust in a model's outcomes.

4. Results and discussion

4.1. Analysis of hot spots

The optimized hot-spot analysis showed that there were highly clustered land-price hot and cold spots in the study area, with a confidence value of 99% (Figure 3). This indicated that it was necessary to use spatial autocorrelation and spatial regressions to define the patterns and distribution across the study area.

Figure 3. *Hot spot distribution of land price in study area*



4.2. Geographical distribution pattern of land prices

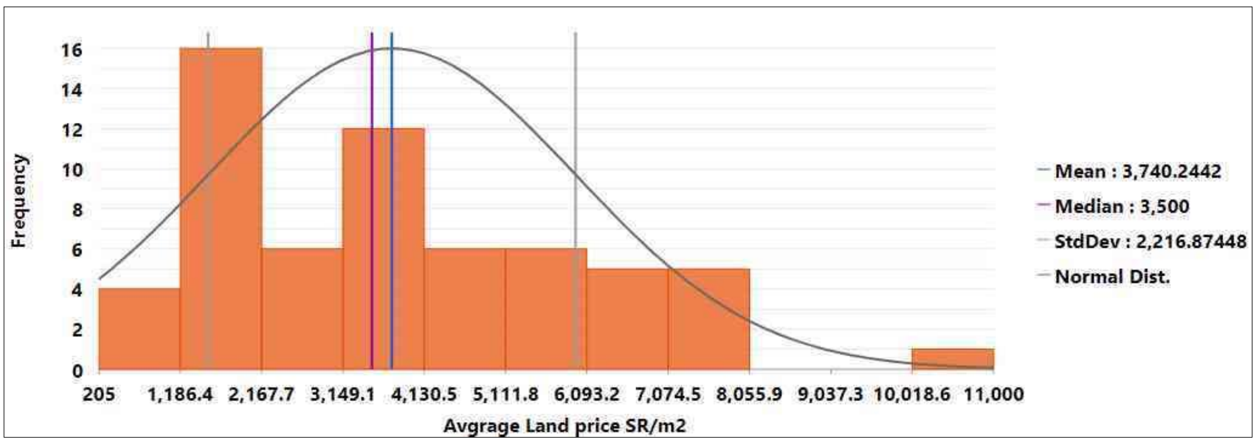
The mean price/m^2 in the study sample was about 3,740 Saudi riyals/m^2, while the coefficient of variation for those prices was approximately 76.6%. This indicated that the intensity of the variation in the price differed from one place to another in Riyadh. Hence, there was a need to examine the reasons for this discrepancy and identify the most important effective factors (Table 1).

Table 1. Statistical analysis of the land price in the study area

Mean	3,740
Standard deviation	2,216
Median	3,500
N	61

Figure 4 shows the histogram that was used to identify the mean and median land prices. Notably, most of the land prices were between 1,186 and 2,167 Saudi riyals/m^2.

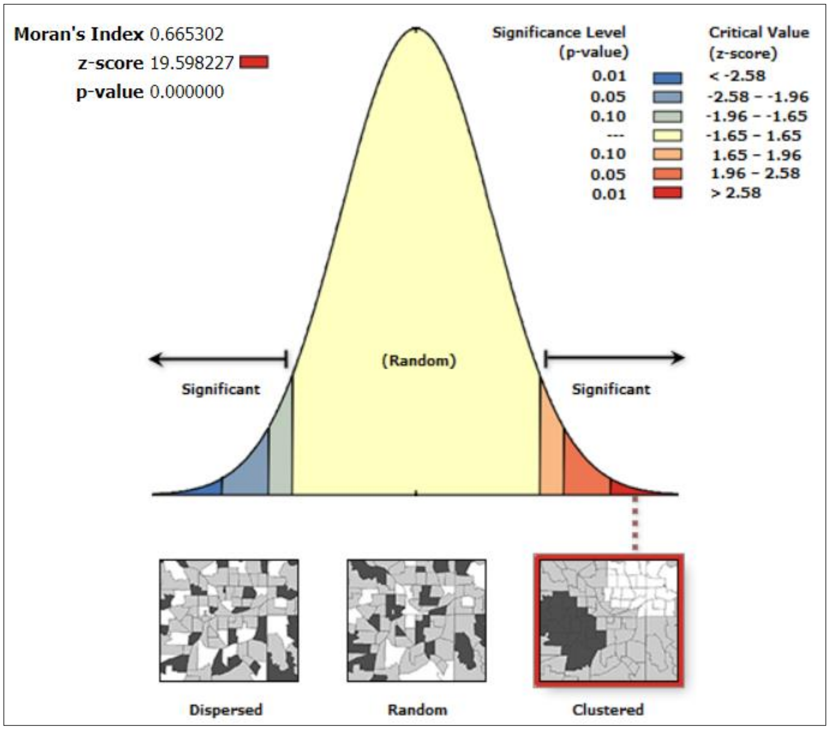
Figure 4. *Land price distribution in Riyadh, 2021 (Saudi riyals/m^2)*



A spatial autocorrelation coefficient, Moran’s index, was used to identify the geographical distribution pattern of the land prices in the study area. It was found that the land prices in the study area were clustered (Figure 5). Thus, the null hypothesis, which states that the land prices in the study area are randomly distributed at a level of statistical significance (0.05), is rejected. The value of Moran’s index was approximately 0.66, which is close to +1, indicating a clustered distribution. This revealed that land parcels with similar prices were located close together; in other words, the closer the parcels of land, the more similar their prices, and the difference between the land prices increased with the distance between the parcels of land (Figure 5).

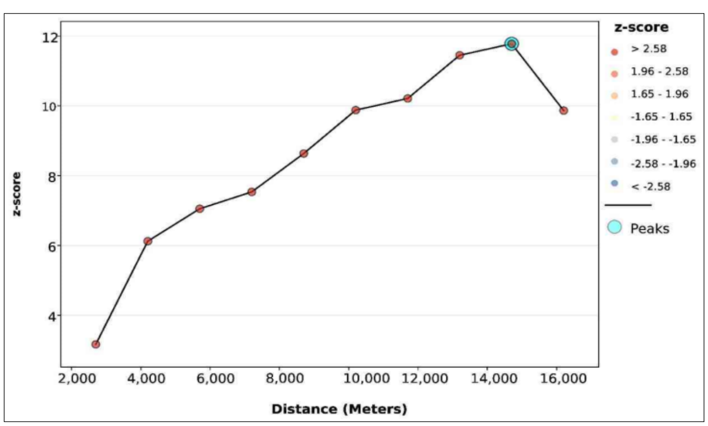
The z-score value was 19.59, which was outside the confidence-level range (< 2.58). This indicated that the distribution of the land prices in the study area was not random. Therefore, the results were accepted, and the null hypothesis was rejected in favor of the alternative hypothesis, which states that the land prices displayed a geographically clustered pattern of distribution (Figure 5). Furthermore, the P-value was 0.00, which indicated that the distribution was not random.

Figure 5. *Plot showing that the land prices in the study area were geographically clustered, and Moran's index is also shown.*



The spatial autocorrelation tool (global Moran's *I*) was used to measure the intensity of the spatial clustering for a series of increasing distances in the study area, and the results are shown in Figure 6. The z-score values shown in Figure 6 reflect the intensity of the spatial clustering, and the statistically significant peak z-score indicates the distance at which the spatial processes that promote clustering was the most pronounced. It is often appropriate to include such peak distances when using tools that have a distance band or distance radius parameter. In this study, the peak distance in terms of land price was 14,700 m.

Figure 6. *Incremental spatial autocorrelation of the distance between parcels of land in the study area*



4.3. OLS

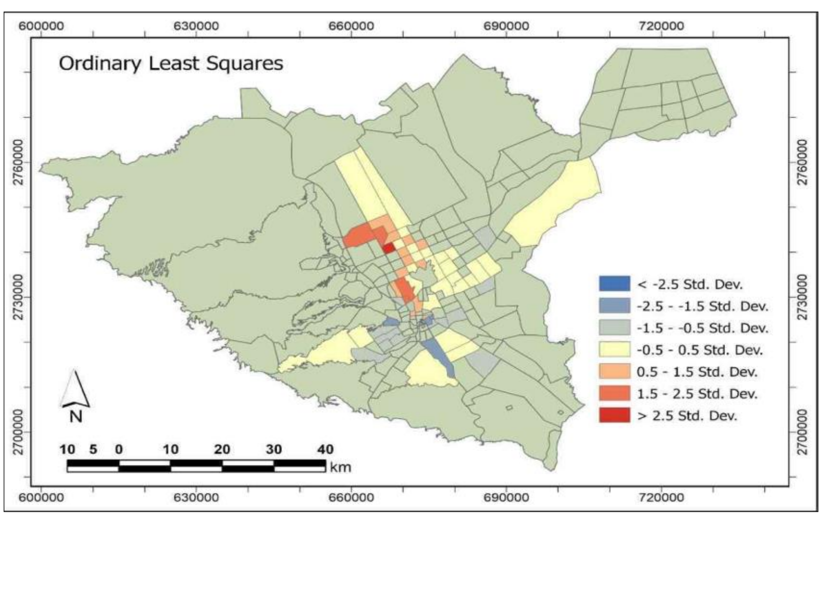
Table 2 displays the results of the OLS analysis of land prices in the study area. Two variables, population density and population size, were used as factors that affect the increase in land prices. A strong and influential correlation was found between the population size and the increase in land prices in the study area. The probability value was 0.0168, and the Robust_Pr (VIF)value was 0.0012, which was considered good as it was less than the standard value. A weak correlation was found between the population density and the high price of land in the study area. The probability value was 0.3336, which showed that the population density had a weak effect on the high price of land in the study area. The adjusted R^2 value of the OLS regression model was 0.0986, which was deemed to be weak. This indicated that the analysis method was not suitable for assessing small areas and that the results were not spatially autocorrelated. These findings suggested that the two variables (population size and population density) were not sufficient to explain the variation in the land prices in the study area and that there may be other variables that affect the land prices in the study area.

Figure 7 shows the z-score values for the impact of the two variables (population size and population density) on the land prices in the study area. It is evident that the highest land prices were concentrated near the downtown area along the highway network.

Table 2. ordinary least squares (OLS) analysis of the land prices in the study area

Variable	Coefficient	Probability	Robust_Pr (VIF)
Intercept	4170.2527	0.000000*	0.000000*
POPULATION (2016)	-0.0134	0.016804*	0.001212*
POPULATION DENSITY (km^2)	0.0425	0.3336	0.2350

Figure 7. *The OLS analysis results showing the impact of the two variables (population size and population density) on the land prices in the study area*



4.4. GWR and MGWR

The results of the GWR model are shown in Figure 8. The land prices appeared to be less clustered when the GWR model was used compared to when the OLS model was used. The R-value was 0.52, indicating a reasonable result. The adjusted R^2 was 0.3996, which indicated greater reliability compared to the OLS model result.

GWR models are not as robust as OLS models; however, they are better suited to modeling small areas with a limited number of explanatory variables. Furthermore, when GWR is used, every feature in a study area can be calibrated based on neighboring features. As a result of this capability of GWR, the coefficients of the land-price features varied across the study area.

Figure 8. *The GWR analysis results showing the impact of the two variables (population size and population density) on the land prices in the study area*

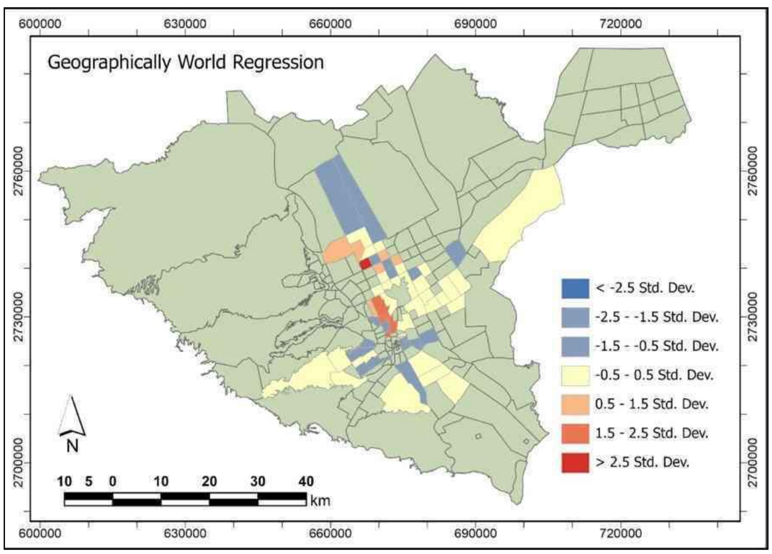


Table 3 presents the results of the MGWR analysis of the land prices in the study area. Two variables, population size and population density, were considered as the factors affecting the increase in land prices. The coefficient standard deviation result indicated that both variables had an impact on the land prices in the study area, with values of 0.0147 for population size and 0.0088 for population density. The MGWR R-value was 0.586, indicating favorable results. The adjusted R^2 was 0.516, which indicated greater reliability than the OLS and GWR model results.

Figure 9 shows the MGWR results and illustrates that the MGWR model was visibly superior to the GWR model. Figure 10 displays the land prices predicted by the MGWR model, and the highest land prices were concentrated along the highway networks closest to the downtown area.

Table 3. The results of the MGWR analysis of the land prices in the study area

VAR_NAME	NBR_COUNT	Coeff_STD
INTRCPT	30.0000	0.5573
POBULTION_2016	61.0000	0.0147
POBULTION DENSITY km^2	61.0000	0.0088

Figure 9. *The MGWR analysis results showing the impact of the two variables (population size and population density) on the land prices in the study area*

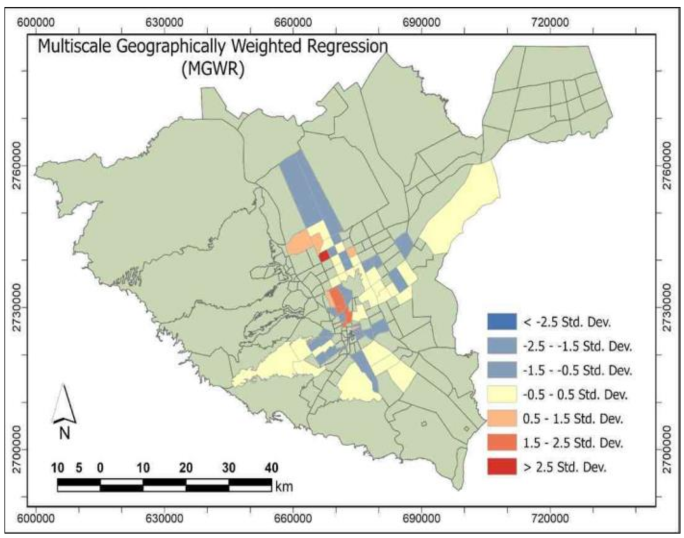
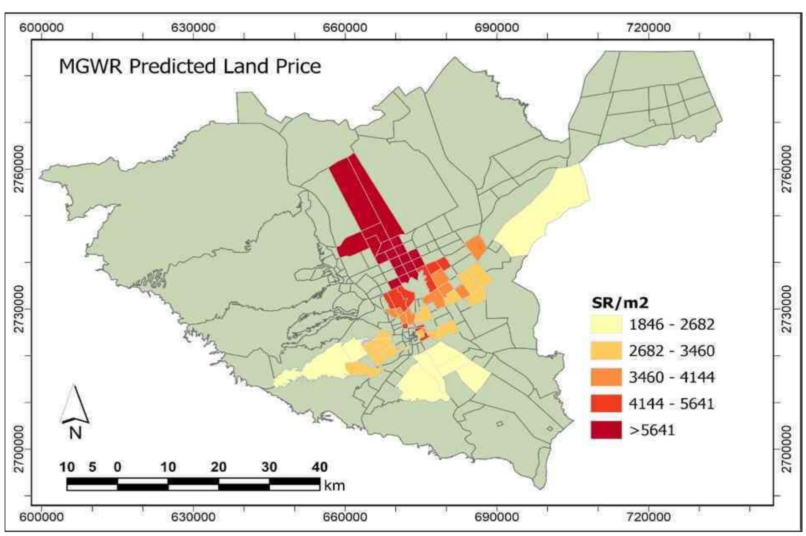


Figure 10 . *The land prices in the study area predicted by the MGWR model.*



5.Conclusions

This study has highlighted the importance of using spatial regression techniques to predict land prices and determine their geographical distribution in Riyadh. Using such techniques, it was found that the land prices in the study area were not randomly distributed in a statistically significant manner. Moran's index was about 0.66, which is close to +1, and thus indicated a clustered distribution of the land prices. Also, there was a strong and influential correlation between the land prices in the study area and the population size. The probability (0.0168) and VIF (0.0012) values, which were both lower than the standard values, indicated a strong correlation between population growth and land prices in the study area. Furthermore, the GWR model was found to be more accurate than the OLS regression model. Even though the GWR results indicated less clustering, R reached 0.528 (an acceptable value) and R^2 reached 0.399, which was higher than that achieved with the OLS model. In addition, a weak correlation was found between the population density and land prices in the study area (probability value of 0.3336). Therefore, it is recommended that studies be conducted to further examine the relationship between land prices and population density, given the importance of both factors in population growth, urbanization, and the social sciences in general. Additionally, the value of the standard error in the OLS regression analysis showed the effect of two independent variables—population density and population size—on the price of land in the study area. The highest land prices were found to be concentrated near the city center and along the highway network. Thus, it is recommended that future studies investigate the effect of road networks on land prices.

Three different methods were used and compared in this study: OLS, GWR, and MGWR. When GWR and OLS were compared, it was found that OLS is a global model that can be utilized to model large areas with many independent variables, while GWR can be used to model small areas and can calibrate each feature separately. The GWR model equation can be calibrated based on neighboring phenomena. Therefore, GWR should be used when studying large areas that include several independent variables. The MGWR results showed that the MGWR model clearly outperformed the GWR model. Notably, it had the capacity to spatially analyze and predict the land prices in the study area. The MGWR results showed that the highest land prices were concentrated along highway networks and close to the city center. Thus, the findings of this study emphasize the importance of using MGWR methods in applied geographical studies due to their capacity to determine spatial relationships.

Finally, this study's results suggest that population size and density may impact the geographical distribution of land prices. The findings and methodologies of this study can be applied to the study area or other areas. This can be achieved by utilizing datasets with larger sample sizes and broader geographical coverage.

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Biographical Statement

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معلومات عن الباحث

أ. جمعه بنت إبراهيم بن أحمد عين، محاضرة في قسم الجغرافيا بكلية العلوم الإنسانية والاجتماعية في جامعة الملك سعود (المملكة العربية السعودية). مرشحة للحصول على درجة الدكتوراه في الفلسفة (تخصص الجغرافيا البشرية) من جامعة الملك سعود. تدور اهتماماتها البحثية حول قضايا السكان والعمران وتخطيط المدن والتحليل المكاني.

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