



A Machine-Learning Clustering Framework for Spatial Urban Livability Assessment: A Case Study of Sari City, Iran

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Article Info	ABSTRACT
Article type: Research Article	Urban livability assessment remains challenging due to its multidimensional nature and the limitations of conventional evaluation methods, which often rely on subjective weighting or a narrow set of indicators. A significant gap exists in the systematic use and comparison of unsupervised machine-learning algorithms for livability classification, particularly in rapidly urbanizing cities of the Global South where spatial inequalities are substantial and data availability is uneven. This study aims to develop and validate a machine-learning clustering framework for spatial urban livability assessment using fourteen GIS-derived indicators covering infrastructure, services, environmental conditions, security, and socio-demographic characteristics. Three clustering algorithms K-Means, K-Means++, and Hierarchical Clustering were applied to classify the 20 districts of Sari City, northern Iran. While all methods revealed a consistent core-periphery pattern in livability, they differed in cluster separation and stability. Hierarchical clustering produced more distinct partitions, whereas K-Means offered more stable and computationally efficient results. The study avoids case-specific enumeration of district rankings and instead emphasizes the methodological insight gained from the comparative analysis. The findings demonstrate that integrating machine-learning clustering with spatial indicators provides a transparent, data-driven, and general framework for evaluating urban livability. The proposed approach can be readily applied to other cities facing similar planning and equity challenges.
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1. Introduction:

Cities today serve as the principal nodes of population concentration, socio-economic interaction, and environmental transformation, making the analysis of their functionality and adaptability a central concern in contemporary urban research (Henderson, 2010; Burgess, 2015; Chou et al., 2024). Rapid urbanization, particularly in developing regions, continues to reshape settlement patterns, alter ecological processes, and generate both opportunities and pressures for urban communities. These transformations have intensified scholarly and policy interest in the concepts of urban resilience and livability, which together reflect a city's capacity to provide safe, healthy, and sustainable living conditions while withstanding emerging challenges (Ribeiro & Gonçalves, 2019; Zeng et al., 2022). Urban resilience typically refers to the robustness and adaptability of urban systems in the face of shocks including socio-economic instability, environmental hazards, infrastructure failures, and climate-related risks emphasizing a city's ability to maintain critical functions under stress (Sharifi et al., 2021; Țigănașu et al., 2023). Livability, although closely linked, centers more directly on the everyday experiences and well-being of residents and reflects the quality and accessibility of essential services, infrastructure, socio-environmental conditions, and institutional support (Mirzahosseini & Moghaddam, 2021; Sheikh & van Ameijde, 2022). Livability encompasses a multidimensional set of characteristics, including but not limited to housing conditions, transportation access, availability of public and green spaces, environmental quality, safety, socio-demographic balance, and equitable access to essential services (Finn, 2006; Parker & Simpson, 2018; Appleyard et al., 2023). These factors interact in complex ways, often resulting in spatial disparities across urban districts. Prior research has emphasized that livability cannot be captured through a single metric; instead, it requires an integrated evaluation that considers physical, social, economic, and environmental dimensions simultaneously (Al-Thani et al., 2019; Martino et al., 2021). As a result, the demand for spatially explicit, data-driven tools for livability assessment has grown, particularly in cities experiencing rapid demographic and land-use change. Despite significant progress, the literature on livability assessment still exhibits several critical gaps. First, many studies continue to rely on subjective weighting, expert-based scoring, or composite indices that embed implicit biases and limit reproducibility. These approaches often assume linear relationships between indicators and livability outcomes, which may oversimplify socio-spatial dynamics. Second, indicator selection is often narrow, focusing on a limited set of variables that fail to capture the full range of environmental, infrastructural, and socio-demographic conditions influencing urban quality of life. Third, while numerous studies employ GIS for spatial analysis, relatively few integrate modern machine-learning (ML) approaches particularly unsupervised clustering algorithms that are capable of detecting hidden patterns and grouping urban areas based on intrinsic similarities rather than predefined assumptions. More importantly, comparative analyses of multiple clustering algorithms remain rare. Although machine-learning methods have been increasingly applied to urban studies, most livability research still employs either a single clustering

technique or conventional index-based approaches. Studies comparing multiple unsupervised algorithms remain limited, particularly in Global South contexts. For example, several Iranian and regional studies applied only one clustering or classification model such as K-Means (Maleki et al., 2023), Fuzzy C-Means (Kenger et al., 2023; Zare Naghadehi et al., 2021), or single-model SVM/ANN frameworks (Mahmon & Ya'acob, 2014; Saraei & Yarahmadi, 2022) without evaluating alternative clustering algorithms. Similar patterns are observed across Asian and Middle Eastern cities, where livability and urban quality-of-life assessments typically rely on weighted indices, entropy-based scores, or single-method clustering (Kutty et al., 2022; Liang et al., 2020; Pan et al., 2021). Only a few recent works outside Iran have compared clustering models for urban spatial evaluation, and these focus on smart-city performance or environmental indicators rather than livability (Özceylan & Mrugalska, 2023; Champlin et al., 2023). Therefore, the systematic comparison of K-Means, K-Means++, and HC within a GIS-based livability framework remains largely unexplored in Iranian and Global South contexts, highlighting the methodological gap this study addresses. A systematic comparison of clustering performance, including internal validation measures such as the Silhouette score, Calinski–Harabasz index, and Davies–Bouldin index, is still lacking in the livability literature, particularly in urban contexts of the Global South. A further gap relates to the integration of ML clustering methods with GIS-based spatial indicators. While both methodological domains machine learning and GIS have individually advanced, their combined use for livability assessment is still underdeveloped. This is especially evident in rapidly urbanizing regions such as Iran, South Asia, and other parts of the Global South, where spatial inequality, environmental pressures, and inconsistent infrastructural investment create sharply differentiated living conditions. Limited access to high-resolution socio-environmental datasets, combined with fragmented planning practices, restricts the application of sophisticated analytical tools. Consequently, many cities continue to rely on traditional assessment frameworks that lack the computational rigor and spatial precision required for equitable and sustainable decision-making. These gaps collectively highlight the need for a robust, transparent, and generalizable methodology that integrates diverse spatial indicators with advanced clustering algorithms to identify spatial patterns of livability more objectively. In response to these gaps, the present study develops a machine-learning clustering framework for assessing urban livability based on 14 GIS-derived indicators representing five key dimensions: infrastructure, public services, environmental conditions, safety and security, and socio-demographic characteristics. The study systematically compares the performance of three widely used unsupervised clustering algorithms K-Means, K-Means++, and HC to examine their classification consistency, robustness, and ability to differentiate urban districts based on multidimensional livability characteristics. By incorporating internal validation indices (Silhouette, Calinski–Harabasz, and Davies–Bouldin) and an uncertainty analysis of cluster assignments, the research enhances methodological transparency and enables a more rigorous interpretation of clustering outputs. This approach contributes to the broader literature in several ways. First, it introduces a

comparative clustering framework that evaluates the strengths and limitations of different algorithms for livability classification. Second, it provides a multidimensional spatial dataset integrating environmental, infrastructural, and socio-demographic indicators offering a more holistic representation of urban living conditions. Third, it advances the methodological rigor of livability assessment by incorporating validation and uncertainty metrics, which remain largely neglected in prior studies. Fourth, while Sari City in northern Iran serves as the empirical case, the proposed framework is generalizable and can be adapted to other data-limited or rapidly urbanizing contexts. By addressing methodological limitations, expanding indicator coverage, and presenting a reproducible clustering-based approach, this study aims to support more equitable and evidence-based urban planning. The findings offer planners, policymakers, and researchers clearer insights into intra-urban disparities, enabling more targeted interventions and contributing to long-term strategies for sustainable and inclusive urban development.

2. Case study:

Sari City, with an area of approximately 30 square kilometers, is the capital of Mazandaran Province in northern Iran (Davari et al., 2022). Geographically, the city is located between 52°58' and 53°10' east longitude and 36°30' and 36°37' north latitude (Hashmi et al., 2019). It lies about 150 kilometers northeast of Tehran, the capital of Iran, and sits at an elevation of 54 meters above sea level (Niknejad et al., 2023). Sari experiences a humid subtropical climate, with an average annual humidity of 85.83% and rainfall distributed throughout the year. The mean annual temperature is approximately 17°C (Gholami et al., 2011). According to the 2016 census, the population of Sari was recorded at 429,620. Notably, a census was not conducted in 2021 due to the COVID-19 pandemic (Mesri Alamdari & Rasouli, 2021).

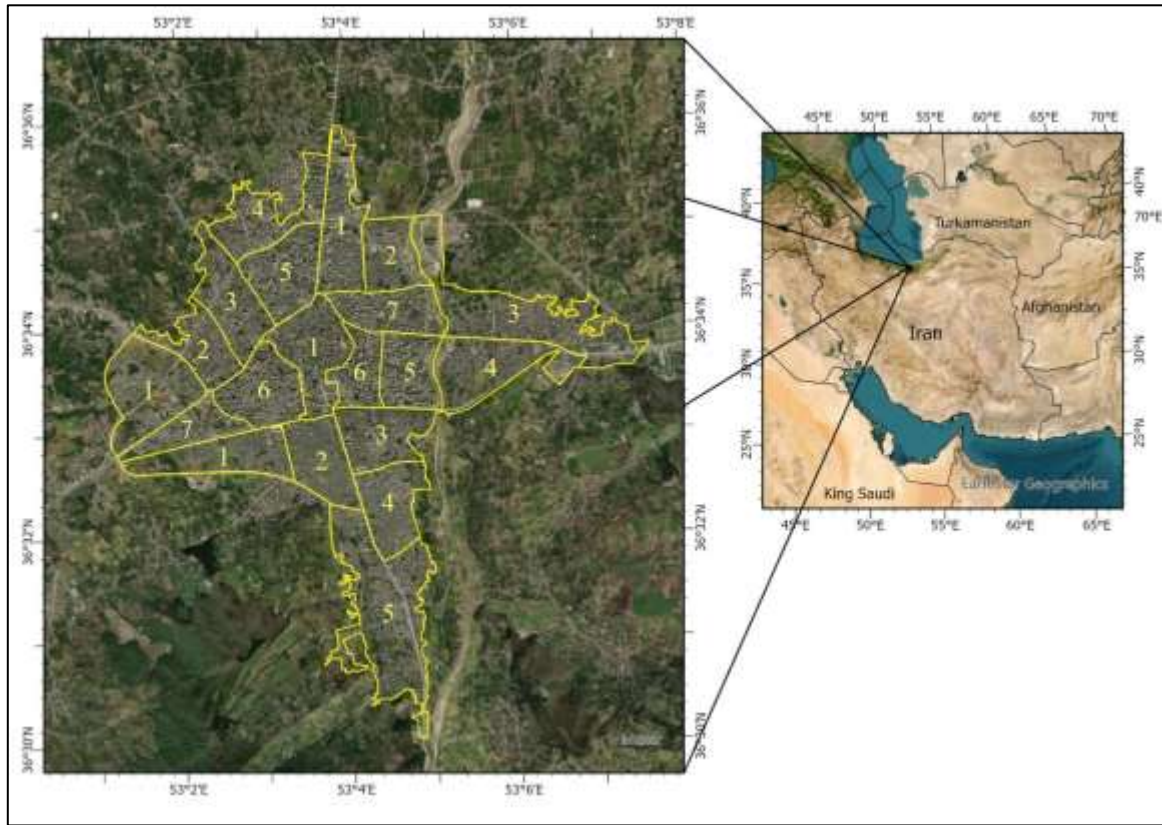


Figure 1 illustrates the location and spatial extent of the study area

3. Methodology:

This study was conducted with the aim of classifying the urban livability of different districts in Sari and prioritizing urban areas with low livability through the integration of spatial criteria using three machine learning methods: 1) K-Means Clustering, 2) K-Means++, and 3), and HC. The research steps are as follows (Figure 2):

3.1 Datasets:

The spatial layers used as inputs in this study were derived from a combination of remote sensing products, statistical datasets, and GIS-based spatial analyses. Fourteen indicators representing environmental conditions, infrastructure, public services, security, and socio-demographic characteristics were compiled at a uniform spatial resolution of 30 m for compatibility with clustering algorithms.

3.1.1 Remote Sensing-Derived Indicators

Land Surface Temperature (LST) and PM₁₀ were generated from Landsat imagery following standardized preprocessing protocols. LST was extracted using the Single Channel Algorithm applied to thermal bands from Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI/TIRS

(Jiménez-Muñoz & Sobrino, 2003). All images underwent radiometric calibration, atmospheric correction, emissivity estimation, cloud masking, and were resampled to 30 m resolution. PM_{10} was estimated using the regression-based model proposed by Saraswat et al. (2017) applied to aerosol-sensitive reflectance bands from Landsat 8 OLI. Only cloud-free (<10%) scenes acquired during June–August were used to maintain seasonal consistency across indicators.

3.1.2 Socio-Demographic and Built-Environment Indicators

Statistical datasets from the Statistical Center of Iran were employed to generate layers for employment rate, structural adequacy of buildings, population density, housing shortages, gender ratio, and age ratio. These tabular data were spatially joined to district boundaries and converted to raster format at 30 m resolution using GIS interpolation and zonal assignment techniques.

3.1.3 Service Accessibility and Proximity Layers

Point and line datasets representing the locations of fire stations, hospitals, police stations, recreational areas, shopping centers, and rivers were acquired from municipal and provincial authorities. Euclidean distance tools in ArcGIS Pro were used to create continuous raster surfaces representing accessibility to each service. These layers were also standardized to a 30 m grid.

3.2 Criteria Classification and Standardization

To account for their differing influences on livability, indicators were categorized into three groups:

- Positive indicators (e.g., employment rate, structural adequacy), where higher values imply improved livability.
- Balanced indicators (population density, gender ratio, distance to rivers), where optimal not extreme values are desirable.
- Limiting indicators (e.g., PM_{10} concentration, distance to hospitals, distance to police stations), where higher values reflect reduced livability.

All indicators were reclassified and normalized using min–max scaling (0–1) to ensure comparability across heterogeneous units.

3.3 Multiband Raster Construction

Following preprocessing, all 14 indicators were aligned to a common projection (UTM Zone 39N, WGS84) and stacked into a multiband raster dataset to provide pixel-level consistency for machine-learning clustering. This composite dataset served as the primary input for the three clustering algorithms applied in the analysis.

3.4 Indicator Selection and Justification

The selection of the fourteen livability indicators in this study was grounded in established literature on urban quality of life, environmental sustainability, accessibility, and socio-

demographic well-being. The criteria were not chosen arbitrarily but follow internationally recognized frameworks (e.g., Finn, 2006; Parker & Simpson, 2018; Al-Thani et al., 2019; Martino et al., 2021; Kutty et al., 2022) that emphasize the importance of integrating environmental, infrastructural, service-based, and demographic dimensions in livability assessment. Environmental indicators such as LST and PM₁₀ capture thermal comfort and air-quality conditions, both of which are known to significantly influence urban livability and public health (Jiménez-Muñoz & Sobrino, 2003; Saraswat et al., 2017; Doostvandi et al., 2024). Service accessibility indicators including distance to hospitals, fire stations, police stations, shopping centers, and recreational areas were selected based on extensive empirical evidence showing that proximity to essential services enhances safety, mobility, and overall quality of life (Pan et al., 2021; Ghanbari et al., 2016; Mulliner & Maliene, 2011). Socio-demographic indicators (employment rate, population density, gender ratio, age ratio, and housing shortages) were chosen due to their widely documented influence on economic stability, social cohesion, equity, and urban resilience (Khorrami et al., 2021; Liang et al., 2020; Saraei & Yarahmadi, 2022). The inclusion of structural adequacy of buildings is supported by resilience research showing that building quality directly affects vulnerability to hazards and urban safety (Kashef, 2016; Parizi et al., 2022). Overall, the combination of these indicators aligns with best practices in livability assessment and reflects a multidimensional conceptualization of urban well-being supported by prior studies.

Table 1 summarizes the indicators, their data sources, and their conceptual relevance to livability assessment.

Table 1. This table shows information on the criteria used in the research and where generate and extracted.

Indicator	Category	Reason for Inclusion	Supporting References
LST	Environmental	Reflects thermal comfort & heat-stress conditions	Jiménez-Muñoz & Sobrino (2003); Doostvandi et al. (2024)
PM₁₀	Environmental	Air quality strongly impacts public health	Saraswat et al. (2017); Maleki et al. (2023)
Distance to hospitals	Services	Access to healthcare is a core livability dimension	Mabadi (2021); Pan et al. (2021)
Distance to fire stations	Safety	Reduces response time in emergencies	Ghanbari et al. (2016)
Distance to police stations	Safety	Social security is fundamental to livability	Hankins & Powers (2009)
Distance to shopping centers	Services	Access to daily needs improves convenience	Mulliner & Maliene (2011)
Distance to recreational areas	Services/Well-being	Enhances mental health, social interaction	Mulliner & Maliene (2011)
Distance to rivers	Environmental/Balance	Affects flood exposure & amenity	Yang et al. (2021)

Employment rate	Socio-economic	Linked to economic stability & social well-being	Khorrami et al. (2021)
Structural adequacy of buildings	Infrastructure	Determines safety, resilience, and hazard susceptibility	Parizi et al. (2022)
Population density	Socio-demographic	Influences transport, infrastructure demand	Satu (2014)
Housing shortage	Socio-economic	Indicates pressure on infrastructure & affordability	Safdari Molan et al. (2019)
Gender ratio	Demographic	Reflects social balance, migration, equity	Patil & Sharma (2022)
Age ratio	Demographic	Determines service needs & demographic vitality	Liang et al. (2020)

3.5. Clustering methodology

In this study, quantitative urban livability criteria (such as population density, service accessibility, environmental quality, transportation access, etc.) were first extracted and prepared as spatial information layers within the GIS environment. Then, the values of these layers were normalized and input numerically into the clustering algorithms.

3.5.1.K-Means Algorithm

The K-Means clustering algorithm was used as a data-driven method to identify homogeneous clusters of urban livability (Kenger et al., 2023). K-Means is an unsupervised learning method that aims to minimize the sum of squared distances between data points and the cluster centroids (Tavallali et al., 2021). For implementation, each spatial unit (e.g., urban block or neighborhood) was defined as an observation with n numerical features (livability indicators) in a multi-dimensional space. The algorithm initiates by selecting k (the number of clusters) and iteratively updates the cluster centers, assigning each data point to the cluster whose centroid is closest based on Euclidean distance. This process continues until convergence (i.e., negligible changes in centroid positions). The final output consists of clusters of urban areas with similar livability patterns, visualized and analyzed as classified maps in the GIS environment.

3.5.2. K-Means++ Algorithm

The K-Means++ algorithm, an improved version of K-Means, reduces the chance of falling into local minima by choosing initial cluster centers more strategically (Baldassi, 2022; Vardakas & Likas, 2024). By selecting initial centroids more strategically, it reduces the chances of poor clustering results and accelerates convergence (Daoudi et al., 2021). This leads to more accurate and stable clustering outcomes, especially in large datasets (Agarwal et al., 2015). In this study, the number of clusters was set to 5, and the parameter `nstart = 25` was used to run the algorithm

multiple times with different starting points. Lloyd's optimization method was applied for internal refinement. The final results were converted into raster format and saved as spatial distribution maps.

3.5.3. Hierarchical Clustering (HC)

HC is a machine learning algorithm that builds nested clusters by either agglomerative (bottom-up) or divisive (top-down) approaches (Nasiriani et al., 2019). It creates a dendrogram representing data relationships, enabling flexible cluster selection without predefined cluster numbers (Murtagh & Contreras, 2017). It is widely used in spatial and biological data analysis. To leverage a tree-structured analysis, the HC algorithm using the Ward.D2 linkage method was employed. This method minimizes the within-cluster sum of squares and produces highly homogeneous clusters with an interpretable structure. After computing the distance matrix and executing the algorithm, a dendrogram (tree diagram) was generated to provide an overall view of the data relationships. The dendrogram served as a key visual tool for understanding interrelations among data subsets. The optimal number of clusters was determined using the 'cutree' function, with the number of clusters set to 5. Finally, the clustering output was converted into raster format for spatial analysis.

3.5.4 Validation and Uncertainty Assessment

To ensure the robustness of the clustering results, multiple internal validation indices were employed. In addition to the Silhouette Score, which measures the cohesion and separation of clusters ranging from -1 (poor clustering) to $+1$ (optimal clustering) (Rousseeuw, 1987), two complementary indices were considered. The Calinski–Harabasz Index (CH) evaluates the ratio of between-cluster dispersion to within-cluster dispersion, with higher values indicating more distinct and well-separated clusters (Calinski & Harabasz, 1974). The Davies–Bouldin Index (DBI) measures the average similarity between each cluster and its most similar counterpart, where lower values represent better clustering quality (Davies & Bouldin, 1979). Using a combination of these indices provides a more comprehensive evaluation of clustering performance, overcoming the limitations of relying on a single metric (Arbelaitz et al., 2013). In addition to validation, cluster assignment uncertainty was also assessed. Traditional hard clustering assigns each observation exclusively to one cluster, which may obscure cases where the boundary between clusters is not well defined. To quantify this, the uncertainty ratio was computed for each observation as the distance to its assigned cluster centroid relative to the distance to the second closest centroid (Hennig, 2015). Higher ratios indicate lower cluster stability and greater ambiguity in assignment. This metric allows for the identification of “borderline” urban district that could be sensitive to changes in clustering parameters or data perturbations. Incorporating uncertainty analysis not only strengthens methodological rigor but also provides urban planners with more nuanced insights into which districts may require flexible or staged interventions. After running each algorithm, the clustering outputs were separately saved in raster format and corresponding spatial distribution maps were produced.

The results of the algorithms were comparatively analyzed based on clustering quality, spatial pattern differences, processing speed, and resource consumption. Overall, the K-Means++ and K-Means algorithms demonstrated favorable performance for large-scale data analysis, offering a good balance between accuracy and computational efficiency. In contrast, HC, while offering interpretable structures, faced limitations due to high memory requirements, making it less practical for processing extensive spatial datasets.

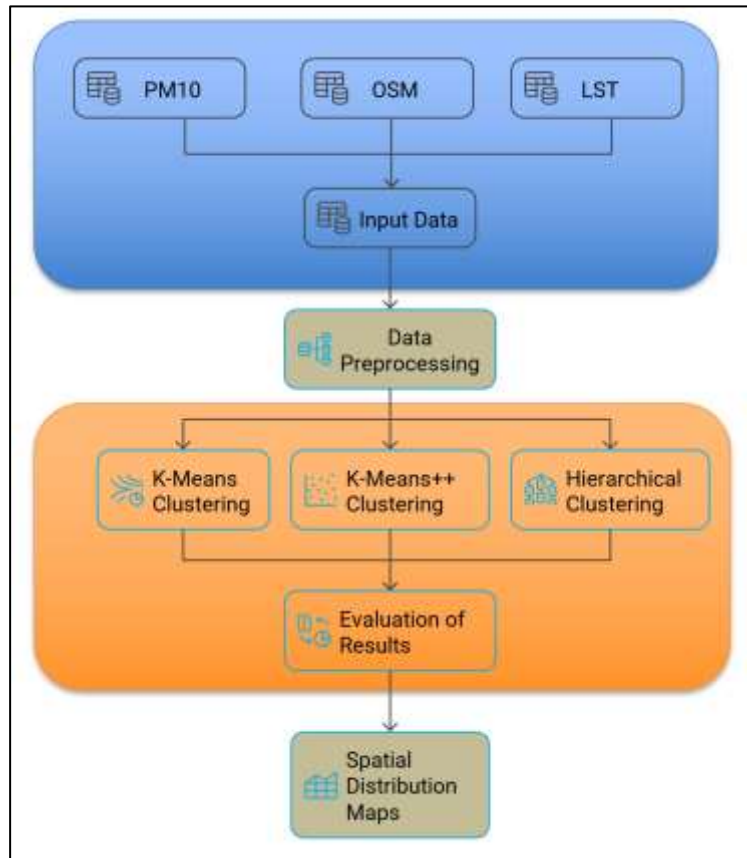


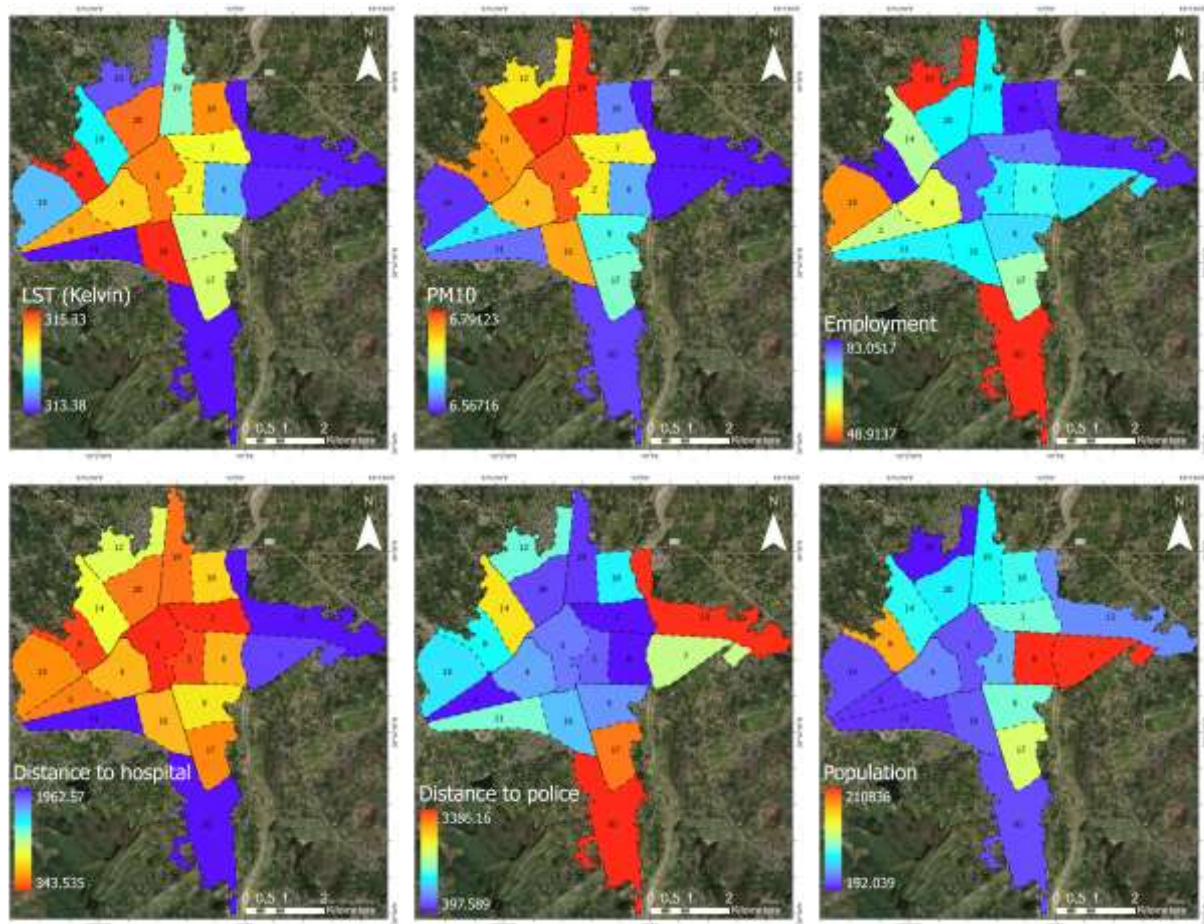
Figure 2. this shows the flowchart of this research

4. Results:

4.1 Spatial Distribution of Livability Indicators

To support the clustering analysis, the spatial distribution of the fourteen livability indicators was first examined using GIS-derived raster layers. Figures 3 and 4 present the spatial patterns of all environmental, infrastructural, service-based, and socio-demographic variables used in this study. These maps illustrate the variability of key livability determinants across the 20 districts of Sari City, including land surface temperature, air quality (PM₁₀), accessibility to essential services, structural building conditions, population characteristics, and proximity-based measures. The visualization of these indicators provides an essential foundation for interpreting the clustering outputs and understanding the underlying drivers of livability.

disparities identified in subsequent sections. The classification of values was based on the Natural Breaks method. All maps presented in this section (Figures 2-a to 2-h) were generated by the authors using ArcGIS Pro 3.2 (Esri, 2023, <https://www.esri.com/arcgis>). Figure 2-a illustrates the spatial distribution of average Land Surface Temperature (LST) across Sari. District 16 records the highest LST, while five districts exhibit very low values. Peripheral areas generally experience low to very low LST, whereas the city center is characterized by moderate to high values. Figure 2-b shows the PM10 concentration map, representing air pollution levels. Districts 5, 19, and 20 display very high PM10 concentrations. Four additional districts with high values are located in the urban periphery, similar to the LST distribution. Districts 7 and 13 simultaneously exhibit low LST and low PM10, while in total, seven districts are classified as highly polluted. Overall, the northern and western parts of the city suffer from higher air pollution compared to the south and east. Figure 2-c presents the employment rate. Districts 1, 5, 8, 13, and 18 demonstrate very high employment levels, while Districts 10, 12, and 15 mostly located on the outskirts exhibit very low rates. These results indicate that the northern and eastern parts of the city have better employment conditions than the southern and western district. The fire station accessibility map reveals that Districts 4, 6, 7, and 18 have the shortest distances to fire stations, whereas Districts 11, 12, and 15 are the farthest (Figure 2-d). Generally, the northern districts enjoy better coverage compared to the south, and the east significantly outperforms the west. Figure 2-e illustrates accessibility to hospitals. Hospital density is higher in the periphery, while central areas are farthest from healthcare facilities. Districts 7, 10, 11, and 13 benefit from the shortest distances. Figure 2-f shows the structural quality of buildings. Districts 10, 11, 12, and 15 primarily in the urban fringe demonstrate poor construction quality, reflecting the growth of informal settlements. In contrast, District 8 exhibits the highest structural adequacy. The city center and eastern districts are generally characterized by medium to high building quality. Proximity to police stations is mapped in Figure 2-g. The city center is better served than peripheral areas, with only District 10 exhibiting very poor accessibility. Finally, Figure 2-h depicts population density. District 6 records very high density, while seven districts in the western and southwestern areas are classified as very low density. Overall, the eastern and northern parts of the city are more densely populated than the west and south.



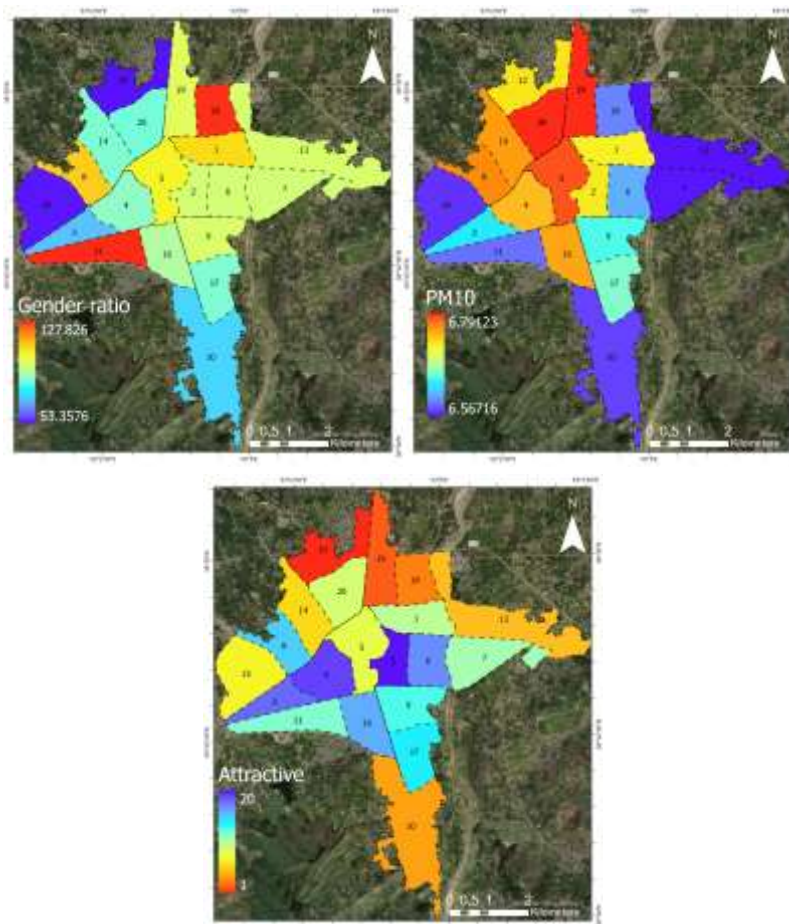


Figure 3 Part 1 of the criteria maps used

Figure 4 (Part 2) illustrates the additional livability indicators used in the study. All maps were generated by the authors using ArcGIS Pro 3.2 as well. Figure 3-a shows the distance to the river. Since the river enters the city from the north, Districts 5, 18, 19, and 20 have very close proximity to it. In contrast, Districts 6, 7, and 11 are the farthest from the river. Figure 3-b represents accessibility to retail stores. Due to the high concentration of shops in the city center, centrally located Districts 2 and 5 have the shortest distances to stores, while Districts 10 and 15 on the urban fringe are the farthest. Overall, northern districts generally demonstrate better accessibility to retail services. Figure 3-c depicts the shortage of formal residential units. Districts 7, 10, and 11 face the highest housing shortages, whereas Districts 13 and 18 show the lowest. This highlights the widespread challenge of insufficient formal housing across Sari. Figure 3-d presents accessibility to recreational areas. Districts 12, 18, and 19 in the north, as well as District 10 in the south, enjoy the shortest distances. Given Sari's natural proximity to the sea and forests, peripheral districts typically benefit from better access to recreational opportunities. Figure 3-e shows the population age ratio. District 11 records a very low age ratio, while Districts 12 and 15 have the highest. Overall, Sari demonstrates a relatively balanced age

structure, with only three districts deviating significantly from the average. Figure 3-f illustrates the gender ratio. An inverse relationship is evident between age ratio and gender ratio: District 11, with the lowest age ratio, shows the highest gender ratio, whereas Districts 12 and 15, with the highest age ratios, record the lowest gender ratios. Despite these variations, the gender ratio across the city remains generally balanced.

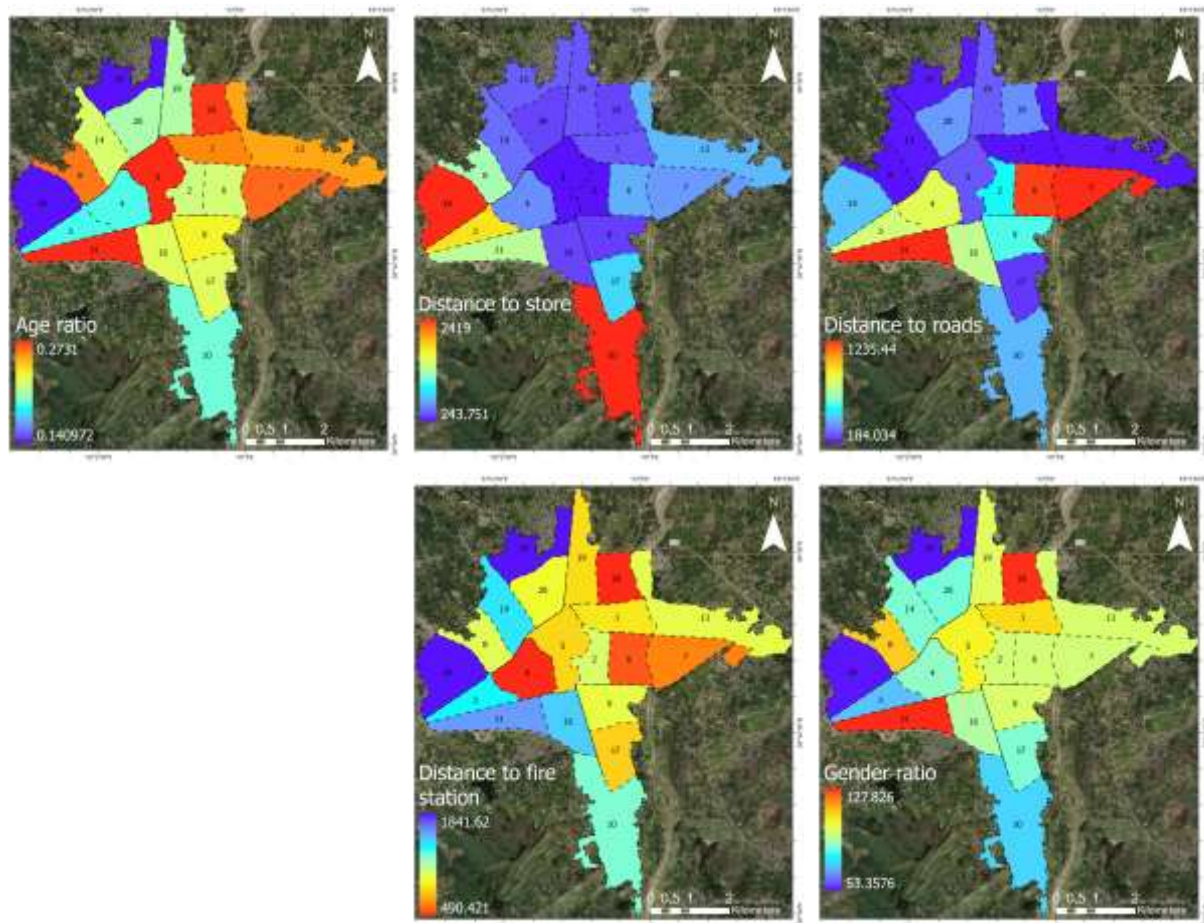


Figure 4: Part 2 of the criteria maps used

4.2 Spatial Patterns of Livability Indicators

Figure 3 Part 1 illustrates the maps of the selected indicators used in the analysis. These include maps of LST, PM10, employment rate, distance to fire stations, distance to hospitals, structural stability percentage,

Figure 5 shows the livability map of Sari city based on the K-Means clustering algorithm. According to this figure, the city's livability is classified into five categories ranging from very low to very high. Based on this map, five districts exhibit very high urban livability: Districts 1, 5, 8, 18, and 19. Conversely, three districts have the lowest urban livability levels, namely Districts 10, 12, and 15. Observing the livability map produced by the K-Means clustering, it is

clear that areas located in or near the city center tend to have high to very high livability. In contrast, peripheral districts mostly show low to very low livability.

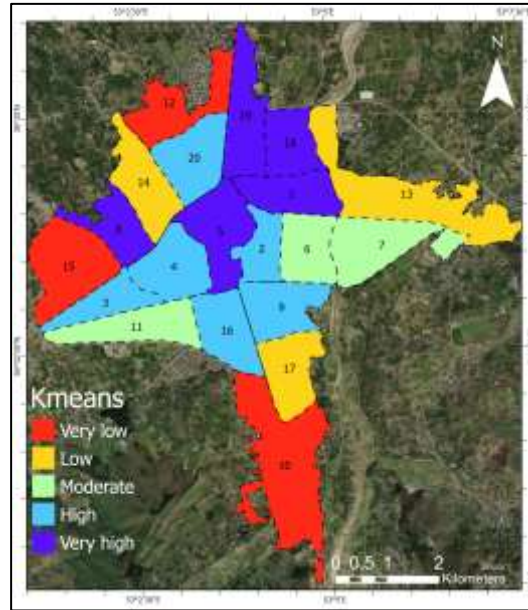


Figure 5. Urban livability map of Sari city using the K-Means algorithm.

Figure 5 shows the livability of Sari city using the K-Means++ algorithm. The pattern of this map is very similar to the map produced by the K-Means clustering algorithm. According to the results of this algorithm, regions 1, 5, 8, 18, and 19 in Sari city also exhibit the highest livability, while regions 10, 12, and 15 show the lowest livability. The only difference between this map and the one produced by the K-Means algorithm is that region 3 is classified as having high livability in K-Means, but it is categorized as medium livability in K-Means++.

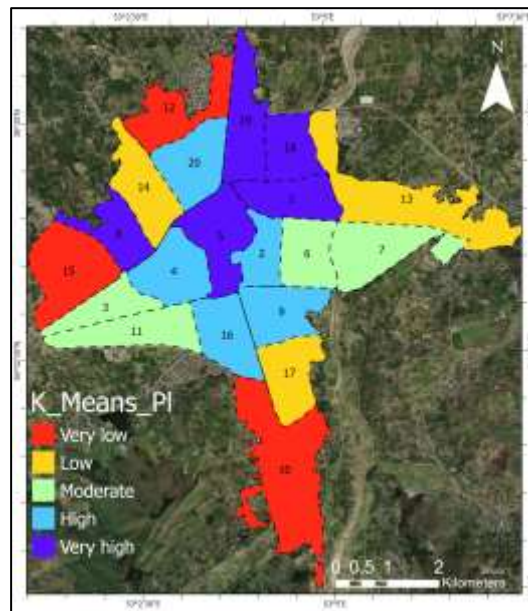


Figure 6. Urban livability map of Sari city using the K-Means++ algorithm

Figure 7. presents the livability clustering map based on HC. At first glance, some differences can be observed in this map. The first difference is that although most regions share the highest livability class, in this method HC, region 8 is classified as having high livability, whereas in the two previous algorithms it was classified as very high livability. The next difference is that region 11, which was classified as medium livability in the two previous algorithms, is classified as low livability according to this algorithm. The third difference between this map and the maps from the two previous algorithms concerns region 17. Region 17 was classified as low livability in the previous two algorithms, but in the HC ing algorithm it falls into the very low urban livability class.

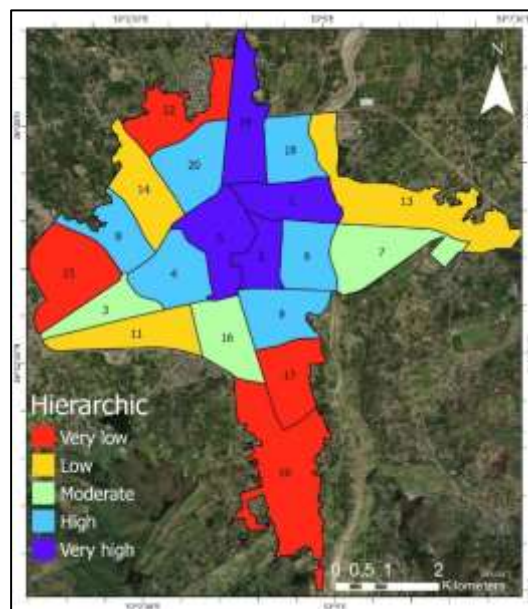


Figure 7. Urban livability map of Sari city based on the HC algorithm

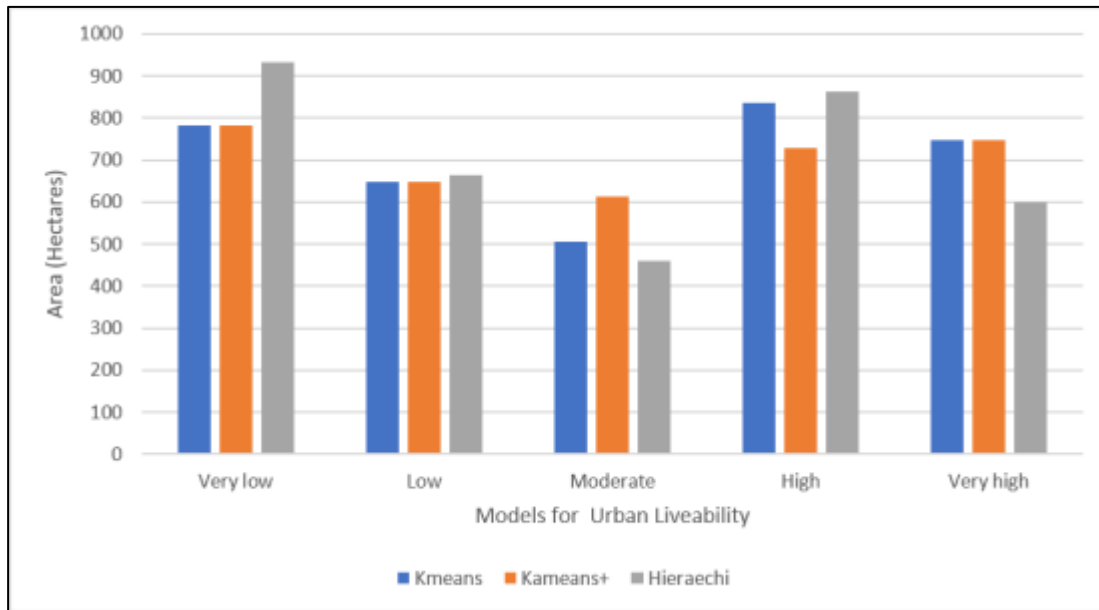


Figure 8. This figure shows that Area of every method that classified by models and dedicated

4.3 Comparative Analysis of Indicator Trends Across Clusters

For comparative line plots generated that showing the mean values of 14 urban livability indicators across five clusters derived from three different clustering algorithms: K-Means, K-Means++, and HC. The patterns across clusters vary, reflecting differences in how each algorithm groups urban areas based on the indicators. For instance, LST (Land Surface Temperature) and PM10 generally increase from lower to higher clusters across all algorithms, suggesting a correlation between certain clusters and environmental stressors. Conversely, indicators like distance to police stations, fire stations, and hospitals decrease in higher-ranking clusters in most algorithms, implying better service accessibility in these districts. Notably, Cluster 2 or 3 in several indicators often shows extreme highs or lows, hinting that these clusters may represent either the most or least livable districts, depending on the variable. Sociodemographic and infrastructure indicators such as employment rate, population, age ratio, and building ratio show significant variation between clusters. For example, the employment rate is consistently higher in clusters 1 and 2, indicating economically vibrant areas, while population density spikes sharply in one or two clusters, particularly under HC. Gender ratio and lack of buildings show less consistency across algorithms, suggesting these may be more sensitive to how the clusters are defined. Overall, K-Means++ tends to smooth the cluster transitions, while HC produces sharper contrasts, especially in accessibility-related indicators. This comparative pattern analysis reveals that while all three clustering methods detect livability trends, they differ in sensitivity and classification precision, which has implications for urban planning based on the chosen algorithm (Figure 9).



Figure 9. The figure displays comparative line plots showing the mean values of 14 urban livability indicators

4.4 Validation assessments

The performance of the clustering algorithms was evaluated using three internal validation indices: the Silhouette score, the Calinski–Harabasz (CH) index, and the Davies–Bouldin Index (DBI). Overall, the results reveal noteworthy differences in clustering quality across the methods. The Silhouette scores for both K-Means and K-Means++ were relatively low (~ 0.16), suggesting limited cohesion within clusters and a degree of overlap between groups. By contrast, the HC method achieved a substantially higher Silhouette score (~ 0.25), indicating clearer separation between clusters and stronger within-group similarity (Table 1). Although the absolute values remain modest, the relative difference demonstrates that HC provides more interpretable partitions of urban districts in this dataset. The Calinski–Harabasz index further supported this conclusion. HC produced higher CH values compared to both K-Means and K-Means++, implying that the between-cluster dispersion is substantially greater relative to the within-cluster dispersion. This aligns with the Silhouette-based evidence that HC produces more distinct clusters. Similarly, the Davies–Bouldin index, which penalizes high similarity between clusters, yielded lower values for the hierarchical approach than for the partitioning methods. Lower DBI scores imply that HC generated clusters with reduced overlap and greater internal homogeneity. Taken together, these indices highlight that while all three methods are capable of segmenting urban livability patterns, HC provided the most consistent and statistically robust partitions of the study area. However, the relatively low Silhouette values across all models indicate that urban livability is a complex, multidimensional construct where strict separations between groups are challenging to establish. This reinforces the need for complementary approaches, such as uncertainty analysis or hybrid models, to capture the nuances of urban dynamics more effectively.

Table 2. this table assesses validation indices (Silhouette, Calinski–Harabasz, Davies–Bouldin) for three clustering methods

Algorithm	Silhouette	Calinski–Harabasz	Davies–Bouldin
K-Means++	~ 0.16	Moderate	Moderate–High
Hierarchical	~ 0.25	Higher	Lower (better)
K-Means	~ 0.16	Moderate	Moderate–High

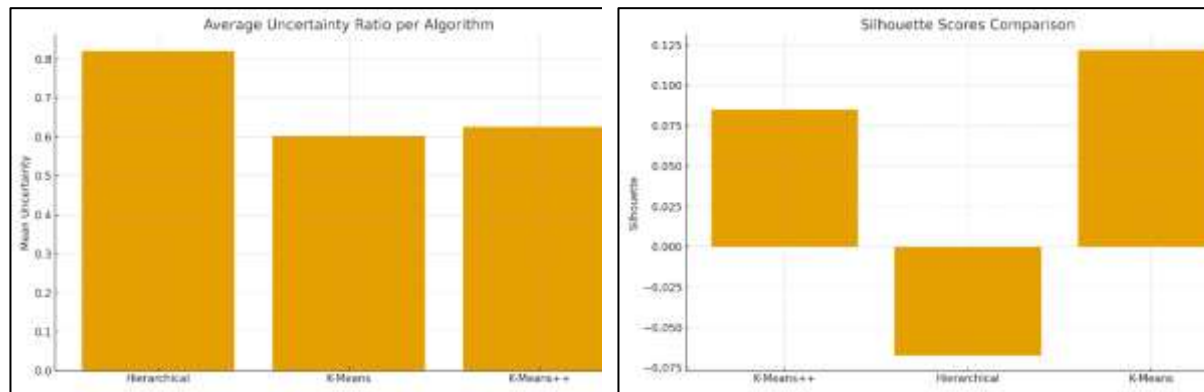


Figure 10. These Graphs illustrate uncertainty and Silhouette score comparison in three models

4.5 Comparative Results

Across all three clustering algorithms, a clear and consistent spatial pattern of livability emerged. Districts 5, 18, and 19 were repeatedly identified as the highest-livability districts due to their strong accessibility, infrastructure conditions, and favorable environmental indicators. Conversely, districts 10, 12, and 15 were consistently classified as low-livability areas across all models, reflecting structural deficiencies, environmental stress, and limited service provision. Transitional districts such as 3, 11, and 17 showed higher variability between the algorithms, indicating moderate uncertainty and sensitivity to methodological differences. Overall, the comparative analysis reveals strong agreement among the models regarding both the highest and lowest livability districts, while also identifying districts where targeted interventions and further monitoring are needed.

Table 3, Comparative Summary of Clustering Outputs Across Three Algorithms

District	K-Means	K-Means++	Hierarchical	Consensus Interpretation
1	Very High	Very High	High	Consistently High Livability
5	Very High	Very High	Very High	Strong Consensus High Livability
8	Very High	Very High	High	High Livability (Stable)
18	Very High	Very High	Very High	Strong Consensus High Livability
19	Very High	Very High	Very High	Strong Consensus High Livability
10	Very Low	Very Low	Very Low	Strong Consensus Low Livability
12	Very Low	Very Low	Low	Low Livability
15	Very Low	Very Low	Very Low	Strong Consensus Low Livability
3	Medium	Medium	Low	Transitional / Moderate Uncertainty
11	Medium	Medium	Low	Transitional districts
17	Low	Low	Very Low	Transitional–Poor

5. Discussion

The spatial patterns identified by the clustering algorithms reveal systemic socio-environmental inequalities that are deeply rooted in the urban development trajectory of Sari City. The consistent classification of central districts as high-livability districts reflects the historical

concentration of infrastructure, public services, and economic opportunities in the urban core. This pattern aligns with urban spatial theories suggesting that accessibility and service agglomeration drive enhanced livability outcomes (Mulliner & Maliene, 2011; Pan et al., 2021). Conversely, the persistent clustering of peripheral districts into low-livability categories can be causally linked to limited investment in public services, higher environmental burdens such as elevated LST and PM₁₀, and weaker structural building conditions. These findings demonstrate not only spatial disparities but also the underlying mechanisms through which infrastructure allocation, environmental exposure, and socio-economic attributes interact to shape urban well-being. The results also underscore how service proximity directly influences livability. Districts lacking adequate access to hospitals, police stations, recreational areas, and commercial centers were consistently associated with lower livability clusters. This reflects broader evidence that accessibility deficits disproportionately affect vulnerable populations and contribute to spatial injustice. In Sari, the location of emergency services and healthcare facilities appears to be a principal driver of the divergence between central and peripheral districts, suggesting that targeted redistribution of essential services could significantly reduce urban inequality. From a methodological perspective, this study demonstrates the value of integrating multiple unsupervised clustering algorithms and evaluating their consistency. The comparative framework provides a more robust classification than single-method approaches commonly used in previous urban livability studies. The application of K-Means, K-Means++, and Hierarchical Clustering (HC) in parallel enhances methodological transparency, while internal validation indices clarify cluster stability. The consistency observed among the models for high- and low-livability districts strengthens confidence in the results and establishes this approach as a replicable tool for urban analysis. This innovation is particularly relevant for data-limited cities in the Global South, where traditional index-based methods may over-rely on subjective weighting and expert opinion. The findings have several implications for policy and planning. First, the clear spatial divide between central and peripheral districts suggests the need for geographically targeted interventions, particularly in districts classified as consistently low-livability (e.g., 10, 12, and 15). Policies should prioritize improved access to essential services, investment in structural building upgrades, and mitigation of environmental stressors such as high surface temperatures and air pollution. Second, the identification of transitional districts where algorithm outputs varied highlights areas where incremental improvements could shift neighborhood conditions significantly. These districts offer strategic opportunities for cost-effective interventions. Third, the study provides evidence to support integrated urban planning frameworks that align environmental management, service distribution, and socio-economic development strategies. For example, cooling strategies (urban greening, reflective surfaces) could be coordinated with socio-economic programs to address both environmental and demographic vulnerabilities. Finally, the methodological framework introduced in this study can serve as a decision-support tool for municipalities aiming to monitor livability changes over time, evaluate the effectiveness of interventions, or simulate future scenarios. The revised

analysis not only identifies existing spatial inequalities but also reveals the causal mechanisms behind them and provides actionable pathways for creating a more equitable and resilient urban environment.

5. Conclusion

Cities, as dynamic and continuously evolving social systems, are frequently studied to address emerging urban challenges (Batty, 2009; Khan et al., 2023). Their dynamic nature not only makes urban change an engaging research topic but also introduces complex, interrelated features that shape future urban studies (Wentz et al., 2014; Bikis et al., 2025). Among the most critical components in this context is urban livability, a key indicator that reflects the overall quality of urban life (Kabisch et al., 2019; Liu et al., 2025). Livability is inherently multidimensional, encompassing infrastructural, physical, social, economic, and environmental factors. Achieving a livable city depends on the optimal combination and balance of these criteria. In this study, a spatially explicit assessment of livability in Sari City was conducted using 14 spatial indicators grouped under five core dimensions: urban infrastructure, public services, environmental quality, security (including financial, physical, and psychological aspects), and social characteristics. Three machine learning clustering algorithms K-Means, K-Means++, and HC were employed to classify the city's districts into five livability levels, ranging from very low to very high. Despite some differences in the outputs, districts 1, 5, 18, and 19 were consistently identified as the most livable across all methods, confirming their high livability status. Conversely, districts 10, 12, and 15 were consistently ranked as having the lowest livability, highlighting significant deficiencies in services, infrastructure, and environmental conditions. The results underscore a clear spatial pattern: central areas of Sari, characterized by better access to healthcare, education, transportation, and green spaces, exhibited higher livability, while peripheral districts especially those in the southwest and northeast were associated with low livability due to dense population, inadequate infrastructure, limited green spaces, and poor service distribution. These findings highlight the significance of spatial justice in urban policy, emphasizing the need not only to enhance service levels but to ensure their equitable spatial distribution across the city. The study demonstrates that integrating machine learning clustering with GIS-based spatial analysis provides a robust and insightful approach to understanding urban livability. This combination facilitates the identification of disparities, supports evidence-based planning, and helps guide policies toward sustainable and equitable urban development. The comparative use of three clustering algorithms also revealed that while there is general agreement among the models, notable differences exist.

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