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Hybrid Spatial Analysis of Rurban Dynamics Using Geospatial and Socio-Economic Data: Case of Casablanca–Settat Region

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Abstract

Rurbanization and peri-urbanization are among the most dynamic territorial processes affecting metropolitan regions in Morocco, particularly within the Casablanca–Settat region. These transformations, driven by rapid urban growth, demographic pressure, and socio-economic change, generate complex transitional spaces between rural and urban environments. In this context, the present study proposes a hybrid methodology for detecting, classifying, and analyzing the rural–urban continuum by using remote sensing data and artificial intelligence techniques. The approach integrates Sentinel-2 satellite imagery, spectral indices, Global Human Settlement Layer datasets, and socio-demographic indicators derived from the Moroccan census. Two models, Self-Organizing Maps (SOM) and Graph Neural Networks (GNN), were applied to classify territories into four categories: urban, peri-urban, rurban, and rural. Model outputs were combined with expert-based decision rules to improve classification robustness and interpretability. The SOM model achieved up to 89.3% agreement with expert classifications and a Cohen's Kappa coefficient of 0.842, demonstrating strong interpretability and consistency, while the GNN model reached 53% agreement and effectively modeled spatial dependencies and neighborhood interactions. Diachronic analysis between 2014 and 2024 revealed a 54% increase in peri-urban municipalities, a 24% decrease in rurban territories, and a decline in rural municipalities, highlighting intensified urban sprawl and fragmentation of agricultural landscapes. Beyond its scientific contribution, this study provides a valuable decision-support framework for urban planners, environmental agencies, and policy makers involved in territorial governance and sustainable development. It can support land-use planning, monitoring of urban sprawl, protection of agricultural lands, and the implementation of adaptive territorial policies aimed at improving the resilience and sustainability of rurban environments.

Keywords: rurbanization; peri-urbanization; Self-Organizing Maps (SOM); Graph Neural Networks (GNN); rurban continuum; territorial dynamics; machine learning

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1. Introduction

Urbanization is one of the defining global megatrends of the twenty-first century: the share of the world's population living in urban areas rose from 30% in 1950 to 55% in 2018 and is projected to reach 68% by 2050, adding roughly 2.5 billion urban dwellers, with close to 90% of this growth concentrated in Africa and Asia [1]. This expansion rarely stops at administrative city limits; it spills into surrounding rural land, frequently producing

low-density and fragmented sprawl that consumes increasingly large territories [2]. A substantial share of this growth takes place on fertile soils: global urban expansion is expected to cause a 1.8–2.4% loss of croplands by 2030, about 80% of it in Africa and Asia and disproportionately on highly productive land, with North African countries among the most severely affected [3]. These dynamics place rurbanization and peri-urbanization at the core of the international sustainability agenda, most directly Sustainable Development Goal 11, whose Target 11.A explicitly calls for strengthening the economic, social and environmental linkages between urban, peri-urban and rural areas, while linking them to global concerns over land degradation, food security, and the resilience of metropolitan regions [4]. Understanding precisely where, how fast, and along which gradients these rural-to-urban transitions occur is therefore a prerequisite for sustainable territorial planning, the protection of agricultural land, and climate-resilient development.

The demographic growth over the past decade, coupled with improved living conditions, expanded transportation networks, and various social, economic, and professional factors, has led to a redefinition of urban boundaries, particularly highlighting the role of medium-sized cities [5]. The phenomenon of rurbanization was first identified in the 1982 French National Population Census, marking a shift in population dynamics. This change saw a reversal in migration patterns, with an increasing number of people moving from urban areas to rural ones, rather than the traditional rural-to-urban migration [6]. A definition of the rurbanization phenomenon presents its effect on rural patterns: "rurbanization is a process of altering rural forms with pre-selected urban patterns and lifestyles, which creates new genetically altered rurban forms" [5,7]. Morocco, like other countries around the world, has experienced intensive urban growth influenced by economic, demographic, and social developments. This growth, in turn, affects the nature of the region's socio-economic activities, particularly the transition from rural to urban settings. This process leads to a shift toward industry at the expense of agriculture, which, under the umbrella of intensive urbanization driven by metropolitan expansion and social changes, reflects a reallocation of farmland to urban activities, thus reducing cultivable land on one hand and threatening the agricultural potential of the regions on the other [8].

Today, it is imperative to first understand and then map land-use changes by detecting subtle variations among the general characteristics of each category. To date, most studies have been limited to rural and urban areas, often overlooking the intermediate varieties that exist between these two classification poles. This diversity gives rise to "Rurban" areas, describing regions transitioning from agricultural to urban spheres, and "Peri-urban" areas, which are directly influenced by urbanization due to their proximity to urban or metropolitan zones [6].

Despite the growing availability of high-resolution satellite imagery and socio-economic datasets, most studies on territorial dynamics remain limited to broad urban–rural classifications and rarely explore the fine-scale transitions between these categories. Existing approaches often focus either on land-use changes derived from remote sensing data or on socio-economic indicators analyzed separately, which limits their ability to capture the multidimensional nature of the rural–urban continuum. The novelty of the present study lies in combining (i) the preprocessing of Sentinel-2 satellite data and extraction of spectral indices for the Casablanca–Settat region, (ii) the integration of multi-temporal statistical data from the General Population and Housing Census provided by the High Commission for Planning (HCP), and (iii) the use of neural network modeling, specifically Self-Organizing Maps (SOM) and GNN, to compare their effectiveness in producing detailed cartographic representations of the resulting classes.

The main objective of this study was to develop a comprehensive methodology for detecting, classifying, and analyzing the evolution of rurban and peri-urban areas in the

Casablanca–Settat region. This approach provides a fine-scale, diachronic understanding of territorial dynamics.

2. Related Works

2.1. Defining Urban Areas

The urban space and its delimitation represent one of the most controversial topics within human geography and urban planning. This controversy results from the variety of perspectives and methods used, as well as differences in spatial and temporal reality [7,8].

Perhaps the biggest scientific and political issue is connected to the statistical delimitation of urban space, which ensures the comparability of data, public investment distribution, and territorial planning. As stated by Bairoch and Goertz [9], the criteria adopted for defining the boundaries are very varied, making the analysis very tricky and possibly erroneous [10,11]. In the French case, for instance, the INSEE has created a hierarchy of zoning in order to account for the urban reality. The notion of "urban unit" represents a set of contiguous communes making up a built-up area with at least 2000 people as its primary urban boundary [12,13]. Then, the "urban attraction zone" takes into account communes having at least 15% of workers who commute to the urban core [14]. Furthermore, other agencies have suggested other criteria for improving the urban statistical delimitation. Population density profiles represent the most empirically verified regularity in urban geography, where the classic model of negative exponent,

$$D(x) = D_0 \times \exp(-\alpha \times x), \quad (1)$$

describes the decay of density with distance from the city center.
where:

- $D(x)$ is the population density at distance x from the urban center;
- D_0 is the theoretical central population density;
- x is the distance from the urban center;
- α is the population density gradient (density decay coefficient), controlling the rate of density decrease with distance from the urban center;

2.2. Defining Rural Areas

There is a wide range of socio-spatial characteristics that distinguish rural areas. Although these characteristics are changing rapidly, they still represent distinctive traits compared to urban spaces. Universally, low population density is the most recognized criterion for defining such territories. The Organization for Economic Cooperation and Development suggests that a territory is rural if more than 50% of its population resides in communities whose population density does not exceed 150 inhabitants/km^2. Even though it is rather subjective, the said criterion helps compare rural areas worldwide.

Rural areas are characterized by the predominance of agricultural, livestock, and forestry activities, which remain limited in generating significant economic growth due to population dispersion and illiteracy [11]. In developed countries, the contribution of these activities to GDP and employment has declined, reflecting a shift toward industrial sectors [14]. Socially, rural areas exhibit a distinct structure based on close ties of proximity, kinship, and neighborhood, stronger than in large cities, which helps to understand population dynamics and differentiate these areas from others [15].

2.3. Defining Peri-Urban Areas

The term "peri-urban" originates from the prefix "peri-", meaning "around" or "near," combined with "urban," which pertains to cities or densely populated areas. The concept

emerged in the 20th century as urbanization spurred the expansion of cities, leading to the formation of transitional zones on the outskirts [15]. These zones, characterized by a blend of urban and rural land uses, faced distinct challenges related to land use, infrastructure, and governance [11].

Peri-urban areas are understood as transitional interfaces between rural and urban spaces, where urban and rural dynamics coexist. These territories experience continuous pressure driven by the outward expansion and exogenous growth of urban areas [16–19]. They are often characterized by a fragmented and heterogeneous combination of urban and rural functions, while accommodating land uses that may be undesirable for local communities, such as business parks, large entertainment facilities, and shopping centers [20,21].

Peri-urban refers to the space surrounding the city and is characterized by urban influences, ready access to markets and facilities in the city [22]. The peri-urban areas are normally loosely defined as the interface between urban land use and rural land use. Alternatively, they may be regarded as the countryside of the city. There are no firm boundaries for such peri-urban areas since they are diffused zones and are also viewed as transitional zones [23]. Conventionally, the transitional zones were viewed as areas with diversified land uses and active land markets, as well as mixed labor, both rural and urban. The peri-urban zones are also characterized by heterogeneous populations, mostly comprising poor migrants from the countryside searching for jobs.

Peri-urban areas are commonly described as transitional spaces between urban and rural land uses, often referred to as the "city's countryside." Their boundaries are generally fluid and poorly defined, reflecting their diffuse and evolving nature. These zones are traditionally characterized by diverse land uses, dynamic land markets, and mixed employment structures combining rural labor and urban-based activities [24]. They also host heterogeneous populations, including many low-income rural migrants engaged in informal and multiple income-generating activities. Furthermore, peri-urban areas exhibit distinct characteristics in developed (Northern) and developing (Southern) countries [22].

National criteria used to classify areas as urban generally rely on one or several indicators, including population size, population density, the share of non-agricultural employment, and the availability of infrastructure. Nevertheless, distinctions between urban, rural, and peri-urban spaces continue to shape and influence planning policies and territorial development strategies [25,26].

2.4. Defining Rurban Areas

Introduced by Bauer and Roux in their seminal work [27], this concept refers to an urban-origin population settling in rural communes located beyond the immediate peri-urban areas, without these communes losing their fundamental rural character. This definition distinguishes rurbanization from suburbanization: while suburbanization transforms the invaded areas into urban spaces, rurbanization implants urban elements within a structurally intact rural fabric.

"Rurbanization" is inevitably an evolving process that affects the periphery of urban agglomerations. On a small scale, it is part of the overall process of population concentration in urban regions, at the expense of rural areas [28]. On a larger scale, it contributes to the dispersion of urban activities and functions over an increasingly extensive territory, regardless of the intensity of urban growth [29,30]. All processes of evolution in peri-urban rural areas can be considered "rurban," provided that they are accompanied, at least temporarily, by discontinuity in the built environment and its intermingling with forest and agricultural lands. The concept of "rurban" can be limited to the growth of rural municipalities due to the arrival of a predominantly urban population [28].

The term "rurban" was reintroduced and used more consistently when several Indian researchers adopted it to describe urbanization processes in India, though with some nuances in their specific definitions [31]. Revi defines "rurbanism" as a process that integrates the urban and the rural, allowing for the co-evolution of the countryside and the city that is embedded within it. In 2016, the term even lent its name to a national rural development program in India, "India's National Rurban Mission" [32].

The concept of rurbanization encompasses two perspectives. On one hand, it refers to the residential migration of the urban population to surrounding rural areas, implying an outflow of people from the city center to peripheral rural regions [21]. On the other hand, it includes all processes reflecting the decentralization of urban functions to peri-urban areas [30].

Several studies have been conducted by different sociologists, including the French sociologist Henri Lefebvre, on rurbanization. He described it as a "total" phenomenon that suspended the rural–urban divide and thus the historical categories of urban and rural. Accepting that the rural and urban continue to coexist, they are organized in specific intertwinements called "rurban." Therefore, "rurban" is considered a continuous reconfiguration of material flows, practices, contexts of meaning, and spatial structures. The analysis of "rurbanity" thus involves a constant repositioning within the dynamic relationships between the rural and the urban [32].

Rurban areas are characterized by the persistence of rural landscapes, traditional activities, and strong local identity, despite increasing urban influence and the emergence of new services and transport infrastructure [33]. These territories tend to preserve traditional social practices and develop their own socio-cultural dynamics as interfaces between the countryside and the city. Morphologically, they are generally defined by low-density residential settlements with high landscape value, although they are increasingly exposed to environmental pressures and considered fragile ecosystems. Unlike suburban or peripheral zones, rurban areas are typically located farther from the urban core [16].

2.5. Contribution of Deep Learning and Machine Learning to Urban–Rural Spatial Analysis

Data-driven and spatially explicit approaches play a fundamental role in capturing the complexity of rural–urban areas [16]. The integration of multi-source spatial indicators, such as land-use patterns, population density, and accessibility measures, enables a more objective and comprehensive delineation of peri-urban landscapes [34]. By moving beyond traditional binary classifications of urban and rural spaces, this perspective emphasizes the existence of a continuous gradient and highlights the transitional and heterogeneous nature of peri-urban environments [35].

In the context of urban–rural transition zones, the challenges of land use/land cover (LULC) classification are particularly acute. Rurban areas are characterized by exceptional spatial heterogeneity, where agricultural plots, residential subdivisions, vacant lands undergoing urbanization, and natural residential spaces coexist within small areas [36]. This heterogeneity generates significant inter-class confusion, particularly between "peri-urban," "rurban," and "bare agricultural land" classes, which exhibit similar spectral signatures in Sentinel-2 imagery [37].

Image classification using parametric approaches, like the maximum likelihood classifier (MLC) [38], had been used, assuming that distributions of spectra were normal, while this was hardly ever the case for mixed classes, e.g., rurban areas. Development of new non-parametric classifiers: firstly, decision trees [39]; secondly, support vector machines [40]; thirdly, random forests have gradually improved classification accuracy, especially for highly detailed nomenclature and intricate landscapes [41].

Machine learning has played a crucial role in automatized LULC classification [42,43]. Firstly, ML is capable of working with multidimensional input data: images from satellites like Sentinel-2 containing 13 bands supplemented by textural parameters and indices result in 30–100-dimensional vectors, which could be used by non-parametric techniques without any assumptions regarding the distribution of data. Secondly, machine learning algorithms have no limitations with regard to small sample sizes within rurban areas, e.g., a lack of certified ground truthing, which allows them to use, e.g., SOM [44].

Among unsupervised methods, Kohonen's Self-Organizing Maps (SOM) occupy a distinctive position in the taxonomy of LULC classification algorithms [24]. Unlike standard clustering methods such as K-Means or ISODATA, the SOM performs a non-linear dimensionality reduction while preserving the topology of the input space, so that spectrally or statistically similar classes are represented by neighboring neurons on the two-dimensional output grid [24,45]. This topology-preserving property is particularly valuable for visualizing and interpreting the gradual transitions between land-use classes that characterize rurban–peri-urban interfaces. Recent quantitative work supports its effectiveness for territorial typologies: Tonini et al. [43], working at the municipal scale in Switzerland with 18 physical, demographic and socio-economic variables, coupled a SOM with hierarchical clustering and identified six distinct typologies along the rural–urban continuum, explicitly capturing critical phenomena such as agricultural-land loss and encroachment into ecologically sensitive areas. Their study is methodologically close to ours, yet it differs on two points that motivate our contribution: it is mono-temporal and does not benchmark the SOM against an explicit expert reference, so the agreement between the data-driven typology and domain knowledge is not quantified. Our study addresses both gaps by introducing a diachronic design (2014 vs. 2024) and an explicit external validation against expert rules [24,43,45–49].

Nonetheless, while the SOM excels at topological preservation and interpretability, it organizes spatial units primarily on the basis of their feature similarity and does not explicitly model the relational structure that links neighboring entities, that is, the interactions that arise when territorial dependencies extend beyond local feature resemblance. Graph Neural Networks, among the most recent contributions to deep learning in non-Euclidean space, adopt a different representational strategy by encoding spatial units as nodes and their relationships as edges, thereby making neighborhood interactions explicit. Comparing these two paradigms, one feature-driven and topology-preserving, the other relation-driven, therefore offers a means of examining how alternative representations of spatial structure perform in delineating the rural–urban continuum [50].

Bai et al. [51] applied Graph Clustering Neural Networks to delineate urban functional areas in Beijing, reporting improved accuracy and efficiency over traditional attribute-only or image-based clustering precisely by exploiting spatial relations between territorial entities. Building on this paradigm, Zhang et al. [52] introduced a multilevel GNN combined with multimodal geospatial data, whose hierarchical graph captures both local connections between neighboring units and city-wide dependencies, demonstrating clear gains for urban–rural continuum assessment. The reported performance of such supervised, multi-source graph frameworks achieves overall accuracies of roughly 76% across cities such as Zhuhai and Singapore [53], with human-mobility features contributing measurably to the discrimination of functional patterns.

3. Materials and Methods

3.1. Overall Methodological Framework

In this study, a hybrid classification method is introduced with the goal of describing the rural-to-urban continuum in the Casablanca–Settat Region. This hybrid classification

framework involves applying machine learning unsupervised classification algorithms such as SOMs and GNNs and combining the results through expert rules and a hybrid classification fusion scheme.

This process will be conducted using data from two years (2014 and 2024). The proposed method consists of the following three components as represented in Figure 1:

A data-based classification technique (SOM or GNN) that discovers hidden structures within the data
An expert rule set based on the underlying domain knowledge and statistical thresholds
A hybrid decision-making process resolving any contradictions and increasing robustness



Figure 1. Methodology.

3.2. Study Area

The Casablanca–Settat region covers 19,448 km^2 in the center-west of Morocco [11] as represented in Figure 2. It encompasses 168 communes, extending from the Atlantic coast to the Chaouia plains, and represents 20.3% of the national population, with an urbanization rate of 82.4%, the highest in the country [8].

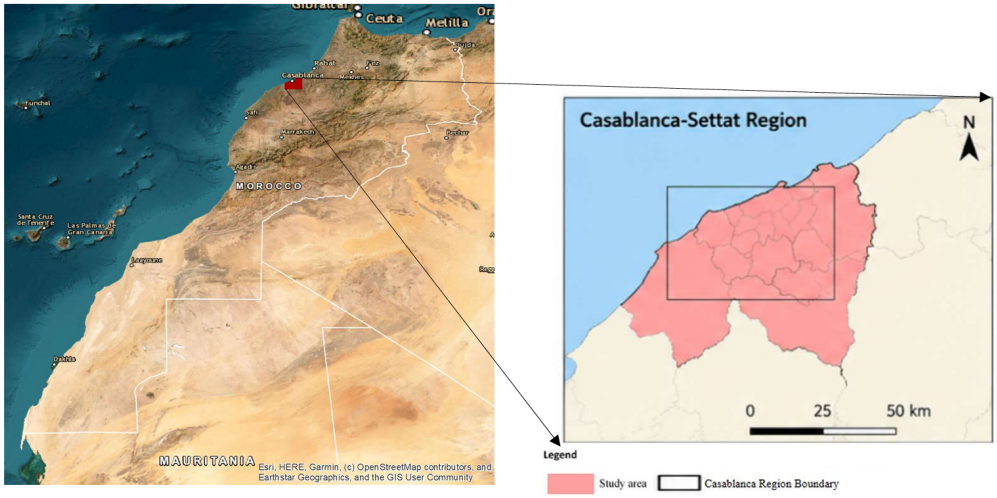


Figure 2. Study area.

3.3. Data Analysis

This study uses a dataset that combines multi-sourced spatial, environmental, socio-economic, and demographic variables at the level of the commune within the Casablanca–Settat region. The spatial variables consist of the administrative units and indices such as NDVI, NDWI, and SAVI derived from the Sentinel-2 images, which describe vegetation coverage, moisture condition, and surface properties respectively. Environmental factors are supplemented by built-up and population layers from the Global Human Settlement Layer, which provides consistent settlement and population information. The socio-economic variables consist of educational attainment, illiteracy percentage, employment, activity ratio, and service accessibility, which are collected through the Moroccan national census (RGPH), as represented in Table 1. All datasets have been harmonized and merged based on the commune codes, followed by pre-processing tasks.

Table 1. Datasets and indicators used in the study.

Features	Dataset	Indicator	Description and Source
Spatial & Environmental	Administrative boundaries	Geometry	Commune boundaries used as spatial units. Source: regional GIS shapefile.
	Sentinel-2 indices (March 2014/ March 2024)	NDVI	Vegetation density indicator. Source: Sentinel-2 imagery.
		NDWI	Surface water/moisture indicator. Source: Sentinel-2 imagery.
		SAVI	Vegetation index adjusted for soil effects. Source: Sentinel-2 imagery.
	GHSL layers	Built-up Surface (GHS-BUILT-S)	Built-up area extent. Source: GHSL (Copernicus).
		Settlement Model (GHS-SMOD)	Urban–rural classification. Source: GHSL (Copernicus).
Demographic	Census and GHSL population 2014/2024	Total Population	Population per commune. Source: RGPH census.
		Population Grid (GHS-POP)	Spatial population distribution. Source: GHSL (Copernicus).
Socio-economic	Education	School Enrollment (6–11)	Primary education rate. Source: RGPH.
		Illiteracy Rate	Population without basic education. Source: RGPH.
		Higher Education Rate	Population with tertiary education. Source: RGPH.
		Preschool Enrollment	Early education participation. Source: RGPH.
	Employment	Unemployment Rate	Labor market condition. Source: RGPH.
		Activity Rate (>15)	Economic participation rate. Source: RGPH.
	Infrastructure	Service Facilities	Number of public services. Source: RGPH.

The input feature vectors combine normalized socio-economic and environmental indicators, including population structure, education level, unemployment rate, and land-use proxies derived from spatial analysis. All variables were scaled using robust normalization to reduce the influence of outliers and ensure comparability across indicators. The resulting feature matrix constitutes the input to the hybrid classification framework, where it is processed through dimensionality reduction (PCA), which was applied to reduce redundancy among the socio-economic and environmental indicators and to mitigate potential multicollinearity effects. The use of PCA also facilitates computational efficiency and improves the stability of subsequent clustering and graph-learning processes by concentrating the dominant variance structure into a reduced set of orthogonal components. The objective of PCA in this study was to provide a robust and interpretable feature space suitable for comparative SOM and GNN analyses, which was combined with K-Means and expert rule-based inference to generate the final four-class territorial segmentation; 0 corresponds to Urban, 1 to Peri-urban, 2 to Rurban, and 3 to Rural.

3.4. Statistical Thresholding and Expert-Based Rules

An important part of the methodology is the creation of an adaptive expert classification system, which consists of the transformation of the information about the domain into a specific set of decision rules. In contrast to the traditional approach based on pre-set threshold values, this technique uses dynamically computed thresholds according to the empirical distribution of the studied variable over time.

The 10th, 25th, 50th, 75th and 90th percentiles for each indicator are calculated, as represented in Table A1. Further, the thresholds are determined according to the theory concerning the relation between the variables and the class in question. Thus, high population and low NDVI are typical characteristics of urbanized zones, whereas low population and high NDVI indicate the presence of rural zones. The percentiles are then clamped in scientifically reasonable boundaries, based on the existing literature.

As for the classification process, it involves the creation of the hierarchical decision tree, where the best criteria (the ones that provide maximal information gain) are tested first. Thus, urban zones can be detected as having a high population, a high service index, and socio-economic development. Rural zones are characterized by the opposite parameters. As for intermediate classes, including rurban and peri-urban classes, other sets of criteria are used.

To handle ambiguous cases, a composite urbanization score is introduced. This score aggregates multiple normalized indicators using weighted coefficients reflecting their relative importance in urban theory. It serves as a fallback mechanism, ensuring that all communes can be classified even when strict rule conditions are not met.

This hybrid rule-based system ensures both interpretability and adaptability, making it particularly suitable for territorial analysis.

3.5. Self-Organizing Map (SOM) for Classification

Regarding the 2024 dataset, a Self-Organizing Map (SOM) is used for finding the internal structure of the data without supervision. SOM is an artificial neural network projecting high-dimensional data onto a two-dimensional grid in order to preserve topological properties.

For the 2024 dataset, the SOM is constructed as a 6×5 grid (30 neurons), whereas the 2014 dataset uses an 8×8 configuration (64 neurons), as represented in Table A2. This difference in grid size is explained by changes in the underlying data structure between the two years. The 2024 dataset is characterized by a higher degree of spatial continuity and more pronounced transitional patterns, reflecting the intensification of urbanization

processes. This leads to reduced separability between some municipal profiles within the feature space. During training, which lasts for 2000 iterations and uses PCA-transformed input data, each commune corresponds to a Best Matching Unit (BMU), that is, to a neuron having the closest weight vector compared to the vector of an observation. Neurons adjacent to a certain BMU are updated at the same time as the latter.

The use of topology allows the SOM to represent the smooth transition between classes rather than imposing a strict border on them. As for classification, the profile of each neuron is calculated based on original variables, and then expert decision rules are applied at the neuron level. Finally, each commune obtains the class label from its BMU.

This method provides some smoothing of spatial distribution because it reduces sensitivity to local phenomena. Thus, it is especially useful when analyzing data that has some continuity, for example, urbanization.

3.6. Graph Neural Network (GNN) for Classification

Graph Neural Network (GNN) relies on the topology of the territory and models interactions between neighboring communes. The input data consist of 12 normalized socio-economic and environmental variables processed using the RobustScaler method and subsequently reduced through Principal Component Analysis (PCA) into 8 principal components in order to reduce dimensionality while preserving the main variance structure of the dataset.

A spatial graph is constructed in which nodes represent communes, and edges are created between nodes whose corresponding communes share common borders, reflecting the spatial contiguity between territorial units. A Graph Autoencoder (GAE) is then applied to this graph using a two-layer Graph Convolutional Network (GCNConv) architecture that projects node representations from 16 to 8 latent dimensions. The model is trained for 500 epochs on the spatial adjacency graph in order to generate low-dimensional embeddings that preserve both attribute similarity and spatial connectivity. The GAE is optimized using a combined reconstruction loss based on Mean Squared Error (MSE) and Binary Cross-Entropy (BCE).

The training process is performed using a joint objective function that includes reconstruction of node features as well as the adjacency structure of the graph. As a result, the embedding space of communes contains clusters grouping territories with similar socio-environmental characteristics while also preserving geographical proximity. The resulting embeddings are L2-normalized before the clustering stage.

Cluster assignment is subsequently performed using an over-partitioned K-Means clustering approach (K = 8) applied to the normalized embeddings in order to capture finer spatial structures and transitional territorial forms. The final cluster classification is then determined according to a triple voting criterion including average cluster classification, median classification, and the individual class assignment, as represented in Table A3.

3.7. Hybrid Classification and Decision Fusion

To leverage the strengths of both machine learning and expert knowledge, a hybrid classification strategy is implemented. This step combines the outputs of the SOM or GNN models with the results of the rule-based classification.

The fusion process follows a hierarchical logic. When both approaches agree, the classification is considered highly reliable and assigned a high confidence level. In cases of minor disagreement, typically between adjacent classes such as rural and rurban, the rule-based classification is retained, and a medium confidence level is assigned.

More complex disagreements, particularly between rurban and peri-urban classes, are resolved using additional criteria based on population size, NDVI, and unemployment

rate. These variables serve as tie-breakers, reflecting key dimensions of territorial transition. When inconsistencies cannot be resolved, the classification is retained with a low confidence level, explicitly acknowledging uncertainty.

This fusion mechanism enhances the robustness of the classification by combining data-driven insights, spatial coherence, and theoretical consistency while also providing a transparent measure of uncertainty.

3.8. Model Validation and Performance Assessment

Performance evaluation of classification consists of external and internal validation measures to ensure reliable results.

External validation evaluates the degree of correspondence between machine learning-based predictions and expert classification results. It is quantified with the help of the overall agreement percentage and the value of Cohen's kappa, taking into account agreement due to coincidence. Results demonstrate moderate agreement, highlighting the complementary aspects of each approach.

Internal validation evaluates the quality of clustering in a feature space. For that purpose, Silhouette index, Davies–Bouldin index, and Calinski–Harabasz index were used to quantify cluster compactness and separability. As a result, it was found that there is little separability between classes with overlapping clusters and dispersed points.

4. Results

4.1. GNN-Based Spatial Classification Results

These findings reveal a global stability of the spatial configuration from 2014 to 2024, with urban nuclei maintaining high levels of concentration while rural regions continue to occupy peripheral positions. Nonetheless, such stability conceals essential rearrangements on the inside, especially in the transitional regions. The most prominent rearrangements take place in peri-urban and rurban environments, which serve as the interface between rural and urban systems. This underscores the notion that the study region operates within a spatial continuum rather than a rigid binary system.

The development of extended peri-urban zones occurs throughout the whole course of observation. Along with this, an increased degree of fragmentation of neighboring rural zones is noted. Such a pattern of spatial dynamics reflects an existing process of expansion of urban zones due to population growth, changes in the land use type, and construction. Peri-urban zones grow and start functioning as intermediary zones of communication between rural and urban zones.

It should be said that among all zones considered, rurban ones demonstrate the highest degree of instability, showing significant spatial dynamics toward either rural or peri-urban zones. In this way, it confirms their hybrid character, where the presence of both rural and urban functions can be seen. They serve as transitional zones with socio-economic heterogeneity.

In contrast, rural areas show a relative decline in spatial continuity, with increased fragmentation in 2024. This trend suggests a gradual integration of rural spaces into the broader urban system, driven by increasing urban pressure. Meanwhile, urban areas remain structurally stable and spatially compact, reflecting strong centrality and consolidation processes typical of established urban cores, as represented in Figure 3.

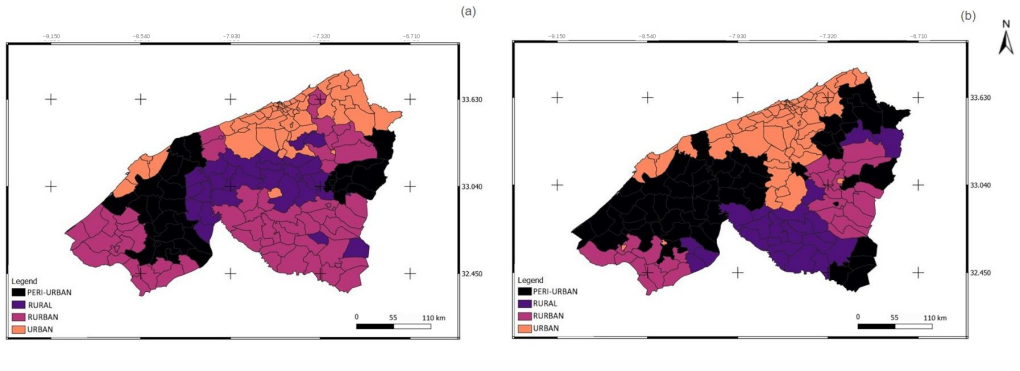


Figure 3. Spatial delineation of urban, peri-urban, rurban, and rural areas using GNN model for 2014 and 2024 (**a**,**b**).

4.2. Validation of the GNN-Based Classification

The quality of the classification is assessed along two complementary dimensions: (i) the agreement between the Graph Neural Network (GNN) predictions and expert-defined rules (external validation); (ii) the geometric quality of clusters obtained via K-Means in the embedding space learned by the GNN (internal validation), as represented in Table 2.

Table 2. Validation metrics of the GNN-based classification (2014 vs. 2024).

Metric	2014	2024	Interpretation
Silhouette Score	≈0.12	≈0.10	Weak but positive cluster structure; slightly reduced separability in 2024 due to a stronger urban continuum.
Davies–Bouldin Index	≈2.1	≈2.3	Slight increase in 2024, indicating greater overlap between clusters and reduced compactness.
Calinski–Harabasz Index	≈28	≈25	Decrease in 2024, reflecting weaker inter/intra-cluster separation and a more continuous spatial structure.
GNN vs. Rules Agreement	53.0%	≈51%	Moderate and stable agreement between the GNN model and expert rules across both years.
Cohen's Kappa	0.326	≈0.31	Fair agreement level according to expert rules, remaining relatively stable over time.

Spatially explicit measures of the confidence, resulting from comparing classification performed by the GNN and expert rules, indicate the existence of a spatial variation in classification reliability. Indeed, high-confidence cells tend to be concentrated on homogeneous territories, especially in clearly rural and urban communes, since both classification methods give the same results based on easily identifiable socio-environmental profiles. Medium-confidence cells, on the other hand, are distributed throughout the territory because they correspond to moderate disagreements between the two methods, possibly related to the dynamics of transition. Low-confidence cells are more specifically found in peri-urban and rurban communes, as represented in Figure 4.

These territories, indeed, being at the intersection of rural and urban spaces, are characterized by a variety of criteria leading to their indetermination. It therefore confirms that uncertainty does not occur randomly but structurally within transition zones, in accordance with the inherent complexity of the rural–urban gradient.

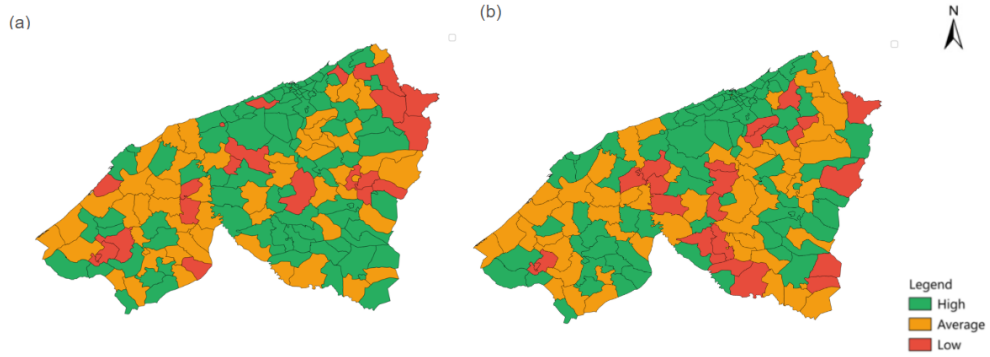


Figure 4. Confidence level GNN in 2014 and 2024 (**a**,**b**).

4.3. SOM-Based Spatial Classification Results

4.3.1. Mapping and Visualization of Results

The SOM-based classification highlights the spatio-temporal evolution of the rural–urban continuum between 2014 and 2024, revealing a substantial transformation in the territorial structure. Based on the integration of socio-economic and environmental variables, four main classes are identified: urban, peri-urban, rural, and rurban. These classes form a continuous spatial gradient, reflecting different levels of urban influence and land-use intensity, as represented in Figure 5.

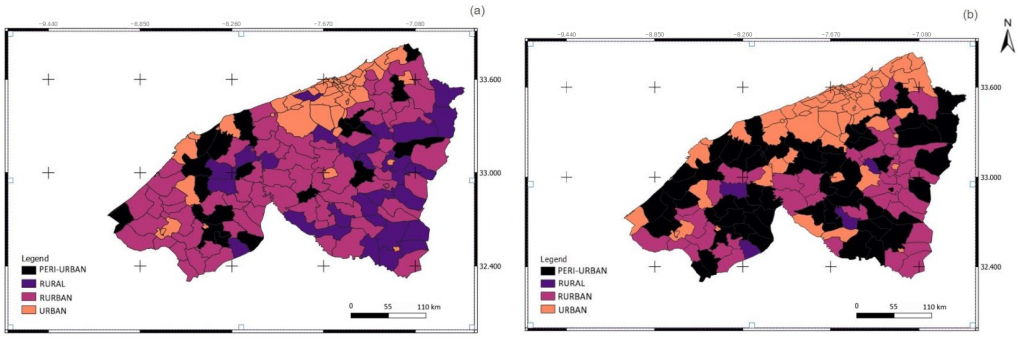


Figure 5. Spatial delineation of urban, peri-urban, rurban, and rural areas using SOM model for 2014 and 2024 (**a**,**b**).

For the year 2014 (Figure 5a), the spatial structure is relatively organized and is characterized by rural and rurban types of settlements. The rural type covers large areas continuously, especially in the middle and lower regions of the area, suggesting the predominance of agriculture and minimal influence from urbanization. On the other hand, the rurban type is prevalent across the whole region, including transition zones of rural and urban features with moderate and dispersed urbanization activities. The urban type is located mostly in the northern and northwestern regions, forming dense clusters corresponding to established urban areas. Contrarily, the peri-urban type appears in small and scattered forms, existing around the edges of urban areas.

As can be observed in Figure 5b related to the year 2024, there is an enormous change in terms of spatial configuration in relation to the urbanization process. The main thing that should be mentioned in this regard relates to the significant growth of the peri-urban spatial class, which becomes the leading one. It becomes much larger and more continuous because of intense urban sprawl. Additionally, the urban spatial class has moderate expansion toward the outside, which means that it becomes less dense and scattered as a result of urbanization processes and infrastructure development. On the contrary, the rural spatial

class regresses significantly and becomes fragmented and isolated in nature as it comprises only small patches located in peripheries. It also indicates increased pressure on agriculture. Finally, the rurban spatial class regresses and becomes fragmented and embedded in peri-urban spatial classes.

Thus, a comparison of figures in 2014 and 2024 indicates a transition from a rather balanced structure of rural–rurban dominated landscape to a peri-urban dominated landscape. It can be stated that it is due to the growing intensity of urban sprawl, rural fragmentation, and mutual influence between land use spatial classes.

4.3.2. Classification Performance Metrics

The validation results highlight contrasting clustering behaviors between 2014 and 2024, reflecting the evolving complexity of the urbanization process, as represented in Table 3.

Table 3. Synthesis of SOM-based classification validation metrics (2014 vs. 2024).

Metric	2014	2024	Interpretation
Silhouette Score	0.142	−0.036	Decrease from positive to slightly negative values, indicating increasing overlap and a stronger urban continuum in 2024.
Davies–Bouldin Index	1.18	1.190	Remains stable and low, confirming consistent cluster compactness across years, with slight degradation in 2024.
Calinski–Harabasz Index	42.5	12.1	Strong decrease in 2024, reflecting weaker cluster separability and a more continuous spatial structure.
SOM vs. Rules Agreement	89.3%	58.9%	Significant drop, showing reduced correspondence with expert rules due to increased heterogeneity of the urban system.
Cohen's Kappa	0.842	0.428	Transition from almost perfect to moderate agreement, confirming a structural shift in spatial organization and increased class ambiguity.

Internal validation measures clearly demonstrate for 2014 that there is a structured and improvable clustering. According to the value of the Silhouette coefficient (≈0.14), one may conclude that the classes have some intersection because, in case of ordinal classification, classes' boundaries are not sharp and there exists the continuum of urbanization between rural, peri-urban, and urban territories. In turn, the Davies–Bouldin index (≈2.0) lies within reasonable limits and proves the superiority of inter-cluster distances over intra-cluster ones. Finally, according to the Calinski–Harabasz index (≈42.5), the clustering structure is moderate but real. This conclusion is supported by the type of clustering. For ordinal classifications, it is characteristic that class boundaries are semantic and not geometrical; thus, classes may be elongated or non-convex. External validation clearly confirms this idea: Cohen's Kappa ($\kappa = 0.842$) reveals a strong agreement between SOM and expert rules, meaning that an unsupervised method captures the intrinsic data structure and is in line with human knowledge.

Additionally, a direct comparison between 2014 and 2024 further helps explain the observed degradation in SOM performance. The internal validation metrics consistently indicate a progressive loss of cluster separability over time. The Silhouette score decreases from a positive value in 2014 (≈0.142), indicating a relatively structured clustering, to a slightly negative value in 2024 (≈−0.036), reflecting increased overlap between classes and a stronger expression of a continuous urban gradient. Similarly, the Calinski–Harabasz index drops substantially from ≈42.5 in 2014 to ≈12.1 in 2024, confirming a marked

reduction in inter-class separability and a shift toward a more diffuse spatial organization. Although the Davies–Bouldin index remains relatively stable (≈1.18 to ≈1.190), suggesting that intra-class compactness does not significantly deteriorate, the overall pattern indicates that classes become less distinguishable in terms of between-class structure.

This temporal contrast is also reflected in external validation results. The agreement between SOM outputs and expert rules decreases from 89.3% in 2014 to 58.9% in 2024, while Cohen's Kappa declines from 0.842 (almost perfect agreement) to 0.428 (moderate agreement), as represented in Figure 6. Rather than indicating methodological instability, this evolution is better interpreted as evidence of increasing territorial complexity and blurring of functional boundaries within the rural–urban continuum. In particular, the 2024 landscape appears to be characterized by stronger peri-urban diffusion, higher spatial heterogeneity, and more gradual transitions between classes, all of which reduce the sharpness of rule-based and clustering-based separations.



Figure 6. Classification confidence levels of communes in 2014 and 2024 (**a**,**b**).

In contrast, the 2024 classification (Figure 6b) exhibits a marked increase in uncertainty. The proportion of high-confidence communes decreases noticeably, while medium- and low-confidence classes expand spatially across the study area. Low-confidence zones become more frequent and less localized, reflecting a broader mismatch between SOM outputs and expert rules. This shift indicates that a larger number of communes now fall within transitional or hybrid profiles, where distinguishing between rural, peri-urban, and urban characteristics becomes more challenging.

4.4. Discussion: Selection of the Most Suitable Model

The comparative analysis of SOM vs. GNN methods in 2014 vs. 2024 years reveals that there is always a distinction between the ability to learn spatial structures and the interpretability of rural–urban continuum patterns. In general, both models can discover the spatial structure behind the urbanization process but with different strategies of representing this structure in accordance with domain knowledge.

GNN models mainly improve the learning process of spatial dependencies and provide representations that heavily rely on local neighborhood dependencies. Such an approach

guarantees that embeddings are highly flexible and efficient enough to represent complex spatial interactions, especially in areas with high spatial heterogeneity and urban–rural transitions. Nevertheless, such a high level of flexibility may lead to lower interpretability of discovered classes in comparison with the expert definition of urbanity.

Conversely, the SOM method offers an alternative strategy based on the hybrid formulation of the SOM model. It allows us to not only improve the stability and consistency of embeddings with the help of SOM but also provide interpretable and understandable classes according to domain knowledge.

Across both years, the evolution of results reflects a general increase in urban continuity and class overlap, which naturally challenges strict classification boundaries. In this context, the SOM demonstrates greater robustness in maintaining meaningful and interpretable structures, while the GNN offers complementary advantages in capturing fine-grained spatial dependencies.

Therefore, considering the objectives of the study, namely the extraction of meaningful and interpretable urbanization patterns, the SOM-based model is selected as the most appropriate framework for subsequent analysis, as it ensures a better balance between spatial representation, temporal stability, and expert consistency.

4.5. Spatial and Socio-Demographic Characterization of SOM-Derived Urbanity Classes

4.5.1. Class-Specific Spatial Distribution

From 2014 to 2024, the territory structure in question underwent substantial change, being characterized by a clear sequence of urbanization processes and reclassification of the intermediate types. The decrease in the number of rural municipalities (from 29 to 23) and rurban territories (from 62 to 47 units) demonstrates a reduction of the intermediate territories. On the other hand, there was a growth of urban municipalities (from 53 to 61) and the share of their population, as well as a significant increase in peri-urban areas (from 24 to 37). Such trends can be considered a territorial transition where former rurban areas mainly transform to either peri-urban or urban status, implying the emergence of a clearer rural–urban gradient. Therefore, one should note that these changes involve not only the growth of the urban core but also a more substantial expansion of urbanization processes to the periphery, a decline in intermediate territories, and, accordingly, an example of both intensive and extensive urbanization, illustrated by Figure 7.



Figure 7. Distribution of municipalities across rural, rurban, peri-Urban, and urban classes in 2014 and 2024 (**a**,**b**).

Between 2014 and 2024, the statistical distributions of environmental and socio-demographic variables across urbanity classes reveal a clear intensification of the urbanization process, accompanied by structural transformations in both landscape and population characteristics. Population distributions confirm a strong and increasing concentration in

urban areas, with a noticeable upward shift in median values in 2024, while peri-urban classes also experience growth, reflecting the expansion of intermediate urban forms. Rural areas, in contrast, remain relatively stable with lower population levels.

From an environmental standpoint, the NDVI scores retain their gradient between the rural and urban classes, that is, high values for the former and low ones for the latter. In 2024, the gradient appears weaker, notably between the peri-urban and urban classes, which is likely due to the spread of urbanization and blurring of the boundaries between vegetated and built environments. Socio-demographic indicators confirm the trend toward greater homogeneity between the classes.

Schooling rates, or the percentage of the population aged 6–11 who went to school, show a high level (99–100) and do not discriminate among the classes in 2024 as they used to in 2014. At the same time, the rates of analphabetism have a similar behavior, with a general decrease and closing difference between the classes. Finally, unemployment is more differentiated in 2024 with higher variability in urban and peri-urban areas.

Last, but not least, is the number of establishments. In 2014, it was nearly non-discriminative, whereas in 2024 it became more discriminating, particularly for the urban class, which shows significantly higher values and variability, as represented in Figure 8.

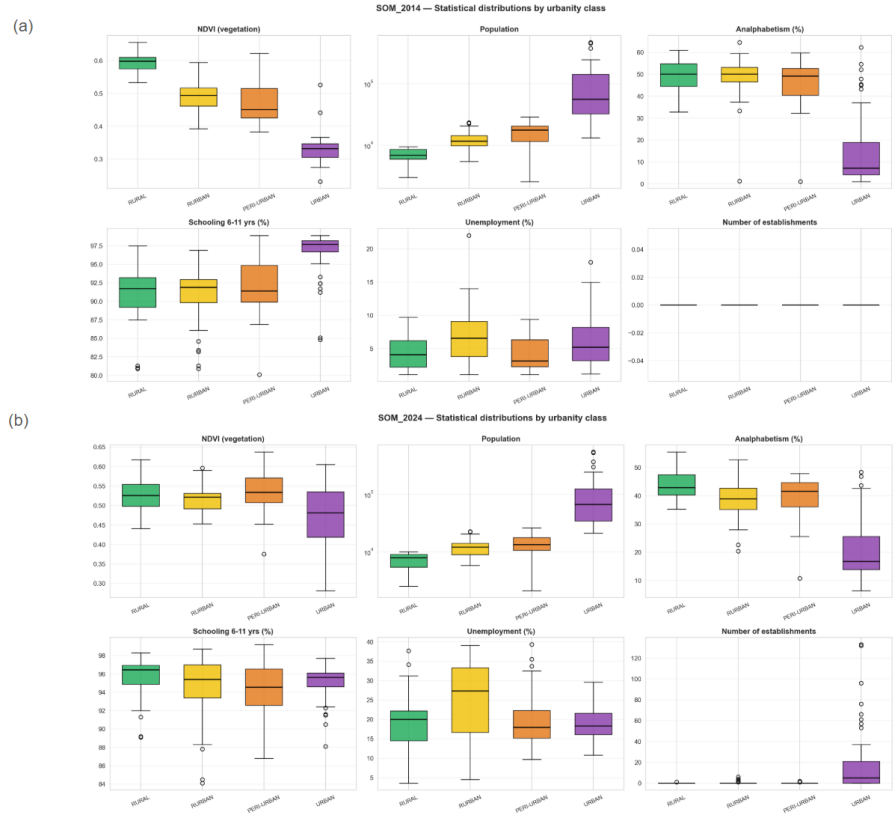


Figure 8. Urban expansion, environmental change, and socio-demographic dynamics between 2014 and 2024 (**a**,**b**).

4.5.2. Extraction of Discriminant Thresholds from SOM Clustering Results

1. Thresholds Defining the Urban Class

The urban cluster corresponds to the completely developed metro cities having dense built-up zones and well-established socio-economic structures. Very low NDVI readings (<0.10) demonstrate the almost complete transformation of natural vegetation into artificial land use, indicating a high level of urbanization, as represented in Table 4.

Table 4. Discriminant thresholds for the urban class.

Indicator	Threshold	Interpretation
NDVI	<0.10	Almost complete absence of vegetation, fully built-up environment
Population	>30,000 inhabitants OR very high indicators	High-density urban cores
Illiteracy rate	<15.0%	High educational attainment
Schooling rate	>92.0%	Strong access to education infrastructure
Higher education rate	>4.0%	Presence of advanced educational attainment
Number of establishments	>10	Dense service and economic infrastructure

The existence of more than 30,000 people indicates very good demographic concentrations and urban centrality. On the social dimension, there is evidence of high socio-economic performance, with over 92% in school and less than 15% being illiterate, demonstrating very good human capital endowments and accessibility to institutions. Also, the proportion of tertiary schools (>4%) is indicative of highly educated people and specialized knowledge industries.

Moreover, the large number of businesses (>10) implies a high level of economic diversification and service sector orientation, which is in accordance with the classic urban structure theory framework. Such a cluster is expected in completely developed urban centers, where the entire infrastructure and socio-economic systems have matured.

2. Thresholds Defining the Rural Class

The rural cluster corresponds to predominantly agricultural areas characterized by low population density and strong vegetation dominance. High NDVI values (>0.54) reflect extensive natural or cultivated land cover, including cereals and forested areas, confirming the ecological dominance of non-urban land uses, as represented in Table 5.

Table 5. Discriminant thresholds for the rural class.

Indicator	Threshold	Interpretation
NDVI	>0.54	Vegetation-dominated landscape (cereals, forests)
Population	<5000 inhabitants	Low-density dispersed settlements (douars)
Illiteracy rate	>35.0%	Limited access to education services
Schooling rate	<90.0%	Educational infrastructure scarcity and remoteness
Number of establishments	<1	Nearly absent socio-economic infrastructure

Population levels below 5000 inhabitants indicate highly dispersed settlements, typically organized in small hamlets or douars. Social indicators reveal structural disadvantages, with illiteracy rates exceeding 35% and schooling rates below 90%, highlighting limited access to education and basic services. The near absence of establishments confirms a very weak economic and infrastructural base.

Overall, this cluster reflects classical rural characteristics described in the literature, where agricultural activity dominates and accessibility to public services remains limited.

3. Thresholds Defining the Peri-Urban Class

Peri-urban class is a socio-spatial boundary between urban areas and rural zones. Indeed, the very low values of NDVI (<0.20) show that there was a clear decline in vegetation because of continuous land consumption and urban sprawl. Population size from 12,000 to 30,000 indicates a medium level of population density, which can be typical for expanding communes in relation to urban centers, as represented in Table 6.

Table 6. Discriminant thresholds for the peri-urban class.

Indicator	Threshold	Interpretation
NDVI	<0.20	Very low vegetation cover, indicating strong land artificialization.
Population	12,000–30,000 inhabitants	Medium-density settlements, typically expanding communes.
Schooling rate	>88.0%	Relatively good access to education services.
Illiteracy rate	<25.0%	Moderate social development, still showing inequalities.
Activity rate	>45.0%	High labor mobility, often linked to commuting toward urban centers.
Number of establishments	>4	Presence of basic services and local economic activity.

Nevertheless, some social parameters, namely the schooling index higher than 88% and the illiteracy rate lower than 25%, indicate that human resources improve and that people gain better access to public services. Nevertheless, all these values are lower compared to those in urban agglomerations, thus proving that the process of development of this region is still intermediate. The activity rate higher than 45% proves the functional dependence on urban zones and intensive commuting patterns.

In general, this cluster refers to a peri-urban continuum that has features of fragmentation, transitional dynamics, and increasing urban impact.

4. Thresholds Defining the Rurban Class

The rurban cluster can be defined as intermediary territories that lie between rural and urban systems and are known for their mixed land use and socio-economic development. NDVI ranging from 0.22 to 0.54 shows a decreasing trend in the vegetation cover due to growing human impact, as represented in Table 7.

A population of 9536 to 20,000 individuals points to an average degree of demographic concentration, which is characteristic for semi-urbanizing communes. A marked social disparity is evident from the high level of illiteracy (ranging from 20% to 52%) and the schooling level (about 90%).

The relatively high unemployment rate of more than 12% indicates socio-economic transformation, when the traditional farming sector operates alongside other employment sources. The presence of three to five establishments signals partial economic development.

Table 7. Discriminant thresholds for the rurban class.

Indicator	Threshold	Interpretation
NDVI	0.22–0.54	Decreasing vegetation cover, indicating land-use transition
Population	9536–20,000 inhabitants	Intermediate demographic concentration
Illiteracy rate	20.0–52.0%	Social transition and inequality gradients
Schooling rate	90.0–90.5%	Moderate access to education services
Unemployment rate	>12.0%	Ongoing economic restructuring
Number of establishments	3–5	Emerging but incomplete local economic structure

4.6. Geospatial Evaluation of Agricultural Suitability Across Rural–Urban Gradients

Having established the four-class urbanity typology and its diachronic evolution, we now examine its environmental corollary: the agricultural potential of each territorial class. Because peri-urbanization in the region proceeds largely at the expense of farmland (Sections 4.5 and 5), characterising where agricultural suitability is highest—and how it aligns with the urbanity gradient—directly informs which communes face the sharpest land-use trade-offs. The Potential Agricultural Score (PAS) introduced here therefore serves not as a standalone assessment but as a way to read the classification through the lens of agricultural value at risk. To this end, an agricultural suitability assessment was conducted across the urban, peri-urban, rurban, and rural territories of the Casablanca–Settat region using a geospatial multi-criteria approach, with the aim of supporting the integration of urban and peri-urban agriculture within the rural–urban continuum.

The methodology combines multispectral indices derived from Sentinel-2 imagery with the Analytic Hierarchy Process (AHP) applied to 2024 data. Four complementary spectral indicators at 10 m spatial resolution were integrated into the analysis: NDVI to evaluate vegetation vigor, SAVI to account for soil-adjusted vegetation conditions, NDWI to characterize water availability and surface moisture, and BUI to quantify built-up intensity and urbanization pressure. This integrated framework aims to identify territories with favorable conditions for the development and sustainable integration of urban and peri-urban agricultural practices within the rural–urban continuum.

The multispectral indices have been weighted using the AHP algorithm by means of the Saaty pairwise comparisons matrix. Vegetation-based indices have been more heavily weighted than the others according to their agricultural importance, while the BUI index was used to weight artificialized zones negatively. The consistency ratio computed using the AHP technique has shown that the approach is reliable (CR = 0.011).

Following strong normalization of the spectral indices, the Potential Agricultural Score (PAS) was generated based on a weighted linear combination per pixel. To prevent any overestimation of agricultural suitability in areas with high built-up intensity, an exclusion mask was created where only the pixels with built-up intensity higher than 0.15 were excluded from the analysis. The generated PAS values were subsequently classified according to five suitability classes, including very low to very high agricultural potential, allowing for the delineation of both suitable and unsuitable territories.

At last, zonal statistics were calculated for each commune. This technique allows for the quantification of the spatial variation of agricultural suitability in all territorial types.

The distribution maps show that there is significant variability in the agricultural suitability index within the Casablanca–Settat region. High and very high PAS regions are found mostly in agricultural regions, irrigation regions, and coastal regions where there is vegetation vigor and moisture availability. On the other hand, low PAS regions are found mostly in highly urbanized regions, arid regions, and regions with poor environmental quality, as shown in Figure 9.

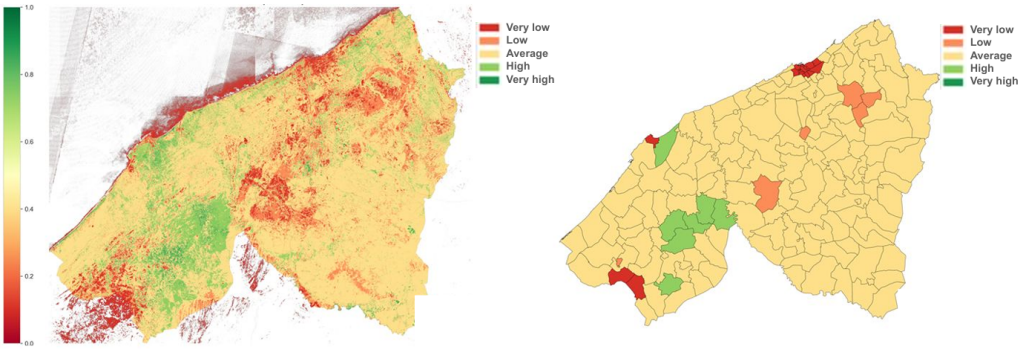


Figure 9. Spatial distribution of the agricultural suitability index in the Casablanca–Settat region.

The distribution of agricultural potential across the four urbanity classes reveals notable territorial differences. Peri-urban municipalities exhibit the highest average PAS value (0.397), indicating particularly favorable conditions for agricultural development. This result reflects the coexistence of agricultural land resources and relatively limited urban land consumption, allowing these territories to maintain significant agricultural functions while benefiting from proximity to urban markets and infrastructure.

Rurban and rural municipalities display comparable average PAS values (0.375 and 0.371, respectively). In rural areas, these values are associated with the predominance of natural and agricultural landscapes, lower levels of land artificialization, and generally favorable environmental conditions. Rurban municipalities, although increasingly influenced by urban expansion, still retain substantial agricultural land and ecological characteristics, resulting in moderate-to-high agricultural potential.

In contrast, urban municipalities present the lowest average PAS value (0.327). This lower suitability is primarily related to high levels of built-up land, reduced vegetation cover, and increasing environmental constraints associated with urbanization processes. The considerable variability observed within the urban class suggests that some municipalities still preserve localized agricultural opportunities; however, the overall trend indicates a progressive decline in agricultural potential as urbanization intensifies, as represented in Figure 10.

For the regional level, there is the emergence of a gradual shift from highly urbanized coastal/metro centers to inland/rural zones that favor agriculture, reinforcing the existence of a close association between the level of urbanization and the distribution of agricultural suitability zones.

The PAS score distribution indicates that the study site is dominated by medium potential for agriculture. The graph depicts a near-normal distribution curve with a mean and median of 0.403 and 0.400, respectively, demonstrating an even distribution of suitability zones within the region. There is also a higher concentration of pixels that fall under the category of 0.30–0.50, representing the average suitability class as shown in Figure 11.

The classification outcome proves this point further, as 63.3% of the total number of pixels were found to belong to the average category, 12.8% and 10.6% being in the very low and low suitability categories. At the same time, only 11.7% and 1.7% of the pixels

have been placed in the high and very high suitability categories. It can be seen from this result that although cultivation is possible all over the area, there are only few places with extremely favorable conditions. One reason for the occurrence of moderately suitable zones could be the environmental restrictions, such as poor soils or lack of water, as illustrated in Figure 11 below.

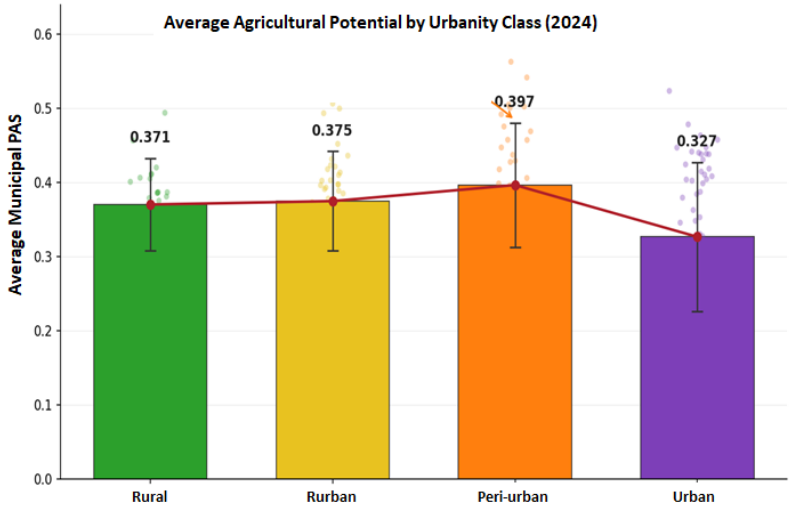


Figure 10. Average Agricultural Potential Score (PAS) by urbanity class in 2024.

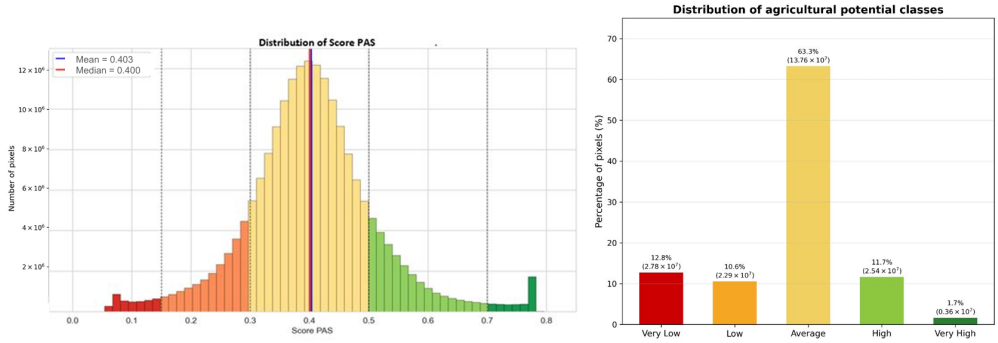


Figure 11. Statistical distribution of PAS values.

5. Discussion

The present study demonstrates that the rural–urban continuum in the Casablanca–Settat region cannot be adequately represented through a simple binary distinction between rural and urban territories. Instead, the results confirm the existence of intermediate and highly dynamic spatial forms, particularly peri-urban and rurban areas, whose evolution reflects ongoing territorial restructuring processes driven by demographic growth, urban sprawl, and socio-economic transformation.

As evidenced by the comparison of 2014 and 2024, the urbanization process has intensified across the region. The increase of peri-urban areas along with the degradation and fragmentation of rural territories shows the expansion of urban influence not only to the outskirts of urban territory but also to surrounding communes. As confirmed by the existing literature, peri-urbanization implies the spatial diffusion process that combines fragmentation and diversity of land use as well as the growing functional dependence of peri-urban area on the city [18,19,21–24,26]. Moreover, rurban territories have been found to act as unstable transitional spaces which combine both characteristics of rural and urban territories.

The environmental indicators, particularly NDVI, reveal a significant decline in vegetation cover in urban and peri-urban areas between 2014 and 2024. This trend reflects

increasing artificialization of land surfaces and agricultural land conversion under urban pressure. Similar dynamics have been reported in studies on Mediterranean and North African metropolitan regions, where urban expansion contributes to the fragmentation of agricultural landscapes and ecological degradation [11]. The weakening distinction between peri-urban and urban NDVI distributions in 2024 also suggests that the urbanization gradient is becoming increasingly continuous and diffuse.

From a socio-demographic perspective, the results indicate a progressive homogenization between territorial classes. Indicators such as schooling rates and illiteracy levels become less discriminative over time, particularly between peri-urban and urban areas. This convergence may reflect improved access to education, infrastructure, and public services throughout the region. However, unemployment variability increases in peri-urban and rurban communes, highlighting the socio-economic instability associated with transitional territories. These findings support the idea that peri-urban areas are not merely spatial interfaces but also zones of social and economic restructuring characterized by changing labor dynamics and mobility patterns.

In terms of comparing methodologies, the analysis of SOMs and GNNs reveals essential findings with regard to territorial dynamics modeling. While the graph neural network methodology shows good performance in detecting spatial dependencies, its potential lies in its ability to represent neighborhood interactions. However, the moderate level of concordance with expert assessments indicates that overly flexible graphs might be difficult to interpret in the case of socio-spatial categories.

Alternatively, the SOM model shows a higher degree of concordance with expert assessments and offers greater interpretability. Being topology-preserving, SOM allows representing the transition between classes while maintaining their semantic consistency with the concepts of rural, peri-urban, rurban, and urban territories. The high level of Cohen's Kappa coefficient obtained in 2014 highlights the potential of SOMs for modeling latent structure in multivariate socio-environmental data. While the decrease in the quality of clustering in 2024 is related to the growing spatial continuity and overlapping between classes, SOM performs better in gradual urbanization cases.

The decrease in classification separability observed in both SOM and GNN models between 2014 and 2024 reflects an important conceptual reality: urbanization is not a discrete phenomenon but rather a continuous and evolving gradient. The increase in medium- and low-confidence areas, particularly in peri-urban and rurban communes, confirms that territorial transitions generate ambiguous spatial profiles that challenge rigid classifications. This result supports contemporary approaches in urban geography, emphasizing the fuzzy and hybrid nature of peri-urban territories rather than fixed categorical boundaries.

The extraction of discriminant thresholds from SOM-derived classes also provides an operational contribution for territorial monitoring and planning. The identified thresholds related to NDVI, population, education, unemployment, and service infrastructure offer interpretable indicators that may support future regional planning strategies and spatial decision-making. In particular, they enable the identification of communes undergoing rapid transition and potentially vulnerable to uncontrolled urban sprawl or agricultural land loss.

The study also confirms that the separability between rural, peri-urban, and urban classes decreases over time, reflecting the increasing fuzziness of territorial boundaries under ongoing urbanization processes. This result emphasizes the necessity of moving beyond binary rural–urban classifications toward multidimensional and continuous representations of spatial organization. Despite these contributions, several limitations should be acknowledged. First, the study relies primarily on commune-level aggregation, which may mask intra-communal heterogeneity and local-scale spatial processes. This choise is primar-

ily justified by data availability and consistency constraints across all socio-environmental indicators. In particular, most of the datasets used in this analysis are only reliably available at the administrative commune scale, while intra-communal data remain incomplete, heterogeneous, or unavailable for several key variables. This constraint makes commune-level analysis the most robust and reproducible unit for ensuring full spatial coverage across the study area. Although finer-scale representations (e.g., intra-communal or parcel-level data) would potentially allow a more detailed characterization of local spatial processes, their absence or inconsistency in the current context limits their operational use. Second, although the integration of Sentinel-2 and census data improves multidimensional analysis, additional variables such as transportation accessibility, housing dynamics, land prices, or mobility flows could further refine the characterization of transitional territories. Third, the GNN framework was implemented using municipalities as graph nodes and first-order binary adjacency relationships. This representation may not fully capture the continuous and multi-scalar nature of rural–urban transitions, particularly in contexts where substantial intra-municipal heterogeneity exists. Future research could explore finer-resolution spatial units, larger training datasets, and alternative graph constructions, such as distance-weighted or similarity-based edges, to better represent gradual spatial transitions.

Our quantitative findings align with and extend comparable studies across several world regions. Within Morocco, Loulad et al. [34] reported a 473% increase in built-up area in the coastal Rabat–Salé–Kénitra region (from 63.4 to 299.9 km^2), accompanied by the emergence of a rural–urban interface on city outskirts, a trajectory of agricultural-land conversion and fringe formation consistent with the 54% increase in peri-urban municipalities and the rural fragmentation we observe in the neighboring Casablanca–Settat region. Beyond Morocco, the instability of intermediate zones that we document echoes findings from fast-growing metropolitan regions of the Global South: peri-urban transformation driven by metropolitan diffusion in Jakarta [21], the mixed and spectrally ambiguous peri-urban fabric of Tamale, Ghana [26], and the rurban dynamics of Bengaluru, India [28]. In the European and Mediterranean context, our observation of increasingly fluid and diffuse rural–urban boundaries is consistent with studies of "territories-in-between" across Europe [20], peri-urban landscape change in the Turin metropolitan area [18], urban sprawl in the Lyon region [36], and the continuous rural–urban typologies identified in Switzerland [43]. Taken together, these comparisons indicate that the intensification of peri-urbanization, the contraction of intermediate (rurban) territories, and the blurring of categorical boundaries are not specific to Casablanca–Settat but constitute a broadly shared signature of contemporary metropolitan growth, while the magnitude and pace we quantify place the region among the more rapidly transforming Mediterranean–North African metropolitan systems.

6. Conclusions

This study proposed an integrated methodological framework combining remote sensing indicators, socio-demographic variables, Self-Organizing Maps (SOM), and Graph Neural Networks (GNN) to analyze the evolution of the rural–urban continuum in the Casablanca–Settat region between 2014 and 2024. The results demonstrate that territorial organization within the region has undergone substantial transformation, which is characterized by increasing urbanization, the expansion of peri-urban spaces, and the progressive reduction and fragmentation of rural territories.

This study underscores the presence of an urbanization continuum and gradient rather than strict boundaries. Transitioning areas known as peri-urban and rurban communes represent a new type of territory characterized by ambiguous environmental and socio-economic features. The emergence of such territories is driven by the process of

metropolitan influence spreading into surrounding areas, thus reflecting the growing complexity of territorial changes observed in fast-growing urban environments.

The analysis shows that the area under investigation experiences a reduction in vegetation due to land artificialization and urbanization. Simultaneously, socio-demographic indicators demonstrate a gradual process of convergence among territorial classes, which could be interpreted as increasing spatial cohesion in the region. However, this process also emphasizes the fragility and instability of transitional territories due to uncontrolled urban sprawl and socio-economic restructuring.

Methodologically speaking, a comparative analysis of SOM and GNN models shows that both approaches complement each other and possess distinctive advantages. Specifically, GNN models are efficient in modeling spatial dependencies, whereas SOM classification allows obtaining interpretable and meaningful results corresponding to expert knowledge of the territorial system. The SOM model turns out to be especially suitable for gradual transition representation and extraction of discriminant boundaries for territorial monitoring and management.

Recent advances in geospatial representation learning indicate that adaptive, nonlinear feature reconfiguration can significantly enhance the integration of multi-resolution and multi-modal inputs. In particular, intelligent reconfiguration approaches based on optimized transformer architectures and multi-source feature supervision have shown strong potential in preserving spatial detail while effectively capturing complex interactions within heterogeneous remote sensing data, as demonstrated in recent studies on high-precision InSAR-based DEM reconstruction, which constitutes a promising direction for future research [54].

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Abbreviations

The following abbreviations are used in this manuscript:

GHSL	Global Human Settlement Layer
SOM	Self-Organizing Map
GNN	Graph Neural Network
GAE	Graph Autoencoder
NDVI	Normalized Difference Vegetation Index
ML	Machine Learning
DL	Deep Learning
RGPH	Recensement Général de la Population et de l'Habitat

Appendix A

Table A1. Percentile-based decision thresholds used by the expert-rule system, with the rationale for each cut-point. Pxx = xx-th percentile of the regional distribution; "clamp" = bounds applied to the percentile; Rn = rule number; values given as 2014 → 2024 where they differ.

Variable	Direction	Boundary—Percentile (Clamp 2014/2024)	Why These Percentiles
NDVI	Inverse (veg. = rural)	RURAL low: P75 (0.40–0.65); RURBAN low: P40 (0.22–0.40); PERI-URB upp: P35 (0.20–0.38); URBAN upp: P20 (0.10–0.25)	Inverse proxy, so cut-points descend along the gradient. RURAL = top greenness quartile (P75), URBAN = least-vegetated fifth (P20); the rurban/peri-urban frontier (P40, P35) sits just below the center where mixed cover dominates. Identical across years (spectrally stable).
Total population	Direct (scale signal)	RURAL upp: P30 (5k–15k); RURBAN low: P25 (4k–12k); RURBAN upp: P65 (20k–40k); PERI-URB low: P55 (12k–25k); URBAN low: P80 (30k–80k)	Primary scale signal, so cut-points rise. RURAL = lower third (P30); the wide RURBAN band (P25–P65) overlaps the rural ceiling (gradual, fuzzy transition); URBAN is the top quintile (P80), matching the absolute floor (>80k) in R1. Unchanged across years.
Illiteracy rate	Inverse (illit. = rural)	RURAL low: P65 (45–65 → 35–55); RURBAN upp: P75 (48–65 → 40–55); RURBAN low: P35 (25–48 → 20–40); PERI-URB upp: P45 (28–50 → 25–40); URBAN upp: P25 (15–40 → 15–30)	Inverse proxy, cut-points descend. RURAL $>\approx$ P65, URBAN $\leq$ P25; the widest band (RURBAN, P35–P75) captures the educational middle. Percentiles fixed for comparability, but clamps lowered in 2024 (URBAN 40 → 30) to track the region-wide fall in illiteracy.
School enrolment (6–11)	Direct	RURAL upp: P20 (75–92 → 80–95); RURBAN low: P25 (78–92 → 85–95); RURBAN upp: P65 (88–97 → 90–98); PERI-URB low: P60 (85–96 → 90–97); URBAN low: P80 (92–99 → 94–99)	Direct proxy, cut-points rise (RURAL = P20, URBAN = P80). By 2024 enrolment was near-universal (>95%), compressing the distribution; clamp minima raised (URBAN 92 → 94), and the RURAL rule switched from strict AND (2014) to a 3-of-4 score (2024), so high enrolment alone no longer blocks a rural label.
Unemployment rate	Non-monotonic (secondary)	RURBAN low (high-NDVI branch): P75 (3–10 → 8–25); PERI-URB upp: P60 (4–12 → 8–20); URBAN upp: P60 (3–10 → 5–15)	Non-monotonic (high in deprived rurban fringes and parts of the urban core), so secondary only, never primary. The rurban high-NDVI branch (R5) uses P75 to isolate the high tail; peri-urban/urban ceilings (P60) stop moderate values, forcing an urban label. Clamps raised sharply in 2024 (3–10 → 8–25).
Number of establishments	Direct (centrality)	RURAL upp: P25 (1–5); RURBAN upp: P55 (5–15); PERI-URB low: P45 (4–12); URBAN low: P75 (10–25)	Proxy of functional centrality, cut-points rise (RURAL = P25, URBAN = P75). The peri-urban floor (P45) and rurban ceiling (P55) straddle the median, reflecting a moderate, growing service base. Identical across years (stable distribution).
Activity rate (>15)	Direct (support)	PERI-URB low: P55 (47–62 → 40–50)	Supports only the peri-urban decision (R7, as an OR to the establishment count), so one cut-point above the median (P55) suffices. Clamp lowered in 2024 (47–62 → 40–50) to reflect declining measured activity, same relative position.
Higher-education share	Direct (qualification)	URBAN low: P65 (2–8); PERI-URB low: P45 (1–5)	Qualification proxy confirms URBAN (R1) and supports peri-urban. Two ascending cut-points: peri-urban near median (P45), urban upper third (P65). Clamps low in absolute terms (1–8%) as shares are small region-wide; unchanged across years.

Table A2. Configuration of the Graph Neural Network (GNN) classifier: a graph autoencoder followed by over-partitioned K-Means and expert-rule fusion. The architecture is identical for 2014 and 2024.

Characteristic	Value (GNN 2014 & 2024)
Framework	PyTorch V2.12 + PyTorch Geometric
Model type	Graph Autoencoder (GAE)
Encoder	2 × GCNConv layers (graph convolution)
Layer dimensions	input → hidden 16 → latent 8
Activation/regularization	ReLU + dropout $p = 0.1$
Decoders	Attribute decoder (Linear) + inner-product link decoder (sigmoid)
Loss	MSE (attribute reconstruction) + binary cross-entropy (link reconstruction)
Optimizer	Adam, learning rate = 0.01
Training epochs	500
Graph construction	Spatial contiguity (shared-boundary adjacency); isolated nodes → self-loop

Table A2. *Cont.*

Characteristic	Value (GNN 2014 & 2024)
Embedding post-processing	L2 normalization of latent embeddings
Clustering	K-Means, over-partitioned $K_{over} = 8$ ($=2 \times n_{classes}$)
Label assignment	Cluster → class by expert-rule triple vote, then re-aggregation to 4 classes
Feature scaling	RobustScaler
Random seed	42 (torch + numpy)
Final classes	4 (RURAL < RURBAN < PERI-URBAN < URBAN)

Table A3. Configuration of the hybrid Self-Organizing Map (SOM) classifier for 2014 and 2024.

Characteristic	SOM 2014	SOM 2024
Library/model	MiniSom (Kohonen self-organizing map)	MiniSom (Kohonen self-organizing map)
SOM grid size	8 × 8 neurons	6 × 5 neurons
Neighborhood function	Gaussian	Gaussian
Learning rate	0.5	0.5
Sigma (initial radius)	1.0	1.0
Training iterations	2000	2000
Weight initialization	PCA-based init	Random init
Multi-run stabilization	Single run	10 runs (best by quantization error)
Feature scaling	RobustScaler	RobustScaler
Dimensionality reduction	PCA—3 components (seed 42)	PCA—3 components (or 'auto' 2–6 by silhouette)
Input feature vector	8 de-duplicated features	8 de-duplicated features
Random seed	42	42
Final classes	4 (RURAL < RURBAN < PERI-URBAN < URBAN)	4 (RURAL < RURBAN < PERI-URBAN < URBAN)
Fusion	SOM label × expert rules → hybrid + confidence	SOM label × expert rules → hybrid + confidence

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