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Spatial Pattern of Residential Land Prices in Dar es Salaam City, Tanzania

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Abstract
The analysis of spatial patterns and variations in urban land prices aids urban planning, socioeconomic analysis, investment decisions, resource allocation, and monitoring of urban spatial growth and land market dynamics. However, scholarly research on the spatial patterns of urban land prices in Sub-Saharan African cities with predominantly informal land markets and settlements remains limited. This study applied spatial statistics to analyse the spatial autocorrelation of residential land prices (RLPs) in Dar es Salaam, Tanzania, aiming to understand their spatial distribution and variation. Global indicators of spatial association (GISA) and Local Indicators of Spatial Association (LISA) were utilised, calculating global Moran's I and local Moran's I, respectively, using 452 RLP data from 2020 collected by the Government Chief Valuer. GISA results revealed highly clustered RLPs with strong positive spatial autocorrelation (Moran's $I = 0.83$). LISA analysis identified clusters of sub-wards with lower RLPs below the mean, dominating the city's land market. Statistically significant and non-significant LISA results delineated peri-urban and rapidly growing areas. This study provided evidence-based insights for urban planning, policies, infrastructure development, and investor decisions, highlighting the importance of spatial statistics at the regional and sub-regional levels in understanding and improving urban dynamics and land market efficiency.

Keywords: *Spatial pattern; Spatial autocorrelation; Land markets; Residential land price; Dar es Salaam*

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1. Introduction

Land markets encompass more than just land and locations; they also impact the welfare and social issues of urban populations (Cheshire and Sheppard, 2004; Deng, 2024). Additionally, the characteristics of urban land markets may influence the spatial pattern of land prices, impacting the preferences and decisions of prospective land purchasers (Alonso, 1960; Jiang, 2024). The land market in Dar es Salaam is characterised by both formal and informal land transaction channels (Nyakamwe et al., 2022). Consequently, the complexity of urban expansion and development in the city is largely influenced by the spatial pattern of land prices, which results from its complex land market (Bhanjee and Zhang, 2018; Brigham, 1965; Msuya et al., 2021). Analysing the spatial pattern of land prices is an essential and effective way to improve urban planning and management, resource allocation, modeling and forecasting land use changes, and estimating property taxes (Hu et al., 2013; Wang et al., 2024).

In the context of the study, spatial pattern refers to the arrangement or distribution of land prices across different locations in the urban area (Anselin and Getis, 2010; Gamal et al., 2024). Urban land prices are intricately tied to specific locations and their neighbourhoods. The spatial pattern of urban land prices has been studied in various forms, primarily through spatial autocorrelation analysis. Liu et al. (2006) found positive spatial autocorrelation of land prices, with residential land prices showing a much stronger positive autocorrelation than commercial and industrial land. Additionally, Jiao and Liu (2012) studied the spatial autocorrelation of urban land prices from a regional perspective and discovered that land price distribution is influenced by economic factors and local factors such as population, transport infrastructure, and land supply. Similar analyses have been conducted to examine the spatial distribution of industrial land prices, their variations, and industrial impacts (Chen et al., 2018; Wang et al., 2020), as well as the spatial-temporal variations of commercial land prices (Garang et al., 2021). Gamal et al. (2024) further established the relationship between urban clusters and land price variation. These studies demonstrated that real estate prices are spatially autocorrelated variables at various scales and levels. However, none of the existing literature on spatial autocorrelation has been conducted in a city with predominantly informal land markets and settlements to discover the spatial pattern of their respective prices.

Informal land markets, which operate without oversight from authorities, are the primary drivers of urban sprawl and expansion in African countries (Bhanjee and Zhang, 2018). They catalysed the formation of informal settlements in urban areas due to the high demand for housing caused by rapid population growth, leading to informal land transactions (Nyakamwe et al., 2022; Peter and Yang, 2019). It is estimated that over 70% of Africa's urban population resides in informal settlements (Andreasen et al., 2017; Parsa et al., 2011). These settlements are characterised by poor infrastructure and a lack of essential public services and amenities (Peter and Yang, 2019).

In a market economy, land prices tend to increase due to factors such as the natural and socio-economic environment, the availability of public services, and market demand. Conversely, a weak land market and inadequate regional development result in lower land prices (Yang et al., 2020). The vibrant informal land markets in Dar es Salaam reflect the high demand for land; however, these markets are challenged by informal settlements and socio-economic issues (Andreasen et al., 2017; Peter and Yang, 2019).

The focus of this study is to analyse the spatial pattern of residential land prices (RLPs) in Dar es Salaam, Tanzania, to capture their distribution and variation. The study has two specific objectives: (1) to determine the spatial pattern of RLPs by testing the null hypothesis H0: The Dar es Salaam RLPs are random; and (2) to assess the spatial heterogeneity of prices. The study used the Global Indicators of Spatial Association (GISA) and Local Indicators of Spatial Association (LISA), calculating global Moran's I and local Moran's I, respectively. The GISA analysis assumes homogeneity across the study area, providing an overall spatial autocorrelation of the RLPs (Barreca et al., 2018), while LISA, a decomposition of GISA, examines spatial autocorrelation of RLPs at the local level (Anselin, 1995). This study utilised RLP data for the year 2020, collected from the office of the Tanzania Government Chief Valuer. Significantly, the study will provide evidence-based insights for urban planning, policy-making, infrastructure development, and investment decisions to improve urban dynamics and land market efficiency.

2. Materials and Methods

2.1. Study area

Dar es Salaam city in Tanzania is the chosen study area. The city covers a total area of 1,393 square kilometres (km^2), which is equivalent to 0.15% of the entire land area of Tanzania. It is bordered by the Coast Region to the North, West, and South, and by the Indian Ocean to the East. The city comprises five municipalities: Ilala, Kinondoni, Ubungo, Temeke, and Kigamboni [Figure 1(a)]. It is one of the top ten fastest-growing cities in Africa and is expected to reach a population of more than 10 million people within 15 years (Güneralp et al., 2018; UN, 2018). The city's growth is primarily driven by rapid population growth rather than industrialisation, unlike cities in developed countries (Mkalawa and Haixiao, 2014). Consequently, this population growth has created a high demand for residential land. According to the 2012 census data, Dar es Salaam city comprises a total of 452 administrative sub-wards. The Kivukoni sub-ward is considered the Central Business District (CBD) of the city. Historically, Dar es Salaam, formerly known as 'Mzizima', originated around the natural sea port located in the Kivukoni area. Dar es Salaam is regarded as the most important economic centre in Tanzania, generating the highest volume of manufactured products and total tax collection across the country (BoT, 2020). The city's unique geographical and socio-economic factors make it an interesting case study area for examining the spatial distribution of RLP.

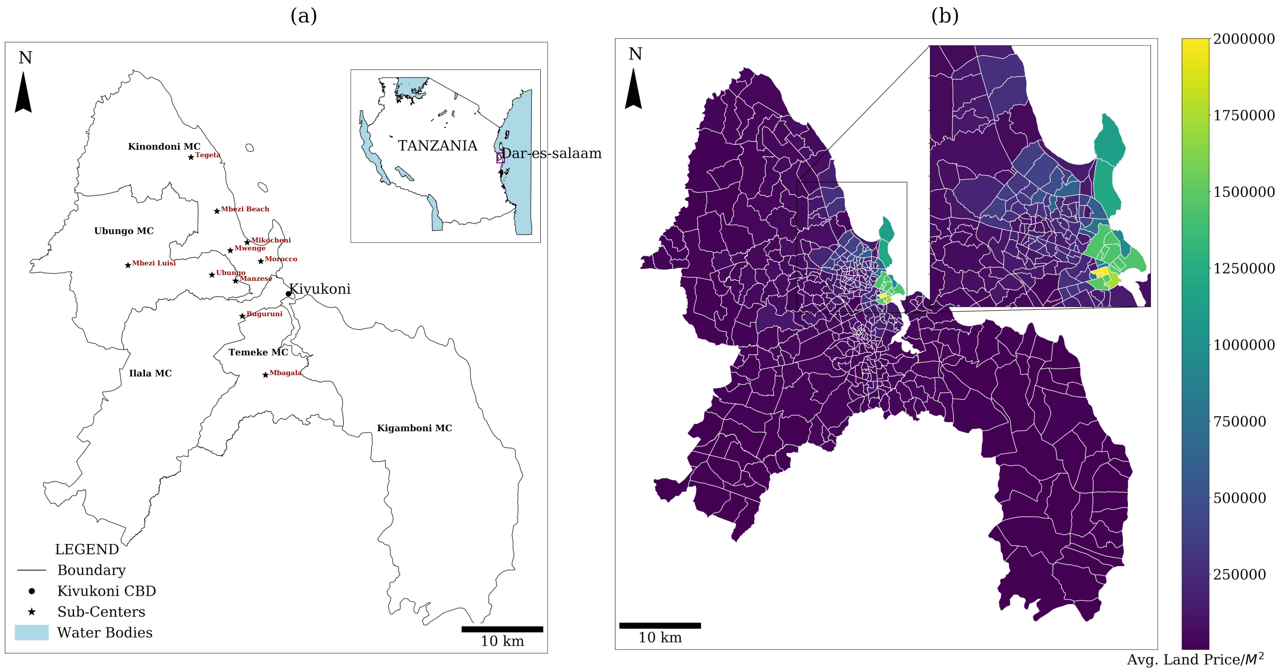

Figure 1: (a) The Dar es Salaam city map in Tanzania with its municipalities (MCs) and CBD location, (b) Mapped Dar es Salaam residential land prices (in Tanzanian Shillings) in 452 sub-wards for the year 2020.

Source: Marandu et al. (2023)

2.2. Data source and pre-processing

Two main types of data were sourced for this study. Firstly, residential land price (RLP) data for the year 2020 were collected from the Government Chief Valuer's office, located in the Ministry of Lands, Housing, and Human Settlements Development. The Chief Valuer's office collects this data through survey methods at specific intervals (every 2-3 years), and the prices are recorded in Tanzanian Shillings (TZS), mostly at the neighbourhood or sub-ward level. Secondly, spatial data, including an administrative map of Dar es Salaam and its 452 sub-ward boundaries, were obtained from the National Bureau of Statistics (NBS) based on the census conducted in 2012.

Average prices were calculated and associated with the respective sub-ward administrative boundaries as aggregate units. Missing data were imputed using the k-Nearest Neighbour (kNN) method (Marandu et al., 2023). Subsequently, a complete sub-ward map and residential land price dataset were generated [Figure 1(b)]. Table 1 presents some descriptive statistics of the RLP data.

Table 1: Basic descriptive statistics of Dar es Salaam residential land prices for the year 2020

No. of records	mean	mode	median	std	Min.	Max.
452	154067.3	35000	53750	306619.72	3750	2000000

2.3. Spatial pattern analysis of residential land price

The spatial pattern analysis in this context refers to analysing the distribution of land prices directly from their defined territorial units or localisation (Souris, 2019). Quantitatively, this includes accounting for the spatial autocorrelation of the phenomena. The spatial autocorrelation is a statistical concept used to define the correlation between the values of objects based on their topological or metric relationships. The resulting coefficient or index accounts for spatial interdependence and reveals the spatial patterns of phenomena, identifying clustering or dispersing patterns that differ significantly from random patterns (Souris, 2019). This concept assumes that spatial dependency exists to a certain extent among the spatial attributes of geographic phenomena (Lee and Li, 2017), reflecting the first law of geography, which states that "everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p.236). For over four decades, spatial autocorrelation and its approaches have been explored in the literature (Anselin and Getis, 2010; Cliff and Ord, 1970). The spatial autocorrelation indices, such as Moran's index or Moran's *I* (1950) and Geary's C (1954), are widely used to assess whether the geographic phenomena under study exhibit spatial autocorrelation (Jiao and Liu, 2012; Souris, 2019).

The following sections present the methods used to investigate the relationship between the spatial distribution of RLPs at the sub-ward level polygon and their proximity. The analysis was performed at both the global and local levels to gain a broad understanding of the spatial distribution of RLPs. The aim was to test whether the geographical distribution of land prices was random or clustered, and to determine their spatial dependence. Autocorrelation indices were used to investigate the global and local clustering of RLPs (Souris, 2019). Therefore, the following steps were performed: (1) testing the null hypothesis by calculating the global spatial autocorrelation Moran's *I*, and (2) assessing the spatial significance of RLP through local indicators of spatial association (LISA) provided by the local Moran's *I*.

2.3.1. Global assessment of spatial autocorrelation of RLP

The spatial autocorrelation coefficient provided an assessment of the spatial dependence of the Dar es Salaam RLP data. Moran's Index, also known as Moran's *I*, is a widely used spatial autocorrelation measure and was applied to test whether the RLP data were spatially clustered, dispersed, or randomly distributed (Lee and Li, 2017; Moran, 1950). Geographically, the RLP data are represented in sub-ward polygons [Figure 1(b)]. Thus, Moran's *I* can be defined as the mean product of the normalised land prices of pairs of polygons, weighted by "spatial weight" which depends on the contiguity between the polygons in our case study area (Souris, 2019). Since normalisation was performed, the index was expected to range between -1.0 and +1.0. If a positive index was obtained, the null hypothesis that the RLP data were randomly distributed was rejected in favour of the alternative hypothesis that the RLP data were clustered, and vice versa. Equation (1) below represents Moran's *I* (Lee and Li, 2017).

$$I = \frac{n\sum\sum w_{ij}(p_i-\bar{p})(p_j-\bar{p})}{\sum\sum w_{ij}\sum(p_i-\bar{p})(p_i-\bar{p})} \tag{1}$$

In equation (1), n represents the total number of sub-ward polygons being analysed, which is 452 for this study. p_i is the land price of a particular sub-ward polygon $i\bar{p}$ is the mean of land prices p. p_j is the land price from the neighbouring polygon j relative to i; and w_{ij} is the calculated spatial weight for the polygons i and j. The study adopted the queen contiguity first-order method to calculate spatial weights and define neighbours. The standardised weight matrix from a queen contiguity method is essential for calculating statistical spatial dependence (Barreca et al., 2017, 2018). The queen contiguity weight was calculated using *libpysal*, and Moran's *I* was calculated using *esda.Moran*, both of which are Python language packages from *PySAL (pysal.org)*.

2.3.2. Local assessment of spatial autocorrelation of RLP

The global spatial analysis explained in the above section (Moran's *I*) provides only the overall spatial autocorrelation of RLPs within Dar es Salaam as our study area (Lee and Li, 2017). However, this section aims to closely examine and detail how the spatial autocorrelation of RLP differs from one sub-ward to another in Dar es Salaam. The study adopts the suggested local indicators of spatial association (LISA) for this type of analysis. LISA, also known as the local Moran's index (see Equation (2)), is the decomposition of the global Moran's *I* (Anselin, 1995).

The main goal of this section, as with previous studies, is to highlight the areas or sub-wards that significantly exhibit positive spatial autocorrelation outcomes (hot spots and cold spots) and those that contribute significantly to negative spatial autocorrelation (potential spatial outliers). To achieve this goal, LISA and Moran scatter plots were derived. The Moran scatter plot visually displayed the spatial relationships and identified local clusters (Barreca et al., 2017). Additionally, a map was produced to highlight sub-wards with realisable local clusters (significant positive) and those that were not significant or were potential spatial outliers. Statistical significance was determined using a p-value threshold of 5% ($p < 0.05$), which was calculated for each LISA result.

The Local Moran's Index is defined by the equation below:

$$I_i = z_i \sum_j w_{ij} z_j \qquad (2)$$

In the equation (2) above, z_i, and z_j represent observed deviations from the mean. The summation over j will only include neighbouring values, thus $j \in J_i$. For the simplified interpretation, the spatial weights w_{ij} are mostly in row standardised form, and by convention $w_{ii} = 0$ (Anselin, 1995). The spatial weights were calculated using the queen contiguity method as explained in the previous section, and the same Python language packages and libraries mentioned were utilised in this section.

3. Results and Discussion

3.1 Global assessment of spatial autocorrelation of RLP

The global assessment of spatial dependence of residential land price (RLP) results yielded Moran's $I = 0.83$ and a p-value = 0.001, indicating that the RLPs are significantly clustered. Therefore, we reject the *null* hypothesis (that the Dar es Salaam RLPs are random) and accept the alternative hypothesis, which states that the Dar es Salaam RLPs are spatially clustered. Figure 2(a) (reference distribution) represents the graphical representation of the empirical test used to obtain the p-value. The p-value = 0.001 implies that only 0.1% of random permutations could produce a larger Moran's *I* than the one observed, while 99.9% would result in a smaller Moran's *I*. Hence, the test results are significant.

The significance of our testing results is further confirmed by the Moran Plot [Figure 2(b)]. The red line represents the best linear fit between the normalised RLP variable (Attribute) and the normalised ordinate spatial lag of the RLP variable (Anselin, 1995; Barreca et al., 2018). The obtained Moran's $I = 0.83$ represents the slope of this linear fit, showing the specific spatial arrangement of the RLPs across space and indicating that a large percentage of the values are concentrated along the line. Thus, the global spatial analysis depicts the positive autocorrelation of the RLPs across space.

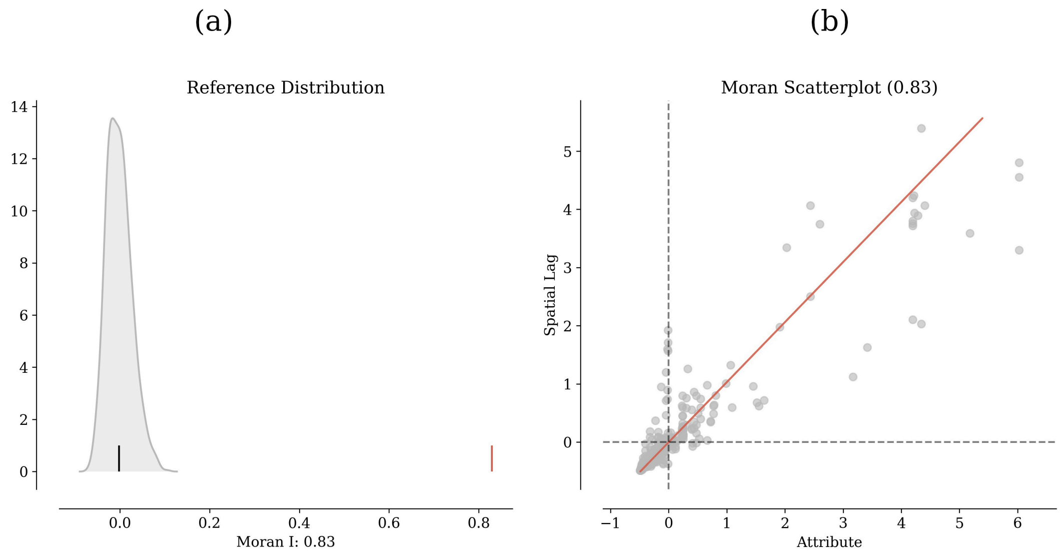

Figure 2: (a) Shows graphical representation of the empirical test and (b) Moran scatter plot showing positive spatial autocorrelation of residential land price in Dar es Salaam.

3.2 Local assessment of spatial autocorrelation of RLP

The local indicators of spatial association (LISA) results are presented in a Moran scatter plot (Figure 3) generated with four descriptive quadrants: High-High (HH), known as hot spots (high prices surrounded by high prices), Low-Low (LL), known as cold spots (low prices surrounded by low prices). Low prices surrounded by high prices are known as Low-High (LH), and high prices surrounded by low prices are known as High-Low (HL), representing the spatial outliers. Colored dots in each quadrant represent statistically significant values at the 5% (p-value < 0.05) level.

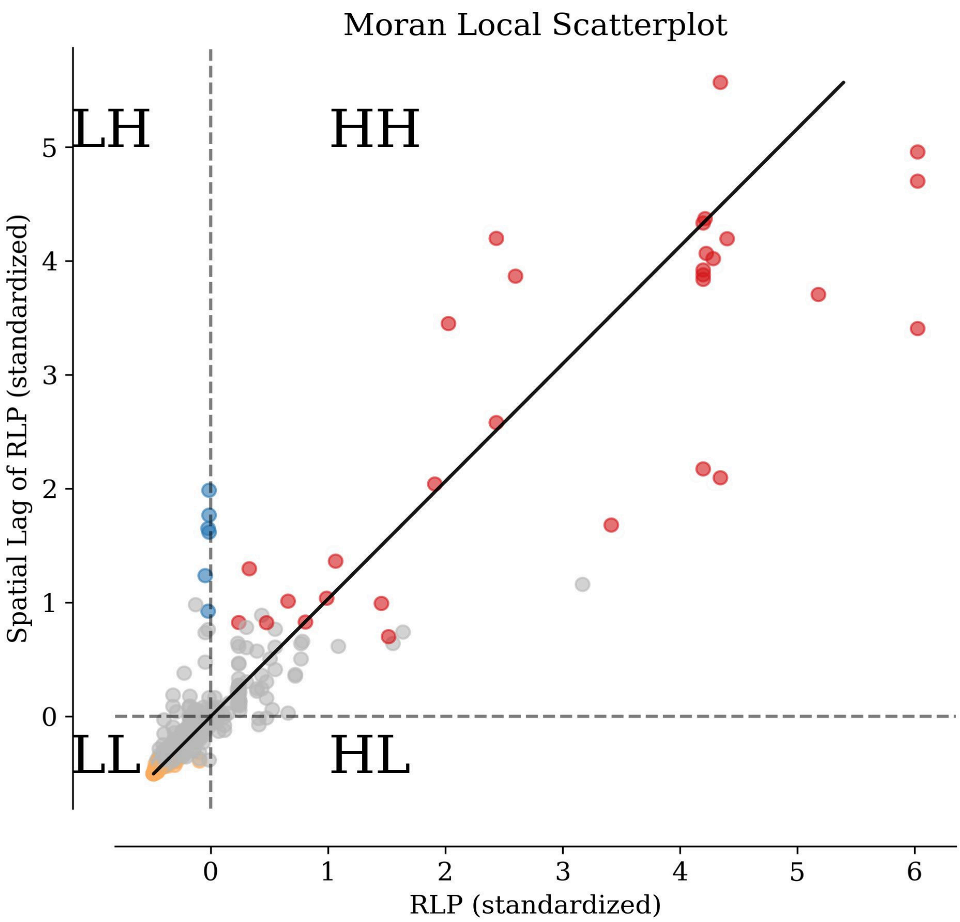

Figure 3: Shows local Moran scatter plot of Dar es Salaam residential land prices with quadrants High-High (HH), Low-Low (LL), Low-High (LH), and High-Low (HL).

From the Moran scatter plot, it is evident that quadrant 1 (Q1), labelled HH and quadrant 3 (Q3), labelled LL, are dominated by a larger number of sub-wards compared to quadrant 2 (Q2), labelled LH and quadrant 4 (Q4), labelled HL. This dominance is further demonstrated by the map in Figure 4(a). The land market is dominated by land prices that are lower than the average, suggesting that the analysed data are right-skewed, as shown by the histogram in Figure 4(b) and the statistical details in Table 1. This skewness aligns with findings from other studies on land price analysis, which demonstrated that land price data tend to be right-skewed and follow non-normal probability distributions such as lognormal (Hu et al., 2013). However, further independent investigation is needed to determine which specific probability distribution best fits the land price data of Dar es Salaam. Moreover, the results could also suggest that the city still follows a monocentric structure.

Additionally, the results could suggest that areas with extremely high prices result from more intensive bidding for space by households with higher incomes. This could be attributed to the availability of important amenities, robust business activity and employment opportunities, easy accessibility, good transport systems, and well-planned land (Alonso, 1960; Brigham, 1965; Grimes and Liang, 2009; Kironde, 2000). However, further independent studies are needed to identify the specific spatial determinants that can better explain the distribution of RLPs in Dar es Salaam.

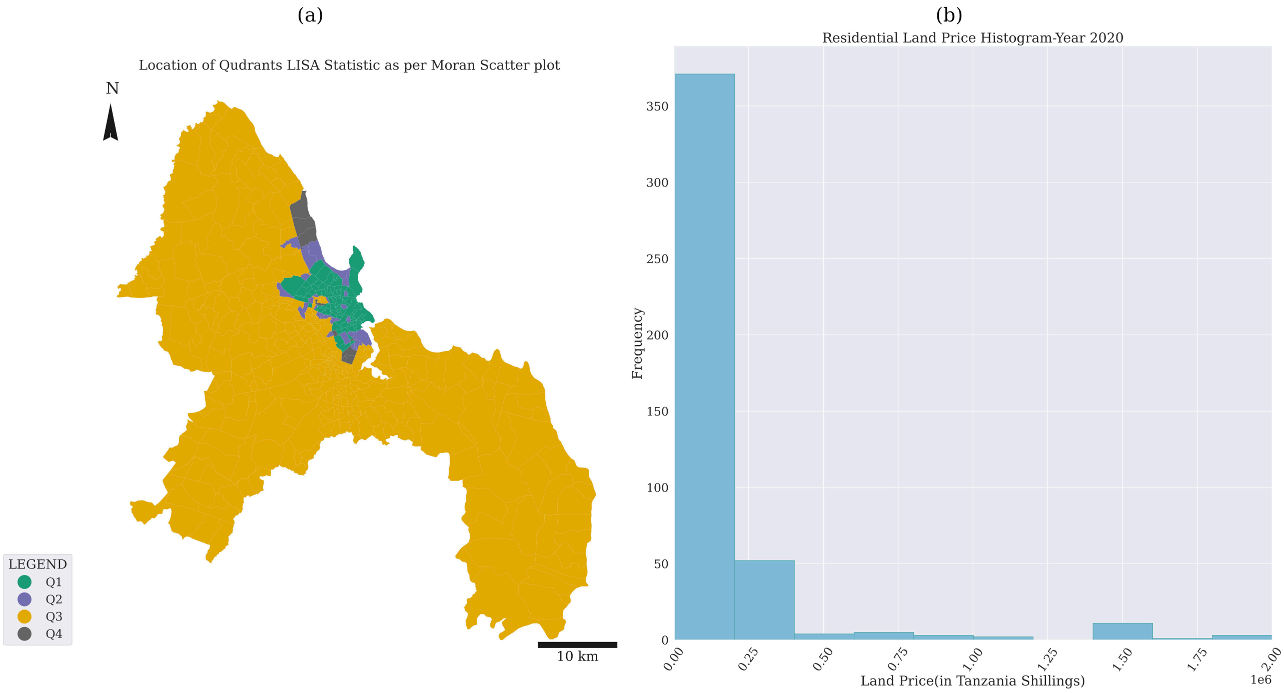

Figure 4: (a) The map shows the location of sub-wards as per local Moran scatter plots quadrants, (b) The histogram shows the frequency of the prices

Considering the significance level for each LISA result with a calculated p-value threshold of 5% (0.05), Figure 5(a) displays the significant and non-significant sub-ward results based on the p-values. Only 159 sub-wards (35%) were found to have significant results, while 293 sub-wards (65%) were deemed non-significant (noise results), as seen in Table 2. Moreover, Figure 5(b) illustrates the sub-wards that are significantly clustered according to the quadrants shown in the local Moran Scatter plot (Figure 3). Specifically, sub-wards characterised by positive local spatial autocorrelation with High-High (HH) land prices show that only 30 out of 88 were significantly clustered, most of which are areas around the city centre (CBD). Similarly, those with positive autocorrelation and Low-Low (LL) land prices show that only 123 out of 327 were significantly clustered, predominantly located on the outskirts of the city.

In addition, sub-wards characterised by negative local spatial autocorrelation (spatial outliers) included only 6 sub-wards out of 27 in the Low-High (LH) price category that were significantly clustered, primarily located not far from the CBD areas. Conversely, all 10 sub-wards categorised as High-Low (HL) with negative autocorrelation results were found to be non-significant (ns). The sub-wards with non-significant p-values begin from areas close to the CBD and extend towards the outskirts of the city with significantly low clustered prices. These results may suggest the presence of socioeconomic services or activities, improved transport, high housing density, and a growing population in those areas. These characteristics progressively decrease and differ as they move further from the CBD towards the outskirts of the city with significantly low-low spatially clustered land prices (Alonso, 1960; Hu et al., 2013). Moreover, these areas are considered metropolitan parts of the city and are characterised by consolidated planned and informal settlements (Three City Land Nexus Research Team, 2020). Furthermore, they contain growing sub-centres [Figure 1(a)] such as Mwenge, Tegeta, Mbezi Beach, Manzese, and Mikocheni (Peter and Yang, 2019), which have evidently contributed to the discrete jumps in RLP as shown in an inset map in Figure 1(b).

Contrarily, those areas with significantly low-low spatially clustered RLP could be regarded as peri-urban areas of the city characterised by socioeconomic challenges such as poor transport infrastructure, social services, and low housing density, as suggested by Wolff et al. (2021). Moreover, these peri-urban areas demonstrated signs of urban sprawl, characterised by low-density development, sparse population, and a significant presence of informal settlements (Bhanjee and Zhang, 2018; Msuya et al., 2021).

Generally, the LISA results might represent the growth and expansion of the land market and the city. The urban land market pattern and city development largely expanded as it moved to the north and west sides from the CBD.

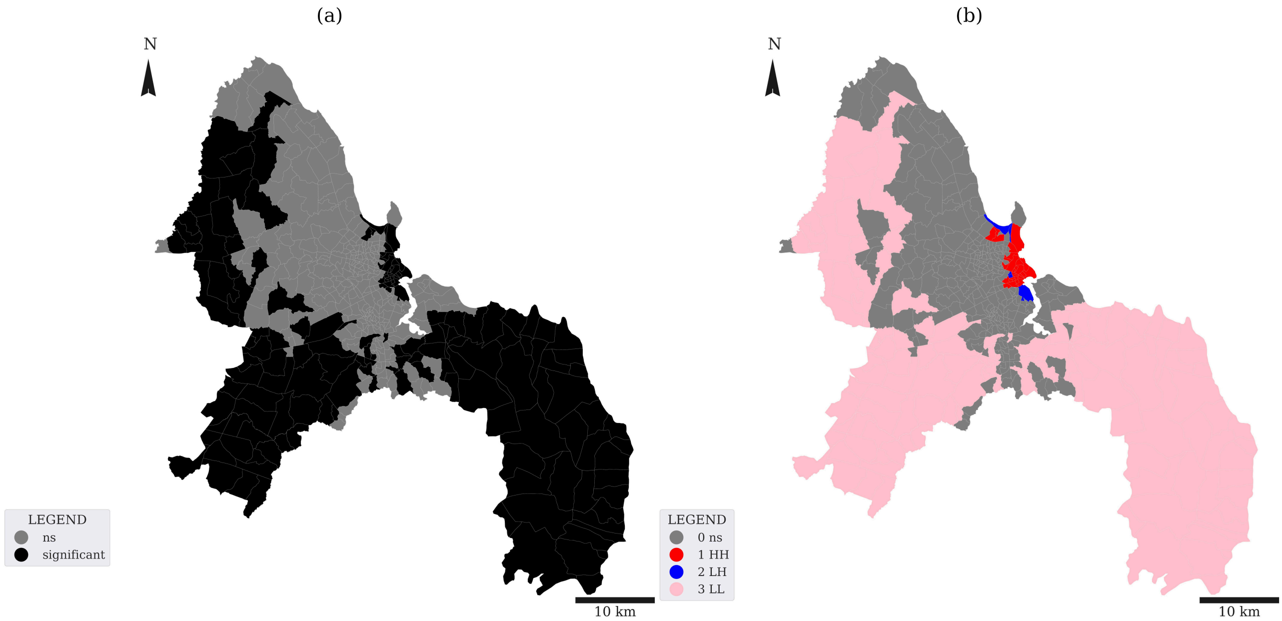

Figure 5: The map (a) shows the sub-wards with significant and non-significant (ns) of local Morans results as per p-value; whilst the map (b) shows significant clustered sub-wards as per quadrants in local moran scatter plot

Table 2: Summary of significant and non-significant LISA's results

	Significant	Not-Significant	Total Number
High-High	30	58	88
Low-High	6	21	27
Low-Low	123	204	327
High-Low	0	10	10
Overall Total Number of sub-wards	**159**	**293**	**452**

4. Conclusion

This study successfully analysed the spatial pattern of RLPs in Dar es Salaam city, Tanzania, at the sub-ward level, capturing their spatial distribution and variation. The study contributes to existing regional and sub-regional literature on land markets, real estate, and urban studies in two key perspectives. Firstly, it reveals the spatial patterns of RLPs in one of Sub-Saharan Africa's fastest-growing cities, which is predominantly characterised by an informal land market, with over 70% of residents living in informal settlements (Andreasen et al., 2020). Before this study, there was a lack of cartographic resources explaining the spatial auto-correlation of land prices in the city. Secondly, the study examined the dynamics of the land market and urban growth of Dar es Salaam by identifying different local clusters, including areas with high, low, and outlier prices. These findings are then connected to existing literature on urban growth and expansion to enhance understanding of these dynamics.

The study applied and utilised the concepts of GISA and LISA by computing global Moran's *I* and local Moran's *I*, respectively. The global analysis convincingly shows that the RLPs in the city are highly spatially clustered rather than random, thus rejecting the null hypothesis. Meanwhile, LISA results demonstrated that most of the sub-wards with clustered RLPs have prices lower than or below the average. Moreover, LISA results demonstrated that only 35% of the Dar es Salaam sub-wards are statistically significantly clustered, primarily located on the outskirts (peri-urban) with lower prices, while only a small portion is around the CBD areas with higher prices. The other 65% of the city's sub-wards exhibit statistically insignificant clustering (noise), representing areas undergoing continuous socio-economic development, experiencing high demand for land, vibrant land price fluctuations between nearby sub-wards, increased housing density and population, and consolidated planned and informal settlements. Therefore, the LISA results can be used to study the expansion of the city's land markets as well as urban growth.

Generally, global and local Moran's *I* proved to be effective tools for studying the spatial distribution and variation of RLPs in Dar es Salaam city. The results could aid decision-making for land management departments, policymakers, investors, and resource allocation. Moreover, the results could be generalised, and the methodological approach could be extended to other cities in the country and in Sub-Saharan Africa that share similar geographic, socioeconomic, urban growth, and land market characteristics. However, further study is needed to reveal the spatial and temporal factors that drive RLPs in Dar es Salaam.

Acknowledgments

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Declaration of Interest

The authors declare that there are no conflicts of interest.

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