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Real Estate Market Dynamics in New Cairo: A Geospatial Perspective Using Spatial Autocorrelation

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ABSTRACT: The integration of spatial autocorrelation models into real estate market analysis has gained significant attention due to the inherent spatial dependence in property values. This study examines the impact of spatial lag on real estate market dynamics, highlighting how spatial interactions among properties influence price formation and market stability. By employing spatial econometric techniques, including Global Moran's I and Local Indicators of Spatial Association (LISA), this research quantifies the degree of spatial dependence and assesses its implications for property valuation and investment decisions. The analysis is based on data collected from 500 properties in New Cairo City, Egypt, geocoded and processed using GIS. Spatial weights matrices and proximity-based modeling were used to interpret the spatial patterns. The findings reveal that spatial lag significantly affects property prices, with clusters of high- and low-value properties emerging due to localized dependencies. High-value clusters are predominantly located in well-developed areas with strong infrastructure and accessibility, while low-value clusters are concentrated in peripheral zones with limited amenities. The spatial lag model confirms a moderate positive spatial autocorrelation, with a coefficient of 0.37, indicating that property values are significantly influenced by neighboring prices. Additionally, the results suggest that transitional zones with lower-priced properties surrounded by high-value areas may indicate future growth and gentrification potential. These insights provide valuable information for policymakers, urban planners, and investors seeking to optimize market strategies, infrastructure planning, and land-use policies. By incorporating spatial dependencies into real estate valuation, this study underscores the importance of geospatial analytics in sustainable urban development and investment decision-making.

1. INTRODUCTION

Urban development and planning and real estate development plays a vital role in economic growth and infrastructure planning. Understand the spatial distribution of the real estate prices or property values is essential in influencing planning and investment decisions. While conventional economic models provide insights into real estate pricing based on supply and demand dynamics, spatial analytics offer a more nuanced perspective by incorporating the geographic dimension of price variations. This study leverages spatial autocorrelation techniques, particularly Global Moran's I and Local Indicators of Spatial Association (LISA), to analyze pricing patterns within New Cairo City, Egypt. This study aims to highlight the underlying spatial dependencies driving properties market values trends in this region by identifying clusters of high and low values.

Spatial autocorrelation analysis provides a framework for measuring the degree to which real estate prices in one location are influenced by those in neighboring areas. Studying global Moran's I examines the overall spatial dependence highlighting the overall picture where high valued properties are clustered together or dispersed around the region. However, the LISA method, by studying the local Moran's I values, examine the region more deep identifying the locations and types of clusters, including hotspots (high-value property clusters), cold spots (low-value property clusters), high-low clusters (expensive properties surrounded by less expensive ones), and low-high clusters (low-priced properties adjacent to higher-value areas).
The findings of this study involve studying and investigating the underlying factors of the clusters giving recommendations for urban planners and investors. Moreover, it could provide a predictive framework by applying a spatial lag model for estimating property pricing in other urban contexts.

Research Objectives
This study has the following research objectives:

- To analyze spatial dependencies in real estate pricing using Moran's I and LISA.
- To identify high-value and low-value clusters and their implications for construction and infrastructure planning.
- To uncover the underlying spatial dependencies that drive housing market trends in the region.
- To develop a predictive spatial model for real estate pricing based on spatial and contextual factors.

Significance
The study bridges the gap between the traditional real estate valuation and construction management through applying geospatial analytics. This will provide the knowledge to stakeholders to make informed decisions.

2. LITERATURE REVIEW

2.1 Spatial Autocorrelation

Studying spatial autocorrelation in construction sites relies on precise and accurate data about the location of various objects and features within construction sites. Thus, there are different methods of assigning the locations to spatial objects depending on the type of objects and the available data. In this section, three types of assigning locations to objects will be used, point objects, irregularly shaped area objects referred to as zones, and regularly shaped area objects referred to as grids. Each of the three types has a special pattern and different applications (Moharram, 2023).

Spatial autocorrelation analysis involves calculating indices to find patterns. Generally, autocorrelation measures are more concerned with the correlation between neighboring observations of a variable. Two main similarities are studied in this area, the similarity of observations (value similarity Wij mentioned in the previous section) and the similarity among locations (Griffith, 2009). This notion is best summarized by Tobler's first law, which states that ‘‘everything is related to everything else, but near things are more related than distant things’’ (Anselin, 1988). Global measures are used to assess whether the spatial pattern is clustered or dispersed across the whole study area and local measures are used to identify hotspots and Coldspots highlighting their locations.

2.2 Spatial Lag

Spatial lag refers to the phenomenon where the value of a property is influenced by the values of neighboring properties. This spatial dependence arises due to factors such as geographic proximity, socio-economic conditions, and urban development patterns. According to Anselin (1988), spatial econometrics provides a robust framework for modeling such dependencies, particularly through spatial autoregressive (SAR) models that capture the impact of adjacent properties on a given property's price.

2.3 Real Estate Market Dynamics

Understanding real estate market dynamics requires accounting for spatial dependencies, as property values are rarely independent of their surroundings. Case et al. (1991) highlighted how price changes in one area often spill over into adjacent locations due to migration trends, economic shifts, and policy interventions. Spatial autocorrelation, as discussed by Can (1992), results in localized market trends that deviate from broader economic patterns, creating clusters of high- or low-value properties.

Empirical research underscores the significance of spatial lag in shaping property markets. Pace et al. (1998) demonstrated that ignoring spatial effects can lead to misleading conclusions in property valuation and market efficiency. LeSage and Pace (2009) introduced Bayesian spatial models to improve price predictions by integrating neighborhood effects, reinforcing the need for spatial econometrics in hedonic pricing models.

Gelfand et al. (2004) applied hierarchical spatial models to analyze price diffusion across market segments, showing that interdependencies significantly influence long-term trends. Holly et al. (2011) further demonstrated how economic shocks in one region can propagate through housing networks, reinforcing the interconnected nature of real estate markets.

The role of spatial lag is also evident in construction planning. Moharram (2021) explored spatial autocorrelation in construction sites, emphasizing how spatial dependencies shape project organization and execution. Similarly, Brasington and Hite (2005) warned that overlooking spatial dependence can lead to pricing errors and inefficient investment strategies, underscoring the importance of spatial analysis in market assessments.

3. METHODOLOGY

3.1 Study Area

Over the past two decades, New Cairo City, an urban extension of Greater Cairo in Egypt has experienced a rapid developed in diverse residential development including gated communities and affordable housing projects. Analyzing the spatial distribution of properties pricing in this region provides valuable insights for strategic urban planning and infrastructure investment.

3.2 Data Collection and Processing

Real estate data (500 property) were collected through online platforms that have property listings. Properties data includes, area, number of bedrooms, number of bathrooms and locations were collected. Data were cleaned and pricing per square meter were calculated to ensure a non-biased analysis. The collected data were standardized and geocoded into GIS. The following framework took place for the analysis:

Grid cells were used to divide the study area to cells (100x100). Euclidean distances were calculated between the centroid of each grid cell to create the weight matrix. All attributes (price per square meter of a given property) are normalized to ensure that all the variables are fairly comparable and neglect any potentially biased results.

3.3 Spatial Autocorrelation Analysis

To examine spatial dependence in real estate pricing, two primary spatial autocorrelation techniques were applied:

Global Moran's I: This measure was employed to assess the overall spatial clustering of real estate prices. A statistically significant Moran's I value indicates a non-random spatial pattern, suggesting either clustering (positive autocorrelation) or dispersion (negative autocorrelation). The Global Moran's I index was calculated using spatial weight matrices to determine the most appropriate spatial relationship definition for the dataset. The global Moran's I is calculated according to the following equation:

Equation 1: Global Moran's I (Anselin, 1988)

$$I = \frac{n}{W_o} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(z_i - \bar{z})(z_j - \bar{z})}{\sum_{i=1}^{n}(z_i - \bar{z})^2}$$

Where n is number of areas in the sample, i,j is any two of the areal units, zi is the value (observation) of the variable of interest for region i, Wij is the similarity of i's and j's locations.

Local Moran's I: This measure was employed to assess the spatial clustering of each grid cells. Local Indicators of Spatial Association (LISA) method was used to detect localized spatial clusters and outliers. This technique enabled the identification of:

- Hotspots: Clusters of high-priced properties, indicating areas of strong investment potential.
- Cold spots: Clusters of low-priced properties, potentially signaling underdeveloped or undervalued regions.
- High-low clusters: High-priced properties surrounded by low-priced properties, suggesting potential spillover effects from high-value zones.
- Low-high clusters: Low-priced properties surrounded by high-priced properties, indicating areas of potential gentrification or market anomalies.

Local Moran's I value is calculated according to the following equation:

Equation 2: Local Moran's I equation (Anselin, 1988)

$$I_i = (z_i - \bar{z}) \sum_{j \in J_i}^{n} W_{ij}(z_j - \bar{z})$$

LISA cluster maps were, then, generated to visualize these spatial patterns, and statistical significance was assessed.

3.4 Data Interpretation and Proximity Analysis

To determine the factors influencing the spatial clustering of real estate prices, additional urban and infrastructural datasets were integrated. The LISA results were layered with road networks, public transport accessibility, and commercial zones to examine the role of accessibility. Additionally, proximity to essential amenities was assessed through network analysis. Land use zoning and planned developments were mapped to analyze their impact on real estate pricing. This process enabled a deeper understanding of the underlying causes shaping the real estate pricing landscape in New Cairo City, Egypt.

3.5 Spatial Lag

Spatial Lag model was developed to provide a predictive tool for property values in the given region. The model accounts for the influence of the property values in the neighborhood to the property in a given location. The spatial lag model was developed according to Equation 3 as follows:

Equation 3: Spatial Lag Equation (Anselin, 1988)

$$Y = \rho WY + X\beta + \epsilon$$

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where:

- Y is the dependent variable
- W is the spatial weights matrix, defining the influence of neighboring locations.
- ρ is the spatial autoregressive coefficient, showing the strength of spatial dependence.
- $X\beta$ represents other explanatory variables.
- ϵ is the error term.

The predictive tool will work according to the following workflow:

1. The user identifies the coordinates of the given property location
2. The model will locate the given coordinates to be matched to a given cell (area)
3. The model will calculate the Spatial Lag Value which is the weighted average of the attribute values in neighboring cells for a specific cell
4. Predict the Attribute

4. RESULTS AND DISCUSSION

4.1 Data Visualization

Data were collected and were geocoded on GIS as shown in Figure 1 where most of the data are in the east part of New Cairo City.

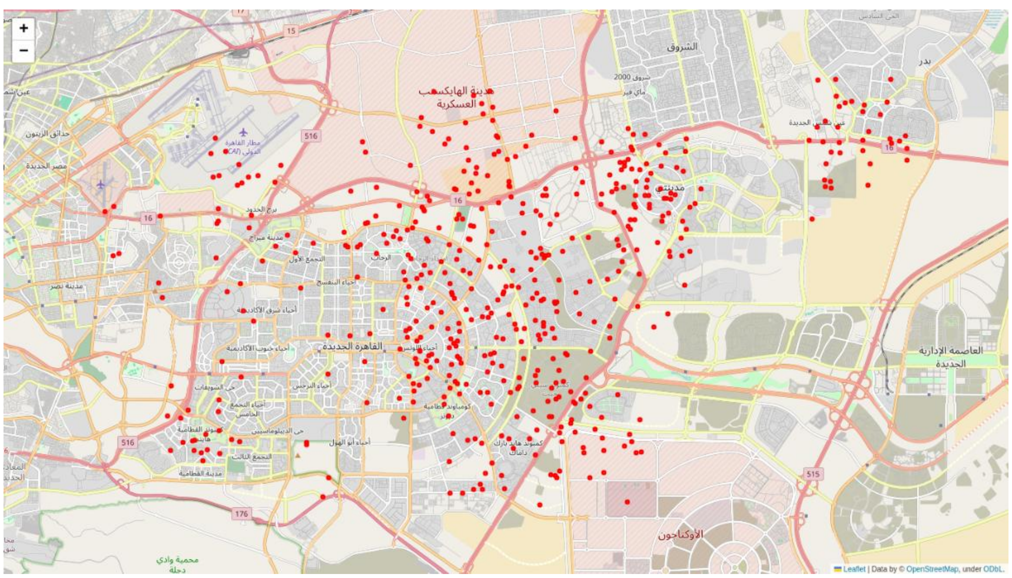

Figure 1: Data Points on Map

4.2 Spatial Autocorrelation Analysis

The global Moran's I value was calculated as 0.24, indicating a moderate positive spatial autocorrelation confirming that housing prices are not randomly distributed but exhibit distinct clusters of high and low values. The LISA analysis further provided granular insights into the specific locations of these clusters as shown in Figure 2.

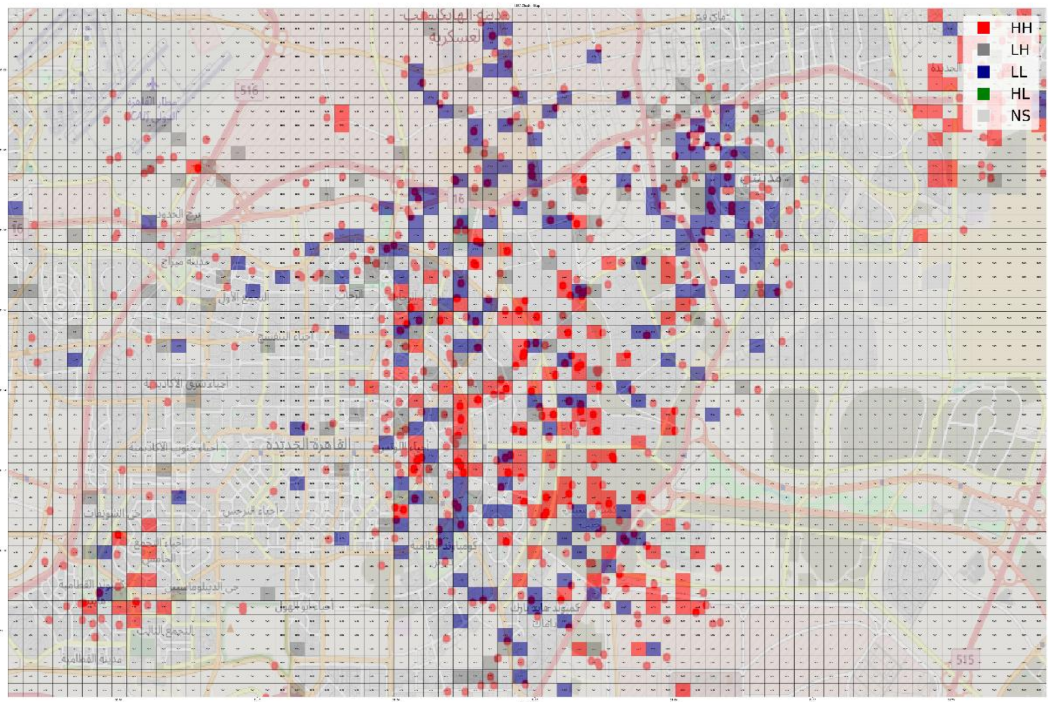

Figure 2: LISA Cluster Map

Following the geo-mapping, the LISA cluster analysis was applied to identify statistically significant spatial clusters. The results showed:

- Hotspots (HH): 13 zones, mainly located in well-developed areas with robust infrastructure and high demand.
- Cold spots (LL): 168 zones, primarily in underdeveloped areas lacking essential urban services.
- Low-high clusters (LH): 118 zones, indicative of transitional zones where lower-priced properties exist near high-value developments.
- No high-low clusters (HL): Suggesting a lack of isolated high-value properties in otherwise low-value areas.

4.3 Analysis of Underlying Causes

Closer of analysis of the LISA map highlights the underlying factors of the factors influencing the spatial patterns. Areas of HH clusters were investigated, it was found that these zones are predominantly found in regions with strong communities to commercial hubs in New Cairo City such as Mivida Compound, Golden Square, Kattameya Heights. These areas are strongly connected to main roads indicating higher accessibility of properties. Conversely, cold spots are concentrated in peripheral zones with limited infrastructure, lower population density, and fewer amenities

Areas of LH clusters were investigated it suggest emerging development areas where lower-priced properties are surrounded by higher-value zones, potentially signaling future growth or gentrification trends. The lack of having HL zones is predictable since premium properties are rarely to be surrounded by low-value neighborhoods.

4.4 Spatial Lag

For further analysis of the spatial dependencies in properties values, a spatial lag model was developed using the influence of the values of neighboring properties on the target property prices. The model aimed to quantify how price variations propagate across geographic space and assess the strength of spatial dependence in New Cairo’s housing market.

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                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                 -0.001
Method:                 Least Squares   F-statistic:                    0.6320
Date:                Fri, 07 Feb 2025   Prob (F-statistic):              0.427
Time:                        22:58:43   Log-Likelihood:                -5841.0
No. Observations:                 497   AIC:                         1.169e+04
Df Residuals:                     495   BIC:                         1.169e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       4.55e+04   3.33e+04      1.365      0.173      -2e+04    1.11e+05
x1            0.3682      0.463      0.795      0.427      -0.542       1.278
==============================================================================
Omnibus:                       72.445   Durbin-Watson:                   1.865
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              112.366
Skew:                           0.934   Prob(JB):                     3.98e-25
Kurtosis:                       4.391   Cond. No.                     1.74e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.74e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
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Figure 3: Regression Model

A regression analysis was conducted using the spatially lagged price variable as a predictor as shown in Figure 3. The final regression equation in Equation 4 derived from the model is:

Equation 4: Spatial Lag Regression Model

$$attribute = 45500.83 + 0.37 * spatial\ lag + error$$

The spatial lag coefficient (0.37) shows that for every unit increase in the spatially lagged property price, the target property price increases by 37% of that amount. The model confirms the positive spatial autocorrelation dependencies, where properties values are influenced by their neighbouring prices.

4.5 Potential impact

The findings of this study provide key insights into the spatial distribution of real estate prices in New Cairo, offering implications for various stakeholders, including investors, policymakers, urban planners, and real estate developers. The identified spatial clusters of property values highlight the structured nature of urban growth in this rapidly developing city and provide valuable guidance for future decision-making.

Investment Strategies

The spatial clustering of high-value properties (hotspots) within well-developed areas, such as Mivida Compound, Golden Square, and Kattameya Heights, suggests a strong preference for regions with robust infrastructure and accessibility. Investors can leverage these insights to identify emerging high-growth zones, particularly areas classified as low-high clusters, which indicate transitional neighborhoods with future development potential. Understanding the impact of spatial dependencies on pricing trends can optimize investment portfolios and mitigate risks associated with underdeveloped regions.

Urban Planning and Infrastructure Development

The concentration of cold spots in peripheral zones underscores the need for strategic infrastructure planning to balance urban expansion. The spatial lag model highlights how property values in underdeveloped areas can benefit from proximity to high-value clusters, reinforcing the importance of targeted infrastructure investments. Policymakers and planners should prioritize improving accessibility, transportation networks, and public services in cold spot areas to enhance their attractiveness and promote sustainable urban development.

Transportation and Accessibility

The study's results indicate a strong correlation between high-value clusters and proximity to major transportation routes and commercial hubs. This emphasizes the need for integrating real estate planning with transportation infrastructure. Enhanced public transit accessibility can elevate property values in currently undervalued areas, potentially reducing spatial inequality and supporting inclusive urban growth.

Regulatory and Policy Implications

Real estate regulations, zoning laws, and government incentives play a crucial role in shaping the spatial distribution of property prices. The identified clusters can guide policy interventions, such as tax incentives for development in cold spots or stricter zoning regulations in already congested high-value areas to maintain balanced growth. Moreover, predictive models based on spatial lag analysis can assist authorities in forecasting real estate trends and implementing proactive policies to regulate market fluctuations effectively.

Predictive Model for Real Estate Valuation

The spatial lag model developed in this study provides a powerful tool for estimating property prices based on geographic dependencies. Real estate professionals and financial institutions can integrate this model into valuation methodologies to enhance pricing accuracy. By considering spatial dependencies, valuation models can better account for market trends and improve real estate appraisals for financing and investment purposes.

Overall, these insights reinforce the necessity of incorporating spatial analysis in real estate planning and market evaluations. The structured nature of real estate pricing in New Cairo, as revealed through this study, highlights the influence of accessibility, infrastructure, and urban zoning on housing market trends.

5. CONCLUSION & RECOMMENDATIONS

This study employed spatial autocorrelation analysis to examine the geographic distribution of real estate prices in New Cairo, identifying significant spatial clusters and underlying factors influencing property values. The findings confirm a moderate positive spatial autocorrelation, with pricing trends exhibiting clear clustering patterns driven by accessibility, infrastructure, and urban planning.

Key conclusions include:

- Hotspots of high-value properties are concentrated in well-developed, accessible regions with strong infrastructure, whereas cold spots are predominantly found in peripheral areas with limited amenities.
- Low-high clusters indicate areas of potential growth, suggesting that transitional zones near high-value developments could experience future price appreciation.
- Spatial lag effects confirm that property values are significantly influenced by neighboring prices, reinforcing the need for localized investment strategies and planning interventions.

Based on these findings, the following recommendations are proposed:

1. Urban Development and Planning

   - Prioritize the infrastructure investments in cold spot areas to stimulate development and attract investment.
   - Implement mixed-use zoning policies to encourage balanced urban growth and reduce market disparities.
   - Enhance public transportation connectivity to improve accessibility and increase property values in undervalued areas.

2. Investment Strategies

   - Real estate investors should focus on transitional low-high clusters as potential high-return opportunities.
   - Developers should incorporate spatial dependencies into feasibility studies to optimize project locations and maximize returns.

3. Policy and Regulation

   - Introduce tax incentives or subsidies for developers investing in cold spot regions to encourage balanced urban expansion.
   - Enforce zoning laws that prevent market saturation in high-density areas while promoting controlled development in emerging regions.

4. Predictive Modeling and Data Utilization

   - Further refine the spatial lag model by incorporating additional socio-economic variables such as population growth, income levels, and employment density.
   - Develop a real-time GIS-based decision support system for urban planners and investors to track spatial market trends and forecast pricing fluctuations.
   - By integrating spatial autocorrelation analysis into real estate market evaluations, this study underscores the importance of geospatial data in shaping sustainable urban development strategies. Future research can extend these methodologies to other urban contexts, further refining predictive models for real estate valuation and market forecasting.

6. RECOMMENDATIONS

This study acknowledges certain limitations. First, the data sample is limited to 500 properties sourced from publicly available online platforms, which may not comprehensively represent all real estate dynamics in New Cairo. Second, the spatial lag model considered a limited set of variables, primarily focusing on pricing and spatial location.

Future research could incorporate additional variables such as property age, building attributes, proximity to facilities, and socio-economic indicators. Expanding the dataset and applying the methodology to different urban contexts may also help validate and enhance the robustness of the findings.

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