Spatial Heat Resilience Mapping Using Graph Neural Networks

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Abstract. Urban heat is intensifying across Mediterranean cities due to dense urban morphology and increasing climate extremes. While machine learning is widely used to assess urban heat, most spatial regression approaches treat data points as independent observations and aggregate data into broad administrative neighbourhoods, inherently failing to capture localized, micro-climatic interactions. This study proposes a novel, micro-scale Graph Neural Network (GNN) framework to assess and predict Urban Heat Vulnerability at the individual building level in Seville, Spain. A spatial graph was constructed wherein 29,542 individual buildings operate as nodes, with edges computationally defining physical adjacency to capture thermodynamic neighbourhood spillover effects. Node features strictly integrate satellite-derived Land Surface Temperature (LST) and the Normalized Difference Vegetation Index (NDVI) acquired during an extreme heatwave in 2025, alongside architectural compactness and Euclidean distance to major parks. A composite Urban Heat Vulnerability Index (UHVI) was formulated as the supervised learning target. Deploying a Graph Convolutional Network (GCN) via a message-passing architecture, the model successfully captured nonlinear spatial interactions, achieving exceptional predictive accuracy (Mean Absolute Error of 2.81 on a 100-point scale). Subsequent feature importance analysis revealed that extreme micro-scale vulnerability is primarily driven by a building's spatial isolation from major green infrastructure, substantially outweighing localized deficits in street-level vegetation. By shifting from macro-scale approximations to building-level topological deep learning, this study advances computational urban climatology and provides a highly precise, actionable framework for targeted climate adaptation planning in Mediterranean cities.

Keywords: Graph Neural Networks · Urban Heat Resilience · Mediterranean Districts · Urban Heat Vulnerability · Spatial Deep Learning · Climate Adaptation

1 Introduction

The accelerating pace of urbanisation in the Mediterranean region has produced cities characterised by high building densities, expansive impervious surfaces, and pronounced disparities in green infrastructure provision [1] The phenomenon of urban overheating is

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receiving increasing attention in the Mediterranean basin, where rapid urban growth has intensified impervious surface cover—a key driver of land surface temperature elevation and urban heat island intensification [1–3]. These structural conditions, combined with escalating climate extremes driven by anthropogenic warming [4], have elevated urban heat from a seasonal inconvenience into a persistent public health and territorial justice concern. The IPCC Sixth Assessment Report identifies the Mediterranean as a major climate change hotspot: temperature extremes and heatwaves have increased in intensity, frequency, and duration in recent decades, and are projected to continue intensifying with high confidence under all Shared Socioeconomic Pathways through the twenty-first century [5]. Under SSP2-4.5 and SSP5-8.5 scenarios, urban heatwave exposure risk is projected to increase by 619% and 1,740% respectively by 2100, with elderly urban populations facing disproportionately elevated exposure—rising between 1,642% and 5,529% [6]. Seville exemplifies this compounding vulnerability. Its dense historic core, expansive peri-urban residential belts developed during rapid post-war urbanisation, and spatially uneven distribution of parks and street trees create sharp intra-urban thermal gradients. The broader Mediterranean basin and south-eastern European regions are already emerging as major hotspots for climate-related health impacts, with a substantial rise in heat-related mortality projected throughout the twenty-first century [7]. Heatwave mortality statistics consistently identify elderly residents, low-income households, and neighbourhoods with limited green infrastructure as disproportionately exposed populations. Existing evidence confirms that groups most vulnerable to heatwave health impacts include the elderly, low-income populations, outdoor workers, and individuals living alone, vulnerabilities that compound significantly when green space access is constrained [8]. In Mediterranean dry climates in particular, the scarcity of green-blue infrastructure is especially consequential, as limited vegetation cover reduces the cooling benefits that green space provides in more temperate urban environments [9, 10]. Yet policy responses have remained largely reactive, targeting individual buildings or isolated green interventions rather than the systemic spatial configuration that underpins resilience, or its absence.

The application of machine learning to urban climate analysis has proliferated over the past decade. Convolutional neural networks (CNNs), random forests, and support vector machines have been deployed to downscale land surface temperature (LST) retrievals, predict thermal comfort indices, and classify urban heat island intensity. However, these methods share a critical structural limitation: they treat spatial observation units, like census tracts, planning districts, grid cells, as statistically independent entities. This assumption ignores the well-established phenomenon of spatial autocorrelation, wherein proximate places tend to exhibit more similar attributes than distant ones, and more importantly, it cannot represent the spatial spillover of heat stress and adaptive capacity deficits across neighbourhood boundaries. Graph Neural Networks (GNNs) offer a principled alternative; by encoding spatial units as nodes in a graph and their adjacency relationships as edges, GNN architectures can learn representations that explicitly incorporate the influence of spatial neighbours. Recent applications in urban remote sensing [11], traffic forecasting [12], building and civil infrastructure operation and maintenance [13], building attribute and energy predictions [14, 15], have proved the effectiveness and good results of such methods.

Traditional approaches also tend to treat buildings as isolated data points, ignoring the complex topological reality of urban environments where a building's thermal performance is heavily influenced by the shading, density, and environmental context of its immediate neighbours. To bridge this critical research gap, this study introduces a novel, micro-scale predictive framework leveraging GNN's ability to model complex spatial relationships that shape the city's urban heat distribution [16].

The novelty of this approach lies in the deployment of a Graph Convolutional Network (GCN) to mathematically simulate how physical proximity, architectural compactness, and local environmental deficits compounded heat stress during the extreme 2025 heatwave. By predicting a composite Urban Heat Vulnerability Index (UHVI) at the individual building level, this methodology provides a transition from urban heat mitigation from neighbourhood-level generalizations to building-specific interventions.

1.1 Research Objectives

The primary aim of this study is to develop and validate a spatially aware deep learning model capable of evaluating urban heat vulnerability at the individual building scale. To achieve this, the research is guided by the following specific objectives:

- **To formulate a micro-scale Urban Heat Vulnerability Index (UHVI):** To construct a comprehensive composite metric that integrates satellite-derived thermal exposure (LST), micro-level vegetation presence (NDVI), architectural heat-trapping potential (Building Compactness), and infrastructural isolation (Distance to Parks) for over 29,000 individual structures.
- **To develop a topological deep learning architecture:** To design and train a Graph Convolutional Network (GCN) that successfully maps the spatial relationships between buildings, allowing the model to learn the contextual, neighbourhood-level drivers of heat vulnerability.
- **To evaluate predictive performance and spatial error:** To assess the accuracy of the GNN against ground-truth index calculations and map spatial prediction errors to identify geometric or geographic anomalies within the urban fabric.
- **To identify primary drivers of micro-scale vulnerability:** To conduct a feature importance analysis on the model's highest-risk predictions, isolating whether architectural geometry, lack of vegetation, or distance to cooling infrastructure acts as the primary catalyst for severe, localized urban heat stress.

2 Study Area

The study focuses on the metropolitan area of Seville, Andalusia, southern Spain (37.39°N, 5.99°W). Seville exhibits pronounced intra-urban heterogeneity in morphology, socio-economic structure, and green infrastructure provision—conditions widely documented as primary drivers of differential heat exposure across Mediterranean cities [1, 17]. The historic centre (*Casco Antiguo*) is characterised by compact morphology, enclosed courtyards, limited street canopy, and a predominantly elderly population; its high building density makes heat mitigation interventions particularly difficult to implement and amplifies nocturnal urban heat island intensity.

Seville's Köppen–Geiger *Csa* classification [18], produces some of the highest summer temperatures in continental Europe, with multiple heatwave episodes recorded in a single season and heat stress disproportionately concentrated in dense, low-vegetation urban zones [17, 19]. Heatwave mortality risk is the highest of any major Spanish city, with excess mortality at the 99th temperature percentile reaching a relative risk of 2.73 (95% CI: 2.34–3.18) [20].

Under high-emissions trajectories, and its climatic, morphological, and socio-demographic conditions, Seville would make an exemplary and scientifically compelling case for building-level heat resilience research.

3 Methodology

This study proposes a spatially aware, deep learning framework to assess and predict Urban Heat Vulnerability at the building level. The methodology is divided into four primary stages: data acquisition and feature engineering, formulation of the vulnerability index, spatial graph construction, and the design and training of a Graph Convolutional Network (GCN). Unlike traditional studies that aggregate data into arbitrary administrative neighbourhood units (*barrios*), the spatial extent of this analysis is defined strictly at the micro-scale, utilizing individual buildings as the fundamental units (nodes) of observation. The study area encompasses 29,542 distinct building geometries across the urban extent of Seville, extracted via OpenStreetMap (OSM).

By conceptualizing the city as a topological spatial graph, where each building acts as a discrete node connected to its immediate physical neighbours, this high-resolution approach bypasses the modifiable areal unit problem (MAUP) inherent to rigid census boundaries [21]. This extreme level of granularity ensures that highly localized environmental and structural indicators are captured with precise spatial accuracy, rather than being artificially averaged out across heterogeneous areas ranging from dense historic cores to sprawling peri-urban growth zones. The research is divided into five primary phases that encompass data acquisition, spatial graph construction, and GNN-based vulnerability assessment, Fig. 1.

3.1 Data Acquisition

Remote Sensing Inputs During the 2025 Extreme Heatwave

To capture the thermal and biophysical properties of the urban environment under severe climate stress, remote sensing data were exclusively acquired during the extreme heatwave of 2025. Land Surface Temperature (LST) retrievals were extracted to quantify localised, building-level heat exposure across the city. Concurrently, the Normalized Difference Vegetation Index (NDVI) was computed to measure the density of micro-level vegetation and green canopy presence immediately surrounding each structure. These two metrics served as environmental inputs for assessing localized heat risk and natural cooling capacity.

Urban Morphology and Green Space Proximity

To model the physical urban form and its potential to trap or exacerbate heat, building compactness was calculated for every individual structure in the dataset.

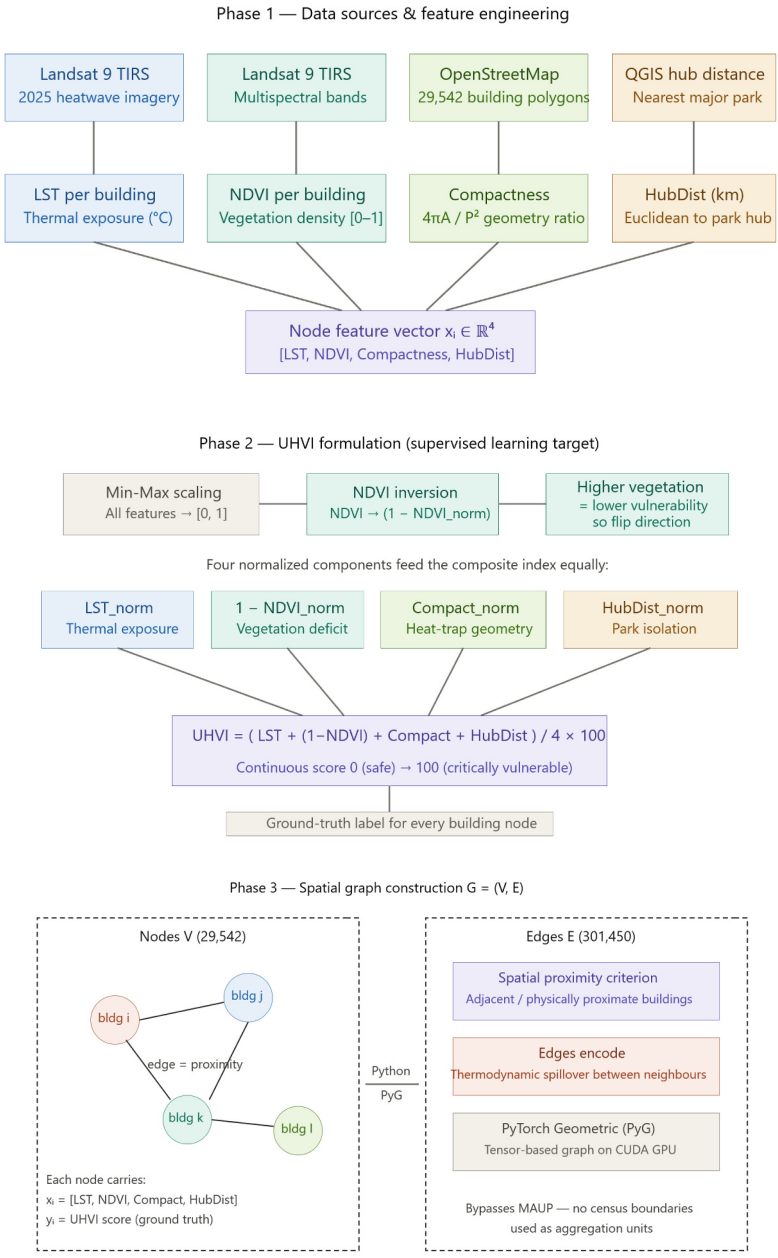


Fig. 1. Proposed study workflow, illustrating the integration of spatial data, graph construction, and GNN-based vulnerability assessment.

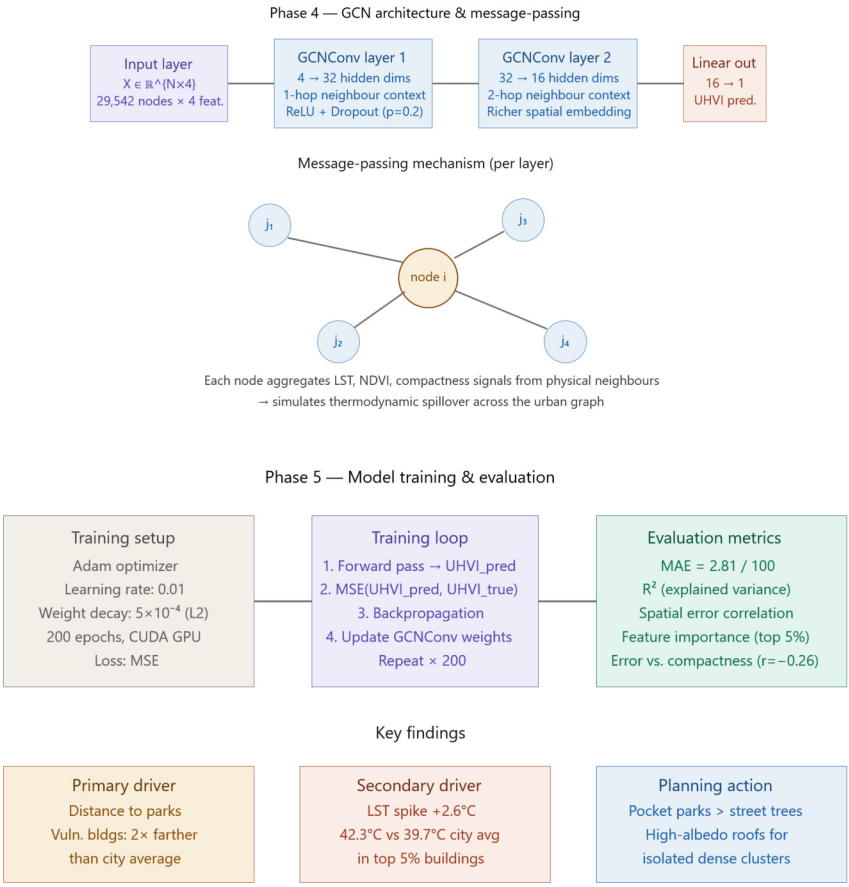


Fig. 1. (*continued*)

Furthermore, access to natural thermal relief was quantified by measuring the distance from each building to the nearest major green space. The distance to parks was calculated spatially using QGIS (Quantum GIS), providing a highly accurate, continuous metric of infrastructural isolation for every building in the study area.

Spatial Graph Construction

To capture the complex thermodynamic interactions between neighbouring structures, the dataset was modelled as a spatial graph utilizing a micro-scale topological approach where:

Nodes (Vertices): Individual buildings were designated as the fundamental nodes of the graph. Each node was attributed with a strict four-dimensional feature vector consisting of: LST, NDVI, Compactness, and Distance to Parks.

Edges (Relations): The spatial relationships between the buildings were defined computationally using Python. Edges were generated to connect adjacent and physically

proximate buildings, allowing the model to simulate how heat and cooling effects diffuse through localised urban clusters. Table 1 summarizes the node features used in the GNN framework, including their data sources, processing methods, and their alignment with the Exposure–Sensitivity–Adaptive Capacity (ESAC) dimensions of vulnerability.

Table 1. Summary of node features used in the GNN framework.

Feature	Description	Source	Processing Software/Method	ESAC Dimension
Land Surface Temperature (LST)	Thermal exposure during the 2025 extreme heatwave	Landsat 9 TIRS	Remote Sensing Extraction	Exposure
Vegetation Index (NDVI)	Green canopy density and vegetation presence	Landsat 9 TIRS	Remote Sensing Extraction	Adaptive Capacity
Compactness	Morphological metric of heat-trapping potential, computed as $4\pi A/P^2$	OSM	Spatial geometry calculation in QGIS/Python	Sensitivity
Distance to Parks (HubDist)	Euclidean distance from each building centroid to the nearest major green space or cooling hub	OSM	Calculated in QGIS	Adaptive Capacity

Distance to Parks (HubDist): The Euclidean distance to the nearest major green space or cooling hub was used as a proxy for accessibility to natural thermal relief. This metric captures the spatial availability of urban cooling infrastructure, reflecting the extent to which buildings can benefit from the mitigating effects of vegetation and shaded environments [22]. Proximity to parks has been widely associated with reduced land surface temperatures, improved microclimatic conditions, and enhanced thermal comfort, particularly during extreme heat events. Moreover, accessibility to green infrastructure is increasingly recognised as a critical component of adaptive capacity within urban heat vulnerability frameworks [23], as limited access to cooling spaces disproportionately affects vulnerable populations. These thresholds, Table 2, are informed by empirical studies on the spatial influence of urban green spaces, which indicate that the cooling effects of vegetation typically diminish with distance, often within a few hundred meters

from the source. Distances exceeding 1 km are therefore considered indicative of limited access to effective cooling infrastructure, contributing to heightened exposure and reduced adaptive capacity.

Table 2. Interpretation of distance to parks (adapted from literature)

Distance	Meaning
0–0.2 km	Excellent access (strong cooling benefit)
0.2–0.5 km	Good access
0.5–1 km	Moderate access
>1 km	Poor access (increased heat vulnerability)

3.2 Formulation of the Urban Heat Vulnerability Index (UHVI)

To generate a target variable for the predictive model, a composite Urban Heat Vulnerability Index (UHVI) was formulated. Because the input variables operate on entirely different mathematical scales, a Min-Max scaling technique was applied to normalize all features to a standard range of [0, 1].

Since higher vegetation corresponds to lower vulnerability, the normalized NDVI values were inverted. The UHVI for each building i was then computed as the unweighted average of the four standardized components:

$$UHVI_i = \frac{LST_{norm} + Compactness_{norm} + (1 - NDVI_{norm}) + HubDist_{norm}}{4} \times 100 \quad (1)$$

This formulation yields a continuous vulnerability score ranging from 0 (lowest vulnerability) to 100 (highest vulnerability), representing a balanced integration of thermal exposure, morphology, and accessibility to cooling resources.

This produced a ground-truth vulnerability score for every building in the dataset, ranging from 0 (minimal risk) to 100 (severe risk).

3.3 Spatial Graph Construction and GNN Architecture

To explicitly model spatial interdependencies, the dataset was represented as a graph:

$$G = (V, E)$$

The Vertices (V): each building is represented as a node with a feature matrix $X \in R^{NxF}$ which contains N = 29,542 nodes (individual buildings) and F = 4 features (LST, NDVI, Compactness, and Distance to Parks) extracted during the 2025 extreme heatwave. All features were normalized to a [0, 1] scale using Min-Max scaling. Edges (E): connections were established based on spatial proximity, resulting in 301,450 edges capturing neighbourhood relationships.

This graph structure, Fig. 2, enables the modelling of spatial spillover effects, where thermal conditions and urban form are influenced by adjacent buildings.

The graph was implemented using the PyTorch Geometric (PyG) framework, allowing efficient tensor-based processing and integration with deep learning architectures.

To predict the UHVI of buildings while accounting for neighbourhood context, a Graph Convolutional Network (GCN) was deployed. The GCN architecture leverages a message-passing mechanism to capture thermodynamic spatial spillovers between adjacent buildings. The model utilizes two GCNConv layers. The first layer maps the 4 input features to a hidden dimension of 32 to capture immediate neighbourhood effects, followed by a Rectified Linear Unit (ReLU) activation function and a Dropout layer $P = 0.2$ for regularization. A second GCNConv layer compresses the embeddings to a 16-dimensional space, followed by a final linear output layer projecting to the continuous scalar UHVI prediction.

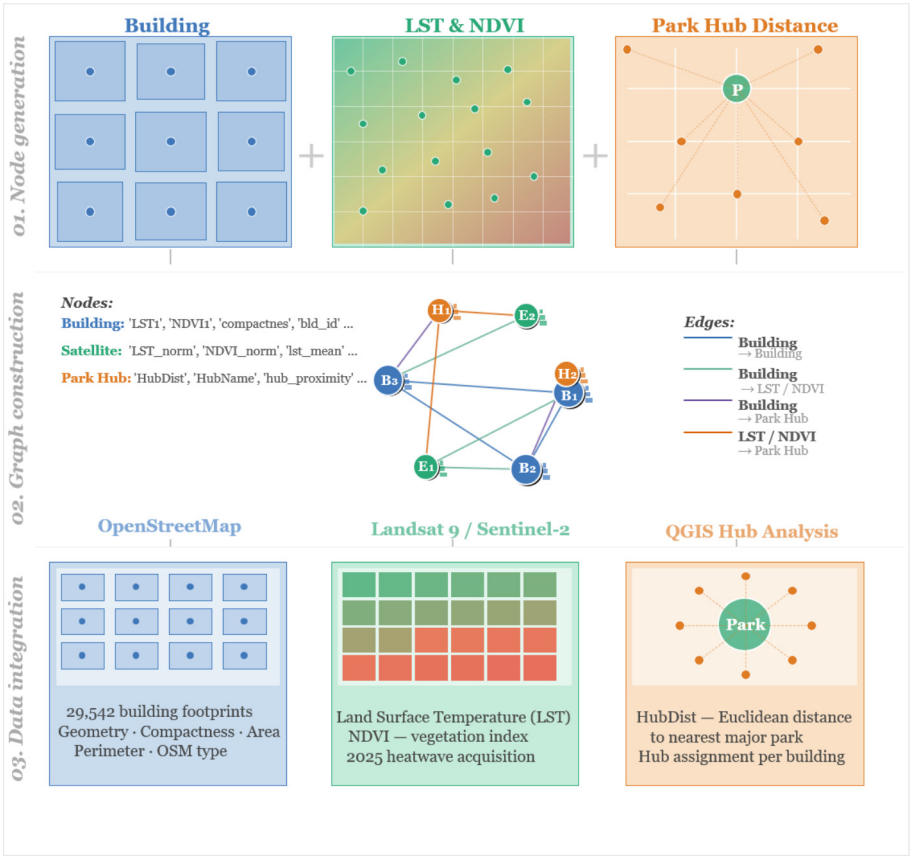


Fig. 2. Schematic of the three-stage GNN graph construction pipeline for Seville

3.4 Model Training and Evaluation

The model was trained to perform node-level regression. The dataset was loaded onto a CUDA-enabled GPU for accelerated processing. Training was executed over 200 epochs using the Adam optimizer with a learning rate of (0.01) and a weight decay of 5×10^{-4} for L2 regularization.

The loss function was defined as Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2 \tag{2}$$

Where Y_i denotes the ground-truth UHVI and $\widehat{Y}_i$ the predicted value.

Model performance was evaluated using Mean Absolute Error (MAE): for interpretability of prediction error, and Coefficient of Determination (R^2): to assess explained variance.

4 Results

4.1 Distribution of Predicted Vulnerability

Analysis of the predicted UHVI across the 29,542 building nodes, Fig. 3, revealed a predominantly unimodal distribution, with the majority of Seville's urban fabric registering moderate vulnerability scores between 40 and 60 on a 100-point scale. Notably, the distribution exhibited a pronounced right skew, isolating the top 5% of buildings that face critical exposure (scores $\geq$75). Spatial visualization of these high-risk predictions highlighted intense micro-scale clustering, demonstrating that severe urban heat vulnerability is not a diffuse, district-wide phenomenon, but is instead acutely localized within specific high-density blocks.

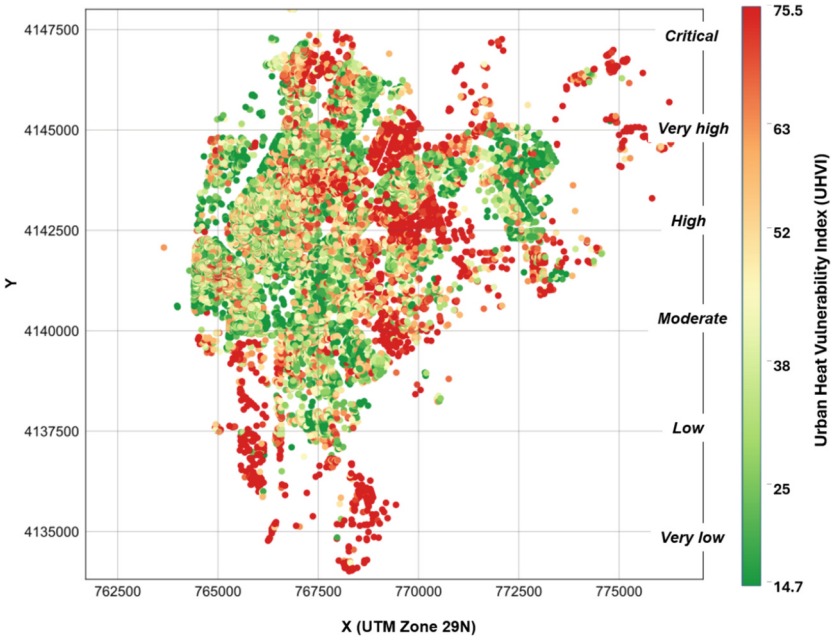


Fig. 3. Urban Heat Vulnerability distribution.

4.2 Feature Importance in High-Risk Zones

A contrastive feature analysis comparing the top 5% most vulnerable buildings against the city-wide baseline, Figs. 4 and 5, identified the primary structural and environmental drivers of extreme heat stress. The most discriminating feature was building compactness, with the highest-risk buildings recording a mean normalised value of 0.74 compared to the city average of 0.57 ($\Delta = +0.17$), indicating that geometrically compact, heat-trapping morphologies are the strongest predictor of severe localised vulnerability.

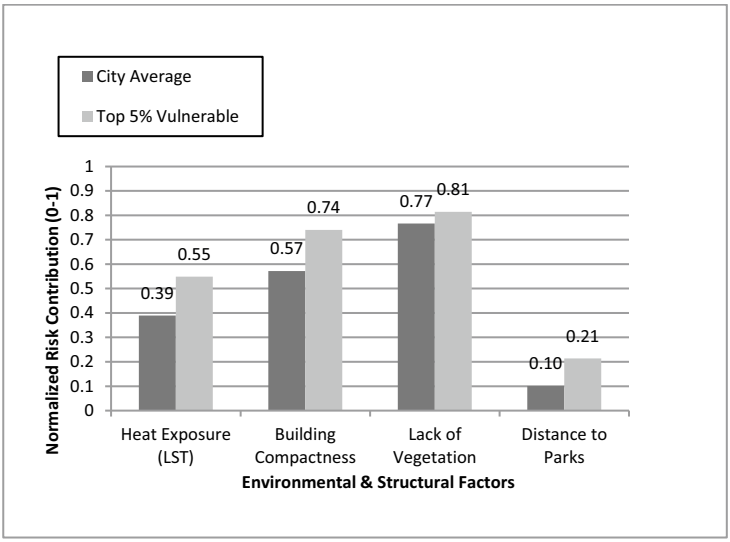


Fig. 4. Contrastive feature analysis of GCN-predicted vulnerability. Compares mean normalised risk factors (0 = minimal risk, 1 = maximum penalty) of the urban baseline (N = 29,542) against the top 5% highest-risk buildings.

Thermal exposure (LST) emerged as the second most critical driver, with the top 5% of buildings recording a mean surface temperature of 42.28 °C against the city average of 39.72 °C—a statistically meaningful gap of 2.56 °C ($\Delta = +0.16$ normalised). Distance to parks contributed a moderate differential (city average: 0.595 km; top 5%: 1.249 km—more than double), confirming that structural isolation from major green cooling infrastructure compounds vulnerability, though its normalised contribution ($\Delta = +0.11$) was smaller than compactness and thermal exposure. Notably, vegetation deficit (NDVI) showed the weakest discriminating power ($\Delta = +0.05$), indicating that localised differences in street-level greening between the most exposed buildings and the city average are marginal, and that building geometry and direct thermal loading are the principal catalysts of micro-scale heat stress in Seville's urban fabric.

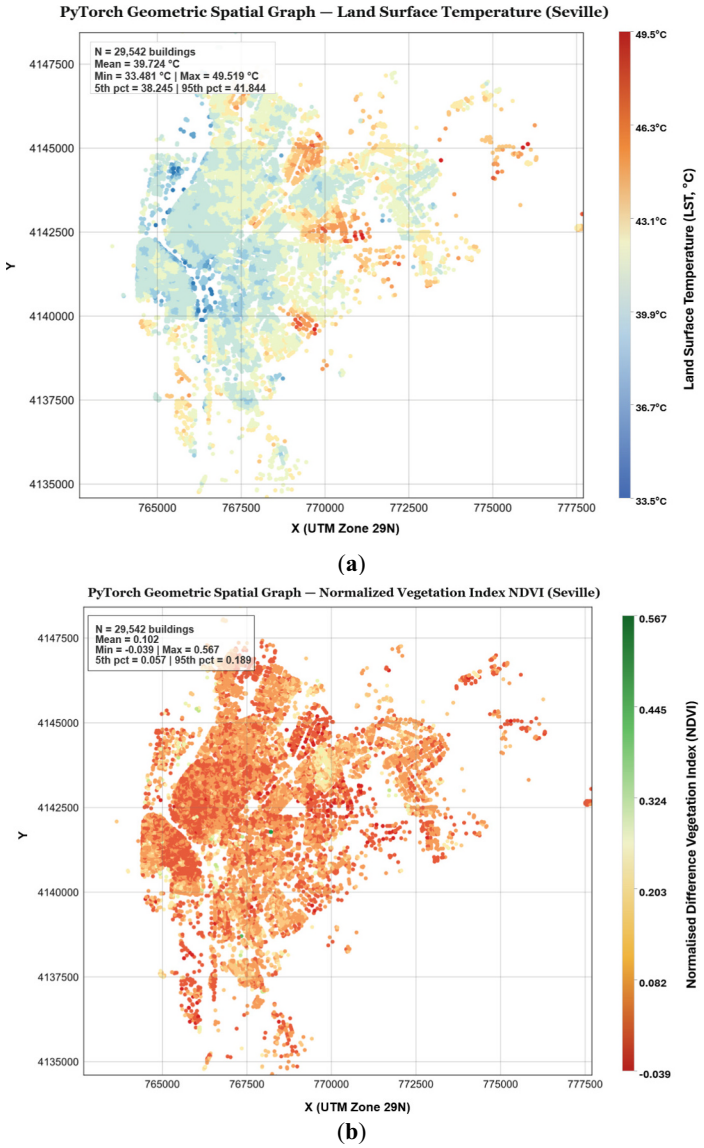
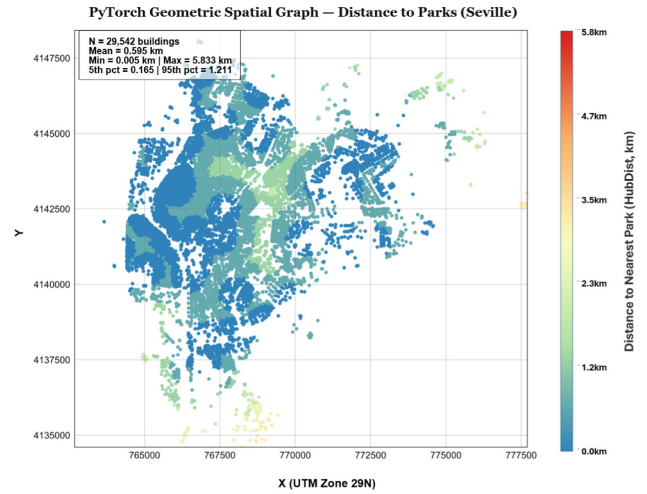


Fig. 5. Spatial distribution of the four GNN node features across 29,542 building nodes in Seville. (a) Land Surface Temperature (LST, °C), (b) Normalized Difference Vegetation Index (NDVI), (c) Distance to nearest park (HubDist, km), (d) Building compactness, indicating dense, heat-trapping morphologies typical of traditional Mediterranean urban blocks.



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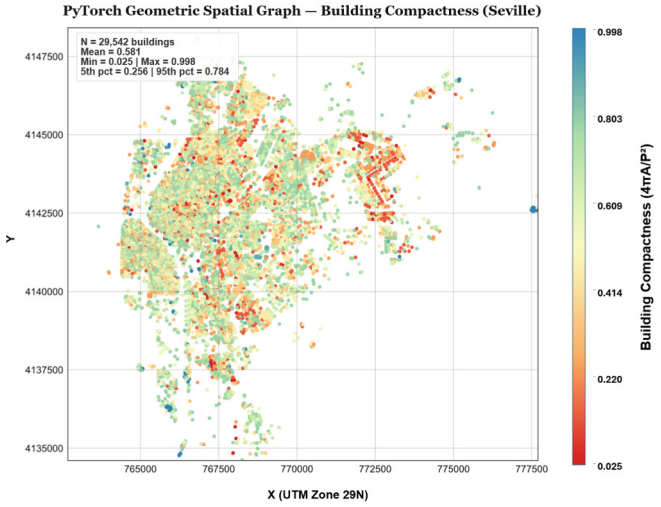

(**d**)

Fig. 5. (*continued*)

4.3 Predictive Performance

The trained GCN achieved high predictive accuracy at the building level, producing an average Mean Absolute Error (MAE) of just 2.81 points (out of 100). This minimal error margin confirms that the message-passing architecture successfully learned the nonlinear spatial interactions between building geometry and environmental exposure. The network accurately simulated how localized heat (LST) and cooling sources (NDVI) diffuse across physical adjacency edges, providing predictive information far beyond what standard, attribute-only linear regressions could achieve.

5 Discussion

This This study advances urban heat research along two principal methodological axes. First, by operationalising a micro-scale building-level graph of 29,542 individual nodes, it structurally bypasses the MAUP that systematically distorts vulnerability assessments conducted at the census-tract or administrative-district level Second, the application of a Graph Convolutional Network to extreme heatwave data acquired during the 2025 event embeds urban thermodynamic spillover directly into the learning architecture: each graph edge encodes the physical adjacency through which the heat-trapping geometry of one building propagates thermal stress to its immediate neighbours—a spatial dependency that conventional regression and grid-based deep learning models cannot represent. The finding that building compactness is the dominant predictor of micro-scale heat vulnerability, followed closely by direct thermal exposure (LST), carries concrete implications for climate adaptation planning in Seville and analogous Mediterranean cities. The data indicate that for the most critically exposed buildings—characterised by dense, geometrically compact morphologies and elevated surface temperatures—localised street-tree planting will yield only marginal risk reduction, given that vegetation deficit (NDVI) showed the weakest discriminating power between high-risk and baseline structures. Municipal interventions for identified hotspots should instead prioritise morphological and material upgrades: mandatory installation of high-albedo roofing systems to reduce direct solar absorption, and the targeted conversion of impervious surfaces within compact clusters into pocket parks or permeable green corridors that interrupt heat accumulation at source.

The primary limitation of this study lies in the two-dimensional nature of its input feature set. Although the spatial graph successfully captured plan-view physical proximity and building footprint compactness, it lacked three-dimensional architectural context—specifically, building height, street canyon aspect ratio, vertical shading patterns, and roof material properties. These volumetric characteristics govern wind flow channelling, shortwave radiation trapping, and nocturnal longwave emission; their absence directly accounts for the model's moderately elevated error margins in the most compact urban zones. Future iterations of this framework should incorporate 3D node features derived from LiDAR point clouds or urban digital twins to fully resolve the thermodynamic complexity of dense Seville street canyons.

6 Conclusion

As urban heat stress intensifies across Mediterranean cities under accelerating climate change, mitigation strategies must transition from macro-scale generalisation to precise, building-level intervention. This study presented a novel micro-scale GCN framework to map and predict Urban Heat Vulnerability across 29,542 individual buildings in Seville during the extreme 2025 heatwave—operationalising the city not as a collection of administrative districts, but as a continuous topological fabric of thermodynamic relationships.

By encoding buildings as interconnected graph nodes and physical adjacency as edges, the GCN successfully captured the spatial diffusion of heat stress across the

urban fabric, achieving a Mean Absolute Error of 2.81 on a 100-point vulnerability index. Contrastive feature analysis of the highest-risk buildings revealed that building compactness is the primary structural driver of extreme localised vulnerability, followed by direct thermal exposure (LST), with vegetation deficit (NDVI) and park distance contributing comparatively smaller differentials. These findings reframe the dominant narrative in urban heat adaptation: geometric morphology—not green infrastructure scarcity alone—is the critical determinant of micro-scale heat risk in Seville's densest urban zones. The resulting building-level vulnerability surface provides municipal planners with a spatially precise, actionable framework for deploying cooling interventions where topological and environmental risk factors compound most severely. Future research should prioritise three principal extensions: the integration of 3D architectural features—including building height, street canyon aspect ratios, and roof albedo—into the graph node feature set; the incorporation of socio-demographic vulnerability indicators to construct a composite climate justice index; and the temporal extension of the model across multiple heatwave events to assess inter-annual stability of the identified risk patterns.

Disclosure of Interests. The authors declare no competing interests.

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