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AI-Driven Geospatial Intelligence for Urban Heat Island Monitoring and Climate Resilience

Pradeep T [#1] and Prof. Nayana K [*2]

[#] *Department of Computer Science & Engineering at GM University, Davanagere*

[*] *Department of Computer Science & Engineering at GM University, Davanagere*

Abstract*— Rapid urbanization is transforming natural landscapes into densely built environments dominated by impervious surfaces such as concrete, asphalt, and buildings. While urban growth supports economic development, it also intensifies environmental challenges, including the Urban Heat Island (UHI) effect, increased flood risk, reduced groundwater recharge, and declining urban green spaces. Conventional urban environmental assessment methods often depend on complex Geographic Information Systems (GIS), costly datasets, and specialized expertise, making them less accessible for many planning authorities. This paper presents a GeoAI-based Urban Heat Intelligence Platform, a web-based decision support system that integrates satellite image analysis, artificial intelligence, and environmental simulation to enable efficient urban environmental assessment [1]. The proposed framework combines Random Forest, Support Vector Machine (SVM), XGBoost, and a U-Net model with a pre-trained ResNet-34 encoder to accurately extract building footprints from RGB satellite imagery through semantic segmentation. The extracted spatial information is further utilized to estimate Urban Heat Island intensity, flood vulnerability, and green space coverage using lightweight environmental simulation models. The platform also includes an intelligent mitigation planning module that recommends interventions such as green roofs, permeable pavements, and urban forests, along with an interactive vegetation simulator that allows users to evaluate the potential impact of green infrastructure before implementation. Experimental results validate the effectiveness of the proposed GeoAI-based Urban Heat Intelligence Platform for intelligent urban environmental assessment. Among the evaluated models, U-Net with a ResNet-34 encoder delivered the most reliable segmentation performance, achieving a Dice score of 0.616, Recall of 0.703, and the highest Boundary F1-score of 0.822, demonstrating superior spatial consistency and building boundary extraction [2]. Although XGBoost attained the highest IoU (0.469) and AUC (0.946), its lower boundary accuracy limited its effectiveness for precise building delineation. In contrast, SVM and Random Forest showed comparatively lower segmentation performance. These findings confirm that deep learning-based semantic segmentation provides a robust foundation for Urban Heat Island, flood risk, and green space analysis. Furthermore, the lightweight Flask-based web platform enables scalable, GIS-independent deployment, making advanced GeoAI capabilities readily accessible for researchers, urban planners, policymakers, and local authorities to support climate-resilient and sustainable smart city development.

***Index Terms*— GeoAI, Remote Sensing, Semantic Segmentation Flood Risk Assessment, Sustainable Smart Cities, Urban Heat Island (UHI)**

I. Introduction

Urbanization has become a defining feature of modern development, fostering economic growth, industrialization, and improved infrastructure while simultaneously creating significant environmental challenges. The rapid expansion of impervious surfaces such as concrete, asphalt, and rooftops has intensified the Urban Heat Island (UHI) effect, increased flood susceptibility, reduced groundwater recharge, and accelerated the loss of urban green spaces. Satellite imagery clearly illustrates the contrast between densely built urban regions and surrounding vegetated landscapes, where the absence of natural vegetation leads to higher surface temperatures and greater surface runoff during rainfall events. Despite the World Health Organization (WHO) recommending approximately 30% urban green coverage for healthier cities, many rapidly growing metropolitan areas remain well below this benchmark. Although recent advances in Artificial Intelligence (AI) and remote sensing have enabled large-scale urban environmental monitoring, existing solutions often depend on expensive Geographic Information Systems (GIS), multispectral or thermal imagery, and specialized expertise, limiting their accessibility and practical adoption, particularly in developing regions [3]. These limitations highlight the need for an intelligent, scalable, and cost-effective framework capable of transforming freely available satellite imagery into actionable insights for sustainable urban planning.

To address these challenges, this research proposes a GeoAI-based Urban Heat Intelligence Platform, an integrated browser-based decision support system that combines machine learning, deep learning, remote sensing, and physics-inspired environmental simulations within a unified framework. The platform comparatively evaluates Random Forest, Support Vector Machine (SVM), XGBoost, and U-Net with a pre-trained ResNet-34 encoder for accurate building footprint extraction from RGB satellite imagery, which subsequently supports the estimation of Urban Heat Island intensity, flood vulnerability, and green space distribution [4]. Furthermore, the framework incorporates an intelligent mitigation planning module and an interactive vegetation simulator to evaluate sustainable interventions such as green roofs, permeable pavements, cool roofs, and urban forests before implementation. Designed as a lightweight web application, the proposed system eliminates the need for specialized GIS software or dedicated hardware while providing an accessible and computationally efficient solution for researchers, urban planners, policymakers, and local authorities. Although the framework relies on RGB imagery and physics-based environmental models rather than thermal, multispectral, or terrain datasets, it establishes a robust foundation for low-cost urban environmental assessment and offers significant potential for future integration with advanced remote sensing technologies to support climate-resilient, data-driven, and sustainable smart city development.

II. Related Work

Recent research has demonstrated significant progress in applying deep learning, remote sensing, and machine learning to urban environmental analysis. In the field of building segmentation, Mnih and Hinton introduced the Massachusetts Building Dataset, which established a benchmark for automatic building footprint extraction and demonstrated the effectiveness of convolutional neural networks over traditional handcrafted feature-based methods. Building on this work, Iglovikov and Shvets improved segmentation accuracy by integrating ImageNet pre-trained encoders with the U-Net architecture, highlighting the advantages of transfer learning. Hamaguchi et al**.** further enhanced building extraction by introducing watershed-based post-processing to accurately separate adjacent structures. More recently, transformer-based architectures such as the Pyramid Vision Transformer (PVT) and SegFormer have shown remarkable capability in capturing long-range spatial features, providing competitive alternatives to conventional CNN-based segmentation models.

Urban Heat Island (UHI) studies have primarily relied on thermal remote sensing for estimating land surface temperature [4]. Weng established the relationship between land surface temperature, building density, vegetation, and surface albedo, demonstrating that reliable UHI assessment can also be achieved using proxy variables derived from RGB imagery. Studies by Li et al. and Santamouris et al. confirmed the significant cooling benefits of urban vegetation and cool-roof technologies, while Rasul et al. demonstrated that RGB-based vegetation indices provide a practical alternative to multispectral imagery for estimating green space coverage in urban environments.

Urban flood risk modelling has traditionally been based on hydrological principles such as the Rational Method, where impervious surface coverage is a dominant factor influencing runoff generation. Studies by Schubert et al., Brody et al., and Tehrany et al. demonstrated that building density and impervious surface fraction extracted from satellite imagery are reliable predictors of flood susceptibility, supporting the integration of satellite-derived building footprints into flood risk assessment models [6].

Traditional machine learning algorithms, including Random Forest, Support Vector Machine (SVM), and XGBoost, have also shown strong performance in remote sensing applications. Breiman established Random Forest as a robust classifier for high-dimensional geospatial data [3], while Melgani and Bruzzone demonstrated the effectiveness of SVM for complex satellite image classification. Chen and Guestrin introduced XGBoost, which provides improved classification accuracy and computational efficiency, particularly for imbalanced datasets. Comparative studies by Demir et al. and Shi et al. concluded that deep learning models generally outperform conventional machine learning when sufficient training data are available, whereas traditional algorithms remain effective under computational and data constraints.

Although previous studies have achieved notable success in building extraction, UHI analysis, flood modelling, and urban remote sensing, most address these problems independently and depend on thermal imagery, multispectral datasets, or specialized GIS platforms [5]. Such requirements limit their accessibility and practical deployment. In contrast, the proposed GeoAI-based Urban Heat Intelligence Platform integrates building segmentation, Urban Heat Island assessment, flood risk estimation, green space analysis, mitigation planning, and vegetation simulation into a single browser-based framework using only freely available RGB satellite imagery. This integrated, low-cost, and user-friendly approach provides a practical decision-support tool for climate-resilient and sustainable urban planning while eliminating the dependence on expensive software and specialized geospatial expertise.

III. Proposed Methodology

A. *Overview of the Proposed Framework*

This research presents a GeoAI-based Urban Heat Intelligence Platform**,** an integrated framework that combines remote sensing, artificial intelligence, semantic segmentation, and environmental modelling to support sustainable urban planning [7]. Rapid urbanization has intensified challenges such as Urban Heat Island (UHI) effects, loss of green spaces, and increased environmental risks. Unlike conventional methods that analyze UHI, flood risk, or vegetation separately, the proposed framework integrates these analyses into a unified browser-based decision support system using only RGB satellite imagery.

The methodology transforms raw satellite images into actionable urban intelligence through a structured workflow involving image pre-processing, land-use and land-cover classification, deep learning-based semantic segmentation, environmental analysis, and mitigation planning. Semantic segmentation models identify key urban features, including buildings, roads, vegetation, water bodies, and bare land, enabling accurate assessment of heat-prone areas and environmental conditions [8]. The extracted spatial information is further used to estimate UHI intensity, evaluate green space distribution, and support predictive environmental analysis.

The platform also incorporates simulation capabilities to evaluate mitigation strategies such as urban greening, reflective roofing, and expansion of green infrastructure. The results are presented through an interactive web-based interface that enables planners and policymakers to visualize urban heat hotspots, environmental risks, and recommended interventions. By integrating GeoAI, remote sensing, and environmental intelligence into a single platform, the proposed framework provides an efficient, scalable, and cost-effective solution for climate-resilient urban planning and sustainable city development[9].

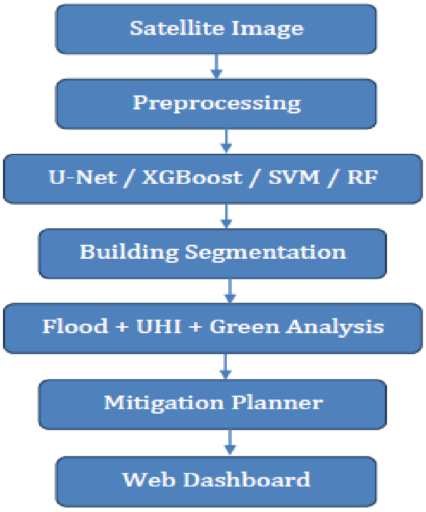

Figure 3.1: Overall methodological pipeline of the proposed Urban Heat Intelligence Platform.

B. *Data Acquisition and Image Pre-processing*

The proposed framework utilizes the Massachusetts Buildings Dataset, which contains high-resolution RGB satellite images and corresponding building masks for supervised learning. Before model training, all images are resized to a uniform resolution and normalized to improve computational efficiency and training stability. Data augmentation techniques such as horizontal flipping, rotation, and brightness variation are employed to increase dataset diversity and improve the model's ability to generalize across different urban scenarios. This preprocessing stage reduces noise and enhances feature consistency, enabling robust building segmentation under varying lighting conditions and urban layouts.

C. *Building Footprint Segmentation*

Accurate building detection forms the foundation of the proposed framework because building density directly influences heat accumulation, runoff generation, and green space availability. To identify the most suitable segmentation technique, the framework comparatively evaluates Random Forest, Support Vector Machine (SVM), XGBoost, and U-Net with a pre-trained ResNet-34 encoder [10]. Classical machine learning models classify image patches using handcrafted texture features, whereas U-Net performs end-to-end semantic segmentation by learning hierarchical spatial representations directly from the input imagery. Transfer learning with the ResNet-34 encoder improves feature extraction while reducing training time and computational cost.

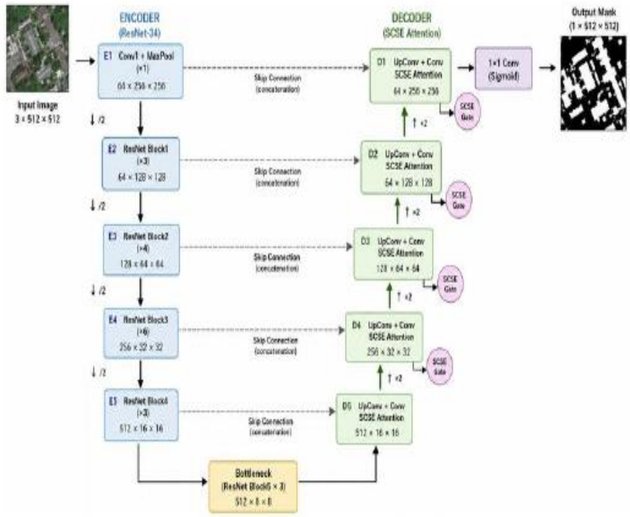

Figure 3.3: U-Net architecture with pertained ResNet-34 encoder and SCSE attention decoder.

D. *Building Footprint Extraction*

The binary segmentation output is further refined using the watershed segmentation algorithm to accurately distinguish individual buildings that are adjacent or connected in densely developed urban areas. During semantic segmentation, neighboring buildings often appear as merged regions due to overlapping boundaries or limited spatial separation, reducing the accuracy of subsequent environmental analyses. Watershed segmentation addresses this limitation by treating the binary building mask as a topographic surface and separating connected structures based on distance transformation and marker-controlled region growing. This process effectively preserves individual building boundaries, eliminates merged building artifacts, and improves the geometric accuracy of extracted building footprints.

The refined building footprints provide a more realistic representation of the urban landscape and form the foundation for subsequent environmental modelling. Using these footprints, the platform estimates impervious surface coverage**,** which represents the proportion of land occupied by buildings and other non-permeable surfaces. Impervious surface estimation is a critical indicator for evaluating urban environmental conditions, as it directly influences surface runoff, heat accumulation, and vegetation distribution. The calculated impervious surface information serves as the primary input for the platform's environmental simulation modules, including Urban Heat Island (UHI) estimation**,** flood risk assessment**,** and green-space analysis**.** Consequently, watershed-based post-processing significantly enhances the reliability, precision, and practical applicability of the proposed GeoAI framework for intelligent urban environmental monitoring and sustainable urban planning.

E. *Environmental Simulation*

The extracted building footprints are transformed into a set of meaningful environmental indicators using computationally efficient simulation models that support urban sustainability assessment and evidence-based decision-making. Rather than relying on expensive thermal sensors, multispectral imagery, or complex GIS workflows, the proposed framework utilizes accurately segmented building footprints derived from RGB satellite imagery to estimate key urban environmental characteristics. This approach significantly reduces computational complexity while maintaining practical applicability for large-scale urban analysis.

The extracted spatial information is used to estimate impervious surface coverage**,** which serves as a fundamental indicator of urbanization and forms the basis for multiple environmental simulations. High concentrations of impervious surfaces are associated with increased surface temperatures, reduced rainwater infiltration, higher runoff generation, and limited vegetation growth. Based on these relationships, the framework generates environmental indicators including Urban Heat Island (UHI) intensity**,** flood vulnerability**,** and green-space distribution. These indicators provide a comprehensive understanding of urban environmental conditions by identifying heat-prone regions, flood-sensitive areas, and locations lacking adequate vegetation. The simulation results are further integrated into the browser-based GeoAI platform, allowing planners and decision-makers to visualize environmental risks and evaluate sustainable mitigation strategies. By converting building footprints into actionable environmental intelligence, the proposed framework offers a scalable, cost-effective, and accessible solution for climate-resilient urban planning, enabling informed decisions without the need for additional multispectral, thermal, or LiDAR datasets.

Urban Heat Island (UHI) Estimation: Urban Heat Island (UHI) intensity is estimated using building density and surface albedo proxies derived from RGB satellite imagery, enabling efficient heat assessment without the need for thermal sensors. Building footprints extracted through semantic segmentation are first used to calculate building density and impervious surface coverage across the study area. Regions characterized by dense urban development, extensive impervious surfaces, and low surface reflectance are more likely to absorb and retain solar radiation, resulting in elevated surface temperatures. Based on these spatial characteristics, the proposed simulation model assigns heat intensity scores to different urban regions and generates detailed spatial heat maps that highlight potential UHI hotspots. These maps provide valuable insights into the spatial distribution of urban heat and identify locations that are particularly vulnerable to heat accumulation. The estimated UHI intensity supports urban planners and policymakers in understanding the environmental impacts of rapid urbanization and prioritizing areas requiring mitigation. Furthermore, the generated heat maps enable the evaluation of sustainable intervention strategies, including tree plantation, urban forests, green roofs, cool roofs, reflective pavements, and expansion of green infrastructure**,** which are known to reduce surface temperatures and improve urban thermal comfort. By utilizing only RGB satellite imagery and computationally efficient modelling techniques, the proposed approach offers a scalable, cost-effective, and accessible solution for continuous urban heat assessment. This enables climate-resilient urban planning and supports evidence-based decision-making aimed at reducing heat-related risks, improving environmental quality, and promoting sustainable and livable cities.

Flood Risk Assessment: Flood vulnerability is estimated by analyzing impervious surface coverage derived from the extracted building footprints and applying runoff coefficient principles inspired by the Rational Method. The segmented building footprints are first used to calculate the proportion of built-up and non-permeable surfaces within the study area. High levels of impervious surfaces, such as buildings, roads, and paved infrastructure, significantly reduce rainwater infiltration and increase surface runoff during heavy rainfall events. Based on the estimated impervious surface coverage, the proposed simulation model computes runoff potential and classifies urban regions into low-, medium-, and high-risk flood zones**.** Areas with dense building concentrations and limited permeable land are identified as highly vulnerable due to their greater likelihood of water accumulation and drainage overflow. The resulting flood vulnerability maps provide a clear spatial representation of flood-prone locations, enabling planners and decision-makers to prioritize regions requiring immediate intervention. These maps support the development of effective flood mitigation strategies, including the implementation of sustainable urban drainage systems (SUDS)**,** permeable pavements, rainwater harvesting, green infrastructure, detention basins, and improved stormwater management. By utilizing only RGB satellite imagery and computationally efficient environmental modelling, the proposed framework offers a scalable, cost-effective, and practical approach for urban flood risk assessment. This enables proactive planning, enhances urban resilience to extreme weather events, and supports sustainable city development by reducing flood-related risks and improving overall environmental management.

Green Space Assessment: Urban green-space distribution is estimated using RGB-based image analysis and thresholding techniques to identify vegetation-covered areas from high-resolution satellite imagery. Unlike approaches that require multispectral imagery or vegetation indices such as the Normalized Difference Vegetation Index (NDVI), the proposed framework utilizes only RGB images, making the assessment more accessible and cost-effective. Image processing techniques are applied to distinguish vegetation from built-up surfaces, roads, and other land-cover types, enabling the calculation of the percentage of green space within the study area. The estimated vegetation coverage is then compared with the World Health Organization (WHO) recommendation of approximately 30% urban green-space coverage to identify regions with insufficient vegetation. Areas falling below this benchmark are considered environmentally vulnerable, as limited green space contributes to increased Urban Heat Island (UHI) intensity, poor air quality, reduced biodiversity, and lower climate resilience. The generated green-space distribution maps provide valuable information for urban planners and policymakers by highlighting priority locations for ecological restoration and sustainable land-use planning. These results support the implementation of mitigation measures such as tree plantation, urban forests, green roofs, community parks, green corridors, and landscape restoration to enhance environmental quality. By integrating green-space assessment into the GeoAI platform, the proposed framework enables evidence-based decision-making, promotes sustainable urban development, improves thermal comfort, and contributes to the creation of healthier, more resilient, and climate-adaptive smart cities.

IV. Experimental Results and Discussion

A. Experimental Setup

The proposed GeoAI-based Urban Heat Intelligence Platform was comprehensively evaluated using the Massachusetts Buildings Dataset**,** one of the most widely recognized benchmark datasets for aerial building footprint extraction and semantic segmentation. The dataset comprises 151 high-resolution RGB satellite images, each with a spatial resolution of 1500 × 1500 pixels, accompanied by manually annotated ground-truth building masks. It is divided into 137 training images**,** 4 validation images**,** and 10 testing images, providing a standardized framework for model development, hyper parameter tuning, and performance evaluation. The dataset encompasses a diverse range of urban environments, including dense residential neighbourhoods, commercial districts, varying building geometries, complex road networks, vegetation, and shadow-affected regions. These challenging characteristics make it particularly suitable for assessing the robustness, generalization capability, and spatial accuracy of semantic segmentation algorithms in real-world urban scenarios.

To investigate the effectiveness of different computational approaches, four representative segmentation models were implemented and comparatively analyzed: Random Forest**,** Support Vector Machine (SVM)**,** XGBoost**,** and a U-Net deep learning architecture with a pre-trained ResNet-34 encoder**.** The classical machine learning models served as baseline approaches for pixel-wise classification, while the U-Net model was designed to exploit hierarchical spatial features and contextual information for accurate building boundary extraction. This comparative analysis enabled a comprehensive assessment of both traditional and deep learning techniques for urban building segmentation.

Model performance was quantitatively evaluated using six widely accepted metrics: Intersection over Union (IoU)**,** Dice Coefficient**,** Area Under the Receiver Operating Characteristic Curve (AUC-ROC)**,** Precision**,** Recall**,** and Boundary F1-Score. These complementary evaluation metrics provide a holistic assessment of segmentation quality by measuring pixel-level classification accuracy, overlap between predicted and reference building masks, boundary preservation, detection capability, and geometric consistency. Together, they offer a rigorous and comprehensive evaluation framework for identifying the most effective segmentation model to support the proposed GeoAI platform's environmental analyses, including Urban Heat Island estimation, flood risk assessment, and green-space distribution mapping.

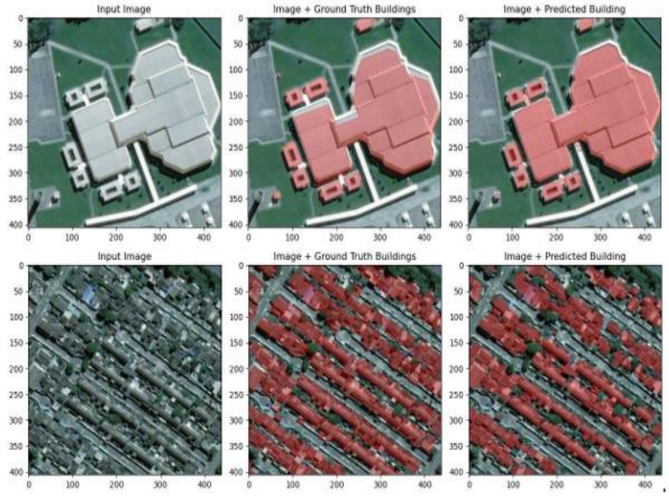

Fig: Satellite image and Ground Truth Building's

B. Performance Comparison of Building Segmentation Models

Table 1 summarizes the quantitative performance of the evaluated machine learning and deep learning models for building footprint extraction from high-resolution RGB satellite imagery. Among the traditional machine learning methods, XGBoost achieved the highest overlap-based performance, recording an Intersection over Union (IoU) of 0.469**,** a Dice coefficient of 0.639, and an AUC-ROC of 0.946**.** These results demonstrate its strong capability for pixel-wise classification. However, qualitative analysis revealed that XGBoost produced fragmented building masks with noticeable checkerboard artefacts because predictions were performed independently on local image patches without considering the broader spatial context. Consequently, the extracted building footprints lacked geometric continuity and realistic boundary representation.

The proposed U-Net with a ResNet-34 encoder demonstrated superior spatial learning by leveraging its encoder-decoder architecture to capture both local features and global contextual information. Although its IoU (0.445) and Dice coefficient (0.616) were slightly lower than those of XGBoost, it achieved the highest Boundary F1-Score of 0.822 and a Recall of 0.703**,** producing smoother, more coherent, and geometrically accurate building boundaries. These characteristics are particularly valuable for urban environmental applications, where precise building geometry directly influences downstream analyses such as Urban Heat Island (UHI) estimation, flood risk assessment, and environmental simulation.

In comparison, Random Forest and Support Vector Machine (SVM) exhibited lower segmentation performance due to their dependence on handcrafted features and limited ability to capture complex spatial relationships in high-resolution imagery. Their predictions contained fragmented structures, inconsistent building boundaries, and reduced spatial accuracy. Overall, the experimental results demonstrate that deep learning-based semantic segmentation provides a more comprehensive understanding of urban spatial patterns than conventional machine learning techniques. The proposed U-Net framework therefore offers a robust and reliable solution for extracting high-quality building footprints that support intelligent urban planning, environmental monitoring, and GeoAI-based decision support systems.

Table 1. Performance Comparison of Building Segmentation Models

Model	IoU	Dice	AUC	Precision	Recall	Boundary F1
U-Net (ResNet-34)	**0.445**	**0.616**	0.889	0.548	**0.703**	**0.822**
XGBoost	**0.469**	**0.639**	**0.946**	0.481	0.612	0.315
SVM	0.362	0.531	0.930	0.395	0.518	0.220
Random Forest	0.350	0.518	0.902	0.374	0.499	0.195

C. Urban Environmental Analysis

Following the building segmentation process, the extracted building footprints were utilized to estimate key environmental indicators, including Urban Heat Island (UHI) intensity**,** flood vulnerability, and green-space distribution**,** using computationally efficient, physics-inspired environmental simulation models. These simulations demonstrate how accurate building extraction can support urban environmental assessment and sustainable planning without requiring expensive thermal or multispectral datasets.

The watershed segmentation algorithm successfully identified 106 individual building structures, providing a reliable representation of the urban landscape for subsequent environmental analysis. Based on the segmented building footprints, impervious surface estimation revealed that approximately 78.9% of the study area consisted of built-up surfaces such as buildings and paved infrastructure, indicating a highly urbanized environment with limited natural land cover. Such a high proportion of impervious surfaces significantly reduces rainwater infiltration and increases surface runoff.

Flood risk simulation, developed using runoff coefficient principles inspired by the Rational Method, classified 76.2% of the study area as high flood-risk. This result reflects the limited drainage and infiltration capacity associated with dense urban development and highlights the need for improved stormwater management and sustainable urban drainage systems. In parallel, the Urban Heat Island (UHI) simulation estimated an average temperature increase of 2.47°C above the surrounding rural baseline. This value falls within the range commonly reported for medium-density urban environments and indicates the presence of significant heat accumulation caused by dense building concentrations and extensive impervious surfaces.

Green-space assessment further showed that vegetation covered only 4.5% of the study area, which is substantially below the 30% urban green-space recommendation suggested by the World Health Organization (WHO)**.** The limited vegetation reduces natural cooling, biodiversity, and ecological resilience. Collectively, these findings demonstrate that the study area is environmentally vulnerable and would benefit from targeted mitigation strategies, including urban greening, tree plantation, green roofs, permeable pavements, and sustainable land-use planning to enhance climate resilience and environmental sustainability.

Table 2. Urban Environmental Assessment Results

Parameter
Buildings Detected
Impervious Surface
High Flood Risk Area
Urban Heat Island
Green Space Coverage
WHO Recommended Green Cover

D. Mitigation Planning and Environmental Impact

To support sustainable urban planning, the proposed platform automatically recommends mitigation strategies based on the environmental conditions identified during analysis. For the evaluated study area, the system suggested increasing permeable pavements across 61.8% of the urban surface and implementing green roofs over 14.2% of suitable buildings to reduce heat accumulation and improve stormwater infiltration. Urban forests were recommended only in limited regions because of the scarcity of available open spaces.

Simulation results demonstrated significant environmental improvements after implementing the proposed mitigation strategies. The proportion of high flood-risk areas decreased from 76.2% to 54.1%, while the estimated UHI intensity was reduced from 2.47°C to 0.69°C. Green-space coverage increased from 4.5% to 34.5%, exceeding the WHO recommendation and highlighting the effectiveness of nature-based urban interventions.

Table 3. Environmental Conditions Before and After Mitigation

Metric	Before	After
High Flood Risk	76.2%	54.1%
UHI Intensity	2.47°C	0.69°C
Green Coverage	4.5%	34.5%
WHO Green Standard	Not Achieved	Achieved

V. Conclusion and Future Work

A. Conclusion

This research introduces a GeoAI-based Urban Heat Intelligence Platform, a next-generation decision-support framework that seamlessly integrates remote sensing, machine learning, deep learning, and physics-inspired environmental simulations into a unified, browser-based ecosystem for intelligent urban environmental assessment. Leveraging only freely available RGB satellite imagery, the platform accurately extracts building footprints and comprehensively evaluates Urban Heat Island (UHI) intensity, flood vulnerability, and urban green-space distribution**,** eliminating the dependence on costly thermal imagery, proprietary GIS software, and specialized technical expertise. By making advanced geospatial analytics more accessible, the proposed framework enables scalable and cost-effective urban monitoring for cities of all sizes.

A comprehensive comparative evaluation of Random Forest, Support Vector Machine (SVM), XGBoost, and U-Net with a ResNet-34 encoder demonstrates that the proposed deep learning approach delivers the most spatially consistent and geometrically accurate building segmentation, providing a robust foundation for reliable environmental modelling and urban intelligence generation.

Experimental results validate the effectiveness of the framework by successfully identifying 106 building footprints**,** estimating 78.9% impervious surface coverage**,** detecting 76.2% of the study area as high flood-risk**,** and predicting an average Urban Heat Island intensity of 2.47°C**,** clearly revealing the environmental pressures associated with rapid urbanization. Furthermore, the platform incorporates an intelligent mitigation and scenario-analysis module capable of simulating sustainable urban interventions. The simulation results indicate that strategies such **as** green roofs, permeable pavements, cool roofs, and urban forests can significantly enhance urban resilience by reducing UHI intensity from 2.47°C to 0.69°C**,** decreasing high flood-risk areas from 76.2% to 54.1%, and increasing urban green-space coverage from 4.5% to 34.5%**.**

Overall, the proposed GeoAI framework transforms satellite imagery into actionable urban intelligence, bridging the gap between advanced artificial intelligence research and practical smart-city implementation. By combining high segmentation accuracy, environmental simulation, and interactive decision support within a single scalable platform, it provides an innovative, accessible, and cost-effective solution for climate-resilient urban planning, empowering researchers, urban planners, policymakers, and local authorities to make informed, data-driven decisions for building more sustainable, resilient, and livable cities.

B. Future Work

The proposed GeoAI-based Urban Heat Intelligence Platform establishes a robust foundation for AI-driven urban environmental assessment and sustainable city planning. Nevertheless, several promising research directions can further enhance its predictive capability, scalability, and practical deployment in real-world smart city ecosystems. Future work should integrate multispectral and thermal satellite imagery (e.g., Sentinel-2 and Landsat-8/9), Digital Elevation Models (DEM), and hydrological datasets to enable more accurate Urban Heat Island (UHI) characterization, flood susceptibility mapping, and terrain-aware environmental modelling. Incorporating advanced state-of-the-art semantic segmentation architectures, including SegFormer, Mask2Former, Swin Transformer**,** and the Segment Anything Model (SAM)**,** together with multimodal geospatial data such as LiDAR, Synthetic Aperture Radar (SAR), hyperspectral imagery, and UAV observations**,** can substantially improve building footprint extraction and land-cover classification, particularly in dense and heterogeneous urban environments.

Beyond static environmental analysis, the platform can evolve into an intelligent, real-time Smart City Decision Support System by integrating continuous satellite observations, IoT sensor networks, weather forecasting services, traffic information, and cloud-edge geospatial analytics for dynamic urban monitoring and predictive environmental management. Furthermore, the incorporation of Explainable Artificial Intelligence (XAI) will enhance model transparency and trustworthiness, while Digital Twin technology will enable real-time virtual representations of urban environments for scenario simulation and infrastructure planning. Emerging technologies such as Generative AI can assist planners in automatically designing optimized urban layouts and mitigation strategies, whereas Reinforcement Learning can facilitate adaptive and autonomous decision-making for sustainable urban resource management. Collectively, these advancements have the potential to transform the proposed framework into a next-generation GeoAI-powered Urban Intelligence Platform**,** capable of supporting climate-resilient, carbon-neutral, data-driven, and sustainable smart cities**,** while empowering policymakers, urban planners, researchers, and local authorities with intelligent tools for proactive environmental governance and long-term urban resilience.

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