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# A DEEP-LEARNING ENVIRONMENTAL DIGITAL TWIN FOR URBAN HEAT MITIGATION IN OLD MOSUL

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**ABSTRACT**

Cities, particularly in hot and arid regions, are increasingly affected by pronounced urban overheating due to high urban density, impervious surfaces, limited vegetation, and reduced natural ventilation within built fabrics. These conditions intensify heat retention and raise street- and neighborhood-level temperatures, affecting outdoor thermal comfort, open-space performance, building energy demand, and public health. This issue becomes more critical in historic urban areas, where reconstruction must respect urban form, materials, and solid–void relationships. Accordingly, this study focuses on Old Mosul, particularly the Al-Qlay'at urban fabric, as a reconstruction context that requires not only physical restoration but also the recovery of environmental performance. The research problem lies in the absence of an operational framework linking reconstruction decisions—such as alley height-to-width ratios, courtyards, orientation, material properties, and vegetation cover—to measurable, simulatable, predictable, and optimizable thermal outputs. This gap may produce unintended negative thermal impacts at street and neighborhood scales. The research proposes a deep-learning-based environmental digital twin to support reconstruction decisions in Old Mosul by optimizing measures intended to limit heat-island effects. Methodologically, it identifies key morphological and material variables, constructs a spatial and environmental data layer, conducts and calibrates urban climate simulations, develops a deep-learning surrogate model for rapid thermal-performance prediction, and integrates it within an optimization layer to generate reconstruction alternatives that are thermally efficient and compatible with the historic urban fabric. The expected contribution is an applied framework and decision-support tool for evaluating reconstruction scenarios environmentally before implementation and guiding Old Mosul's reconstruction toward climate-responsive solutions that reduce urban heat island intensification.

**Keywords:** Environmental Digital Twin; Deep Learning; Urban Heat-Island Mitigation; Reconstruction of Old Mosul; Urban Climate Simulation; Optimization.

## 1. INTRODUCTION

Urban heat islands constitute a major environmental challenge for contemporary cities, particularly those located in hot–arid regions. The phenomenon emerges from the combined influence of compact built forms, extensive impervious surfaces, sparse vegetation, and restricted airflow, producing urban temperatures that exceed those recorded in adjacent less-developed areas [1] [2]. Urban heat islands are no longer viewed solely as localized temperature anomalies; they are also associated with increased heat exposure, outdoor thermal discomfort, higher energy demand, and adverse health outcomes during extreme-heat events [3] [4]. Furthermore, the interaction between urban heat islands and urban air pollution may negatively affect residents' health and quality of life [5]. Recent evidence indicates that the intensity of urban thermal conditions is governed not only by the regional climate but also by the spatial and material configuration of the built fabric, including urban-canyon height-to-width ratios, sky view factor, surface roughness, material distribution, shading patterns, and vegetation cover. Urban heat should therefore be addressed as both a climatic and a morphological–environmental issue [1] [6].

Research on urban heat islands has undergone substantial methodological advancement, particularly in the techniques used for environmental monitoring and simulation. Earlier descriptive approaches have increasingly been replaced by quantitative and multi-scale models that connect urban structure with microclimatic conditions and thermal performance at neighborhood, street, and pedestrian levels. Current research combines remote sensing, geographic information systems, microclimate simulation, and integrated urban climate–building energy models to assess how massing, open spaces, materials, vegetation, and shading influence thermal conditions under different scenarios [6] [2]. Studies conducted in hot and arid environments further indicate that effective heat mitigation generally requires coordinated interventions rather than a single isolated measure.

These interventions may include vegetation, shading, reflective or cool materials, and modifications to urban form [7] [9]. Their effectiveness varies according to the physical characteristics of the site, including urban density, orientation, street configuration, and the spatial distribution of vegetation [7] [9]. Generative modeling also provides a means of producing and evaluating alternative urban configurations according to their thermal performance [8]. Consequently, environmental simulation should not be limited to evaluating completed designs; it can also function as a prospective tool for comparing design alternatives before implementation.

In parallel, artificial intelligence—particularly machine learning and deep learning—has become increasingly relevant to urban heat research because it can capture nonlinear associations within complex spatial and environmental datasets while substantially reducing the processing time associated with detailed physics-based simulations [10] [11].

. Recent reviews show that its applications extend beyond temperature forecasting and hotspot detection to include data-driven surrogate models, comparative scenario testing, multi-objective optimization, and planning-oriented decision support [10] [11]. Deep-learning approaches can also generate building-resolved maps of pedestrian heat stress at very fine spatial resolution much faster than conventional modeling procedures, making them suitable for contexts in which numerous design alternatives must be assessed rapidly [12]. A further development links generative artificial intelligence with urban climate modeling to explore thermally improved urban configurations, thereby strengthening the integration of prediction, simulation, and optimization within digital-twin decision-support environments [8].

Against this background, the reconstruction of Old Mosul is particularly significant because it involves more than rebuilding a damaged physical fabric; it also requires recovering the morphological and environmental qualities of a historic urban setting. UNESCO documentation describes the Old City as a compact urban system characterized by narrow and irregular streets, closely grouped housing units, inward-oriented dwellings, internal courtyards, and the use of local construction materials [13] [14]. These characteristics represent essential components of Mosul's architectural identity and should be considered in reconstruction decisions [13] [14]. Research conducted in the Al-Qlay'at district further indicates that reconstruction should respond to the spatial structure, accessibility, activities, and contemporary requirements of residents while retaining the identity of the historic urban fabric [15]. Material selection is equally important, since replacing traditional construction materials with inappropriate alternatives can alter building energy performance and indoor thermal comfort during restoration [16]. Therefore, the reconstruction of Old Mosul, particularly Al-Qlay'at, requires an operational framework that connects decisions concerning built mass, open spaces, materials, and vegetation with measurable thermal performance. Such a framework can prevent reconstruction from creating a hotter and less climate-responsive environment while preserving the defining qualities of the historic fabric and limiting further amplification of urban heat island effects [13] [15] [16].

## 2. LITERATURE REVIEW

Building on the preceding discussion, this section examines selected studies concerned with urban heat islands and their mitigation, with particular attention to research employing digital simulation and artificial intelligence for analysis, prediction, interpretation, and assessment of mitigation alternatives. The review investigates how urban morphology, surface and material properties, and environmental conditions interact to influence the magnitude and spatial distribution of thermal effects. It also identifies the analytical tools, variables, and performance indicators that repeatedly demonstrate explanatory relevance across previous studies. The selected research is therefore examined to derive a concise set of variables applicable to the Old Mosul case study. Rather than presenting a purely descriptive summary, the review establishes the methodological basis for selecting the research variables, structuring the spatial–environmental dataset, and formulating the proposed environmental digital twin through the integration of simulation, artificial intelligence, and urban heat mitigation.

Recent studies have moved beyond traditional monitoring toward analytical and predictive tools that support urban planning and design decisions. Vitanova et al. employed urban digital-twin modeling and climate simulation to understand the spatial distribution of urban heat, while Bahadori et al. integrated urban heat island and building-energy models to assess mitigation effects at urban and architectural scales [17] [6]. Snaiki and Merabtine reviewed the role of machine learning in urban heat prediction, monitoring, optimization, and management [11].

Li et al. applied remote sensing and deep learning to identify the spatial potential for roof greening [18], whereas Hussainzad and Gou developed an explainable machine-learning framework that connected land-surface temperature with urban-form indicators in the formal and informal settlements of Kabul [19]. Zhao et al. examined the construction of an urban heat island network from a landscape-connectivity perspective [20]. Wang and Hu mapped urban heat island networks in Nanjing by analyzing thermal sources, corridors, nodes, and spatial connectivity [21]. Another study by Zhao et al. proposed multi-level mitigation pathways that integrated cold- and heat-island sources, connectivity analysis, circuit theory, and future urban simulation [22]. Su, Zhang, and Chang investigated nature-based heat-mitigation solutions within the historic fabric of Beijing Old City [23]. Abedrabboh et al. reviewed combined mitigation measures for hot–arid cities [7], while Khalvandi and Karimimoshaver examined morphological solutions related to urban street canyons, orientation, aspect ratios, shading, and airflow [24]. Aslani, Sereshti, and Sharifi analyzed the spatial distribution and principal drivers of urban heat islands across Tehran's districts [25]. You, Huang, and Guan examined how the form, spatial layout, development stage, and land-use functions of new towns influence urban heat island patterns [26]. Rahmani and Sharifi systematically reviewed urban heat dynamics across Local Climate Zones and compared the thermal behavior of different urban forms [27]. Collectively, these studies demonstrate a clear movement toward integrating simulation, artificial intelligence, spatial analysis, and optimization to diagnose, predict, and mitigate urban heat island effects at different urban scales.

**Table 1. Analysis of Previous Studies and Identification of Study Variables (Source: Authors)**

| Author & Year | Methodology | Case Study | Variables | Tool | Scale | Key Findings |
|---|---|---|---|---|---|---|
| **Vitanova et al. (2025) [17]** | Urban digital twin with climate simulation | Sofia, Bulgaria | Land use, air temperature, surface properties | Urban Digital Twin + WRF + SLUCM | City | Demonstrated the effectiveness of digital twins in understanding spatial distribution of UHI and supporting decision-making |
| **Snaiki and Merabtine (2025) [11]** | Systematic critical review | Multiple studies | Prediction, monitoring, optimization, management | Machine-learning techniques | Multi-scale | Identified ML as a key tool in UHI analysis and mitigation |
| **Kim et al. (2025) [28]** | Deep learning with Pareto optimization | Greater Seoul region | Green roofs, cool roofs, heat stress, cost | Multi-ResNet + WRF-UCM | Urban/Regional | Showed optimal distribution reduces heat stress and computational time |
| **Rezaei et al. (2024) [29]** | Spatial network analysis of cooling corridors | Urban network | Cool corridors, connectivity, heat intensity | Spatial network analysis + GIS | City | Highlighted the importance of improving corridor connectivity for mitigation efficiency |
| **Hussainzad and Gou (2025) [19]** | Explainable machine-learning framework | Kabul, Afghanistan | LST, urban-form indicators, density, greening | RF + XGBoost + GBM + SHAP | City/Informal settlements | Found vertical densification and greening reduce heat in informal areas |
| **Zhao et al. (2024) [20]** | Landscape connectivity analysis of thermal network | Chinese city | Heat sources, thermal paths, spatial connectivity | Landscape Connectivity + GIS | City | Showed thermal-network analysis helps prioritize cooling interventions |
| **Wang and Hu (2025) [21]** | Thermal-network mapping using landscape connectivity | Nanjing, China | Hotspots, links, connectivity | Landscape Connectivity | City | Demonstrated effectiveness in guiding spatial mitigation strategies |
| **Su et al. (2022) [23]** | Nature-based solutions with thermal evaluation | Historic Beijing | Vegetation, shading, heritage | NbS + environmental analysis | Historic fabric/Neighborhood | Confirmed NbS reduce heat while preserving heritage value |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | context, thermal comfort | | | |
| **Abedrabboh et al. (2025) [7]** | Systematic review | Hot–arid cities | Vegetation, shading, cool materials, thermal comfort | Literature review | Multi-scale | Confirmed the effectiveness of combined mitigation strategies |
| **Bahadori et al. (2025) [6]** | Coupled UHI and building-energy modeling | Applied urban case | Urban heat, building energy, mitigation strategies | Coupled UHI + BEM | Neighborhood/City | Showed integrated evaluation improves the accuracy of mitigation-impact assessment |
| **Aslani et al. (2025) [25]** | Regional analysis and key drivers | Tehran, Iran | LST, land cover, density, climate drivers | AIRS + MODIS + ERA5-Land | Region/City | Identified key spatial drivers of UHI intensity |
| **You et al. (2023) [26]** | Morphological and planning analysis | New cities | Urban form, function, land use | Spatial urban analysis | City | Showed planning and form influence UHI intensity |
| **Rahmani and Sharifi (2025) [27]** | Systematic review | Multiple studies | LCZs, surface temperature, air temperature, urban form | Local Climate Zones | Multi-scale | Highlighted the importance of LCZs in explaining thermal variations |
| **Zhao et al. (2025) [22]** | Thermal-mitigation network framework | Chinese city | Thermal connectivity, hotspots, intervention priority | Urban Heat Network | City | Proposed using thermal networks as planning tools |
| **Khalvandi and Karimimoshaver (2025) [24]** | Systematic review of morphological solutions | Multiple studies | H/W ratio, orientation, shading, canyon form | Systematic review | Street/Canyon | Confirmed that street-level morphology strongly affects local heat |

### 2.1. Theoretical Framework of the Study

- Table 1 shows that previous studies mostly treat the urban heat island phenomenon as a multi-factorial issue rather than the outcome of a single variable. Recurrent factors such as surface properties, land cover, urban density, shading, vegetation, and height-to-width ratio indicate the need for a model that integrates morphological, material, and environmental dimensions.
- The reviewed literature also reveals clear methodological diversity, including climate simulation, digital modeling, thermal network analysis, machine learning, and deep learning. This confirms that urban heat island research has moved beyond description and monitoring toward explanatory, predictive, and optimization-based approaches.
- Digital simulation remains a central tool because it enables the spatial distribution of heat to be analyzed and mitigation scenarios to be tested before implementation. However, recent studies increasingly combine simulation with digital twins, machine learning, and coupled models, enhancing both explanatory capacity and practical decision support.
- Artificial intelligence has become a key method for prediction, computational acceleration, and modeling nonlinear relationships between urban fabric variables and heat intensity. This is important for the present study because reconstruction requires testing many scenarios, which is difficult through conventional simulation alone.
- The literature also shows a shift from diagnosis toward mitigation, including green roofs, cool materials, vegetation, shading, cool corridors, and nature-based solutions. This indicates a broader transition from understanding urban heat to translating thermal knowledge into applicable design and planning decisions.

- Network-based studies further suggest that urban heat should be understood as a spatially connected system rather than isolated hotspots. This supports the present study's focus on treating the historic fabric of Old Mosul as an interconnected thermal structure, rather than addressing individual elements separately.
- Most previous studies operate at city or neighborhood scales, while fewer address street-scale or historic urban fabrics. This reveals a research gap, particularly in damaged heritage contexts undergoing reconstruction, where the relationship between preservation and environmental performance is highly sensitive.
- Although some studies discuss historic fabrics and nature-based solutions, the explicit integration of historic reconstruction, environmental digital twins, and optimization remains limited. This gap supports the originality of the present research.
- Finally, the reviewed studies provide three methodological pathways: climate simulation and thermal evaluation, machine learning and rapid prediction, and optimization-based alternative selection. The present study builds on these pathways by integrating them into a single framework for supporting climate-responsive reconstruction in Old Mosul.

## 3. RESEARCH ASPECTS

### 3.1. Research Problem

The ongoing reconstruction of Old Mosul lacks an operational system that links reconstruction decisions—massing, voids, materials, and vegetation—with measured or simulated thermal outputs. This may unintentionally intensify the urban heat island effect at street and neighborhood scales. Moreover, relying on a separate simulation for each reconstruction option makes decision-making slow and costly, while reconstruction requires testing thousands of possible scenarios. This highlights the value of machine learning models as fast surrogate tools for simulation within an optimization framework.

### 3.2. Research Question

How can an environmental digital twin for Old Mosul be developed by integrating urban climate simulation, deep learning, and optimization to generate reconstruction alternatives that reduce urban heat island indicators without compromising the characteristics of the historic urban fabric?

### 3.3. Research Aim

This study aims to develop an intelligent model combining digital twins, deep learning, and optimization to support reconstruction decisions in Old Mosul by reducing urban heat island indicators at street and neighborhood scales, based on variables related to traditional urban fabric, surface materials, and vegetation cover.

### 3.4. Research Methodology

The case study was divided into seven main sectors to facilitate simulation across the study area. Within each sector, several simulation points were distributed across the sector area, ranging from approximately 100 points in larger sectors to 70 points in smaller ones. New reconstruction elements currently used along the riverfront were considered in Sectors 5 and 7, while the remaining sectors retained their traditional character. This division enables a comparative analysis between sectors in terms of (UHI) indicators.

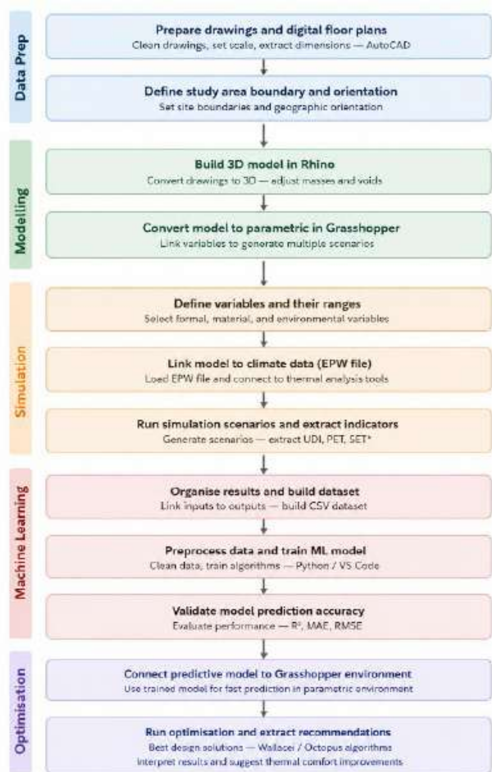
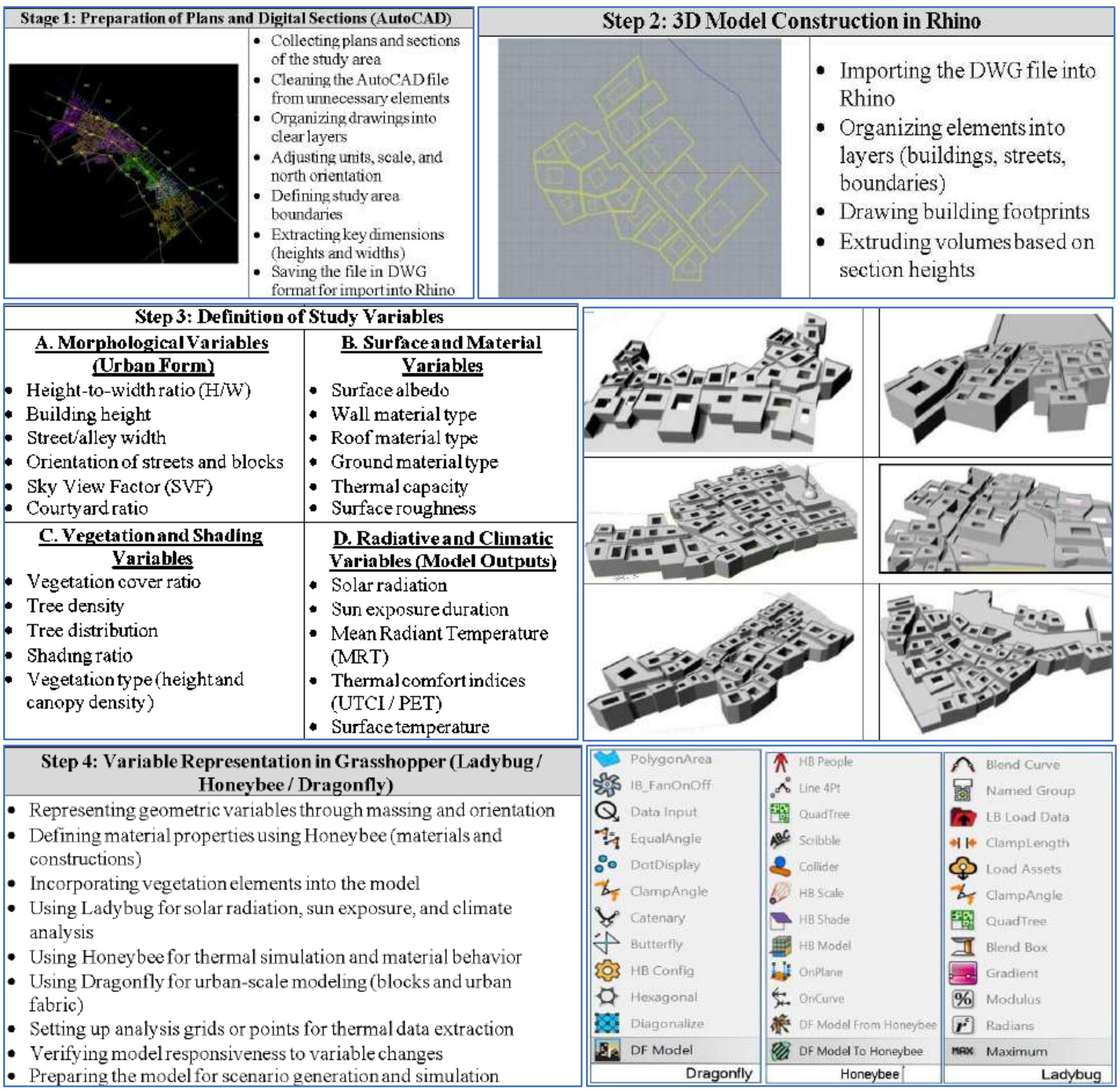
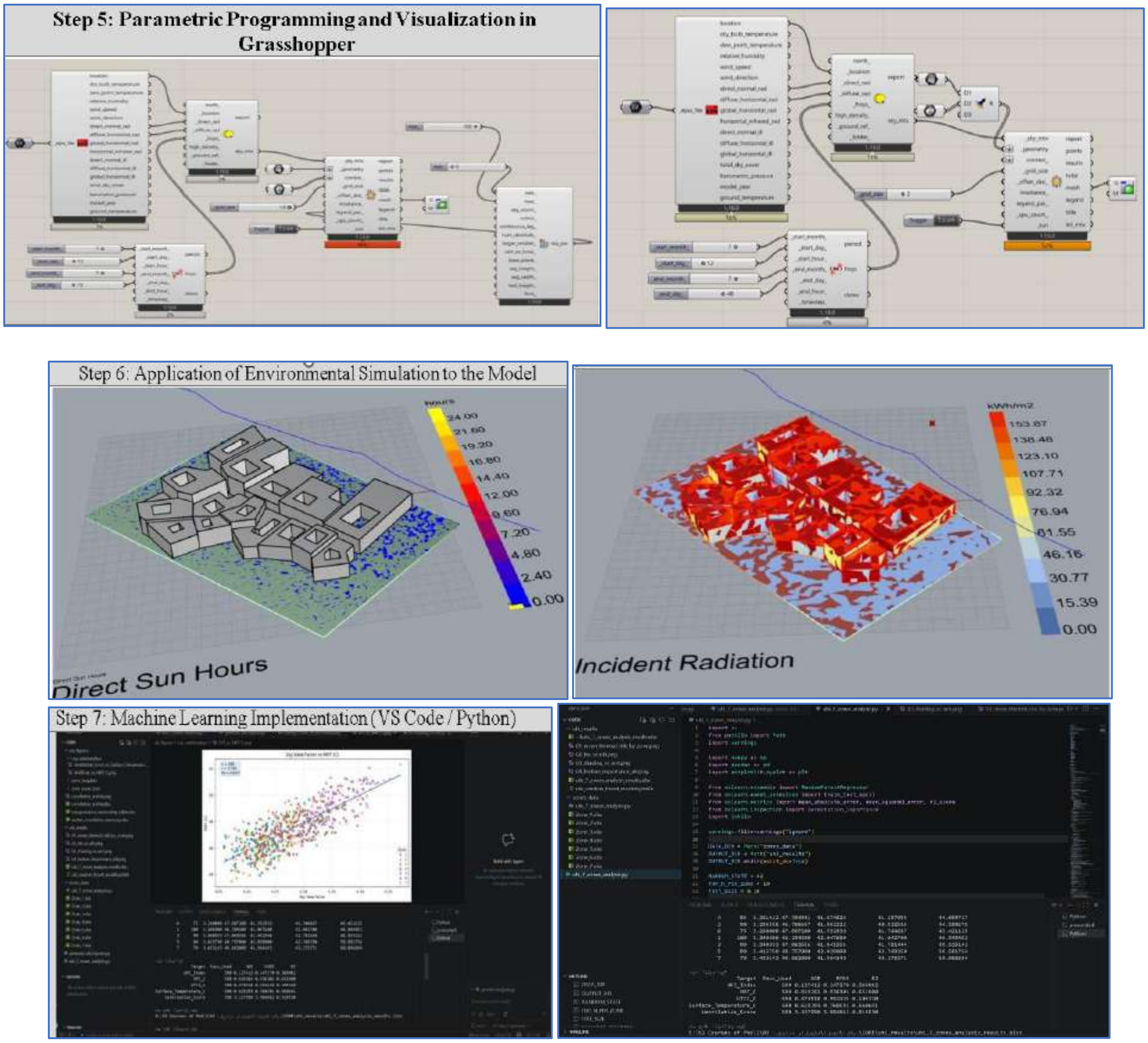



**Figure 1. Research methodology (Source: the authors)**

**Figure 2. Images from the case study area in Al-Qlay'at (Source: Author)**

3.5. Methodological Implementation Steps:



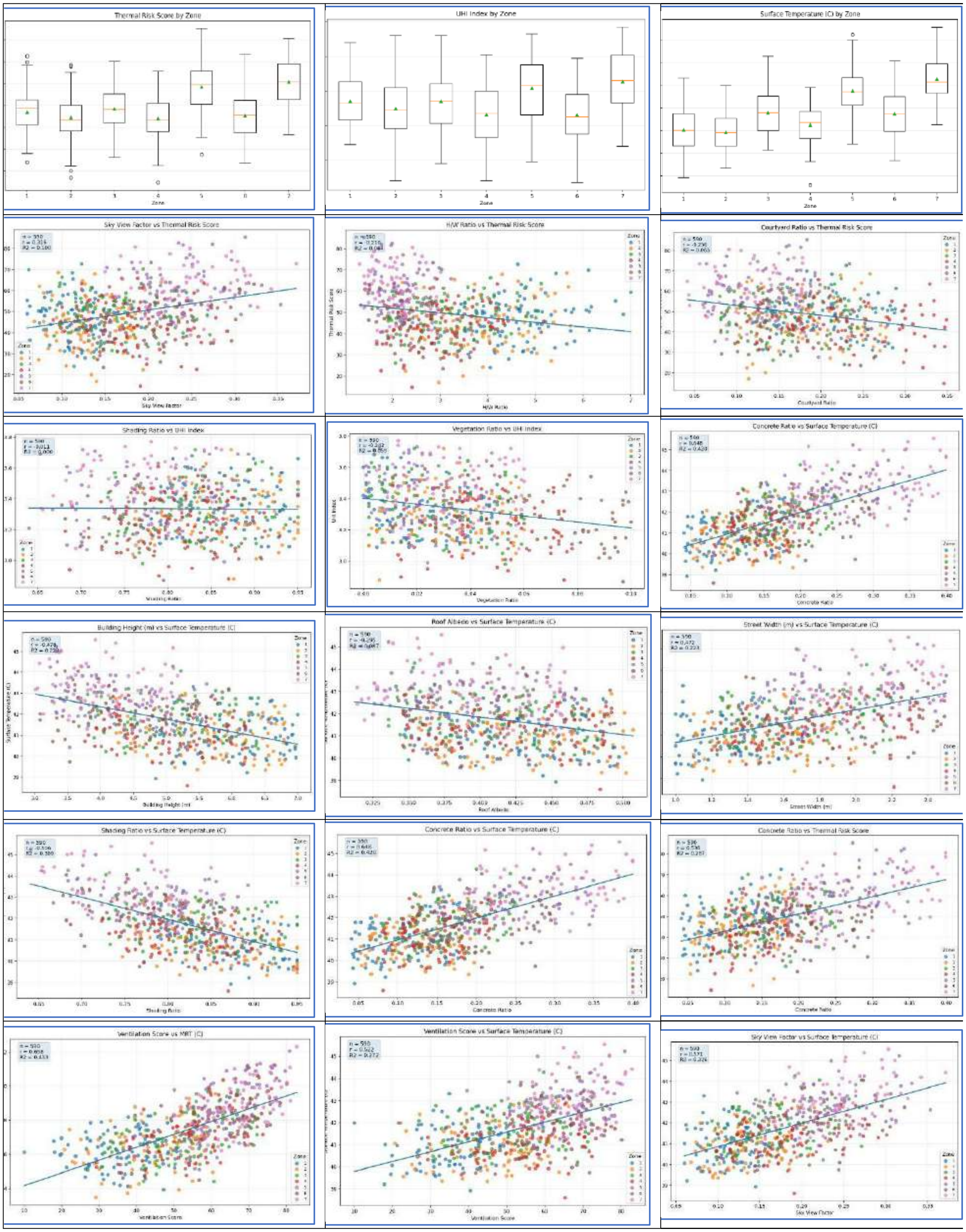



### 3.6. Thermal Differences Between Modern Reconstruction and Traditional Areas

The results show a clear thermal difference between modern reconstruction areas (Sectors 5 and 7) and areas that largely retained traditional construction techniques. The average thermal risk index reached 59.74 in modern areas compared to 45.92 in traditional ones (≈30.1% increase). Surface temperature rose from 41.35°C to 43.01°C (≈1.66°C difference), while MRT increased from 47.05°C to 48.81°C (≈1.76°C difference). These findings demonstrate that modern reconstruction is likely to produce more thermally stressful environments, particularly in surface temperature and radiative load. UHI values showed a smaller increase (from 3.30 to 3.43, ≈4.1%), while UTCI differences remained minimal (≈0.19°C), suggesting that surface- and radiation-related indicators capture reconstruction impacts more effectively than composite comfort indices like UTCI.

### 3.7. Impact of Modern vs. Traditional Materials

Material differences play a key role in explaining thermal variation, particularly through the relationship between Concrete Ratio and thermal indicators. Higher concrete ratios were associated with increased surface temperature, thermal risk, and UHI intensity. In modern areas, especially Sectors 5 and 7, extensive use of hard surfaces increased heat absorption and re-radiation.


Thermal Risk Score by Zone
UHI Index by Zone
Surface Temperature (C) by Zone
Sky View Factor vs Thermal Risk Score
H/W Ratio vs Thermal Risk Score
Courtyard Ratio vs Thermal Risk Score
Shading Ratio vs UHI Index
Vegetation Ratio vs UHI Index
Concrete Ratio vs Surface Temperature (C)
Building Height (m) vs Surface Temperature (C)
Roof Albedo vs Surface Temperature (C)
Street Width (m) vs Surface Temperature (C)
Shading Ratio vs Surface Temperature (C)
Concrete Ratio vs Surface Temperature (C)
Concrete Ratio vs Thermal Risk Score
Ventilation Score vs MRT (C)
Ventilation Score vs Surface Temperature (C)
Sky View Factor vs Surface Temperature (C)

Traditional materials do not inherently prevent UHI effects but offer different thermal responses when combined with compact urban forms, narrow streets, and self-shading conditions. Therefore, the difference between modern and traditional areas is not due to material alone, but to the integration of material with urban morphology. Improving thermal performance does not require reverting entirely to traditional materials, but rather optimizing modern materials, reducing exposed concrete, increasing appropriate reflectivity, and incorporating shading and vegetation.

### 3.8. Role of Shading and Sky Exposure

Results show that Sky View Factor (SVF) and Shading Ratio are key variables controlling thermal variation. Higher SVF values correlate with increased MRT and surface temperature, while higher shading ratios reduce them. This confirms that solar exposure significantly influences thermal load at the pedestrian level. MRT is particularly sensitive to radiative conditions; open sky exposure increases solar gain, while shading reduces thermal stress. However, SVF is not inherently negative—it can enhance nighttime heat dissipation, but during hot daytime conditions it increases solar gain unless balanced with shading and suitable materials. Therefore, thermal performance depends on achieving a balance between exposure and shading rather than maximizing one over the other.

### 3.9. Why MRT Was More Sensitive Than UTCI

MRT showed stronger relationships with morphological and radiative variables such as SVF, shading ratio, H/W ratio, building height, and street width. This is expected, as MRT directly reflects radiative heat exchange experienced by pedestrians. In contrast, UTCI showed weaker correlations because it is a composite index influenced by multiple factors, including air temperature, humidity, wind speed, and radiation. Thus, while morphological variables strongly affect MRT, their impact becomes less isolated within UTCI due to these additional parameters. This suggests that MRT is more suitable for interpreting the effects of urban form and radiation, whereas UTCI is better used as a complementary indicator for overall thermal comfort.

### 3.10. interpreting (UHIs) as a Multi-Factor Outcome

The results indicate that urban heat islands in the study area cannot be explained by a single variable such as material type, street width, or vegetation alone. Instead, heat emerges from the interaction of multiple factors: higher concrete ratios increase surface temperature, higher Sky View Factor (SVF) intensifies solar exposure, while shading and higher H/W ratios reduce radiative load at the pedestrian level.

This implies that thermal hotspots are not caused by one condition, but by the accumulation of several factors—hard surfaces, limited shading, high exposure, and insufficient ventilation. Conversely, thermal conditions improve when mitigation factors are combined, such as adequate shading, less heat-absorbing materials, and reduced direct solar exposure. Therefore, urban heat should be understood systemically, as a product of interactions between material properties, urban form, shading, exposure, and ventilation. This also explains why stronger relationships appeared with MRT and surface temperature, while weaker responses were observed in UHI and UTCI, as these indices do not respond equally to individual variables.

### 3.11. Design Implications

The results demonstrate that mitigating (UHIs) cannot be achieved through a single intervention, but requires an integrated set of design decisions. Thermal problems result from the interaction of material, shading, exposure, and ventilation; therefore, effective interventions must address these elements collectively.

Shading emerges as a primary strategy, given its strong association with reductions in MRT and surface temperature. Improving thermal comfort thus depends not only on vegetation but also on designing built-form shading through massing, overhangs, arcades, and façade elements. In this sense, shading is not merely an aesthetic feature but a direct mechanism for reducing radiative load at the pedestrian level.

The results also highlight the importance of reducing exposed hard surfaces, particularly those with high heat absorption capacity. This can be achieved by selecting materials with appropriate albedo, minimizing exposed concrete, and strategically integrating vegetation and shading in the hottest locations rather than increasing greenery indiscriminately.

At the urban form level, controlling SVF and H/W ratios is critical. Excessive openness increases solar exposure, while excessive enclosure may limit ventilation and nocturnal heat dissipation. Therefore, a balanced approach is required—one that maintains airflow and visual permeability while minimizing excessive heat gain.Accordingly, climate-responsive reconstruction does not imply a literal return to traditional forms nor the uncritical adoption of modern ones. Instead, it requires developing a hybrid design approach that draws from the shading logic and compact morphology of traditional fabrics while integrating modern materials and technologies in a thermally optimized manner.

### 3.12. Discussion Summary

The results confirm that thermal differences across the study area arise from the interaction between material properties, urban morphology, shading, sky exposure, and ventilation. Surface temperature and MRT showed stronger sensitivity to these variables, while UHI and UTCI exhibited weaker responses when variables were analyzed individually. The findings also demonstrate that relying on average values alone is insufficient; understanding the relationships between variables is essential to explain why certain locations exhibit higher temperatures. Thermal hotspots typically result from the accumulation of unfavorable conditions—hard surfaces, limited shading, high exposure, and insufficient vegetation distribution—rather than a single factor. Therefore, effective thermal mitigation in reconstruction requires integrated solutions rather than isolated measures. Optimal design decisions should simultaneously reduce hard surfaces, increase shading, regulate sky exposure, improve material properties, and strategically distribute vegetation where it is most needed.

## 4. CONCLUSIONS

The analysis shows that thermal performance in the study area is not evenly distributed across the seven sectors. Rather, it varies according to reconstruction type, material properties, and urban fabric morphology. Sectors 5 and 7, which represent modern reconstruction along the riverfront, recorded higher thermal levels compared with most areas that retained characteristics closer to traditional construction techniques. This difference was most evident in the thermal risk index, surface temperature, and MRT, all of which are directly related to heat absorption, radiative exposure, and thermal load at the pedestrian level. Therefore, the current form of modern reconstruction has not achieved sufficient thermal responsiveness, particularly when associated with increased hard surfaces, limited shading, and high exposure within open spaces.

The results also indicate that the urban heat island phenomenon in the study area cannot be explained by a single factor, but by the interaction of several variables. Concrete ratio and Sky View Factor (SVF) were associated with higher thermal values, while shading and higher height-to-width ratios (H/W) helped reduce radiative load, especially in relation to MRT. This means that neither material nor urban form alone is sufficient to explain the phenomenon. Instead, thermal performance is shaped by the relationship between material properties, shading, sky exposure, ventilation, and surface characteristics. Thus, the relatively better thermal performance of some traditional areas is not due only to older materials, but to the integration of these materials within a more compact fabric capable of producing shade and reducing direct solar exposure.

Accordingly, the study concludes that the reconstruction of Old Mosul requires a climate-responsive design approach that moves beyond restoring urban image or replacing materials alone, toward linking reconstruction decisions with actual thermal performance. The findings support the development of a hybrid reconstruction model that combines the advantages of traditional urban fabric—such as shading, compactness, and controlled alley widths—with the potential of modern technologies, provided that their thermal and material properties are carefully controlled. Reducing urban heat islands cannot be achieved through a single intervention, but through an integrated strategy that includes reducing exposed hard surfaces, improving shading, regulating sky exposure, selecting climate-appropriate materials, and directing vegetation toward the most heat-exposed locations. In this way, reconstruction shifts from merely restoring urban form to also restoring the environmental performance of the historic fabric.

Finally, the study recommends the following:

- Adopting climate-responsive reconstruction rather than merely formal reconstruction by reducing exposed concrete and hard surfaces, especially along the riverfront.
- Increasing shading through trees, overhangs, covered pathways, and compact urban massing.
- Developing a hybrid reconstruction model that combines modern construction techniques with the logic of traditional fabric in terms of shading, materials, and sky exposure control.

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