

Informal Urban Expansion Under Displacement: A Spatial–Relational Analysis of Building Patterns

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Abstract: Understanding how informal urban expansion unfolds under displacement pressure is essential for planning and governance in conflict-affected cities where conventional data and planning instruments are unavailable. Existing quantitative approaches to urban morphology tend to analyse buildings as isolated entities or rely on predefined spatial contexts, limiting their capacity to capture the relational processes through which informal settlements emerge and adapt. This study introduces an analytical framework that integrates Morphological Cells with an unsupervised Graph Attention Network (GAT) to jointly model building-level morphometrics and inter-building spatial relationships. Applied to nearly 50,000 manually digitised buildings in Marib, Yemen, the framework identifies 13 morphological clusters that consolidate into four process-driven urban patterns: displacement-driven densification, tenure-enabled incremental expansion, semi-formal historic continuity, and transitional hybridisation. A controlled comparison against morphology-only and ablation baselines at identical cluster counts ($K = 13$) confirms that incorporating relational topology produces a fundamentally different classification (Adjusted Rand Index = 0.067 relative to the morphology-only baseline), with substantially greater spatial coherence aligned to documented displacement dynamics. Stability analysis across ten independent training runs indicates that while individual building assignments are sensitive to initialisation, the macro-level taxonomy of four super-types remains structurally recoverable. The findings demonstrate that informal expansion under displacement follows structured spatial logics shaped by tribal land tenure, humanitarian material restrictions, and caste-based exclusion, rather than chaotic sprawl. By transforming building footprints into a cadastral-free diagnostic tool for adaptive urban processes, the framework offers transferable insights for context-sensitive governance in cities where formal planning capacity has collapsed.

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1. Introduction

In cities shaped by conflict and forced displacement, urban form does not follow master plans. It emerges through incremental, self-built construction by populations navigating land scarcity, institutional collapse, and the immediate need for shelter. While many cities in the developed world have shifted toward technology-driven urban management, large parts of the developing world continue to experience rapid, unplanned growth fuelled by conflict, political instability, and weak planning institutions. In these settings, informal settlements emerge as a direct response to internal displacement and the absence of planned land and housing provision (Camila et al., 2024; United Nations, 2017). More than one billion people across the Global South currently reside in such settlements (World Resources Institute, 2021), and this figure continues to rise, particularly in conflict-affected regions (Purwanto et al., 2017). As an urban form, informal settlements are defined by continuous transformation through self-built, incremental construction (Samper et al., 2020), a dynamic that profoundly shapes urban morphology and complicates its systematic analysis (Bartlett et al., 2012; Camacho et al., 2025; Chaturvedi et al., 2020).

The relationship between population displacement and urban restructuring is well documented. In Kabul, unplanned expansion grew 4.5 times faster than planned development between 2001 and 2017 (Chaturvedi et al., 2020). In Nyala, Sudan, inflows of internally displaced persons transformed a small commercial town into a rapidly expanding centre characterised by peripheral informal settlements (Bartlett et al., 2012). Comparable dynamics have been observed in Gulu, northern Uganda, and Goma, Democratic Republic of Congo, where displacement reshaped the urban fabric through fragmented and uneven morphological configurations (Branch, 2008; Vlassenroot & Büscher, 2013). Across these cases, conflict-induced displacement produces composite urban forms, fragmented structures, and encroachment into agricultural land (Gerrits, 2012; Myers, 2011).

Yemen has experienced continuous conflict since 2011, triggering major urban transformations. Marib exemplifies this phenomenon. Before the conflict, the city had approximately 55,000 inhabitants; by 2020, mass inflows of internally displaced people had driven the population beyond 630,000, with recent reports suggesting nearly one million (ACAPS, 2020). This unprecedented demographic pressure occurred entirely outside formal planning frameworks, generating widespread informal expansion ranging from spontaneous host-community construction to displacement camps and agricultural encroachment.

Despite a growing body of work in quantitative urban morphology and machine learning, the systematic characterisation of informal expansion under displacement remains limited. Existing morphometric approaches describe individual building attributes or aggregate density indicators, treating structures as spatially independent. Recent applications of graph neural networks in urban studies have focused predominantly on planned or data-rich environments, emphasising functional classification, land-use prediction, or mobility modelling. These methods inadequately capture the adaptive, fragmented, and relational morphologies that emerge under conditions of forced displacement and institutional collapse.

There remains a need for frameworks capable of jointly modelling building-level morphology and inter-building spatial dependencies in such contexts.

This paper addresses the following research question: how can building-level morphological and inter-building spatial relationships be jointly learned to reveal adaptive patterns of informal urban expansion in conflict-affected cities? The study proposes a hybrid analytical framework that integrates Morphological Cell (MC) based morphometrics with a Graph Attention Network (GAT) to model informal expansion as a relational morphological process. The work makes three contributions. First, it conceptualises informal growth as an emergent spatial structure shaped by inter-building topological relationships, moving beyond density-based or land-use framings. Second, it introduces an unsupervised, graph-based learning framework for extracting adaptive morphological patterns from manually digitised building data where no labelled training sets or cadastral records exist. Third, it positions Marib as a theory-building case: an extreme yet analytically generative context through which broader insights into the spatial logic of displacement-induced expansion can be derived.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 presents the methodological framework. Section 4 applies the framework to Marib. Section 5 validates the model, discusses conceptual and planning implications, and addresses limitations. Section 6 concludes.

2. Literature Background

Quantitative approaches to informal urban expansion have evolved through three broad methodological paradigms, each embedding distinct assumptions about how urban form should be represented and learned. This section reviews these paradigms with attention to their analytical capacities and their limitations in contexts where displacement drives rapid, relational, and path-dependent morphological change.

2.1 Building Morphometrics and Conventional Machine Learning

Early analyses of informal settlement morphology relied on expert-driven protocols combining local knowledge, manual boundary delineation, and visual interpretation of high-resolution imagery (Davis, 2006; Dovey & Kamalipour, 2017; Dovey & King, 2011; Hasan, 2006; Kamalipour, 2016; Kohli et al., 2012; Samper et al., 2020). These foundational studies provided rich descriptive insight into the diversity of informal morphologies and established the morphometric vocabulary upon which subsequent computational work has built. Notably, they demonstrated that informality is not a single morphological condition, but a spectrum of configurations shaped by tenure systems, construction materials, topography, and the pace of settlement formation.

More recently, machine learning methods have been applied to building morphology using GIS datasets and satellite imagery (Liu & Song, 2025). Classical supervised and unsupervised algorithms, including support vector machines (Karimi et al., 2019), random forests (Ruiz & Shi, 2018), k-nearest neighbours (Liu et al., 2021), and decision trees (Jun, 2021), have enabled the identification of morphological typologies by learning patterns from

building-level features such as size, shape, density, and orientation. Empirical studies confirm that these descriptors can effectively differentiate formal from informal urban fabrics and reveal morphological variation across urban contexts (Wang et al., 2023; Jochem et al., 2021; Li et al., 2023; Cheng et al., 2022). Such approaches have proven effective for large-area mapping and cross-city comparison, where compact feature sets and scalable models support efficient pattern discovery.

Despite their effectiveness for broad classification, these methods encounter specific limitations when applied to the irregular geometries and heterogeneous fabrics characteristic of informal settlements. Support vector machines perform well in high-dimensional feature spaces but struggle to discriminate subtle morphological differences in complex building geometries. Random forests are robust to heterogeneous features but are sensitive to the class imbalance that frequently arises in urban datasets where small informal structures vastly outnumber large formal buildings. K-nearest neighbour classifiers suffer from declining performance as feature dimensionality increases, while decision trees are prone to noise and overfitting in real-world building-level analyses. More fundamentally, all of these methods represent urban form through independent building attributes or aggregated feature vectors: each structure is treated as a self-contained observation, and the spatial relationships between buildings, which encode incremental alignment, collective densification, and adaptive clustering, remain implicit in the analysis.

2.2 Contextual and Non-Relational Spatial Learning

To extend morphology-only analyses, a second line of research has incorporated contextual and neighbourhood-level information into conventional machine learning and statistical frameworks. In these approaches, building-level morphometric features are augmented with aggregated spatial metrics, including local density measures, proximity indices, and neighbourhood summaries, allowing models to approximate spatial context and localised interaction effects. This strategy represents an important step toward acknowledging that urban form is shaped not only by individual building attributes but also by the surrounding environment.

Empirical applications illustrate the analytical value of this paradigm. Fan et al. (2025) extracted multi-scale contextual features from very-high-resolution imagery and Sentinel-2 data to map urban attributes and population distributions, demonstrating that neighbourhood-level metrics can capture spatial heterogeneity that building-level features alone miss. Rhee (2019) similarly analysed buildings in relation to their immediate urban context, identifying clusters of morphologically similar areas and generating insights into city-specific typologies. These studies show that contextual enrichment improves descriptive capacity and enables finer spatial differentiation than purely attribute-based approaches.

At the same time, the representation of spatial structure in such models remains indirect. Contextual information is operationalised through predefined aggregation rules and fixed neighbourhood definitions (James et al., 2014), which embed analytical decisions prior to learning. As a result, inter-building relationships are summarised rather than explicitly

represented, and the spatial logic through which informal fabrics adapt, including incremental alignment, localised clustering, and uneven densification, remains implicit within aggregated metrics. This limitation becomes particularly salient in informal and displacement-driven settings, where urban form evolves through fine-grained, relational, and path-dependent processes that are difficult to capture through static contextual summaries alone (McCartney & Krishnamurthy, 2018).

2.3 Graph-Based Learning in Urban Morphology

Graph-based methods represent a conceptual shift in the quantitative analysis of urban morphology by explicitly modelling urban form as a relational system rather than as a collection of independent spatial units. The broader application of network analysis to urban spatial structure has a rich precedent: Boeing (2017) demonstrated the analytical power of graph representations for characterising street network morphology across cities, establishing that topological properties encode urban form in ways that geometric measures alone cannot capture. Within Graph Neural Networks (GNNs), this relational logic is extended to the building scale, where urban elements are represented as nodes and edges encode adjacency, proximity, or other forms of spatial interaction (Batty, 2009; Caruso et al., 2017). Through message-passing and aggregation mechanisms, these models jointly learn node attributes and inter-element dependencies, enabling structure-aware representations that align with the inherently relational nature of urban morphology (Fan et al., 2024).

Recent urban studies have applied graph-based learning to a range of morphological tasks. Approaches integrating building shape descriptors with graph representations have improved recognition of spatial configurations such as collinearity and alignment, albeit with sensitivity to geometric complexity (Zhang et al., 2024). Adaptive GCN architectures have been shown to handle heterogeneous spatial distributions and multi-scale structures, enhancing generalisation across dense urban environments while revealing challenges related to annotation ambiguity (Bei et al., 2019; H. Wang et al., 2025). Interpretable GNN frameworks have linked learned morphological representations to urban functions across building, plot, and neighbourhood scales, illustrating the capacity of relational learning to bridge form and function (Chen et al., 2025). Beyond descriptive analysis, graph-based models have been integrated into simulation frameworks where GATs combined with Cellular Automata and Agent-Based Models capture higher-order spatial dependencies in urban expansion (Gao et al., 2025).

Within this body of work, a common pattern emerges: graph-based methods consistently outperform attribute-based and contextual models in capturing complex spatial structure, yet their application remains largely confined to planned or data-rich urban environments. Most existing studies rely on labelled datasets, cadastral information, or auxiliary socio-economic data, implicitly assuming stable urban form and data availability. This limits their transferability to informal, rapidly evolving cities where building footprints often constitute the sole reliable spatial data source. Unsupervised graph-based learning for

characterising informal urban form at the building scale remains rare, and the gap is especially pronounced in conflict-affected cities of the Global South.

The present study responds to this gap at the intersection of three under-connected fields: informal urban morphology, displacement-driven expansion, and unsupervised graph-based machine learning. Existing morphology-only and non-relational approaches lack the capacity to capture the adaptive, fragmented, and relational dynamics that underpin informal expansion under forced displacement. Addressing this limitation requires a framework capable of jointly learning building-level morphometrics and inter-building spatial dependencies without reliance on labelled data. The unsupervised MC-based GAT framework proposed here is designed to meet this requirement, extending relational urban morphology analysis to dynamically evolving cities under displacement pressure.

3. Research Design

3.1 Methodological Framework

The study introduces a data-driven framework for analysing adaptive patterns in informal urban expansion. As illustrated in **Figure 1**, the framework proceeds through three stages: (1) generation of Morphological Cells (MCs) from building footprints, enriched with morphometric attributes; (2) construction of a building adjacency graph to represent spatial relationships; and (3) relational embedding learning through a GAT that captures multi-step spatial interactions among buildings. These stages are supported by the computation of building-level morphometric features, the aggregation of node embeddings at the MC level, and the integration of relational embeddings with intrinsic morphometric attributes. The steps are implemented sequentially, reflecting the premise that urban form emerges from the interaction between local building attributes and topological relations.

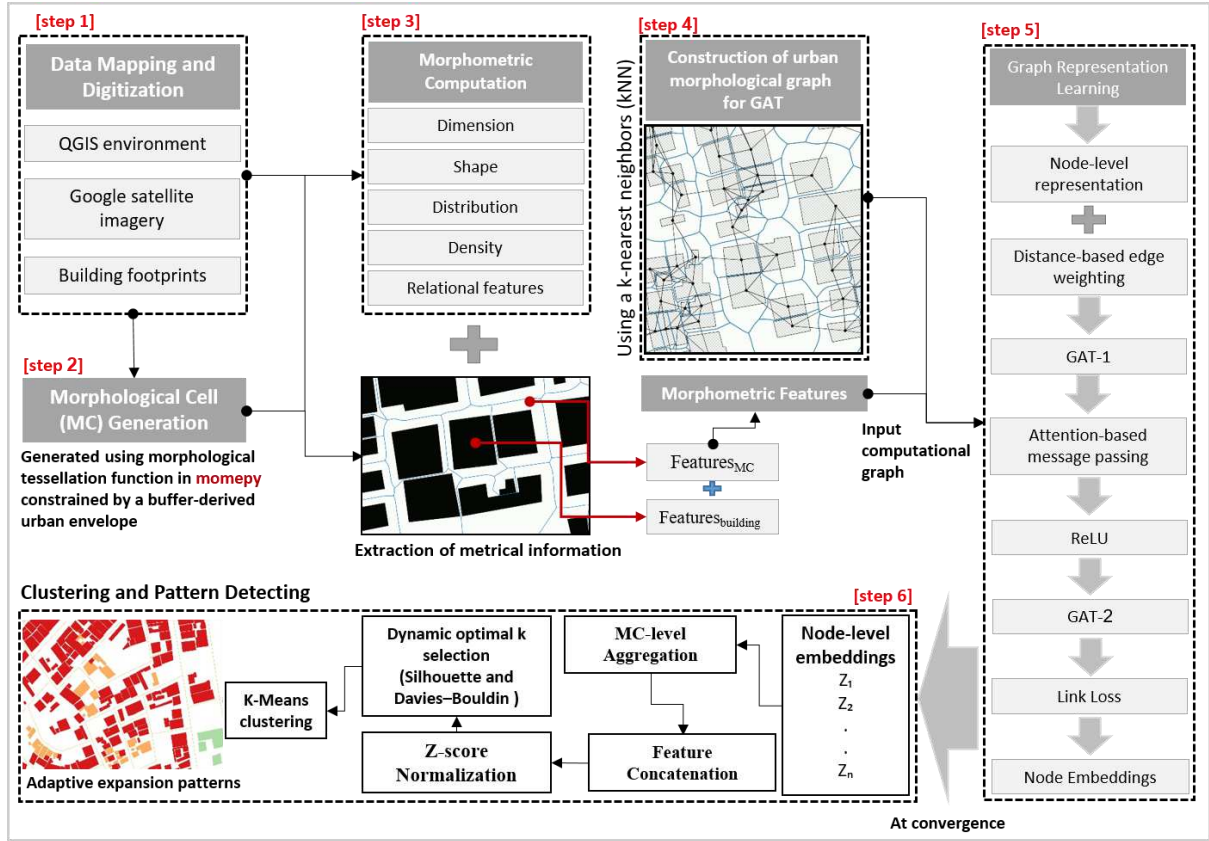


Figure 1. Workflow of the proposed Relation-Optimized GAT framework.

3.2 Morphological Cells

3.2.1 Definition and Rationale

To enable an operational understanding of urban form under data-constrained conditions, this study adopts MCs as the fundamental spatial unit. Introduced by Fleischmann et al. (2020, 2022) and building on earlier work by Hamaina et al. (2012) and Usui and Asami (2013), MCs provide a plot-equivalent alternative to conventional cadastral parcels, derived directly from building footprints. This approach is particularly relevant in informally developed or displacement-affected cities, where cadastral records are often incomplete or absent (Arribas-Bel & Fleischmann, 2022; Fan et al., 2025; Fleischmann et al., 2020). MCs are generated through morphological tessellation, a polygon-based extension of Voronoi tessellation that uses building footprints as spatial anchors to delineate catchment areas representing each building's morphological sphere of influence while preserving adjacency relations (Arribas-Bel & Fleischmann, 2022; Usui & Asami, 2018).

3.2.2 Operationalisation

Local urban influence is defined using a fixed-distance buffer. Previous studies demonstrate that buffers between 50 m and 100 m are effective for capturing localised spatial interactions (Biljecki & Chow, 2022; Z. Wang et al., 2025). All building geometries were standardised to single-part polygons. A continuous urban envelope was constructed by buffering footprints by 75 m, clipping to the city boundary, and dissolving into a single

polygon. This buffer-based approach is necessary because the irregular street network, fragmented fabric, and large interstitial open spaces render conventional tessellation methods (such as classical Voronoi or adaptive tessellation) prone to distortion (Li & Liu, 2025; Ma et al., 2024). The 75 m value was selected after testing alternatives: 50 m failed to capture buildings separated by wide streets, while 100 m overextended the local context; 75 m provided the best compromise. Tessellation was performed using momepy’s morphological_tessellation function. The resulting MCs form a continuous, non-overlapping partition that covers the built-up area while preserving adjacency.

3.3 Morphometric Feature Extraction

Buildings are modelled as graph nodes, and their morphological characteristics are described across four domains: dimension, shape, distribution, and density (Chen et al., 2025). A targeted subset of features was selected to capture both intrinsic building form and immediate spatial context. At the building level, dimension-related features include area and perimeter. Shape descriptors include circular compactness, equivalent rectangular index, elongation, number of corners, squareness, and centroid-to-corner distance statistics. Distribution features include building orientation and cell alignment. At the MC level, cell area and coverage area ratio capture land subdivision and built-up intensity. A first-order spatial context was introduced through neighbouring MCs, yielding area covered by neighbours and mean inter-building distance. All features are summarised in *Table 1*.

Table 1. Morphometric features for building and morphological cell levels.

Feature	Category	Element	Level
Area	Dimension	Building	Single building
Perimeter	Dimension	Building	Single building
Circular Compactness	Shape	Building	Single building
Equivalent Rectangular Index	Shape	Building	Single building
Elongation	Shape	Building	Single building
Corners	Shape	Building	Single building
Squareness	Shape	Building	Single building
Centroid - corner distance deviation	Shape	Building	Single building
Centroid - corner mean distance	Shape	Building	Single building
Orientation	Distribution	Building	Single building
Cell alignment	Distribution	Building	Single building
Area	Dimension	MC	Morphological Cell (MC)
Coverage area ratio	Density	MC	Morphological Cell (MC)
Area covered	Dimension	MC	Aggregated MC / Neighboring MCs
Mean inter-building distance	Distribution	Buildings	Aggregated MC / Neighboring MCs

3.4 Graph Construction and GAT Learning

A building-level spatial adjacency graph was constructed in which each building is a node and edges indicate spatial proximity. This graph construction extends the network-analytical tradition established for street morphology (Boeing, 2017) to the building scale, where relational structure among individual structures encodes adaptive processes invisible to

aggregate metrics. Building centroids were computed and a k-nearest neighbours' strategy ($k = 4$) was applied to define connectivity, providing a consistent neighbourhood size without relying on administrative boundaries. The value $k = 4$ was selected after testing alternatives: fewer neighbours caused loss of local interaction information, while larger values introduced connections that distorted the representation of immediate spatial context, particularly in dense and irregular informal settlements. Edges were treated as undirected links. To account for spatial intensity, edge weights were defined as the inverse of the Euclidean distance between connected centroids, normalised using min-max scaling so that the normalised weight for each edge ranged from 0 (most distant pair) to 1 (closest pair). This weighting reflects a distance-decay assumption consistent with the idea that spatial influence between buildings diminishes with separation and avoids introducing social or functional relationship assumptions unavailable in data-scarce contexts. The resulting network forms a spatially embedded adjacency graph that maintains local continuity and is compatible with GATs. A partial example is shown in **Figure 2**; the complete graph is provided in Appendix A (Figure A1).

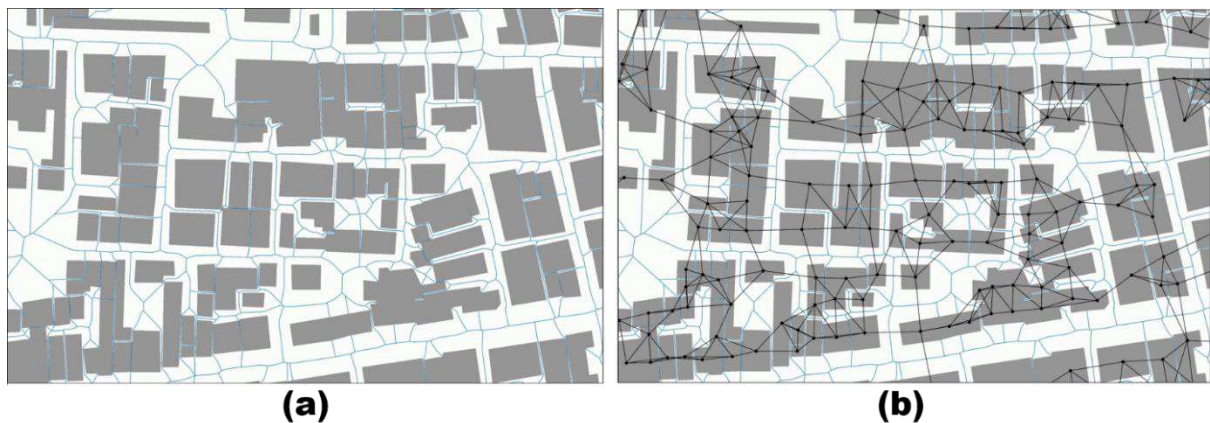


Figure 2. Partial graph construction example: (a) morphological cells and buildings; (b) k-NN building graph.

All morphometric features were standardised via z-score normalisation to ensure comparability across dimensions and prevent any single attribute from dominating the learned representations. After normalisation, the features were assembled into a unified node-feature matrix F of dimension N by D , where N denotes the number of building nodes and D represents the total feature dimensionality.

The GAT architecture was configured with two stacked attention layers following iterative tuning. The first layer contained 128 hidden channels and the second produced 64 output channels, using a single attention head and a dropout rate of 0.1. These hyperparameters were selected based on preliminary experiments indicating that this configuration provides stable representation learning, ensures convergence, and balances computational efficiency. Training was conducted for 100 epochs using the Adam optimiser with a learning rate of 0.001. The first attention layer aggregated neighbourhood information and applied a non-linear transformation (ReLU), while the second layer generated the final low-dimensional building embeddings.

The model was trained in an unsupervised manner using a weighted link reconstruction objective. For each connected node pair (i, j) , the predicted similarity was computed as the dot

product of their embedding vectors. The training loss was then defined as the mean squared deviation between predicted similarity and the target value of 1 (indicating an existing link), weighted by the normalised spatial proximity of each pair. Formally, the loss averaged over all edges the quantity w_{ij} multiplied by the squared difference between the dot-product similarity and unity, where w_{ij} denotes the normalised edge weight. This formulation ensures that pairs of buildings located in close proximity exert greater influence on the learned representations, while more distant connections contribute proportionally less. Through iterative optimisation over 100 epochs, the GAT learned node embeddings that jointly encoded intrinsic building morphometrics and multi-step topological relationships. These embeddings then served as the basis for subsequent aggregation at the Morphological Cell level and unsupervised clustering of adaptive urban patterns.

3.5 Unsupervised Clustering

The learned embeddings were subjected to MiniBatch K-Means clustering to identify latent adaptive urban patterns (Fan et al., 2025; Liu & Song, 2025). This algorithm ensures computational efficiency over large datasets by iteratively updating centroids from randomly sampled batches. The optimal K was determined through the convergent evaluation of clustering quality metrics and structural interpretability criteria described in Section 4.1.3. Each building was assigned a cluster label, producing a spatially explicit classification. These assignments were re-integrated into the spatial dataset for analysis of cluster composition, distribution, and association with formal, informal, and camp-based expansion.

4. Analysis and Results

4.1 Characterising Adaptive Expansion Patterns

4.1.1 Urban Context

The framework was applied to Marib City, capital of Marib Governorate. The governorate spans 17,405 km² and is situated 173 km northeast of Sana'a. Marib's position along the N5 road, combined with surrounding deserts and mountain barriers, historically provided relative security, reinforced by oil resources, electricity infrastructure, and tribal alliances (ACAPS, 2020) (**Figure 3**). These factors elevated its strategic importance during the conflict, transforming it into an economic hub and a major IDP destination.

The population grew from approximately 16,794 in 2004 to 55,000 by 2014 and surged beyond 630,000 by 2020 (ACAPS, 2020). This growth produced unplanned expansion into peripheral desert areas, generating informal neighbourhoods and IDP camps forming distinct belts around the urban core. The absence of a master plan resulted in a fragmented urban structure.

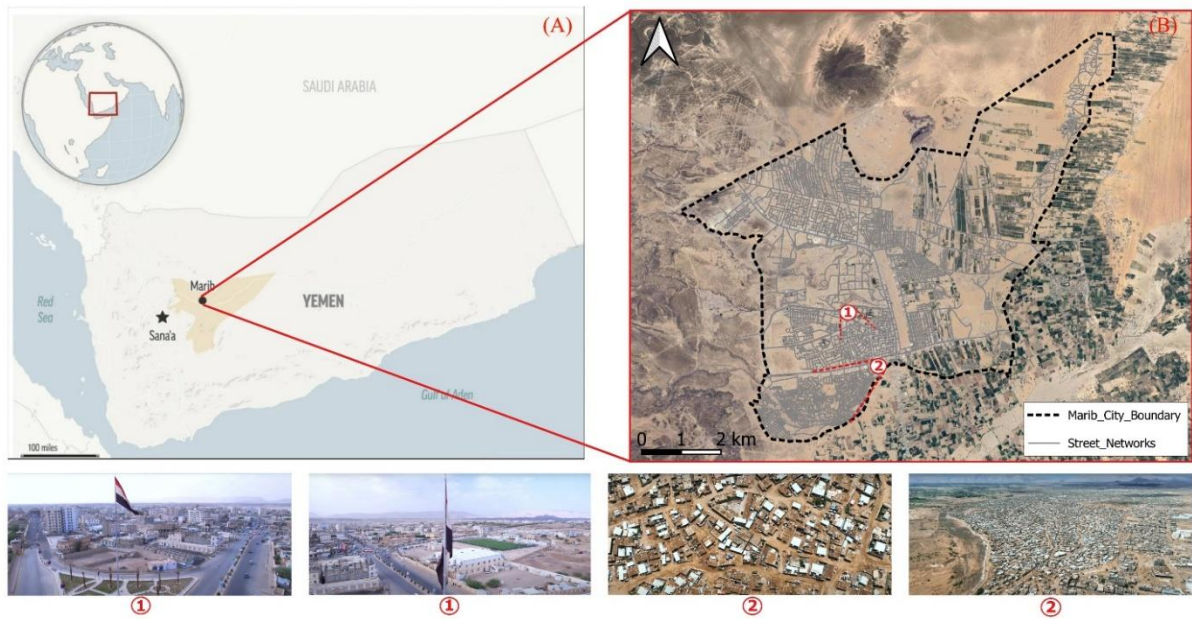


Figure 3. Study area of Marib, Yemen.

4.1.2 Building Footprint Extraction

Mapping informal settlements remains a complex task. Although advances in remote sensing and automated extraction have expanded the capacity to delineate settlements using standardised workflows, a degree of imprecision persists due to the heterogeneous and context-dependent nature of informality across regions (Taubenböck et al., 2018). Semi-automatic and deep learning approaches often rely on small training datasets and complex architectures, increasing the risk of overfitting and reduced generalisation, particularly in morphologically ambiguous areas where informal and formal fabrics merge (Jochem et al., 2021; Wang et al., 2023; Yuan, 2018). These limitations are compounded in conflict-affected contexts, where access restrictions prevent field verification and where the built environment changes rapidly between satellite acquisition dates.

In response to these challenges, building footprints in Marib were manually digitised from high-resolution satellite imagery within the QGIS environment. The digitisation was constrained by official administrative city boundaries provided by the General Authority for Land Survey and Urban Planning (GALSUP), Yemen (ACAPS, 2020), and followed data preparation strategies adopted in previous mapping efforts (Gunter, 2009; Joshi et al., 2002; Samper et al., 2020). Manual digitisation was selected to ensure geometric precision and consistent boundary delineation, overcoming the inaccuracies commonly associated with automated extraction in morphologically ambiguous settings (Kuffer et al., 2016). As Jochem et al. (2021) emphasise, manual tracing from very high-resolution imagery preserves the true geometry and spatial context of buildings, which is critical for reliable morphometric computation. This level of geometric fidelity is especially important in Marib, where hybrid formal-informal fabrics and rapid morphological change require precise representation of individual structures to support robust graph-based analysis.

A total of 49,773 building footprints were digitised within the administrative boundaries, encompassing both formal and informal fabrics. Following digitisation, comprehensive data cleaning and pre-processing procedures were conducted: multi-part geometries were dissolved into single-part polygons, overlapping footprints were corrected, and slivers below a minimum area threshold were removed. To assess completeness, digitised footprints were cross-referenced against the satellite imagery at multiple spatial scales, and a random sample of 500 buildings was independently re-digitised to evaluate inter-operator consistency. The precision, completeness, and spatial coverage of the resulting dataset are illustrated through representative areas at finer scales, capturing formal neighbourhoods, informal settlements, IDP camps, and residential encroachment onto agricultural land (*Figure 4a–f*). This validated dataset serves as the primary input for subsequent morphometric analysis and graph-based modelling.

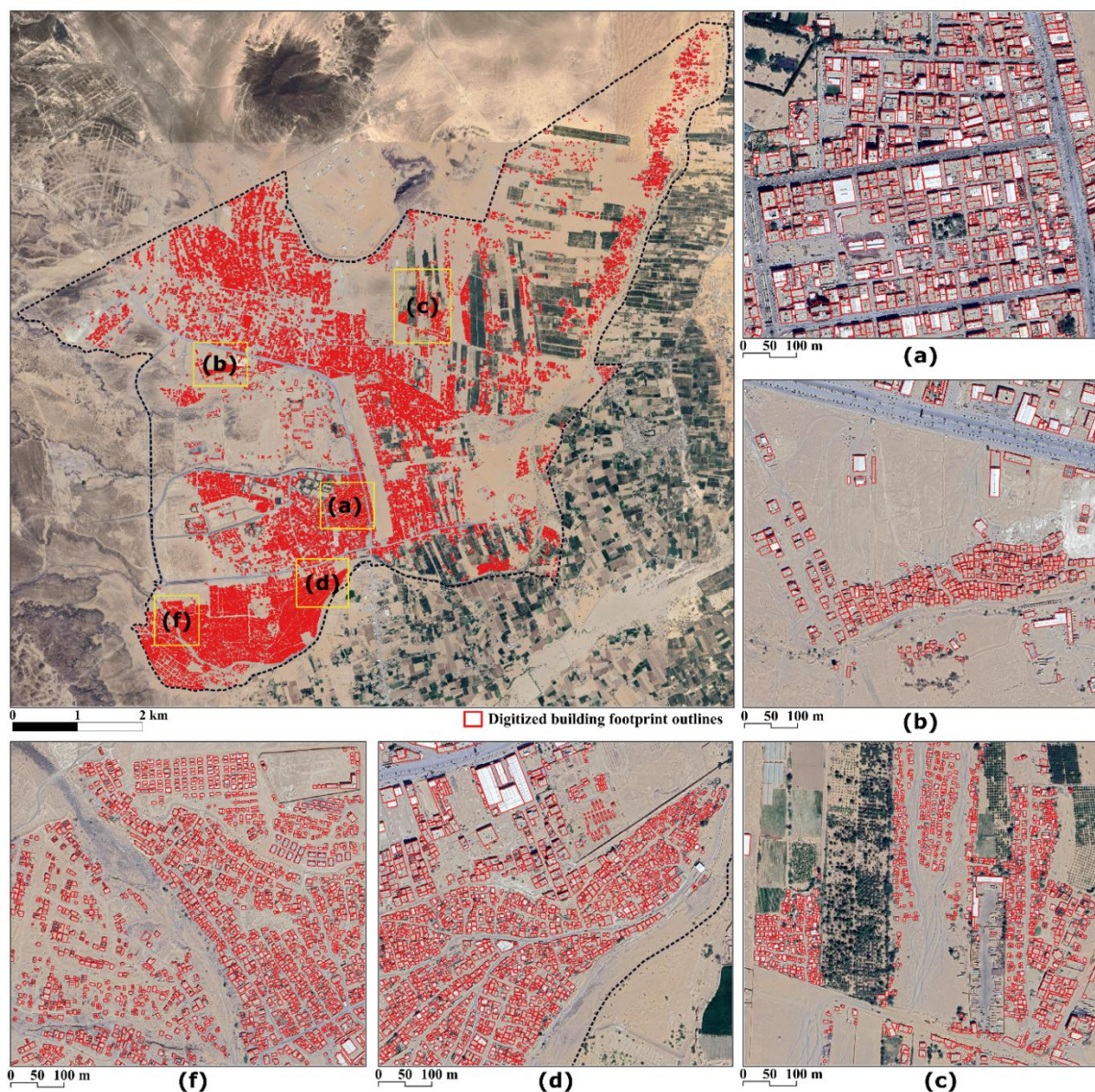


Figure 4 Manually digitised building footprints with zoomed-in areas (a–f).

4.1.3 Determining the Number of Clusters

The selection of 13 morphological clusters was guided by a convergent evaluation of internal clustering quality metrics and structural interpretability. *Table 2* presents the Davies–Bouldin (DB), Silhouette, and Calinski–Harabasz (CH) indices for $K = 2$ to 20.

Table 2. Clustering quality metrics for GAT-derived embeddings ($K = 2$ –20).

K	Davies–Bouldin	Silhouette	Calinski–Harabasz
2	2.571	0.156	5,622
3	2.181	0.115	5,770
4	2.056	0.130	5,435
5	1.983	0.128	5,091
6	1.876	0.131	4,654
7	1.981	0.120	4,357
8	1.918	0.111	4,112
9	1.945	0.103	3,887
10	1.918	0.099	3,710
11	1.897	0.097	3,522
12	1.887	0.096	3,360
13	1.781	0.095	3,221
14	1.892	0.093	3,098
15	1.861	0.093	2,998
16	1.854	0.094	2,908
17	1.841	0.092	2,819
18	1.823	0.092	2,750
19	1.807	0.089	2,665
20	1.817	0.088	2,596

The DB index reaches a clear local minimum at $K = 13$ (DB = 1.781), representing a 5.6% reduction relative to $K = 12$ (1.887) and followed by a sharp rebound at $K = 14$ (1.892, a 6.2% increase). Beyond $K = 15$, the index resumes a gradual decline, but per-step reductions are below 1.1% and accompanied by progressive loss of interpretive coherence (*Figure 6*).

The Silhouette and CH indices follow monotonic trajectories without a local optimum at $K = 13$, reflecting their sensitivity to geometric compactness, which favours coarse partitions. In the context of GAT embeddings, where morphologically similar buildings are differentiated by relational topology rather than feature distances, the DB index provides a more appropriate criterion (Liu & Song, 2025).

This quantitative case is reinforced by the clustergram (*Figure 5*). Between $K = 10$ and $K = 12$, branch instability signals sensitivity to fine-grained variation. At $K = 13$, the structure stabilises while isolating three outlier clusters (4, 9, 12) corresponding to undeveloped reserves (*Figure 8*). Further splitting erodes clarity without new process-level distinctions.

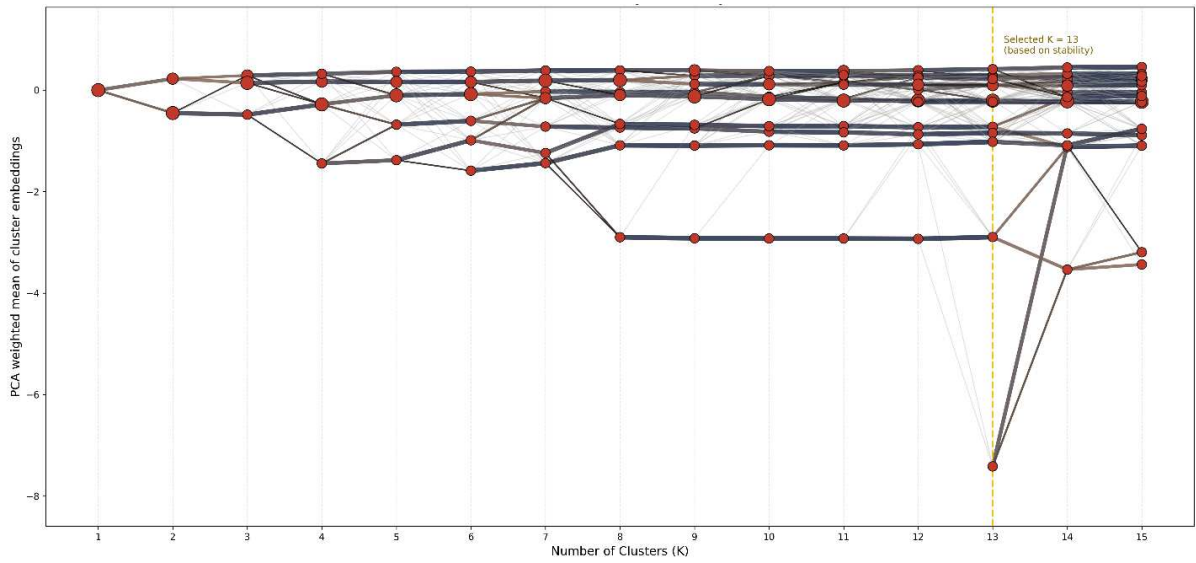


Figure 5. Clustergram showing cluster evolution across K .

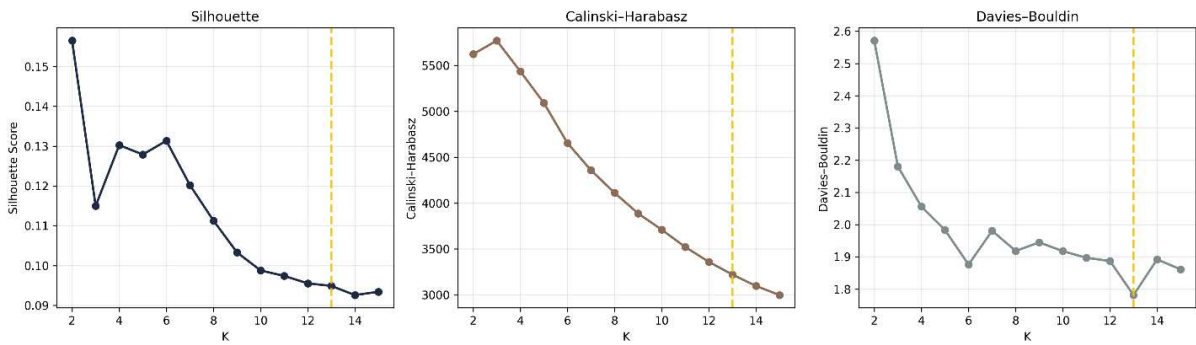


Figure 6. Goodness-of-fit metrics for $K \leq 15$.

4.1.4 Morphological Taxonomy

Ward's hierarchical clustering applied to the 13 centroids (**Figure 7**) reveals a stable taxonomy. Three outlier clusters merge only at large cophenetic distances. The remaining ten clusters coalesce into four process-driven super-types mapped in **Figure 8**.

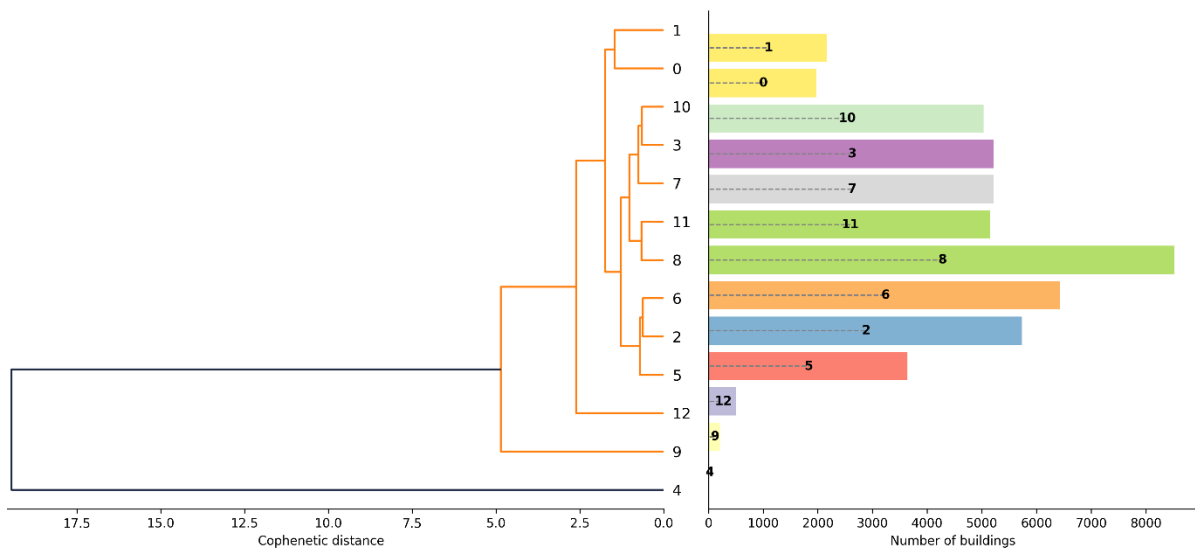


Figure 7. Ward's hierarchical taxonomy of 13 morphological types.

Displacement-driven densification (Clusters 2, 6): Concentrated in the southwestern IDP camps (**Figure 8**, zoom a), these clusters exhibit compact statistical distributions, small morphological cell areas (below 0.03), and elevated building coverage ratios (median approximately 0.16 to 0.18). This configuration reflects crisis densification: rapid shelter provision within constrained parcels where displacement pressure overrides spatial efficiency. The wide interquartile ranges in coverage ratios indicate incremental, self-organised construction under severe demographic stress. Within these areas, buildings are arranged in dense adjacency networks that the GAT embeddings capture as a distinctive topological signature, distinguishing them from other small-footprint clusters that share similar area statistics but exhibit different spatial organisation.

Tenure-enabled incremental expansion (Clusters 0, 7, 10): Located predominantly at peripheral desert margins near agricultural lands, these clusters display small footprints, low coverage ratios (median 0.02 to 0.06), and narrow statistical dispersion in cell area. This pattern reflects Yemen's flexible land tenure system, in which private ownership under tribal authority permits incremental subdivision without formal approval. The result is a low-intensity expansion front where land parcelling precedes full building occupation, a process visible in the imagery as temporary shelters (caravans, relief tents) that gradually densify over time. The narrow dispersion of morphometric values suggests a systematic, quasi-orderly subdivision logic rather than random peripheral sprawl.

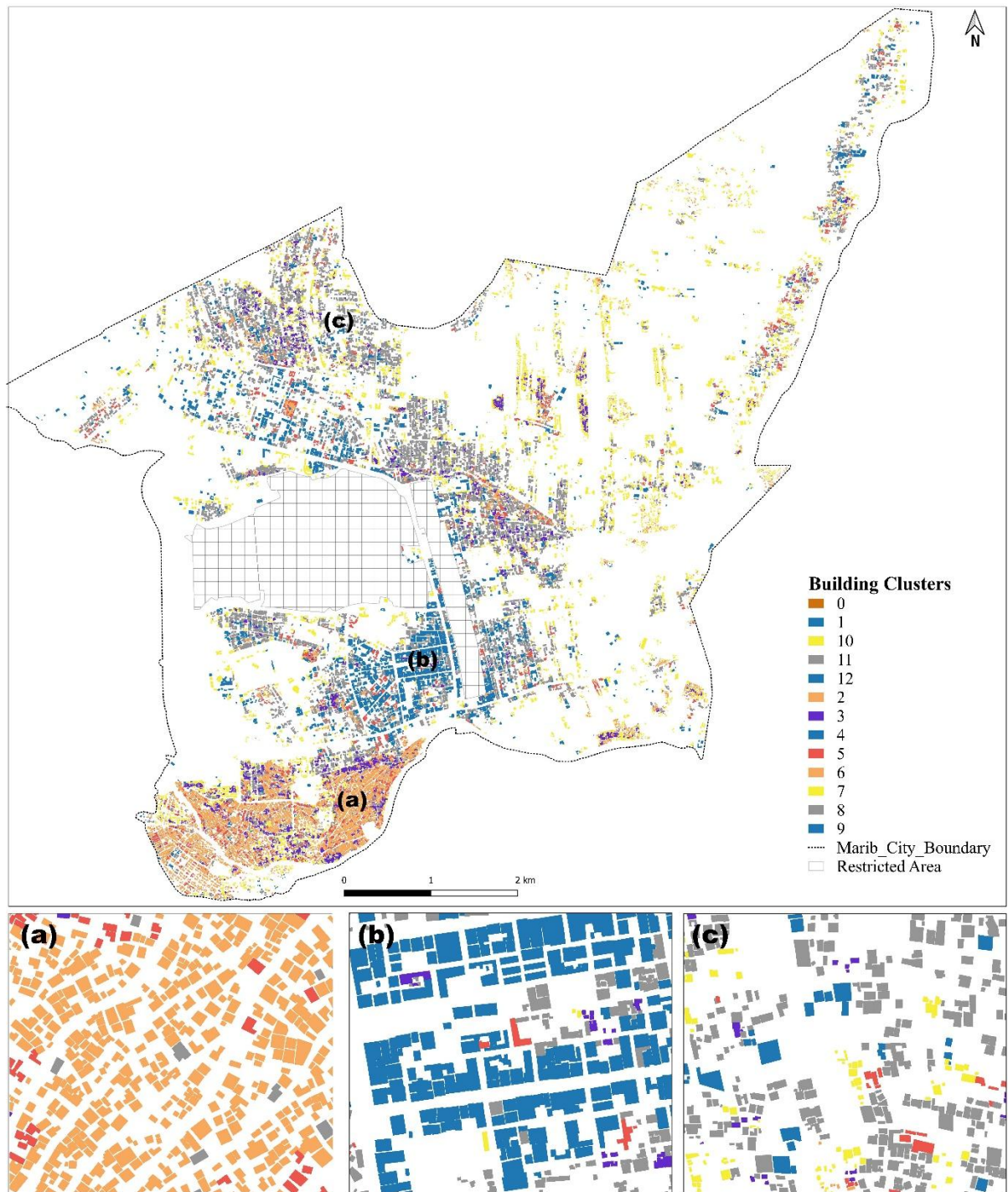


Figure 8. Spatial distribution of building clusters in Marib with zoomed-in views (a–c).

Semi-formal historic core (Cluster 1): Concentrated in the pre-conflict urban centre and along the N5 arterial corridor (**Figure 8**, zoom b), this cluster exhibits large plots (median area above 0.07), moderate building coverage (approximately 0.15), and high variance in area metrics alongside stable coverage values. This configuration reflects morphological continuity rather than adaptive response: a legacy fabric with planned street networks and regular plot layouts that persists amid crisis, absorbing limited infill without fundamental reconfiguration. Its theoretical value lies in providing a baseline against which adaptive morphologies can be

measured, revealing that Marib's expansion is not wholesale transformation but a differential process in which crisis dynamics overlay pre-existing urban structures.

Transitional hybridisation (Clusters 3, 5, 8, 11): These clusters occupy interstitial zones between formal and informal fabrics (**Figure 8**, zoom c), displaying medium morphological cell areas (0.02 to 0.03), variable coverage ratios (0.08 to 0.12), and elevated internal heterogeneity across all metrics. Cluster 11, though exhibiting higher coverage than Clusters 3, 5, and 8, is spatially embedded within mixed formal-informal matrices, reflecting bottom-up infill where displaced populations occupy residual spaces within planned areas. This super-type captures spatial negotiation: a process in which adaptive capacity emerges through the recombination of formal and informal building elements, challenging binary formal/informal frameworks by revealing informality as an active spatial strategy rather than a residual condition.

Figure 9 presents the distribution of four key morphological metrics across the 13 clusters: building area, morphological cell area, building coverage ratio, and mean inter-building distance. The first three indicators capture the intensity and extent of built occupation, while the fourth reflects the spatial configuration of open space. Most core morphological types (Clusters 0 to 3, 5 to 8, 10, and 11) exhibit uniformly low inter-building distances, confirming that spatial proximity aligns with the coverage-driven densification patterns already identified. In contrast, the outlier clusters (4, 9, 12) display markedly higher values and wider dispersions, reinforcing their classification as non-residential reserves or fragmented edge zones. Importantly, mean inter-building distance does not introduce new differentiation among the core clusters, confirming that morphological distinction in Marib's adaptive expansion is driven primarily by relational topology encoded in the GAT embeddings rather than by simple building spacing.

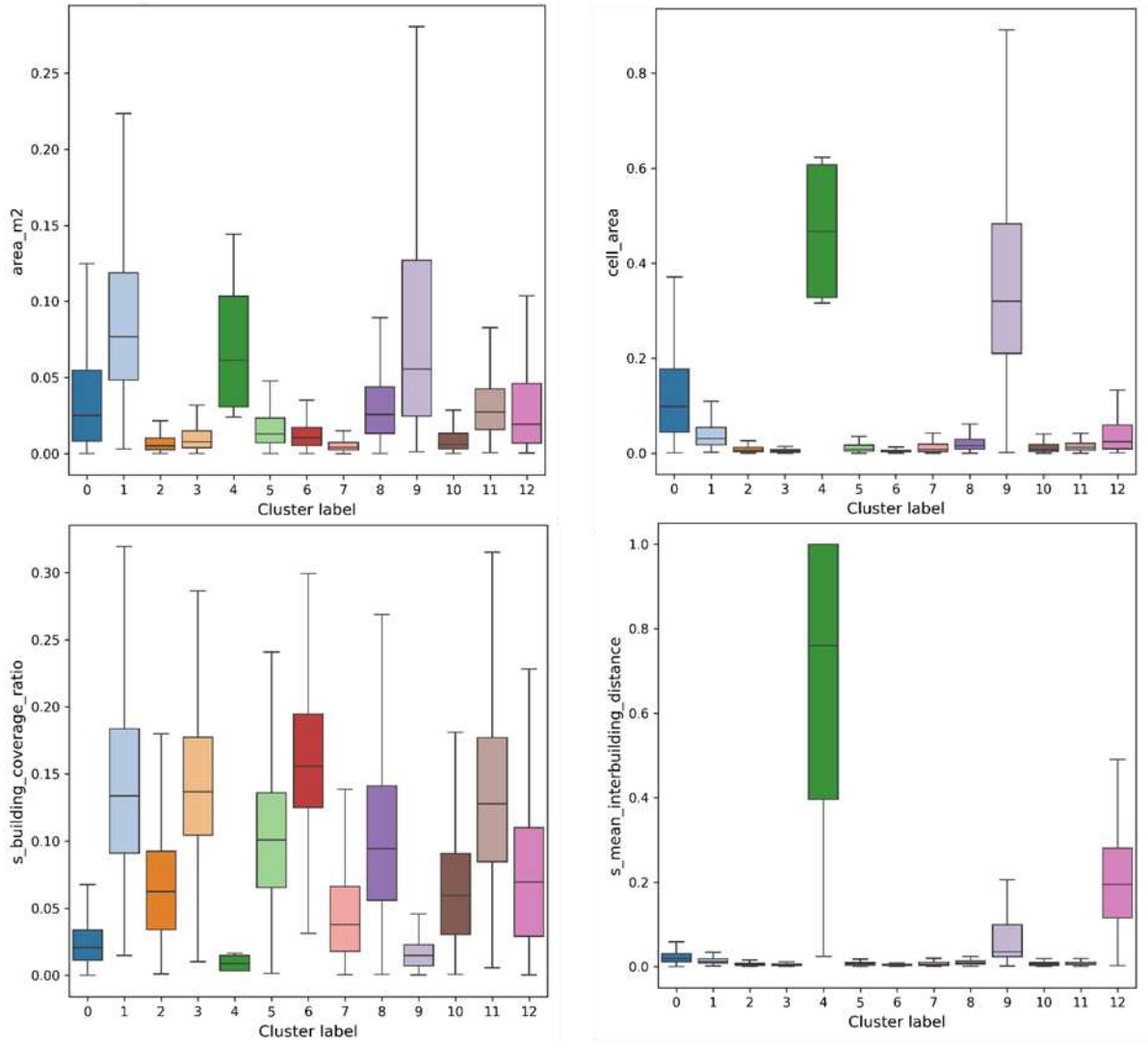


Figure 9. Distribution of morphological metrics across urban types.

4.1.5 Contextual Validation Through Ground Evidence

The attribution of morphological clusters to specific urban processes was validated through triangulation with three independent sources of contextual evidence. First, the spatial distribution of Clusters 2 and 6 was cross-referenced against the known locations of IDP camp sites documented by ACAPS (2020) and the Camp Coordination and Camp Management (CCCM) cluster records for Marib Governorate. The correspondence was consistent: these clusters concentrate within and immediately adjacent to designated camp perimeters in the southwestern sector of the city, confirming that the GAT embeddings capture displacement-related densification rather than merely identifying small buildings in general.

Second, ground-level photographs sourced locally (Figure 3, panels 1 and 2) were used to corroborate the material and spatial characteristics inferred from satellite imagery. The photographs confirm the presence of brick-only construction with minimal concrete in camp zones (consistent with the material restrictions described in ACAPS, 2020), the coexistence of temporary shelters (caravans, tents) alongside permanent structures in peripheral expansion fronts, and the mixed formal-informal fabric visible in transitional zones. Third, the location of

Cluster 1 along the N5 arterial corridor and the pre-conflict urban core was verified against the city's known settlement history, confirming that this cluster reflects legacy urban structure rather than displacement-driven adaptation.

These three lines of evidence, while not constituting formal ground-truth validation in the supervised learning sense, provide converging support for the process-to-pattern attributions presented in Section 4.1.4. The interpretive framework is strengthened by the consistency between morphological signatures detected by the model and independently documented socio-spatial conditions. Where such convergence is absent or ambiguous, the interpretations are presented as provisional hypotheses rather than established findings.

5. Findings and Discussion

5.1 Model Validation

To assess the contribution of relational learning, the proposed GAT was evaluated against two reference models under identical clustering conditions ($K = 13$, MiniBatch K-Means). This controlled design ensures that differences in clustering structure are attributable to the embedding method rather than to partition granularity. Three strategies were employed: internal quality indices, ARI measuring pairwise agreement, and spatial distribution analysis.

5.1.1 Comparison with Baseline 0 (Morphology-Only)

Baseline 0 clusters buildings solely from intrinsic morphometric attributes (**Table 1**), without graph-based information. When optimised independently, it converges to two clusters ($K = 2$), yielding a coarse binary partition driven by building size (**Figure 10**, zooms a–c). At $K = 13$, it achieves Silhouette = 0.145 and CH = 6,552, both higher than the GAT (0.095 and 3,221), with a lower DB (1.418 vs. 1.781). These tighter geometric clusters reflect the expected behaviour of morphology-only features in Euclidean space.



Figure 10. Baseline 0 at $K = 2$, zooms a–c.

The ARI between Baseline 0 and the full GAT at $K = 13$ is 0.067, indicating near-complete disagreement. The GAT produces a qualitatively different classification. Baseline 0 at $K = 13$ (**Figure 11**) exhibits a salt-and-pepper pattern: in the IDP camp zone (**Figure 11**, zoom a), buildings are scattered across all cluster types with no concentration; along the historic core (**Figure 11**, zoom b), a fragmented mosaic obscures the coherent fabric the GAT identifies as Cluster 1 (**Figure 8**, zoom b); in peripheral zones (**Figure 11**, zoom c), buildings of similar area are grouped regardless of expansion trajectory, whereas the GAT differentiates tenure-enabled growth from transitional hybridisation (**Figure 8**, zoom c).

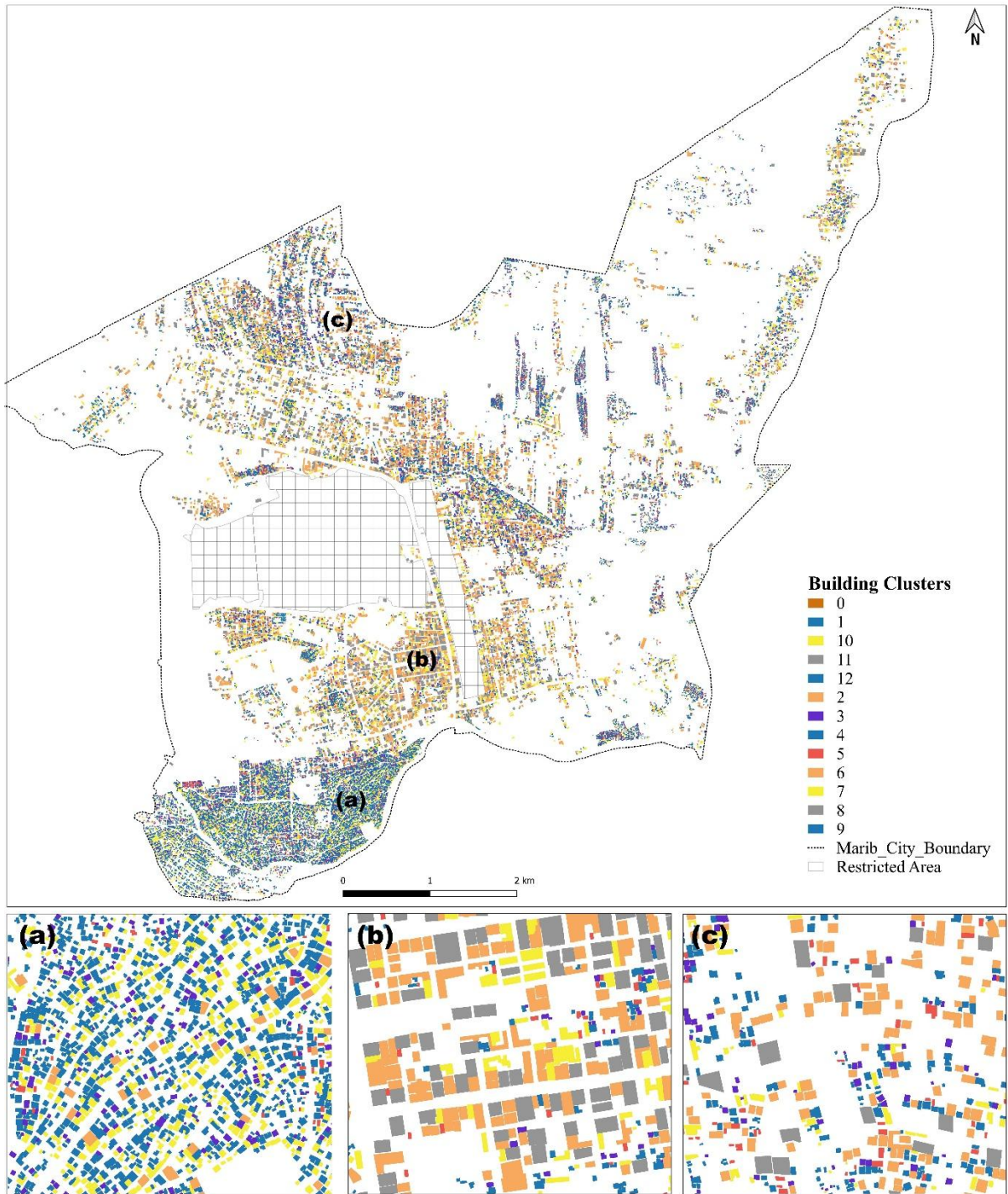


Figure 11. Spatial distribution of building clusters in Marib under Baseline 0 ($K = 13$) with zoomed-in views (a–c).

Visualising the results in the Area-Perimeter space matrix (Figure 10) further clarifies the distinction. In Baseline 0, data points collapse into a few wedge-shaped regions where cluster separation is driven almost entirely by the geometric relationship between compactness and normalised area. This produces visually compact but morphologically coarse groupings that mask the internal diversity of building forms. In the GAT-based classification, multiple clusters coexist within identical or overlapping area-perimeter ranges, demonstrating that buildings with similar geometric compactness can still be distinguished by deeper relational

characteristics. Rather than forming isolated wedges, clusters interpenetrate across the space matrix, confirming that geometric similarity alone cannot capture building form diversity. This overlap reflects a strength of the model: the GAT identifies buildings based on latent relational features, including adjacency patterns and local connectivity, that are not visible in two-dimensional metric projections.

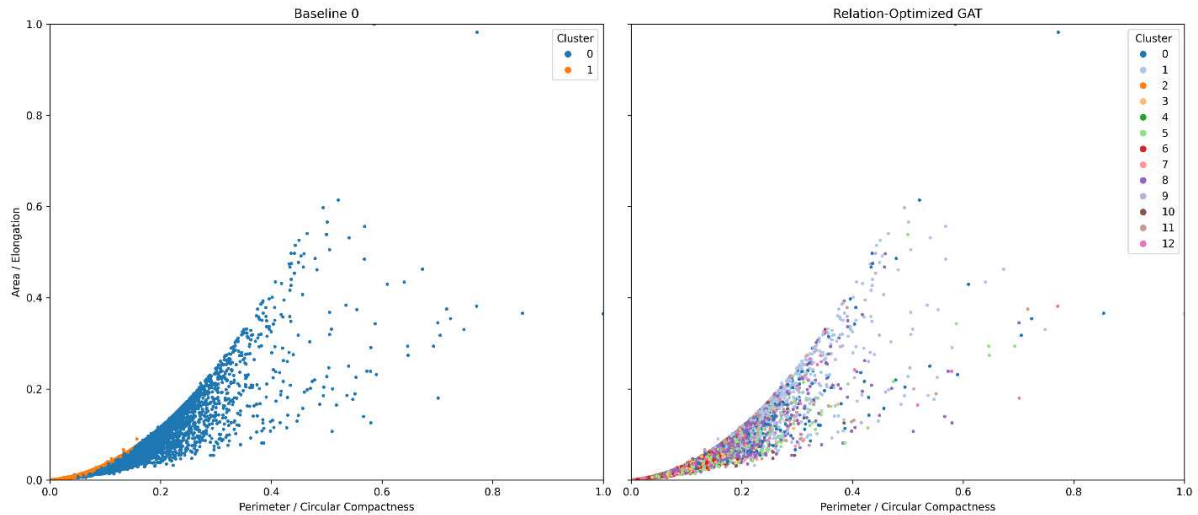


Figure 12. Space Matrix comparison: Baseline 0 (left) vs. GAT (right).

5.1.2 Ablation: Effect of Link Prediction Loss (Baseline 1)

Baseline 1 retains the GAT graph but removes the link prediction loss. When optimised independently, it converges to three clusters ($K = 3$; **Figure 13**, zooms a–c). At $K = 13$, it yields Silhouette = 0.139, CH = 6,849, DB = 1.467, and ARI = 0.208 relative to the full GAT. The higher ARI compared to Baseline 0 confirms that message passing encodes some structural information, but approximately 80% of assignments still change when the relational loss is disabled.



Figure 13. Baseline 0 at $K = 13$, zooms a–c.

Baseline 1 at $K = 13$ (Figure 14) offers a more structured spatial distribution than Baseline 0 but falls short of the full model’s coherence. In the IDP camp zone (**Figure 14**, zoom a), partial grouping appears but the concentrated densification pattern of Clusters 2 and 6 remains fragmented. Along the historic core (**Figure 14**, zoom b), building-size clusters partially recover the large-plot character without isolating Cluster 1. In peripheral zones (**Figure 14**, zoom c), Baseline 1 shows greater consistency than Baseline 0 but does not resolve tenure-

enabled from transitional patterns. Explicit optimisation of link structure is essential for resolving process-driven adaptive patterns.

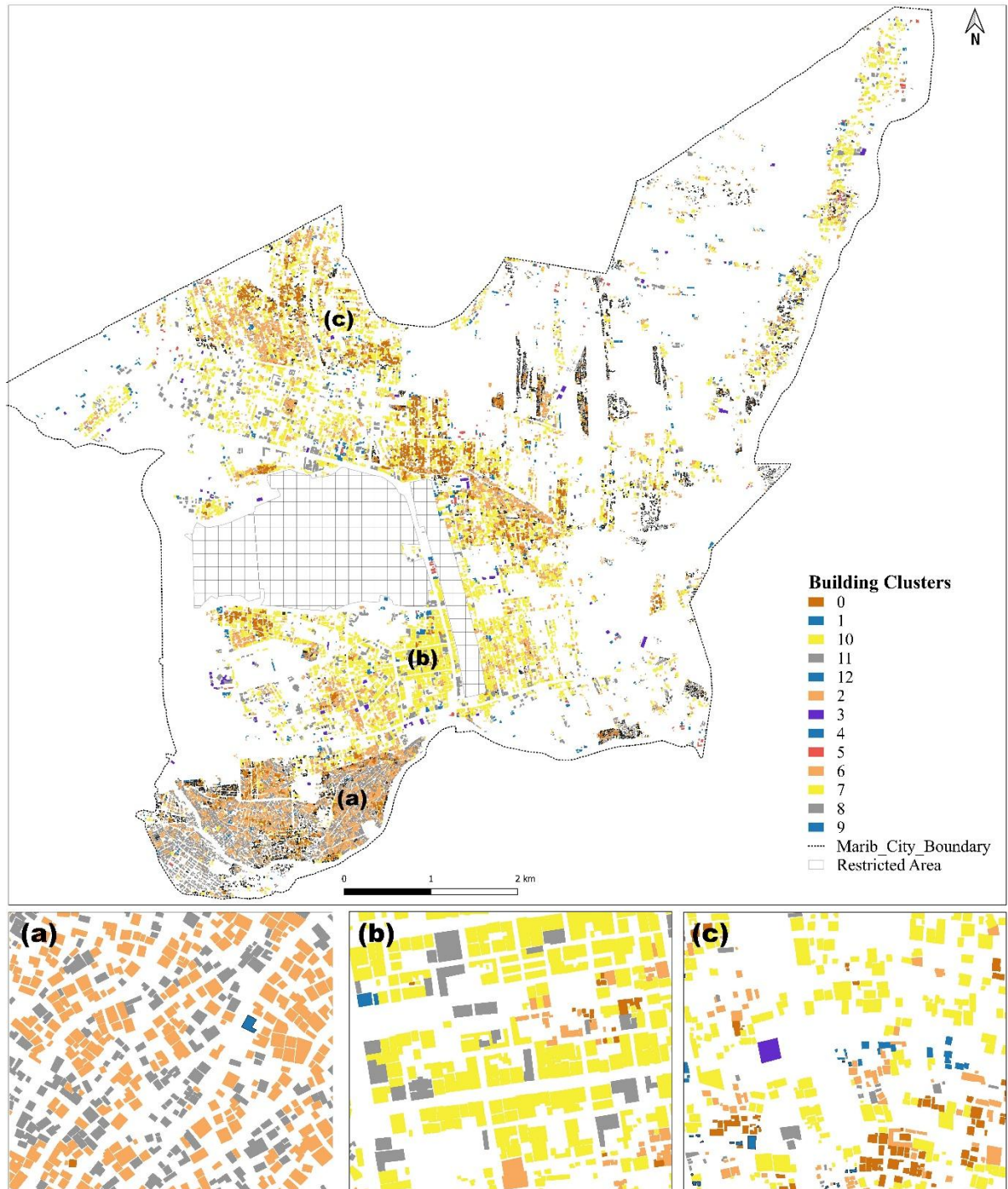


Figure 14. Spatial distribution of building clusters in Marib under Baseline 1 ($K = 13$) with zoomed-in views (a–c).

Both baselines achieve higher Silhouette and CH scores because they produce geometrically tighter clusters, yet those clusters lack the relational differentiation needed to distinguish buildings that share morphometric properties but occupy different roles (*Table 3*). The lower Silhouette and CH of the full model reflect the cost of embedding relational topology; this cost is justified by its greater capacity to resolve process-driven patterns aligned with documented displacement dynamics (ACAPS, 2020).

Table 3. Clustering quality metrics at K = 13 across models.

Model	DB	Silhouette	CH	ARI vs. GAT
Full GAT (proposed)	1.781	0.095	3,221	n/a
Baseline 0 (morphology-only)	1.418	0.145	6,552	0.067
Baseline 1 (GAT w/o link loss)	1.467	0.139	6,849	0.208

5.1.3 Cluster Stability

The full GAT was trained ten times with different random seeds at K = 13. **Table 4** summarises the results. Quality metrics show moderate variability (DB: 1.962 ± 0.138 ; Silhouette: 0.082 ± 0.008), consistent with unsupervised graph representation learning (Fan et al., 2024; Liu & Song, 2025). The mean pairwise ARI of 0.240 confirms that building-level assignments differ across runs.

Table 4. Cluster stability across 10 independent runs (K = 13).

Metric	Mean	Std. dev.
Silhouette	0.082	0.008
Calinski–Harabasz	2,743	314
Davies–Bouldin	1.962	0.138
Mean pairwise ARI	0.240	n/a

Quality metrics show moderate variability (DB: 1.962 ± 0.138 ; Silhouette: 0.082 ± 0.008), consistent with unsupervised graph representation learning (Fan et al., 2024; Liu & Song, 2025). The mean pairwise ARI of 0.240 confirms that building-level assignments differ across runs.

This variability requires careful interpretation. Buildings near morphological boundaries may be classified differently across initialisations. However, the low coefficients of variation (DB: 7.0%; Silhouette: 9.8%) suggest that the *structural properties* of the partitions are preserved: each run produces comparable clusters with similar composition. The macro-level taxonomy of four super-types remains recoverable, anchored to robust features of the urban fabric (cell area, coverage ratio, adjacency density) rather than artifacts of a single training run. Future work could mitigate initialisation sensitivity through ensemble strategies or spectral seeding (see Section 5.3).

5.2 Conceptual and Planning Implications

Before discussing the conceptual significance of the four super-types, it is important to clarify the relationship between what the model detects and what we interpret. The GAT framework operates on morphometric and topological features alone; it has no access to socio-economic data, tenure records, or household surveys. The model identifies spatial patterns. The attribution of these patterns to specific urban processes (displacement pressure, tribal tenure, caste-based exclusion) rests on contextual knowledge derived from field observations, ground-level photography, and the ACAPS (2020) district profile. This interpretive step is characteristic of unsupervised urban morphology analysis, where the analyst bridges

quantitative clusters and socio-spatial meaning through triangulation. The strength of this approach is that it reveals spatial signatures beyond the reach of conventional data collection; its limitation is that the process-to-pattern mapping is informed rather than deterministic. We present the following interpretations as well-grounded hypotheses anchored in converging evidence, not as causal claims.

5.2.1 Theoretical Contributions

The findings advance three conceptual shifts in understanding urbanisation under institutional fragmentation.

From chaotic sprawl to structured intensification: Clusters 2 and 6, concentrated in IDP camps with small cells (below 0.03) yet elevated coverage ratios (0.16 to 0.18), reveal that informal densification follows spatially coherent logics even under severe constraints. Local authorities prohibit permanent structures for IDPs, permitting only brick with narrowly defined concrete use (ACAPS, 2020). Within these restrictions, the GAT embeddings detect dense adjacency networks reflecting collective shelter strategies where displaced households self-organise to maximise limited resources. This challenges Turner's (1968) incremental urbanism by showing that urgency does not erase spatial order; it produces compressed morphologies where social coordination substitutes for formal planning, extending assemblage urbanism into crisis contexts where morphology encodes collective adaptation rather than disorder.

From land scarcity to tenure-enabled fragmentation: Clusters 0, 7, and 10, characterised by low coverage (below 0.06) yet small cells, embody Yemen's land governance in which private ownership under tribal authority permits incremental subdivision without state oversight (ACAPS, 2020). This produces expansion fronts where land is parcelled before occupation, a process invisible to area-based metrics but captured by the GAT's relational topology. Such patterns reframe informality not as regulatory absence but as layered governance where state decentralisation coexists with tribal control, extending Roy's insight that informality constitutes a mode of governing into contexts of contested sovereignty.

From binary formal/informal to spatial bricolage: Transitional zones (Clusters 3, 5, 8, 11) occupy interstitial spaces where planned structures embed within informal matrices. Cluster 11's elevated coverage (0.12) within mixed fabrics (Figure 8, zoom c) exemplifies how displaced populations, particularly vulnerable groups such as female-headed households and the Al Muhamasheen minority, recombine formal and informal elements through bottom-up infill to access protection denied through formal channels (ACAPS, 2020). Morphology becomes a proxy for protection-seeking behaviour, reframing spatial justice as materially inscribed negotiation rather than abstract entitlement.

A cross-cutting observation unites these contributions. Density metrics capture spatial intensity but remain blind to how buildings relate under constraint. In Marib, settlements with near-identical coverage ratios encode divergent adaptive logics: dense adjacency networks reflect collective shelter coordination, whereas fragmented topologies signal externally imposed layouts with weaker cohesion. Only relational embeddings detect this distinction. Density describes pressure; topology reveals response. This aligns with space syntax critiques

of density-only analysis (Hillier & Hanson, 1984; Salvadori et al., 2021): spatial configuration determines accessibility, service delivery, and social resilience in rapidly expanding settlements.

5.2.2 Governance Implications

The super-types reveal transferable signatures of adaptive urbanism under constraint, recurring across displacement contexts from Lebanon (Sanyal, 2021) to Cox’s Bazar (IOM, 2018) and Mogadishu (Bryld et al., 2020). Three governance principles emerge.

Principle 1: Sequence infrastructure after tenure mapping in low-coverage expansion fronts. Low-coverage peripheral clusters (Clusters 0, 7, 10) signal anticipatory subdivision under customary tenure (Fawaz, 2017). Two areas with identical coverage may encode divergent processes: consolidated occupation versus fragmentation in progress. Without mapping subdivision patterns first, infrastructure risks severance through future fragmentation (Bryld et al., 2020). Corridors must be pre-positioned alongside community-based mapping, leveraging tribal sheikhs and community elders as co-governors.

Principle 2: Prioritise WASH before tenure regularisation in camp morphologies. Dense clusters (2, 6) encode collective shelter strategies under humanitarian restrictions (Sanyal, 2014). High coverage combined with fragmented topology signals sanitation collapse risk. In Marib, over 180,000 camp residents lack waste management. WASH retrofitting must precede tenure formalisation; without concurrent sanitation, land rights alone cannot prevent disease outbreaks.

Principle 3: Deploy participatory upgrading in hybrid morphologies. Transitional zones (Clusters 3, 5, 8, 11) exhibit morphological signatures of negotiated coexistence under exclusion. Relational topology reveals protection-seeking bricolage invisible to density metrics. In-situ upgrading with community mediation preserves adaptive social networks; top-down relocation severs the survival strategies that morphology encodes.

Table 5 operationalises these principles within Marib’s institutional ecology. The framework shifts humanitarian response from one-size-fits-all toward adaptive governance calibrated to layered sovereignty, where morphology serves as a diagnostic tool for reading socio-spatial processes invisible to conventional metrics. Stability in displacement cities emerges from hybrid configurations of tribal authority, municipal actors, and humanitarian agencies (Agier, 2011), a reality that intervention design must engage rather than abstract away.

Table 5. Morphological super-types and governance-calibrated intervention strategies for adaptive urban expansion.

Super-type	Morphological signature (Fig. 9)	Generalizable risk	Principle-based intervention	Contextual actor (Marib)
- Displacement-driven densification (Clusters 2, 6)	- Small cells (<0.03) - high coverage (0.16–0.18) - Dense adjacency	- Sanitation collapse under material restrictions	- BWASH retrofitting before tenure regularization - Incremental service upgrading	- Local authorities - Tribal councils

			preserving social networks	- International humanitarian organizations
- Tenure-enabled incremental expansion (Clusters 0, 7, 10)	- Small cells (<0.02)	- Irreversible fragmentation pre-occupation	- Anticipatory land-use guidance via community mapping	- Tribal sheikhs
- Transitional hybridization (Clusters 3, 5, 8, 11)	- Low coverage (<0.06)		- Pre-positioned infrastructure corridors	- Estajabah Foundation
	- Narrow dispersion	- Protection gaps for excluded groups	- Participatory upgrading co-designed with residents	- Community organizations
	- Medium cells (0.02–0.03)		- Negotiated land sharing via localized mediators	- Tribal mediators
	- Variable coverage (0.08–0.12)	- Disconnection from adaptive zones	- Strategic connectivity respecting tenure boundaries	- Municipal planning
- Semi-formal historic core (Cluster 1)	- Large plots (>0.07)		- Edge-sensitive infill regulation	- Governor's office
	- Moderate coverage (0.15)			
	- High area variance			

5.3 Research Limitations

Several limitations suggest directions for future research. First, the model relies on two-dimensional footprints, limiting its capacity to account for height or volumetric density. Three-dimensional data from UAVs could enhance the embeddings (Colomina & Molina, 2014; Nex & Remondino, 2014). Second, loss component weights were fixed; dynamic weighting could improve sensitivity to subtle spatial configurations. Third, the analysis captures a single temporal snapshot; a temporal GAT could distinguish transient from permanent patterns. Fourth, as shown in Section 5.1.3, moderate initialisation sensitivity (mean pairwise ARI = 0.240) means individual boundary assignments vary across runs, though the macro-level taxonomy remains recoverable. Ensemble strategies or spectral seeding could mitigate this. Finally, choices regarding cluster count, graph construction method, and neighbourhood radius influence the results; systematic parameter evaluation could enhance generalisability.

6. Conclusion

This study proposed a relation-aware graph learning framework integrating Morphological Cells with an unsupervised GAT to characterise adaptive patterns of informal expansion under displacement. Applied to nearly 50,000 buildings in Marib, Yemen, the framework identified 13 clusters consolidating into four super-types: displacement-driven densification, tenure-enabled incremental expansion, semi-formal historic continuity, and transitional hybridisation. Controlled comparisons at $K = 13$ confirmed that relational modelling produces a fundamentally different and more spatially coherent classification than attribute-only approaches (ARI = 0.067 vs. Baseline 0).

The findings challenge the characterisation of informal expansion as chaotic sprawl, demonstrating that building arrangements under displacement encode structured logics shaped

by tribal land tenure, humanitarian restrictions, and caste-based exclusion. Where density metrics capture only intensity, relational topology reveals who neighbours whom: dense adjacency networks signalling collective coordination, fragmented cells indicating anticipatory subdivision, and hybrid topologies exposing protection-seeking by marginalised groups. The framework transforms building footprints into a cadastral-free diagnostic tool for evidence-based intervention sequencing. At the same time, the moderate sensitivity to random initialisation observed in stability testing (mean pairwise ARI = 0.240) indicates that while the macro-level taxonomy is structurally robust, individual boundary assignments should be interpreted as probabilistic rather than deterministic, and ensemble strategies may be needed for operational deployment.

Three directions merit pursuit. First, longitudinal tracking would distinguish transient configurations from permanent consolidation. Second, integrating morphological signatures with spatially explicit protection risks (fire hazard, flood exposure) could strengthen humanitarian targeting. Third, testing transferability across diverse displacement contexts, from Lebanon to Bangladesh, would assess whether relational topology consistently decodes adaptive logics beyond Marib's ecology. Together, these advances would position urban morphology as active evidence for adaptive governance in crisis urbanism.

References

- ACAPS. (2020). Marib Governorate—Marib city and Marib Al Wadi District profile. <https://reliefweb.int/report/yemen/marib-governorate-marib-city-and-marib-al-wadi-district-profile-19-november-2020>
- Agier, M. (2011). Managing the undesirables: Refugee camps and humanitarian government. *Polity*.
- Arribas-Bel, D., & Fleischmann, M. (2022). Spatial Signatures—Understanding (urban) spaces through form and function. *Habitat International*, 128, 102641. <https://doi.org/10.1016/j.habitatint.2022.102641>
- Bartlett, A., Alix-Garcia, J., & Saah, D. S. (2012). City Growth under Conflict Conditions: The View from Nyala, Darfur. *City and Community*, 11(2), 151–170.
- Batty, M. (2009). Cities as Complex Systems. In *Encyclopedia of Complexity and Systems Science* (pp. 1041–1071). Springer.
- Batty, M. (2013). *The New Science of Cities*. MIT Press.
- Bei, W., Guo, M., & Huang, Y. (2019). A Spatial Adaptive Algorithm Framework for Building Pattern Recognition Using Graph Convolutional Networks. *Sensors*, 19(24), 5518.
- Biljecki, F., & Chow, Y. S. (2022). Global Building Morphology Indicators. *Computers, Environment and Urban Systems*, 95, 101809.
- Boeing, G. (2017). OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. *Computers, Environment and Urban Systems*, 65, 126–139.
- Branch, A. (2008). Gulu Town in War... and Peace? Displacement, Humanitarianism and Post-War Crisis.
- Bryld, E., Kamau, C., & Mohamoud, M. A. (2020). Using an adaptive approach to making gatekeepers accountable to IDPs in Mogadishu. *Development in Practice*, 30(8), 982–993.
- Camacho, R., Aryal, J., & Rajabifard, A. (2025). How do disasters disrupt the spatial growth of informal settlements? *Habitat International*, 156, 103272.
- Camila, T., Pereira, R. S. D., Bonnin, C., Duarte, D., Mills, G., Eniolu Morakinyo, T., & Holloway, P. (2024). A global (South) collective burden: A systematic review of the current state of climate-related hazards in informal settlements. *International Journal of Disaster Risk Reduction*, 114, 104940.
- Caruso, G., Hilal, M., & Thomas, I. (2017). Measuring urban forms from inter-building distances. *Landscape and Urban Planning*, 163, 80–89.
- Chaturvedi, V., Kuffer, M., & Kohli, D. (2020). Analysing Urban Development Patterns in a Conflict Zone: A Case Study of Kabul. *Remote Sensing*, 12(21), 3662.
- Chen, D., Feng, Y., Li, X., Qu, M., Luo, P., & Meng, L. (2025). Interpreting core forms of urban morphology linked to urban functions with explainable graph neural network. *Computers, Environment and Urban Systems*, 118, 102267.
- Cheng, Q., Zaber, M., Rahman, A. M., Zhang, H., Guo, Z., Okabe, A., & Shibasaki, R. (2022). Understanding the Urban Environment from Satellite Images with New Classification Method. *Sustainability*, 14(7), 4336.
- Colomina, I., & Molina, P. (2014). Unmanned aerial systems for photogrammetry and remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, 92, 79–97.
- Davis, M. (2006). *Planet of Slums*. Verso.
- Dovey, K., & Kamalipour, H. (2017). Informal/Formal Morphologies. In *Mapping Urbanities*. Routledge.

- Dovey, K., & King, R. (2011). Forms of Informality: Morphology and Visibility of Informal Settlements. *Built Environment*, 37(1), 11–29.
- Fan, C., Yang, Y., & Mostafavi, A. (2024). Neural embeddings of urban big data reveal spatial structures in cities. *Humanities and Social Sciences Communications*, 11(1), 409.
- Fan, Y., Zou, H., Zhao, T., Fan, B., & Cheng, Y. (2025). Typological Mapping of Urban Landscape Spatial Characteristics from the Perspective of Morphometrics. *Land*, 14(9), 1854.
- Fawaz, M. (2017). Planning and the refugee crisis: Informality as a framework of analysis. *Planning Theory*, 16(1), 99–115.
- Fleischmann, M., Feliciotti, A., Romice, O., & Porta, S. (2020). Morphological tessellation as a way of partitioning space. *Computers, Environment and Urban Systems*, 80, 101441.
- Fleischmann, M., Feliciotti, A., Romice, O., & Porta, S. (2022). Methodological foundation of a numerical taxonomy of urban form. *Environment and Planning B*, 49(4), 1283–1299.
- Gao, Y., Liu, D., Zheng, X., Wang, X., & Ai, G. (2025). Urban Expansion Scenario Prediction Model: Combining Multi-Source Big Data, a Graph Attention Network, a Vector Cellular Automata, and an Agent-Based Model. *Remote Sensing*, 17(13), 2272.
- Gerrits, L. (2012). City futures: Confronting the crisis of urban development. *Planning Theory*, 11(2), 215–218.
- Gunter, A. W. (2009). Getting it for free: Using Google Earth and ILWIS to map squatter settlements. *IEEE IGARSS*, 3, III-388–III-391.
- Hamaina, R., Leduc, T., & Moreau, G. (2012). Towards Urban Fabrics Characterization Based on Buildings Footprints. In *Bridging the Geographic Information Sciences* (pp. 327–346). Springer.
- Hasan, A. (2006). Orangi Pilot Project. *Environment & Urbanization*, 18(2), 451–480.
- Hillier, B. (2007). *Space Is the Machine*. Cambridge University Press.
- Hillier, B., & Hanson, J. (1984). *The Social Logic of Space*. Cambridge University Press.
- IOM. (2018). *Saving Lives Protecting Migrants: Annual Report 2018*. IOM Bangladesh.
- James, P., Berrigan, D., Hart, J. E., Hipp, J. A., Hoehner, C. M., Kerr, J., Major, J. M., Oka, M., & Laden, F. (2014). Effects of buffer size and shape on associations between the built environment and energy balance. *Health & Place*, 27, 162–170.
- Jochem, W. C., Leasure, D. R., Pannell, O., Chamberlain, H. R., Jones, P., & Tatem, A. J. (2021). Classifying settlement types from multi-scale spatial patterns of building footprints. *Environment and Planning B*, 48(5), 1161–1179.
- Joshi, P., Sen, S., & Hobson, J. (2002). Experiences with surveying and mapping Pune and Sangli slums on a GIS. *Environment & Urbanization*, 14(2), 225–240.
- Jun, M.-J. (2021). A comparison of a gradient boosting decision tree, random forests, and ANNs to model urban land use changes. *International Journal of Geographical Information Science*, 35(11), 2282–2304.
- Kamalipour, H. (2016). Forms of informality and adaptations in informal settlements. *ArchNet-IJAR*, 10(3), 60–75.
- Karimi, F., Sultana, S., Shirzadi Babakan, A., & Suthaharan, S. (2019). An enhanced SVM model for urban expansion prediction. *Computers, Environment and Urban Systems*, 75, 61–75.
- Kohli, D., Sliuzas, R., Kerle, N., & Stein, A. (2012). An ontology of slums for image-based classification. *Computers, Environment and Urban Systems*, 36(2), 154–163.

- Kuffer, M., Pfeffer, K., & Sliuzas, R. (2016). Slums from Space—15 Years of Slum Mapping Using Remote Sensing. *Remote Sensing*, 8(6), 455.
- Li, C., & Liu, X. (2025). Optimising Urban Morphological Tessellation. In *Advances in the Integration of Technology and the Built Environment* (pp. 38–46). Springer.
- Li, C., Yu, L., Oloo, F., Chimimba, E. G., Kambombe, O., Asamoah, M., Opoku, P. D., Ogwen, V. W., Fawcett, D., Hong, J., Deng, X., Gong, P., & Wright, J. (2023). Slum and urban deprivation in sub-Saharan Africa. *Sustainable Cities and Society*, 99, 104863.
- Liu, S., Liu, R., & Tan, N. (2021). A Spatial Improved-kNN-Based Flood Inundation Risk Framework. *Sustainability*, 13(5), 2859.
- Liu, Z., & Song, Y. (2025). Unsupervised Plot Morphology Classification via Graph Attention Networks. *Land*, 14(7), 1469.
- Ma, J., Huang, H., Peng, M., & Zhou, Y. (2024). Investigating the Heterogeneity Effects of Urban Morphology on Building Energy Consumption. *Land*, 13(10), 1683.
- McCartney, S., & Krishnamurthy, S. (2018). Neglected? Strengthening the Morphological Study of Informal Settlements. *Sage Open*, 8(1), 2158244018760375.
- Myers, G. (2011). *African Cities: Alternative Visions of Urban Theory and Practice*. Zed Books.
- Nex, F., & Remondino, F. (2014). UAV for 3D mapping applications: A review. *Applied Geomatics*, 6(1), 1–15.
- Purwanto, E., Sugiri, A., & Novian, R. (2017). Determined Slum Upgrading: A Challenge to Participatory Planning. *Sustainability*, 9(7), 1261.
- Rhee, J. (2019). *Context-rich Urban Analysis Using Machine Learning: A Case Study in Pittsburgh*. Carnegie Mellon University.
- Roy, A. (2005). Urban informality: Toward an epistemology of planning. *Journal of the American Planning Association*, 71(2), 147–158.
- Ruiz, I., & Shi, W. (2018). A Random Forests classification method for urban land-use mapping. *International Journal of Remote Sensing*, 39, 1175–1198.
- Salvadori, L., Badas, M. G., Di Bernardino, A., Querzoli, G., & Ferrari, S. (2021). A Street Graph-Based Morphometric Characterization of Two Large Urban Areas. *Sustainability*, 13(3), 1025.
- Samper, J., Shelby, J. A., & Behary, D. (2020). The Paradox of Informal Settlements Revealed in an ATLAS of Informality. *Sustainability*, 12(22), 9510.
- Sanyal, R. (2014). Urbanizing Refuge: Interrogating Spaces of Displacement. *International Journal of Urban and Regional Research*, 38(2), 558–572.
- Sanyal, R. (2021). Making urban humanitarian policy: The ‘neighbourhood approach’ in Lebanon. *Urban Geography*, 42(7), 937–957.
- Taubenböck, H., & Kraff, N. J. (2014). The physical face of slums. *Journal of Housing and the Built Environment*, 29(1), 15–38.
- Taubenböck, H., Kraff, N. J., & Wurm, M. (2018). The morphology of the Arrival City. *Applied Geography*, 92, 150–167.
- Turner, J. C. (1968). Housing Priorities, Settlement Patterns, and Urban Development. *Journal of the American Institute of Planners*, 34(6), 354–363.
- United Nations. (2017). *Progress towards the Sustainable Development Goals*. United Nations.
- Usui, H., & Asami, Y. (2013). Estimation of Mean Lot Depth and Its Accuracy. *Journal of the City Planning Institute of Japan*, 48, 357–362.

- Usui, H., & Asami, Y. (2018). Size distribution of urban blocks in the Tokyo Metropolitan Region. *International Journal of Geographical Information Science*, 32(1), 120–139.
- Vlassenroot, K., & Büscher, K. (2013). Borderlands, Identity and Urban Development: The Case of Goma. *Urban Studies*, 50(15), 3168–3184.
- Wang, H., Xu, Y., Hu, A., Xie, X., Chen, S., & Xie, Z. (2025). Building pattern recognition by using an edge-attention multi-head GCN. *International Journal of Geographical Information Science*.
- Wang, J., Fleischmann, M., Venerandi, A., Romice, O., Kuffer, M., & Porta, S. (2023). EO + Morphometrics: Understanding cities through urban morphology at large scale. *Landscape and Urban Planning*, 233, 104691.
- Wang, Z., Hu, K., Wang, Z., Yang, B., & Chen, Z. (2025). Impact of Urban Neighborhood Morphology on PM2.5 Concentration Distribution. *Land*, 14(1), 7.
- World Resources Institute. (2021). The Realities of Current Urbanization in the Global South. World Resources Report.
- Yuan, J. (2018). Learning Building Extraction in Aerial Scenes with Convolutional Networks. *IEEE TPAMI*, 40(11), 2793–2798.
- Zhang, F., Sun, Q., Huang, W., Su, Y., Ma, J., & Xing, R. (2024). Enhancing the Recognition of Collinear Building Patterns by Shape Cognition Based on GNNs. *Applied Artificial Intelligence*.