Composite Indices for Urban Blight Assessment: A Decision Support Approach for Urban Regeneration

Pierluigi Morano[1], Emma Sabatelli[2(✉)], Debora Anelli[2], and Francesco Tajani[2]

[1] Department of Civil, Environmental, Land, Building Engineering and Chemistry (DICATECh), Polytechnic University of Bari, 70126 Bari, Italy
[2] Department of Architecture and Design, "Sapienza" University of Rome, 00196 Rome, Italy
emma.sabatelli@uniroma1.it

Abstract. Urban regeneration policies require operational tools capable of identifying priority areas, justifying investment choices, and monitoring change over time. In this context, urban blight can be understood as a multidimensional and context-dependent phenomenon, shaped by combinations of physical deterioration, socio-economic vulnerability, functional decline, and perceived insecurity. This work proposes a methodological framework for assessing urban blight at the intra-urban scale in a comparative and spatially explicit way. The framework draws on established practices for composite index construction and structures urban blight into three interrelated components: physical–environmental, economic, and social. The procedure includes: (i) the construction of three component indices, one for each dimension, through a TOPSIS-based aggregation of weighted indicators; (ii) the synthesis of the component indices into an overall index by means of the arithmetic mean; and (iii) the spatial representation of results through thematic maps. Indicators are selected and harmonized from available data sources; weights are derived through an entropy-based method; robustness checks are performed to assess result stability; and GIS-based mapping supports the identification and communication of priority areas. The proposed framework is intended to support priority setting, monitoring, and communication in urban regeneration policies, while remaining transferable across different urban contexts, subject to data quality and zoning choices.

Keywords: Urban blight · composite indicator · entropy weighting · TOPSIS · urban regeneration

1 Introduction

In recent years, urban policy has increasingly emphasized the need for regeneration strategies grounded in explicit and comparable evidence. This orientation is reflected in international and European sustainable urban development agendas that increasingly require integrated, evidence-based strategies to promote inclusive, safe, resilient and

© The Author(s), under exclusive license to Springer Nature Switzerland AG 2027
O. Gervasi et al. (Eds.): ICCSA 2026 Workshops, LNCS 16764, pp. 21–37, 2027.
https://doi.org/10.1007/978-3-032-30533-6_2

sustainable cities. The 2030 Agenda explicitly recognizes the importance of the urban dimension, with Goal 11 dedicated to making cities and human settlements inclusive, safe, resilient, and sustainable [1]. At the European level, this orientation is reflected in the promotion of integrated and place-based approaches through the Urban Agenda for the European Union, established by the Pact of Amsterdam (2016), and the New Leipzig Charter (2020), both of which strengthen multilevel coordination and the principles of good urban governance. In the same direction, initiatives linked to the green transition and the regeneration of the existing built heritage stress the need to combine sustainability and inclusion. Within this framework, the New European Bauhaus has been presented as a Green Deal initiative aimed at integrating sustainability, beauty, and inclusion in the transformation of living spaces [2].

These frameworks share a common operational implication: to make regeneration strategies effective and to guide public and private investment, it is essential to identify territorial priorities, justify decisions through explicit criteria, and monitor outcomes over time. Because cities are complex and differentiated systems, urban transformation does not occur evenly across space. While some areas concentrate opportunities and adaptive capacity, others tend to accumulate critical issues and signs of decline, with consequences for urban quality and territorial cohesion [3].

In both academic debate and planning practice, these conditions are often associated with the concept of urban blight, used to describe sets of critical issues affecting the built environment, the socio-economic structure, and urban functionality [4]. A key feature of the concept is the absence of a single, universally accepted definition. Urban blight varies according to the objectives of the analysis, the territorial scale, and the institutional context considered [5]. This ambiguity is not merely terminological, since it directly affects measurement and decision making. If urban blight may refer to physical deterioration, underuse, abandonment, socio economic vulnerability, loss of functions and services, negative reputation, or perceived insecurity, then the criteria used to identify and assess it must be made explicit [6]. This makes it necessary to move from generic definitions to operational ones that translate the phenomenon into observable and comparable measures.

From an interpretative perspective, urban blight can be understood as the result of relationships among physical and environmental, economic, and social components. These dimensions do not operate separately. On the contrary, the literature often describes urban blight as a set of interdependent and potentially self-reinforcing processes in which changes in one dimension affect the others [7]. For example, signs of deterioration such as building obsolescence, poor maintenance, and low-quality public space may reduce the perceived attractiveness of an area for residents, users, and firms. This can lead to lower demand, higher turnover, and a gradual contraction of activities and services [8]. In turn, the reduction of functions and economic activity may encourage further public and private disinvestment, worsening physical conditions and limiting available resources for maintenance and management [9]. At the same time, these dynamics can also affect the social dimension by increasing vulnerability, marginalization, and perceived insecurity [10, 11]. Urban blight may therefore emerge as a cumulative process in which the deterioration of one subsystem reinforces the fragility of the others and consolidates a negative reputation of the area [12].

Within urban policy, urban regeneration is one of the main strategies for addressing and mitigating the dynamics associated with urban blight by acting in an integrated way on the built environment, urban functions, and socio-economic conditions [13, 14]. In regeneration programmes, the identification of priority areas and the definition of the most effective solutions often fall to local administrations and other territorial actors, usually within the eligibility constraints and criteria established by funding programmes [15]. These decisions must be technically sound, but also justifiable and accountable. It is necessary to explain why one area should be prioritized over another, which dimensions of criticality are most relevant, and how such assessments can be updated and compared over time [16]. In this context, tools capable of measuring urban blight in a transparent, replicable, and comparable way play a strategic role, since they reduce discretion and interpretative fragmentation while strengthening the knowledge base for planning and monitoring activities [17].

2 Aim

Against this background, the present study proposes a methodological approach for assessing urban blight as a decision support tool for urban regeneration. The aim is to assist public authorities and private actors in identifying territorial criticalities, comparing different areas, and supporting the selection of intervention priorities. From a technical and analytical perspective, urban blight is treated as a multidimensional and process-based phenomenon articulated into three interconnected components: the physical–environmental component, which refers to the material and environmental conditions of the urban context; the economic component, which concerns dynamics of attractiveness, disinvestment, and territorial performance; and the social component, which relates to quality of life, vulnerability, and cohesion.

To address this objective, the paper develops a replicable procedure for constructing composite indices for the comparative assessment of urban blight. The methodological framework combines entropy-based weighting with TOPSIS aggregation to produce three component indices and a comparative synthesis across territorial units. Robustness checks are also included in order to assess the stability of the results. The procedure is intended to generate outputs that are interpretable and operationally useful, including rankings, component-based readings, and spatial representations, while keeping the main methodological assumptions explicit and facilitating transferability to different urban contexts.

The contribution does not rely on introducing a new weighting or aggregation technique, but on the structured integration of established methods into a transparent and replicable workflow specifically tailored to the assessment of urban blight. In particular, the framework combines component-based interpretation, entropy-based weighting, TOPSIS aggregation, robustness checks, and GIS representation in order to support not only measurement, but also priority setting and decision-making in urban regeneration policies.

The remainder of the paper is structured as follows. Section 3 reviews the background literature on multidimensional composite indices, with particular attention to applications based on the Entropy weight–TOPSIS approach. Section 4 illustrates the proposed

methodological approach through its 11 steps. Section 5 concludes by outlining the main implications of the study, its limitations, and avenues for future research.

3 Background

The quantitative measurement of complex and multidimensional phenomena such as urban blight often relies on composite indices. These indices aggregate sets of individual indicators into a synthetic measure that is interpretable and comparable. In fields such as sustainability and territorial assessment, this approach makes it possible to integrate heterogeneous dimensions and produce results that can support decision making. The literature on composite indices identifies a recurring sequence of stages in the construction of such measures and emphasizes the importance of ensuring transparency and replicability [18].

Even when the operational stages are partly standardized, the quality and validity of an index depend significantly on a number of methodological choices. Different choices may lead to different scores and rankings. Among the most influential are weighting and aggregation [19]. In general, weighting may rely on equal weights, subjective methods such as AHP, or objective data driven approaches. With regard to aggregation, the most common distinction concerns the degree of compensability among criteria, namely compensatory, non compensatory, and partially compensatory approaches.

Within this context, the Entropy weight–TOPSIS approach has often been adopted when the aim is to obtain a synthesis that is both replicable and easy to communicate. Entropy makes it possible to estimate weights in a data driven way, while TOPSIS produces a continuous score and facilitates comparison across territorial units. This combination is therefore well suited to rankings and cartographic representations.

The literature documents the use of Entropy weight–TOPSIS in several fields of territorial assessment. A first strand concerns sustainability and environmental assessment. Wang et al. (2019) [20] apply Entropy weight–TOPSIS to measure the development capacity of the green economy at the regional scale. Jing et al. (2024) [21] combine a DPSIR framework (Driving forces, Pressures, State, Impact, and Response) with Entropy weight–TOPSIS to assess cultivated land ecological security from a spatial and temporal perspective. Similarly, Deng et al. (2024) [22] use a DPSIR based framework for water environment assessment, while Guo et al. (2024) [23] apply DPSIR and Entropy weight–TOPSIS to tourism ecological security. Taken together, these studies show that the approach is effective in synthesizing heterogeneous environmental dimensions and making territorial differences more clearly interpretable.

A second strand concerns resilience and the response capacity of territories. Yang et al. (2022) [24] use Entropy weight–TOPSIS to construct an urban resilience index and complement the synthetic measure with an analysis of the factors associated with the observed differences. On large samples, Wang et al. (2024) [25] apply Entropy weight–TOPSIS within a multidimensional framework to compare a broad set of cities. Other studies adapt the same scheme to more local scales, for example for territorial classification and rural resilience assessment within PSR frameworks. These contributions show the usefulness of the approach for comparative assessment across both large and small territorial samples.

A third area concerns urban liveability and wellbeing. In these cases, the aim is to produce synthetic scores that are clear and comparable. Xiao et al. (2022) [26] apply Entropy weight–TOPSIS to an urban liveability index and use it to interpret differences across contexts. Similar approaches also appear in policy adjacent assessments, such as healthy city rankings based on multi indicator sets [27]. In this strand, the main contribution of the approach lies in its capacity to provide readable comparative outputs that can support interpretation and communication.

Finally, Entropy weight–TOPSIS is also used in contexts oriented towards the prioritization of investments and interventions. Zhang et al. (2021) [28] apply this combination to assess the multidimensional impacts of transport networks in a metropolitan area, obtaining scores that can be ranked and compared. An example closer to regeneration can be found in studies on mapping priorities, where entropy and TOPSIS are used to produce priority scores for planning units, such as ageing residential districts. Zhao et al. (2022) [29] also use this combination in comparative assessment exercises aimed at supporting planning and investment choices. These studies are particularly relevant because they show the potential of the approach for priority setting in spatially differentiated decision contexts.

Overall, these contributions show that Entropy weight–TOPSIS is a recurring operational scheme for constructing comparative composite indices in the territorial field. Its diffusion is linked to the replicability of the procedure, the readability of the outputs, and its capacity to support spatial comparison and decision making.

4 Methodology

The proposed approach falls within the field of multidimensional composite indices and follows the main established stages for their construction [18, 19]. The methodology is designed to address explicit objectives of objectivity, replicability, and comparability across territorial units, while producing interpretable and communicable results to support the planning and monitoring of urban regeneration policies.

Consistently with the multidimensional nature of the phenomenon, the procedure includes: (i) the construction of three component indices, namely physical-environmental, economic, and social, based on sets of indicators consistent with each dimension; (ii) the synthesis of these component indices into an overall index to support comparison and priority setting; and (iii) the spatial representation of results through thematic maps. The operational choices privilege a data driven logic, reducing dependence on subjective judgments that are difficult to replicate and enhancing the applicability of the procedure across different territorial contexts.

The methodological approach is structured into 11 steps, summarized in Fig. 1.

4.1 Step 1. Definition of the Phenomenon and of the Components to Be Measured

The first step is the operational definition of what is to be measured. The literature on urban blight shows that the concept is not univocal and can be interpreted in different ways; for this reason, the definition stage is essential to reduce ambiguity and make the index defensible from an interpretative perspective. In this framework, urban

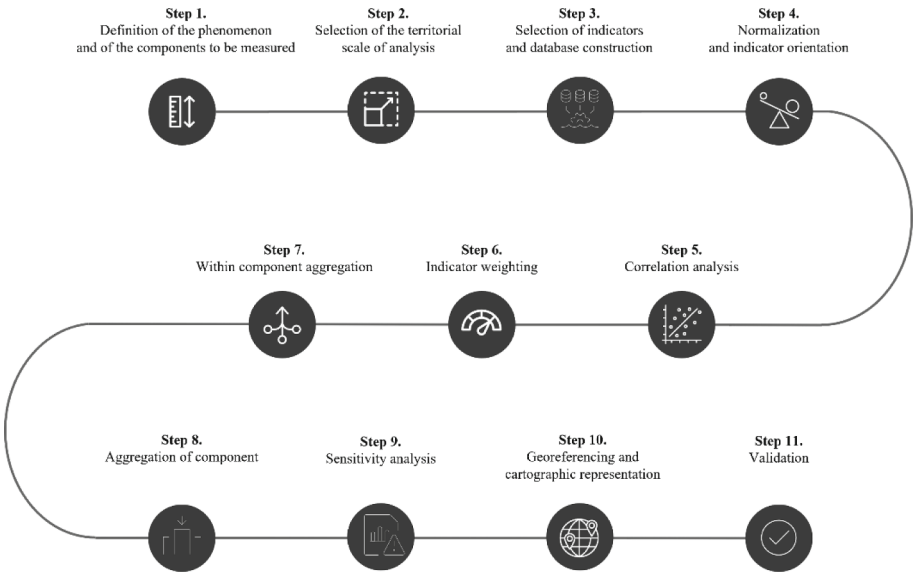

Fig. 1. Workflow of the proposed methodological approach.

blight is treated as a latent variable and, according to a formative measurement model, is determined by the combination of indicators: the latent construct is not reflected in the observed variables, but rather the observed variables contribute to defining the phenomenon [30].

The adopted framework therefore decomposes the phenomenon into three components, namely physical-environmental, economic, and social, which represent recurring forms through which urban blight manifests itself and allow for an integrated reading of the phenomenon, while keeping explicit the link between conceptual dimensions and the indicator system.

4.2 Step 2. Selection of the Territorial Scale of Analysis

The next stage consists in identifying the geographical scale at which the analysis is to be carried out, in order to ensure consistency between the territorial level considered, the nature of the observed phenomenon, and the operational purposes of the index. The choice of scale is relevant because it affects the interpretation of spatial concentrations and, consequently, the identification of priority areas. For this reason, the scale is defined by balancing analytical needs and informational constraints, taking into account: (i) decision making usefulness; (ii) sample size; (iii) data availability and quality; (iv) unit homogeneity; and (v) temporal stability.

In this context, the Modifiable Areal Unit Problem (MAUP) [31] must be considered: results may vary depending on the adopted scale and zoning system, since aggregation into areal units modifies the observed intensity and variability of the phenomenon. In practical terms, larger units tend to average out internal differences and reduce the ability to detect local hotspots; smaller units increase sensitivity to spatial discontinuities but

may prove more unstable in the presence of small numbers or greater data uncertainty. In sum, the territorial scale represents a compromise among descriptive capacity, statistical robustness, and operational feasibility, acknowledging that the unit of analysis is an integral part of the model.

4.3 Step 3: Selection of Elementary Indicators and Database Construction

Once the conceptual framework and the dimensions to be measured have been defined, the next stage concerns the construction of the information base of the index, which includes: (i) the selection of indicators and (ii) the collection, structuring, and quality checking of the underlying data. Indicator selection follows widely recognized methodological criteria adopted by international organizations such as OECD, Eurostat, and IMF, including relevance, accuracy, timeliness, accessibility, interpretability, and comparability. Operationally, the procedure starts with a literature review and the compilation of an initial list of candidate indicators, which is then screened against these criteria and the availability of verifiable data.

To support this stage, an indicator inventory was derived from the literature review (Table 1). The reported frequency, expressed as the number of studies, is based on counting the occurrences of each indicator within the review corpus. For each contribution, an indicator was recorded when it was explicitly adopted and operationalized as a variable for measuring urban blight, or closely related constructs. In this context the indicator inventory is used to guide the selection of candidate indicators, while the final selection depends on conceptual fit, the scale of analysis, and data availability.

Once the indicator set has been defined, data are collected, organized, and validated by prioritizing official and institutional sources, such as national and European statistics, administrative archives, and public open data. Consistency checks are performed on definitions, measurement units, spatial coverage, and reference periods in order to ensure homogeneity and comparability across territorial units. When data are available at spatial levels that differ from the chosen unit of analysis, GIS based processing may be required to harmonize the information according to a common zoning scheme, for example through spatial joins, overlays, and areal aggregation or disaggregation, while keeping the workflow transparent and replicable.

For each component, the final dataset is organized into a raw data matrix $X = [x_{ij}]$ of size $m \times n$, where the m rows represent territorial units and the n columns represent elementary indicators:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$$

4.4 Step 4. Normalization and Indicator Orientation

The next step concerns the normalization of indicators, which makes it possible to compare variables expressed in different units of measurement and orders of magnitude

Table 1. Indicator inventory from the literature review: frequency of occurrence by component

Component	Indicator	No. studies
Physical–environmental	Litter / waste	8
	Dilapidated / deteriorated buildings	6
	Graffiti	5
	Abandoned / underused buildings	5
	Vacant lots	4
	Pollutant emissions	3
	Unpleasant odours	3
	Weeds / overgrown vegetation	3
	Poor street lighting	3
	Traffic	2
	Limited access to public transport	2
	Energy performance	2
Economic	Businesses and retail presence	4
	Unemployment	3
	Land and housing values	3
	Household expenditure	2
Social	Crime / safety	6
	Income	4
	Poverty	3
	Out-migration from the neighbourhood	3
	School quality	2
	Population density	2

by transforming raw data into dimensionless values on a common scale. A preliminary issue concerns indicator orientation, that is, their polarity with respect to the phenomenon under analysis. Within the set of variables, positively oriented indicators may coexist with negatively oriented ones. In the first case, higher values indicate more critical conditions and are therefore associated with higher levels of urban blight; in the second case, higher values indicate better conditions and are therefore inversely related to the phenomenon. For aggregation purposes, all indicators must be oriented in the same interpretative direction.

In the present approach, Min–Max normalization is adopted, as it produces values between 0 and 1 and preserves the relative distances among observations. Denoting by $x_{min\,j}$ and $x_{max\,j}$ the minimum and maximum values of indicator j in the sample, the transformation is defined as follows:

$$r_{ij} = \frac{x_{ij} - x_{minj}}{x_{maxj} - x_{minj}} \text{for positively oriented indicators}$$

$$r_{ij} = \frac{x_{maxj} - x_{ij}}{x_{maxj} - x_{minj}} \text{for negatively oriented indicators}$$

The application of this procedure allows the transition from the raw data matrix X = [x_{ij}] to the normalized matrix R = [r_{ij}]:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}$$

4.5 Step 5. Correlation Analysis

Once normalization has been completed, the next stage consists of a correlation analysis among indicators in order to identify possible informational redundancies. Strongly correlated indicators, whether positively or negatively, may capture very similar aspects of the phenomenon, and their simultaneous inclusion may introduce double counting. In such cases, one of the indicators may be excluded, giving preference to the one that is more robust or theoretically more relevant, or alternatively replaced with a less redundant variable [19]. In the present approach, consistently with the quantitative nature of the indicators and with the aim of detecting linear overlap, Pearson's correlation coefficient is adopted.

Following this check, an Exploratory Spatial Data Analysis (ESDA) may be included as an additional interpretative step in order to assess whether indicators or indices display patterns of spatial concentration, such as clusters or outliers. This possibility is relevant because urban blight is associated with spatial dynamics and discontinuities. ESDA supports the territorial interpretation of results but does not intervene in the weighting or aggregation of the index.

4.6 Step 6. Indicator Weighting

The next stage concerns the weighting of indicators. Weighting assigns to each indicator a weight w_j, representing its relative importance in the construction of the composite index. This step is crucial, since different weights may affect both scores and rankings. In the absence of clear normative grounds for differentiating the importance of indicators, the adopted approach privileges an objective and replicable logic, reducing dependence on discretionary assessments. From this perspective, the entropy method is used as a data driven weighting technique [25]. In information theory, entropy measures the degree of uniformity of a distribution. In the context of composite indices, an indicator is considered more informative when it better discriminates among units. Indicators with a more uniform distribution, that is, higher entropy, contribute less to differentiation and therefore receive lower weights; conversely, indicators with greater variability, that is, lower entropy, receive higher weights [24]. Starting from the normalized matrix R = [r_{ij}], the calculation proceeds as follows.

First, the proportion of the normalized value of indicator j for territorial unit i is computed as:

$$p_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}$$

Second, the entropy of indicator j is calculated as:

$$E_j = -\frac{1}{ln(m)} \sum_{i=1}^{m} p_{ij} ln\left(p_{ij}\right)$$

Third, the degree of divergence is obtained as:

$$d_j = 1 - E_j$$

Finally, the normalized weight is computed as:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}$$

The resulting weights are then applied to the normalized matrix in order to obtain the weighted matrix $V = [v_{ij}]$:

$$v_{ij} = w_j \cdot r_{ij}$$

$$V = \begin{bmatrix} w_1 \cdot r_{11} & w_2 \cdot r_{12} & \cdots & w_n \cdot r_{1n} \\ w_1 \cdot r_{21} & w_2 \cdot r_{22} & \cdots & w_n \cdot r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_1 \cdot r_{m1} & w_2 \cdot r_{m2} & \cdots & w_n \cdot r_{mn} \end{bmatrix}$$

4.7 Step 7. Within Component Aggregation: TOPSIS

At this stage, the weighted indicators are combined into a component composite index. The choice of the aggregation technique is relevant because it incorporates assumptions about the degree of compensability among indicators, that is, the extent to which low performance in one criterion may be offset by high performance in other criteria. Consistently with the objective of obtaining a continuous, comparable, and easily mappable output, within component aggregation is carried out through TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), a distance-based method widely used in multicriteria problems. Compared with outranking methods such as ELECTRE and PROMETHEE, which require additional thresholds and parameters and mainly produce rankings, TOPSIS provides an immediate synthesis in the form of a cardinal score.

The principle of TOPSIS consists in evaluating each territorial unit according to its distance from two reference profiles: the ideal solution A^+ and the anti-ideal solution A^-

In the standard formulation, A^+ collects, for each indicator, the most desirable value, whereas A^- collects the least desirable one. In the approach adopted here, however, the indicators are previously normalized and oriented with respect to urban blight, so that higher values indicate more critical conditions. As a result, A^+ represents the profile of maximum urban blight, whereas A^- represents the profile of minimum urban blight.

The procedure is applied to the weighted matrix $V = [v_{ij}]$. The two solutions are defined as follows:

$$A^+ = \left\{v_1^+, v_2^+, \ldots, v_n^+\right\} A^- = \left\{v_1^-, v_2^-, \ldots, v_n^-\right\},$$

where, for each indicator j,

$$v_j^+ = max\left(v_{ij}\right), v_j^- = min(v_{ij})$$

The Euclidean distances of each territorial unit i from the two solutions are then calculated as:

$$D_i^+ = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2}$$

The closeness coefficient is defined as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, 0 \leq C_i \leq 1$$

In the proposed approach, the closeness coefficient is interpreted as a relative urban blight score. Since the indicators are oriented so that higher values correspond to more critical conditions, values of C_i closer to 1 indicate territorial units that are closer to the ideal profile of maximum urban blight, whereas values closer to 0 indicate proximity to the anti-ideal profile of minimum urban blight. Therefore, for each component, the resulting scores I_i^{PE}, I_i^{EC}, and I_i^{SC} can be read as component-specific indices of relative criticality. These indices do not provide an absolute diagnosis, but position each territorial unit within the observed sample and make it possible to identify where physical-environmental, economic, or social criticalities are comparatively more intense. Within-component aggregation also reduces the risk of poorly justified compensations, since the aggregated indicators belong to the same conceptual dimension.

4.8 Step 8. Aggregation of Components: Overall Index Through the Arithmetic Mean

Once the three component indices, I_i^{PE}, I_i^{EC}, I_i^{SC} , have been calculated, an overall urban blight index is constructed for synthesis and priority setting purposes. In the absence of robust theoretical grounds or unequivocal empirical evidence for assigning differential weights to the components, the simple arithmetic mean is adopted, as it preserves the transparency of the model and avoids an additional weighting step that could be potentially arbitrary.

The arithmetic mean implies compensability among components. However, the operational diagnosis remains supported by the component indices:

$$I_i^{TOT} = \frac{I_i^{PE} + I_i^{EC} + I_i^{SC}}{3}$$

For decision-making purposes, the overall index should therefore be interpreted as a screening and prioritization tool, rather than as a substitute for the component indices. Territorial units with high values of the overall index may be considered priority areas for intervention, but the interpretation of the three component indices is necessary to understand the nature of the criticality and to define appropriate regeneration strategies. For example, two areas may obtain similar overall scores while presenting different profiles: one may be mainly affected by physical-environmental deterioration, while another may combine moderate physical, economic, and social weaknesses. In this sense, the framework helps decision-makers manage trade-offs among components and supports a more targeted allocation of resources.

As an illustrative example, a territorial unit with a high overall urban blight index and particularly high physical-environmental and social component scores could be interpreted as an area where regeneration priorities should focus on the improvement of public space, building conditions, services, and social vulnerability. Conversely, an area with a high economic component score but lower physical and social criticalities may require interventions aimed primarily at strengthening local attractiveness, economic functions, and investment conditions. This type of component-based reading allows the index to move beyond a simple ranking and to support the definition of differentiated intervention strategies.

4.9 Step 9. Sensitivity Analysis

Sensitivity analysis is used to assess the robustness of the results with respect to methodological choices and the main sources of uncertainty that may affect a composite index [32]. In the present approach, sensitivity analysis focuses on weighting and adopts a one at a time, or OAT, procedure: one input is varied at a time while all others are kept constant, and the effects on the output are then observed. More specifically, for each indicator, the entropy weight is perturbed through progressive variations of $\pm 10\%$, $\pm 20\%$, and $\pm 30\%$, with the index recalculated each time using the same aggregation procedure, namely TOPSIS. The effects are assessed through: (i) the absolute difference from the reference value; (ii) the percentage difference; and (iii) changes in the ranking of territorial units.

4.10 Step 10. Georeferencing and Cartographic Representation of the Indices

Georeferencing makes it possible to move from a tabular reading to the spatial representation of the indices, highlighting patterns, concentrations, and territorial discontinuities, while supporting communication and priority setting. Operationally, index values are linked to the territorial units adopted as the scale of analysis and integrated with their corresponding geometries through GIS tools, so as to produce thematic maps. Different criteria may be used for the cartographic classification of values; in the present approach, a quintile classification is adopted, which divides the distribution into five classes of similar size, corresponding to about 20 per cent of the units in each class.

This facilitates comparison and interpretation in terms of relative position and priority. In this way, the cartographic output can be interpreted as a five level scale of urban

blight, ranging from very low to very high, and can be used to identify the most critical areas at a glance.

4.11 Step 11. Validation

The final stage concerns the validation of the approach, which can be tested in terms of its ability to be updated and its capacity to support decision making, considering that urban blight is linked to spatial dynamics and discontinuities and is therefore subject to change over time. From this perspective, the model can also be used ex-ante through *"what if"* exercises, by simulating the expected effects of urban regeneration interventions through the updating of indicators that are potentially sensitive to transformation. Operationally, the procedure includes: (i) the translation of the main project quantities into measurable variables; (ii) the identification and updating of the indicators involved through direct data, conversion parameters, or proxies; and (iii) the recalculation of the indices while keeping the model structure and the normalization, weighting, and aggregation rules unchanged, in order to preserve comparability with the reference framework.

Further checks may include comparisons with official measures or benchmarks and stability tests with respect to alternative methodological choices, for example by adopting less compensatory or non compensatory aggregation rules.

Taken together, these steps define the overall structure of the proposed methodological approach; Table 2 summarizes the methodological choices adopted and the corresponding main outputs associated with each step.

Table 2. Summary of the 11 steps of the proposed methodological approach, including the methodological choices adopted and the corresponding main outputs.

Step	Methodological choice	Main output
Step 1. Definition of the phenomenon and of the components to be measured	Formative measurement model; three component structure	Conceptual framework and index structure, including components and indicator domains
Step 2. Selection of the territorial scale of analysis	Decision making usefulness; sample size; data quality and availability; homogeneity; temporal stability; MAUP consideration	Unit of analysis and territorial scope for index construction and comparison
Step 3. Selection of indicators and database construction	Quality criteria; data availability; database construction; data harmonization	Raw data matrix $X = x_{ij}$ for each component
Step 4. Normalization and indicator orientation	Indicator orientation; Min–Max normalization	Normalized matrix R = rij

(*continued*)

Table 2. (*continued*)

Step	Methodological choice	Main output
Step 5. Correlation analysis	Pearson correlation; optional ESDA	Refined indicator set controlled for double counting, plus optional interpretative evidence
Step 6. Indicator weighting	Entropy based weighting	Weight vector $w = [w_j]$ and weighted matrix $V = v = [v_j]$
Step 7. Within component aggregation: TOPSIS	TOPSIS aggregation	Component indices I_i^{PE}, I_i^{EC}, I_i^{SC}
Step 8. Aggregation of components: overall index through the arithmetic mean	Arithmetic mean aggregation	Overall index I_i^{TOT}
Step 9. Sensitivity analysis	One at a time sensitivity analysis on entropy weights	Robustness measures, including absolute and percentage variations and ranking stability
Step 10. Georeferencing and cartographic representation of the indices	GIS based georeferencing; quintile classification	Thematic maps and comparable urban blight classes across territorial units
Step 11. Validation	Dynamic updating; optional what if analysis; benchmark comparison	Evidence on coherence and transferability, and indications for ex ante and ex post uses

5 Conclusions

Urban blight cannot be reduced to a single physical condition or to a purely aesthetic or public order issue. Rather, it emerges from the interaction of physical and environmental deterioration, socio-economic fragility, functional weakness, and perceived insecurity, and may affect both central and peripheral areas, as well as consolidated and more recent urban fabrics. In this context, urban regeneration represents one of the main strategies for addressing these dynamics. Yet many policy instruments and regeneration programmes require local authorities to identify and justify priority areas under conditions of limited resources. Without clear and comparable metrics, these choices risk becoming discretionary and difficult to justify. This makes it necessary to adopt transparent procedures, based on explicit rules and observable data, that can support comparison, prioritization, and accountability [33, 34].

This study responds to that need by proposing a data-driven methodological framework for constructing composite indices for the comparative assessment of urban blight.

Its main contribution lies in defining a replicable procedure that makes the main methodological choices explicit, from indicator selection and normalization to weighting and aggregation, while aiming to preserve comparability across territorial units. The three-component structure, physical–environmental, economic, and social, makes it possible to combine an overall synthetic assessment for priority setting with a component-based reading that can inform more targeted and integrated intervention strategies.

From an operational point of view, the outputs of the framework are intended to be directly usable in decision-making processes. The component indices help distinguish different profiles of territorial criticality; the overall index supports ranking and comparison; and thematic maps make spatial patterns and discontinuities easier to interpret and communicate, including to non-specialist audiences. In this form, the framework can support three recurrent functions in urban regeneration governance: identifying priorities and target areas, monitoring territorial conditions and policy outcomes over time, and strengthening negotiation and accountability processes by making the assumptions behind decisions more explicit.

At the same time, the framework also has some limitations, many of which are typical of composite measures applied to complex territorial phenomena. First, the quality of the results depends on the quality, coverage, and temporal consistency of the underlying data. Missing values, non-homogeneous measures, or misalignments across data sources may weaken the reliability of the outputs. Second, even when methodological assumptions are made transparent, some choices continue to influence the results, including indicator selection, scaling procedures, missing data treatment, and assumptions about compensability. In addition, the indices are descriptive rather than causal: they support comparison and ranking, but do not in themselves explain the causes of urban blight. Finally, the analysis is affected by the Modifiable Areal Unit Problem, meaning that results may vary according to the scale and zoning system adopted. For this reason, qualitative checks and, where possible, multi-scale readings remain advisable when the framework is used to support operational decisions.

These limitations also suggest possible directions for further development. One improvement would be to explore weighting schemes that combine data-driven criteria with participatory inputs, so as to reflect contextual priorities without undermining transparency. A second direction concerns the extension of the framework across multiple spatial scales, particularly where more detailed territorial readings are required for operational purposes. Finally, applying the model to different urban contexts and comparing its outputs with external benchmarks or recognized measures could help strengthen both its transferability and its credibility in decision-making settings.

Future developments may also include the empirical application of the framework to specific case studies, the integration of participatory procedures for discussing component weights and intervention priorities, and the use of longitudinal data to monitor the evolution of urban blight before and after regeneration policies. In this way, the framework could be progressively extended from a comparative assessment tool to a monitoring and evaluation device for urban regeneration strategies.

Note

The research has been developed within the project “MISTRAL - a toolkit for dynaMic

health Impact analysiS to predicT disability-Related costs in the Ag"- HORIZON-HLTH-2022-ENVHLTH04 - Grant Agreement Project n. 101095119 of the Polytechnic of Bari (Italy).

References

1. United Nations: Transforming our world: The 2030 Agenda for Sustainable Development (A/RES/70/1). United Nations, New York (2015)
2. European Commission: A New European Bauhaus: Shaping a More Beautiful, Sustainable and Inclusive Form of Living Together, Brussels (2020)
3. Anelli, D., Morano, P., Tajani, F., Sabatelli, E.: Impacts of urban decay on the residential property market: an application to the City of Rome (Italy). In: Gervasi, O., Murgante, B., Garau, C., Taniar, D., Rocha, A.M.A.C., Faginas Lago, M.N. (eds.) ICCSA 2024. LNCS, vol. 14822, pp. 36–48. Springer, Cham (2024). https://doi.org/10.1007/978-3-031-65318-6_3
4. Breger, G.E.: The concept and causes of urban blight. Land Econ. **43**(4), 369–376 (1967)
5. Lousada, A.L., Ferreira, F.A., Meidutė-Kavaliauskienė, I., Spahr, R.W., Sunderman, M.A., Pereira, L.F.: A sociotechnical approach to causes of urban blight using fuzzy cognitive mapping and system dynamics. Cities **108**, 102963 (2021)
6. Chakraborty, B., Dey, P.: A Composite urban blight identification and evaluation index (CUBIE): a systems-driven approach based on empirical evidence from Kolkata, India. Soc. Indic. Res. **176**(3), 1043–1070 (2025)
7. Ndhlovu, S., Mata, J.: Urban decay and the resilience factor in Bulawayo's downtown precinct (2019)
8. Hortas-Rico, M.: Sprawl, blight, and the role of urban containment policies: evidence from US cities. J. Reg. Sci. **55**(2), 298–323 (2015)
9. Pinto, A.M., Ferreira, F.A., Spahr, R.W., Sunderman, M.A., Govindan, K., Meidutė-Kavaliauskienė, I.: Analyzing blight impacts on urban areas: a multi-criteria approach. Land Use Policy **108**, 105661 (2021)
10. Gbekor, V.M.: Machine learning-based detection of urban blight. Carinthia Univ. Appl. Sci. (2021)
11. Costa, J.B., Ferreira, F.A., Spahr, R.W., Sunderman, M.A., Pereira, L.F.: Intervention strategies for urban blight: a participatory approach. Sustain. Cities Soc. **70**, 102901 (2021)
12. Barão, M.V., Ferreira, F.A., Spahr, R.W., Sunderman, M.A., Govindan, K., Meidutė-Kavaliauskienė, I.: Strengthening urban sustainability: Identification and analysis of proactive measures to combat blight. J. Clean. Prod. **292**, 126026 (2021)
13. Guarini, M.R., D'Addabbo, N., Morano, P., Tajani, F.: Multi-criteria analysis in compound decision processes: the AHP and the architectural competition for the chamber of deputies in Rome (Italy). Buildings **7**(2), 38 (2017)
14. Anelli, D., Morano, P., Fariello, F., Sabatelli, E.: Environmental, social and governance (ESG) assessment with a two-phase goal-programming-based optimization model: a comparative study of Envipark and Kalundborg eco-industrial parks. Front. Built Environ. **12**, 1731282
15. Grigorut, I.: Le politiche pubbliche nazionali per le città e le periferie nella prospettiva della rigenerazione urbana. WORKING PAPERS (1/2019), 1–11 (2019)
16. Morano, P., Tajani, F., Guarnaccia, C., Anelli, D.: An optimization decision support model for sustainable urban regeneration investments. WSEAS Trans. Environ. Dev. **17**, 1245–1251 (2021)
17. Manganelli, B., Murgante, B., Saganeiti, L.: The social cost of urban sprinkling. Sustainability **12**, Article no. 2236 (2020)

18. Joint Research Centre: Handbook on Constructing Composite Indicators: Methodology and User Guide. OECD Publishing (2008)
19. Greco, S., Ishizaka, A., Tasiou, M., Torrisi, G.: On the methodological framework of composite indices: a review of the issues of weighting, aggregation, and robustness. Soc. Indic. Res. **141**(1), 61–94 (2019)
20. Wang, M., Zhao, X., Gong, Q., Ji, Z.: Measurement of regional green economy sustainable development ability based on entropy weight-TOPSIS-coupling coordination degree: a case study in Shandong Province, China. Sustainability **11**(1), 280 (2019)
21. Jing, X., Tao, S., Hu, H., Sun, M., Wang, M.: Spatio-temporal evaluation of ecological security of cultivated land in China based on DPSIR-entropy weight TOPSIS model and analysis of obstacle factors. Ecol. Indic. **166**, 112579 (2024)
22. Deng, W., Li, X., Guo, Y., Huang, J., Zhang, L.: Ecological assessment of water environment in Huizhou region of China based on DPSIR theory and entropy weight TOPSIS model. Water **16**(18), 2579 (2024)
23. Guo, Y., Song, Y., Huang, J., Zhang, L.: Water Environment assessment of Xin'an River Basin in China based on DPSIR and entropy weight–TOPSIS models. Water **17**(6), 781 (2025)
24. Yang, M., Jiao, M., Zhang, J.: Research on urban resilience and influencing factors of Chengdu-Chongqing economic circle. Sustainability **14**(17), 10585 (2022)
25. Wang, J., Wang, Y., Lin, G.: Study on rural classification and resilience evaluation based on PSR model: a case study of Lvshunkou District, Dalian City, China. Sustainability **16**(15), 6708 (2024)
26. Xiao, Y., Chai, J., Wang, R., Huang, H.: Assessment and key factors of urban liveability in underdeveloped regions: a case study of the Loess Plateau, China. Sustain. Cities Soc. **79**, 103674 (2022)
27. Wen, Y., Li, Y., Zhang, Y., Liu, B.: Comprehensive evaluation of global health cities development levels. Front. Public Health **12**, 1437647 (2024)
28. Murgante, B., Tilio, L., Lanza, V., Scorza, F.: Using participative GIS and e-tools for involving citizens of Marmo Platano - Melandro area in European programming activities. J. Balkan Near East Stud. **13**, 97–115 (2011)
29. Zhao, D.-Y., Ma, Y.-Y., Lin, H.-L.: Using the Entropy and TOPSIS models to evaluate sustainable development of islands: a case in China. Sustainability **14**(6), 3707 (2022)
30. Anelli, D., Ranieri, R.: Resilience of complex urban systems: a multicriteria methodology for the construction of an assessment index. In: Calabrò, F., Della Spina, L., Piñeira Mantiñán, M.J. (eds.) NMP 2022. LNNS, vol. 482, pp. 690–701. Springer, Cham (2022). https://doi.org/10.1007/978-3-031-06825-6_65
31. Dark, S.J., Bram, D.: The modifiable areal unit problem (MAUP) in physical geography. Prog. Phys. Geogr. **31**(5), 471–479 (2007)
32. Saltelli, A., Tarantola, S., Campolongo, F.: Sensitivity analysis as an ingredient of modeling. Stat. Sci., 377–395 (2000)
33. Calabrò, F., Minniti, G.E., Fotia, A., Pucinotti, R.: Recovery of historic real estate: life cycle costing and economic feasibility. Procedia Struct. Integr. **64**, 1759–1766 (2024)
34. Spatari, G., Lorè, I., Viglianisi, A., Calabrò, F.: Economic feasibility of an integrated program for the enhancement of the Byzantine heritage in the Aspromonte National Park. the case of Staiti. In: Calabrò, F., Della Spina, L., Piñeira Mantiñán, M.J. (eds.) NMP 2022. LNNS, vol. 482, pp. 313–323. Springer, Cham (2022). https://doi.org/10.1007/978-3-031-06825-6_30