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Spatial Dependencies in Construction Cost Prediction A Multi-Source Spatial Lag Analysis of Project Locations and Material Supply Networks

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ABSTRACT: This study investigates the spatial distribution of housing costs for finishes and painting in New Cairo using spatial autocorrelation analysis. Traditional cost estimation methods often overlook the influence of spatial dependencies, yet construction costs exhibit distinct geographic patterns driven by supplier proximity, infrastructure, and urban development trends. The global Moran's I value (0.68) confirms a moderate positive spatial autocorrelation, indicating that housing costs are not randomly distributed but form significant clusters. Local Indicators of Spatial Association (LISA) analysis further reveals high-cost hotspots concentrated in well-developed areas farther from suppliers, while low-cost clusters are primarily located near supply sources, benefiting from reduced transportation expenses. Additionally, low-high transition zones suggest areas undergoing development where prices may rise as infrastructure improves.

To quantify these spatial effects, a spatial lag model is developed, demonstrating that both supplier distance and neighboring cost values significantly influence local prices. The model highlights the importance of accessibility in cost variations, reinforcing the need for strategic supplier placement and optimized logistics in construction planning. These findings provide valuable insights for urban planners, developers, and investors, emphasizing the role of geospatial analysis in cost management and decision-making. By integrating spatial dependencies into construction cost assessments, this research contributes to a more comprehensive understanding of pricing dynamics, offering practical applications for future cost optimization and sustainable urban growth.

1. INTRODUCTION

Construction cost estimation is influenced by various factors, including material prices, labor costs, project specifications, and market conditions. However, spatial dependencies, particularly in relation to supplier accessibility and regional market dynamics, remain underexplored in cost modeling. Geographic variations in supply chains and material transportation introduce significant cost disparities, particularly in urban areas where supplier distribution and infrastructure conditions vary across different locations.

In New Cairo (126), housing costs for finishes and painting exhibit spatial variations that warrant further investigation. Spatial autocorrelation analysis offers a methodological framework for identifying clustering patterns in cost distributions, revealing the extent to which cost variations are geographically dependent. Global Moran's I and Local Indicators of Spatial Association (LISA) cluster mapping provide insights into spatial patterns, including hotspots, cold spots, and areas of spatial anomalies.

To further analyze cost variations, a spatial lag model incorporating the distance to the nearest supplier as a dependent variable is considered. This approach allows for an assessment of how supplier accessibility influences pricing trends and cost clustering. Integrating spatial econometrics with construction cost analysis contributes to a more comprehensive understanding of the factors shaping housing costs, particularly in rapidly growing urban environments.

1.1 Research Objectives

This study focuses on the spatial distribution of housing costs for finishes and painting in New Cairo (126) and examines the role of supplier proximity in cost variations. The primary objectives include:

- Identifying spatial clustering in housing costs through spatial autocorrelation analysis, utilizing Global Moran's I and LISA cluster mapping.
- Assessing the impact of supplier accessibility on cost variations by incorporating the distance to the nearest supplier into a spatial lag model.
- Enhancing cost estimation methodologies through the integration of spatial dependencies in construction cost analysis.
- Providing insights into cost distribution patterns to support decision-making in construction planning, supplier selection, and budgeting.

1.2 Significance

Understanding the spatial distribution of construction costs is essential for optimizing resource allocation and cost estimation. This study enhances cost modeling by incorporating spatial autocorrelation and supplier proximity, providing insights into how location influences material pricing. By integrating spatial lag analysis, the research offers a data-driven approach to identifying cost clusters and supply chain inefficiencies. The findings support more accurate budgeting, procurement planning, and decision-making for construction professionals operating in geographically diverse markets.

2. LITERATURE REVIEW

2.1 Spatial Autocorrelation

Analyzing spatial autocorrelation in construction requires precise geospatial data to accurately define the location of various objects and features within a site. Different methods are used to assign spatial attributes depending on the type of objects and data availability. The three primary approaches include point-based representation, irregularly shaped zones, and structured grid-based divisions. Each method serves distinct analytical purposes, with point objects commonly used for tracking resource movement, zones for localized land-use analysis, and grids for broader spatial distribution assessments (Moharram, 2023).

Spatial autocorrelation analysis quantifies the degree to which a variable's values correlate across neighboring locations. This relationship is evaluated based on two key aspects: the similarity in observed values and the spatial proximity between locations (Griffith, 2009). Tobler's First Law of Geography states that "everything is related to everything else, but near things are more related than distant things" (Anselin, 1988), emphasizing the significance of spatial relationships in cost distribution. Global measures assess overall spatial clustering or dispersion, while local indicators of spatial association (LISA) identify specific hotspots and cold spots, providing detailed insights into spatial cost patterns.

2.2 Spatial Lag

Spatial lag describes the dependency of a property's value on the characteristics of its neighboring locations. This spatial dependence arises due to various factors, including geographic proximity, market dynamics, and regional development trends. Previous research has applied spatial lag models in urban housing, real estate pricing, and infrastructure evaluation. For example, McCord et al. (2014) demonstrated the use of spatial lag in modeling rental prices in UK housing markets. Gelfand et al. (2004) applied hierarchical models to reveal interdependence across housing segments.

Anselin (1988) highlights the role of spatial econometrics in modeling these dependencies, particularly through spatial autoregressive (SAR) models. These models account for the influence of adjacent properties, capturing the extent to which location-specific factors drive cost variations. By incorporating spatial lag effects, cost estimation models achieve greater accuracy in predicting localized construction expenses.

2.3 Real Estate Market Dynamics

Supplier proximity significantly influences construction costs where projects farther from suppliers tend to incur higher costs, particularly for materials such as finishes and paint, where transportation and logistical factors contribute to price variations. Holguín-Veras et al. (2012) highlight that projects closer to supply hubs benefit from lower costs due to reduced transportation expenses, while remote projects face higher material prices due to logistical inefficiencies and limited supplier competition (Skitmore & Smyth, 2009). The spatial distribution of suppliers impacts both direct procurement costs and indirect factors such as material availability and delivery times (Teye et al., 2018).

Spatial econometric studies emphasize the role of supplier networks in shaping construction costs. LeSage and Pace (2009) argue that incorporating supplier distance into cost estimation models enhances predictive accuracy by capturing spatial dependencies. McCord et al. (2014) note that urban projects clustered near supplier hubs experience cost advantages, while peripheral developments often incur price premiums due to supply chain constraints. Additionally, Ballesteros-Pérez et al. (2018) suggest that supply chain connectivity influences not only material costs but also overall project efficiency, including labor and equipment availability.

Integrating supplier proximity into spatial cost models allows for a more comprehensive analysis of construction expenses. By quantifying the impact of supplier accessibility on spatial cost variations, this study contributes to a better understanding of cost clustering and procurement efficiency for finishes and painting in New Cairo (126).

3. METHODOLOGY

3.1 Study Area

New Cairo (126), a major residential and commercial district within New Cairo City, has witnessed significant urban expansion. The area includes various housing developments ranging from high-end residential compounds to middle-income housing. Understanding the spatial distribution of construction costs for finishes and painting in this region provides critical insights into cost variations and supply chain efficiencies.

3.2 Data Collection and Processing

Data on housing costs for finishes and painting were collected for 126 housing units in New Cairo. The dataset includes cost records, location information, and supplier details. To ensure consistency and reliability, data were cleaned and standardized before analysis. The spatial component was geocoded into a GIS framework to enable spatial analysis. A representative sample is illustrated in Figure 1.

The study utilizes spatial autocorrelation techniques to assess cost distribution. Grid cells were used to divide the study area. Euclidean distances between housing units and suppliers were calculated to construct a spatial weights matrix. Normalization techniques were applied to ensure comparability of cost variations across different locations.

3.3 Spatial Autocorrelation Analysis

To examine spatial dependencies in construction costs, both global and local spatial autocorrelation measures were applied:

Global Moran's I

This index was calculated to assess whether construction costs exhibit clustering or dispersion across the study area. A statistically significant Moran's I value indicates a non-random spatial pattern, either clustered (positive autocorrelation) or dispersed (negative autocorrelation).

The Global Moran's I formula is expressed as:

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 method was applied to detect local spatial clusters and outliers in construction costs. LISA cluster maps were generated to classify:

- Hotspots: High-cost clusters indicating expensive areas.
- Cold spots: Low-cost clusters suggesting cost-efficient zones.
- High-low clusters: High-cost locations surrounded by low-cost areas.
- Low-high clusters: Low-cost locations surrounded by high-cost areas.

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 generated to visualize these spatial patterns, and statistical significance was assessed.

3.4 Data Interpretation and Proximity Analysis

To analyze the impact of supplier proximity on cost variations, the locations of finishing and painting suppliers were mapped. Distance to the nearest supplier was calculated for each housing unit. Additional contextual layers, including road networks and accessibility, were integrated to assess cost influences beyond spatial clustering.

3.5 Spatial Lag

A spatial lag model was developed to quantify the effect of supplier proximity on construction costs. The model accounts for spatial dependencies by incorporating neighboring cost influences. The spatial lag model was developed according to Equation 3 as follows:

Equation 3: Spatial Lag Equation (Anselin, 1988)

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

where:

- Y is the dependent variable (construction cost per square meter)
- 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 model follows this workflow:

- Identify the coordinates of the housing unit.
- Locate the corresponding grid cell in the study area.
- Compute the spatial lag value, representing the weighted average cost in neighboring locations.
- Predict the cost based on spatial and explanatory variables.

4. RESULTS AND DISCUSSION

4.1 Data Visualization

The collected data on housing costs for finishes and painting were geocoded and mapped using GIS. Figure 1 illustrates the spatial distribution of data points, with a notable concentration in the eastern part of New Cairo.

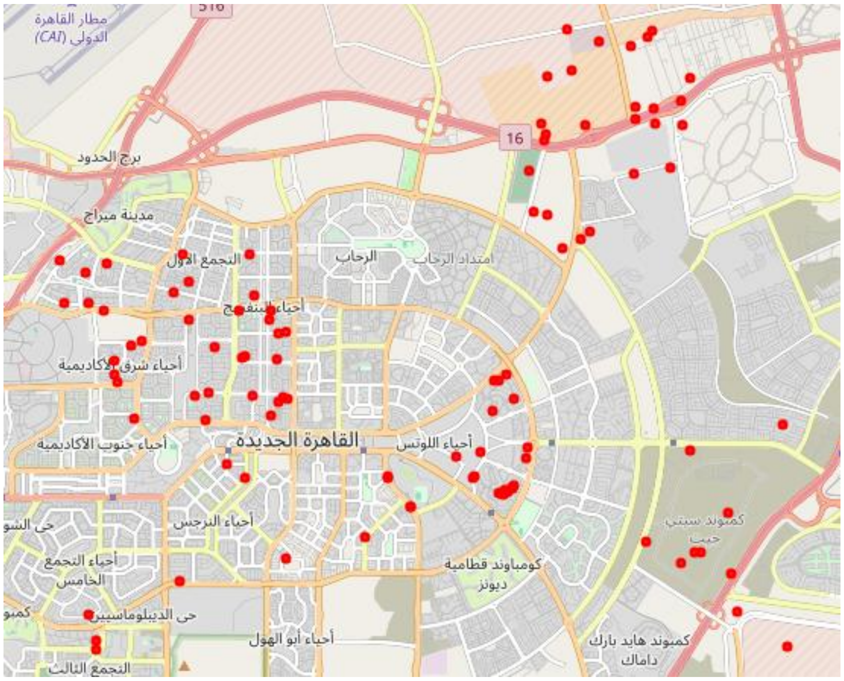

Figure 1: Data Points on Map

4.2 Spatial Autocorrelation Analysis

The global Moran's I value was calculated as 0.68, indicating a moderate positive spatial autocorrelation. This suggests that housing costs for finishes and painting are not randomly distributed but instead exhibit distinct spatial clustering of high and low values. The Local Indicators of Spatial Association (LISA) analysis provided further insight into these clusters, as depicted in Figure 2.

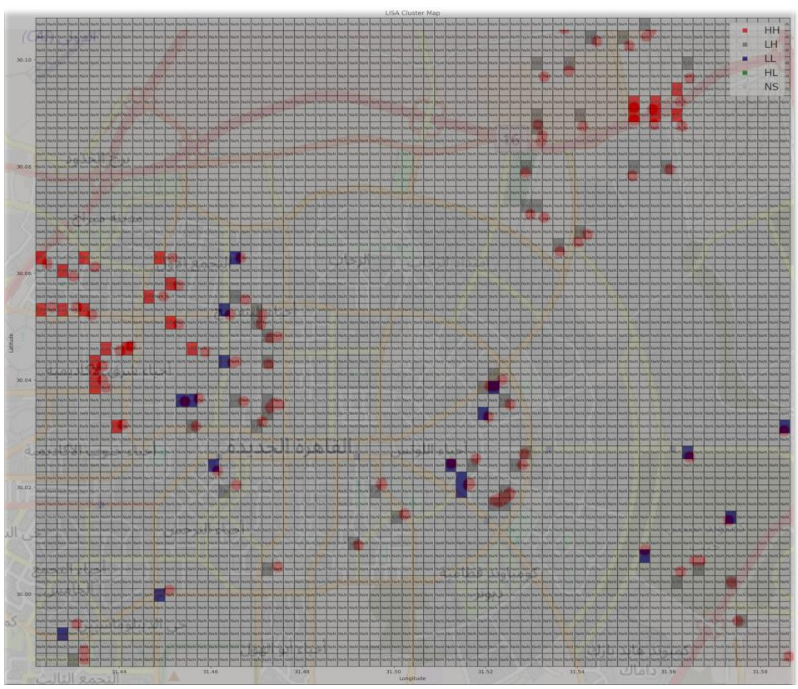

Figure 2: LISA Cluster Map

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

- Hotspots (HH)
  23 zones, primarily located in high-end residential areas with strong infrastructure and accessibility

- Cold spots (LL)
  17 zones, mainly found in areas with limited development and supplier presence

- Low-high clusters (LH)
  45 zones, representing transitional regions where lower-cost projects exist near high-cost developments

Figure 3 presents the LISA map with supplier locations highlighted in green, reinforcing the observed relationship between supplier proximity and cost variations.

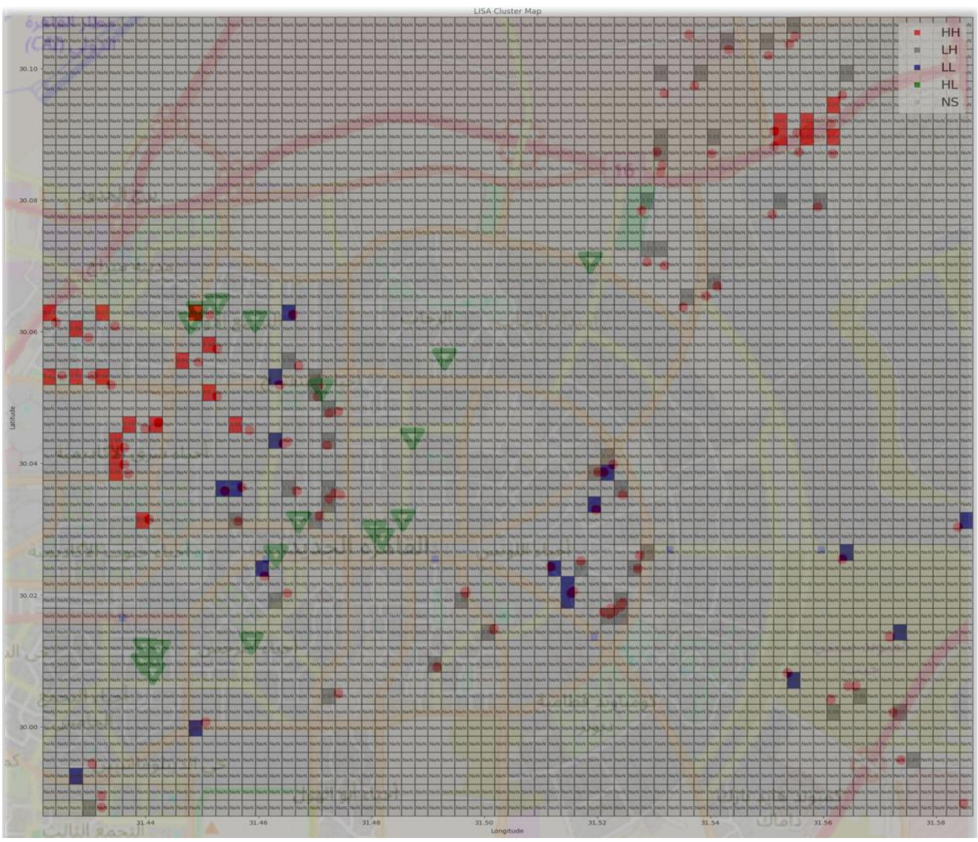

Figure 3: LISA Cluster map with suppliers

4.3 Analysis of Underlying Causes

A closer analysis of the LISA map, particularly when overlaid with supplier locations, reveals key insights into cost distribution:

- Hotspots tend to be farther from suppliers, located in high-demand areas, where increased transportation costs contribute to higher prices.

- Cold spots are concentrated near suppliers, benefiting from reduced material transportation costs and lower demand for high-end finishes.
- Low-high clusters indicate areas undergoing transformation, where cost differences could be leveraged for investment and future growth.

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 pf 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:                       0.265
Model:                            OLS   Adj. R-squared:                  0.247
Method:                 Least Squares   F-statistic:                     14.80
Date:                Mon, 24 Feb 2025   Prob (F-statistic):           3.26e-06
Time:                        19:48:04   Log-Likelihood:                -766.07
No. Observations:                  85   AIC:                             1538.
Df Residuals:                      82   BIC:                             1545.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -9421.2914   2387.366     -3.946      0.000   -1.42e+04   -4672.060
x1             3.7013      0.680      5.439      0.000       2.348       5.055
x2          4.701e+04   1.32e+04      3.561      0.001    2.07e+04    7.33e+04
==============================================================================
Omnibus:                       17.850   Durbin-Watson:                   1.715
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               21.738
Skew:                           1.046   Prob(JB):                     1.90e-05
Kurtosis:                       4.327   Cond. No.                     1.91e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.91e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
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Figure 4: Regression Model

$R^2 = 0.265$. While this value may appear modest, it is acceptable in spatial econometric contexts where local variations and unexplained heterogeneity are high. The model captures key spatial patterns and supplier proximity effects, providing actionable insights even with moderate explanatory power.

To better understand spatial dependencies in construction costs, a spatial lag model was developed, incorporating the influence of neighboring property costs and supplier proximity. The final regression equation in Equation 4 derived from the model is:

Equation 4: Spatial Lag Regression Model

$$attribute = -9421.29 + 3.70 * spatial\ lag + 47010.91 * min\ distance + error$$

The spatial lag coefficient (3.70) indicates that for every unit increase in the spatially lagged construction cost, the target cost increases by 3.70 units, confirming positive spatial dependency. The minimum distance to the nearest supplier coefficient (47010.91) demonstrates that as the distance from suppliers increases, costs rise due to higher transportation and logistical expenses.

4.5 Potential impact

Cost Management Strategies

The identification of cold spots near suppliers presents an opportunity for cost-efficient material procurement and project planning. Developers can optimize logistics to mitigate rising costs in hotspot areas.

Urban Planning and Infrastructure Development

The study underscores the role of supplier accessibility in cost variations. Policymakers should focus on improving infrastructure in cold spot areas to balance cost disparities and support sustainable urban expansion.

Investment and Real Estate Market Considerations

The clustering of high-cost areas in prime residential zones suggests that supplier accessibility significantly influences construction costs. Investors can utilize these insights to assess market trends and identify areas with potential for cost-efficient developments.

5. CONCLUSION & RECOMMENDATIONS

This study employed spatial autocorrelation analysis to examine the geographic distribution of housing costs for finishes and painting in New Cairo, identifying significant spatial clusters and key factors influencing cost variations. The findings confirm a moderate positive spatial autocorrelation, with cost trends shaped by supplier proximity, infrastructure, and urban development patterns. High-cost hotspots are primarily located in well-developed areas that are farther from suppliers, whereas low-cost clusters tend to be near suppliers, benefiting from logistical advantages. The identification of low-high transition zones highlights areas with the potential for future cost increases as development progresses. Additionally, the spatial lag effect confirms that construction costs are influenced by neighboring values and supplier distance, underscoring the role of spatial dependencies in cost dynamics.

Based on these insights, several recommendations are proposed. From an urban development perspective, investing in infrastructure improvements in low-cost zones can stimulate development and attract investment, while zoning policies should encourage balanced urban expansion to reduce extreme cost disparities. Enhancing transportation networks can improve supplier accessibility and mitigate cost inefficiencies. In terms of cost optimization, developers should prioritize supplier proximity when planning projects to minimize material costs and logistics expenses, while construction firms should integrate spatial data analysis into cost planning to predict price fluctuations and optimize procurement. Policy interventions, such as incentives for developers investing in low-cost zones, can promote balanced growth, and zoning regulations should control market saturation in high-cost areas while supporting development in emerging zones. Finally, predictive modeling can be refined by incorporating additional socio-economic variables such as labor costs and material availability. GIS-based decision support systems can further assist urban planners and developers in monitoring spatial cost trends and predicting market shifts.

By integrating spatial autocorrelation analysis into construction cost assessments, this study highlights the importance of geospatial data in optimizing project planning, investment strategies, and urban development. Future research can expand these methodologies to other construction sectors, further refining predictive models for cost estimation and market forecasting.

While this study confirms that transportation costs affect housing prices, we acknowledge that other factors (e.g., labor rates, rental values, property taxes) may also contribute. These confounding variables were not controlled in this analysis and should be explored in future work. Further model refinements can improve explanatory strength by including additional socio-economic and contextual data.

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