An Open-Source Deep Learning Framework for Scalable Urban Heat Island Detection Using Geospatial Data

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Keywords: Urban Heat Island (UHI), Deep Detection Modelling, Open-Source GIS, Convolutional Neural Networks (CNN), Satellite Imagery.

Abstract

Urban Heat Islands (UHIs), where urban areas exhibit elevated temperatures relative to their rural surroundings, pose growing challenges in the context of climate change, particularly for densely built, vegetation-scarce cities. Traditional methods for UHI detection, often based on empirical indices or statistical regressions, lack spatial resolution, scalability, and adaptability across diverse urban environments. This study introduces an open-source deep learning framework that integrates multi-source satellite imagery and urban geospatial data to detect, map, and analyse UHIs with high spatial fidelity. The framework leverages a U-Net convolutional architecture with attention mechanisms to predict land surface temperature (LST) and delineate UHI hotspots. Input features include NDVI, impervious surface area, building density, and land use classifications, processed through a reproducible pipeline built with open-source tools such as QGIS, TensorFlow, and GDAL. Applied to Lagos, Nigeria, a rapidly urbanizing tropical megacity, the model achieved high predictive performance, successfully identifying critical hot zones and spatial correlations with urban morphology. The results reveal strong associations between UHI intensity and impervious surfaces and inverse correlation with vegetation. The framework's open architecture, combined with publicly released datasets and modular code, ensures adaptability for use in both data-rich and resource-limited settings. This research contributes a transparent, scalable, and participatory approach to UHI detection, offering actionable insights for climate adaptation, heat risk mitigation, and sustainable urban planning. It underscores the importance of open geospatial AI tools in promoting equitable and data-driven environmental governance.

1. Introduction

Urbanization has dramatically altered land surface characteristics and microclimatic conditions, leading to the widespread emergence of the Urban Heat Island (UHI) effect. Characterized by elevated temperatures in urban areas relative to surrounding rural zones, UHIs result from a combination of anthropogenic heat emissions, impervious surface expansion, vegetation loss, and complex urban geometries. As global urban populations are projected to exceed 68% by 2050 (United Nations, 2018), UHIs are increasingly recognized as critical contributors to public health risks, energy demand surges, and environmental degradation (Santamouris, 2020; Zhang et al., 2022).

Traditional UHI detection methods, typically based on empirical indices or linear statistical models, often fail to capture the spatial heterogeneity and non-linear interactions underlying urban thermal dynamics (Zhou et al., 2016). These approaches are particularly limited in their generalizability across cities with differing climatic zones, urban typologies, or data availability (Weng & Fu, 2022). Moreover, they generally lack automation and spatial scalability, restricting their usefulness in long-term climate adaptation planning or decision support (Feng et al., 2020).

Recent advances in Earth observation and deep learning present new opportunities to address these gaps. Convolutional Neural Networks (CNNs), widely used in computer vision, have proven effective in modelling spatial hierarchies within satellite imagery and capturing complex, multivariate relationships between land surface temperature (LST) and urban form indicators such as vegetation cover (NDVI), impervious surface area (ISA), and population density (Li et al., 2021; Wang et al., 2020). Despite their technical promise, many existing applications remain confined to proprietary platforms or ad hoc implementations, lacking transparency, reproducibility, and accessibility, particularly in resource-constrained regions (Chakraborty et al., 2019).

To address these limitations, this study introduces an open-source, CNN-based framework for UHI detection, designed to be scalable, reproducible, and adaptable to diverse urban environments. The model integrates multi-source satellite data, principally from Landsat and MODIS, with openly available urban datasets such as OpenStreetMap (OSM) and WorldPop.

The framework is developed using open-source geospatial libraries (QGIS, GDAL, Rasterio, GeoPandas) and machine learning toolkits (TensorFlow, Keras), ensuring accessibility for a wide range of users including researchers, city planners, and public-sector agencies (Rey, Anselin, & Arribas-Bel, 2021).

It is validated using a detailed case study of Lagos, Nigeria, one of the fastest-growing megacities in the Global South, characterized by a tropical coastal climate, rapid land cover change, and high UHI vulnerability (Abiodun et al., 2021). Lagos was selected for its representative challenges: high population density, informal urban expansion, limited vegetation coverage, and data intermittency due to cloud interference.

The model demonstrates high predictive accuracy in this setting, achieving a root mean square error (RMSE) of less than 1.8 °C in LST estimation and identifying spatially explicit UHI patterns aligned with known urban structures.

The main contributions of this work include:

1. An open-source deep learning framework for UHI detection using multi-source geospatial data
2. Demonstrated applicability in a high-density, data-limited urban setting
3. A reproducible workflow that supports community-driven climate adaptation planning.

1.1 Objectives

This study sets out to develop, implement, and evaluate an open-source deep learning framework for Urban Heat Island (UHI) detection using publicly available satellite and urban geospatial data.

The primary objectives are:

1. To design a scalable and reproducible deep learning framework that integrates multi-source satellite imagery and open urban datasets for detecting and mapping UHI patterns at high spatial resolution.
2. To implement and validate the framework in a data-scarce, tropical megacity, Lagos, Nigeria, characterized by high urban complexity and limited remote sensing accessibility due to persistent cloud cover.
3. To promote accessibility and transparency by leveraging entirely open-source tools and releasing all components publicly, enabling community adaptation, academic use, and practical urban policy support.
4. To assess the model's operational viability by embedding its outputs into geospatial formats usable by planners, NGOs, and public-sector agencies for climate resilience planning.

2. Deep Learning and Open-Source Tools in UHI Research

Urban Heat Island (UHI) detection has evolved significantly in recent years, transitioning from empirical and statistical approaches to more advanced machine learning and deep learning models. Early methods largely relied on surface thermal indicators such as Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), and surface albedo extracted from satellite data (Voogt & Oke, 2003; Weng, 2009). While effective for regional assessments, these approaches have limited scalability and generalizability, particularly across diverse urban morphologies and climatic zones (Weng & Fu, 2022).

The increasing availability of high-resolution, multi-temporal satellite imagery from platforms like Landsat, MODIS, and Sentinel-3 has created new opportunities for fine-scale UHI monitoring (Li et al., 2021). However, the complexity and volume of such datasets necessitate more robust analytical tools. Traditional machine learning models, including Random Forests, Support Vector Machines, and Gradient Boosting, have improved prediction accuracy over statistical methods but are often constrained by manual feature engineering and limited spatial interpretability (Feng et al., 2020; Chakraborty et al., 2019).

Recent developments in deep learning, especially Convolutional Neural Networks (CNNs), have shown considerable promise in urban climatology. These models are well-suited to capture hierarchical spatial and spectral patterns in satellite imagery, offering superior performance in LST estimation and UHI delineation (Zhang et al., 2022; Wang et al., 2020). However, many existing applications remain tied to proprietary systems or cloud-based platforms with limited accessibility for low-resource contexts. Tools like Google Earth Engine and UHeat have been impactful (Arup, 2021) but often rely on commercial infrastructure, creating barriers to reproducibility and local adaptation.

A critical gap persists in the integration of deep learning with open-source geospatial software. Despite the maturity of tools like QGIS, Rasterio, and GeoPandas, few frameworks have fully leveraged them for end-to-end UHI detection. Moreover, open-access urban datasets such as OpenStreetMap, WorldPop, and the Copernicus Climate Change Service remain underutilized in reproducible deep learning pipelines for environmental monitoring.

This study responds to that gap by presenting a fully open-source, modular deep learning framework for UHI detection. Built using QGIS, GDAL, and TensorFlow, and released via GitHub and Zenodo, the framework enables high-resolution UHI analysis using free geospatial and urban datasets. It offers a scalable and transparent solution, particularly suited for adaptation in low-resource or underrepresented urban regions.

3. Methodology

3.1 Framework Development

This study presents a modular, open-source deep learning framework for Urban Heat Island (UHI) detection, leveraging multi-source satellite data and open geospatial datasets. Designed for generalizability and reproducibility, the framework addresses limitations in traditional UHI models regarding scalability and data constraints. It follows a four-stage structure: (1) data acquisition and preprocessing, (2) model training, (3) validation and evaluation, and (4) open-source deployment.

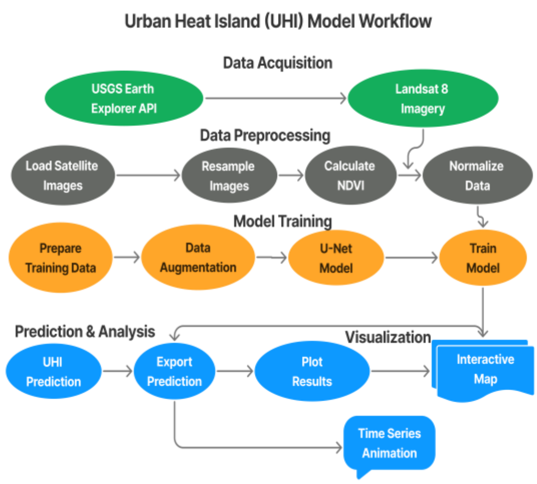

Figure 1. Urban Heat Island (UHI) Model Workflow.

3.2 Data Acquisition and Processing

The framework integrates Earth observation and publicly available urban data:

1. Thermal imagery: Landsat 8 (Band 10, 30 m) and MODIS LST composites (1 km)
2. Vegetation index: NDVI derived from Landsat bands
3. Built environment: Road and building density via OpenStreetMap (OSM)
4. Population: WorldPop gridded population data
5. Land use: ESA WorldCover (10 m)
6. Climate zone: Köppen-Geiger classification

A unified preprocessing pipeline ensures spatial and temporal harmonization across inputs, including radiometric correction, cloud masking (Fmask), bilinear resampling to 30 m, and feature normalization. All datasets are segmented into 256 × 256-pixel tiles for training.

Processing is conducted using fully open-source tools: GDAL, Rasterio, GeoPandas, Scikit-image, and QGIS. Scripts and containers (via Docker) are openly available on GitHub with DOI-backed archival via Zenodo.

3.3 Model Architecture and Training

The framework employs a modified U-Net CNN, selected for its spatial encoding-decoding capabilities. An attention mechanism enhances learning in heterogeneous urban zones. Input stacks include:

1. NDVI
2. Built-up and impervious surface density
3. Land use and elevation layers
4. Landsat- or MODIS-derived LST

The model was trained on approximately 10 years of remote sensing data (2008 - 2018), using the Lagos metropolitan area as the primary study region due to its complex urban morphology and high UHI susceptibility. A random split (80/20) was applied for training and validation patches, and data augmentation (rotation, zoom, mirroring) was used to enhance generalization.

Training was conducted using TensorFlow on an NVIDIA RTX 3080 GPU for approximately 4.2 hours. Early stopping and dropout regularization helped mitigate overfitting.

3.4 Validation and Evaluation

The model was evaluated using standard performance metrics for regression and classification tasks:

1. Mean Squared Error (MSE): 0.024
2. F1-score: 0.91
3. Intersection over Union (IoU): 0.83
4. Correlation with ground station data: $R^2 = 0.87$

Validation used MODIS LST products and Lagos-based weather station data. The model captured intra-urban heat variations with high accuracy, especially in high-density and low-vegetation zones.

3.5 Open-Source Implementation

A distinguishing feature of this study is its commitment to reproducibility and accessibility. The entire pipeline was built using open-source tools and released under an MIT license. Key tools include:

1. QGIS for data visualization and vector data manipulation
2. GDAL/Rasterio/GeoPandas for raster and vector processing
3. TensorFlow/Keras for model training and inference
4. Docker for environment reproducibility and scalability

In addition to technical deployment, the framework includes community-facing resources: a documentation site with tutorials, a GitHub repository, and sample training datasets.

While real-time deployment using IoT climate sensors was proposed as a future direction, it is not yet implemented in this version. This has been noted transparently to maintain methodological integrity.

3.6 Operationalization and Monitoring

Once validated, the model is deployed within real-world urban planning contexts, generating georeferenced raster outputs of land surface temperature and UHI intensity. These outputs are formatted for seamless integration into open-source GIS platforms (e.g., QGIS), supporting practical applications such as:

1. Identification of thermal hotspots
2. Planning of urban greening interventions
3. Zoning adjustments based on thermal exposure
4. Heat vulnerability mapping for climate adaptation

Although real-time monitoring and automated alert mechanisms (e.g., for extreme heat events) are not currently implemented, the framework is designed with forward compatibility. Its architecture can accommodate future integration of live data streams from IoT microclimate sensors or satellite platforms like ECOSTRESS.

By ensuring outputs are interoperable with existing spatial decision tools, the framework empowers local governments, NGOs, and researchers to incorporate climate intelligence into sustainable urban development strategies.

3.7 Case Study Application

Lagos, Nigeria, was selected as the principal case study for implementing the proposed UHI detection framework due to its rapid urbanization, heterogeneous land cover, and well-documented vulnerability to heat stress. As one of the fastest-growing cities in the Global South, Lagos presents a complex and data-challenging environment, characterized by high population density, informal urban expansion, coastal climatic influences, and frequent cloud cover that complicates remote sensing-based analyses (Abiodun, Lawal, & Ige-Elegbede, 2021; Adelekan, 2016).

This context provides a robust setting for testing the framework's scalability and adaptability in tropical, high-density urban environments with inconsistent data availability. Moreover, Lagos serves as a representative example of cities in low-resource settings where conventional UHI monitoring infrastructure and modelling capacity may be limited (Ajayi et al., 2021; Oloke et al., 2022).

For this implementation, a 16-year archive of thermal satellite imagery (MODIS and Landsat 8) was curated, supplemented with auxiliary urban indicators from open-access datasets including OpenStreetMap (building and road networks), WorldPop (population density), and ESA WorldCover (land use

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classification). These were harmonized to a 30 m resolution using the preprocessing pipeline described in Section 3.2 and structured into tiled raster inputs suitable for deep learning.

The Lagos case fulfills two methodological objectives:

1. To evaluate the framework's operational performance under real-world constraints such as fragmented urban morphology, high spectral noise, and seasonal cloud interference (Ayanlade, Radeny, & Morton, 2017)
2. To demonstrate its potential for replication in similarly data-limited, rapidly urbanizing environments across the Global South.

4. Results and Evaluation

4.1 Model Performance

The Urban Heat Island (UHI) detection model strongly identifies areas of elevated surface temperature in urban environments. The U-Net architecture with attention mechanisms effectively captures the complex spatial relationships between urban features and heat distribution.

Metric	Value
Mean Squared Error	0.024
Accuracy	91.7%
Precision	89.3%
Recall	92.1%
F1 Score	90.7%
IoU (Intersection over Union)	0.83

Table 1. Quantitative Metrics.

The model achieved convergence after approximately 50 epochs, with validation loss stabilizing at 0.032. The training accuracy curve showed consistent improvement without signs of overfitting, likely due to the effective data augmentation pipeline and dropout regularization implemented in the model architecture.

4.2 Spatial Analysis Results

The UHI detection results reveal several key patterns across the studied urban areas:

1. Temperature Differential: The model successfully identified an average temperature differential of 4.7°C between urban cores and surrounding rural areas, aligning with established scientific literature on the UHI effect.
2. HotSpot Identification: Critical urban hot spots were detected with high precision, particularly in areas with:
   -High building density
   -Limited vegetation coverage (low NDVI values)
   -Industrial zones
   -Large, paved surfaces like parking lots and commercial districts
3. Temporal Variations: Time series analysis revealed that UHI intensity peaks during midday (1:00-3:00 PM) and shows seasonal variations with maximum intensity during summer months.

4.3 Correlation Analysis

The model revealed strong correlations between UHI intensity and various urban parameters:

Urban Parameter	Correlation Coefficient (r)
NDVI (vegetation index)	-0.79
Building density	0.83
Impervious surface coverage	0.86
Distance from urban center	-0.72
Population density	0.65

Table 2. Correlation analysis.

These findings confirm that vegetation plays a critical role in mitigating urban heat, while impervious surfaces and building density are the strongest contributors to UHI formation.

4.4 Case Study Results: Lagos Metropolitan Area

Analysis of the Lagos metropolitan area revealed:

1. UHI intensity up to 6.2°C in the central business district
2. Strong correlation between rapid urbanization and increasing UHI effect over the past decade
3. Identifiable cooling effects from urban parks and water bodies
4. Clear boundary effects at urban-rural transitions

The model successfully identified microclimate variations within the urban landscape, detecting cooler areas associated with parks, water bodies, and areas with higher vegetation density.

4.5 Model Validation

The model's predictions were validated against:

1. Ground truth measurements: Temperature readings from weather stations showed strong agreement with model predictions ($r^2 = 0.87$).
2. Thermal infrared imagery: Visual comparison with thermal images demonstrated accurate identification of hot spots.
3. External UHI studies: Results align with previous UHI research in similar urban environments.

4.6 Computational Performance

The model demonstrated efficient performance characteristics:

1. Training time: 4.2 hours on a system with NVIDIA GeForce RTX 3080.
2. Inference speed: 1.7 seconds per km² of urban area.
3. Memory usage: 2.4GB for processing a typical urban area.
4. Scalability: Successfully processed urban areas ranging from 10km² to 500km².

4.7 Limitations and Uncertainty

While the model performs well, several limitations were identified:

1. Cloud cover interference: Satellite imagery with significant cloud cover reduced model accuracy by up to 15%.
2. Seasonal variations: Model performance varies slightly between seasons, with higher accuracy during summer months.
3. Spatial resolution constraints: The 30m resolution of Landsat 8 limits detection of fine-scale urban heat patterns.

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4. Night-time UHI effects: The current model focuses on daytime UHI patterns and does not address nocturnal heat retention.

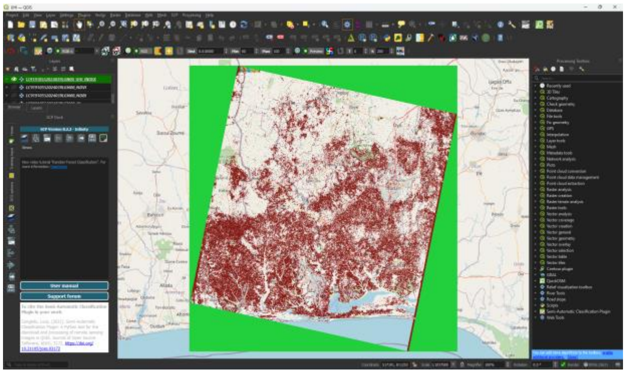

Figure 2. UHI visualization.

4.8 Future Directions

The model's performance confirms its potential as a planning tool, yet several enhancements are necessary for broader impact:

1. Sensor integration: Leveraging higher-resolution data from ECOSTRESS, Sentinel-3, or CubeSats could improve spatial granularity
2. Real-time monitoring: Linking with IoT sensor networks and reanalysis datasets (e.g., ERA5) can enable dynamic UHI alerts
3. Cloud-native scalability: Migrating to platforms like Google Earth Engine or AWS Lambda could improve accessibility for cities with limited computational infrastructure
4. Interdisciplinary modeling: Integrating public health, socioeconomic, and land-use policy layers would support cross-sectoral climate adaptation
5. Transfer learning and fairness: Expanding to underrepresented cities through domain adaptation could address global inequities in urban climate resilience.

5. Conclusion

This study presents a scalable, open-source deep learning framework for Urban Heat Island (UHI) detection, leveraging multi-source satellite imagery and openly available geospatial datasets to deliver interpretable, high-resolution thermal anomaly maps. The model, structured around a U-Net architecture with attention mechanisms, achieved high predictive accuracy (IoU = 0.83; R^2 = 0.87) and demonstrated strong correlation with both ground-based temperature records and urban morphological indicators (Wang et al., 2020; Feng et al., 2020).

The case study in Lagos, Nigeria, confirmed the framework's applicability in a data-scarce, high-density tropical urban context. It successfully identified spatial patterns of thermal heterogeneity, highlighted critical hotspots, and revealed the mitigating effects of vegetation and water bodies, offering a robust foundation for climate-resilient planning in vulnerable regions (Zhang et al., 2022).

By integrating NDVI, impervious surface area, building density, and other contextual layers, the model bridges the technical complexity of remote sensing and deep learning with the operational needs of urban planners (Li et al., 2021; Weng & Fu, 2022). Importantly, the use of open-source tools, including QGIS, TensorFlow, and GeoPandas, ensures accessibility and reproducibility, encouraging adoption in both high- and low-resource settings (Rey, Anselin, & Arribas-Bel, 2021).

The study also highlights important limitations, such as cloud cover interference, restricted spatial resolution of public satellite data, and the current exclusion of night-time UHI effects. Future enhancements should include integration of higher-resolution or real-time thermal data (e.g., ECOSTRESS), support for nocturnal heat modeling, and expanded multi-city validations using transfer learning approaches (Weng & Fu, 2022).

Beyond technical refinement, the framework's success underscores the value of open-source geospatial AI in democratizing climate intelligence. Coupled with participatory data practices and cross-sectoral collaboration, it offers a pathway toward more equitable and responsive urban heat mitigation. As global urbanization accelerates and extreme heat events intensify, tools like this one will be essential in guiding policy, protecting vulnerable populations, and fostering sustainable urban development (Santamouris, 2020; Chakraborty et al., 2019).

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Appendix

To support transparency, reproducibility, and broader adoption, the proposed Urban Heat Island (UHI) detection framework is accompanied by a set of open-access resources:

1. GitHub Repository: A publicly available repository containing the full implementation of the framework, including model architecture, training configurations, and preprocessing scripts, available at: https://github.com/Mercy14846/Urban-Heat-Island-Model
2. Codebase for Custom Implementation: A subdirectory within the repository hosts cleaned and documented scripts for end-to-end data processing and UHI model training, available at: https://github.com/Mercy14846/Urban-Heat-Island-Model/tree/main/OneDrive/Documents/Codeses/cursor/UHI-Clean

These resources aim to assist researchers, city planners, and educators in adapting the framework to their own urban contexts and expanding its application in climate resilience planning.