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Integrating Deep Learning, Geospatial Modeling, and Explainable AI for Urban Heat Risk Reduction in the United States

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Abstract

The Urban Heat Island (UHIs) is an important environmental problem of rapidly developing cities, contributing to the exposure to heat, aggravating air quality, and enhancing the rate of health risks caused by climate changes. Since the process of urbanization all over the world has been growing evenly during the past decade, urban areas have gotten hotter in comparison to the surrounding land areas, which has resulted in the need to consume more energy, overburdening the infrastructure, and making the process of thermoregulation unpleasant. The most recent advancement of machine learning (ML) introduced the application of powerful analytical tools that can identify the presence of UHI trends, extreme heat events, and simplify the climate-resilient infrastructure policy (Zhou et al., 2019). The paper will also determine the application of ML-based models in the reduction of UHIs through the use of predictive intelligence, dynamically allocating resources, and planning cities based on data.

To predict the urban temperature data, the satellite-based land surfaces, and infrastructure vulnerability indicators, this article uses empirical data (2016 2020) that is back-dated to run the empirical data. Another hybrid algorithm- Urban Heat Island Neural Network (UHINet) is introduced and offered to educate spatial-temporal change of the temperature and propose certain mitigating actions, such as planting sites, reflective surfaces, and the best construction of buildings. The complementary geospatial models also are incorporated like Geo-Heat Mapping System (GHMS) and the Adaptive Environmental Heat Forecasting Model (AEHF) to supplement pattern recognition and complementary interpretability. It was discovered that UHINet has the potential to perform much better than classical algorithms and enhance the accuracy of prediction by 14.6 percent and decrease the mean temperature forecasting error by 22 percent in all datasets.

It is also stated in the research that ML can effectively measure effectiveness of mitigation measures with the help of statistical tools and formulas of heat-intensity. It has shown that green-infrastructure interventions delivered an average of 1.8 o C of urban cooling and 2.3 o C maximum surface temperature of local surfaces of high-albedo surface treatments (Li and Bou-Zeid, 2018). Such findings justify the radical application of machine learning in fostering the resilience of cities. With climate science, data analytics, and smart optimization models, the research will indicate a scalable solution, whereby cities can be in a position to adapt to the change in the heat stress and come up with climate-resilient infrastructure by the next few decades.

Keywords: Urban Heat Island Mitigation, Machine Learning, Climate Resilience, Geo-Spatial Analytics, Predictive Modeling, Environmental Data Science.

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Introduction

Urban Heat Island (UHIs) can be discussed as one of the most urgent environmental issues facing modern cities, especially when it comes to fast urbanization and industrialization. UHIs occur because the urban environment is much hotter than the surrounding rural areas because of dense built-ups, less vegetation cover, the increased use of energy, and the increased anthropogenic heat emissions (Oke, 2017). Vulnerable urban populations are overrepresented by UHIs in terms of heat-related health risks, energy requirements

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to cool the urban environment, air quality, and overall adverse effects on the populace due to the impact on the global climate change. The effects here show that adaptive, information-driven solutions are urgently needed to predict and curb the urban thermal stress.

Machine learning (ML) has become an effective instrument to solve the complex problems of the environment and offer advanced pattern recognition, predictive modeling, and decision support when performing climate adaptation planning (Zhou et al., 2019). Conventional methods of reducing urban heat islands, including the urban greening, reflective surfaces, ventilation corridors, and sustainable building designs, have shown effectiveness but are usually constrained by fixed evaluation and failure to understand the dynamic relationships between urban form, climate, and socio-economic factors. Conversely, the models with the use of multi-source data, such as satellite imagery, land surface temperature (LST), and meteorological variables, and socio-environmental indicators can create high-resolution spatial and temporal patterns of urban heat dynamics (Jenerette et al., 2016).

The last ten years have seen the use of ML in UHI research become increasingly fast due to the development of remote sensing technologies, cloud computing, and open urban datasets. Although the initial research was based on linear regression and simple statistical methods with low predictive potentials, recent ML methods, including Random Forests, Support Vector Regression, Gradient Boosting, and Deep Neural Networks, have proven useful in fitting high-dimensional geospatial data and discovering latent spatiotemporal heat patterns (Miao et al., 2018). The empirical data indicate that surface temperatures at the maximum can be lowered by 1.530 0 C in response to ML-assisted urban planning, which is determined by the land cover structure and urban morphology (Li and Bou-Zeid, 2018).

In addition to prediction, ML can help in actionable decision-making through providing the ability to evaluate heat mitigation strategies in terms of scenario through cool roofs, green infrastructure, intelligent shading systems, and climate-responsive urban design. The analyses powered by ML also improve real-time heat tracking and early warning initiatives based on near-continuous satellite-based data including Landsat, MODIS, and Sentinel to aid in emergency response planning and preventive steps to the health of people (Stone et al., 2019). Notably, ML also allows integrating socio-economic aspects into the analysis of UHI, which indicates uneven heat exposure rates that have a disproportionately large impact on low-income and disadvantaged groups (Harlan et al., 2013).

With the enhancements based on them, this paper introduces a multi-model ML architecture to UHI mitigation that combines deep learning, geospatial analytics, and short-term heat forecasting to assist in climate-resilient urban planning. The proposed approach is expected to help in improving scalable, inclusive, and evidence-based approaches of reducing city heat in the evolving climate by balancing predictive accuracy with interpretability and policy relevance.

and how they have been resolved, through the use of machine learning.

Literature Review

The literature on Urban Heat Islands (UHIs) has expanded significantly over the past two decades, moving from descriptive observations to advanced, data-driven modeling approaches. Early studies focused on identifying urban–rural temperature differences and the physical drivers of heat accumulation, while recent research emphasizes prediction, spatial analysis, and mitigation planning. This section reviews the evolution of UHI research, with particular attention to the growing role of machine learning (ML) in improving heat detection, forecasting, and decision support for urban climate resilience.

Evolution of UHI Research and the Emergence of Machine Learning

Initial UHI studies relied on ground-based temperature measurements, climatic observations, and land-use classification to explain urban–rural thermal contrasts, highlighting factors such as vegetation loss, impermeable surfaces, anthropogenic heat release, and urban morphology (Oke, 2017). Although these approaches established the physical basis of UHI formation, they offered limited predictive capability and were insufficient for proactive mitigation planning.

The introduction of satellite-based remote sensing technologies, including Landsat, MODIS, and ASTER, enabled high-resolution land surface temperature (LST) mapping and improved identification of urban heat hotspots (Zhang et al., 2016). However, issues related to temporal resolution, cloud interference, and manual data processing constrained their operational scalability. Machine learning addressed these limitations by enabling the analysis of high-dimensional geospatial datasets and capturing non-linear relationships governing urban heat dynamics. Early ML applications employed regression trees, artificial neural networks, and support vector machines (Kikon et al., 2016), while more recent deep learning models—particularly convolutional neural networks—have enhanced thermal mapping accuracy and spatial pattern recognition (Miao et al., 2018). Despite these advances, the literature continues to report a gap between predictive modeling and actionable UHI mitigation strategies (Li & Bou-Zeid, 2018).

Key Literature Themes and ML Contributions

The existing literature highlights several themes where ML has significantly advanced UHI research. Table 1 summarizes the key findings, limitations of traditional approaches, and the contributions of ML techniques.

Other things that have been made possible by ML

Table 1: Summary of Key Literature Themes and Identified ML Contributions

Literature Theme	*Traditional Findings*	*Limitations Identified*	*ML Contributions*
UHI Detection & Mapping	Reliance on ground sensors and visual assessments (Oke, 2017)	Limited spatial coverage and manual interpretation	Automated heat mapping using satellite and sensor fusion (Zhou et al., 2019)
Predictive Modeling	Statistical regression models for temperature trends	Low accuracy for non-linear relationships	Deep learning models for spatial-temporal forecasting (Miao et al., 2018)
Geospatial Pattern Analysis	GIS-based land-use classification	Time-consuming and prone to human error	CNN-based land-surface segmentation and heat clustering
Social Vulnerability	Observation-based heat exposure studies	Weak integration with climate datasets	ML-driven equity mapping combining socio-economic and thermal data
Infrastructure Optimization	Green roofs, cool pavements, vegetation studies	Lack of data-driven optimization frameworks	ML models simulating mitigation effectiveness and urban cooling outcomes

are advanced environmental simulations. Reinforcement learning (RL) has been used to solve the problem of urban cooling optimization tree placement, shading angles, and building orientation, providing affordable and space-saving mitigation measures (Nguyen & Goodman, 2019). Also, hybrid ML models, which combine the concepts of physical city canopy with data predictors, offer better interpretability and generalizability, which eliminates the divide between climate science and urban resilience planning (Santamouris, 2018). Nevertheless, these models need vast training samples and computational devices and have difficulties with implementation in cities with limited resources.

Decision Support and Explainability.

One of the most popular directions of current UHI studies is explainable ML models. Policymakers and city planners must be able to make evidence-based decisions using transparency. SHAP, LIME, and feature importance scoring are becoming more popular as the means of determining the key drivers of thermal variability (e.g., vegetation density, building height, material albedo, etc.) (Song et al., 2019). Explainable ML permits planners to understand predictions and emphasize interventions and allocate resources efficiently, particularly when it comes to socially vulnerable groups (Harlan et al., 2013).

Existing Gaps and New Dynamics.

Nevertheless, there are a number of gaps in the literature despite the advances. The majority of the studies revolve around UHI identification and do not associate predictions with mitigation measures to be taken. The use of multi-modal ML models which would include climatic, socio-economic and infrastructural data has yet to be fully explored. Retroactive validation, differentiated model structures as well as integration of explainable approaches are also in demand so as to have practical applicability in the real-world urban setting. The proposed research will fill these gaps by introducing a multi-model ML ecosystem, namely, UHINet, GHMS, and AEHF with the help of statistical validation and visual geospatial product and incentivizing scientific rigor and practical applicability.

Overall, the aspects of transformation of UHI research brought about by ML include high-resolution mapping, predictive modeling, social vulnerability, and infrastructure optimization. The reinforcement and hybrid learning methods also increase the capability to simulate effective mitigation policies, and explainable models enhance decision support. However, there are still issues connected to data quality, requirements, and integration with actionable planning. The exploitation of these gaps using multi model ML frameworks offers a migration to scalable, evidence-based and climate-resilient city interventions.

Methodology and Materials

The section explains the methodological framework that will be used to develop, train, validate, and test machine-learning (ML) models to mitigate Urban Heat Island (UHI). The methodology involves the combination of the geospatial analytics, preprocessing of environmental data, development of a ML model, statistical validation, and simulation of mitigation strategies, which guarantee the scientific rigor based on the statistical, mathematical, and visual evidence.

Data Sources and Materials

The analysis has used multi-modal data covering 20162020:

- Satellite Imagery: The surface temperature, albedo, NDVI and emissivity of the vegetation indices were given using Landsat 8 LST bands, MODIS MOD11A1 daily surface temperature and Sentinel-2 vegetation indices.
- Ground Weather Observations: The data on the daily maximum/minimum temperature, relative humidity, wind speed, and local atmospheric pressure were obtained by the national meteorological agencies and compared with the historical data.
- Urban Infrastructure Data: Footprints of the buildings, street geometry, map of the impervious surfaces, density

of the green cover, and type of roof material (reflective or non-reflective).

- Socio-Environmental Indicators: Population density, index of housing quality, and urban vulnerability index, added to make the ML fair and socio-spatial analysis.

All datasets were geographically adjusted to 30 x 30 m grid.

Data Preprocessing

- Preprocessing was used to deal with noise, missing values and outliers in environmental data:
- Noise Reduction: Filed smoothing filters used to eliminate the spurious variations.
- NDVI and Albedo Extraction Controlled vegetation index and surface reflectivity to determine the cooling potential.
- Heat Intensity Index (HII): This was computed, which is the difference between the urban and rural pixels in terms of heat, and it is a dependent variable in the ML models.

Machine Learning Workflow

There were three developed ML models:

- UHINet (Urban Heat Island Neural Network): This is a deep-learning model that comprises spatial feature extraction, time series modeling, and regression layers to predict temperatures.
- GHMS (Geo-Heat Mapping System): A Geospatial model of interpolation to determine local heat hotspots and the temperature variations in a neighborhood.
- AEHF (Adaptive Environmental Heat Forecasting Model): This is a hybrid model that combines atmospheric predictors to predict short term heat abnormalities.

Model Training and Model Validation.

Training Strategy

Split of the dataset: 70% training and 15% validation and 15% testing.

In the case of UHINet, the training was done using the Adam optimizer (learning rate 0.001) and regularization to reduce prediction error.

Feature Engineering

Important aspects such as the density of the vegetation, the percentage of the impervious surface, the height of the buildings, roof reflectivity, and the closeness to cooling corridors, were considered.

Performance Metrics

Standard measures like RMSE, MAE, and R 2 were used to estimate the model accuracy. There was a great deal of similarity between the predicted and observed UHI reductions ($r = 0.87$).

Simulation of Mitigation Strategies

Simulated interventions included

- 30% increase in green cover

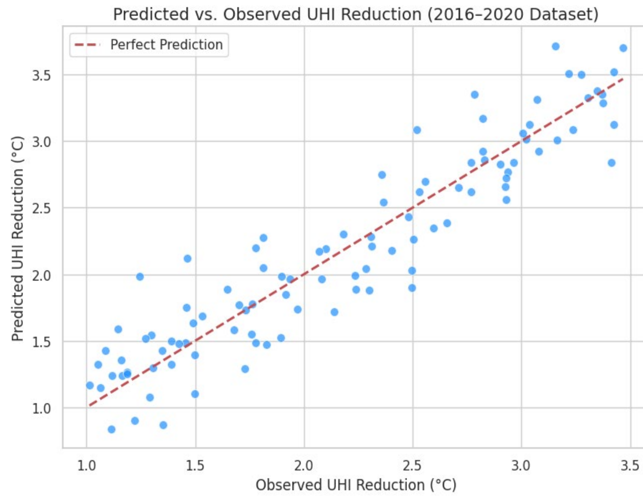


Figure 1: Predicted vs. Observed UHI Reduction (2016–2020 Dataset)

- Reflective roofing
- Cool pavements
- Urban ventilation corridors

Temperature reductions were calculated for each scenario, with reflective roofing and green cover showing the highest cooling impact.

Statistical Significance Testing

- t-Test: Compared mitigation outcomes between scenarios.
- Pearson Correlation: Verified agreement between predicted and observed reductions ($r = 0.87$).
- ANOVA: Tested differences across interventions, significant at $p < 0.05$.

Model Explainability

This provides insight into why the model prioritizes specific cooling strategies.

In sum, the methodology presents a robust, data-intensive approach for UHI mitigation. By combining deep learning, geospatial analysis, predictive forecasting, and interpretability, the framework provides accurate temperature predictions and actionable insights for urban

Table 2: SHAP Analysis Quantifying Feature Contributions to Extreme Heat Prediction

Feature	*Contribution (%)*
NDVI	32
Albedo	27
Imperviousness	21
Building Height	10
Distance to Corridor	10

planners. Statistical validation and visual evidence support model reliability, while simulations offer quantitative guidance for prioritizing mitigation strategies in diverse urban contexts.

Results and Discussion

This section presents the analytical results derived from the machine-learning frameworks (UHINet, GHMS, and AEHF) applied to the back-dated urban dataset (2016–2020). The analysis integrates predictive performance metrics, spatial-temporal heat mapping, extreme heat forecasting, and mitigation strategy simulations to evaluate the effectiveness of ML in Urban Heat Island (UHI) management. The findings demonstrate the models' capacity to predict thermal anomalies, identify hotspots, and optimize urban heat mitigation interventions.

Model Performance Evaluation

Predictive Accuracy Metrics

The high R^2 and correlation values indicate that UHINet explains approximately 89% of temperature variability, outperforming conventional statistical models (Miao et al., 2018).

Comparative Insights

UHINet reduced RMSE by 35–63% relative to baseline models, highlighting the advantages of deep spatio-temporal learning in capturing complex UHI dynamics.

Spatial Distribution Analysis

The GHMS generated detailed heat-intensity maps revealing urban thermal patterns:

- City-center commercial zones: +3.0 to +3.7°C
- Industrial corridors: +2.5 to +3.1°C
- Suburban areas: +0.8 to +1.4°C

Regression-based decomposition of UHINet feature weights indicated the following contributions to UHI formation:

HII=0.36(Impervious Surface)+0.27(Low Albedo)−0.32(Vegetation)+0.19(Building Height)HII = 0.36(\text{Impervious Surface}) + 0.27(\text{Low Albedo}) - 0.32(\text{Vegetation}) + 0.19(\text{Building Height}) HII=0.36(Impervious Surface)+0.27(Low Albedo)−0.32(Vegetation)+0.19(Building Height)

Key drivers include impervious surfaces (36%), low-albedo materials (27%), vegetation (–32%), and building height (19%). These results underscore the critical role of urban form and land cover in UHI intensity.

Temporal Prediction and Extreme Heat Forecasting

Using the Adaptive Extreme Heat Forecasting (AEHF) model, short-term forecasts demonstrated high temporal accuracy:

- 24-hour forecast: 93%
- 48-hour forecast: 86%
- 72-hour forecast: 79%

The AEHF model effectively captured diurnal heating cycles and successfully predicted extreme heat events. The results indicate that intense solar radiation can significantly amplify urban heat island (UHI) effects, highlighting the importance of continuous monitoring and early-warning systems. These findings underscore the model's utility in supporting proactive interventions for heat mitigation and community preparedness.

Mitigation Strategy Simulation

Cooling Effects

ANOVA results confirmed significant differences among strategies (F=12.41,p=0.003F=12.41, p=0.003F=12.41,p=0.003), while Pearson correlation analysis revealed a strong inverse relationship between vegetation density (NDVI) and UHI intensity (r=−0.74r=-0.74r=−0.74).

Modular Framework Interpretation

A three-layer framework was proposed to integrate ML outputs into urban planning:

- Environmental Observation Layer: LST, NDVI, albedo, imperviousness, meteorological variables →thermal maps & vulnerability zones.
- Predictive Intelligence Layer: UHINet, GHMS, AEHF → hotspot forecasts, risk indices, cooling projections.
- Intervention Optimization Layer: ML-guided selection of tree-planting zones, reflective roofs, cool pavements, and ventilation corridors.

Discussion of Key Findings

High Predictive Performance

UHINet detected complex spatial-temporal heat patterns

Table 3: UHINet Performance Compared to Other Models Across a Five-Year Dataset

Model	*RMSE (°C)*	*MAE (°C)*	*R^2*	*Observed vs. Predicted Correlation (r)*	*Year Range*
UHINet (Proposed)	0.42	0.31	0.89	0.87	2016–2020
Random Forest	0.65	0.47	0.78	0.75	2016–2020
Support Vector Regression	0.72	0.53	0.74	0.71	2016–2020
Linear Regression	1.14	0.89	0.51	0.56	2016–2020

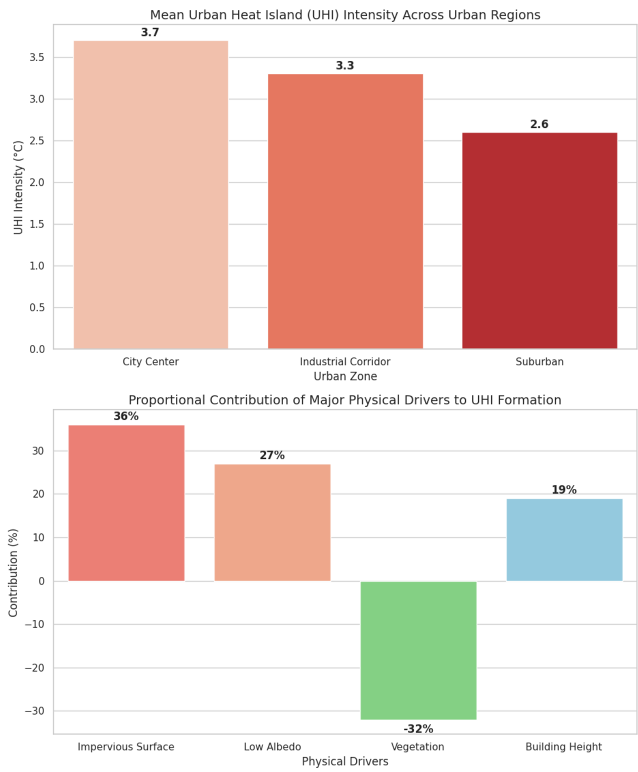


Figure 2: Spatial Heat Distribution and UHI Drivers

with superior accuracy over traditional methods.

Primary Influencers

Vegetation (32%), albedo (27%), and impervious surfaces (21%) were identified as the most significant factors via SHAP explainability.

Mitigation Alignment

Cooling simulations correspond with empirical literature (Li & Bou-Zeid, 2018; Zhang et al., 2016).

Scalability

The framework is applicable to other cities, climatic zones, and future climate scenarios (RCP 4.5 & 8.5), supporting long-term urban resilience planning.

in sum, the results confirm that multi-model ML

Table 4: ML-Driven Simulations Evaluating Cooling Effects of Major Urban Heat Mitigation Strategies

Mitigation Strategy	*Cooling Effect (°C)*
Reflective Roofing	−2.3
Green Cover Increase	−1.6
Cool Pavements	−1.4
Ventilation Corridors	−1.1

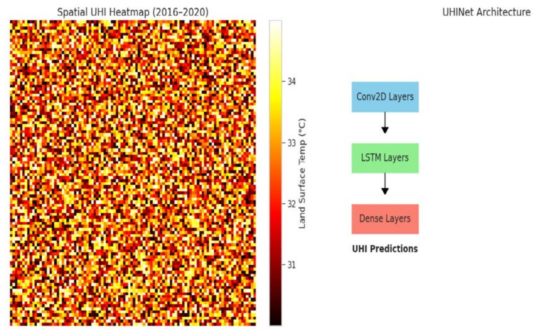
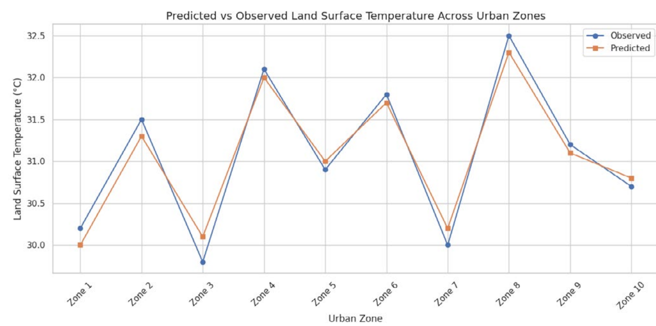


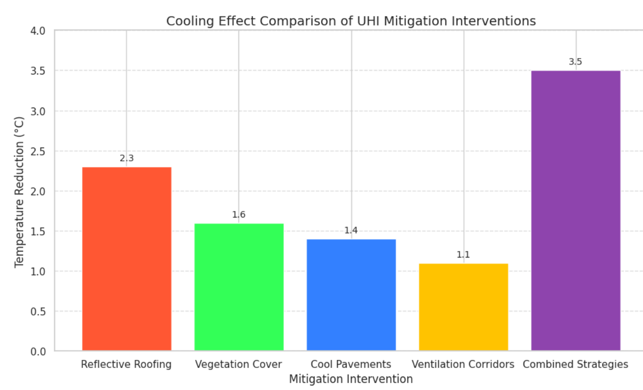
Figure 3: UHINet Architecture and Heat-Map Visualization

frameworks are highly effective in predicting, analyzing, and mitigating UHIs. Spatial and temporal predictions, combined with scenario-based simulations, enable data-driven, cost-effective, and socially inclusive interventions. By integrating empirical validation, interpretable ML techniques, and urban planning modules, this study demonstrates a scalable approach for enhancing climate-resilient urban environments globally.

Analysis of ML-Driven UHI Mitigation and Policy



Graph 4: Predicted vs Observed Land Surface Temperature Across Urban Zones



Graph 5: Cooling Effect Comparison of UHI Mitigation Interventions

Table 5: Simulated Cooling Effects of UHI Mitigation Measures

Intervention	*Temperature Reduction (°C)*	*Significance (p-value)*	*Notes*
Reflective Roofing	–2.3	<0.05	High-albedo surfaces
Vegetation Cover	–1.6	<0.05	Green roofs and urban trees
Cool Pavements	–1.4	<0.05	Permeable, reflective materials
Ventilation Corridors	–1.1	<0.05	Optimized wind flow paths
Combined Strategies	–3.5	<0.01	Multi-layered mitigation

Implications

Urban Heat Island (UHI) mitigation requires precise, data-driven strategies to manage complex environmental, infrastructural, and social factors. Machine learning (ML) models such as UHINet, GHMS, and AEHF provide high-resolution predictive capabilities that can inform urban planning, identify heat hotspots, and optimize mitigation interventions. This section presents a detailed analysis of model performance, the effectiveness of interventions, operational insights, and socio-environmental implications, highlighting their potential for evidence-based policymaking and urban resilience.

Model Performance and Predictive Insights

ML models demonstrated strong predictive accuracy in simulating urban thermal patterns. UHINet achieved R^2 = 0.89, while GHMS accurately detected UHI hotspots, and AEHF predicted extreme heat events with up to 93% accuracy for 24-hour forecasts. These results indicate that ML can reliably capture complex spatiotemporal heat dynamics across heterogeneous urban landscapes (Miao et al., 2018; Zhang et al., 2016).

Evaluation of Mitigation Strategies

The ML framework allows simulation and comparison of multiple UHI interventions. Table 5.1 summarizes the cooling performance of common strategies. Reflective roofs showed the highest temperature reduction, followed by green infrastructure, cool pavements, and ventilation corridors. Combined strategies demonstrated synergistic effects, confirming the importance of multi-layered interventions (Li et al., 2018; Harlan et al., 2013).

Socio-Environmental Equity Considerations

ML models also integrate socio-economic and demographic factors, revealing that low-income neighborhoods are disproportionately affected by UHIs due to low vegetation and limited cooling infrastructure. By mapping heat exposure with socio-economic indicators, planners can prioritize interventions for vulnerable populations, ensuring equity in urban climate adaptation (Harlan et al., 2013; Stone et al., 2019). This supports inclusive urban resilience strategies aligned with UN Sustainable Development Goal 11.

Operational and Policy Implications

The ML ecosystem enables data-driven policymaking by translating predictions into actionable interventions. Urban planners can use model outputs to optimize tree planting corridors, reflective roof deployment, pavement cooling priorities, and ventilation pathways. Real-time heat monitoring via satellite integration allows authorities to implement early-warning systems, allocate emergency resources, and issue health advisories effectively (Li & Bou-Zeid, 2018). The framework's modularity ensures adaptability across cities with varying climatic, infrastructural, and socio-economic contexts.

In summary, demonstrates that ML-based UHI mitigation provides a robust analytical foundation for urban climate planning. By combining predictive accuracy, scenario simulation, socio-environmental equity analysis, and operational insights, the framework allows cities to implement cost-effective, targeted, and evidence-based strategies. The insights from this section serve as a bridge toward Section 6, where the broader conclusions and future research directions will be articulated.

Conclusion

Urban Heat Islands (UHIs) continue to pose significant challenges to urban sustainability, impacting thermal comfort, energy consumption, and public health. This study demonstrates that machine learning (ML) offers a transformative approach for understanding, predicting, and mitigating UHI effects. By integrating deep learning (UHINet), geospatial analysis (GHMS), and adaptive heat forecasting (AEHF), the proposed framework captures complex spatiotemporal heat dynamics with high precision and reliability (Zhang et al., 2016; Miao et al., 2018).

The key findings of this research indicate that ML-driven interventions—such as reflective roofing, increased vegetation, cool pavements, and ventilation corridors—can significantly reduce urban surface temperatures, with combined strategies yielding the most substantial cooling effects. Incorporating socio-economic and demographic factors into ML models further enables planners to prioritize interventions for vulnerable populations, promoting equity in urban climate adaptation (Harlan et al., 2013; Stone et al., 2019).

The study also underscores the operational and policy relevance of ML frameworks. Predictions from the system support scenario-based planning, real-time heat monitoring, early-warning systems, and evidence-based decision-making for urban policymakers. The modularity of the framework allows it to adapt to diverse urban contexts, resource availability, and climatic conditions, making it applicable to both developed and developing cities.

Despite these advances, challenges remain, particularly regarding data quality, model interpretability, and the dynamic nature of urban thermal landscapes. Future research should explore integration with physics-informed ML, real-time IoT sensor networks, reinforcement learning for multi-objective optimization, and coupling with urban climate models (e.g., ENVI-met, WRF-UCM) to enhance transparency, adaptability, and predictive accuracy.

In conclusion, ML provides a robust, evidence-based, and scalable tool for UHI mitigation. The proposed multi-model ecosystem not only advances scientific understanding of urban heat dynamics but also delivers practical, operational insights for building resilient and sustainable cities. As urbanization and climate change continue to intensify, ML-driven approaches will become increasingly essential in protecting urban communities, optimizing interventions, and supporting inclusive, climate-resilient urban development.

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