MULTIDISCIPLINARY SCIENCE JOURNAL

RESEARCH ARTICLE
Published Online: August 7, 2025
https://doi.org/10.31893/multiscience.2026053

Estimation of population density and detection of hot spot settlements in Bandar Lampung city, Indonesia

Tika Widayanti[ab] | Khoirin Nisa[c] ✉ | Netti Herawati[c]

[a]Doctoral Program of Mathematics and Natural Sciences, Universitas Lampung, Indonesia.
[b]Department of Geomatics, Institut Teknologi Sumatera, Indonesia.
[c]Department of Mathematics, Universitas Lampung Indonesia.

Abstract. This study aimed to determine the factors capable of influencing population density to provide broad insights and valuable information for policy considerations needed to ensure a well-ordered and prosperous living environment. The focus is on Bandar Lampung, which is a city consisting of 20 districts. The results revealed that Bandar Lampung city had a high cluster residential settlement pattern, with the hotspot centered on Way Halim, parts of Sukarame, Labuhan Ratu, Kedaton, and Enggal districts. Moreover, the settlements were developing toward the southwest and slightly to the north, with the increase identified to be accompanied by a 2.04% conversion of non-built-up areas to built-up land. This was due to the increase in the population density of the city by 16.78% over the past 10 years based on different factors, including the population growth rate as well as the number of schools, healthcare facilities, live births, and industries.

Keywords: spatial analysis, Getis-Ord G, population map, residential area

1. Introduction

Residential settlements are closely related to population density due to population distribution and land use in cities throughout the world, especially large cities (Bertaud, 2014). Therefore, studying the factors influencing population density through a comprehensive framework is very challenging. This phenomenon is closely related to urban sprawl (Shao et al., 2021) (Wang et al., 2023) (Ansar & de Vries, 2024), which is influenced by various factors that drive urban development, including social and economic factors (Moos et al., 2021) (Liu & Li, 2022).This is despite the importance of this study in providing valuable insights and information for policy considerations to establish better and more prosperous living environments. The process often leads to the application of spatial statistics as an example of the analytical tools used to conduct such studies.

Spatial statistics is a subdiscipline of statistics that involves geographical or spatial data characterizing geographical areas in terms of latitude and longitude to be map-bound in nature. The method applies statistical approaches in analyzing patterns of relations and variations within data that are related to geography or space. The goal is to detect spatial configurations and processes that exist and take place in geographic spaces and, thereby, outline the connected patterns and trends (Bivand et al., 2013).

The described method can be used in various fields, such as the environmental sciences (Yang, 2021), epidemiology (Urdangarin et al., 2025) (Srinivasan et al., 2025), economic geography (Griffith et al., 2021) (Horiike et al., 2024), urban planning (Páez & Scott, 2004) (Kisiala & Rącka, 2021), and social sciences (Jing et al., 2023). This research focuses on residential settlements, which are currently experiencing increasing population density. In addition to statistical methods, Geographic Information Systems (GIS) offer a valuable approach for estimating population distribution (Lwin & Murayama, 2009) (Wu et al., 2005). GIS is widely used in various forms of spatial analysis, including population mapping (Langford & Unwin, 1994) (Mossoux et al., 2018), development planning (Stylianidis et al., 2012) (Jiménez-Espada et al., 2023) (Raffay et al., 2025), navigation (Baylon & Santos, 2013), and resource management (Tsou, 2004) (Gong & He, 2022) (Kofidou, 2024) (Sharma et al., 2024), among others. Similarly, spatial statistical analysis can be employed for mapping population density, identifying clusters, performing spatial interpolation, analyzing spatial patterns, and conducting spatial modeling. This research utilizes spatial statistics to examine the distribution patterns of settlement points through spatial pattern analysis, specifically using the Getis-Ord G statistic, which was first introduced in 1992.

Getis-Ord G is used to identify the relationships between places in a cluster to identify the information not found under statistical values presented in global data (Getis & Ord, 1992). Additionally, Getis-Ord G* has the advantage of examining the vicinity of each point, making the technique more suitable for screening hot and cold spots. The method results in three kinds of clusters: low- or cold-spot clusters, random-spot clusters and high- or hot-spot clusters.

Previous studies have used this method, as observed in the application of local Getis-Ord G to AIDS spread data (Ord & Getis, 1995). In ecology, it has been applied to identify clusters of specific species or the distribution of environmental phenomena (Fortin & Dale, 2005). Others have also adopted Getis-Ord G to identify hot spots on highways (Songhitruksa & Zeng, 2010) and areas with high crime rates to allocate police resources more efficiently (Chainey & Ratcliffe, 2013). Moreover, the method was used in the clustering analysis of plantation areas to determine hot and cold spot regions (Peters et al., 2015) as well as in the study of urban resilience in China (Zhao et al., 2024).

The case studies revealed the possibility of applying Getis-Ord G in specific contexts, such as the mapping of urban poverty distributions or identifying patterns related to population decline due to climate change. The method has been further developed through integration with other methods, such as machine learning, to increase the accuracy and efficiency of analysis (Anselin, 2016). Getis–Ord G analysis was used in this study as a tool to detect hot and cold spot areas within residential settlements to identify areas with high and low population concentrations.

This study was conducted in Bandar Lampung city at 5°20'–5°30' south latitude and 105°28'–105°37' east longitude in Indonesia, with an area of 197.2 km². It is located on the west coast of Sumatra Island along the Sunda Strait and separates the city from Java Island. The strategic position makes Bandar Lampung a major gateway for trade and transportation between Sumatra and Java. The city also has different topographies, including coastal areas, lowlands, and some hill regions, with extended beaches along the coast and several small hills inland. Moreover, it has a tropical climate with average temperatures ranging from 24°C to 31°C and experiences two seasons, including the rainy season from November to March, with high rainfall, and the dry season from April to October. Bandar Lampung city has 20 districts with a current population of 1,184,949 people, comprising 603,532 males and 581,417 females. Economically, most of the population works in trade and services, while regional revenue is derived primarily from taxes.

2. Materials and Methods

Getis–Ord G statistics are used here to describe local spatial autocorrelation that incorporates spatial dependency through the application of a contiguity matrix based on distance. The G statistic is capable of detecting the presence of hot or cold spot areas across the entire observation area to determine the spatial concentration. Like Moran's index and Geary's ratio, the G statistic is also based on cross-product calculations as a measure of spatial relationships and can be defined as follows (Getis, 1991).

$$G(d) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(d) x_i x_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j}, j \neq i. \tag{1}$$

The G statistic is defined by distance *d*, where a unit area is considered a neighbor *I,* while the weight w_{ij} is assigned a value of 1 when the area unit *j* is within *d* and a value of 0 otherwise. Therefore, the weighting matrix is considered a symmetric binary with the neighborhood relationships determined through distance *d*. The value of G ranges from 0 to 1, and the test conducted is presented as follows:

$$Z(G) = \frac{G - E[G]}{\sqrt{Var[G]}} \tag{2}$$

Where the expected value is:

$$E[G(d)] = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(d)}{n(n-1)}; j \neq i \tag{3}$$

And the variance is:

$$Var(G) = E(G^2) - [E(G)]^2 \tag{4}$$

Moreover,

$$E(G^2) = \frac{1}{(m_1^2 - m_2)^2 \cdot n(n-1)(n-2)(n-3)} (B_0 m_2^2 + B_1 m_4 + B_2 m_1^2 m_2 + B_3 m_1 m_3 + B_4 m_1^4) \tag{5}$$

$$m_j = \sum_{i=1}^{n} x_i^j \ ; j = 1,2,3,4, \tag{6}$$

And $n^{(r)} = n(n-1)(n-2)(n-3) \dots (n-r+1)$.

The coefficients *B* are as follows:

$$\begin{aligned} B_0 &= (n^2 - 3n + 3)S_1 - nS_2 + 3W^2 \\ B_1 &= -[(n^2 - n)S_1 - 2nS_2 + 3W^2] \\ B_2 &= -[2nS_1 - (n+3)S_2 + 6W^2 \\ B_3 &= 4(n-1)S_1 - 2(n+1)S_2 + 8W^2 \\ B_4 &= S_1 - S_2 + W^2 \end{aligned} \tag{7}$$

Where

$$S_1 = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(w_{ij} + w_{ji})^2 \ ; j \neq i$$

$$S_2 = \sum_{i=1}^{n}(w_{i\cdot} + w_{\cdot i})^2 \ ; \ w_{i\cdot} = \sum_{j=1}^{n} w_{ij} \ , j \neq i \qquad (8)$$

(Getis & Ord, 1992).

Regression analysis is a statistical method used to determine the relationship between one or more independent variables (predictors) and a dependent variable (response). This analysis helps in understanding, predicting, and interpreting the relationships between variables. The purpose of regression analysis is to measure whether there is a relationship between variables and to make estimations. The multiple regression equation can be written as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \qquad (9)$$

Where
Y: dependent variable
X_i: independent variable
β_0: intercept
β_i: coefficient regression:
ε: Error (Tranmer et al., 2020).

After the estimated regression model is obtained, it is necessary to conduct assumption tests to determine whether the model is valid and can be properly interpreted. These tests include the normality test, multicollinearity test, linearity test, and heteroscedasticity test. The normality test aims to examine whether the residuals are normally distributed, and this test is conducted via the Kolmogorov–Smirnov test (Massey, 1951).

The second test is the multicollinearity test, which aims to determine whether there is a high correlation between independent variables. The multicollinearity test is examined using the variance inflation factor (VIF) statistics (Kim, 2019). A linearity test is used to determine whether the relationship between the independent and dependent variables is linear. The next test is the heteroscedasticity test, which aims to determine whether there is a variance difference in the residuals. This test is conducted via the Glejser test (Ilori & Tanimowo, 2022).

3. Results and Discussion

The residential data from Bandar Lampung city covering the years 2013 and 2023 were obtained from the residential infrastructure center (BPP) Lampung Region for this study. The population density was concentrated in the central areas of the city, including Labuhan Ratu, Way Halim, Enggal, Tanjung Karang Barat, and Tanjung Karang Pusat districts, in 2013, as presented in the places marked in red in Figure 1. The yellow color represents regions with moderate population density, and the green color represents areas with less density, which spreads more than the other levels do. Some of the less dense areas include the Kemiling, Tanjung Karang Barat, Teluk Betung Barat, Teluk Betung Timur, Sukabumi, and Panjang districts.

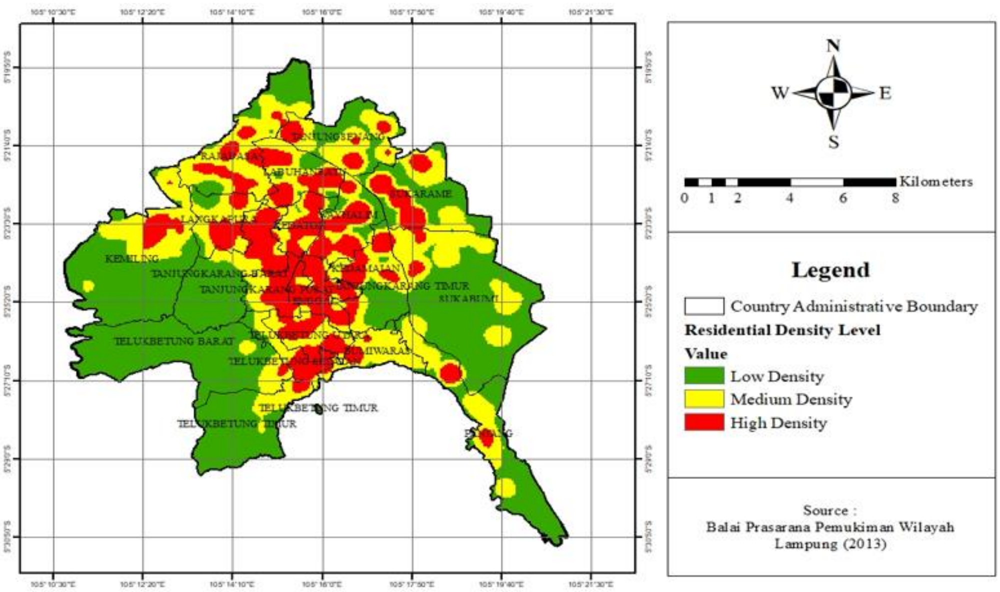

Figure 1 Map of population density in Bandar Lampung city, 2013.

The trend in areas with high and low population density did not change significantly in 2023, but considerable variation was identified in moderate areas such as the Kemiling, Tanjung Senang, and Teluk Betung Barat districts. This is observed from the changes in yellow color, which shifted more toward the west and north than did the 2013 map, as presented in Figure 2.

The trend in population density was further reflected in the number of residential area polygons. There were 815 residential points in 2013, but the number changed to 864 in 2023, showing an increase of 49 points over the span of 10 years.

Moreover, the coverage of the residential areas also increased, as presented in Table 1. The districts that recorded significant changes were Teluk Betung Barat, with a 27.21% increase; Tanjung Senang, with 14.31%; and Tanjung Karang Barat, with 10.71%. The map of Bandar Lampung city also shows that residential development is directed toward the west and north.

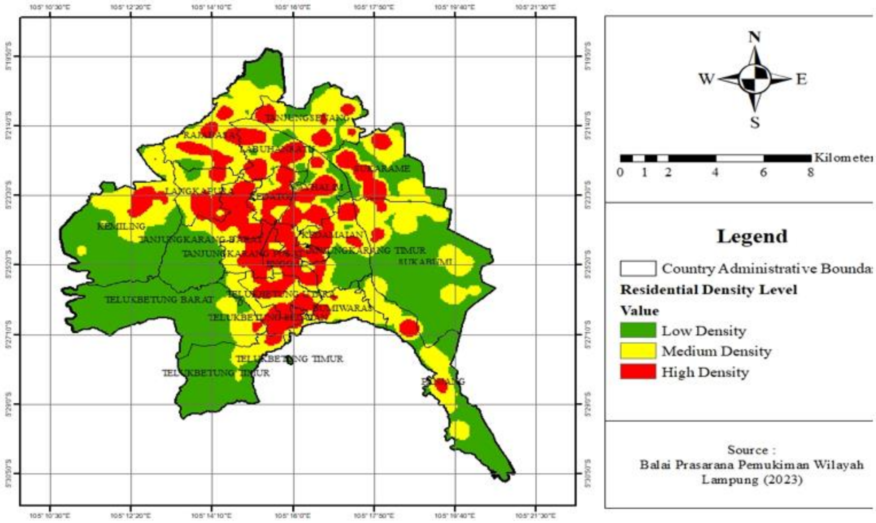

Figure 2 Map of population density in Bandar Lampung city, 2023.

The increase in residential areas was associated with population growth. This was confirmed through the data presented by the Central Statistics Agency data that the population of Teluk Betung Barat increased from 28,671 in 2013 to 38,527 in 2023. Tanjung Senang recorded an increase from 44,042 to 62,402 during the same period, and Tanjung Karang Barat experienced growth from 52,640 to 63,194. The trend was attributed to the development of infrastructure such as roads and public facilities, as well as the implementation of government policies related to housing development attracting people to these districts. This is consistent with the findings of Pang et al. (2024) and Peterson (2017) that the key drivers of population growth are economic conditions, education, healthcare, environment, security, and technological development. For example, Tanjung Karang Barat experienced rapid growth due to increased local economic activities, such as micro, small, and medium enterprises, and a significant boom in property development with several housing developers.

Table 1 Changes in the Residential Area of Bandar Lampung City for 2013 and 2023.

No	Residential/District	Area (Ha)		Changes
		2013	2023	
1	Teluk Betung Barat	148,23	188,57	40,34
2	Teluk Betung Timur	171,79	177,95	6,16
3	Teluk Bentung Selatan	189,93	198,61	8,68
4	Bumi Waras	275,02	277,69	2,67
5	Panjang	384,56	401,85	17,29
6	Tanjung Karang Timur	177,82	179,64	1,82
7	Kedamaian	461,43	464,08	2,65
8	Teluk Betung Utara	340,85	344,38	3,53
9	Tanjung Karang Pusat	264,10	276,00	11,90
10	Enggal	258,76	259,45	0,69
11	Tanjung Karang Barat	399,67	442,47	42,80
12	Kemiling	521,55	562,88	41,33
13	Langkapura	314,33	331,50	17,17
14	Kedaton	316,27	320,14	3,87
15	Rajabasa	612,98	639,40	26,42
16	Tanjung Senang	422,76	483,49	60,73
17	Labuhan Ratu	437,81	465,36	27,55
18	Sukarame	550,91	577,87	26,95
19	Sukabumi	502,34	539,64	37,30
20	Way Halim	461,62	468,16	6,54
	Total	7212,71	7599,11	386,40

Ha: hectare

In addition to the residential area, land cover is another factor that has experienced changes. The results of the overlay analysis revealed that the percentage of shrubland converted to residential areas increased by 0.14%, that of rice fields increased by 0.72%, that of plantations increased by 0.73%, and that of dry fields increased by 0.45%. This result revealed that the total change in land cover to residential areas in Bandar Lampung city was 2.04%. This trend was due to the rapid increase in the activities of housing developers. This was confirmed by data from the Central Agency of Statistics of Bandar Lampung City, which revealed that there were 1,267 new housing developers in the past 10 years, significantly causing the conversion of nonbuilt-up land to residential areas.

The determination of settlement patterns as low, random, or high clusters is significantly related to population density (Rodriguez Lopez et al., 2017) (Duman et al., 2024). Therefore, the Getis–Ord G index was adopted to analyze the settlement pattern of Bandar Lampung city in this study. The results revealed that the city was highly clustered in 2023, as shown in Figure 3, with a Getis–Ord G index value of 0.000058 and a z score of 10.523471. Moreover, the changes in hot and cold spot areas between 2013 and 2023 were determined. The areas marked in red and orange are hot spots with high settlement density and include the Halim, Sukarame, Labuhan Ratu, Kedaton, and Enggal districts. Moreover, the areas colored dark and light blue represent cold spots with a low settlement density. The gray areas are regions without any significant patterns and cannot be classified into either hot or cold spots such as Tanjung Karang Barat, Teluk Betung Selatan, Langkapura, and parts of the Kemiling districts. This finding aligns with the research conducted by Dai et al., which used hotspot analysis to assess the quality of a given area (Dai et al., 2023).

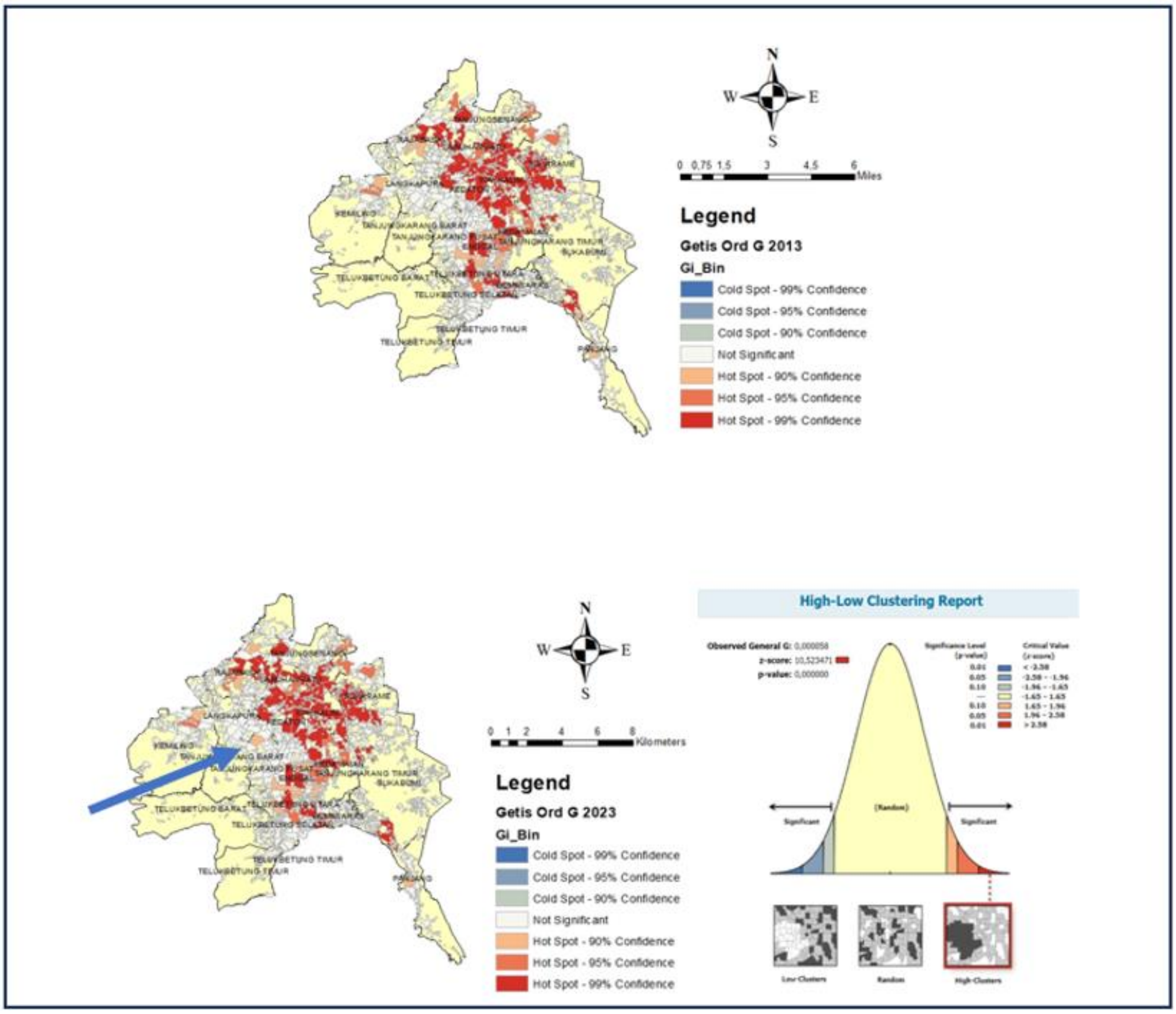

Figure 3 Map of the Getis–Ord G analysis results.

The results revealed only a slight difference in hot spot areas from 2013-2023. For example, the orange area marked with an arrow in Figure 3 shows the absence of hot spot areas in the Tanjung Karang Barat District in 2013, but these areas will eventually start in 2023. This was in line with previous results that revealed an increase in the residential areas of the district. The trend showed that the residential area and the Getis–Ord G analyses provided the same result, indicating an increase in the settlement density of the Tanjung Karang Barat District.

This study further determined the factors influencing the increase in population density through linear regression. The analysis was conducted by using the population density of 20 districts in 2023 as the dependent variable (Y), while the independent variables were the seven factors identified in Table 2.

Table 2 Factor indicators.

No	Code	Variable	Description
1	Y	Population Density	
2	x_1	Distance to Capital	Kilometers
3	x_2	Population Growth Rate	The average annual population increase rate
4	x_3	Number of Schools	The number of primary, secondary, and higher education schools
5	x_4	Number of Health Facilities	The number of healthcare facilities such as hospitals, clinics, community health centers, and pharmacies
6	x_5	Number of Births	The number of live births
7	x_6	Number of Marriages	The number of marriages registered at religious offices
8	x_7	Number of Industries	The number of large (more than 100 employees) and medium (20-99 employees) industries

The data on these variables were obtained from Statistics Indonesia (i.e. Central Agency of Statistics of Indonesia) and subjected to assumption tests, including normality, multicollinearity, linearity, and heteroscedasticity. A normality test was conducted to determine the ability of the data to follow a normal distribution via the Kolmogorov–Smirnov Z test. The results showed that the data satisfied the assumption at a significance value of 0.200 > 0.05, thereby indicating a normal distribution. The multicollinearity test was used to determine the presence of a high correlation among the variables. This was achieved through the variance inflation factor (VIF), which measures the extent of variance in the regression coefficient estimates due to the independent variables. A VIF value that exceeds 10 indicates the presence of multicollinearity (Akinwande et al., 2015; Shrestha, 2020). The results presented in Table 3 show that the variance inflation factor (VIF) values for all the variables were less than 10, indicating the absence of multicollinearity.

Table 3 Results of the VIF calculation.

Variable	Collinearity Statistics	
	Tolerance	VIF
x_1	0,436	2,291
x_2	0,488	2,049
x_3	0,317	3,151
x_4	0,259	3,863
x_5	0,321	3,113
x_6	0,350	2,860
x_7	0,445	2,249

VIF: Variance Inflation Factor

A linearity test was applied to determine the existence of a linear relationship between the dependent variable Y and the independent variables x. The results revealed that x_1, x_3, x_4, and x_7 deviated from linearity values greater than 0.05, indicating the presence of a linear relationship.

The next test was the heteroscedasticity test, which was used to determine the consistency or variation of residual variance among observations. A consistent residual variance is known as homoscedasticity, whereas the presence of any variation is called heteroscedasticity. However, the heteroscedasticity assumption must be satisfied for regression analysis. The analysis was conducted via the Glejser method (Machado & Silva, 2020), and the results revealed that the significance values for all the variables were greater than 0.05, as shown in Table 4. This simply shows the absence of heteroscedasticity and the possibility of using the data for further analysis.

Table 4 Glejser Test.

Variable	t	sig.
Constant	1,089	0,298
x_1	-0,878	0,397
x_2	0,043	0,966
x_3	-1,509	0,157
x_4	0,91	0,381
x_5	0,065	0,949
x_6	0,345	0,736
x_7	-0,237	0,816

t: t test, sig.: significance.

The satisfaction of the assumption tests was followed by the calculation of the regression model with the results presented in Table 5. The significance value of F was found to be 0.003, which was less than 0.05, suggesting that the independent variables had a significant effect on the dependent variable.

The regression analysis was conducted using seven independent variables, but only five significantly affected population density, as observed from the significance values less than 0.05. The variables were the population growth rate as well as the number of schools, healthcare facilities, live births, and industries.

Table 5 Model parameters.

Variable	Coefficient	t	Sig. t	F	Sig. F
Constant	10269,763	3,353	0,006	6,439	0,003
x_1	-71,882	-0,277	0,787		
x_2	-3493,913	-3,420	0,005		
x_3	-160,729	-2,536	0,026		
x_4	244,395	2,191	0,049		
x_5	-8,666	-2,218	0,047		
x_6	25,915	2,000	0,069		
x_7	-445,635	-3,750	0,003		

t: t test, Sig.t: Significance of t, F: F test, Sig. F: Significance of F.

The number of schools influences population density because of the ability to attract factors related to quality of life. For example, high-quality education in a community enhances well-being (Alali & Walid, 2011). This is because the presence of schools increases accessibility to education for local residents and makes the area more attractive for living. Similarly, Maclean (2018) reported that access to quality education affects the growth and attractiveness of an area as a place to live.

The population density was further reported to be influenced by the number of healthcare facilities. This finding showed that the presence of good and adequate healthcare facilities could improve the quality of life in an area (Kruk et al., 2018). This trend can further make the area more appealing to families seeking an environment that supports health and well-being. Moreover, hospitals, clinics, and health centers affect residential decisions, especially for families with children, elderly individuals, or people with specific medical needs.

Birth rates are another factor with a direct effect on population density because they contribute to population growth. A higher birth rate leads to faster population growth, which subsequently increases population density. Furthermore, an increase in the number of births can influence the need for more infrastructure, such as schools and healthcare facilities, leading to alterations in density patterns and urban planning (Rotella et al., 2020). The number of births influenced population density, with a coefficient of 25.915.

The results revealed that the number of industries affected population density because of the close relationship between industrial activities and population dynamics. This is possible because industries often provide numerous job opportunities that attract the migration of people from other areas. A region with several industries can typically offer more available jobs, which often leads people to move to the area in search of employment, thereby increasing the local economy. This was in line with the observation of a previous study that economic activities in a region increased population density (Yegorov, 2015). The trend shows that industries have the capacity to provide direct jobs with additional effects on related sectors, such as services, trade, and others, which are considered dependent on the main industry. The effects can subsequently lead to an increase in population density due to the overall improvement in economic activity.

4. Conclusions

In conclusion, the residential pattern in Bandar Lampung city was highly clustered with the hot spot areas located in Way Halim, parts of Sukarame, Labuhan Ratu, Kedaton, and Enggal districts. The development of settlements was oriented toward the southwest and slightly toward the north. Policymakers or government authorities can consider the findings of this study as a basis for guiding the development of Bandar Lampung City, to create a livable environment by providing adequate public facilities in the area.

Moreover, the advancing residential areas were accompanied by a 2.04% conversion of non-built-up land to built-up land due to the 16.78% increase in population density over a period of 10 years. The influential factors were reported to be the population growth rate as well as the number of schools, healthcare facilities, live births, and industries. The effects of these factors occur through mechanisms such as job creation, infrastructure improvement, urbanization, and enhanced quality of life. Future research is encouraged to incorporate additional factors not included in this study, such as security and technological development.

Acknowledgment

The author(s) would like to thank the Indonesian Ministry of Higher Education, Sciences, and Technology which has funded this research as well as the Institute of Research and Community Service of Universitas Lampung for supporting this research.

Conflict of Interest

The authors declare no conflicts of interest.

Funding

The research leading to these results has received funding from the Indonesian Ministry of Higher Education, Sciences, and Technology with grant number 057/E5/PG.02.00.PL/2024.

References

Akinwande, M. O., Dikko, H. G., & Samson, A. (2015). Variance Inflation Factor: As a Condition for the Inclusion of Suppressor Variable(s) in Regression Analysis. *Open Journal of Statistics,* 5, 754-767. http://dx. doi.org.10.4236/ojs.2015.57075

Alali, W. Y. (2011). The Contributor of Education to Economic Development. *Munich Personal RePEc Archive,* 115614, 1-15.

Ansar, Z., & de Vries, W. T. (2024). Urban Sprawl Symptoms in Bandar Lampung Suburban Area, Indonesia. *Geoplanning: Journal of Geomatics and Planning*, *11*(2), 205–222. https://doi.org/10.14710/geoplanning.11.2.205-222

Anselin, L. (2016). Spatial Autocorrelation. [https://spatial.uchicago.edu/sites/ spatial.uchicago.edu/files/3_spatial_autocorrelation_r.pdf. Accessed on 2nd of July 2023.

Badan Pusat Statistik (2024). https://lampung.bps.go.id/id. Accessed on 2nd of August 2024.

Baylon, A., & Santos, E. M. (2013). Introducing GIS to TransNav and its Extensive Maritime Application: An Innovative Tool for Intelligent Decision Making? *TransNav, the International Journal on Marine Navigation and Safety of Sea Transportation*, *7*(4), 557–566. https://doi.org/10.12716/1001.07.04.11

Bertaud, A. (2004). *The Spatial Organization of Cities: Deliberate Outcome or Unforeseen Consequence?*. Working Paper 2004:1, Institute of Urban and Regional Development University of California at Berkeley.

Bivand, R. S., Pebesma, E., & Gómez-Rubio, V. (2013). *Applied Spatial Data Analysis with R*. Springer.

Dai, Y., Du, S., & Min, H. (2023). Comparative Hotspot Analysis of Urban Living Environments and Transit-Oriented Development (TOD) Strategies: A Case Study of Beijing and Xi'an. *ISPRS International Journal of Geo-Information*, *12*(11). https://doi.org/10.3390/ijgi12110446

Duman, S., Ünsal, Ö., & Zaman, S. (2024). The Clustering of the Population at Building Scale in Bursa City (Türkiye). *Sustainability (Switzerland)*, *16*(19). https://doi.org/10.3390/su16198615

Fortin, M., Dale, M. R.t., & Hoef, J.V. (2013). Spatial Analysis in Ecology. *Encyclopedia of Environment*, 4, 2051-2058. https://doi.org/10.1002/9780470057339.vas039.pub2

Gentleman, R., Hornik, K., & Parmigiani, G. (2008). Use R ! *Applied Spatial Data Analysis with R*, 21–54. https://doi.org/10.1007/978-0-387-78171-6

Getis, A. & Ord, J.K. (1992). The Analysis of Spatial Association by Use of Distance Statistics. *Geographical Analysis,* 24(3), 189-206. https://doi.org/10.1111/j.1538-4632.1992.tb00261.x

Getis, A. (1991). Spatial Interaction and Spatial Autocorrelation: A Cross-product Approach. *Environment and Planning A,* 23 (9), 1269-1277. https://doi.org/10.1068/a231269

Gong, H., & He, C. (2022). Intelligent Management of Land Resources Based on Internet of Things and GIS Technology. *Journal of Sensors*, *2022*. https://doi.org/10.1155/2022/2216581

Griffith, D. A., Chun, Y., & Lee, M. (2021). Deeper spatial statistical insights into small geographic area data uncertainty. *International Journal of Environmental Research and Public Health*, *18*(1), 1–16. https://doi.org/10.3390/ijerph18010231

Horiike, R., Itatani, T., Nakai, H., Nishioka, D., Kataoka, A., & Ito, Y. (2024). Using Spatial Scan Statistics and Geographic Information Systems to Detect Monthly Human Mobility Clusters and Analyze Cluster Area Characteristics. *JMA Journal*, *7*(3), 319–327. https://doi.org/10.31662/jmaj.2023-0208

https://doi.org/10.1111/j.1538-4632.1995.tb00912.x

Ilori, O. O., & Tanimowo, F. O. (2022). Heteroscedasticity Detection in Cross-Sectional Diabetes Pedigree Function: A Comparison of Breusch-Pagan-Godfrey, Harvey and Glejser Tests. *International Journal of Scientific and Management Research*, *05*(12), 150–163. https://doi.org/10.37502/ijsmr.2022.51211.

Jiménez-Espada, M., Martínez García, F. M., & González-Escobar, R. (2023). Sustainability Indicators and GIS as Land-Use Planning Instrument Tools for Urban Model Assessment. *ISPRS International Journal of Geo-Information*, *12*(2). https://doi.org/10.3390/ijgi12020042

Jing, F., Li, Z., Qiao, S., Zhang, J., Olatosi, B., & Li, X. (2023). Using geospatial social media data for infectious disease studies: a systematic review. *International Journal of Digital Earth*, *16*(1), 130–157. https://doi.org/10.1080/17538947.2022.2161652

Kim, J. H. (2019). Multicollinearity and misleading statistical results. *Korean Journal of Anesthesiology*, *72*(6), 558–569. https://stat.duke.edu/~kfl5/Lock_RREE_Results_2010.pdf

Kisiala, W., & Rącka, I. (2021). Spatial and statistical analysis of urban poverty for sustainable city development. *Sustainability,* MDPI, *13*(2), 1–18. https://doi.org/10.3390/su13020858

Kofidou, M. (2024). Involvement of Remote Sensing and GIS in Sustainable Groundwater Monitoring: An Overview. *JSM Environmental Science and Ecology*, 12(2): 1097. https://doi.org/10.47739/2333-7141/1097

Kruk, M.E., Gage, A.D., Arsenault, C., Jordan, K., Leslie H.H., and Roder-Dewan, S., et al. (2018). High-Quality Health Systems in the Sustainable Development Goals Era: Time for a Revolution. *The Lancet Global Health Commission*, 6, 1196-1251 E1196-E1252. https://doi.org/10.1016/s2214-109x(18)30386-3

Langford, M., & Unwin, D. J. (1994). Generating and mapping population density surfaces within a geographical information system. *The Cartographic Journal*, *31*(1), 21–26. https://doi.org/10.1179/000870494787073718

Liu, H., & Li, X. (2022). Understanding the Driving Factors for Urban Human Settlement Vitality at Street Level: A Case Study of Dalian, China. *Land*, *11*(5), 1-20. https://doi.org/10.3390/land11050646

Lwin, K. K., & Murayama, Y. (2009). A GIS approach to estimation of building population for micro-spatial analysis. *Transactions in GIS*, *13*(4), 401–414. https://doi.org/10.1111/j.1467-9671.2009.01171.x

Machado, J.A.F., & Silva, J.M.C.S. (2020). Glejser's test revisited. *Journal of Econometrics,* 97, 189-202. https://doi.org/10.1016/S0304-4076(00)00016-6

Maclean, R., Panth, B., & Jagannathan, S. (2018). *Education and Skills for Inclusive Growth, Green Jobs and the Greening of Economies in Asia: case study summaries of India, Indonesia, Sri Lanka and Vietnam*. Springer.

Massey Jr., F.J. (1951) The Kolmogorov-Smirnov Test for Goodness of Fit. Journal of the American Statistical Association, 46, 68-78. https://doi.org/10.1080/01621459.1951.10500769

Moos, N., Juergens, C., & Redecker, A. P. (2021). Geo-spatial analysis of population density and annual income to identify large-scale socio-demographic disparities. *ISPRS International Journal of Geo-Information*, *10*(7):432. https://doi.org/10.3390/ijgi10070432

Mossoux, S., Kervyn, M., Soulé, H., & Canters, F. (2018). Mapping population distribution from high resolution remotely sensed imagery in a data poor setting. *Remote Sensing*, *10*(9):1409. https://doi.org/10.3390/rs10091409

Ord, J.K.,& Getis, A. (1995). Local Spatial autocorrelation Statistics: Distributional Issues and an Application. *Geographical Analysis,* 27(4), 286-306.

Páez, A., & Scott, D. M. (2004). Spatial statistics for urban analysis: A review of techniques with examples. *GeoJournal*, *61*(1), 53–67. https://doi.org/10.1007/s10708-005-0877-5

Pang, F., Miao, G., Li, Y., & Shi, Y. (2024). Key factors influencing sustainable population growth: A DEMATEL-ANP combined approach. *Heliyon*, *10*(21), e39404. https://doi.org/10.1016/j.heliyon.2024.e39404

Peter, A., Zude, M., Kathner, J., Unla, M., Kanber, R., Hetzroni, A., Gebbers, R., & Ben-Gal, A. (2015). Getis-Ord's hot-and cold-spot statistics as a basis for multivariate spatial clustering of orchard tree data. *Computers and Electronics in Agriculture,* 111, 140 – 150. https://doi.org/10.1016/j.compag.2014.12.011

Peterson, E. W. F. (2017). The role of population in economic growth. *SAGE Open*, *7*(4). https://doi.org/10.1177/2158244017736094

Raffay, M. R. M., Bagheri, M., Marzuki, A., Gholami, I., & Anuar, M. A. K. (2025). Monitoring and analyzing land use changes for sustainable development in Teluk Bahang, Penang, Malaysia: a GIS-based approach. *Journal of Engineering and Applied Science,* 72 (1): 36. https://doi.org/10.1186/s44147-025-00601-3

Rodriguez Lopez, J. M., Heider, K., & Scheffran, J. (2017). Frontiers of urbanization: Identifying and explaining urbanization hot spots in the south of Mexico City using human and remote sensing. *Applied Geography*, *79*, 1–10. https://doi.org/10.1016/j.apgeog.2016.12.001

Rotella, A., Varmun, M.E.W., Sng, O., & Grossmann, I. (2021). Increasing popilation density predict decreasing fertility rates over time: A 174-nation investigation. *American Psyhologist, 76(6,), 933-946.* DOI:10.1037/amp0000862

Shao, Z., Sumari, N. S., Portnov, A., Ujoh, F., Musakwa, W., & Mandela, P. J. (2021). Urban sprawl and its impact on sustaina ble urban development: a combination of remote sensing and social media data. *Geo-Spatial Information Science*, *24*(2), 241–255. https://doi.org/10.1080/10095020.2020.1787800

Sharma, S., Beslity, J. O., Rustad, L., Shelby, L. J., Manos, P. T., Khanal, P., Reinmann, A. B., & Khanal, C. (2024). Remote Sensing and GIS in Natural Resource Management: Comparing Tools and Emphasizing the Importance of In-Situ Data. *Remote Sensing*, *16*(22). https://doi.org/10.3390/rs16224161

Shrestha, N. (2020). Detecting Multicollinearity in Regression Analysisi. *American Journal of Applied Mathematics and Statistics,* 8(2), 39-42. http://dx.doi.org/10.12691/ajams-8-2-1

Songchitruksa, P., & Zeng, X. (2010). Getis-Ord Spatial Statistics to Identify Hot Spots by Using Incident Management Data. *Journal oh the Transportation research,* 2165(1), 42-51. https://doi.org/10.3141/2165-05

Srinivasan, S., Shrestha, S., Harris, D. R., Lewis, O., Rock, P., Silwal, A., Pustz, J., Oh, S., Barboza-salerno, G., & Stopka, T. J. (2025). Spatial and Spatio-temporal Epidemiology Employment industry and opioid overdose risk : A pre- and post-COVID-19 comparison in Kentucky and Massachusetts 2018 – 2021. *Spatial and Spatio-Temporal Epidemiology*, *52*(August 2024), 100701. https://doi.org/10.1016/j.sste.2024.100701

Stylianidis, E., Karanikolas, N., & Kaimaris, D. (2012). A GIS for urban sustainability indicators in spatial planning. *International Journal of Sustainable Development and Planning*, *7*(1), 1–13. https://doi.org/10.2495/SDP-V7-N1-1-13

Tranmer, M., Murphy, J., Elliot, M., & Pampaka, M. (2020). Multiple Linear Regression (2nd Edition); Cathie Marsh Institute Working Paper 2020-01. https://hummedia.manchester.ac.uk/institutes/cmist/a rchive-publications/working-papers/2020/2020-1- multiple-linear-regression.pdf

Tsou, M. H. (2004). Integrating Web-based GIS and image processing tools for environmental monitoring and natural resource management. *Journal of Geographical Systems*, *6*(2), 155–174. https://doi.org/10.1007/s10109-004-0131-6

Urdangarin, A., Goicoa, T., Congdon, P., & Ugarte, M. D. (2025). A fast approach for analyzing spatio-temporal patterns in ischemic heart disease mortality across US counties (1999–2021). *Spatial and Spatio-Temporal Epidemiology*, *52*(October 2024), 100700. https://doi.org/10.1016/j.sste.2024.100700

Wang, G., Peng, W., & Zhang, L. (2023). Estimate of population density and diagnosis of main factors of spatial heterogeneity in the metropolitan scale, western China. *Heliyon*, *9*(6), e16285. https://doi.org/10.1016/j.heliyon.2023.e16285

Wu, S. S., Qiu, X., & Wang, L. (2005). Population estimation methods in GIS and remote sensing: A review. *GIScience and Remote Sensing*, *42*(1), 80–96. https://doi.org/10.2747/1548-1603.42.1.80

Yang, H. (2021). An empirical analysis on spatial effects of environmental protection. *Journal of King Saud University - Science*, *33*(6), 101525. https://doi.org/10.1016/j.jksus.2021.101525

Yogorov, Y. (2015). Economic Role of Population density. *Paper of ESRA. https://www-sre.wu.ac.at/ersa/ersaconfs/ersa15/e150825aFinal00207.pdf.* Accessed on August 20, 2024.

Zhao, Z., Hu, X., Han, X., Chen, L., Li, Z. (2024). Evaluation of Urban Resilience and Its Influencing Factors: A Case Study of the Yichang-Jingzhou-Jingmen-Enshi Urban Agglomeration in China. *Sustainability,* 16(16), 7090. https://doi.org/10.3390/su16167090