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Research article

Uncovering the Spatial Logic of Tourism Attractions: A Geospatial Analysis of Distribution Patterns and Driving Forces in Luxor, Egypt

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Abstract

The spatial distribution of tourism attractions plays an important role in shaping visitor travel behaviour, accessibility to tourism locations, and tourist destination management and planning. This study examines the spatial patterns of tourism attractions in Luxor Governorate, Egypt, and the factors influencing these spatial relationships using a variety of geospatial analysis techniques. These techniques include Nearest Neighbour Index (NNI), Standard Deviational Ellipse (SDE), Kernel Density Estimation (KDE), and Local Moran's I. In addition, a combination of the Analytic Hierarchy Process (AHP) and Geodetector were applied to determine which of sixteen identified factors influenced the distribution of tourist attractions in Luxor. Finally, the spatial relationships between the identified factors and the distribution of tourist attractions were analysed through the use of Multiscale Geographically Weighted Regression (MGWR). The results show that there is a strong clustering of tourism attractions in Luxor within three main hubs: Luxor City (East Bank), Qurna (West Bank), and Esna. The results further indicate that the most influential factors influencing the distribution of tourist attractions in Luxor include regional services centrality, GDP index, proximity to urban centres, tourism workforce localisation, urbanisation level, and environmental quality, respectfully. The implications of this research provide practical applications for developing more sustainable and balanced tourism development strategies in heritage-rich regions such as Luxor.

Keywords: Spatial Analysis; Urban Tourism; Tourism Attractions; Geodetector; Egypt.

1. Introduction

Tourism attractions are the most important factors in determining where a traveller will go, what the traveller will do while at that destination, and the impact of travel on the region (Edelheim, 2015; Leiper, 1990). As spatial locations for the organisation of tourism services and industry (accommodation, transportation, etc.), attractions provide areas with the potential to be transformed from just transit zones into unique tourism destinations (Var & Gunn, 2002). Attractions also serve as experiential goods, creating an emotional connection with travellers based on cultural narratives (Pine & Gilmore, 2011; Vittersø *et al.,* 2000). The way in which attractions are distributed geographically directly affects the flow of tourists and the infrastructure that is allocated to support those tourists and the equitable distribution of economic benefits derived from tourism activities. If not strategically planned, the concentration of tourism attractions in major cities can lead to negative environmental impacts and increase urban-rural disparities (Hall & Page, 2014; Tan *et al.,* 2023).

Understanding the geographic distribution of tourism attractions requires conceptual models such as Central Place Theory (Christaller, 1966), Gravity Models (Smith, 1987), Anchor Point Theory (Couclelis *et al.,* 1987), and Butler's Tourism Area Life Cycle (Butler, 2024). The recent advances in quantitative geography have provided a methodological framework to apply these theoretical concepts using spatial statistical techniques (e.g., Kernel Density Estimation, Local Moran's I, Geographically Weighted Regression, etc.) to precisely measure and analyse clustering patterns and accessibility dynamics (Brunsdon, 2018; Fotheringham & Sachdeva, 2022; Goodchild, 2007). While these spatial statistical techniques have been used to model and analyse the geographic distribution of tourism attractions, they primarily use homogeneous unitary representations of different attraction types. Also, these techniques typically rely on single-scale analytical models that do not account for how specific attraction types interact with local socio-economic conditions (Jiang *et al.,* 2024; Maia & Varajão, 2019).

A typology of attractions, which is commonly divided by origin (natural vs. man-made), purpose (recreational, cultural/heritage), and size, shapes the spatial behaviour fundamentally (Biswas *et al.,* 2020; Leiper, 1990). For example, a typical pattern for cultural/heritage attractions is clustering surrounding urban centres due to preservation needs (Cros & McKercher, 2020; García-Hernández *et al.,* 2017; Timothy & Boyd, 2015), while natural attractions often tend to be linearly distributed along rivers or other natural elements (Lue *et al.,* 1993; Timothy & Boyd, 2015).

Nonetheless, very few studies examine how these different types of attractions exhibit differing spatial logic at the same destination, particularly in heritage-rich contexts in the Global South (Ding *et al.,* 2024; Zhang *et al.,* 2023). Research on empirical travel and spatial tourist development is mostly geographically limited to those destinations that have a strong and comprehensive GIS database, such as China (Ma *et al.,* 2022; Peng & Gao, 2023), Europe (Lascu *et al.,* 2018; Vu *et al.,* 2020), and North America (Feng & Morrison, 2002). Very little research has been done in destinations in the Global South, such as Egypt. Additionally, western planning models have rarely been translated into the Arabic or African context; therefore, colonial history, conservation constraint and informal economy influence spatial behaviour differently than the traditional spatial behaviour associated with most western countries. As a result, theoretical explanations for why tourism attractions are distributed in these contexts are underrepresented, which is where the value of this study resides.

This study goes beyond previous studies in spatial tourism research because it makes three distinct contributions toward addressing the issues found in previous studies. The first contribution is conceptual: Previous spatial analyses have generally treated tourism attractions as a homogenous set of points (e.g., Jiang *et al.,* 2024; Ma *et al.,* 2022; Peng & Gao, 2023; Zhang *et al.,* 2023; however, this study extends the field of spatial tourism research by showing that different types of attractions generate fundamentally different spatial logics (e.g., clustering intensity, directionality, and density) within the same destination. For example, historical attractions form tight clusters of nodes surrounding heritage cores, while leisure attractions display long, thin lines of development along linear transportation corridors (e.g., rivers), which is considered an important distinction that cannot be seen in aggregated analyses.

The second contribution is methodological. Previous studies have relied heavily on using single-scale spatial models (i.e., standard GWR or OLS regression) or aspatial statistical methods that assume stationary relationships between the distribution of tourism attractions and their explanatory variables across space (Ding *et al.,* 2024; Fotheringham & Sachdeva, 2022; Maia & Varajão, 2019). In contrast, this study combines Analytic Hierarchy Process (AHP), Geodetector, and Multiscale Geographically Weighted Regression (MGWR), a combination of methodologies not previously used in tourism geography, to (a) use expert opinion to determine the relative importance of factors, (b) identify spatial stratified heterogeneity, and (c) measure localized, non-stationary variations in the influence of factors at multiple spatial scales. Therefore, this study's multi-method approach addresses the criticism that Western developed planning paradigms are unable to account for localised contextual differences in the Global South.

The third contribution is empirical. As previously mentioned, this study introduces a different and new geographical context for spatial tourism attractions analysis (Luxor Governorate, Egypt), which has not been explored before. Luxor is an extremely complex heritage destination featuring archaeological layering, informal tourism economies, and a unique rural-urban morphology. Therefore, this study applies sophisticated quantitative geographic methods to a relatively understudied context to provide evidence-based insights into heritage tourism planning in archaeologically rich regions of the Arab world and Africa.

Accordingly, this research investigates the spatial distributions of tourism attractions in Luxor and explores the characteristics of the locations where they are situated. Utilising advanced spatial statistical techniques combined with a typological approach, the study shows how social, economic and physical variables influence each other and contribute to shaping tourism geographies in regions with rich archaeological histories. The results offer planners a spatially-targeted approach to balancing the preservation of heritage resources with sustainable economic development, and also provide a replicable analytical framework for conducting similar research in other culturally significant destinations.

2. Methods

2.1. Study Area and Data Collection

This study examines how tourism attractions are distributed within Luxor Governorate, located in Upper Egypt along the Nile River. Luxor Governorate is a premium tourism destination due to its famous ancient archaeological and heritage sites that exist in both urban areas (e.g., Luxor, Armant, and Esna) and rural areas (e.g., surrounding villages). The region has been identified as having several world-famous tourist destinations such as the Valley of the Kings, the Karnak. Temple Complex, and Hatshepsut's Mortuary Temple. Spatially, Luxor Governorate is split between the east and west sides of the Nile with each side possessing a unique combination of tourism capacity, physical planning, and land use characteristics.

For data collection purposes, this study employed two main sources to collect tourism attractions in Luxor Governorate: OpenStreetMap (OSM) accessed on 6 July 2025 and official documentation. The POIs associated with tourism contained in OSM provided a base spatial dataset from which the georeferenced POI data were extracted. Official government sources were also consulted to validate and enhance the data collected through OSM; these included the Centre for Documentation of Cultural and Natural Heritage (CULTNAT) and the General Organisation for Physical Planning (GOPP). Both sources provided authoritative classifications, site descriptions, and spatial verification. The compiled data from these aforementioned sources were then placed into a single geospatial database, which contained detailed information about each attraction (e.g., location, name, and classification). Also, it is worth mentioning that the attractions were categorized into four categories: historical (e.g., Luxor Temple, Hatshepsut Temple, Medinet Habu); cultural (e.g., Luxor Museum, Local festivals, and folklore shows); scenic (e.g., Nile River riverfront, Banana Island, and Theban Mountain backdrop); and leisure (Nile cruises, hot air balloon, and local markets) (Biswas *et al.,* 2020; Shafiee *et al.,* 2025). Figure 1 below presents the geographic location of the study area, as well as its various tourism attractions.

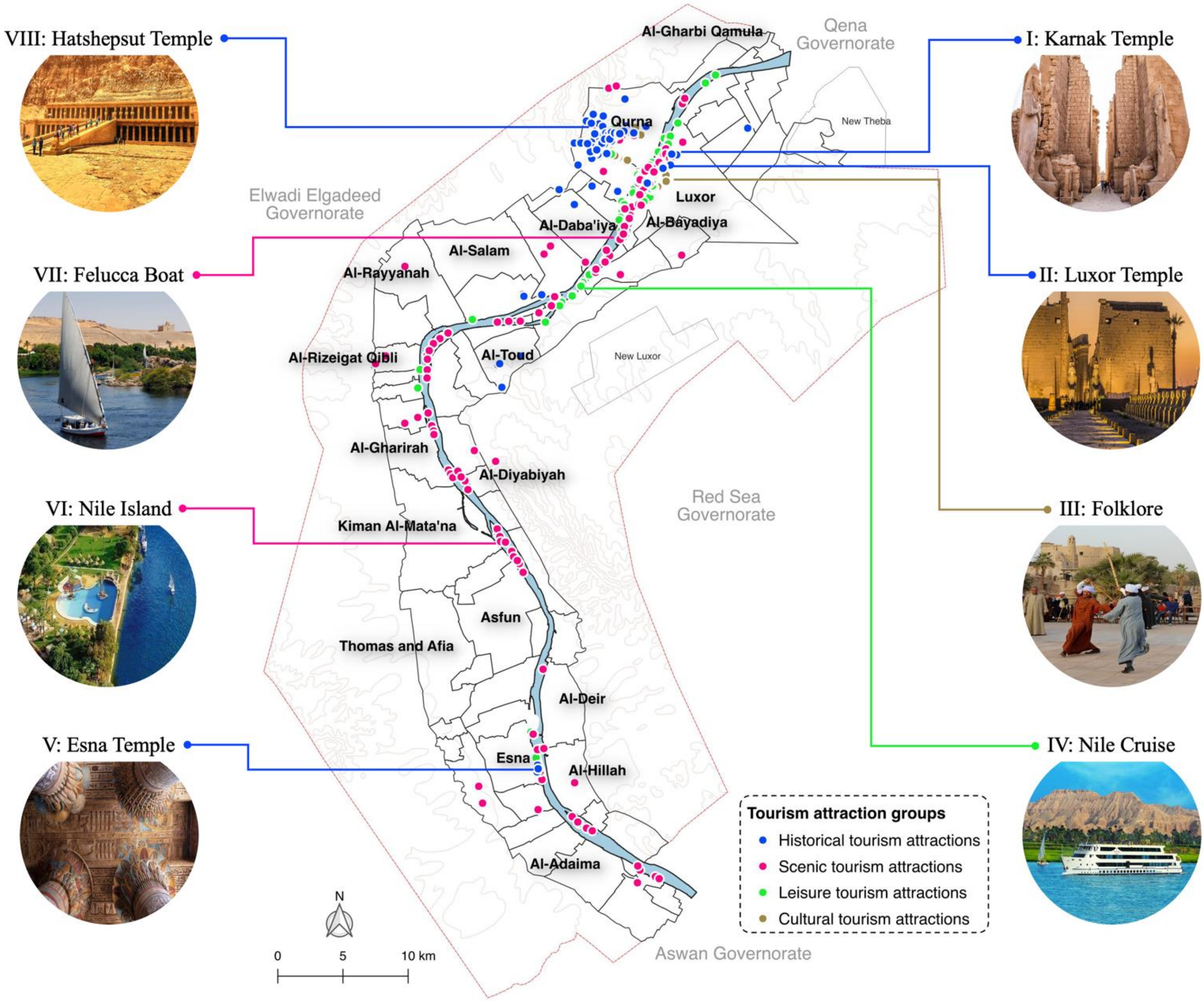

Figure 1. Luxor Governorate, the Study Area.

2.2. Research Methodology

After conducting the data collection process, there are two main analytical components to the research methodology for this study: (1) an examination of the spatial distribution of tourism attractions, and (2) an assessment and analysis of the factors that affect it. The workflow that integrates these analyses is shown in the following Figure 2.

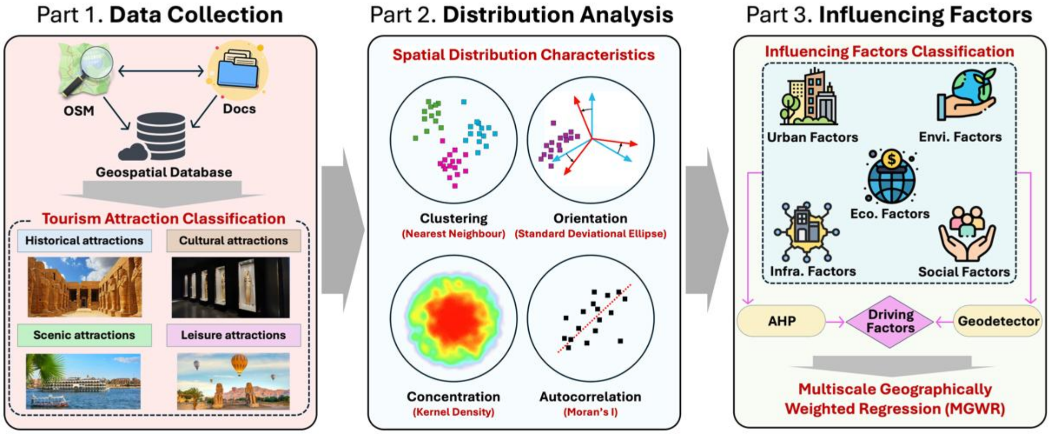

Figure 2. Research Methodological Framework.

2.2.1 Spatial Distribution Analysis

The first component of the analysis provides important insights into the spatial distribution of attractions as they relate to accessibility, tourism development potential, and spatial equity. This analysis aims to examine the geometric, directional, and statistical characteristics of attraction distributions to determine if these attractions are either clustered or dispersed, located primarily in certain locations, and/or located in a linear fashion. To achieve this aim, a variety of complementary spatial tools is used, each of which examines a specific characteristic of the distribution of attractions, such as clustering, orientation, density, and spatial autocorrelation.

a- Clustering

The Nearest Neighbour Index (NNI) has been used to measure the clustering aspect of tourist attractions. The NNI measures how clustered the attractions are, how randomly distributed they are in space, and how far apart they are. The NNI compared the actual mean distance from each attraction to that of its closest neighbour with the expected mean distance for a random distribution using the following Equation 1:

$$NNI = \frac{\overline{d_o}}{0.5/\sqrt{A/n}} \tag{1}$$

where $\overline{d_o}$ is the average distance to the nearest neighbor, n is the number of points representing the tourism attractions, and A is the total area of the study region (Luxor Governorate). (Note: The denominator is the expected mean distance for a random distribution; $0.5 \times \sqrt{A/n}$

b- Orientation

For a description of the directional trend and geographical scope of tourism attractions, we have used the Centre of Gravity (mean centre) and the Standard Deviational Ellipse (SDE). For the first step, the Centre of Gravity (mean centre) is determined through an average of the X and Y coordinates of all the tourism attraction points, which yields the geographic centre of the distribution (Equation 2).

$$\bar{X} = \frac{\sum_{i=1}^{n} x_i}{n}, \ \bar{Y} = \frac{\sum_{i=1}^{n} y_i}{n} \tag{2}$$

where x_i and y_i indicate the coordinates of the individual tourism attraction point, and $\bar{X}$ and $\bar{Y}$ represent the mean centre coordinates.

With the mean centre as a starting point, we can determine the direction of the tourism attraction distribution with the help of the rotation angle θ of the ellipse, which represents the main directional trend of the attraction points. To do so, the calculation of the variance of the X and Y directions is needed, as well as the covariance between these two directions. With the help of the following trigonometric relationship (Equation 3), the rotation angle can be derived:

$$tan(2\theta) = \frac{2\sum_{i=1}^{n} \widetilde{x_i y_i}}{\sum_{i=1}^{n} \widetilde{x_i^2} - \sum_{i=1}^{n} \widetilde{y_i^2}} \tag{3}$$

Here, $\widetilde{x_i} = (x_i - \bar{X})$ and $\widetilde{y_i} = (y_i - \bar{Y})$ represent the differences of each point's coordinates from the mean centre. Therefore, we get the angle θ as follows: $\theta = \frac{1}{2}\arctan\left(\frac{2\sum(\widetilde{xy})}{\sum(\widetilde{x^2}) - \sum(\widetilde{y^2})}\right)$

In the final step, we calculate the lengths of the semi-major and semi-minor axes (σ_x and σ_y) to describe the spatial extent of the tourism attraction distribution. We do that by determining how far each point deviates from the centre along the rotated axes. In addition, we square the deviations, average them, and take their square root to determine the total spatial dispersion (Equation 4):

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^{n}(\tilde{x}_i \cos\theta - \tilde{y}_i \sin\theta)^2}{n}}, \quad \sigma_y = \sqrt{\frac{\sum_{i=1}^{n}(\tilde{x}_i \sin\theta + \tilde{y}_i \cos\theta)^2}{n}} \tag{4}$$

The variables σ_x and σ_y define the elongation and orientation of the ellipse, while θ defines the main directional trend of the tourism attractions distribution.

c- Concentration

Spatial concentration was assessed using Kernel Density Estimation (KDE). KDE creates a continuous surface that displays the intensity of tourism attractions across space. To this end, KDE identifies the areas of high or low concentrations by evaluating the density of points (tourism attractions) within a predetermined search radius around each location. In details, the KDE formula is calculated as Equation 5:

$$f(x) = \frac{1}{nh^2}\sum_{i=1}^{n} K\left(\frac{d_i}{h}\right) \tag{5}$$

where $f(x)$ represents the estimated density at location x, K denotes the kernel function (Gaussian), d_i represents the distance between x and observation i, and h denotes the bandwidth parameter.

d- Spatial Autocorrelation

Finally, the autocorrelation was evaluated through Local Moran's I, which is commonly referred to as Anselin's LISA. Local Moran's I is an especially useful tool to assess whether or not there exist similarities between neighbouring locations in terms of their spatially intensive properties. It is particularly useful for identifying local clusters of high or low values, such as tourism hotspots or zones of low performance. The Local Moran's I statistic is calculated as Equation 6:

$$I_i = (x_i - \bar{x})\sum_{j} w_{ij}(x_j - \bar{x}) \tag{6}$$

where x_i and x_j represent the attribute value of each observation, $\bar{x}$ represents the mean, and w_{ij} represents the spatial weight of the relationship between observations.

2.2.2. Analysis of Influencing Factors

The second component of the analysis for this study is to find the most important factors that influence the spatial distribution of tourism attractions in Luxor. At first, all factors that could affect the spatial distribution of tourism attractions were collected from previous literature. Next, they were filtered to be relevant to the local context of Luxor and the availability of sufficient data for the analysis. Finally, the importance of these factors was evaluated using both of the tools (Analytic Hierarchy Process, AHP and Geodetector). AHP helped to evaluate the importance of each factor according to the opinion and experience of the experts. Geodetector is a statistical tool that uses the actual data to estimate how much of the pattern of the distribution of the tourism attractions on the map can be explained by each factor. Therefore, the combined application of both tools provides a more complete and balanced evaluation of the factors that are responsible for the spatial distribution of tourism attractions in Luxor.

a- Analytic Hierarchy Process (AHP)

The process of the AHP starts by creating a pairwise comparison matrix $= a_{ij}$, where each element a_{ij} represents the relative importance of factor i versus factor j , as judged by experts (panel list). The matrix is constructed in the following Equation 7:

$$A = \begin{bmatrix} 1 & \frac{w_1}{w_2} & \cdots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & 1 & \cdots & \frac{w_2}{w_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \cdots & 1 \end{bmatrix} \tag{7}$$

This matrix is reciprocal, meaning $a_{ij} = 1/a_{ij}$, and each diagonal entry is 1 because a factor is equally important as itself. To populate the comparison matrix, fifteen experts were selected through purposeful sampling by using specific eligibility criteria to ensure they had appropriate knowledge and expertise. For example, each participant was required to have at least seven years of professional experience in either tourism planning, heritage management or urban development.

The 15 participants included six senior planners from the General Organisation for Physical Planning (GOPP); two tourism development specialists from the Ministry of Tourism and Antiquities; five university professors whose specialisations include regional tourism development and urban planning; and two local government representatives from Luxor Governorate. Each expert independently performed pairwise comparisons of the factors using the standard scale (1-9), where higher values represent a stronger perceived importance of one factor over another. Once the matrix was formed, the geometric mean method was used to compute the relative importance of each factor. For each row, the geometric mean $\overline{W_i}$ is calculated as Equation 8:

$$\overline{W_i} = \left(\prod_{j=1}^{n} a_{ij}\right)^{1/n} , \quad i = 1,2, \dots , n \tag{8}$$

These geometric means are then normalized to derive the final priority weights W_i , using the equation 9:

$$W_i = \frac{\overline{W_i}}{\sum_{j=1}^{n} \overline{W_j}}, \quad i = 1,2, \dots , n \tag{9}$$

To validate the consistency of the expert judgments, the maximum eigenvalue $\lambda_{\max}$ is calculated using the following Equation 10:

$$\lambda_{max} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\sum_{j=1}^{n} a_{ij}W_j}{W_i}\right) \tag{10}$$

Also, the Consistency Index (CI) is then computed using Equation 11:

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{11}$$

And the Consistency Ratio (CR) is finally calculated as Equation 12:

$$CR = \frac{CI}{RI} \tag{12}$$

b- Geodetector

Geodetector is a spatial statistical tool used to identify and explain spatial stratified heterogeneity by measuring how strongly an explanatory variable (e.g., influencing factors) accounts for the observed spatial variation in a dependent variable (e.g., tourism attractions). Geodetector was chosen over other methods (OLS regression or Pearson Correlation) since it does not require a linear relationship between variables, nor does it require that all data be either categorical or continuous. Geodetector measures explanatory power by calculating variances within spatially stratified sub-regions (unlike global regression models which calculate associations across entire study areas).

Therefore, Geodetector has the ability to capture local variations and non-stationary patterns that would not be captured by standard models. Additionally, Geodetector's ability to provide robust results when dealing with multi-collinear data, combined with the complementary nature of Geodetector and the AHP results (which provide data-driven support for expert judgments), makes Geodetector an ideal method to analyse the complex spatial phenomenon of the different kinds of tourism attractions in this study.

As shown in Figure 3, the study area is divided into sub-regions $h = 1, 2, \dots, L$. For each, the mean and variance of the dependent variable Y (i.e., tourism attractions) are calculated as $\bar{Y}_h$ and ${\sigma^2}_h$, respectively. These are then compared to the overall mean $\bar{Y}$ and variance σ^2 for the entire Luxor governorate. The explanatory power of each factor is calculated using the q-statistic, ranges from 0 to 1, the higher q value indicating stronger explanatory power.

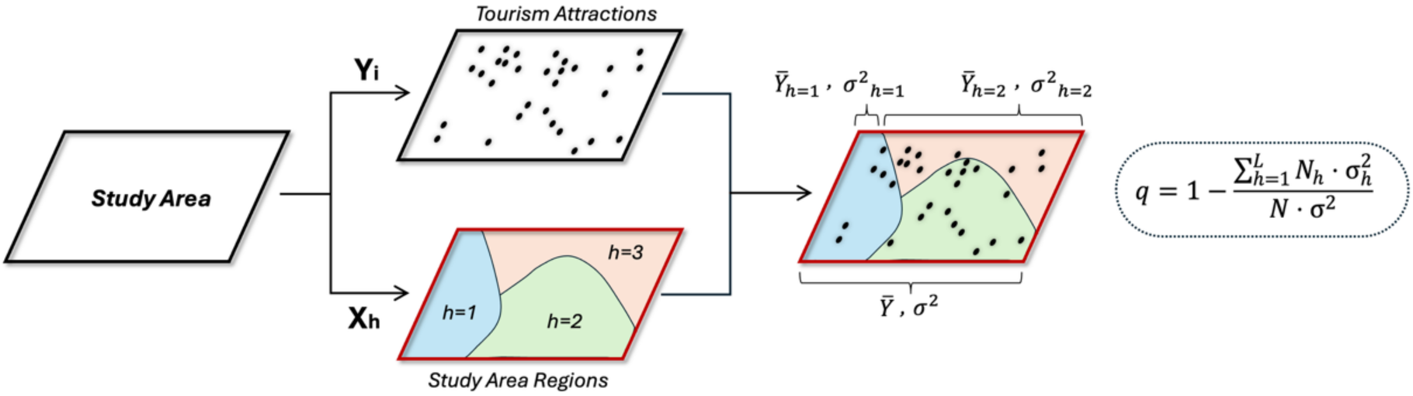

Figure 3. Geodetector Principles and Ideas.

c- Multiscale Geographically Weighted Regression (MGWR)

The MGWR model used in this study estimates how the relationship between the dependent variable and a set of explanatory variables changes across space. More specifically, an adaptive bisquare kernel function was utilised, and bandwidth sizes were independently optimised for each covariate based on the Akaike Information Criteria adjusted for small sample size (AICc). The model assumes that the value of the dependent variable (e.g., tourism attractions) at a given location is a function of locally varying coefficients associated with each independent variable (e.g., influencing factors). All MGWR models were run using the "mgwr 2.2.1" Python software package (Oshan et al., 2019), which utilises the back-fitting algorithm to determine the best fit of local regression coefficients at various spatial scales. The model takes the Equation 13:

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) \cdot X_{ik} + \varepsilon_i \tag{13}$$

Where X_{ik} is the K explanatory variable at location i, $\beta_k(u_i, v_i)$ represents the coefficient of that variable at coordinates (u_i, v_i), $\beta_0(u_i, v_i)$ is the location-specific intercept, and ε_i is the random error term. It is worth mentioning that the adaptive bandwidths were between 30 and 64 nearest neighbours (see Table 4) for the MGWR models. These bandwidths are calculated utilising an iterative golden section search to find the minimum AICc, while also ensuring that each local regression has sufficient spatial resolution to capture meaningful spatial patterns, and does not over-fit the data.

3. Results and Data Analysis

3.1. Spatial Patterns of Tourism Attractions Agglomeration

The overall spatial distribution of the four categories of tourism attractions in Luxor shows a statistically significant clustered pattern. The range of values for the Nearest Neighbour Index (NNI) varies from 0 (perfect agglomeration - all the data coincides) to 1.0 (spatial randomness - no data coincidence) and approaches 0 as agglomeration increases and exceeds 1.0 as data disperses. Therefore, it is essential to evaluate both the Z-Score and p-values simultaneously when interpreting NNIs. Although NNIs measure effect size, they do not verify if the observed pattern of agglomeration differs from randomly occurring patterns unless evaluated using Z-Scores and p-values (Mitchell & Griffin, 2021).

Following established conventions in spatial statistics, this study interprets NNI values of < .10 as extreme agglomeration, .10 to .25 as strong agglomeration, .25 to .50 as moderate agglomeration, and values > .50 as little agglomeration. All four categories of tourism attractions showed evidence of statistically significant agglomeration ($p < .01$) with Z-Scores varying from -18.55 to -24.51 (less than 1% probability of occurrence due to random chance).

As presented in Table 2, historical tourism attractions exhibit the strongest clustering, with a nearest neighbour index of only 0.004 and a remarkably high z-score of -22.86. This explains that Luxor's ancient monuments (e.g., temples, tombs, etc.) are densely concentrated, especially in the East and West Bank archaeological zones. Cultural tourism attractions were also found to be strongly clustered (NNI = 0.122, z-score = -18.55), which suggests many cultural attractions (e.g., museums, cultural centres, and folklore venues) are co-located near the primary historical landmarks or are located in urban centres close to those attractions. The leisure tourism attractions demonstrated a similar level of clustering (NNI = 0.202), which indicates that many of the leisure-related tourism attractions (e.g., shopping, dining, recreational activities, etc.) may be located in more commercially viable or accessible areas, but the majority are still within walking distance to the most popular tourist locations. Lastly, while scenic tourism attractions are still clustered (NNI = 0.301), they demonstrate the least value of density of all four categories and therefore have the widest geographic dispersion along the Nile River and riverbanks. Generally, all four categories of tourism attractions have shown consistently negative Z-Scores and all p-values are less than .01, thus validating that the spatial distributions of the four categories of tourism attractions are not the result of random variation, and that the NNIs demonstrate increasing degrees of agglomeration The detailed results of the nearest neighbour analysis are presented in Appendix (A) and the summary results of the nearest neighbour index (NNI) are presented in the following Table 1.

Table 1. Nearest Neighbour Analysis Results.

Tourism attractions group	Observed mean distance (km)	Expected mean distance (km)	Nearest Neighbour Index (NNI)	z-score	p-value	Clustering status
Historical	0.005	1.065	0.004	-22.85	0.00	Very strong
Cultural	0.095	0.779	0.122	-18.55	0.00	Strong
Leisure	0.206	1.016	0.202	-24.51	0.00	Strong
Scenic	0.399	1.322	0.302	-18.99	0.00	Moderate

To further analyse the spatial logic and directional patterns of tourism attraction clusters in Luxor, Figure 4 shows the results of the Standard Deviational Ellipse (SDE) and Centre of Gravity. Both analyses resulted in the identification of a clearly defined North-South axis for all four categories of tourist attractions, which run almost directly along the Nile River corridor. The two categories of historical and cultural attractions (red and blue), are both centred on Luxor City and the Qurna area and demonstrate compact ellipses which indicate strong centralisation of these attractions around the major historic zones of Luxor (e.g., Karnak, Luxor Temple, and the Valley of the Kings). The relatively narrow and concentrated nature of the orientations of these two types of attractions also indicates the high density and spatial compactness of the historically layered archaeological sites. In contrast, leisure and scenic tourism attractions (pink and black) have slightly larger ellipses which extend further to the South than those other two categories, indicating a greater spatial distribution and lower clustering intensity. These two categories tend to follow areas which are more accessible or natural scenery, especially along the riverbanks, viewpoints, and in rural leisure spots.

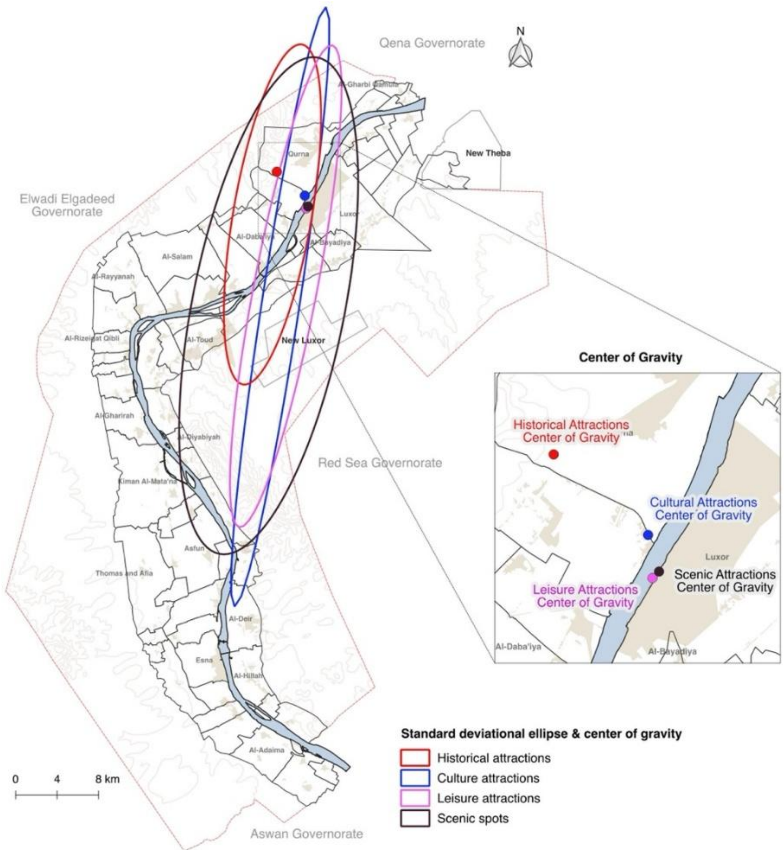

Figure 4. Standard Deviation, Ellipse and Centre of Gravity Results.

Building upon the established directional and cluster trends from the NNI and SDE analyses, the KDE was used to explore how concentrations vary by type of tourism attractions. As shown in the density maps (Figure 5), there are varying degrees of concentration for each category of attractions. For example, historical attractions (Figure 5b) have a dense, highly concentrated hotspot at Qurna and Luxor city, which corresponds with the well-preserved archaeological zones. This confirms that historical tourism is driving much of the development and movement of visitors within Luxor and is responsible for an extreme amount of attractions with a maximum intensity value of 144. Cultural attractions (Figure 5c) have a similar but slightly less concentrated pattern of density centres at both Luxor and Esna. This distribution reflects the close relationship between cultural destinations and major heritage landmarks and the many traditional markets, cultural folklore, and local art galleries.

Unlike the other two tourism attraction categories (historical attractions and cultural attractions), the leisure attractions category (Figure 5d) has both a high level of concentration as well as a wider spatial distribution. The core area for leisure attractions is located in Luxor and Qurna, but there are many secondary clusters that are located along the southern part of the Nile River, particularly near Armant and El-Tod. Additionally, the leisure attractions recorded the highest maximum density of all four categories at 258 attractions due to several factors, such as the popularity of Nile cruises, which is considered the main transportation link between Luxor in the north and Aswan in the south. Finally, the scenic spots category (Figure 5a) has the widest geographic distribution with many moderate-density zones throughout the entire governorate (from Esna in the south to Luxor in the north). This pattern demonstrates how visually appealing and environmentally attractive the Nile River corridor is. Scenic spots had a lower peak density of 240, however due to their linear and dispersed patterns of clustering reflects tourists' interest in natural landscapes, riverbank views, and panoramic vistas rather than specific or fixed monuments.

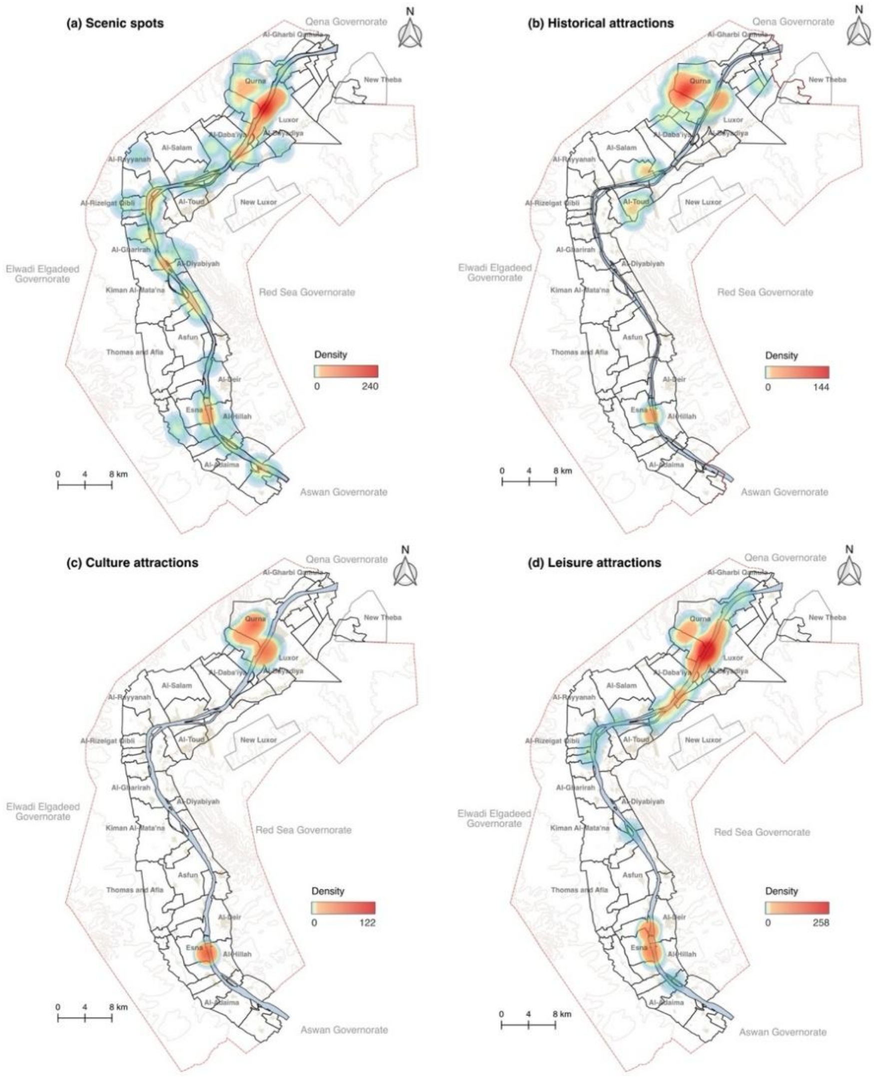

Figure 5. Kernel Density Maps of Tourism Attraction Groups in Luxor. (a) Scenic Spots, (b) Historical Attractions, (c) Cultural Attractions, and (d) Leisure Attractions. Note: Colours Indicate the Gradient in Tourism Attractions Intensity, where Blue (Low) and Red (High).

Lastly, Local Moran's I spatial autocorrelation analysis results indicate various levels of clustering and spatial outliers distribution of tourism attraction densities throughout the Luxor Governorate. As shown in the following Figure 6, the majority of the governorate falls into the "Low-Low" category (dark blue), which indicates low tourism values in surrounding areas. These areas are primarily found in Luxor governorate's south and central parts (e.g., Al-Adaimah, Al-Deir, and Asfun). The fact that these areas are generally underdeveloped in terms of tourism may create opportunities for investment or planning focus. In contrast, few areas show the exact opposite pattern. For example, Esna has been highlighted in red as a "High-High" cluster; an indication that it is a local tourism hotspot with high attraction density surrounded by similarly high-value areas, thereby making it a key tourism hub. Additionally, areas identified in light red (e.g., Al-Toud and Al-Dabaiya) are classified as "High-Low"; an indication that while they have high tourism values, they are surrounded by areas with significantly lower tourism values. Due to this, they can be viewed as being situated as potential strategic nodes linking tourism-based urban centres with the surrounding rural tourism areas. Finally, the grey areas are considered "Not Significant", meaning there was no discernible tourism-related spatial pattern evident. The grey areas can therefore be seen as transitional zones between tourism hub areas.

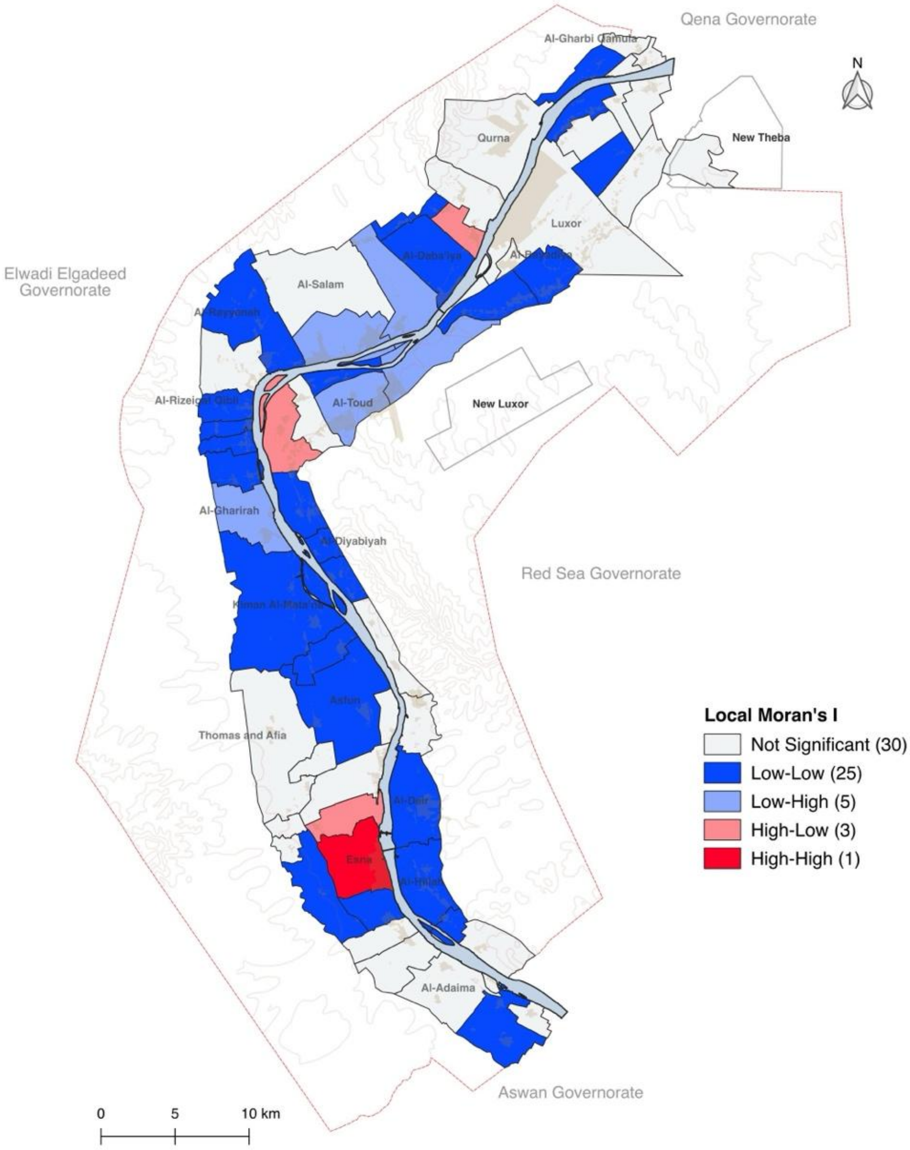

Figure 6. Standard Deviation Ellipse and Centre of Gravity Results.

3.2. Analysis of Influencing Factors

The next step after assessing the spatial distribution of tourism attractions in Luxor, is to assess the factors that affect and support the development in tourism attractions. Table 2 shows an overview of the 16 selected factors in this study. These selected factors have been categorised into five main categories: urban (four factors), social (three factors), infrastructural (three factors), environmental (one factor), and economic (five factors).

The different categories represent the dimensions of how tourism developments occur geographically within the governorate. For a detailed view of the spatial distribution of these factors, see the mapping of the 16 selected factors in Appendix (B).

Table 2. Factors Influencing the Tourism Attraction in Luxor.

Factors		**Calculation**	**Description**
	Population (POP)	**Total population**	
Urban	Urbanization Level (URB)	$\frac{NAW}{TEW}$	NAW: non-agricultural workers, TEW: total economic workers
	Regional Services Centrality (RSC)	$\left(\frac{100}{TGS}\right) \times NRS$	TGS: total governorate services, NRS: regional services in settlement
	Proximity to the Nearest Urban Center (PUC)	Distance from settlement to nearest urban center (GIS)	
Social	Human Development Index (HDI)	$\frac{1}{3}(HI + EI + II)$	HI: Health Index, EI: Education Index, II: Income Index
	Literacy Rate (LIT)	$\left(\frac{LA}{TAP}\right) \times 100$	LA: literate adults, TAP: total adult population
	% Population with Tertiary Education (TER)	$\left(\frac{NTE}{PEA}\right) \times 100$	NTE: number with tertiary education, PEA: population of education age
Infrastructural	Connectivity Index (CONN)	$\sum(RL_i \times RW_i)$	RL: road length, RW: road class weight
	Road Buffer (RBUF)	1 km buffer zone around major roads (GIS)	
	Nile Buffer (NBUF)	2 km buffer zone around Nile River (GIS)	
Environmental	Clean and Healthy Environment Index (CHEI)	$\frac{E + G + W + S}{4}$	%E: % buildings connected to electricity, %G: % connected to gas, %W: % connected to water, %S: % connected to sanitation
Economic	GDP Index (GDP)	GDP per capita based on purchasing power parity	
	Tourism Workforce Localization (TWL)	$\left(\frac{TW_u/TW_t}{TW_g/TGW_g}\right)$	TWu: tourism workers in settlement, TWt: total workers in settlement, TWg: tourism workers in governorate, TGWg: total workers in governorate
	Labor Force Participation Rate (LFPR)	$\left(\frac{LF}{TP}\right) \times 100$	LF: labor force, TP: total population
	Tourism Services Centrality (TSC)	$\left(\frac{100}{TTS}\right) \times NTS$	TTS: total tourism services in governorate, NTS: tourism services in settlement
	Tourism Accommodation Services Centrality Index (TAC)	$\left(\frac{100}{TAS}\right) \times NAS$	TAS: total accommodation services in governorate, NAS: accommodation services in settlement

After identifying the 16 selected influencing factors, the study applied AHP and Geodetector analyses to determine the relative importance of the factors in shaping the spatial distribution of tourism attractions in Luxor. The AHP analysis found that the 10 tourism experts ranked the following as the most important factors: proximity to the nearest urban centre (PUC), with a weight of 0.10. This was followed by the GDP index (0.08), regional services centrality (RSC, 0.08), road buffer (RBUF, 0.07), tourism workforce localisation (TWL, 0.07), and connectivity index (CONN, 0.07).

The Geodetector analysis also identified the following six factors as the top influences in terms of creating the patterns of tourism attractions in Luxor: regional services centrality (RSC), GDP index (GDP), proximity to the nearest urban centre (PUC), population (POP), urbanisation level (URB), and tourism workforce localisation (TWL). These six factors are associated with q-values of 0.20, 0.17, 0.12, 0.11, 0.10, and 0.10, respectively. To ensure comparability, the AHP weights and q-values for each factor were normalised to a common 0-1 scale. The normalised scores were then averaged to generate a balanced ranking that reflects both expert-based priorities (from AHP) and empirical spatial influence (from Geodetector). The final results revealed that the most influential factors affecting the distribution of tourism attractions in Luxor are: regional services centrality (RSC), GDP index (GDP), proximity to the nearest urban centre (PUC), tourism workforce localisation (TWL), urbanisation level (URB), and the clean and healthy environment index (CHEI). The following Table 3 presents the final rankings of the most influential factors based on the combination of both results.

Table 3. Ranking the Factors Influencing the Tourism Attractions in Luxor Based on AHP and Geodetector.

Rank	Influencing Factors	AHP	Geodetector (q-value)	Final Score
1	Regional Services Centrality (RSC)	0.08	0.20	0.90
2	GDP Index (GDP)	0.08	0.17	0.83
3	Proximity to the Nearest Urban Center (PUC)	0.10	0.12	0.80
4	Tourism Workforce Localization (TWL)	0.07	0.10	0.63
5	Urbanization Level (URB)	0.07	0.10	0.61
6	Clean and Healthy Enviroment Index (CHEI)	0.06	0.10	0.58
7	Population (POP)	0.05	0.11	0.55
8	Connectivity Index (CONN)	0.07	0.04	0.49
9	Road Buffer (RBUF)	0.07	0.02	0.43
10	Labor Force Participation Rate (LFPR)	0.04	0.06	0.36
11	% Population with Tertiary Education (TER)	0.04	0.05	0.35
12	Nile Buffer (NBUF)	0.06	0.01	0.33
13	Human Development Index (HDI)	0.05	0.02	0.33
14	Literacy Rate (LIT)	0.04	0.04	0.30
15	Tourism Services Centrality (TSC)	0.06	0.004	0.30
16	Services Centrality Index (TAC)	0.06	0.003	0.29

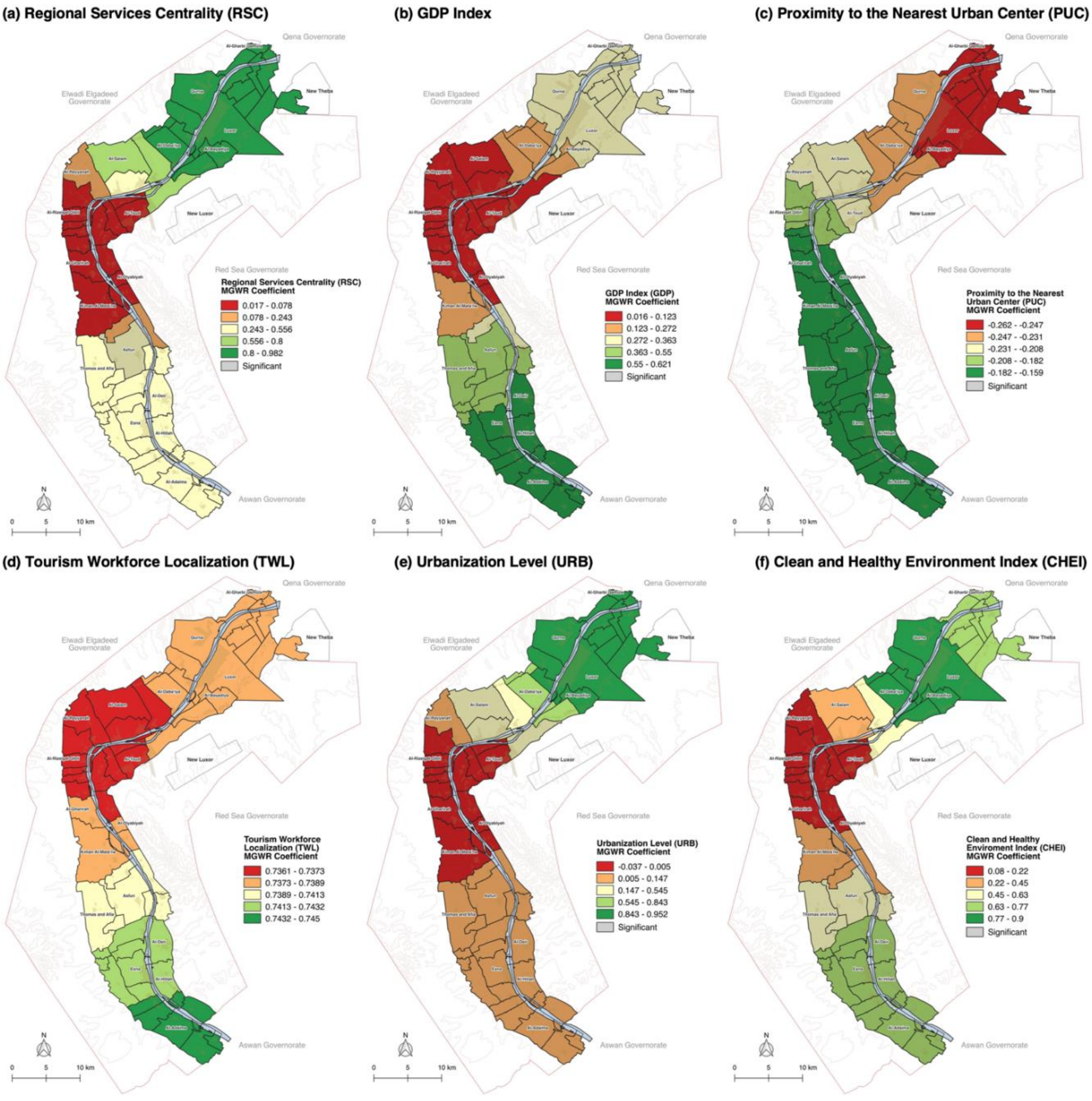

Figure 7. Spatial Distribution of MGWR Coefficients and Significance Levels for the Six Key Influencing Factors.

To gain an improved understanding of these most influential factors, MGWR was used. Table 4 presents the outputs from the local regression for each factor (e.g., mean, minimum, maximum, and SD of coefficients), as well as the statistical significance and bandwidths associated with each factor. This table also provides visual evidence for how the effect of each factor is different across different areas of Luxor governorate. Spatial representations of the variation in the coefficient values of each factor can be seen in Figure 7. Areas with stronger positive influence (green) or negative influence (red) are clearly observed, showing the unevenness of the spatial impacts of each factor across Luxor governorate. It is also important to note that only statistically significant effects at $p < 0.05$ have been emphasised by using a hatched diagonal area representation, while non-significant areas have been represented as completely transparent (and therefore, indicate no significant effect).

Table 4. Summary of MGWR Results for the Six Most Influential Factors.

Factor	Bandwidth	Pseudo-t Critical Value	Mean Coef.	Min	Median	Max	Std Dev
RSC	30	2.483	0.530	0.017	0.489	0.982	0.350
GDP	43	2.371	0.324	0.016	0.335	0.621	0.204
PUC	64	2.237	-0.201	-0.262	-0.185	-0.159	0.037
TWL	64	2.017	0.739	0.736	0.738	0.745	0.003
URB	30	2.556	0.357	-0.037	0.139	0.952	0.381
CHEI	30	2.233	0.575	0.082	0.703	0.897	0.252

4. Discussion

The geographic pattern of tourism attractions in Luxor is both similar to and different from that of other global heritage tourism destinations/areas reported in the literature. Like many other heritage tourism destinations/areas, Luxor has formed into a polycentric area (with three main hubs located on the East Bank, the West Bank, and at Esna); however, it also differs from these other areas in the level of distribution of each type of tourist attraction. For example, Luxor's NNI for historic attractions is 0.004, which represents a significant level of clustering compared to reports of approximately 0.59-0.84 for tourist sites in other studies (Biswas *et al.,* 2020; Ding *et al.,* 2024). The aggregation of Luxor's historic attractions is due to the unique geologic layering found in Luxor, where ancient Egyptian monuments are found in separate geo-morphically defined areas (e.g., the West Bank necropolis vs. the East Bank temple complexes), creating spatial barriers to tourist access less present in historically developed European heritage cities.

Quantitatively, the three major tourist hubs in Luxor have emerged from three distinctly defined density thresholds determined using kernel density estimation: high-density cores representing the East Bank (Karnak/Luxor Temple complex) and West Bank (Valley of the Kings/Qurna) areas, while Esna represents a secondary node that can be identified as a spatial outlier (per local Moran's I). Unlike the linear, corridor-based pattern seen in riverine tourist systems along the Yangtze and Huanghe Rivers (Du *et al.,* 2023), the tourism attractions in Luxor are aggregated into discrete, morphologically constrained clusters.

The identified driving factors, regional services centrality (RSC), GDP Index, proximity to urban centres (PUC), and tourism workforce localisation (TWL), are spatial drivers of attraction distribution in the Luxor Governorate. However, they are part of recursive social-economic processes and not causal agents. For example, in our study, the RSC has the highest q value ($q = 0.20$) among the spatial driver variables, a finding similar to that noted by Maia & Varajão (2019). They found that the concentration of public service infrastructure in Brazil's Diamond Circuit was the best predictor of node formation in the tourist circuit. However, there is no stationary relationship between RSC and attraction density in the Luxor Governorate; MGWR coefficients for RSC are between 0.017 and 0.982 depending on the area of the governorate, which indicates that in urban cores, the centrality of public service infrastructure has strong predictive power on attraction density whereas in the periphery of the governorate (i.e., desert areas such as Al-Adaimah) the explanatory power is very weak. This spatial variation in the explanatory power of RSC highlights the fact that a large number of previous spatial tourism studies have used uniform regression models (standard OLS or Global GWR) that do not allow for variation in the explanatory power of spatial drivers at different locations.

The CHEI has a relatively high q value (0.10) compared to European environments (Prus *et al.,* 2021), which suggests that basic infrastructure provision (e.g., electricity and sanitation) is an important threshold variable for determining whether a destination is viable for tourism in developing heritage environments, and not simply a marginally enhancing factor. The negative coefficient for PUC in certain MGWR bandwidths (-0.262 to -0.159) indicates that, due to the strict archaeological conservation requirements of some of the West Bank monuments, the typical agglomeration effects associated with tourism in urban areas are inverted in Luxor. This is consistent with the findings of Zhang *et al.* (2023) those who noted that the agglomeration effects associated with urbanisation were also absent in some of China's heritage tourism sites.

The spatial tourism methodology used in this study, through the combination of Analytic Hierarchy Process (AHP), Geodetector and Multiscale Geographically Weighted Regression (MGWR) presented a triangulated framework which addresses the limitations of singular method use for analysing tourism attractions. Previous research has utilised either traditional geographic weighted regression (GWR) or aspatial regression techniques, which typically make assumptions that relationships among the variables in question are stationary (Fotheringham & Sachdeva, 2022; Harris, 2016). In contrast, the AHP-Geodetector-MGWR framework used in this study utilises an advanced validation chain: AHP establishes hierarchical structures of factors based upon input from experts; Geodetector identifies areas of heterogeneous spatial variation (using q-statistic values); and MGWR identifies localised coefficient variability at variable band widths (variable band width 30-64 units).

Theoretically, this study builds upon Butler's (2024), the Tourism Area Life Cycle (TALC) model by demonstrating that the spatial evolution of tourist destinations follows specific typology-based evolutionary paths rather than consistent patterns throughout each destination area. Specifically, historical attractions follow a “consolidated clustering” pattern (i.e., mature stages of TALC phases which are restricted to archaeological zones), while leisure attractions follow a “dispersed expansion” pattern (i.e., linear expansion along transportation corridors), indicating that heritage destinations evolve as mosaics of unique spatial logics rather than as coherent unitary systems.

The results of this study provide a number of practical strategies for developing urban plans for high cultural value areas within the global south. Firstly, the finding that two low-low clusters (Al-Adaimah & Al-Deir) have highly significant levels of spatial autocorrelation ($p < 0.01$), which suggests that these areas would benefit from specific and targeted investment in their infrastructure to support the growth of secondary nodes. These investments could be made in regional services (RSC) and environmental infrastructure (CHEI) in these low-low clusters to stimulate the formation of secondary nodes and alleviate some of the pressures being placed upon the three main hubs that are suffering from density-related degradation (NNI < 0.01 indicates extreme overcrowding). Secondly, the findings of the MGWR analysis demonstrate that there is a need for zone-based management strategies as opposed to governance-wide policies. Micro-scale interventions (such as pedestrianisation and museum expansions) will be best suited to address the spatially tight clustering of culture found in East Bank cultural clusters, while macro-scale linear infrastructures (such as Nile bridge connections and desert road improvements) will best fit the wider spatial processes operating along West Bank scenic/leisure corridors (bandwidth = 64). Thirdly, the localised nature of the tourism workforce (TWL coefficient = 0.736 – 0.745, $p < 0.05$) has implications for developing training programs for community-based tourism in the currently less developed southern districts of the Esna periphery. Such training programs may lead to self-reinforcing cycles of attraction development where the increased number of trained staff coincides with an increase in service centrality. The current literature has identified a “spatial mismatch” between the availability of labour and opportunities to develop tourism in Egypt; the results of this study have the potential to begin addressing this issue through the creation of community-based tourism training programs.

5. Conclusion

This study provides a thorough geospatial analysis of the distribution patterns of tourism attractions in Luxor, Egypt, and the main factors that influence the location patterns of these attractions. By combining spatial statistics with multiscale regression modelling, this study presents an explanation of how and why tourism attractions concentrate in specific areas in Luxor governorate.

The findings show that tourism attractions in Luxor are not randomly distributed; rather, there is evidence ofdistinct spatial aggregation or clustering due to the interplay of urban, environmental, and socio-economic factors. Tools such as Nearest Neighbour Index, Standard Deviational Ellipse, and Kernel Density Estimation, were employed to identify spatial concentrations of specific types of attraction and spatial orientations of these concentrations. Additionally, the use of Geodetector and MGWR provided a deeper understanding of how the influence of several of these factors changes across the governorate. The spatial distribution of tourism attractions in Luxor was shown to be significantly influenced by regional services centrality, GDP index, proximity to urban centres, tourism workforce localisation, urbanisation level, and environmental quality.

These results highlight the importance of location-specific planning and a more holistic approach that considers infrastructure and socio-economic dynamics in addition to the value of heritage. Therefore, tourism planning in Luxor, and other similar heritage-rich regions, developed based on local conditions, investment potential, accessibility and environmental readiness. By combining expert-based assessment (AHP) with spatially explicit data-driven analysis (Geodetector), this study provides a replicable methodological framework to identify the main success factors that influence tourism distribution in different types of tourism destinations. The study's results also provide useful and valuable information for policymakers, planners, and investors looking to enhance tourism competitiveness and promote sustainable and regionally balanced tourism development.

Despite the use of a holistic spatial and statistical approach in this study, there are some limitations that have to be taken into consideration. First, the analysis was carried out using OpenStreetMap (OSM) tourism attractiveness data. Even though these data were refined and verified, the data may contain gaps regards to unofficial or emerging attractions in rural or developing areas. Second, the influencing factors were developed based on cross-sectional data, which restricts the possibility to assess long-term changes or trends in the tourism patterns of a region. Third, the MGWR model can take into account the spatial heterogeneity very well, but the MGWR model is based on locally linear relationships, and therefore cannot fully reflect complex interactions amongst the variables examined in the Geodetector. Finally, the AHP evaluation based on expert knowledge is very valuable, but it may carry some biases depending on the expertise and diversity of the selected expert group.

Future research building upon the findings of this study should focus on the sue of temporal data to examine the change of tourism attraction patterns in different times, especially due to changes in policies, investments in infrastructure, or global trends such as the post-COVID recovery. Future research could further improve the insights in tourism behaviour, especially in high-demand areas, using real-time data (e.g., GPS tracking, social media check-ins, mobile apps data, etc.). Also, it would be possible to extend the scope of the analysis to a comparative regional level by applying the same analytical approach in other governorates or heritage destinations in Egypt. This would allow for a larger base for policy learning and comparison. Finally, future studies may benefit from the combination of spatial analysis with qualitative data of local stakeholders to better understand the socio-political conditions of tourism development, particularly in politically sensitive regions such as the Middle East, with Egypt at the centre of attention.

Appendices

Appendix (A): Detailed results of the Nearest Neighbour Analysis (NNA).

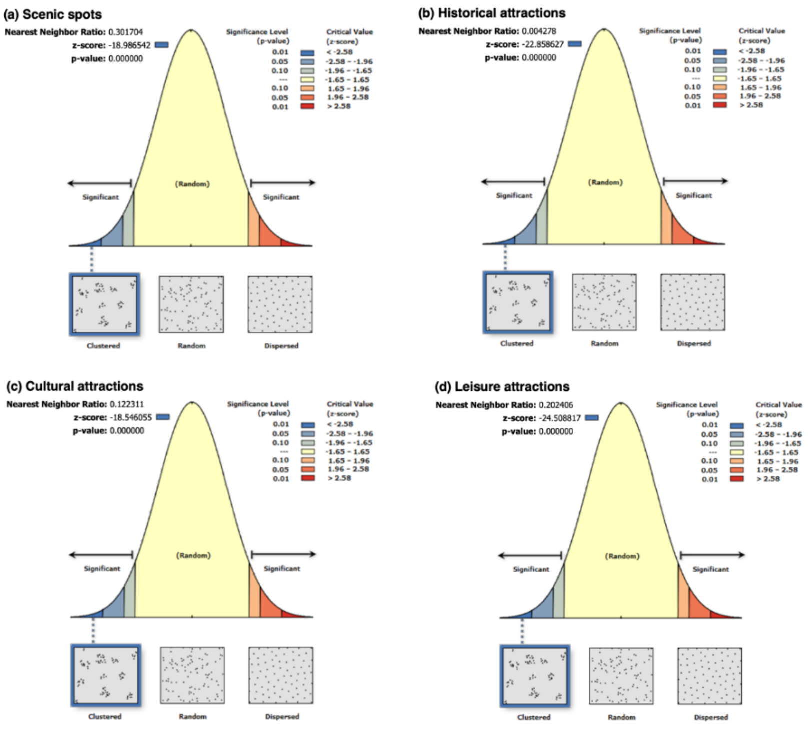

Figure a1. Nearest Neighbour Index (NNI) Results.

Appendix (B): The spatial distribution of the 16 investigated influencing factors.

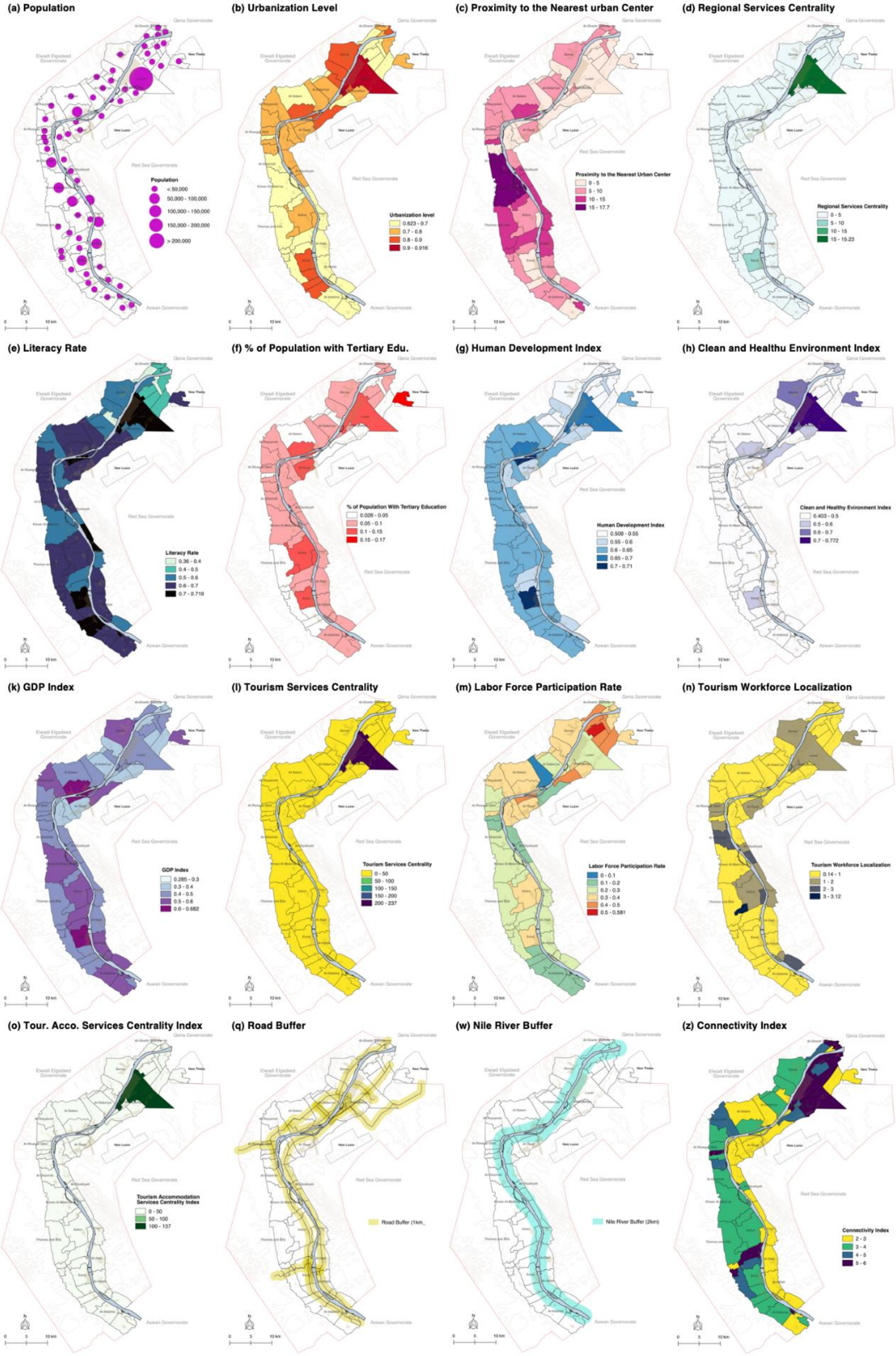

Figure b1. Spatial Distribution of the Investigated Influencing Factors.

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Author Contributions

Conceptualization: Kabil, M., Abdel Moneim, M. A. & Hassan, H. M.; **methodology**: Kabil, M. & Abdel Moneim, M. A.; **investigation**: Hassan, H. M.; **writing—original** Kabil, M. & Dávid, L. D.; **draft preparation**: Abdel Moneim, M. A. & Hassan, H. M.; **writing—review and editing**: Kabil, M. & Dávid, L. D.; **visualization**: Kabil, M. & Abdel Moneim, M. A. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

All authors declare that they have no conflicts of interest.

Data availability

Data is available upon Request.

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