ISBN 9789928347220
DOI 10.37199/c41000400

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Territorial Reasoning Beyond Coordination

Prototyping Urban Suitability Score Maps for custom readings of post-transition Tirana

MSc. Fulvio PAPADHOPULLI,
IF, POLIS University, Albania,
fulvio_papadhopulli@universitetipolis.edu.al
ORCID: *0009-0002-1693-664X*

MSc. Megi TAFAJ,
FAD, POLIS University, Albania,
megi_tafaj@universitetipolis.edu.al

DOI: 10.37199/c41000409

Abstract

In some post-transition cities characterized by dense urban palimpsest, we observe that urban transformation advances through a patchwork of opportunistic interventions that often contrast approved, city-wide strategies. In Tirana, the cumulative effect of such decisions is a territory where large-scale masterplans coexist with fragmentary, site-specific developments, producing both visible dynamism and deep spatial incoherence.

This paper introduces a lightweight, data-driven methodology for prototyping Urban Suitability Scores (USS) as adaptable metrics which can inform and support decision-making.

Using cadastral parcel data, a compact set of urban indicators (e.g., accessibility, regulatory capacity, amenity proximity), and by introducing a Lean Canvas Model as an interpretative reading bridge, we developed a generative workflow in Grasshopper (Rhinoceros 3D) that tests the possibility to translate qualitative stakeholders' priorities into quantitative, weighted attributes. These are later clustered via a Gaussian Mixture Model (GMM) algorithm (LunchBox ML plugin) to evidence suitability classes' fluctuation trend for targeted interventions. The clustering output renders them into spatially explicit, optimized, gradient-coded maps.

This back-testing frames the tool not as a predictive engine, but as an experimental diagnostic device for territorial reasoning. This research contributes a transferable framework for reading the fractured development trajectories of post-transitional urbanism, to reveal hidden dependencies or patterns that inform and support different urban scale related decision-making processes.

Keywords:
Gaussian Mixture Model, Territorial Reasoning, Tirana, Unsupervised Learning, Urban Suitability Score, USS

INTRODUCTION

Post-transition cities, emerging from post-socialist or otherwise centrally regulated regimes, are frequently marked by discontinuous trajectories in which mega-projects puncture inherited plans through strategic political and economic alliances. Cases such as Belgrade's Waterfront, Moscow's MIBC, Gran Torre Santiago in Chile, Tbilisi hotels or Astana's emblematic skyline reveal how high-impact architectural "punctures" become instruments of modernization while sidestepping normative planning strategies. This phenomenon is not approached here in a critical register, for we recognize the intricacy of governing such layered and fragile urban conditions; rather, it is understood as an opportunity to enrich the a priori analytical reasoning of territories. Within this frame, Tirana is chosen as the focal case, due to the intensity of operationalizing these fragmented interventions, through politically driven and superpositioned planning strategies which coexist alongside officially approved ones (Papadhopulli & Beqiri, 2024). We thereby introduce an early-stage prototype as workflow pipelines which can reveal custom, user-specific analytical fluctuations in a territorial city-scale, by channeling data-driven dynamics into clustering maps of suitability. During the "Bread & Heart Festival", held for the first time in Tirana in June 2025, a physical scaled model curated with traditional crafting techniques, showed all the emerging "Archi-punctures" of the reinvented new Tirana, which is step by step creating a new structural urban spine of the city. Therefore, it is important to analyze the impacts and risks of their geographical placement implications (Figure 1).

More than three decades after the full collapse of centralized planning, Tirana continues to evolve through a sequence of these fragmented and overlapping interventions. Formal urban planning is nominally structured by the General Local Plan (PPV) and guided towards the TR030 vision, conceived by Stefano Boeri's team and approved in 2017 - envisioning a polycentric "kaleidoscopic city" that balances urban growth with ecological restoration, social inclusion, and infrastructural renewal. The objective is to convert Tirana into a sustainable and accessible metropolitan network through the integration of peri-urban areas, enhanced transit, an orbital forest, and vertical densification (Stefano Boeri Architetti, n.d.).

This vision operates in parallel with the "booming" approvals of the National Territorial Council (KKT/NTC); which is a collegial body led by the Prime Minister and empowered to grant permits of strategic interventions (National Territorial Planning Agency [AKPT], n.d.). In practice, the Council has repeatedly introduced high-density, parcel-by-parcel developments that diverge from municipal planning objectives or structural urban unit coordination, as part of a parallel strategy with national priority. In 2024 and 2025 alone, the NTC approved and published at least 27 archipunctures spread around the city, ranging from a minimum height of 20 to a maximum of 65 stories along major corridors, including a proposed 100-storey skyscraper; thereby surpassing the scale/spread envisioned by TR030 (Figure 2). These bypassing decisions are a prime example of a recentralized, top-down spatial development logic that often contrasts the TR030 growth model. As a result, Tirana's planning politics often devolve into the adjudication of these puncturing mega-projects, while territorial consequences such as strained mobility networks, amenity provision spread, and uneven regulatory application across neighborhoods, accumulate incrementally; producing both visible chaoticism and persistent spatial incoherence.

Figure 1. Mockup exhibited at "Bread & Heart" festival. Source: authors (2025).

Urban studies literature describes that Tirana's history is marked by repeated "restarts," shaped both by residents informally setting their own rules and by authorities struggling to reassert control (Dhamo, 2021). Although contemporary urban development benefits from more consolidated institutional structures and legislative frameworks compared to the time before we had a General Local Plan, the mode of city-making continues to reflect the fragmented urban fabric that emerged during the 1990s bottom-up urban sprawl; only now, on a larger scale, through top-down interventions. Urban growth in Tirana exemplifies what Smart and Koster (2024) describe as the entanglement of formality and informality, where state-led planning, legislative improvisations, and retroactive legalizations coexist with irregular practices, producing a dual layer of urban governance in which formal regulatory frameworks are continually negotiated, adapted, and operationalized. Acknowledging this condition, we propose an explorative extension tool of urban analytics that

Figure 2 - Bulevardi “Dëshmorët e Kombit”, central axis of the city, marshals the historical heritages of the 20th century. TR030. Source: Stefano Boeri Architetti. Retrived 2025

democratizes the ability to read the city in custom ways, by supporting decision-making in different scales and fields, opening up new possibilities for participatory urbanism (Ma, 2025). A flexible parametric workflow is introduced to analyze the Tirana “archipuncturing” phenomenon, exploring possible operational extensions of suitability zones, adaptable to the diverse needs of citizens, public institutions and private stakeholders/investors.

As Koolhaas (1995) has stated, future urbanism will no longer pursue control, permanence, or strict definitions. Rather, it will cultivate adaptable fields that enable processes to unfold without crystallizing into fixed forms. Instead of focusing on stable configurations, it must engage with the reconfiguration of infrastructures, the expansion of possibilities, and the acceptance of continuous modification and uneven development. Building upon this viewpoint, as well as similar approaches (Esri, n.d., 2025, WambuaLouis, 2024, Li, Zhou, Gu, Guo, & Deng, 2022), the paper proposes an explorative contextualization in reading urban fragmentation through cluster maps. These custom maps reveal a latent potential of territorial reasoning. We investigate this latency through the case of archipunctures, which are large and programmatically intense architectural intervention, positioned as a strategic nodes across the city, capable of affecting wider urban performance. It operates as a lens for interpreting the methodological results involved, which intend to identify strategic sites of intervention via adaptable indicators. These interventions are envisioned as leverage points that have a future potential to reshape urban flows, redistribute accessibility, and stabilize fragile morphologies. The primary obstacle is the identification of such potential sites in the presence of incomplete information, contested priorities, and limited institutional capacity. To address this issue, the workflow tries to translate the aspirations of qualitative stakeholders into spatially legible and interpretable guidance. The approach is not deterministic, but open-ended. It prioritizes iterative, data-driven insights that facilitate targeted yet scalable forms of urban transformation, rather than striving for comprehensive control. Such data-driven approaches echo broader debates on how big data and urban informatics can extend the analytical repertoire of urbanism by uncovering hidden patterns and enabling new forms of territorial reasoning (Offenhuber & Ratti, 2014).

Methodologically, the paper explores a compact, parametric clustering model designed to translate divergent priorities into intervention maps, while introducing a reinterpretation of spatial optimization modelling (Ligmann-Zielinska, 2013), generating suitability zones/surfaces. Indicators such as transit accessibility, amenity density, allowable FAR, parcel geometry, proximity to open spaces, etc. can be derived from cadastral and open datasets, normalized, and combined within a Grasshopper pipeline through stakeholder-defined weight vectors. A Gaussian Mixture Model (GMM) clustering routine then produces suitability classes, rendered as gradient maps across the urban fabric. This process raises an important research question: can such models capture qualitative differences in stakeholder agendas and render them spatially legible through mapping fluctuation trends? By exposing the effects of shifting weight vectors, the tool allows the same territory to be “read” simultaneously through the perspectives of developers, municipalities, infrastructure agencies, or even students and citizens.

In this study, clustering was approached not as a fixed partition but as a probabilistic modeling of latent structures through Gaussian mixtures. To determine both the number and stability of groupings, optimization was conducted over cluster count and initialization parameters, prioritizing global likelihood and parsimony rather than point-level assignment. This procedure ensures that the resulting categorizations remain both statistically robust and interpretively coherent for urban analysis.

Methodology

Workflow Anatomy

This approach is intended and better serves to read the complexity of cities

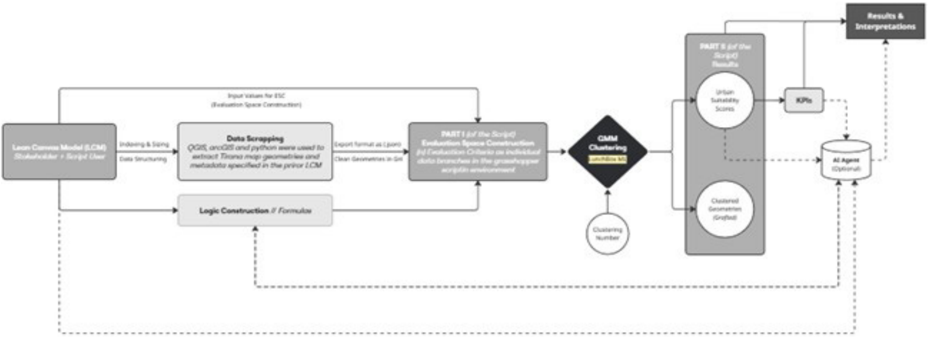


Figure 3 - Workflow anatomy - Pseudocode. AI Agents are a possible extension to the workflow.
Source: Authors (2025)

which are characterized by dense urban palimpsest and governed by unconsolidated data regimes. As a consequence, the case study is anchored in Tirana. Urban Structural Units (USU) strike a balance between the unmanageable granularity of parcel-scale data (which stand at a threshold with big data operations) and the vagueness of administrative zones; offering a territorial "pixel" that condenses morphology, function, and relational position; while remaining accessible through NTPA (National Territorial Planning Agency/ AKPT) datasets. At the same time, they match the scale at which traffic patterns, amenity distribution, and morphological coherence can be meaningfully grasped, and at which municipalities and market actors typically operate. The pipeline is implemented through a GIS-CAD bridge in which data are curated in QGIS, serialized to interoperable formats, and computed in Rhinoceros/Grasshopper with modular components for normalization, weighting, and unsupervised clustering. The method is explicitly designed for extensibility: stakeholders can introduce new indicators, revise formulae, alter decision thresholds or even connect an AI agent for continuous feedback, without disrupting the structure of the pipeline. (Figure 3)

Suitability surfaces found in existing models, are further specified as Urban Suitability Scores (USS), visualized as continuous spatial fields that synthesize heterogeneous criteria into a single scalar representation of how favorable each location is for a stated objective at a certain time. Built through multi-criteria decision analysis, indicators are first standardized (e.g., min–max, z-scores), then weighted to reflect stakeholder priorities, and aggregated via operators such as weighted linear combination or ordered-weighted averaging. The resulting surfaces can be ranked, thresholded, or embedded as objectives or constraints in location-allocation and land-use optimization models. By converting discrete rules and trade-offs into a transparent gradient rather than binary masks, they provide an auditable bridge between empirical evidence and spatial optimization routines (Malczewski & Rinner, 2015).

Adopting a Lean Canvas Model (LCM)

The starting point is explicit articulation of the reading objective, because different urban stakeholders interrogate the same territory with incommensurate questions: translating stakeholder's objectives in quantified input values. In the present case, the objective is to introduce and compute an Urban Suitability Score (USS) across all Urban Suitability Units (USUs) to identify locations most conducive to hosting the next "archipuncture". To make the translation from goals to code auditable, a Lean Canvas Model (LCM), - originally derived from business-oriented frameworks for its directness, specificity, and clarity - is here adopted and adapted to the urban analytical context (Osterwalder & Pigneur, 2010). It is important to note that this scenario remains a hypothetical construct, employed solely to test and validate the methodological pipeline as a first prototype, rather than to reproduce an empirically exact planning case. Nevertheless, the LCM itself is not intended to build a conceptual narrative, but a clear articulated vision with compact design specification which can be interpreted and translated into operationable input values for the later coming parametric script (Table 1). For this reason, it reframes the analytical workflow into a dual register: (a) the language of the stakeholder and (b) the translation apparatus of the urban/architectural specialist. Rather than enumerating every computational detail, the canvas captures the essentials of decision-making by naming the unit of analysis (USU), aligning it with stakeholder objectives, and rendering qualitative aspirations into quantifiable proxies. Objectives such as prestige, visibility, or cost efficiency are assumed for the investor as a relevant case study. Each row of the canvas documents how raw features like distance to the city center (aerial, by walking, by car), proximity to adjacent units, or surface area are converted into normalized indicators and weighted formulas that structure the Urban Suitability Score (USS) metric. In this way, the table functions as both a communicative device and a computational lead; revealing the logic of translation from human-readable ambitions to machine-operable values. The significance of this process lies in its precision of translation. In a time where LLMs are constantly gaining momentum, this approach also contributes to increasing the cognitive capacities of a "prompting" procedure for the users/specialists. The success of the entire workflow, in fact, depends on how accurately qualitative objectives are transcribed into computational formulas at this early stage. By explicitly defining the structure of the USS, the user can anticipate what constitutes a high suitability score and why. For example, if the normalized USS equals 1, it signals that a given USU is the most adequate within the modeled system, falling into the highest-performing cluster. This numerical optimum is not abstract; it is tied to concrete spatial values, which may reveal, for instance, that the most suitable unit privileges proximity to the city center while simultaneously rewarding compactness of form (referring to scenario shown in

Table 1). Such revelations underscore why formula-writing is not a secondary technicality but a central act of urban reasoning. LLM reasoning could serve as an explorative and extensive option to the pipeline, which is further encouraged in future works, by leveraging AI agents' operative platforms like n8n. (Figure 3)

Section	Stakeholder View (Investor)	Urban Specialist Translation (Architect/Planner)	Quantifiable Proxy / Formula
Objective	Identify the most promising location in Tirana to propose a new tower to authorities, maximizing return and visibility.	Translate investor ambitions into measurable spatial indicators to ensure credibility in urban decision-making.	Urban Suitability Score (USS) = Weighted combination of indicators.
Problem / Need	"I need to avoid wasted capital on parcels/zones where approvals will be difficult or where infrastructure doesn't support high-profile investment."	Urban sprawl and fragmented administrative boundaries make ad-hoc speculation risky without systematic analysis.	Problem reframed as: locate Urban Structural Units (USU) with favorable attributes (centrality, density adjacency, adequate size).
Qualitative Interests	Prestige location (close to the city center, visible skyline impact); balance between land cost and growth potential.	Translate 'prestige' into distance-to-center (flexible), adjacency to other active USUs, and capacity of USU area.	(i) Distance to city center (inverse relation), (ii) Proximity index (higher is better), (iii) Area (threshold adequate for tower footprint).
Existing Alternatives	Rely on brokers, media, news, or political lobbying, intuition.	Data-poor intuition produces speculative bubbles, inefficiencies, and regulatory friction.	USS offers transparent, reproducible, and scalable decision support.
Key Metrics	Land value appreciation; approval success rate, potential of high-profile visibility.	Develop scalable metrics from available data inputs: centrality, proximity, area.	USS = w1*(1/Distance) + w2*(Proximity Index) + w3*(Area/MaxArea).
Stakeholder Limitations	Does not understand GIS or Grasshopper logic; thinks in terms of cost, risk, and opportunity.	Must simplify and communicate outputs as ranked maps, heatmaps, or simple scores per USU.	Visual maps + indexed ranking tables.
Resources & Inputs	*Capital investment, lobbying, timeline pressure for project delivery.*	Spatial datasets: USU boundaries from AKPT, city center coordinates, adjacency matrix.	Normalized data tables: distance, adjacency, area.
Unique Value Proposition	"I can make a tower investment decision backed by data-driven urban logic instead of pure speculation."	"We can simulate and compute which USUs objectively score higher for impactful interventions."	USS score per USU, color-graded on Tirana map.
Channels of Communication	Reports to board, negotiation with municipality, media visibility.	Deliverables: executive-friendly maps, index tables, clear narrative bridging business and urban rationality.	Ranked list of top 10 USUs for tower placement.
Success Criterion	*Securing municipal approval and ensuring long-term profitability of the tower.*	Ensuring analysis aligns with real planning constraints and stakeholder expectations.	Top-ranked USUs overlap with infrastructure corridors, high-value proximity zones, and adequate area size.

Table 1. Lean Canvas Model (LCM) - Hypothetical construct - case study example to operationalize the pipeline. Source: Authors (2025)

Base GIS Environment and Data Preparation

The second pipeline proposition starts in QGIS software, an open-source GIS platform selected for its extensibility and ability to integrate Python scripting for custom formulae, as well as for its seamless bridging with Grasshopper for subsequent computational modeling. The Tirana city map was initialized by connecting to official geospatial repositories and importing all relevant vector layers, including cadastral parcels, infrastructural networks (roads, utilities), public greenery, and georeferenced amenity locations (Figure 4/a). Each layer was harmonized into a unified coordinate reference system (Tirana - 34N, EPSG:32634), cleaned of inconsistencies, and stored in a project-level GeoPackage to ensure reproducibility.

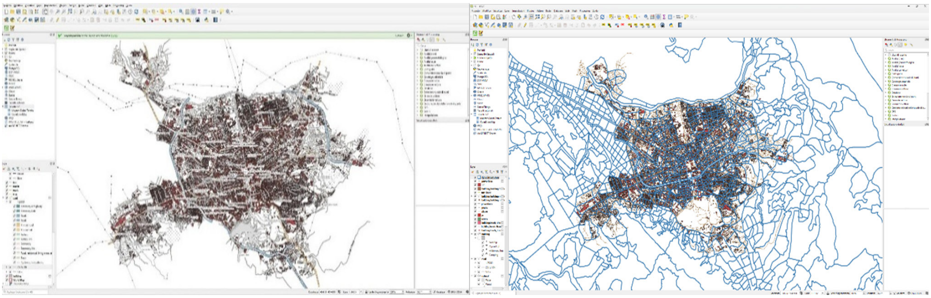


Figure 4 – Extract all data from OSM plugin for QGIS in specific layers (A-Left). Overlap of all OSM geometries with extracted USUs as layers (B-Blue colored, on the right). At this stage, layers are ready to be exported as shapefiles (.shp). Source: Authors (2025)

Data Scrapping

The geometries of Tirana's Urban Structural Units (USUs) were retrieved from the ArcGIS REST services published by the NTPA (National Territorial Planning Agency/ AKPT), publicly accessible through their online portal. The procedure involved connecting QGIS to the ArcGIS online feature service endpoint, which exposes vector data as FeatureServer layers. The service URL was accessed through the ArcGIS REST API, and layers corresponding to USU boundaries were selected and imported into QGIS using the Add ArcGIS Feature Server Layer functionality (Figure 4/b). This ensured that the full polygonal geometries, along with their attribute tables (metadata such as identifiers, surface area, and administrative classification), were preserved. Once imported, the USU layer was exported from the temporary web connection into a local geospatial format (GeoPackage) to guarantee reproducibility and offline accessibility. Metadata were inspected, normalized, and cleaned to align with subsequent analytical needs. The QuickOSM plug-in in QGIS served as a search engine for data scraping in the city scale. Parcels' IDs, Buildings' footprints and IDs, heights, Ground levels, amenities, function, infrastructure, building-parcel correspondence etc. were extracted when available (Figure 4/a). When missing attributes applied, the data structures were preserved and therefore these items are assigned as nulls. Nulls are later replaced or reduced depending on the data structure's strategy in Grasshopper (Figure 5).

GIS-CAD Bridge & Export Format Recommendations

To establish an operative bridge between the QGIS environment and the algorithmic design pipeline, it is essential to ensure that both spatial geometries and their associated attributes are transferred in a format that preserves the integrity of embedded metadata. This prototype considers Shapefile (.shp) format as one of the most effective to achieve full readability of QGIS layers in the grasshopper environment, by retaining both geometry and attribute structures with high fidelity. Within the Grasshopper for Rhino environment, these files can be ingested through the Heron v4.4 plug-in components, available for download through Rhino's Package Manager. Since we are dealing with GIS data, we need to assure prior to import that the UTM Zone matches with the one of the shapefile. For that, we need to call the SetSpatialReferenceSystem component and

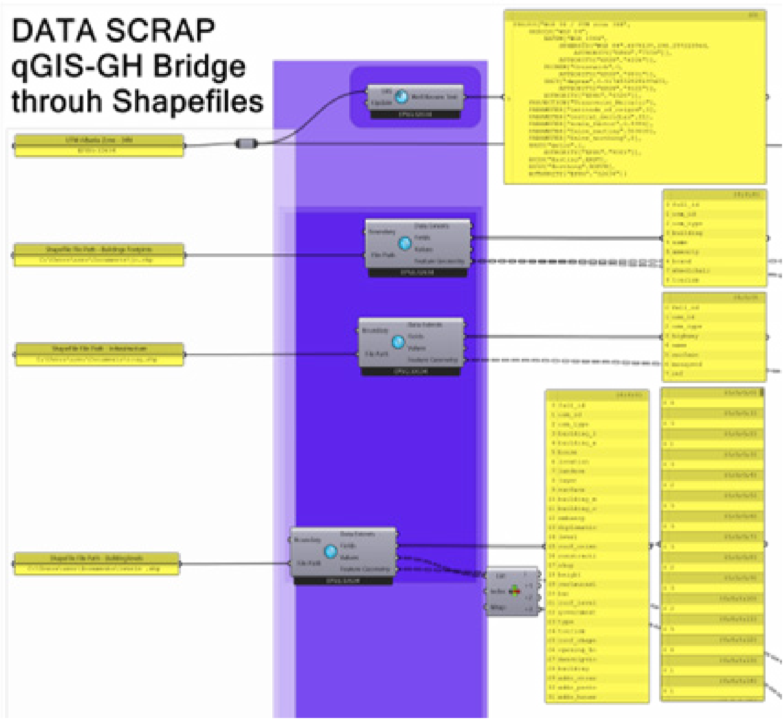


Figure 5 – Data scrapping + Setting Zone 34N EPSG in Grasshopper through Heron Source: Authors (2025).

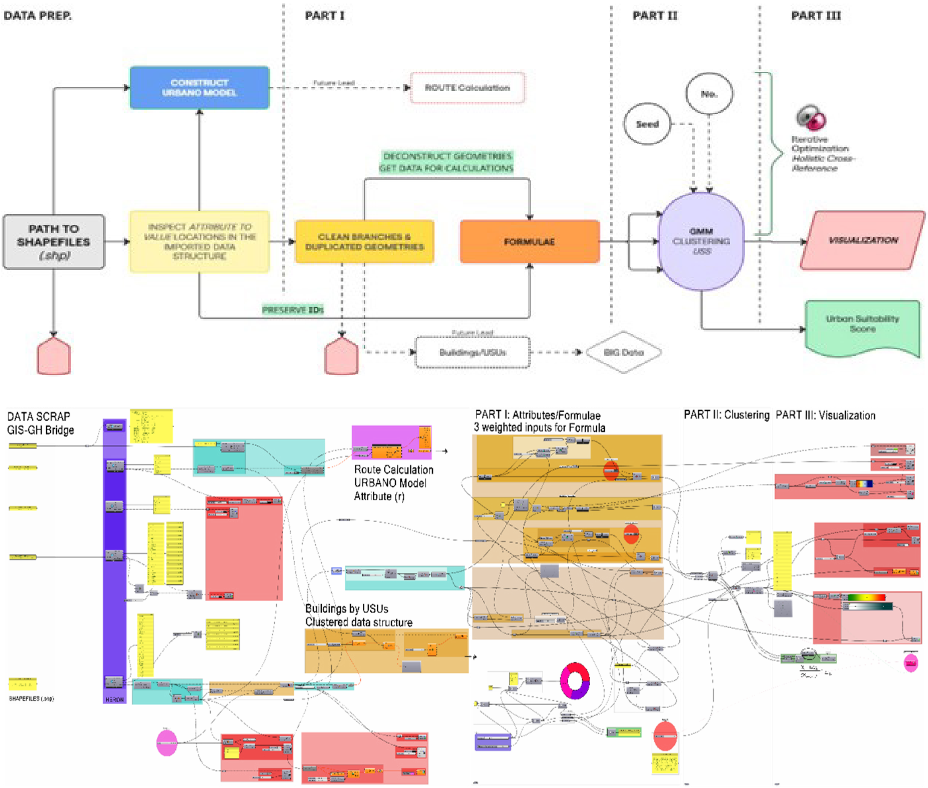


Figure 6 –Scripting pseudocode scheme organized in 3 parts: I, II, III (Above). Script detailed anatomy, organized in 3 parts (Below). Source: Authors (2025)

assign Tirana's Zone 34N, by adding a string "EPSG:32634" as input (Figure 5). The advantage of this method lies in the fact that the component not only imports the geometrical framework but also maintains the relational data structures, enabling their subsequent manipulation, recombination, and transformation within the parametric domain of Grasshopper. It is equally important to recognize that QGIS is not merely a preparatory platform but also a computational environment in its own. The software allows users to calculate and attach derived attributes directly to spatial features through its built-in field calculator and expression system. In practice, this means that certain formulae - particularly those requiring relatively simple arithmetic or aggregation across feature sets - can be pre-computed at the GIS stage before the dataset is transferred into Grasshopper. Such pre-processing can significantly reduce the computational burden on the parametric model, especially in workflows where high-frequency iterations or clustering algorithms are deployed. Thus, the decision of where to compute specific indicators, upstream in QGIS or downstream in Grasshopper, becomes a methodological consideration in itself, contingent upon the needs of the Lean Canvas Model (LCM) and the scale or complexity of the urban analysis being undertaken. A pseudocode followed by the full script is then constructed (Figure 6)

Parametric Pipeline – PART I: Attributes

Prior to computation, the USU layer is checked for topology errors (gaps, overlaps). Invalid geometries are repaired, and a planar coordinate reference system with metric units is enforced to ensure that distances and densities acquire matching virtual proportions. Where city center is referenced as a distance anchor, the center point is defined a priori and documented (e.g., the centroid of a designated central business district polygon), noting that a different anchor can be substituted if a stakeholder's objective differs. In our case, the city center will serve as an attractor attribute, as priorly specified in the LCM (Table 1). But geographical features of Tirana restrict the existence of high-density urbanism to an area much smaller than its administrative expansion. For this reason, the map needs to consider the scope of expansion in relation to the scaling needs of reading it. Figure 7 shows how in our case, USUs were culled under a conditional expression in relation to their distance from the city center. A radius of 10 kilometers was considered adequate for investigating the archipunctural potentials of Tirana today, covering up an area which corresponds also to the one of Tirana 2030.

Figure 7 –a) Import all layers in the Grasshopper environment. b) Select only USUs inside a 10km radius area. c) Cull and restructure data branches accordingly. Elefront plugin was used for visualization.

Attributes definition. The Urban Suitability Score (USS) must derive from the systematic translation of investor objectives into normalized, weighted attributes assigned to each Urban Structural Unit (USU) taken under analysis. The method ensures that qualitative ambitions (prestige, visibility, feasibility) are transformed into reproducible spatial indicators. From the use case, 3 main attributes were calculated and used as a testbed for the pipeline:

a) Centrality - is calculated as the inverse Euclidean distance between the USU centroid and the city-center coordinates:

This captures the investor's preference for locations whose spatial centrality

$$Centrality_i = \frac{1}{Distance_i}$$

amplifies visibility, symbolic leverage, and infrastructural integration. Yet centrality may be conceptualized and measured through multiple operative registers. One can, for instance, compute the aerial distance to the center, which expresses not only a geometrical proximity but also a strategic positioning within the territorial frame of the city - an index often correlated with institutional priorities for urban interventions and the escalation of real estate values. A different reading emerges when centrality is traced along pedestrian accessibility. Since the walking time required to reach the city's core mediates tourism-related potentials, diverging from mere aerial measures privileges experiential and infrastructural continuity. Finally, vehicular centrality introduces an additional layer of interpretation, where distance is recalibrated through road-network routing and traffic patterns, disclosing those urban units that, while slightly displaced in geometric terms, are effectively more integrated into the metabolic flows of the city, offering a distinct advantage in relation to central amenities and the dynamics of urban fluxes. All these could be route calculated by constructing an additional Urbano Model through the Urbano plugin for Grasshopper, available under the PackageManager of Rhino 8. It is suggested to not compute all parcel calculations at once, due to the heavy amount of computational time needed to have the whole model of Tirana. Instead, this step can be integrated as a secondary testbed for USUs which are under final considerations.

b) Adjacency is expressed through a proximity index based on contigui-

$$Adjacency_i = \frac{\sum_j A_{ij} \cdot D_j}{\max(\sum_j A_{ij} \cdot D_j)}$$

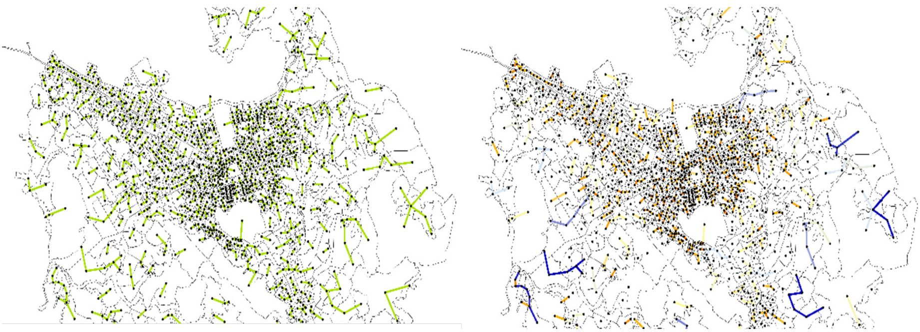


Figure 8 –(a) - Proximity Links, merged & joined (Left); (b) - Proximity Links, clustered by surrounding density (blue< to red>) (Right). Source: Authors (2025).

ty. For each USU, the number and quality of its direct neighbors are quantified through an adjacency matrix. Neighboring USUs with higher density or activity scores increase the adjacency index, normalized between 0 and 1:

where Aij indicates adjacency and Dj denotes the density/activity score of unit j.

By clustering the 3D point proximities of USU centroids in relation to their distance from the city center and their respective area sizes, one can expose the latent structure of the urban fabric beyond its visible geometry. Such an analysis reveals whether parcels tend to consolidate into tightly packed central clusters or remain peripheral enclaves, thereby disclosing patterns of cohesion and fragmentation in the city's growth. The inclusion of area size differentiates expansive parcels, often associated with institutional or infrastructural logics, from fine-grained units more likely tied to residential or incremental development; while the centrality gradient exposes tensions between small, over-pressured inner-city lots and large, underutilized tracts at the edges.

c) *Capacity / Structural Capacity (SC)* is related to the area of each USU alongside its normative indicators, providing insights on its spatial potential for archipunctural insertion. Structural Capacity (SC) in this case is considered as an aggregate of 3 attributes: existing Floor Area Ratio (FAR) - measures current built intensity and indicates revealed market demand, Building Coverage Ratio (BCR) - expresses the degree of ground coverage, where higher values reduce open space and increase ecological stress.

, and Regulatory Headroom (RH) - quantifies the remaining allowance before statutory limits are reached. Three structural archetypes can be generally deducted:

High FAR + High BCR + Low headroom → saturated morphology, high market signal but low insertion capacity.

Moderate FAR + Moderate BCR + High headroom → balanced morphology, prime candidate for intensification.

Low FAR + Low BCR + Very high headroom → slack condition; suitability depends on adjacency and accessibility.

Capacity is normalized relative to the largest USU.

Weight Assignment and Formula Construction.

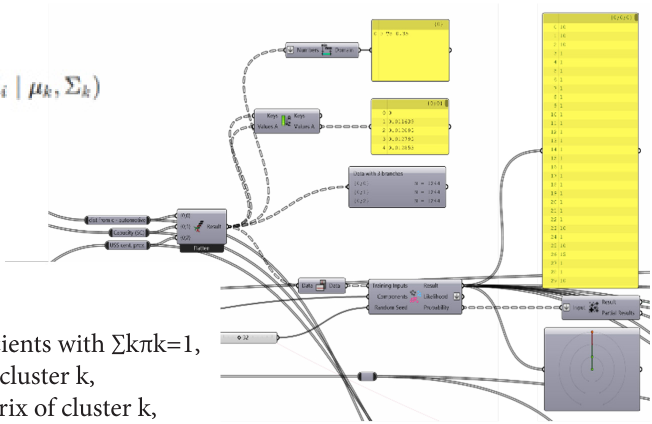
Weights (w1, w2, w3…wn) are introduced to align the formula with investor priorities: centrality as a measure of prestige, adjacency as a measure of visibility and synergy, and structural capacity as a measure of feasibility. Weights must sum to 1. The USS is defined for each USU as:

$$USS_i = w_1 \cdot Centrality_i + w_2 \cdot Adjacency_i + w_3 \cdot Capacity_i$$

Parametric Pipeline – PART II: Clustering

Each USU is represented as a vector xi= [Centrality i, Adjacency i, Capacity i]. The dataset of all vectors is partitioned using the Gaussian Mixture Model (GMM) clustering algorithm. Unlike K-means clustering, which partitions data by minimizing Euclidean distance to centroids, GMM models the distribution of the data as a weighted sum of K Gaussian components, allowing clusters to vary in orientation and spread. This probabilistic formulation is considered as more appropriate because of the hypothesis that urban units may belong to overlapping morphological regimes rather than mutually exclusive types. Formally, the likelihood of an observation xi is:

$$p(\mathbf{X}_i \mid \Theta) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{X}_i \mid \mu_k, \Sigma_k)$$



where:
πk - are the mixing coefficients with Σkπk=1,
μk - is the mean vector of cluster k,
Σk - is the covariance matrix of cluster k,
N ( ) - denotes the multivariate normal density,
Θ={πk,μk,Σk}K/k=1 are the parameters estimated.

Figure 8 –(a) - Proximity Links, merged & joined (Left); (b) - Proximity Links, clustered by surrounding density (blue< to red>) (Right). Source: Authors (2025).

In the GMM framework, reproducibility and variability are governed not by centroid initialization but by the specification of the random seed in the Expectation–Maximization (EM) algorithm on the GMM likelihood results. The seed determines the starting values for means, covariances, and mixture weights. Fixing the seed ensures identical log-likelihood trajectories and stable cluster assignments across runs. Allowing variability, by contrast, enables the testing of robustness, as different initializations may converge toward alternative local maxima of the likelihood function.

Parametric Pipeline – PART III: Visualization

The geo-visualization translates the clustering output into a legible territorial field. Each Urban Structural Unit (USU) inherits a discrete cluster label, indexed to the Urban Suitability Score (USS) domain, as well as a continuous USS value with a normalized domain [0, 1]. For communicative clarity, we layer a georeferenced choropleth that assigns a stable hue to each cluster class (the categorical reading). We construct a gradient heatmap that encodes the detailed normalized USS, revealing deep intra-cluster intensities. However, this would be more beneficial and preferred in a context where more data are taken into consideration for detailing more clusters (the scalar reading). The map is produced directly on the USU polygonal surfaces, preserving topology and IDs, while a light contiguity-aware smoothing of the scalar surface (queen adjacency) can be optionally applied to prevent false visual discontinuities at unit edges (without distorting computed d values). This dual rendering opens up the possibility for exploring the threshold between reproducibility (cluster classes) and sensitivity (local USS variation) in a single cartographic frame. (Figure 9)

Figure 9. Example Map, colored in base of the USUs' Urban Suitability Scores, structured along a 3 clusters' resolution. Infrastructure is exposed through overlapping route calculations through the Urbano Model, from each parcel to the center. (a) Above - Map showing USS's as per Table 1, overlapped with infrastructural flows; (b) Below - Clean USS Map + Buildings. Source: Authors (2025)

Optimization until Trend Stabilization

While the GMM clustering routine provides an initial partitioning of Urban Structural Units (USUs), the stochastic nature of centroid initialization renders each run susceptible to variability. To mitigate this dependency and ensure robustness, the workflow integrates an optimization loop via the Galapagos evolutionary solver embedded in Grasshopper. Unlike deterministic algorithms, Galapagos treats clustering as an evolving search space in which both the number of clusters and the random seed of initialization are framed as genomes to be iteratively recombined and tested. The domain for cluster size is bounded between 3 and 100, capturing both coarse-grained and fine-grained interpretations of the urban field, while the seed is allowed to vary continuously to explore alternative local minima.

The fitness criterion guiding the evolutionary process is defined as the maximization of intra-cluster probability, or more specifically, the likelihood that an input vector of normalized attributes (centrality, adjacency, structural capacity) consistently belongs to a stable cluster. This probabilistic framing aligns with the methodological aim of producing territorial readings that are not contingent upon single random initializations but instead converge toward solutions that remain valid across multiple stochastic conditions. Through successive generations, Galapagos executes crossover, mutation, and selection functions that gradually steer the population of candidate solutions toward higher stability: pruning configurations that overfit or collapse prematurely. (Figure 10)

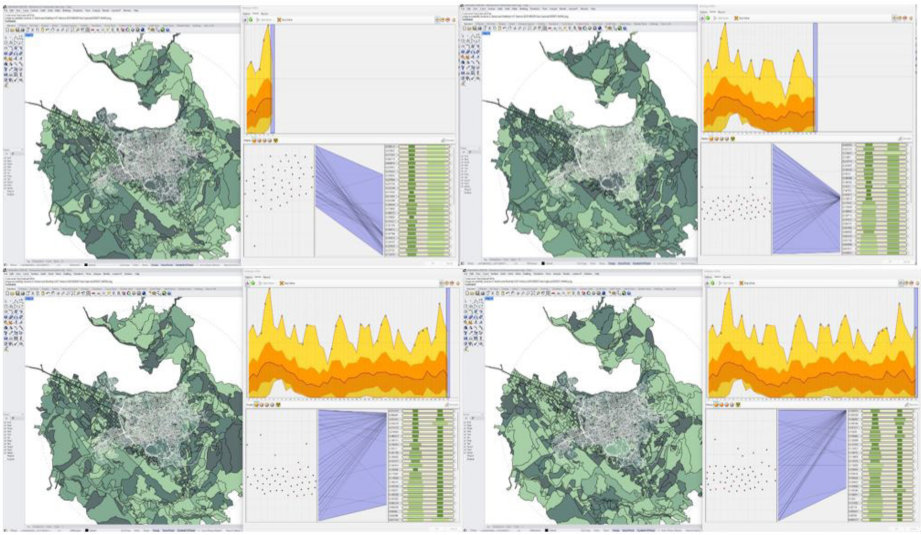


Figure 10. Stabilization of USS waves of possibilities when searching to maximize probability of likelihood results. Observed over 10 optimizations of 5 minutes each, showing trends in the visual results, suggesting the highest probability through overlapping similarities per each scenario. Source: Authors (2025)

Results

The stabilized clustering scenarios, as derived through the evolutionary optimization process, revealed a consistent pattern of urban suitability across Tirana's structural units. High-scoring clusters converged around central and infrastructurally privileged zones, particularly those adjacent to the city center, while peripheral units showed greater volatility before reaching stabilization. This differentiation underscores the model's capacity to translate qualitative investor objectives into spatialized outputs that persist beyond stochastic variance. (Figures 10, 11)

Figure 11. Explorative Maps of USS, colored in base of the USUs' Urban Suitability Scores, structured along a 23 clusters' resolution. Source: Authors (2025)

Read in time, the Galapagos runs map a register of "waves of dependencies": probability-weighted vectorial alignments that thicken or recede, as the evolutionary solver converges (Figure 11). The result is a more flexible and less abstract territorial reasoning model. It captures latent fluctuations of opportunities and risks as gradients of probability dependencies. Stabilized clusters mark potential strategic investment logic while the semi-stable ones suggest contested morphologies and governance seams. In post-transition conditions, these overlays have the potential to provide stakeholders with a clear audit trial, which can help inform spatial consequences and make visible how interests condense into durable corridors. This creates space for negotiated urban futures.

Refering to figure 10, the early iterations show a lot of instabilities: cluster centroids shift rapidly and assignments fluctuate. This exposes the models sensitivity to both seed values and cluster size. However, after the first wave of evolutionary iterations, the trajectories begin to stabilize. Local impacts that initially oscillated across competing clusters gradually consolidate into coherent patterns. This stabilization does not imply a single absolute partition. Instead, it suggests a probabilistic field in which chertain USUs emerge as consistent high-probability members of particular clusters, regardless of seed varation. As a consequence, the evolutionary solver transforms randomness into a way to check the structure of its own generative model, revealing which configurations are structurally robust on map, and which are artifacts of initialization.

The time-dependent nature of this optimization adds another layer of complexity to the analysis. By observing how clusters consolidate across generations, it becomes possible to distinguish between temporary groupings and those with durable structural logic. For example, central USUs near the city center often become high-performing clusters only after a limited number of iterations, while peripheral or morphologically ambiguous units oscillate longer before stabilizing. This differential rate of stabilization offers insight into how resilient spatial patterns are under conditions of incomplete information and shifting priorities. However, the mapping of such oscillations is suggested to be further explored and analyzed in the future.

To evaluate its computational robustness and interpretive clarity, the prototype workflow was tested in a pedagogical experiment during Tirana Architecture Weeks (TAW24) at POLIS University, in November 2024. A group of 37 fourth-year architecture and urban design students was tasked to engage with the workflow, in order to construct and analyze possible archipuncturing scenarios across Tirana. Students speculated about different scenarios and translated the set of qualitative goals into weighted attributes. We saw how GMM clustering, together with evolutionary stabilization, rendered these goals into simplified, data-driven territorial maps on which we could understand and interpret upon. As illustrated in Figure 12, the exercise facilitated a collective understanding of how complex urban dynamics can be re-encoded into operational models without oversimplifying the qualitative underpinnings. The USUs in the maps used by the students were further narrowed down based on the specific topographical and rural characteristics, as a “discriminative” input. In their scenarios, this was a key step to better understand interests on a pre-confined and adequate territorial scale. This step minimizes the risk of interpretive distortion by removing USUs that do not meaningfully participate in the city’s active urban fabric for that specific scenario.

The workshop confimed that the methodology is not only computationally viable but also communicable across different levels of expertise. Students, many of whom had no prior experience with clustering algorithms, were able to comprehend the translation logic between stakeholder objectives and urban outputs. Furthermore, they were able to engage in critical discussions regarding the implications of varying weight assignments or optimization parameters. This demonstrates that the workflow is as much a tool for territorial reasoning as it holds also potential to become a pedagogical instrument, capable of fostering analytical literacy in urban studies and design education.

Discussion

This study proposes a compact, auditable workflow that converts heterogeneous stakeholder aims into reproducible territorial readings. Three design decisions were central. First, the Urban Structural Unit (USU) was adopted as the operative spatial kernel, permitting city-scale reasoning without collapsing into

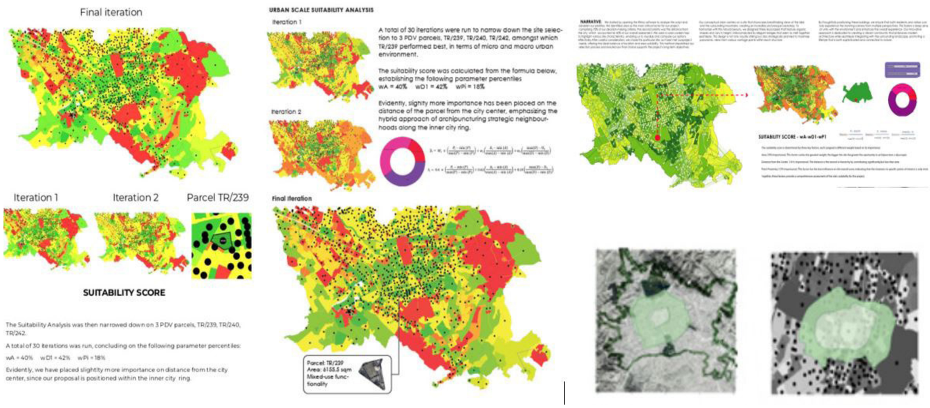


Figure 12. Students' urban analyses by introducing their interpretation of the Urban Suitability Scores. Source: Retrieved from authors in 2025. Part of POLIS archive, under the Tirana Architecture Weeks 2024 Documentation Materials - accessible through internal platforms and published online on social media and official TAW website. Students: Gledis Sinanaj, Sara Nini, Joana Veizi (Right side) - Ankela Doci, Klea Maci, Jonian Celaj (Left side). Workshop leaders: Marco Mondello, Fulvio Papadhopulli, Albi Alliaj. Also available on the Miro board: https://miro.com/app/board/uXjV-LcOoqRU=/

parcel-level noise or drifting into administrative abstraction. Second, qualitative objectives are rendered into normalized indicators through a Lean Canvas Model translation, making the path from intent to computation explicit and revisable. Third, GMM clustering was regularized by an evolutionary loop, where clustering number and initialization seed were treated as genomes, and solutions were selected by their capacity to maximize membership likelihood and remain stable under stochastic variation. Together, these steps turn a potentially fragile classification into a stabilized ensemble that can be interrogated, compared, and replicated.

The stabilized patterns have practical meaning. Units consistently converging into high-performing clusters align with centrality, adjacency, and structural capacity in ways that are legible to decision-makers; units that oscillate longer before convergence are revealed as ambiguous opportunities or risk zones. In other words, optimization is not a cosmetic post-processing step but an epistemic filter that distinguishes robust territorial signals from artifacts of initialization. For actors negotiating post-transition urbanism - where permits, infrastructures, and market cycles rarely cohere - this distinction is not trivial; it informs whether an "archipunctural" proposal is grounded in structure or in noise.

Pedagogically, the workflow proved communicable and transferable. When introduced to 37 fourth-year students during TAW24, participants could articulate objectives, assign weights, and read back the territorial consequences in Figure 12's gradient maps. The exercise validated two claims: that the translation apparatus makes the computational core inspectable by non-specialists; and that stabilized clustering supports comparative reasoning across scenarios without presuming a single “correct” map. These are non-trivial capacities for studios, municipal units, and private offices alike.

At the same time, this remains a prototype. Its outputs are contingent on indicator choice, normalization strategy, and weight vectors; GMM assumes roughly convex clusters and similar within-cluster variance; and data incompleteness can bias centrality and adjacency measures. These constraints are not disqualifying; they are parameters to manage. In practice, they can be addressed by: (i) subjecting weight vectors to sensitivity analysis; (ii) triangulating GMM ensembles with alternative partitions (e.g., K-Means, spectral, or density-based models) to test invariants; and (iii) incrementally enriching inputs with regulatory, mobility, or temporal permit data as they become available. The point is not to freeze a definitive taxonomy of Tirana, but to maintain an ever-evolving, inspectable and transferrable pipeline where assumptions are explicit and can be tested.

Future extensions are direct and pragmatic: embed uncertainty reporting next to each map; implement multi-objective evolutionary search when stakeholders compete on incompatible criteria; and formalize a cross-validation routine against realized interventions to calibrate indicators and weights over time. These steps preserve the prototype’s agility while tightening its evidentiary claims, advancing it from a catalyst for informed debate toward a deployable instrument for practice.

Lastly, an important structural question arised during the workshop, which far exceeds the intentions of the research itself. How does the outter overall perimeter of the considered maps, affect the overall results? This question opens up many uncertainties we have about the digital world in general, about when and what to consider as “the end” of the pysical boundaries in a digital realm? How do we know where is the right scale to break dependencies across them for a specific analytical process? These are to be tested, not only throughout our methodological proposal, but also in other analytical or reasoning models.

Further Suggestions. Traffic and temporal dynamics can be integrated without changing the core design pattern. Time-stamped exposures (e.g., average speeds or counts by hour) are aggregated to USUs by joining sensor locations to the network and then to USUs via network-constrained buffers; a temporal weighting kernel (for example, emphasizing peak periods) collapses the hourly profile into a scalar per USU, which is then normalized and introduced as another indicator in USS. Where market “boom/recession” mapping is required, the same logic applies: price change gradients or listing density dynamics are computed over moving windows, smoothed to reduce noise, and aggregated to USUs before normalization. The method treats these additions as plug-ins:

the LCM declares the new indicator, the import block reads its layer, and the downstream machinery remains unchanged.

Because data accessibility in Tirana can be intermittent, the pipeline anticipates manual digitization or attribute entry when scraping fails. In Grasshopper, each indicator has an optional manual override port that accepts a user-supplied value per USU. If a manual value is present, it supersedes the computed value for that indicator and USU; the override is logged in an audit table with a timestamp and a free-text justification. This design preserves the ability to proceed under imperfect data while preventing silent substitutions that would undermine reproducibility. Where entire layers are missing (for example, parcel polygons in a newly annexed area), the LCM can specify a mask so that excluded USUs are clearly rendered as “no-data” rather than spuriously assigned low suitability.

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