

Article

Measuring Retail Resilience Using a Geospatial Multi-Criteria Model: A Case Study of Saida, Lebanon

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Abstract

Urban retail environments are social and economic manifestations of a city, enhancing economic growth and social cohesion. However, they increasingly face challenges from economic downturns, changing consumer preferences, and spatial dynamics, making their ability to adapt and remain viable a critical concern. In this context, retail resilience refers to the capacity of urban retail environments to absorb disturbances, adapt to change, and sustain their economic and social functions over time. Despite growing interest in urban resilience, the operationalization of retail resilience through spatially explicit and measurable indicators remains limited, as many assessments focus on city or regional scales and overlook variations at the neighborhood level. Thus, this paper aims to develop a geospatial multi-criteria model yielding a composite Urban Retail Resilience Index (URRI) to analyze and interpret retail resilience in Saida's urban retail environment through an adaptive cycle lens. The URRI combines indicators related to diversity, spatial proximity, and socioeconomic conditions, and is applied using two weighting scenarios—baseline and stakeholder-based weights—to test the model's robustness and reflect local priorities. The results reveal distinct spatial variations in retail resilience across the study area, enabling the identification of hotspots for interventions and highlighting the role of accessibility and diversity in shaping the adaptive capacity. These findings confirm that Saida's retail resilience is closely linked to walkability and socio-cultural characteristics. The proposed geospatial multi-criteria model provides a robust and replicable framework for assessing retail resilience, offering practical insights for urban planners and policymakers.

Keywords: retail resilience; urban environment; Geographic Information Systems (GIS); geospatial analysis; multi-criteria model; Urban Retail Resilience Index (URRI); adaptive cycle



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1. Background

Retailing has always been a primary urban function for consumers, as urban retail environments reflect the social and economic fabric of a city, sometimes called the city's economic veins [1]. However, the dialog between retailing and the city, at present, has evolved functionally from shopping places as utilitarian premises to places of experiences and economy of fascination [2]. Nevertheless, urban retail spaces face challenges due to factors such as the economy (e-commerce shopping) and social disturbances (pandemics/conflict) [3,4], as well as changing consumer preferences. Such pressures are more acute in cities, where

retail resilience is paramount as they struggle to survive and adapt [5–8]. Retail resilience, defined as “the ability of stores or shopping districts to tolerate and adapt to changing environments that challenge the retail system’s equilibrium, without failing to perform its functions sustainably”, is a complex concept influenced by multiple stakeholders [9–13]. More specifically, the approach is more strictly focused on adaptation within the context of evolutionary principles. Essentially, more resilient retail environments would be able to “bounce forward” instead of merely trying to move back to a positive equilibrium. They would therefore be able to effectively cope with new norms instead of returning to a pre-shock state [9,11,14]. The involvement of various stakeholders is crucial in retail resilience because the retail system is multi-dimensional, encompassing economic, social, cultural, and spatial aspects, and its resilience depends on the collective capacity to adapt to changes, crises, or shocks [6]. Specifically, retail resilience emerges from the interplay between public and private actors, where policies, governance arrangements, and everyday market practices co-evolve [14]. The public sector, including national and municipal authorities, provides regulatory frameworks, infrastructure necessities, and strategic visions that address vulnerabilities and adaptive capacities, defining the structural conditions within which retail activities operate [5,15]. City center managers and place-based organizations often operate within public–private partnership arrangements, translating policy objectives into coordinated local actions such as district management, branding, events, and mixed-use programming, thereby mediating between public institutions, property owners, retailers, and citizens [15]. On the private sector side, retailers, consumers, and citizens play a direct role in the everyday functioning and adaptability of urban retail systems. Previous studies have emphasized the central role of retailers as active agents of adaptation, whose decisions regarding tenant mix, investment, innovation, and daily practices directly influence the capacity of retail areas to respond to change [16–18], while consumers shape resilience through shopping behavior, mobility patterns, preferences for accessible and mixed-use environments, and local patronage [1,19]. Although retail resilience emerges from the interaction of public and private actors, retailers and consumers play a particularly influential role, as consumer behavior directly shapes retailer strategies and the spatial viability of urban retail environments, especially during periods of disruption [18,20,21].

Resilience in urban systems involves adaptation, transformation, recovery, and resistance [22]. Holling [23] initially developed the adaptive cycle, as it offers a dynamic, process-oriented approach to recognizing resilience in complex systems. Previous studies discussed how this approach has been applied to different urban systems, but it has been scarce in the urban retail system. Dolega and Celinska [9] tailored this framework to target retail. Their framework of the adaptive cycle helps to effectively explore the phases of retail systems in terms of release, reorientation, growth, and consolidation [9]. (1) The Release Phase (collapse) is exemplified by extremely high vacancy rates, business closures, and decreased commercial activities. The overall structure is released in this stage, and its resources are weakened, entering a collapse phase. (2) The Reorientation Phase (renewal) is characterized by high vacancy and low commercial activity, but there is a high opportunity for change and renewal. Retail areas experiencing revitalization, repurposing, or reinvention control in this phase. (3) The Growth Phase (expansion) is described by established retail presence, increasing diversity, stable conditions, and potential rigidity. However, in this phase, the opening of new businesses and innovative activities begins. (4) The Consolidation Phase (conservation and maturity) is characterized by great diversity, easy accessibility, and sound socioeconomic conditions. The stability, efficiency, and interconnectedness become more rigid during this phase. Although it is currently high, it is exposed to shocks that may challenge the phase to raise the level of vulnerability. It is high but declining, as it is exposed to sudden shocks that may challenge this phase to increase

vulnerability [7,9,24]. These phases illustrate the dynamic evolution of retail centers, where adaptive capacity is key to navigating shocks and changes.

Retail resilience manifests through diversity and redundancy, connectivity and accessibility, and socioeconomic variables [25–27]. Despite growing interest in urban resilience, few retail-specific frameworks exist in urban studies. Additionally, many resilience assessments focus on the city or regional level, overlooking neighborhood variations. Most retail studies emphasize economic indicators rather than urban parameters of the built environment [5,28]. Because urban retail involves many interconnected variables that form a system in which influencing one affects others, measuring resilience in a retail context requires combining indicators into a composite index [29–31]. Regardless of these challenges, a geospatial multi-criteria approach has proven to be a reliable method for assessing such complex urban phenomena that need the consideration of multiple criteria [32,33]. The utilization of Geographic Information Systems (GIS) and multi-criteria analysis enables spatialization, correlation of different types of data, scenario analysis, and the identification of hotspots for intervention [34–37]. The authors propose developing a geospatial multi-criteria model to analyze retail resilience in Saida’s urban retail landscape. In Saida, retail activity remains fragmented, facing a compounding set of challenges, including spatial and social fragmentation, economic crisis, and the emergence of new retail formats, underscoring the need for retail resilience [38–40]. To formulate evidence-informed strategies, it is necessary to understand the spatial patterns of retail resilience. This paper aims to develop a geospatial multi-criteria model to produce a composite Urban Retail Resilience Index (URRI), integrating diversity, proximity, and socioeconomic indicators, that provides insights into retail resilience challenges. To achieve this aim, the paper includes specific objectives:

- Employing spatial analytical GIS methods to obtain the URRI based on a set of measurable indicators that sustain a resilient urban retail environment.
- Classifying the URRI into adaptive cycle stages of retail resilience.
- Examining spatial and statistical outcomes of the URRI, through identifying strengths and vulnerabilities (hotspot analysis) for targeted interventions.
- Employing multiple weighting scenarios for the sensitivity and robustness of the URRI.
- Aiding stakeholders to guide interventions toward more resilient urban retail environments (a diagnostic tool).

2. Methods and Materials

2.1. Methodology

According to OECD (Organization of Economic Co-operation and Development) [41] guidelines, ESRI’s (Environmental Systems Research Institute) composite index methodology [42], and other prominent studies [30,43–45], a systematic seven-step workflow is applied to construct the URRI composite index (Figure 1). Each step is explicitly defined in terms of data inputs, quantification procedures, and interpretation of retail resilience outcomes, ensuring methodological transparency and enabling the URRI framework to be systematically replicated or adapted in other urban contexts where comparable datasets are available. A GIS-based multi-criteria model is built, comprising several spatial and socioeconomic indicators to support the development of the URRI. In practical terms, the URRI synthesizes these indicators to analyze the relative capacity of urban retail areas to sustain activity and adapt to change, with higher values reflecting structurally supportive retail environments and lower values indicating spatial or functional vulnerability.

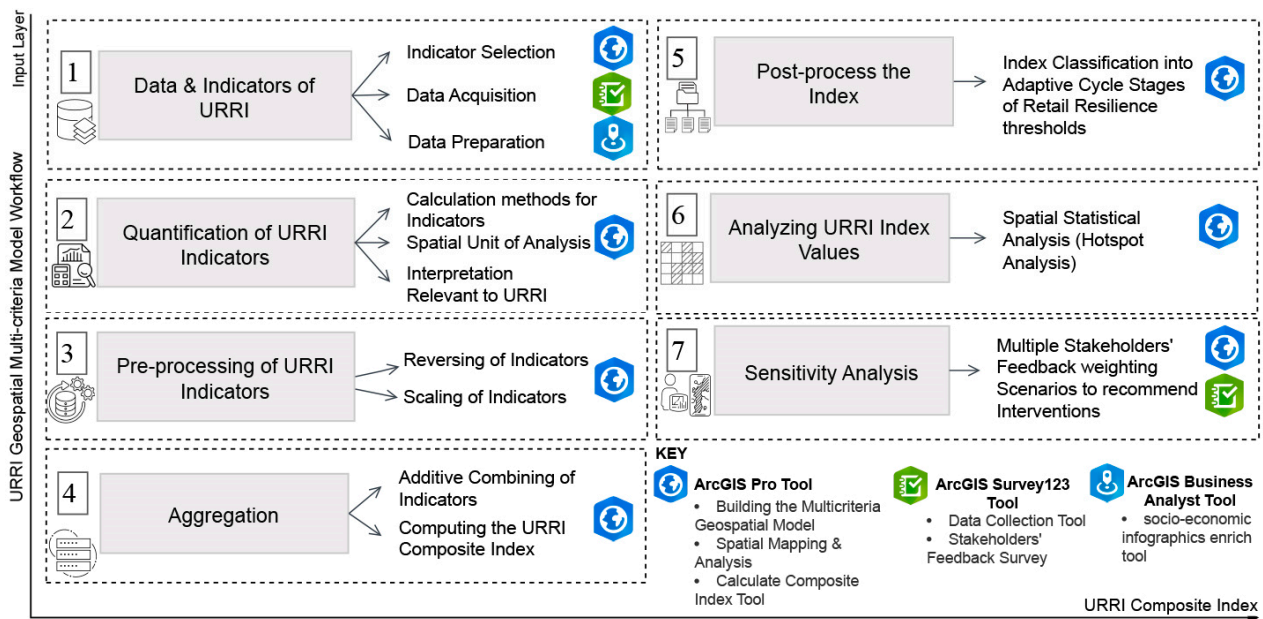


Figure 1. Methodology workflow of analysis.

The study employs a quantitative research method, starting with (1) Data and Indicators: 12 indicators were selected across diversity criteria (retail and services, functional diversity), proximity criteria (parking, amenities, public transit, shopping malls with anchors, landmarks), and socioeconomic criteria (dependency ratio, educational attainment, unemployment rate, vacancy rate, commercial density), with data acquired from field surveys, Open Street Map, municipal GIS, census projections, and the Central Administration of Statistics, and then prepared through georeferencing and validation. (2) Quantification: Diversity indicators were calculated using the Simpson diversity index, proximity indicators were calculated using the ArcGIS Closest Facility tool in ArcGIS Pro version 3.6.0 [46] on a pedestrian network with a 10 min cutoff as a walking distance, and socioeconomic indicators were extracted from the ArcGIS Business Analyst enrich tool. All indicators were spatially joined and analyzed across 15×15 square-meter fishnet cells to capture spatial heterogeneity, with higher diversity, shorter distances, and stronger socioeconomic indicators interpreted as higher resilience. (3) Pre-processing: The min–max normalization technique was used to normalize all indicators to a range of 0–1 values, with reverse for negative indicators to maintain that higher values contribute greater resilience. (4) Aggregation: A weighted linear combination was computed to obtain the overall URRI. An equal-weight combination was performed to determine a base scenario by utilizing the “Calculate Composite Index” geoprocessing tool in ArcGIS Pro [42,47]. (5) Post-processing: Values of the URRI were categorized into quarters of the adaptive cycle to allow for interventions tailored to the phase. (6) Hotspot Analysis: *Getis-Ord Gi** statistics revealed the critical spatial clusters of hotspots for high resilience and cold spots for low resilience. (7) Sensitivity Analysis: Feedback from stakeholders was used to obtain alternative weights of the twelve indicators using the Borda count ranking technique [43,48] to carry out a comparative scenario analysis based on a survey developed in ArcGIS Survey123.

2.2. Introducing the Case Study: Saida Urban Retail Environment

Saida (also called Sidon) is the third largest city in Lebanon. It is located on the Mediterranean coast. The urban area population of Saida city is around 80,000. Over 200,000 people live in the wider metropolitan region of Saida. Existing infrastructure is under strain due to demographic growth in recent decades. This has resulted in induced

demand, driven by social, economic, and physical factors. Saida's urban fabric is a blend of complementary typologies. Primarily, the historic center of the city includes the traditional Souk named Saida Old Souk, ancient commercial streets known as Saida's city center Souk, and contemporary retail formats such as shopping malls and shopping strips outside the Souks. The Saida Old Souk area is known for its active market, dense urban form, and its status as the commercial center of Saida. Recently, contemporary retail formats have introduced competition and diverse consumer patterns and preferences. The focus area encompasses the historic core market and the city center shopping streets, with central new retail nodes (shopping malls) as attractors (see Figure 2). However, this urban retail environment faces socioeconomic and spatial fragmentation between the historic core and the city, creating border vacuums that interrupt spatial continuity [25,49].

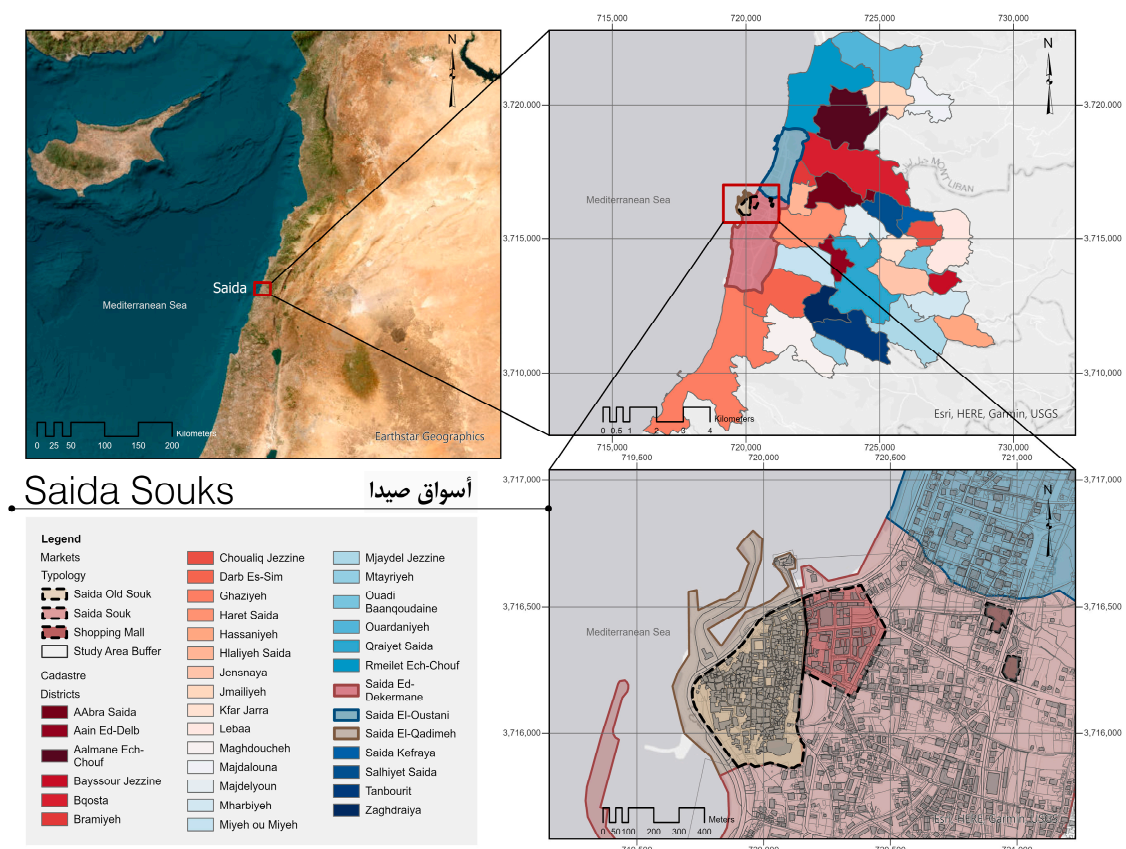


Figure 2. Study Area Maps with Surrounding Context (Authors).

2.3. Data Acquisition and Preparation

The data for this study were compiled from multiple sources to develop the individual indicator maps. The study included primary data collection using a survey built on ArcGIS Survey123 with 87 stakeholders, including retailers and consumers in the study area, to rank the criteria by importance and convert them into weights for analysis. Participation in the survey was voluntary and conducted in the field, and the final number of respondents reflects stakeholders who were available and willing to participate during the data collection period. A purposeful sampling approach was adopted, targeting retailers and consumers with direct experience of the local retail environment. Secondary data collection involved GIS spatial and statistical data selected to provide reliable, accurate, and spatially continuous base layers at the urban scale, enabling systematic indicator calculation within a GIS environment and supporting the construction of retail resilience patterns across the study area. These data included administrative boundaries, building footprints,

street networks, and land-use data with their attributes. Additionally, retail and service data for ground floors were gathered from various sources and supplemented by field surveys to identify and validate the distribution and types of retail and services. These data were then mapped in GIS from scratch, with their relevant attributes aligned with the analysis criteria. In addition, statistical data were collected from authorized resources and reports. Table 1 provides details on the data features, formats, sources, and acquisition tools. After collecting and developing the data, they were correlated within a unified GIS environment and aligned with a common coordinate system to compute the indicators. The overall workflow of data acquisition, preprocessing, spatial unit definition, and weighting procedures adopted in this study is summarized in Figure 3. All spatial datasets and analyses were projected using the Universal Transverse Mercator (UTM) Zone 36N (EPSG: 32636) coordinate system based on the WGS 1984 datum, which is appropriate for precise urban-scale geospatial analysis in Lebanon, including Saidra.

Table 1. Data Features, format, and source with the relevant acquisition tool.

Data Features	Format	Data Source/Acquisition Tool
Map of Building Footprints and their attributes	GIS Spatial and Statistical Data	UN-Habitat and UNICEF Lebanon Geoportal + Municipal GIS databases
Map of Retail Shops and Services Data with their attributes	GIS Spatial and Statistical data	ArcGIS Survey123 Field Survey + UN-Habitat, and UNICEF Lebanon Geoportal + Municipal Data
Land Use Data	GIS Spatial and Statistical Data	UN-Habitat, and UNICEF Lebanon Geoportal + Reports (LCPS ³ , USUDS ⁴)
Socioeconomic Data	GIS Statistical Data	ArcGIS Business Analyst, Lebanon ESRI ¹ Demographic Data + CAS ² Reports
Street Network Data and its attributes	GIS Spatial and Statistical Data	ESRI Lebanon GIS Data

Notes: All data features are integrated in ArcGIS Pro, including formats such as shapefiles, geodatabases, and Excel sheets. ¹ ESRI: Environmental Systems Research Institute. ² CAS: Central Administration of Statistics. ³ LCPS: The Lebanese Center for Policy Studies. ⁴ USUDS: Urban Sustainable Development of Saidra.

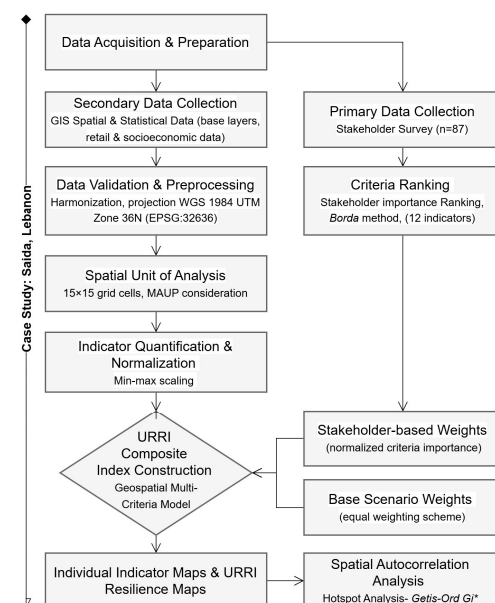


Figure 3. Workflow of data acquisition, spatial processing, and weighting procedures used to construct the Urban Retail Resilience Index (URRI) for Saidra, Lebanon case study. The asterisk in Gi* denotes the standardized Getis–Ord statistic used in hotspot analysis (Authors).

2.4. Spatial Unit of Analysis

The spatial unit of analysis is critical for a meaningful index [42]. According to [9], building resilience and adaptive capacity in retail areas depends significantly on the scales at which they are embedded. A retail location is nested in a hierarchy of several sizes, including local, regional, and national, which interact with one another in a somewhat complex manner. Referring to [8], there are two main ways in which these interactions take place: first, larger scales affect smaller scales, and second, local systems affect regional and national systems. The features of the three key performance domains—social, economic, and physical built environment—as well as the location of a center within an adaptive cycle, together determine a retail center's overall resilience [9,50,51]. At the local scale, retail resilience depends on how shops, street segments, and proximity to facilities vary from block to block. To construct a meaningful URRI, a fine-grained analysis should be adopted that captures block and building-level retail variation while remaining coarse enough for computational tractability. This builds on prior studies that used coarser grids and reflects the demonstrated accuracy of smaller, homogeneous units [52,53]. To address this microspatial variation, fishnet tessellation using GIS is widely recognized as a practical approach to ensure spatial comparability and scalability across variables [54]. It helps model spatial dynamics by using a uniform grid cell to represent multiple spatial features, and it establishes an efficient, manageable geospatial model along with calculation measures. Each fishnet cell functions as the basic spatial unit for analysis, onto which attribute data from multiple datasets are linked. This process converts various input geometries into a standardized geospatial dataset suitable for aggregation and the creation of composite indices [55–57]. Accordingly, grid tessellations of 15×15 , 50×50 , 100×100 , and 150×150 m were created using the Fishnet geoprocessing tool in ArcGIS Pro. Since the study area focuses on the local level, which includes a historic, densely built fabric with traditional shopping streets, a cell size of 15×15 m was chosen as the basic analysis scale for URRI (see Figure 4).

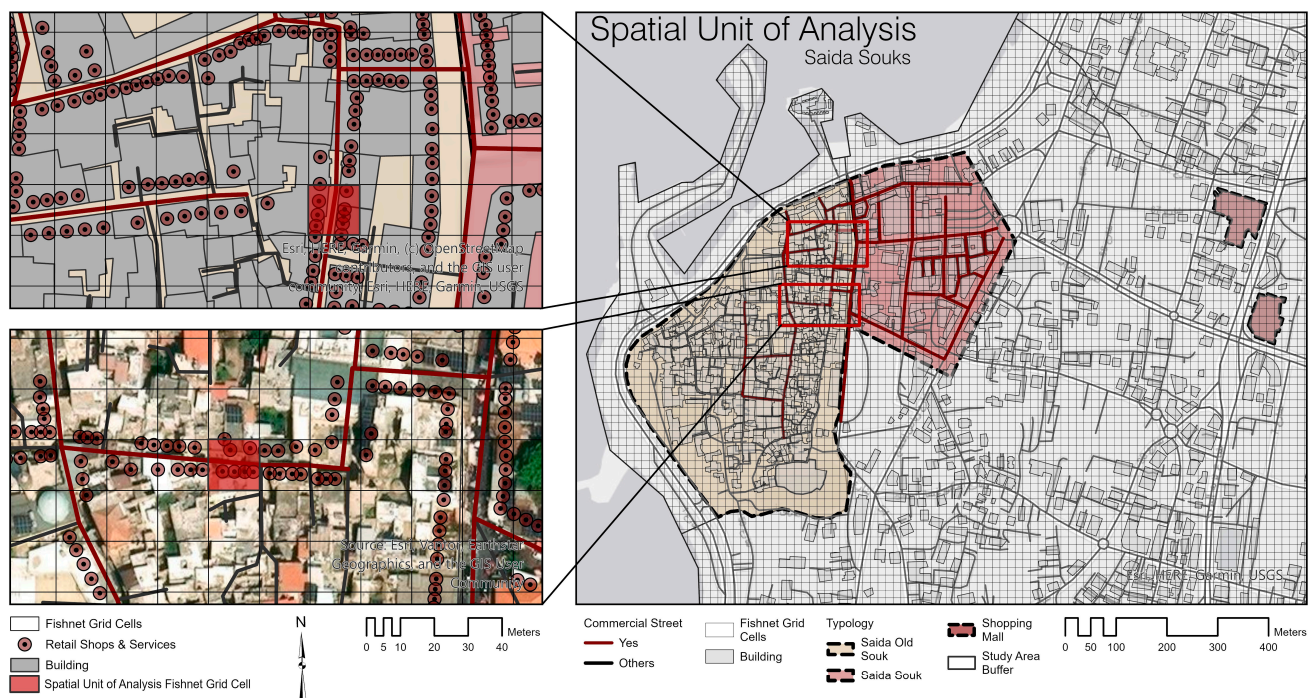


Figure 4. Spatial Unit of Analysis (Authors).

This cell size addresses the Modifiable Areal Unit Problem (MAUP) by aligning the unit of analysis with the fine-grained morphology and functional scale of retail activity in Saida's historic fabric, characterized by narrow alleys and micro-scale retail units. In such compact urban environments, the 15×15 m cells limit aggregation bias associated with coarser units while preserving localized retail resilience patterns, without introducing excessive data sparsity. At this spatial resolution, indicators are spatially attributed and interpreted at the cell level, allowing URRI values to reflect localized retail resilience patterns while accommodating indicators derived from broader neighborhood-scale datasets.

2.5. Identification of Assessment Criteria and Selection of Indicators

URRI indicators cover primary criteria including diversity, proximity, and socioeconomic status. The choice of indicators was influenced by data availability. The chosen indicators were considered sufficiently representative of the essential URRI criteria as discussed by [9,10,58–61] (see Table 2). Regarding design criteria, including the quality of retail fabric, they were not included in the analysis due to limited data availability and reliability.

Table 2. Criteria for measuring retail resilience and the adopted indicators for the study area.

Criteria	URRI Indicators		
	Measurable Indicators	Adopted	Type of Measure
Diversity	Retail and Services Diversity (Simpson Diversity Index)	✓	Built Environment
	Functional Diversity (Simpson Diversity Index)	✓	
Design	Quality of Streetscape/Retail Fabric	X	
	Proximity to Parking Spaces	✓	
Proximity	Proximity to Public Transit	✓	
	Proximity to Key Amenities	✓	
	Proximity to Shopping Malls	✓	
	Proximity to Landmarks	✓	
	Dependency Ratio	✓	
Socioeconomic	Educational Attainment	✓	Social
	Unemployment Rate	✓	Economic
	Retail Vacancy Rate	✓	
	Commercial Density	✓	

Notes: ✓ indicates that the indicator is adopted; X indicates that the indicator is not adopted.

3. Quantification of URRI Indicators

3.1. Diversity Indicators

URRI stresses the need for diversity in the mix of shops on the ground floor, in retail and service offerings, and in the building's functions [9,31,58,62,63]. These diversity measures are essential for urban retail resilience because they disperse economic risk across different categories and time periods, encourage varied patterns of foot traffic, support a broader range of livelihoods, and adapt to changing consumer behaviors. In ecological resilience theory, redundancy and diversity are recognized as mechanisms for absorbing shocks that directly affect urban retail systems. Retail and services diversity is an indicator that measures the diversity of commercial streets, as classified into the primary and sub-retail categories. The classification of retail and services is based on [9,50,58,64,65], which depends on the type of goods, categorizing them into comparison, convenience, retail services, leisure services, and financial and business services. A mix of retail and services is more proficient at adjusting to economic disruptions and changing consumer behaviors [9,50,53,58]. Functional diversity is an indicator at the building-use level. Buildings are classified into mixed-use, residential, commercial, touristic, religious, educational,

institutional, social services, healthcare, and others [39]. A mix of building uses provides different activity flows across the day and helps urban retail environments maintain foot traffic outside traditional shopping hours [55,66]. It tends to support social cohesion and economic resilience by ensuring consistent usage of the area and reducing reliance on a single function [55,66]. Simpson's Diversity Index (Equation (1)) is used to quantify the diversity measures adapted from [67,68].

$$SDI = 1 - \left[\frac{\sum n_i(n_i - 1)}{N_T(N_T - 1)} \right] \quad (1)$$

where SDI is the Simpson diversity index, n_i is the number of buildings/shops of a single type i , $n_i(n_i - 1)$ is calculated for every single type, and N_T is the total number of buildings/shops.

The value measures between 0 and 1. A high value suggests a vigorous environment in which no single type is overlooked. A low value suggests that the environment relies on a limited kind of usage, making it more susceptible to downturns in particular areas [50,58,69–71].

3.2. Proximity Indicators

Proximity indicators play a critical role in URRI as they boost pedestrian activity and functionality in the urban retail environment. Accessibility and centrality are the main factors responsible for retail location patterns [1]. They have a positive influence on retail resilience by providing a diversified economy in the locality. They also make the urban retail environment more attractive. This synergy creates a robust, adaptive urban retail area that can better withstand economic shocks and competition from attractors [10,11,18,72]. They are computed using ArcGIS Network Analyst's Closest Facility Tool on the pedestrian network, with an 800 m walking cut-off (approximately 10 min walking), measuring the actual travel distance across roads from cell centroids to the nearest features.

$$P_dist = \frac{d_i}{d_{max}} \quad (2)$$

where P_dist is the normalized distance from each cell i to the nearest instance of each feature type in meters, d_i is the walking distance (10 min walking) from each cell i to the nearest facility location in meters, and d_{max} is the maximum distance between feature types and cells.

Proximity features are represented as vector point and polygon data in ArcGIS Pro. Equation (2) is applied solely to every type of feature. These indicators capture different dimensions of accessibility, including the following:

Proximity to Parking Spaces (PP): This indicator includes public parking lots, excluding on-street parking spaces. Previous studies showed that attractive retail locations require sufficient accessibility by private and public transport, whereas a high number of parking spaces in the immediate locality decreases attractiveness [73]. Specifically, extreme on-street parking makes the area less attractive. On the contrary, enough off-street parking tends to have a positive effect on Resilience by allowing enough space for car parking close to the point of purchase. The role of car parking may vary in diverse settings. For some urban settings, encouraging walkability shows a negative correlation with parking spaces [74,75].

Proximity to Public Transit (PT): This involves the distance to the nearest public transit (bus stop nodes) sustaining regular retail activity. This enables the retail area to remain functional during mobility interruptions [67,71,76]. This criterion enhances accessibility for a larger customer base beyond the influence of factors such as traffic congestion and lack of parking spaces [77–79]. Yet, this would affect people who largely depend on public transit.

Proximity to Key Amenities (PK): This comprises the distance to the nearest crucial civic and institutional amenities, including educational and healthcare facilities, as well as emergency services [67]. This criterion provides insights into how well the location has access to community support services that create stable, non-discretionary pedestrian movements; these movements better enhance the community activity points relative to external support services.

Proximity to Shopping Malls (PS) (an external anchor/competitor): Shopping malls are part of the urban retail system in the city. They act as primary attractors, sometimes called magnets, to regional customers, with a mixed impact; potentially positive spillovers through increased foot traffic, but also serving as competitors, since they contain anchor stores that can challenge small local retailers [10,14,80,81].

Proximity to Landmarks (PL): This involves the distance to the nearest landmarks, ranging from historical, cultural, or religious sites. They attract visitors who, in turn, visit the shopping area, thereby increasing the foot traffic. This is evident in heritage sites where tourism and business meet [82–84].

These values range between 0 and 1. A lower value indicates closer proximity, while a higher value indicates greater distance. With high accessibility, having a positive effect on retail resilience [11], proximity acts as a negative indicator where its raw values need to be reversed before incorporating it into the composite index. This provides consistency among indicators and supports proximity values with the positive influence direction required for the URRI computation.

3.3. Socioeconomic Indicators

These indicators have been calculated from ArcGIS Business Analyst-enriched data and checked for accuracy by several authoritative sources. The Dependency Ratio (DR), Educational Attainment (EA), and the Unemployment Rate (UR) have been aggregated into a single uniform value across the whole study area (neighborhood level) and then allocated to grid cells using spatial join. The Commercial density (CD) and the Retail Vacancy Rate (RV) have been aggregated on active commercial streets in the study area. The formulas for each indicator are as follows:

3.3.1. Dependency Ratio (DR)

DR is a measure of the nonworking-age population relative to the working-age population and can be used to determine a community's age structure. This measure expresses the relationship between three age groups in a population: under 18, 18–64, and 65+ years old [85,86]. Equation (3) is adapted from [87].

$$DR = \frac{Pop_{<18} + Pop_{>64}}{Pop_{18-64}} \times 100 \quad (3)$$

where $Pop_{<18}$ is the population under 18 years, $Pop_{>64}$ is the population over 65 years, and Pop_{18-64} is the working-age population, in accordance with the demographic classification used in ArcGIS Business Analyst.

A high dependency ratio indicates a larger proportion of dependents relative to the working-age population, weakening local economic resilience by reducing labor participation, purchasing power, and the capacity of retail areas to sustain their adaptive capacity. In addition, high values can decrease retail resilience by shifting consumer spending patterns. Low dependency suggests a strong labor force and consumer market, which usually boosts resilience, meaning more people are working to support those who depend on them [88,89]. It serves as a negative indicator, suggesting its raw values must be reversed to the positive influence direction required for the URRI computation.

3.3.2. Educational Attainment (EA)

EA is measured as the percentage of the population who have completed secondary education, indicating the skill level and economic potential of the total population [90,91]. Equation (4) is adapted from [91].

$$EA = \frac{Pop_{secondary+}}{Pop_{total}} \times 100 \quad (4)$$

where $Pop_{secondary+}$ is the population with a secondary education completion rate or higher, and Pop_{total} is the total population.

A high EA in a retail area is better positioned to respond to and recover from shocks and other disruptions, which directly benefit the urban retail environment [91–93].

3.3.3. Unemployment Rate (UR)

UR is calculated as the proportion of the labor force that is currently unemployed and actively seeking employment. It is a significant sign of the health of the economy and the job market in a specific location, in addition to the financial challenges people may face in that area [9,91,94]. Equation (5) is adapted from [95].

$$UR = \frac{Unemployed\ Population}{Civilian\ Labor\ Force} \times 100 \quad (5)$$

where *Unemployed Population* refers to the number of unemployed individuals aged 16+ years old, and *Civilian Labor Force* includes the sum of all employed and unemployed individuals aged 16+ years old.

A high unemployment rate reduces consumer purchasing power and retail demand, contributing to higher commercial vacancy rates and, in turn, to social vulnerability [91,93,96]. Thus, UR is a negative indicator that needs to be reversed, as discussed in prior indicators.

3.3.4. Retail Vacancy Rate (VR)

VR is measured as the proportion of unoccupied retail shops and service establishments on the ground floor, specifically along commercial streets, relative to the total number of shops in the study area (Equation (6)). Vacant shops serve as an indicator of retail decline, signaling reduced demand that creates negative externalities through lower foot traffic. In previous studies, vacancy rates have been widely used as an indicator of retail resilience [9,50,58,97]. VR is a negative indicator that must be reversed, as discussed in prior indicators.

$$VR = \frac{VacantRetailShops}{TotalRetailShops} \times 100 \quad (6)$$

3.3.5. Commercial Density (CD)

CD affects the resilience of urban retail environments by leveraging the benefits of agglomeration economies and competition. These effects constitute a vital factor of retail resilience. This criterion measures the concentration of retail shops in each cell along active commercial streets [43] (Equation (7)).

$$CD = \frac{N_{CE}}{CellArea_{sq.m}} \quad (7)$$

where N_{CE} is the number of shops per cell area in square meters ($CellArea_{sq.m}$).

High commercial density implies a dense, compact retail environment in urban contexts. A dense retail setting would have positive effects on walkability, offer an array

of consumer choices, and increase footfall and pedestrian activity. Conversely, it may also have adverse effects of being susceptible to shocks. These may occur in unplanned commercial environments, depending on the context [98–100].

4. Calculating the Composite URRI

4.1. Normalization of Indicators

Normalizing indicators matters as different indicators have different units of measure. To combine them meaningfully, each indicator has been scaled by a min–max method to a 0–1 range. Thus, the interpretation is simple: 0 indicates the least resilient scenario, while 1 indicates the most resilient scenario, with reference points to adaptive cycle thresholds. This methodological choice ensures uniformity across indicators in a dataset for a specific context and bolsters the analytical rigor and clarity of the URRI, aligning with existing resilience and sustainability indices [41,101–104]. Equation (8) includes the min–max normalization calculation:

$$x' = \frac{(x - \min(x))}{\max(x) - \min(x)} \quad (8)$$

where x is the original value, $\min(x)$ is the minimum value found in the index, $\max(x)$ is the maximum value found in the index, and x' is the scaled value.

4.2. Weighting of Indicators

After normalization, multiple weighting scenarios were adopted, including a base scenario (equal weights) to maintain equal indicator importance and a participatory scenario to combine stakeholders' feedback. It is vital to integrate diverse viewpoints, aligning with previous practices for transparency and relevance and ensuring that the URRI reflects a compromise of values and aligns with community priorities. Stakeholders include consumers, retailers, and other prominent groups ($n = 87$). Their feedback effectively provides a ranking of the URRI indicators by perceived importance, on a scale from 1 to 12. Using the "Borda Count Method" [48,105], ranks are aggregated to create a composite priority order by assigning scores to each variable based on their ranks using Equation (9), adopted from [43]. The variables are then ranked so that the variable with the highest score is the top priority (rank = 1) and the variable with the lowest score is the lowest (rank = 12). Then, the combined ranks are transformed into weights using Equation (10), implemented from [43]. The survey was built on ArcGIS Survey123, comprising the indicators.

$$Sc = \sum_{i=1}^{n=12} Kn_i * n \quad (9)$$

where Sc is the criterion scores, and Kn_i is the number of stakeholders who assigned n rank to survey criterion i .

$$W(k) = \frac{n + 1 - k}{\sum_{i=1}^n (n + 1 - i)} \quad (10)$$

where $W(k)$ is the normalized weight for the survey criteria with rank k , n is the total number of criteria, and i is the index showing the summation that takes the value from 1 to n .

Based on the results of the survey, Table 3 shows the ranking order and normalized weight for each indicator.

Table 3. Showing criterion survey-based weights and rank order for retail resilience in Saida.

Criteria	Measurable Indicators	Rank Order	Total Points (<i>n</i> = 87)	Normalized Weight
Diversity	Retail and Services Diversity (Simpson Diversity Index)	2	957	0.14
	Functional Diversity (Simpson Diversity Index)	9	348	0.05
Proximity	Proximity to Parking Spaces	8	435	0.06
	Proximity to Public Transit	3	870	0.13
	Proximity to Key Amenities	5	696	0.10
	Proximity to Shopping Malls	7	522	0.08
	Proximity to Landmarks	10	261	0.04
Socioeconomic	Dependency Ratio	12	87	0.01
	Educational Attainment	11	174	0.03
	Unemployment Rate	6	609	0.09
	Retail Vacancy Rate	1	1044	0.15
	Commercial Density	4	783	0.12
		Rank 1–12	Total points = 6786	Sum = 1

4.3. URRI Computation

Composite URRI values were calculated using the “Calculate Composite Index” geoprocessing tool in ArcGIS Pro. This tool includes the compilation of criteria, scaling, weighting, reversing, and aggregation to the creation of the composite index, including spatial and statistical results [42,47]. They are calculated under multiple weighting scenarios, resulting in a range from 0 (lowest resilience) to 1 (highest resilience). Equation (11) is the URRI computation formula.

$$URRI_i = \sum_{i=1}^n w_i \times I_i \quad (11)$$

where $URRI_i$ is the composite urban retail resilience index for each cell i , w_i is the result of all the weights of the indicators, I_i is the normalized value of each cell i , and n is the total number of indicators.

4.4. Sensitivity Analysis

To assess the robustness of the findings to alternative weightings, a sensitivity analysis compared composite URRI values between equal and stakeholder-based scenarios. Sensitivity analysis reveals whether results are robust across weighting scenarios or sensitive to the choice of weights (Table 4).

Table 4. Showing multiple weighting scenarios tested.

Criteria	Measurable Indicators	Normalized Weight	
		Stakeholder-Based Scenario	Base Scenario
Diversity	Retail and Services Diversity (Simpson Diversity Index)	0.14	0.08
	Functional Diversity (Simpson Diversity Index)	0.05	0.08
Proximity	Proximity to Parking Spaces	0.06	0.08
	Proximity to Public Transit	0.13	0.08
	Proximity to Key Amenities	0.10	0.08
	Proximity to Shopping Malls	0.08	0.08
	Proximity to Landmarks	0.04	0.08
Socioeconomic	Dependency Ratio	0.01	0.08
	Educational Attainment	0.03	0.08
	Unemployment Rate	0.09	0.08
	Retail Vacancy Rate	0.15	0.08
	Commercial Density	0.12	0.08

- **Base Scenario (equal weights):** This scenario assigns equal weight to all indicators to prevent bias from influencing the URRI results. This baseline structure aligns with [41] recommendations for establishing a neutral benchmark in composite index construction.
- **Stakeholder-Based Scenario:** This scenario is based on the ranking of indicators and the weights obtained from the stakeholders' survey. It captures local perceptions of retail needs and aligns with previous practices in composite indices [41,43,106].

5. Analyzing the Values of the URRI

5.1. URRI Classification into the Adaptive Cycle Stages of Retail Resilience

This study extends Dolega and Celinska's [9] framework for retail resilience by developing indicators that capture the key criteria of the adaptive cycle phases of retail resilience in urban contexts and demonstrate their statistical and spatial patterns using GIS. A qualitative assessment of URRI indicator patterns categorized the composite index into four resilience quarters related to the adaptive cycle stages (Figure 5). This classification enables identification of phase-appropriate intervention strategies. URRI resilience stages include the following:

- **Release Phase (Collapse):** Low URRI (0.00–0.25).
- **Reorientation Phase (Renewal):** Low–Moderate URRI (0.26–0.50)
- **Growth Phase (Expansion):** Moderate–High URRI (0.51–0.75)
- **Consolidation Phase (Conservation and Maturity):** High but declining URRI (0.76–1.00)

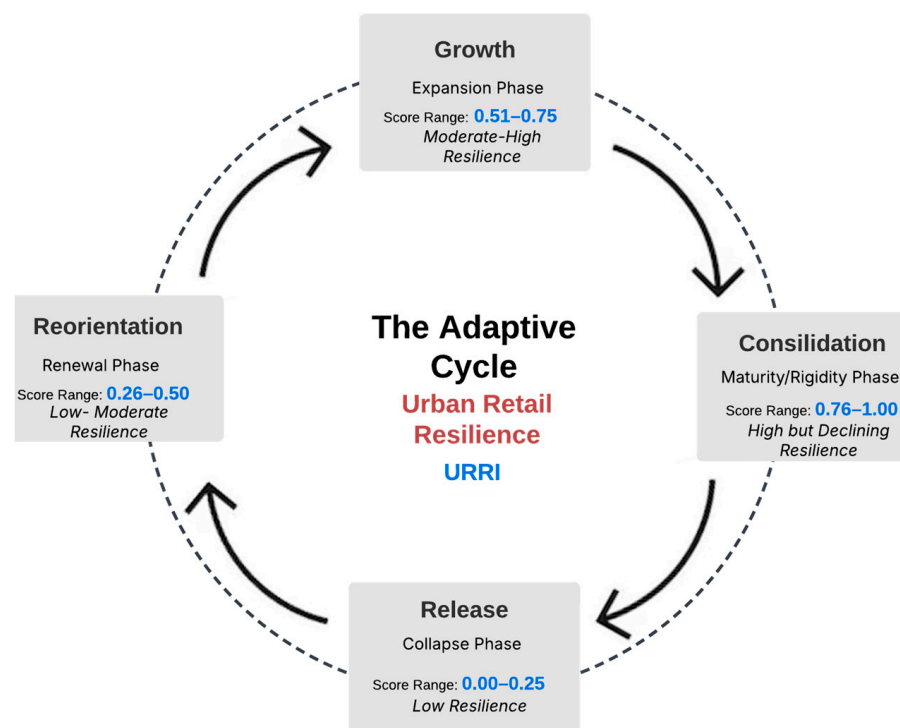


Figure 5. Adaptive Cycle Stages of Retail Resilience with Score Ranges Relative to URRI Classification. Source: Adapted from [7,9].

URRI adaptive cycle values will be explored for each cell in the study area and averaged across the study area to examine the stage of retail resilience of the urban retail environment and to gain insights into future interventions at the micro and neighborhood scales.

5.2. Hotspot Analysis

Spatial clustering of URRI values was analyzed using *Getis-Ord Gi** statistics in ArcGIS Pro. Significant positive *Gi** values indicate hotspots (clusters of high values), while substantial negative values indicate cold spots (clusters of low values) [107], which are vital for recommending targeted interventions. It was calculated for each cell according to Equation (12):

$$G_i^* = \frac{\sum_{j=1}^n w_{ij}x_j - \bar{X}\sum_{j=1}^n w_{ij}}{S\sqrt{\frac{n\sum_{j=1}^n w_{ij}^2 - (\sum_{j=1}^n w_{ij})^2}{n-1}}} \quad (12)$$

where x_j is the attribute value at location j , w_{ij} is the spatial weight between locations i and j , n is the number of locations, $\bar{X}$ is the mean, and S is the standard deviation.

6. Results and Discussion

6.1. Indicator Descriptive Results Statistics

The study of 12 indicators throughout Saidia's urban retail environment shows critical spatial change in the criteria contributing to retail resilience (Table 5). This section presents the statistical characteristics of each indicator before examining the composite index results.

Table 5. Indicator aggregation results statistics.

Criteria	Indicator	Min	Max	Mean	SD
Diversity	Retail and Services Diversity (RD)	0	0.93	0.89	0.05
	Functional Diversity (FD)	0	0.69	0.62	0.15
	Proximity to Parking Spaces (PP)	0	1	0.36	0.23
Proximity	Proximity to Public Transit (PT)	0	1	0.79	0.17
	Proximity to Key Amenities (PK)	0	1	0.35	0.20
	Proximity to shopping malls (PS)	0	1	0.73	0.25
	Proximity to Landmarks (PL)	0	1	0.45	0.33
Socioeconomic	Dependency Ratio (DR)	0.41	0.41	0.41	0
	Educational Attainment (EA)	0.12	0.12	0.12	0
	Unemployment Rate (UR)	0.03	0.03	0.03	0
	Retail Vacancy Rate (VR)	0	0.23	0.19	0.06
	Commercial Density (CD)	0	0.89	0.55	0.25

Notes: SD: Standard Deviation, Min: minimum, Max: maximum. All the values are normalized (0–1 scale) with higher values indicating greater impact on resilience. Proximity indicators are reversed (shorter distances = higher values). Socioeconomic indicators with SD = 0 show uniform values of the study area at the neighborhood aggregation level.

6.1.1. Diversity Indicators Results

The index for Retail and Services Diversity (RD) has the highest mean among all indicators, at 0.89, and a standard deviation of 0.05. This shows that Saidia has a reasonable diversity of retail types and services. The high mean value indicates redundancy and a reduced reliance on one retail format, which gives it a theoretical robustness [108]. A low standard deviation (SD = 0.05) indicates that the diversity is spatially consistent across commercial streets, with minimal variation between locations, since it is aggregated as a uniform value across the entire study area, which lowers the SD value. In addition, adaptability in the area is a key characteristic of retail resilience, with no extreme clustering of one shop type in particular zones. The maximum value (0.93) is close to the theoretical upper limit, indicating that some areas are nearly optimal according to the Simpson diversity index. On the contrary, the minimum value (0) identifies areas that lack retail diversity, ranging from peripheral to non-commercial street areas, showing typical previous urban commercial geography patterns [109]. Functional Diversity (FD), reflecting land use categories, had a lower mean (mean = 0.624, SD = 0.150) than retail and service diversity,

indicating that although retail types may be diverse, the functional purposes served by these establishments show greater spatial variation. SD (0.15) exhibits significant spatial heterogeneity in functional diversity, suggesting that some areas show functional coverage, while others focus on limited functions. This discrepancy between the different types of diversity analyzed is theoretically significant [55,58]. While retail and services diversity is uniformly high and consistent across Saida's commercial streets, functional diversity is more moderate and spatially uneven, indicating that the retail area is highly resilient in terms of shop-type variety but is supported by a land use mixture of varying strength (see Figure 6).

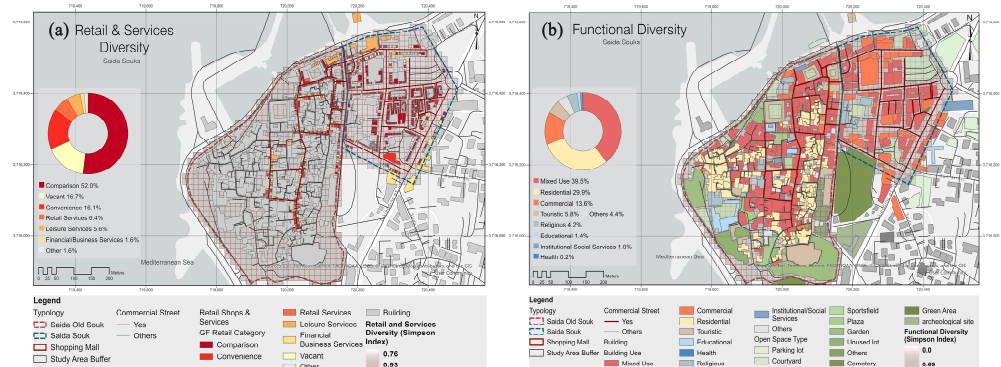


Figure 6. (a) Retail and Services Diversity Indicator Map (b) Functional Diversity Indicator Map (Authors).

6.1.2. Proximity Indicators Results

Proximity indicators include the following measures (see Figure 7):

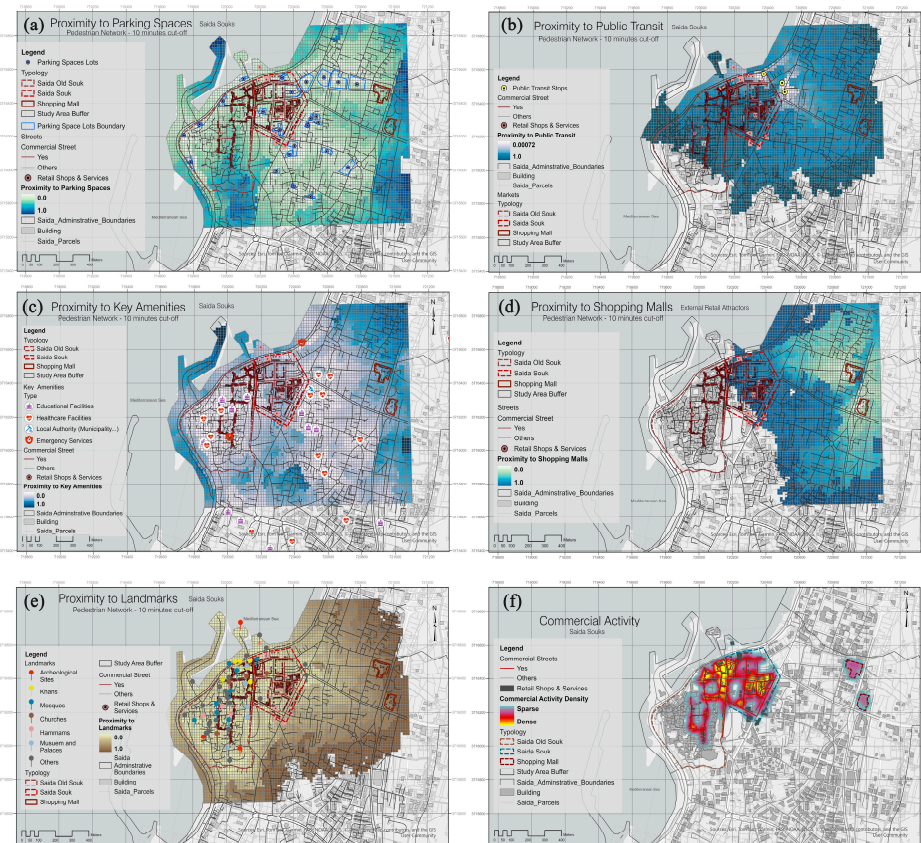


Figure 7. Indicator Spatial Maps: Proximity Maps (a) to Parking Spaces, (b) to Public Transit, (c) to Key amenities, (d) to Shopping Malls, (e) to Landmarks, and (f) Commercial Density (Authors).

Proximity to Parking Spaces (PP) showed a mean = 0.36, indicating that parking proximity across the study area is moderate; most fishnet cells are neither extremely close nor extremely far from designated off-street parking lots. This illustrates the spatial reality of Saida Souk, where parking is available but allocated at random. SD = 0.23 indicates substantial variation in access to parking spaces. This variability is expected, since Saida Old Souk is fully pedestrianized and has a highly constrained urban fabric, with low proximity. In opposition, Saida Souk has shared streets accessible by vehicles with several off-street parking lots, creating a much higher accessible area. Due to Saida's hybrid mobility context, proximity to parking is a secondary but relevant determinant of the retail resilience of Saida Souk. A high SD (0.23) indicates that some areas benefit from strong accessibility for car users. On the contrary, others (particularly in the historic core) keep pedestrian-oriented resilience and are less reliant on cars, highlighting the uncertain role of parking in sustaining retail liveliness.

Proximity to Public Transit (PT) showed the highest mean value (0.79) among all proximity indicators. This indicates that the study area is within a close walking distance of bus stops (10 min walking distance). Specifically, Saida Old Souk heavily relies on public transport due to socioeconomic problems. The historic core of Saida is compact in morphology, making its location suitable for transit-dependent access. Thus, proximity to transit is one of the most influential accessibility variables in Saida. The moderate standard deviation (0.17) shows that, while most cells are close to transit nodes, some outlier areas (especially the periphery of narrow alleys) are further away.

Proximity to Key Amenities (PK) has the lowest mean (0.35, SD = 0.20) among all proximity indicators, showing limited accessibility to amenities such as educational facilities, health care, local authorities, and emergency services. The mean value of 0.35 indicates that the retail area is reasonably far from these amenities, which may restrict its multi-functionality. With a moderate SD of 0.17, this shows there may be spatial variation, suggesting a likelihood of concentration in the central areas. A value between 0 and 1 shows that there are rich amenity cores and poor amenity peripheries.

Proximity to Shopping Malls (PS) resulted in a high mean (0.73), revealing a strong spatial influence on surrounding areas. A significant part of Saida Souk is within the 10 min walking distance cut-off on the pedestrian network (SD = 0.25), while Saida's old Souk is beyond the walkable threshold. Shopping malls are anchor-based attractors that attract people and groups from various socioeconomic strata by offering a combination of international brands, leisure services, and a controlled climate. Although these malls are geographically adjacent to Saida Souk, they are primarily car-oriented, as they are located on the main Saida highway and have their own parking areas. Saida Souk gathers the benefits of mall spill-over and footfall while creating an accessibility contrast. Saida Old Souk, located farther within the pedestrianized fabric, is less functional despite being closer. According to previous studies, shopping malls regularly bolster regional commercial gravity while at the same time struggling with traditional marketplaces [7,80,81,110]. Shopping malls in Saida are shaping mobility patterns and consumer preferences while challenging other smaller retailers. This indicator captures an external influence over the resiliency of retail, emphasizing that shopping mall proximity is contextually relevant but randomly experienced.

Proximity to Landmarks (PL) had a moderate mean result of 0.45. This value proposes a balanced distribution, with nearly equal proportions of areas near and far from landmarks. A very high standard deviation score (SD = 0.33), the highest between all indicators, indicates that there is an ultimate spatial array. This reflects that the geography of landmarks, including historic sites, cultural facilities, and others, has been concentrated in specific zones, particularly Saida Old Souk with its unique khans, Souks, mosques,

archeological sites, churches, hammams, museums, and palaces. Tourism-related foot traffic, place identity, and heritage retail specialization are advantageous for places in close proximity to landmarks, while distant areas lack these advantages [33,111,112].

6.1.3. Socioeconomic Indicator Results

The Dependency Ratio (DR), Educational Attainment (EA), and Unemployment Rate (UR) had a standard deviation of 0. This indicates that these indicators are uniform across all cells in the study area, with the same value in each cell. This uniformity reflects the spatial aggregation level of the available data, specifically at the neighborhood level, which is coarser than the selected spatial unit and is usually aggregated at this scale.

A Dependency Ratio (DR) of 0.41 (41%) reflects a moderate demographic burden, with the non-working-age population involving a considerable share of the total population. This shows Saida's demographic structure, described by both a young population and aging movements in urban areas [38,113,114]. A moderate dependency ratio implies moderate limits on household purchasing power and discretionary spending, as resources support dependents with working-age adults [115]. As per the World Bank, Lebanon's dependency ratio was estimated at 57% in 2024. According to [116], the lowest national dependency ratio threshold across countries worldwide was 20%. However, Saida is still somewhat included within the recognized limit.

The Educational Attainment (EA) of 0.12 (12%) is very low, indicating that only a small portion of Saida's population has completed secondary education or higher. This reflects broader educational challenges in Lebanon, where, regardless of the historical strength for capable education, present crises have impacted access to education [38,117]. Low educational attainment is linked to reduced earning potential, limited entrepreneurship capacity, and different patterns of retail consumption. In 2020, Saida city achieved a rate of 53.80% according to the Central Administration of Statistics [118], considered a moderate level. According to UN-Habitat, Old Saida had an educational attainment rate of 60.10%, which is considered above the mid-range.

Using ArcGIS Business Analyst enriched data, the Unemployment Rate (UR) resulted in a value of 0.03 (3%), which is a favorable result. However, it does not reflect the reality of Saida nor the severe economic decline of Lebanon since 2019. Lebanon's national unemployment rate rose to approximately 32.60% as of late 2024, and Saida likely has a much higher unemployment rate than the national average. According to UN-Habitat [39], Old Saida showed an extremely high unemployment rate of 45.10% in 2019. The Central Administration of Statistics (CAS) observed a 14.30% unemployment rate for Saida City [118,119]. International standards [120], including the SDGs (Sustainable Development Goals), in particular SDG 8, which targets "*full and productive employment*", propose that an unemployment rate of less than 5% is healthy. Given informal unemployment and unstable income, Saida's situation may suggest that the indicator results of the business analyst understate the actual socioeconomic pressure.

The Retail Vacancy Rate (VR) had a mean of 0.19 (19%) and a maximum of 0.23 (23%), indicating a pervasive challenge across the active commercial streets in the study area. Reference [97] mentions that a healthy vacancy rate is between 5 and 10%. The resulting value exceeds the threshold, showing pressures facing Saida Souks. The standard deviation was 0.06, indicating that some places, such as Saida Old Souk, had very high vacancy rates. Vacant storefronts indicate diminished demand and business viability, while concurrently generating adverse externalities through decreased foot traffic, deteriorating streetscapes, and perceptions of decline that discourage consumers and enterprises [121,122].

Commercial Density (CD) showed a mean of 0.55, which is slightly above the midpoint, indicating moderate commercial density, with balanced distribution between high-density

commercial areas and low-density peripheral or residential areas, especially in Saida Old Souks, since active commercial streets are concentrated in the heart of Saida's old city. In contrast, other areas include residential, mixed-use, tourist spaces, and others. The significant standard deviation (0.25) indicates that some areas have high commercial concentrations (max = 0.89, approaching saturation), especially in Saida Souks, while others possess minimal commercial presence (min = 0). This polarization reflects typical urban retail geography, with commercial activity clustering in central business districts and major corridors combined with predominantly residential zones, especially in Saida Old Souks. This area is characterized by a “crowd and density”, both physically and demographically. Commercial establishments are a core part of this dense, historic urban fabric, featuring narrow alleys and tightly packed buildings, characterized by a mix of traditional and modern challenges to retail resilience. High density generates economies and vibrancy with retail viability.

6.2. URRI Composite Index Computation Results

After calculating all the URRI indicators in ArcGIS Pro, they are combined into a single composite URRI metric for each cell. By using the previously discussed min–max normalization method, applying multiple weighting scenarios for indicators, and, when necessary, reversing indicators, a spatial map of the URRI is finally generated with statistical scatterplot matrices showing relationships under both baseline and stakeholder-based weighting scenarios. The index map (Figure 8) shows the current urban retail resilience across the study area, with an index ranging from 0 to 1 and classified into four categories corresponding to the adaptive cycle stages, where 0 indicates the least resilience and 1 the highest.

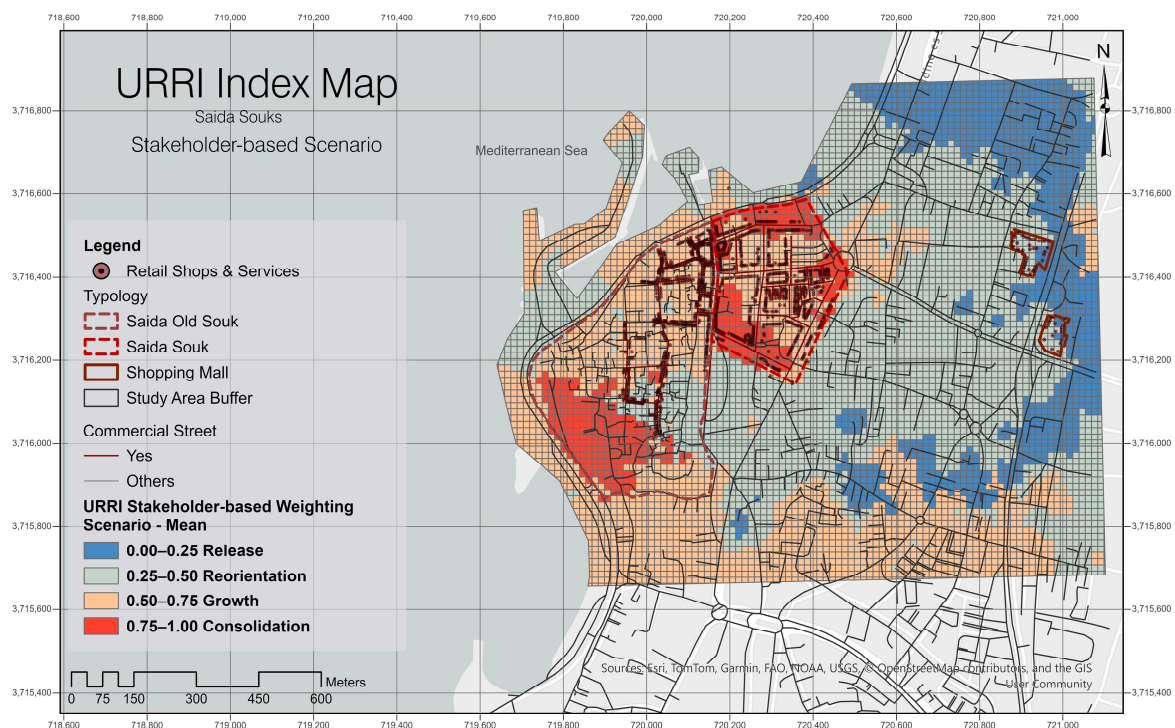


Figure 8. URRI Spatial Map (Authors).

6.2.1. URRI Base Scenario Results

In the URRI Base Scenario, the mean resulted in 0.50, positioning the study area at the edge of the reorientation phase (0.26–0.50 range) in the adaptive cycle, with pocket zones progressing into the growth phase where URRI values exceed 0.51. This analysis shows

that the study area's overall retail resilience is moderate to high, neither predominantly strong nor weak; instead, there is a balanced distribution across higher and lower zones.

The scatterplot correlation matrix (Figure 9) provides a statistical understanding of the relationship between specific indicators and the URRI values. The matrix presents many correlations highlighting the main drivers that enhance retail resilience in Saida. The color gradient represents the direction and strength of the relationship between two indicators. In the indicator cells in the matrix, the red–orange color shows strong positive correlations, the blue color indicates strong negative correlations, and the yellow–gray color shows weak or no correlation, considered insignificant. The Pearson correlation coefficient (' r ' value) conveys the strength and direction of a linear relationship between indicators and the URRI score.

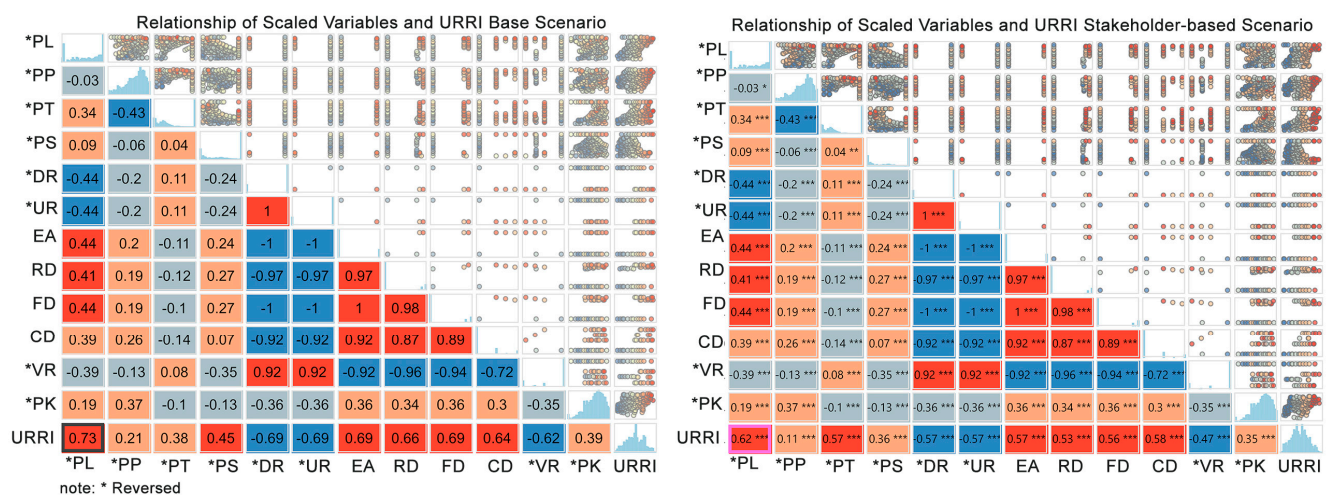


Figure 9. URRI Weighting Scenarios Scatterplot Matrix Results. Asterisks indicate the significance level (p -value) of the Pearson correlation coefficients: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Scatterplots are colored by URRI values, following the same color scale as the URRI spatial map (Authors).

(1) Strong Positive Correlations (red–orange cells): PL has a value of $r = 0.73$, which dominates the URRI, indicating that accessibility to landmarks contributes to retail resilience by attracting foot traffic to the area. This is apparent when consumers shop and visit tourist sites simultaneously, especially in the old city, which is historically and culturally rich and home to traditional markets. In addition, diversity indicators showed positive correlations with RD ($r = 0.66$) and FD ($r = 0.69$), confirming the theoretical importance of retail mix as a vital indicator of retail resilience. The CD ($r = 0.64$) correlation indicates that commercial activity enhances resilience through agglomeration effects. And lastly, EA ($r = 0.69$) highlights the role of human capital in improving resilience.

(2) Moderate Positive Correlations (light orange cells): These correlations include several proximity indicators starting with PS ($r = 0.45$), indicating that external retail attractors influence retail resilience positively, specifically attracting consumers with diverse socioeconomic conditions, knowing that they contain anchor stores. PT ($r = 0.38$) and PK ($r = 0.39$) suggest that accessibility acts positively but secondarily to retail resilience.

(3) Negative Correlations (blue cells): DR ($r = -0.69$), UR ($r = -0.69$), and VR ($r = -0.62$) show the underlying socioeconomic vulnerabilities in the study area. When more people are unemployed or have stopped looking for jobs, it indicates less resilience. The findings also confirm a long-established pattern of decline associated with higher vacancy rates, as discussed in previous studies.

(4) Weak or No Correlation (yellow–gray cells): PP had the lowest value among all indicators ($r = 0.21$), indicating that parking availability does not influence resilience in compact Souk environments dominated by walkability.

Therefore, retail resilience in Saida mainly depends on commercial clustering, functional mixing, and cultural proximity, according to the URRI base scenario. Some commercial areas are more resilient than others because of the existing conditions present. High-resilience areas are dense, diverse, and characterized by urban retail with strong cultural roots. Meanwhile, low-resilience areas are most likely caused by socioeconomic stresses and commercial fragmentation.

6.2.2. URRI Stakeholder-Based Scenario Results

The stakeholder weighting scenario changes the weight of the indicators according to a ranking survey in Saida to examine the community's preference in the study area. As expected, the weighting alters the contribution of indicators to the URRI, yielding a mean value of (0.45), which is slightly less than the base scenario. In both cases, the resilience drivers are consistent, but vary in strength and order of relationships (Figure 9). In the stakeholder-based scenario, specific proximity indicators vary in strength, with PT ($r = 0.57$) and PS ($r = 0.36$), compared to the base scenario ($r = 0.38$ and $r = 0.45$, respectively). In this scenario, PT is nearly as important as diversity indicators, indicating that Saida consumers value public transportation more than in the base scenario. These mobility nodes are usually essential for low to middle-income shoppers.

Socioeconomic indicators remained strongly negative, gradually reducing resilience in both scenarios, including DR and UR ($r = -0.65$) and VR ($r = -0.47$). But stakeholders focus on reducing vacancy and unemployment, prioritizing diversity and accessibility, and determining a reasonable preference for opportunity over demographic limitations. Saida consumers specifically requested more leisure options, such as sidewalk cafés and restaurants, although Saida Souk offers a limited selection.

The core drivers of retail resilience are based on the URRI multi-criteria geospatial model. In the base scenario, the strongest URRI correlations were:

- PL: Proximity to Landmarks ($r = 0.73$);
- RD: Retail and Services Diversity ($r = 0.66$);
- FD: Functional Diversity ($r = 0.66$);
- CD: Commercial Density ($r = 0.64$);
- EA: Educational Attainment ($r = 0.69$);
- PS: Proximity to shopping malls ($r = 0.45$).

In the stakeholder-based scenario, the strongest URRI correlations were:

- PL: Proximity to Landmarks ($r = 0.62$);
- RD: Retail and Services Diversity ($r = 0.53$);
- FD: Functional Diversity ($r = 0.56$);
- CD: Commercial Density ($r = 0.58$);
- EA: Educational Attainment ($r = 0.57$);
- PT: Proximity to Public Transit ($r = 0.57$).

The observed variation between the equal-weighted (mean URRI = 0.50) and stakeholder-weighted (mean URRI = 0.45) scenarios indicates moderate sensitivity to weight choices. While some variation is present, the spatial distribution patterns and general ranking of resilience across areas remain broadly consistent. This suggests that the index is both responsive to stakeholder input and stable enough to support robust resilience diagnostics. As highlighted by [123], sensitivity analysis is essential for validating the stability and reliability of composite indexes built with stakeholder-derived weights. It helps address the subjectivity inherent in participatory weighting processes, clarifies

how weight choices shape spatial outputs, and ultimately enhances the transparency and credibility of the outcomes. In this study, incorporating both weighting approaches and comparing their outputs contributes to a more nuanced and trustworthy assessment of retail resilience in Saida's urban fabric.

Spatially, the URRI map (Figure 8) shows a distinct resilience gradient across Saida's urban retail environment, with strong clustering of high and low URRI resilience scores. High-resilience zones (0.75–1: consolidation—red cells) appear in specific areas, the western edge of Saida's old city and the southern fringe of Saida Souks, characterized by high functional diversity and proximity advantages. Some high values are found in non-commercial parcels, reflecting the strong structural features of the historic core, with high diversity, accessibility, and cultural proximity, rather than just retail activity. These values indicate a hidden capacity for resilience, showing that the surrounding urban structure strongly supports potential retail activity. This results from the use of uniform indicators (RD, FD, UR, DR, and EA), which are assigned constant values across the study area rather than varying by cell. Since Saida's old city generally performs well on these indicators, they lift the entire URRI score, giving even non-commercial cells a high value. This effect is expanded under the stakeholder-based weighting scenario because respondents prioritized these uniform indicators, which therefore have a greater influence than spatially heterogeneous cell-based variables. This spatial rise is recognized as a limitation of multi-scale composite indices in dense urban fabrics, where socioeconomic uniformity can overshadow microspatial variations. Still, the index map uncovers essential insights, particularly in the commercial heart of both Souks, where it maintains a moderate–high-resilience zone (0.50–0.75: growth—orange cells). These areas include the traditional market that spreads along narrow, vaulted streets lined with cultural landmarks and specialized souks (e.g., the Gold Souk, the Carpenters Souk, and the Weavers Souk, among others). This is a positive issue that highlights areas requiring targeted interventions. Moderate–low-resilience zones (0.25–0.50: reorientation—yellow–gray cells) are spread minimally in the southern area of Saida old city, with decreasing proximity variables, and the area is more residential and less commercially vibrant. Low-resilience zones (0–0.25: release—blue cells) are not present within either Souk boundary, indicating that the overall retail system of Saida Souks remains stable and is not in decline. A few release class cells are only visible at the outer eastern edge, far from commercial influences. Specifically, some blue cells appear over shopping malls, reflecting their presence outside the Souk's boundary as external attractors, which are analyzed as one of the proximity indicators. Since the model found that closer shopping malls have a greater influence, they received a lower influence score, indicating low resilience.

6.3. Hotspot Analysis Interpretation and Implications for Targeted Interventions

The *Getis-Ord Gi** hotspot analysis statistically reveals large, closely spaced hot spots (99% and 95% confidence) concentrated within Saida Old Souk and the denser parts of Saida Souk, indicating clusters of high URRI values that persist beyond what would be expected (Figure 10). These hotspots overlap with areas previously identified as high-scoring URRI, characterized by strong commercial density, high retail and functional diversity, proximity to landmarks, and high pedestrian activity. This reinforces the interpretation that the study area remains structurally resilient, functioning as a consolidated retail ecosystem within the adaptive cycle. Some hotspots (orange cells with 90% confidence) are concentrated in the central part of Saida's old city, indicating that these cells coincide with dense, fine-grained residential and commercial areas, where everyday commerce, local services, and historic pathways converge. They are less uniformly distributed than in the primary hotspots, acting as transition zones between consolidation and growth phases. In contrast, cold

spots (95% and 99% confidence) emerge predominantly outside the Souks' boundary, where the urban area becomes more car-oriented, and distant from key retail attractors and other prominent measures, as previously discussed. Several targeted interventions—based on spatial patterns revealed through hotspot analysis and on-ground stakeholder-prioritized needs observed during the field survey—were identified to strengthen urban retail resilience in the Saida case study. These include: (1) introducing anchor retail within the Souk to enhance footfall, reduce reliance on car-oriented shopping malls, and strengthen the retail gravity of walkable commercial streets; (2) adding leisure activities within the Souk because it enhances diversity and retail mix by adding sidewalk cafés, small restaurants, and resting areas to boost spending time, attract diverse users, and reinforce social vibrancy and economic resilience of the Souk; (3) revitalizing the historic core's identity, which accordingly attracts a broader range of consumers, especially to specialized markets, and must be accompanied by improved wayfinding; and (4) enhancing public transit access and micro-mobility by adding transit stops, shaded waiting areas, and micro-mobility routes to improve accessibility, ease parking congestion, and create pedestrian linkages with shopping malls through better pedestrian infrastructure. While these reflect broad-based spatial needs, particular attention is given to zones identified in the Release and Reorientation adaptive cycle phases, where targeted interventions can either halt further decline or support recovery [9,24]. Areas in the Release phase, characterized by decline, fragmentation, and increasing vacancies, can particularly benefit from tactical urbanism as a targeted intervention [124]. This approach recovers vacant and neglected areas by implementing quick, tailored interventions that transform these spaces into public areas, thereby creating opportunities for temporary uses such as pop-up retail to emerge and revitalize the urban environment. These interventions help stabilize declining areas and signal future potential. Areas in the Reorientation phase, showing early signs of renewal and structural adjustment, require longer-term investments to support functional transformation and attract sustained activity. In these contexts, urban regeneration should emphasize mixed-use redevelopment, façade rehabilitation, and repurposing obsolete retail accumulations into community-oriented functions such as co-working hubs, cultural venues, or flexible marketplaces. Public realm upgrades, including durable pedestrian infrastructure, enhanced transit connectivity, and high-quality street furniture, can reinforce accessibility and placemaking during recovery [125,126].

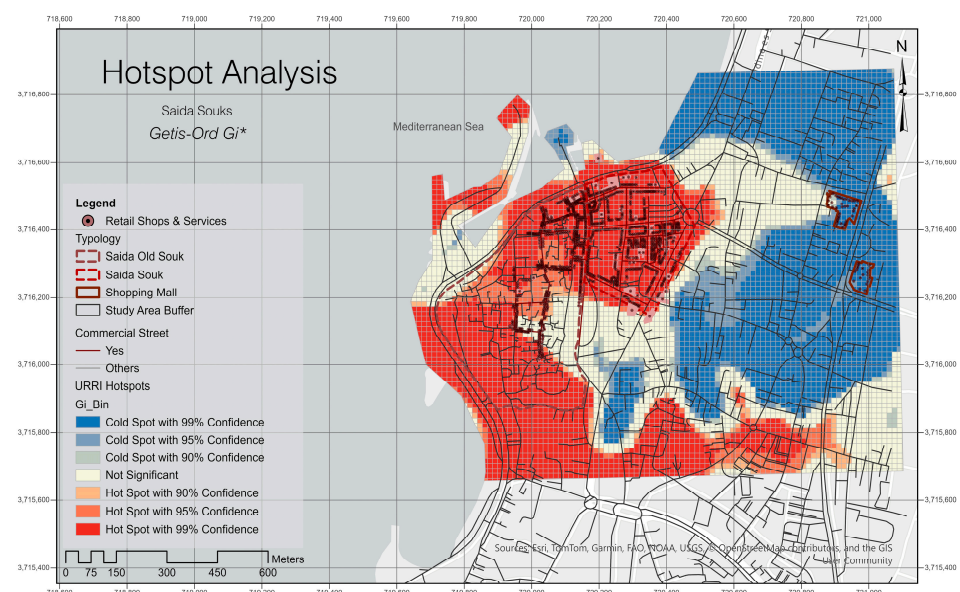


Figure 10. *Getis-Ord Gi** Hotspot Analysis Map (Authors).

7. Conclusions

In conclusion, this paper developed a comprehensive multi-criteria geospatial model integrating twelve indicators to evaluate retail resilience in Saida, Lebanon. The comparison between the URRI stakeholder-based scenario and the base scenario shows that while retail and services diversity remain key factors in retail resilience, stakeholders' preferences highlight the importance of accessibility-related indicators. This shift indicates that resilience in Saida depends not only on urban form but also on people's movement patterns, retail choices, and access to major destinations. Incorporating stakeholder feedback, therefore, results in a more behaviorally grounded retail resilience model that supplements the structural focus of the baseline URRI. Spatial clustering analysis identified distinct hotspots of high resilience and cold spots. This framework demonstrates robustness across weighting scenarios and shows that different weights emphasize different vulnerabilities. The adaptive cycle framework provides a functional intervention logic by requiring adaptation in crisis contexts where natural cycling might be disrupted. For Saida, the study provides an evidence-based resource for retail planning research. Within this framework, the URRI outputs allow key stakeholders—retailers and consumers—to operationalize retail resilience by interpreting spatial patterns associated with retail diversity, accessibility, and surrounding socioeconomic conditions, thereby supporting more informed location decisions, retail strategies, and consumption behaviors across the urban environment. In cities facing ongoing challenges, retail resilience is not just an economic concern but is also vital for urban sustainability, social equity, and community well-being, and must be incorporated into urban design and planning studies. Beyond the spatial patterns and core resilience indicators emphasized in the URRI, emerging literature also highlights the importance of retail ownership structures and temporal dynamics [6,14,127]. Specifically, small-scale independent retailers—often family-run and locally embedded—foster strong community ties and lively adaptability that bolster resilience (for instance, by sustaining diverse, interdependent local retail mixes), yet their limited resources leave them more vulnerable to shocks and displacement by larger competitors. Conversely, large chain stores may have advantages like big networks and cost savings that help them during crises, but because they are less connected to local communities and follow a standardized approach, they struggle to adapt. This is shown by the growing number of failing “dead malls” around the world, proving that being large does not always mean being resilient [80,81]. Accordingly, resilience is increasingly conceptualized as a dynamic, evolutionary process rather than a static state, with retailers' post-disturbance trajectories ranging from simple “bounce-back” recovery to transformative reorganization [17,18]. In Saida, many shops are family-run and based in traditional markets, showing how local, community-based retail can support resilience. However, small businesses need supportive measures to strengthen small merchants' shock absorption and adaptive capacity.

This model acts as a diagnostic tool to support the challenge of building retail resilience in evolving urban environments. However, its application and interpretation are shaped by specific methodological and contextual considerations. In this context, several limitations should be acknowledged when interpreting the findings of this study. Although the Urban Retail Resilience Index (URRI) is developed as a transferable methodological framework, its empirical application reflects the specific spatial structure, retail typologies, governance context, and data availability of the case study area. As a result, indicator quantification and weighting are context-sensitive, and findings should be interpreted within the local conditions of the study area. In addition, the URRI relies on static and semi-static GIS-based indicators, which capture structural and functional characteristics of urban retail systems but do not reflect short-term temporal dynamics or real-time behavioral change. Finally, the interpretation of resilience patterns is influenced by the selected spatial units and

analytical resolution, indicating a degree of scale dependency in the results. Recognizing these conditions clarifies the scope within which the current findings should be interpreted.

In the end, the analysis yields a set of recommendations. First, the indicators used in the study constitute a coherent, methodologically justified subset of retail resilience determinants; however, future work should consider integrating a broader range of variables to achieve more precise results and refine the model's sensitivity, thereby offering a more nuanced representation of urban retail dynamics. To support this expansion, the URRI indicator set could be complemented by Artificial Intelligence of Things (AIoT)-based analytical approaches that leverage device-generated data and algorithmic processing to introduce additional behavioral and operational variables. As highlighted by Pratas et al. [128,129], such AIoT-driven approaches systematically integrate these data through structured analytical and creativity-based techniques, such as mind mapping and morphological analysis, to inform retail decision-making and innovation. Second, future research could incorporate temporal data to monitor urban retail dynamics over time, enabling the URRI framework to evolve from a diagnostic model into a tool for tracking resilience trajectories and adaptive shifts in response to changing urban conditions. In addition, expanding the weighting scenarios in future applications would further strengthen the model's robustness and provide a more precise assessment of sensitivity across stakeholder priorities that may influence resilience outcomes. In this regard, the analytical scope of the URRI could be extended by explicitly incorporating additional stakeholder groups—such as public authorities, city center managers, and community actors—into the weighting and evaluation process, allowing the framework to capture a wider range of decision perspectives shaping retail resilience. In addition, it is recommended to develop context-specific adaptations that strengthen the long-term evolution of a geospatial multi-criteria framework tailored to different urban retail environments. Lastly, it is recommended to test different spatial units for analysis and to increase cell-specific aggregation rather than uniform aggregation to obtain more spatial variability across the study area.

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